Multi-cognitive network resource allocation based on improved artificial bee colony algorithm

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Abstract. This paper introduces a graph theory model for resource allocation in multi-cognitive wireless network scenarios. Aiming at the problems of low search accuracy and slow convergence speed of the basic artificial bee colony algorithm, an improved bee colony algorithm is proposed. The improved algorithm introduces an adaptive t-distribution mutation strategy. Compared with the original algorithm, the performance of the improved algorithm has greatly improved. At the same time, the improved bee colony algorithm is applied to multi-cognitive wireless network scenarios for resource allocation in the model. The experimental results show that the improved artificial bee colony algorithm can obtain greater system throughput and effectively reduce the performance of multi-cognitive wireless network systems, and can allocate resources more reasonably.

1. Introduction
Cognitive radio [1] [2] is a new technology that can improve spectrum utilization, and has been widely used in vehicle networking [3] and UWB communication [4]. Cognitive radio ad hoc networks have many excellent features such as independent networking, no center, self-organization, dynamic topology, and multi-hop routing. It has broad application prospects in military communications and other fields. Therefore, this paper studies the coexistence and coordination of resource management and configuration of multi-distributed cognitive wireless networks, and researches on swarm intelligence algorithms. Starting from transmission power control and channel resource reallocation, based on the improved artificial bee colony algorithm, it can explore reasonable coordination, intelligence and order.

2. Improved artificial bee colony algorithm.
In 2005, Dr. Karaboga [5] proposed the Artificial Bee Colony Algorithm (ABC) algorithm based on the honey-picking behavior of bees. The problem that the accuracy of the new solution is not high [6] or raised [7], and an improved adaptive t-distribution mutation search strategy is proposed. The adaptive t-distribution mutation proposed in this paper uses chaotic search at the initial stage, and introduces the current best food source into the search formula of scout bees. The formulas that lead the bees and followers to search for updates are as follows:

\[ v_{id} = x_{id} + \beta \cdot t(n) \cdot (x_{jd} - x_{id}) \]  \hspace{1cm} (1)

\( v_{id} \) is the location of the new food source, and \( \beta \) is a random number in the range of \((0,1)\). The closer the \( \beta \) value is to 1, the greater the role of the mutation, and the closer the \( \beta \) value to 0, the
smaller the role of the mutation. \( f(n) \) is a t-distribution subject to degrees of freedom \( n \). The values of degrees of freedom \( n \) are as follows:

\[
n = 1 + \frac{n_0 \cdot k}{MCN}
\]

(2)

MCN represents the maximum number of iterations, \( n_0 \) is a constant, and represents the maximum value of the degree of freedom of the t distribution. At the initial stage of the algorithm, the value of the degree of freedom \( n \) obtained according to formula 2 is small, and the change of the t distribution is similar to that of the Cauchy distribution. Enhanced the global exploration ability at the beginning of the algorithm. In the later stage of the algorithm, the value of the degree of freedom \( n \) obtained according to formula 2 gradually approaches \( n_0 \) and the variation of the t distribution is similar to the Gaussian distribution, which has a good local development capability. In the middle of the algorithm, the variation of the t distribution is between the Cauchy and Gaussian distributions.

3. Resource allocation of multi-cognitive network based on graph theory model
This paper considers a cognitive system that includes three distributed cognitive radio networks. Assume that the system includes a set of three distributed cognitive networks with a total of \( N \) cognitive users. The cognitive users in each cognitive network are random and even. When distributed, they can share a group of channels \( C \), and each channel has equal bandwidth \( B \), different cognitive networks have a unique network ID, and each cognitive user will bring this network ID when they are interfered with and collaborate. And each distributed cognitive network is composed of multiple cognitive users, their transmission ranges on different channels may be different, so a given pair of nodes (from the same or different cognitive networks) may Interference can occur on some channels and coexistence can be achieved on other channels. Figure 1 is a schematic model of the coexistence of cognitive radio systems composed of three distributed cognitive radio networks.

![Figure 1. Coexistence model of multiple distributed cognitive radio networks](image)

Interference between cognitive users is measured using a protocol interference model [8]. The protocol interference model judges whether the transmission is successful or not according to the effective transmission range of the user, that is, from the perspective of the transmitting end, and only when the target node is within the transmission range of the corresponding transmitting node, the interference of other cognitive users outside the range, the transmission is successful. When two or more nodes communicate on the same channel and are within the interference range of each other, they will cause interference on this channel, which will cause the transmission to fail. In Overlay mode, the behavior and number of authorized users will affect the availability of the channel [9]. To simplify the analysis, this article models the channel availability, rather than the behavior and number of authorized users. Therefore, all available channels in the cognitive system are modeled as a two-level Markov chain ON-OFF model, as shown in Figure 4.2:
In Figure 2 above, the parameters $\alpha$ and $\beta$ represent the probability that an authorized user will change from ON to OFF state and from OFF to ON state on a given channel, respectively.

In this study, both spectrum and power resources are included in the resource allocation model. Under the premise of meeting communication requirements, by dynamically adjusting the transmit power of each cognitive user, its transmission range and interference range can be dynamically changed. Further reducing interference in cognitive systems and improve the performance of each cognitive radio network. In summary, the set of interfered users under the coexistence condition of multiple distributed cognitive radio networks can be modeled as an undirected interference graph[10] represented by $G = (V, E, L)$. $V$ is a set of vertices representing the composition of disturbed cognitive users, $L$ is a set of lists representing the channels available to each cognitive user, and $E$ is a set of edges consisting of cognitive users with interference. The edge between two nodes indicates that there is interference on some channels between a group of user pairs. If two subscriber users have interference on at least one channel, there will be an edge between them. For any two cognitive users who are connected, they cannot use the same channel to communicate at the same time. Through this mechanism, although the number of channels available to cognitive users in each network may actually be reduced, the network or Inter-network interference will also be reduced, which will ultimately increase the spectral efficiency of each network and the throughput of the system.

For cognitive user $i$ who wants to communicate with channel $c$, in order to meet his own communication needs, there are certain requirements for SINR:

$$SINR_{i,c} = \frac{a_{i,c}g_{i,c}p_{i,c}}{\sigma^2 + \sum_{j=1}^{N} a_{j,c}g_{j,c}p_{j,c}}$$

(3)

$a_{i,c}$ indicates whether the cognitive user can use channel $c$, $p_{i,c}$ is the transmit power of the cognitive user on channel $c$, $\sigma^2$ is the channel gain of the cognitive user on channel $c$, and $g_{i,c}$ is the additive Gaussian received by the cognitive user at the receiving end White noise power, $\sum_{j=1}^{N} a_{j,c}g_{j,c}p_{j,c}$ indicates that the cognitive user $i$ is interfered by cognitive users from the same cognitive network or different cognitive networks on channel $c$. If the minimum SINR requirement of the cognitive user is assumed to be $mm$, $SINR_{i,c}$ The conditions that should be met are:

$$SINR_{i,c} \geq mm$$

(4)

In this paper, under the premise of ensuring that the communication of authorized user on each channel is not disturbed and improving the communication quality of the cognitive user as much as possible, the throughput of the cognitive radio system composed of multiple distributed cognitive radio networks is maximized. The method of constructing the system throughput objective function in reference [11], the objective function proposed in this paper is shown below:
\[
\max \sum_{n=1}^{N} \sum_{c=1}^{C} B_c \cdot \log_2 \left(1 + \text{SINR}_{n,c}\right)
\]  

(5)

4. Experiments

4.1. Effectiveness analysis of improved artificial bee colony algorithm

In this paper, the multi-peak and multi-extremum functions Schaffer and Salomon with countless local extreme points in the search space in the Benchmark [12] library are tested. The test results are shown in Figure 3. Their test results also differ by two orders of magnitude. At the same time, the accuracy of the test results is worse than that of the single bee function and multi-peak and extreme values, indicating that in the case of more extreme points, the performance of both algorithms is affected. The original artificial bee colony algorithm and improved artificial bee colony algorithm. When there are two multi-peak multi-extremity test functions, that is, there are countless local extremums, the iterative search obviously produces different degrees of iterative convergence, slowing down or falling into local extremities value. However, from the test results, the improved artificial bee colony algorithm achieved faster convergence speed than the original algorithm, that is to say, the improved artificial bee colony algorithm improved the global exploration ability and local development ability.

![Figure 3. Contrast of multi-peak and multi-extreme function values](image)

4.2. Throughput analysis of multi-cognitive radio network systems

This article uses matlab 2017b to simulate and verify the JCPC-ATMABC algorithm. The simulation experiment scenario considers a scenario where three distributed cognitive radio networks coexist in a 30m×30m area, and the cognitive users of each distributed cognitive radio network are randomly and uniformly distributed in the area. Channel availability parameter selection parameters \(\alpha\) and \(\beta\) are uniform random values in the range \([0.1, 0.9]\). The control experiment based on the improved artificial bee colony algorithm, which is based on the random channel allocation algorithm CA-ATMABC without power control, once a plurality of cognitive users generate interference on the same channel, randomly assign a cognitive user to use the channel.

The number of authorized users and the number of available channels are equal to 20, each channel is mutually orthogonal and the size is 1 MHz, the number of cognitive users in each distributed cognitive network is 10, and the maximum number of cognitive users in each channel is the transmit power \(P_{\text{max}}\) is 50mw, the total maximum transmit power \(P_{\text{max}}\) is 0.5w, the Gaussian white noise power spectral density is \(10^{-10}\) W/Hz, and the maximum evolution number of the algorithm is set to 400. The comparison results of the throughput analysis of the multi-cognitive radio network system are shown in Figure 4:
From the results in Figure 4.a, it can be seen that the channel throughput with power control is significantly higher than the system throughput with random channel allocation without power control, which is mainly because in the no power control model, the channel allocation will correspond to give a fixed power allocation value, so the difference in interference between different available channels and cognitive users is not taken into account. In the joint power control and channel allocation model, when allocating power, first know whether the allocation is based on the channel allocation result, and then determine the specific value of power allocation based on the interference situation and the characteristics of the channel. Larger transmission power can be obtained on the channel, and on channels with less interference, more cognitive users can be accommodated by limiting the transmission power.

From the results in Figure 4.b, When the number of available channels of the cognitive radio system changes from 5 to 50, it can be clearly seen that the system throughput increases with the number of channels. This is mainly because when the number of cognitive users is the same, as the number of channels increases, competition between and within each cognitive radio network will decrease accordingly, so cognitive users can use more channels for information transmission, and the throughput of the entire cognitive radio system increases, and it can be seen from the experimental results. The performance of the JCPC-ATMABC algorithm is significantly better than the performance of the CA-ATMABC algorithm.

From the results in Figure 4.c, When the number of cognitive users in each distributed cognitive radio network changes from 5 to 50, it can be clearly seen that the system throughput decreases as the number of cognitive users increases. This is mainly due to the limited number of available channels. In the case, as the number of cognitive users in the system increases, competition between and within each cognitive radio network increases, so that the number of channels that cognitive users can be assigned to decreases, and the entire cognitive radio system throughput decreases.

5. Conclusion
This paper describes the joint allocation of channel and power resources in detail, and focuses on the analysis of multi-distributed cognitive radio network coexistence graph theory models. Second, it starts with the problems that need to be solved, and introduces the system objective functions and system functions corresponding to the modified coexistence model and application background. Finally, simulation experiments were performed to analyze the performance differences and influencing factors of the JCPC-ATMABC algorithm. The simulation results show that the improved allocation algorithm has good performance in resource allocation, and can intelligently and orderly use limited spectrum resources.

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