Chapter 4
Concurrent Spectrum Access

Abstract Concurrent spectrum access (CSA), which allows different communication systems simultaneously transmit on the same frequency band, has been recognized as one of the most important techniques to realize the dynamic spectrum management (DSM). By regulating the interference to be received by primary users, the secondary users are able to gain continuous transmission opportunity. Without the need of frequent spectrum detection and reconfiguration, the CSA has the merit of low cost and easy implementation in practice. In this chapter, we will present some important CSA models, discuss the key problems existing in these CSA systems, and review the techniques to deal with these problems.

4.1 Introduction

Compared with the opportunistic spectrum access (OSA), in recent years, the concurrent spectrum access (CSA) has been attracting increasing interests from academia and industry [1, 2]. The main reason is three-fold. Firstly, the CSA allows one or multiple secondary users (SUs) simultaneously transmit on the primary spectrum, provided that the interference to the primary users (PUs) can be regulated. Thus, the SUs can transmission continuously regardless whether the PU is transmitting or not. Secondly, neither inquiry of geolocation database nor spectrum sensing is needed, and thus frequent spectrum reconfiguration can be avoided. This makes the cognitive device be with low-cost hardware, which is thus more easier to be deployed. Thirdly, the CSA can achieve higher area spectral efficiency due to its spatial reuse of spectrum [3, 4], and therefore, can be used to accommodate the dense wireless traffic in host-spot areas.

To enable CSA, the secondary transmitter (SU-Tx) needs to refrain the interference power produced to primary receiver (PU-Rx) by designing its transmit strategy, such as transmit power, bit-rate, bandwidth and antenna beam, according to the channel state information (CSI) of the primary and the secondary systems. Mathematically, the design problem can be formulated to optimize the secondary performance under the restrictions of the physical resource limitation of secondary system and the protection requirement of primary system. The physical resource constraint has been

taken into consideration in the transmission design for the traditional communication system with dedicated operation spectrum [5–7]. While, the additional primary protection constraint poses new challenges to the design of both single-antenna and multi-antenna CSA systems.

According to whether the interference temperature is explicitly given, the primary protection constraint is rendered in two forms. When the interference temperature is given as a predefined value, the primary protection constraint can be explicitly expressed as *interference power constraint*. There are basically two types of interference power constraint which are known as *peak* interference power constraint and *average* interference power constraint [8]. Peak interference power constraint restricts the interference power levels for all the channel states, while the average interference power constraint regulates the average interference power across all the channel states. The peak interference power constraint is more stringent with which the PUs can be protected all the time. Thus, it is suitable for protecting the PUs with delay-sensitive services. The average interference power constraint is less stringent compared with the former one, since it allows the interference power exceed the interference temperature for some channel states. Thus, it is suitable to protect the PUs with delay-insensitive services. On the other hand, when the explicit interference temperature is unavailable, *primary performance loss constraint* is used to protect the PUs [9, 10]. In fact, this is a fundamental formulation of primary protection constraint, and can help the SUs to exploit the sharing opportunity more efficiently. However, this constraint requires the information including the CSI of the primary signal link and the transmit power of the PU, which is hard to be obtained in practice due to the lack of cooperation between the primary and secondary systems.

The research on the CSA system with SUs being equipped with single antenna mainly focuses on the analysis of secondary channel capacity. It has been shown that the capacity of secondary system with fading channel exceeds that with additive white Gaussian noise (AWGN) channel, under the interference power constraint [11]. The reason lies in that the fading channel with variation can provide more transmission opportunities for the secondary system. For flat-fading channel, the secondary channel capacity under the peak and the average interference power constraints are studied in [12], whereas the ergodic capacity and the outage capacity under various combinations of the peak/average interference power constraint and the peak/average transmit power constraint are studied in [13]. It shows that the capacity under the average power constraint outperforms that under the peak power constraint, since the former one can provide more flexibilities for the SU transmit power design. In [9], the ergodic capacity and the outage capacity under the PU-Rx outage constraint are analysed. It shows that to fulfill the same level of outage loss of PU-Rx, the SU can achieve larger transmission rate under the PU outage constraint. With zero outage loss permitted, the SU still achieves scalable transmit rate with the PU outage constraint. In [14], the primary channel information is exploited to further improve the secondary performance. To predict the interference power received by the PU-Rx, the CSI from the SU-Tx to the PU-Rx, which is referred to as cross channel state information (C-CSI), should be known by the SU-Tx. The mean secondary link capacity with imperfect knowledge of C-CSI is addressed in [15]. To protect the

PU under imperfect C-CSI, it is shown that the interference temperature should be decreased, which thus leads to a decrement of secondary link capacity.

The use of multiple antennas provides both multiplexing and diversity gains in wireless transmissions [16, 17]. In particular, its function of co-channel interference suppression for multiuser transmission makes it a promising technique to enhance the CSA performance [18]. Generally speaking, multiple antennas can provide the SU-Tx in an CSA system more degrees of freedom in space, which can be split between the signal transmission to maximize the secondary transmit rate and the interference avoidance for the PUs. In [19], the multiple-input multiple-output (MIMO) channel capacity of the SU in a multi-antenna CSA system has been investigated. It shows that the primary protection constraint makes the methods proposed for the traditional MIMO system inapplicable for the CR transmit and receive design. Similar to the single-antenna CSA, moreover, the C-CSI is critical for the transmit design for interference avoidance in the multi-antenna CSA. In [20], it shows that when the effective interference channel can be perfectly estimated, the interference power received by the PUs can be perfectly avoided via cognitive beamforming. In [21], it further shows that the joint transmit and receive beamforming can effectively improve the secondary transmit rate by suppressing the interference produced by the PU-Tx. The use of multiple antennas also facilitates the multiple access and the broadcasting of secondary system [22]. Similar to the single-antenna case, due to the restriction of both transmit power and interference power, the transmit and receive design for the traditional multiple-access channel and the broadcasting channel in multi-antenna system is inapplicable and thus should be revisited [23, 24]. Moreover, the design for multi-antenna CSA should take into consideration the uncertainty in the estimated channel [25, 26] and the security issue [27, 28].

In the remainder of this chapter, we first present the single-antenna CSA system and discuss the optimal transmit power design under different types of power constraint to maximize the secondary channel capacity. Then, the multi-antenna CSA is discussed and the transceiver beamforming is presented under the condition of known and unknown related CSI. After that, the transmit and receive design for the cognitive multiple-access channel and the cognitive broadcasting channel are presented, which is followed by the discussion of robust design for the multi-antenna CSA. As an application of CSA in practice, the spectrum refarming technique is presented. Finally, the chapter is concluded with a summary.

4.2 Single-Antenna CSA

The simplest but most fundamental CSA system is comprised by a pair of SUs and a pair of PUs. Each of the terminals is equipped with single antenna. A single narrow frequency band is shared by the primary and secondary transmission. All the channels involved in the system are independent block fading (BF) channels. As shown in Fig. 4.1, g_{pp}, g_{ps}, g_{sp} and g_{ss} denote the instantaneous channel power gains from PU-Tx to PU-Rx, PU-Tx to SU-Rx, SU-Tx to SU-Rx, and SU-Tx to SU-Rx,

Fig. 4.1 The model of
single-antenna CSA system
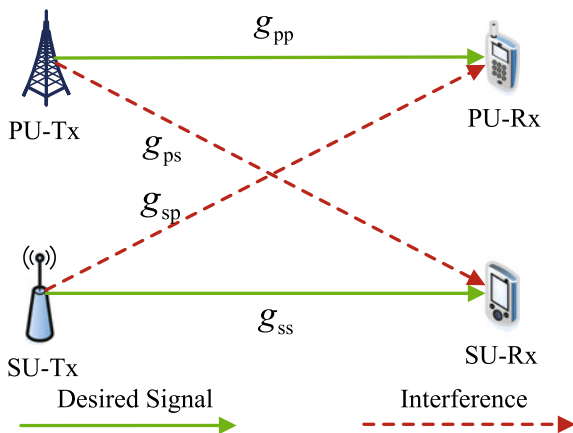
respectively. All the channel power gains are assumed to be independent with each other and be ergodic and stationary with continuous probability density function. In order to study the limit of the secondary channel capacity, we consider that the instantaneous channel power gains at each fading state are available at the SU-Tx. The AWGN at the PU-Rx and the SU-Rx is assumed to be independent circularly symmetric complex Gaussian variables with zero mean and variance N_0. We consider that the PU-Tx is not aware of the coexistence of SU, and thus adopts fixed transmit power P_p. Note that in practice, the transmission of SU can be noticed by the PU since the interference power received by the PU is increased. To compensate its performance loss, the PU can increase its transmit power. Thus, rather than being fixed, the PU transmit power can be adaptive according the secondary transmission. This property has been utilized in the CR design for indirectly exploiting the primary system information [14].

4.2.1 Power Constraints

In this CR system, the SU-Tx needs to regulate its transmit power to protect the PU service. There are mainly two categories of power constraints, which are the transmit power constraint and the primary protection constraint.

(1) *Transmit Power Constraint*

This is a physical resource constraint that restricts the transmit power of the SU according to its power budget. Let $v = (g_{pp}, g_{ps}, g_{sp}, g_{ss})$, and the SU transmit power under v be $P(v)$. Given the maximum peak and average transmit power of the SU as P_{pk} and P_{av}, respectively, the transmit power constraint can be formulated as

$$P(v) \geq 0, \ \forall v \tag{4.1}$$

$$P(v) \leq P_{pk}, \ \forall v \tag{4.2}$$

$$\mathbb{E}[P(v)] \leq P_{av} \tag{4.3}$$

Equation (4.2) is known as the *peak transmit power constraint*, which is used to address the non-linearity of the power amplifier of SU. Equation (4.3) is known as the *average transmit power constraint*, which describes that the power consumption of the SU should be affordable in a long-term sense.

(2) *Primary Protection Constraint*

The transmission of SU is allowed only when the primary service can be well protected. Thus, the primary protection constraint should be properly formulated. This constraint also differentiates the CR design from the traditional one which is solely restricted by the physical resource constraint. Generally, there are two kinds of primary protection constraints:

- *Interference power constraint*: When the peak or average interference temperature, which are respectively denoted by Q_{pk} and Q_{av}, can be known by the SU-Tx, the primary protection constraint can be expressed as the interference power constraint, i.e.,

$$g_{\mathrm{sp}}P(v) \leq Q_{pk}, \ \forall v \tag{4.4}$$

$$\mathbb{E}[g_{\mathrm{sp}}P(v)] \leq Q_{av} \tag{4.5}$$

Equation (4.4) is known as the *peak interference power constraint*. It can be seen that the PU under this constraint can be fully protected at any fading status; thus, this constraint is suitable for protecting the delay-sensitive services. Equation (4.5) is known as the *average interference power constraint*. Since this constraint only protects the PU in a long-term sense, and there can be cases that the interference power exceeds the interference temperature at some fading states. Thus, it is suitable to protect the delay-insensitive services.
- *Primary performance loss constraint*: When the peak or average interference temperature is not available, the primary protection constraint can be formulated as

$$\varepsilon_p \leq \varepsilon_0, \tag{4.6}$$

$$\Delta r_p \leq \delta_0, \ \forall v \tag{4.7}$$

Equation (4.6) is known as the *PU outage constraint* [29], in which ε_0 denotes the target outage probability of the PU that should be maintained, and ε_p is the outage probability of PU under the co-transmission of SU. Letting γ_p be the target signal-to-interference-plus-noise ratio (SINR) of the PU, ε_p can be derived as $\varepsilon_p = \mathrm{Pr}\left\{\frac{g_{\mathrm{pp}}P_p}{g_{\mathrm{sp}}P(v)+N_0} < \gamma_p\right\}$. Equation (4.7) is known as the *primary rate loss constraint* [10], in which δ_0 is the maximum rate loss that is tolerable by the PU.

Note that in either (4.6) or (4.7), the primary system information, including g_{pp} and P_p should be known by the SU-Tx. Such information can be transmitted from PU to SU if the cooperation between the two systems is available. When the inter-system cooperation is unavailable, the authors in [14] propose a scheme to allow the SU-Tx send probing signal which triggers the power adaptation of primary system. By doing so, the information of primary system can be exploited to improve the performance of secondary system.

Thus, the power constraints of the SU-Tx can be formulated as different combinations of the transmit power constraint and the primary protection constraint, i.e.,

$$\mathcal{F}_1 = \{P(\nu) : (4.1), (4.2), (4.4)\}$$
$$\mathcal{F}_2 = \{P(\nu) : (4.1), (4.2), (4.5)\}$$
$$\mathcal{F}_3 = \{P(\nu) : (4.1), (4.3), (4.4)\}$$
$$\mathcal{F}_4 = \{P(\nu) : (4.1), (4.3), (4.5)\}$$
$$\mathcal{F}_5 = \{P(\nu) : (4.1), (4.2), (4.6)\}$$
$$\mathcal{F}_6 = \{P(\nu) : (4.1), (4.3), (4.6)\}$$
$$\mathcal{F}_7 = \{P(\nu) : (4.1), (4.2), (4.7)\}$$
$$\mathcal{F}_8 = \{P(\nu) : (4.1), (4.3), (4.7)\}$$

4.2.2 Optimal Transmit Power Design

The transmit power of the SU can be optimized to achieve different kinds of secondary channel capacity. Here, we discuss the optimization of the SU transmit power for maximizing the ergodic capacity and minimizing the outage capacity of secondary system under different power constraints, respectively.

(1) *Maximizing Ergodic Capacity*

The ergodic capacity of BF channels is defined as the achievable rate averaged over all the fading blocks. Note that the interference from the PU-Tx to the SU-Rx can be ignored or treated as AWGN, the ergodic capacity of the secondary system can be expressed as

$$C_{\text{erg}} = \mathbb{E}\left[\log_2\left(1 + \frac{g_{\text{ss}}P(\nu)}{N_0}\right)\right] \tag{4.8}$$

where the expectation is taken over ν. Then, the achievable ergodic capacity under different sets of power constraint can be formulated as

$$\max_{P(\nu)\in\mathcal{F}_i} C_{\text{erg}} \tag{P4-1}$$

(2) *Minimizing Outage Capacity*

The outage capacity of BF channels is defined as the maximum rate that can be maintained over the fading blocks with a given outage probability. Equivalently, given the outage capacity of the secondary system, denoted by r_0, the corresponding outage probability can be expressed as

$$p_{\text{out}} = \Pr\left\{\log_2\left(1 + \frac{g_{\text{ss}}P(\nu)}{N_0}\right) < r_0\right\} \tag{4.9}$$

Thus, maximizing the outage capacity is equivalent to minimizing the outage probability given the target outage capacity, i.e.,

$$\min_{P(\nu)\in\mathcal{F}_i} p_{\text{out}} \tag{P4-2}$$

Solving P4-1 and P4-2 gives the following observations.

- P4-1 and P4-2 have structural optimal solutions. For example, in P4-1, under the peak transmit and peak interference power constraints ($\mathcal{F}_1$), $P(\nu) = P_{pk}$ when $g_{\text{sp}} < \frac{Q_{pk}}{P_{pk}}$. When $g_{\text{sp}} \geq \frac{Q_{pk}}{P_{pk}}$, the optimal transmit power follows channel inversion with g_{sp}, i.e., $P(\nu) = \frac{Q_{pk}}{g_{\text{sp}}}$. This indicates that deep fading in the interference channel is helpful to the secondary performance. Under the average transmit and peak interference power constraints ($\mathcal{F}_3$), the SU transmit power is capped by $\frac{Q_{pk}}{g_{\text{sp}}}$, and is decided by g_{sp} and g_{ss} simultaneously. Specifically, the transmit power is higher when the interference channel suffers from deep fading while the secondary signal channel is not faded. In P4-2, under the peak transmit and peak interference power constraints ($\mathcal{F}_1$), $P(\nu)$ has the truncated channel inversion structure which is similar to the conventional fading channel [5]. The difference lies in that the condition for channel inversion here is determined by both the secondary signal channel and the interference channel, while that in [5] it is determined by signal channel solely. Therefore, this power allocation strategy is also referred to as two-dimensional-truncated channel-inversion (2D-TCI).
- For both problems, the average interference power constraint is superior to the peak counterpart, as the former one provides more flexibility to the power allocation of the SU. Specifically, with the average interference power constraint, more power can be used when the interference channel experiences deep fading while the secondary signal channel is not faded.
- For both problems, the primary performance loss constraint is superior to the peak interference power constraint, since the SU can transmit more opportunistically with the former constraint. Moreover, when no additional outage of the PU is allowed, the SU transmission is not possible under the peak interference power constraint. However, under the primary performance loss constraint, the SU transmission is not only allowed, but also sustains capacity increase with the transmit power.

4.3   Cognitive Beamforming

The use of multiple antennas in wireless communication can achieve beamforming gain. Specifically, receive beamforming can suppress interference, while transmit beamforming can avoid interference. By equipping multiple antennas, the SUs can jointly design the transmit precoding and transmit power to effectively balance between the interference avoidance to the PU and the performance optimization for the secondary link. Such a technique is known as cognitive beamforming (CB).

A model of CB is shown in Fig. 4.2, where an SU-Tx transmits signal to the SU-Rx by concurrently sharing the spectrum of primary system in which two PUs communicate with each other. The SU-Tx is required to be equipped with more than one antennas, and the other terminals can be equipped with one or multiple antennas. Let M_1, M_2, M_{st}, and M_{sr} be the number of antennas on PU$_1$, PU$_2$, SU-Tx and SU-Rx, respectively. The full-rank transmit beamforming matrix of PU$_j$ is denoted by $\mathbf{A}_j \in \mathbb{C}^{M_j \times d_j}$ where $j \in \{1, 2\}$, d_j denotes the corresponding number of transmit data streams and $1 \leq d_j \leq M_j$. Then, the transmit covariance matrix of PU$_j$ can be written as $\mathbf{S}_j = \mathbf{A}_j \mathbf{A}_j^H$. The receive beamforming matrix of PU$_j$ is denoted by $\mathbf{B}_j \in \mathbb{C}^{d_j \times M_j}$, where $j \in \{1, 2\}$. The primary terminals are considered to be oblivious to the SUs, and treat the interference from the SU-Tx as additional noise. In the secondary system, the transmit beamforming matrix of the SU-Tx is denoted by the full-rank matrix $\mathbf{A}_c \in \mathbb{C}^{M_{st} \times d_c}$, where $d_c \leq M_{st}$. Then, $\mathbf{S}_c = \mathbf{A}_c \mathbf{A}_c^H$ is the transmit covariance matrix of the SU-Tx. Finally, $\mathbf{H} \in \mathbb{C}^{M_{sr} \times M_{st}}$ denotes the secondary signal channel matrix and $\mathbf{G}_j \in \mathbb{C}^{M_{sr} \times M_{st}}$ denotes the matrix of interference channel from the SU-Tx to PU$_j$.

4.3.1   Interference Channel Learning

The beamforming design, no matter at the receiver side or the transmitter side, heavily relies on channel matrix. The beamforming in the conventional multi-antenna system with dedicated spectrum is designed based on the signal channel matrix. However, the CB design needs the information of both the secondary signal channel matrix and the interference channel matrix from the SU-Tx to the PUs. The CB design with

Fig. 4.2 A model of cognitive beamforming
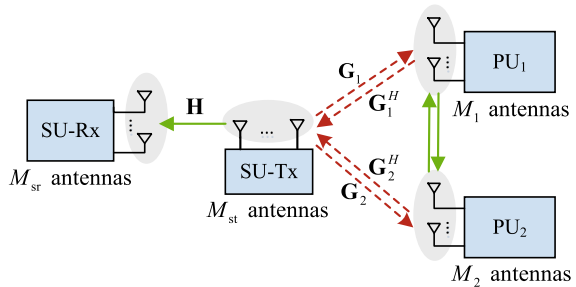
Fig. 4.3 The two-phase protocol of learning-based CSA

Channel Learning | Data Transmission

τ | $T - \tau$

perfect knowledge of interference channel matrix is studied in [30]. However, in a CSA network, the primary system is usually legacy that has been deployed and operating for a period of time. The primary and secondary systems can also belong to different operators. Therefore, although sharing the same spectrum, it is hard for the primary system to provide cooperation for the secondary system in terms of estimating and sending back the information of interference channel. Thus, the key problem for the practical CB is how to obtain the interference channel matrix at the SU-Tx.

To get some knowledge of the interference channel, a viable way is to allow the SU-Tx listen to the signal sent by the PUs before its own transmission, and estimate the channel from the PUs to the SU-Tx. Since the system operates at time-division duplex (TDD) mode, the estimated channel can be treated as the interference channel from the SU-Tx to the PUs according to channel reciprocity. This process is referred to as *channel learning*. The learning-and-transmission protocol is illustrated in Fig. 4.3, in which T is the frame length, τ is the time duration used for learning the interference channel and the remainder $T - \tau$ is used for data transmission.

In the channel learning phase, the SU-Tx listens to the transmission of PUs on the spectrum of interest for N symbol periods. The received signal can be written as

$$\mathbf{y}(n) = \mathbf{G}_j^H \mathbf{A}_j \mathbf{x}_j(n) + \mathbf{z}(n), \ n = 1, \ldots, N \tag{4.10}$$

where $j = 1$ indicates that the signal is transmitted from PU$_1$; otherwise $j = 2$. The vector $\mathbf{x}(n)$ contains the encoded signals without power allocation and precoding. Then, the covariance matrix of the received signals at the SU-Tx can be derived as

$$\mathbf{Q}_y = \mathbb{E}[\mathbf{y}(n)(\mathbf{y}(n))^H] = \mathbf{Q}_s + \rho_0 \mathbf{I} \tag{4.11}$$

where $\mathbf{Q}_s$ represents the covariance matrix due to the signals from the two PUs, and $\rho_0 \mathbf{I}$ is the variance matrix of AWGN noise. At the SU-Tx, only the sample covariance matrix can be obtained, i.e.,

$$\hat{\mathbf{Q}}_y = \frac{1}{N} \sum_{n=1}^{N} \mathbf{y}(n)(\mathbf{y}(n))^H \tag{4.12}$$

Denote $\hat{\mathbf{Q}}_s$ as the estimation of $\mathbf{Q}_s$ that can be abstracted from $\hat{\mathbf{Q}}_y$. The aggregate "effective" channel from both PUs to the SU-Tx can be derived as

$$\mathbf{G}_{\text{eff}}^H = \hat{\mathbf{Q}}_s^{1/2} \tag{4.13}$$

It should be noted that the channel which has been estimated is the so called *effective interference channel* (EIC) rather than the actual interference channel. This channel propagates interference to both of the PUs. Under the assumption of channel reciprocity, EIC from SU-Tx to both PUs can be denoted by $\mathbf{G}_{\text{eff}}$.

4.3.2 CB with Perfect Channel Learning

In this part, the transmit beamforming at the SU-Tx, including the transmit precoding and power allocation, under perfect learning of EIC is discussed. In the EIC learning, the noise effect on estimating $\mathbf{Q}_s$ based on $\hat{\mathbf{Q}}_y$ can be completely removed by choosing a large enough N, i.e., $N \to \infty$.

To avoid the interference caused by the SU-Tx to both of the PUs, the precoding matrix of the SU-Tx should meet

$$\mathbf{G}_{\text{eff}}\mathbf{A}_c = \mathbf{0} \tag{4.14}$$

Denote d_{eff} as the rank of $\mathbf{G}_{\text{eff}}$. The eigenvalue decomposition (EVD) of $\mathbf{Q}_s$ can be written as $\mathbf{Q}_s = \mathbf{V}\Sigma\mathbf{V}^H$, where $\mathbf{V} \in \mathbb{C}^{M_{\text{st}} \times d_{\text{eff}}}$ and Σ is a positive $d_{\text{eff}} \times d_{\text{eff}}$ diagonal matrix. Letting $\mathbf{U} \in \mathbb{C}^{M_{\text{st}} \times (M_{\text{st}} - d_{\text{eff}})}$ satisfies $\mathbf{V}^H\mathbf{U} = \mathbf{0}$, the transmit beamforming matrix of the SU-Tx can be written as

$$\mathbf{A}_c = \mathbf{U}\mathbf{C}_c^{1/2} \tag{4.15}$$

where $\mathbf{C}_c^{1/2} \in \mathbb{C}^{(M_{\text{st}} - d_{\text{eff}}) \times d_c}$ and d_c denotes the number of transmit data streams of the SU-Tx. $\mathbf{C}_c$ satisfies $\mathbf{C}_c \succeq \mathbf{0}$ and $\text{Tr}(\mathbf{C}_c) \leq P_t$, where P_t denotes the maximum transmit power of the SU-Tx. Equation (4.15) indicates that the design of transmit beamforming matrix for the CR channel is equivalent to the design of transmit covariance matrix $\mathbf{C}_c$ for an auxiliary multi-antenna channel, i.e., $\mathbf{HU}$, subject to the transmit power constraint, i.e., $\text{Tr}(\mathbf{C}_c) \leq P_t$. This simplifies the design of $\mathbf{C}_c$, since the existing solutions are available for this well-studied precoder design problem (see [31] and the references therein).

When the conditions $\mathbf{A}_j^H\mathbf{G}_j \sqsubseteq \mathbf{B}_j\mathbf{G}_j$, $j \in \{1, 2\}$ hold,[1] and one or both of the PUs have multiple antennas but transmit only through a subspace of the overall spatial dimensions, i.e., $d_j < \min\{M_1, M_2\}$, the proposed CB scheme based on (4.15) outperforms the "P-SVD" scheme proposed in [30] where $\mathbf{G}_j$'s are perfectly known by the SU-Tx, in terms of the achievable degree of freedom (DoF) of CR transmission. The reason lies in that the $\mathbf{G}_{\text{eff}}$ contains the information of $\mathbf{A}_j^H\mathbf{G}_j$. Based on the condition $\mathbf{A}_j^H\mathbf{G}_j \sqsubseteq \mathbf{B}_j\mathbf{G}_j$, $\mathbf{G}_{\text{eff}}$ also contains the information of $\mathbf{B}_j\mathbf{G}_j$. Thus, the propose scheme can have a strictly positive DoF even when $M_1 + M_2 \geq M_{\text{st}}$, provided that $d_1 + d_2 < M_{\text{st}}$. In contrary, the $\mathbf{B}_j\mathbf{G}_j$ is unknown in the P-SVD scheme.

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[1]$\mathbf{X} \sqsubseteq \mathbf{Y}$ means that for two given matrices with the same column size, $\mathbf{X}$ and $\mathbf{Y}$, if $\mathbf{X}\mathbf{e} = 0$ for any arbitrary vector $\mathbf{e}$, then $\mathbf{Y}\mathbf{e} = 0$ always holds.

Therefore, the DoF becomes zero when $M_1 + M_2 \geq M_{st}$. In most practical scenarios, it has $(d_1 + d_2) \leq (M_1 + M_2)$, and thereby the DoF gain achieved by the proposed scheme $((\min(M_{st} - d_1 - d_2)^+, M_{sr}))$ is always no less than the DoF achieved by the P-SVD $((\min(M_{st} - M_1 - M_2)^+, M_{sr}))$. Moreover, the maximum DoF is achieved when $d_1 = d_2 = 0$, i.e., the PU links are switched off.

4.3.3 CB with Imperfect Channel Learning: A Learning-Throughput Tradeoff

In this part, the CB with imperfect estimation of EIC due to finite sample size is discussed. With finite N, the noise effect on estimating $\mathbf{Q}_s$ cannot be removed, and thus error appears in the EIC estimation. Denote $\hat{\mathbf{G}}_{eff}$ as the estimated EIC with error. Recall the two-phase protocol given in Fig. 4.3. It can be seen that the number of sample size N increases as the learning duration τ increases. This improves the estimation accuracy of $\hat{\mathbf{G}}_{eff}$, and therefore contributes to the CR throughput. However, increasing the learning duration will lead to a decrement of data transmission duration, which harms the CR throughput. Given that the overall frame length is limited by the delay requirement of the secondary service, there exists an optimal learning duration that maximizes the CR throughput. This is the so called *learning-throughput tradeoff* in the CB design.

To exploit the learning-throughput tradeoff, the optimization problem can be formulated as

$$\max_{\tau, \mathbf{C}_c} \frac{T - \tau}{T} \log \left| \mathbf{I} + \mathbf{H} \hat{\mathbf{U}} \mathbf{C}_c \hat{\mathbf{U}}^H \mathbf{H} / \rho_1 \right| \tag{P4-3}$$

$$s.t. \ \text{Tr}(\mathbf{C}_c) \leq J, \ \mathbf{C}_c \succeq \mathbf{0}, \ 0 \leq \tau \leq T$$

where $\hat{\mathbf{U}}$ is obtained from $\hat{\mathbf{G}}_{eff}$, and J is the threshold that considers the interference power limit and the transmit power limit. In what follows, we present the imperfect estimation of EIC and the derivation of J.

(1) *Imperfect Estimation of EIC*

Since $\hat{\mathbf{G}}_{eff}$ depends solely on $\hat{\mathbf{Q}}_s$, we derive $\hat{\mathbf{Q}}_s$ based on $\hat{\mathbf{Q}}_y$, whose EVD is

$$\hat{\mathbf{Q}}_y = \hat{\mathbf{T}}_y \hat{\Lambda}_y \hat{\mathbf{T}}_y^H \tag{4.16}$$

where $\hat{\Lambda}_y = \text{Diag}(\hat{\lambda}_1, \hat{\lambda}_2, \ldots, \hat{\lambda}_{M_{st}})$ is the eigenvalue matrix of $\hat{\mathbf{Q}}_y$. Then, we consider two cases:

- *With known noise power*: When the noise power ρ_0 is known, the estimation of $\mathbf{Q}_s$ based on the maximum likelihood criterion can be written as

$$\hat{\mathbf{Q}}_s = \hat{\mathbf{T}}_y \text{Diag}\left((\hat{\lambda}_1 - \rho_0)^+, \ldots, (\hat{\lambda}_{M_{\text{st}}} - \rho_0)^+\right)\hat{\mathbf{T}}_y^H \tag{4.17}$$

whose rank is $\hat{d}_{\text{eff}}$. The first $\hat{d}_{\text{eff}}$ columns of $\hat{\mathbf{T}}_y$ give the estimate of $\mathbf{V}$, and the last $M_{\text{st}} - \hat{d}_{\text{eff}}$ columns of $\hat{\mathbf{T}}_y$ give $\hat{\mathbf{U}}$. This will be used to design the CB precoding matrix.

- *With unknown noise power*: When the noise power ρ_0 is unknown, the noise power should be estimated along with $\hat{\mathbf{Q}}_s$. By obtaining $\hat{\rho}_0$, $\hat{d}_{\text{eff}}$, $\hat{\mathbf{V}}$ and $\hat{\mathbf{U}}$, the maximum likelihood estimate of $\mathbf{Q}_s$ can be derived as

$$\hat{\mathbf{Q}}_s = \hat{\mathbf{V}}\text{Diag}\left(\hat{\lambda}_1 - \hat{\rho}_0, \ldots, \hat{\lambda}_{\hat{d}_{\text{eff}}} - \hat{\rho}_0\right)\hat{\mathbf{V}}^H \tag{4.18}$$

which has the same structure with (4.17).

With $\hat{\mathbf{Q}}_s$ being derived, the estimate of EIC can be determined according to (4.13).

(2) *Interference Leakage to PUs*

Since the estimated EIC is imperfect, there will be interference power leaked to the PUs. Thus, the power constraint $\text{Tr}(\mathbf{C}_c) \leq J$ should consider the interference leakage and transmit power limit simultaneously. Based on the CB design in (4.15) with $\mathbf{U}$ being replaced with $\hat{\mathbf{U}}$, the precoded transmit signal at the SU-Tx can be written as $\mathbf{s}_c(n) = \hat{\mathbf{U}}\mathbf{C}_c^{1/2}\mathbf{t}_c(n), n > N$. Then, the average interference leakage to PU$_j$ can be expressed as

$$I_j = \mathbb{E}[\|\mathbf{B}_j\mathbf{G}_j\mathbf{s}_c(n)\|^2] \tag{4.19}$$

The normalized interference leakage with respective to $\rho_0\text{Tr}(\mathbf{B}_j\mathbf{B}_j^H)$ is then upper bounded by

$$\bar{I}_j \leq \frac{\text{Tr}(\mathbf{C}_c)}{\alpha_j N} \frac{\lambda_{\max}(\mathbf{G}_j\mathbf{G}_j^H)}{\lambda_{\min}(\mathbf{A}_j^H\mathbf{G}_j\mathbf{G}_j^H\mathbf{A}_j)} \tag{4.20}$$

where α_j is defined as $\mathbb{E}\left[\frac{N_j}{N}\right]$, and N_j is the number of samples during the transmission of PU$_j$. The upper bound of the average interference leakage in (4.20) has some interesting properties:

- The upper bound is finite, since $\alpha_j > 0$;
- The upper bound is invariant with any scaler multiplication with $\mathbf{G}_j$. This means that the normalized interference received by each PU is independent with its position.
- The upper bound is inversely proportional to the number of samples and the transmit power of the PU. Therefore, the PU with longer transmit time within the learning duration and/or with higher transmit power will suffer from less interference. This is the main principle based on which the SU-Tx designs a fair transmit scheme in terms of distributing the interference among PUs.

With the upper bound of interference leakage, the SINR of PU_j, denoted by γ_j, can be derived. Let $\gamma = \min_{j \in \{1,2\}} \{\gamma_j\}$. The threshold J in the constraint of P4-3 can be derived as $J = \min(P_t, \gamma\tau)$ with peak transmit power constraint, and $J = \min\left(\frac{T}{T-\tau}P_t, \gamma\tau\right)$ with average transmit power constraint.

After $\hat{\mathbf{U}}$ and J are determined, P4-3 can be solved. It can be seen that by introducing learning phase before data transmission, the multi-antenna SU-Tx is able to estimate the interference channel information which is indispensable for interference control, and has a good balance between the interference avoidance and throughput maximization.

4.4 Cognitive MIMO

In this section, we exploit multi-antennas at the secondary terminals to effectively balance between the spatial multiplexing at the SU-Tx and the interference avoidance at the PUs. The main challenges to be addressed include:

- The spatial spectrum design for the SU-Tx under the condition that the secondary signal channel and the interference channel are perfectly known;
- The joint transmit and receive beamforming for the SUs to avoid interference to the PUs and suppress interference from the PUs simultaneously, under the condition that the secondary signal channel and the interference channel are unknown.

The model of the cognitive multiple-input multiple-output (MIMO) system is shown in Fig. 4.4, where a pair of SUs shares the same spectrum with K primary users. The number of antennas of PU k is denoted by M_k, and the number of antennas of the SU-Tx and that of the SU-Rx are denoted by M_{st} and M_{sr}, respectively. The single-band frequency is shared by the primary and secondary systems. $\mathbf{H} \in \mathbb{C}^{M_{st} \times M_{sr}}$ denotes the secondary signal channel matrix and $\mathbf{G}_k \in \mathbb{C}^{M_k \times M_{st}}$ denotes the interference channel matrix from the SU-Tx to PU_k.

Fig. 4.4 The model of cognitive MIMO system
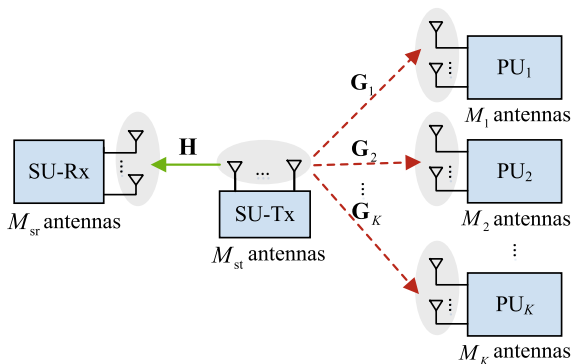
4.4.1 Spatial Spectrum Design

In this part, we discuss the spatial spectrum design for the SU-Tx to optimize the CR throughput and avoid the interference to the PUs. To exploit the performance limit, we consider that the channel matrices from the SU-Tx to the SU-Rx and that from the SU-Tx to each PU are perfectly known by the SU-Tx. Let $\mathbf{x}(n)$ be the transmit signal vector of the SU-Tx, which has been encoded and precoded. The received signal at the SU-Rx can be represented by

$$\mathbf{y}(n) = \mathbf{H}\mathbf{x}(n) + \mathbf{z}(n) \tag{4.21}$$

where $\mathbf{z}(n)$ is the AWGN vector with normalized variance $\mathbf{I}$. Let $\mathbf{S}$ be the transmit covariance matrix of the secondary system. It has $\mathbf{S} = \mathbb{E}[\mathbf{x}(n)\mathbf{x}(n)^H]$ where the expectation is taken over the codebook. Assuming that the ideal Gaussian codebook with infinitely large number of codeword symbols is used, it has $\mathbf{x}(n) \sim \mathcal{CN}(0, \mathbf{S}), n = 1, 2, \ldots$. Then, by applying EVD, the transmit covariance matrix can be written as

$$\mathbf{S} = \mathbf{V}\Sigma\mathbf{V}^H \tag{4.22}$$

where $\mathbf{V} \in \mathbb{C}^{M_{st} \times d_c}$ is the precoding matrix with $\mathbf{V}\mathbf{V}^H = \mathbf{I}$, and $d_c \leq M_{st}$ is the length of transmit data stream. d_c is usually referred to as the degree of spatial multiplexing because it measures the number of transmit dimensions in the spatial domain. When $d_c = 1$, the transmit strategy is known as beamforming, while when $d_c > 1$, it is known as spatial multiplexing. The transmit power of the SU-Tx is limited by its power budget P_t. Thus, the transmit power constraint can be formulated as $\text{Tr}(\mathbf{S}) \leq P_t$. Letting $\mathbf{g}_{k,j} \in \mathbb{C}^{1 \times M_{st}}$ be the channel vector from the SU-Tx to the jth receive antenna of the kth PU, it has $\mathbf{G}_k = \left[\mathbf{g}_{k,1}^T, \ldots, \mathbf{g}_{k,M_k}^T\right]^T$. Then, two kinds of interference power constraint can be formulated:

- *Total interference power constraint*: If the total interference power received by all the receive antennas of each PU is limited, the interference power constraint can be formulated as

$$\text{Tr}(\mathbf{G}_k\mathbf{S}\mathbf{G}_k^H) \leq Q_k, \ k = 1, \ldots, K \tag{4.23}$$

  where Q_k is the total interference temperature of PU_k.
- *Individual interference power constraint*: If the individual interference power received by each antenna of the PU is limited, the interference power constraint can be formulated as

$$\mathbf{g}_{k,j}\mathbf{S}\mathbf{g}_{k,j}^H \leq q_k, \ j = 1, \ldots, M_k, \ k = 1, \ldots, K \tag{4.24}$$

  where q_k is the individual interference temperature of PU_k on each of its antennas.

Then, the problem that aims to maximize the secondary capacity by optimizing the spatial spectrum $\mathbf{S}$ of the SU-Tx can be formulated as

$$\max_{\mathbf{S}} \quad \log_2 \left| \mathbf{I} + \mathbf{HSH}^H \right| \tag{P4-4}$$

$$s.t. \quad \mathrm{Tr}(\mathbf{S}) \le P_t$$

$$(4.23) \text{ or } (4.24)$$

$$\mathbf{S} \succeq \mathbf{0}$$

In what follows, we will discuss the solving of P4-4.

4.4.1.1 One Single-Antenna PU

When $K = 1$ and $M_k = 1$, there is only one single-antenna PU in the primary system. In this case, the channel from the SU-Tx to the PU is a multiple-input single-output (MISO) channel which can be represented as $\mathbf{g} \in \mathbb{C}^{1 \times M_{\text{st}}}$. Then, P4-4 can be simplified as

$$\max_{\mathbf{S}} \quad \log_2 \left| \mathbf{I} + \mathbf{HSH}^H \right| \tag{P4-5}$$

$$s.t. \quad \mathrm{Tr}(\mathbf{S}) \le P_t$$

$$\mathbf{gSg}^H \le q$$

$$\mathbf{S} \succeq \mathbf{0}$$

where q denotes the interference temperature of the PU. To solve this problem, we consider the following two cases.

(1) *MISO Secondary Channel, i.e., $M_{\text{sr}} = 1$*

In this case, $\mathbf{H}$ can be written as $\mathbf{h} \in \mathbb{C}^{1 \times M_{\text{st}}}$, and the rank of $\mathbf{S}$ is one. This indicates that beamforming is optimal for the secondary transmission, and $\mathbf{S}$ can be written as $\mathbf{S} = \mathbf{v}\mathbf{v}^H$, where $\mathbf{v} \in \mathbb{C}^{M_{\text{st}} \times 1}$. Then, P4-5 can be simplified as

$$\max_{\mathbf{v}} \quad \log_2 \left(1 + \|\mathbf{hv}\|^2 \right) \tag{P4-6}$$

$$s.t. \quad \|\mathbf{v}\|^2 \le P_t$$

$$\|\mathbf{gv}\|^2 \le q$$

(2) *MIMO Secondary Channel, i.e., $M_{\text{sr}} > 1$*

In this case, the rank of $\mathbf{S}$ is larger than one, and thus spatial multiplexing is optimal instead of beamforming. In general, there is no closed-form solution of the optimal $\mathbf{S}$. Thus, two suboptimal algorithms that achieve the closed-form solution of $\mathbf{S}$ are proposed as follows.

- **D-SVD**:
  Direct-channel SVD (D-SVD) method applies singular value decomposition (SVD) to the secondary signal channel matrix, which can be expressed as $\mathbf{H} = \mathbf{Q}\Lambda^{1/2}\mathbf{U}^H$. Thus, the precoding matrix $\mathbf{V}$ can be obtained as $\mathbf{V} = \mathbf{U}$. Let $M_s = \min\{M_{\text{st}}, M_{\text{sr}}\}$. The optimal power allocation $\mathbf{p} = [p_1, \dots, M_s]$ can be obtained by solving

$$\max_{\mathbf{p}} \quad \sum_{i=1}^{M_s} \log_2(1 + p_i\lambda_i) \tag{P4-7}$$

$$s.t. \quad \sum_{i=1}^{M_s} p_i \leq P_t$$

$$\sum_{i=1}^{M_s} \alpha_i p_i \leq q$$

$$\mathbf{p} \succeq \mathbf{0}$$

where λ_i is the diagonal element of Λ, $\alpha_i = \|\mathbf{g}\mathbf{u}_i\|^2$ and $\mathbf{u}_i$ is the ith column of $\mathbf{U}$. The problem is shown convex and the closed-form optimal p_i is given by

$$p_i = \left(\frac{1}{\nu + \alpha_i\mu} - \frac{1}{\lambda_i}\right)^+, \quad i = 1, \dots, M_s \tag{4.25}$$

where ν and μ are the nonnegative dual variables associated with the transmit power constraint and the interference power constraint, respectively. Therefore, it can be seen that by using D-SVD method, the optimal power allocation for the MIMO secondary channel follows multi-level water-filling form.

- **P-SVD**:
  Projected-channel SVD (P-SVD) method applies SVD to the projected channel of $\mathbf{H}$, i.e., $\mathbf{H}_\perp = \mathbf{H}(\mathbf{I} - \hat{\mathbf{g}}\hat{\mathbf{g}}^H)$ with $\hat{\mathbf{g}} = \mathbf{g}^H/\|\mathbf{g}\|$. Applying SVD to $\mathbf{H}_\perp$ yields $\mathbf{H}_\perp = \mathbf{Q}_\perp\Lambda_\perp^{1/2}(\mathbf{U}_\perp)^H$. Thus, the precoding matrix $\mathbf{V}$ can be obtained as $\mathbf{V} = \mathbf{U}_\perp$, and the optimal power allocation can be derived as

$$p_i = \left(\nu - \frac{1}{\lambda_i^\perp}\right)^+, \quad i = 1, \dots, M_s \tag{4.26}$$

where $\lambda_i^\perp$ is the diagonal element of $\Lambda_\perp$ and ν is the dual variable associated with the transmit power constraint. Here we can see that, by using P-SVD, it has $(\mathbf{U}_\perp)^H\hat{\mathbf{g}} = 0$. Since $\mathbf{S} = \mathbf{U}_\perp\Sigma(\mathbf{U}_\perp)^H$, we have $\mathbf{g}\mathbf{S}\mathbf{g}^H = \mathbf{0}$, which indicates that the interference power produced to the PU can be perfectly avoided.

4.4.1.2 Multiple Multi-antenna PUs

With multiple PUs which are equipped with single or multiple antennas, the transmission of the SU-Tx can be designed by considering the following two cases.

(1) *MISO Secondary Channel, $M_{\mathrm{sr}} = 1$*

Since the closed-form solution of the optimal $\mathbf{S}$ is hard to achieve in this case, efficient numerical optimization method can be proposed to solve the equivalent problem:

$$\max_{\mathbf{v}} \quad \|\mathbf{hv}\|^2 \tag{P4-8}$$
$$s.t. \quad \|\mathbf{v}\|^2 \le P_t$$
$$\|\mathbf{G}_k\mathbf{v}\|^2 \le Q_k, \ k = 1, \dots, K$$

Although both of the constraints in P4-8 specify convex set of $\mathbf{v}$, the non-convexity of the objective function makes the overall problem non-concave in its current form. However, we can observe that given any value of θ, $e^{j\theta}\mathbf{v}$ satisfies the constraints of P4-8, if $\mathbf{v}$ satisfies these constraints. At the meantime, the objective value is maintained. Thus, we can assume that $\mathbf{hv}$ is a real number, and P4-8 can be transformed to

$$\max_{\mathbf{v}} \quad \mathrm{Re}(\mathbf{hv}) \tag{P4-9}$$
$$s.t. \quad \mathrm{Im}(\mathbf{hv}) = 0$$
$$\|\mathbf{v}\|^2 \le P_t$$
$$\|\mathbf{G}_k\mathbf{v}\|^2 \le Q_k, \ k = 1, \dots, K$$

This problem can be cast as a second-order cone programming (SOCP) [32], which can be solved by standard numerical optimization software.

(2) *MIMO Secondary Channel, i.e., $M_{\mathrm{sr}} > 1$*

In this case, the D-SVD and the P-SVD methods which are proposed for the one single-antenna PU can be used. Specifically, the multi-level water-filling power allocation by using D-SVD in this case becomes

$$p_i = \left(\frac{1}{\nu + \sum_{k=1}^{K} \sum_{j=1}^{M_k} \alpha_{i,k,j}\mu_k} - \frac{1}{\lambda_i} \right)^+, \ i = 1, 2, \dots, M_s \tag{4.27}$$

where $\alpha_{i,k,j} = \|\mathbf{g}_{k,j}\mathbf{u}_i\|^2$. ν and μ_k are the non-negative dual variables associated with the transmit power constraint and the interference power constraint for PU_k, respectively. For P-SVD method, we construct the matrix of channel from the SU-Tx to all primary receivers/antennas, denoted as $\mathbf{G} \in \mathbb{C}^{M_k \times M_{\mathrm{st}}}$, by taking each $\mathbf{g}_{k,j}$ as the $\left(\sum_{k'=1}^{k} M_{k'-1} + j \right)$th row of the matrix. Then, the SVD of $\mathbf{G} = [\mathbf{G}_1^T, \dots, \mathbf{G}_K^T]^T$ can be expressed as $\mathbf{G} = \mathbf{Q}_G \Lambda_G^{1/2} \mathbf{U}_G^H$. Thus, given $M_{\mathrm{st}} > M_k$ (otherwise, the projection will be trivial), the projection of $\mathbf{H}$ can be expressed as $\mathbf{H}_\perp = \mathbf{H}(\mathbf{I} - \mathbf{U}_G\mathbf{U}_G^H)$.
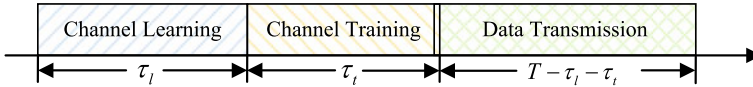
Channel Learning	Channel Training	Data Transmission
τ_l	τ_t	$T - \tau_l - \tau_t$

Fig. 4.5 The three-phase protocol for the cognitive MIMO system

4.4.2 Learning-Based Joint Spatial Spectrum Design

In this part, we investigate the cognitive MIMO by solving the two problems:

- The secondary signal channel and the interference channel are unknown;
- The interference from the PUs is suppressed by designing the spatial spectrum at the SU-Rx.

For simplicity, we consider there are two PUs in the primary system, i.e., $K = 2$, and only one of the PUs is located within the coverage of secondary transmission. However, the proposed method is applicable without this assumption by using the EIC which has been introduced in the previous section.

To enable the CR transmission, a three-phase protocol is proposed as shown in Fig. 4.5, whose interpretation is as follows.

- *Channel Learning Stage*: A duration of τ_l is used for channel learning, in which the SU-Tx and SU-Rx gain partial knowledge on the interference channel $\mathbf{G}_1$ and $\mathbf{G}_2$ via listening to the transmission of the PUs. Specifically, the SUs blindly estimate the noise subspace matrix from the covariance matrix of the received signal. It should be noted that, due to the finite number of samples, perturbation inevitably appears in the noise subspace matrix.
- *Channel Training Stage*: Since the secondary signal channel is unknown by the SU-Tx, in the training stage with duration of τ_t, the SUs estimate the channel after applying joint transmit and receive beamforming. By considering the interference to and from the PUs, the optimal training structure can be derived to minimize the channel estimation error. It is noted that the channel to be estimated is not the actual channel from the SU-Tx to the SU-Rx, but is the effective channel, which contains the information of transmit and receive beamforming matrices and the actual signal channel.
- *Data Transmission Stage*: With the interference channel information learnt in the first stage and the signal channel information estimated in the second stage, the SU-Tx transmits signal during the data transmission stage with length of $T - \tau_l - \tau_t$.

It is worth noting that the parameter τ_l plays an important role in the CR performance. Intuitively, a larger τ_l might be preferred in terms of better space estimation, so that the interference to and from the PUs can be minimized. However, increasing learning time will decease the data transmission time, if the training duration is fixed. This harms the CR throughput. Moreover, taking the interference constraints into

consideration during training and data transmitting, the freedom of power allocation is reduced. Thus, to investigate the CR performance, the lower bound of the secondary ergodic capacity is evaluated, which is related to both the channel-estimation error and the interference leakage to and from the PUs [33]. The lower bound of the CR ergodic capacity is then maximized by optimizing the transmit power and the time allocation over learning, training and transmission stages. A closed-form optimal power allocation can be found for a given time allocation, whereas the optimal time allocation can be found via two-dimensional search over a confined set [21].

4.5 Cognitive Multiple-Access and Broadcasting Channels

In the previous sections, the CR system under investigation has only one pair of SUs. In this section, we present the CR system that contains multiple transmitters or receivers, which forms the cognitive multiple-access channel (C-MAC) and the cognitive broadcasting channel (C-BC), respectively.

4.5.1 Cognitive Multiple-Access Channel

In some practical scenarios, there are multiple SUs concurrently transmit signals to their common receiver, such as the base station (BS) in the cellular networks or the WiFi access point (AP). Such a secondary system can be modelled as the C-MAC as is shown in Fig. 4.6. In this model, N SUs concurrently transmit signals to the BS by sharing the primary spectrum. There are K PUs, each of which is equipped with single antenna. To enable the multi-access of the SUs, the BS is equipped with M_r receive antennas. Denote $\mathbf{H} = [\mathbf{h}_1, \ldots, \mathbf{h}_N] \in \mathbb{C}^{M_r \times N}$ and $\tilde{\mathbf{H}} = [\tilde{\mathbf{h}}_1, \ldots, \tilde{\mathbf{h}}_K] \in \mathbb{C}^{M_r \times K}$ as the channel matrices from the SUs and the PUs to the BS, respectively. The signal vector received by the BS can be written as

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \tilde{\mathbf{H}}\tilde{\mathbf{x}} + \mathbf{z} \qquad (4.28)$$

where $\mathbf{x}$ and $\tilde{\mathbf{x}}$ are the vectors of transmit signal from the SUs and the PUs, and $\mathbf{z}$ is the AWGN vector whose entries are assumed to be with zero mean and variance N_0. Then, the following two optimization problems can be formulated.

(1) *Sum-Rate Maximization Problem*

With the aim of maximizing the total transmission rate of all the N SUs, the sum-rate maximization problem for the single-input multiple-output multiple-access channel can be formulated as

Fig. 4.6 The system model of C-MAC
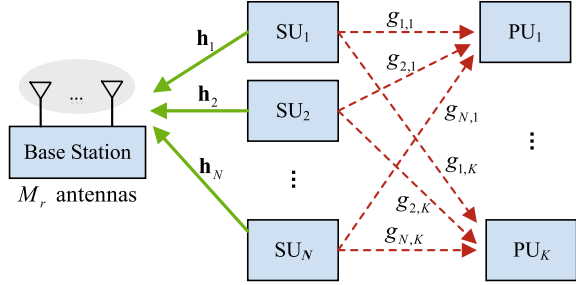
$$\max_{\mathbf{U},\mathbf{p}} \sum_{n=1}^{N} r_n \tag{P4-10}$$

$$s.t. \quad p_n \le P_t, \ n = 1, \ldots N \tag{4.29}$$

$$\mathbf{g}_k^T \mathbf{p} \le Q_k, \ k = 1, \ldots, K \tag{4.30}$$

where $\mathbf{U} = [\mathbf{u}_1, \ldots, \mathbf{u}_N]$ with $\mathbf{u}_i$ denoting the beamforming vector of SU_i, and r_i is the information rate of SU_i. Equation (4.29) is the peak transmit power constraint with P_t being the maximum allowable transmit power. Equation (4.30) indicates the interference power constraints where $\mathbf{g}_k$ is the channel power gain from the SUs to PU_k and Q_k is the interference temperature of PU_k. Using the zero-forcing based decision feedback equalizer (ZF-DFE) at the BS and applying QR decomposition to the channel matrix $\mathbf{H}$, the channel can be decomposed as independent subchannels, each of which is associated with one SU. This receiver can thus be viewed as receive beamforming, where the beamforming vector is determined by the QR decomposition of $\mathbf{H}$. Thus, only the power vector $\mathbf{p}$ is remained to be optimized, and the objective of the problem can be rewritten as $\max_{\mathbf{p}} \sum_{n=1}^{N} \log\left(1 + \frac{p_n \lambda_n}{N_0}\right)$, where λ_n is the effective channel gain.

In P4-10, if the interference constraints are replaced with the single sum transmit power constraint, the optimal power allocation can be derived as the conventional water-filling solution. The multiple interference power constraints complicate the solving of the problem, and thus, we solve the problem by considering the following two cases.

- *Single-PU case*: When there is only one PU, and thus there remains one interference power constraint, the optimal power allocation follows water-filling form. Different from the conventional water-filling power allocation which has a common water level, this solution has different water levels for different SUs. Moreover, each water level is upper-bounded by the individual maximum allowable transmit power. Therefore, this power allocation scheme is also referred to as capped multi-level (CML) water-filling. Figure 4.7 gives an example of the CML

Fig. 4.7 The CML water-filling power allocation
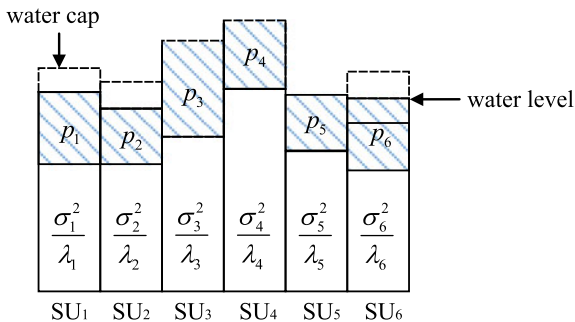
water-filling, where we can see that the power allocated to each SU is limited by the minimum value between its specific water level and the water cap.

• *Multiple-PU case*: The method to solve P4-10 with multiple interference constraints is summarized as follows. The method first removes the non-effective interference constraints. Suppose m effective constraints remain. It starts with the sub-problems with a single interference constraint. For the case of i constraints, we select i out of N constraints (thus, there are C_m^i combinations) and check whether the solution of the sub-problems also satisfies the remained $(m - i)$ constraints. If yes, this solution is globally optimal; otherwise, we continue to search the case of $(i + 1)$.

(2) *SINR Balancing Problem*

Taking the fairness among the SUs into consideration, the SINR balancing problem is formulated as

$$\max_{\mathbf{U},\mathbf{p}} \min_{1 \leq n \leq N} \frac{\gamma_n(\mathbf{u}_n, \mathbf{p})}{\gamma_{n,0}} \tag{P4-11}$$

$$s.t. \quad (4.29), \ (4.30)$$

where $\gamma_{n,0}$ is the target SINR of SU_n and $\gamma_n(\mathbf{u}_n, \mathbf{p})$ is the SINR of SU_n which can be derived as

$$\gamma_n(\mathbf{u}_n, \mathbf{p}) = \frac{p_n \mathbf{u}_n^H \mathbf{R}_n \mathbf{u}_n}{\mathbf{u}_n^H \left(\sum_{i \neq n} p_i \mathbf{R}_i + N_0 \mathbf{I} + \sum_{k=1}^{K} \tilde{p}_k \tilde{\mathbf{R}}_k \right) \mathbf{u}_n} \tag{4.31}$$

where $\mathbf{R}_i = \mathbf{h}_i \mathbf{h}_i^H$, $\tilde{\mathbf{R}}_k = \tilde{\mathbf{h}}_k \tilde{\mathbf{h}}_k^H$ and $\tilde{p}_k$ is the transmit power of PU_k. By investigating the property of P4-11, we can see that (1) the N power constraints and K interference constraints can be equally treated; (2) there is only one dominant constraint in the problem, and thus the problem can be decoupled into $(N + K)$ sub-problems each of which is with single constraint; (3) the sub-problems can be sequentially solved, which profoundly reduces the complexing of the algorithm. In fact, when one solution of a sub-optimal problem is obtained, we can check whether it satisfies the other

Fig. 4.8 The system model
of C-BC
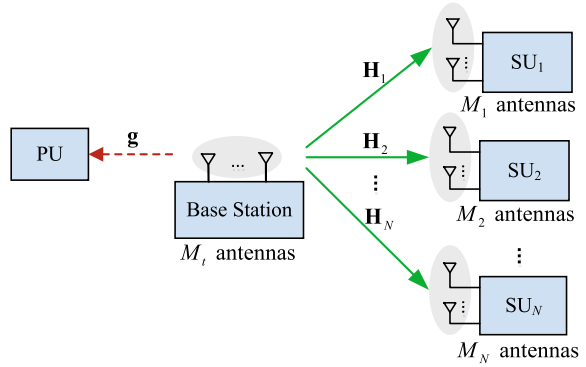
constraints. If yes, it can be treated as the global optimum without solving the other
sub-problems.

4.5.2   Cognitive Broadcasting Channel

When a BS is equipped with M_t antennas and broadcasts information to N SUs,
cognitive broadcasting channel (C-BC) is built. A typical C-BC model is shown in
Fig. 4.8, in which $\mathbf{g}$ denotes the vector of channel from the BS to the PU. The SU$_n$
has M_n antennas. The precoding design for the C-BC is different from that for the
conventional MIMO-BC, because the transmission of the BS is restricted not only by
a sum-power constraint, but also by an interference power constraint. In literatures,
the MIMO-BC precoding design is solved by establishing the BC-MAC duality.
As one type of BC-MAC duality, the *conventional BC-MAC duality* is proposed to
derive the capacity region of MIMO-BC under a sum-power constraint [34, 35]. As
another type of BC-MAC duality, the *minimax duality* can obtain any boundary point
of a broadcasting channel capacity region under the single sum-power constraint or
multiple linear transmit covariance constraints (LTCC) [36, 37]. For solving the C-
BC precoding problem which is restricted by both of the sum-power constraint and
the interference power constraint, the *general BC-MAC duality* is proposed which
handles the multiple general LTCCs and simplifies the problem formulation [24].

The general LTCC is expressed as

$$\text{Tr}(\mathbf{QA}) \leq J \tag{2.32}$$

where $\mathbf{Q}$ is the transmit covariance matrix, $\mathbf{A}$ is a positive semidefinite matrix, and
J is a predefined threshold. The general LTCC includes various practical power
constraints, such as

- *Total transmit power constraint*: if $\mathbf{A}$ is an identity matrix;

- *Individual transmit power constraint*: if $\mathbf{A}$ is a diagonal matrix in which one of the diagonal elements is one and the others are zeros;
- *Interference power constraint*: if $\mathbf{A} = \mathbf{g}\mathbf{g}^H$ where $\mathbf{g}$ is the vector of channel response from the SU to the PU.

Then, the C-BC precoding problem can be formulated with subject to any combination of the above constraints. For demonstrating how to transform the C-BC precoding problem to its dual C-MAC problem, we take the following weighted sum-rate maximization problem as an example.

$$\max_{\mathbf{U}_i^b} \ \sum_{n=1}^{N} w_n r_n \tag{P4-12}$$

$$s.t. \ \sum_{n=1}^{N} \mathrm{Tr}(\mathbf{U}_n^b) \le P$$

$$\sum_{n=1}^{N} \mathbf{g}^H \mathbf{U}_n^b \mathbf{g} \le Q$$

where r_n and w_n are the achievable rate and the weight coefficient of SU_n, respectively. $\mathbf{U}_i^b$ denotes the precoding matrix of the BS. By applying the general BC-MAC duality, non-negative auxiliary variables q_t, q_u are introduced, with which P4-12 can be transformed to

$$\min_{q_t,q_u} \max_{\mathbf{U}_n^b} \ \sum_{n=1}^{N} w_n r_n$$

$$s.t. \ q_u \left(\sum_{n=1}^{N} \mathrm{Tr}(\mathbf{U}_n^b) - P \right) + q_t \left(\sum_{n=1}^{N} \mathbf{g}^H \mathbf{U}_n^b \mathbf{g} - Q \right) \le 0$$

Letting $J = q_t P + q_u Q$, the equivalent C-BC problem can be written as

$$\max_{\mathbf{U}_n^b} \ \sum_{n=1}^{N} w_n r_n$$

$$s.t. \ q_u \sum_{n=1}^{N} \mathrm{Tr}(\mathbf{U}_n^b) + q_t \sum_{n=1}^{N} \mathbf{g}^H \mathbf{U}_n^b \mathbf{g} \le J$$

based on which the dual C-MAC problem can be written as

$$\max_{\mathbf{U}_i^m} \sum_{n=1}^{N} w_n r_n^m$$

$$s.t. \sum_{n=1}^{N} \text{Tr}(\mathbf{U}_n^m)\sigma^2 \leq J$$

where the noise covariance matrix is $q_t \mathbf{g}\mathbf{g}^H + q_u \mathbf{I}$.

4.6   Robust Design

The CSI, including the C-CSI and S-CSI, is critical for the CR system to control interference and optimize its performance. In practice, the CSI obtained by the SU is normally imperfect, for which robust design is needed to be identified so that the cognitive transmission strategy is less sensitive to the uncertainty in the CSI. In the literature, there are a few of related robust designs. One kind of ideas is to design the robust beamforming so that a high probability that the interference power constraint is satisfied can be achieved. Another kind of ideas is to model the uncertainty in related CSI with boundary and design the robust beamforming to guarantee the interference power constraint. In this part, we consider two scenarios, i.e., only the C-CSI contains uncertainty [38] and both of the C-CSI and S-CSI contain uncertainty [26], respectively.

4.6.1   Uncertain Interference Channel

To focus on the uncertainty in the interference channel, we consider that the secondary S-CSI is perfectly known by the SU-Tx, and the uncertainty in the interference channel is caused by the PU in moving environment or caused by the indistinguishable PU-Rx due to mutual transmission between two PUs in TDD mode. In both cases, the PU can be protected by considering that the degree of arrival (DoA) varies within a certain range. The model of the system can be referred to Fig. 4.9 by letting $K = 1$ and $N = 1$, meaning that there is a single PU and a pair of SU-Tx and SU-Rx. To characterize the interference channel, we use the spatial multipath model. Let L and $\theta^{(l)}$ be the number of multipaths and the DoA of the lth path, respectively. The fading coefficient of the lth path can be denoted by α_l. Then, the channel from the SU-Tx to the PU can be expressed as

$$\mathbf{g} = \sum_{l=1}^{L} \alpha_l \mathbf{a}(\theta^{(l)}) \tag{4.32}$$

where $\mathbf{a}(\theta^{(l)})$ is the steering vector of the lth path. Note that given the angular spread of the PU, denoted by Δ_θ, the range of the DoA can be written as $\theta^{(l)} \in [\bar{\theta} - \Delta_\theta/2, \bar{\theta} + \Delta_\theta/2]$, where $\bar{\theta}$ is the nominal DoA with respect ot the SU-Tx antenna array. Generally, if the DoA region of the PU, denoted by $\Theta = [\theta_1, \theta_2]$, can be perfectly known, we can set $\bar{\theta} - \Delta_\theta/2 = \theta_1$ and $\bar{\theta} + \Delta_\theta/2 = \theta_2$. If Θ is unknown, we can choose a larger angular spread for estimating the position of the PU so that sufficient protection to the PU can be provided. The rate optimization problem with the aim of maximizing the secondary throughput can be formulated as

$$\max_{\mathbf{w}} \quad r \qquad \text{(P4-13)}$$
$$s.t. \quad |\mathbf{a}^H(\theta^{(l)})\mathbf{w}|^2 \leq Q, \ \forall \theta^{(l)} \in \Theta$$
$$\|\mathbf{w}\|^2 \leq 1$$

where r is the downlink rate that achieved by the secondary transmission, which can be derived as $r = |\mathbf{h}^H\mathbf{w}|^2$. The first constraint is the interference power constraint and the second constraint is the transmit power constraint in which the maximum peak transmit power is normalized as one. Thus, similar to P4-8, the problem can be transformed to

$$\max_{\mathbf{w}} \quad \text{Re}[\mathbf{h}^H\mathbf{w}]$$
$$s.t. \ \text{Im}[\mathbf{h}^H\mathbf{w}] = 0,$$
$$|\mathbf{a}^H(\theta^{(l)})\mathbf{w}| \leq \sqrt{Q}, \ \forall l$$
$$\|\mathbf{w}\|^2 \leq 1 \qquad (4.33)$$

Such a robust beamforming design can allocate the majority of the SU transmit power along the SU-Rx DoA with refraining the transmit power along the DoA of the PU below the interference temperature.

4.6.2 Uncertain Interference and Secondary Signal Channels

This part discusses the robust beamforming design for a multi-user MISO system to address the uncertainty in both of the C-CSI and the secondary S-CSI. Only partial knowledge of these channels are available. As shown in Fig. 4.9, the SU-Tx with M antennas transmits independent signal to the N SU-Rx's, each of which is equipped with single antenna. The channel from the SU-Tx to the nth SU-Rx is denoted by $\mathbf{h}_n \in \mathbb{C}^{M \times 1}$. The uncertainty in $\mathbf{h}_n$ is described by the Euclidean ball

$$\mathcal{H}_n = \left\{ \mathbf{h} : \|\mathbf{h} - \tilde{\mathbf{h}}_n\| \leq \delta_n \right\} \qquad (4.34)$$
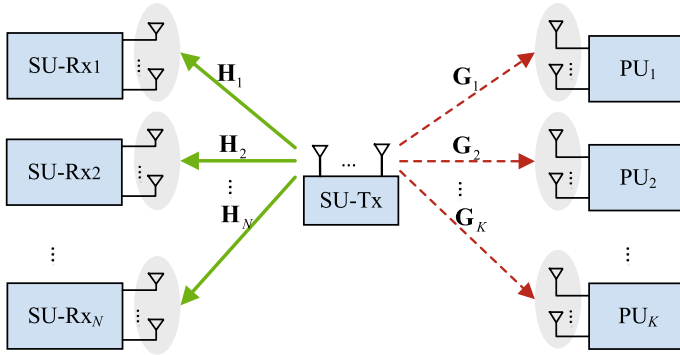
Fig. 4.9 The system model for robust design

where $\tilde{\mathbf{h}}_n$ is the actual channel to the nth SU-Rx, and $\delta_n > 0$ is the radius of the Euclidean ball. Then, the channel from SU-Tx to the nth SU-Rx can be modelled as

$$\mathbf{h}_n = \tilde{\mathbf{h}}_n + \mathbf{a}_n, \ n = 1, \ldots, N \tag{4.35}$$

where $\mathbf{a}_n$ is a norm-bounded uncertainty vector with $\|\mathbf{a}_n\| \leq \delta_n$. Similarly, the channel from the SU-Tx to PU_k can be modelled as

$$\mathbf{g}_k = \tilde{\mathbf{g}}_k + \mathbf{b}_k, \ k = 1, \ldots, K \tag{4.36}$$

and the uncertainty set of $\mathbf{g}_k$ is $\mathcal{G}_k$. Denoting the SU-Tx precoding matrix by $\mathbf{W} = [\mathbf{w}_1, \ldots, \mathbf{w}_N] \in \mathbb{C}^{K \times N}$, the total transmit power of the SU-Tx, denoted by P_s, can be derived as $\mathbb{E}[\|\mathbf{x}\|^2] = \sum_{n=1}^{N} \|\mathbf{w}_n\|^2$. At the receiver side, the SINR at the nth SU-Rx can be derived as $\gamma_n = \frac{|\mathbf{w}_n^H \mathbf{h}_n|^2}{N_0 + \sum_{i=1, \neq n}^{N} |\mathbf{w}_n^H \mathbf{h}_n|^2}$. The interference received by PU_k, denoted by P_{int}^k, can be derived as $\sum_{n=1}^{N} |\mathbf{w}_n^H \mathbf{g}_k|^2$. With Γ_n and Q_k representing the target SINR of the nth SU-Rx and the interference temperature of PU_k, the beamforming design problem can be formulated as

$$\min_{\mathbf{W}} \quad P_s \tag{P4-14}$$
$$s.t. \quad \gamma_n \geq \Gamma_n, \ \forall \mathbf{h} \in \mathcal{H}_n \text{ and } \forall n$$
$$P_{\text{int}}^k \leq Q_k, \ \forall \mathbf{g}_k \in \mathcal{G}_k \text{ and } \forall k$$

This problem aims to minimize the transmit power of the SU-Tx with guaranteeing the QoS requirement for each SU-Rx and keeping the interference received by each PU below its interference temperature. Note that the constraints should be satisfied under all possible channel conditions with the bounded uncertainty. In another word, the QoS of SUs and the interference constraints should be satisfied for the worst case, i.e., the constraints can be transformed as $\min_{\mathbf{h}_n \in \mathcal{H}_n} \gamma_n \geq \Gamma_n, \forall n$ and $\max_{\mathbf{g}_k \in \mathcal{G}_k} P_{\text{int}}^k \leq Q_k, \forall k$. Thus, before solving P4-14, the problem $\min_{\mathbf{h}_n \in \mathcal{H}_n} \gamma_n$ and $\max_{\mathbf{g}_k \in \mathcal{G}_k} P_{\text{int}}^k$ should be solved first.

For solving these problems, loose bounds, strict bounds and exact robust methods are proposed in [26], which shows that the robust design allows the SU-Tx transmit with higher power than the non-robust design, and thus can achieve better secondary performance.

4.7   Application: Spectrum Refarming

Applying the CSA technique in cellular networks is by no mean a trivial task [39]. Although the resource allocation for the traditional cellular networks has been extensively investigated both in single-cell [40] and multi-cell scenarios [41], the spectrum sharing among cellular networks is challenging due to the additional interference power constraint. Moreover, the concrete characteristics of each cellular network, such as the infrastructure deployment and the radio access technique (RAT) profoundly affect the CSA design. Quite a few of literatures have investigated the spectrum sharing between systems with the same RAT. For example, an orthogonal frequency division multiple access (OFDMA) secondary system shares the spectrum of an OFDMA primary system, or both of them are CDMA-based. In fact, due to the explosive growth of the fourth generation (4G) wireless traffic, spectrum sharing among OFDMA systems will be increasingly difficult as the 4G licensed spectrum has been crowded. In addition, since the 4G wireless network outperforms the second generation (2G) and the third generation (3G) in terms of peak data rate, latency and throughput, the legacy subscribers have been migrating to the 4G cellular networks. The out-moving of the legacy users decreases the utilization of the legacy licensed spectrum, which thus provides sharing opportunity for the 4G networks. To this end, the CSA between different generations of cellular networks, which is known as *spectrum refarming* (SR), attracts more attentions in recent years.

There are two SR models, i.e., the *opportunistic SR* model and the *concurrent SR* model, which are developed based on OSA and CSA, respectively.

- *Opportunistic SR* allows the OFDMA system dynamically access the spectrum hole in the legacy bands. Due to the narrowband nature of global system for mobile communications (GSM), the SR on GSM spectrum belongs to this model. As the traffic of GSM decreases, there exist idle subbands that can be opportunistically accessed. The authors in [42] proposed an Long-Term Evolution (LTE)/GSM SR by reserving partial subbands for GSM transmission and controlling the transmit power for both GSM and LTE to refrain the inter-technology interference. This model was further extended to the heterogeneous cellular networks where the OFDMA small cells access the idle spectrum of the GSM macrocell [43].
- *Concurrent SR* allows the different generations of networks co-transmit at the same legacy band, provided that the primary system can be protected. The SR between the OFDMA and CDMA systems belongs to this model, due to the wideband nature for both systems. Since the channel destroys the orthogonality among the CDMA users, there exists inter-user interference which is related to the number

of CDMA users [44]. When the number of CDMA users decreases, each CDMA user will experience less inter-user interference. Thus, they can tolerate an amount of interference introduced by the OFDMA system, with which the target SINR of the CDMA user can be maintained.

In what follows, we discuss the OFDMA/CDMA concurrent SR. The key challenges to be addressed include: (1) Quantification of interference temperature: In related literatures, the interference temperature is usually given as a predefined threshold without any justification [45, 46]; (2) Joint optimization of the primary and secondary resource allocation: By taking the interference from the PU-Tx to the SU-Rx into consideration, the primary and secondary power allocation can be jointly optimized through exploiting the primary inner power control scheme. (3) Robust power allocation: Without the information of C-CSI, robust power allocation should be designed for the OFDMA system to provide sufficient protection to CDMA users. The study also extends to the SR of multi-band CDMA system [47] and the heterogeneous SR systems [48, 49].

4.7.1   SR with Active Infrastructure Sharing

For the easy of deployment, the OFDMA can share the same cell site and same BS antenna with the CDMA system, as shown in Fig. 4.10 (Scenario I). This kind of infrastructure sharing is known as active infrastructure sharing. Take the wideband CDMA uplink as an example. In practice, it operates at a 5 MHz bandwidth with the chip rate of 3.84 Mcps. The spreading gain can vary from 2 to 256 [50]. The LTE can adopt 256 subcarriers when working at 5 MHz mode with subcarrier spacing of 15 kHz. The sampling rate is thus 15 kHz × 256 = 3.84 MHz that equals the wideband CDMA chip rate. Thus, the two systems can easily get synchronized with the same clock reference.

(1) *Quantification of Interference Temperature*

To quantify the interference temperature provided by the CDMA users, the SINR of CDMA users with the interference from OFDMA system should be derived. Given the number of CDMA users (denoted by U) and the spreading gain (denoted by N), the SINR of CDMA user is determined by the specific spreading codes assigned among users and the instantaneous S-CSI of the CDMA system. Due to the lack of cooperation between the CDMA and OFDMA systems, these information is unknown by the OFDMA system, and thus it is hard for the OFDMA system to predict the CDMA SINR. By considering a large-dimension system where $U, N \to \infty$ and $\frac{U}{N}$ approaches a finite constant, the SINR of the CDMA users approaches an asymptotic value which is independent with the specific codes and instantaneous S-CSI. Thus, by limiting the asymptotic SINR to be no less than the target SINR, the closed-form interference temperature can be obtained [51].
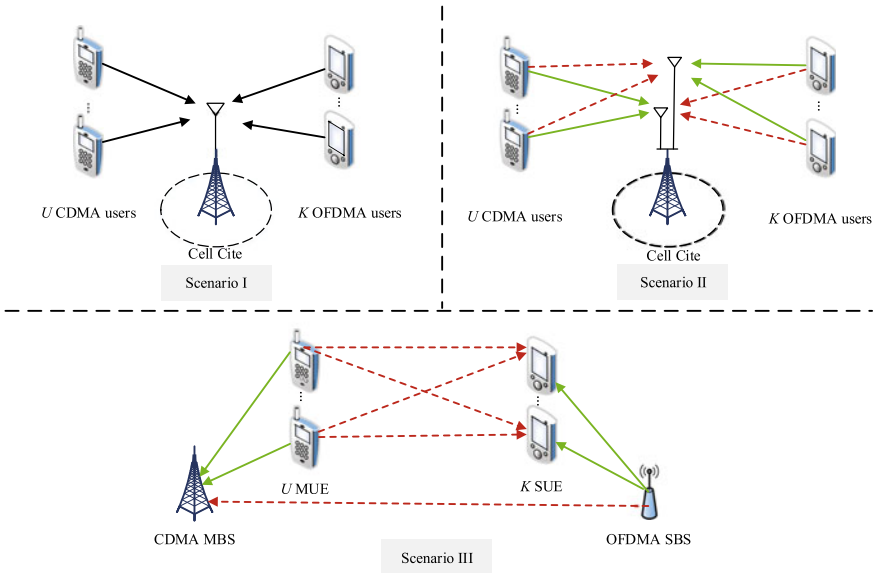
Fig. 4.10 Different scenarios of the concurrent SR. Scenario I: SR with active infrastructure sharing; Scenario II: SR with passive infrastructure sharing; Scenario III: SR in heterogeneous networks

(2) *Joint Resource Optimization of CDMA and OFDMA Systems*

Note that the interference temperature of the CDMA system is a function of the transmit power of the CDMA user. A larger transmit power provides a higher interference temperature but also introduces higher interference to the OFDMA user. Thus, there exists an optimal CDMA transmit power to maximize the OFDMA throughput. An efficient algorithm was proposed in [52] to solve the joint resource optimization of the CDMA and OFDMA systems by investigating the convexity of the problem over the CDMA transmit power and the OFDMA resource allocation. Moreover, although the transmit power of CDMA and OFDMA systems are jointly optimized, it is unnecessary to inform the CDMA user with the optimal value of the transmit power in practice. In fact, once the OFDMA system operates with its optimal transmit power and subcarrier allocation, so as the CDMA system due to the inner power control of the CDMA system.

4.7.2 SR with Passive Infrastructure Sharing

Passive infrastructure sharing refers to the sharing of passive elements in their radio access networks, such as cell sites. When the SR technique is applied with passive infrastructure sharing, the licensed legacy system and the unlicensed system are equipped with separate BS antennas, as shown in Fig. 4.10 (Scenario II). Intuitively,

this additional BS antenna should bring along more diversity that can be exploited by the OFDMA system to improve the refarming performance [11, 53, 54]. However, without active participation of the legacy system, it is difficult to obtain the C-CSI, which is the necessary information for the OFDMA system to predict the produced interference.

To solve this problem, a robust resource allocation scheme was proposed in [55], where the S-CSI of the OFDMA system is used as the C-CSI to predict the interference power. It has been proved that under this scheme, the CDMA service can be over-protected, i.e., the actual interference power is always no larger than the interference temperature. Furthermore, to fully utilize the interference temperature, an iterative resource allocation scheme is proposed which gradually increases the transmit power of OFDMA users until the actual interference received by the CDMA system reaches the interference temperature.

4.7.3   SR in Heterogeneous Networks

To provide high throughput and seamless coverage for the wireless communications, small cells have been proposed to overlay the existing cellular networks [56]. Conventionally, small cells are deployed to share the radio spectrum by using the same RAT with the macrocell [57, 58]. By doing so, the small cells can offload macrocell traffic directly. However, they inevitably introduce interference to the macrocell users and thus degrade their performance. To address this problem, SR in heterogeneous networks is a viable solution.

Consider a heterogeneous network as shown in Fig. 4.10 (Scenario III), where multiple OFDMA small cells share the spectrum of CDMA macrocell. Specifically, the downlink of small cells share the spectrum used for the CDMA uplink, since the uplink traffic of the CDMA system is normally lighter than the downlink. By quantifying the interference power produced by each small cell, the resource allocation problem can be formulated, where the objective is to maximize the total throughput of all small cells and the constraints are the total interference power constraint and individual transmit power constraint. The problem is transformed to optimize the transmit power and the allocation of interference temperature among small cells [48].

In practice, due to the limited signaling between the macrocell and the small cells, the C-CSI between the small cell BS (SBS) and macrocell base station (MBS) is usually absent. Since the C-CSI accounts for the distance-based path loss, the small-scale fading and the large-scale shadowing, only the latter two are to be determined, as the distance between SBS and MBS is fixed and can be easily known from the global geographical information. It is found that the optimal power allocation for the SR heterogeneous networks is essentially independent with the fading and shadowing components of the C-CSI and is only related to the distance-based path loss. Therefore, the need of instantaneous information about the fading and shadowing of C-CSI can be avoided.

4.8 Summary

In this chapter, we have discussed the CSA technique by introducing the single-antenna CSA system, the multi-antenna cognitive beamforming, the cognitive MIMO, the C-MAC and C-BC, and the robust design for the CSA system. The application of the CSA technique to operating the LTE cellular system on the legacy spectrum, also known as the spectrum refarming, has been discussed. Several critical problems in the CSA have been addressed, including the absence of the interference channel and signal channel knowledge, the optimal beamforming and multiplexing, as well as the interference avoidance and suppression.

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