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Energy-Efficient Cooperative Spectrum Sensing With Reporting Errors in Hybrid Spectrum Sharing CRNs

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ABSTRACT Recently, cooperative spectrum sensing (CSS) in cognitive radio networks has been extensively researched. However, most of the studies mainly focus on maximizing the spectral efficiency while the energy consumption is generally ignored. However, since the secondary users (SUs) are usually battery-powered devices, energy saving is very important. This paper studies the mean energy efficiency (EE) maximization problem of the CSS system using the hybrid spectrum sharing (HSS) scheme. Specifically, the effects of imperfect spectrum sensing and reporting channel errors on the EE are considered. Our goal is to maximize the mean EE of SUs while maintaining the detection accuracy by jointly optimizing the sensing time and the number of cooperative SUs, subject to the SUs' average/peak transmission power constraints (ATPC/PTPC) and minimum data rate constraint, and the average interference power constraint of primary user. To address the non-convexity of the optimization problem, an energy-efficient iterative power allocation algorithm is developed. Simulations compare the achievable mean EE under ATPC/PTPC with three hard combining fusing rules using the HSS scheme and the opportunistic spectrum access (OSA) scheme, respectively; the results show that our proposed HSS scheme can obtain higher mean EE than the conventional OSA scheme and that the EE achieved under ATPC is better than that under PTPC. Moreover, among the three hard combining fusing rules, the Majority rule has the best EE.

INDEX TERMS Cooperative spectrum sensing, energy efficiency, hybrid spectrum sharing, reporting channel errors, power allocation.

I. INTRODUCTION

With the increasing demand for radio spectrum in wireless communications, cognitive radio (CR) has been proposed to increase the spectral efficiency (SE). CR systems allow secondary users (SUs) (i.e., unlicensed users) to access the licensed spectrum under the condition that the primary users (PUs) (i.e., licensed users) are not present or the interference caused to PU is tolerable [1]–[3]. Therefore, spectrum sensing is required to determine the presence of PU in cognitive radio networks (CRNs). However, due to channel impairments, multipath fading or hidden terminal problem, the detection performance of spectrum sensing by a single SU may be seriously deteriorated. To mitigate these negative effects, cooperative spectrum sensing (CSS) has been proposed to improve the detection accuracy by combining the sensing information from multiple SUs [4]–[6]. In CSS, multiple SUs sense the channel status (i.e., idle or busy) independently and then report their local hard or soft decisions to the fusion center (FC). The FC will then make a global hard or soft decision based on all the received decisions. As the hard decisions cause less reporting overhead, we focus on hard decision fusion rules in this paper. However, in CSS, more SUs participating spectrum sensing will bring more sensing, reporting and transmission energy consumption, which can be detrimental to the CRNs as the SUs are mostly powered by battery with limited energy. Hence, increasing energy efficiency (EE) is also crucial for CR, which can not only lower the network cost, but also extend the battery life and reduce carbon dioxide emissions [7]–[9].

Currently, three spectrum access schemes have been developed for CR: (i) opportunistic spectrum access (OSA), where the SUs firstly sense the channel status and then transmit only when the channel is detected to be idle. (ii) spectrum sharing (SS), where the SUs can share the same spectrum with the PUs, and sensing is not required as long as the quality of service (QoS) of the PUs is ensured. (iii) hybrid spectrum sharing (HSS), where the SUs first perform spectrum sensing to determine the PU's state and then adapt their transmission power based on the sensing results. If the PU is detected to be absent, the SU can access the primary band with a higher transmit power. Otherwise, it will transmit at a lower power to guarantee the QoS of the PU. According to [10] and [11], this scheme is also termed as sensing-based spectrum sharing, can achieve better performance than OSA and SS. Hence, we consider HSS scheme in this paper.

Motivated by the above discussion, in this paper, we study the mean EE maximization problem of SUs for CSS CR system that operates under the HSS scheme.

A. RELATED WORK

In CRNs, since a single SU may not be able to reliably detect the presence of PU, CSS has been extensively investigated in existing works [12]–[21]. The sensing information combination can be performed in different manners, such as hard combination rule (e.g., AND, OR, and k-out-of-N rule) [13]–[16], soft combination rule [17]–[20], and weighted data based fusion rule [21]. In [13], based on the k-out-of-N fusion rule, the sensing time τ and the fusion parameter k were jointly optimized to maximize the throughput of SUs for single-channel CR. In [14], based on the OR fusion rule, the throughput maximization for a multi-channel CR scenario was studied and each SU might have its own energy detection threshold. In [15], the optimal number of SUs and the optimal detection threshold were derived to minimize the total of the global false alarm and missed detection probabilities. The multiband CSS with imperfect reporting channels was studied in [16], and the corresponding false alarm and missed detection probabilities at the FC were derived in terms of the reporting error probability. The effects of reporting channel errors on the hard or soft CSS performance were analyzed in [17]. While a new CSS scheme that could operate without the dedicated reporting channels was proposed in [18]. In [19], the optimal linear combining weights and the optimal transmit power allocation scheme for SUs were derived to maximize the detection probability of soft combining CSS.

All the above works mainly focused on the detection performance or the system throughput. However, CSS incurs more energy consumption as there are more SUs participating in spectrum sensing. Besides, most of the mobile devices in CRNs are battery-powered, so EE is vital to the life time of these terminals. Energy-efficient CSS has been extensively studied in recent years [22]–[27]. In [24], the k-out-of-N fusion rule was adopted to maximize the EE by jointly optimizing k and energy detector threshold in the CRNs. An iterative algorithm was proposed in [25] to solve the EE maximization problem for CSS with AND rule by jointly and individually optimizing transmit power, energy detector threshold, sensing time and the number of cooperative users. In [26], the energy-efficient CSS and transmission in multichannel CRNs was designed. In [27], the EE maximization problem for CSS in cognitive sensor networks was investigated under the constraint on the detection performance.

However, works [24]–[27] assumed that the SU could access the licensed spectrum only when the PU is detected to be absent, known as the OSA scheme. On the other hand, [28]–[31] assumed that the SU could coexist with the PU as long as the interference caused to PU is tolerable, known as the SS scheme. To further improve SE, HSS, which can be seen as a hybrid scheme of OSA and SS, has drawn considerable attention recently [32]–[35]. In HSS, the SUs first sense the channel status and then initiate data transmission with two power levels according to the sensing results. In [32], the ergodic throughput maximization of CR working at the wideband HSS scheme and the wideband OSA scheme were studied and compared by designing the optimal sensing time and optimal transmit power. The problem of the energy consumption minimization in CRNs under a multiband HSS scheme was investigated in [33] by designing the power allocation strategy. In [34], an iterative power control algorithm was proposed to maximize the EE for a HSS cognitive small cell network. In [35], energy-efficient power adaptation schemes were developed for HSS CR system under the constraints of average/peak transmit power and average/peak interference power with imperfect spectrum sensing. Nevertheless, in works [32]–[35], only single spectrum sensing was considered and the proposed schemes could not be directly applied in the cognitive cooperative communication.

B. MOTIVATION AND CONTRIBUTIONS

As mentioned above, there were few studies considering the utilization of HSS scheme with CSS in CRNs under imperfect reporting channels. Besides, the EE analysis and comparison between the OSA scheme and the HSS scheme under different power constraints were seldom investigated. Motivated by these concerns, in this paper, we study the mean EE maximization problem of CSS with imperfect reporting channels using the HSS scheme. The effects of imperfect spectrum sensing and reporting channel errors on the EE are analyzed [34], [37]. The EEs of two spectrum access schemes (HSS and OSA) under SUs' average transmission power constraints (ATPC) and peak transmission power constraints (PTPC) are also analyzed. The main contributions of our work are summarized as follows:

- First, we have considered a new energy-efficient CSS scenario with imperfect reporting channels using the HSS scheme for the first time. Specifically, we set minimum data rate requirements for SUs to ensure their QoS and impose an average interference power constraint (AIPC) on the primary receiver (PR) to protect the PU from harmful interferences. We have then formulated the mean EE maximization problem of SUs while maintaining the detection accuracy by jointly optimizing the sensing time and the number of cooperative SUs, subject to SUs' ATPC/PTPC and data rate constraint,

and PU's AIPC. The mean EE maximization problem under this scenario has not considered before.
- Second, to address the non-convexity of the optimization problem, based on the fractional programming theory and Dinkelbach's method [40], we have transformed the optimization problem into an equivalent parameterized concave problem, and an energy-efficient iterative power allocation algorithm has been developed to obtain the optimal transmission powers of SUs.
- Third, extensive numerical results have been presented to compare and analyze the EEs of the proposed HSS scheme and traditional OSA scheme under ATPC/PTPC with three hard combining fusing rules. The impacts of the detection accuracy and the reporting channel errors on the EE have also been analyzed.

The rest of this paper is organized as follows. Section II introduces the system model. Section III defines the EE of SUs in the presence of imperfect spectrum sensing. Section IV formulates the mean EE maximization problems subject to the constraints of average/peak transmit power and average interference power and the corresponding optimal power allocation strategies are derived. Simulation results and performance comparisons are provided in Section V. Finally, the conclusions are drawn in Section VI.

Table 1 summarizes the acronyms that used in this paper.

TABLE 1. Acronyms used in the paper.

Acronyms	Definiton
CR	Cognitive radio
PU	Primary user
SU	Secondary user
SE	Spectral efficiency
EE	Energy efficiency
CSS	Cooperative spectrum sensing
FC	Fusion center
OSA	Opportunistic spectrum access
SS	Spectrum sharing
HSS	Hybrid spectrum sharing
QoS	Quality of service
SNR	Signal-to-noise ratio
ATPC	Average transmission power constraint
PTPC	Peak transmission power constraint
AIPC	Average interference power constraint
ST	Secondary transmitter
PR	Primary receiver

II. SYSTEM MODEL AND PRELIMINARIES

A. SYSTEM MODEL

As shown in Fig. 1, we consider a centralized CRN composed of one PU, K SUs and one FC. The sensing and reporting channels are imperfect.

During the sensing period, K SUs independently perform spectrum sensing to detect the PU's state and make their own binary decisions. Then, through dedicated reporting channels, SUs will forward their local decisions to the FC. Finally, according to specific fusion rules, the FC makes a global decision to judge the presence of the PU. If the FC decides

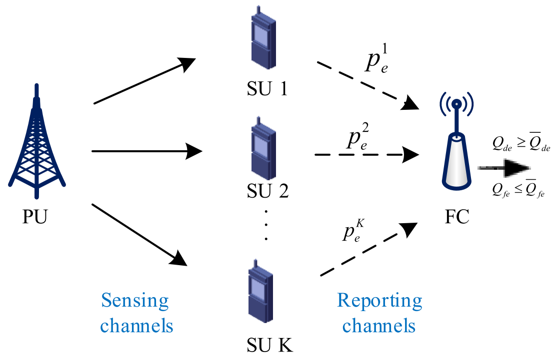

FIGURE 1. System model.

that the PU is absent, at the moment of data transmission, one of the SUs will transmit data with a higher power P_0, otherwise, the SU will transmit data with a lower power P_1 [10], [24]. In such a HSS scheme, the SUs take full advantage of the idle and busy bands, thus the SE can be improved.

The frame structure of CSS is shown in Fig. 2. The total frame length is kept fixed and denoted by T and consists of three parts: sensing time τ, reporting time T_r and data transmission time T_d. Intuitively, longer sensing time will enhance the sensing performance, however, with a fixed frame period, the data transmission time will be shorten. Therefore, the sensing-throughput tradeoff problem was formulated in [36], and it was proved that there indeed exists an optimal sensing duration to maximize the throughput of SUs while providing PU with its desired interference protection.

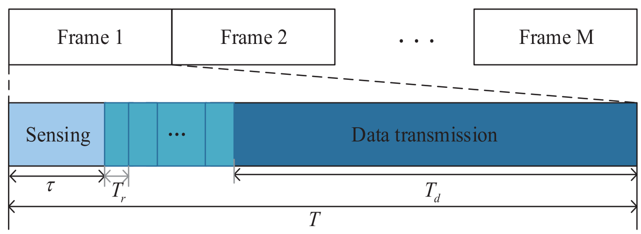

FIGURE 2. The frame structure of CSS.

Denote $y_i(n)$ is the nth received signal sample at the ith SU during the sensing period, the spectrum sensing problem can be formulated as a binary hypothesis test: Hypothesis H_0 (the PU is absent) and Hypothesis H_1 (the PU is present) [15]

$$H_0 : y_i(n) = w_i(n) \quad n = 1, 2, \cdots, N \tag{1}$$

$$H_1 : y_i(n) = s_i(n) + w_i(n) \quad n = 1, 2, \cdots, N \tag{2}$$

where $w_i(n)$ is the circularly symmetric complex Gaussian noise with zero mean and variance σ_n^2 at the ith SU, $s_i(n)$ is the PU signal received at the ith SU. N is the number of samples, $N = \tau f_s$, f_s is the sampling frequency.

Energy detector is adopted at each SU to detect the primary signal [15]. The test statistic of the received signal energy at SU i is given by

$$Y=\frac{1}{N}\sum_{n=1}^{N}|y_i(n)|^2 \tag{3}$$

Based on the test statistic, each SU makes its own decisions. The local false alarm probability p_f^i and detection probability p_d^i at the ith SU can be respectively approximated as [36]

$$p_f^i=\Pr(Y>\varepsilon_i\mid H_0)=Q\Big(\big(\frac{\varepsilon_i}{\sigma_n^2}-1\big)\sqrt{\tau f_s}\Big) \tag{4}$$

$$p_d^i=\Pr(Y>\varepsilon_i\mid H_1)=Q\Big(\big(\frac{\varepsilon_i}{\sigma_n^2}-\gamma-1\big)\sqrt{\frac{\tau f_s}{2\gamma+1}}\Big) \tag{5}$$

where $i\in\{1,2,\cdots,K\}$, $Q(x)=\frac{1}{\sqrt{2\pi}}\int_x^{\infty}e^{-\frac{t^2}{2}}dt$, ε_i is the energy detector threshold of the ith SU. γ is the received average signal-to-noise ratio (SNR) of PU's signal measured at the SUs. For a target detection probability $\overline{p}_d$, the false alarm probability can be expressed as $p_f(\tau)=Q\big(\sqrt{2\gamma+1}Q^{-1}(\overline{p}_d)+\gamma\sqrt{\tau f_s}\big)$, where $Q^{-1}(x)$ is the inverse function of $Q(x)$.

B. COOPERATIVE SPECTRUM SENSING

In this paper, we assume that the channels are block flat-fading and the distances between SUs are much smaller than the distance from any SU to the PU such that the SUs experience almost the same path loss, and the average SNR γ of the PU's signal received at the SUs are identical.

A CSS scheme generally performed in two successive stages, namely, the sensing and reporting phases. In the sensing phase, each SU individually performs spectrum sensing and makes a binary decision d_i to determine the presence of PU. If the PU is detected to be present, sets $d_i=1$, otherwise, sets $d_i=0$. Then, in the reporting stage, all SUs forward their one bit of the decision d_i to the FC. Finally, the FC will fuse all 1-bit decisions together according to logic rule

$$D=\sum_{i=1}^{K}d_i\begin{cases}\geq k, & H_1,\\ <k, & H_0.\end{cases} \tag{6}$$

where k is the counting threshold ranging from 1 to K, (6) means that if the number of the SUs who supports H_1 is greater than k, H_1 would be drawn, otherwise H_0 would be drawn. In (6), it can be seen that the case of $k=1$ corresponds to the OR rule, the case of $k=K$ corresponds to the AND rule, and the case of $k>K/2$ corresponds to the Majority rule [15], [36]. That is, for OR rule, the FC declares that the PU is present when at least one local decision says that the PU is present. For AND rule, the FC declares that the PU is present when all the local decisions say that the PU is present. For Majority rule, the FC declares that the PU is present if half or more of the decisions say that the PU is present.

In practice, the reporting channels between the SUs and the FC are always subject to the fading effects, it is impossible for the FC to receive decisions from SUs without any error. Hence, we consider reporting channel errors in the system model, suppose the reporting channel error probability between the ith SU and the FC is p_e^i, then the effective false alarm and detection probabilities of the ith SU at the FC are respectively [37]:

$$p_{fe}^i = p_f^i(1-p_e^i)+(1-p_f^i)p_e^i=f(p_f^i,p_e^i) \tag{7}$$

$$p_{de}^i = p_d^i(1-p_e^i)+(1-p_d^i)p_e^i=f(p_d^i,p_e^i) \tag{8}$$

where f is a function defined as $f(a,b)=a(1-b)+(1-a)b$.

Assume a common energy detector threshold ε is used across all the SUs and each SU experiences identical but independent reporting channel fading, we have, $p_f^i=p_f, p_d^i=p_d$ and $p_e^i=p_e$, $\forall i$. Besides, let $S_p\in\{0(\text{idle}),1(\text{busy})\}$ denotes PU's actual state, $S_{fc}\in\{0(\text{idle}),1(\text{busy})\}$ denotes the final decision at the FC, $Q_{fe}=\Pr\{S_{fc}=1\mid S_p=0\}$ and $Q_{de}=\Pr\{S_{fc}=1\mid S_p=1\}$ are defined as the global false alarm probability and the global detection probability, respectively. Based on the above assumptions and analysis, Q_{fe} and Q_{de} can be given by [37]

$$Q_{fe}=\sum_{i=k}^{K}\binom{K}{i}(p_{fe})^i(1-p_{fe})^{K-i} \tag{9}$$

$$Q_{de}=\sum_{i=k}^{K}\binom{K}{i}(p_{de})^i(1-p_{de})^{K-i} \tag{10}$$

where Q_{de} denotes the probability that the FC correctly identifies a busy channel as the busy state, whereas Q_{fe} denotes the probability that the FC falsely identifies a free channel as the busy state. It is evident that a high Q_{de} limits the interference from SUs to the licensed users and a low Q_{fe} means more spectrum opportunities can be utilized by the SUs when they are available.

In general, to protect the QoS of PU, the global detection probability Q_{de} should be above a certain threshold, say, 0.5. Meanwhile, to guarantee the opportunistic spectrum access of SUs, the global false alarm probability Q_{fe} should be under a prescribed threshold, e.g. $Q_{fe}\leq 0.5$ [43].

III. ENERGY EFFICIENCY

Let $\Phi_{H_0}=\Pr\{S_p=0\}$ and $\Phi_{H_1}=\Pr\{S_p=1\}$ respectively denote the probabilities that the PU is absent and present. Since spectrum sensing is imperfect, four different scenarios may occur, based on the PU's actual state S_p and the FC's final decision S_{fc}, as shown in table 2:

TABLE 2. Possible scenarios and transmission power.

PU's state S_p	FC's decision S_{fc}	Scenarios	ST's power
0 (idle)	0 (idle)	$\Phi_{H_0}(1-Q_{fe})$	P_0
0 (idle)	1 (busy)	$\Phi_{H_0}Q_{fe}$	P_1
1 (busy)	0 (idle)	$\Phi_{H_1}(1-Q_{de})$	P_0
1 (busy)	1 (busy)	$\Phi_{H_1}Q_{de}$	P_1

S1 $\{S_p=0,S_{fc}=0\}$: In this scenario, the PU's idle state is correctly decided by the FC with the probability $\Phi_{H_0}(1-Q_{fe})$. Then, in the data transmission stage, one of the

SUs will adopt a higher power P_0 to transmit data. The total average energy consumption E_{tot} within a frame includes the energy consumed during the local sensing, local result reporting and data transmission by all the SUs as well as the circuit power P_c, and can be given by $kP_s\tau + kP_0T_r + P_0T_d + P_cT$, where P_s denote the sensing power, $T_d = T - \tau - kT_r$.

S2 $\{S_p = 0, S_{fc} = 1\}$: In this case, the PU's idle state is falsely decided by the FC as the busy state with the probability $\Phi_{H_0}Q_{fe}$. Then, in the data transmission stage, one of the SUs will adopt a lower power P_1 for data transmission. The energy consumption is $kP_s\tau + kP_1T_r + P_1T_d + P_cT$.

S3 $\{S_p = 1, S_{fc} = 0\}$: This scenario denotes that the PU's busy state is falsely decided by the FC as idle with the probability $\Phi_{H_1}(1 - Q_{de})$. Then, in the data transmission stage, one of the SUs will adopt a higher power P_0 to transmit data. The energy consumption is the same as S1.

S4 $\{S_p = 1, S_{fc} = 1\}$: This is the case where the PU's busy state is correctly decided by the FC with the probability $\Phi_{H_1}Q_{de}$. Then, in the data transmission stage, one of the SUs will adopt a lower power P_1 for data transmission. The energy consumption is the same as S2.

In scenarios S1 and S4, the FC makes correct decisions, while the second scenario S2 is false alarm, and the third scenario S3 is mis-detection. Let θ_0, θ_1, w_0, and w_1 respectively denote the above mentioned four probabilities: $\theta_0 = \Phi_{H_0}(1 - Q_{fe})$, $\theta_1 = \Phi_{H_0}Q_{fe}$, $w_0 = \Phi_{H_1}(1 - Q_{de})$, and $w_1 = \Phi_{H_1}Q_{de}$, define φ_0 and φ_1 as the probability that the PU is deemed to be inactive and active by the FC, respectively. Then we get:

$$\varphi_0 = \theta_0 + w_0 \tag{11}$$
$$\varphi_1 = \theta_1 + w_1 \tag{12}$$

In addition, ρ_0 and ρ_1 indicate the probability that an occupied channel is deemed available or occupied by the FC and can be expressed as

$$\rho_0 = \Pr\{S_p = 1 \mid S_{fc} = 0\} = \frac{w_0}{\theta_0 + w_0} \tag{13}$$
$$\rho_1 = \Pr\{S_p = 1 \mid S_{fc} = 1\} = \frac{w_1}{\theta_1 + w_1} \tag{14}$$

Based on the above analysis, E_{tot} can be given by

$$E_{tot} = kP_s\tau + (kT_r + T_d)\mathbb{E}\{\varphi_0P_0 + \varphi_1P_1\} + P_cT \tag{15}$$

The achievable average throughput R_{tot} is defined as the average successfully transmitted data by all the SUs in one frame. R_{tot} can be approximated by [25], [35]:

$$R_{tot} = R_0 + R_1 \tag{16}$$

where

$$R_0 = T_d\varphi_0\mathbb{E}\left\{\log_2\left(1 + \frac{g_{ss}P_0}{\rho_0\sigma_s^2 + \sigma_n^2}\right)\right\} \tag{17}$$
$$R_1 = T_d\varphi_1\mathbb{E}\left\{\log_2\left(1 + \frac{g_{ss}P_1}{\rho_1\sigma_s^2 + \sigma_n^2}\right)\right\} \tag{18}$$

where k is the number of cooperative SUs, R_0 and R_1 respectively denote the achievable data rate of SUs when $S_{fc} = 0$ or $S_{fc} = 1$, g_{ss} denotes the instantaneous channel power gain from secondary transmitter (ST) to secondary receiver, $\mathbb{E}\{\cdot\}$ is the expectation operation with respect to the channel power gains, σ_s^2 is the variance of the received fading signal of PU.

The mean EE of SUs is defined as the ratio of the achieved average throughput to the total power consumption in a time slot, and can be expressed as

$$EE = \frac{R_{tot}}{E_{tot}} \tag{19}$$

Based on this definition, it can be seen that EE is a comprehensive metric to assess the system performance, since the throughput, the overall energy consumption and the global detection accuracy are all inherently considered in the metric. Hence, it attains a balance between the different facets of the system performance.

IV. ENERGY-EFFICIENT POWER ALLOCATION STRATEGY

Since the priority of a CRN is to protect the QoS of PUs, the design of the power allocation strategies of SUs should consider the interference caused to PUs for protect the PUs' normal communication. In [38], it was proved that imposing an AIPC on the primary link could not only better protect PU communication but also provide SU with the higher capacity than imposing a peak interference power constraint. Hence, we consider AIPC in this paper. In addition, two types of power constrains of the SUs are usually applied [39]. One is the ATPC to keep the long-term power budget of SUs, the other is the PTPC which is related to the nonlinearity of power amplifiers. PTPC is more rigorous than ATPC and their impacts on the EE are separately studied below.

A. AVERAGE TRANSMIT POWER CONSTRAINT AND AVERAGE INTERFERENCE POWER CONSTRAINT

In this subsection, we study the optimal power allocation strategy to maximize the mean EE of HSS CR under the ATPC at the ST and the AIPC at the primary receiver (PR).

Under the condition that the primary communication is protected, our goal is to maximize the mean EE while maintaining the detection accuracy by jointly optimizing the sensing duration and the number of cooperative SUs, subject to the constraints of SUs' average transmit power and date rate, and PU's average tolerable interference power. Thus, the optimization problem is formulated as follows:

$$\text{P1}: \quad \max_{\tau,k,P_0,P_1} EE(\tau, k, P_0, P_1) = \frac{R_{tot}(\tau, k, P_0, P_1)}{E_{tot}(\tau, k, P_0, P_1)} \tag{20}$$
$$\text{s.t. } Q_{de} \geq \bar{Q}_{de} \tag{20a}$$
$$Q_{fe} \leq \bar{Q}_{fe}x \tag{20b}$$
$$0 \leq \tau \leq T - kT_r \tag{20c}$$
$$0 \leq k \leq K \tag{20d}$$
$$T_d\mathbb{E}\{\varphi_0P_0 + \varphi_1P_1\} \leq P_{av} \tag{20e}$$
$$T_d\mathbb{E}\{[w_0P_0 + w_1P_1]g_{sp}\} \leq I_{av} \tag{20f}$$
$$R_{tot} \geq R_{min} \tag{20g}$$
$$P_0 \geq 0, \quad P_1 \geq 0 \tag{20h}$$

where $\bar{Q}_{de}$ is the minimum detection probability that the FC needs to achieve to protect the PU, $\bar{Q}_{fe}$ is the upper limit of the false alarm probability, P_{av} is the maximum average transmission power limit of the SUs, I_{av} is the maximum average interference power that the PU can tolerate, R_{min} denotes the minimum data rate demands of SUs, g_{sp} is the channel power gain from ST to PR.

Constraints (20a) and (20b) set the global detection probability and the global false alarm probability, respectively. Constraints (20c) and (20d) are effective ranges of the spectrum sensing time and number of cooperative SUs, respectively. Constraint (20e) restricts the SUs' maximum average transmit power for keep the long-term power budget of the SUs. Constraint (20f) specifies that the interference caused to the PU cannot exceed its threshold for protect the primary transmission. Constraint (20g) sets the SUs' minimum data rate requirements. Constraint (20h) is the non-negative transmit power constraints of SUs.

Problem P1 can achieve the maximum when constraint (20a) is at equality for any given pair of k and τ. A similar conclusion is also proposed in [25] and [26]. For any given pair of k and τ, the energy detection threshold ε that is able to satisfy $Q_{de} = \bar{Q}_{de}$ can be determined by

$$\varepsilon(\tau,k) = \sigma_n^2\left[\sqrt{\frac{2\gamma+1}{\tau f_s}}Q^{-1}\left(\frac{\bar{p}_{de}(k)-p_e}{1-2p_e}\right)+\gamma+1\right] \quad (21)$$

substituting (21) into (4), (7) and (9), the effective false alarm probability p_{fe} and the global false alarm probability Q_{fe} can be derived. When $k = K$, With $Q_{de} = \bar{Q}_{de}, Q_{fe} \leq \bar{Q}_{fe}$, we have $\tau \geq \tau_1$, where $\tau_1 = \left(\frac{Q^{-1}(\phi)-\sqrt{2\gamma+1}Q^{-1}(\psi)}{\gamma\sqrt{f_s}}\right)^2$, $\phi = \frac{\sqrt[k]{\bar{Q}_{fe}}-p_e}{1-2p_e}$, and $\psi = \frac{\sqrt[k]{\bar{Q}_{de}}-p_e}{1-2p_e}$. In general, constraints (20a) and (20b) can be satisfied at the same time, and Q_{de} is chosen to be close to but less than 1, especially in low SNR. For the SNR of -20 dB, we set $\bar{Q}_{de} = 0.9$ to ensure the detection performance.

Note that in Problem P1, constraints (20e), (20f) and (20g) are composed of products of the data transmission time $T-\tau-kT_r$, the transmit powers P_0 and P_1, and the global detection probability Q_{de} (or the global false alarm probability Q_{fe}). Both Q_{de} and Q_{fe} are determined by the sensing duration τ, the number of cooperative SUs k and the reporting error probability p_e. Due to the complicated coupling among the optimization variables, Problem P1 is non-convex, we cannot use the convex optimization techniques to acquire the optimal sensing time. However, since τ lies within the interval $(0, T-kT_r)$, it can be easily obtained by using the exhaustive searching method [32], [33].

Besides, considering the imperfect reporting channels, the analysis of CSS is more complex. When the number of cooperative SUs k is small, the advantage of CSS is not significant. When the k is large, the energy consumption increases and the adverse effects on the throughput may be accumulated due to the errors in reporting local results. Thus, there exists an optimal k to maximize the EE of SUs in CRN. No closed-form solution for k is available in this optimization problem. However, since k is an integer within the interval $[1, K]$, the exhaustive searching method can be used to get the optimal k, which can be expressed as [13], [26]

$$k^* = \arg\max_k EE(\tau,k,P_0,P_1) \quad (22)$$

Therefore, in the following, we mainly investigate the optimal power allocation strategy that maximizes the mean EE with specific k and τ.

Given the k and τ, Problem P1 can be reformulated as

$$\begin{aligned} \text{P2}: \quad & \max_{P_0,P_1} EE(P_0,P_1) = \frac{R_{tot}(P_0,P_1)}{E_{tot}(P_0,P_1)} \\ & \text{s.t. (20e)-(20h)} \end{aligned} \quad (23)$$

Problem P2 is quasi-concave because $R_{tot}(P_0,P_1)$ is concave with regard to the transmission powers and $E_{tot}(P_0,P_1)$ is an affine function [41]. We use fractional programming to transform Problem P2 into a convex one and reformulate P2 as P3:

$$\begin{aligned} \text{P3}: \quad & \max_{P_0,P_1} F(\eta) = R_{tot}(P_0,P_1) - \eta E_{tot}(P_0,P_1) \\ & \text{s.t. (20e)-(20h)} \end{aligned} \quad (24)$$

where η is a nonnegative parameter. The relation between P2 and P3 is given in Lemma1, and the detailed proof is provided in [40].

Lemma 1: η^* and P_0^*, P_1^* are respectively the optimal mean EE and the optimal transmission powers of P2 if and only if

$$P_0^*, P_1^* = \arg\max_{P_0,P_1}\{R_{tot}(P_0,P_1) - \eta^* E_{tot}(P_0,P_1) | P_0, P_1 \in S\} \quad (25)$$

$$F(\eta^*) = F(\eta^*, P_0^*, P_1^*) = 0 \quad (26)$$

where S is the feasible zone of P_0, P_1 in P2. From Lemma 1, we can see that at the optimal η^*, P2 and P3 have the same solution. Thus, by searching the optimal power of P3 for a given η and then update η until (26) is satisfied, P2 can be solved and its optimal EE is equal to η^*. Since $F(\eta)$ is a concave function of P_0 and P_1 with a fixed η, the optimal power can be obtained by forming the Lagrangian function of P3 as

$$\begin{aligned} L(P_0,P_1,\eta,\mu,\nu,\xi) = & R_{tot}(P_0,P_1) - \eta E_{tot}(P_0,P_1) \\ & - \mu\left(T_d\mathbb{E}\{\varphi_0 P_0 + \varphi_1 P_1\} - P_{av}\right) \\ & - \nu\left(T_d\mathbb{E}\{(w_0P_0 + w_1P_1)g_{sp}\} - I_{av}\right) \\ & + \xi\left(R_{tot} - R_{min}\right) \end{aligned} \quad (27)$$

where μ, ν, and ξ are the nonnegative Lagrange multipliers related to (20e), (20f), and (20g), respectively. According to the Karush-Kuhn-Tucker (KKT) conditions, letting $\frac{\partial L}{\partial P_0} = 0$, $\frac{\partial L}{\partial P_1} = 0$, the optimal values of P_0 and P_1 are derived as

$$P_0^* = \left[\frac{\varphi_0(1+\xi)}{\big((\eta+\mu)\varphi_0+\nu w_0 g_{sp}\big)\ln 2} - \frac{\rho_0\sigma_s^2+\sigma_n^2}{g_{ss}}\right]^+ \tag{28}$$

$$P_1^* = \left[\frac{\varphi_1(1+\xi)}{\big((\eta+\mu)\varphi_1+\nu w_1 g_{sp}\big)\ln 2} - \frac{\rho_1\sigma_s^2+\sigma_n^2}{g_{ss}}\right]^+ \tag{29}$$

where $[x]^+ = \max\{x, 0\}$. To obtain the optimal Lagrange multipliers μ, ν, and ξ, we utilize the sub-gradient method [42] to iteratively update μ, ν, and ξ in the sub-gradient direction with a suitable step size s until convergence as follows

$$\mu^{(n+1)} = \Big[\mu^{(n)} - s\big(P_{av} - T_d\mathbb{E}\{\varphi_0 P_0 + \varphi_1 P_1\}\big)\Big]^+ \tag{30}$$

$$\nu^{(n+1)} = \Big[\nu^{(n)} - s\big(I_{av} - T_d\mathbb{E}\{[w_0 P_0 + w_1 P_1] g_{sp}\}\big)\Big]^+ \tag{31}$$

$$\xi^{(n+1)} = \Big[\xi^{(n)} - s\big(R_{tot} - R_{min}\big)\Big]^+ \tag{32}$$

where n refers to the iteration index. When s is constant, the sub-gradient method is guaranteed to converge to the optimal value.

By iterating Eqs. (28)-(32), the optimal transmission powers P_0^* and P_1^* are solved until $F(\eta) \le \delta_2$ is satisfied. When $F(\eta) = 0$ in Eq. (26), the solution is optimal. Otherwise, a δ_2 optimal solution is achieved. To find the optimal η^* of P2, the fast converging Dinkelbach's algorithm is adopted to tackle the fractional programming problem [40]. Algorithm 1 describes the proposed energy-efficient iterative power allocation algorithm.

In Algorithm 1, the optimal power allocation process for P2 is divide into the outer iteration and the inner iteration. The outer iteration is exploited to find the EE $\eta^{(i)}$, and the inner iteration is used to acquire the powers P_0^* and P_1^* for a fixed $\eta^{(i)}$.

Algorithm 1 Energy-Efficient Iterative Power Allocation Algorithm

given: the iteration index $i = 0, j = 0, M = \frac{(T-kT_r)}{\Delta\tau}$, $\Delta\tau$ is the step-size of sensing time, and the error tolerances $\delta_1 > 0, \delta_2 > 0$;
Initialization: $Q_{de} = \bar{Q}_{de}$, $\eta^{(0)} = \eta_0$, $\mu^{(0)} = \mu_0$, $\nu^{(0)} = \nu_0$, $\xi^{(0)} = \xi_0$, $s > 0$;
for $k = 1 : K$ **do**
  for $m = 1 : M$ **do**
    $\tau = m\Delta\tau$;
    repeat
      calculate P_0^* and P_1^* using (28) and (29), respectively;
      update μ, ν, and ξ via sub-gradient method as follows:
      repeat
        $\mu^{(j+1)} = \big[\mu^{(j)} - s\big(P_{av} - T_d\mathbb{E}\{\varphi_0 P_0 + \varphi_1 P_1\}\big)\big]^+$;
        $\nu^{(j+1)} = [\nu^{(j)} - s\big(I_{av} - T_d\mathbb{E}\{[w_0 P_0 + w_1 P_1] g_{sp}\}\big)]^+$;
        $\xi^{(j+1)} = [\xi^{(j)} - s(R_{tot} - R_{min})]^+$;
        $j = j + 1$;
      until $|\mu^{(j)}(P_{av} - T_d\mathbb{E}\{\varphi_0 P_0 + \varphi_1 P_1\})| \le \delta_1$, $|\nu^{(j)}\big(I_{av} - T_d\mathbb{E}\{[w_0 P_0 + w_1 P_1] g_{sp}\}\big)| \le \delta_1$, and $|\xi^{(j)}(R_{tot} - R_{min})| \le \delta_1$
      $\eta^{(i+1)} = \frac{R_{tot}(P_0^*, P_1^*)}{E_{tot}(P_0^*, P_1^*)}$;
      $i = i + 1$;
    until $|F(\eta^{(i)})| \le \delta_2$
  end for
end for
return $\eta^* = \eta^{(i)}$.

B. PEAK TRANSMIT POWER CONSTRAINT AND AVERAGE INTERFERENCE POWER CONSTRAINT

In this subsection, we consider the PTPC at the ST instead of the ATPC for EE maximization, while the interference at the PR still adopt the AIPC. PTPC restricts the instantaneous transmit power of the ST. Therefore, compared to the ATPC, PTPC corresponds to a stricter constraint.

Let $P_{k,0}$ and $P_{k,1}$ denote the peak transmit power limits of P_0 and P_1, respectively, and substitute (20e) with PTPC, then Problem P1 is rewritten as P4

$$\text{P4}: \quad \max_{\tau,k,P_0,P_1} EE(\tau,k,P_0,P_1) = \frac{R_{tot}(\tau,k,P_0,P_1)}{E_{tot}(\tau,k,P_0,P_1)} \tag{33}$$

$$\text{s.t. } P_0(g_{ss}, g_{sp}) \le P_{k,0} \tag{33a}$$

$$P_1(g_{ss}, g_{sp}) \le P_{k,1} \tag{33b}$$

$$\text{(20a)-(20d)}, \quad \text{(20f)-20(h)} \tag{33c}$$

Similarly, according to the way to solve P1, Problem P4 is first reformulated as P5 with fixed k and τ as follows

$$\text{P5}: \quad \max_{P_0,P_1} EE(P_0,P_1) = \frac{R_{tot}(P_0,P_1)}{E_{tot}(P_0,P_1)} \tag{34}$$

$$\text{s.t. } P_0(g_{ss}, g_{sp}) \le P_{k,0} \tag{34a}$$

$$P_1(g_{ss}, g_{sp}) \le P_{k,1} \tag{34b}$$

$$\text{(20f)-20(h)} \tag{34c}$$

After transforming Problem P5 into an equivalent parametrized concave form, according to the same steps as in Subsection A, the optimal power allocation under the PTPC and the AIPC are determined as follows

$$P_0^* = \begin{cases} P_{k,0} & g_{sp} \le B_0 \\ \dfrac{\varphi_0(1+\xi)}{\big(\eta\varphi_0 + \nu w_0 g_{sp}\big)\ln 2} - \dfrac{\sigma_n^2 + \rho_0\sigma_s^2}{g_{ss}} & B_0 < g_{sp} < A_0 \\ 0 & g_{sp} \ge A_0 \end{cases} \tag{35}$$

$$P_1^* = \begin{cases} P_{k,1} & g_{sp} \le B_1 \\ \dfrac{\varphi_1(1+\xi)}{\big(\eta\varphi_1 + \nu w_1 g_{sp}\big)\ln 2} - \dfrac{\sigma_n^2 + \rho_1\sigma_s^2}{g_{ss}} & B_1 < g_{sp} < A_1 \\ 0 & g_{sp} \ge A_1 \end{cases} \tag{36}$$

where

$$A_j = \frac{1}{\Delta_j}\Big[\frac{\varphi_j g_{ss}(1+\xi)}{(\rho_j\sigma_s^2+\sigma_n^2)\ln 2} - \eta\varphi_j\Big] \quad (37)$$

$$B_j = \frac{1}{\Delta_j}\Big[\frac{\varphi_j g_{ss}(1+\xi)}{(P_{k,j}g_{ss}+\rho_j\sigma_s^2+\sigma_n^2)\ln 2} - \eta\varphi_j\Big] \quad (38)$$

and $j \in \{0, 1\}$, $\Delta_0 = \nu w_0$, $\Delta_1 = \nu w_1$.

Then, to maximize the EE, we modify Algorithm 1 by computing P_0^* and P_1^* respectively according to Eqs. (35) and (36) and updating Lagrange multipliers ν and ξ according to Eqs. (31) and (32).

C. COMPLEXITY ANALYSIS

In this subsection, the complexity of the proposed algorithm is discussed. Suppose I and J respectively represent the iteration numbers of the outer loop (line 6 to 17 in Algorithm 1) and the inner loop (line 9 to 14 in Algorithm 1), then the complexity of the fractional programming and the sub-gradient method can be expressed as $O(IJ)$. Note that we only need to update three dual variables, i.e., μ, ν, and ξ for convergence. Therefore, I and J can be small enough if the step size value, the initial values of μ, ν, and ξ are set appropriately. The complexity of searching the optimal k and the optimal τ is $O(KM)$, so the total complexity of Algorithm 1 is $O(KMIJ)$.

V. SIMULATION RESULTS

In this section, simulation results are provided to evaluate the performance of the proposed scheme. For comparison, we include the conventional OSA scheme [32]. Unless otherwise stated, we assume that the frame duration is fixed and $T = 100$ ms, the reporting time $T_r = 10$ us, the sampling frequency $f_s = 6$ MHz, the number of SUs $K = 10$, and the circuit power $P_c = 0.1$ W, sensing power $P_s = 0.02$ W, the target detection probability $\bar{Q}_{de} = 0.9$, the reporting error probability $p_e = 0.005$, and $\sigma_n^2 = 0.2$, $\sigma_s^2 = 1$, the received average SNR from the PU $\gamma = -20$ dB. We set the average transmit power constraint $P_{av} = -15$ dB, the peak transmit power constraints $P_{k,0} = P_{k,1} = -15$ dB, the average interference power constraint $I_{av} = -20$ dB, and the minimum data rate constraint $R_{min} = 0.05$ bits/Hz. Besides, the channel idle probability Φ_{H_0} and the channel busy probability Φ_{H_1} are assumed to be 0.7 and 0.3, respectively, which are reasonable as the Federal Communications Commission reports that the licensed spectrum is underutilized [2]. The step sizes μ, ν, and ξ are set to be 0.1 and the tolerances δ_1 and δ_2 are set to be 0.0001, respectively. The channel power gains are assumed to be block faded and follow the exponential distribution with unit mean.

Fig. 3 shows the mean EE versus the sensing time for the proposed HSS and the conventional OSA scheme under ATPC with different rules. We provide the single spectrum sensing as a baseline to analyze the performance improvement due to CSS. As shown in Fig. 3, as the sensing time increases, the EE first increases and then drops. It is clear from the figure that, for each rule, our proposed HSS scheme can achieve better EE than the respective OSA scheme.

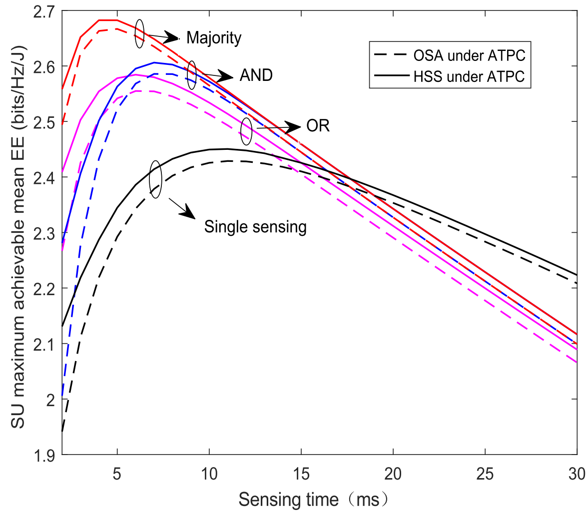

FIGURE 3. Achievable mean EE vs. the sensing time under ATPC.

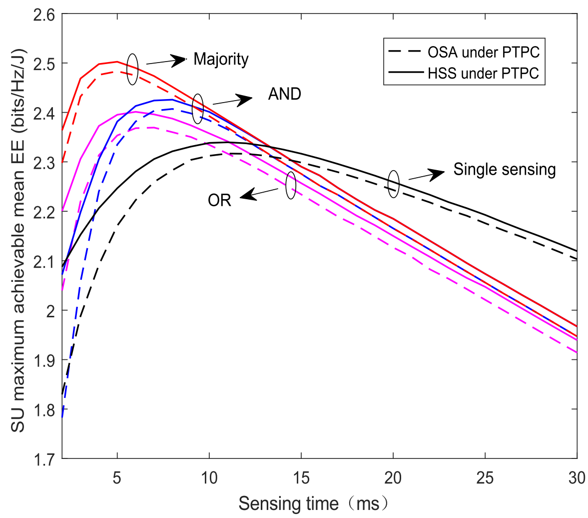

FIGURE 4. Achievable mean EE vs. the sensing time under PTPC.

This is due to the fact that under the HSS, data transmission is allowed even when the PU is detected to be active. It is also observed that compared with the 'OR' and 'AND' rules, the Majority rule has the best EE, these results illustrate the superiority of the Majority rule and are similar to the results in [36].

In Fig. 4, we plot the achievable mean EE versus the sensing time for the proposed HSS and the conventional OSA scheme under PTPC with different rules. Compare Fig. 4 with Fig. 3, we can discover that for each rule, the EEs achieved under the ATPC are always higher than the EEs achieved under the PTPC. This is because compared to the PTPC, the ATPC is looser and its power allocation is more flexible. Under ATPC, more power can be allocated by the transmitter under good channel conditions. Besides, from Figs. 3 and 4, it is noticed that when the sensing time is small, three hard combining rules provide better performance, but as the

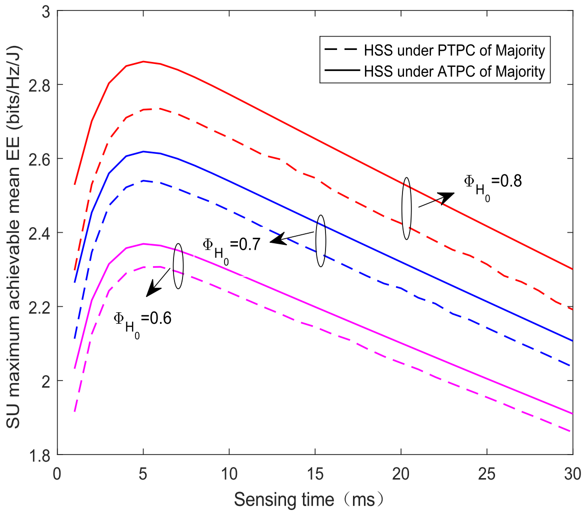

FIGURE 5. Achievable mean EE vs. the sensing time with different Φ_{H_0}.

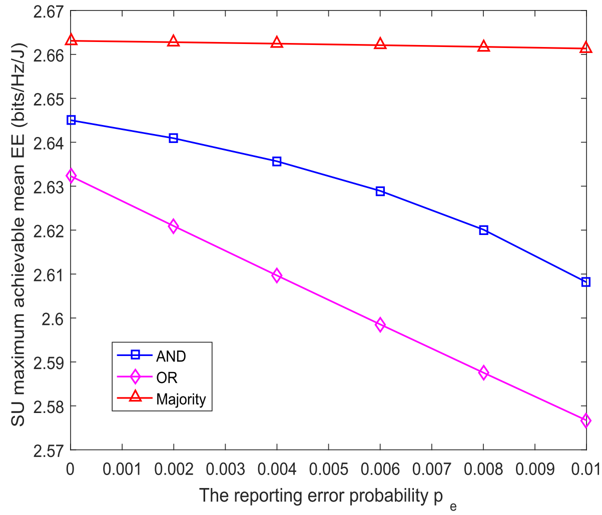

FIGURE 6. Achievable mean EE vs. p_e with different rules.

sensing time increases they are outperformed by the single spectrum sensing. This is because long sensing time with CSS decreases the data transmission time, consumes more sensing energy, and results in the decline of EE.

Moreover, from Figs. 3 and 4, it is seen that, at first, OR rule has a better EE than AND rule, however, as the sensing time increases, it is exceeded by the curve of AND rule. This is because when the sensing time is below 5.17 ms, OR rule leads to a lower Q_{fe}, but when the sensing time increases to above 5.17 ms, AND rule will lead to a lower Q_{fe}. From the SUs' perspective, a low false-alarm probability means that more transmission opportunities can be utilized by the SUs, thus improving the throughput and the EE of the system.

Fig. 5 demonstrates the achievable mean EE versus the sensing time for the proposed HSS scheme under ATPC and PTPC of Majority rule with $\Phi_{H_0} = 0.6, 0.7, 0.8$. As shown in Fig. 5, the mean EE decreases with the decrease in Φ_{H_0}. This is comprehensible as a lower Φ_{H_0} implies a higher active probability of the PU, and the spectrum is occupied by the PU in most of the time. Therefore, there will be little chance for the SU to transmit data with higher power P_0, thus fewer benefits can be obtained by SUs and the EE declines. We can conclude from this observation that it is wasteful for SUs to perform CSS when Φ_{H_0} is small. It is reasonable to assume that Φ_{H_0} is not less than 0.5. We study the optimization problem under this precondition.

Fig. 6 displays the mean EE versus the reporting error probability p_e for the proposed HSS scheme under ATPC with different rules. Obviously, as the p_e increases, the mean EE of the 'OR' and 'AND' rules significantly decreases, whereas the mean EE of the Majority rule decreases slightly, indicating that compared to the 'OR' and 'AND' rules, the Majority rule has the higher performance against reporting channel errors.

Fig. 7 depicts the achievable mean EE versus the reporting error probability p_e for the proposed HSS scheme and the

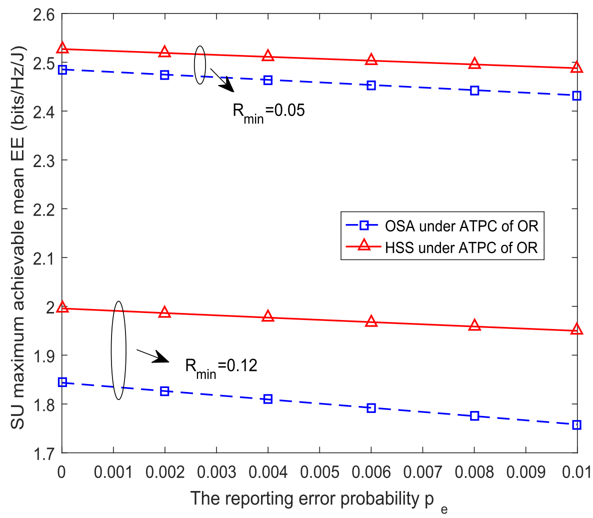

FIGURE 7. Achievable mean EE vs. p_e with different R_{min}.

conventional OSA scheme under ATPC of OR rule with $R_{min} = 0.05, 0.12$ bits/Hz. Similar to Figs. 3 and 4, under the same R_{min}, the HSS scheme always has a higher EE than the traditional OSA scheme. This once again demonstrate the superiority of our proposed HSS scheme. It is also seen that with the increase in R_{min}, the EE decreases. The reason is that in order to meet the minimum rate requirement of SUs, ST have to adopt a higher power to transmit data, thus consuming more energy and reducing the EE.

Fig. 8 plots the achievable mean EE versus the number of cooperative SUs for the proposed HSS scheme under ATPC and PTPC of AND rule with $p_e = 0, 0.005$. It is seen that the EE first increases with the increase in the number of cooperative SUs K, indicating that the improvement in sensing performance exceeds the loss caused by less data transmission time and larger energy consumption. However, EE decreases as K further increases, because the more cooperative SUs lead to the more energy consumption and the larger cooperation

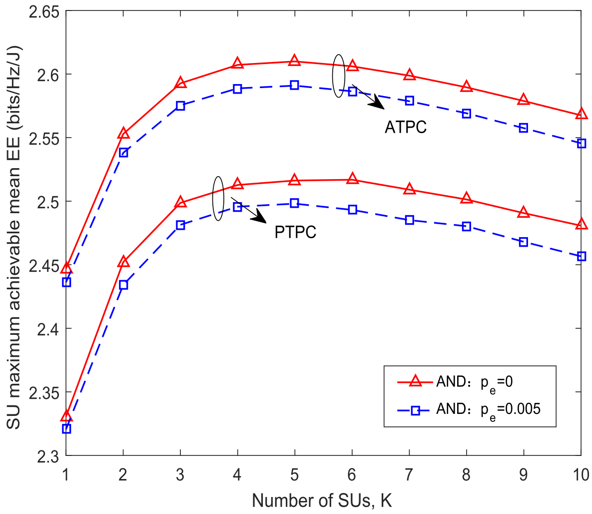

FIGURE 8. **Achievable mean EE vs.** K **with different** p_e**.**

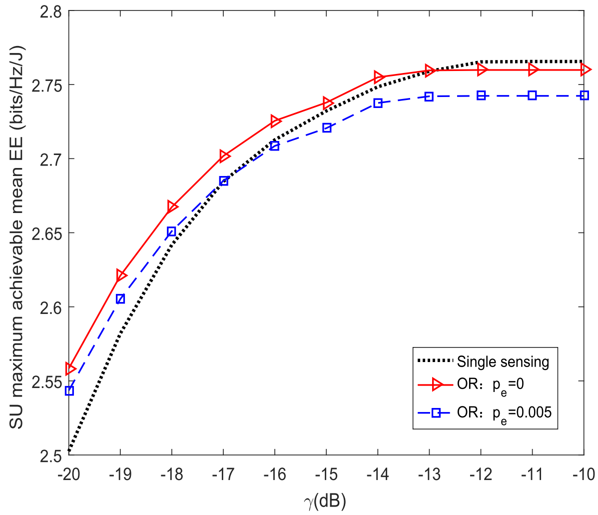

FIGURE 10. **Achievable mean EE vs.** γ **of Single and OR rule.**

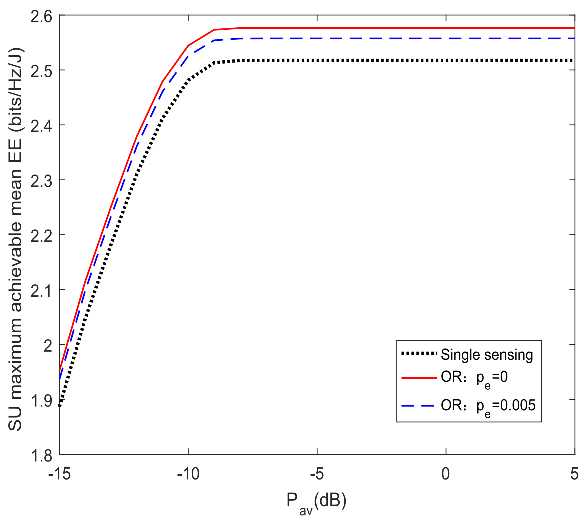

FIGURE 9. **Achievable mean EE vs.** P_{av} **of Single and OR rule.**

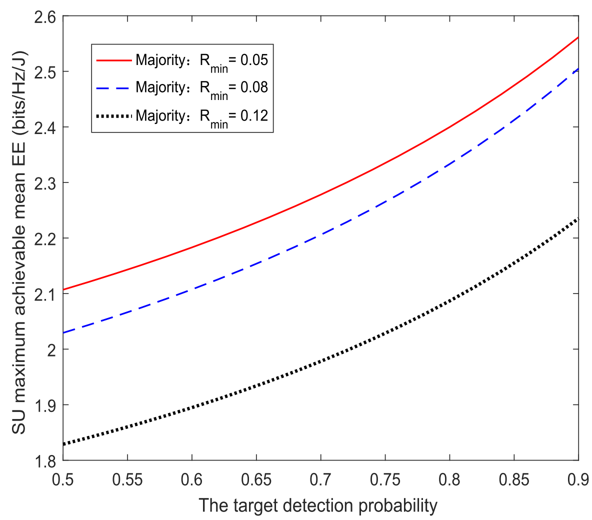

FIGURE 11. **Achievable mean EE vs.** Q_{de} **with different** R_{min}**.**

overhead, but the sensing performance cannot be improved anymore, thus resulting in the declining EE. Hence, it is necessary to balance the energy consumption against the number of SUs when designing cooperative CR systems. Similar to Figs. 3, 4, and 5, Fig. 8 shows that the ATPC has a better performance than the PTPC, because the ATPC can provide the more flexibility for the transmit power allocation of SUs than the PTPC.

Fig. 9 illustrates the achievable mean EE versus the average transmit power constraint P_{av} for the proposed HSS scheme. We assume that the AIPC is $I_{av} = -10$dB. It can be seen that the EE of OR rule with perfect reporting channel, $p_e = 0$, is the best, revealing that reporting channel errors indeed deteriorate the CSS performance and decrease the EE. It is also shown that the maximum mean EE first increases with P_{av} and then converges when P_{av} is larger than -10dB. This is because a higher P_{av} enlarges the feasible domain of P1, but when P_{av} becomes sufficiently looser than I_{av}, it becomes inactive and the transmission power depends on I_{av} rather than P_{av}. Thus, the achievable EE remains unchanged.

Fig. 10 depicts the trend of the achievable mean EE versus γ for the proposed HSS scheme under ATPC of single spectrum sensing and OR rule. Obviously, as γ increases, the maximum mean EE becomes higher and finally converges. The reason is that spectrum sensing can be more accurate with a larger γ. It is also noticed that when γ is low, the mean EE of OR rule is greater than that of single spectrum sensing. However, as γ further increases, OR rule will be surpassed by single spectrum sensing because in this case, fewer users are required to participate in the spectrum sensing to achieve the good sensing performance. This indicates that CSS is more applicable in the poor SNR environment. Moreover, when the reporting channel condition is bad, the cooperative sensing would be less advantageous.

Fig. 11 shows the achievable mean EE vs. the target detection probability Q_{de} for the proposed HSS scheme under

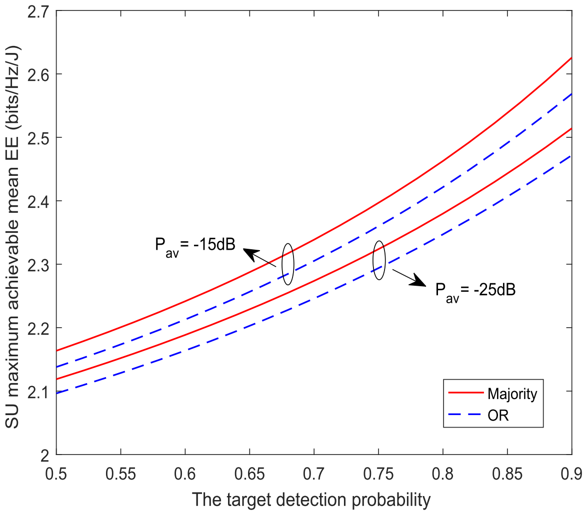

FIGURE 12. Achievable mean EE vs. Q_{de} with different P_{av}.

the ATPC of Majority rule with different R_{min}. Similar to the results shown in Fig. 7, the EE decreases with the increase in R_{min}. The trend can be similarly interpreted by the fact that a larger R_{min} means the ST has to transmit data with a higher power, thus consuming more energy and decreasing the EE. It is also seen that the EE increases with Q_{de} because a larger Q_{de} indicates that the SUs have more reliable cooperative sensing performance. Thus, the SUs will experience less missed detection events, which increases the achievable throughput. Meanwhile, as Q_{de} increases, P_0 under the channel idle decision increases while P_1 under the channel busy decision decreases. That is, the achievable throughput increases and the total transmission power slightly increases. Hence, as the sensing performance is improved, the maximum achievable EE of SUs increases.

In Fig. 12, the achievable mean EE vs. the target detection probability Q_{de} is compared between Majority rule and OR rule for the proposed HSS scheme under ATPC with $P_{av} = -25, -15$ dB, $I_{av} = -20$ dB. Again, it is observed from the figure that a larger Q_{de} results in a higher EE, this is because a larger Q_{de} makes the global detection performance more accurate. Also, for both fusion rules, the EE under $P_{av} = -15$ dB is higher than that under $P_{av} = -25$ dB, which is due to the fact that a larger value of P_{av} leads to a larger optimal power in (20).

VI. CONCLUSIONS

In this paper, we study the mean EE maximization problem of hard decision based CSS system using the HSS scheme. In particular, we consider imperfect spectrum sensing and reporting channel errors in the system model. The mean EE maximization problem is formulated by jointly optimizing the sensing time and the number of cooperative SUs, subject to the SUs' ATPC/PTPC and data rate constraint, as well as PU's AIPC. Since the joint optimization problem is complicated and non-convex, based on fractional programming theory and Dinkelbach's method, we transform the optimization problem into an equivalent parameterized concave problem, and an energy-efficient iterative power allocation algorithm is proposed to solve the problem efficiently.

Simulation results validate the feasibility of the proposed scheme. It is shown that under the same parameter settings, the EE of our proposed HSS scheme always outperforms that of the traditional OSA scheme, and the EE achieved under the ATPC is always better than that under the PTPC. It is also shown that the EE depends on global detection probability, false alarm probability, channel idle probability, reporting error probability, minimum data rate demands of SUs, and the received average SNR of the primary signal. We can see that the reporting channel errors indeed deteriorate the detection performance and lead to the decline of EE. Moreover, compared with 'OR' and 'AND' rules, the Majority rule has the best EE.

As our future works, we will account for the heterogeneity of the SUs and the influence of imperfect channel state information, and we plan to incorporate soft combining-based CSS into our model.

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