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Location-Aware Resource Allocation based Spectrum Accessing on Cognitive Radio Network Systems

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Abstract:

Cooperative spectrum sensing for cognitive radio networks is recently being studied to simultaneously minimize uncertainty in primary user detection and solve hidden terminal problem. Sensing wideband spectrum is another challenging task for a single cognitive radio due to large sensing time required. Sensing and power strategy optimization is important research topics in cognitive radio systems that hold the promise of advancing green communication. This concept gives us a brief overview of the existing power allocation design in the literature and unifies them into a general power allocation framework. Based on the closed-form solution derived for this general problem, the impact of network topology on the system performance is highlighted, which motivates us to propose a novel location-aware strategy that intelligently utilizes frequency and space opportunities and minimizes the overall power consumption while maintaining the quality of service of the primary system. This work shows that in addition to exploring spectrum holes in time and frequency domains, spatial opportunities can be utilized to further enhance energy efficiency for CR systems.

I.INTRODUCTION

The dramatic growth of mobile data services driven by wireless Internet and smart devices has triggered the investigation of fifth generation (5G) for the next generation of terrestrial mobile telecommunications [1]. Facing great challenges of future mobile networks, the essential requirements for 5G which mainly include higher traffic volume, spectrum, energy, and cost efficiency are pointed out. Therein, cognitive radio (CR) technology, which provides the authorized spectrum of primary users (PUs) to various unlicensed users also called secondary users (SUs) in an opportunistic (time-limited), interference-limited, or paid way [2], handles flexibly the predicament of spectrum underutilization and spectrum shortage resulting from the surging wireless requirements and applications and, thus, has been regarded as the inevitable option for 5G to improve spectrum efficiency [3, 4]. Particularly, cognitive cooperation, not only allowing SUs in cognitive radio networks (CRNs) to share authorized spectrum but also inheriting the unique advantages of cooperative communications that promise significant capacity and multiplexing gain increase through distributed transmission/processing, has been becoming an appealing communication paradigm [5,6].

Meanwhile, due to its high spectrum utilization, multicast transmission has become an indispensable part of mobile communication systems nowadays [7]. In this paper, cognitive cooperation and multicast are joint considered. For the primary-secondary cooperation in cognitive multicast networks (CMNs), the secondary source (SS) with limited transmit power needs to broadcast message to multiple secondary destinations (SDs), and hence, the transmission data rate is confined to the worst channel condition among all SDs. Thus, the quality of service (QoS) of the SU suffers severely, and the spectrum accessed by the SU might not be able to afford satisfactory communication services for the SU. One effective protection countermeasure is that the SU assists simultaneously multiple PUs to gain more spectrum access opportunities. Moreover, the SU turns to spend least power and spectrum on transmission data for PUs and scrambles to save resources any way for multicast members. Wireless network coding (NC), which mixes the data from different sessions before signal forwarding to increase per-transmission information content, has been a promising approach [8,9]. Motivated by all these profits, NC technique is adopted by the SU. Furthermore, to enhance the spectrum efficiency, orthogonal frequency division multiplexing (OFDM) [10] is considered in this paper. Combining these technologies mentioned above, this paper investigates the resource

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allocation strategy for the one-secondary-user and two-primary-user (1S2P) cooperation with NC in OFDM modulated CMNs.

Cognitive Radio Network Architecture

A comprehensive description of the CR network architecture is essential for the development of communication protocols that address the dynamic spectrum challenges. The CR network architecture is presented in this section. NETWORK COMPONENTS The components of the CR network architecture, as shown in Figure1, can be classified as two groups: the primary network and the CR network [11].

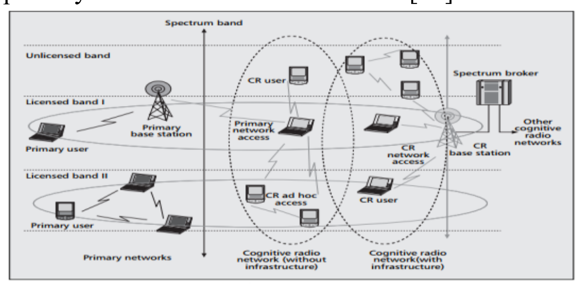

Figure1: Cognitive radio network architecture.

The primary network (or licensed network) is referred to as an existing network [12], where the primary users have a license to operate in a certain spectrum band. If primary networks have an infrastructure, primary user activities are controlled through primary base stations. Due to their priority in spectrum access, the operations of primary users should not be affected by unlicensed users. The CR network (also called the dynamic spectrum access network, secondary network, or unlicensed network) does not have a license to operate in a desired band. Hence, additional functionality is required for CR users to share the licensed spectrum band. CR networks also can be equipped with CR base stations that provide single-hop connection to CR users. Finally, CR networks may include spectrum brokers that play a role in distributing the spectrum resources among different CR networks [13].

II.LITERATURE SURVEY

Recently, power and channel allocation in orthogonal frequency-division multiplexing (OFDM)-based CR systems have received a great deal of attention [14-21]. In either overlay-based systems or underlay-based systems, many resource allocation strategies have been proposed in these works. We have introduced overlay-based strategies in Chapter 2, such as hard-decision resource allocation (HDRA) and probabilistic resource allocation (PRA). For the underlay-based system, the interference management among the SUs and the primary users (PUs) play a key role in the resource allocation. In order to protect the primary system, most literatures constrain the interference caused by the SUs below a threshold in either average (long term) or instantaneous (short term) sense, e.g., [22], [23] and [15]. Unlike the previous literature that takes into account the amount of interference to the primary system as the protection criterion, the authors of [38] reconsider the protection to the primary system and SUs through different levels of protection in signal to interference-and-noise ratio (SINR). Besides, many researchers consider the resource allocation with joint overlay and underlay spectrum access. For instance, subcarrier-and-power-allocation schemes for a joint overlay and underlay spectrum access mechanism are proposed in [16] for a downlink transmission scenario in a centralized multi-user CR network, where both unused and underused spectrum resources are utilized and the interference introduced to the PU is kept below given thresholds with a certain probability. In [20], the authors employ a hybrid overlay/underlay spectrum sharing scheme for a distributed CR network, allowing the SU to adapt its way of accessing the licensed spectrum according to the status of the channel. If the selected channel is detected to be unoccupied, the SU works in an overlay mode, otherwise it works in spectrum underlay. An auction-based power allocation scheme is proposed as well to solve power competition of multiple SUs. All these works mentioned are based on the maximum data rate design subject to an overall power constraint. On the other hand, energy-efficient design attracts the attention from the researchers recently. The energy-efficient power allocation problem of OFDM-based CR systems is studied in [21], where the energy efficiency is taken as the objective function in the optimization for the purpose of holding the promise of advancing green communications.

All the existing work aforementioned studied the resource allocation based on spectrum sensing results, and assumed the SUs work with the overlay, underlay or joint overlay/underlay mechanism. There are several problems in designing resource allocation for the multi-user case.

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We identify and summarize the two main challenges as well as the contributions of this work as follows:

Optimization algorithm for multi-user system: The optimization algorithm would be more complicated compared to the single user case, since we not only consider the power allocation for certain individual user, but also the channel allocation for all the users. The optimization problem is no longer a straightforward convex optimization. Thus, in this work, we propose an iterative algorithm based on time-sharing condition introduced by [24] to obtain the optimal resource allocation.

***Energy for spectrum sensing*:** Unnecessary spectrum sensing leads to extra energy consumption. As mentioned previously, for the SUs being far away, spectrum sensing is a waste of energy. Therefore, a novel adaptive resource allocation algorithm based on an interference violation test is proposed in this chapter for those SUs located far away from the primary system to decide the parameter settings in the general problem formulation. The proposed algorithm helps the SUs utilize the optimal resource allocation scheme and decide whether spectrum sensing is necessary to further enhance the energy efficiency of this system.

III.PROPOSED METHOD

A. Location-Aware Multi-User Resource Allocation

This chapter considers a scenario that one CR system coexists with one primary system, where K mobile SUs are communicating with the cognitive base station (CBS) in the uplink and the corresponding worst-case PUs receiving signals from the primary base station (PBS), as depicted in Figure2.

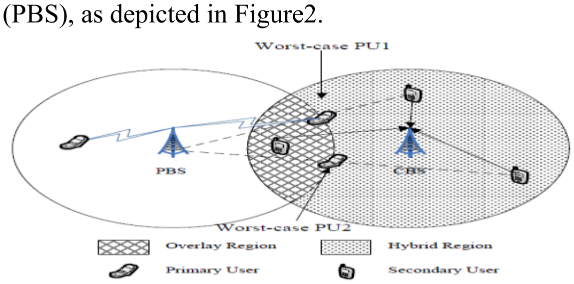

Figure2: A CR system coexisting with a primary system (uplink scenario for the CR system). Two regions are highlighted for the CR system to operate different resource allocation strategies.

To demonstrate the efficacy of the scheme proposed in this chapter, we assume the worst case location of a PU (being located at the intersection of the PBS service region boundary and the line between the PBS and the relevant mobile SUs) as shown in Figure2. We believe that if the worst case PU is protected, all the PUs within the coverage area of the primary system are also protected. The problem formulation and analysis thereafter apply similarly to the secondary downlink scenario and hence this paper focuses on the secondary uplink. We assume that the primary system and CR system are OFDM based systems, with the licensed spectrum being divided into N sub-channels of the same bandwidth with each sub-channel experiencing flat fading. In Figure2, the circle to the left represents the service range of the primary system and the shaded circle to the right represents that of the CR system. The intersection of the two circles forms what we call Overlay Region. The remaining part of the CR service region is called Hybrid Region. As we shall show, depending on the location of the SUs, resource allocation design should exhibit an adaptive structure, applying diverse methods when the SUs fall into different service regions. In order to avoid mutual interference among SUs, we assume that each sub-channel can be at most allocated to one SU and each SU may be allocated more than one sub-channel. Therefore, channel allocation will be considered in addition to power allocation and we assume that the CBS coordinates the resource allocation and spectrum sensing (if necessary) in a centralized manner.

Problem Formulation for P1

With the location information of the SUs, the key part of the proposed resource allocation scheme in this work is selecting the appropriate parameters for P1 and solving it. In this section, we focus on solving P1 with the assumption that all the parameters have been determined. Transmit power control plays an important role in energy efficient communication to prolong the lifetime of the network and achieve the goal of green communication. Therefore, instead of maximizing the system data rate over limited power resource [25] as most of the relevant works do, we formulate here a complementary QoS problem [26] with the objective of minimizing the overall power consumption subject to a minimum data rate requirement. The QoS problem for

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different cognitive power allocation strategies can be formulated by a general framework as

$$\textbf{(P1)} \quad \min_{P_{i,k},\rho_{i,k}\forall i,k} \sum_{k=1}^{K}\sum_{i\in\mathcal{A}\bigcup\mathcal{N}} \rho_{i,k}P_{i,k}$$

$$\text{s.t.} \quad R_k = \sum_{i\in\mathcal{A}} \rho_{i,k}\mathcal{C}\left(\frac{P_{i,k}h_{i,k}^{SS}}{\sigma^2}\right)$$

$$+\alpha^{(k)}\sum_{i\in\mathcal{N}} \rho_{i,k}\mathcal{C}\left(\frac{P_{i,k}h_{i,k}^{SS}}{\sigma^2+P_p h_i^{PS}}\right) \geq R^{\min}, \forall k \qquad (1)$$

$$\sum_{i\in\mathcal{A}\bigcup\mathcal{N}} \rho_{i,k}P_{i,k} \leq P_k^{\max}, \forall k \qquad (2)$$

$$\alpha^{(k)}\rho_{i,k}P_{i,k}L_{i,k}^{SP} \leq I_i^{\max}, \qquad \forall i\in\mathcal{N}, \forall k, \qquad (3)$$

$$\sum_{k=1}^{K}\rho_{i,k} \leq 1, \rho_{i,k}\in\{0,1\}, \forall k, i, \qquad (4)$$

Where the parameters are explained in Table I, the function C(x) = log2 (1+x) denotes the Shannon rate, the bandwidth of each sub-channel is assumed to be unitary, the minimum data requirements for all the users are assumed to be identical and P_p is assumed to be known.

Table1: Parameter Definitions in Problem P1

	Overlay	Underlay	SFRA
$\mathcal{A}$	the set of detected unoccupied sub-channels		N/A ($=\emptyset$)
$\mathcal{N}$	the set of detected occupied sub-channels		$\{1, 2, ..., N\}$
$P_{i,k}$	transmit power allocated on the ith sub-channel for the kth SU		
P_p	transmit power of the PBS		
$R^{\min}$	minimum rate requirement of the SUs		
$P_k^{\max}$	power budget of the kth SU		
$I_i^{\max}$	QoS threshold of the ith sub-channel for the primary system		
h_i^{PS}	instantaneous channel gain on the ith sub-channel from PBS to CBS (path loss, shadowing, and small scale fading)		
$h_{i,k}^{SS}$	instantaneous channel gain on the ith sub-channel from the kth SU to CBS (path loss, shadowing, and small scale fading)		
$L_{i,k}^{SP}$	average channel gain on the ith sub-channel from the kth SU to the worst-case PU (path loss and shadowing)		
σ^2	noise power of each sub-channel at the CBS		
$\alpha^{(k)}$	spectrum sharing indicator of the kth SU ($\alpha^{(k)} = 0$ for Overlay Region user and $\alpha^{(k)} = 1$ otherwise)		
$\rho_{i,k}$	channel allocation indicator ($\rho_{i,k}$=1 represents allocating the ith sub-channel to the kth SU)		

The average channel gains from system A to system B, L^{AB}, are obtained based on path loss attenuation model d^{-r} for a distance d with exponent r, i.e, $L^{AB} = d^{-r}_{AB}$, where d_{AB} denotes the distance between the transmitter in system A to the receiver in system B. The overlay-based approaches utilize only unoccupied sub-channels based on sensing results and thus the spectrum sharing indicator $\alpha^{(k)} = 0$. The underlay-based approaches allow spectrum sharing and thus we have $\alpha^{(k)} = 1$. Unlike traditional overlay systems, underlay-based systems further utilize those occupied sub-channels with additional protection to the PUs. Note that for underlay-based systems, the interference constraint (3) in P1 guarantees protection to the primary system on an average sense and hence supports primary system QoS. Another resource allocation scheme is sensing-free resource allocation (SFRA), which lets the SUs operate on all the sub-channels without spectrum sensing while incorporating the interference constraint (3). Therefore, the spectrum sharing indicator α = 1 and the other parameters are set according to Table1 with A = ∅, and N = {1, 2…., N}.

In this work, for each SU, depending on its location, one of the three resource allocation schemes may be applicable. In a nutshell, the problem P1 should be solved considering different sets of parameters for different SUs, with details given in the next sections. The process for solving P1 can be summarized in Algorithm 1 as shown below.

Algorithm 1 Solving P1

Require:
$\mathcal{A}$ = unoccupied channels, $\mathcal{N}$ = occupied channels;
$\mu_{1,k}$, $\mu_{2,k}$ and $\mu_{3,i}$;
$P_k^{\max}$, $R^{\min}$, $I_i^{\max}$;

Ensure:
1. For each user k, calculate $P_{i,k}$ according to (eq 6) and $u^*_{i,k}$ according to (eq 5), respectively.
2. Allocate the channel i to the user having the minimal $u^*_{i,k}$ and update $\mu_{3,i}$ according to (eq 9).
3. With the channel allocation result, update $\mu_{1,k}$ and $\mu_{2,k}$ according to (eq 7) and (eq 8), respectively.

Until
the Lagrangian multipliers converge.

Lastcon:
Optimal solution P and $\rho_{i,k}$;

For certain channel i, we can compute the optimal $u^*_{i,k}$ for the kth SU in the lower layer as

$$u^*_{i,k} = P_{i,k} - \mu_{1,k}\log_2(1+\frac{P_{i,k}h_{i,k}^{SS}}{\sigma^2}) + \mu_{2,k}P_{i,k}$$
$$+\mu_{3,i}P_{i,k}L_{i,k}^{SP} + \mu_{4,i}, \qquad (5)$$

When the ith channel is allocated to the kth SU, i.e., $\rho_{i,k} = 1$, the power allocation can be determined in a water-filling fashion such that

$$P_{i,k} = \left(\frac{\mu_{1,k}}{(1+\mu_{2,k})\ln 2} - \frac{\sigma^2}{h_{i,k}^{SS}}\right)^+. \qquad (6)$$

Then for any channel, $\rho_{i,k}$ is chosen to be 1 for the user having the minimal $u^*_{i,k}$ which is calculated by substituting $P_{i,k}$ obtained through (6) into (5). To obtain the Lagrangian multipliers in the lower layer, we can use the sub gradient method introduced by [27] to update the multipliers as below:

$$\mu_{1,k}^{(j+1)} = \left(\mu_{1,k}^{(j)} + s^{(j)}\left(R^{\min} - R_k\right)\right)^{+}, \qquad (7)$$

$$\mu_{2,k}^{(j+1)} = \left(\mu_{2,k}^{(j)} + s^{(j)}\Big(\sum_{i\in\mathcal{A}\bigcup\mathcal{N}} \rho_{i,k}P_{i,k} - P_k^{\max}\Big)\right)^{+}, \qquad (8)$$

$$\mu_{3,i}^{(j+1)} = \left(\mu_{3,i}^{(j)} + s^{(j)}\left(\alpha^{(k)}\rho_{i,k}P_{i,k}L_{i,k}^{SP} - I_i^{\max}\right)\right)^{+}, \qquad (9)$$

Where s (j) represents a sequence of step sizes and each value should be sufficiently small [28].

Problem Formulation for P2

Problem P1 can be infeasible due to the presence of the total power constraint (2) and interference constraint (3). This occurs when the total power budget $P_k^{\max}$ cannot support the target minimum rate $R^{\min}$ for a given channel realization. When P1 is feasible, it cannot be solved directly since it is a non-convex problem.

To solve P1, we utilize the dual decomposition approach [27] and the dual problem of P1 can be given as

$$\begin{aligned} \textbf{(P2)} \quad & \underset{\mu}{\text{maximize}} \quad \min_{P_{i,k},\rho_{i,k}\forall i,k} \mathcal{L} \\ & \text{s.t.} \quad \mu_{\mathbf{k}} \succeq 0, \end{aligned} \qquad (10)$$

Where μ_k is a vector of non-negative Lagrangian multipliers for user k and L is the Lagrangian and it is given by

$$\mathcal{L} = \sum_{k=1}^{K}\sum_{i\in\mathcal{A}\bigcup\mathcal{N}} \rho_{i,k}P_{i,k} + \sum_{k=1}^{K}\mu_{1,k}\left(R^{\min} - R_k\right) \qquad (11)$$

$$+ \sum_{k=1}^{K}\mu_{2,k}\left(\sum_{i\in\mathcal{A}\bigcup\mathcal{N}} \rho_{i,k}P_{i,k} - P_k^{\max}\right) \qquad (12)$$

$$+ \sum_{i\in\mathcal{N}}\mu_{3,i}\left(\alpha^{(k)}\rho_{i,k}P_{i,k}L_{i,k}^{SP} - I_i^{\max}\right) \qquad (13)$$

$$+ \sum_{i\in\mathcal{A}}\mu_{4,i}\sum_{k=1}^{K}\left(\rho_{i,k} - 1\right). \qquad (14)$$

Since P1 is not convex, the dual problem P2 provides a solution, which is an upper bound to the solution of P1. The upper bound is not always tight, and the difference between the upper bound and the true optimum is called the "duality gap." When the duality gap is zero, they have identical solutions. To show the duality gap between P1 and P2 is zero, we first introduce the definition of time-sharing condition [28].

B. Adaptive Resource Allocation Process

Before solving P1, the CBS should decide the parameters that indicate the adopted spectrum access method for each SU. For instance, one of the key points of the proposed scheme is to determine the A and N before solving P1, which can be obtained by spectrum sensing. However, if an SU is in the Hybrid Region, SFRA may be applicable and in this case, spectrum sensing is unnecessary A and N are selected according to Table I. For a given network topology, each SU begins with calculating the distance to the PBS and determines if it falls into the Overlay Region. If this is true, the channels allocated to such an SU should be sensed as unoccupied channels, and the SU can only adopt overlay-based spectrum access. If there exists an SU that falls into the Hybrid Region, an interference violation test should be activated. Since SFRA can be a choice to avoid unnecessary spectrum sensing, this interference violation test is conducted to find out the parameter settings in P1 for SFRA users.

The interference violation test is based on the fact that, if the primary system QoS can be maintained (constraint (3) in P1 holds) regardless whether the respective channels are occupied or not, it is not necessary to perform spectrum sensing. To be more specific, in the test procedure, the coordinator (CBS) first calculates the traditional water-filling solution without accounting for the interference generated to the primary system by solving P3.

$$\text{(P3)} \quad \min_{P_{i,k},\rho_{i,k}\forall i,k} \sum_{k=1}^{K}\sum_{i\in\mathcal{A}\bigcup\mathcal{N}} \rho_{i,k}P_{i,k}$$

$$\text{s.t.} \quad R_k = \sum_{i\in\mathcal{A}} \rho_{i,k}\mathcal{C}\left(\frac{P_{i,k}h_{i,k}^{SS}}{\sigma^2}\right)$$

$$+ \sum_{i\in\mathcal{N}} \rho_{i,k}\mathcal{C}\left(\frac{P_{i,k}h_{i,k}^{SS}}{\sigma^2 + P_p h_i^{PS}}\right) \geq R^{\min}, \forall k \qquad (15)$$

$$\sum_{i\in\mathcal{A}\bigcup\mathcal{N}} \rho_{i,k}P_{i,k} \leq P_k^{\max}, \forall k \qquad (16)$$

$$\rho_{i,k}P_{i,k}L_{i,k}^{SP} \leq I_i^{\max}, \qquad \forall i \in \mathcal{V} \qquad (17)$$

$$\sum_{k=1}^{K} \rho_{i,k} \leq 1, \rho_{i,k} \in \{0,1\}, \forall k, i, \qquad (18)$$

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Where V is a channel set representing those sub-channels that cannot support primary system QoS, and at the beginning of the interference violation test, V is initialized to ∅. Mathematically, solving P3 is equivalent to solving P1 by using SFRA for those SUs located in the Hybrid Region with the interference constraints only for sub-channels belonging to V, and using the overlay strategy for those SUs located in the Overlay Region. It is worth noting that the I_i^{max} for the channel allocated to the SUs located in the Overlay Region should be set to 0, and thus the according channel must be sensed. With the obtained power and channel allocation results, the generated interference to PUs will be checked to find out whether the primary system QoS is maintained. Those channels that cannot support the primary system QoS will be added into the channel set V. With the current result of the interference violation test, for those channels belonging to V, SFRA is not applicable. As a result, spectrum sensing is required. According to the spectrum sensing results, if the sub channels in V are available, they can be removed from V. At this moment, if V is empty, the interference violation test can be stopped since the primary systems QoS is maintained. Unfortunately, the sub-channels sometimes are detected unavailable and thus another interference violation test is required to update V and resource allocation result according to the most recently obtained spectrum sensing results until V = ∅. Then the optimal solution for resource allocation can be obtained. The algorithm for the proposed adaptive resource allocation scheme is given in Algorithm 2 as shown below. In this algorithm, the Algorithm 1 is applied to solve P3 for each iteration.

Algorithm 2 Proposed resource allocation algorithm

Require:

$\mathcal{A} = \emptyset$, $\mathcal{N} = \{1, 2, ..., N\}$ for all the users;

P_k^{max}, R^{min}, I_i^{max}, violated channel set $\mathcal{V} = \emptyset$;

Ensure:

1. Solve **P3** with interference constraint for those channels belonging to $\mathcal{V}$ to get the corresponding power allocation **P** and channel allocation result $\rho_{i,k}$.
2. Update $\mathcal{V}$ according to interference violation test result. If $\mathcal{V} = \emptyset$, $\mathbf{P}^* = \mathbf{P}$ and $\rho^*_{i,k} = \rho_{i,k}$; else, corresponding SUs do spectrum sensing for the channels in $\mathcal{V}$. Update $\mathcal{A}$ and $\mathcal{N}$.
3. For each channel in $\mathcal{V}$, if it is available, remove it from $\mathcal{V}$. Update $\mathcal{V}$.

Until

$\mathcal{V} = \emptyset$, $\mathbf{P}^* = \mathbf{P}$, $\rho^*_{i,k} = \rho_{i,k}$.

Lastcon:

Optimal solution $\mathbf{P}^*$ and $\rho^*_{i,k}$;

Based on the optimal power and channel allocation results obtained here, those sub-channels that are able to support primary system QoS constitute the sub-channel groups for the corresponding SUs that operates the sensing-free strategy, SFRA. For the sub-channels that do violate the interference constraints in the iteration process of the proposed algorithm, the CBS has to perform spectrum sensing for these sub channels and then include the results in the next iteration of power and channel allocation calculation as shown in Algorithm 2. The proposed algorithm avoids unnecessary spectrum sensing and hence reduces the energy consumption, at the price of more optimization computation of P3. This provides a tradeoff between sensing energy consumption and signal processing power consumption. When the number of channels is large, it is believed that the proposed algorithm is more promising.

IV.EXPERIMENTAL RESULTS

In this section, we present simulation results to demonstrate the performance of the proposed resource allocation strategy and algorithms. We first consider the scenario shown in Figure2, where the secondary links attempt to access the spectrum of the primary system. Both the service radius of the primary system, R_1, and that of the CR system, R_2, are set to be 1000 m. The coordinates of CBS and PBS are (0, 0) and (−1500, 0), respectively. There are 5 SUs existing in this area with different x coordinates, and they have identical y coordinate of −200. We assume that the bandwidth of the primary system is 1.5 MHz, and is divided into 12 sub-channels, each having a bandwidth of 125 kHz. The total path-loss of each transceiver pair is assumed to be affected by both small-scale Rayleigh fading and large-scale path loss, where the path-loss exponent r is 3. The probability of each sub-channel being unoccupied is 50%, the maximum transmission power of the SU P^{max} is 20 W, and the transmission power of the PBS Pp is 50 W. Unless stated otherwise, the minimum data rate requirement for each user is identical and R_k^{min} is 0.2 Mb/s, the noise power at CBS σ2 and the QoS threshold of the primary system Imax are set to be −20 dBmW and −25 dBmW, respectively. All the results in this section for all the schemes are obtained under perfect spectrum sensing, and the case of imperfect sensing is out of the scope of this paper.

The SUs are located in different regions as shown in Figure2 and the distance between SUs located in Hybrid Region to a cell-edge PU can be calculated by

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$d^{(k)}_{SP} = D_k - R_1$, where D_k denotes the distance between the kth SU to the PBS. The results in the simulation are obtained by using a same set of random channel realizations for each value of $d^{(k)}_{SP}$. Figure3 shows the power consumption of SUs versus user ID with different resource allocation strategies when $R_k^{min} = 0.2$ Mb/s. With the overlay-based scheme, only the channels being sensed idle are utilized.

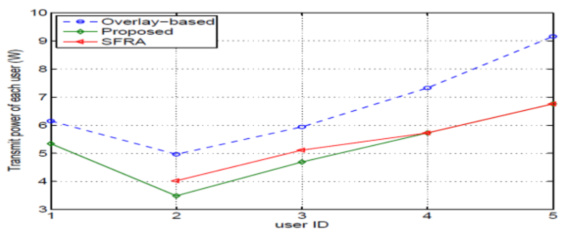

Figure3: The transmit power of SUs versus user ID with different resource allocation strategies (x coordinates increase from −300 to 900).

We do not give the results with the underlay-based scheme since the resource allocation results using the underlay-based and the proposed scheme are identical for users in the Hybrid Region, which is the case in Figure4. The only difference lies in the power spent on spectrum sensing. The x coordinates of these SUs are set to increase from −300 to 900 with the distance of the adjacent SUs being 300 m as shown in Figure4.

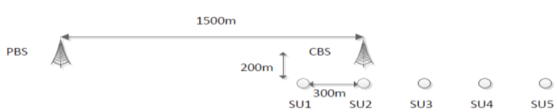

Figure4: The location information for simulation.

From the coordinates of the SUs, we know that all the SUs locate in the Hybrid Region. The corresponding channel allocation results with the proposed scheme are shown in Table2.

Table2: Channel allocation results

	SU 1	SU 2	SU 3	SU 4	SU 5	violate
channel 1	0	0	0	0	1	NO
channel 2	0	1	0	0	0	YES
channel 3	0	0	0	1	0	NO
channel 4	0	1	0	0	0	YES
channel 5	0	0	0	0	1	NO
channel 6	0	0	1	0	0	YES
channel 7	1	0	0	0	0	YES
channel 8	0	0	0	1	0	NO
channel 9	1	0	0	0	0	YES
channel 10	0	0	0	1	0	NO
channel 11	0	0	0	0	1	NO
channel 12	0	0	1	0	0	NO

In this table we can see that SU 4 and SU 5 are assigned one more channel since they are relatively far away from the CBS compared to other SUs which leads to less channel gain due to the large scale fading. The number of iterations for executing Algorithm 2 is 3, and the interference violation test results are shown in Table2. "YES" represents that the channel has ever been in the violated channel set V. It can be seen that spectrum sensing was performed for only 5 channels which means we saved 58% energy for spectrum sensing. For the SUs being close to the worst-case PU ($d^{(k)}_{SP} = 217$ m), the interference constraints translate into very stringent transmit power constraints, so that SFRA provides no solution to guarantee the minimum data requirement as shown in Figure3. For the SU that is closest to the CBS ($d^{(k)}_{SP} = 513$ m), the consumed power curves for both the proposed scheme and overlay-based scheme decrease rapidly as a result of less path loss, attaining the minimum value around 3.5 W and 5 W, respectively. For the SUs located far away from the worst-case PU, the consumed power curves for all the schemes increase and we observe that the proposed approach is strictly superior to the overlay-based approach in terms of power consumption, and coincides with SFRA for the SUs which are sufficiently far from the worst-case PU.

Figure5 shows the energy efficiency of SUs versus user ID with different resource allocation strategy when $R_k^{min} = 0.2$ Mb/s. We define energy efficiency for user k as

$$E^{(k)} = \frac{R^{(k)}_{act}}{\sum_{i \in \mathcal{A}^{(k)} \bigcup \mathcal{N}^{(k)}} P_{i,k}},$$

Where $R^{(k)}_{act}$ is the actual data rate based on a feasible power allocation solution. The equivalent metric for energy. We notice that for the overlay/underlay based approach, we have $R^{(k)}_{act} = R^{min}_k$. However, for SFRA, which is based on the worst-case design, the actual achieved data rate $R^{(k)}_{act}$ is usually larger than the required data rate, i.e., $R^{(k)}_{act} > R^{min}_k$. More specifically, when SFRA is applied, the resource allocation algorithm computes the achieved data rate using the second term in (1) which considers the interference from the PBS. However, such an interference does not exist if the spectrum resource is unoccupied by the primary system. Therefore, the actual achieved data rate in this case is a bit larger than the required data rate. From this figure, we can see that the proposed scheme outperforms the overlay-based scheme since more channel resources are utilized. When the SU is close to the CBS ($d^{(k)}_{SP} = 513$ m), the energy efficiency of the proposed scheme is better than SFPA since the interference constraints of some channels are relaxed according to potential spectrum sensing results.

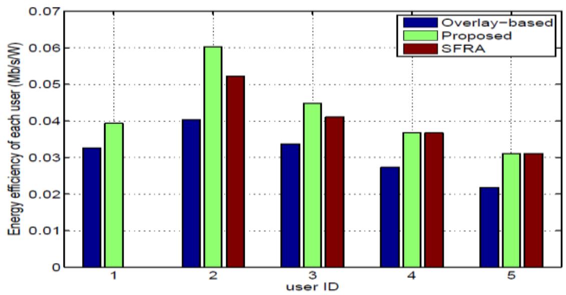

Figure5: The energy efficiency of SUs versus user ID with different resource allocation strategies.

To demonstrate the impact of geographical locations on energy efficiency, all the simulation results above are obtained by using a same set of random channel realizations for different users. We now consider instantaneous random channels for each SU to provide some detailed statistical insight into the simulations. Figure6 shows the probability density functions of energy efficiency for SU4 in Figure4 obtained by simulation of 1000 sets of channel realizations with different resource allocation schemes. The used simulation parameters are the same as those mentioned at the beginning of this section except the channel information. Here we only give the result of SU4 since all the SUs have similar probability density functions and hence we take SU4 as an example.

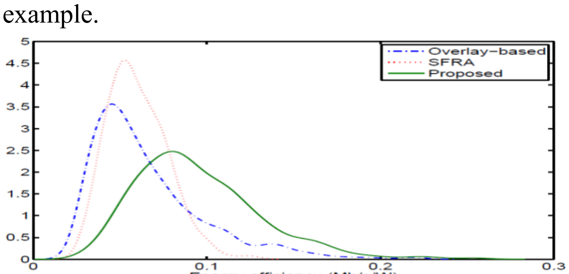

Figure6: The probability density functions of energy efficiency with different resource allocation strategies.

From this figure, we can see that the mean value of energy efficiency with proposed scheme is around 0.07 Mbps/W while it is only about 0.03 for overlay and 0.05 for SFRA, respectively. Therefore, we can conclude that the SUs have the best performance by applying the proposed scheme. In summary, the proposed scheme is able to adapt to different resource allocation strategies for SUs located at different locations and achieves the maximal energy efficiency or minimal power consumptions in all scenarios.

V.CONCLUSION

This paper has elaborated the role of adaptive resource allocation in CR networks in terms of energy efficiency since energy-efficiency oriented design is more and more important for wireless communications. Based on the existing research on resource allocation for OFDM-based CR networks, this chapter proposes an adaptive hybrid resource allocation strategy to enhance the energy efficiency by utilizing spectrum and spatial opportunities. A novel adaptive power and channel allocation algorithm has been proposed to fulfill the proposed resource allocation strategy based on the interference violation test. In comparison between the existing scheme and the proposed resource allocation scheme, we have found that resource allocation by considering spatial information enhances the energy efficiency and avoids unnecessary spectrum sensing.

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