Energy-Efficient Power Allocation Strategy in Cognitive Relay Networks

Zongsheng ZHANG, Qihui WU, Jinlong WANG

Wireless Lab, PLA University of Science and Technology, Street YuDao, Nanjing, China

zhangzongsheng1984@163.com, 532692271@qq.com, 15951803143@163.com

Abstract. *Cognitive radio and cooperative technique are two essential techniques for the future generation green communication paradigm owing to its inherent advantages of adaptability and cognition. Typically, previous studies on power allocation in the cognitive relay networks often concentrate on two goals independently: the first goal is to minimize the transmit power to reduce energy consumption, as depicted in strategy 1; the second goal is to maximize the transmit rate, as depicted in strategy 2. In this paper, we shift our focus to energy-efficient-oriented design, that is, green power allocation between source and relay. Therefore, we present a novel power allocation strategy considering the two goals jointly, as depicted in strategy 3, and compare the proposed strategy with two previous strategies. Specifically, because the strategy 3 is nonlinear, we use the Lagrange dual method to solve it effectively. Finally, the numerical results are presented to validate our theoretical results through theory simulation and Monte Carlo simulation. Numerical performance results show that the proposed strategy works better than that of the two previous strategies from the viewpoints of energy-efficient.*

Keywords

Cognitive relay networks (CRN), energy-efficient (EE), secondary user (SU), primary user (PU).

1. Introduction

There are increasing demands for the wireless radio spectrum with the emergency of many new wireless communication networks. Meanwhile, according to the Federal Communication Commission (FCC), large portions of the licensed wireless spectrum resources are under utilized [1]. This motivates the concept of spectrum reuse that allows secondary users (SU) to utilize the radio spectrum licensed to the primary users (PU) when the spectrum is temporarily not being utilized. The key technology behind spectrum reuse is cognitive radio (CR) [2]-[11], which consists of three essential components: (1) spectrum sensing: The SUs are required to sense and monitor the radio spectrum environment within their operating range to detect the frequency bands that are not occupied by PU; (2) Dynamic spectrum management: cognitive radio networks are required to dynamically select the best available bands for communications; and (3) Adaptive communication: a cognitive radio device can configure its transmission parameters to opportunistically make best use of the ever-changing available spectrum.

Driven by the trend to promote spectrum utilization significantly and increase transmission diversity gain in various types of wireless networks, cooperative relay technology has been introduced into cognitive radio networks [12]-[14]. The majority of existing works on CRN focused on the throughput, outage probability and power allocation. For example, a distributed algorithm for channel access and power control was proposed for cognitive multi-hop relays in [15]; in [16], the authors analyzed the delay of a cognitive relay assisted multi-access network, however, they did not consider the impact of PU activities and dynamic spectrum-sharing; the close expression of outage probability in CRN was given in Rayleigh fading channel in [17]; in [18], the authors deduced the close expression of effective throughput in the single relay and multi relays in the Rayleigh fading channel; the frequency efficient can be increased through cognitive relay in Rayleigh fading channel, and proposed two multi hops route protocols: nearest-neighbor routing (NNR) and farther-neighbor routing (FNR) in [19]; in [20], a model was established to minimize the transmit power of the cognitive source and the cognitive relay.

Previous studies on the power allocation in the cognitive relay networks listed above focused on either the throughput or the transmit rate of the system independently, therefore, it may be not energy-efficient. As we know, energy-efficient is an important issue in the design communication system, and there is a pressure on reducing the power consumption in order to maximize the battery operation time. Thus, in this article, the main objective of power allocation is to provide optimal energy-efficient normalized throughput in the cognitive relay networks. In summary, the main contributions of this paper are twofold. Firstly, we jointly consider the transmit rate and power consumption, and propose a strategy to maximize power-normalized transmit rate. Secondly, we use the Lagrange dual method to solve it effectively, and this strategy can be realized in a distributed way.

2. System Model

A basic cooperative relay communication model in cognitive relay networks consists of five terminals, i.e. a cognitive source (CS), a cognitive relay, a cognitive destination (CD), a primary source (PS), and a primary destination (PD), as depicted in Fig. 1. Relay locates randomly between the cognitive transmitter and cognitive receiver. The channels over links PS-PD, PS-R, PS-CD, R-PD, R-CD, CS-R, CS-PD, CS-CD are modeled to be Rayleigh flat fading with channel coefficients denoted by $H_{PP}, H_{PR}, H_{PS}, H_{RP}, H_{RS}, H_{SP}, H_{SR}$ and H_{SS} respectively. We have $H_{ij} \sim CN(0, d_{ij}^{-a})$ where a is the path loss exponent and d_{ij} is the normalized distance between the respective transmitters and receivers. This normalization is done with respect to the distance between PS and PD. Thus each of the links can be characterized by the set of parameters $\{h_{ij}, d_i\}$. The transmit power at PS and CS is denoted as P_{PS} and P_{CS} respectively. Specifically, σ_j^2 denotes the variance of additive white Gaussian noise (AWGN) at node j, for simplicity of analysis, we assume $\sigma_j^2 = \sigma^2$.

Relaying protocols mainly include Decode-and-Forward (DF), where the cognitive relay decodes the received signal and then re-encodes it to the cognitive destination, and Amplify-and-Forward (AF), where the cognitive relay sends a scaled version of its received signal to the cognitive destination. For simplicity of analysis, we select the DF protocol in this paper. Specifically, the AF protocol can be analyzed in the same way.

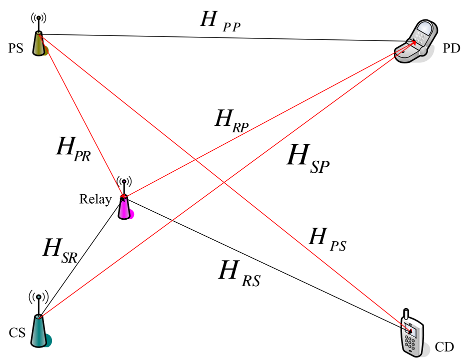

Fig. 1. System model.

3. Problem Formulations

In this section, we firstly summarize two previous power allocation strategies in the cognitive relay networks. The first previous strategy focused on minimizing the transmitting power consumption; the second previous strategy focused on maximizing the transmit rate. Followed we propose a novel strategy jointly considering the power consumption and transmit rate, and focus on the energy-efficient power allocation because of limited battery power. Unlike to the two previous strategies, the proposed power allocation scheme is nonlinear, and can not be solved in the same way to the previous strategies. As a result, we select the Lagrange dual method to solve it effectively.

3.1 Strategy 1

In this strategy, the constrained transmit power was allocated to both cognitive source and cognitive relay, in order to minimize the total power consumption while satisfying the target QoS constraint of SU. Besides, we should also consider maintaining the interference introduced to the PU within a given interference limit since SU coexists with the PU in the same frequency band. Therefore, strategy 1 can be formulated to the following constrained optimization problem:

$$min \;\; P = P_{CS} + P_{Relay}, \tag{1}$$

$$s.t. \;\; P_{CS}, P_{Relay} \in [0, \; P_{\max}], \tag{2}$$

$$P_{CS}|H_{SP}|^2, \;\; P_{Relay}|H_{RP}|^2 \leq \Theta, \tag{3}$$

$$Out\{R_{DF} < R_{target}\} \leq \theta \tag{4}$$

where P_{CS} denotes the transmit power of cognitive source, P_{Relay} represents the transmit power of cognitive relay, Θ is the interference threshold of the PR, θ denotes the cognitive outage threshold, R_{target} represents the target transmit rate of cognitive relay networks in the DF mode. Moreover, constraint (2) satisfies the minimum and maximum transmit power, respectively, and constraint (3) guarantees the protection of PU. In the system, we assume that the direct link is blocked because of deep fading. According to Shannon's Capacity formula, the transmit rate of cognitive system is given by

$$\begin{aligned} R_{DF} = \tfrac{1}{2}Bmin\{log_2(1+\tfrac{P_{CS}|H_{SR}|^2}{P_{PS}|H_{PR}|^2\phi+N_0B}), \\ log_2(1+\tfrac{P_{Relay}|H_{RD}|^2}{P_{PS}|H_{PD}|^2\phi+N_0B})\} \end{aligned} \tag{5}$$

where B represents the bandwidth of the channel, and ϕ denotes the state of primary user. $\phi = 1$ denotes that the primary user is busy, and $\phi = 0$ denotes that the primary user is idle. We set $\phi = 1$ in this paper, which makes the analysis much more fairly general. This optimization problem can be solved in the same way to [20].

3.2 Strategy 2

In this strategy, the objective was to allocate constrained transmit power to both cognitive source and cognitive relay, in order to maximize the total transmit rate while satisfying the target QoS constraint of SU. Besides, we should also consider maintaining the inference introduced to the PU within a given interference limit since SU coexists with the PU in the same frequency band. Therefore, the strategy 2 can be formulated as the following constrained optimization problem:

$$\max_{\{P_{CS}, P_{Relay}\}} \;\; R_{DF}, \tag{6}$$

$$s.t. \;\; P_{CS}, P_{Relay} \in [0, \; P_{\max}], \tag{7}$$

$$P_{CS}|H_{SP}|^2, \;\; P_{Relay}|H_{RP}|^2 \leq \Theta, \tag{8}$$

$$Out\{R_{DF} < R_{target}\} \leq \theta. \tag{9}$$

This optimization problem can be solved in the same way to the strategy 1.

3.3 Strategy 3 (Proposed Strategy)

The two previous strategies focus on the power consumption and transmit rate independently. However, the power consumption and transmit rate are correlated, i.e., the larger the transmit power is, the larger the throughput it obtains, but it also increases the interference to other users, therefore, decreasing the throughput of the other users. As a result, the other users would require you to low the transmit power, or improve their transmit power to guarantee the QoS. Specifically, we should consider the transmit power and transmit rate jointly to make system much more energy-efficient. Therefore, we formulate the strategy 3 to the following optimization problem:

$$\textbf{Opt. 1} \quad \max_{\{P_{CS},P_{Relay}\}} \quad R_{DF}/P, \tag{10}$$

$$s.t.\ P_{CS}, P_{Relay} \in [0,\ P_{\max}], \tag{11}$$

$$P_{CS}|H_{SP}|^2,\ P_{Relay}|H_{RP}|^2 \leq \Theta, \tag{12}$$

$$Out\{R_{DF} < R_{target}\} \leq \theta, \tag{13}$$

$$P = P_{CS} + P_{Relay}. \tag{14}$$

From (5), we can directly conclude that we can obtain the optimal capacity in the cooperative system when the capacity of the first hop equals to the capacity of the second hop. Therefore, we have:

$$\frac{P_{CS}|H_{SR}|^2}{P_{PS}|H_{PR}|^2 + N_0 B} = \frac{P_{Relay}|H_{RD}|^2}{P_{PS}|H_{PD}|^2 + N_0 B}. \tag{15}$$

Because the **Opt. 1** is nonlinear, strategy 3 can not be solved in the same way to two previous strategies. Therefore, we use the Lagrange dual method to solve the **Opt. 1**. We first derive the corresponding Lagrange function as follows:

$$\begin{aligned} M(P_{CS}, P_{Relay}, \alpha, \beta, \gamma) = \tfrac{1}{2}B\tfrac{R_{DF}}{P} + \alpha(Out\{R_{DF} < R_{target}\} \\ -P_{target}^{out}) + \beta(P_{CS}|H_{SP}|^2 - \Theta) + \gamma(R_{Relay}|H_{RP}|^2 - \Theta) \end{aligned} \tag{16}$$

where $[\alpha, \beta, \gamma]^T$ is the vector of dual variables for the network constrains in (11), (12), (13), (14).

Substituting (15) into (13), the outage probability of cognitive system is

$$\begin{aligned} P_{CS}^{Outage} = 1 - \frac{P_{CS}\sigma_{SR}^2}{\sigma_{PR}^2(2^{2R_{target}-1})P_{PS} + P_{CS}\sigma_{SR}^2} \\ *exp\{\frac{(2^{2R_{target}-1})N_0 B}{P_{CS}\sigma_{SR}^2}\}. \end{aligned} \tag{17}$$

More details are given in Appendix A.

According to the Lagrange dual theory, the Lagrange dual problem can therefore be converted to **Opt. 2**:

$$\textbf{Opt. 2} \quad Q(\alpha, \beta, \gamma) = \max_{P_{CS}} \quad M(P_{CS}, \alpha, \beta, \gamma) \tag{18}$$

$$s.t.\ \ P_{CS} \in [0, P_{max}] \tag{19}$$

The **Opt. 2** can be solved by sub-gradient method. Therefore, we have

$$P_{CS}(n+1) = P_{CS}(n) + \Delta(n) g(P_{CS}) \tag{20}$$

where $g(P_{CS}) = \frac{\partial M(P_{CS},\alpha,\beta,\gamma)}{\partial P_{CS}}$, $\Delta(n)$ is the proper step size, n is the times of iterations.

Dual variables are updated by the sub-gradient method in parallel as follows:

$$\alpha(m+1) = [\alpha(m) - \varepsilon(m) g(\alpha)], \tag{21}$$

$$\beta(m+1) = [\beta(m) - \varepsilon(m) g(\beta)], \tag{22}$$

$$\gamma(m+1) = [\gamma(m) - \varepsilon(m) g(\gamma)] \tag{23}$$

where $[x]^+ = max(0,x)$, $\varepsilon(m)$ is the proper step size. The above update is guaranteed to coverage to the optimal dual variables if $\varepsilon(m)$ is chosen following a diminishing step size rule. Since our problem has zero duality gap as mentioned before, the optimal power allocation strategy algorithm can be summarized in Fig. 2.

Remarks: According to Lagrange dual method, we can allocate the power resource in a distributed way. For example, the cognitive relay node can get to know the channel gain through feedbacks or learning the environment. After obtaining the channel state information, the relay node can use the Lagrange dual method to calculate the power allocation between source and relay. Specifically, the overhead in feedback stage or learning stage is relatively small compared to transmitting stage, so it can be omitted.

***Algorithm 1:** Lagrange dual method power allocation strategy*

Step 1: Initialize the dual variables $P_S^*(0)$, $(\lambda(0),\mu(0),\nu(0))^T$ and proper step size $[\Delta(0),\varepsilon(0)]^T$;
Step 2: Given power variable in (20).
Step 3: Set $n = n+1$. Return to Step 4 if coverage; else return to Step 2.
Step 4: Using the result in Step 2, given the new dual variables according to (21)(22)(23).
Step 5: Set $m = m+1$, return to Step 2 until convergence.

Fig. 2. Algorithm 1: Power allocation strategy based on Lagrange dual method from the viewpoints of energy-efficient.

4. Numerical Results

In this section, simulation results are presented to verify the performance of our approach, as well as the effect of adjustable parameters. We mainly evaluate the performance of proposed strategy 3, compared with conventional strategies which focus on transmit power consumption and transmit rate independently. Specifically, we confirm the analytical results derived in this paper through comparison with Monte Carlo simulations. Particularly, all simulation results in this section are obtained by taking expectation over 10^4 independent trials.

First, we evaluate the performance of three strategies with adjustable power of PU in different values of interference threshold θ. In Fig. 3, we can observe that the larger is the outage probability threshold, the lower is the transmit rate of SU. This can be interpreted as follows: larger outage probability threshold means that we can use less power to maintain the QoS of SU. On the other hand, we can also clearly see that the optimal strategy is the proposed strategy (Strategy 3 in this paper), followed by strategy 2, strategy 1. Particularly, the theoretical results perfectly match the Monte Carlo simulated results.

Second, we evaluate the lowest transmit power of SU satisfied QoS of SU and PU. In Fig. 4, we can clearly observe that the transit power increases as the transmit power of PU increases. This can be interpreted as follows: the larger the transmit power of PU, the larger interference the PU introduces, as a result, the SU needs to increase the transmit power to satisfy the QoS of the system. Specifically, the performance of strategy 3 is very close to the strategy 1.

Next, we evaluate the energy-efficient performance of three strategies. In Fig. 5, we can directly see that the larger is the transmit power of SU, the more energy-efficient is the system. Specifically, we can clearly observe that the strategy 3 is optimally energy-efficient among the three strategies.

Fig. 6 depicts the relationship between the iteration number n and transmit power of cognitive transmitter. It is directly verified that when the iteration number exceeding 200, the transmit power of cognitive transmitter is convergence. Therefore, the Lagrange dual method can be effectively used to solve the proposed strategy.

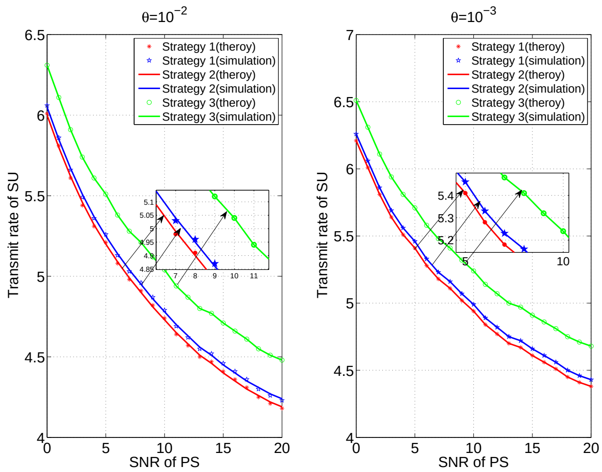

Fig. 3. Relationship between the transmit power of PU and transmit rate of SU.

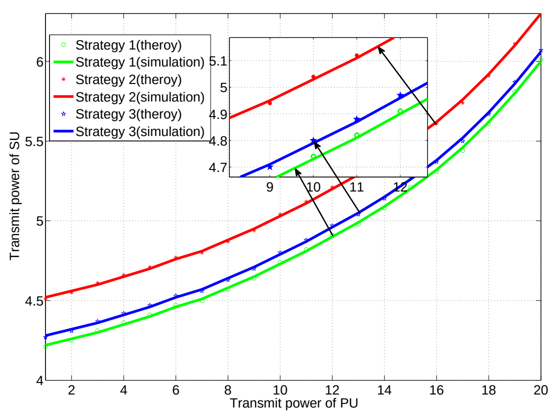

Fig. 4. Relationship between the transmit power of PU and transmit power of SU.

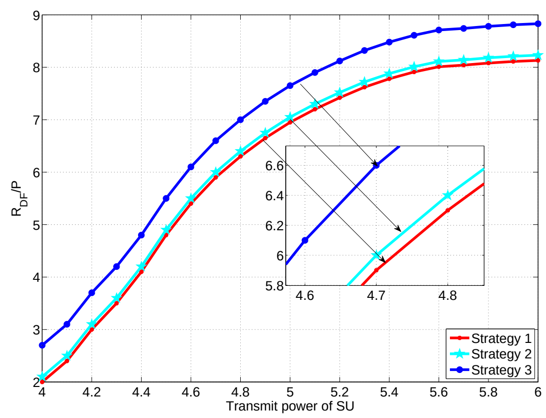

Fig. 5. Relationship between the transmit power of SU and ratio of R[n] to transmit power of SU.

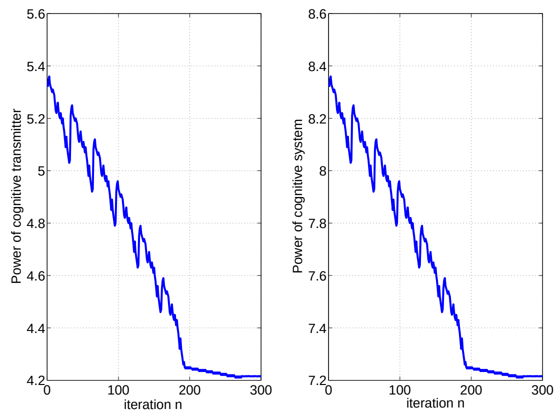

Fig. 6. Relationship between of iteration number n and transmit power of cognitive transmitter.

5. Conclusion

This correspondence has demonstrated that the proposed strategy provides an effective approach to improve the energy-efficient under the QoS constraint of PU and SU. We have given a Lagrange algorithm to solve the proposed strategy effectively. The simulation results have validated our proposed strategy from the viewpoints of energy efficiency, and the theoretical results perfectly match the Monte Carlo simulated results. In our future work, we intend to extend and generalize our work to cases of multiple relays and multiple hops in which distributed control strategy and multiple hops power allocation need to be designed jointly to the cognitive relay networks function well and much more energy-efficient, and issues such an fairness among cognitive users need to be taken into consideration.

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Appendix A

Detailed deduction of (17).

$$\begin{aligned} P_{CS}^{outage} &= Out\{R_{DF} \leq R_{target}\} \\ &= Out\{|H_{SR}|^2 \leq \frac{(2^{2R_{target}}-1)(P_{PS}|H_{PR}|^2+N_0B)}{P_{CS}}\}. \end{aligned} \quad (24)$$

According to the assumption in the above sections, we know $|H_{SR}|^2$, $|H_{PR}|^2$ are exponential distributed, so their Probability Density Functions (PDF) are given by

$$f(|H_{PR}|^2) = \frac{1}{\sigma_{PR}^2} exp\left(-\frac{|H_{PR}|^2}{\sigma_{PR}^2}\right), \quad (25)$$

$$f(|H_{SR}|^2) = \frac{1}{\sigma_{SR}^2} exp\left(-\frac{|H_{SR}|^2}{\sigma_{SR}^2}\right). \quad (26)$$

Combining with (24), (25) and (26), we can get (17).

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About Authors ...

Zongsheng Zhang was born in 1986. He received his B.S. degree in communications engineering from Institute of Communications, Nanjing, China, in 2009. He is currently pursuing the Ph.D. degree in Communications and information system at the Institute of Communications, PLA University of Science and Technology. His research interests focus on wireless communications and cognitive radio.

Jinlong Wang was born in 1963. He received his B.S. degree in wireless communications, M.S.degree and Ph.D. degree in communications and electronic systems from Institute of Communications Engineering, Nanjing, China, in 1983, 1986 and 1992, respectively. He is currently professor at the PLA University of Science and Technology, China. He is also the cochairman of IEEE Nanjing Section. He has published widely in the areas of signal processing for communications, information theory, and wireless networks. His current research interests include wireless communication, cognitive radio and soft-defined radio

Qihui Wu was born in 1970. He received his B.S. degree in communications engineering, M.S. degree and Ph.D. degree in communications and information system from Institute of Communications Engineering, Nanjing, China, in 1994, 1997 and 2000, respectively. He is currently professor at the PLA University of Science and Technology, China. His current research interests are algorithms and optimization for cognitive wireless networks and soft-defined radio.