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Utilization-Oriented Spectrum Allocation in an Underlay Cognitive Radio Network

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ABSTRACT Spectrum access and assignment in cognitive radio networks (CRNs) are hot topics in wireless communications. Dynamic spectrum access and assignment could greatly improve spectrum resource efficiency and help to satisfy the explosively increasing communication demands of wireless devices. The problem of spectrum access and assignment in an underlay CRN is considered in this paper. The problem is modeled as a global optimization problem by considering the interference between primary and secondary users, the interference between secondary users and the utilization of the entire network. The utilization of the underlay CRN is maximized in the optimization model. To effectively solve this combinatorial optimization problem, a modified binary artificial bee colony algorithm is proposed. Numerical experiments are conducted to simulate the network and verify the proposed assignment method. The simulation results show that the proposed assignment method offers good performance in improving the spectrum usage efficiency and reducing the interference among primary and secondary users. Furthermore, the proposed algorithm is also very effective in achieving optimal allocation solutions compared with other methods.

INDEX TERMS Artificial bee colony, cognitive radio network, resource allocation, spectrum assignment.

I. INTRODUCTION

The usage of wireless devices, such as vehicles, mobile phones, tablets, and various wireless sensors, has been rapidly increasing over the past decade [1]. This has promoted the development of fifth-generation (5G) wireless communication, which is currently being actively studied. In 5G wireless networks, the data rates are expected to be 10 times the present rates, and robust connectivity and 100% coverage are anticipated to provide a better quality of service and user experience [2]. Spectrum resources are limited, especially in real-world scenarios, since spectrum usage is regulated by the government due to security, safety and stability considerations [3]. Spectrum access is usually granted to licensed users, and unlicensed users are not allowed to transmit and receive data over ungranted regions of the spectrum. Thus, a contradiction arises between the limits on spectrum resources and the increasing number of users. Therefore, dynamic approaches to spectrum usage have been designed to improve the spectrum usage efficiency. Cognitive Radio Network (CRN) is one such approach [4]. In a CRN, unauthorized users are allowed to communicate over licensed regions of the spectrum as long as that portion of the spectrum is not being used by authorized users. Studies have verified the feasibility of this method [5].

Cognitive radio is driving a revolution, moving away from fixed spectrum access and assignment. In the cognitive radio approach, ‘‘spectrum holes’’ are found through detection of the usage of spectrum resources by wireless communication devices. Then, spectrum sharing can be realized by tuning the transmitter power of cognitive users. Because cognitive users can control their transmitter power, interference among users often arises, especially when users are densely distributed in a cell or CRN. From the user perspective, a high transmission power will enlarge the communication range and ensure good Quality of Service (QoS). On the other hand, a high transmission power also leads to increased interference. To reach a good balance between QoS and mutual interference, many solutions have been designed for CRNs. Typically, the problem of resource allocation, including both power and spectrum allocation, is modeled as an optimization problem. The problem is then addressed based on optimization theory, convex optimization, relaxation and other techniques [6], [7]. Zhao *et al.* [8] constructed a power control model based on small cell base stations and used a sequential convex programming method to solve this problem.

Resource allocation in CRNs has been widely studied [9]–[13]. Zhao *et al.* [14] used fractional frequency reuse technology to handle spectrum auctions in cognitive cellular systems. Spectrum assignment is usually modeled as a combinatorial optimization problem with binary variable. It has been reported that such problem is Non-deterministic Polynomial (NP)-hard problem, which are hard to solve due to high complexity [15], [16]. Generally, Lagrange multiplier theory, duality theory and graph theory are applied to solve resource allocation problems. Mathematical models of resource allocation in ad-hoc networks, CRNs and/or heterogeneous networks usually require combinatorial optimization. Such models involve integer variables which are non-differentiable, traditional non-linear programming methods requiring derivatives have difficulty in handling integer variables [17]. Recently, evolutionary algorithms has been introduced to solve resource allocation problems. He et al. presented a survey of bio-inspired approaches for CRNs, including ant colony optimization, differential evolution [18], particle swarm optimization [19], [20] and Artificial Bee Colony (ABC) [21]. Yousefvand *et al.* [22] built a spectrum allocation model based on an interference temperature condition and proposed a radix-tree-based algorithm for spectrum management. Jia *et al.* [23] used linear programming and a genetic algorithm to optimize cross-layer parameters in wireless mesh networks. Han *et al.* [24] studied relay placement and power allocation in cooperative relaying networks.

Although many resource allocation solutions have been proposed, spectrum allocation in underlay CRNs is seldom studied. Therefore, this paper addresses spectrum allocation in underlay CRNs. The considered scenario includes ad-hoc transmission in a cellular network containing a number of primary and secondary users. Both interference between primary and secondary users and interference between secondary users are considered. An optimization model is formulated by maximizing the spectrum utilization of the allocation solution in a CRN. The problem is then solved by means of an improved artificial bee colony algorithm. In the Modified Binary ABC (MBABC) algorithm, binary variables of spectrum assignment are encoded as bit strings, and the initial bit strings are refined by binary variation operators.

Numerical experiments are conducted to analyze the proposed allocation model and the MBABC algorithm. To benchmark the proposed method, Binary ABC (BABC) [25], Memetic ABC (MemABC) [21] and random method (RAND) are chosen for comparison. BABC was used for constructing spanning trees in ad-hoc networks. MemABC was used for the synthesis of an end effector. RAND refers to perform spectrum assignment in a random manner. It is often taken as a baseline for comparison. The simulation results are discussed and compared with BABC, MemABC and RAND methods.

In the following, Section II presents the optimization model for spectrum allocation. Section III introduces the modified ABC algorithm. Section IV describes the numerical simulations, along with discussions and analysis. Section V concludes the paper.

II. OPTIMIZATION MODEL FOR SPECTRUM ALLOCATION

This section describes the CRN scenario discussed in the paper. In this scenario, secondary users (unauthorized users) are allowed to transmit or receive messages using spectrum resources assigned to primary users (authorized users). Secondary users may occupy channels assigned to primary users as long as those channels are not being used by the primary users or the resulting interference to the primary users is below a given interference temperature. According to a survey conducted by the Federal Communications Commission on licensed spectrum usage, a fixed spectrum assignment scheme, although it ensures good QoS, results in wastage of spectrum resources because the efficiency of such a fixed scheme is very low [26]. Hence, dynamic spectrum allocation is a sensible alternative. To fully explore the white space spectrum, an optimal allocation scheme is needed to ensure that both the spectrum efficiency and the QoS can be improved. Utilization and fairness are considered in spectrum assignment [26], though they focused on open spectrum systems. This section concentrates on spectrum allocation in underlay CRN scenario, which is more complicated than the case in [26]. Moreover, interference among the users is the main concern to model the problem.

Consider a set of primary users located in a cellular network. A base station is the transmitter used by all primary users, and each primary user possesses a receiver. The network also contains a number of secondary users. Each secondary user has a transmitter and a receiver. Let P, S and M denote the number of primary users, the number of secondary users and the number of channels, respectively. The channels are assumed to be non-overlapping orthogonal. Changes in the network topology will occur due to the mobility of the primary users or the data transmission traffic. Hence, spectrum allocation must be completed as soon as possible. At present, the allocation time is quite low due to the high available computing power. Thus, it is assumed that the communication environment in the network will remain unchanged during the allocation optimization period.

Let Rp denote the protection area for each primary user, meaning that they all have protection areas of the same size. Let Rs denote the range of the interference produced by secondary users. Fig. 1 presents an example of secondary users interfering with a primary user, where the solid square symbol denotes the receiver of the primary user; the solid and hollow circle symbols denote the transmitter and receiver, respectively, of a secondary user. It can be seen from the figure that the interference ranges of both Secondary

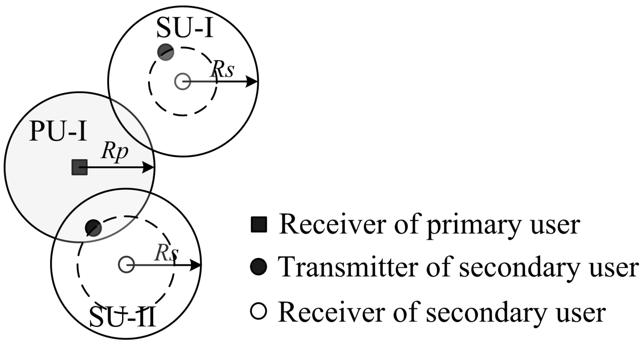

FIGURE 1. Interference between primary and secondary users.

User I (SU-I) and Secondary User II (SU-II) overlap with the protection area of Primary User I (PU-I). Generally, SU-I or SU-II have two ways to void mutual interference. First, they could adjust Rs to avoid interference when they transmit data through the same channel. In case mutual interference could not be avoided by adjusting Rs, the second way is resort to different channels. SU-I or SU-II could select a channel different from that of PI to avoid mutual interference. The dashed lines in Fig. 1 show the minimum Rs values at which SU-I and SU-II can operate. SU-I could shrink Rs sufficiently to eliminate the interference with PU-I. By contrast, the minimum range Rs of SU-II still overlaps with the Rp of PU-I; thus, SU-II may instead use a different channel from that of PU-I. Fig. 2 presents an example of interference among SU-I, SU-II and Secondary User III (SU-III), where the solid and hollow circle symbols denote transmitters and receivers, respectively, of secondary users. It can be seen from the figure that the receivers of SU-I and SU-III are distant from each other. Hence, mutual interference between them could be avoided through suitable tuning of their transmission power. By contrast, the receivers of SU-II and SU-III are very close to each other. In this case, they should use different channels to avoid mutual interference.

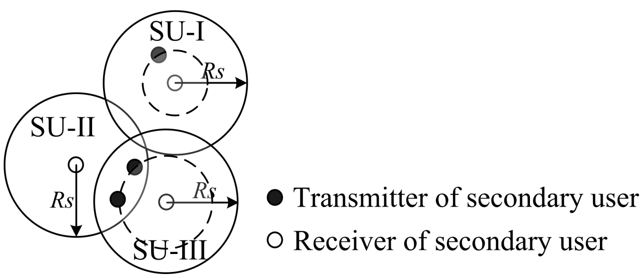

FIGURE 2. Interference among secondary users.

In general, it is assumed that a secondary user s can occupy the same channel m as the nearest primary user p only if $d(s, m) \leq Dist(s, p) - d(p, m)$, where $d(s, m)$ denotes the transmission power of s on channel m, $Dist(s, p)$ is the distance between s and p, and $d(p, m) = Rp$. The interference ranges Rs of the secondary users are assumed to lie in the interval $[d_{min}, d_{max}]$, which corresponds to the minimum and maximum transmission power levels for secondary users.

First, let us define the matrix of channel availability, $\mathbf{L} = \{l_{s,m}\}$. $\mathbf{L}$ is an S-by-M matrix in which each element $l_{s,m}$ that is equal to 1 indicates that secondary user s can use channel m; otherwise, the corresponding element is equal to 0. Thus, as described above, $l_{s,m} = 1$ if $d(s, m) \leq Dist(s, p) - d(p, m)$ and $d_{min} \leq d(s, m) \leq d_{max}$.

Let $\mathbf{A} = \{a_{s,m}\}$ denote the channel assignment matrix. This matrix is of the same dimensions as $\mathbf{L}$. $a_{s,m} = 1$ if channel m is assigned to secondary user s; otherwise $a_{s,m} = 0$. Note that the assignment must satisfy certain channel demand constraints. Let $\mathbf{C} = \{c_{s,k,m}\}$ denote the constraints on the channel demands of the secondary users. $c_{s,k,m} = 1$ indicates that secondary user s and secondary user k would interfere with each other if both were to use channel m. The matrix $\mathbf{C}$ can be computed based on the Euclidean distances between the receiver locations of the secondary users. Thus, the following constraints for $a_{s,m}$ are built:

$$a_{s,m} + a_{k,m} \leq \begin{cases} 1, & \text{if } c_{s,k,m} = 1 \\ 2, & \text{otherwise,} \end{cases} \tag{1}$$

$$\sum_{m=1}^{M} a_{s,m} \leq C_{max}, \tag{2}$$

where $1 \leq n, k \leq S$, and C_{max} is the maximum number of channels that secondary user s could use.

Furthermore, dynamic spectrum allocation should not strongly affect primary users on the same channel. Let $\mathbf{G}_{SP}$ denote the channel gain matrix between secondary users on each channel. This matrix has dimensions of M by S by S. Let $\mathbf{G}_{SP}$ denote the channel gain matrix between the transmitters of secondary users and the receivers of primary users on each channel. In an underlay CRN, secondary users can use the same channels as primary users as long as the resulting interference to primary users is no greater than an interference temperature (IT) threshold IT_p^m:

$$\sum_{s=1}^{S} a_{s,m} * P_s(m) * g_{SP}(m) \leq IT_p^m, \tag{3}$$

where $P_s(m)$ denotes the transmission power of secondary user s on channel m and $g_{SP}(m)$ is the channel gain between a secondary user's transmitter and a primary user's receiver on channel m.

Based on the Shannon capacity theorem, the signal-to-noise ratio (SNR) is assumed to be a function of the transmission power of secondary users on a channel. The following equation is used:

$$r_{s,m} = \log(1 + \gamma_{s,m}), \tag{4}$$

where $\mathbf{R}_s = \{r_{s,m}\}$ is a channel reward matrix denoting the rate gained by s on channel m and $\gamma_{s,m}$ is the signal-to-interference-plus-noise ratio due to secondary user s on channel m. Hence, the total channel reward of a given allocation solution is calculated as

$$R_S = \sum_{s=1}^{S} \sum_{m=1}^{M} r_{s,m} * a_{s,m}. \tag{5}$$

Clearly, the spectrum utilization of a CRN increases with the increase of the total channel reward summed over all secondary users on all channels. Finally, the optimization model of the spectrum assignment problem is expressed as follows:

$$\begin{aligned} &max\ R_S = \sum_{s=1}^{S}\sum_{m=1}^{M} r_{s,m} * a_{s,m} \\ &s.t.\ a_{s,m} + a_{k,m} \leq \begin{cases} 1, & \text{if } c_{s,k,m} = 1 \\ 2, & \text{otherwise} \end{cases} \\ &\quad \sum_{m=1}^{M} a_{s,m} \leq C_{max} \\ &\quad \sum_{s=1}^{S} a_{s,m} * P_s(m) * g_{SP}(m) \leq IT_p^m, \end{aligned} \tag{6}$$

where the elements of $\mathbf{A} = \{a_{s,m}\}$ are binary variables. Solving optimization model (6) requires solving a combinatorial optimization problem. It is well known that such problems are NP hard. Some researchers have attempted to cope with such problems by means of graph theory [26] or game theory [27], [28]. As a necessary resource in base stations, the sum energy is maximized harvested by the energy harvesters [29]. The problem is then solved by relaxation to convexity and Lagrangian method. In heterogeneous cellular networks, overlapping of coverage areas results interference coordination. A distributed resource allocation algorithm is proposed to reduce the interference between macrocell base stations and low-power base stations [30]. Different from researches in [29] and [30], we aim to maximize network utilization by allocating channel resources, and we apply a modified ABC algorithm to solve the problem (6). The modified ABC method will be presented in the next section.

III. MODIFIED ARTIFICIAL BEE COLONY ALGORITHM

The ABC algorithm belongs to the class of swarm intelligence algorithms. Since it was first proposed in 2005, it has been widely studied, both with regard to the algorithm structure [31] and for practical applications [25], [32]. These studies have shown that the ABC approach is an effective paradigm for combinatorial optimization and continuous optimization. Although much successful research has been reported over the past decade, the effectiveness of the ABC approach could still be improved through the appropriate choice of variation operators and a proper selection pressure. Moreover, suitable links between the characteristics of the algorithm and the problem to be solved are also important to achieve the best performance. The modified ABC algorithm adopted here is detailed as follows.

As introduced in Section II, the matrix **A** contains S by M decision variables to be optimized. Because not every channel is available to each secondary user, the number of variables can be reduced based on the matrix **L**. For example, Fig. 3 shows a matrix **L** with $S = 3$ and $M = 5$. Clearly, seven of the elements of **L** are equal to 1, and the others are 0. Hence,

$$\mathbf{L} = \begin{bmatrix} 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \end{bmatrix} \quad \mathbf{A} = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad \mathbf{x} = [1, 0, 1, 1, 0, 0, 1]$$

FIGURE 3. Channel availability matrix L, spectrum assignment matrix A and encoding method.

this structure can be encoded as a vector of length 7 (shown as **x** in Fig. 3). The vector **x** can be transformed back into **A** based on a row-column rule, as shown in Fig. 3. It can be seen that the number of variables can be greatly reduced by removing those corresponding to unavailable channels.

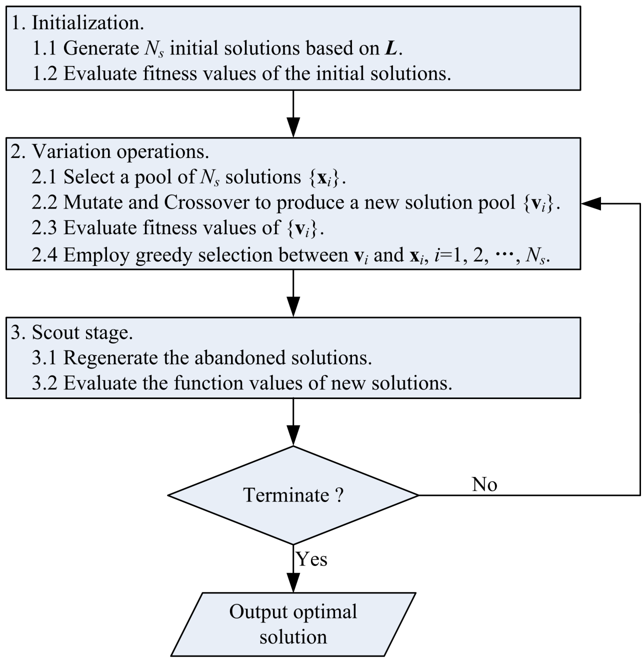

FIGURE 4. Flow chart of the modified ABC algorithm.

Fig. 4 presents the main procedures of the proposed algorithm. The modified ABC algorithm is inspired by our previous work [25] and the selection pressure used in GAs. The first step is initialization, in which a number of initial solutions N_s are generated via the encoding method for a given **L**. The fitness values of these solutions are evaluated based on optimization model (6).

The second step is the application of variations in operation. A pool of N_s solutions is chosen from the current colony based on different selection pressure schemes. Uniform random selection means that each solution has an equal probability of being chosen. Roulette wheel selection means that fitter solutions have a higher probability of being chosen. Then, one-gene-flip mutation is used to mutate the selected solutions [33]. The idea of one-gene-flip mutation is that only one gene is mutated when mutation is needed. Standard ABC mutation is performed on one position of a solution [25].

The one-gene-flip mutation process is performed on binary variables. Hence, its effect is as follows:

$$v_{ij} = \begin{cases} 1 - x_{ij}, & \text{if } j = j1 \\ x_{ij}, & \text{otherwise,} \end{cases} \tag{7}$$

where $j1 \in [1, D]$ is a randomly chosen mutation position, with D being the number of variables in $\mathbf{x}$. Two-point crossover is then applied after the mutation operation. Two positions $j2$ and $j3$ between 1 and D are randomly chosen. Then, two new solutions are produced by swapping the chosen positions $j2$ and $j3$. Note that to retain the effect of the mutation, position $j1$ is prevented from being selected to be swapped in the crossover operation. Greedy selection between $\mathbf{x}_i$ and $\mathbf{v}_i$ is performed based on their fitness, and the fitter solution is reserved for the next cycle. The selection pressure of greedy selection method is useful to balance exploration and exploitation of the optimization algorithm. It is the most popular selection method in swarm intelligence approaches. Thus, the modified ABC algorithm uses this selection method. Because mutation and crossover shed different effect on the algorithm, both operations are used in the second step to assure the efficacy of the resulting algorithm.

The third step is the scout stage, which improves the global convergence. Scout stage is the imitation of the foraging behavior of scout bees. When a food source runs out of nectar, scout bees fly out searching for another food source. After evolving over many cycles, some solutions in the colony may lose their diversity, e.g., become trapped in local optima or a state of stagnation. If fitness improvement does not occur within a number of variations equal to *limit*, the related solutions are considered to have lost their diversity and are regenerated as follows:

$$x_{kj} = \begin{cases} 1, & \text{if } r_j \leq 0.5 \\ 0, & \text{otherwise} \end{cases}, \quad j = 1, 2, \ldots, D, \tag{8}$$

where r_j is a random number between 0 and 1.

If the termination conditions have not been met, a new iteration of step 2 and step 3 is executed; otherwise, the algorithm terminates and outputs the optimal solution and related information. This modified ABC algorithm is designed to solve combinatorial problems; hence, the proposed algorithm is called the modified binary artificial bee colony (MBABC) algorithm.

IV. NUMERICAL EXPERIMENT

This section presents a numerical experiment conducted to study the effectiveness of optimization model (6) and the MBABC algorithm in CRN systems. Because the spectrum allocation problem is expressed as a single optimization problem, the optimal solution obtained from the MBABC algorithm is taken as the allocation solution for the network.

A. SIMULATION SCENARIO

Consider an underlay CRN deployed in a square area with dimensions of 10 by 10, where all primary and secondary users are located within this area. It is assumed that the primary and secondary users are uniformly distributed throughout the area. The transmitter used by the primary users is a base station lying in the center of the area. Each primary user possesses a receiver. The transmitters used by the secondary users are then created throughout the area. The secondary users' receivers are randomly created near their transmitters under the constraint that the distance must be covered by the transmitter. Moreover, the distance is also constrained by d_{min} and d_{max}. Table 1 gives the simulation parameters. To achieve good statistical performance, CRN deployments were independently simulated 100 times in accordance with the parameters in Table 1. That is 100 instances of spectrum assignment problem were created.

TABLE 1. Parameters of the simulated cognitive radio network.

Parameter	Value
number of primary users, P	20
number of secondary users, S	10
number of channels, M	10
maximum channels used by a secondary user, C_{max}	10
protection range of a primary user, Rp	2
interference range of a secondary user, Rs	1
d_{min}	1
d_{max}	4
interference temperature threshold, IT_p^m	5 dB

B. SIMULATION RESULTS

To demonstrate the advantages of the proposed optimization model (6) and the proposed MBABC algorithm, the BABC, MemABC and RAND algorithms were chosen as comparison methods. BABC encodes variables as binary strings and uses two-element variation technique. It shows good performance in solving spanning tree problems [25]. MemABC hybridizes ABC with random walk and uses ϵ-constraint scheme. It shows good performance in the control of the gripping force along the opening range of the calculated mechanisms. [21]. Moreover, RAND was chosen as a baseline for the comparison. This method randomly allocates resources in an iteration and records the best allocation as the result. Each method was independently run 25 times to allow the average performance to be evaluated. In each run, the termination condition was set to 100,000 function evaluations. The parameters of the MBABC and BABC algorithms were set to $N_s = 30$ and $limit = 0.5 * N_s * D$. For the crossover operation in the MBABC algorithm, the crossover rate was set to 1, meaning that the crossover operation was applied to every solution. For the RAND method, a colony of size N_s was also used to ensure a fair comparison among the three methods.

Spectrum usage efficiency could be obtained based on (4) for a network with one user. In the proposed optimization model (6), when R_S grows bigger, spectrum usage efficiency also increases at the same time. Thus, the efficiency is approximated by averaging R_S over all secondary users. Fig. 5 shows the spectrum usage efficiency for 100 instances. In this figure, the MBABC results are shown as the solid line, the BABC results are shown as the dashed line, the MemABC results are

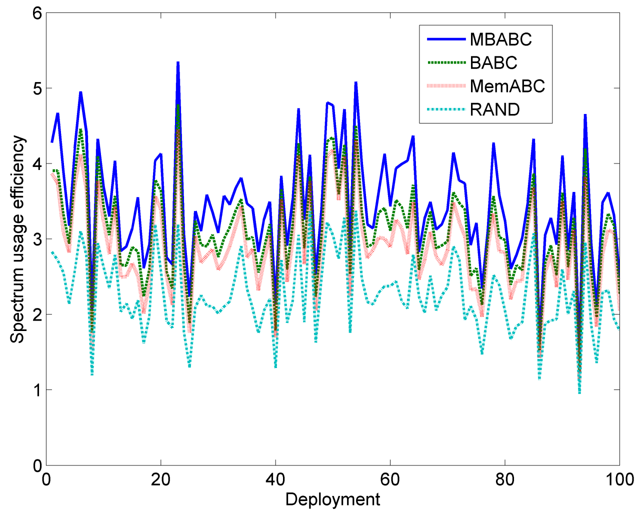

FIGURE 5. Spectrum usage efficiency for 100 CRN instances as found using the MBABC, BABC, MemABC and RAND methods.

shown as the dotted line, and the RAND results are shown as the dash-dot line. It can be seen from the figure that the MBABC curve lies above those of BABC, MemABC and RAND, and the BABC curve lies above that of MemABC and RAND. This indicates that the RAND method cannot effectively improve the efficiency of the CRN. By contrast, the proposed MBABC method greatly improves the network utilization and thus the spectrum usage efficiency, as indicated by the very large differences with respect to the BABC and MemABC results. From these simulations of 100 instances, it is seen that the optimization model (6) enables efficient data transmission and good network utilization.

Table 2 presents the results of the MBABC, BABC, MemABC and RAND algorithms. The Median (Med) and Standard deviation (Std) metrics are used to assess the performance of the four methods. This table presents the results for the first 20 instances; the results for the remaining 80 instances are not shown to save space. It can be seen from Table 2 that the Med values for the MBABC algorithm are greater than those for the BABC, MemABC and RAND methods. Moreover, the Std values for the proposed method are much lower than those for the BABC, MemABC and RAND methods. Thus, the proposed method is more effective than the other three methods. The MBABC algorithm is also more robust than the BABC, MemABC and RAND methods. Averaged over the 100 instances, the MBABC algorithm shows an 8.94% improvement in spectrum usage efficiency compared with the BABC algorithm, a 14.31% improvement compared with the MemABC method, and a 37.02% improvement compared with the RAND method. Therefore, the proposed method is suitable for solving spectrum allocation problems in CRNs.

C. IMPACT OF THE COLONY SIZE

The proposed MBABC algorithm has two parameters, N_s and *limit*. *limit* is defined based on N_s and D; it is a default setting

TABLE 2. Comparison of the MBABC, BABC, MemABC and RAND methods on 20 cognitive radio network instances.

Method	Metric	D_1	D_2	D_3	D_4
MBABC	Med	4.398E+00	4.727E+00	4.075E+00	3.481E+00
	Std	1.944E-02	5.262E-02	6.494E-02	8.330E-03
BABC	Med	4.088E+00	4.088E+00	3.606E+00	3.283E+00
	Std	9.133E-02	1.243E-01	1.709E-01	8.192E-02
	p	4.764E-10	4.750E-10	1.358E-09	1.347E-09
MemABC	Med	4.054E+00	3.950E+00	3.407E+00	3.187E+00
	Std	5.221E-01	5.092E-01	3.669E-01	3.861E-01
	p	4.764E-10	4.750E-10	1.358E-09	1.347E-09
RAND	Med	3.191E+00	3.099E+00	2.964E+00	2.613E+00
	Std	1.730E-01	1.347E-01	1.510E-01	1.265E-01
	p	4.764E-10	4.750E-10	1.358E-09	1.347E-09
Method	Metric	D_5	D_6	D_7	D_8
MBABC	Med	4.339E+00	4.963E+00	4.516E+00	2.560E+00
	Std	1.420E-02	4.000E-02	3.910E-02	3.475E-02
BABC	Med	4.048E+00	4.550E+00	4.059E+00	2.301E+00
	Std	9.739E-02	1.726E-01	1.420E-01	9.449E-02
	p	9.957E-10	1.087E-09	1.580E-09	1.714E-09
MemABC	Med	3.941E+00	4.261E+00	3.880E+00	2.128E+00
	Std	5.476E-01	5.716E-01	4.680E-01	2.552E-01
	p	9.957E-10	9.615E-10	1.400E-09	1.345E-09
RAND	Med	2.986E+00	3.423E+00	3.153E+00	1.829E+00
	Std	1.832E-01	2.225E-01	1.649E-01	9.279E-02
	p	7.772E-10	9.615E-10	1.400E-09	1.054E-09
Method	Metric	D_9	D_{10}	D_{11}	D_{12}
MBABC	Med	4.439E+00	3.905E+00	3.584E+00	4.198E+00
	Std	6.156E-03	2.161E-02	4.263E-03	2.321E-02
BABC	Med	4.251E+00	3.686E+00	3.378E+00	3.809E+00
	Std	1.250E-01	9.634E-02	8.790E-02	9.682E-02
	p	4.745E-10	8.430E-10	9.199E-10	9.251E-10
MemABC	Med	3.978E+00	3.522E+00	3.169E+00	3.693E+00
	Std	4.805E-01	3.777E-01	3.087E-01	4.008E-01
	p	4.745E-10	8.430E-10	9.199E-10	9.251E-10
RAND	Med	3.287E+00	3.019E+00	2.788E+00	3.157E+00
	Std	1.774E-01	2.093E-01	1.384E-01	1.536E-01
	p	4.745E-10	6.566E-10	9.199E-10	9.251E-10
Method	Metric	D_{13}	D_{14}	D_{15}	D_{16}
MBABC	Med	3.201E+00	3.251E+00	3.444E+00	3.794E+00
	Std	2.982E-02	1.663E-02	3.400E-02	5.524E-02
BABC	Med	3.047E+00	3.041E+00	3.244E+00	3.194E+00
	Std	6.062E-02	7.336E-02	7.849E-02	1.364E-01
	p	6.688E-10	1.213E-09	3.058E-09	1.305E-09
MemABC	Med	2.913E+00	2.918E+00	3.065E+00	2.924E+00
	Std	2.792E-01	2.576E-01	3.983E-01	3.174E-01
	p	6.695E-10	1.213E-09	1.896E-09	1.305E-09
RAND	Med	2.532E+00	2.621E+00	2.447E+00	2.658E+00
	Std	9.736E-02	1.229E-01	2.046E-01	1.373E-01
	p	3.126E-10	1.213E-09	1.169E-09	1.305E-09
Method	Metric	D_{17}	D_{18}	D_{19}	D_{20}
MBABC	Med	3.011E+00	3.277E+00	4.199E+00	4.277E+00
	Std	3.175E-02	2.302E-02	2.799E-02	2.005E-02
BABC	Med	2.697E+00	3.001E+00	3.988E+00	3.866E+00
	Std	1.116E-01	9.598E-02	8.341E-02	1.528E-01
	p	1.433E-09	3.586E-10	1.429E-09	4.745E-10
MemABC	Med	2.514E+00	2.834E+00	3.808E+00	3.660E+00
	Std	2.867E-01	2.811E-01	2.647E-01	4.623E-01
	p	1.123E-09	3.597E-10	1.266E-09	4.745E-10
RAND	Med	2.181E+00	2.484E+00	3.493E+00	2.970E+00
	Std	1.415E-01	1.125E-01	1.139E-01	1.720E-01
	p	1.123E-09	3.159E-10	1.266E-09	4.745E-10

and has shown good performance in an extensive numerical study [25]. Hence, N_s is the only parameter that needs to be discussed. In general, the value of N_s is set to an integer between 15 and 50. Hence, five values were tested here: $N_s \in \{10, 20, 30, 40, 50\}$. The results are shown in Fig. 6. This figure shows the mean value of the best utilizations

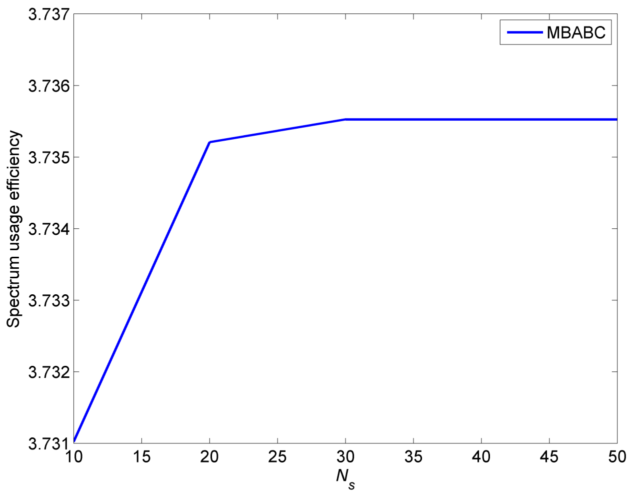

FIGURE 6. Mean of the best spectrum usage efficiency over 100 CRN instances as found by the MBABC algorithm with different colony sizes.

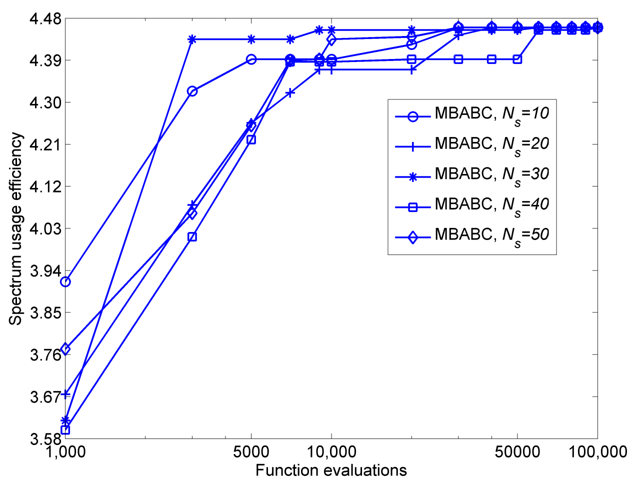

FIGURE 7. Convergence graphs of the MBABC method with different colony sizes on the same instance.

over 100 instances as found by the MBABC algorithm with each of the five different N_s values. Clearly, the algorithm performs worse with $N_s = 10$ or $N_s = 20$ than it does with $N_s = 30$, 40 or 50. Moreover, the MBABC algorithm achieves essentially the same value with $N_s = 30$, 40 or 50. Thus, a colony size between 30 and 50 is recommended based on Fig. 6.

Fig. 6 shows the results of the MBABC method with different colony sizes. In addition, let us discuss and analyze the convergence process on individual instances. For simplicity, we take the first deployment instance as an example; the others are not shown because they exhibit similar behavior. The convergence graphs of the MBABC algorithm with the five colony sizes are shown in Fig. 7. It can be seen that among the five curves, the MBABC algorithm with $N_s = 30$ (the graph with star symbols) converges the fastest when the number of Function Evaluations (FEs) is greater than 2000. The algorithm with $N_s = 50$ converges the second fastest when FEs is greater than 10,000. The curve corresponding to $N_s = 40$ lags behind the other four until FEs = 50,000. The main reason is that it starts at the worst initial solution (the lowest point at FEs=1000 in Fig. 7). By contrast, although the curves corresponding to $N_s = 10$ and 20 have good initial solutions, they converge more slowly than the $N_s = 30$ curve. Thus, based on this analysis of the convergence process, $N_s = 30$ is the suggested setting for the MBABC method.

V. CONCLUSION

Spectrum resources are limited in real-world applications, and dynamic spectrum allocation mechanisms are in high demand because of the high QoS requirements of 5G wireless communication. Consequently, cognitive radio is driving a revolution, moving away from fixed spectrum access and assignment. Typically, the allocation of resources, including both power and spectrum resources, is modeled as an optimization problem.

This paper proposes a spectrum allocation model based on the interference among primary and secondary users. An optimization model is formulated that maximizes the spectrum utilization of the allocation solution for a CRN. The problem is then solved using an improved artificial bee colony algorithm called the MBABC algorithm. In the MBABC algorithm, each possible spectrum assignment solution is encoded as a bit string. A solution pool is chosen based on different selection pressure schemes. Mutation and crossover operations are then applied to produce new solutions. Through a series of evolution cycles, a good allocation solution can be reached.

Numerical experiments conducted to analyze the proposed allocation model and the MBABC algorithm are presented. The simulation results are also discussed and compared with the results of the BABC, MemABC and RAND methods. First, efficient data transmission and QoS can be achieved by using the proposed allocation model. Second, the MBABC method finds better allocation solutions than the BABC, MemABC and RAND methods do. Third, the parameter N_s of the MBABC algorithm may affect its performance. Based on the results of a simulation study, $N_s = 30$ is the suggested setting for the MBABC method. Under this setting, the required number of function evaluations can be reduced to 10,000, enabling a considerable savings in computation time, which is useful in real-world applications.

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