

Optimal Power Allocations for Multichannel Energy Harvesting Cognitive Radio

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Abstract—In this paper, we study spectrum overlay access to share spectrum between primary users (PUs) and secondary users (SUs). Our goal is to maximize the average throughput by optimal power allocation within finite time duration. To do this, we formulate this optimization problem as a Markov Decision Process with continuous state. An approximate value method with pre-allocation mechanism is proposed, which can effectively protect the PUs by obtaining a continuous closed-form solution rather than a discrete one. Numerical results show that the proposed algorithm exhibits better performance than traditional methods while guaranteeing non-interference to PUs.

I. INTRODUCTION

SPECTRUM scarcity and power consumption have become major bottlenecks in the development of current wireless communication systems. In the 5G era, for example, there are more and more devices needed to access complicated networks, and present spectrum allocation policy has hardly satisfied the current requirements. Cognitive radio (CR) technique [1] has been widely recognised as one of the most effective methods to tackle this problem. In this system, secondary users (SUs) can utilize white spectrum which primary users (PUs) temporarily do not access (referred to as spectrum overlay) or they can share same band of frequency with PUs without causing harmful interference to them (referred to as spectrum underlay). However, due to complex spectrum sensing algorithms, channel identification and power control, more and more energy is needed, especially for the cognitive radio device [2]. However the limited battery energy life of SUs has obstacle the further development of cognitive radio. Recently, energy harvesting technology [3] has enabled wireless devices to scavenge energy physically or chemically from natural or man-made phenomena, there by gaining attention as a viable solution to Recently, a promising technique that combines cognitive radio (CR) [2] with energy harvesting [3] was proposed to solve the problems effectively. However, how to use the harvested energy efficiently while protecting primary user from harmful interference at the same time has become a challenge.

To handle this issue, some research efforts have been made. In [4], the authors use dynamic programming to derive an optimal power control policy to minimize outage

probability. This optimization problem is solved for block fading channels under energy harvesting constraint. In [5], the authors propose a transmission power policy based on 1-bit feedback of CSI from receiver for an energy harvesting communication system over the Rayleigh fading channels. In this policy, RX periodically sends 1-bit feedback by comparing the channel power gain with a predetermined threshold, and a constrained optimization problem to maximize throughput under an arbitrarily deterministic energy harvesting process is formulated. In consideration of non-causal and causal energy harvesting models in [6], an optimal offline power and rate allocation scheme is developed by exploiting hidden convexity of the problem. In [7], the joint resource allocation and admission control schemes for energy-harvesting based cooperative overlay cognitive radio networks under imperfect channel state information condition is proposed to guarantee quality-of-service (QoS) requirements of both PU communication-pair and all SU pair. Cognitive and energy harvesting-based device-to-device communication underlying cellular networks were investigated in [8], where the system performance is characterized in terms of transmission probability and SINR outage probabilities by the stochastic geometry approach. The joint impact of sensing probability, access probability, and energy queue capacity on the maximum achievable throughput in a multiuser CR network incorporating energy harvesting is investigated in [9]. In [10], power allocation strategies are proposed for multiple source-destination pair cooperative energy harvesting relay networks where non-regenerative protocol was also considered. In [11], a static channel with causal knowledge of the stationary Poisson energy arrival process is considered and an MDP-based solution is given to maximize the average throughput with unconstrained transmission power. In order to achieve optimal average throughput over a finite horizon, a “rate loss constraint” based power scheduling algorithm is proposed in [12] for a static channel with finite battery capacity and non-causal energy harvesting state. In [13], the authors study the resource allocation for multiuser multiple-input-single-output secondary communication systems with multiple system design objectives. In particular, a multi-objective optimization framework for the design of a Pareto-optimal resource allocation algorithm based on the weighted Tchebycheff approach was proposed. However, these methods

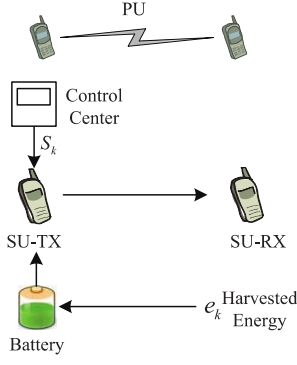


Fig. 1. Hybrid energy harvesting cognitive radio communication system

mostly quantize the continuous variables such as channel gain, battery energy and transmission power to a finite number of discrete levels. With such discretization, an exhaustive search on the available set of all discretized states is often introduced, which increases dramatically the computational complexity when the discrete level rises high and we can only obtain discrete power levels. To handle this problem, in [14], an approximate value function method was adopted for a single channel system. Though this method can significantly reduce computation complexity, it is still not applicable to the multi-channel case.

In this paper, we propose a new optimal power allocation paradigm to maximize average throughput over finite horizon with causal channel information in a multichannel energy harvesting cognitive radio system. The main contributions of our work are as follows. (1) We formulate this stochastic optimization problem of energy harvesting cognitive radio systems power allocation as a Markov decision process. By defining different subchannel state to describe PU activity, the proposed algorithm can guarantee QoS of PU. (2) We obtain the continuous power allocation by piecewise linear approximation with closed form solution rather than discrete one. In order to balance system performance and algorithm computation complexity, a pre-allocation mechanism is proposed.

The remainder of this paper is organized as follows. In Section II, we present the system model and describe the subchannel state as a Section III, we formulate the power allocation problem as a continuous-state MDP problem and define an approximate value function. In Section IV, a pre-allocation based approximate algorithm is proposed and an optimal closed-form solution for the power allocation of SU. Numerical results are presented in Section V to show the validity and comparison of the proposed algorithm with two traditional methods. Finally, Section VI concludes the paper.

II. SYSTEM MODEL

We consider an overlay OFDM based cognitive radio system shown in Fig. 1. It consists of one pair of PUs and another pair of SUs who share same frequency band and

SU is equipped with an energy harvesting device to take energy from the ambient environment and a rechargeable battery. The battery buffering the harvested energy has a finite capacity denoted by B_{max} . A control center provides subchannel usage state and also subchannel gain between the transmitter of SU and its receiver. Let $s_k^n \in \{0, 1\}$ denote subchannel usage status for current time slot, where $s_k^n = 0$ indicates that the n th subchannel is used by PU for the slot k while $s_k^n = 1$ indicates otherwise. Since this subchannel usage status is related with time, it is reasonable to assume that the evolution of each subchannel independently follows a first-order two states Markov chain. Its transition probabilities are given as $\Pr(s_{k+1}^n = 0 | s_k^n = 1) = q_k^n$ and $\Pr(s_{k+1}^n = 0 | s_k^n = 0) = f_k^n$. The whole channel usage status is denoted as $\mathbf{S}_k^i = [s_k^1, s_k^2, \dots, s_k^N]^T$ where N is the total number of subchannels, and $i \in \mathcal{M} \triangleq \{1, 2, \dots, 2^N\}$ denotes the i th channel usage status. Because the evolution of each subchannel is independent, we can define the channel usage status transition probability as follows

$$\Pr\{\mathbf{S}_{k+1}^j | \mathbf{S}_k^i\} = \prod_{n=1}^N \Pr\{s_{k+1}^n | s_k^n\}, \quad i, j \in \mathcal{M} \quad (1)$$

A slow fading channel model is considered where the channel gain is constant for a coherence time of T_c and changes independently across the time slots. Let h_k^n be the n th subchannel gain at the slot k which can be provided by the control center. The transmitter of SU is powered by the energy harvesting device and the rechargeable battery. The battery stores the harvested energy until it reaches its maximum capacity B_{max} . Here, we consider the energy harvesting process known in advance over the K time slots and denoted as e_k , since the energy is harvested from steady sources such as solar, wind, etc. Hence, the evolution of the battery energy in each time slot is

$$b_{k+1} = \min\{b_k - P_k T_c + e_k, B_{max}\} \quad (2)$$

where $P_k = \sum_{n=1}^N p_k^n$ is the transmission power of SU, p_k^n denotes the n th subchannel transmission power at the slot k . According to the overlay pattern, we know that SUs will stop using the subchannels immediately when PUs occupy them, so we set $p_k^n = 0$ when $s_k^n = 1$. On the other hand, we need to decide the transmission power when $s_k^n = 0$, while keeping this power by the available energy b_k as follows

$$0 \leq P_k \leq \frac{b_k}{T_c} \quad (3)$$

III. PROBLEM FORMULATION

We use Shannon capacity as the upper bound on the achievable rate in each time slot as a reward function of p_k^n and h_k^n as follows

$$g(p_k^n, h_k^n) = \sum_{n=1}^N \log_2(1 + p_k^n (\Omega_k^n) h_k^n) \quad (4)$$

where $\Omega_k^n \triangleq (b_k, h_k^n, s_k^n)$ are the observations at the beginning of the slot k . Specifically, at the beginning of the slot k , given Ω_k , if the n th subchannel is used by PU, let $p_k^n = 0$, otherwise, the transmitter determines the transmission power based on the current battery energy level b_k and h_k^n .

After denoting $\mathbf{H} \triangleq [\mathbf{h}_1, \mathbf{h}_2, \dots, \mathbf{h}_K]^T$ where $\mathbf{h}_k = [h_k^1, h_k^2, \dots, h_k^N]$, and $\mathbf{S} \triangleq [\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_K]^T$ where $\mathbf{s}_k = [s_k^1, s_k^2, \dots, s_k^N]$, and K is the total slot number, we aim to maximize the expected total reward in K time slots by dynamic allocation for the transmission power of SU. To reach this goal, we formulate an optimization problem as follows

$$(P1) \quad \begin{aligned} \max_p \mathbb{E}_{\mathbf{H}, \mathbf{S}} & \left\{ \frac{1}{K} \sum_{k=0}^{K-1} \sum_{n=1}^N \log_2 (1 + h_k^n p_k^n) \right\} \\ \text{s.t.} \quad & \sum_{n=1}^N p_k^n \leq \frac{B_k}{T} \quad k = 0, 1, \dots, K-1 \\ & p_k^n \geq 0 \quad k = 0, 1, \dots, K-1 \end{aligned} \quad (5)$$

This problem can be converted to its equivalent MDP recursive form according to the reward function which represents the total reward received in the current slot and expectation of future slots. For this problem, the battery energy b_k can be seen as a continuous-state first-order Markov chain and subchannel status $\mathbf{S}_k$ as a discrete-state Markov chain. Let $(b_k, \mathbf{S}_k)$ represent the state of a MDP model, h_k^n as the observation, and p_k^n as the decision. According to the MDP theory, the state space becomes $\{0 \leq b \leq B_{\max}\} \times \{\mathbf{S}\}$, the decision space is $\mathcal{D}_1(b) = \{0 \leq \sum p \leq \frac{b}{T_c}\}$, and $\mathcal{D}_0(b) = \{0\}$. The reward function is then recursively defined as

$$y^k(b_k, \mathbf{S}_k) = \mathbb{E}_{h_k} \left[\max_{p_k(\Omega_k) \in \mathcal{C}_{S_k}(b_k)} \left\{ \sum_{n=1}^N \log_2 (1 + h_k^n p_k^n) + u^k(b_k, p_k, \mathbf{S}_k) \right\} \right] \quad (6)$$

where

$$u^k(b_k, p_k, \mathbf{S}_k) = \mathbb{E}_{\mathbf{S}_{k+1}|\mathbf{S}_k} [y^{k+1}(\min\{b_{\max}, b_k + e_k - \sum_{n=1}^N p_k^n T\}, \mathbf{S}_{k+1})] \quad (7)$$

and

$$y^{K+1}(b, \mathbf{S}) = 0 \text{ for all } b \in [0, B_{\max}] \quad (8)$$

To solve the above convex optimal problem, many classical methods can be used. However, it is hard to derive a closed form solution when $K > 2$. For this reason, we adopt dynamic programming method [15] to handle this issue by converting it to its equivalent iteration form in terms of the reward function, which represents the total payoff received in the current slot and expected to be received in the future slots.

For example, if $K = 2$ and with the given policy, (6) can be simplified as

$$\begin{aligned} R &= y(b_1, P_1(\mathbf{S}_1)) + \mathbb{E}_{\mathbf{S}_2} [y(b_2, P_2(\mathbf{S}_2)) | \mathbf{S}_1] \\ \text{s.t.} \quad & 0 \leq P_1 \leq b_1 \\ & 0 \leq P_2 \leq b_2 \end{aligned} \quad (9)$$

where $b_2 = \min\{b_1 - P_1 + e_1, B_{\max}\}$. Clearly, the transmission power in the first slot affects the stored energy b_2 available in the second slot, which in turn affects the power P_2 to be allocated.

In general, the optimization of $\{P_k\}$ cannot be performed independently due to the energy harvesting constraints. As a result, we can optimize P_2 first under all possible given P_1 (and hence all possible $(b_2, \mathbf{S}_2)$), then optimize P_1 with P_2 replaced by the optimized value (as a function of P_2).

However, due to the feature of dynamic programming, an exhaustive-like method, it cannot directly resolve optimization problem in the continuous variables case. A typical approach is to quantize the continuous variables to a finite number of discrete levels, i.e. to convert the original problem to a discrete MDP problem [16]. However, this method has the following limitations: 1) we can only obtain the discrete power levels rather than a closed form solution; 2) it has high computational complexities due to its exhaustive search method. Interestingly, an approximate value function method introduced in [14] can be used to solve this problem.

With an approximation precision parameter δ , a piecewise linear approximation operator is defined as follows

$$\mathcal{T}[y^k(b, S), \delta] = y^k(\lfloor b/\delta \rfloor \delta, A) + \frac{b - \lfloor b/\delta \rfloor \delta}{\delta} (y^k(\lceil b/\delta \rceil \delta, A) - y^k(\lfloor b/\delta \rfloor \delta, A)), b \in [0, b_{\max}] \quad (10)$$

First, we define approximation value for the final slot K

$$\Phi_\delta^K(b, S) \triangleq \mathcal{T}[y^K(b, S), \delta] = y(b_{\max}, A) \text{ for any } b > b_{\max} \quad (11)$$

Then, we use the approximate value function recursively from $k = K-1$ to $k = 1$ to replace the original value function in (7)

$$U^k(b_k, p_k, \mathbf{S}_k) \triangleq \mathbb{E}_{\mathbf{S}_{k+1}|\mathbf{S}_k} [\Phi_\delta^{k+1}(\min\{b_{\max}, b_k + e_k - p_k T\}, \mathbf{S}_{k+1})] \quad (12)$$

Replacing $u^k(b_k, p_k, \mathbf{S}_k)$ with the approximation value $U^k(b_k, p_k, \mathbf{S}_k)$ in (6), we have

$$Y^k(b_k, S_k) \triangleq \mathbb{E}_{h_k} \left[\max_{p_k \in \mathcal{C}_{S_k}(b_k)} \left\{ \sum_{n=1}^N \log_2 (1 + h_k^n p_k^n) + U^k(b_k, p_k, \mathbf{S}_k) \right\} \right] \quad (13)$$

Finally, we write the approximate value function as

$$\Phi_\delta^k(b, \mathbf{S}) = \mathcal{T}[\mathbf{Y}^k(\mathbf{b}, \mathbf{S}), \delta] \quad (14)$$

In the next section, we will take a pre-allocation and approximate value function based optimization method to solve this problem.

IV. PRE-ALLOCATION ALGORITHM

A. Pre-allocation Process

As mentioned previously, the channel gains of each subchannel at the k th time slot are denoted by $h_k^1, h_k^2, \dots, h_k^N$. We first normalize them, and then define proportional coefficients

$\gamma_i, i = 1, 2, \dots, M$, where M is the subchannel number used by secondary user. We can determine the value of each γ_i by

$$\gamma_1 : \gamma_2 : \dots : \gamma_M = \frac{h_k^1}{\sum_{n=1}^M h_k^n} : \frac{h_k^2}{\sum_{n=1}^M h_k^n} : \dots : \frac{h_k^M}{\sum_{n=1}^M h_k^n} \quad (15)$$

If the current battery energy is b_k , we can obtain the corresponding power for each subchannel as

$$p_k^j = \gamma_j (b_k / T_c), j = 1, 2, \dots, M \quad (16)$$

Thus, we finally have

$$\sum_{j=1}^M p_k^j = \frac{b_k}{T_c} \quad (17)$$

B. Optimal Solution to P1

Before we derive the optimal solution to problem of (P1), we need to analyze the approximate value function $U^k(B, p, 1)$, which is the key point of the continuous solution. It can be proved that $U^k(B, p, 1)$ is concave and non-decreasing with respect to p .

Since $U^k(B, p, 1)$ is a piecewise linear function, we define $\mathbf{Z} = \{\mathbf{z}_0, \mathbf{z}_1, \dots, \mathbf{z}_N\}$ as the set of discontinuous points, where $z_0 = 0, z_N = \min\{p_{\max}, B/T\}$ and z_i is the i th smallest element. We also define $\mathbf{A} = \{\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_N\}$ as the set of the corresponding slopes, where a_i is the slope of the segment $[z_{i-1}, z_i]$ given by

$$a_i \triangleq -\frac{\gamma T}{\delta} \mathbf{E}_{S|1} \left\{ Y^{k+1}(\lceil \min\{b_{\max}, B + e_k - p_i T\} / \delta \rceil \delta, S) - Y^{k+1}(\lfloor \min\{b_{\max}, B + e_k - p_i T\} / \delta \rfloor \delta, S) \right\} \quad (18)$$

derived from (12) and (14). Hence, the derivative of $U^k(B, p, 1)$ for $p \in C_1(B) / \mathbf{Z}$ is

$$\frac{\partial U^k(B, p, 1)}{\partial p} = a(p) = a_i, \text{ if } p \in (z_{i-1}, z_i) \quad (19)$$

Since $U^k(B, p, 1)$ is concave and non-decreasing with respect to p , we have $0 \geq a_0 \geq a_1 \geq \dots \geq a_N$.

Then, for the n th subchannel at any k th time slot, we have

$$\left[W_k^j(p_k^j) \right]' = \frac{\partial W_k^j(p_k^j)}{\partial p_k^j} = \frac{1}{1/h_k^j + p_k^j} + a(p_k^j) = 0 \quad (20)$$

Meanwhile, at the non-differentiable points in Z , the right-derivative and the left-derivative of $\left[W_k^j(p_k^j) \right]'$ can be written as

$$\left[W_k^j(p_k^j+) \right]' \triangleq \frac{1}{1/h_k^j + p_k^j} + a(p_k^j+) \quad (21)$$

and

$$\left[W_k^j(p_k^j-) \right]' \triangleq \frac{1}{1/h_k^j + p_k^j} + a(p_k^j-) \quad (22)$$

respectively.

At the end, by resolving the above problem, we can obtain a piecewise optimal solution as described by (23) on the next page.

TABLE I
PRE-ALLOCATION ALGORITHM FOR PROBLEM (P1)

Finite-Horizon Power Allocation	
Input:	Slot size K ; distributions of $\mathbf{H}, \mathbf{S}$; value of e_k for $k = 1, 2, \dots, K$; approximation precision $\delta > 0$
Output:	Optimal power allocation strategy $\{p_k^{j*}\}$
Phase-I:	Compute the approximate value function offline
	FOR $k = K$ to 1
	//1. Pre-allocation power of each subchannel
	Calculate $\gamma_1, \gamma_2, \dots, \gamma_M$ using (15)
	Compute $d_k^j = \gamma_k^j b_k$.
	//2. Calculate approximation function for each subchannel
	for $j = 1$ to M
	Calculate $Y_k^j(d_k^j, h_k^j, S_k^j)$ for $d_k^j \in \mathcal{B}_\delta, S_k^j \in \mathbf{S}$ using (23)
	Calculate $\Phi_\delta^k(d_k^j, S)$ from $Y_k^j(d_k^j, S_k^j)$ using (14) then store it.
	endfor
	ENDFOR
Phase-II:	Allocate power online
	FOR $k = 1$ to K
	Obtain the observations $\Omega_k^j \triangleq (d_k^j, h_k^j, s_k^j)$
	Fetch $\Phi_\delta^{k+1}(d_k^j, S)$ and calculate $\gamma_k^j U^k(d_k^j, p_k^j, S_k^j)$ using (12)
	Calculate $p_k^{j*}(h_k^j)$ using (23)
	ENDFOR

The entire procedure for above pre-allocation based power allocation algorithm is given in Table I.

V. NUMERICAL RESULTS

In this section, we evaluate the performance of the proposed algorithm and compare it with other two methods, greedy policy [17] and balanced policy [18]. We assume that there is one primary user and one secondary user sharing total bandwidth of $B = 1\text{MHz}$. We adopt the overlay access pattern which means when the primary user has occupied a certain subchannel, the secondary user cannot use it. We set subchannel number $N = 4$, and each subchannel fading h_k^j is an i.i.d. random variable following the Rayleigh distribution. Furthermore, we set the probabilities of the channel state transmission $q = 0.2$ and $f = 0.5$. Meanwhile, we assume $T_c = 1\text{s}$ and the harvesting energy prediction value is randomly generated following a positive truncated-Gaussian

$$p_k^{j*}(h_k^j) = \begin{cases} -\frac{1}{a_i} - \frac{1}{h_k^j}, & \frac{1}{h_k^j} \in [-\frac{1}{a_i} - z_i, -\frac{1}{a_i} - z_{i-1}] \cap [0, +\infty) \\ z_i, & \frac{1}{h_k^j} \in [-\frac{1}{a_{i+1}} - z_i, -\frac{1}{a_i} - z_i] \cap [0, +\infty) \\ 0, & \frac{1}{h_k^j} \in [-\frac{1}{a_i} - z_0, \infty) \\ z_N, & \frac{1}{h_k^j} \in [0, -\frac{1}{a_N} - z_N) \end{cases} \quad (23)$$

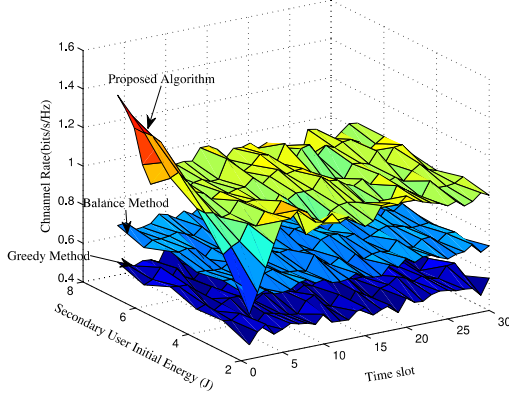


Fig. 2. Throughput comparisons among three methods with $\sigma = 0.8$

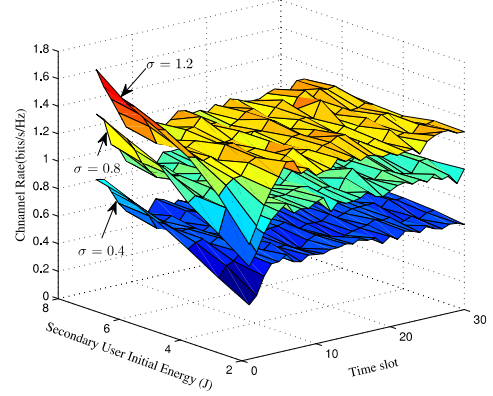


Fig. 3. Throughput comparisons of the proposed algorithm using different Rayleigh fading parameters

distribution with a variance of 2. Finally, we set the total time number of slots $K = 30$ and the initial battery level $B_0 = 2J$.

Fig. 2 shows the overall throughput of the secondary user using our proposed algorithm in comparison with other two traditional methods such as the greedy policy and the balanced policy during the whole transmission process. Specifically, we find that the greedy policy tries to allocate as much power as possible in each time slot subject to the energy availability, and the balanced policy tries to allocate a constant power in each time slot. For instance, the mean value of the harvested energy. From Fig. 2, we can see that the proposed algorithm has much higher throughput than the other two methods.

For the Rayleigh fading channel, the throughput of the proposed algorithm with different Rayleigh parameters σ is given in Fig. 3. The capacity of SU increases as σ increases. Meanwhile, for same σ , taking $\sigma = 1.2$ for instance, this capacity increases gradually with the increase of battery initial energy, since we can use more power for data transmission by large energy storage. From time dimension, the capacity does not reduce even though the time advances, since the harvested energy from the ambient environment can provide permanent energy for SU.

For the scenario of zero initial battery energy, throughput comparisons are shown in Fig. 4. In this scenario, we assume that the transmitter is only powered by the harvested energy from the ambient environment. We compare the throughput of the proposed algorithm with those of the two methods. From Fig. 4, we can see that the throughput of these methods start at 0 in the initial time slot, and then increase gradually over time. The transmitter sends data with the harvested energy and

constantly harvests energy from the environment, and finally maintains a stable data transmission.

Fig. 5 shows the protection for PU by the proposed algorithm. We arbitrarily take three time slots to present the interference protection process. For instance, we randomly selected 6 timeslots (such as timeslot 3-8), and use symbol 0 and 1 to denote the channel utilization state, where symbol "1" denotes the channel occupation state by PU and otherwise is denoted as "0". From Fig. 5, we find the all subchannels occupied by PU whatever in which time slot are set to zero due to the spectrum overlay access pattern. This can effectively

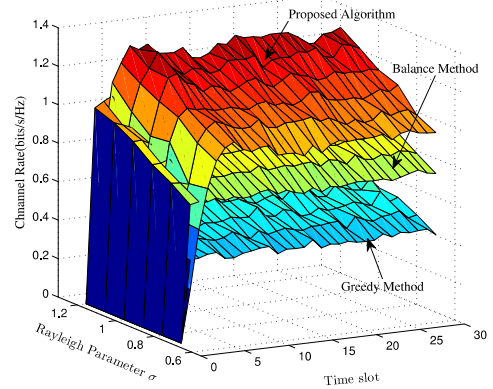


Fig. 4. Throughput comparisons in zero initial energy storage scenario

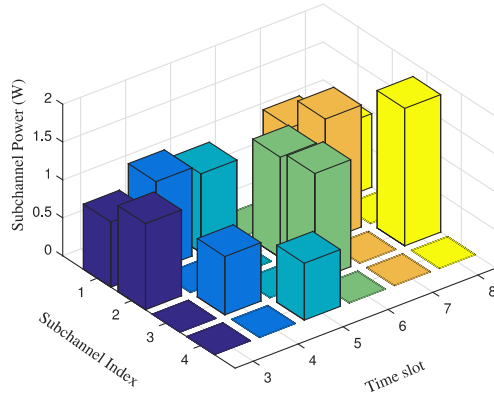


Fig. 5. Power allocation on each subchannels

reduce the interference to PU.

The performance of the proposed algorithm under different approximation precisions is shown in Fig. 6. From Fig. 6 the throughput of SU improves as δ decreases, since the reduction of approximation precision means the number of energy segmentation increases, the original objective function can be precisely approximated. Therefore, the transmission power of SU is closer to the theoretical optimal solution. However, this advantage is at cost of calculation quantity of the proposed algorithm. Meanwhile, the channel rate increases as σ increases, which is also shown in Fig. 6.

VI. CONCLUSION

In this paper, we have proposed an optimal transmission power policy for an overlay multichannel energy harvesting cognitive radio system. Using a first-order two-state Markov chain to describe the channel state, this algorithm can make SU access the network via an overlay pattern, and PU can be well protected from the interference of SU. We also obtain an approximately optimal continuous power allocation solution in close-form based on causal observations of the channel

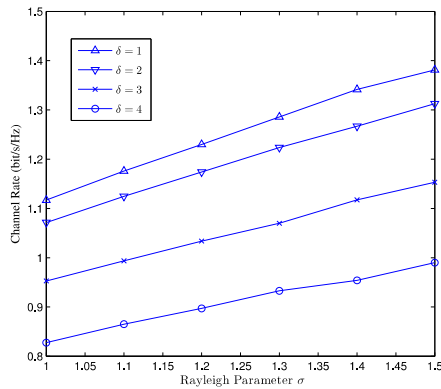


Fig. 6. Throughput comparisons under different approximation precisions

fading state rather than non-causal channel state information used by other methods. The numerical results demonstrate that the proposed algorithm has better performance than other two traditional methods.

ACKNOWLEDGMENT

This work was supported by the National Natural Science Foundation of China (Grant No. 61501202).

REFERENCES

- [1] J. Mitola and J. Maguire, G.Q., "Cognitive radio: making software radios more personal," *IEEE Pers Commun*, vol. 6, no. 4, pp. 13–18, 1999.
- [2] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 2, pp. 201–220, 2005.
- [3] M. L. Ku, W. Li, Y. Chen, and K. J. R. Liu, "Advances in energy harvesting communications: Past, present, and future challenges," *IEEE Communications Surveys Tutorials*, vol. 18, no. 2, pp. 1384–1412, 2016.
- [4] C. Huang, R. Zhang, and S. Cui, "Optimal power allocation for outage probability minimization in fading channels with energy harvesting constraints," *IEEE Trans. Wireless Commun.*, vol. 13, no. 2, pp. 1074–1087, Feb. 2014.
- [5] R. Ma and W. Zhang, "Optimal power allocation for energy harvesting communications with limited channel feedback," in *Signal and Information Processing (GlobalSIP), 2014 IEEE Global Conference on*, Dec. 2014, pp. 193–197.
- [6] D. Zhao, C. Huang, Y. Chen, F. Alsaadi, and S. Cui, "Resource allocation for multiple access channel with conferencing links and shared renewable energy sources," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 423–437, Mar. 2015.
- [7] F. Wang and X. Zhang, "Joint resource allocation and admission control for energy harvesting based cooperative overlay cognitive radio networks," in *2016 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, Apr. 2016, pp. 796–801.
- [8] A. H. Sakr and E. Hossain, "Cognitive and energy harvesting-based d2d communication in cellular networks: Stochastic geometry modeling and analysis," *IEEE Trans. Commun.*, vol. 63, no. 5, pp. 1867–1880, May 2015.
- [9] Y. H. Bae and J. W. Baek, "Achievable throughput analysis of opportunistic spectrum access in cognitive radio networks with energy harvesting," *IEEE Trans. Commun.*, vol. 64, no. 4, pp. 1399–1410, Apr. 2016.
- [10] Z. Ding, S. M. Perlaza, I. Esnaola, and H. V. Poor, "Power allocation strategies in energy harvesting wireless cooperative networks," *IEEE Trans. Wireless Commun.*, vol. 13, no. 2, pp. 846–860, Feb. 2014.
- [11] Q. Bai, R. A. Amjad, and J. A. Nossek, "Average throughput maximization for energy harvesting transmitters with causal energy arrival information," in *2013 IEEE Wireless Communications and Networking Conference (WCNC)*, Apr. 2013, pp. 4232–4237.
- [12] H. Liang and X. Zhao, "Optimal power allocation for energy harvesting cognitive radio networks with primary rate protection," in *2016 International Conference on Computing, Networking and Communications (ICNC)*, Feb. 2016, pp. 1–6.
- [13] D. W. K. Ng, E. S. Lo, and R. Schober, "Multiobjective resource allocation for secure communication in cognitive radio networks with wireless information and power transfer," *IEEE Trans. Veh. Technol.*, vol. 65, no. 5, pp. 3166–3184, May 2016.
- [14] Z. Wang, V. Aggarwal, and X. Wang, "Power allocation for energy harvesting transmitter with causal information," *IEEE Trans. Commun.*, vol. 62, no. 11, pp. 4080–4093, Nov. 2014.
- [15] D. P. Bertsekas, *Dynamic Programming and Optimal Control*. Belmont, MA: Athena Scientific, 1995, vol. 1.
- [16] P. Blasco, D. Gunduz, and M. Dohler, "A learning theoretic approach to energy harvesting communication system optimization," *IEEE Trans. Wireless Commun.*, vol. 12, no. 4, pp. 1872–1882, Apr. 2013.
- [17] N. A. Odhah, M. I. Dessouky, W. E. Al-Hanafy, and F. E. A. El-Samie, "C32. greedy power allocation algorithm for proportional resource allocation in multi-user OFDM systems," in *Proc. 29th National Radio Science Conf. (NRSC)*, Apr. 2012, pp. 421–428.
- [18] L. P. Qian, G. Feng, and V. C. M. Leung, "Optimal transmission policies for relay communication networks with ambient energy harvesting relays," *IEEE Journal on Selected Areas in Communications*, vol. PP, no. 99, p. 1, 2016.