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A Novel Spectrum Scheduling Scheme with Ant Colony Optimization Algorithm

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Abstract: Cognitive radio is a promising technology for improving spectrum utilization, which allows cognitive users access to the licensed spectrum while primary users are absent. In this paper, we design a resource allocation framework based on graph theory for spectrum assignment in cognitive radio networks. The framework takes into account the constraints that interference for primary users and possible collision among cognitive users. Based on the proposed model, we formulate a system utility function to maximize the system benefit. Based on the proposed model and objective problem, we design an improved ant colony optimization algorithm (IACO) from two aspects: first, we introduce differential evolution (DE) process to accelerate convergence speed by monitoring mechanism; then we design a variable neighborhood search (VNS) process to avoid the algorithm falling into the local optimal. Simulation results demonstrate that the improved algorithm achieves better performance.

Keywords: spectrum scheduling; ACO; DE; VNS; system utility

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1. Introduction

With the development of wireless technology, the massive growth of wireless products increases the demand for spectrum resources [1]. The fixed spectrum allocation policy limits the utilization of aspectrum that is one of the non-renewable natural resources, which leads to underutilization for a licensed spectrum and overutilization for unlicensed bands [2,3]. According to a report by the Federal Communications Commission [4], the spatial and temporal variations in the licensed spectrum utilization range from 15 to 85%. Therefore, achieving high utilization for licensed bands is one of the most critical approaches to solving the spectrum-scarcity problem in the next generation wireless systems. Cognitive radio (CR) [5] is a promising technology for dynamic spectrum management, which can achieve better exploitation for spectrum resources. CR is able to intelligently detect 'spectrum holes' (which means available licensed spectrum) and effectively allocate them to cognitive users (who can also be named as secondary users or unlicensed users) in accordance with the distribution objective. The main objective of spectrum allocation is to maximize spectrum utilization while avoiding the possible interference to authorized users (who are referred to as primary users). Thus, how to perform spectrum allocation to achieve maximization objectives while guarantee fairness constraints for cognitive users and interference constraints for primary users become the main question in dynamic spectrum assignment.

To address the spectrum allocation problem, we need to formulate a framework to guarantee interference protection for primary users and build a relationship among cognitive users. Scholars have done a lot of research about the mathematical model for spectrum allocation. In [6], Lu focuses on using bipartite graphs to solve the resource allocation problem, in which cognitive users and primary users are treated as two partite sets and an allocation scheme can be seen as a matching of the corresponding bipartite graph. A mathematical cross-layered model for the cognitive radio network link scheduling problem under the interference temperature model is presented in [7], which maximizes the number of scheduled links within a time frame while satisfying interference temperature constraints. In [8], Changyan integrates an auction model and Stackelberg game theory to deal with the different stage issues for spectrum sharing in CR networks. Game theory is adopted in [9] to reduce power waste caused by some cognitive users' SINR over the target value. To maximize system utility in this paper, we perform spectrum allocation based on graph theory. However, the graph-theory-based allocation issue is a nondeterministic polynomial (NP) problem whose solution can be found in polynomial time on a non-deterministic machine. Intelligent optimization algorithms are effective methods to find a close-to-optimal solution for NP-hard issues.

In this paper, we adopt the ant colony optimization algorithm (ACO) for available licensed spectrum allocation. ACO [10] was first introduced by Dorigo in 1992, which is a popular means of dealing with assignment issues. The basic idea of ACO comes from the natural phenomena that ants can find the shortest path between nest and food efficiently due to their positive feedback attribute [11]. However, ACO is prone to being premature and stagnate when the problem scale is too big. These flaws would certainly drag the effectiveness of the algorithm down [12]. Based on the above, we design a novel spectrum allocation algorithm (IACO) based on ACO, which introduces the differential evolution (DE) [13] process to accelerates convergence speed by the monitoring mechanism, in addition, we employ a variable neighborhood search (VNS) process [14] to avoid falling into the local optimum. We can see from the simulation results that either the system utility or the other performance of IACO are greatly promoted.

2. System Model and Problem Formulation

In this framework, we consider the three matters of spectrum allocation issue as suggested in [15]: (a) possible interference to primary users; (b) collision with cognitive users; (c) system utility and the fairness of spectrum access. We build a graph-based mathematical model [16] to demonstrate the spectrum allocation problem, as shown in Figure 1, where PUi represents the primary user who has the authority using a certain licensed spectrum channel, and SUi denotes the cognitive user who can only access to 'spectrum holes' in an opportunistic manner. Each user has coverage area with radius $d_{p,m}$ or $d_{n,m}$ on channel m, where $d_{p,m}$ indicates the protection radius of the primary user p on channel m, whereas $d_{n,m}$ represents the interference radius of the cognitive user n with access to channel m. SUi cannot access the licensed band that overlays with SUi in some area to avoid interfering with primary user, meanwhile, any two cognitive users cannot use the same band if they overlap in some area to diminish collision with each other.

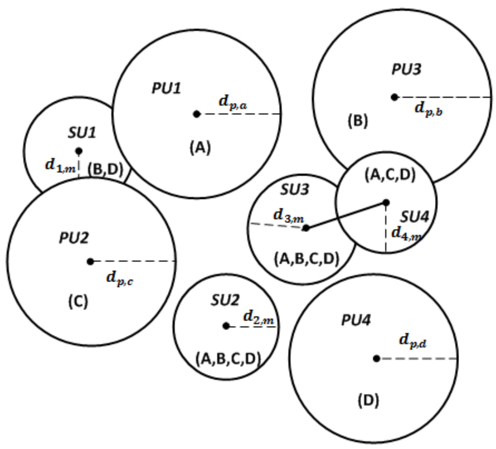

Figure 1. Graph-based System Model.

We define a graph $G(V, E)$, where V is a set of vertices representing the cognitive users that compete for the licensed spectrum, E is a set of undirected edges between vertices denoting interference between any two vertices. For any two vertices $n, k \in V$, an edge exists between n and k if $c_{n,k,m} = 1$. The existence of the edge depends on the interference constraint C (see Section 2.1).

2.1. Matrices for Spectrum Allocation

Matrices Definition (See Table 1).

Table 1. Matrices Definition.

Name of Matrix	Definition of Matrix
Available matrix	$L = \{l_{n,m} \mid l_{n,m} \in \{0,1\}\}_{N\times M}, \quad 1 \le n \le N, 1 \le m \le M$
Benefit matrix	$B = \{b_{n,m} \mid b_{n,m} \ge 0\}_{N\times M}, \quad 1 \le n \le N, 1 \le m \le M$
Interference matrix	$C = \{c_{n,n,m} \mid c_{n,n,m} \in \{0,1\}\}_{N\times N\times M}, \quad 1 \le n \le N, 1 \le m \le M$
Allocation matrix	$A = \{a_{n,m} \mid a_{n,m} \in \{0,1\}\}_{N\times M}, \quad 1 \le n \le N, 1 \le m \le M$
Degree matrix for cognitive users	$Z = \{z_n \mid z_n = \{0,1,\ldots,M\}\}_N, \quad 1 \le n \le N$
Degree ascending matrix	$K = \{k_{n,m} \mid k_{n,m} \in \{0,1\}\}_{N\times M}, \quad 1 \le n \le N, 1 \le m \le M$

Explanation for Matrices

- *Available matrix L*. The matrix represents the availability of licensed bands for cognitive users. If $l_{n,m} = 1$, user n can access spectrum m without interference to primary users, otherwise $l_{n,m} = 0$. As shown in Figure 1, spectrum channel B is available for $SU1$, then $l_{1,2} = 1$.
- *Benefit matrix B*. The matrix indicates the benefit that a cognitive user gets by successful access to a licensed spectrum band, where $b_{n,m} > 0$ only if $l_{n,m} = 1$.
- *Interference matrix C*. The three-axis matrix describes the interference relationship of any two vertices n and k when they access spectrum m. As shown in Figure 1, $SU3$ and $SU4$ overlap in some area, then $c_{3,4,1} = 1$, $c_{3,4,3} = 1$, $c_{3,4,4} = 1$.
- *Allocation matrix A*. The matrix is a spectrum allocation result which is interference free. If $a_{n,m} = 1$, cognitive user n can access spectrum m and transmission data in this band. A conflict free allocation needs to satisfy the interference constraints: $a_{n,m} + a_{k,m} \le 1, \text{if } c_{n,k,m} = 1, \forall n, k < N, m < M$.
- *Degree matrix for cognitive users Z*. The matrix represents the available spectrum number for each cognitive users. In Figure 1, $z_1 = 2, z_2 = 4, z_3 = 4, z_4 = 3$.
- *Degree ascending matrix K*. The matrix is another representation of the available matrix, which incrementally orders the rows according to the degree matrix Z.

2.2. Problem Formulation and Measure Functions

Given the model above, we formulate the spectrum allocation problem by the following optimization function:

$$
\begin{aligned}
&\max_{A\in\Lambda_{n,m}(L,C)} \sum_{n=1}^{N}\sum_{m=1}^{M} a_{n,m} \times b_{n,m} \\
&s.t. \quad \forall 1 \le n, k \le N, 1 \le m \le M \\
&\quad a_{n,m} + a_{k,m} \le 1, if\ c_{n,k,m} = 1 \\
&\quad A = \{a_{n,m}\}_{N\times M} \\
&\quad L = \{l_{n,m}\}_{N\times M} \\
&\quad C = \{c_{n,k,m}\}_{N\times N\times M}
\end{aligned} \tag{1}
$$

where $\Lambda_{n,m}(L, C)$ is the set of interference free spectrum assignments for a given set of N cognitive users and M spectrum bands and constraints C.

There is always more than one allocation solution that would satisfy all the constraints. In order to choose the optimum solution in terms of different applications and measure the algorithm thoroughly, we use three different measure functions that already exist in the literature [17] to evaluate the solution.

(1) Max-Sum-Reward-Mean (MSRM): This function is used to measure the average of total spectrum utilization in the system, which is the average of the sum user rewards.

$$U_{mean} = \frac{1}{n} \sum_{n=1}^{N} \sum_{m=1}^{M} a_{n,m} \times b_{n,m} \tag{2}$$

(2) Max-Proportional-Fair (MPF): The function is to measure the fairness among cognitive users accessing the spectrum in the system, which is driven by $\sum_{m=1}^{M} a_{n,m} \times b_{n,m}$.

$$U_{fair} = (\prod_{n=1}^{N} \sum_{m=1}^{M} a_{n,m} \times b_{n,m} + 10^{-4})^{\frac{1}{N}} \tag{3}$$

(3) Max-Min-Reward (MMR): The function is to maximize the spectrum utilization at the bottleneck cognitive users who receive the lowest reward, which is a simple notion of fairness.

$$U_{min} = \min_{1 \le n \le N} (\sum_{m=1}^{M} a_{n,m} \times b_{n,m}) \tag{4}$$

3. The IACO-Based Spectrum Allocation Method

3.1. The Basic Idea

In nature, ants usually find the shortest route paths from their nest to food efficiently even though obstacles exists in the path. It was found that there is an important medium used to communicate information among individuals regarding paths, and it is called the pheromone. On the one hand, a moving ant lays pheromone on the ground to mark the path, and the pheromone concentration on the path gets reinforced; on the other hand, the path with a greater concentration of pheromones will attract more ants to detect and select it with a greater probability. Based on the intelligence-ability of an ant colony, some scholars propose the ant colony optimization (ACO) algorithm and try to solve combinatorial optimization problems by mimicking the ants' behavior [18].

ACO simulates the process of ants finding the shortest paths to obtain the close-to-optimal solution for NP-hard issues. The positive feedback mechanism is the drive of the algorithm, the process of which can be explained by two steps: first, each ant selects the path with the maximum pheromone concentration and releases its pheromone to this path while it moves; then, more ants are attracted to select the path. This not only accounts for the rapid discovery of good solutions but facilitates the process of finding the optimal solution.

However, ACO is slow to converge while problem scale is large, and also it is prone to be trapped in a local optimum in the later evolution. Based on these deficiencies of ACO, we design an improved ant colony optimization IACO for spectrum allocation, which employs DE and VNS for performance improvement. DE is a greedy genetic algorithm with retained thought, which evolves by mutation, crossover, and selection in the population. In this paper, we adopt DE to optimize the moving mode of the ants to improve the global convergence ability of the algorithm and maintain diversity of the population. Besides, VNS is a local search metaheuristic employing a set of neighborhood search methods to find the local optimum in each neighborhood iteratively and finally to reach the global optimum at the end. In this paper, we design a set of neighborhoods for VNS to improve the local searchability of the algorithm.

3.2. Transform for the Spectrum Allocation Problem

The graph-theoretic model based spectrum allocation problem is NP-hard, so we introduce the IACO to obtain the efficient assignment for cognitive users. We convert the assignment issue into the shortest paths finding in a special undirected graph using IACO, for example, the model in Figure 1 is transformed into an undirected graph (Figure 2d) by the transform process shown in Figure 2.

The transform process takes three steps: first, given the high computational complexity of resources allocation, IACO names only the non-zero elements in matrix K into binary sequences (the process of a to b in Figure 2); second, according to the row-major principle, we encode all letters into a row vector $P = [A, B, C, \ldots, L, M]$ with the length of l that is the non-zero elements in K or K' (the process of b to c in Figure 2); third, based on the row vector P, we transform the letters into vertices of a special undirected graph except for the starting point SS and the ending point EE (the process of c to d in Figure 2). The ants move back and forth between SS to EE in the special graph to obtain the shortest paths (the optimal assignment scheme).

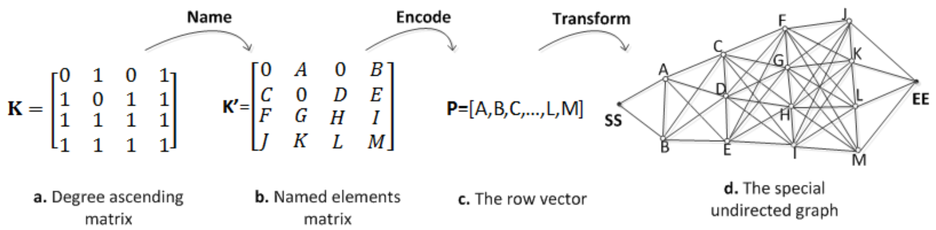

Figure 2. Transform Process.

3.3. Differential Evolution Process in IACO

DE generate new individuals by cooperation and competition among populations to guide the direction for optimization searching. It is operated by three stochastic steps: mutation and crossover as well as selection. The DE process in IACO with l-dimensional space, and N is the number of individuals. In IACO, we use DE to generate a new individual to optimize the convergence speed. Specifically, we use the following steps to get the new individual m_i of generation i. Firstly, mutate the population to get the variant v_i:

$$v_{i,j} = x_{r1,j} + K \times (x_{r2,j} - x_{r3,j}) \tag{5}$$

where $r1, r2, r3 \in \{1, 2, \ldots, N\}$ are three individuals randomly selected from current population, the mutation factor K is a real parameter in $(0, 1]$. We choose $DE/rand/1/bin$ to mutation the population instead of $DE/best/1/bin$ [19]. Next, crossover is applied to generate vector u_i by crossing element x_i and variant v_i with a certain probability, which is used to increase the diversity of the trial vector u_i, as shown:

$$u_{i,j} = \begin{cases} v_{i,j}, & rand(j) \leq CR \text{ or } j = rnbr(i) \\ x_{i,j}, & \text{otherwise} \end{cases} \tag{6}$$

where $rand(i)$ is a uniform random number in $[0, 1]$, CR means crossover probability in $[0, 1]$ and $rnbr(i)$ is a random quantity in $1, 2, \ldots, D$. Finally, the new individual m_i is selected from u_i and x_i based on the greedy thought, and the selection operation can be expressed as:

$$m_i = \begin{cases} u_i, & f(u_i) < f(x_i) \\ x_i, & \text{otherwise} \end{cases} \tag{7}$$

3.4. Variable Neighborhood Search Process in IACO

The DE-based ACO is a good way for seeking large search spaces. On the other hand, the combined algorithm has a weakness in which it fails to intensify the search in the promising area. Thus, we use VNS to enhance the local searchability of the improved algorithm. The VNS process in IACO has l-dimensional solution space, and N^s is the set of neighborhood space for solution s. The process of VNS for local search is shown as follows:

Construct the neighborhood N^s. The main objective of the improved algorithm is to maximize the spectrum utilization. To achieve this we first randomly choose a user $x_i \in s$, and get a benefit list $L = (b_1^x, b_2^x, ..., b_m^x)$ according to matrix B, where m is the available channel number. Then, we assign the channel with the highest reward b_i^x to user x_i. Using this procedure, a new set of neighborhoods is constructed. *Local search*. In order to search around the initial solution s, we construct the neighborhood N^s for local search. If the neighborhood search obtains a better fitness value, then the initial solution s is replaced by N^s. Finally, the global optimum with the highest system utility is obtained after finishing the local search.

3.5. The Process and Description of IACO

The process of IACO-based spectrum allocation is described as below (see Algorithm 1):

Step 1: Initialization. Generate the initial vector $P_{initial}$ and initialize pheromone of each path with τ_0 (the edge between vertices is connected) or τ_1 (the edge between vertices is available). Set the maximum evolution time E_{max}, the maximum evolution time with low convergence speed $E_{convergence}$, the number of population Num.

Step 2: Interference removal. The spectrum allocation scheme A must be interference free, and therefore A needs to satisfy the interference constraints from matrix C. Based on this, we would remove the interference-path to correct the solution. While A does not satisfy constraints defined by C, it is necessary to equiprobably set one value to 0.

Step 3: Fitness evaluation. Calculating fitness value is a way to convert binary sequence solutions into real space R, which can be expressed as: $f \to R^+$. Get the best path sequence P_{best} and the highest fitness value f_{max}.

Step 4: Monitor convergence rate. The monitoring mechanism is designed in IACO to detect the rate-of-change in fitness. If the growth rate stays slow and meets Equation (8) during Δt, then turn to the 7th step to accelerate convergence speed of IACO by employing DE, otherwise, go to the 5th step for ACO traversing.

$$f' = \frac{f(x_{t+2\times\Delta t}) - f(x_{t+\Delta t})}{f(x_{t+\Delta t}) - f(x_t)} < 1 \tag{8}$$

where $f(x_i)$ is the fitness value of x_i, Δt is the evolution times, f' indicates the rate-of-change.

Step 5: Ants traversal. All ants move back and forth between the starting point and the ending point. As described below in Figure 3, spectrum allocation can be seen as row traversal, where row and column represent cognitive users and bands, respectively. In this row traversal, if the available channel number $z_i > 0$ and $k_{i,j} = 1$, then band j is available for user i, that is to say node i in column j is visitable for ants, otherwise the ants skip the node. Then the evolution time $E = E + 1$.

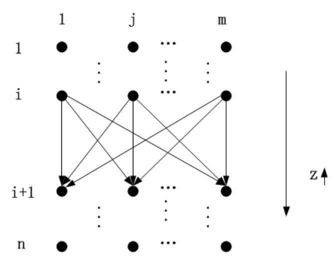

Figure 3. The way of IACO for spectrum allocation.

(1) Path selection. The transfer probability between node i and s in the choice process is presented as follows:

$$s = \begin{cases} arg\max_{j \in allowed_l} \{\tau_{i,j}^{\alpha}\mu_{i,j}^{\beta}\}, & q \le q_0 \\ J, & q > q_0 \end{cases} \tag{9}$$

where q_0 is a constant in the scope $[0,1]$, and J is a random variable generated by the following formula:

$$p_{i,s} = \begin{cases} \frac{\tau_{i,s}^{\alpha}\mu_{i,s}^{\beta}}{\sum \max_{j \in allowed_l} \tau_{i,j}^{\alpha}\mu_{i,j}^{\beta}}, & s \in allowed_l \\ 0, & s \notin allowed_l \end{cases} \tag{10}$$

where α and β are the weighted factor of information and expectation heuristic respectively. $allowed_l$ is the available node-set for ant l at node i, $tabu_l$ is the infeasible node-set for ant l and it would be cleared after l finishes traversal.

(2) Update pheromone. Using an elitist strategy to update pheromone. The pheromone concentration on path(i,j) is updated as the following rules:

$$\tau_{i,j} = (1-\rho) \times \tau_{i,j} + \Delta\tau_{i,j} \tag{11}$$

$$\Delta\tau_{i,j} = \sum_{k=1}^{m} \Delta\tau_{i,j}^{k} \tag{12}$$

$$\Delta\tau_{i,j}^{k} = \frac{Q}{f_{min}} \tag{13}$$

where $\rho (0 < \rho < 1)$ is the pheromone evaporation coefficient, $1-\rho$ is the residual factor of pheromone. Q is a constant of total pheromone released from all ants in each traversal, f_{min} is the cost calculated by fitness function.

Step 6: Termination judgment. If reach the maximum iteration times E_{max}, the solving process is over. Then map the best solution P_{best} to allocation matrix A. If $E < E_{max}$ and the convergence speed is slow and and satisfy $E_{convergence}$, then go to the 7th step, otherwise, go to the 8th.

Step 7: Accelerate the convergence speed. Adopting DE to accelerate the global convergence speed by optimizing the searching mode of the ants and guaranteeing the diversity of the population. Initialize DE with the subpopulation of ACO, $E_{convergence} = E_{convergence} + 1$.

Step 8: Local search. Employing VNS to improve the local searchability of the improved algorithm by searching around the initial solution.

3.6. Pseudocode of IACO

Algorithm 1: An Improved Ant Colony Optimization Algorithm

```
Input: T: network topology; N: the number of node in undirected graph; Δt: the evolution
       times in change rate monitoring; E_max: the maximum of iteration; E_convergence: the
       maximum evolution time with low convergence speed.
Output: the optimum spectrum allocation solution X
initialization population N(N_1, N_2, N_3, ..., N_Num)
while E < E_max do
    E ← E + 1
    Interference removal
    Fitness Evaluation
    if Equation (8) and E_convergence then
        Initialize DE with subpopulation of ACO
        E_convergence ← E_convergence + 1
        Mutation
        Crossover
        Selection
    all ants start traversal in the solution space
    The ants select path by Equation (9)
    Update pheromone according to Equation (11)
    if !E_convergence then
        Initialize VNS with local optimal solution s
        Construct reverse neighborhood N^s
        Local search
```

4. Simulation Results and Discussion

To validate the performance of the IACO, we compare IACO with the ACO, GA, and PSO [15] from four aspects: convergence speed, MSRM, MMR and MPF in this section. We use the topology structure of the cognitive radio system as suggested in [6]. The user nodes are randomly generated in the rectangle region of 10×10. The number of primary users M is equal to orthogonal available spectrum number; the number of cognitive users is N.

Initialize IACO and ACO with $\alpha = 1, \beta = 3, \rho = 0.1, \tau_0 = 5, \tau_1 = 1$; In GA, the crossover rate $pc = 0.8$, mutation rate $pm = 0.8$; In PSO, two acceleration coefficients $c_1 = c_2 = 2$, inertia weight $\omega = 0.5$, maximum speed $v_x = 4$. The population sizes are all N in IACO, ACO, PSO and GA, the maximum evolution generation is 200. The four algorithms use the same topology, the iteration times in the convergence experiment are 500 while others are 50, finally taking the mean of the result.

Experiment 1. *Figure 4 shows the MSRM trend with the increasing times of iteration under $M = 15, N = 10$ for different algorithms. In the first 50 iterations, GA is the slowest, ACO speeds up all the time but still inferior to PSO, and IACO is the best due to DE accelerating its convergence speed. At the later iteration, although PSO reaches the optimum firstly, its MSRM is lower than IACO; IACO has the highest MSRM in the end, because it adopts the VNS process to jump out of the local optimum.*

Experiment 2. *In this experiment, we show the MSRM, MPF and MMR trends with the increasing number of available licensed spectrum for different algorithms in Figures 5–7, where the number of cognitive users is fixed on $N = 15$. In Figures 5–7, all curves increase all the time. It can be seen that, if $M < N$, MSRM grows quickly whereas MPF and MMR increase slowly because of the competition for access to spectrum in cognitive* *users. If M > N, with the increasing of licensed spectrum number, MPF and MMR grow rapidly. Also, IACO is the best all the time.*

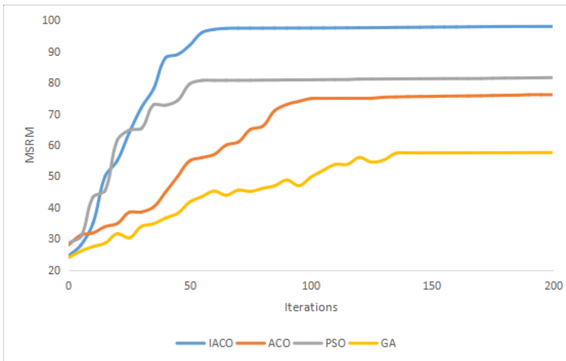

Figure 4. The average system benefit with increasing of iterations.

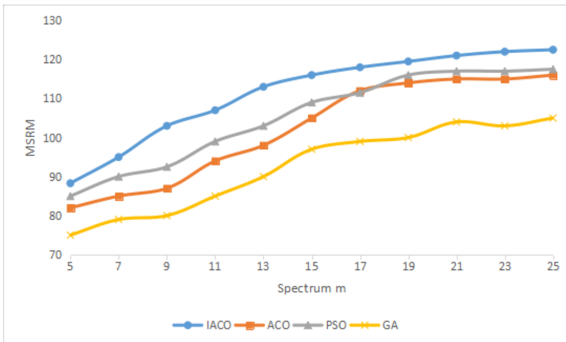

Figure 5. MSRM change with $N = 15$.

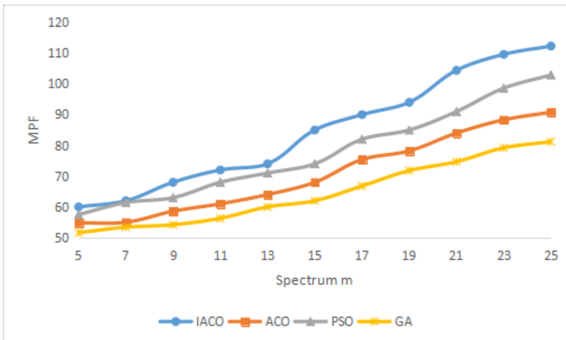

Figure 6. MPF change with $N = 15$.

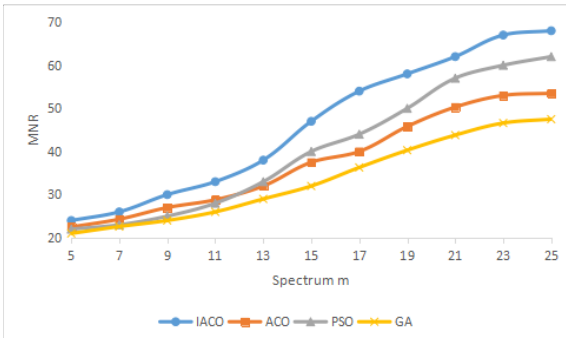

Figure 7. MMR change with $N = 15$.

Finally, we fix the cognitive user on $N = 5$, available spectrum $M = 5$ and use exhaustive method to obtain the optimal solution. The relative difference between each algorithm and the highest ideal value is obtained from $rd = 1 - \frac{b}{B}$, where b is the efficiency value of algorithms, B is the highest ideal value. This experiment is based on MSRM, MMR, MPF. As shown in Table 2, IACO is already close to the optimal value at the 100 iterations, only MPF has a slight relative difference. IACO has the advantage of convergence and can reach the optimal value quickly.

Table 2. Optimal Value.

Iteration	Algorithm	Relative Difference (%)		
		MSRM	MMR	MPF
30	IACO	0.366	0.447	1.711
	ACO	1.144	1.676	3.017
	PSO	0.324	1.275	2.083
	GA	1.033	2.876	3.496
100	IACO	0	0	0.013
	ACO	0	1.514	2.504
	PSO	0	1.309	0.952
	GA	0.472	2.666	3.224
200	IACO	0	0	0.012
	ACO	0	1.177	2.299
	PSO	0	0.616	0.564
	GA	0.063	2.282	2.71

5. Conclusions

In this paper, we developed an efficient method IACO for available licensed spectrum allocation. The main target is to maximize the system utility by using IACO. In IACO, the monitoring mechanism detects the convergence speed for the algorithm to introduce DE in a timely manner. Besides, VNS is employed to help IACO get rid of the local optimum. Therefore, the new allocation algorithm IACO conquers the limits of ACO, and not only achieves high convergence speed but reduces the risk of trapping to the local maximum. The results show that the IACO-based spectrum allocation achieves the best performance in MSRM, MPF and MMR.

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Conflicts of Interest: The authors declare no conflicts of interest.

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