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The research on multiuser resource allocation optimization in cognitive radio

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Abstract. Spectrum resource allocation optimization is still a research hotspot in the field of cognitive radio. The optimization framework based on Bandwidth-Power Product (BPP) proposed in recent years provides a new direction for this field. Compared with the traditional waterfilling algorithm, the new optimization framework has effectively improved the utilization of spectrum resources. However, there are few further studies on BPP in recent years. Based on the work of predecessors, this paper improves the criterion of BPP by taking into account the impact of the multiplexing of spectrum resource in different spatial locations on the spectrum utilization. The simulation results show that the improved BPP framework can further improve the utilization of spectrum resource; besides, the framework is more in line with the actual cognitive radio environment.

1. Introduction
In recent years, wireless communication has been developing extremely fast, and there has been a problem of spectrum shortage that has to be faced. The static spectrum allocation in the existing spectrum management approach results in extremely low spectrum utilization, which is clearly a great waste of limited spectrum resource. In order to improve the spectrum efficiency, cognitive radio has been proposed and getting more and more attention[1][2][3][4]. The character of cognitive radio is that cognitive users can access the licensed spectrum through an opportunistic approach. In cognitive radio networks, cognitive users periodically detect the use of surrounding spectrum through spectrum sensing, and make better use of spectrum resources by changing their own radio parameters.

The optimal allocation strategy of spectrum resource has always been a research difficulty in cognitive radio. Multidimensional joint spectrum resource allocation has always been an important direction in this field. In the face of a complex and volatile radio environment, we should establish an appropriate model to analyse the spectrum environment requirements, and find the characteristics of the spectrum resource in the multi-dimension such as frequency domain, space domain and power domain, so as to improve spectrum efficiency.

The principle of waterfilling algorithm for improving spectrum utilization is that under a fixed total transmission power limit, a high SNR channel allocates higher power and a low SNR channel allocates lower power, thus finally reaching a "horizontal" state, which maximizes the transmission rate[5]. However, in this classical algorithm, the joint influence of power and bandwidth on system efficiency is not considered together. Therefore, Yahia Tachwali et al. proposed a resource metric framework called BPP[6], which clarifies the bandwidth and the power allocated to each channel belong to spectrum resource. In [6], author proves that the BPP framework could effectively improve spectrum resource utilization.
However, the BPP framework ignores the division of the space occupied by different users in a multi-user environment, that is, the same channel may be allocated to the same user which is ignored in BPP framework. For overcoming the deficiency of BPP, we propose an improved framework based on BPP. This framework considers the impact of spatial dimension on allocation strategy, and considers the gain of spectrum resource reuse in spatial dimension. The simulation results show that compared with the classical waterfilling algorithm and original BPP framework, the improved framework could significantly improve the spectrum utilization.

2. System Model
We consider the downlink resource allocation based on CRN-OFDM system, and its wireless channel model is based on the outdoor COST-Hata loss model[7]. Fig.1 is a specific example of the system, in which a cognitive base station provides services to cognitive users. The system consists of a cognitive base station(CBS), multiple authorized base stations(ABS), multiple cognitive users(CUs) and multiple authorized users(AUs). We define $C$ to represent the set of cognitive users in the system, and $A$ to represent the set of authorized users. Suppose that the total number of channels available for allocation is $N$ and the bandwidth of each channel is $B$. We denote the channel number by $n$, then $n \in N$. We assume that the cognitive base station in system can perfectly obtain the channel state information (CSI) of any CU on any channel[8]. It is necessary to provide services to CU as much as possible while ensuring the quality of the AU communication[9][10][11].

2.1. The cognitive user interference on the authorized user
Obviously, the communication of cognitive user can interfere with the communication of authorized user. However, it is acceptable as long as the interference value is below a certain threshold. In our system, we define $I$ as interference, then the cognitive user interference on the authorized user can be described as follows:

$$I_{cu-au}^n = \left| g_{a'}^n \right|^2 \int_{d-\frac{B}{2}}^{d+\frac{B}{2}} p_c^n T \left( \frac{\sin(\pi f T)}{\pi f T} \right)^2 df$$

Where $I_{cu-au}^n$ is the CU interference on AU and where $d$ is the spectral distance between channel $n$ used by CR and channel $n'$ used by AU. $p_c^n$ is the power allocated to CU $c$ on channel $n$ and $g_{a'}^n$ is the channel gain between CBS and AU on channel $n'$.

2.2. The authorized user interference on the cognitive user
Within our system, the communication of authorized user will also cause interference to cognitive user, which could be described as follows:
Where $g_{a-c}^n$ is the channel gain between AU and CU on channel $n$, and where $\rho_{n'}^f$ is the power spectral density of AU signal at channel $n'$. According to equations (1)(2), the channel gain to interference and noise ratio (CINR) at CU $c$ at channel $n$ could be described as follows:

$$h_c^n = \frac{g_c^n}{\Gamma[\eta + \sum |g_{a-c}^n|^2 \int_{-\frac{f}{2}}^{+\frac{f}{2}} \rho_{n'}(f) df]}$$  

(3)

$\eta$ is the Gaussian noise, $\Gamma$ is the SNR gap to Shannon capacity limit[12], and $g_c^n$ is the channel gain between CU and CBS on channel $n$.

### 2.3. Spatial characteristic of spectrum resource

Intuitively, users in different locations may either multiplex the same channel or compete on it. Therefore, we need to quantify the impact of spatial dimension on channel allocation. Here, spatial correlation is be proposed, which could be described as follows:

$$\mu_{ij}^n = \frac{P(C_j^n | C_i^n)}{P(C_i^n)}$$  

(4)

$P(C_i^n)$ indicates the accessible probability which CU $i$ independently observes on channel $n$ in the area where it is located. $P(C_j^n | C_i^n)$ indicates the accessible probability which CU $i$ observes on channel $n$ given that CU $j$ already observes the channel $n$ could be accessed. And $\mu_{ij}^n$, which is defined as spatial correlation, could quantify the impact of distance between CU $i$ and CU $j$ on resource allocation.

Let’s illustrate the conception with an example. As is shown in Fig.2 below, it is assumed that only one channel, whose ordinal is $n$, could be accessed. Since the CU $i$ and the CU $j$ are far apart due to the spatial distance, it can be considered that the accessibility at the channel $n$ observed by CU $j$ does not affect the accessibility at the channel $n$ observed by the CU $i$, and we could conclude that $\mu_{ij}^n = 1$. However, since CU $i$ and CU $k$ are very close together, the $\mu_{ij}^n$ observed in the system will be much larger than 1. For the sake of simplicity, we think $\mu_{ij}^n \in \{1, v\}$, $v$ represents a value greater than 1. That is, if $\mu_{ij}^n = 1$, we think CU $i$ and CU $j$ could multiplex the same channel, otherwise, they couldn’t.

In order to make the system space gain higher, we need to reuse the spectrum resource as much as possible. Obviously, in Fig.2, the optimal multiplexing factor of channel $n$ is 2, that is, it is simultaneously accessed by CU $i$ and CU $j$.

![Fig.2 Spatial correlation](image-url)

### 3. Problem Formulation

We assume that the CUs will reuse the same channel as much as possible. It is also assumed that AUs and CUs are uniformly distributed within the limited area. The system optimization problem is formulated as follows:
We assume that the CUs will reuse the same channel as much as possible. It is also assumed that AUs and CUs are uniformly distributed within the limited area. The system optimization problem is formulated as follows:

$$\min \{ F_p F_p \} : \quad (5)$$

$$F_B = G_s \sum_n B \cdot \text{sgn}\left( \sum_c x^n_c \right)$$

$$F_p = \sum_c \sum_n p^n_c$$

subject to

$$\forall x^n_c \in \{0,1\} \quad (6)$$

$$G_s = \frac{\sum_n (\sum_c x^n_c)^2 - 1}{\sum_n \text{sgn}(\sum_c x^n_c)^2}$$

$$\sum_c I^n_{cu-au} y^n_c \leq I^n_{th}, \forall y^n_c \in \{0,1\} \quad (8)$$

$$Q = \sum_N B x^n_c \log \left( 1 + \frac{g^n_c p^n_c}{\eta + \sum_{AU} I^n_{au-cu}} \right) \geq \phi_c, \forall c \in C \quad (9)$$

### 3.1. System constraints

In equation (6), $x^n_c$ indicates whether the channel $n$ is assigned to the CU $c$, and if it is, $x^n_c = 1$; otherwise, $x^n_c = 0$.

In equation (7), $G_s$ is used to measure the system efficiency gain brought by channel multiplexing in spatial dimension. $\text{sgn}(\cdot)$ is the symbol function whose value could be only 0 or 1. We utilize equation (7) to calculate the average gain from all channel multiplexing in spatial dimension.

In equation (8), $I^n_{th}$ is the system interference threshold. $y^n_c$ indicates whether the current CU communication activity will cause interference to AU. If interference is caused, $y^n_c = 1$; otherwise, $y^n_c = 0$.

In equation (9), $\phi_c$ stands for the minimum QoS requirement for CU.

### 3.2. Multiuser allocation

According to paper [6], we would get the optimal $N'$ in the situation of single user:

$$N' \approx \frac{\phi_c}{2.3B} \quad (10)$$

Then, we need to solve the allocation problem of multiusers. Within existing algorithm theories, vertical decomposition can be applied to the optimization problem with a coupled variable[13]. In this paper, the joint spectrum resource allocation problem can be decomposed into channel allocation problem and power allocation problem. And channel allocation is the master problem. We aim to fix its power allocation variable to a feasible value at first, and then solve the channel allocation problem. Finally, we can find the optimal solution for minimizing resource allocation.

(1) master problem

First, we fix the assigned power value of each cognitive user as a feasible value $p^{\ast(n)}_c$. The equation (5) is simplified as follows:

$$\min B \cdot \sum_N \frac{1}{\sum_c x^n_c} \quad (11)$$
subject to equations (6)(7)(8)(9).

In order to find the minimum value of equation (16), the problem can be solved by applying a variant of the Hungarian algorithm[14]. The algorithm is as follows:

1. According to equation (10), we estimate different $N_c^i$ of different CU. Then we construct a $C \times C$ spatial correlation matrix $R$. Each element in $R$ is calculated by equation (4). Therefore, we can scan the elements in $R$ row by row and divide the users into groups that are orthogonal to each other. The meaning of orthogonality here means that the same channel can be multiplexed among different groups but cannot be multiplexed within group. Next, we perform the following algorithm for the users in each group, and we agree that $C$ in the following steps refers to the set of CUs in each group.

2. Construct a $C \times N$ cost matrix $|C|$, whose element $C_{cn}$ represents the cost value of assigning channel $n$ to CU $c$. It could be described as follows:

$$C_{cn} = \frac{\eta + \sum_{AU} I_{au-cu}^n}{g_c^N}$$

(12)

3. According to the channel budget $N_c^i$ obtained by each cognitive user (that’s could be estimated by single user), we repeat $N_c^i$ times for each user's row vector in matrix $C$, thus obtaining new cost matrix $C'$. If the number of rows in $C'$ is greater than the number of columns, we believe that there is no feasible solution for the channel allocation problem. Otherwise, go to step 4.

4. According to $C'$, the channel allocation problem is solved by using the original Hungarian algorithm.

Finally, we solve the channel allocation problem and get the optimal $N^*$. (2) sub-problem

Now, the optimization problem could be simplified as follows:

$$\min F_B^* \sum_c \sum_{N^*} p_c^n x_c^n$$

subject to equations (6)(7)(8)(9).

The above problem can be solved using dual-decomposition method, that is, the Lagrangian variable is updated by the iterative sub-gradient algorithm, and the problem is transformed as follows:

$$p_c^n = \arg \min H(p, \alpha, \beta)$$

$$H(p, \alpha, \beta) = \sum_c \left( F_B^* \sum_{N^*} p_c^n + \alpha_c \left( \sum_{N^*} I_{cu-au}^n - l^n_{th} \right) + \beta_c \left( \phi_c - Q \right) \right)$$

(15)

Where the $\alpha, \beta$ multiplier is formulated as follows:

$$\alpha_c(n+1) = \alpha_c(n) + \omega(n) \left( \sum_{N^*} I_{cu-au}^n - l^n_{th} \right)$$

(16)

$$\beta_c(n+1) = \beta_c(n) + \omega(n) \left( \phi_c - Q \right)$$

(17)

Where $\omega(n)$ is the iterative step size of decreasing, and $\lim_{n \rightarrow \infty} \omega(n) = 0$. And the initial value is input into the system. After several iterations, we obtain the optimal solution of the power allocation in the system.

(3) the gradient descent iteration

Through solving master problem and sub-problem, we obtain one iterative solution in the overall resource allocation process. According to the gradient descent algorithm, we can get a new bandwidth budget $N^*$ again. At this time, Repeat the above procedure to get a new optimal solution. Through such iteration, we could get next value of improved BPP. When the difference of these values is below a certain threshold, we stop iterating and use that value as the final solution.
4. Simulation Results

Assuming the system contains 4 users, the channel bandwidth $B$ is 15 kHz, the minimum QoS requirement is -90 dBm, and the ambient background noise power is -110 dBm. We can get the following simulation results:

As shown in Fig.3, when the improved BPP algorithm has a redundant channel number, the number of allocated channels is significantly lower than that of water filling algorithm. As the data rates requirements increase, all available channels are gradually occupied.

In Fig.4, it can be seen that the power level required by the water filling algorithm is gradually increased, and the improved BPP tends to rise steadily, but there will be a small number of “spikes” during the ascent, which is due to the channel allocation has a jump at a specific rate.

It is seen from the results shown in Fig.5 that when the rate requirement in the system is not high, the system resources consumed by the improved BPP will be significantly lower than the resource consumed by water filling algorithm. And we can conclude that our improved BPP has significantly lower system resource consumption than water filling, and the spectrum utilization is higher, and the simulation results are in line with our expectations.

To measure the gain of the improved BPP framework in the spatial dimension, we compare it to the original BPP algorithm. We compare them under the condition that the system rate requirement is 100 kbps and total number of channels is 12. And the result is shown in Fig.6.

As can be seen from Fig.6, there are 3 channel which reuse times are 4 in improved BPP framework, and the number of channels required for BPP is 12, which is in line with expectations, because channel multiplexing could be considered that more channels could be accessed in the system. It could be
concluded that the improved BPP measures the gain of multiplexing of channels in the spatial dimension and improves spectrum efficiency.

![Fig.5 Consumption of spectrum resource](image1)

![Fig.6 Comparison of multiplexing](image2)

5. Conclusion
In this paper, we study the problem of spectrum resource allocation under the coexistence system of CUs and AUs. Considering the impact of channel multiplexing in spatial dimension, we propose an improved BPP framework to measure the spectrum resource occupancy in the system. The simulation results show that the improved BPP can effectively measure the resource consumption in the system. Compared with the waterfilling algorithm and original BPP, the improved BPP could further improve the spectrum efficiency.

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