Channel Capacity Optimization via Exploiting Multi-SU Coexistence in Cognitive Radio Networks

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***Abstract*—In *Cognitive Radio Networks* (CRNs), when the *Primary Users* (PUs) appear, the SUs have to evacuate the licensed spectrum in use or reduce the transmit power so that no harmful interference is introduced to the PUs. In this paper, we explore the multiple *Secondary Users* (SUs) coexistence system in CRNs based on power control mechanism and interference temperature model. We propose an optimal solution that can maximize the channel capacity and minimize the spectrum handover overhead, constrained by the accumulated interference of both the SUs-to-PU and SUs-to-SUs. We formulate this problem as a non-linear optimization problem and propose a heuristic algorithm to solve it efficiently. Experimental results show that compared with two alternative approaches, our algorithm can improve the usage of the spectrum by up to 51% (with a random approach) and up to 278% (with a conservative approach).**

I. Introduction

Cognitive radio (CR) is an effective method to alleviate the frequency scarcity problem [1]. While PUs have the priority to access the licensed spectrum, SUs can opportunistically use spectrum when no harmful effects to the PUs are introduced [2]. When the PUs appear, the SUs have to evacuate the occupied spectrum and move to some other validated ones. This is the so called spectrum handover. Frequent spectrum handovers will cause significant performance degradation for the SUs because of the large handover overhead such as the reconstruction of the wireless connections, re-establishment of the TCP links, and etc.

Indeed, spectrum handover is not the only option for the SUs when the PUs appear. FCC [3] suggested the *Interference Temperature Model* (ITM) to regulate the SUs' behavior. According to this model, the SUs are allowed to co-exist with the PUs when the SUs' aggregated interference on the PUs is below a certain level. In other words, SUs can appropriately adjust their transmit power to fully exploit all the spectrum opportunities, while the interference to the PUs is low enough to have no harmful effect. This is called power control based spectrum handover [4].

In the existing power-control based spectrum handover, researchers mainly focus on the cumulative effects of SUs on PU, and the basic goal is to maximize the individual link capacity while no harmful effect is introduced. This is, however, not necessary to be optimal solution that can fully exploit the spectrum opportunity. Besides the interference caused by the PUs, there may be interference between SUs when multiple SUs co-exist with the PUs. Such interference between SUs will severely affect the communications in between, causing a significantly degraded communication capacity.

To maximize the utilization of the spectrum opportunity and the network capacity, in this paper, we analyze the accumulated interference constraints on both the SUs-to-PU and SUs-to-SUs. We extend the ITM to a multi-SU spectrum sharing cognitive network. We formulate the problem as a constrained non-linear optimization problem and show that the problem is in general an NP-hard problem. To address the problem in a feasible way, we design a heuristic algorithm based on a 0-1 knapsack problem. We prove that the algorithm is guaranteed to converge. Simulation experiments show that compared with two alternative approaches, namely a random algorithm and a conservative algorithm, the network capacity can be increased by up to 51% and 278% respectively.

The rest of the paper is organized as follows. Section II reviews the related literature on the spectrum access and hanover. Section III presents the system model. We formulate the multi-SU spectrum handover problem as a constrained optimization model in section IV. Section V simplifies the optimization model and an optimal solution is given. Section VI shows our simulation results. Finally, we conclude the paper in section VII.

II. Related Work

The prior works on spectrum access in the CR network can be divided into two categories: the overlay access and the underlay access. In the overlay way, SUs use the licensed channel opportunistically. Zheng et al. [5] propose a color-sensitive graph approach which characterizes the interference between the PUs and the SUs using a binary model. In [6] and [7], the authors present a proactive and a cooperative sensing model respectively to discover as many spectrum opportunities as possible. However, in their work, the coexistence of PUs and SUs on the same channel is not considered. In the underlay way, an SU can operate on the same frequency with PUs, provided the interference temperature at each licensed receiver does not exceed an interference temperature threshold [8]. Power control is usually applied to avoid interference to PUs in the underlay access [9] [10].

As a critical issue in cognitive radio networks, spectrum handover plays an important role in spectrum access. Mo-

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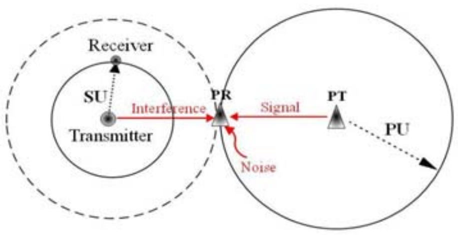

Fig. 1. The coexistence system of PU and SU.

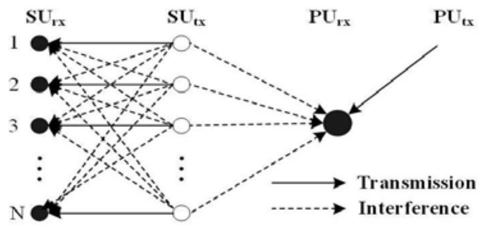

Fig. 2. Interference model in multi-user CR network.

hamed et al. [11] propose a scheme to reduce the spectrum handover. In this scheme, unlicensed channels are used as backup channels. However, if the number of unlicensed channels reduces, the scheme degenerates to the traditional one. L.Giupponi et al. [12] propose a fuzzy-based approach which makes effective decisions on spectrum handover in the context characterized by uncertain, incomplete and heterogeneous information. But it is difficult to determine an appropriate decision threshold. Feng et al. [13] extend the spectrum handover problem to multi-hop networks in which they formulate an optimization problem to minimize the total latency under the constraint of network connectivity. Different to their work, we focus on optimizing the spectrum handover scheme through power control. In our prior work [14], we propose a power control based spectrum handover scheme to improve the transmission efficiency by avoiding some of the handovers. In that scheme, a combination of dynamic spectrum allocation and power control is adopted. However, the accumulated interference introduced by SUs-to-SUs will degrade the channel capacity since there is no coordination among the SUs using the same channel. Different to the prior works, in this paper, we consider the interference among multiple secondary users besides the interference of SUs-to-PU.

III. System Model

We consider a cognitive radio network in which a PU and several SUs coexist on licensed channel c. As we can see from Fig. 1, PT (PU transmitter) is far from the PR (PU receiver). SU transmitters and receivers are in the PU receiver location area, where the emissions from undesired SU transmitters could cause unbearable interference exceeding the interference temperature limit. The receiver measures the inference temperature for the region and broadcasts a message indicating the temperature values over that region. Then the transmitter could adopt the power control mechanism to reduce the transmit power on channel c or switch to an idle channel. In the "best" case, when PU appears, all SUs switch to an idle channel without causing harmful interference to the PU receiver. But this will increase the spectrum sensing and switching cost and decrease the capacity of channel c . If all SUs remain in the channel and coordinate to keep the transmit power below the interference temperature limit, some of the SUs would transmit while some may not. In the "worst" case, all SUs cause non-harmful interference to the PU receiver. For a given SU, however, the rest of the SU transmitters could cause harmful cumulative interference to block its communication. In this paper, we consider the accumulated interference of both the SUs-to-PU and SUs-to-SUs to maximize the capacity on the licensed channel and minimize the spectrum handover overhead of the multi-SU CR network.

A. Interference Temperature

For a given area, FCC establishes an interference temperature limit T_L. This value of T_L would be a maximum amount of tolerable interference for a given frequency band in a particular location. In this paper, we use the following formulation [15]

$$T_I(f_c, B) + T_N \leq T_L(f_c, B), \tag{1}$$

where $T_I(f_c, B)$ is the interference temperature for channel c , with central frequency f_c and bandwidth B. T_N is the original noise floor. $T_I(f_c, B)$ can be given

$$T_I(f_c, B) = \frac{P_I(f_c, B)}{kB}, \tag{2}$$

where Boltzmann's constant k is $1.38 \cdot 10^{-23}$ Joules per Kelvin degree. $P_I(f_c, B)$ is the interference power over the channel with central frequency f_c and bandwidth B.

Any SU transmitter on the band c must guarantee that the introduced interference of its transmission to the existing interference must not exceed the interference temperature limit T_L at a PU receiver. Moreover, in our model, the receiving interference of any SU receiver utilizing this band also must not exceed T_L. The model is shown in Fig. 2. From the PU receiver, we can get

$$T_N(f_c, B) + \frac{\sum_{i=1}^{N} M_i P_{su\_tx}^i}{kB} \leq T_L(f_c, B), \tag{3}$$

where M_i is a fractional value between 0 and 1, representing a multiplicative attenuation due to fading and path loss between the ith SU transmitter and the licensed receiver. $P_{su\_tx}^i$ is the ith SU's transmit power, N is the number of SU transmission pairs.

To guarantee that the SINR at the SU receiver is greater than the minimum SINR γ_{min} required for decoding the signal, $P^i_{su\_tx}$ must be no less than $P^i_{su\_tx\_min}$. Then we can get

$$\frac{P^i_{su\_tx\_min} - f(r_i)}{kBT_L} = \gamma_{min}, \tag{4}$$

where $f(r_i)$ is a path loss function, and $f(r_i) = 10n\log(r_i)$. r_i is the distance between the transmitter and the receiver, n is the path loss exponent which is usually a constant in the range of $2 \sim 4$. For the jth SU receiver, the following equation could be obtained.

$$T_N(f_c, B) + \frac{\sum\limits_{i=1, i\neq j}^{N} L_i P^i_{su\_tx}}{kB} \leq T_L(f_c, B)\ , \tag{5}$$

where L_i is similar to M_i, except that it represents multiplicative path loss between the ith SU transmitter and SU receiver. Our goal is to maximize the capacity on licensed channel while minimizing the spectrum switching overhead to accommodate more SUs. At the same time, the receiving interference of both PU and SU receivers which utilize the licensed channel should not exceed the interference temperature limit T_L.

B. Calculation of Secondary Users' Capacity

For the definition of channel capacity C, Shannon-Hartley theorem states

$$C = Blog_2(1 + \frac{S}{N_o}), \tag{6}$$

where B is the bandwidth of the licensed channel, S is the received signal power at the SU receiver. N_o is the noise and interference power over the band.

To investigate the performance of multiple secondary users, we consider the capacity of the secondary users. At the ith SU receiver, capacity can be formulated as follows

$$C_i = Blog_2(1 + \frac{L_i P^i_{su\_tx}}{kBT_L(f_c, B)}). \tag{7}$$

IV. The Optimization Model

In this section, we formulate the spectrum handover scheme as a constrained optimization problem in terms of interference caused by multi-SU CR network. As mentioned above, when PU appears, each SU has two options, switching to another channel or lowering its transmit power. When there is no unlicensed channels available, SUs have to remain in the licensed channel. Then the global capacity of SUs is formulated as a constrained optimization problem

$$\begin{aligned} & max\{max(\boldsymbol{x}_1 \cdot Blog(\mathbf{1} + \delta\boldsymbol{a})), \cdots, \\ & max(\boldsymbol{x}_N \cdot Blog(\mathbf{1} + \delta\boldsymbol{a}))\} \qquad s.t. \\ & \sum_{j=1, j\neq i}^{N} x_{ij} a_j < \beta_i, 1 \leq i \leq N \\ & x_{ij} = x_{ji}, 1 \leq i \leq N, 1 \leq j \leq N \\ & x_{ij} \in \{0, 1\}, 1 \leq i \leq N, 1 \leq j \leq N, \end{aligned} \tag{8}$$

where $\mathbf{x}_i = (x_{i1}, \ldots, x_{iN})$, $\mathbf{a} = (a_1, \ldots, a_N)$, $a_i = P^i_{su\_tx}$ and $\delta = L_i/kBT_L(f_c, B)$, $\beta_i = (T_L - T_N)kB/L_i$. $max(\boldsymbol{x}_i \cdot Blog(\mathbf{1} + \delta\boldsymbol{a}))$ is the maximum element of the vector $\boldsymbol{x}_i \cdot Blog(\mathbf{1} + \delta\boldsymbol{a})$. Without loss of generality, we assume the SUs in a given area have the same multiplicative attenuation M between the SU transmitter and the PU Receiver. Then each component of vector $\mathbf{a}$ is a constant with an upper bound and lower bound

$$\begin{aligned} & \sum_{i=1}^{N} a_i \leq \alpha \\ & a_i \geq \gamma, 1 \leq i \leq N, \end{aligned} \tag{9}$$

where $\alpha = (T_L - T_N)kB/M$ and γ is the minimum transmit power of SUs.

Formulation (8) shows the objective function followed by a set of constraints. The first constraint shows the accumulated interference of SU receivers utilizing the licensed channel should not exceed the interference temperature limit. The second constraint means that the interference among the SUs is symmetrical. As long as the SU does not switch to another channel, the interference exists. The last constraint shows that the value of SU's behavior is 0 (switch) or 1 (lower power). The equation (9) is a constraint on the interference of SUs-to-PU, which means that the receiving interference of PU receivers on the licensed channel should not exceed the interference temperature threshold.

V. Optimization Model Solution

In this section, we employ a heuristic algorithm to simplify the optimization model and then the optimization problem can be transformed into a 0-1 knapsack problem. Finally, the dynamic programming method is adopted to obtain the optimal solution.

A. Analysis of Our Optimization Model

Let $y_i = \mathbf{x}_i \cdot B\log(\mathbf{1} + \delta\mathbf{a})$. Therefore, to optimize formulation (8), we are required to obtain the maximum value of each element y_i and then select the maximum one among N elements. Since there are many algorithms to find the maximum value of an array, we just need to focus on how to get the optimal value of each y_i here. The optimization model is then reformulated. For each element y_i, we have

$$\begin{aligned} & max(y_i) \qquad s.t. \\ & \sum_{j=1, j\neq i}^{N} x_{ij} a_j < \beta_i, 1 \leq i \leq N \\ & x_{ij} = x_{ji}, 1 \leq i \leq N, 1 \leq j \leq N \\ & x_{ij} \in \{0, 1\}, 1 \leq i \leq N, 1 \leq j \leq N. \end{aligned} \tag{10}$$

Obviously, formulation (10) represents a typical binary integer programming or 0-1 integer programming problem (BIP). It is considered that there unlikely exists an efficient algorithm to solve a BIP. Related works often adopt linear programming-based branch and bound algorithm to solve BIP problems. The central idea of the branch and bound algorithm is to create a binary-search tree by repeatedly adding constraints to the problem, and each constraint is represented as a node of the binary tree. However, constructing such a binary tree is both expensive and memory demanding. To solve this problem, we will give a simplified model in the next subsection.

B. The Simplified Model Based on 0-1 Knapsack Problem

To reduce the time and space complexity when solving equation (10), we simplify the optimization model according to heuristics rules and convert our model into a well-known *0-1 knapsack problem* [16]. The heuristics principle depends on such an observation: y_i could get a maximum value only when $\mathbf{x}_i \cdot \mathbf{a}$ is maximized because $Blog(\cdot)$ is an increasing function. To get the optimal value of y_i, we first determine the largest possible value of $x_{ij}(1 \leq i,j \leq N, j \neq i)$ and then find the best solution that satisfies the constraint

$$\sum_{j=1,j\neq i}^{N} x_{ij}a_j \leq \beta_i, 1 \leq i \leq N. \tag{11}$$

As for each x_{ij} in the ith row of equation (11), there is $x_{ij} = x_{ji}$. So the constraint imposed on x_{ij}, $j \neq i$ is

$$\begin{aligned} &x_{ij} = x_{ji} \leq \beta_j/a_i - \sum_{s=1,s\neq i,j}^{N} x_{js}a_s/a_i \leq \beta_j/a_i \\ &x_{ij} \in \{0,1\}. \end{aligned} \tag{12}$$

So we get $x_{ij} \leq \min(1, \lfloor \beta_j/\alpha_i \rfloor), i \neq j$. It can be deduced that x_{ij} equals to zero when $\lfloor \beta_j/\alpha_i \rfloor < 1$. Here, we do not consider the components that definitely equal to zero in $\mathbf{x}_i$, but only decide the remaining components that could be either 0 or 1. Let $Z = \{z_t = x_{ij} \mid j \neq i \ and \ \lfloor \beta_j/a_i \rfloor \geq 1\}$ be the current unknowns. Let $W = \{w_t = a_j \mid j \neq i \ and \ \lfloor \beta_j/a_i \rfloor \geq 1\}$ be the weight of each unknown. n is the size of Z and W. we solve the value of each elements of Z according to

$$\begin{aligned} &max(\sum_{t=1}^{n} w_t z_t) \qquad\qquad s.t. \\ &\sum_{t=1}^{n} w_t z_t \leq \beta_i, z_t \in \{0,1\}. \end{aligned} \tag{13}$$

Formulation (13) shows a typical 0-1 knapsack problem. We will determine each element of Z to be included in a collection so that the total weight is less than β_i and the total value $\sum_{t=1}^{n} w_t z_t$ is optimized. With the solution of equation (13), the optimal value of y_i is $opt\_y_i = \mathbf{opt\_x}_i \cdot B\log(1 + \delta\mathbf{a})$ where each component of $\mathbf{opt\_x}_i$ equals to

$$opt\_x_{ij} = \begin{cases} 0 & \lfloor \beta_j/a_i \rfloor < 1 \quad and \quad i \neq j \\ z_t & \lfloor \beta_j/a_i \rfloor \geq 1 \quad and \quad i \neq j \\ 1 & i = j \end{cases}. \tag{14}$$

C. Model Solution

Given the simplified optimization model shown in equation (13) and (14), we obtain the largest opt_y_i and the corresponding $\mathbf{opt\_x}_i$ as the optimal solution. Algorithm 1 shows the pseudo code of solving the optimization model. Note that *Zeros* returns a zero vector, AddtoSet gets the set W, *Copytox* copies the values of Z to vector $\mathbf{x}$, *getmax* computes the largest opt_y_i and the corresponding $\mathbf{opt\_x}_i$.

In *dynamic_prog_knapsack*, we solve the 0-1 knapsack problem using dynamic programming. Dynamic programming is an optimization method that is often used when the solution can be recursively described in terms of solutions to subproblems. A dynamic programming solution for the 0-1 knapsack problem generally runs in pseudo-polynomial time. Since the dynamic programming method is guaranteed to converge to the optimal solution, so the optimization method used in this paper also converges.

Algorithm 1: Algorithm for solving the optimal model

```
Input: B, δ, a, β
Output: opt_value, opt_x_value
begin
    for i ← 1 to N do
        Zeros(x_i);
        for j ← 1 to N do
            if i ≠ j then
                x_ij ⟵ min(1, ⌊β_j/a_i⌋);
                if x_ij == 1 then
                    AddtoSet(W, a_j);
                end
            end
        end
        if W is not empty then
            Z ⟵ dynamic_prog_knapsack(W, β_i);
            Copytox(Z, x_i);
        end
        x_ii ⟵ 1;
        opt_x_i ⟵ x_i;
        opt_y_i ⟵ opt_x_i · Blog(1 + δa);
        (opt_x_value, opt_value) ⟵
        getmax(opt_y_i, opt_x_i);
    end
end
```

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Carrier Frequency	2.4GHz
Bandwidth	$20 \sim 50$MHz
Minimum SINR γ_{min}	10dB
Temperature Interference Limit T_L	$148 \sim 150$dB
Noise Floor T_N	5dB
Overhead of Frequency Sensing and Handover	3.5ms
Distance R	$2 \sim 6$ m
Path Loss Exponent n	2

VI. Numerical Results

In this section, we investigate the performance of our proposed optimization algorithm. System parameters used are shown in Table I.

Fig. 3 shows the cumulated capacity of all the secondary users using the same channel. Without loss of generality, we assume that the distance between the SU transmitters and receivers are uniformly distributed. As a comparison, we evaluate three approaches: Conservative, Random and our pro-

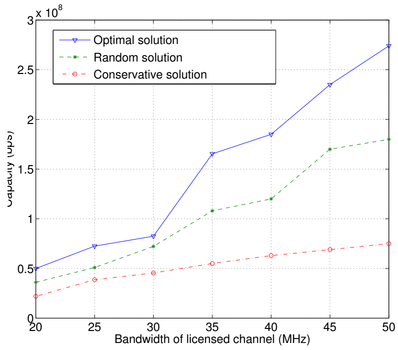

Fig. 3. Capacity vs. Bandwidth of licensed channel

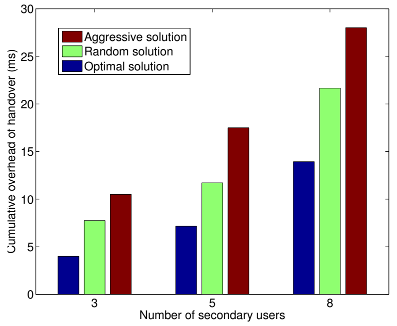

Fig. 4. Cumulative overhead vs. Number of secondary users

posed optimization algorithm. In the conservative algorithm, all secondary users lower the transmit power when the primary users come. Since the transmission cannot be guaranteed to succeed after the power falls, the network performance will degrade. It can be seen from Fig. 3 that as the bandwidth of the licensed channel rises, the cumulated capacity of secondary users on this channel is greatly increased. As we also can see, our optimization algorithm outperforms the other two algorithms as the bandwidth rises. The capacity can be increased up to 51% and 278% respectively than the random algorithm and the conservative algorithm.

In Fig. 4, we compare the spectrum handover overhead of three approaches with respect to the number of secondary users. In the aggressive algorithm, all SUs on the licensed channel switch to other available channels as soon as the PU appears. Assume that the SU receivers are uniformly distributed in the coverage of the corresponding SU transmitter with the distance ranging from 2 to 6 meters, and a handover costs 3.5ms, we can calculate the cumulative overhead of all the handovers. As shown in Fig. 4, the overhead of the aggressive algorithm is larger than others since the handovers lead to longer latency. Obviously, our approach can drastically reduce the spectrum handover overhead through optimally handling the SUs' coexistence.

VII. Conclusion

Spectrum handover is a critical issue in cognitive radio networks. Frequent spectrum handover leads to disruptions of SU's transmissions. In a multi-SU cognitive network, this problem becomes even more urgent. In this paper, we explore the coexistence potential of SUs and PU to maximize the capacity of licensed channels and minimize the spectrum switching overhead considering the accumulated interference at SUs. We formulate the spectrum handover problem as a constrained optimization problem, and then give the optimal solution. Numerical results show that our algorithm can improve the network performance efficiently.

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