An Energy-Efficient Strategy for Secondary Users in Cooperative Cognitive Radio Networks for Green Communications

Jianqing Liu, Haichuan Ding, Ying Cai, Hao Yue, Yuguang Fang, and Shigang Chen

***Abstract*—In cognitive radio networks (CRNs), primary users (PUs) can leverage secondary users (SUs) as cooperative relays to increase their transmission rates, while SUs will in return obtain more spectrum access opportunities, leading to cooperative CRNs (CCRNs). Prior research works in CCRNs mainly focus on providing ubiquitous access and high throughput for users, but have rarely taken energy efficiency into consideration. Besides, most existing works assume that the SUs are passively selected by PUs regardless of SUs' willingness to help, which is obviously not practical. To address energy issue, this paper proposes an energy-efficient cooperative strategy by leveraging temporal and spatial diversity of the primary network. Specifically, SUs with delay-tolerant packets can proactively make the cooperative decisions by jointly considering primary channel availability, channel state information, PUs' traffic load, and their own transmission requirements. We formulate this decision-making problem based on the optimal stopping theory to maximize SUs' energy efficiency. We solve this problem using a dynamic programming approach and derive the optimal cooperative policy. Extensive simulations are then conducted to evaluate the performance of our proposed strategy. The results show significant improvements of SUs' energy efficiency compared with existing cooperative schemes, which demonstrate the benefits of our proposed cooperative strategy in conserving energy for SUs.**

***Index Terms*—Green communications, energy efficiency, cognitive radio networks, cooperative communication, relay selection.**

I. Introduction

RECENTLY, energy consumption in modern wireless networks has become a growing concern due to the huge amount of greenhouse gases generated by the unprecedented usage of wireless devices [1]. According to a recent survey [2], the current Information and Communication Technology (ICT) industry is responsible for about $2-4\%$ of all the carbon footprint generated by human activities, which corresponds to about 25% of all car emissions and is approximately equal to that from all airplanes. In light of this, the trend of reducing energy consumption motivates researchers to explore novel technologies to achieve energy-efficient "Green" communications. One of the feasible solutions is to utilize the spectrum more efficiently. The reason lies in the Shannon's capacity, which reveals the tradeoff between power and bandwidth. Specifically, link capacity increases only logarithmically with power but linearly with bandwidth, which indicates that more bandwidth brings down power consumption. Holland *et al.* [3] also showed that more than 50% of power can be saved by dynamic spectrum management. Hence, the cognitive radio (CR) technology, which can be traced back to Mitola and Maguire [4] in 1999, can be applied to improve the spectrum efficiency and thus reduces the energy consumption.

With ever-increasing growth of data generated from mobile devices, some spectrum bands are getting congested while other spectrum bands such as the TV bands are still underutilized [5]. The CR technology can be applied to address the unbalanced usage of spectrum by allowing unlicensed secondary users (SUs) to opportunistically access the spectrum bands unoccupied by licensed primary users (PUs). Generally, CR devices are designed based on software-defined radios to allow SUs to have the capabilities to sense, learn and adapt to wireless environments and then coexist with PUs in such a way that SUs' transmissions will not interfere with PUs [6]. There are three paradigms to make the coexistence of PUs and SUs possible: underlay, overlay and interweave [7]. The underlay paradigm allows SUs to transmit simultaneously with PUs as long as the interference to PUs is below a certain threshold. In the overlay paradigm, SUs obtain spectrum from PUs by helping maintain or improve the communication of PUs with sophisticated signal processing and coding. In the interweave paradigm, SUs opportunistically access spectrum holes without interfering PUs. With the evolution of all these paradigms, the spectrum efficiency can be improved significantly, and hence SUs' energy consumption can be reduced.

In practical wireless propagation environments, PUs' transmissions may suffer from severe attenuation due to multipath fading, which will greatly degrade PUs' network performance and reduce battery lifetime, and consequently impact

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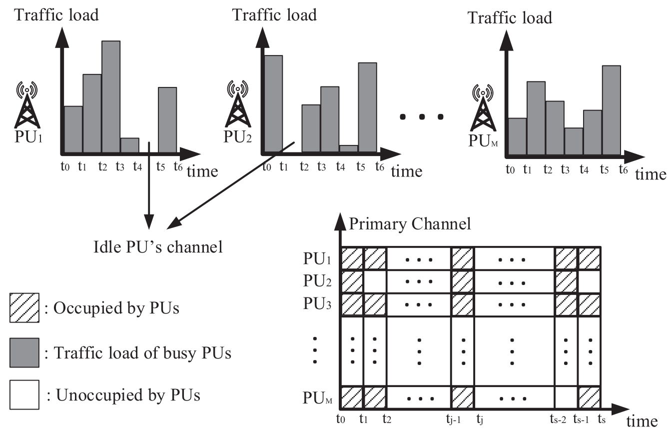

Fig. 1. Time-varying characteristics of PUs' channel availability and traffic load.

SUs' access to primary channels. To tackle this problem, cooperative communications (CC) have been proposed as a powerful tool to mitigate multipath fading by dividing a direct path into several shorter links and can be introduced into cognitive radio networks (CRNs). CC is also proven to be energy-efficient by exploiting the spatial diversity offered by relay nodes so that wireless channel impairments are less destructive and lower transmission power can be used in the source and relays [8]. CC can be designed in two ways: decode-and-forward (DF) and amplify-and-forward (AF) [9]. In CRNs, cooperative communications can be classified into two categories: i) cooperation among SUs; ii) cooperation between PUs and SUs. In this paper, we will focus on the latter where SUs firstly serve as cooperative relays to help PUs finish their transmissions earlier, and in return obtain the PUs' channels as a reward [10], [18]. This framework is well-known as cooperative cognitive radio networks (CCRNs), wherein the mutual benefit between PUs and SUs is realized.

The cooperation communications between PUs and SUs in CCRNs have been widely studied in the literature [11]–[20], most of which focused on providing ubiquitous access and high throughput for both PUs and SUs. Besides, some of them have an implicit premise that SUs will be engaged in cooperation as long as some forms of rewards are guaranteed by PUs, such as throughput, energy-efficiency, or in general utilities (e.g., a function of reward and payment). However, in practice, without incentives, SUs may not be interested in cooperation if they have light-loaded and delay-tolerant traffic or if the received rewards from CC is no more than what will be obtained by directly using PUs' idle channels in the future. Therefore, SUs may hold their transmissions for later time instead of cooperating immediately. To further illustrate SUs' cooperative strategy in CCRNs, we use a toy example as shown in Fig.1. Suppose that in a CCRN there are M PUs occupying different spectrum bands. Due to the time-varying characteristics of PUs' channel availability and traffic load, SUs need to make decisions on when and with which PU to cooperate. For example at time t_0, an SU can either choose PU_1 to cooperate with and then obtain its channel for secondary transmissions or wait till time t_1 to directly use PU_2's channel. Clearly, different strategies result in different energy consumption, delay and throughput, which makes the problem of finding the optimal cooperation strategy for SUs challenging.

In addition, to further stimulate "Green" communications in the context of CCRNs, more efforts are required on studying the energy efficiency of SUs other than that of PUs. The reason is that the number of secondary wireless devices is and will be significant in current and foreseeable ICT industry and these devices only have limited battery storage while the energy dissipation rate is one of the primary concerns for users. However, among recent research work in CCRNs, developing an energy-efficient cooperative strategy from SUs' perspective has rarely been investigated carefully as yet. Therefore, in this paper, we attempt to address this issue by exploring SUs' cooperative strategy in CCRNs with the objective to maximize their energy efficiency. Specifically, we consider a time-slotted CCRN where SUs have delay-tolerant packets to transmit by a certain deadline. SUs observe the primary network slot by slot in time sequence and make the cooperation decision in both temporal (i.e., what time) and spatial (i.e., which PU) domains. Due to time non-reversibility and uncertainty of PUs' future channel availability and traffic load, an SU needs to select an optimal stopping time for data transmission to achieve the maximum energy efficiency. Thus, we formulate this decision-related problem based on the optimal stopping theory [21] and obtain the solution from a dynamic programming approach called *backward induction*. In particular, this paper firstly discusses optimal cooperative strategy when SUs attempt to transmit fixed amount of packets, and then explores the one when SUs have continuously new arriving packets during the decision process. Our major contributions are summarized as follows:

- This is the first work to study SUs' energy-efficient cooperation strategy in CCRNs with consideration of PUs' temporal and spatial diversity in channel availability and traffic load.
- We consider two practical scenarios in this paper. The first one is that SUs schedule the transmission for fixed amount of packets. The other one is that SUs have continuously new arriving packets during the observation and decision process and the transmission deadline is dynamic depending on SUs' buffer overflow probability. The decision-related problems for both scenarios are formulated based on the optimal stopping theory and the backward induction is applied to derive their corresponding optimal strategies.
- We thoroughly investigate SUs' optimal cooperative strategies in both spatial and temporal domains. On one hand, SUs select the PUs of minimum traffic load in spatial domain. On the other hand, in temporal domain, we consider the instantaneous and the long-term expected energy efficiency and select the first time slot wherein the instantaneous reward is greater than the expected one.

The rest of this paper is organized as follows. The related work is first reviewed in Section II. The proposed system model is then described in Section III. In Section IV, we formulate the energy efficiency optimization problem using optimal stopping theory for both considered scenarios. In Section V, the backward induction is utilized to derive optimal cooperative strategies. Extensive simulations and analysis are carried out in Section VI and finally we conclude the paper in Section VII.

II. Related Work

In recent years, researchers have devoted great efforts to developing CCRNs from different perspectives. Simeone *et al.* [11] propose a cooperation scheme wherein PUs' transmission rates are maximized with help of SUs and certain time slots are in return leased to SUs, which afterwards compete for transmissions following a distributed power control mechanism. Zhang and Zhang [12] improve the work [11] in a way that PUs can collect revenues from SUs when PUs' transmission rates are satisfied and TDMA is adopted as SUs' access model for primary channels. Cao *et al.* [13] study the optimal communication strategy for PUs by quantifying the impacts of energy and power consumptions on PUs' utilities. These work formulate hierarchical Stackelberg games where PUs are the leaders who make the cooperation rules while SUs as a group of followers obey the rules. Besides, some other work focus on searching for secondary relays for PUs. Li *et al.* [14] consider a multi-hop secondary relay selection problem, in which the path is computed via performing PUs' strategies. Jing *et al.* [15] model the relay selection problem using optimal stopping theory to guide PUs to find the SU relay that can maximize the throughput for PUs. However, in aforementioned papers, SUs are considered not to proactively choose their cooperative strategies, which may not be appropriate considering SUs are rational or selfish.

To address this issue, there exists several works studying cooperative schemes from SUs' perspective. Jayaweera *et al.* [16] propose both centralized and decentralized decision-making architectures for SUs to place bids indicating how much power they are willing to spend for relaying PUs' traffic. Zou *et al.* [17] study a new CCRN where PUs lease their spectrum as well as transmit power to relay data for SUs while PUs in return collect revenues from SUs. The spectrum access and power allocation problem is formulated as an auction model to maximize SUs' aggregated throughput. Long *et al.* [18] focus on secondary network throughput maximization by allowing SUs to optimally share the cooperation-generated spectrum resources. Zhang *et al.* [19] exploit a novel CCRN paradigm with antenna polarization and energy-harvesting capability, which allows SUs to relay PUs' traffic and concurrently transmit SUs' own data. Cao *et al.* [20] apply this CCRN model and achieve maximization of the weighted sum throughput of PUs and SUs using dynamic Markov decision process subject to energy constraints.

Although SUs' energy-efficiency issues have been investigated in some of these literatures, our scheme is distinct from them in that SUs exploit the temporal and spatial diversity of the primary network and proactively make cooperative decisions based on their own transmission requirements (e.g., transmission deadline, buffer overflow probability, and etc.). Furthermore, we capture the feature of time non-reversibility in decision-making process and apply optimal stopping theory to drive SUs' cooperative strategy. In particular, we explore the impacts of two practical scenarios on SUs' cooperative strategy and demonstrate that the achieved energy-efficiency outperforms what is obtained using conventional cooperative schemes.

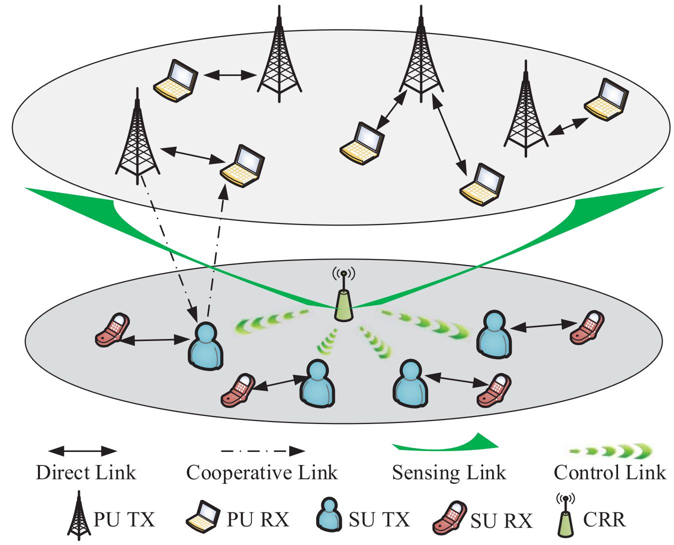

Fig. 2. Network topology of a CCRN.

III. System Model

A. Network Model

To elaborate our basic idea, we consider a CCRN as shown in Fig.2, where a cognitive radio router (CRR), M PUs and a group of SUs are distributed in the same network area. PUs are assumed to occupy orthogonal primary channels of equal bandwidth W while the CRR is equipped with CR capability to collect PUs' channel availability, channel state information (CSI), and PUs' traffic load [22]. The interactions between these entities are described as follows. First, PUs with traffic to transmit will send their traffic information to the CRR attempting to seek for possible secondary relays, while PUs without traffic to transmit will remain silent. After that, the CRR receives PUs' requests, probes the CSI and then broadcasts them to SUs in its coverage area. Based on the received information from CRR and the knowledge about its own traffic and power budget, an SU who needs primary channels calculates the energy efficiency and sends back the cooperation decision to CRR, i.e., cooperation or not. At the end, the CRR obtains SU's decision and notifies the specific PU to build wireless connection with the SU if possible. Above all, the whole process is similar to the RTS/CTS access mechanism designed for the 802.11 medium access control protocol [23]. It is also worth noting that even though certain SUs may refuse to cooperate, PUs can still be easily paired with secondary relays due to the significant number of SUs that we envision for future cognitive radio networks.

In our model, a time-slotted system is assumed for both PUs and SUs. The slot length can be a design parameter depending on the transmission block of data. In each time

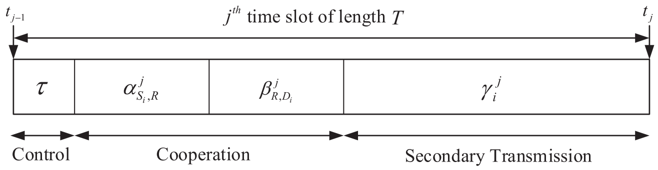

Fig. 3. Multi-phase time slot of a SU.

slot j where $j \in \{1, 2, ..., S\}$, we assume that each PU has different state of channel availability and traffic load, which can be represented using the toy example as shown in Fig.1. On the other hand, SUs are synchronized with PUs and the cooperation decisions are made in each time slot. The synchronization could be implemented through the CRR which makes the MAC-layer coordination between PUs and SUs. For SUs, each time slot of length T is generally partitioned into four phases, as shown in Fig.3. In the first phase (i.e., control period), network information is exchanged between PUs and the secondary network and the wireless connection between a pair of PU and SU is established. In the second phase (i.e., first part of cooperation period), the PU transmits its traffic to the SU. In the third phase (i.e., second part of cooperation period), the SU relays the received traffic to PU's receiver using either AF or DF mode. In the fourth phase (i.e., secondary transmission period), the SU transmits its own traffic using the corresponding primary channel as a reward. In particular, if the SU finds an idle channel and decides to access it without cooperation, then the cooperation period will not exist and the whole time slot except the first phase can be used for the secondary transmission. On the other hand, if there is no cooperation or idle channel opportunity and the SU decides to skip the current time slot, SU's device stays in idle state during the cooperation and secondary transmission periods and will wait till the next time slot and repeat the same process. Furthermore, we assume that a PU can only be paired with one SU during the cooperation period. This is realized by CRR that makes the coordination in the control period for the secondary network to avoid the interference among SUs. Thus, in this paper, we focus on the cooperative strategy for a single SU, which can be applied to all SUs afterwards.

B. Primary User's Traffic Load and Channel Availability

We assume that PUs' traffic is delay-sensitive. When the traffic arrives at the beginning of each time slot, it has to be completely transmitted during the same slot. In this paper, the number of arriving packets in each time slot is assumed to be a random variable Ψ which takes positive values and follows a probability distribution with probability mass function (PMF) $f_\Psi(\psi)$. We assume that slot-wise packet arrivals for each PU can be modeled as an independent and identically distributed ($i.i.d.$) random sequence and are independent of the arrival processes of other PUs.

For the channel availability of each PU, when its traffic load is zero, i.e., $\psi = 0$, at a given time slot, we assume that the PU is in idle state and the SU is allowed to access its idle channel directly. On the other hand, when PU's traffic load is non-zero at a specific time slot, we assume that the PU is in busy state and the SU can potentially cooperate with the PU and obtain the channel access opportunity as a reward. Clearly, the probability that a channel is idle or busy can be, respectively, represented by: $p_{idle} = f_\Psi(\psi = 0)$, $p_{busy} = \sum_{\psi>0}^{\infty} f_\Psi(\psi)$.

C. Channel Model and Power Control

In our proposed CCRN, we consider the power propagation model ([22]): $P_r = \xi \cdot d^{-\sigma} \cdot P_t$ where P_r and P_t represent the receiving power at the destination node and the transmission power at the source node, respectively. ξ is a constant related to antenna's working frequency, gain and radiation pattern. d is the physical distance between the source and destination while σ is the path loss exponent. Then, according to Shannon capacity theorem, the capacity of a source-destination link (denoted as (S, D)) can be calculated as follows:

$$c_{S,D} = W \log_2 \left(1 + \frac{\xi \cdot d_{S,D}^{-\sigma} \cdot P_t}{W \cdot N_0}\right)$$

where N_0 is the power spectrum density of the additive white Gaussian noise (AWGN) in the considered wireless environment and $W \cdot N_0$ is the received noise power level at the destination.

Generally, the transmission power of PUs is fixed and we denote it as P^{pu}. For simplicity, SUs' power allocated in the state of idle, in reception, in cooperation and in secondary transmission are also assumed to be constants and they are denoted as P^{idle}, P^{rx}, P^{Ctx} and P^{Stx}, respectively.

D. Secondary User's Traffic Load and Activity

In this paper, we focus on developing the cooperative strategy for a single SU whose data packets are assumed to be delay-tolerant. In the following sections, we will elaborate SU's cooperative strategies for two scenarios. Specifically, the first scenario has been studied in our previous paper [25] where we assume that the SU has k packets of data size $D = k \cdot \upsilon$ to transmit where υ is per packet data size. Suppose that there exists a hard deadline by which all packets have to be transmitted or otherwise will be expired. In the second scenario, we consider a more general case where the SU has continuously arriving packets during its observation and decision-making process. Here, we use l^j to represent the number of SU's queued packets in the j^{th} time slot of data size $A^j = l^j \cdot \upsilon$ and we also consider a finite buffer for the SU. To avoid the buffer overflow due to the increasing number of packets, the SU needs to dynamically adjust its cooperative strategy according to different packet arrival rates. Furthermore, we assume that packets arrive at the beginning of each time slot and it follows a Batch Bernoulli process which can be described by a vector $\eta = [\eta_0, \eta_1, ..., \eta_N]$, where η_μ indicates the probability of μ packets arriving, where $\mu \in \{0, 1, ..., N\}$. Then the average arrival rate λ_{su} can be calculated as $\lambda_{su} = \sum_{\mu=0}^{N} \mu \eta_\mu$. Clearly, the benefit of assuming the arrival model to be Batch Bernoulli process is that it can capture the characteristic of different level of burstiness in packet arrivals [24].

IV. Problem Formulation

Since an SU can only obtain current, not the future, information of primary network, it needs to decide at which time slot to stop observing and with which PU to cooperate in order to maximize its energy efficiency. In this section, we first propose SU's spatial cooperative strategy at each time slot as selecting the PU with minimum traffic load which should not exceed a certain threshold posed by SU's own transmission requirement. Then, the utility function is defined as an instantaneous reward (i.e., energy-efficiency) at current time slot. Finally, we apply the optimal stopping theory to address the problem of finding SU's temporal optimal cooperative strategy and solutions are derived through backward induction, which will be elaborated in Section V.

A. Cooperation Incentive

The underlying assumption that makes the CCRN feasible is that both PUs and SUs have incentives to engage in cooperation. Specifically, PUs could gain better transmission rate by leveraging relays while SUs would obtain the access to PUs' channels. In this paper, since we study the scenario where the targeted SU has packets to transmit but its own channel is congested, the cooperation incentive for the SU to access PU's channel has been satisfied. However, we need to provide the incentive for the PUs, which can be characterized as the inequality in below:

$$\log_2\left(1+SNR_{S_i,D_i}\right) \leq \min\{\frac{\alpha^j_{S_i,R}}{T}\cdot\log_2\left(1+SNR_{S_i,R}\right), \times\frac{\beta^j_{R,D_i}}{T}\cdot\log_2\left(1+SNR_{R,D_i}\right)\}$$

where the right-hand-side (RHS) of the inequality represents the cooperation transmission rate per unit bandwidth, provided that the Decode-and-Forward (DF) mode is adopted as a relaying strategy [26]. Here, the cooperation rate does not consider the direct link, and $SNR_{S_i,D_i} = \frac{\xi\cdot d^{-\sigma}_{S_i,D_i}\cdot P^{pu}}{W\cdot N_0}$, $SNR_{S_i,R} = \frac{\xi\cdot d^{-\sigma}_{S_i,R}\cdot P^{pu}}{W\cdot N_0}$ and $SNR_{R,D_i} = \frac{\xi\cdot d^{-\sigma}_{R,D_i}\cdot P^{Ctx}}{W\cdot N_0}$. The above constraint guarantees that the primary transmission rate under cooperation mode is no less than that without cooperation.

B. Packet Relay and Time Slot Constraint

In the framework of our CCRN, the validity of the cooperation requires that all the packets received by the SU from the i^{th} PU's source at the second phase should be delivered by the SU to the i^{th} PU's destination at the third phase. Thus, the packet relay constraint is given by:

$$\alpha^j_{S_i,R}\cdot W\log_2\left(1+\frac{\xi\cdot d^{-\sigma}_{S_i,R}\cdot P^{pu}}{W\cdot N_0}\right) = \beta^j_{R,D_i}\cdot W\log_2\left(1+\frac{\xi\cdot d^{-\sigma}_{R,D_i}\cdot P^{Ctx}}{W\cdot N_0}\right) \quad (1)$$

When Eq.1 holds, the cooperation incentive inequality could be rewritten as $\log_2\left(1+SNR_{S_i,D_i}\right) \leq \frac{\alpha^j_{S_i,R}}{T}\cdot\log_2\left(1+SNR_{S_i,R}\right)$, which is satisfied anyway.

According to the time frame structure as shown in Fig.3, another constraint should be satisfied as well:

$$\tau+\alpha^j_{S_i,R}+\beta^j_{R,D_i}+\gamma^j_i \leq T \quad (2)$$

where $\alpha^j_{S_i,R}$ and β^j_{R,D_i} can be calculated as follows:

$$\alpha^j_{S_i,R} = \frac{\psi\cdot\upsilon}{W\log_2\left(1+\frac{\xi\cdot d^{-\sigma}_{S_i,R}\cdot P^{pu}}{W\cdot N_0}\right)} \quad (3)$$

$$\beta^j_{R,D_i} = \frac{\psi\cdot\upsilon}{W\log_2\left(1+\frac{\xi\cdot d^{-\sigma}_{R,D_i}\cdot P^{Ctx}}{W\cdot N_0}\right)} \quad (4)$$

It should be noted that γ^j_i depends on SU's own traffic load and the channel capacity between SU's source/detination pairs, but we will elaborate this parameter later since the scenario of SU without newly arriving packets and the scenario of SU with continuously arriving packets are discussed separately. In addition, we assume a fixed length of time slot, i.e., T and a constant portion of the *control phase* for sensing and decision, i.e., τ as shown in Fig.3.

C. Cooperative Strategy in Spatial Domain and Threshold Selection

Given the received CSI from CRR and the knowledge of its own traffic load during a time slot, the SU can find a traffic load threshold to select the qualified PU. Thus, the spatial domain cooperative strategy for the SU is to select the qualified PU with the lowest traffic load. Obviously, the most energy-efficient case is that the selected PU has zero traffic load, i.e., the primary channel is idle and SU can directly access the channel without wasting the energy in cooperation. As we mentioned in Section III.B, PUs' packet arrivals form a random process that can be characterized by *i.i.d.* process across time slots for a specific PU and are independent of packet arrivals from other PUs. We can first rearrange the random variables in a non-descending order of magnitude, i.e., $\Psi_{(1)} \leq \Psi_{(2)} \leq \ldots \leq \Psi_{(M)}$ where $\Psi_{(r)}$ is the r^{th} smallest number among the group of M PUs. Then the PMF of the minimum traffic load can be derived based on the theory of order statistics in [27].

$$f_{\Psi_{(1)}}(\psi) = \sum_{k=1}^{M}\frac{M!}{k!\,(M-k)!}[f_{\Psi}(\psi)]^k\cdot[1-F_{\Psi}(\psi)]^{M-k} \quad (5)$$

where $F_{\Psi}(\psi)$ is the cumulative distribution function (CDF) of random variable Ψ. Note that the random variable of minimum traffic load, i.e., the 1^{st} smallest order statistic is also *i.i.d.* across time slots. The proof of the above formula is described at Appendix A. Next, we derive traffic thresholds for different scenarios.

1) Threshold Selection of SU Without Newly Arriving Packets: In this scenario, the SU has initial packets to transmit and there is no arriving packets during the observation and decision process. Based on Eq.2-4, the traffic threshold can be calculated as follows:

$$\psi^i_{th} = \left(T-\tau-\frac{D}{c_{R,R}}\right)\cdot\left(\frac{1}{c_{S_i,R}}+\frac{1}{c_{R,D_i}}\right)^{-1} \quad (6)$$

where $c_{R,R} = W\log_2(1+\frac{\xi\cdot d_{R,R}^{-\sigma}\cdot P^{Stx}}{W\cdot N_0})$, $c_{S_i,R} = W\cdot\log_2(1+\frac{\xi\cdot d_{S_i,R}^{-\sigma}\cdot P^{pu}}{W\cdot N_0})$, $c_{R,D_i} = W\log_2(1+\frac{\xi\cdot d_{R,D_i}^{-\sigma}\cdot P^{Ctx}}{W\cdot N_0})$ and $\gamma_i^j = \frac{D}{c_{R,R}}$ is secondary transmission time. It can be seen that traffic thresholds are different for different PUs in a given time slot due to PUs' different channel conditions. Thus, based on Eq.6, we can determine a unique traffic threshold for each PU given the knowledge of CSI of the links and SU's own traffic information.

Given the proposed spatially cooperative strategy and all the variables we have derived so far, the cooperation opportunity exists as long as the smallest traffic load is no more than the threshold level. Since each specific PU has equal probability to take the smallest traffic load, the minimum threshold among all PUs should be used to compare against the smallest traffic load. We define $\psi_{th} = \min\left\{\psi_{th}^1, \psi_{th}^2, ..., \psi_{th}^M\right\}$ as the effective threshold. Thus, we can compute the probability that a qualified PU is eligible to setup cooperation link with the SU. Note that the case where the SU directly utilizes primary channel without cooperation with a PU is included as a special case since the minimum traffic load could be equal to zero that captures the scenario of idle primary channel. The probability is given by:

$$p_j^{\nabla} = p\left(0 < \Psi_{(1)} \le \psi_{th}\right) + p\left(\Psi_{(1)} = 0\right) = \sum_{\psi=0}^{\psi_{th}} f_{\Psi_{(1)}}(\psi) \tag{7}$$

where p_j^{∇} reveals the total probability that the SU finds a transmission opportunity either by cooperation or through direct access at the j^{th} time slot.

2) Threshold Selection of SU With Continuously Arriving Packets: When the SU has arriving packets at the beginning of each time slot, the number of SU's packets in the buffer increases as time goes on. Similarly, according to Eq.2-4, the traffic load threshold is given by

$$\psi_{th}^{i,j} = \left(T - \tau - \frac{A^j}{c_{R,R}}\right)\cdot\left(\frac{1}{c_{S_i,R}} + \frac{1}{c_{R,D_i}}\right)^{-1} \tag{8}$$

where A^j is the data size of queued packets at j^{th} time slot. Since the value of A^j is non-decreasing with the increment of time slots, the above threshold used as the selection criterion decreases when the SU observes more time slots. At j^{th} time slot, A^j can be determined and a spatially effective threshold can be calculated similarly as $\psi_{th}^j = \min\left\{\psi_{th}^{1,j}, \psi_{th}^{2,j}, ..., \psi_{th}^{M,j}\right\}$ which is utilized to compare against PUs' smallest traffic load at the j^{th} time slot.

As we have discussed in Section III.D, the number of arriving packets at each time slot is a random variable which follows the probability vector $\eta = [\eta_0, \eta_1, ..., \eta_N]$. Thus, at the j^{th} time slot the number of queued packets l^j could take the value $x \in \{k, k+1, ..., k+Nj\}$, which implies the cardinality of random variable l^j is $Nj+1$, where $j = 1, 2, ..., S$. Therefore, the cardinality of the random variable A^j and ψ_{th}^j are also equal to $Nj+1$ and the values of ψ_{th}^j can be calculated based on Eq.8.

On the other hand, in order to obtain the PMF of the random variable ψ_{th}^j, the PMF for A^j needs to be calculated first. For this, we have

Lemma 1: The PMF of random variable A^j can be calculated using $(j-1)^{th}$ order convolution of the probability vector η, which is given below:

$$f_{A^j}(x) = \sum_{\mu_{j-1}=0}^{N} \eta_{\mu_{j-1}} \cdots \sum_{\mu_2=0}^{N} \eta_{\mu_2} \sum_{\mu_1=0}^{N} \eta_{\mu_1} \cdot \eta_{x-k-\mu_1-\ldots-\mu_{j-1}} \tag{9}$$

Proof: See Appendix B. ■

Given $f_{A^j}(x)$, the PMF of ψ_{th}^j can be easily obtained. Therefore, in the scenario of SU with continuously arriving packets, provided with the spatially cooperative strategy and all the calculated parameters, the probability of successfully selecting a qualified PU to cooperate with is equal to the probability that the minimum traffic load of PUs is no more than the threshold. Similar to Eq.7, the probability is given as

$$\begin{aligned} p_j^{\Delta} &= p\left(0 \le \Psi_{(1)} \le \psi_{th}^j\right) \\ &= p\left(0 \le \Psi_{(1)} \le a | \psi_{th}^j = a\right) p\left(\psi_{th}^j = a\right) \\ &= \sum_{a=0}^{\infty}\sum_{\psi=0}^{a} f_{\Psi_{(1)}}(\psi)\cdot p\left(\psi_{th}^j = a\right) \end{aligned} \tag{10}$$

Moreover, we consider a practical scenario that SU has limited buffer size. If the SU holds the transmission, due to the continuous arrival of packets, the buffer could be full after certain time slots and new arriving packets will be dropped. To guarantee the performance, the cooperative strategy in the temporal domain should be designed accordingly to keep packet dropping probability below a certain level during the observation and decision process. Suppose that the maximum data size that the buffer can handle is $A_{\max}$ and a pre-defined packet dropping probability threshold is q. Then, the following inequality must be satisfied:

$$p\left(A^j > A_{\max}\right) < q \tag{11}$$

Since A^j is non-decreasing with the increment of time slots, if at j^{th} time slot the above inequality is met while at $(j+1)^{th}$ time slot it is not, the consecutive time slots up to S will have the packet dropping probabilities even higher than the threshold. Thus, we state that the new observation and decision horizon is up to j, which is denoted as $S^{'}$ for convenience.

D. Utility Function

Next, we derive the energy-efficiency function at each time slot. While most existing works uses the function of SU's total energy consumption, our proposed function jointly considers the total energy cost and the SU's throughput. From the time frame structure shown in Fig.3, the total energy consumption in the cooperation mode consists of four parts: control phase due to sensing and decision, receiving PU's traffic, relaying PU's traffic and SU's self transmission. However, the energy consumption in the cooperation phase is zero if the SU selects an idle channel, while control phase and the consecutive idle period contribute the only energy cost if the SU decides to remain silent in one time slot and wait till the next one. Therefore, if the SU decides to access PU's channel at j^{th} time slot, its total energy consumption can be expressed as follows:

$$EC^j = (j-1)(T-\tau) \cdot P^{idle} + j\tau \cdot P^{rx} + \alpha_{S_i,R}^j \cdot P^{rx} + \beta_{R,D_i}^j \cdot P^{Ctx} + \gamma_i^j \cdot P^{Stx} \tag{12}$$

where the first term on the RHS of the equation represents the energy cost for being silent in the previous $(j-1)$ time slots, the second term indicates the total control phase energy consumption up to j^{th} time slot, while the latter three terms are contributed by the cooperation and secondary transmission. Note that $\gamma_i^{j,\nabla} = \frac{D}{c_{R,R}}$ and $\gamma_i^{j,\Delta} = \frac{A^j}{c_{R,R}}$ represent the secondary transmission time for the scenario of SU without newly arriving packets and for the one that SU has continuously arriving packets, respectively. Then we calculate the throughput for the SU below:

$$c_{SU}^{j,\nabla} = \frac{D}{jT}, \quad c_{SU}^{j,\Delta} = \frac{A^j}{jT}. \tag{13}$$

where $c_{SU}^{j,\nabla}$ and $c_{SU}^{j,\Delta}$ represent the throughput for aforementioned scenarios respectively. The throughput is defined as the ratio of SU's traffic at j^{th} time slot to the total elapsed time. Noticing that if the SU decides to access PU's channel at j^{th} time slot, its preceding throughput is zero since no traffic is transmitted until j^{th} time slot. After the throughput function is derived, the energy-efficiency function can be calculated based on Eq.14 as shown below, where U_j is used to represent the energy-efficiency function for both scenarios for notational convenience. It should be mentioned that in contrast to the traditional definition, our energy efficiency function is an instantaneous reward for SUs that is dependent on the cooperative strategy.

$$U_j = \frac{c_{SU}^j}{EC^j} \tag{14}$$

In SU's cooperative decision process, we can intuitively see that the SU may wait for an idle primary channel for direct transmission so that the energy for cooperation can be saved. However, it may take a long time till an idle channel shows up so that the saved energy cannot compensate the cumulated observation energy cost. Besides, SU's throughput may be degraded according to Eq.13 when j increases. Therefore, the balance between high throughput and low energy consumption should be neatly considered in the SU's cooperative decision strategy so as to achieve maximum energy efficiency as described in Eq.14.

V. The Optimal Stopping Rule

In our proposed time slotted CCRN, since the SU sequentially observes the primary network and its decision is timely irreversible, the optimal stopping theory is a powerful tool to let the SU find the optimal stopping time to maximize its energy efficiency. In this section, we first elaborate the cooperative strategy in temporal domain and then apply the optimal stopping theory to this decision problem. After that, a dynamic programming approach called *backward induction* is utilized to derive the cooperative strategy for SU.

As we mentioned in Section IV, SU selects the qualified PU with minimum traffic load at a given time slot. In the temporal domain, our proposed stopping rule is that the SU firstly compares the instantaneous value of utility function at current time slot with the expected value of the utility function in the future and then stops whenever the former value is greater than the latter one. Otherwise, the SU waits till next time slot and repeats the same process. Denote Y_j as the maximum energy efficiency that the SU can obtain when observing the j^{th} time slot. It is given as follows:

$$Y_j = \max\left\{U_j, E\left[Y_{j+1}\right]\right\} \tag{15}$$

where U_j is the instantaneous value of utility function at j^{th} time slot while $E\left[Y_{j+1}\right]$ represents the expected value of energy efficiency by proceeding to observe the next time slot. In our proposed temporal cooperative strategy, SU stops at j^{th} time slot if $Y_j = U_j$ and skips current time slot if $Y_j = E\left[Y_{j+1}\right]$. In other words, the optimal stopping rule is to stop at the earliest j^{th} time slot when $U_j \geq E\left[Y_{j+1}\right]$ first shows up. In the following discussion, optimal stopping problem is solved by the backward induction.

A. Backward Induction for the Scenario of SU Without Newly Arriving Packets

In this case, since SU's delay-tolerant packets have a hard deadline to be transmitted, i.e., before S^{th} time slot, the solution process starts with finding the expected value of the maximum energy efficiency at $(S-1)^{th}$ time slot. To better understand the backward induction, we define Z_{S-j}^{∇} as the expected value $E\left[Y_{j+1}\right]$. We assume that $Z_0^{\nabla} = 0$ since SU has to stop at the S^{th} time slot and the expected energy efficiency at the $(S+1)^{th}$ time slot, i.e., $E\left[Y_{S+1}\right]$ is zero. More generally, when SU conducts the observation at the j^{th} time slot, Z_{S-j}^{∇} can be calculated as follows:

$$\begin{aligned} Z_{S-j}^{\nabla} &= E\left[Y_{j+1}\right] = E\left[\max\left\{U_{j+1}, Z_{S-j-1}^{\nabla}\right\}\right] \\ &= \sum_m U_{j+1} \cdot f_{\Psi_{(1)}}(\psi) + \sum_n Z_{S-j-1}^{\nabla} \cdot f_{\Psi_{(1)}}(\psi) \\ &\quad + \sum_{\psi=\psi_{th}}^{\infty} Z_{S-j-1}^{\nabla} \cdot f_{\Psi_{(1)}}(\psi) \end{aligned} \tag{16}$$

where $m \in \left\{\psi | U_{j+1} \geq Z_{S-j-1}^{\nabla}, \psi = 0, 1, ..., \psi_{th}\right\}$, $n \in \left\{\psi | U_{j+1} < Z_{S-j-1}^{\nabla}, \psi = 0, 1, ..., \psi_{th}\right\}$, $j \in \{1, 2, ..., S\}$ and the probability calculation is based on Eq.5 and Eq.7 Algorithm 1 presents the detailed steps to select the PU in spatial domain and the time slot to stop in temporal domains.

B. Backward Induction for the Scenario of SU With Continuously Arriving Packets

In contrast to the aforementioned scenario, there exists no similar hard deadline in this case. Due to the continuously arriving packets, the buffer will be full at a specific stage like

Algorithm 1 The Optimal Stopping Rule for Scenario of SU Without Newly Arriving Packets

```
CRR obtains the information of network parameters, e.g., d, σ, ξ and etc, coordinates the communication order among SUs and synchronizes time-slotted system between the SU and PUs;
for j=1 to S do
  CRR broadcasts PUs' real-time traffic to the SU;
  SU selects the PU with minimum traffic and calculates instantaneous utility U_j according to Eq.14;
  SU obtains the expected energy efficiency Z^∇_{S−j} based on Eq.16;
  if U_j < Z^∇_{S−j} then
    SU waits for next time slot j + 1;
  else
    SU stops at current time slot j, selects the PU with minimum traffic load;
  end if
end for
```

Algorithm 2 The Optimal Stopping Rule for Scenario of SU With Continuously Arriving Packets

```
CRR obtains the information of network parameters, e.g., d, σ, ξ and etc, coordinates the communication order among SUs and synchronizes time-slotted system between the SU and PUs;
The SU calculates the observation deadline S' based on its buffer size A_max, probability threshold q and packet arrival rate;
for j=1 to S' do
  CRR broadcasts PUs' real-time traffic to the SU;
  SU selects the PU with minimum traffic and calculates instantaneous utility U_j according to Eq.14;
  SU obtains the expected energy efficiency Z^Δ_{S'−j} based on Eq.18;
  if U_j < Z^Δ_{S'−j} then
    SU waits for next time slot j + 1;
  else
    SU stops at current time slot j, selects the PU of minimum traffic load;
  end if
end for
```

the $S^{'th}$ time slot where $S^{'} < S$, and the new incoming packets will be dropped. Thus, to keep the buffer overflow probability under a certain level as shown in Eq.11, SU's observation and decision time span should be designed dynamically according to different packet arrival rates λ_{su} in order to completely transmit all the queued packets before the buffer is full. Given SU's buffer size $A_{\max}$ and the pre-defined overflow probability threshold q, we can derive an intermediate equation to find the packet transmission deadline based on Eq.9 and Eq.11:

$$\sum_{A_{\max}/\upsilon}^{k+Nj} f_{A^j}(x) < q \tag{17}$$

where $f_{A^j}(x)$ depends on the packet arrival rate $\lambda_{su} = \sum_{\mu=0}^{N} \mu\eta_{\mu}$. Then, $S^{'}$ can be inversely calculated from Eq.17.

After the scheduling time span is determined, backward induction can be applied to address the optimal stopping problem. We still use Eq.15 as SU's stopping rule and set $E\left[Y_{S'+1}\right] = 0$. However, the reason for this is not due to expiration of packets but instead because of buffer overflow. Then, the backward induction procedures are performed as the same as we mentioned before. The expected energy efficiency at $(S^{'}-1)^{th}$ time slot is firstly calculated. We then derive the value at $(S^{'}-2)^{th}$ time slot, so on and so forth to 1^{st} time slot. For convenience, the same notation $Z^{\Delta}_{S'-j}$ is utilized to represent $E\left[Y_{j+1}\right]$. When the SU conducts observation at j^{th} time slot, $Z^{\Delta}_{S'-j}$ can be calculated as follows:

$$\begin{aligned} Z^{\Delta}_{S'-j} &= E\left[Y_{j+1}\right] = E\left[\max\left\{U_{j+1}, Z^{\Delta}_{S'-j-1}\right\}\right] \\ &= \sum_{a=0}^{\infty}\sum_{m} U_{j+1}\cdot f_{\Psi_{(1)}}(\psi)p\left(\psi^{j}_{th}=a\right) \\ &\quad + \sum_{a=0}^{\infty}\sum_{n} Z^{\Delta}_{S'-j-1}\cdot f_{\Psi_{(1)}}(\psi)p\left(\psi^{j}_{th}=a\right) \\ &\quad + \sum_{a=0}^{\infty}\sum_{\psi=a}^{\infty} Z^{\Delta}_{S'-j-1}\cdot f_{\Psi_{(1)}}(\psi)p\left(\psi^{j}_{th}=a\right) \end{aligned} \tag{18}$$

where $m \in \left\{\psi | U_{j+1} \geq Z^{\Delta}_{S'-j-1}, \psi = 0, 1, ..., a\right\}$, $n \in \left\{\psi | U_{j+1} < Z^{\Delta}_{S'-j-1}, \psi = 0, 1, ..., a\right\}$, $j \in \left\{1, 2, ..., S^{'}\right\}$ and the probability calculation is based on Eq.9-10. Then, the algorithm to address the optimal stopping problem is presented in Algorithm 2.

VI. Performance Evaluation

A. Simulation Setup

We consider a cooperative cognitive radio network that covers an circular area with a diameter of $1600m$. The CRR is placed inside the area to sense the wireless environment and coordinate the secondary network. Several SUs are distributed in the same area and our focused SU is assumed to be located at the center. On the other hand, many PUs are placed along the edge of the circle and we set the number of PUs as a parameter which reflects the density of the primary network. For simplicity, the distance between PUs' transmitter and receiver pairs are set equally as $d_{S,D} = 1600m$ while the distance between the focused SU's transceiver pairs is set as $d_{R,R} = 100m$. We also set $d_{S,R} = 800m$ and $d_{R,D} = 800m$. Moreover, suppose the path loss exponent $\sigma = 4$ and the antenna parameter $\xi = 2.5$. We assume the fixed power is utilized in both primary and secondary networks. Specifically, $P^{pu} = 5W$, $P^{Ctx} = 3W$, $P^{Stx} = 0.5W$ and $P^{rx} = 0.1W$ while $P^{idle} = 0W$ for simplicity. The noise power spectrum density is assumed to be $N_0 = 7.96 \times 10^{-16} W/Hz$. In the primary network, we assume that PUs occupy different primary channels of equal bandwidth $W = 200KHz$ and each PU's traffic arrival follows a Poisson process with an average rate λ_{pu}. In the time-slotted framework, the length of each

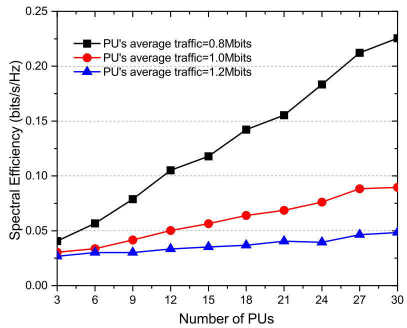

Fig. 4. SU's spectral efficiency with respect to the number of PUs at different PU's average traffic level.

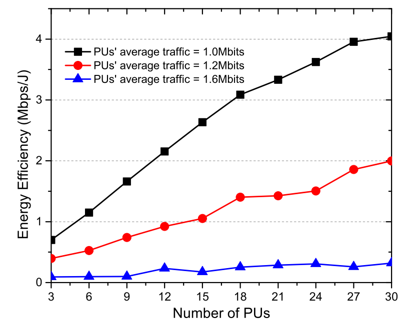

Fig. 5. SU's energy efficiency with respect to the number of PUs at different PU's average traffic level.

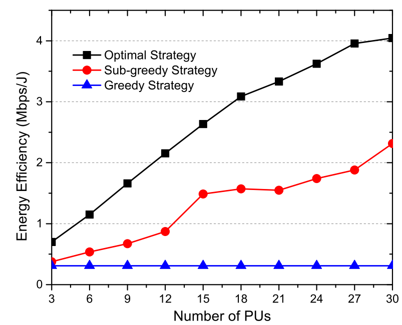

Fig. 6. Comparison of SU's energy efficiency in different cooperative strategy.

time slot is set as $T = 1s$ while the control phase consumes fixed time of $\tau = 1ms$. In the secondary network, each SU is assumed to have initial packets of size $D = 100Kbits$, which is delay-tolerant and expires after $S = 20$ time slots. The buffer size of each SU is set as $A_{\max} = 0.8Mbits$ and the packet dropping probability is pre-defined as $q = 0.01$. In the scenario of SU with continuously arriving packets, suppose that data size per packet is $\upsilon = 50Kbits$ and the average arrival rate λ_{su} has unit of bits/second which is converted from packets/slot for convenience.

The simulation results are averaged over 500 independent runs and then presented along with the analysis for both considered scenarios. To provide a deep insight into the proposed optimal cooperative strategy for SUs, for each scenario, we study the impact of the number of PUs, the diversity of PUs' traffic load and SUs' packets load on the throughput per unit bandwidth (a.k.a. spectral efficiency) and energy efficiency performance of SUs. The greedy and sub-greedy strategies are also exploited as the benchmarks to compare with our proposed cooperative strategy.

B. Performance in the Scenario of SU Without Newly Arriving Packets

In this case, the observation and decision span is up to the S^{th} time slot where we set $S = 20$. We firstly study the impact of the optimal stopping strategy on SU's spectral efficiency with different number of PUs. Based on Eq.13, since D is constant in this scenario, SU's spectral efficiency is only determined by the parameter jT which is the total elapsed time till the stopping time slot. Thus, the results shown in Fig.4 not only indicate the effect of number of PUs on SU's spectral efficiency but also potentially show the relation between the decision stopping time and the density of primary network, i.e., the number of PUs. It can be observed from Fig.4 that SU's spectral efficiency is improved when the number of PUs increases. On the other hand, SU's spectral efficiency decreases when PUs' average traffic loads become larger. The reason is that the SU observes more PUs at each time slot and has a higher chance to find a qualified PU to cooperate with or an idle channel for direct transmission when the number of PUs is large. Hence, the SU has higher potential to stop earlier to obtain larger throughput. Similarly, if the PUs' average traffic loads get larger, it takes longer time for the SU to find a PU to cooperate with or an idle channel to access so the SU's spectral efficiency becomes lower.

After giving the spectral efficiency analysis, we then explore the impact of the density of primary network, i.e., the number of PUs, on the SU's energy efficiency. The results are shown in Fig.5. It can be observed that when the primary network has fewer PUs, the SU's energy efficiency gets lower. On the other hand, the SU obtains higher energy efficiency if there are more PUs distributed in the primary network. The reason is that the SU has better opportunities to select a PU with lower traffic load to cooperate with or an idle channel to utilize when a larger number of PUs are observed in each time slot. In other words, the spatial diversity of primary network increases when the number of PUs becomes larger, which can then be exploited by the SU to select a better cooperation or direct transmission opportunity. In addition, the figure shows that if the number of PUs in the primary network is fixed, the SU obtains higher efficiency when the PUs' average traffic loads decrease. The reason is that when PUs have light traffic loads, the SU only needs to spend small amount of energy in the cooperation which results in higher energy efficiency for the SU. Clearly, the best case for the SU is that PUs' traffic loads are so small that an idle primary channel can be easily found after few time slots. As a result, the SU can obtain very high energy efficiency by transmitting its packets earlier and consuming fewer energy.

Furthermore, in order to demonstrate the advantage of our proposed cooperative strategy in improving SU's energy efficiency, the greedy and sub-greedy cooperative strategies are provided as the benchmarks and the simulation results are presented in Fig.6. The greedy strategy is applied in most

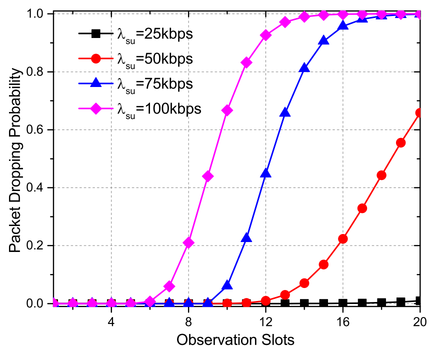

Fig. 7. Impact of SU's packet arrival rate on the packet dropping probability with increasing number of observation slots.

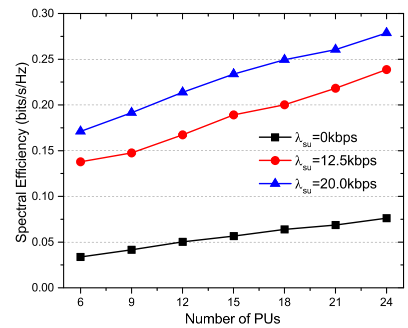

Fig. 8. SU's spectral efficiency with respect to the number of PUs at different SU's packet arrival rate.

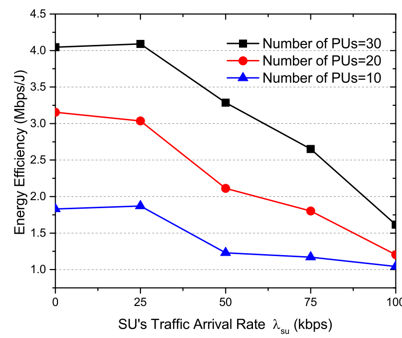

Fig. 9. Impact of packet arrival rate on SU's energy efficiency at different number of PUs.

existing works where SUs as cooperative relays are assumed to follow the decision of PUs as long as a certain level of throughput and energy consumption is guaranteed for SUs. On the other hand, the sub-greedy strategy exploits the spatial diversity of primary network wherein the SU can smartly select the PU with lowest traffic load to cooperate instead of blindly following PU's decision. Given these benchmark strategies, the simulation results shown in Fig.6 demonstrate that our proposed cooperative strategy outperforms the other two strategies in terms of SU's energy efficiency. Moreover, it can be observed that our cooperative strategy obtains more advantages against the other two when the number of PUs increases. The reason is that in the greedy strategy, the SU blindly follows PU's decision and cannot exploit the spatial and temporal diversity of primary network. On the other hand, the SU using sub-greedy strategy selects the PU of minimum traffic load to cooperate with, which yields better energy efficiency than the greedy strategy; but nevertheless the SU fails to exploit the temporal diversity of primary network. An example case is that in our proposed strategy, the SU may find an idle channel for direct transmission after observing more time slots so the energy efficiency becomes higher than that of the sub-greedy strategy. Above all, since our proposed cooperative strategy benefits from the spatial and temporal diversity of primary network, SU's energy efficiency is significantly improved and the goal of energy efficient "Green" communications for SUs in CCRNs is achieved.

C. Performance in the Scenario of SU With Continuously Arriving Packets

After the discussion of previous scenario, we then explore the SU's energy efficiency and spectral efficiency performance if the SU has continuously arriving packets. In contrast to the previous case, a new deadline for observation and decision span should be defined due to the possible buffer overflow after a certain timeline. Based on Eq.17 and pre-defined parameters, the SU can determine a unique transmission deadline by which its queued traffic must be delivered. Otherwise, the packet dropping probability will exceed the threshold in later time. In Fig.7, the curves of packet dropping probability corresponding to different SU's arrival rates are presented. It can be observed that with the increase of observation time slots, the packet dropping probability increases. In addition, the packet dropping probability grows faster when SU's packet arrival rate increases. Based on this figure, the SU can dynamically schedule an observation deadline according to different packet arrival rates, the buffer size, pre-defined overflow probability threshold, etc.

We first study the impact of SU's packet arrival rate on its spectral efficiency in different primary network settings. The simulation results are shown in Fig.8. It can be observed that with the increase of packet arrival rate, SU's throughput is improved. Moreover, for a certain packet arrival rate, SU's spectral efficiency increases when the primary network incorporates more PUs. Note that the previous scenario equals to the case where the packet arrival rate is zero. It can be observed that a higher spectral efficiency is achieved in the scenario of SU with continuously arriving packets than that in the scenario of SU without newly arriving packets, as shown in Fig.8. The explanations are as follows. Since the observation and decision time span is shorter in order to keep the packet dropping probability below the threshold, the SU selects to cooperate with a specific PU much earlier than before, meanwhile the SU has more packets to transmit when the packet arrival rate increases. Based on Eq.13, SU's spectral efficiency will inevitably increase. On the other hand, if there are more PUs distributed in the primary network, SU has better opportunities to select a PU with lower traffic load or directly find an idle channel, which contributes to a higher spectral efficiency as well.

Despite the fact that high packet arrival rate enhances SU's spectral efficiency, SU's energy efficiency is degraded with the increase of its packet arrival rate, as shown in Fig.9. In this part, the relation between SU's packet arrival rate and

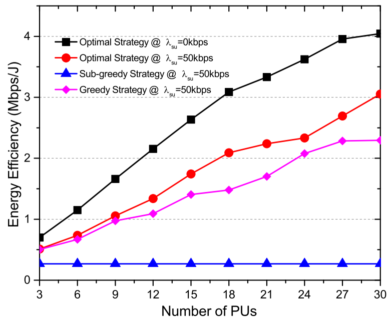

Fig. 10. Comparison of SU's energy efficiency in different cooperative strategy.

its energy efficiency is presented and analyzed. From Fig.9, it can be observed that SU's energy efficiency is improved by increasing the number of PUs but the performance is degraded when the packet arrival rate increases. Note that for the same number of PUs, the scenario of SU without newly arriving packets yields higher energy efficiency than that of the scenario of SU with continuously arriving packets. The reason is that higher packet arrival rate causes more packets to be transmitted for the SU, which results in longer time for the secondary transmission. Hence, the SU poses more stringent selection criterion on the PUs' traffic, which will in turn decrease the number of qualified PUs. In addition, due to the buffer overflow probability constraint, the SU makes the decision earlier and cannot effectively utilize the temporal diversity of primary network, which reduces the chance to select a good PU to cooperate with and thus increases its energy consumption. Combined with the aforementioned reasons, we can conclude that the increase of SU's packet arrival rate has negative impacts on SU's energy efficiency. Therefore, it can be seen that there is a design trade-off between SU's throughput and energy efficiency as shown in Fig.8-9.

Next, we conduct simulations for the energy efficiency performance of greedy and sub-greedy strategies, whose results are compared with our proposed cooperative strategy as shown in Fig.10. It can be observed that applying our strategy in the scenario of continuously arriving packets outperforms applying the greedy and sub-greedy ones. As shown in the figure, the greedy strategy still yields a constant energy efficiency because the spatial diversity is not utilized by the SU. On the other hand, even though the sub-greedy strategy can provide an increasing value of the energy efficiency when the number of PUs increases, it cannot offer a temporal scheduling on the cooperative selection for the SU and thus offers lower energy efficiency than our proposed strategy. In specific, our cooperative strategy provides the SU with more than 400% and 14% higher energy efficiency than that of greedy and sub-greedy strategies respectively when there are 12 PUs in CCRNs. More importantly, the gain scales up dramatically when the number of PUs increases, which makes our proposed strategy more energy-beneficial in densely deployed communication systems.

VII. Conclusion

In this paper, we have proposed an energy-efficient cooperative strategy for SUs in CCRNs to maximize SUs' energy efficiency which is contributed by the throughput and energy consumption. To improve the energy efficiency, in contrast to most existing works, our scheme allows SUs to actively make the cooperative decision by exploiting the spatial and temporal diversity of the primary network. The problem was formulated by the optimal stopping theory and the solution was derived from the backward induction. Our study shows that our cooperative strategy significantly outperforms existing schemes in terms of SUs' energy efficiency, which provides a way to energy efficient "Green" communications in cognitive radio networks.

Appendix A
Proof of Eq.5

Recall that i^{th} PU's traffic load is assumed to be a random variable Ψ_i which is $i.i.d.$ from other PUs at a given time slot and follows the PMF $f_\Psi(\psi)$ where $\psi \geq 0$. We want to find the probability distribution of the minimum Ψ_i at a given time slot. First of all, we rearrange these M number of random variables in a non-descending order of magnitude, i.e., $\Psi_{(1)} \leq \Psi_{(2)} \leq \ldots \leq \Psi_{(r)} \leq \ldots \leq \Psi_{(M)}$, where $\Psi_{(r)}$ is the r^{th} order smallest number in the group. In general, the PMF of $\Psi_{(r)}$ can be calculated as follows

$$
\begin{aligned}
f_{\Psi_{(r)}}(\psi) &= p\left(\Psi_{(r)} = \psi\right) \\
&= p(m \text{ of the } \Psi < \psi, n \text{ of the } \Psi > \psi, \\
&\quad \times (M-m-n) \text{ of the } \Psi = \psi) \\
&= \sum_{m=0}^{r-1} \sum_{n=0}^{M-r} \binom{M}{m} \binom{M-m}{n} p(\Psi < \psi)^m \cdot \\
&\quad \times p(\Psi > \psi)^n p(\Psi = \psi)^{M-m-n} \\
&= \sum_{m=0}^{r-1} \sum_{n=0}^{M-r} \binom{M}{m} \binom{M-m}{n} [F(\psi)]^m \cdot \\
&\quad \times [1 - F(\psi)]^n f(\psi)^{M-m-n}
\end{aligned}
$$

Specifically, we need the PMF of the 1^{st} order statistic, i.e., $\Psi_{(1)} = \min(\Psi_1, \Psi_2, \ldots \Psi_M)$. Then, we can simply set $r = 1$ and let $m = 0$. Its PMF is given below

$$
\begin{aligned}
f_{\Psi_{(1)}}(\psi) &= p\left(\Psi_{(1)} = \psi\right) \\
&= \sum_{n=0}^{M-1} \binom{M}{n} [1 - F(\psi)]^n \cdot f(\psi)^{M-n} \\
&= \sum_{k=1}^{M} \frac{M!}{k!\,(M-k)!} f(\psi)^k \cdot [1 - F(\psi)]^{M-k}
\end{aligned}
$$

The proof is completed.

Appendix B
Proof of Lemma 1

Since the number of arriving packets in each time slot is a random variable which is $i.i.d.$ across time slots and follows a probability vector $\eta = [\eta_0, \eta_1, \ldots, \eta_N]$. Suppose $\mu_j \in \{0, 1, \ldots, N\}$ is the number of arriving packets in the j^{th} time slot. Thus, all the queued packets up to the j^{th} time slot is $x = k + \mu_1 + \mu_2 + ... + \mu_j$. Then, the PMF of total number of queued packets can be calculated as follows:

$$
\begin{aligned}
f_{A^j}(x) &= p\left(k + \mu_1 + \mu_2 + ... + \mu_j = x\right) \\
&= \sum_{\mu_1=0}^{N} p\left(\mu_2 + ... + \mu_j = x - k - \mu_1\right) \cdot \eta_{\mu_1} \\
&= \sum_{\mu_{j-1}=0}^{N} ... \sum_{\mu_1=0}^{N} p\left(\mu_j = x - ... - \mu_{j-1}\right) \cdot \eta_{\mu_1} ... \eta_{\mu_{j-1}} \\
&= \sum_{\mu_{j-1}=0}^{N} ... \sum_{\mu_1=0}^{N} \eta_{x-...-\mu_{j-1}} \cdot \eta_{\mu_1} ... \eta_{\mu_{j-1}} \\
&= \sum_{\mu_{j-1}=0}^{N} \eta_{\mu_{j-1}} ... \sum_{\mu_1=0}^{N} \eta_{\mu_1} \cdot \eta_{x-...-\mu_{j-1}}
\end{aligned}
$$

The proof is completed.

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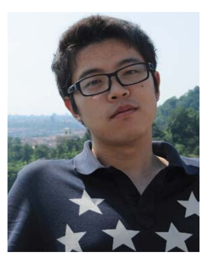

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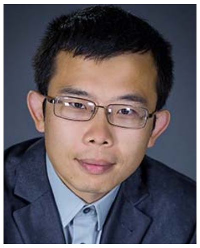

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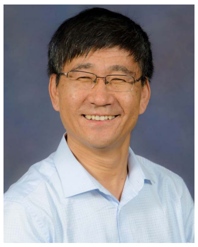

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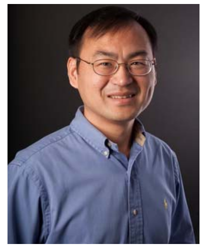

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