A Novel Radio Resource Optimization Scheme in Closed Access Femtocell Networks Based on Bat Algorithm

I Wayan MUSTIKA[†a)], *Member*, Nifty FATH[††], Selo SULISTYO[†], *Nonmembers*, Koji YAMAMOTO[†††], *and* Hidekazu MURATA[†††], *Senior Members*

SUMMARY   Femtocell has been considered as a key promising technology to improve the capacity of a cellular system. However, the femtocells deployed inside a macrocell coverage are potentially suffered from excessive interference. This paper proposes a novel radio resource optimization in closed access femtocell networks based on bat algorithm. Bat algorithm is inspired by the behavior of bats in their echolocation process. While the original bat algorithm is designed to solve the complex optimization problem in continuous search space, the proposed modified bat algorithm extends the search optimization in a discrete search space which is suitable for radio resource allocation problem. The simulation results verify the convergence of the proposed optimization scheme to the global optimal solution and reveal that the proposed scheme based on modified bat algorithm facilitates the improvement of the femtocell network capacity.

key words: heterogeneous network, macrocell, femtocell, resource allocation, optimization, bat algorithm, interference management

1.   Introduction

The communication systems have developed very rapidly, especially for mobile communication systems. Mobile communication systems are becoming more popular because of the flexibility and mobility aspects which revolutionized the way people communicate. The evolution of mobile technology has led to a tremendous increase in mobile data usage. Wireless usage study reports that more than 50% of all voice calls and more than 70% of data traffic originates indoors [1].

Data networks require much higher signal quality than voice networks since the required data rate increases. For data traffic originates indoor, wall penetration loss will make high signal attenuation and thus becomes a weak point of cellular coverage [2]. A new way of thinking leads to the conclusion that it is essential to shrink the cell size to enable short-range and low power link from BS to end users. Thus, the cell coverage and network capacity can be increased [3].

Femtocell is considered as a key promising technology to cope with tremendous traffic growth. This technology is

convinced as a win-win solution between the user and mobile operator. For the user, higher received signal strength and saver phone battery can be achieved because of the reduced distance between the base station and user, which leads to the full speed data transfer. Besides, mobile operator will be able to reduce the amount of traffic from the macrocell network and increase the network capacity [4].

In 3GPP LTE terminology, femto BS is known as home eNB (HeNB). By deploying femto BS, indoor users can get high-quality wireless data connection. Femtocell has been extensively used in many wireless communication standards, e.g., LTE and LTE-Advanced which use orthogonal frequency-division multiple access (OFDMA) [5]. Access modes in femtocell are classified as open access and closed access. In the open access mode, a non-subscriber group which means any user is allowed to connect to HeNB, while in the closed access mode, only a subscriber group is permitted to access HeNBs. The closed access femtocell is more favorable in indoor environments because the femtocell subscribers can receive maximal advantages from the HeNBs [6]. HeNBs that are deployed inside a macrocell coverage form a heterogeneous network (HetNet) as shown in Fig. 1.

Spectrum resource allocation in HetNet can be classified into two categories: spectrum sharing and spectrum splitting. For the former approach, the spectrum is shared among the two tiers whereas the latter is already dedicated to each tier [7]. In a two-tier cellular network, the sharing spectrum approach is generally preferred than splitting spectrum between tiers which yields maximization of spectrum utilization. However, the system performance could be severely degraded due to excessive cross- and co-tier interference if the spectrum resource is not properly managed.
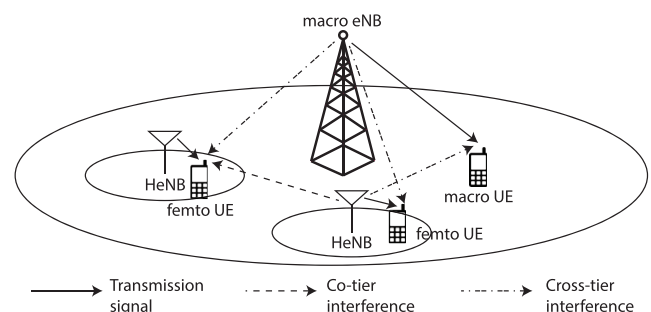

Fig. 1   A heterogeneous network.

Radio resource optimization using nature-inspired metaheuristic algorithms has raised a lot of interest recently due to its properties in using specific behavior of a living thing to formulate the key updating strategies. Swarm intelligence based algorithm is a population-based method where each entity interacts with its environment to produce global functional patterns. For instance, particle swarm optimization (PSO) which is based on the swarming behavior of bird and fish, bat algorithm which is inspired by the behavior of bats in searching for prey, and ant colony optimization (ACO) which is inspired by the behavior of real ants in searching for food [8].

Among these optimization algorithms, bat algorithm has gained popularity due to its simplicity and robustness. It is state-of-the-art and superior metaheuristic algorithm for solving the global optimization problem where the simplicity and flexibility of this algorithm are the key advantages [29], [30]. Bat algorithm is inspired by the echolocation process of bats, especially microbats. They emit a very loud sound pulse then listen to sound pulse bounces back from the surrounding object around the bats. The main key to this algorithm is to control loudness and pulse emission rates of bats while searching for prey. Thus, the balance between diversification and intensification during the search process can be achieved [30].

Bat algorithm is initially designed to solve a continuous problem. However, radio resource allocation problem deals with a discrete solution. Therefore, the original bat algorithm cannot be directly applied to solve the discrete problem. The major contribution of this paper is two folds. First, propose a novel scheme for resource allocation in femtocell network based on bat algorithm. In this scheme, solution matrix for resource block allocation is introduced at the time of initialization of bat population. Second, modify the original bat algorithm to adapt to the discrete domain, i.e., resource allocation problem. Specifically, nearest integer method is proposed for updating strategy of bat algorithm during diversification and intensification search.

The remainder of this paper is organized as follows. In Sect. 2, an overview of the related work on resource optimization in heterogeneous network is presented. The system model of a heterogeneous network is described in Sect. 3. Section 4 presents the proposed radio resource optimization scheme based on modified bat algorithm. The evaluation of the effectiveness of the proposed algorithm is described in Sect. 5. Finally, conclusions of this paper are remarked in Sect. 6.

2. Related Work

There has already been much work that put emphasis on solving the resource optimization problem in the heterogeneous network. In [9], a technique based on sequential quadratic programming (SQP) has been proposed to optimize the rate and transmit power in OFDMA femtocells. In [10], an iterative algorithm based on geometric programming for the joint allocation of subchannels and transmit powers in OFDMA femtocells has been shown to converges to some local maximum solution. In [11], an iterative algorithm based on Chemical-reaction optimization is proposed to solve the energy efficiency problem. In [12], [13], a resource optimization problem to maximize the achievable system rate with predefined locations of pico base station (BS) and optimal pico BS deployment was considered. Energy efficiency optimization problem for two-tier macrocell/femtocell networks by considering transmit beamforming design and power allocation policies has been addressed in [14]. The problem of efficient power control and coverage management in two-tier macrocell/femtocell networks is investigated in [15]. In [16], a mixed-integer programming problem is used to tackle the subchannel and power allocation problem with multiple constraints in OFDMA cognitive femtocells. A novel resource allocation algorithm based on clustering for the closed access femtocell has been proposed in [17]. Most conventional optimization algorithms proposed in [9]–[17], can be classified as deterministic algorithms.

Metaheuristic algorithms, which is a type of stochastic algorithms, uses a certain randomness and local search. Nature-inspired metaheuristic algorithms have been found in literatures, e.g., Cuckoo search, PSO, ACO, genetic algorithm (GA), etc. A resource allocation technique based on Cuckoo search in an OFDMA-LTE system has been proposed in [18]. The proposed technique aims to mitigate the cross-tier interference. In [19], a multi-objective optimization of spectrum sharing based on gradient-based and GA is investigated. Spectrum partitioning approach based on GA which aims to maximize the system throughput is studied in [20], without considering interference mitigation. In [21], interference mitigation is investigated by setting the interference threshold equal to the system noise. In [22], the authors demonstrated that resource optimization could be achieved by maximizing the minimum throughput of the femtocells. The sub-channel allocation algorithm based on ACO is studied in [23] where the goal is to maximize the total sum rate of multiple femto UEs. ACO optimization algorithm for resource block allocation and mobility optimization is also proposed in [24] and [25], respectively. Simulated annealing based meta-heuristic for resource allocation in static and dynamic network is introduced in [26]. In [27], cell and resource block allocation based on Bacterial Foraging Optimization algorithm has been proposed to reduce the power consumption of the femtocell network. Our preliminary study in [28] shows that the modified bat algorithm minimizes the cross- and co-tier interference of the femtocell networks.

3. System Model

The network under consideration consists of macrocells and femtocells. Femtocells are deployed inside an apartment block which is arranged in a 5×5 grid. As shown in Fig. 2, femtocell deployment conforms to the 3GPP simulation scenario for urban deployment.
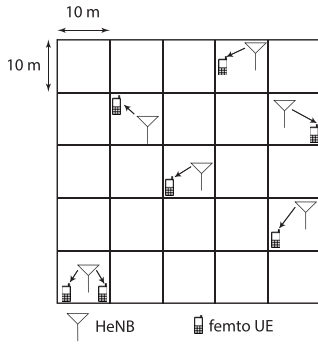
Fig. 2 Femtocell deployment in 5×5 grid model.

3.1 Antenna Pattern

A macrocell is typically partitioned into three 120° sectors or six 60° sectors to minimize the co-channel interference and to improve the capacity. Based on the 3GPP specification [5], a macrocell is divided into three sectors cell sites with fixed sectorized antenna pattern. The horizontal antenna pattern for each sector $A_{\mathrm{H}}(\theta)$ is described by

$$A_{\mathrm{H}}(\theta) = -\min\left[12\left(\frac{\theta}{\theta_{3\,\mathrm{dB}}}\right)^2, A_{\mathrm{m}}\right], \qquad (1)$$

where $-180 \le \theta \le 180$ is the horizontal angle relative to the central antenna lobe. The maximum possible attenuation due to sectorization is denoted by A_{m}.

The total gain of macro eNB antenna in each sector can be calculated as

$$G_{\mathrm{H}}(\theta) = G_{\max} + A_{\mathrm{H}}(\theta), \qquad (2)$$

where $G_{\max}$ is the maximum macrocell BS antenna gain (in dBi). A typical value of $G_{\max}$ for macrocell is 14 dBi.

3.2 Path-Loss Calculation

The path-loss and shadowing are calculated using macro and femto path-loss equation as described below [5].

1. Path-loss (PL) from macro eNB to macro UE (MUE)
   The MUE might be located in outdoor or indoor. Thus, the calculation of path-loss from macro eNB to MUE can be classified to path-loss from macro eNB to MUE indoor and macro eNB to MUE outdoor, given by Eqs. (3) and (4), respectively

   $$PL[\mathrm{dB}] = 128.1 + 37.6\log_{10} d_{\mathrm{m}}[\mathrm{km}] + L_{\mathrm{w}} + X_{\sigma_{\mathrm{M}}}, \quad (3)$$
   $$PL[\mathrm{dB}] = 128.1 + 37.6\log_{10} d_{\mathrm{m}}[\mathrm{km}] + X_{\sigma_{\mathrm{M}}}, \qquad (4)$$

   where L_{w} in Eq. (3) indicates the presence of wall penetration loss.

2. Path-loss from HeNB to MUE
   The MUE might be located in the same, different, or outside the apartment block. The calculation of each condition is respectively given by

$$PL[\mathrm{dB}] = 127 + 30\log 10 d_{\mathrm{m}}[\mathrm{km}] + X_{\sigma_{\mathrm{F}}}, \qquad (5)$$
$$PL[\mathrm{dB}] = 127 + 30\log 10 d_{\mathrm{m}}[\mathrm{km}] + 2L_{\mathrm{w}} + X_{\sigma_{\mathrm{F}}}, \quad (6)$$
$$PL[\mathrm{dB}] = 127 + 30\log 10 d_{\mathrm{m}}[\mathrm{km}] + L_{\mathrm{w}} + X_{\sigma_{\mathrm{F}}}, \quad (7)$$

where $X_{\sigma_{\mathrm{F}}}$ denotes the femtocell shadowing standard deviation.

3. Path-loss from HeNB to femto UE (FUE)
   The path-loss calculation between HeNB and FUE in the same grid and different grid can be respectively expressed as

$$PL[\mathrm{dB}] = 127 + 30\log 10 d_{\mathrm{m}}[\mathrm{km}] + X_{\sigma_{\mathrm{F}}}, \qquad (8)$$
$$PL[\mathrm{dB}] = 127 + 30\log 10 d_{\mathrm{m}}[\mathrm{km}] + L_{\mathrm{w}} + X_{\sigma_{\mathrm{F}}}. \quad (9)$$

4. Path-loss from macro eNB to FUE
   The FUE is always located in indoor apartment block. Thus, the wall penetration loss always occurs. The calculation of path-loss from macro eNB to FUE is given by

$$PL[\mathrm{dB}] = 128.1 + 37.6\log 10 d_{\mathrm{m}}[\mathrm{km}] + L_{\mathrm{w}} + X_{\sigma_{\mathrm{M}}}. \quad (10)$$

3.3 Problem Formulation

In this work, the LTE technology which uses OFDMA is considered. The system bandwidth in OFDMA is typically divided into K resource blocks (RBs). For the sake of simplicity, perfect synchronization in OFDMA is assumed. Under this assumption, the interference to the associating UE occurs when the base station in other cells transmit using the same RB.

The major goal of this research is to improve the femtocell network capacity by minimizing the cross- and co-tier interference. This can be achieved by allocating the resources optimally among FUEs. The RB allocation for all FUEs can be represented by an $F \times H$ of matrix S, where F is the number of HeNB-FUE pairs and H is the number of elements of the subset of RBs. Each column of matrix S represents the subset of RBs, $s_u = \mathcal{R}_u \in \mathcal{S}_u$, where $s_u = \left(c_u^{(1)}, c_u^{(2)}, \ldots, c_u^{(H)}\right) \in \mathcal{S}_u$ is a subset of RBs allocated by HeNB to its corresponding FUE u and $H = |\mathcal{R}_u|, \forall u \in \mathcal{F}$. It is assumed that H is predefined at initial assignment. The subset of RBs is represented in integer domain.

It is assumed that each FUE utilizes the same number of elements in the subset of RBs. Once allocated, these RBs will be occupied at all the time by the HeNB to support its associated FUE. The same scheme of RB allocation is applied to the MUE. Therefore, the following assumptions are considered:

1. Each FUE u and MUE m is associated only with one HeNB and macro eNB, respectively.
2. The number of utilized RBs in each HeNB and macro eNB should be less than or equal to the maximum number of the available RBs.
3. Transmit power per RB is fixed for all HeNBs and macro eNBs.

4. Resource Allocation Using Bat Algorithm

4.1 Bat Algorithm Overview

The main idea of bat algorithm is based on echolocation behavior of bats, especially microbats. Microbats use echolocation, which is one type of sonar. These microbats emit a very loud sound pulse, and they listen to sound pulse bounces back from the surrounding object around the bats. The time between emission and detection echo is called as time delay. Based on the time delay, they can detect distance and orientation of the target, locate their prey, and avoid surrounding obstacles in the dark [30].

Bats fly randomly at position x_i with velocity v_i. The emitting sound pulse has a fixed frequency f_{min} with varying wavelength λ and loudness A_0 for searching the target. The pulse emission rate ($r \in [0, 1]$) and frequency can be automatically adjusted, according to the proximity of their target. The solutions which represent the velocities v_i^t and positions, x_i^t at time step t for the i-bat are given by

$$f_i = f_{min} + (f_{max} - f_{min})\beta, \qquad (11)$$

$$v_i^t = v_i^{t-1} + (x_i^t - x_{gbest})f_i, \qquad (12)$$

$$x_i^t = x_i^{t-1} + v_i^t, \qquad (13)$$

where $\beta \in [0, 1]$ is a uniformly distributed random vector and x_{gbest} represents the current selected global best solution. The intensification search in the original bat algorithm uses a random walk method as defined below.

$$x_{new} = x_{old} + \varepsilon A^t, \qquad (14)$$

where $\varepsilon[1,-1]$ is a uniformly distributed random number and $A^t = \langle A_i^t \rangle$ is the average loudness of all bats at the t-th time step in [30]. As the bat position is getting closer to the target, the loudness decreases; varies from a large (positive) A_0 to a minimum constant value A_{min}, and the rate of pulse emission, denoted by r, increases. Therefore, when the new solution is obtained according to Eq. (14), the loudness and pulse rate will be updated using the equations below.

$$A_i^{t+1} = \alpha A_i^t, \qquad (15)$$

$$r_i^{t+1} = r_i^0[1 - \exp(-\gamma t)]. \qquad (16)$$

For any $0 < \alpha < 1$ and $\gamma > 0$, pulse rate and loudness will converge to a fixed value as shown below.

$$A_i^t \to 0 \text{ and } r_i^t \to r_i^0, \text{ as } t \to \infty. \qquad (17)$$

However, setting the pulse rate into $r_i = 1$ and loudness into $A_i = 0$, the bat algorithm becomes the standard PSO algorithm. The updating process of the positions and velocities of bats also has some similarity with the PSO algorithm [31]. The bat algorithm can be regarded as a combination of the original PSO algorithm with intensive local search controlled by the loudness and pulse rate.

The convergence of the bat algorithm can be controlled by adjusting the parameters α and γ. Thus, the closeness of

the fitness to the global optimal solution can be controlled by the loudness and pulse rate.

4.2 Modification of Bat Algorithm

4.2.1 Bats Position

The main issue in modifying the bat algorithm is designing representation formulation which aims at finding an appropriate mapping between candidate solution and virtual bats. In this work, a straightforward representation is used where the elements of each solution are encoded in a $F \times 1$ matrix. The matrix is called position matrix of bat population i, X_i^t. The position matrix of the bat population represents the RB allocation candidate for all FUEs. Each vector $\bar{x}_u$ represents the subset of selected RBs for FUE u which is represented in a $F \times H$ matrix as shown below.

$$X_i^t = \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \\ \vdots \\ \bar{x}_F \end{bmatrix} = \begin{bmatrix} c_1^{(1)} & c_1^{(2)} & \cdots & c_1^{(H)} \\ c_2^{(1)} & c_2^{(2)} & \cdots & c_2^{(H)} \\ \vdots & \vdots & \vdots & \vdots \\ c_F^{(1)} & c_F^{(2)} & \cdots & c_F^{(H)} \end{bmatrix}.$$

Figure 3 shows an example of solution representation in a resource allocation problem with 3 FUEs and 5 RBs are allocated for each FUE. This solution indicates that FUEs FUE_1, FUE_2, and FUE_3 are assigned a subset of RBs {1, 3, 4, 8, 9}, {2, 6, 7, 10, 12}, and {5, 11, 13, 14, 15}, respectively. According to Fig. 3, the dimension matrix of virtual bats D_{bats} is

$$D_{bats} = F \times H. \qquad (18)$$

4.2.2 Bats Velocity

The velocity of each bat is represented as a $F \times 1$ matrix, called velocity matrix V_i^t. Each vector $\bar{v}_u$ represents the velocity of each element in a subset RBs of each FUE. The velocity matrix is represented in a $F \times H$ matrix as shown below.

$$V_i^t = \begin{bmatrix} \bar{v}_1 \\ \bar{v}_2 \\ \vdots \\ \bar{v}_F \end{bmatrix} = \begin{bmatrix} v_1^{(1)} & v_1^{(2)} & \cdots & v_1^{(H)} \\ v_2^{(1)} & v_2^{(2)} & \cdots & v_2^{(H)} \\ \vdots & \vdots & \vdots & \vdots \\ v_F^{(1)} & v_F^{(2)} & \cdots & v_F^{(H)} \end{bmatrix}.$$

4.2.3 Bats Updating Strategy Using Nearest Integer

Bat algorithm has been widely applied to solve continuous

	$c^{(1)}$	$c^{(2)}$	$c^{(3)}$	$c^{(4)}$	$c^{(5)}$
FUE_1	1	3	4	8	9
FUE_2	2	6	7	10	12
FUE_3	5	11	13	14	15

Fig. 3 Example of solution matrix.

problems. However, the radio resource allocation problem deals with selecting the most appropriate RBs where the candidate solution is in a discrete search space. Therefore, it is essential to modify the original bat algorithm formulation to address the resource allocation problem. We propose the nearest integer method to discretize the solution. The velocity update and random walk in Eqs. (12) and (14), respectively, are modified as follows

$$v_i^t = \text{round}(\omega v_i^{t-1} + (x_i^t - x_{\text{gbest}})f_i), \tag{19}$$

$$x_{\text{new}} = x_{\text{old}} + \text{round}(\varepsilon A^t). \tag{20}$$

The notation of ω, which is adopted from the PSO algorithm with intertia weight, aims to avoid too drastic change of velocity by

$$\omega = \omega_{\text{max}} - \frac{\omega_{\text{max}} - \omega_{\text{min}}}{t_{\text{max}}} t, \tag{21}$$

where ω_{max} and ω_{min} are set to 0.9 and 0.4, respectively. During the generation of position matrix or random walk, if two or more elements in the column of position matrix have an identical index number of elements, then the RB which corresponds to these elements is changed by generating a new random number. In practice, this implementation is reasonable in the sense that the FUE cannot be allocated the same index number of elements in its subset of selected RBs.

4.2.4 Fitness Evaluation

Minimizing the cross- and co-tier interference in the femtocell networks is the objective of the proposed optimization algorithm. Thus, the fitness function of each solution can be formulated as

$$P_u = \sum_{x=1}^{H} \left[\sum_{y=1}^{H} \left(\sum_{b=1, b \neq u}^{F} G_{ub}^{\text{B}} p_b^{\text{B}} \delta_{c_u^{(x)}} \delta_{c_b^{(y)}} \right) \right.$$
$$\left. + \sum_{z=1}^{L} \left(\sum_{m=1}^{M} G_{um}^{\text{M}} p_m^{\text{M}} \delta_{c_m^{(z)}} \delta_{c_u^{(x)}} \right) \right], \tag{22}$$

where G_{ub}^{B} and G_{um}^{M} represent the channel gain between HeNB b to the FUE u and channel gain between macro eNB that serves the MUE m to FUE u, respectively. p_b^{B} represents the transmit power of HeNB b in each RB, and p_m^{M} denotes the transmit power of macro eNB M in each RB. $\delta_{c_u^{(x)} c_b^{(y)}}$ is the Kronecker delta function that represents whether or not the elements of the subset of RBs allocated to FUE u and FUE b are the same: if $c_u^{(x)} = c_b^{(y)}$, $\delta_{c_u^{(x)} c_b^{(y)}} = 1$; otherwise, $\delta_{c_u^{(x)} c_b^{(y)}} = 0$. x and y are the index of elements of subset of RBs that is allocated to FUE u and b, respectively. z is the index of elements of subset of RBs that is allocated to MUE m and M is the total number of MUEs in the central macrocell site.

From Eq. (22), the formulation of the fitness function in the proposed optimization algorithm aims to minimize the

cross- and co-tier interference by finding the most appropriate RBs to each FUE. Thus, the total fitness can be defined as the sum of the fitness value of all FUEs in the population.

Since the proposed optimization algorithm is considered as a centralized approach, we assume that the algorithm is implemented in a central coordinator. We further assume that the central coordinator has perfect knowledge of the channel quality of each FUE. In the practical implementation, each UE reports the channel quality in each selected RBs to the central controller through a common control channel. During the execution of the algorithm, central coordinator requests all HeNBs to update the RBs allocation to its corresponding FUEs.

4.3 Pseudocode of Modified Bat Algorithm

The pseudocode of the proposed bat algorithm is described below.

1. Assume the number of bats population is N. The bigger number of N leads to the longer computation, while the smaller number of N affects the successful chance of finding the optimal solution.
2. Initialize the parameter's values below:

   - Initialize pulse frequency $\left(f_1^0, f_2^0, \ldots, f_N^0\right)$ to zero
   - Initialize velocity $\left(V_1^0, V_2^0, \ldots, V_N^0\right)$ to zero
   - Randomize initial position X_i^0
   - Randomize pulse rate $\left(r_1^0, r_2^0, \ldots, r_N^0\right)$
   - Randomize loudness $\left(A_1^0, A_2^0, \ldots, A_N^0\right)$

3. Calculate the total fitness in the population based on Eq. (22). The fitness values of all bat populations are defined as a vector of $\left\{P(X_1^0), P(X_2^0), \ldots, P(X_N^0)\right\}$. Since the objective of this work is global minimization, select the minimal value of the fitness from the population and record the solution as the current global best solution X_{gbest}.
4. Set the iteration step to $t = 1$.
5. For the bat $i \in 1, 2, \ldots, N$, do the steps 6–12.
6. Update the pulse frequency, velocity, and position of each bat with Eqs. (11), (19), and (13), respectively.
7. Record the updated position.
8. Check each element of the updated position whether it meets the given constraint by applying a simple boundary scheme. For example, the updated position should lie between 0 to 49 since the number of available RBs is 50.
9. Evaluate each element of the updated position whether there are any same number of RB in each FUE. For example, the HeNB 1 assigns a subset of RBs $\left\{c_u^1, c_1^2, c_1^3, c_1^4, c_1^5\right\} = (2, 8, 10, 10, 20)$ to FUE 1. The number of $c_1^3 = c_1^4$ is practically not allowed. Thus, the number of c_1^4 should be changed by regenerating a random value.
10. Do the intensification search for each bat using the proposed random walk. The intensification search is pro-

cessed if meet the following condition: $\left(\text{rand}() > r_i^1\right)$. The execution of local search is computed using Eq. (20).

11. Update the new solution if the fitness value of the new solution obtained from the intensification step is higher than the fitness value of the local solution

12. Perform a diversification process if meet both conditions: $\text{rand}() < A_i^t$ and $P(X_{\text{gbest}}) < P(X_{\text{new}})$. If the new solution is better than X_{gbest}, accept the new solution as a new X_{gbest}. In this step, increase the pulse rate r_i^1 and reduce the loudness A_i^1 using Eqs. (16) and (15), respectively.

13. Update the X_{gbest} and record $P(X_{\text{gbest}})$.

14. Increase the iteration step $t = t + 1$ and return to the step 5. The iteration will be terminated if meets the stopping criteria.

5. Performance Evaluation

5.1 Simulation Scenario and Parameters

The network topology under consideration consists of macrocells and femtocells. The cellular layout of macrocell network consists of 19 cell sites as shown in Fig. 4. MUEs are randomly generated in each sector of macrocells, and each MUE can be located either outdoor or indoor. During the network setup, each HeNB assigns a random subset of RBs to its corresponding FUE. It is assumed that the macro eNB allocates the subset of RBs to its corresponding MUE in such a way that the co-tier interference between macrocells is minimized. All of MUEs are assumed to be always connected to the macro eNB. Log-normal shadowing is considered in the simulation, while the effect of fast fading is eliminated since all UEs are stationary. Table 1 summarizes the other relevant parameters used in the simulation.

5.2 Convergence Analysis

The behavior of HeNB-FUE pair in optimizing their fitness value using bat algorithm depends on two essential parameters: loudness (A) and pulse rate (r), which control the diversification and intensification in the searching process. The loudness and pulse rate are updated accordingly as the iterations proceed using parameters α and γ, respectively. For the sake of simplicity, we set $\alpha = \gamma$.

Four scenarios are considered in analyzing the convergence behavior of the proposed algorithm under the parameters $\alpha = \gamma = 0.9$, $\alpha = \gamma = 0.8$, $\alpha = \gamma = 0.7$, $\alpha = \gamma = 0.6$, and $\alpha = \gamma = 0.5$. These scenarios are also considered as a simple benchmark of the proposed algorithm. When the subset of RBs is appropriately assigned to each FUE, there will be no interference among femtocells. Thus, the global best solution can be easily predicted when the fitness value is zero.

1) Scenario I

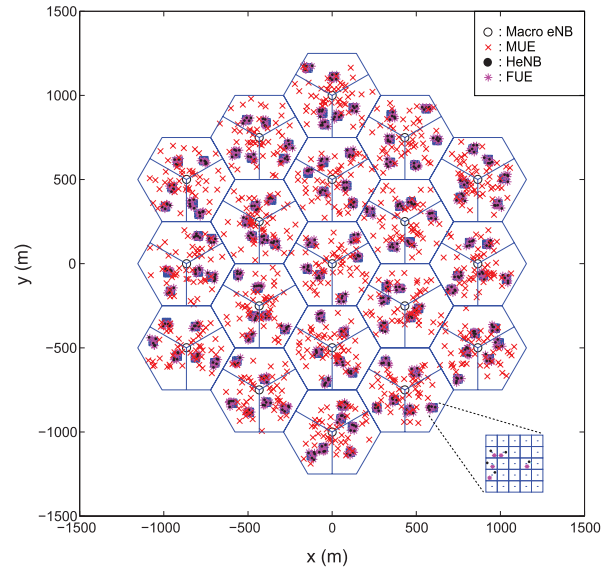In this scenario, there are 5 HeNBs in an apartment

Fig. 4 System model of macrocell-femtocell network.

Table 1 Simulation parameters.

Parameters	Value
Cellular layout of macrocell	Hexagonal grid, 19 cell sites
	3 sectors per site
Macrocell/femtocell radius	288.68 m (ISD = 500 m), 5 m
Shadowing standard deviation	8 dB (outdoor), 10 dB (indoor)
Wall penetration loss	20 dB
HeNB antenna	Omnidirectional
Antenna gain eNB	14 dBi (macro), 0 dBi (femto)
Antenna gain UE	0 dBi
Thermal noise density	−174 dBm/Hz
Number of UEs	10 MUEs/sector, 1 FUE/HeNB
System/RB bandwidth	10 MHz (System), 180 kHz (RB)
Number of available RBs	50
Carrier frequency	2 GHz
Traffic model	Full buffer

block and 10 available RBs, in which 2 RBs are allocated for each FUE. The result is shown in Fig. 5. From Fig. 5, it can be seen that the fitness value of the proposed algorithm that corresponds to the interference among femtocells reaches its minimum (interference = 0) when $\alpha = \gamma = 0.9$ and $\alpha = \gamma = 0.8$. The premature convergence occurs when $(\alpha = \gamma) < 0.8$.

2) Scenario II

Scenario II is evaluated under the following assumptions: 10 HeNBs in an apartment block and 10 available RBs, in which 1 RB is allocated for each FUE. The result is presented in Fig. 6. As shown in Fig. 6, the fitness value of the proposed algorithm reaches its minimum when $\alpha = \gamma = 0.9$ and $\alpha = \gamma = 0.8$ while the minimum fitness value could not be obtained when $(\alpha = \gamma) < 0.8$.
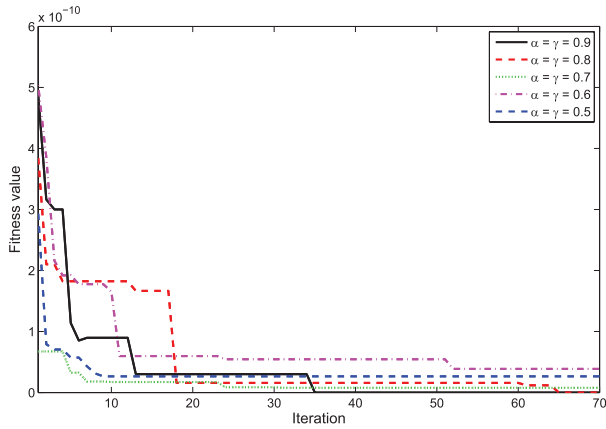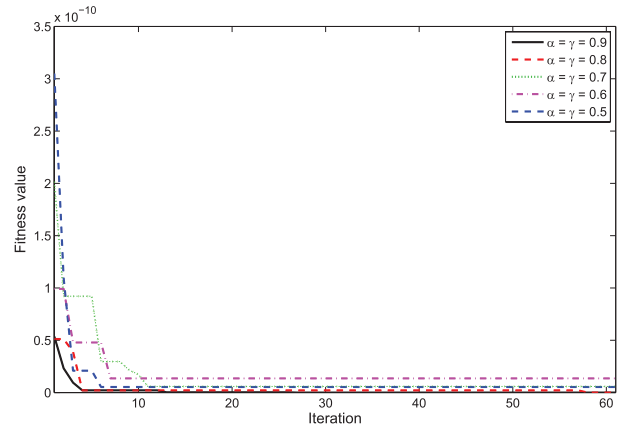
Fig. 5   Convergence analysis for scenario I.
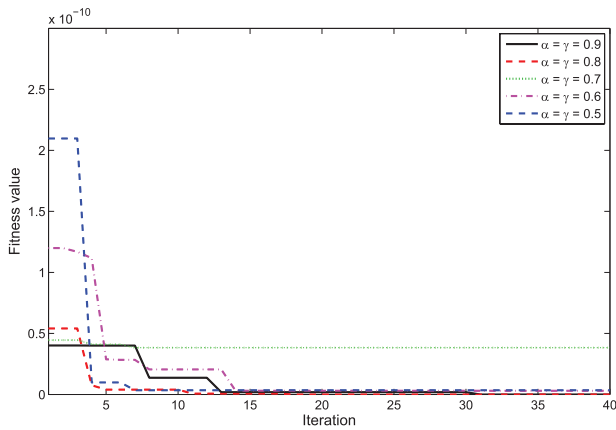

Fig. 6   Convergence analysis for scenario II.
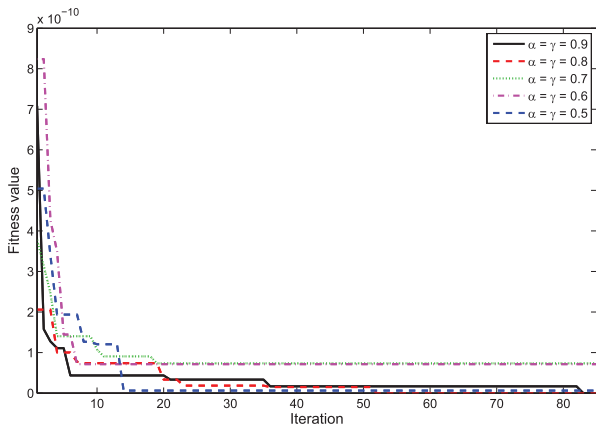

Fig. 7   Convergence analysis for scenario III.

Fig. 8   Convergence analysis for scenario IV.

Table 2   Parameters of the proposed algorithm.

Parameters	Value
Number of bat population	30
$f_{\min}$	0
$f_{\max}$	1
A_i^0	0.25
r_i^0	0.5
ε	[-1,1]
α	0.9
γ	0.9
Stopping criterion	Maximum iteration

Scenario IV is performed under the following assumptions: 6 HeNBs in an apartment block and 12 available RBs, in which 2 RBs are allocated for each FUE. From the result shown in Fig. 8, the fitness value of the proposed algorithm reaches its minimum when $\alpha = \gamma = 0.9$ and $\alpha = \gamma = 0.8$ while the minimum fitness value could not be reached when $(\alpha = \gamma) < 0.8$.

Figures 5–8 demonstrate that the proposed algorithm converges to the global optimal solution when $\alpha = \gamma = 0.9$ and $\alpha = \gamma = 0.8$. Setting $(\alpha = \gamma) < 0.8$ may lead to premature convergence where a sub-optimal solution could be obtained. Unless otherwise specified, the parameter of $\alpha = \gamma = 0.9$ are used in the evaluation of the proposed algorithm. The other parameters of the proposed algorithm are summarized in Table 2.

5.3   Effect of the Introduction of ω

In Sect. 4.2.3, ω is introduced in the proposed bats updating strategy with the aim to avoid drastic change of velocity. As can be observed from Fig. 9, omitting parameter ω leads to a drastic change of the velocity during velocity update which impacts the convergence speed of the proposed algorithm. Introducing ω in Eq. (19) apparently slows the convergence speed of the proposed algorithm with the benefit of higher
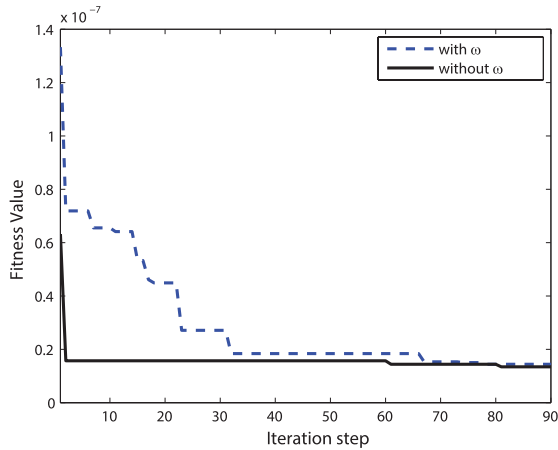
3) Scenario III

In Scenario III, there are 5 HeNBs in an apartment block and 15 available RBs, in which 3 RBs are allocated for each FUE. Based on the result as shown in Fig. 7, it can be seen that the fitness value of the proposed algorithm reaches its minimum when $\alpha = \gamma = 0.9$ and $\alpha = \gamma = 0.8$.

4) Scenario IV

Fig. 9   Convergence performance with and without ω.

Fig. 10   Convergence curve of the proposed algorithm.

Fig. 11   CDF throughput of FUEs.

Table 3   Parameters of DPSO.

Parameters	Value
Number of particles	30
c_1	2
c_2	2
ω_{max}	0.9
ω_{min}	0.4
Stopping criterion	Maximum iteration
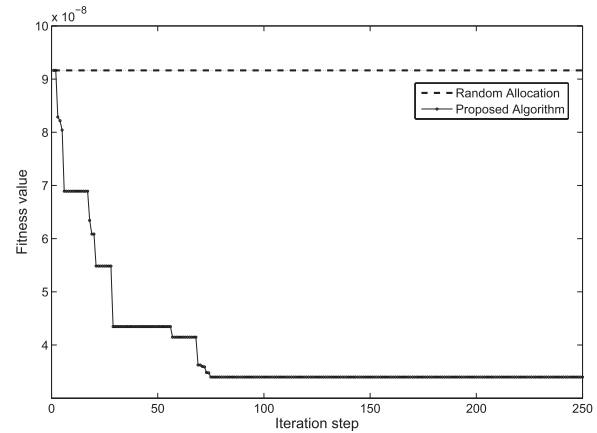
probability to converge to a global optimal solution.

5.4   Performance Comparison

The performance of the proposed algorithm is evaluated under several network scenarios. At the initialization step ($t = 0$), each HeNB assigns a random subset of RBs to its corresponding FUE. Thus, excessive cross- and co-tier interference may occur at the initial network setup. The initial condition of the femtocell network is considered as a random allocation scheme.

In the proposed algorithm, virtual bats and the target solution represent the population of HeNB-FUE pairs and the subset of RBs that corresponds to the HeNB-FUE pairs, respectively. The movement of virtual bats in finding the target is represented by the improvement path of the fitness value to the global minimum solution. After some iteration steps, the solution converges where the bats are not moving due to the closeness from its target.

The fitness value of the proposed algorithm represents the total cross- and co-tier interference received by FUEs. Figure 10 illustrates the improvement path of the fitness value to the global minimum solution under the scenario of 5 HeNBs per apartment block and 4 apartment blocks per sector. From Fig. 10, it can be observed that the proposed algorithm converges to the global minimum solution under a certain number of iteration. The minimization of interference of the femtocell networks at the global minimum point leads to the improvement of the CDF throughput of FUEs as shown in Fig. 11. Throughput of FUE u is calculated using Shannon theoretical throughput given by $T_u = W_{RB} \sum_{k=1}^{H} \log_2(1 + SINR_u^k)$, where W_{RB} is the RB bandwidth and $SINR_u^k$ is the received SINR of FUE u on RB k.

The performance of the proposed algorithm is further compared with discrete particle swarm optimization (DPSO) algorithm under different 30 network topologies. This comparison is fairly reasonable because the bat algorithm and PSO algorithm have some similar properties. The initial parameters and value of DPSO algorithm are listed in Table 3. Figure 12 demonstrates the comparison of the con-
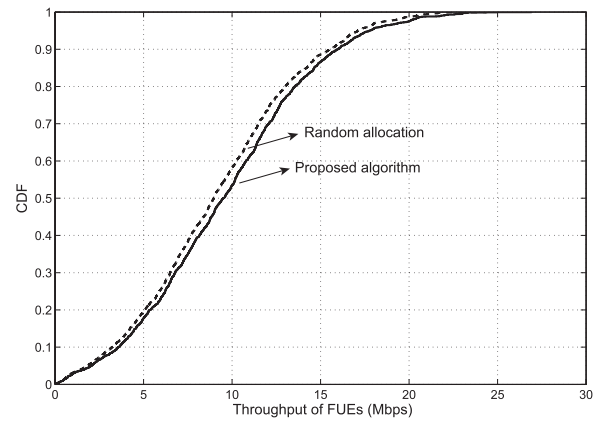
vergence curve of the proposed algorithm and that of DPSO in one network topology. From Fig. 12, it is shown that the proposed algorithm achieves lower fitness value and faster convergence than that of DPSO algorithm. This implies that the proposed algorithm yields better performance in finding the global optimal solution than that of DPSO algorithm under the same initial network condition. Moreover, as can be observed in Fig. 13, the network throughput of the proposed algorithm is higher than that of DPSO and random allocation. These results demonstrate the effectiveness of the proposed algorithm for resource optimization in femtocell networks.
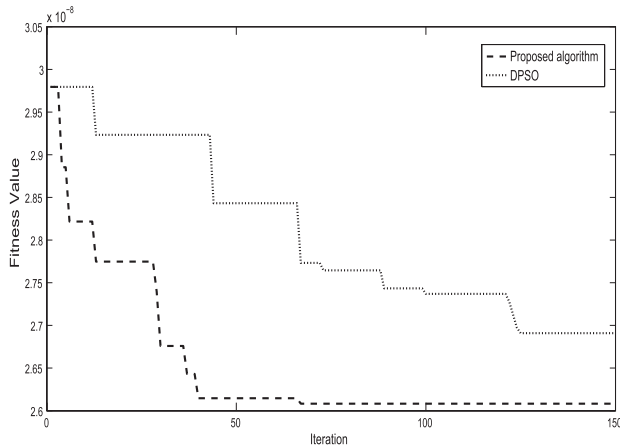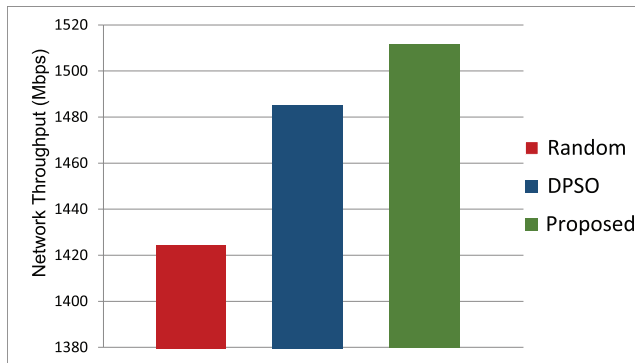
Fig. 12   Convergence comparison.

Fig. 13   Performance comparison.

6.   Conclusion

In this paper, a modified bat algorithm is proposed to solve the resource allocation problem in the closed access femtocell networks. While the original bat algorithm is designed to address the optimization problem in a continuous search space, the proposed modified bat algorithm extends the search optimization in a discrete search space. We demonstrate that the proposed scheme converges to a global minimum solution where the cross- and co-tier interference are minimized. The simulation results reveal that the proposed resource allocation scheme based on modified bat algorithm achieves the performance improvements in terms of femtocell network capacity and faster convergence compared to that of random allocation and discrete particle swarm optimization algorithm.

Acknowledgments

References

[1] S.M. Hanchate, S. Borsune, and S. Shahapure, "3GPP LTE Femtocell - pros and cons," Int. J. Eng. Sci. Adv. Technol., vol.2, no.6, pp.1596–1602, 2012.

[2] 3GPP TR 36.814, "Evolved universal terrestrial radio access (E-UTRA); Further advancement of E-UTRA physical layer aspects (Release 9)," 2010.

[3] H. Claussen, L.T. W. Ho, and L.G. Samuel, "An overview of the femtocell concept," Bell Labs Tech. J., vol.13, no.1, pp.221–245, 2008.

[4] V. Chandrasekhar and J.G. Andrews, "Femtocell networks: A survey," IEEE Commun. Mag., vol.46, no.9, pp.59–67, 2008.

[5] 3GPP TS 36.300, "Evolved universal terrestrial radio access (E-UTRA) and evolved universal terrestrial radio access network (EU-TRAN)," 2009.

[6] J. Zhang and G. de la Roche, Femtocells: Technologies and Deployment, John Wiley Sons, 2010.

[7] R. Estrada, H. Otrok, and Z. Dziong, "Resource allocation model based on particle swarm optimization for OFDMA macro-femtocell networks," IEEE ANTS, 2013.

[8] M. Hinchey, R. Sterritt, and C. Rouff, "Swarm and swarm intelligence," Computer (Long. Beach. Calif)., vol.40, no.4, pp.111–113, 2007.

[9] M.R. Mili, K.A. Hamdi, F. Marvasti, and M. Bennis, "Joint optimization for optimal power allocation in OFDMA Femtocell Networks," IEEE Commun. Lett., vol.20, no.1, pp.133–136, Jan. 2016.

[10] D.T. Ngo, S. Khakurel, and T. Le-Ngoc, "Joint subchannel assignment and power allocation for OFDMA femtocell networks," IEEE Trans. Wireless Commun., vol.13, no.1, pp.342–355, Jan. 2014.

[11] L. Chen, X. Li, and H. Ji, "An interference-mitigation channel allocation algorithm for energy-efficient femtocell networks," 2014 IEEE Wirel. Commun. and Netw. Conf. (WCNC), pp.2318–2323, 2014.

[12] G.K. Tran, S. Tajima, R. Ramamonjison, K. Sakaguchi, K. Araki, S. Kaneko, N. Miyazaki, S. Konishi, and Y. Kishi, "Study on resource optimization for heterogeneous networks," IEICE Trans. Commun., vol.E95-B, no.4, pp.1198–1207, April 2012.

[13] H. Shimodaira, G.K. Tran, K. Sakaguchi, K. Araki, S. Kaneko, N. Miyazaki, S. Konishi, and Y. Kishi, "Optimization of picocell locations and its parameters in heterogeneous networks with hotspots," IEICE Trans. Commun., vol.E96-B, no.6, pp.1338–1347, June 2013.

[14] J. Tang, D.K.C. So, E. Alsusa, K.A. Hamdi, and A. Shojaeifard, "Resource allocation for energy efficiency optimization in heterogeneous networks," IEEE J. Sel. Areas Commun., vol.33, no.10, pp.2104–2117, Oct. 2015.

[15] G. Aristomenopoulos, T. Kastrinogiannis, S. Lamprinakou, and S. Papavassiliou, "Optimal power control and coverage management in two-tier femtocell networks," EURASIP J. Wirel. Commun. Netw., vol.2012:329, 2012.

[16] H. Zhang, C. Jiang, X. Mao, and H. Chen, "Interference-limited resource optimization in cognitive femtocells with fairness and imperfect spectrum sensing," IEEE Trans. Veh. Technol., vol.65, no.3, pp.1761–1771, March 2016.

[17] H. Zhang, D. Jiang, F. Li, K. Liu, H. Song, and H. Dai. "Cluster-based resource allocation for spectrum-sharing femtocell networks," IEEE Access, vol.4, pp.8643–8656, 2016.

[18] M. Al-omari, A.R. Ramli, A. Sali, and R.S. Azmir, "A femtocell cross-tier interference mitigation technique in OFDMA-LTE system: A cuckoo search based approach," Indian J. Sci. and Tech., vol.9, no.2, 2016.

[19] R. Wu, J. Zhu, L. Tang, C. Xu, and X. Wu, "A spectrum-sharing approach in heterogeneous networks based on multi-objective optimization," IEICE Trans. Commun., vol.E100-B, no.7, pp.1145–1151, July 2017.

[20] H. Marshoud, H. Otrok, H. Barada, R. Estrada, A. Jarray, and Z.

Dziong, "Resource allocation in macrocell-femtocell network using genetic algorithm," IEEE 8th Int. Conf. Wirel. Mob. Comput. Netw. Commun., pp.474–479, Oct. 2012.

[21] H. Marshoud, H. Otrok, H. Barada, R. Estrada, and Z. Dziong, "Genetic algorithm based resource allocation and interference mitigation for OFDMA macrocell-femtocells networks," IFIP WMNC, 2013.

[22] Z. Li, S. Guo, W. Li, S. Lu, D. Chen, and V.C. M. Leung, "A particle swarm optimization algorithm for resource allocation in femtocell networks," 2012 IEEE Wirel. Commun. Netw. Conf., pp.1212–1217, April 2012.

[23] D. Liu, H. Zhang, W. Zheng, and X. Wen, "The sub-channel allocation algorithm in femtocell networks based on ant colony optimization," IEEE Military Commun. Conf., 2012.

[24] X. Chen, L. Li, and X. Xiang, "Ant colony learning method for joint MCS and resource block allocation in LTE Femtocell downlink for multimedia applications with QoS guarantees," Multimed. Tools Appl., vol.76, no.3, pp.4035–4054, 2017.

[25] H. Zhang, H. Liu, W. Ma, W. Zheng, X. Wen, and C. Jiang, "Mobility robustness optimization in femtocell networks based on ant colony optimization," IEICE Trans. Commun., vol.E95-B, no.4, pp.1455–1458, April 2012.

[26] F. Ahmed and O. Tirkkonen, "Simulated annealing variants for self-organized resource allocation in small cell networks," Appl. Soft Comput., vol.38, pp.762–770, Jan. 2016.

[27] I.W. Mustika, S. Alam, and S. Sulistyo, "Cell and RBs selection scheme for power consumption reduction in femtocell networks using discrete bacterial foraging optimization," 2017 9th International Conference on Information Technology and Electrical Engineering (ICITEE), 2017.

[28] N. Fath, I.W. Mustika, Selo, K. Yamamoto, and H. Murata, "Optimal resource allocation scheme in femtocell networks based on bat algorithm," 2016 22nd Asia-Pacific Conference on Communications (APCC), pp.281–285, 2016.

[29] X.-S. Yang and A.H. Gandomi, "Bat algorithm: A novel approach for global engineering optimization," Eng. Computation., vol.29, no.5, pp.464–483, 2012.

[30] X.-S. Yang and X. He, "Bat algorithm: Literature review and applications," Int. J. Bio-Inspired Comput., vol.5, no.3, pp.141–149, 2013.

[31] J. Kennedy and R. Eberhart, "Particle swarm optimization," Proc. IEEE Int. Conf. Neural Networks, pp.1942–2945, 1995.

I Wayan Mustika received the B.Eng. degree in Electrical Engineering from Universitas Gadjah Mada, Indonesia, in 2005, the M.Eng. degree in computer engineering from King Mongkut's Institute of Technology Ladkrabang (KMITL), Thailand, in 2008, and the Ph.D. degree in informatics from Kyoto University in 2011, with the support of the Japan International Cooperation Agency (JICA) scholarship. Since 2006, he has been with the Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada, where he is currently an assistant professor. His research interests include radio resource management in cellular networks, game theory, the Internet of Things, and heterogeneous networks. He received the IEEE VTS Japan 2010 Young Researcher's Encouragement Award in 2010, the IEEE Kansai Section Student Paper Award in 2011, and the ICITEE 2015 Best Paper Award in 2015. He is a member of the IEEE.

Nifty Fath received the B.Eng. and the M.Eng. degrees in Electrical Engineering from Universitas Gadjah Mada, Indonesia, in 2015 and 2016, respectively, with support of the Fast-track scholarship program. She is currently a faculty staff in Faculty of Engineering, Universitas Budi Luhur. Her research interests include radio resource management in femtocell networks with a particular emphasis on optimization technique. She received the Sakura Science Research Exchange Program from Shizuoka University in 2015.

Selo Sulistyo received the M.Sc. and Ph.D. from University of Agder, Norway in 2003 and 2012 respectively. He is an associate professor in Information and Communication Technology at the Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada, Indonesia. He is also Head of Electronic System laboratory at Universitas Gadjah Mada. His research interests are including Software Modeling, Service Engineering, Security for the Internet of Things and connected objects.

Koji Yamamoto received the B.E. degree in electrical and electronic engineering from Kyoto University in 2002, and the M.E. and Ph.D. degrees in Informatics from Kyoto University in 2004 and 2005, respectively. From 2004 to 2005, he was a research fellow of the Japan Society for the Promotion of Science (JSPS). Since 2005, he has been with the Graduate School of Informatics, Kyoto University, where he is currently an associate professor. From 2008 to 2009, he was a visiting researcher at Wireless@KTH, Royal Institute of Technology (KTH) in Sweden. He serves as an editor of IEEE Wireless Communications Letters from 2017 and the Track Co-Chairs of APCC 2017 and CCNC 2018. His research interests include radio resource management and applications of game theory. He received the PIMRC 2004 Best Student Paper Award in 2004, the Ericsson Young Scientist Award in 2006. He also received the Young Researcher's Award, the Paper Award, SUEMATSU-Yasuharu Award from the IEICE of Japan in 2008, 2011, and 2016, respectively, and IEEE Kansai Section GOLD Award in 2012. He is a member of the IEEE.

Hidekazu Murata received the B.S., M.E., and Ph.D. degrees in electronic engineering from Kyoto University, Kyoto, Japan, in 1991, 1993, and 2000, respectively. In 1993, he joined the Faculty of Engineering, Kyoto University. From 2002 to 2006, he was an Associate Professor of Tokyo Institute of Technology. He has been at Kyoto University since October 2006 and is currently an Associate Professor of Department of Communications and Computer Engineering, Graduate School of Informatics. His major research interests include signal processing and its hardware implementation, with particular application to cooperative wireless networks with cognitive radio capabilities. He received the Young Researcher's Award from the IEICE of Japan in 1997, the Ericsson Young Scientist Award in 2000, and the Young Scientists' Prize of the Commendation for Science and Technology by the Minister of Education, Culture, Sports, Science and Technology in 2006. He is a member of the IEEE and SITA.