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Multi-Dimensional Resource Allocation for Throughput Maximization in CRIoT with SWIPT

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Abstract: To solve the power supply problem of battery-limited Internet of Things devices (IoDs) and the spectrum scarcity problem, simultaneous wireless information and power transfer (SWIPT) and cognitive radio (CR) technology were integrated into the Internet of Things (IoT) network to build a cognitive radio IoT (CRIoT) with SWIPT. In this network, secondary users (SUs) could adaptively switch between spectrum sensing, SWIPT, and information transmission to improve the total throughput. To solve the complicated multi-dimensional resource allocation problem in CRIoT with SWIPT, we propose a multi-dimensional resource allocation algorithm for maximizing the total throughput. Three-dimensional resources were jointly optimized, which are time resource (the duration of each process), power resource (the transmit power and the power splitting ratio of each node), and spectrum resource, under some constraints, such as maximum transmit power constraint and maximum permissible interference constraint. To solve this intractable mixed-integer nonlinear program (MINLP) problem, firstly, the sensing task assignment for cooperative spectrum sensing (CSS) was obtained by using a greedy sensing algorithm. Secondly, the original problem was transformed into a convex problem via some transformations with fixed-power splitting ratio and time switching. The Lagrange dual method and subgradient method were adopted to obtain the optimal power and channel allocation. Then, a one-dimensional search algorithm was used to obtain the optimal power splitting ratio and the time switching ratio. Finally, a heuristic algorithm was adopted to obtain the optimal sensing duration. The simulation results show that the proposed algorithm can achieve higher total system throughput than other benchmark algorithms, such as a greedy algorithm, an average algorithm, and the Kuhn–Munkres (KM) algorithm.

Keywords: simultaneous wireless information and power transmission (SWIPT); cognitive radio (CR); cooperative spectrum sensing (CSS); heuristic algorithm; Lagrange dual method

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1. Introduction

With the rapid development of communication technology, the Internet of Things (IoT) has been widely used in intelligent medical treatment, intelligent industry, intelligent home, intelligent agriculture, and intelligent transportation [1–3]. The number of Internet of Things devices (IoDs) in the world is expected to nearly triple from 9.7 billion in 2020 to more than 29 billion in 2030 [4]. The future IoT will need to carry a huge quantity of wireless traffic, which will pose a severe challenge to wireless communication technology and limited spectrum resources [5]. The emergence of cognitive radio (CR) technology provides an effective and feasible solution to the spectrum resource shortage problem in IoT. Cognitive radio Internet of Things (CRIoT), which combines IoT with CR technology, can effectively improve the utilization rate of the licensed spectrum and accordingly solve the shortage of wireless spectrum resources in the development of the IoT [6]. In CRIoT, SUs can sense the occupation of the licensed spectrum and use the idle spectrum opportunistically.

Another important factor that limits the development of IoT is the power supply of IoDs. Since a large proportion of IoDs cannot use wired power due to its location or scenario, battery is preferred. However, sometimes it is difficult or impossible to replace the battery for sensors in particular scenarios, such as space, forests, mines, wilderness, tunnels, and underwater. Thus, the IoDs are expected to be passive or renewable. However, some traditional renewable energy sources, such as solar energy and wind energy, are intermittent and inconvenient due to their high cost, large installation space, and high environmental requirements.

Simultaneous wireless information and power transfer (SWIPT) technology is an effective way to solve the energy limitation problem of wireless IoDs [7,8]. In SWIPT, the receiver can harvest energy from the received radio frequency (RF) signals during information transmission, and adopt power splitting (PS) or time splitting (TS) scheme to simultaneously perform information decoding (ID) and energy harvesting (EH) [9]. Therefore, the combination of CRIoT with SWIPT technology can effectively solve the power supply problem of IoDs. In the CRIoT with SWIPT, the main challenge is how to jointly allocate various resources to obtain optimal system performance, while making the tradeoffs between information transmission and energy harvesting, and between spectrum sensing and information transmission.

1.1. Related Work

To improve the performance of the CRIoT network with SWIPT, some resource allocation schemes have been proposed to improve network performance [10–14]. Mokhtarzadeh et al. [10] considered a CR network (CRN) in which each SU was equipped with a multi-antenna full-duplex transceiver. They optimally allocated spectrum resources to maximize the throughput with permissible interference to PU. Das et al. [11] studied a cooperative EH-CRN. When PU was present, the optimal number of SUs served as relay to cooperate in PU transmission, otherwise each SU transmitted its own data. Xu et al. [12] proposed a distributed resource allocation strategy to solve the power minimization problem in a multi-user CRN with SWIPT. They jointly optimized the transmission power and the power allocation ratio in ideal channel status information (CSI) and non-ideal CSI, respectively. Camana et al. [13] studied the multiple input single output (MISO) CRN with SWIPT in a rate-splitting multiple access (RSMA) framework. The transmit power of the cognitive base station (CBS) was minimized under the constraints of minimum energy harvest, minimum data rate, and permissible interference to PU. Zhou et al. [14] studied a MISO cognitive radio downlink network. The goal was to make a tradeoff between the transmit power of the CBS and the energy harvested by an EH receiver. Yang et al. [15] studied an optimal time and power resource allocation scheme to maximize uplink sum throughput while satisfying the minimum downlink transmission requirements and energy harvesting requirements of the users. However, in the above literature, they did not consider the spectrum sensing process, which is essential for CR networks.

To improve the sensing accuracy, cooperative spectrum sensing (CSS) has been studied in CRIoT networks with SWIPT. Sharifi et al. [16] proposed a power and spectrum allocation scheme to maximize reachable data rate and minimize energy consumption in an EH-CRN. SUs cooperatively sensed the spectrum by using an energy detection method and adopted PS scheme in the SWIPT process. Liu et al. [17] studied an optimal CSS strategy through finding the optimal detection threshold (the minimum number of SUs who reported a presence that could indicate the PU's presence) to maximize throughput in an EH-CRN, under the collision constraint and energy causality relationship constraint. Celik et al. [18] developed an EH-CSS CRN framework to maximize the total throughput through jointly optimizing the sensing duration and sensing threshold of each SU, and adopted the heterogeneous K-out of-N rule in CSS. Olawole et al. [19] studied CSS in a multi-channel EH-CRN in which the cognitive network was designed as overlapping clusters. Each SU harvested energy by taking advantage of the multi-channel. The authors formulated a problem which jointly determined the optimal channel allocation, sensing duration, and detection threshold for each SU to maximize throughput under the energy causality constraint and collision constraint. Zheng et al. [20] studied the problem of joint time and power and subchannel allocation in a multi-channel EH-CRN. The authors focused on optimizing the secondary throughput under interference power constraints and maximum power constraints. However, in the above works, all SUs participated in CSS, and each channel was sensed by all SUs, leading to unnecessary energy consumption. In some cases, some channels sensed by only a few SUs instead of all SUs in CSS could already meet the sensing requirement, so that the energy consumption of SUs could be saved. Furthermore, in the above literature, the influence of sensing results on the following transmission were not considered, which is unreasonable.

1.2. Motivation and Contributions

From the aforementioned works, it can be seen that optimally allocating sensing tasks to SUs in CSS and jointly allocate other resources according to sensing result in CRIoT with SWIPT is still an open problem and has not been investigated in the recent literature yet. Unlike the above literature, we consider the sensing process, which is essential for CR networks and can affect both sensing and transmission directly. Furthermore, we adopt CSS and a more flexible sensing task assignment, in which each channel is sensed by only a few SUs instead of all SUs, so that the energy of each node can be saved. In this paper, we focus on multi-dimensional resource allocation for total throughput maximization in the CRIoT network with SWIPT. A heuristic algorithm is proposed to obtain the optimal sensing duration. In CSS process, a greedy sensing algorithm is proposed to obtain the sensing task assignment for SUs. Inspired by [21], we jointly adopt the PS and TS schemes in SWIPT process to further improve the system total throughput. The PS ratio and the TS ratio are optimized by using one-dimensional search method. The other variables, such as the power and transmission channel assignment are jointly optimized by using the Lagrange dual method and subgradient method. The major contributions of this paper are as follows:

(1) We built a multi-user and multi-channel system model in the CRIoT network with SWIPT, and formulated a total throughput maximization problem to a mixed-integer non-linear program (MINLP) problem. To maximize the total throughput, multi-dimensional resource, including the durations for executing each process, power resource for the transmit power, the power splitting ratio in SWIPT, and spectrum resource, were jointly optimized subject to some constraints, such as maximum transmit power constraint, maximum permissible interference constraint, and minimum energy harvest requirement.

(2) To improve the sensing accuracy in multi-user and multi-channel scenario, CSS was adopted in the spectrum sensing process. A greedy sensing algorithm was used to determine the sensing task assignment matrix with given sensing duration. In SWIPT process, the PS and TS schemes were jointly adopted to increase the total throughput.

(3) To solve the formulated MINLP problem, by introducing an auxiliary variable and some transformations, the original problem with given sensing duration was transformed into a convex problem. The Lagrange dual method and subgradient method were adopted to obtain the optimal power and transmission channel assignment, and one-dimensional search algorithm was used to obtain the optimal PS ratio and the TS ratio. Finally, the optimal sensing duration was determined by using a heuristic algorithm.

(4) The simulation results show that the proposed algorithm could obtain higher total system throughput than other benchmark algorithms that are average algorithm, greedy algorithm, and Kuhn–Munkres (KM) algorithm. The performance of the heuristic algorithm is closer and slightly lower than that of the exhaustion algorithm, but the heuristic algorithm has lower computational complexity. The KM algorithm obtains less total system throughput than the proposed algorithm, but more than the average algorithm and the greedy algorithm due to its optimal characteristic. It is also shown that the proposed algorithm can obtain higher total throughput than that of using only PS or TS scheme and that of using single spectrum sensing.

2. System Model

We consider a downlink CRIoT with SWIPT, including a cognitive base station (CBS), a primary base station (PBS), M PUs, and N SUs, as shown in Figure 1. The authorized spectrum is divided into M channels for PUs transmission, and each PU is allocated one channel. These channels may have different bandwidths and a different occupancy probability. The channels set is denoted as $\mathcal{M}$ and the SUs set is denoted as $\mathcal{N}$. Each SU is equipped with a single antenna, an energy harvester, and a rechargeable battery. Firstly, SUs execute CSS to obtain the occupancy of M channels. To protect the normal communication of the PU network, only the channel of which the detection probability is larger than the requirement denoted $P_{d\_ch}^{req}$ can be used for transmission. Then, CBS transmits signals to SUs on their own channels in OFDM mode. PS and TS schemes are jointly used by SUs to split the received signals for ID and EH.

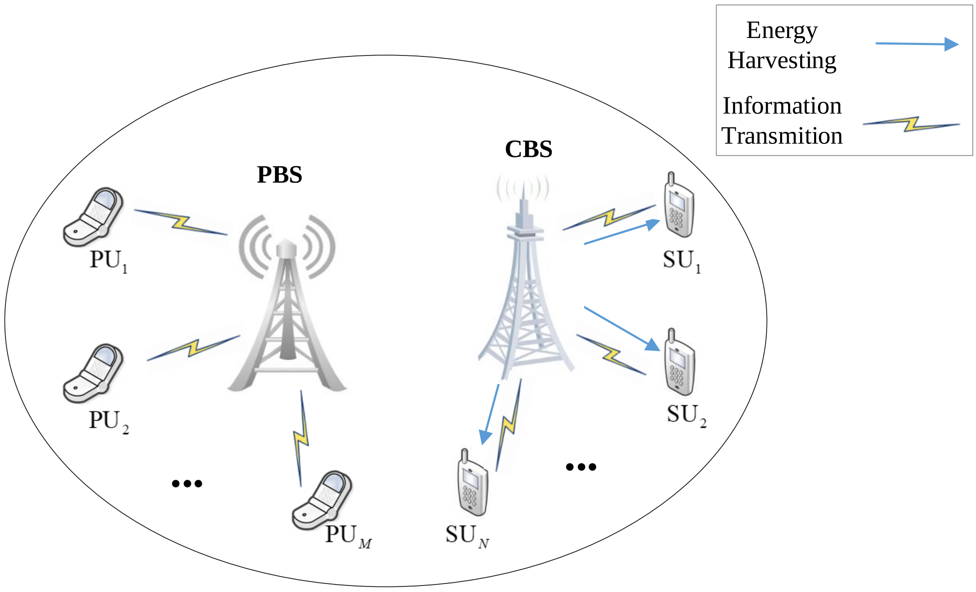

Figure 1. System model.

The time slot model is shown in Figure 2. The entire time slot T consists of the sensing time slot τ and transmission time slot $T - \tau$. In order to facilitate synchronization, the sensing duration can only be selected among K discrete values arranged in ascending order, denoted as $\tau(k)$, where $k = 1, 2, \ldots, K$. Let $\beta_n (0 < \beta_n < 1)$ denote the TS ratio of SU$_n$. The transmission time slot is divided into two parts, which are time slot $t_1 = \beta_n(T - \tau)$ for performing SWIPT including both ID and EH, and time slot $t_2 = (1 - \beta_n)(T - \tau)$ for only performing ID.

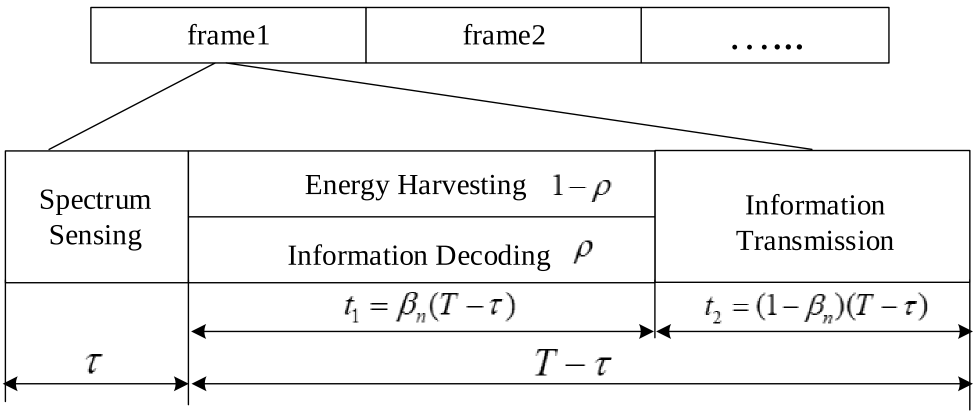

Figure 2. System time flow model.

Let ρ denote the PS ratio of SU. In the time slot t_1, SU uses power splitting to perform EH with ratio $1-\rho$ and ID with ratio ρ. By adjusting the value ρ, the amount of harvested energy by each SU can meet the minimum energy requirement, and the rest time slot can be used to transmit information to increase the throughput. Considering the energy causality, the energy harvest in the current time slot can only be used for the subsequent information transmission in its own time slot.

2.1. Spectrum Sensing

In the sensing process, each SU uses the energy detection method for spectrum sensing. Let H_1 and H_0 denote the presence and absence of PU, respectively, and λ is the detection threshold. We assume that the PU signal is assumed to be a complex phase shift keying (CPSK) signal, and the noise is circularly symmetric complex Gaussian (CSCG) noise with the noise variance σ_n^2. The false alarm probability of SUs is expressed as [22]

$$P_f(\lambda,\tau) = \frac{1}{2}erfc\left(\left(\frac{\lambda}{\sigma_n^2}-1\right)\sqrt{\frac{\tau f_s}{2}}\right), \tag{1}$$

where erfc(.) is the complementary error function, f_s is the sampling rate of the received signal, and τ is sensing duration.

Due to the different location and wireless environment of each user, the signal-to-noise ratio (SNR) values of different channels for different SUs are also different. Let $\gamma_{m,n}$ represent the SNR of SU_n on channel m. The detection probability of SU_n on channel m is [22]

$$P_d^{mn}(\tau) = \frac{1}{2}erfc\left(\left(\frac{\lambda}{\sigma_n^2}-\gamma_{m,n}-1\right)\sqrt{\frac{\tau f_s}{2(2\gamma_{m,n}+1)}}\right) \tag{2}$$

Giving a fixed false alarm probability P_f, the detection probability of the channel m sensed by SU_n denoted as $P_d^{mn}(\tau)$ can be obtained by

$$P_d^{mn}(\tau) = \frac{1}{2}erfc\left\{\frac{1}{\sqrt{2(2\gamma_{m,n}+1)}}\left[\sqrt{2}erf^{-1}\left(1-2P_f\right)-\sqrt{\tau f_s}\gamma_{m,n}\right]\right\}. \tag{3}$$

Let $\mathbf{X} = [x_{m,n}]_{M\times N}$ denote the sensing assignment matrix. When SU_n is assigned to sense channel m, $x_{m,n}=1$, otherwise $x_{m,n}=0$. The OR rule is adopted when the channel is cooperatively sensed by more than one SU. We assume the false alarm probability of each SU is equal, $P_f^{m,n}=P_f$. Thus, for channel m, the detection probability $P_{d\_ch}^m(\mathbf{X},\tau)$ and false alarm probability $P_{f\_ch}^m(\mathbf{X})$ are

$$P_{d\_ch}^m(\mathbf{X},\tau) = 1-\prod_{x_{m,n}=1}\left[1-P_d^{mn}(\tau)\right] \tag{4}$$

$$P_{f\_ch}^m(\mathbf{X}) = 1-\prod_{x_{m,n}=1}\left[1-P_f\right] \tag{5}$$

In CSS, the false alarm probability increases with the increase in the number of SUs participating in cooperation resulting in a decrease in spectrum utilization. Therefore, to ensure an acceptable spectrum utilization, according to OR rule, the maximum number of SUs allowed to sense each channel is expressed as

$$N_{co\_max} = \left\lfloor log_{(1-P_f)}\left(1-Q_f\right)\right\rfloor, \tag{6}$$

where $\lfloor . \rfloor$ denotes round-down operation and Q_f denotes the maximum allowed false alarm probability.

2.2. Information Transmission

In the information transmission phase, each SU is allocated a channel. For each SU, there are two different transmission rates in two cases. Case 1: when channel m is idle and the SUs can sense the idleness accurately, the achievable channel rates in phase t_1 and phase t_2, denoted as $R^{00}_{m,n}(t_1)$ and $R^{00}_{m,n}(t_2)$, respectively, can be expressed as

$$R^{00}_{m,n}(t_1) = log_2\left(1 + \frac{P_{m,n}|h_{m,n}|^2\rho}{\sigma_n^2}\right), \tag{7}$$

$$R^{00}_{m,n}(t_2) = log_2\left(1 + \frac{P_{m,n}|h_{m,n}|^2}{\sigma_n^2}\right), \tag{8}$$

where $P_{m,n}$ represents the transmission power of CBS to SU_n over channel m, $|h_{m,n}|^2$ represents the channel gain from the CBS to SU_n over channel m, σ_n^2 is the CSCG noise variance at SU_n, and ρ is the PS ratio in the SWIPT scheme.

Case 2: when the channel is occupied by PU and the SUs cannot sense the existence of PU. In this case, the channel rates in phase t_1 and phase t_2 can be expressed as

$$R^{10}_{m,n}(t_1) = log_2\left(1 + \frac{P_{m,n}|h_{m,n}|^2\rho}{P_{PU,m}|g_{m,n}|^2 + \sigma_n^2}\right), \tag{9}$$

$$R^{10}_{m,n}(t_2) = log_2\left(1 + \frac{P_{m,n}|h_{m,n}|^2}{P_{PU,m}|g_{m,n}|^2 + \sigma_n^2}\right), \tag{10}$$

where $|g_{m,n}|^2$ represents the channel gain from the PBS to SU_n over channel m.

Let $Pr(H_{0,m})$ and $Pr(H_{1,m})$ denote the probabilities that channel m is idle and busy, respectively. The probabilities of case 1 and case 2 for channel m are

$$a_{0,m} = Pr(H_{0,m})(1 - P^m_{f\_ch}(\mathbf{X})), \tag{11}$$

$$b_{0,m} = Pr(H_{1,m})(1 - P^m_{d\_ch}(\mathbf{X}, \tau)). \tag{12}$$

Therefore, the throughput of the SU_n over channel m can be represented as

$$R_{m,n}(\mathbf{X}, \tau) = B_m\left\{\frac{t_1}{T}\left[a_{0,m}R^{00}_{m,n}(t_1) + b_{0,m}R^{10}_{m,n}(t_1)\right] + \frac{t_2}{T}\left[a_{0,m}R^{00}_{m,n}(t_2) + b_{0,m}R^{10}_{m,n}(t_2)\right]\right\}, \tag{13}$$

where B_m is the bandwidth of channel m.

Let $\mathbf{Y} = [y_{m,n}]_{M\times N}$ denote the transmission assignment matrix. When SU_n is assigned to transmission channel m, $y_{m,n} = 1$, otherwise $y_{m,n} = 0$. Thus, the total throughput of the CR system can be described as

$$R_{total} = \sum_{m=1}^{M}\sum_{n=1}^{N} y_{m,n}R_{m,n}(\mathbf{X}, \tau) \tag{14}$$

2.3. Energy Harvesting and Interference

Let $\eta \in [0, 1]$ denote energy harvesting efficiency. Adopting a linear energy harvesting model, the energy harvested by SU_n can be expressed as

$$P_{EH,n} = \sum_{m=1}^{M} y_{m,n}\frac{t_1}{T}\eta(1-\rho)\left[|h_{m,n}|^2(a_{0,m} + b_{0,m})P_{m,n} + \sigma_n^2\right]. \tag{15}$$

The interference caused by CBS on PU over channel m is

$$I_m = \frac{T-\tau}{T}|k_m|^2\sum_{n=1}^{N} y_{m,n}b_{0,m}P_{m,n}, \tag{16}$$

where $|k_m|^2$ represents the channel power gain from the CBS to the PU over channel m. The interference should not exceed the maximum tolerance range of the PU to protect PU from interference.

The total throughput maximization problem can be formulated as

$$\begin{aligned}
P1: & \max_{x_{m,n}, y_{m,n}, \tau, \rho, \beta_n, P_{m,n}} R_{total} \\
s.t.\ \ & \text{C1}: \sum_{m=1}^{M} \sum_{n=1}^{N} y_{m,n}(a_{0,m} + b_{0,m})P_{m,n} \le P_{max}; \\
& \text{C2}: \frac{T-\tau}{T} |k_m|^2 \sum_{m=1}^{M} \sum_{n=1}^{N} y_{m,n} b_{0,m} P_{m,n} \le I_{th}(m), \forall m \in \mathcal{M}; \\
& \text{C3}: \sum_{m=1}^{M} y_{m,n} \frac{t_1}{T} \eta(1-\rho) \left[|h_{m,n}|^2 (a_{0,m} + b_{0,m}) P_{m,n} + \sigma_n^2 \right] \ge P_{Eq,n}, \forall m \in \mathcal{M}; \\
& \text{C4}: 0 \le \tau \le T; \\
& \text{C5}: 0 \le \rho \le 1; \\
& \text{C6}: 0 \le \beta_n \le 1; \\
& \text{C7}: x_{m,n} \in \{0,1\}, \sum_{m=1}^{M} x_{m,n} = 1, \sum_{n=1}^{N} x_{m,n} \le N_{co\ _max}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}; \\
& \text{C8}: y_{m,n} \in \{0,1\}, \sum_{n=1}^{N} y_{m,n} = 1, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}; \\
& \text{C9}: P_{m,n} \ge 0, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}; \\
& \text{C10}: y_{m,n} = 0, \text{ if } P_{d_ch}^{m}(\mathbf{X}) < P_{d_ch}^{req}, \forall n \in \mathcal{N},
\end{aligned} \tag{17}$$

where P_{max} represents maximum transmit power constraint at the CBS, $I_{th}(m)$ represents maximum interference on channel m, and $P_{Eq,n}$ represents the minimum required harvested power of SU$_n$. C1 represents the transmit power constraint at the CBS, which limits the total transmit power of the CBS. C2 denotes the maximum permissible interference constraint to protect the normal communication of PUs. C3 indicates the minimum energy harvest constraint of SU$_n$. C4–C6 are the ranges of sensing duration, the PS ratio, and the TS ratio, respectively. C7 represents the constraint of the sensing channel assignment. That is, each channel can be sensed by multiple SUs, but each SU can only be assigned a channel to sense, and the SUs assigned to sense each channel cannot be more than $N_{co\ \_max}$. C8 represents a constraint of transmission channel assignment, which means each idle channel can only be accessed by one SU to avoid interference between channels. C9 is the lower bound of transmit power from the CBS to each SU. C10 is constraint of detection probability for channels that can be used for transmission.

3. Problem Solutions

In this section, we solve the problem (17) by maximizing the total throughput. From (17), it can be seen that P1 is a non-convex MINLP problem due to the constraints C7, C8, C10, and the coupling between variables. To solve this problem, firstly, for the given sensing duration, the sensing task assignment is obtained by using a greedy sensing algorithm described in Section 3.1. Secondly, by introducing an auxiliary variable, the original problem with given sensing duration and sensing task assignment is transformed into a convex problem, which is solved by using the Lagrange dual method and subgradient method, which is shown in Section 3.2. Finally, the optimal sensing duration is determined by using the heuristic algorithm described in Section 3.3.

3.1. Sensing Task Assignment

In sensing task assignment, unlike the one-to-one assignment problem that can be solved by some classical algorithms, the one-channel to multiple-SU assignment problem with some constraints makes the problem intractable and difficult to solve. One feasible solution is adopting some swarm intelligence methods [23,24]. In [23], an adaptive resource allocation algorithm based on modified particle swarm optimization (PSO) was proposed to solve the multiple-subcarriers to one-SU assignment problem on downlink transmission in a CR network. In [24], an improved monarch butterfly algorithm was proposed to solve the spectrum allocation problem for a multi-source data stream. However, their computation quantity and computation speed need to be considered. To obtain a sub-optimal solution with lower computation quantity, we propose a greedy sensing algorithm to obtain the sensing task assignment.

In the proposed greedy sensing algorithm, for the given sensing duration, the sensing task assignment is determined by using the greedy sensing algorithm, in which each SU is preferentially assigned to the channel that can be sensed by fewer SUs to meet the detection probability requirement $P_{d\_ch}^{req}$. Then the unassigned channel is assigned to the several unassigned SUs for cooperative sensing.

Firstly, the channel is assigned to the SU for sensing by which the detection probability of this channel can meet the requirement. All channels are arranged in descending order of bandwidth. From the channel with the highest bandwidth, we selected the SU with the largest SNR over this channel, and calculated the detection probability according to (3). If the detection probability met the requirement, the SU was assigned to sense this channel. If not, we continued to check the channel with the second highest bandwidth, and selected the SU with the highest SNR to calculate the detection probability, and so on until all channels had been checked.

Then, the unassigned channel was assigned to the several unassigned SUs for cooperative sensing by which the detection probability of this channel could meet the requirement. Checking the unassigned channels according to descending order of bandwidth, for each channel, we selected two unassigned SUs with the largest SNR values for CSS and calculated the cooperative detection probability according to (3) and (4). If the detection probability was larger than the requirement, this channel was assigned to these two SUs for sensing. If not, the unassigned SU with largest SNR was selected for CSS with the former assigned SUs. Checking the detection probability of this channel, if the detection probability satisfied the requirement, this channel was assigned to these three SUs for sensing. If not, we repeated until one of the following three conditions was satisfied: (1) all SUs had been assigned a sensing task; (2) all channels had been checked; (3) more than $N_{co\ \_max}$ SUs had been assigned to a channel. The specific steps are as follows:

- **Step 1** Arrange the channels in descending order of bandwidth, and start with the channel with the largest bandwidth;
- **Step 2** For this channel, select the SU with the highest SNR on this channel from unassigned SUs, and calculate the detection probability according to (3);
- **Step 3** If the detection probability is larger than $P_{d\_ch}^{req}$, the channel is assigned to this SU for sensing and set $x_{m,n} = 1$. If not, set $x_{m,n} = 0$;
- **Step 4** Continue to check the channel with the highest bandwidth among the unchecked channels, and go to Step 2 until all channels have been checked;
- **Step 5** Arrange the unassigned channels in descending order of bandwidth, and start with the channel with the largest bandwidth;
- **Step 6** For this channel, Select the two SUs with the highest SNR;
- **Step 7** Use (3) and (4), calculate cooperation detection probability $P_{d\_ch}^{m}(\mathbf{X}, \tau)$;
- **Step 8** If the detection probability is larger than $P_{d\_ch}^{req}$, the channel is allocated to these selected SUs for sensing, set the corresponding $x_{m,n} = 1$, and go to Step 9. If not, add another SU with the largest SNR among the unassigned SUs for CSS, and go to Step 7 until $N_{co\ \_max}$ SUs have been assigned to this channel;
- **Step 9** Continue to check the next channel with the highest bandwidth among the unchecked channels, and go to Step 6 until all channels have been checked;
- **Step 10** The final sensing task assignment matrix **X**.

3.2. Optimal Resource Allocation with Fixed Sensing Duration

For the fixed sensing duration τ and the sensing task assignment matrix **X**, the original problem P1 becomes

$$\begin{aligned} P2: & \max_{y_{m,n},\rho,\beta_n,P_{m,n}} R_{total} \\ s.t. & \ \mathrm{C1,C2,C3,C5,C6,C8,C9,C10}. \end{aligned} \tag{18}$$

P2 is a non-convex optimization problem due to the coupling variables. To deal with the coupling between $P_{m,n}$ and $y_{m,n}$, the channel assignment variable $y_{m,n}$ is relaxed into a sharing factor $y_{m,n} \in [0,1]$, and defines auxiliary variable $U_{m,n} = y_{m,n}P_{m,n}$. Substituting $P_{m,n} = \frac{U_{m,n}}{y_{m,n}}$ into (7) and (8), the channel rates of SU_n over channel m in different cases become as follows

$$R^{00\,\prime}_{m,n}(t_1) = log_2\left(1+\frac{U_{m,n}|h_{m,n}|^2\rho}{y_{m,n}\sigma_n^2}\right), \tag{19}$$

$$R^{00\,\prime}_{m,n}(t_2) = log_2\left(1+\frac{U_{m,n}|h_{m,n}|^2}{y_{m,n}\sigma_n^2}\right), \tag{20}$$

$$R^{10\,\prime}_{m,n}(t_1) = log_2\left(1+\frac{U_{m,n}|h_{m,n}|^2\rho}{y_{m,n}\left(P_{PU,m}|g_{m,n}|^2+\sigma_n^2\right)}\right), \tag{21}$$

$$R^{10\,\prime}_{m,n}(t_2) = log_2\left(1+\frac{U_{m,n}|h_{m,n}|^2}{y_{m,n}\left(P_{PU,m}|g_{m,n}|^2+\sigma_n^2\right)}\right). \tag{22}$$

The total throughput of the SUs can be rewritten as

$$\begin{aligned} R'_{total} = \sum_{m=1}^{M}\sum_{n=1}^{N} y_{m,n}B_m\Bigg\{ & \frac{t_1}{T}\left\{a_{0,m}R^{00\,\prime}_{m,n}(t_1) + b_{0,m}R^{10\,\prime}_{m,n}(t_1)\right] \\ & + \frac{t_2}{T}\left[a_{0,m}R^{00\,\prime}_{m,n}(t_2) + b_{0,m}R^{10\,\prime}_{m,n}(t_2)\right]\Bigg\} \end{aligned} \tag{23}$$

P2 becomes P3 as follows

$$\begin{aligned} P3: & \max_{y_{m,n},\tau,\rho,\beta_n,U_{m,n}} R'_{total} \\ s.t. \ & \mathrm{C1}': \sum_{m=1}^{M}\sum_{n=1}^{N}(a_{0,m}+b_{0,m})U_{m,n} \le P_{max}; \\ & \mathrm{C2}': \frac{T-\tau}{T}|k_m|^2\sum_{m=1}^{M}\sum_{n=1}^{N} b_{0,m}U_{m,n} \le I_{th}(m), \forall m \in \mathcal{M}; \\ & \mathrm{C3}': \sum_{m=1}^{M}\frac{t_1}{T}\eta(1-\rho)\left[|h_{m,n}|^2(a_{0,m}+b_{0,m})U_{m,n} + y_{m,n}\sigma_n^2\right] \ge P_{Eq,n}, \forall m \in \mathcal{M}; \\ & \mathrm{C8}': 0 \le y_{m,n} \le 1, \sum_{n=1}^{N} y_{m,n} = 1, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}; \\ & \mathrm{C9}': U_{m,n} \ge 0, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}, \\ & \mathrm{C5,C6,C10}. \end{aligned} \tag{24}$$

P3 is still a non-convex problem due to the coupling relationship among variables $\tau, \rho, \beta_n, y_{m,n}$, and $U_{m,n}$. The optimal value of ρ and β_n, denoted as ρ^{opt} and β_n^{opt}, can be obtained by one-dimensional searching from [0,1]. The optimal τ denoted as τ^{opt} can be determined by using the heuristic algorithm described in Section 3.3. For fixed τ, ρ, β_n, P3 is transformed into P4, which is a convex problem and can be solved by the Lagrange dual method due to satisfing Slater's condition.

$$\begin{aligned} P4: &\max_{y_{m,n},U_{m,n}} R'_{total} \\ s.t.\ &\text{C1}', \text{C2}', \text{C3}', \text{C8}', \text{C9}', \text{C10}. \end{aligned} \tag{25}$$

The Lagrange dual function of P4 is formulated as

$$\begin{aligned} &P5: f(\lambda, \psi_m, \mu_n, \epsilon_m) = \max_{y_{m,n},U_{m,n}} L(\Xi), \\ &s.t. y_{m,n} \geq 0, U_{m,n} \geq 0, \end{aligned} \tag{26}$$

where $L(\Xi)$ is the Lagrange function of P4, $\Xi = \{U_{m,n}, y_{m,n}, \lambda, \psi_m, \mu_n, \epsilon_m\}$ is the collection of all the primal and dual variables, and $\lambda, \psi_m, \mu_n, \epsilon_m$ denote non-negative Lagrange multipliers corresponding to the constraints given by C1′, C2′, C3′, and C8′ of P4. $L(\Xi)$ can be written as

$$\begin{aligned} L(\Xi) = &\sum_{m=1}^{M}\sum_{n=1}^{N}\frac{y_{m,n}B_m}{T}\left\{t_1\left[a_{0,m}R_{m,n}^{00}(t_1) + b_{0,m}R_{m,n}^{10}(t_1)\right] + t_2\left[a_{0,m}R_{m,n}^{00}(t_2) + b_{0,m}R_{m,n}^{10}(t_2)\right]\right\} \\ &+ \lambda\left[P_{max} - \sum_{m=1}^{M}\sum_{n=1}^{N}(a_{0,m}+b_{0,m})U_{m,n}\right] + \sum_{m=1}^{M}\psi_m\left[I_{th}(m) - \frac{T-\tau}{T}|k_m|^2\sum_{m=1}^{M}\sum_{n=1}^{N}b_{0,m}U_{m,n}\right] \\ &+ \sum_{n=1}^{N}\mu_n\left[\sum_{m=1}^{M}\frac{t_1}{T}\eta(1-\rho)\left[|h_{m,n}|^2(a_{0,m}+b_{0,m})U_{m,n} + y_{m,n}\sigma_n^2\right] - P_{Eq,n}\right] \\ &+ \sum_{m=1}^{M}\epsilon_m\left(1 - \sum_{n=1}^{N}y_{m,n}\right). \end{aligned} \tag{27}$$

The dual problem P5 can be expressed as

$$\begin{aligned} &P6: \min_{\lambda,\psi_m,\mu_n,\epsilon_m} f(\lambda, \psi_m, \mu_n, \epsilon_m) \\ &s.t. \lambda \geq 0, \psi_m \geq 0, \mu_n \geq 0, \epsilon_m \geq 0. \end{aligned} \tag{28}$$

To solve P4, firstly, P5 is solved to obtain the optimal $U_{m,n}, y_{m,n}$ for the given Lagrange multipliers $\lambda, \psi_m, \mu_n, \epsilon_m$ that satisfy the constraints of P6. Then, solve P6 by updating the Lagrange multipliers to minimize $f(\lambda, \psi_m, \mu_n, \epsilon_m)$. In this way, P4 can be solved by using such an iterative method [25].

We obtained the optimal transmit power $P_{m,n}^{opt}$ and the optimal channel assignment $y_{m,n}^{opt}$ via the follow two propositions.

Proposition 1. *The optimal transmit power $P_{m,n}^{opt}$ is*

$$P_{m,n}^{opt} = \left[\frac{-\Delta_{0,m,n} + \sqrt{\Delta_{0,m,n}^2 - 4q_{0,m,n}\left|h_{m,n}\right|^2\rho^2\omega_{0,m,n}}}{2q_{0,m,n}\left|h_{m,n}\right|^2\rho^2}\right]^+, \tag{29}$$

where $[z]^+ = max(0,z)$, and $q_{0,m,n}$, $\Delta_{0,m,n}$, and $\omega_{0,m,n}$ are, respectively, given as follows

$$q_{0,m,n} = \left\{(a_{0,m}+b_{0,m})\left[\mu_n\beta_n\eta(1-\rho)|h_{m,n}|^2 - \lambda\right] - b_{0,m}\right\}ln2, \tag{30}$$

$$\Delta_{0,m,n} = (a_{0,m}+b_{0,m})|h_{m,n}|^4\rho(\rho\beta_n + 1 - \beta_n) + |h_{m,n}|^2\rho q_{0,m,n}\left(P_{PU,m}|g_{m,n}|^2 + 2\sigma_n^2\right), \tag{31}$$

$$\omega_{0,m,n} = \left[a_{0,m}|h_{m,n}|^2\rho(\rho\beta_n + 1 - \beta_n) + |h_{m,n}|^2 + q_{0,m,n}\sigma_n^2\right]\left(P_{PU,m}|g_{m,n}|^2 + \sigma_n^2\right) + b_{0,m}|h_{m,n}|^2\sigma_n^2(\rho\beta_n + 1 - \beta_n). \tag{32}$$

Proof. See Appendix A for further details.

In a similar way, by applying KKT conditions [26], the optimal channel allocation $y_{m,n}$ can be obtained from

$$\frac{\partial L(\Xi)}{\partial y_{m,n}} \begin{cases} < 0, & y_{m,n}^{opt} = 0 \\ = 0, & 0 < y_{m,n}^{opt} < 1, \forall m, n. \\ > 0, & y_{m,n}^{opt} = 1 \end{cases} \tag{33}$$

□

Proposition 2. *The optimal channel assignment $y_{m,n}^{opt}$ is*

$$y_{m,n}^{opt} = \begin{cases} 1, & m = \underset{1 \le m \le M}{\arg\max}\, \theta_{m,n} \text{ and } P_{d\_ch}^{m} \ge P_{d\_ch}^{req} \\ 0, & \text{otherwise and } P_{d\_ch}^{m} \ge P_{d\_ch}^{req} \\ 0, & P_{d\_ch}^{m} < P_{d\_ch}^{req} \end{cases}, \tag{34}$$

where

$$\begin{aligned} \theta_{m,n} = {} & B_m a_{0,m} \frac{t_1}{T}\left[R_{m,n}^{00}(t_1) - \theta_{m,n}^{00}(t_1)\right] + B_m b_{0,m} \frac{t_1}{T}\left[R_{m,n}^{10}(t_1) - \theta_{m,n}^{10}(t_1)\right] \\ & + B_m a_{0,m} \frac{t_2}{T}\left[R_{m,n}^{00}(t_2) - \theta_{m,n}^{00}(t_2)\right] + B_m b_{0,m} \frac{t_2}{T}\left[R_{m,n}^{10}(t_2) - \theta_{m,n}^{10}(t_2)\right] + \frac{t_1}{T}\mu_n \eta (1-\rho)\sigma_n^2, \end{aligned} \tag{35}$$

and

$$\theta_{m,n}^{00}(t_1) = \frac{P_{m,n}|h_{m,n}|^2 \rho}{\left(\sigma_n^2 + P_{m,n}|h_{m,n}|^2 \rho\right) ln2}, \tag{36}$$

$$\theta_{m,n}^{10}(t_1) = \frac{P_{m,n}|h_{m,n}|^2}{\left(\sigma_n^2 + P_{m,n}|h_{m,n}|^2\right) ln2}, \tag{37}$$

$$\theta_{m,n}^{00}(t_2) = \frac{P_{m,n}|h_{m,n}|^2 \rho}{\left(P_{PU}|g_{m,n}|^2 + \sigma_n^2 + P_{m,n}|h_{m,n}|^2 \rho\right) ln2}, \tag{38}$$

$$\theta_{m,n}^{10}(t_2) = \frac{P_{m,n}|h_{m,n}|^2}{\left(P_{PU}|g_{m,n}|^2 + \sigma_n^2 + P_{m,n}|h_{m,n}|^2\right) ln2}. \tag{39}$$

Proof. See Appendix B for further details.

The Lagrange multipliers λ, ψ_m, and μ_n are updated by using the subgradient method given as follows

$$\lambda^{(j+1)} = \left[\lambda^{(j)} - \Delta\lambda\left(P_{max} - \sum_{m=1}^{M}\sum_{n=1}^{N}(a_{0,m} + b_{0,m})U_{m,n}^{opt}\right)\right]^{+}, \tag{40}$$

$$\psi_m^{(j+1)} = \left[\psi_m^{(j)} - \Delta\psi_m\left(I_{th}(m) - \frac{T-\tau}{T}|k_m|^2 \sum_{n=1}^{N} b_{0,m}U_{m,n}^{opt}\right)\right]^{+}, \tag{41}$$

$$\mu_n^{(j+1)} = \left[\mu_n^{(j)} - \Delta\mu_n\left(\sum_{m=1}^{M}\frac{t_1}{T}\eta(1-\rho)\left[|h_{m,n}|^2(a_{0,m} + b_{0,m})U_{m,n}^{opt} + y_{m,n}\sigma_n^2\right] - P_{Eq,n}\right)\right]^{+}, \tag{42}$$

where j is the iteration index, $\Delta\lambda$, $\Delta\psi_m$, and $\Delta\mu_n$ are the step sizes. As for the Lagrange multiplier ϵ_m, due to $\sum_{n=1}^{N} y_{m,n} = 1$ in C8, the value of ϵ_m does not affect the algorithm process. Thus, it does not need to be updated and can be set to an initial value.

As mentioned above, the optimal resource allocation algorithm for solving P2 is shown in Algorithm 1. □

Algorithm 1 The optimal resource allocation algorithm for solving P2

Input: sensing duration τ, sensing task assignment matrix $\mathbf{X}$, the error tolerances $\varphi_1 > 0$, $\varphi_2 > 0$, $\varphi_3 > 0$, the dual variables $\lambda(0), \psi_m(0), u_n(0)$, and the step sizes $\alpha_1 > 0$, $\alpha_1 > 0$.

Optimization:

for $\rho = 0 : \alpha_1 : 1$ **do**
  for $\beta_n = 0 : \alpha_2 : 1$ **do**
    set the iteration index $j = 0$;
    repeat
      calculate transmit power $P_{m,n}$ according to (29);
      calculate $\theta_{m,n}$ according to (35);
      allocate channels $y_{m,n}$ according to (34);
      update the dual variables λ, ψ_m, u_n, according to (40), (41) and (42);
      update the iteration index $j = j + 1$;
    until

$$\| \lambda(j+1) - \lambda(j) \|_2 \leq \varphi_1$$
$$\| \psi_m(j+1) - \psi_m(j) \|_2 \leq \varphi_2$$
$$\| \mu_n(j+1) - \mu_n(j) \|_2 \leq \varphi_3$$

    calculate R_{total} according to (23);
  end for
end for
determine the optimal ρ, β_n, and obtain the corresponding $P_{m,n}$ and $\mathbf{Y}$.

Output: $\rho^{opt}, \beta_n^{opt}, P_{m,n}^{opt}, \mathbf{Y}^{opt}$.

3.3. The Optimal Sensing Duration

As mentioned above in Sections 3.1 and 3.2, for a given sensing duration τ, we can obtain the optimal system total throughput $R_{total}(\tau(k))$ by obtaining the optimal sensing task assignment through a greedy sensing algorithm and solving P2. As for the sensing duration, since it directly influences both sensing task assignment and the whole transmission process and the whole problem is a MINLP problem, the optimal sensing duration cannot be obtained by classical optimization methods. To solve this intractable problem, since sensing duration can only be selected among several fixed discrete values, the simple exhaustion algorithm can be adopted with acceptable computation quantity. However, when the number of discrete values is large, the computation quantity still is not affordable. Thus, we propose a sub-optimal and simple method namely a heuristic algorithm to obtain the optimal sensing duration as follows.

Firstly, from the intermediate value $k = round\left(\frac{K}{2}\right)$, calculate the system total throughput R_{total} with sensing duration $\tau(k-1)$, $\tau(k)$, and $\tau(k+1)$, respectively, according to (23). Secondly, compare the values of $R_{total}(\tau(k-1))$, $R_{total}(\tau(k))$, and $R_{total}(\tau(k+1))$. If $R_{total}(\tau(k))$ is maximum, $\tau(k)$ is the optimal sensing duration and the algorithm ends; If $R_{total}(\tau(k+1))$ is maximum, $k = k+1$. If $R_{total}(\tau(k-1))$ is maximum, $k = k-1$. Then, calculate the maximum system total throughput $R_{total}(\tau(k-1))$, $R_{total}(\tau(k))$, and $R_{total}(\tau(k+1))$, compare these values, and so on, until $R_{total}(\tau(k))$ is maximum, or one of $R_{total}(\tau(1))$ and $R_{total}(\tau(K))$ is maximum. Finally, the optimal sensing duration is obtained and the algorithm ends.

Based on the above, the procedure for solving original problem P1 is described in Algorithm 2.

Algorithm 2 Multi-dimensional resource allocation algorithm

Input: the number of PUs M, the number of SUs N, K, sensing duration $\tau(1), \ldots, \tau(K)$, and $k = round\left(\frac{K}{2}\right)$.

Optimization:

1: **repeat**
2: **for** $i = k-1 : 1 : k+1$ **do**
3: (1) With sensing duration $\tau(i)$, use greedy sensing algorithm mentioned in Section 3.1 to obtain sensing task assignment matrix $\mathbf{X}$.
4: (2) Solve P2 according to Algorithm 1;
5: (3) Calculate the total throughput $R_{total}(\tau(i))$;
6: **end for**
7: Compare $R_{total}(\tau(k-1))$, $R_{total}(\tau(k))$, and $R_{total}(\tau(k+1))$.
8: (1) **if** $R_{total}(\tau(k+1))$ is maximum and $k+1 = K$, **then** $\tau^{opt} = \tau(K)$; break; **end if**
9: (2) **if** $R_{total}(\tau(k+1))$ is maximum and $k+1 < K$, **then** $k = k+1$; **end if**
10: (3) **if** $R_{total}(\tau(k-1))$ is maximum and $k-1 = 1$, **then** $\tau^{opt} = \tau(1)$; break; **end if**
11: (4) **if** $R_{total}(\tau(k-1))$ is maximum and $k-1 > 1$, **then** $k = k-1$; **end if**
12: (5) **if** $R_{total}(\tau(k))$ is maximum, **then** $\tau^{opt} = \tau(k)$; break; **end if**
13: **end repeat**

Output: $\tau^{opt}, \rho^{opt}, \beta_n^{opt}, P_{m,n}^{opt}, \mathbf{X}^{opt}$, and $\mathbf{Y}^{opt}$.

4. Simulation Analysis

In this section, we evaluate the proposed algorithm in MATLAB. Set the number of SUs is $N = \{6, 7, 8\}$, the number of PUs is $M = 6$, and the SNR value $\gamma_{m,n}$ of each SU at each channel follows the exponential distribution with the mean value -15dB. All channels are assumed to be Rayleigh fading and independently distributed. Let $g_{m,n} \sim \mathrm{CN}(0, \alpha_1)$ denotes the channel gain from the PBS to SU$_n$ over channel m, where $\alpha_1 = d_1^{-\theta}$ and the distance between the PBS and the SU node is $d_1 = 8$ m. $h_{m,n} \sim \mathrm{CN}(0, \alpha_2)$ represents the channel gain from the CBS to SU$_n$ over channel m, where $\alpha_2 = d_2^{-\theta}$ and the distance between the CBS and the SU node is $d_2 = 5$ m. $k_m \sim \mathrm{CN}(0, \alpha_3)$ represents the channel gain from the CBS to PU$_m$ over channel m, where $\alpha_3 = d_3^{-\theta}$ and the distance between the CBS and the PU node is $d_3 = 10$ m. The path loss coefficient $\theta = 3$. The detection probability requirement is $P_{d\_ch}^{req} = 0.9$, the energy harvesting efficiency $\eta = 0.8$, the sampling frequency $f_s = 6$ MHZ, and the maximum false alarm probability of the channel is $Q_f = 0.05$. The idle probability of each channel $P_r(H_{0,m})$ varies randomly in [0,1] and the bandwidth of each channel varies randomly between 10 kHZ $\sim$ 20 kHZ. The transmit power of PBS $P_{PU,m}^T = 1$ W, and the maximum transmission power of CBS is $P_{max} = 1.5$ W. The interference threshold of PU$_m$ is $I_{th}^m = 0.1$ W, the minimum harvested energy of the SU$_n$ is $P_{Eq,n} = 10$ mW, the noise variance at SU$_n$ is $\sigma_n^2 = 10^{-6}$ W. Each frame duration $T = 0.1$ s, the sensing duration τ can be selected among $K = 15$ discrete values, arranged uniformly from minimum value $\tau(1) = 0.001$ s to maximum value $\tau(K) = 0.03$ s with interval 0.002 s between each value. All the results are averaged over 1000 different random channel realizations by the Monte Carlo method.

Figure 3 shows the variation of the total throughput of single user sensing (SS) scheme and CSS scheme with different energy harvesting efficiency. It can be seen from Figure 3 that, CSS obtains higher total throughput than SS. This is because in CSS, the cooperation of SUs can increase the detection probability and decrease the false alarm probability, leading to an increase in the total throughput. It also can be seen from Figure 3 that with the increase in the energy harvesting efficiency, the total throughput increases, since more energy can be used for transmission. The larger N also leads to the larger total throughput, since more SUs can sense more eligible channels for transmission.

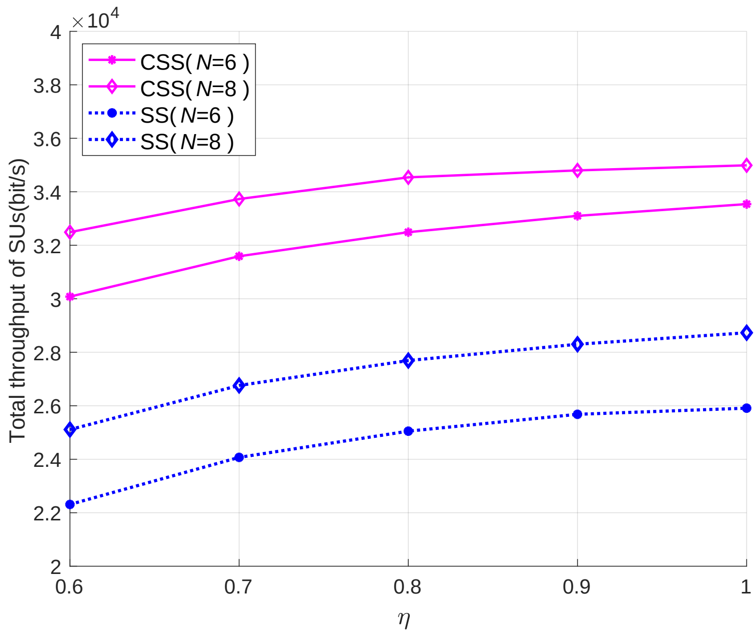

Figure 3. The total throughput of different spectrum sensing schemes versus η.

Figure 4 shows the variation in the total throughput of different SWIPT schemes versus the transmit power of CBS. It can be seen from Figure 4 that jointly using PS and TS scheme, denoted as PTS, can obtain higher total throughput than only using PS scheme or TS scheme due to more flexible power allocation. It also can be seen from Figure 4 that the total throughput increases with the transmit power of the CBS. This is because the high transmit power can easily meet the energy requirement of each SU. Thus, more power can be used to perform ID at the SUs leading to the increase of total throughput. The more SUs can also obtain higher total throughput, since more eligible channels can be sensed for transmission.

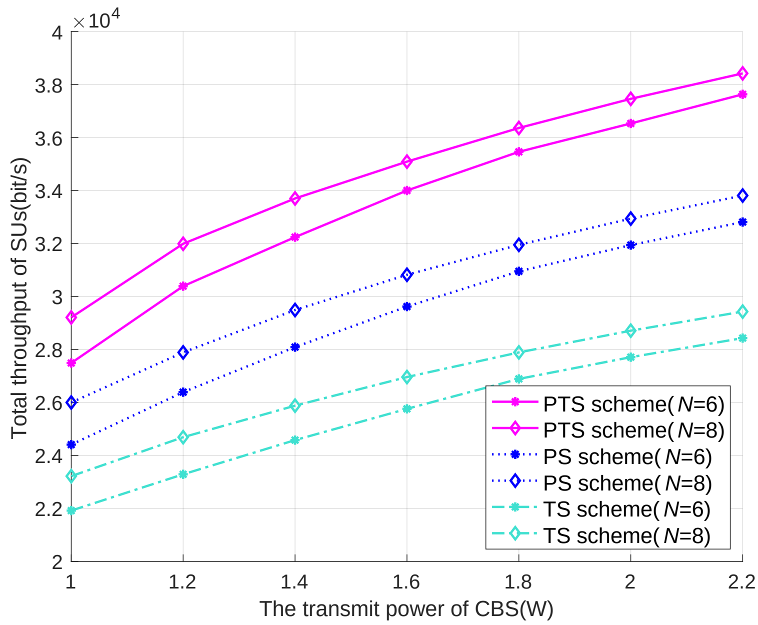

Figure 4. The total throughput of different simultaneous wireless information and power transfer (SWIPT) schemes versus the transmit power of cognitive base station (CBS).

Figure 5 shows the relationship between the transmit power of the CBS and the total throughput of different algorithms, which are average algorithm, greedy algorithm, KM algorithm, and the proposed algorithm in this paper. In average algorithm, the transmission power from the CBS to each SU is equal. The other variables are determined in the same way with our proposed algorithm. In greedy algorithm, the CBS preferentially allocates more transmit power to the SU with larger bandwidth channel assigned. The other variables are also determined in the same way with our proposed algorithm. In the Kuhn–Munkres (KM) algorithm, firstly, the one-channel to one-SU sensing task assignment is obtained by KM algorithm to maximize their total detection probability. Then, for the channel of which the detection probability doesn't meet the requirement, it will be assigned more SUs for cooperative sensing to increase its detection probability. From Figure 5, we can see that the total throughput of four algorithms increases gradually with the increase in the transmit power of the CBS. Due to the flexible resource allocation, the proposed algorithm can obtain higher total throughput than the other three algorithms. The numerical results show that the proposed algorithm obtains 35% higher total throughput than the greedy algorithm, 21% higher than the average algorithm, and 8% higher than the KM algorithm on average. Its high total throughput can help IoT to guarantee the quality of service and scale up the network. The total system throughput of KM algorithm is lower than that of the proposed algorithm, but is higher than those of average algorithm and greedy algorithm due to the optimal characteristic of KM algorithm.

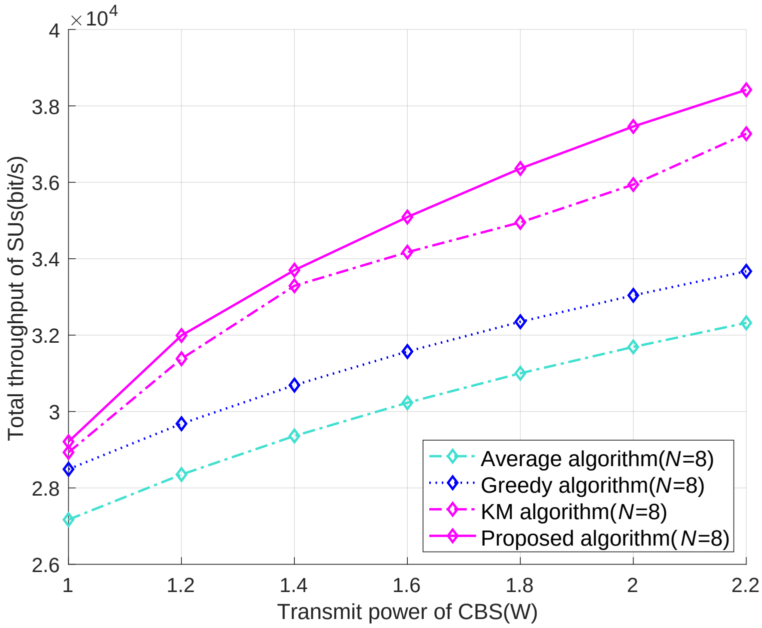

Figure 5. The total throughput of different SWIPT schemes versus the transmit power of CBS.

Figure 6 shows the relationship between the transmit power of the CBS and the total throughput of different sensing duration algorithms, which are the exhaustion algorithm, heuristic algorithm, and fixed τ algorithm. In the exhaustion algorithm, all the available sensing durations are checked and their maximum achievable total throughput is calculated. The sensing duration with the maximum throughput is selected as the optimal one. In fixed τ algorithm, the sensing duration is given and fixed. The other variables are determined in the same way with our proposed algorithm. From Figure 6, we can see that the total throughput of these algorithms increases gradually with the increase in the transmit power of the CBS. The performance of the heuristic algorithm is closer and slightly lower than that of the exhaustion algorithm, but the heuristic algorithm has lower computational complexity. Thus, it can help the IoT to reduce computing costs and improve the service speed. The heuristic algorithm and exhaustion algorithm can obtain higher total throughput than the fixed τ algorithm due to their flexible sensing duration.

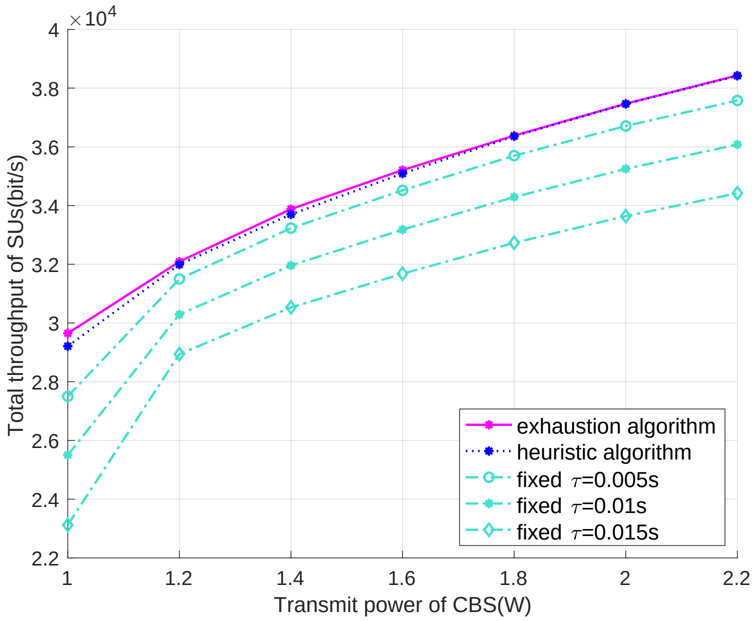

Figure 6. The total throughput of different sensing duration algorithm versus transmit power of CBS.

Figure 7 shows the total throughput of the SUs versus different sensing durations. It can be seen that with the increase of sensing duration, the total throughput firstly increases and then decreases. That is because when the sensing duration is short, the creasing sensing duration can improve the sensing accuracy so as to increase the total throughput. However, the increase in the sensing duration will lead to the decrease of data transmission time in fixed time slots, resulting in the decrease of the total throughput. Therefore, there is a trade-off between the sensing performance and the total throughput of the cognitive network; there is an optimal sensing duration to maximize the total throughput. In addition, the total throughput increases with the number of SUs, since more SUs participated in CSS can improve the detection accuracy and find more eligible channels, so as to improve the system throughput.

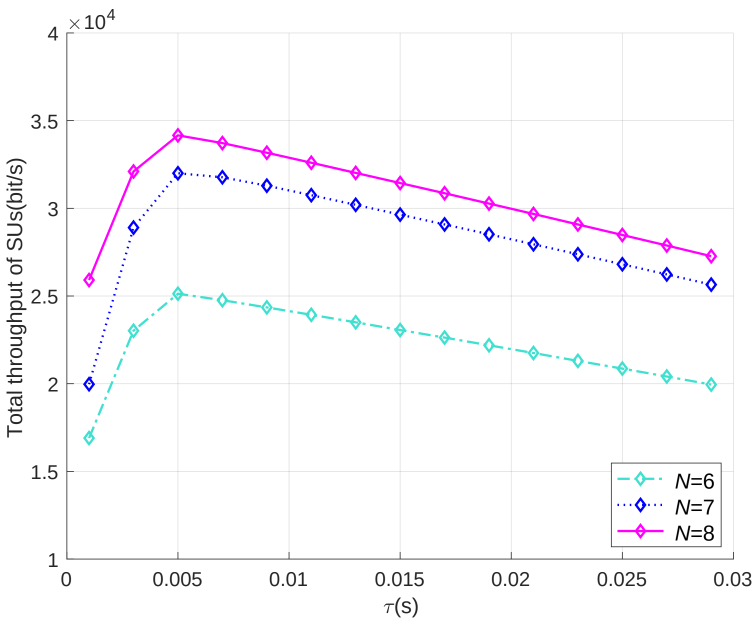

Figure 7. The total throughput versus sensing duration.

Figure 8 shows the total throughput varies with the distance between the CBS and the SUs under different eta. It can be seen that, the shorter the distance between the CBS and the SUs, the higher energy and throughput can be obtained. This is because the shorter the distance between the CBS and the SUs, the more energy can be harvested, leading to the greater total throughput. Higher eta also causes more total throughput, since the required energy can be harvested faster and more time can be used for transmission.

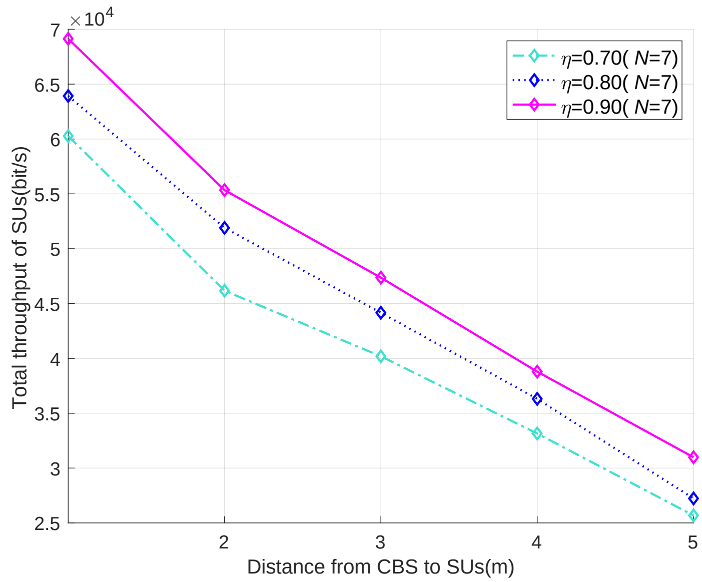

Figure 8. The total throughput versus distances from CBS to secondary users (SUs) with the different η.

Figure 9 shows that the total throughput varies with the mean SNR values under different detection probability requirements $P_{d\_ch}^{req}$. It can be seen from Figure 9 that, as the SNR increases, the system total throughput increases. This is because a higher SNR leads to a larger detection probability of the channel and a lower false alarm probability, so as to achieve a higher system total throughput. It also can be seen that, with the increase of detection probability requirement, more channels can not meet the detection probability requirement, thus the total system throughput decreases.

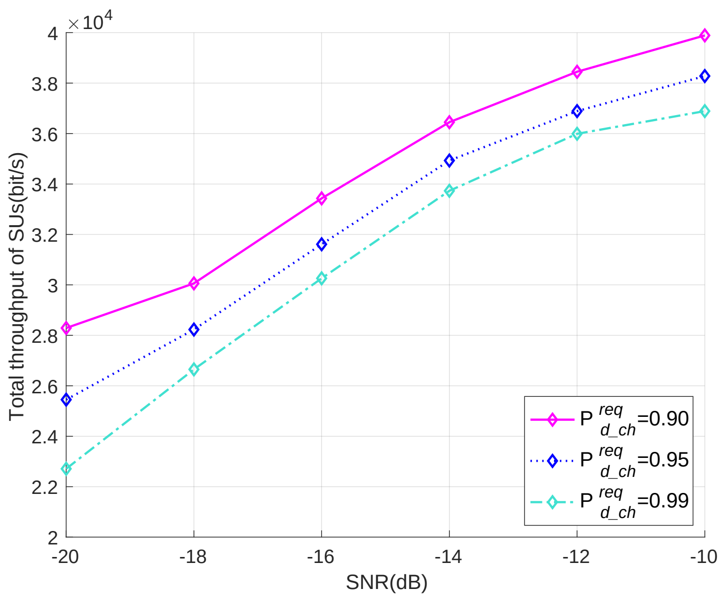

Figure 9. The total throughput versus the mean signal to noise ratio (SNR) values under different detection probabilities.

5. Conclusions

In this paper, we investigated a CRIoT network with SWIPT in which SUs could adaptively switch between spectrum sensing, SWIPT, and information transmission to maximize the total throughput. The multi-dimensional resource allocation problem with some constraints, such as maximum transmit power, maximum permissible interference, and minimum energy harvest requirement, was formulated as an MINLP problem. For a given sensing duration, a greedy sensing algorithm was firstly used to determine the sensing task assignment matrix. Secondly, the original problem was transformed into a convex problem by introducing auxiliary variable, then the Lagrange dual method and subgradient method were adopted to obtain the optimal power and channel allocation. A one-dimensional searching method was used to obtain the optimal PS ratio and TS ratio. Finally, a heuristic algorithm was adopted to obtain the optimal sensing duration. The simulation results showed that the proposed algorithm can obtain higher total system throughput than benchmark algorithms. The proposed algorithm can be applied to the multi-user and multi-channel scenario in CRIoT networks with SWIPT to solve the multi-dimensional resource allocation problem to improve the system performance. The proposed optimization algorithm can also provide reference for the similar optimization problem. It could help IoT to relieve the shortage problem of wireless spectrum, guarantee the quality of service, and save energy consumption to realize green communication. In future works, we will consider the non-linear EH model into our work to be more practical. The uplink transmission of IoDs will also be included.

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Appendix A

Proof of Proposition 1. By applying KKT conditions, it can be obtained that

$$\frac{\partial L(\Xi)}{\partial U_{m,n}}\begin{cases}=0, & U_{m,n}^{opt}>0\\ >0, & U_{m,n}^{opt}<0\end{cases},\forall m,n \tag{A1}$$

Take the partial derivative $R_{m,n}^{00}(t_1)$, $R_{m,n}^{00}(t_2)$, $R_{m,n}^{10}(t_1)$, $R_{m,n}^{10}(t_2)$ with respect to $U_{m,n}$.

$$\frac{\partial R_{m,n}^{00}(t_1)}{\partial U_{m,n}}=\frac{|h_{m,n}|^2\rho}{\left(y_{m,n}\sigma_n^2+U_{m,n}|h_{m,n}|^2\rho\right)\ln 2}, \tag{A2}$$

$$\frac{\partial R_{m,n}^{00}(t_2)}{\partial U_{m,n}}=\frac{|h_{m,n}|^2}{\left(y_{m,n}\sigma_n^2+U_{m,n}|h_{m,n}|^2\right)\ln 2}, \tag{A3}$$

$$\frac{\partial R_{m,n}^{10}(t_1)}{\partial U_{m,n}}=\frac{|h_{m,n}|^2\rho}{\left[y_{m,n}\left(P_{PU,m}|g_{m,n}|^2+\sigma_n^2\right)+U_{m,n}|h_{m,n}|^2\rho\right]\ln 2}, \tag{A4}$$

$$\frac{\partial R_{m,n}^{10}(t_2)}{\partial U_{m,n}}=\frac{|h_{m,n}|^2}{\left[y_{m,n}\left(P_{PU,m}|g_{m,n}|^2+\sigma_n^2\right)+U_{m,n}|h_{m,n}|^2\right]\ln 2}. \tag{A5}$$

Then, the partial derivative of $L(\Xi)$ with respect to $U_{m,n}$ can be obtained as

$$\begin{aligned}\frac{\partial L(\Xi)}{\partial U_{m,n}} &= y_{m,n}B_m\left\{\frac{t_1}{T}\left[a_{0,m}\frac{\partial R^{00}_{m,n}(t_1)}{\partial U_{m,n}}+b_{0,m}\frac{\partial R^{10}_{m,n}(t_1)}{\partial U_{m,n}}\right]\right.\\ &\left.+\frac{t_2}{T}\left[a_{0,m}\frac{\partial R^{00}_{m,n}(t_2)}{\partial U_{m,n}}+b_{0,m}\frac{\partial R^{10}_{m,n}(t_2)}{\partial U_{m,n}}\right]\right\}\\ &+(a_{0,m}+b_{0,m})\left[\frac{T-\tau}{T}\beta_n\mu_n\eta(1-\rho)|h_{m,n}|^2-\lambda\right]-\psi_m|k_m|^2\frac{T-\tau}{T}b_{0,m}.\end{aligned} \tag{A6}$$

By setting $\frac{\partial L(\Xi)}{\partial U_{m,n}}=0$, we have the following equation related to $U_{m,n}$

$$q_{0,m,n}|h_{m,n}|^2\rho^2U^2_{m,n}+y_{m,n}\Delta_{0,m,n}U_{m,n}+\omega_{0,m,n}y^2_{m,n}=0, \tag{A7}$$

where $q_{0,m,n}$, $\Delta_{0,m,n}$ and $\omega_{0,m,n}$ are defined in (30),(31),(32).

Thus, the optimal $U_{m,n}$ can be obtained by

$$U_{m,n}=\frac{-y_{m,n}\Delta_{0,m,n}+y_{m,n}\sqrt{\Delta^2_{0,m,n}-4q_{0,m,n}|h_{m,n}|^2\rho^2\omega_{0,m,n}}}{2q_{0,m,n}|h_{m,n}|^2\rho^2} \tag{A8}$$

As to $P_{m,n}$, it can be obtained by $P_{m,n}=\frac{U_{m,n}}{y_{m,n}}$, then (29) is obtained. □

Appendix B

Proof of Proposition 2. In order to obtain the partial derivative of $L(\Xi)$ with respect to $y_{m,n}$, we firstly calculate the derivatives of $R^{00}_{m,n}(t_1)$, $R^{00}_{m,n}(t_2)$, $R^{10}_{m,n}(t_1)$, and $R^{10}_{m,n}(t_2)$ with respect to $y_{m,n}$.

$$\frac{\partial R^{00}_{mn}(t_1)}{\partial y_{mn}}=\frac{-U_{m,n}|h_{m,n}|^2\rho}{y_{m,n}\left(y_{m,n}\sigma^2_n+U_{m,n}|h_{m,n}|^2\rho\right)\ln 2} \tag{A9}$$

$$\frac{\partial R^{00}_{mn}(t_2)}{\partial y_{mn}}=\frac{-U_{m,n}|h_{m,n}|^2}{y_{m,n}\left(y_{m,n}\sigma^2_n+U_{m,n}|h_{m,n}|^2\right)\ln 2} \tag{A10}$$

$$\frac{\partial R^{10}_{m,n}(t_1)}{\partial y_{m,n}}=\frac{-U_{m,n}|h_{m,n}|^2\rho}{y_{m,n}\left[y_{m,n}\left(P_{PU,m}|g_{m,n}|^2+\sigma^2_n\right)+U_{m,n}|h_{m,n}|^2\rho\right]\ln 2} \tag{A11}$$

$$\frac{\partial R^{10}_{m,n}(t_2)}{\partial y_{m,n}}=\frac{-U_{m,n}|h_{m,n}|^2}{y_{m,n}\left[y_{m,n}\left(P_{PU,m}|g_{m,n}|^2+\sigma^2_n\right)+U_{m,n}|h_{m,n}|^2\right]\ln 2} \tag{A12}$$

Then the derivatives of $L(\Xi)$ with respect to $y_{m,n}$ is obtained as

$$\begin{aligned}\frac{\partial L(\Xi)}{\partial y_{mn}} &= B_m\frac{t_1}{T}\left[a_{0,m}\left(R^{00}_{m,n}(t_1)\right)+\frac{\partial R^{00}_{m,n}(t_1)}{\partial y_{mn}}+b_{0,m}\left(R^{10}_{m,n}(t_1)\right)+\frac{\partial R^{10}_{m,n}(t_1)}{\partial y_{mn}}\right]\\ &+B_m\frac{t_2}{T}\left[a_{0,m}\left(R^{00}_{m,n}(t_2)\right)+\frac{\partial R^{00}_{m,n}(t_2)}{\partial y_{mn}}+b_{0,m}\left(R^{10}_{m,n}(t_2)\right)+\frac{\partial R^{10}_{m,n}(t_2)}{\partial y_{mn}}\right]\\ &+\frac{t_1}{T}\mu_n\eta(1-\rho)\sigma^2_n-\epsilon_m.\end{aligned} \tag{A13}$$

The formula (A13) can be simplified as

$$\frac{\partial L(\Xi)}{\partial y_{mn}}=\theta_{m,n}-\epsilon_m, \tag{A14}$$

where $\theta_{m,n}$ is defined in (35).

The optimal channel allocation can be obtained by [21]

$$y_{m,n}^{opt} = \begin{cases} 0, & \theta_{m,n} < \epsilon_m \\ 1, & \theta_{m,n} > \epsilon_m \end{cases} \tag{A15}$$

In the case $\theta_{m,n} = \epsilon_m$, the $y_{m,n}^{opt}$ is non-unique due to formula $(\theta_{m,n} - \epsilon_m)y_{m,n}$ is always equivalent to 0 for any value of $y_{m,n}$. Thus the optimal solution cannot be obtained directly by the Lagrange dual method. Since each channel can only be accessed by one SU, the channel allocation problem can be transformed into M non-interfering subproblems. Due to the independence of each channel power gains, different SU has different $\theta_{m,n}$. Thus, the optimal channel assignment problem is equivalent to finding the largest $\theta_{m,n}$ for each channel. This kind of method has been widely used in [21,27]. Furthermore, to protect the normal communication of PU networks, the channel of which the detection probability is lower than $P_{d\_ch}^{req}$ cannot be used for transmission. Thus, set $y_{m,n} = 0$ for these channels. Ultimately, (34) is obtained and Proposition 2 is proved. □

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