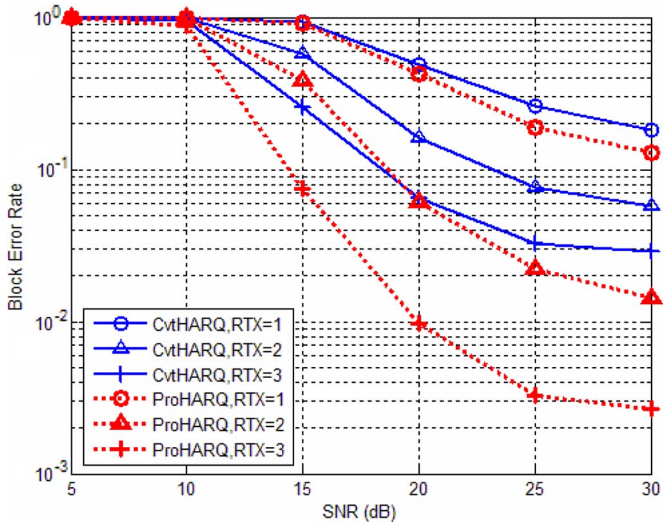

Fig. 5. Comparison of BLER in a 4 × 4 time-varying MIMO channel.

V. CONCLUSION

This paper has presented an enhanced scheme, which realizes ICI and IAI mitigation by encoding the retransmitted signals based on the Hadamard–Walsh code for MIMO-OFDM systems. It orthogonally spreads the frequency-domain signal in the transmission domain to separate the desired signal from interferences, resulting in interference suppression in addition to SNR improvement. Although many interference-cancellation algorithms at PHY had been proposed, this paper has demonstrated the possibility of interference cancellation using a hybrid MAC–PHY technique. By mathematical analyses and numerical simulations, this paper has shown an encouraging performance improvement compared with the conventional HARQ in multipath time-varying Rayleigh fading channels.

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Sensing-Based Spectrum Sharing in Cognitive Radio Networks

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***Abstract*—In this paper, a new spectrum-sharing model called sensing-based spectrum sharing is proposed for cognitive radio networks. This model consists of two phases: In the first phase, the secondary user (SU) listens to the spectrum allocated to the primary user (PU) to detect the state of the PU; in the second phase, the SU adapts its transit power based on the sensing results. If the PU is inactive, the SU allocates the transmit power based on its own benefit. However, if the PU is active, the interference power constraint is imposed to protect the PU. Under this new model, the evaluation of the ergodic capacity of the SU is formulated as an optimization problem over the transmit power and the sensing time. Due to the complexity of this problem, two simplified versions, which are referred to as the *perfect sensing* case and the *imperfect sensing* case, are studied in this paper. For the perfect sensing case, the Lagrange dual decomposition is applied to derive the optimal power allocation policy to achieve the ergodic capacity. For the imperfect sensing case, an iterative algorithm is developed to obtain the optimal sensing time and the corresponding power allocation strategy. Finally, numerical results are presented to validate the proposed studies. It is shown that the SU can achieve a significant capacity gain under the proposed model, compared with that under the opportunistic spectrum access or the conventional spectrum sharing model.**

***Index Terms*—Cognitive radio (CR), convex optimization, dual decomposition, ergodic capactiy, fading channels, opportunistic spectrum access, optimal power control, spectrum sharing.**

I. INTRODUCTION

Due to the convenience brought to people’s lives by wireless products, the 21st century has witnessed a great increase in wireless devices and applications. However, with most of the radio spectrum already allocated, the compelling need for the radio spectrum to accommodate upcoming applications poses a serious problem for the future development of wireless communications. On the other hand, a recent report published by the FCC reveals that most of the licensed

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spectrum is rarely continuously utilized across time and space [1]. This motivates work on cognitive radio (CR) and CR networks (CRNs) [2].

CR is a kind of intelligent wireless device, which is able to adjust its transmission parameters, such as transmit power and transmission frequency band, based on the environment [3]. In a CRN, ordinary wireless devices are referred to as primary users (PUs), and CRs are referred to as secondary users (SUs). Conventionally, a CRN can be formed by allowing either the SUs to opportunistically operate in the frequency bands originally allocated to the PUs when the PUs are inactive or the SUs to coexist with the PUs, as long as the quality of service of the PUs is not degraded to an unacceptable level by the interference from the SUs. The former transmission model is known as *opportunistic spectrum access*, and the latter transmission model is known as *spectrum sharing*.

In this paper, we propose a new transmission model referred to as *sensing-based spectrum sharing*. In this model, the SU first senses the frequency band allocated to the PU to detect the state of the PU and then adapts its transmit power according to the detection result. If the PU is inactive, the SU allocates the transmit power based on its own benefit to achieve a higher transmission rate. If the PU is active, the SU transmits with a lower power to avoid causing harmful interference to the PU. This is different from either opportunistic spectrum access or spectrum sharing. In the opportunistic spectrum access transmission model [4], the SU transmits only when it detects *spectrum holes* [3], which are the time duration that the PU is not transmitting over the band. In the spectrum-sharing transmission model [5], [6], the SU can transmit at any time without having to detect whether the PU is active or not. However, it has to restrict its transmit power to not cause harmful interference to the PU during the whole transmission process. To show the superiority of the new model, we study the ergodic capacity of the SU. The evaluation of the ergodic capacity is formulated as an optimization problem over the transmit power and the sensing time. Two heuristic cases of this problem, which are referred to as the *perfect sensing* case and the *imperfect sensing* case, are studied in this paper. From the obtained results, it is seen that the power allocation strategy is more flexible under the new model. It is also shown that the SU can achieve a significant capacity gain under the new model, compared with that under the opportunistic spectrum access or the conventional spectrum-sharing model.

The rest of this paper is organized as follows: The sensing-based spectrum-sharing model is introduced in Section II. The problem formulation is given in Section III. The ergodic capacity of the SU link under the perfect-sensing assumption for our model is studied in Section IV. Then, the imperfect-sensing scenario is studied in Section V. The numerical results are given in Section VI. Finally, Section VII concludes this paper.

II. System Model

A. System Model

In this paper, we consider a CRN with one primary link and one secondary link. The primary link consists of a PU transmitter (PU-TX) and a PU receiver (PU-RX). The secondary link consists of an SU transmitter (SU-TX) and an SU receiver (SU-RX). We assume that the two links use the same frequency band. Thus, if the two links coexist, there will be interference between them. The primary, secondary, and interference links are all assumed to be flat-fading channels. The additive white Gaussian noises (AWGNs) at the PU-RX and SU-RX are denoted by n_0 and n_1, respectively, where n_0 and n_1 are assumed to be independent and of zero mean with the distribution $\mathcal{CN}(0, N_0)$ (circularly symmetric complex Gaussian). The instantaneous channel power gains for the secondary link, the link between the PU-TX and the SU-RX, and the link between the SU-TX and the PU-RX are denoted by g_{ss}, g_{ps}, and g_{sp}, respectively. All these channel power gains are assumed to be ergodic, stationary, and available to the SU-TX and SU-RX.

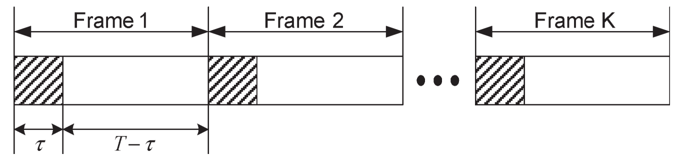

Fig. 1. Frame structure for sensing-based spectrum sharing (τ: sensing slot duration; $T-\tau$: data transmission slot duration).

B. Spectrum-Sensing Model

Spectrum sensing is the technique for determining the active/idle state of the PU between the following two hypotheses:

$$\begin{aligned} \mathcal{H}_0: \quad & y(i) = n(i) \\ \mathcal{H}_1: \quad & y(i) = hx(i) + n(i) \end{aligned} \tag{1}$$

for $i = 1, 2, \ldots, N$, where $y(i)$, without loss of generality, is the signal received by the SU-TX, $x(i)$ is the signal sent by the PU, h is the channel between the PU-TX and the SU-TX, $n(i)$ is the AWGN with zero mean and variance σ_n^2, and N is the number of samples. We assume that h is constant for the current sampling block (all N samples) but different for the different blocks. Furthermore, $N = f_s\tau$, where τ is the sensing time, and f_s is the sampling frequency.

If the PU is active and the sensing result is $\mathcal{H}_1$, this scenario is known as *perfect detection*, and the corresponding probability is referred to as the *probability of detection*, which is denoted by P_d. However, if the PU is inactive and the sensing result is $\mathcal{H}_1$, this scenario is known as *false alarm*, and the corresponding probability is referred to as the *probability of false alarm*, which is denoted by P_f. When an energy detector is used, based on the probability density function of the test static, P_d and P_f are given by [7]

$$P_d = \mathcal{Q}\left(\left(\frac{\varepsilon}{\sigma_n^2} - \gamma - 1\right)\sqrt{\frac{\tau f_s}{2\gamma + 1}}\right)$$
$$P_f = \mathcal{Q}\left(\left(\frac{\varepsilon}{\sigma_n^2} - 1\right)\sqrt{\tau f_s}\right)$$

respectively, where ε is the detection threshold, γ is the received signal-to-noise ratio at the SU-TX, and $\mathcal{Q}(\cdot)$ is the complementary distribution function of the standard Gaussian, i.e., $\mathcal{Q}(x) = (1/\sqrt{2\pi})\int_x^\infty e^{(-(t^2/2))}dt$. For a target-detection probability $\bar{P}_d$, P_f can be obtained by $P_f = \mathcal{Q}(\sqrt{2\gamma+1}\mathcal{Q}^{-1}(\bar{P}_d) + \sqrt{\tau f_s}\gamma)$.

C. Transmission Model

The frame structure for the sensing-based spectrum-sharing model is shown in Fig. 1. We assume that each frame consists of one sensing slot, whose time duration is τ, and one data transmission slot, whose time duration is $T-\tau$. During the sensing slot, the SU senses the frequency band licensed to the PU to determine the state of the PU. During the data transmission slot, the SU adapts its transmit power based on the sensing result obtained in the sensing slot. If the PU is detected to be inactive, the SU transmits with power $P_s^{(0)}$; if the PU is detected to be active, the SU transmits with power $P_s^{(1)}$. In general, we assume that $P_s^{(0)} > P_s^{(1)}$. Moreover, we assume that the PU transmits with a constant power P_p. Therefore, when the PU is inactive and no false alarm happens, the rate of the SU is $r_{00} = \log_2(1 + (g_{ss}P_s^{(0)}/N_0))$; if a false alarm happens, the rate is $r_{01} = \log_2(1 + (g_{ss}P_s^{(1)}/N_0))$. When the PU is active and no miss detection happens, the rate is

TABLE I
POSSIBLE POWER AND RATE ALLOCATION SCENARIOS

PU's State	Sensing Results	Related Probability	Power	Rate
Active ($\mathcal{H}_1$)	$\mathcal{H}_1$	P_d	$P_s^{(1)}$	r_{11}
Active ($\mathcal{H}_1$)	$\mathcal{H}_0$	$P_m = 1 - P_d$	$P_s^{(0)}$	r_{10}
Idle ($\mathcal{H}_0$)	$\mathcal{H}_1$	P_f	$P_s^{(1)}$	r_{01}
Idle ($\mathcal{H}_0$)	$\mathcal{H}_0$	$1 - P_f$	$P_s^{(0)}$	r_{00}

$r_{11} = \log_2(1 + (g_{ss}P_s^{(1)}/g_{ps}P_p + N_0))$; if a miss detection happens, the rate is $r_{10} = \log_2(1 + (g_{ss}P_s^{(0)}/g_{ps}P_p + N_0))$.

III. PROBLEM FORMULATION

Based on the real state of the PU and the sensing results, there are four possible scenarios under our transmission model, which are listed in Table I. As can be seen in Table I, when a miss detection happens, the SU still transmits with $P_s^{(0)}$ as it is not aware of the existence of the PU. On the other hand, when a false alarm happens, the SU still transmits with $P_s^{(1)}$ as it thinks that the PU is active. Thus, if we denote the probability when the PU is idle as $\mathcal{P}(\mathcal{H}_0)$ and denote the probability when the PU is active as $\mathcal{P}(\mathcal{H}_1)$ and based on the four possible scenarios listed in Table I, it is easy to observe that the ergodic rate for the sensing-based spectrum-sharing model can be written as

$$r = \mathbb{E}\left\{ \frac{T-\tau}{T} \left[\mathcal{P}(\mathcal{H}_0)(1-P_f)r_{00} + \mathcal{P}(\mathcal{H}_0)P_f r_{01} + \mathcal{P}(\mathcal{H}_1)(1-P_d)r_{10} + \mathcal{P}(\mathcal{H}_1)P_d r_{11}\right] \right\}. \quad (2)$$

The expression given in (2) is the objective function. Ergodic capacity is obtained by maximizing (2) over the transmit powers, i.e., $P_s^{(0)}$ and $P_s^{(1)}$, and the sensing time τ. Now, we consider the power constraints of this problem. As usual (e.g., [8]), we consider the average power constraint that regulates the average transmit power over all the fading states at the SU-TX. Under our transmission model, the average transmit power constraint can be written as

$$\mathbb{E}\left\{P_s^{(0)}\right\}\mathcal{P}\{\mathcal{H}_0\}(1-P_f) + \mathbb{E}\left\{P_s^{(1)}\right\}\mathcal{P}\{\mathcal{H}_0\}P_f + \mathbb{E}\left\{P_s^{(0)}\right\}\mathcal{P}\{\mathcal{H}_1\}(1-P_d) + \mathbb{E}\left\{P_s^{(1)}\right\}\mathcal{P}\{\mathcal{H}_1\}P_d \le P_{\text{av}} \quad (3)$$

where P_{av} is the maximum average transmit power at the SU-TX.

Next, we consider the average interference power constraint that regulates the average interference power over all the fading states at the PU-RX. In Table I, it is easy to observe that the SU will cause interference to the PU only when the PU is active. Therefore, under our transmission model, the average interference power constraint can be written as

$$\mathbb{E}\left\{g_{sp}P_s^{(0)}\right\}(1-P_d) + \mathbb{E}\left\{g_{sp}P_s^{(1)}\right\}P_d \le Q_{\text{av}} \quad (4)$$

where Q_{av} is the maximum average interference power that the PU can tolerate at its receiver. In practice, for the same type of users, the ability to tolerate the interference is almost the same. Therefore, the value of Q_{av} for each type of users can be pretested and made known to the public. Hence, the value of Q_{av} may be obtained at the SU-TX if the type of PU is known. However, if the type of PU is not available at the SU-TX, it is not so easy for the SU to determine the value of Q_{av}. In such a case, methods for obtaining the value of Q_{av} at the SU-TX are discussed in [3]. (See [3] for details.)

Therefore, the ergodic capacity of the secondary link under our transmission model can be obtained by solving the following optimization problem (P1):

$$\text{P1:} \quad \underset{\left\{P_s^{(0)}, P_s^{(1)}, \tau\right\}}{\text{maximize}} \quad r \quad (5)$$

$$\text{subject to} \quad \text{(3) and (4).} \quad (6)$$

This problem is difficult to solve due to the following four reasons.

1) It is not a convex optimization problem.
2) There are two complicated coupling constraints.
3) P_d and P_f are related to τ by a nonlinear function, i.e., the $\mathcal{Q}$ function.
4) The expectation is taking over three random variables g_{ss}, g_{sp}, and g_{ps}.

Therefore, in this paper, we consider two modified versions of P1 under different assumptions.

IV. SENSING-BASED SPECTRUM SHARING UNDER PERFECT SENSING

In this section, we assume that the SU can achieve 100% detection of the PU without false alarm within a very short sensing duration, i.e., $P_d = 1$ and $P_f = 0$, and we refer to this case as the *perfect sensing problem*. Under this assumption, P1 is reduced to the following problem (P2):

$$\text{P2:} \quad \underset{\left\{P_s^{(0)}\ge 0, P_s^{(1)}\ge 0\right\}}{\text{maximize}} \quad \mathcal{P}(\mathcal{H}_0)C_0 + \mathcal{P}(\mathcal{H}_1)C_1 \quad (7)$$

$$\text{subject to} \quad \mathcal{P}(\mathcal{H}_0)\mathbb{E}\left\{P_s^{(0)}\right\} + \mathcal{P}(\mathcal{H}_1)\mathbb{E}\left\{P_s^{(1)}\right\} \le P_{\text{av}} \quad (8)$$

$$\mathbb{E}\left\{g_{sp}P_s^{(1)}\right\} \le Q_{\text{av}} \quad (9)$$

where $C_0 = \mathbb{E}\{r_{00}\}$, and $C_1 = \mathbb{E}\{r_{11}\}$.

The objective function in (7) is no longer related to τ and is a concave function with respect to $P_s^{(0)}$ and $P_s^{(1)}$. Furthermore, all the power constraints are affine and not related to τ. Therefore, the problem now becomes a convex optimization problem over variables $P_s^{(0)}$ and $P_s^{(1)}$. Compared with P1, this problem is easier to solve since there is only one coupling constraint. Therefore, the dual decomposition method illustrated in [9] can be applied to solve this problem.

Let λ be the nonnegative Lagrange dual variable associated with the coupling constraint (8); then, the partial Lagrangian of P2 can be written as

$$\begin{aligned} L\left(P_s^{(0)}, P_s^{(1)}, \lambda\right) &= \mathcal{P}(\mathcal{H}_0)C_0 + \mathcal{P}(\mathcal{H}_1)C_1 \\ &\quad - \lambda\left\{\mathcal{P}(\mathcal{H}_0)\mathbb{E}\left\{P_s^{(0)}\right\} + \mathcal{P}(\mathcal{H}_1)\mathbb{E}\left\{P_s^{(1)}\right\} - P_{\text{av}}\right\} \\ &= \lambda P_{\text{av}} + \mathcal{P}(\mathcal{H}_0)\left(C_0 - \lambda\mathbb{E}\left\{P_s^{(0)}\right\}\right) \\ &\quad + \mathcal{P}(\mathcal{H}_1)\left(C_1 - \lambda\mathbb{E}\left\{P_s^{(1)}\right\}\right) \end{aligned} \quad (10)$$

and the Lagrangian dual function is defined as

$$\begin{aligned} q(\lambda) &= \sup_{\left\{P_s^{(0)}, P_s^{(1)}\right\}} \left\{L\left(P_s^{(0)}, P_s^{(1)}, \lambda\right) \middle| \mathbb{E}\left\{g_{sp}P_s^{(1)}\right\} \le Q_{\text{av}}\right\} \\ &= \mathcal{P}(\mathcal{H}_1) \sup_{P_s^{(1)}\ge 0} \left\{C_1 - \lambda\mathbb{E}\left\{P_s^{(1)}\right\} \middle| \mathbb{E}\left\{g_{sp}P_s^{(1)}\right\} \le Q_{\text{av}}\right\} \\ &\quad + \mathcal{P}(\mathcal{H}_0) \sup_{P_s^{(0)}\ge 0} \left\{C_0 - \lambda\mathbb{E}\left\{P_s^{(0)}\right\}\right\} + \lambda P_{\text{av}}. \end{aligned} \quad (11)$$

The dual function serves as an upper bound on the optimal value of the primal problem (P2). If we denote the optimal value of P2 by r^*,

TABLE II
ITERATIVE POWER ALLOCATION ALGORITHM FOR PERFECT SENSING

Algorithm 1
1) Initialization: λ_1, $k=1$,
2) Repeat
a) calculate $P_{s,k}^{(0)}$ and $P_{s,k}^{(1)}$ by (13)
b) calculate the subgradient at λ_k by $P_{av} - \mathscr{P}(\mathcal{H}_0)\mathbb{E}\{P_{s,k}^{(0)}\} - \mathscr{P}(\mathcal{H}_1)\mathbb{E}\{P_{s,k}^{(1)}\}$
c) update λ_{k+1} by $\lambda_{k+1} = \lambda_k + \alpha\left\{\mathscr{P}(\mathcal{H}_0)\mathbb{E}\{P_{s,k}^{(0)}\} + \mathscr{P}(\mathcal{H}_1)\mathbb{E}\{P_{s,k}^{(1)}\} - P_{av}\right\}$
3) Stop, when $\lvert\lambda_{k+1} - \lambda_k\rvert \le \epsilon$
where α is the step size, and ϵ is a given small constant.

then the inequality $r^* \le q(\lambda)$ holds for any nonnegative λ. The dual optimization problem is defined as

$$\underset{\lambda \ge 0}{\text{minimize}} \quad q(\lambda). \tag{12}$$

Denote the optimal value of the dual problem as d^*, which is achievable by the optimal dual solution λ^*, i.e., $d^* = g(\lambda^*)$. For a convex optimization problem, the Karush–Kuhn–Tucker (KKT) conditions [10] are satisfied, and thus, the duality gap $r^* - d^*$ is indeed zero.

Since the duality gap is zero, P2 can equivalently be solved by first maximizing its Lagrangian to obtain the dual function for the given dual variable λ and then minimizing the dual function over λ. For a given λ, it is seen that the dual function (11) can be evaluated by solving the following two optimization problems:

$$\begin{aligned} &\text{Subproblem 1 (SP1):} && \underset{P_s^{(0)} \ge 0}{\text{maximize}} && C_0 - \lambda\mathbb{E}\left\{P_s^{(0)}\right\} \\ &\text{Subproblem 2 (SP2):} && \underset{P_s^{(1)} \ge 0}{\text{maximize}} && C_1 - \lambda\mathbb{E}\left\{P_s^{(1)}\right\} \\ &&& \text{subject to} && \mathbb{E}\left\{g_{sp}P_s^{(1)}\right\} \le Q_{\mathrm{av}}. \end{aligned}$$

It is not difficult to observe that both SP1 and SP2 are convex optimization problems. Therefore, by writing their Lagrangian functions and applying the KKT conditions, the optimal solution is obtained as [11]

$$\begin{aligned} P_s^{(0)} &= \left(\frac{1}{\lambda} - \frac{N_0}{g_{ss}}\right)^+ \\ P_s^{(1)} &= \left(\frac{1}{\lambda + \mu g_{sp}} - \frac{g_{ps}P_p + N_0}{g_{ss}}\right)^+ \end{aligned} \tag{13}$$

where $(\cdot)^+$ denotes $\max\{\cdot, 0\}$, and μ can be obtained by solving $\mathbb{E}\{g_{sp}P_s^{(1)}\} = Q_{\mathrm{av}}$.

With the optimal solutions obtained in (13), we are able to evaluate the dual function $q(\lambda)$ for the given λ. Now, we have to minimize the dual function $q(\lambda)$ over λ to determine the optimal λ^*. This problem can be solved by Algorithm 1 (see Table II), which requires the calculation of the subgradient of $q(\lambda)$ at each iteration. The subgradient of $q(\lambda)$ is given by the following proposition.

Proposition 1: Assuming that $P_{s,i}^{(0)}$ and $P_{s,i}^{(1)}$ are the optimal power allocation for the ith iteration, the subgradient for $q(\lambda)$ is $P_{\mathrm{av}} - \mathcal{P}(\mathcal{H}_0)\mathbb{E}\{P_{s,i}^{(0)}\} - \mathcal{P}(\mathcal{H}_1)\mathbb{E}\{P_{s,i}^{(1)}\}$.

The proof is omitted here for brevity.

V. Sensing-Based Spectrum Sharing Under Imperfect Sensing

In practice, due to the limitation of the sensing techniques, sensing errors are unavoidable. Therefore, the perfect sensing case is just an ideal case and can only serve as an upper bound for P1. In this section, we simplify P1 by making more realistic assumptions. In the conventional opportunistic spectrum access, if the detection probability P_d is larger than a prescribed threshold P_{th}, the PU is regarded as being sufficiently protected. Therefore, in practice, P_d is usually very high. For instance, in the IEEE 802.22 wireless regional area network [12], P_d is chosen to be larger than 0.9. On the other hand, P_f is controlled to be low, i.e., usually less than 0.1. Therefore, to simplify P1, we introduce the constraint $P_d \ge P_{\mathrm{th}}$, and P_{th} is chosen such that the items including $1 - P_d$ or P_f in P1 are relatively small. Moreover, we assume that the activity probability of PU $\mathcal{P}\{\mathcal{H}_1\}$ is small, e.g., less than 0.4. This assumption is reasonable since the research report [1] published by the FCC reveals that most of the licensed spectrum is underutilized.

Under the aforementioned assumptions, P1 can be approximated by

$$\text{P3:} \quad \underset{\{P_s^{(0)}, P_s^{(1)}, \tau\}}{\text{maximize}} \quad C = \mathbb{E}\left\{\frac{T-\tau}{T}\left[\mathcal{P}(\mathcal{H}_0)(1-P_f)r_{00} + \mathcal{P}(\mathcal{H}_1)P_d r_{11}\right]\right\} \tag{14}$$

$$\text{subject to} \quad \mathbb{E}\left\{P_s^{(0)}\right\}\mathcal{P}\{\mathcal{H}_0\}(1-P_f) + \mathbb{E}\left\{P_s^{(1)}\right\}\mathcal{P}\{\mathcal{H}_1\}P_d \le P_{\mathrm{av}} \tag{15}$$

$$\mathbb{E}\left\{g_{sp}P_s^{(1)}\right\}P_d \le Q_{\mathrm{av}} \tag{16}$$

$$P_d \ge P_{\mathrm{th}} \quad P_s^{(0)} \ge 0 \quad P_s^{(1)} \ge 0 \quad 0 < \tau < T \tag{17}$$

where T is the frame duration.

This problem is referred to as the *imperfect sensing problem*. It is not difficult to observe that P3 is a convex optimization problem with respect to $P_s^{(0)}$ and $P_s^{(1)}$. However, it is unclear whether P3 is a convex optimization problem with respect to τ. In the following proposition, we show that (14) is concave in τ.

Proposition 2: For the range of τ such that $P_d(\tau)$ is increasing and concave in τ and $P_f(\tau)$ is decreasing and convex in τ, (14) is concave in τ.

Proof: Denote $R(\tau) = (T - \tau/T)[\mathcal{P}(\mathcal{H}_0)(1-P_f)r_{00} + \mathcal{P}(\mathcal{H}_1)P_d r_{11}]$; then, it follows that

$$\begin{aligned} R'(\tau) = \mathcal{P}(\mathcal{H}_0)r_0 &\left[\frac{P_f(\tau)}{T} - \left(1 - \frac{\tau}{T}\right)P_f'(\tau) - \frac{1}{T}\right] \\ - \mathcal{P}(\mathcal{H}_1)r_1 &\left[\frac{P_d(\tau)}{T} - \left(1 - \frac{\tau}{T}\right)P_d'(\tau)\right]. \end{aligned} \tag{18}$$

Using a method similar to that in [7], it is not difficult to show that, for the range of τ in which $P_d(\tau) \ge 0.5$, $P_d(\tau)$ is increasing and concave in τ, and $P_d'(\tau)$ is positive and decreasing in τ. Similarly, for the range of τ in which $P_f(\tau) \le 0.5$, $P_f(\tau)$ is decreasing and convex in τ, and $P_f'(\tau)$ is negative and increasing in τ. Therefore, from (18), it follows that $R'(\tau)$ is decreasing in τ, which implies that $R(\tau)$ is concave in τ. Since the expectation operation will not affect the concavity, (14) is also concave in τ. ■

The constraints in P3 can also be verified to be concave in τ by the same method. Then, it is clear that P3 is a convex optimization problem with respect to $P_s^{(0)}$, $P_s^{(1)}$, and τ. Moreover, it can be verified that (14) is maximized when $P_d = P_{\mathrm{th}}$ for the range where $P_d \ge 0.5$. Therefore, P3 can further be simplified by setting P_d directly equal to P_{th}.

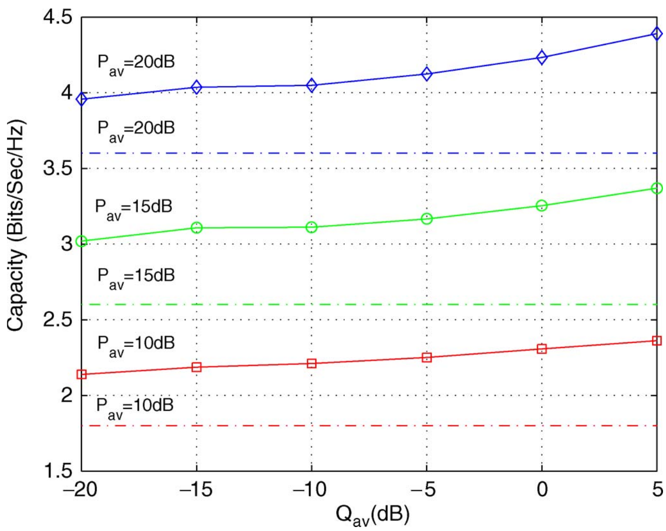

Fig. 2. Capacities versus $Q_{\rm av}$ for different $P_{\rm av}$ under $\mathcal{P}(\mathcal{H}_0) = 0.6$ for the perfect-sensing scenario.

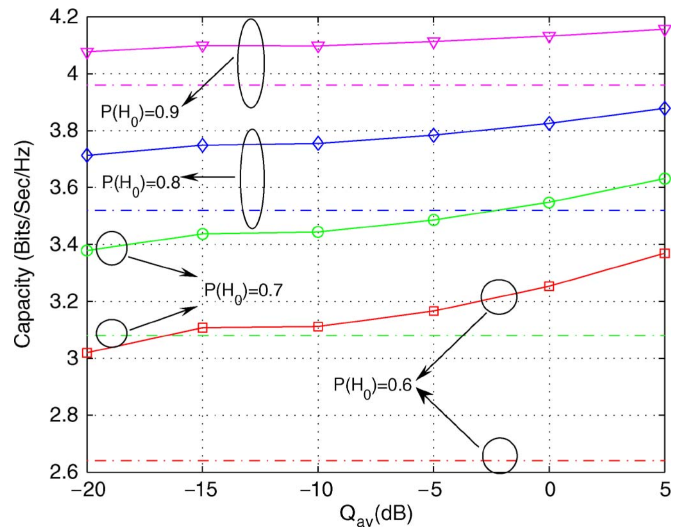

Fig. 3. Capacities versus $Q_{\rm av}$ for different $\mathcal{P}(\mathcal{H}_0)$ under $P_{\rm av} = 15$ dB for the perfect-sensing scenario.

The following method can be used to solve P3. First, we initialize a value for τ. Under this τ, $P_s^{(0)}$ and $P_s^{(1)}$ can be obtained in a manner similar to the algorithm that we developed for the perfect-sensing problem. Then, we update the value of τ by the subgradient algorithm. Under this new τ, $P_s^{(0)}$ and $P_s^{(1)}$ are recomputed. The steps are repeated until the solution converges. The optimal solution of $P_s^{(0)}$, $P_s^{(1)}$, and τ for (14) obtained by this algorithm is unique due to the convexity of the problem.

VI. Numerical Results

In this section, we present the simulation results for the proposed study under the Rayleigh fading channels. All the channel power gains are assumed to be exponentially distributed random variables with unit mean. N_0 is assumed to be 1. The frame duration is chosen to be $T = 100$ ms, the number of frames simulated is 10 000, and the target detection probability $P_{\rm th}$ is set to 0.9, with $\gamma = -15$ dB. The transmit power of PU is assumed to be 10 dB.

A. Perfect Sensing Scenario

Fig. 2 shows the ergodic capacities under joint transmit and interference power constraints for $\mathcal{P}(\mathcal{H}_0) = 0.6$ for the perfect-sensing scenario. The dash-dotted lines show the ergodic capacities under the same setup for the opportunistic spectrum access model. It is clear from the figure that the capacities for our transmission model increase with the increase in both the transmit and the interference power constraints. However, the capacities for the opportunistic access model increase only with the increase in transmit power constraint. This is due to the fact that the opportunistic access model only allows transmission when the PU is absent; thus, the capacities are limited only by the transmit power. In addition, for the same transmit power constraint, it is seen that the capacities for our sensing-based spectrum sharing model are always larger than those for the opportunistic access model. This shows the superiority of the sensing-based spectrum sharing model.

Fig. 3 shows the capacities for different $\mathcal{P}(\mathcal{H}_0)$ under the same transmit power constraint $P_{\rm av} = 15$ dB. It is clear that the capacity increases with the increase in $\mathcal{P}(\mathcal{H}_0)$. This is reasonable due to the fact that a larger $\mathcal{P}(\mathcal{H}_0)$ indicates a higher probability that the PU is idle and that there will be more chances that the SU can transmit with a higher power. In addition, the dash-dotted lines show the capacities under the same setup for the opportunistic spectrum access model. It is evident from the figure that the capacities for our sensing-based spectrum sharing model are always larger than those for the opportunistic spectrum access model. However, the capacity gains decrease with the increase in $\mathcal{P}(\mathcal{H}_0)$. This is because, with the increase in $\mathcal{P}(\mathcal{H}_0)$, the capacity gain obtained from spectrum sharing decreases with the decrease in the probability of coexisting with the PU. This indicates that our model is preferred when the PU has a high probability of activity. On the other hand, if the PU is idle most of the time (more than 90%), the opportunistic spectrum access model is preferred due to its simplicity.

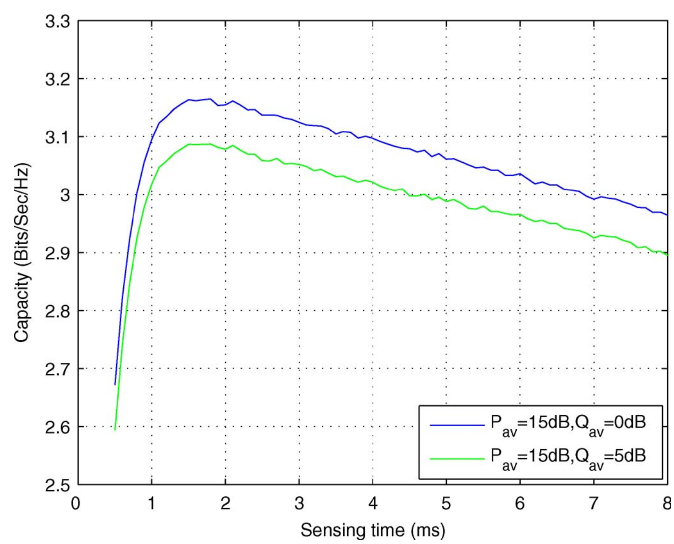

Fig. 4. Capacities versus τ for different $Q_{\rm av}$ under $\mathcal{P}(\mathcal{H}_0) = 0.6$ for imperfect sensing.

B. Imperfect Sensing Scenario

Fig. 4 shows the capacities for different $Q_{\rm av}$ under $\mathcal{P}(\mathcal{H}_0) = 0.6$ for imperfect sensing versus the sensing time. It is clear from the figure that the capacity is a concave function with respect to τ. In addition, it is also noticed that the optimal sensing time for these two curves are almost the same. Moreover, the capacity difference between $Q_{\rm av} = 0$ dB and $Q_{\rm av} = -5$ dB is not so much. Fig. 5 shows the

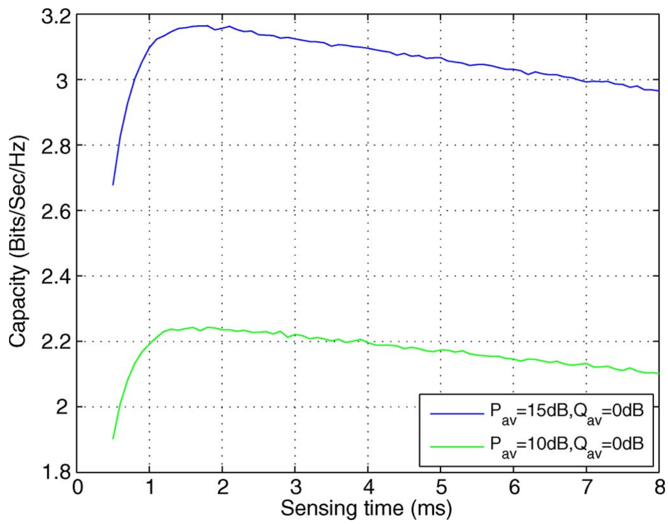

Fig. 5. Capacities versus τ for different P_{av} under $\mathcal{P}(\mathcal{H}_0) = 0.6$ for imperfect sensing.

capacities for different P_{av} under $\mathcal{P}(\mathcal{H}_0) = 0.6$ for imperfect sensing versus the sensing time. It is also shown that the capacity is a concave function with respect to τ. In addition, it is also noticed that the optimal sensing time for these two curves are different. Moreover, the capacity for $P_{\mathrm{av}} = 15$ dB is much larger than that for $P_{\mathrm{av}} = 10$ dB. This indicates that the transmit power constraint has greater influence on our sensing-based spectrum sharing model than the interference power constraint. Furthermore, comparing Figs. 4 and 5 with Fig. 2, it is seen that, under the same transmit and interference power constraints, the capacity for the imperfect sensing case is always lower than that of the perfect sensing case. This indicates that the capacity obtained under perfect sensing can serve as an upper bound of imperfect sensing.

VII. Conclusion

CR is a promising technology for dealing with the spectrum scarcity problem by exploring the underutilized spectrum usage pattern. Currently, in CRNs, there are two prevalent transmission models: 1) opportunistic spectrum access and 2) spectrum sharing. In this paper, we have proposed a new transmission model called *sensing-based spectrum sharing* for CRNs. We have studied this new model by establishing the ergodic capacity of the secondary link under joint transmit and interference power constraints. We have started with the perfect sensing scenario, in which we assume that there are no sensing errors. Then, we have studied a more challenging problem: the ergodic capacity under imperfect sensing. In this scenario, we have formulated the problem as an optimization problem over not only the transmit powers but the sensing time as well. We have derived a general method to obtain the optimal sensing time and the corresponding optimal power allocation strategies. Finally, the simulation results have shown that the SU can achieve a significant capacity gain under the proposed model, compared with that under the opportunistic spectrum access or the conventional spectrum sharing model.

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Iterative Noncoherent Receiver for Differential STBC in Fast Fading Channels

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***Abstract*—An iterative noncoherent receiver that does not exploit channel statistics is proposed for the detection of differential space-time block codes (DSTBCs) in fast-fading channels. For robustness to channel variation, it employs an iterative architecture incorporating *a priori* information from a channel decoder in the Viterbi detection. Computer simulation shows that the performance of this iterative scheme is comparable with that of ideal coherent detection as the number of iterations increases.**

***Index Terms*—Differential space time block code (DSTBC), fast fading, iterative receiver, noncoherent receiver.**

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