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Discrete bacterial foraging optimization for resource allocation in macrocell-femtocell networks

Heng Lalin | **I Wayan Mustika** | **Noor Akhmad Setiawan**

Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada, Yogyakarta, Indonesia.

Correspondence
I Wayan Mustika, Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada, Yogyakarta, Indonesia.
Email: wmustika@ugm.ac.id

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Femtocells are good examples of the ultimate networking technology, offering enhanced indoor coverage and higher data rate. However, the dense deployment of femto base stations (FBSs) and the exploitation of subcarrier reuse between macrocell base stations and FBSs result in significant co-tier and cross-tier interference, thus degrading system performance. Therefore, appropriate resource allocations are required to mitigate the interference. This paper proposes a discrete bacterial foraging optimization (DBFO) algorithm to find the optimal resource allocation in two-tier networks. The simulation results showed that DBFO outperforms the random-resource allocation and discrete particle swarm optimization (DPSO) considering the small number of steps taken by particles and bacteria.

KEYWORDS
Discrete bacterial foraging optimization, resource allocation, macrocell-femtocell network

1 | INTRODUCTION

In the last few decades, the demand for wireless communication has increased at an unprecedented pace. The development of contemporary cellular technologies, such as WiMAX (802.16e), Universal Mobile Telecommunication Service (UMTS), and the promising Long-Term Evolution (LTE) has given users new ways of wirelessly communicating with higher data rates [1]. Femtocells symbolize the upcoming networking technology for indoor environments as they can enhance the capacity and quality of service (QoS) over a macrocell [1]. Furthermore, they offer superb coverage for indoor femto user equipment (FUE) [2]. The signal quality of a macrocell may be attenuated over long distances, so the deployment of femtocells in densely populated areas is a significant advantage. Femtocells represent a cost-effective and energy-effective cellular base station that adopts frequency reuse, which enables the exploitation of spectrum sharing in order to achieve higher bandwidth [3]. The femtocell range is relatively small compared with that of a macrocell; however, it offers a higher capacity in dense and indoor environments. When femto base stations (FBSs) are deployed inside the coverage area of a macro base station (MBS), a two-tier network (heterogeneous network) is constructed. The home eNB was initiated in 2008 as an alternative depiction of a femtocell in the Third Generation Partnership Project (3GPP) LTE terminology [4].

The random deployment of femtocells is commonly installed in the location, whereby macrocells have limited access or unavailable coverage. By utilizing the frequency reuse technique, femtocells and macrocells are able to use the same frequency bands, resulting in the scarcity of available frequency spectrum along with an inefficient spectrum allocation, inducing massive co-tier and cross-tier interference [5,6]. The interference from femtocells and macrocells reduces the desirable signal-to-interference-plus-noise-ratio (SINR), leading to a lower network capacity. While co-tier interference refers to the type of interference generated between neighboring femtocells, cross-tier interference represents interference caused by femtocell to macrocell transmission, or vice versa. In orthogonal frequency-division multiple access (OFDMA) femtocell networks, there are two

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approaches to achieving channel frequency allocation: spectrum sharing and spectrum splitting [7]. The spectrum sharing method allows macrocells and femtocells to occupy the same resource blocks (subchannels), whereas spectrum splitting involves choosing a different part of the spectrum. In two-tier networks, the implementation of spectrum splitting has gained increasing popularity compared to spectrum splitting [8]. There are three fundamental access modes in femtocell networks, namely closed, open, and hybrid access [9]. Closed access is required for home and office environments because only a limited number of registered users have the rights to gain access from the closed access FBS [10]. Therefore, owing to restricted access to unregistered users, the closed access mode offers a significant advantage to legitimate users. On the contrary, in the open access mode, FUEs may have access without any privileges because there is no access constraint to a limited group of users. Meanwhile, hybrid access is a combination of the aforementioned access modes, but there are some obvious criteria that should be considered. Both authorized and unauthorized FUEs can access the FBSs without any restriction, but priority is granted to registered users. A series of power-control applications have been investigated to reduce the interference in two-tier networks. According to [11–13], the interference between femtocells and macrocells can be mitigated by altering maximum power accordingly. Game theory has also been proposed as a resource-allocation scheme to reduce the interference [4,14]. In [14], game theory has been proposed to optimize the SINR of macrocells and the energy efficiency of femtocells, while providing finite interference. Aside from the aforementioned methods, metaheuristic optimizations have attracted much attention in many studies that focus on mitigating the interference using efficient resource-block allocation [2,15–17]. In [2], full spectrum sharing was proposed to maximize the throughput. To eliminate the interference, the joint power and bandwidth allocation based on genetic algorithms (GAs) was investigated [17]. In [18], the authors introduced particle swarm optimization (PSO) to address the resource-allocation issue in a very dense area by considering power adaptation. As a result, the system throughput can be maximized. The proposed work in [18] is capable of defining the most appropriate serving base station, power, and bandwidth. Other metaheuristic optimizations, such as the BAT algorithm and ant colony optimization (ACO) have also been investigated to address the resource-allocation problem in femtocell networks. In [15], the authors achieved an optimal resource allocation by using the BAT algorithm to allocate the resource for each user. In addition, ACO was studied in [16] and [19] to maximize the system performance and guarantee fairness among users. The bacterial foraging algorithm (BFO) is regarded as an emerging metaheuristic optimization algorithm, and was developed by Kevin M. Passino [20]. BFO was proposed to address various problems such as optimal proportional-integral-derivative (PID) control [21], resource scheduling in grid computing [22], adaptive control [23], edge detection [24], and constrained numerical optimization [25]. The previous works show that BFO has excellent features that can solve complex scenarios with a large number of small problems, such as resource-block allocation. Thus, BFO is promising for use in the resource-allocation problem to mitigate the interference by employing the bacteria to search for the optimal resource-block allocation.

This paper focuses on the discrete problem of the resource allocation in femtocell networks using discrete bacterial foraging optimization (DBFO) as the optimization technique. The application of DBFO is expected to significantly mitigate both co-tier and cross-tier interference as well as improve the throughput of the system because many bacteria are deployed to search for the optimal resource allocation. The resource allocation based on discrete PSO was employed to compare the performance.

The rest of this paper is structured as follows. Section 2 discusses the system model and formulation. Section 3 illustrates the fundamental understanding of BFO and the modified version of BFO. Section 4 presents the performance evaluation of the proposed scheme, and Section 5 concludes the paper.

2 | SYSTEM MODEL AND PROBLEM FORMULATION

2.1 | System model

In this network model, we deployed one macrocell site comprising three hexagonal sectors. Based on the 3GPP urban deployment [26], femtocells are installed within apartments under the coverage of macrocells. In this model, co-tier and cross-tier interference are jointly considered owing to the deployment of femtocells inside the coverage area of macrocell sites and the utilization of the frequency reuse technique. In the system model, there are 25 single-floor apartment blocks deployed in a 5×5 grid model, where each grid represents an area of 5×5 m. In each sector of the macrocell, macro user equipment (MUE) devices are arbitrarily and uniformly deployed, and these MUEs may be located indoors or outdoors. p_d and p_a represent the FBS deployment probability and activation probability, respectively. p_d depicts the possibility that an FBS exists in the building, and p_a is assumed to be always active (FBSs are always active).

2.2 | Problem formulation

The proposed DBFO algorithm is designed to seek the most suitable resource-block allocation for each FUE in order to reduce the interference as random resource-block assignment

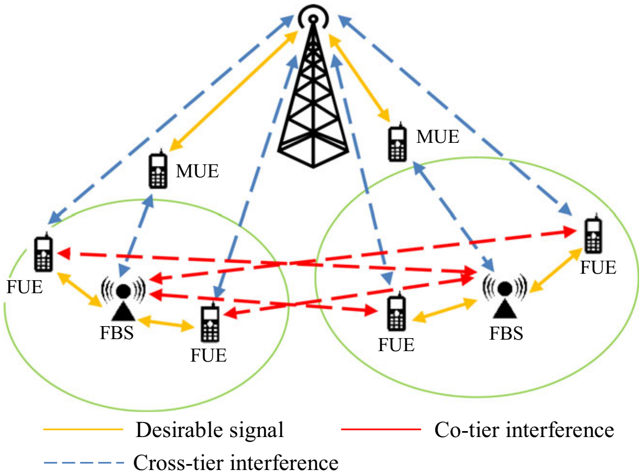

FIGURE 1 Heterogeneous network

for FUE sometimes exhibits inferior performance. This paper examines the resource-allocation problem in FUE within the coverage area of MBSs (Figure 1). This model conforms to a frequency reuse method, and assumes a fair distribution of transmit power for each subcarrier in the system; thus, the transmit power is allocated equally among resource blocks. Power allocation is not considered in this paper since the primary emphasis is on determining the suitable resource-block allocation in order to minimize co-tier and cross-tier interference; this leads to a marked increase in the SINR. In this study, SINR was chosen as the objective function to be optimized. By considering co-tier and cross-tier interference, the interference can be formulated as follows:

$$I = \sum_{x=0}^{H-1}\left[\sum_{y=0}^{H-1}\left(\sum_{b=1,u\neq i}^{N} G_{ub}^{B} p_b^{r_b^{(y)}} \delta_{r_u^{(x)} r_b^{(y)}}\right) + \sum_{z=0}^{L-1}\left(\sum_{m=1,u\neq 1}^{M} G_{um}^{M} p_m^{r_m^{(z)}} \delta_{r_u^{(x)} r_m^{(z)}}\right)\right], \tag{1}$$

where G_{ub}^{B} represents the link gain of FUE u and FBS B, which serves the FUE b. G_{um}^{M} represents the link gain between the FUE m and the MBS M that serves MUE m. $p_b^{r_b^{(y)}}$ denotes the transmit power of FBS B in RB $r_b^{(y)}$, and $p_b^{r_b^{(z)}}$ denotes the MBS B transmit power in RB $r_m^{(z)}$. $\delta_{r_u^{(x)} r_m^{(z)}}$ is the interference function that implies that r_u and r_m are the same. The terms and condition of the interference can be applied as follows:

$$\delta_{r_u^{(x)} r_m^{(z)}} = \begin{cases} 1 & \text{if } r_u^{(x)} = r_m^{(z)} \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

The SINR, which is chosen as the fitness value, is given as:

$$\mathrm{SINR(dB)} = 10\log_{10}\left(\frac{G \cdot P_t}{I + N_0 \cdot B_0}\right) \tag{3}$$

where $G \cdot P_t$ refers to the favorable signal power, which is the product of the power gain G and transmission power P_t. N_0 and B_0 represent the noise density and channel bandwidth, respectively.

From an analysis of the performance, we also consider the calculation of Shannon's capacity so that we can achieve the maximum theoretical data rate. Shannon's capacity formula is given as:

$$C = B_0 \cdot \log_2\left[1 + 10\log_{10}\left(\frac{G \cdot P_t}{I + N_0 \cdot B_0}\right)\right]. \tag{4}$$

2.3 | Fitness function

In this paper, SINR is selected as the fitness function used in DBFO for the network performance evaluation, as in (3). The fitness value is increasingly maximized as bacteria move through a search space to locate the optimal environment. A bacterium represents a set of resource blocks used by all FBSs in the network, so the appropriate resource-block allocation can be obtained as bacteria found the best position as they forage through the search space. The better the SINR, the higher will be the performance of the femtocell network.

3 | DISCRETE BACTERIAL FORAGING OPTIMIZATION APPLICATION IN RESOURCE-ALLOCATION SCHEME

3.1 | Discrete bacterial foraging optimization overview

As introduced by Passino in 2002 [27], BFO is a novel modern search evolutionary algorithm that originated from a biological process involving several types of bacteria called *Escherichia coli (E. coil)*, which is found in the human intestine. *E. coli* is a typical sort of bacteria having a tiny body length of about 2 μm and a diameter of 1 μm. The foraging behavior of *E. coli* can be exploited as the optimization model as the bacteria are inclined to traverse the search space to locate nutrients, with the aim of maximizing their energy levels. Natural selection plays a key role in this algorithm as the healthy bacteria (good foragers) are likely to survive and pass on their genetic compositions to the next-generation bacteria, while the less healthy bacteria (poor foragers) tend to be eliminated. Foraging theory suggests that bacteria have to find the objective function considering that the amount of nutrients consumed per unit time E/T can be increased. During the search process, BFO contains three major mechanisms to achieve the optimal energy: chemotaxis, reproduction, and elimination-dispersal events. It should be noted that bacteria can obtain various solutions throughout the foraging processes, and the results gradually improve either slightly or significantly owing to the complexity of the problem and parameter values of the BFO algorithm.

3.1.1 | Chemotaxis

Nature has given researchers a basic understanding of how to imitate the movement of tiny bacteria which swim and tumble by rotating their flagella. The bacteria take a certain amount of time to move by swimming in the same direction or tumbling to different directions from their previous positions. These maneuvers permit the bacteria to traverse through the entire search space in order to evade noxious environments and find the most nutrient-rich environment. Let $\theta^i(j,k,l)$ denote the bacterium i-th at j-th chemotaxis, k-th and i-th elimination dispersal. Thus, the foraging behavior of bacterium can be represented as follows:

$$\phi(i)=\frac{\Delta(i)}{\sqrt{\Delta(i)^T\Delta(i)}}, \tag{5}$$

$$\theta^i(j+1,k,l)=\theta^i(j,k,l)+\left[C(i)\frac{\Delta(i)}{\sqrt{\Delta(i)^T\Delta(i)}}\right]. \tag{6}$$

In the expression above, $\phi(i)$ indicates the foraging direction vector and $\Delta(i)$ is limited to the interval $[-1,1]$. $C(i)$ refers to the length of the step size and $\theta^i(j,k,l)$ represents the current position of bacterium i. $\theta^i(j+1,k,l)$ is the updated position after swimming or tumbling. If $\theta^i(j+1,k,l)$ results in a value that is greater than the current position $\theta^i(j,k,l)$, the bacterium moves according to the step size $C(i)$ in the same direction until iteration N_c in the chemotactic event reaches its limit; otherwise, the bacterium traverses in a different direction only if the cost of $\theta^i(j+1,k,l)$ is smaller than that of $\theta^i(j,k,l)$.

3.1.2 | Reproduction

In this algorithm, the reproduction event is implemented after the chemotactic step to stimulate the evolutionary rule. The reproduction is based on the fitness value that is sorted from the smallest to the greatest value (ascending order). In the reproduction step, the bacteria that is unable to yield an adequate amount of energy throughout the foraging process would eventually die, while other healthy bacteria would survive and split asexually into two bacteria in the location previously occupied by their parent bacteria. The accumulation of bacteria health J^i_{health} of bacterium i-th after the N_c chemotactic step can be expressed as follows:

$$J^i_{\text{health}}=\sum_{j=0}^{N_c}J^i(j,k,l). \tag{7}$$

Assume that S_r denotes half of the bacteria after the ascending sort. S represents the bacteria population after the ascending sort, so we can represent S_r as follows:

$$S_r=\frac{S}{2}. \tag{8}$$

S_r of the less healthy bacteria would be eradicated from the entire population, while S_r of the healthy bacteria is split into two.

3.1.3 | Elimination-dispersal

The elimination-dispersal takes place, for example, owing to the gradual increase in local temperature, leading to the death of some bacteria in nutrient-rich environments as well as other factors that unpredictably disperse some bacteria from one place to another. The elimination-dispersal event severely influences the chemotaxis performance, but it can disperse bacteria to the sought-after region. To stimulate this biological phenomenon, bacteria are randomly eliminated according to the probability P_{ed}.

The discrete value is required to depict the resource block assignment in each FBS for FUE to be optimized by DBFO. Unfortunately, BFO is primarily introduced to address problems in the continuous domain so that it is inconceivable to implement BFO for resource allocation in femtocell networks without some modifications. The chemotaxis contains an equation that is used to improve the bacteria's position throughout the swimming and tumbling process. The key modification is to vary the updated position of the bacteria $\theta^i(j+1,k,l)$ from the continuous domain to the discrete domain so that the bacteria's position in BFO will remain discrete throughout the foraging process. The modification of the bacteria's position $\theta^i(j+1,k,l)$ can be represented as:

$$\theta^i(j+1,k,l)=\theta^i(j,k,l)+\text{round}\left[C(i)\frac{\Delta(i)}{\sqrt{\Delta(i)^T\Delta(i)}}\right]. \tag{9}$$

The algorithm of the DBFO can be formulated as follows:

[Step 1] Parameter initialization $N, N_c, N_s, N_{\text{re}}, N_{\text{ed}}, P_{\text{ed}}$, C_i and $(i=1,2,3,\ldots,N)$

N: bacteria population,

N_c: chemotactic step,

N_s: swimming iteration,

N_{re}: reproduction step,

N_{ed}: elimination-dispersal step,

P_{ed}: probability of elimination-dispersion step,

C_i: step size produced during each movement of bacteria

[Step 2] Elimination-dispersal loop: $l=l+1$

[Step 3] Reproduction loop: $k=k+1$

[Step 4] Chemotaxis loop: $j=j+1$

(Continues)

[a] For $i = 1, 2, 3, \ldots, S$ bacteria i go through chemotactic step.

[b] Calculate fitness function $J(j, k, l)$, then let $J_{\text{last}} = J^i(j, k, l)$

[c] Tumble: generate a random vector $\Delta(i) \in R$ and $\Delta(i)$ value lies between the interval of $[-1, 1]$.

[d] Move: let $\theta^i(j+1, k, l) = \theta^i(j, k, l) + \text{round}\left[C(i)\frac{\Delta(i)}{\sqrt{\Delta(i)^T\Delta(i)}}\right]$

[e] Calculate fitness function:

$J^i(j, k, l)$ with $\theta^i(j+1, k, l)$

[f] Swim:

[i] Suppose $m = 0$ (counter for swimming length)

[ii] While $m < N_s$ (prevent bacteria from swimming too long in the search space)

- Suppose $m = m + 1$
- If $J(i, j, k, l) > J_{\text{last}}$ then update the $\theta^i(j+1, k, l)$ with equation [d] and $J_{\text{last}} = J^i(j, k, l)$. $\theta^i(j+1, k, l)$ is used to calculate $J^i(j, k, l)$, as seen in [e].

[iii] Else, let $m = N_s$

[g] If $i \neq S$, then go to next bacteria

[Step 5] If $j < N_c$, calculate [step 4] and continue the chemotaxis until there is no bacterium.

[Step 6] Reproduction:

[a] For: $i = 0, 1, 2, \ldots, S$, let

$$J^i_{\text{health}} = \sum_{j=0}^{N_c} J^i(j, k, l)$$

J^i_{health} represents the accumulation of nutrients over the lifespan of bacterium i, and the ability to evade harmful or poisonous environments. In the reproduction step, the cost of J^i_{health} is sorted in ascending order, and S_r denotes half of the cost of the bacteria. S_r bacteria with the lower cost eventually die, and S_r bacteria with the higher cost remain alive and asexually break up into two bacteria (duplicated bacteria are placed in the same location as their hereditary parents).

[Step 7] If $k < N_{re}$, go to [step 3].

[Step 8] Elimination-dispersal step, For $i = 0, 1, 2, \ldots, S$, P_{ed} is used as the probability to disperse. If $l < N_{ed}$, then go to [step 2]; otherwise end.

3.2 | Discrete particle-swarm optimization overview

For comparison, this study used the discrete particle-swarm optimization (DPSO) algorithm. PSO is a metaheuristic and population-based approach developed by Kennedy and Eberhart [28] to explore the optimal global solution by exploiting the communication performed by the particle during the search. PSO is derived from swarm intelligence (SI), with the socially biological characteristics such as swarming and fish schooling [29]. In PSO, for instance, individual particles such as birds may find the best possible solution throughout the search, and the bird population with the poor solution may use the intelligent communication with their neighboring particles and follow the path taken by a bird with an optimal solution, even if they traverse in opposite directions. By possessing this searching trait, the candidate particles tend to gain more optimal solutions throughout the search.

The population of the particle in PSO is dispersed, and each individual particle is likely to traverse across the search space and eventually accumulate in the location in which an optimal solution exists. PSO employs two important vectors, which define the particle position and velocity of individual swarm s at iteration i. The update of the position and velocity is based on the knowledge that a particle gains from its neighbors. The velocity v_s^{i+1} and position x_s^{i+1} of a particle s at iteration i can be expressed as:

$$v_s^{i+1} = \omega v_s^i + c_1 r_1 \left(p_i^{\text{local}} - x_s^i\right) + c_2 r_2 (p_i^{\text{global}} - x_s^i), \tag{10}$$

$$x_s^{i+1} = x_s^i + v_s^i, \tag{11}$$

where ω represents the inertia weight that controls the exploration capability of the particle population, and r_1, r_2 are the two random functions in the range between [0, 1]. c_1 and c_2 denote the parameters that influence the convergence characteristics of PSO. These parameters are defined empirically depending on the specific problem. p_i^{local} is the best local position found by particle i, and p_i^{global} is the best global position found by all particle populations. A higher ωv_s^i generates a greater velocity v_s^{i+1}, permitting particles to explore the search space globally rather than locally. However, a lower ωv_s^i produces a smaller velocity v_s^{i+1}, allowing bacteria to search more locally. $c_1 r_1 (p_i^{\text{local}} x_s^i)$ and $c_2 r_2 (p_i^{\text{global}} x_s^i)$ represent the cognitive knowledge and social interaction between individual swarms, respectively.

3.3 | Bacteria position in resource-allocation model

Proper resource allocation is among the most significant solutions as it can mitigate the interference in the femtocell network. In this paper, both co-tier and cross-tier interference are considered as an MBS is placed in the middle of the network and FBSs are deployed around the MBS. The problem mentioned above needs to be solved in the discrete domain; however, the original BFO is designed to deal with continuous problems. To address this problem, we modified the original algorithm using the nearest-integer method.

It is challenging to design a resource-allocation scheme for an individual bacterium to search for the most

	r_1	r_2	r_3	r_4	r_5
$\overrightarrow{f_1}$	1	4	5	6	2
$\overrightarrow{f_2}$	8	9	15	23	11

FIGURE 2 Representation of resource block used by FUEs

appropriate combination of resource blocks. In this model, there are up to 50 RBs used by FUEs, and each FUE selects 5 RBs. One bacterium represents all resource blocks used in all FBSs; nevertheless, only one FBS is considered in this scenario. F refers to the position of bacterium representing the resource blocks occupied by FUEs in the FBS. The vector $\overrightarrow{f_u}$ represents the subset of resource blocks occupied by FUEs, where u is the number of FUEs in the FBS. $r_{n,u}$ symbolizes the individual resource block n that belongs to FBS u, having an integer interval of $\{\text{rb}|\text{rb} \in N, 0 \le \text{rb} \le 49\}$.

$$\mathrm{F} = \begin{bmatrix} \overrightarrow{f_1} \\ \overrightarrow{f_2} \\ \vdots \\ \overrightarrow{f_u} \end{bmatrix} = \begin{bmatrix} r_{1,1} & r_{2,1} & \cdots & r_{n,1} \\ r_{1,2} & r_{2,2} & \cdots & r_{n,2} \\ \vdots & \vdots & \vdots & \vdots \\ r_{1,u} & r_{2,u} & \cdots & r_{n,u} \end{bmatrix}.$$

The apparent representation of the resource blocks is illustrated below, where one FBS serves five FUEs, and five RBs are assigned to each user.

As shown in Figure 2, the representation illustrates that FUE 1 occupies a subset of resource blocks $\overrightarrow{f_1}$ (1, 4, 5, 6, 2), and FUE 2 occupies a subset of resource blocks $\overrightarrow{f_2}$ (8, 9, 15, 23, 11).

4 | PERFORMANCE EVALUATION

4.1 | Simulation model

The performance of the proposed method was evaluated by performing simulations using the following model. The network environment consists of one MBS site, which is deployed at the center of the network configuration. FBSs are deployed inside apartment blocks within the MBS coverage area, as depicted in Figure 3. The MBS coverage area is divided into three sectorized areas. Two apartment blocks are sited in each sector, and there are therefore six apartment blocks in three sectors. MUEs are deployed randomly within the MBS coverage area; meanwhile, FUEs are only deployed inside the apartment blocks. The deployment of FBSs and FUEs in one apartment block is illustrated in more detail in Figure 4. One FBS has 50 RBs, and 5 RBs are allocated to each corresponding FUE. The proposed method aims to optimize the allocation of RBs to each FUE so that the SINR and throughput can be increased. Simulations of the resource allocation using DPSO were also performed, and the performances are evaluated along with simulations using the proposed method. Furthermore, the network parameters and values used in this simulation are listed in Table 1. Parameters of DBFO and DPSO are given in Tables 2 and 3, respectively.

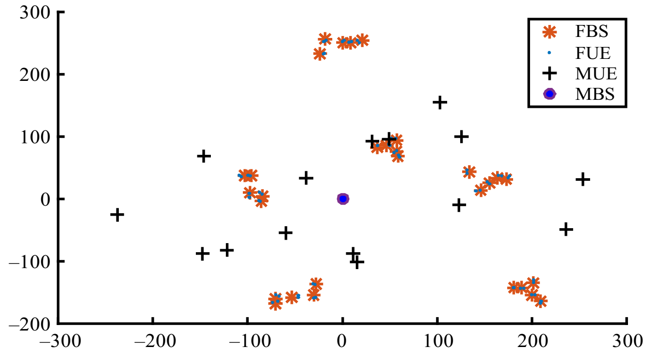

FIGURE 3 Macrocell-femtocell network environment

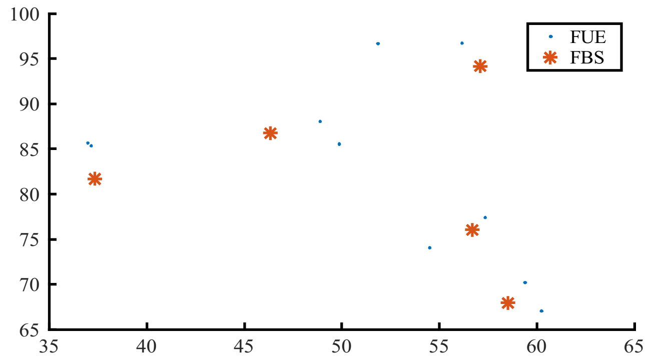

FIGURE 4 Femtocell network in one apartment block

4.2 | Simulation results

At the start of the simulation, the FBS randomly assigns the subset of RBs to its associated FUEs. However, random allocation does not provide an optimal solution for RB allocation because some adjacent FUEs may obtain the same RBs. As a result, the interference level increases and the SINR decreases. The DBFO scheme aims to improve the SINR by allocating the most appropriate RBs to each FUE. Thus, interference can be reduced and the SINR can converge to the higher value during DBFO iteration, as shown in Figure 5. In this problem, the parameters setting for DBFO can influence the convergence of SINR. For example, the assignment of more bacteria helps to obtain improved solutions at the cost of computation complexity. Therefore, the parameters of DBFO should be adjusted carefully.

If more bacteria are deployed, it is highly likely that some bacteria may assume better positions at the starting

TABLE 1 Femtocell environment parameters

Parameters	Value
Cellular layout of macrocell	Hexagonal grid, 1 cell site with 3 sectors
Macro path loss	$128.1 + 37.6\log_{10}(d_m[\text{km}])\text{dB}$
Femto path loss	$127.7 + 30\log_{10}(d_f[\text{km}])\text{dB}$
Number of UEs	5 MUEs/Sector, 2 FUEs/FBS
Number of apartment block	2 apartment/sector
RB bandwidth	180 kHz
System bandwidth	10 MHz
Shadowing standard deviation	10 dB
Femto BS antenna	Omnidirectional
FBS deployment probability	0.8
Noise density	−174 dBm/Hz
Antenna gain FBS, FUE	0 dBi, 0 dBi
Transmit power/RB	3 dBm
FBS activation probability	1
Wall penetration loss	20 dB
Antenna gain MBS, FBS	14 dBi, 0 dBi
Number of available RBs	50
RB allocated	5 RBs/UE
Macrocell/femtocell radius	ISD = 500 m, 5 m
Cellular layout of femtocell	5 × 5 grid model

TABLE 2 Discrete BFO parameters

Parameters	Value
Bacteria population (S)	5
Chemotactic step (N_c)	5
Reproduction step (N_{re})	5
Elimination-dispersal (N_{ed})	15
Swim step (N_s)	5
Elimination-dispersal probability (P_{ed})	0.25
Step size C	0.1
Search space boundary	[0, 49]

TABLE 3 Discrete PSO parameters

Parameters	Value
Population of particle (S)	5
Inertia weight (ω_{min})	0.09
Inertia weight (ω_{max})	0.04
Cognitive and social acceleration constants (C_1)	0.01
Cognitive and social acceleration constants (C_2)	0.01
Search space boundary	[0, 49]

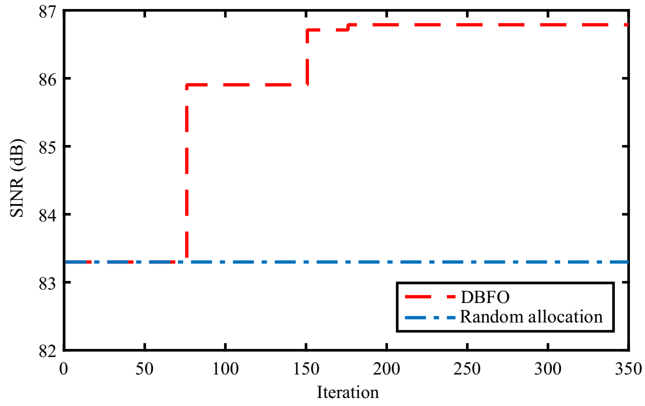

FIGURE 5 SINR convergence analysis

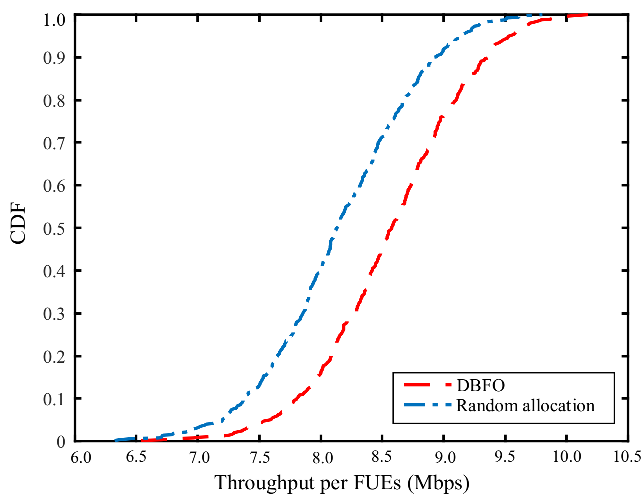

FIGURE 6 Cumulative distribution function of throughput (Mbps)

point. A larger step size C allows bacteria to traverse with the extensive step through search space, but each bacterium may not pass through the optimal result. In contrast, a smaller step size triggers slow convergence, but permits bacteria to search more extensively near the optimal solution. Increasing the number of N_c and N_{re} may permit bacteria to find more optimal solutions and escape from premature convergence. Employing a larger number of N_{ed} steps allows bacteria to avoid toxic environments as some of the bacteria may be dispersed to different parts of the search space, so that the bacteria can escape from the local optimal solution.

In Figure 5, DBFO can converge to optimal solutions by taking various steps when compared to the random-resource allocation as a new and improved resource-block allocation can be found. As shown in Figures 6 and 7, the proposed DBFO can significantly mitigate interference compared with the random-resource allocation. In addition, by using DBFO, the throughput of each FUE can be

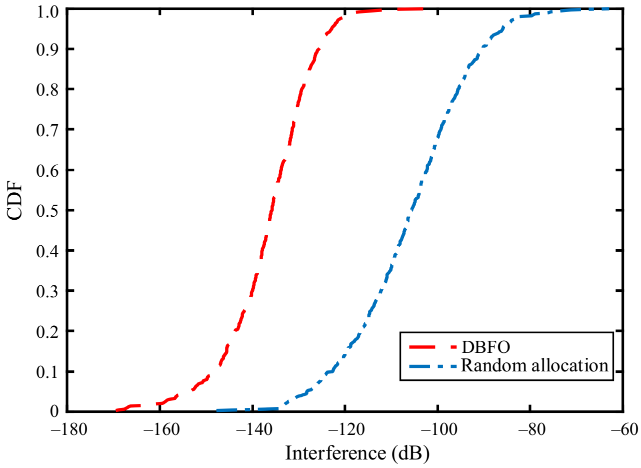

FIGURE 7 Cumulative distribution function of interference (dB)

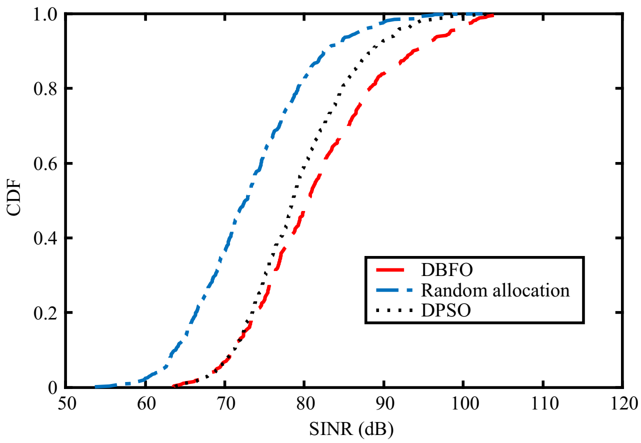

FIGURE 8 Cumulative distribution function of SINR after 350 iterations

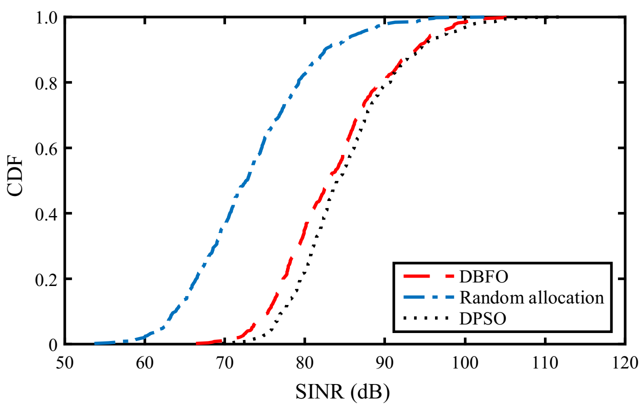

FIGURE 9 Cumulative distribution function of SINR after 2,250 iterations

significantly enhanced, resulting in an improvement in the system performance.

The simulation was extended by implementing DPSO for resource-block allocation in femtocell networks.

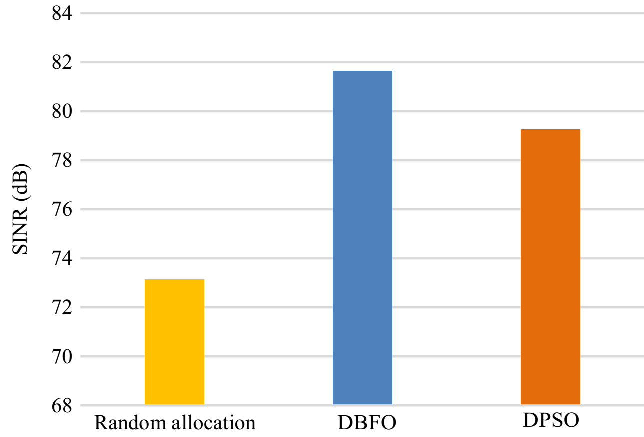

FIGURE 10 SINR performance comparison after 350 iterations

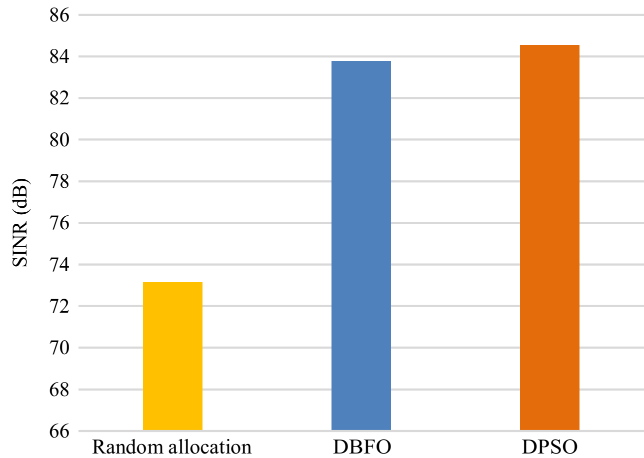

FIGURE 11 SINR performance comparison after 2,250 iterations

However, DPSO and DBFO are two different methods with their own characteristics. Therefore, the simulation results obtained using DPSO are presented as parallel solutions to the resource-block allocation problem. The cumulative distribution function (CDF) graphs of the SINR obtained from 1,000 simulation iterations using random allocation, DBFO, and DPSO are presented in Figures 8 and 9 with 350 and 2,250 iterations, respectively. In the random allocation method, only one-time resource block allocation is performed in one simulation, and thus there is no iteration step. Meanwhile, in simulations that employ DBFO, one iteration is equal to one loop of chemotaxis. In simulations that employ DPSO, one iteration is equal to one position update for all particles. Based on Figure 8, DBFO can achieve a higher SINR than other methods in early iterations. This indicates a faster convergence of DBFO than DPSO in this resource-allocation problem. However, this faster convergence does not mean that the optimal solution has been obtained, but it means that the algorithm can reach a better solution early in the simulation (the 350-th iteration is considered as early point of the simulation). Furthermore, if the iteration is extended, the convergence characteristics could change depending on the network topology. As can be seen in Figure 9, if the number of iterations is extended to 2,250, DPSO can achieve an SINR that is slightly higher than DBFO.

Figures 10 and 11 compare the SINR values obtained for random allocation, DBFO, and DPSO, which confirm the results obtained in Figures 8 and 9. In an optimization problem with high complexity, such as resource-block allocation, it is not possible to guarantee that DBFO or DPSO can reach the optimal solution because it depends on the condition and topology of the networks, which are very dynamic. However, it should be noted that DBFO can perform better in simulations with fewer iterations. This scheme is preferable if the goal of the research is to obtain a better solution in a shorter computation time.

5 | CONCLUSION

The proposed scheme uses the DBFO algorithm to address the resource-block allocation problem in macrocell-femtocell networks. The primary goal of this paper is to enable FUEs to select the optimal resource-block allocation while considering macrocells that coexist with femtocell networks. The proposed algorithm could also enhance the SINR and throughput while mitigating interference. The simulation results showed that DBFO outperforms the random-resource allocation in terms of interference reduction as well as realizes an enhanced SINR and throughput.

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ORCID

I Wayan Mustika http://orcid.org/0000-0002-0207-261X

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AUTHOR BIOGRAPHIES

Heng Lalin received his BE degree in computer science from the Department of Information and Communication Technology, Institute of Technology of Cambodia, Cambodia, in 2015, and his ME degree in electrical engineering from the Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada, Indonesia, in 2017. He is currently working at the Institute of Technology of Cambodia, where he is now a lecturer. His main research interests are heterogeneous networks, optimization algorithm, and the Internet of Things.

I Wayan Mustika received the BE degree in electrical engineering from Universitas Gadjah Mada, Indonesia, in 2005, the ME degree in computer engineering from King Mongkut's Institute of Technology Ladkrabang (KMITL), Thailand, in 2008, and the PhD 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.

Noor Akhmad Setiawan received his BE and ME degrees in electrical engineering from Universitas Gadjah Mada, Indonesia, in 1998 and 2003, respectively. He received his PhD degree in electrical and electronics engineering from Universiti Teknologi PETRONAS, Malaysia in 2009. He is currently an assistant professor in the Department of Electrical Engineering and Information Technology, Universitas Gadjah Mada. His main research interests are soft computing and machine learning.