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Optimal Resource Allocation in Simultaneous Cooperative Spectrum Sensing and Energy Harvesting for Multichannel Cognitive Radio

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ABSTRACT In this paper, a simultaneous cooperative spectrum sensing and energy harvesting model is proposed to improve the transmission performance of the multichannel cognitive radio. The frame structure is divided into sensing slot and transmission slot. In the sensing slot, the secondary user (SU) splits the subchannels into two subchannel sets, one for sensing the primary user (PU) by multichannel cooperative spectrum sensing and the other one for collecting the radio frequency energy of the PU signal and noise by multichannel energy harvesting. In the transmission slot, the harvested energy is supplied to compensate the sensing energy loss in order to guarantee the throughput. We have formulated the resource allocation of the proposed model as a class of optimization problems, which maximize aggregate throughput, harvested energy, and energy efficiency of the SU over all the subchannels through jointly optimizing subchannel set, sensing time, and transmission power, respectively. To achieve the sub-optimal solutions to the optimization problems, we have proposed the subchannel allocation algorithm and the joint optimization algorithm of sensing time and transmission power based on the Greedy algorithm and the alternating direction optimization. The stopping criteria of SU is described, when the PU is not present but the harvested energy is not enough. The simulation results are presented to demonstrate the validity and predominance of our proposed algorithms.

INDEX TERMS Cognitive radio, cooperative spectrum sensing, energy harvesting, throughput, joint optimization.

I. INTRODUCTION

The traditional communication systems adopt the static spectrum allocation scheme, thus the spectrum utilization is sometimes very low. However, the spectrum resource allocated to the primary user (PU) is not completely used in the full time, the licensed spectrum shortly unused is called the idle spectrum or the spectrum hole [1], [2]. Hence, cognitive radio (CR) has been proposed to allow the secondary user (SU) to make full use of these spectrum holes opportunistically [3]. The spectrum hole state is always changed dynamically due to the random presence of the PU, whose channel parameters vary with time and space. The SU searches for an idle spectrum by performing spectrum sensing and occupies the idle spectrum after the absence of the PU is detected accurately. In order to avoid causing any harmful interference to the PU, the SU must vacate the idle spectrum if the PU is present in the spectrum again [4], [5].

Energy detection is widely performed for the SU to sense the PU. Unlike other spectrum sensing methods, the energy detection doesn't need any prior information of the detected signal [6]. The energy detection performance is reflected by false alarm probability and detection probability. The spectrum utilization improves as the false alarm probability decreases, while the interference to the PU decreases as the detection probability improves [7]. However, the energy detection performance may degrade greatly, when the channel path between the PU and the SU is in severe fading or shadowing. Hence, cooperative spectrum sensing has been proposed to improve the spectrum sensing performance in fading channel, through letting multiple SUs locating in different areas sense the PU collaboratively. In cooperative spectrum sensing, the sensing diversity gain can be obtained, i.e., if one SU fails to detect the PU, the other SUs will help to achieve an accurate detection result [8]. In cooperative spectrum sensing, every SU first gets a local detection result, then all the local detection results are combined to obtain a final decision. The combined decision includes hard decision and soft decision. In the hard decision, every SU must make a local 1-bit decision 0 or 1 by energy detection, then these 1-bit decisions are fused by "OR Rule", "AND Rule" or "K-OUT-N Rule". While in the soft decision, every SU just obtains the energy statistic without making any decision, all the energy statistics are fused to perform energy detection [9]– [11].

In 4G or 5G mobile communications, the PU may occupy a broadband spectrum across multiple subchannels, thus multichannel cooperative spectrum sensing is proposed to sense the broadband PU through detecting different subchannels collaboratively. The local detection results from all the subchannels are combined to obtain a final decision on the presence of the PU [12]. In [13], the SU performs spectrum sensing and data transmission periodically by dividing the frame structure into sensing slot and transmission slot, the SU first senses the PU and then transmits data according to the sensing decision. It has been proven that there is a sensing-throughput tradeoff in CR, i.e., there exists an optimal sensing time that maximizes the throughput of the SU [14]. An optimal multichannel cooperative spectrum sensing is proposed to maximize the throughput of the SU over all the subchannels, while keeping the detection probability of every subchannel above the presettled threshold [15]. The joint resource allocation of cooperative sensing threshold and transmission power is proposed, which can improve the throughput and decrease the interference, while guaranteeing both the probabilities of false alarm and detection [16].

However, compared with the traditional communication systems, the SU will consume more electrical power for spectrum sensing, thus the transmission performance of the SU may decrease greatly. The sensing energy loss rises with the increasing number of the signal sampling nodes. Recently, energy harvesting has been proposed to reuse the radio frequency (RF) energy of the surrounding signal resources. Through an energy harvesting device, the received RF energy is converted to the direct current (DC) power, which is then stored in a rechargeable battery of the communication system instead of a fixed power supply [17]– [19]. In CR, the SU may harvest the RF energy of the PU signal when the PU is present in the channel. In the traditional energy harvesting models of the SU, the spectrum sensing and the energy harvesting are two completely independent processes, the SU can perform spectrum sensing or energy harvesting at a specific time [20]. The simultaneous wireless information and power transfer model has been investigated hotly, which performs data transmission and energy harvesting simultaneously by splitting the received signal power into two different power streams [21]. Based on this research, we have proposed a simultaneous cooperative spectrum sensing and energy harvesting model for a multichannel CR in this paper. The contributions of the paper are listed as follows:

- To decrease the energy loss of the multichannel SU, we have proposed a novel simultaneous cooperative spectrum sensing and energy harvesting model. We split all the subchannels into sensing subchannle set and harvesting subchannel set. In the sensing slot, the SU uses the sensing subchannel set to perform multichannel cooperative spectrum sensing and the harvesting subchannel set to collect the RF energy simultaneously. The harvested energy can compensate the energy loss for the spectrum sensing in order to guarantee the throughput in the transmission slot.
- Based on the proposed model, we have formulated the resource allocation as a joint optimization problem. The optimization problem seeks to maximize the aggregate throughput of the multichannel SU by jointly allocating subchannels, sensing time and transmission power, while guaranteeing the spectrum sensing performance, the harvested energy, the interference level and the total power. Then we also investigate other resource allocation schemes, which have been formulated as the optimization problems to maximize the overall harvested energy and energy efficiency, respectively.
- We have proposed the resource optimization algorithms to solve the formulated optimization problems. The proposed algorithms can achieve the sub-optimal solutions to the optimization problems.

The rest of the paper is organized as follows. The related works are introduced in Section II. The system model is described in Section III, in which we describe both the multichannel cooperative spectrum sensing and multichannel energy harvesting and formulate the optimization problem of the system model to maximize the throughput. The optimal resource allocation of the system model, including the subchannel allocation and the joint allocation of sensing time and transmission power, is addressed in Section IV; the other resource allocation schemes together with the stopping criteria of the SU are also investigated in this section. The simulation results are presented and discussed in Section V. Finally the conclusions are drawn in Section VI.

II. RELATED WORKS

Cooperative spectrum sensing has been proposed to improve the detection performance through allowing multiple SUs to sense the PU collaboratively, when the sensing path between the PU and the SU is in fading or shadowing [9]- [11]. Every SU first senses the PU to obtain a local detection result by energy detection and then sends the local detection result to a fusion center, the fusion center will combine all the local detection results to get a final decision on the presence of

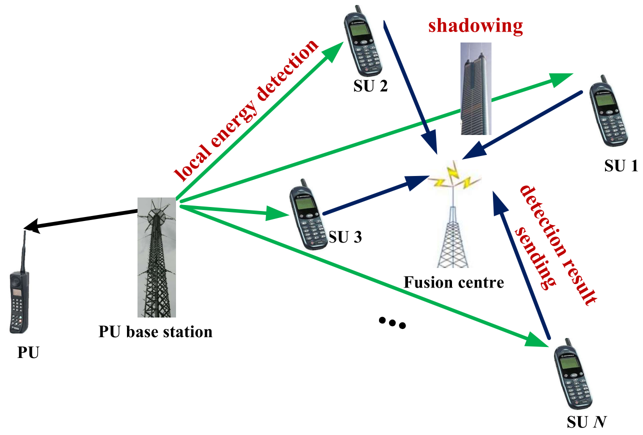

FIGURE 1. Cooperative spectrum sensing model.

the PU, as shown in Fig. 1. If the local detection result is 1-bit decision such as 0, denoting the absence of the PU, or 1, denoting the presence of the PU, the fusion center will combine these one-bit decisions by the logic rule such as "OR rule", "AND rule" and "'K-OUT-N rule". In the "OR rule", the presence of the PU is detected if one SU has detected the PU to be present, while in the "AND Rule", the PU is detected to be present only when all the SUs have detected the presence of the PU. And in the "K-OUT-N" rule, we decide the presence of the PU if at least K SUs have detected the PU to be present. We call this detection process as the hard decisional cooperative spectrum sensing. While if the local detection result is energy statistic, the fusion center will accumulate these energy statistics to get an overall energy statistic and compare the overall energy statistic to a preset threshold for getting the final decision. This sensing process is called as the soft decisional cooperative spectrum sensing. The performance of cooperative spectrum sensing can be improved greatly due to the achieved cooperative diversity gain. In this paper, we have proposed multichannel cooperative spectrum sensing. From different subchannels, one SU senses the PU to get multiple local detection results for combining, which has the same function as the traditional cooperative spectrum sensing.

The simultaneous wireless information and power transfer has been proposed, which may allow the communication system to process data information and harvest RF energy simultaneously. The transmission power is split into two power streams with a preset power splitting factor ρ [21]. In the receiver, one power stream is used for information decoding while the other stream is used for energy harvesting, as shown in Fig. 2. Based on this research, we have proposed simultaneous cooperative spectrum sensing and energy harvesting for multichannel CR. Differing from the traditional power splitting, here we use the subchannel splitting, which splits all the subchannels into sensing subchannel set and harvesting subchannel set.

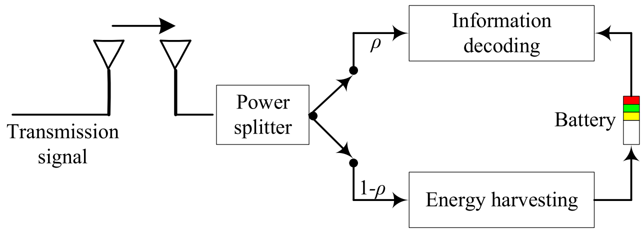

FIGURE 2. Simultaneous wireless information and power transfer model.

III. SYSTEM MODEL

We consider one broadband PU occupying multiple nonoverlapping narrowband subchannels and one SU sharing these subchannels with the PU. Within a particular period of time, the frequency band may not be used by the PU and is available for the spectrum access of the SU. However, the SU must sense the subchannels to decide the absence of the PU before accessing these subchannels. The SU has the function of energy harvesting, which can convert the harvested RF energy from the environmental signal resources to the electrical power. The electrical power is then stored in the rechargeable battery of the SU in order to supply the transmission energy.

A. SIMULTANEOUS COOPERATIVE SPECTRUM SENSING AND ENERGY HARVESTING

To improve the sensing performance, multichannel cooperative spectrum sensing is adopted, which allows the SU to get a final decision through combining the local sensing results from these subchannels. In this paper, a simultaneous cooperative spectrum sensing and energy harvesting model is proposed for multichannel CR. The SU senses the PU and transmits data periodically. The SU may work only when the absence of the PU is detected during spectrum sensing. Thus the frame structure of the SU is divided into sensing slot and transmission slot, the SU performs spectrum sensing in the sensing slot while forwarding data in the transmission slot, as shown in Fig. 3.

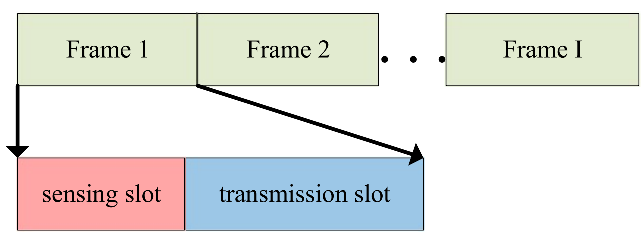

FIGURE 3. Frame structure of the SU.

In an energy harvesting CR, the SU transmitter deploys an energy harvesting device to harvest the RF energy of the environmental signal sources. If the PU is present, the energy of both the PU signal and the noise can be harvested, otherwise, only the energy of the noise can be harvested. The harvested energy is stored in a rechargeable battery, which

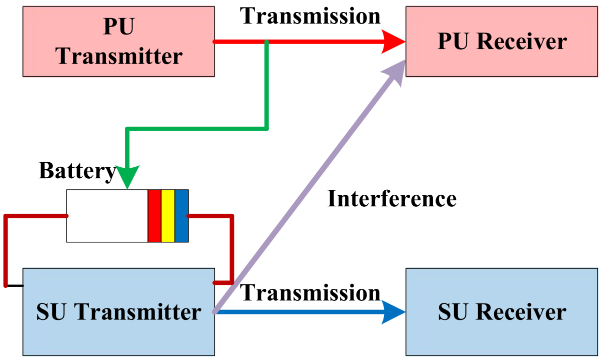

FIGURE 4. Energy-harvesting CR model.

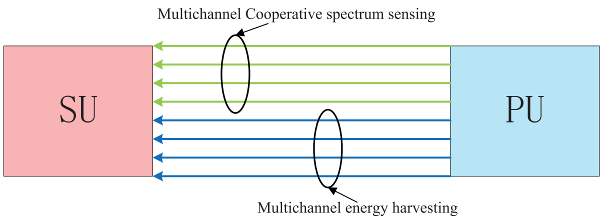

FIGURE 5. Simultaneous cooperative spectrum sensing and energy harvesting model.

is then used for data transmission if the absence of the PU is detected. However, if the absence of the PU is falsely detected, the SU may also access the subchannels and bring interference to the PU during transmission, as shown in Fig. 4. In the sensing slot, the SU senses the PU and harvests the RF energy simultaneously. The SU uses some of the subchannels to sense the PU cooperatively and the residual subchannels to harvest the RF energy of the PU signal and the noise, as shown in Fig. 5. Since for spectrum sensing the SU may consume some stored energy that is primarily used for data transmission, in order to guarantee the transmission performance, the harvested energy must be enough to compensate the sensing energy loss. Thus, the harvested energy should be no less than the consumed spectrum sensing energy. Moreover, the spectrum sensing performance improves with the increasing of the sensing subchannels, while the harvesting performance strengthens as the harvesting subchannels increase. Thus it is important to allocate sensing and harvesting subchannels reasonably.

We suppose the number of all the subchannels is L, the number of the sensing subchannels is L_1 and the number of the harvesting subchannels is L_2; the corresponding aggregate subchannel set, sensing subchannel set and harvesting subchannel set are $\boldsymbol{\Phi}$, $\boldsymbol{\Psi}$ and $\boldsymbol{\Omega}$, respectively. Thus we have $L = L_1 + L_2$ and $\boldsymbol{\Phi} = \boldsymbol{\Psi} \cup \boldsymbol{\Omega}$. We also suppose one subchannel only performs sensing or harvesting within a sensing slot, i.e., $\boldsymbol{\Psi} \cap \boldsymbol{\Omega} = \emptyset$. All the subchannels are selected for $\boldsymbol{\Psi}$ and $\boldsymbol{\Omega}$ in order to guarantee both the performances of spectrum sensing and energy harvesting.

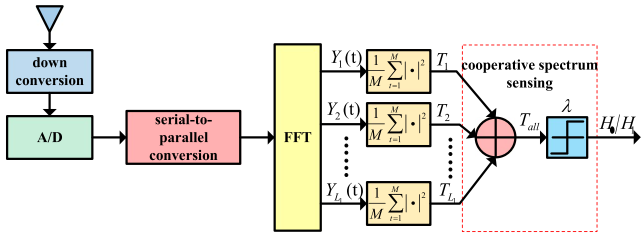

FIGURE 6. Multichannel cooperative spectrum sensing model.

B. MULTICHANNEL COOPERATIVE SPECTRUM SENSING

In the multichannel cooperative spectrum sensing, the SU firstly senses to get the local energy statistics of the PU signal from L_1 sensing subchannels by energy detection, and then combines the L_1 local energy statistics to get an overall energy statistic in the sensing slot, as shown in Fig. 6 [12]. Using the soft decision, the overall energy statistic is finally compared with a threshold λ to achieve the final decision, . Let τ and f_s denote sensing time and sampling rate, respectively, the number of the signal sampling nodes is $M = \tau f_s$. So within the sensing duration, sensing the PU in subchannel l obeys a binary hypothesis as follows

$$y_l(t) = \begin{cases} n_l(t), & H_0 \\ g_l(t)s_l(t) + n_l(t), & H_1 \end{cases} \quad t = 1, 2, \ldots, \tau f_s \tag{1}$$

where H_0 and H_1 denote absence and presence of the PU, respectively; y_l, s_l and n_l denote sensing signal, PU signal and noise in the subchannel l, respectively; g_l denotes the subchannel gain between the PU and the SU. We suppose $s_l(t)$ for $t = 1, 2, \ldots, \tau f_s$ as the independently and identically distributed random variables with variance σ_s^2 and $n_l(t)$ for $t = 1, 2, \ldots, \tau f_s$ as the Gaussian distributed random variables with variance σ_n^2. We also suppose the fast fourier transformation (FFT) of $\{y_l(t)\}$ are $\{Y_l(t)\}$. Thus the local energy statistic of the PU signal in subchannel l is calculated as

$$T_l(Y) = \frac{1}{\tau f_s} \sum_{t=1}^{\tau f_s} |Y_l(t)|^2 \tag{2}$$

At the end of the sensing slot, all the local energy statistics are combined to get the overall energy statistic as

$$T_{all}(Y) = \frac{1}{L_1} \sum_{l=1}^{L_1} T_l(Y) \tag{3}$$

If τf_s is large enough, according to the Center Limit Theorem, $T_{all}(Y)$ obeys the Gaussian distribution approximately as

$$T_{all}(Y) \sim \begin{cases} N\left(\sigma_n^2, \dfrac{\sigma_n^4}{L_1 \tau f_s}\right), & H_0 \\ N\left(\left(1 + \overline{\gamma}(\boldsymbol{\Psi})\right)\sigma_n^2, \dfrac{\sigma_n^4 (1 + \overline{\gamma}(\boldsymbol{\Psi}))^2}{L_1 \tau f_s}\right), & H_1 \end{cases} \tag{4}$$

where $N(a, b)$ denotes the Gaussian distribution with mean a and variance b, $\overline{\gamma}(\boldsymbol{\Psi}) = \frac{1}{L_1} \sum_{l=1}^{L_1} \frac{\sigma_s^2 g_l^2}{\sigma_n^2}$ denotes the average

PU signal to noise ratio (PSNR) of the subchannels belong to the set $\mathbf{\Psi}$.

Comparing $T_{all}(Y)$ with λ, the PU is decided to be absent if $T_{all}(Y) \leq \lambda$, or present otherwise. From (4), the cooperative probabilities of false alarm and detection, which are related with sensing time, subchannel set and sensing threshold, are calculated as

$$\begin{aligned} P_f(\tau, \mathbf{\Psi}, \lambda) &= P_r(T_{all}(Y) > \lambda | H_0) \\ &= Q\Big(\big(\frac{\lambda}{\sigma_n^2} - 1\big)\sqrt{L_1 \tau f_s} \Big) \end{aligned} \tag{5}$$

and

$$\begin{aligned} P_d(\tau, \mathbf{\Psi}, \lambda) &= P_r(T_{all}(Y) > \lambda | H_1) \\ &= Q\Big(\big(\frac{\lambda}{\sigma_n^2} - \overline{\gamma}(\mathbf{\Psi}) - 1\big)\sqrt{\frac{L_1 \tau f_s}{(\overline{\gamma}(\mathbf{\Psi})+1)^2}} \Big) \end{aligned} \tag{6}$$

where the function $Q(x)$ is described as

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{+\infty} \exp(-\frac{z^2}{2})\, dz \tag{7}$$

The detection probability is often presettled according to the communication demands for controlling the interference to the PU. Hence, with the fixed detection probability P_d, the sensing threshold is obtained from (6) as

$$\lambda = \left(Q^{-1}(P_d)\sqrt{\frac{(\overline{\gamma}(\mathbf{\Psi})+1)^2}{L_1 \tau f_s}} + \overline{\gamma}(\mathbf{\Psi}) + 1 \right) \sigma_n^2 \tag{8}$$

Substituting (8) into (5), the false alarm probability P_f denoted by P_d is calculated as

$$P_f(\tau, \mathbf{\Psi}) = Q\Big(Q^{-1}(P_d)\big(\overline{\gamma}(\mathbf{\Psi}) + 1\big) + \overline{\gamma}(\mathbf{\Psi})\sqrt{L_1 \tau f_s} \Big) \tag{9}$$

In order to guarantee enough spectrum access, from (9) we often set $P_f \leq 0.5$ to get the lower limit of sensing time as

$$\tau \geq \tau_{low} \;\text{ where }\; \tau_{low} = \frac{\Big(Q^{-1}(P_d)\big(\overline{\gamma}(\mathbf{\Psi}) + 1\big) \Big)^2}{\big(\overline{\gamma}(\mathbf{\Psi})\big)^2 L_1 f_s} \tag{10}$$

Supposing the frame duration is T and ordering $T \geq \tau_{low}$ with any subchannel PSNRs, from (10) we can get

$$T \geq \frac{\Big(Q^{-1}(P_d)(\gamma_{min} + 1) \Big)^2}{\gamma_{min}^2 f_s} \tag{11}$$

where γ_{min} denotes the minimal PSNR among those of all the subchannels.

C. MULTICHANNEL ENERGY HARVESTING

In simultaneous cooperative spectrum sensing and energy harvesting model, the SU is consisted of one spectrum sensing device and one energy harvesting device. The SU detects the PU while storing the arriving RF energy of the PU signal in a rechargeable battery. The energy harvesting process is implemented by an energy harvesting circuit consisting of band-pass filter, rectifying circuit and low-pass filter. The out-of-band electromagnetism interference to the received signal is first filtered through the band-pass filter, then the RF output of the band-pass filter is converted to the DC signal with the rectifying circuit, finally the DC power is obtained through filtering the harmonic and fundamental signals of the DC signal with the low-pass filter, as shown in Fig 7 [22], [23]. But some of the received RF energy may be leaked to the surrounding environment due to the circuit electromagnetism compatibility, so we assume $0 < \mu < 1$ is the energy harvesting efficiency.

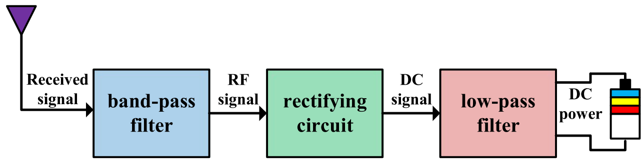

FIGURE 7. Energy harvesting structure.

During the sensing time, the SU harvests the RF energy of the received PU signal and noise from the subchannels belong to $\mathbf{\Omega}$. However, the energy of the PU signal can be harvested only when the PU is present actually. We suppose that the probabilities of H_0 and H_1 are $P_r(H_0)$ and $P_r(H_1)$, respectively. From (1), the overall harvesting energy, which is related with sensing time and harvesting subchannel set, is calculated as

$$\begin{aligned} E_H(\tau, \mathbf{\Omega}) &= \mu\tau \sum_{l=1}^{L_2} \big(P_r(H_1)\sigma_s^2 g_l^2 + \sigma_n^2\big) \\ &= \mu\tau L_2 \sigma_n^2 \big(1 + P_r(H_1)\overline{\gamma}(\mathbf{\Omega})\big) \end{aligned} \tag{12}$$

where $\overline{\gamma}(\mathbf{\Omega})$ denotes the average PSNR of the subchannels belong to $\mathbf{\Omega}$. In order to guarantee the transmission power is not losing, the harvested energy E_H should be no less than the sensing energy loss E_S, i.e., $E_H \geq E_S$. Supposing the average electrical energy for processing one signal sampling is Δe, the aggregate energy consumed by cooperative spectrum sensing is $E_S = L_1 \tau f_s \Delta e$. Then from (12) we have

$$\frac{L_1}{L_2} \leq \frac{\mu\sigma_n^2\big(1 + P_r(H_1)\overline{\gamma}(\mathbf{\Omega})\big)}{f_s \Delta e} \tag{13}$$

D. OPTIMIZATION PROBLEM FORMULATION

The transmission time of the SU is $T - \tau$. The SU can transmit data effectively only when the absence of the PU is detected accurately. Hence, within one frame the aggregate throughput of the SU over L subchannels, which is related with sensing time, subchannel set and transmission power, is give as

$$\begin{aligned} R(\tau, \{p_l\}, \mathbf{\Psi}) = &(T - \tau)\big(1 - P_f(\tau, \mathbf{\Psi})\big)P_r(H_0) \\ &\times \sum_{l=1}^{L} \log\left(1 + \frac{p_l h_l^2}{\sigma_n^2}\right) \end{aligned} \tag{14}$$

where $\{p_l\}$ is the transmission power set of the SU in L subchannels, h_l is the subchannel gain between the transmitter and receiver of the SU. Then we also define the spectrum access probability as

$$P_{Acc}(\tau,\mathbf{\Psi}) = \big(1-P_f(\tau,\mathbf{\Psi})\big)P_r(H_0)$$
$$= P_r(H_0)\Big(1-Q\Big(Q^{-1}(P_d)\big(\overline{\gamma}(\mathbf{\Psi})+1\big)+\overline{\gamma}(\mathbf{\Psi})\sqrt{L_1\tau f_s}\Big)\Big) \tag{15}$$

Our goal of resource allocation is to maximize the aggregate throughput of the SU by jointly optimizing sensing time, subchannel and transmission power, subject to the constraints that the false alarm probability p_f is below 0.5, the detection probability p_d is above the lower limit β, the harvested energy E_H is above the sensing energy loss E_S, the aggregate interference power to the PU is within the maximal interference level I_{max} and the aggregate transmission power is within the maximal power p_{max}. So the optimization problem is formulated as

$$\max_{\tau,\{p_l\},\mathbf{\Psi}} \ R(\tau,\{p_l\},\mathbf{\Psi}) \tag{16a}$$
$$\text{s.t. } P_f \le 0.5, \quad P_d \ge \beta \tag{16b}$$
$$E_H \ge E_S \tag{16c}$$
$$\sum_{l=1}^{L} p_l g_l^2 \le I_{max} \tag{16d}$$
$$\sum_{l=1}^{L} p_l \le p_{max} \tag{16e}$$
$$0 \le \tau \le T \tag{16f}$$
$$p_l \ge 0, \quad l = 1,2,\ldots,L \tag{16g}$$

IV. OPTIMAL RESOURCE ALLOCATION

The proposed optimization problem (16) is NP-hard, thus we calculate the sub-optimal solution. To simplify the optimization problem, we give the *Remark 1*.

Remark 1: Since $Q(x)$ is a monotonously decreasing function, from (5) and (6) both P_f and P_d decrease as λ increases. To maximize R, we should decrease P_f as low as possible, thus λ should be increased until P_d achieves the lower limit, i.e., $P_d = \beta$.

Substituting $P_d = \beta$ into (9) and (18), we can get the upper limit of R as (17), as shown at the bottom of this page.

A. SUBCHANNEL ALLOCATION

We fix τ and $\{p_l\}$, then the optimization problem (16) is solved through optimizing $\mathbf{\Psi}$. From (13), the satisfaction of the constraint (16c) is calculated as

$$L_1 \le \frac{\eta}{\eta+1}L \ \text{ where } \ \eta = \frac{\mu\sigma_n^2\big(1+P_r(H_1)\gamma_{min}\big)}{f_s\Delta e} \tag{18}$$

Hence, from (14) the objective function about $\mathbf{\Psi}$ is simply rewritten as

$$R(\mathbf{\Psi}) = \xi\Big(1-Q\Big(Q^{-1}(\beta)\big(\overline{\gamma}(\mathbf{\Psi})+1\big)+\overline{\gamma}(\mathbf{\Psi})\sqrt{L_1\tau f_s}\Big)\Big) \tag{19}$$

where $\xi = (T-\tau)P_r(H_0)\sum_{l=1}^{L}\log\big(1+\frac{p_l h_l^2}{\sigma_n^2}\big)$ is a constant due to the fixed τ and $\{p_l\}$. So the optimization problem (16) is rewritten as

$$\max_{\mathbf{\Psi}} \ R(\mathbf{\Psi}) \tag{20a}$$
$$\text{s.t. } L_1 \le \frac{\eta}{\eta+1}L \tag{20b}$$

The optimization problem (20) can be solved by the Greedy algorithm. We define the L subchannels as SC_l for $l = 1,2,\ldots,L$. The subchannels allocation algorithm is described as the *Algorithm 1* with the time complexity $O(\frac{\eta}{\eta+1}L\log L)$. Since ξ is only a coefficient in (19), the subchannel allocation result will not be affected by $\{p_l\}$.

Algorithm 1 Subchannel Allocation Based on the Greedy Algorithm

1: Fix τ and $\{p_l\}$ with presettled values; initialize $\mathbf{\Psi} = \emptyset$, $\mathbf{\Phi} = \{SC_1, SC_2, \ldots,, SC_L\}$, $R(\mathbf{\Psi}) = 0$ and $i = 0$;
2: **while** $i \le \frac{\eta}{\eta+1}L$ **do**
3: Search $SC_i^* = \text{argmax}\big(\Delta R_i = R(\mathbf{\Psi}\cup SC_l) - R(\mathbf{\Psi})\big)$ for $SC_l \in \mathbf{\Phi}$ according to (19);
4: **if** $\Delta R_i \le 0$ **then**
5: break;
6: **else**
7: Set $\mathbf{\Psi} = \mathbf{\Psi}\cup SC_i^*$, $\mathbf{\Phi} = \mathbf{\Phi} - SC_i^*$ and $i = i+1$;
8: **end if**
9: **end while**
10: Output $L_1 = i$, $\mathbf{\Psi}$ and $\mathbf{\Omega} = \mathbf{\Phi}$.

B. JOINT ALLOCATION OF SENSING TIME AND TRANSMISSION POWER

After we have achieved the subchannel allocation result $\mathbf{\Psi}$, $\overline{\gamma}(\mathbf{\Psi})$ will be a constant $\overline{\gamma}$, thus we can get the optimization problem about sensing time τ by fixing $\{p_l\}$. Then the objective function about τ is simply rewritten as follows

$$R(\tau) = \epsilon(T-\tau)\Big(1-Q\Big(\varphi+\overline{\gamma}\sqrt{L_1\tau f_s}\Big)\Big) \tag{21}$$

where both $\epsilon = P_r(H_0)\sum_{l=1}^{L}\log\big(1+\frac{p_l h_l^2}{\sigma_n^2}\big)$ and $\varphi = Q^{-1}(\beta)(\overline{\gamma}+1)$ are constants. Then from (10) and (21), the

$$R\big(\tau,\{p_l\},\mathbf{\Psi}\big) \le (T-\tau)P_r(H_0)\Big(1-Q\Big(Q^{-1}(\beta)\big(\overline{\gamma}(\mathbf{\Psi})+1\big)+\overline{\gamma}(\mathbf{\Psi})\sqrt{L_1\tau f_s}\Big)\Big)\sum_{l=1}^{L}\log\left(1+\frac{p_l h_l^2}{\sigma_n^2}\right) \tag{17}$$

optimization problem (16) is rewritten as

$$\max_{\tau} \ R(\tau) \tag{22a}$$
$$\text{s.t. } \tau_{low} \le \tau \le T \tag{22b}$$

To solve the optimization problem (22), we give the following *Theorem 1* with the proof in the *Appendix A*.

Theorem 1: when $P_f \le 0.5$, Eq. (22) is a convex optimization problem, i.e., there exists some $\tau_0 \in [0, T]$ that makes $R(\tau_0)$ achieve the maximum.

We suppose $\nabla R(\tau)$ is the first-order partial derivative of $R(\tau)$ in τ. The maximal node τ_0 can be achieved through the half searching algorithm, as shown in *Algorithm 2*. The time complexity of the *Algorithm 2* is $O(\log(\frac{T}{\delta}))$. Since $\tau \ge \tau_{low}$

Algorithm 2 Sensing Time Optimization Based on the Half Searching

1: Initialize $\tau_{min} = 0$, $\tau_{max} = T$ and the searching precision δ;
2: **while** $|\tau_{max} - \tau_{min}| > \delta$ **do**
3: Let $\overline{\tau} = \frac{\tau_{max}+\tau_{min}}{2}$;
4: **if** $\nabla R(\overline{\tau}) \equiv \nabla R(\tau_{min})$ **then**
5: Let $\tau_{min} = \tau$;
6: **else**
7: Let $\tau_{max} = \tau$;
8: **end if**
9: **end while**
10: Output $\tau_0 = \overline{\tau}$.

must be satisfied, the optimal value τ^* is given as

$$\tau^* = \max\{\tau_{low}, \tau_0\} \tag{23}$$

When fixing τ, the optimization problem (16) is solved by optimizing $\{p_l\}$. Then the objective function about $\{p_l\}$ is rewritten as

$$R(\{p_l\}) = \omega \sum_{l=1}^{L} \log\left(1 + \frac{p_l h_l^2}{\sigma_n^2}\right) \tag{24}$$

where $\omega = (T - \tau)\big(1 - P_f(\tau, \boldsymbol{\Psi})\big)P_r(H_0)$ is a constant. The optimization problem of $\{p_l\}$ is given as

$$\max_{\{p_l\}} \ R(\{p_l\}) \tag{25a}$$
$$\text{s.t. } \sum_{l=1}^{L} p_l g_l^2 \le I_{max} \tag{25b}$$
$$\sum_{l=1}^{L} p_l \le p_{max} \tag{25c}$$
$$p_l \ge 0, \quad l = 1, 2, \ldots, L \tag{25d}$$

According to the Karush-Kuhn-Tucker (KKT) condition, the Lagrange multiplier formula is given as [24]

$$\Gamma(\alpha_1, \alpha_2, \{p_l\}) = \omega \sum_{l=1}^{L} \log\left(1 + \frac{p_l h_l^2}{\sigma_n^2}\right) - \alpha_1\left(\sum_{l=1}^{L} p_l g_l^2 - I_{max}\right) - \alpha_2\left(\sum_{l=1}^{L} p_l - p_{max}\right) \tag{26}$$

where α_1 and α_2 are the Lagrange multipliers. The optimal $\{p_l\}$ can be obtained by $\frac{\partial \Gamma(\alpha_1,\alpha_2,p_l)}{\partial p_l} = 0$ for $l = 1, 2, \ldots, L$, as follows

$$p_l^* = \left[\frac{\omega}{\alpha_1 g_l^2 + \alpha_2} - \frac{\sigma_n^2}{h_l^2}\right]^+ \tag{27}$$

where the Lagrange multipliers α_1 and α_2 can be obtained by using the gradient method that leads to the following update equations

$$\alpha_1(\kappa+1) = \left[\alpha_1(\kappa) + \varepsilon_1(\kappa) \times \left(\sum_{l=1}^{L} p_l^* g_l^2 - I_{max}\right)\right]^+ \tag{28}$$

$$\alpha_2(\kappa+1) = \left[\alpha_2(\kappa) + \varepsilon_2(\kappa) \times \left(\sum_{l=1}^{L} p_l^* - p_{max}\right)\right]^+ \tag{29}$$

where $\kappa \ge 0$ is the iteration index, $\varepsilon_1(\kappa)$ and $\varepsilon_2(\kappa)$ are both the positive step sizes. Then, the updated Lagrange multipliers in (28) and (29) are used for updating the power allocation in (27). The power optimization is described in the *Algorithm 3*.

Algorithm 3 Power Optimization Based on KKT

1: Initialize $\kappa = 0$, $\alpha_1(\kappa)$, $\alpha_2(\kappa)$, $\varepsilon_1(\kappa)$ and $\varepsilon_2(\kappa)$ with the presettled values;
2: **while** $\alpha_1(\kappa)$ and $\alpha_2(\kappa)$ are not convergent **do**
3: Update $\{p_l^*\}$ by (27) with $\alpha_1(\kappa)$ and $\alpha_2(\kappa)$;
4: Update $\alpha_1(\kappa+1)$ and $\alpha_2(\kappa+1)$ by (28) and (29) with updated $\{p_l^*\}$, $\varepsilon_1(\kappa)$ and $\varepsilon_2(\kappa)$;
5: Let $\kappa = \kappa + 1$;
6: **end while**
7: Output $\{p_l^*\}$.

We use alternating direction optimization (ADO) to jointly allocating sensing time and transmission power as follows [25]: with the given $\boldsymbol{\Psi}$, we first optimize τ by fixing $\{p_l\}$ with certain values and then optimize $\{p_l\}$ with the optimized τ; this process is implemented iteratively until both τ and $\{p_l\}$ are convergent; we finally update $\boldsymbol{\Psi}$ with the convergent τ and $\{p_l\}$. We repeat to perform ADO until $\boldsymbol{\Psi}$ is not changed. The joint allocation algorithm of sensing time and transmission power is described in the *Algorithm 4*. Note that the value of R is not decreasing in every iteration of the joint optimization algorithm, as follows

$$R\Big(\tau(i), \{p_l(i)\}\Big) \le R\Big(\tau(i+1), \{p_l(i)\}\Big) \le R\Big(\tau(i+1), \{p_l(i+1)\}\Big) \tag{30}$$

where i is the iteration index. Eq. (30) indicates R is convergent when both τ and $\{p_l(i)\}$ are convergent.

Algorithm 4 Joint Optimization Algorithm Based on ADO

Initialize $i = 0$, $\{p_l(i)\}$ with any positive values that satisfy $\sum_{l=1}^{L} p_l g_l^2 \leq I_{max}$ and $\sum_{l=1}^{L} p_l \leq p_{max}$, and $\tau(i)$ with any value within (0, 1); calculate $\boldsymbol{\Psi}$ with $\{p_l(i)\}$ and $\tau(i)$ by **Algorithm** (1);
while $\boldsymbol{\Psi}$ is changed **do**
  while $\{p_l(i)\}$ and $\tau(i)$ are not convergent **do**
    Using $\boldsymbol{\Psi}$, optimize to get τ^* by **Algorithm** (2) with $\{p_l(i)\}$;
    Set $\tau(i+1) = \tau^*$;
    Optimize to get $\{p_l^*\}$ by **Algorithm** (3) with $\tau(i+1)$;
    Set $\{p_l(i+1)\} = \{p_l^*\}$ and $i = i + 1$;
  end while
  Update $\boldsymbol{\Psi}$ with $\{p_l(i)\}$ and $\tau(i)$ by **Algorithm** (1);
end while
Output $\{p_l\} = \{p_l(i)\}$ and $\tau = \tau(i)$.

C. OTHER RESOURCE ALLOCATION SCHEMES

1) HARVESTING ENERGY MAXIMIZATION

this resource allocation scheme is to maximize the harvested energy of the SU, while guaranteeing that the throughput of the SU is above the lower limit R_{low}, as follows

$$\max_{\tau,\{p_l\},\boldsymbol{\Omega}} E_H(\tau, \boldsymbol{\Omega}) = \mu\tau L_2\sigma_n^2\big(1 + P_r(H_1)\overline{\gamma}(\boldsymbol{\Omega})\big) \quad (31a)$$
$$\text{s.t. } P_f \leq 0.5, \quad P_d \geq \beta \quad (31b)$$
$$R(\tau, \{p_l\}, \boldsymbol{\Psi}) \geq R_{low} \quad (31c)$$
$$\sum_{l=1}^{L} p_l g_l^2 \leq I_{max} \quad (31d)$$
$$\sum_{l=1}^{L} p_l \leq p_{max} \quad (31e)$$
$$0 \leq \tau \leq T \quad (31f)$$
$$p_l \geq 0, \quad l = 1, 2, \ldots, L \quad (31g)$$

After getting the subchannel allocation, the solution to (31) can be achieved through jointly optimizing sensing time and transmission power, which is similar with the proposed joint optimization in the *Algorithm 4*. Thus fixing τ and $\{p_l\}$, we rewrite E_H with $\boldsymbol{\Omega}$ as

$$E_H(\boldsymbol{\Omega}) = \zeta L_2\big(1 + P_r(H_1)\overline{\gamma}(\boldsymbol{\Omega})\big) \quad (32)$$

where $\zeta = \mu\tau\sigma_n^2$. Since $\boldsymbol{\Phi} = \boldsymbol{\Omega} \cup \boldsymbol{\Psi}$, we may get

$$R(\boldsymbol{\Omega}) = R(\boldsymbol{\Phi}) - R(\boldsymbol{\Psi}) \quad (33)$$

where $R(\boldsymbol{x})$ is calculated by (19). Obviously, $R(\boldsymbol{\Phi})$ is a constant. Since the constraint $R(\boldsymbol{\Psi}) \geq R_{low}$ must be satisfied, we can get $R(\boldsymbol{\Omega}) \leq R(\boldsymbol{\Phi}) - R_{low}$. Hence, we can also use the Greedy algorithm to obtain the subchannel allocation, as shown in the *Algorithm 5*. Then substituting the *Algorithm 5* in to the *Algorithm 4* instead of the *Algorithm 1*, we can get the optimal solution.

Algorithm 5 Subchannel Allocation for Harvesting Energy Maximization

Fix τ and $\{p_l\}$ with presettled values; initialize $\boldsymbol{\Omega} = \emptyset$, $\boldsymbol{\Phi} = \{SC_1, SC_2, \ldots, , SC_L\}$, $R(\boldsymbol{\Omega}) = 0$ and $i = 0$;
Calculate $\widetilde{R} = R(\boldsymbol{\Phi}) - R_{low}$ by (19) with all the L subchannels;
while $R(\boldsymbol{\Omega}) \leq \widetilde{R}$ **do**
  Search $SC_i^* = \text{argmax}\,\big(\triangle E_H = E_H(\boldsymbol{\Omega} \cup SC_l) - E_H(\boldsymbol{\Omega})\big)$ for $SC_l \in \boldsymbol{\Phi}$ according to (32);
  if $\triangle E_H \leq 0$ **then**
    break;
  else
    Set $\boldsymbol{\Omega} = \boldsymbol{\Omega} \cup SC_i^*$ and $\boldsymbol{\Phi} = \boldsymbol{\Phi} - SC_i^*$;
    Set $i = i + 1$ and calculate $R(\boldsymbol{\Omega})$;
  end if
end while
Output $L_2 = i$, $\boldsymbol{\Omega}$ and $\boldsymbol{\Psi} = \boldsymbol{\Phi}$.

2) ENERGY EFFICIENCY MAXIMIZATION

Supposing the consumed transmission energy is $E_T = p_{max}(T - \tau)$, the overall consumed energy stored in the battery is given by $E_C = E_T + E_S - E_H$. For describing both the energy harvesting and transmission performance, we define the energy efficiency of the SU as the aggregate throughput to the overall consumed energy ratio, as follows

$$\begin{aligned}\rho(\tau, \{p_l\}, \boldsymbol{\Omega}) &= \frac{R(\tau, \{p_l\}, \boldsymbol{\Omega})}{E_C(\tau, \{p_l\}, \boldsymbol{\Omega})} \\ &= \frac{(T-\tau)P_r(H_0)\big(1 - P_f(\tau, \boldsymbol{\Psi})\big)\sum_{l=1}^{L}\log\left(1 + \frac{p_l h_l^2}{\sigma_n^2}\right)}{p_{max}(T-\tau) + L_1 f_s \tau \triangle e - \mu\tau L_2\sigma_n^2\big(1 + P_r(H_1)\overline{\gamma}(\boldsymbol{\Omega})\big)}\end{aligned} \quad (34)$$

Thus we can also formulate the joint resource allocation as another optimization problem for maximizing the energy efficiency of the SU, as follows

$$\max_{\tau,\{p_l\},\boldsymbol{\Omega}} \rho(\tau, \{p_l\}, \boldsymbol{\Omega}) \quad (35a)$$
$$\text{s.t. } P_f \leq 0.5, \quad P_d \geq \beta \quad (35b)$$
$$\sum_{l=1}^{L} p_l g_l^2 \leq I_{max} \quad (35c)$$
$$\sum_{l=1}^{L} p_l \leq p_{max} \quad (35d)$$
$$0 \leq \tau \leq T \quad (35e)$$
$$p_l \geq 0, \quad l = 1, 2, \ldots, L \quad (35f)$$

The optimization problem (35) can be solve by the Dinkelbach's optimization method [26], as described in the *Algorithm 6*.

D. STOPPING CRITERIA OF THE SU

Sometimes the PU may not be present within the current frame duration, i.e., $P_r(H_1) = 0$ in (12). Then the SU will

Algorithm 6 Energy Efficiency Optimization Based on the Dinkelbach's Optimization

1: Initialize $\nu(i) = 0$, $i = 1$ and the calculation precision δ;
2: Find the optimal solution $\left(\tau(i), \{p_l(i)\}, \mathbf{\Omega}(i)\right)$ to the optimization problem $G(\nu(i)) = \max\left(R\left(\tau(i), \{p_l(i)\}, \mathbf{\Omega}(i)\right) - \nu(i) \times E_C\left(\tau(i), \{p_l(i)\}, \mathbf{\Omega}(i)\right)\right)$;
3: **if** $G(\nu(i)) \leq \delta$ **then**
4: Proceed to **Step** (9);
5: **else**
6: Proceed to **Step** (8);
7: **end if**
8: Calculate $\nu(i+1) = \frac{R\left(\tau(i), \{p_l(i)\}, \mathbf{\Omega}(i)\right)}{E_C\left(\tau(i), \{p_l(i)\}, \mathbf{\Omega}(i)\right)}$, set $i = i+1$, then return to **Step** (2);
9: Output the optimal solution $(\tau, \{p_l\}, \mathbf{\Omega}) = \left(\tau(i), \{p_l(i)\}, \mathbf{\Omega}(i)\right)$.

not harvest enough energy during the sensing slot, thus the SU has to stop communicating in the transmission slot and continue harvesting the noise energy with all the subchannels. If the harvested energy has been enough, the SU will transmit data again in the following frame. This stopping case happens when the harvested energy adding the stored battery energy is less than the consumed energy of both cooperative spectrum sensing and data transmission, as follows

$$\mu\tau L_2\sigma_n^2 + E_b < L_1 f_s \tau \triangle e + p_{max}(T - \tau) \tag{36}$$

where E_b is the primarily stored energy in the battery. The SU stops transmission if the sensing time satisfies

$$\tau < \frac{p_{max}T - E_b}{\mu L_2\sigma_n^2 + p_{max} - f_s L_1 \triangle e} \tag{37}$$

Then the SU will continue harvesting the noise energy during the whole transmission slot with L subchannels. Thus the overall harvested noise energy within the current frame is given by

$$E_H = \mu\sigma_n^2\left(\tau L_2 + (T - \tau)L\right) \tag{38}$$

If the SU can transmit data without any energy loss in the following frame, the overall harvested energy adding the stored energy must be no less than the maximal consumed transmission energy, which is given as

$$\mu\sigma_n^2\left(\tau L_2 + (T - \tau)L\right) + E_b \geq p_{max}(T - \tau) \tag{39}$$

where we can get the upper limit of the frame duration as

$$T \leq \frac{(p_{max} - \mu L_1\sigma_n^2)\tau + E_b}{p_{max} - \mu L\sigma_n^2} \tag{40}$$

If (40) is satisfied for any τ, we may let $\tau = 0$ and then have

$$T \leq \frac{E_b}{p_{max} - \mu L\sigma_n^2} \tag{41}$$

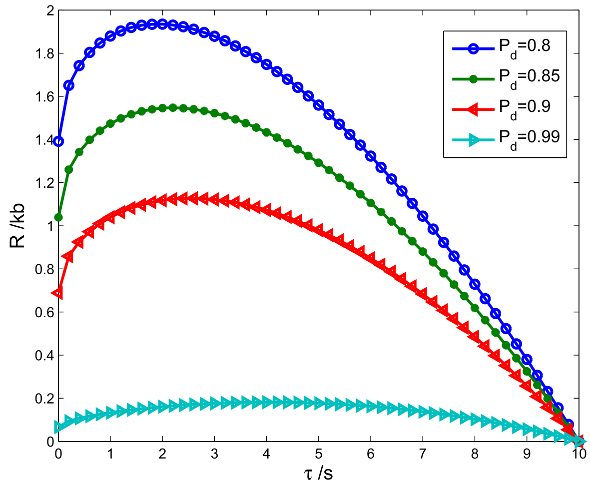

FIGURE 8. Throughput vs. detection probability with different sensing time.

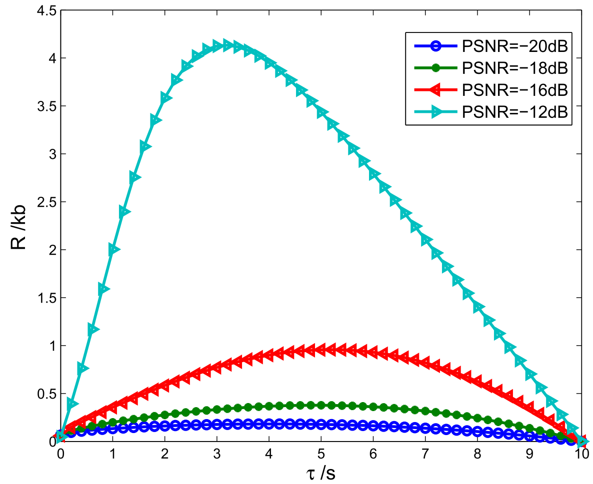

FIGURE 9. Throughput vs. PSNR with different sensing time.

V. SIMULATIONS AND DISCUSSIONS

The assumptions in the simulations are given as follows. There are $L = 20$ subchannels, which obeys the Rayleigh distribution with the mean -15dB; the absence and presence probabilities of the PU are $P_r(H_0) = P_r(H_1) = 0.5$, respectively; the frame duration is $T = 10$s and the bandwidth of the subchannel is 1kHz; the maximal transmission power of the SU is $p_{max} = 10$mW, the maximal interference power to the PU is $I_{max} = 0.01$mW, and the noise power is $\sigma_n^2 = 10^{-3}$mW; the power of the PU is various according to the presettled PSNR; the energy harvesting efficiency is $\mu = 0.8$.

Fig. 8 and Fig. 9 show the SU's throughput R vs. detection probability P_d and PSNR, respectively, with different sensing time τ. We can see that R is lower both with shorter and longer τ. Because the false alarm probability P_f is larger with shorter τ, which decreases the spectrum access probability P_{Acc}; while the transmission time $T - \tau$ decreases with longer τ. Thus there exists an optimal τ that makes R achieve the maximum. From Fig. 8, We also see that

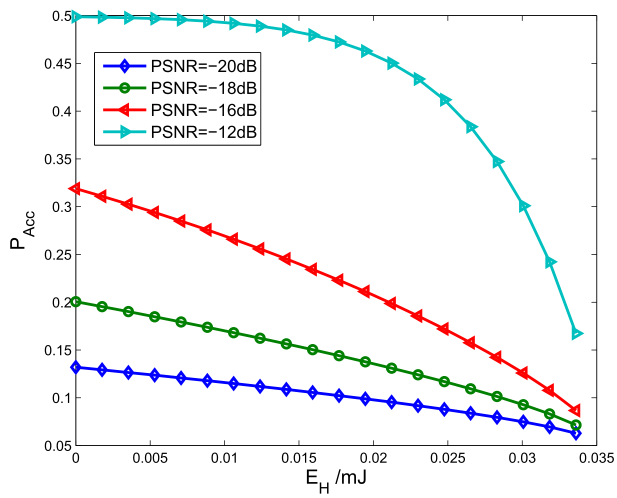

FIGURE 10. Spectrum access probability vs. PSNR with different harvested energy.

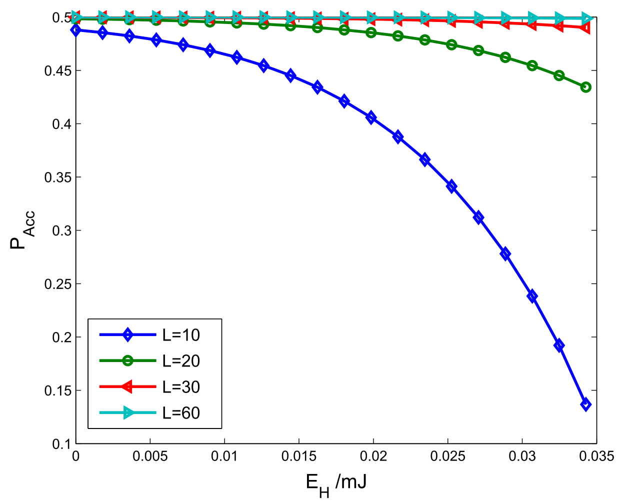

FIGURE 11. Spectrum access probability vs. the number of subchannels with different harvested energy.

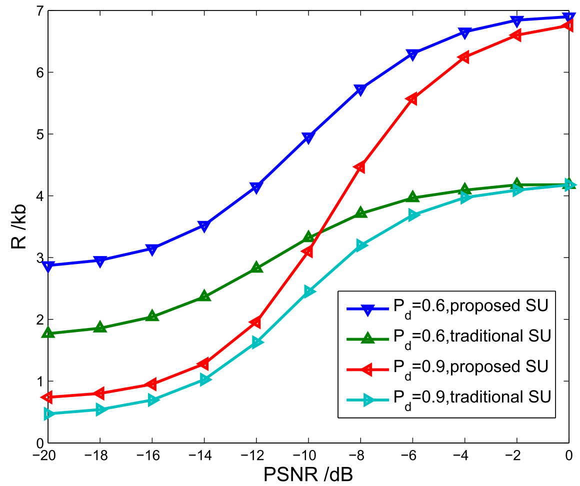

FIGURE 12. Maximal throughput vs. different models with different PSNR.

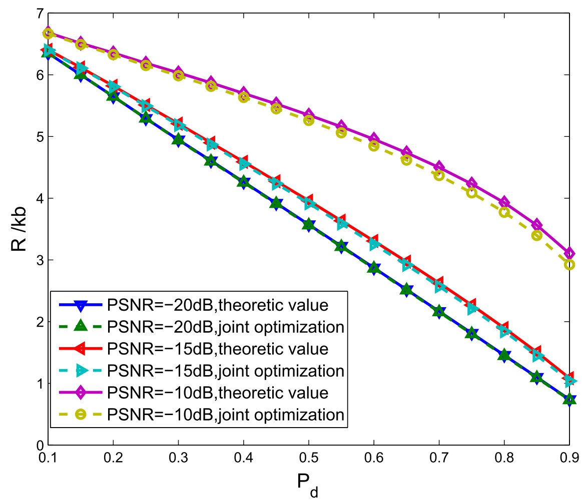

FIGURE 13. Maximal throughput vs. theoretic value and joint optimization.

R improves as P_d decreases, which indicates R may achieve the maximum only when P_d equals to the lower limit. All these verify the correctness of our theory.

Fig. 10 and Fig. 11 indicate the spectrum access probability P_{Acc} vs. PSNR and the number of subchannels L, respectively, with different harvested energy E_H. In these two figures, P_{Acc} decreases as E_H increases. Because increasing E_H needs to use more subchannels for energy harvesting, while the performance of cooperative spectrum sensing may degrade with less sensing subchannels. Thus increasing the harvested energy will not always improve the throughput of the SU, there is a tradeoff between energy harvesting and data transmission. Hence, it is feasible that we let the harvested energy compensate the sensing energy loss justly. However, Fig. 11 shows P_{Acc} will not be affected by the increasing of E_H if L is large enough, because there will be more subchannels to sense the PU collaboratively for guaranteeing the cooperative spectrum sensing performance.

Fig. 12 compares the maximal throughputs of the SU achieved in the proposed model and the traditional model, respectively. It is seen that the proposed simultaneous cooperative spectrum sensing and energy harvesting model results in higher throughput than the traditional model in [15]. And the predominance of the proposed model is obvious when PSNR is low. Fig. 13 compares the theoretically maximal throughput and the maximal throughput obtained by the proposed joint optimization algorithm. We can see that the maximum throughput obtained by the joint optimization algorithm accords with the corresponding theoretical maximum.

Fig. 14 shows energy efficiency ρ vs. PSNR with different sensing time τ. We can see that there is the optimal τ that maximizes the energy efficiency of the SU. Because the throughput reduces as the sensing time decreases, while the sensing energy loss increases as the sensing time improves. Both reducing throughput and increasing energy loss will decrease the energy efficiency. Thus there is also a tradeoff between spectrum sensing and energy efficiency.

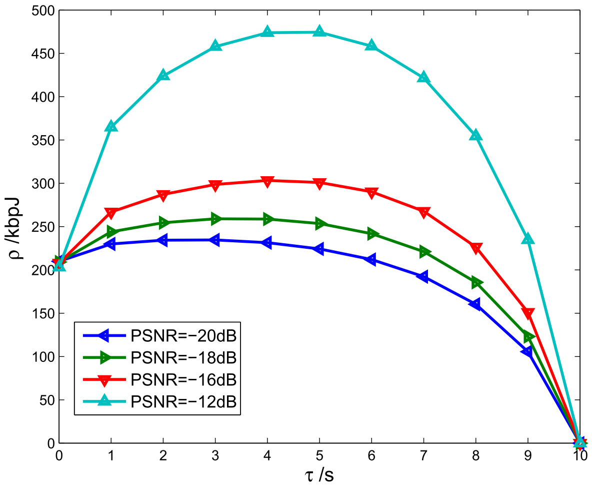

FIGURE 14. Energy efficiency vs. PSNR with different sensing time.

VI. CONCLUSIONS

In this paper, we have proposed the simultaneous cooperative spectrum sensing and energy harvesting model for multichannel CR together with its resource allocation schemes. The basic strategy is to take into account the simultaneous implementation of spectrum sensing and energy harvesting for the multichannel SU in the sensing slot through splitting the subchannels. The harvested energy in the sensing slot is stored in a rechargeable battery and later used to compensate the sensing energy loss in the transmission slot, in order to guarantee the throughput of the SU. We have formulated the different resource allocation schemes into a class of joint optimization problems to maximize throughput, harvested energy and energy efficiency, respectively. To obtain a suboptimal solution, we have proposed the subchannel allocation algorithm and the joint optimization algorithm of sensing time and transmission power based on the Greedy algorithm and ADO. The stopping criteria of the SU is also analyzed, when the PU is not present but the harvested energy is not enough.

From the simulation results we have got several conclusions as follows.

- The performance of cooperative spectrum sensing will not improve much when the number of cooperative subchannels is large enough, thus the energy consumption of spectrum sensing can be compensated while guaranteeing spectrum sensing performance through using some of the subchannels for energy harvesting.
- The throughput can be decreased with both less or larger sensing time. Thus, there exists a sensing-throughput tradeoff in CR, and we need to obtain the optimal sensing time to maximize the throughput of the SU.
- The performance of cooperative spectrum sensing improves with the increasing of sensing subchannels, while the performance of energy harvesting reduces with the decreasing of harvesting subchannels. Thus, there is also a tradeoff between energy harvesting and spectrum sensing. The subchannels should be allocated to spectrum sensing and energy harvesting reasonably.
- Energy harvesting can compensate the sensing energy loss and guarantee enough transmission power. Thus, the proposed model can achieve higher throughput compared with the traditional model especially with low PSNR.
- The throughput reduces as the sensing time decreases, while the sensing energy loss increases as the sensing time improves. However, both reducing throughput and increasing energy loss will decrease the energy efficiency. Thus, there is also a tradeoff between spectrum sensing and energy efficiency.

APPENDIX
PROOF OF THEOREM 1

From (21), we have $P_f(\tau) = Q\big(\varphi + \overline{\gamma}\sqrt{L_1\tau f_s}\big)$ and $R(\tau) = \epsilon(T-\tau)(1-P_f(\tau))$, thus the first-order and secondary-order partial derivatives of $P_f(\tau)$ in τ are respectively calculated as

$$\nabla P_f(\tau) = -\frac{\overline{\gamma}\sqrt{L_1 f_s}}{2\sqrt{2\pi\tau}}\exp\left(-\frac{(\varphi+\overline{\gamma}\sqrt{L_1\tau f_s})^2}{2}\right) \tag{42}$$

and

$$\nabla^2 P_f(\tau) = \frac{\overline{\gamma}^2 L_1 f_s}{4\sqrt{2\pi\tau}}\left(\frac{1}{\overline{\gamma}\sqrt{L_1\tau f_s}} + \varphi + \overline{\gamma}\sqrt{L_1\tau f_s}\right) \times \exp\left(-\frac{(\varphi+\overline{\gamma}\sqrt{L_1\tau f_s})^2}{2}\right) \tag{43}$$

Since $P_f \le 0.5$, we have $\varphi + \overline{\gamma}\sqrt{L_1\tau f_s} \ge 0$, then from (42) and (43) we get $\nabla P_f < 0$ and $\nabla^2 P_f > 0$, respectively. When $\tau \to 0$, we also get $\nabla P_f \to -\infty$. We can also calculate the first-order and secondary-order partial derivatives of $R(\tau)$ in τ as

$$\nabla R(\tau) = -\epsilon(1-P_f) - \epsilon(T-\tau)\nabla P_f \tag{44}$$

and

$$\nabla^2 R(\tau) = \epsilon(2\nabla P_f - \nabla^2 P_f) \tag{45}$$

Since $0 \le P_f \le 1$, from (44) we have

$$\begin{aligned} \lim_{\tau\to 0} \nabla R(\tau) &= -\epsilon T \lim_{\tau\to 0} \nabla P_f \to +\infty \\ \lim_{\tau\to T} \nabla R(\tau) &= -\epsilon\big(1-P_f(T)\big) < 0 \end{aligned} \tag{46}$$

which indicates there is a value $\tau_0 \in [0, T]$ that makes $\nabla R(\tau_0) = 0$, i.e., τ_0 is an extremum node of the function $R(\tau)$. Then from (45), we have $\nabla^2 R < 0$, which indicates that $\nabla R(\tau)$ is a monotonously decreasing function. Hence, τ_0 is the uniquely maximal node.

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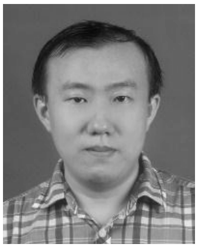

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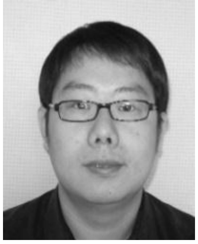

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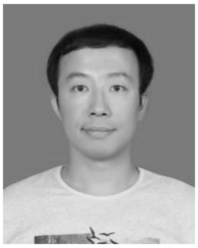

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