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

Jianqing Liu[1], Hao Yue[1], Haichuan Ding[1], Pengbo Si[2], and Yuguang Fang[1]

[1]Dept. of Electrical and Computer Engineering, University of Florida, Gainesville, Florida 32611 USA,
Email:{jianqingliu, hyue}@ufl.edu, dhcbit@gmail.com, fang@ece.ufl.edu
[2]College of Electronic Information and Control Engineering, Beijing University of Technology, Beijing 100124 China
Email:sipengbo@bjut.edu.cn

***Abstract*—In cognitive radio networks, primary users (PUs) can leverage secondary users (SUs) as cooperative relays to increase their transmission rates, and SUs will in turn obtain more spectrum access opportunities. While most existing works assume that SUs are passively selected by PUs regardless of SUs' willingness, in this paper, we propose a cooperative strategy for SUs to actively decide whether to cooperate or not. Basically, due to PUs' time-varying traffic demands, it is essential for SUs to firstly observe the channels and then select a specific PU to cooperate with in order to save the energy. In our paper, this decision related problem is formulated based on optimal stopping theory where SUs observe PUs in time sequence and then make decisions whether to stop observation and cooperate right away or wait till next time slot to repeat the same process. We address this problem by using backward induction and derive the energy-efficient strategy for SUs. To validate the feasibility of our proposed scheme, extensive simulations are conducted to show the impact of PUs' traffic demands on SUs' decisions. The results also reveal that the proposed optimal rule outperforms the greedy selection strategy and is thus more energy-efficient to be applied to the cooperative cognitive radio networks.**

I. Introduction

Cognitive Radio (CR), as a promising solution to addressing the unbalanced usage of electromagnetic radio spectrum [1], has attracted extensive attentions from both academia and industry. Cognitive radio networks (CRNs) are designed such that the licensed spectrum holes unoccupied by primary users (PUs) can be opportunistically accessed by unlicensed secondary users (SUs). In the real wireless propagation environment, however, PUs' transmissions are subject to severe damage due to multipath fading, which will greatly degrade PUs network performance and then consequently impact SUs' access to primary channels. To tackle this problem, cooperative communication between PUs and SUs has been proposed as an effective solution [2]. This regime exploits spatial diversity by enabling SUs as cooperative relays to help PUs finish their transmission as quickly as possible, while the SUs will in return obtain more spectrum access opportunities as a reward [3]. This framework is well known as a cooperative cognitive radio network (CCRN), wherein the mutual benefit, i.e., a "win-win" situation between PUs and SUs is realized.

As a combination of two promising techniques, cooperative communication in cognitive radio networks has been recently studied in many literatures. In [2], CCRNs are proposed to fully utilize spectrum resource and fulfill SUs' demands. Based on Universal Software Radio Peripheral (USRP) testbed, the experiment shows the improvement of system performance compared to traditional CRNs without cooperative communication. To study the spectrum sharing problem in CCRNs, game theory has been widely used in [4]-[6]. Basically, these game-theoretic schemes are based on hierarchial Stackelberg model where PU is the leader and decides the fraction of time for cooperation while SUs as a group of followers must obey the decisions. In [7], to address cooperative relay selection problem in CCRNs, the authors apply the optimal stopping theory as the tool where the PU leads the decision as well and the selected SU is forced to involve into the cooperative communication with the PU.

However, given the increasing concern of the energy efficiency in CCRNs and the fairness for SU network, it should be noted that the selfish SUs may not be interested to cooperate if they have no desire to access the channel or if the received transmission opportunity is not enough to compensate their energy cost during the cooperation. On the other hand, in the aforementioned frameworks, the group of SUs with low battery level can not be selected as relays even if they have the willingness to cooperate, which is neither efficient nor fair. In this sense, incorporating a more fair and energy-efficient mechanism into CCRNs is essential to encourage the cooperation among SUs. In this paper, we will focus on the cooperative pair selection problem from SUs' perspective. In particular, we consider a cooperative framework in which SUs will decide to cooperate with PUs or not based on their energy concerns. When SUs have delay-tolerant packets, they could wait for a better cooperation opportunity to obtain a lower energy consumption. In our framework, we propose a CCRN architecture consisting of entities that can reliably and continuously sense the PUs' traffic demands. The SUs then query the sensing results from these entities and calculate the instantaneous cooperation-induced energy cost. Afterwards, the SUs compare the current energy cost with the expected energy consumption and make the decision whether to stop and cooperate right away or not. Our proposed strategy is that SUs stop at the first time slot where the instantaneous cost is no more than the expected cost and then pick the PU with minimum traffic demand to cooperate. This strategy is derived by firstly formulating the decision problem with the

This work was partially supported by the US National Science Foundation under grant CNS-1343356.

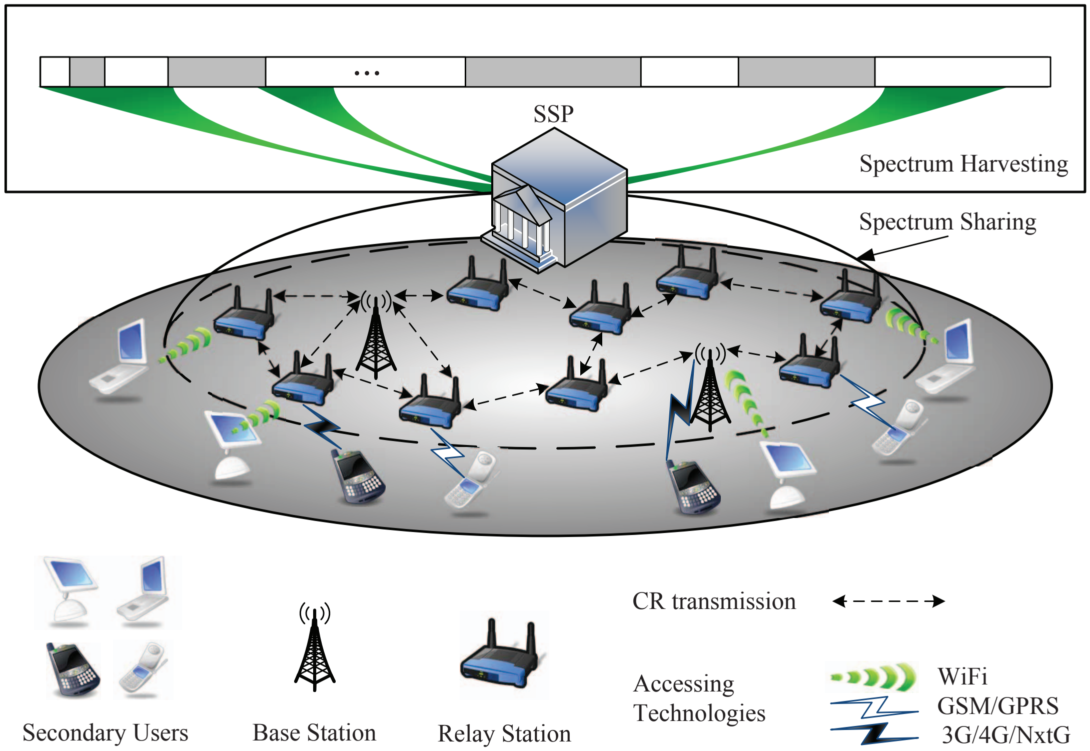

Fig. 1. Cognitive Capacity Harvesting Network.

optimal stopping theory [8] and then solving by backward induction. Extensive simulations are conducted to show the impacts of PUs' traffic demands on SUs' decisions. The results also indicate higher energy efficiency of our proposed strategy compared to that of the greedy cooperation strategy.

The rest of the paper is organized as follows. The overview of the system architecture is described in Section II. We discuss the adopted optimal stopping rule and the protocol implementation in Section III. In Section IV, the simulation results of performance evaluation are given. Finally we conclude our paper in Section V.

II. System Architecture

A. Network Model

In [9], we have introduced a flexible architecture for CRNs, which is called the cognitive capacity harvesting network as shown in Fig.1. The network consists of four types of entities: a secondary service provider (SSP), several base stations (BSs), many relay stations (RSs) and SUs. Each entity in this hierarchical architecture has functions as follows. As an independent wireless service provider, the SSP possesses its own spectrum while harvests additional spectrum resources from primary networks as well to enhance the QoS for SUs. The BSs are interconnected through high-speed wired links while SUs can communicate with BSs to further connect to Internet or other data networks. The RSs are deployed to facilitate the access of SUs and they can be viewed as a collection of cognitive radio routers. BSs and RSs can switch to either basic bands or harvested bands to communicate with SUs, which poses no requirement of cognitive capacity on SUs. Hence, SUs can be any devices using whatever accessing technology, e.g., laptops using Wi-Fi or cell phones using GSM.

In this paper, we consider a CCRN that deploys our aforementioned architecture where a number of PUs are distributed in SSP's coverage area. Suppose there are M PUs occupying different licensed channels denoted as PU_i, $i = 1, 2, ..., M$, and their real-time traffic is different. When each primary transmitter needs to deliver the packets to its corresponding receiver, a secondary relay node which has better channel condition can be selected to relay its packets. In our network model, the primary users will broadcast their traffic demands information to the secondary network to search for the qualified helping nodes. The cognitive radio routers, which continuously monitor PUs' channel conditions and traffic demands, will construct a real-time database for local PUs, as shown in Fig.2. Given a specific time slot t_j, $j = 1, 2, ..., N$, all the PUs' instantaneous traffic information is stored vertically in the table as $L_{PU_i}(t_j)$, $i = 1, 2, ..., M$. Note that the duration of each time slot is T.

The SUs, which have delay-tolerant packets, are interested in accessing the primary channels. By periodically querying the database at each time slot from the cognitive radio routers, each SU will decide at which time to stop observing and with which PU to cooperate. If none of the primary candidates are satisfied, the SU will choose to wait till next time slot to repeat the same process. Note that SUs' delay-tolerant packets will expire and be automatically dropped at t_N if the cooperation communication link is still not constructed, which is the worst scenario.

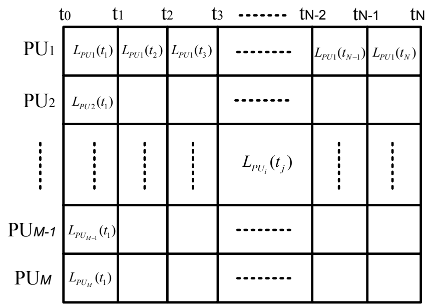

Fig. 2. Real-Time PUs' Traffic Table.

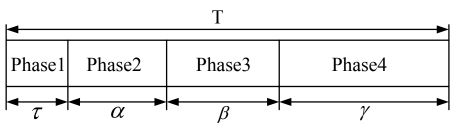

Fig. 3. Multi-phase Time Frame in SU.

B. Time Frame Structure

In this paper, a TDMA-based multi-phase cooperation scheme [10] is adopted for both PUs and SUs. The time frame of duration T in the secondary user is partitioned into four phases, as illustrated in Fig.3. In the first phase, the SU queries the database from cognitive radio router, finds the best candidate to cooperate with and then builds up the connection. The PU then broadcasts its traffic in the second phase while the SU relays in the third phase. In return, the SU's packets are transmitted over the corresponding primary channel in the fourth phase. In SU's relay phase, Decode-and-Forward (DF) mode is used due to its flexibility regarding the time sharing between direct transmission and cooperation [4].

Here, τ, α, β and γ are the time duration of each corresponding phase. In particular, τ is identical for different time slots, while α, β and γ vary and are dependent on the load of relaying traffic and channel conditions. However, the underlying condition $\alpha+\beta+\gamma \leq T-\tau$ poses a constraint for the selection of PUs, which is explained in details in Section III.

III. Optimal Stopping Policy Based Energy-Efficient Cooperation Strategy

From the previous description, we know that the cooperative pair selection is performed by SUs which observe the PUs on time sequence $t_1, t_2, ..., t_N$. In this paper, we focus on the selection strategy for a single SU. At each time stage, the SU calculates an instantaneous cost based on current observation and the expected cost of future observations. By comparing these two costs, the SU may stop and take current cooperation opportunity, or continue and observe the next stage. Note that the observation has a finite horizon known as the upper bound t_N, at which the secondary user has to stop and take the cost. Therefore, the selection of cooperative PU can be formulated as a sequential decision problem and can be applied to the optimal stopping theory domain. Next, we formulate the problem in the following parts.

A. Problem Formulation

In the framework of CCRNs, the validity of cooperation requires the traffic from PUs to be reliably relayed by SUs. Therefore, the following constraint must be satisfied:

$$\alpha_i(t_j)C_{i,PS} = \beta_i(t_j)C_{i,SP} \tag{1}$$

where the channel capacity $C_{i,PS} = W_i \log(1 + SNR_{i,PS})$ and $C_{i,SP} = W_i \log(1 + SNR_{i,SP})$ according to Shannon's theorem. W_i is the channel bandwidth for PU_i; $SNR_{i,PS}$ and $SNR_{i,SP}$ represent the signal-to-noise-ratio of the channel between the ith PU transmitter and the SU, and that between the SU and the ith PU receiver, respectively. $\alpha_i(t_j)$ and $\beta_i(t_j)$ denote the time spent in the second and third phase respectively if SU cooperates with the ith PU at time slot t_j, where $i \in \{1, 2, ..., M\}$ and $j \in \{1, 2, ..., N\}$. Specifically, $\alpha_i(t_j)$ and $\beta_i(t_j)$ are calculated as follow:

$$\alpha_i(t_j) = \frac{L_{PU_i}(t_j)}{C_{i,PS}} \tag{2}$$

$$\beta_i(t_j) = \frac{L_{PU_i}(t_j)}{C_{i,SP}} \tag{3}$$

where $L_{PU_i}(t_j)$ denotes the traffic load of primary channel PU_i at time slot t_j.

According to the frame structure described in Section II.B, another constraint should be satisfied as well:

$$\frac{L_{PU_i}(t_j)}{C_{i,PS}} + \frac{L_{PU_i}(t_j)}{C_{i,SP}} + \frac{D}{C_{i,SS}} \leq T - \tau \tag{4}$$

where $C_{i,SS} = W_i \log(1 + SNR_{SS})$. SNR_{SS} represents the signal-to-noise-ratio between the secondary transmitter and receiver; and D denotes the size of SU's delay-tolerant packet. The inequality in Eq.(3) guarantees an upper bound for the total time which is spent from Phase 2 to Phase 4. Note that the right side of the inequality is a constant, while the left side is just a function of the random variable $L_{PU_i}(t_j)$ as long as the channel bandwidth and SNRs are given.

In order to investigate the impact of PUs' traffic on the decision of SUs' cooperative pair selection, we assume that PUs' arrival traffic $L_{PU_i}(t_j)$ follows a distribution with probability mass function (PMF) $f(k)$ and cumulative mass function (CMF) $F(k)$ at each time slot. Here, k is the number of arrival packets for PUs. For simplicity, it is assumed that the probability distribution for each PU's traffic is i.i.d. at any given time slot, and the traffic arrivals in different time slots are independent for each specific PU. In our architecture, the cognitive radio routers preliminarily obtain the information of PUs' channel bandwidth and SNRs, and then broadcast the information to SUs. By jointly considering the collected information and the size of its own data packets, the SU sets an upper bound on PUs' traffic level, which automatically filters out the group of primary users with heavy traffic demands. Based on Eq.(3), the defined upper bound is given as follows:

$$th_i = (T - \tau - \frac{D}{C_{i,SS}}) \cdot \frac{C_{i,PS} \cdot C_{i,SP}}{C_{i,PS} + C_{i,SP}} \tag{5}$$

where th_i is denoted as the upper bound on the traffic over channel PU_i.

In our scheme, we consider that the SU selects one single PU to construct the cooperative communication link. Given the upper bound from Eq.(5), the SU actively screens a collection of primary candidates and picks a single PU of the minimum traffic load. Since $L_{PU_1}(t_j), L_{PU_2}(t_j), ..., L_{PU_M}(t_j)$ are i.i.d. random variables and have the same PMF $f(k)$ and CMF $F(k)$, we can rearrange these discrete random variables in a non-descending order of magnitude, i.e., $L_{(1)}(t_j) \leq L_{(2)}(t_j) \leq ... \leq L_{(M)}(t_j)$, where $L_{(r)}(t_j)$ is the rth order smallest number in the group. Note that these order statistics are also random variables and computing the probability distribution of $L_{(1)}(t_j)$ is of our interest. In general cases, the PMF of the rth order is calculated as follows:

$$f_{L_{(r)}(t_j)}(k) = \sum_{\mu=0}^{r-1} \sum_{\omega=0}^{M-r} \begin{pmatrix} M \\ \mu \end{pmatrix} \begin{pmatrix} M-\mu \\ \omega \end{pmatrix} [F(k-1)]^{\mu} \times [f(k)]^{M-\mu-\omega} \times [1-F(k)]^{\omega} \tag{6}$$

It is obvious that the rth order statistic follows the multinomial distribution [11], where there are μ numbers of PUs less than or equal to $k-1$, ω numbers of PUs greater than or equal to $k+1$ and the other $M-\mu-\omega$ numbers of PUs exactly equal to k. Specifically, the $1st$ order statistic can be easily found by setting r equal to one. The formula is shown below.

$$f_{L_{(1)}(t_j)}(k) = \sum_{\omega=0}^{M-1} \begin{pmatrix} M \\ \omega \end{pmatrix} [f(k)]^{M-\omega} [1-F(k)]^{\omega} \tag{7}$$

Note that the $1st$ order statistics at different time slots are i.i.d. random variables and they have the same PMF $f_{L_{(1)}(t_j)}(k)$ as shown in Eq.(7).

After calculating the probability distribution of the minimum traffic arrival, we define an indicator function Θ to represent the SU's cooperation decision, which is given by

$$\Theta = \begin{cases} 0 & \text{Not cooperate if } k > th_i \\ 1 & \text{Cooperate if } k \leq th_i \end{cases} \tag{8}$$

Next, we derive the instantaneous energy cost function denoted as $Y(t_j)$. From the time frame structure shown in Fig.3, it can be seen that the SU's energy consumption consists of four parts: observing, receiving and relaying the PU's traffic, and transmitting its own packets. At the observation phase in particular, the energy consumption always exits regardless of SU's cooperation decision. Hence, this term can be viewed as the weighting factor when the SU stops after the jth observation. It is obvious that the more time the SU waits for a good PU, the higher chance that the SU will consume more energy. Also in this first phase, the process of querying CR router's database is similar to the IEEE 802.11 RTS/CTS mechanism, wherein the SU first transmits a RTS (Request-To-Send) message to the CR router while the CR router returns a CTS (Clear-To-Send) frame which contains the information of channel conditions and PUs' traffic.

In the following phases, the SU's transceiver generally uses the fixed transmitting power P_{tx} and receiving power P_{rx} during the communication process. Therefore, up to this point, the energy cost function can be described as follow:

$$Y(t_j) = P_{tx}\tau \cdot j + [P_{rx}\alpha(t_j) + P_{tx}\beta(t_j) + P_{tx}\gamma(t_j)] \cdot \Theta \tag{9}$$

where the value $\alpha(t_j)$ measures the time spent in receiving PU's packets and it is a random variable whose probability value is determined by the channel condition and the selected PU's traffic according to Eq.(2). Relaying PU's packets takes time $\beta(t_j)$ and it can be calculated from Eq.(3). The value $\gamma(t_j)$ represents SU's transmission time which is not affected by PU's packets but determined by its own data payload and the channel condition. In our scenario, we assume that the channel bandwidth and SNRs are measured preliminarily and the SU's data payload is known as well. Therefore, the total energy consumption is a random variable which is determined by the selected PU's traffic level and its probability can be calculated from $f_{L_{(1)}(t_j)}(k)$.

B. Optimal Stopping Rule

The cost function has been derived as mentioned above. In this subsection, the optimal stopping rule is applied to solve the cooperative pair selection problem. The scenario can now be summarized as follows: after the jth observation, the SU calculates the energy cost of $Y(t_j)$. Standing at current stage, the SU should decide whether to stop or to continue observing. In principle, this problem can be addressed in the domain of optimal stopping theory by the method of backward induction. Since the observation must stop at t_N, we can first get the optimal rule at t_{N-1}. After the optimal rule at t_{N-1} is known, we then derive the optimal rule at t_{N-2}, and so backward to the initial stage t_1. Denote V_j^N as the minimum energy cost that the SU could obtain at stage j. It can be calculated as follow:

$$V_j^N = \min \left\{ Y(t_j), E\left[V_{j+1}^N\right] \right\} \tag{10}$$

The above equation basically explains the idea of optimal stopping rule: the SU compares the cost $Y(t_j)$ for stopping at stage j with the cost $E\left[V_{j+1}^N\right]$ which is expected to obtain by continuing observation and applying optimal stopping rule for stage $j+1$ towards N. Hence, the optimal decision is to stop at stage j if $Y(t_j)$ is less than $E\left[V_{j+1}^N\right]$, while to continue if otherwise. Note that it is optimal to stop at the earliest j when $Y(t_j) \leq E\left[V_{j+1}^N\right]$ first comes up.

In the following discussion, the expected cost $E\left[V_{j+1}^N\right]$ is derived using backward deduction. Firstly, since the SU must stop at stage N, the expected cost for the last stage is given as

$$Z_1 = E\left[V_N^N\right] = E\left[Y(t_N)\right] = \sum_{k=0}^{th_i} Y(t_N) f_{L_{(1)}(t_j)}(k) + \sum_{k=th_i+1}^{\infty} P_{tx} N \tau f_{L_{(1)}(t_j)}(k) \tag{11}$$

Inductively, at stage j, the expected cost $E\left[V_{j+1}^N\right]$ is shown below

$$Z_{N-j} = E\left[\min\{Y(t_j), Z_{N-j-1}\}\right] = \sum_{k=0}^{th_i^j} Y(t_j) f_{L_{(1)}(t_j)}(k) + \sum_{k=th_i^j+1}^{th_i} Z_{N-j-1} f_{L_{(1)}(t_j)}(k) + \sum_{k=th_i+1}^{\infty} P_{tx} j \tau f_{L_{(1)}(t_j)}(k) \tag{12}$$

For convenience, Z_{N-j} is used to represent the expected cost $E\left[V_{j+1}^{N}\right]$. Note that Z_0=∞ since there is no future observation standing at stage t_N. The th_i^j is an intermediate threshold integer which can be solved by setting $Y(t_j)$ equal to Z_{N-j-1} and is subject to $0 < th_i^j < th_i$.

Algorithm 1 : The Optimal Stopping Rule

The CR router determines the specifications of CCRN architecture, e.g. M, W_i, SNR and etc;
for j=1 to N **do**
  The CR router broadcasts PUs' real-time traffic and SU calculates the energy cost $Y(t_j)$ according to Eq.(9);
  The SU computes the expected energy cost Z_{N-j} from backward based on Eq.(12);
  if $Y(t_j) > Z_{N-j}$ **then**
    The SU waits for next time stage $j+1$ to observe PUs;
  else
    The SU stops at current time stage j, selects the PU of minimum traffic level and takes the energy cost $Y(t_j)$;
  end if
end for

In order to draw a more clear picture of our optimal stopping rule, the Algorithm 1 presents the detailed procedures to select the optimal primary user. In this algorithm, it shows that the selection process stops either at a certain time stage where the instantaneous cost $Y(t_j)$ is less than the expected energy cost or at the last step upon which the effectiveness of the delay tolerant packet is expired.

IV. Performance Evaluation

A. Simulation Setup

In this section, simulations are conducted to evaluate the performance of our proposed scheme. In our network environment, there are $M = 15$ primary users which occupy different licensed channels. The PUs' traffic k follows the poisson distribution of PMF $f_i(k) = \frac{\bar{l}^k}{k!}e^{-\bar{l}}$, where l indicates the average traffic level. For simplicity, the channel conditions, i.e., SNR_{PS}, SNR_{SP} and SNR_{SS} are assumed to be constant during the selection process and the channel bandwidth is $1MHz$ for each PU. In the aspect of SU, suppose it has a delay tolerant packet with $10Mbits$ payload which must be sent out within $200s$. The utilized transmitting and receiving power in SU's transceiver system is assumed to be fixed and of value $1W$ and $0.6W$, respectively. The duration of a time slot is $10s$, i.e., $T = 10s$; the time for observation $\tau = 0.05s$. Hence, these 200 seconds can be equally divided into 20 slots and each of them has the same structure as shown in Fig.3.

We study the impacts of the PU's traffic $L_{PU_i}(t_j)$ on the system performance in terms of energy consumption and average number of observation steps. The simulation results are shown in this section through 300 independent runs. Furthermore, the simulations are also conducted to provide a deep insight of the effect of channel condition $SNRs$ on the aforementioned system performance.

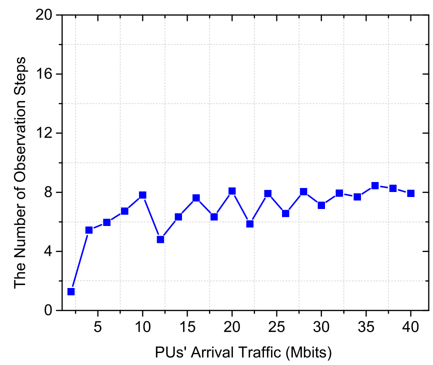

Fig. 4. PU's arrival traffic vs. the number of observation steps.

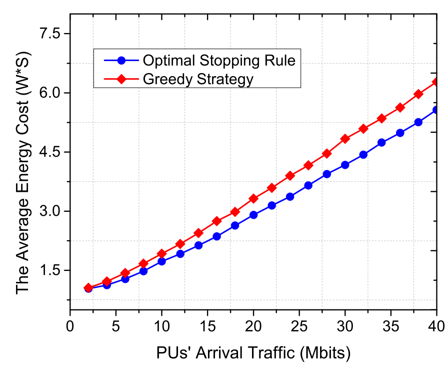

Fig. 5. PU's arrival traffic vs. the average energy cost.

B. Results and Analysis

Firstly, SNR_{PS}, SNR_{SP} and SNR_{SS} are set to be 27dB, 27dB and 30dB, respectively. Based on Eq.(4), the upper bound for PUs' arrival traffic is calculated as $40Mbits$. Hence, the SU's strategy when the average of PUs' arrival traffic ranges from $1Mbits$ to $40Mbits$ is simulated, as shown in Fig.4. The simulation result shows that with the increase of PU's arrival packets, the number of optimal observation steps increase. The reason is that with low PU's traffic level, the SU can easily find a qualified PU with low cooperation energy cost at earlier stage and thus does not need to wait for longer steps which will otherwise brings additional observing cost from τ. While as PUs' traffic increase, the SU prefers to wait for more steps till the qualified PU shows up to minimize the energy cost because observing more steps provides SU more choices to select the best PU candidate.

By applying the optimal stopping rule, the obtained energy cost with respect to PUs' arrival traffic is depicted in Fig.5. For comparison, the energy consumption when using greedy strategy is also shown in the same figure. The idea of greedy strategy is that regardless of energy consideration, the SU chooses to cooperate whenever receiving PU's request, which is the traditional strategy for the SU in existing literatures. It can be seen that with the increase of PUs' arrival traffic,

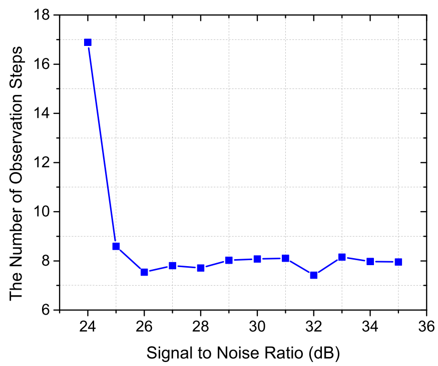

Fig. 6. PU's channel SNR vs. the number of observation steps.

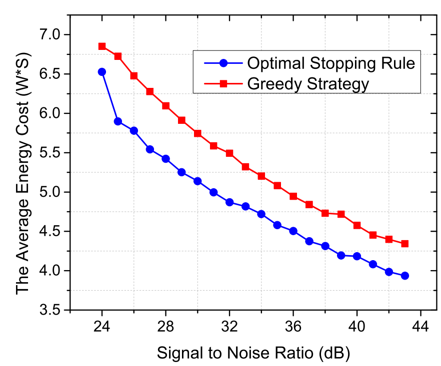

Fig. 7. PU's channel SNR vs. the average energy cost.

the energy cost using whichever strategy also increases simultaneously. This coincides with our intuition because the larger PU's traffic that the SU helps to relay, the longer time it takes for cooperation which results in higher energy cost as a whole. However, the comparison in the figure clearly shows that the system performance by applying optimal stopping rule outperforms that with the greedy strategy, which indicates the higher energy efficiency of our strategy.

To further investigate the impact of PUs' channel qualities SNR_{PS} and SNR_{SP} on the SU's cooperation strategy, we conduct simulations to evaluate the system performance with the variation of SNR_{PS} and SNR_{SP}. For simplicity, suppose SNR_{PS} and SNR_{SP} are equal and both change from $24dB$ to $43dB$ linearly. The simulations are conducted under the situation where PUs' arrival traffic are $40Mbits$ and SU's packet payload is $10Mbits$. The result shown in Fig.6 indicates that when PUs' channel qualities get better, the SU takes less steps to select the PU. Note that as the SNR becomes good enough, the number of observation steps converges to a certain value. The reason is that the SU has few choices when PUs' channel qualities are bad and thus waits for more steps till the qualified PU shows up, while the SU can stop earlier since the good channel qualities provide more PU candidates to select.

The simulation result of the relationship between SU's average energy cost and PUs' channel qualities is given in Fig.7. For comparison, the system performance by applying greedy strategy versus using our proposed optimal stopping rule are plotted in the same graph. The figure leads to the fact that better channel conditions save more energy for the SU; and more importantly, our proposed strategy yields higher energy efficiency than that by the greedy strategy.

V. Conclusions and Future Work

In this paper, we studied the energy-efficient selection strategy for the SU to cooperate with the appropriate PU in CCRNs. Unlike the traditional assumption that SU blindly follows PU's decision in cooperation process, we allowed the SU to actively select the qualified PU to cooperate based on SU's energy concern. This selection problem was formulated by optimal stopping theory. By applying backward induction, we solved the problem and derived the optimal stopping rule for SU's selection strategy. Extensive simulations were conducted to study the impacts of different PUs' channel parameters on SU's decision strategy. We also compare the system performance of the optimal stopping rule with the greedy strategy to validate the benefit of our proposed strategy for the SU.

In the future research, we will extend this work to the case of relay selection by jointly considering the energy efficiency for SU networks and PU networks as a whole.

References

[1] J. Mitola, G. Q. Maguire, "Cognitive radio: making software radios more personal," in *IEEE Pers. Commun.*, vol. 6, no. 4, August 1999, pp. 13-18.

[2] J. Jia, J. Zhang, Q. Zhang, "Cooperative relay for cognitive radio networks," in *IEEE INFOCOM*, April 2009, pp. 2304-2312.

[3] O. Simeone, Y. Bar-Ness, U. Spagnolini, "Stable throughput of cognitive radios with and without relaying capability," in *IEEE Trans. Commun.*, vol. 55, no. 12, December 2007, pp. 2351-2360.

[4] F. Afghah, M. Costa, A. Razi, A. Abedi, A. Ephremides, "A reputation-based Stackelberg game approach for spectrum sharing with cognitive cooperation," in *52nd IEEE Conference on Decision and Control (CDC)*, December 2013, pp. 3287-3292.

[5] H. Wang, L. Gao, X. Gan, X. Wang, E. Hossain, "Cooperative spectrum sharing in cognitive radio networks: a game-theoretic approach," in *Proc. IEEE ICC*, May 2010, pp. 1-5.

[6] B. Cao, J.W. Mark, Q. Zhang, R. Lu, X. Lin, X. Shen, "On optimal communication strategies for cooperative cognitive radio networking," in *IEEE INFOCOM*, April 2013, pp. 1726-1734.

[7] T. Jing, S. Zhu, H. Li, X. Cheng, Y. Huo, "Cooperative relay selection in cognitive radio networks," in *IEEE INFOCOM*, April 2013, pp. 175-179.

[8] T. Ferguson, "Optimal stopping and applications," [Online]. Available: http://doi.acm.org/10.1145/1614320.1614325

[9] H. Yue, M. Pan, Y. Fang, S. Glisic, "Spectrum and energy efficient relay station placement in cognitive radio networks," in *IEEE J. Sel. Areas Commun.*, vol. 31, no. 5, May 2013, pp. 883-893.

[10] J. Zhang, Q. Zhang, "Stackelberg game for utility-based cooperative cognitive radio networks," in *Proc. MobiHoc*, May 2009, pp. 23-32.

[11] L.Diane, "The distribution of order statistics for discrete random variables with applications to bootstrapping," in *Inf. J. Comput.*, vol. 18, no. 1, Feburary 2006, pp. 19-31.