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The Spectrum Allocation Technology Based on Hybrid Particle Swarm Optimization in Cognitive Communication

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Abstract. With the increase of the number of communication users, the high frequency (HF) communication resources are scarce and more precious. Aiming at the problem of frequency allocation in cognitive HF communication, this paper transforms it into the problem of maximizing network revenue, and solves the problem by using particle swarm optimization algorithm based on natural selection (NSPSO), which can get better solution in a short time. The experimental results show that the proposed algorithm is better than the conventional particle swarm optimization (PSO) and genetic algorithm (GA) in the effectiveness and speed.

1. Introduction

As the number of communication users increases, the wireless spectrum becomes more crowded. In HF communication, its spectrum resources are more precious due to the time-varying nature of the ionosphere. However, relevant researches have shown that there are a large number of available spectrum resources in the seemingly crowded HF spectrum [1]. Therefore, the cognitive communication [2][3] was introduced into HF communication.

Many researchers have done a lot of work on HF spectrum sensing and put forward many practical methods, but few pay attention to the problem of multi-user spectrum allocation in cognitive HF communication [4][5]. In HF communication, since the ionosphere changes rapidly, the time availability of the HF frequency is relatively short, and it is necessary to reselect the proper communication frequencies when the communication condition changes. Besides, there are many HF users and frequencies, which results in a huge number of permutation and combinations of them. For these reasons, it is difficult for traditional algorithms to find a better frequency allocation scheme in a short time. In the previous researches, they proposed methods based on game theory [6], price theory [7], and intelligent algorithm [9] to solve frequency allocation in cognitive communication. In essence, the spectrum allocation problem can be attributed to the NP-hard problem, and heuristic algorithms such as genetic algorithm [9] and particle swarm algorithm [10] are often used to solve such problems.

In this paper, the particle swarm optimization algorithm based on natural selection is used to solve the problem, and the result is optimized to improve the efficiency of the solution. Compared with the GA algorithm, the solution of effectiveness and efficiency is greatly improved.

The rest of the paper is organized as follows: Section II presents the mathematical model for spectrum allocation of HF cognitive networks. Section III introduces the frequency allocation step based on selected particle swarm optimization algorithm before the algorithm design descriptions. Section IV gives simulation experiment and result analysis. In the last section are the conclusions.



2. Mathematical model for spectrum allocation of HF cognitive networks

The HF network studied in this paper consists of multiple primary users, namely primary users and multiple secondary users (or called perceived users). The optimization goal of frequency allocation network is based on different regional coverage of different users, which result in the different overall network revenue. Therefore, we propose the algorithm in this paper to choose an optimal solution to maximize the total network revenue as much as possible.

In actual communication, the effective coverage area of HF users is often irregular. In the mathematical model, HF user communication is the centre of the circle. Because HF communication has communication blind spots, we approximate its effective coverage area to a circle ring. Given a target area, all users are randomly distributed in the target area. It is assumed that some users cannot use some frequencies, that is, the network revenue is 0, and others are available frequencies. Therefore, it is assumed that the only factor affecting HF secondary user communication is that each secondary user uses interference between the same frequency communication coverage. If the network senses that the primary user is no longer using the current frequency, the secondary user will be granted permission to use this frequency. When two secondary users use the same frequency, if the communication coverage overlaps, we think there is interference, and this frequency cannot be allocated to the two users at the same time. On the contrary, if the communication coverage of the two users does not overlap, that is, there is no interference. On this basis, we use the particle swarm optimization algorithm of natural selection to find the optimal solution.

Assuming that there are K primary users, M channels, N secondary users in the network ($K < M < N$). According to the characteristics of HF communication, in order to achieve frequency allocation, we define the available frequency matrix A and the network benefit matrix B . In the available frequency matrix A , $A = \{a_{n,m}\}_{N \times M}$, $1 \leq n \leq N$, $1 \leq m \leq M$. If the frequency which is not used by the primary user allocated to the user and there is no interference between the secondary users, then $a_{n,m} = 1$, otherwise, $a_{n,m} = 0$. In the network benefit matrix B , $B = \{b_{n,m}\}_{N \times M}$, $1 \leq n \leq N$, $1 \leq m \leq M$. In a HF network, a user often obtain different earning when using different frequencies, and different users using same frequencies generate different returns. If the frequency assigned to the user cannot be used, the benefit is 0.

In order to evaluate the use effect of the frequency, the algorithm is used to optimize the iteration, and the pursuit of the overall network is the largest, so we define maximum of the network revenue S_{MNR} is

$$S_{MNR} = \sum_{n=1}^N \sum_{m=1}^M a_{n,m} \times b_{n,m} \quad (1)$$

And then we solve the listed frequency assignment problems.

3. Particle Swarm Optimization Algorithm Based on Natural Selection

3.1. Design Descriptions

As an iterative optimization algorithm, the particle swarm algorithm is similar to the genetic algorithm. In an N -dimensional space, a particle has no mass and volume, besides both its position and velocity are vectors. All particles have a fitness determined by the optimized function. Each particle knows its current location and the best location which has been discovered, and it also knows the best location for all particles in the entire particle swarm. The particles use location information to decide the next action.

Assuming that the speed and position of the i^{th} particle in the d -dimensional space are $X^i = (x_{i,1}, x_{i,2} \dots x_{i,d})$ with $V^i = (v_{i,1}, v_{i,2} \dots v_{i,d})$. In each iteration, the particle seeks the optimal solution by itself, namely the individual extreme value p_{best} , and the optimal solution found by other particles in the entire particle swarm (the global optimal solution g_{best}). After finding the two optimal solutions, the particles update their speed and position according to equations (2) and (3).

$$v_{i,j}(t+1) = wv_{i,j}(t) + c_1r_1[p_{i,j} - x_{i,j}(t)] + c_2r_2[p_{g,j} - x_{i,j}(t)] \quad (2)$$

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1), j = 1, 2, \dots, d \quad (3)$$

Where w is the inertia weight, c_1 with c_2 for the learning factor, the random number r_1 and r_2 are evenly distributed between 0 and 1. The performance of the particle swarm optimization algorithm depends largely on the algorithm parameter settings, such as the number of particle swarms, the maximum of particle velocity, the learning factor, and the maximum number of iterations. The value of w adopts the linear differential decrement strategy, to overcome the limitations of the linear decrement strategy, which makes the convergence faster and correspondingly improves the performance of the algorithm. The formula for calculating the weight w is listed as follows:

$$\frac{dw}{dt} = \frac{2(w_{\max} - w_{\min})}{t_{\max}^2} t \quad (4)$$

$$w(t) = w_{\max} - \frac{(w_{\max} - w_{\min})}{t_{\max}^2} t^2 \quad (5)$$

The algorithm proposed in this paper combines the natural selection mechanism with the particle swarm optimization algorithm. The basic idea is to sort the fitness values of all particles at each iteration by using the best half of speed and position the population replace the worst half of the speed and position, and retain the original solution found by each particle, which improve the accuracy and performance for the algorithm.

3.2. Frequency allocation step based on selected particle swarm optimization algorithm

The algorithm in this paper is mainly improved based on the basic particle swarm optimization algorithm. The algorithm mainly includes the following steps.

Step 1. The number of primary users and the number of frequencies are initialized as well as the number of secondary users and the size of the target area. The geographic location of the primary and secondary users is randomly initialized, and the primary user randomly selects the frequency of use. According to the interference constraint and the perceptual principle, the available frequency matrix A and the network benefit matrix B are obtained. We initialize the maximum number of iterations, the number of particle swarms, the learning factor c_1 with c_2 and the upper limit of particle speed. Then initialize the speed and position of the particle.

Step 2. Calculate the fitness value of each particle, record the individual position and velocity, and sort the fitness values of all the particles, replacing the worst half of the speed and position. Save the best p_{best} and global best g_{best} for the individual. And start iterative optimization, constantly updating the location and speed of the population.

Step 3. Determine whether the termination condition is satisfied. If it is satisfied, stop the iteration. If not satisfied, continue the iterative optimization.

Step 4. The solution ends, and the global optimal g_{best} is obtained. Finally the frequency allocation matrix can be solved, so the frequency allocation purpose is achieved.

4. Simulation experiment and result analysis

The target area of this experiment is a matrix of 10×10 , and each HF user has a maximum coverage radius (4) and a minimum (1). In the case where the frequency is available, the coverage of different users selecting different frequencies is randomly determined. The number of initial users is 10, the number of secondary users is 20, and the number of frequencies is 15. In the MATLAB environment, the NSPSO, PSO, GA algorithms are used to optimize the calculation. The NSPSO and PSO algorithm parameters are set to $c_1 = c_2 = 2$, $w_{\min} = 0.8$, $w_{\max} = 1.2$. The number of particles $PN = 40$. The GA algorithm parameter was set to the population size of 40, a crossover probability of 0.9, and a

mutation probability of 0.04. The number of iterations for these three optimization algorithms was 200, and the experiment was repeated 100 times. The maximum network benefit of the evaluation values was averaged.

It can be seen from Fig. 1 that the proposed algorithm significantly improves the network revenue, and the GA algorithm has the worst effect. The final network benefit value converges to 340, and the final network revenue value of the NSPSO algorithm converges to 395, and the network revenue increases 16.1%. In operation, the NSPSO algorithm runs at half the time of the GA algorithm.

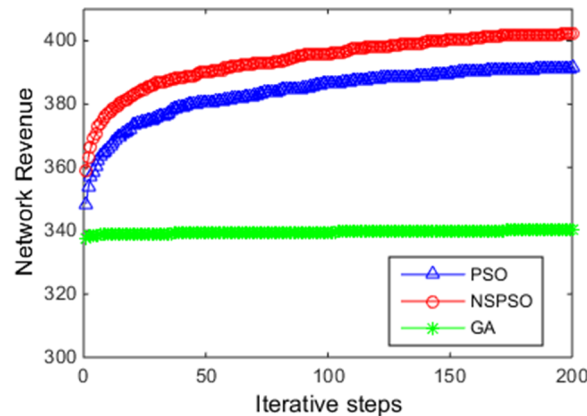


Figure 1. Network benefits compared with different algorithms.

The experiment considers the effect of the number of particles on the algorithm. Set the number of primary users to 10, the number of secondary users to 20, and the number of channels to 15. $c_1 = c_2 = 2$, $w_{min} = 0.8$, $w_{max} = 1.2$. In the case of the simulation of the number of particles of 20, 40, 60, 80, 100, it can be seen that the more the number of particles, the highest network benefit value, but the number of particles increase slowly when the number of particles is more than 40. Considering that as the number of particles increases, the search time increases significantly, but the benefit is not significant. Therefore, the number of particles is determined to be 40 in this experiment.

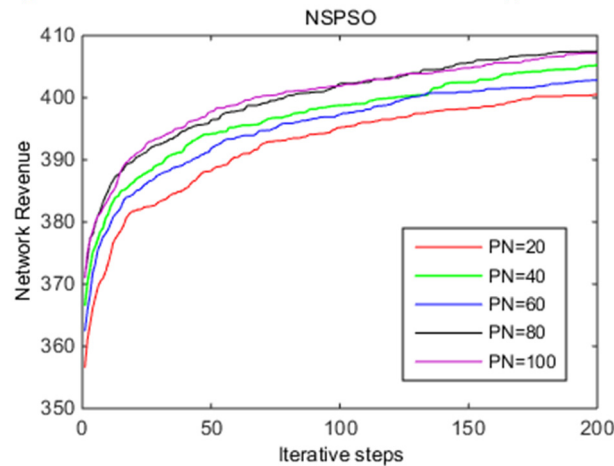


Figure 2. Effect of different particle numbers on the efficiency of NSPSO algorithm

Considering the relationship between frequency and network revenue without changing the initial settings, it can be seen from the figure 3 that as the number of frequencies increases, the available frequency of each user increases, so the overall network revenue also increases as the number of frequencies increases.

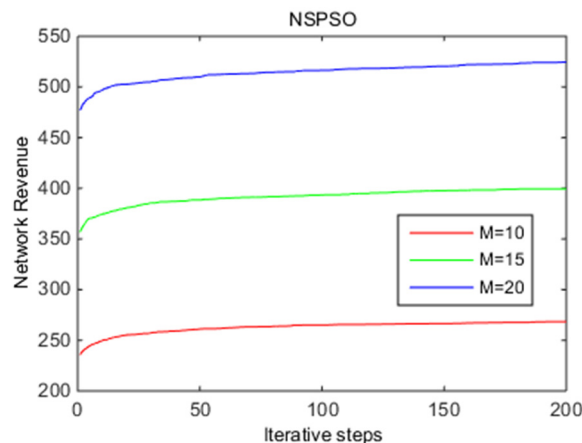


Figure 3. Effect of different frequency numbers on network benefits.

5. Conclusion

In this paper, in order to maximizing network efficiency, a particle swarm optimization algorithm based on natural selection is proposed to solve the frequency allocation problem of cognitive HF communication. Simulation experiments show that the proposed algorithm is far superior to the GA algorithm and the time is about one-half of the GA algorithm. Besides, the proposed algorithm improves the overall network revenue of the cognitive HF network, and can utilize the advantages of the HF network effectively. The next step is to use the actual frequency detection data to study the frequency allocation problem of the conventional HF network.

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