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Joint throughput and transmission range optimization for triple-hop networks with cognitive relay*

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Abstract: The optimization of the network throughput and transmission range is one of the most important issues in cognitive relay networks (CRNs). Existing research has focused on the dual-hop network, which cannot be extended to a triple-hop network due to its shortcomings, including the limited transmission range and one-way communication. In this paper, a novel, triple-hop relay scheme is proposed to implement time-division duplex (TDD) transmission among secondary users (SUs) in a three-phase transmission. Moreover, a superposition coding (SC) method is adopted for handling two-receiver cases in triple-hop networks with a cognitive relay. We studied a joint optimization of time and power allocation in all three phases, which is formulated as a nonlinear and concave problem. Both analytical and numerical results show that the proposed scheme is able to improve the throughput of SUs, and enlarge the transmission range of primary users (PUs) without increasing the number of hops.

Key words: Decode-and-forward (DF); Triple-hop; Cognitive relay networks (CRNs); Time and power allocation; Superposition coding

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1 Introduction

The frequency spectrum is critical for wireless communications. The Federal Communications Commission (FCC) reports in its survey that the licensed spectrum is not fully used, with its utilization ranging from 15% to 85% (Spectrum Efficiency Working Group, 2002). Cognitive radio (CR) is considered a promising technology to improve spectrum utilization. The technique allows secondary users (SUs) to use the spectrum licensed to primary users (PUs) when that spectrum is not fully used (He *et al.*, 2012; Guimarães *et al.*, 2014; Jo *et al.*, 2014; Liu and Tan, 2014).

Cognitive relay networks (CRNs) were introduced with the purpose of guaranteeing the quality of service (QoS) and overcoming interference (Lee *et al.*, 2011; Zhang *et al.*, 2016). SUs can transmit their own data, and meanwhile guarantee the data transmission of PUs. Amplify-and-forward (AF) and decode-and-forward (DF) are the two main protocols of relay systems. CRN systems can feasibly promote these relay protocols by improving the spectral efficiency and extending the transmission range. To implement these benefits in a CRN communication system, the efficiency of wireless resource allocation is important. Moreover, the formulation for the optimization problem may differ significantly in relaying protocols (DF or AF), power constraints (total or individual power constraint), and system architectures (dual-hop or multi-hop). Several works have been devoted to

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studying these problems. Zhong *et al.* (2014) optimized relay selection and power allocation for throughput. Huang *et al.* (2015) considered channel fading in both sensing and transmission, and optimized the system performance by alternating the optimization. Chen and Huang (2012) investigated a distributed spectrum-sharing mechanism design with spatial reuse, which is able to achieve a centralized optimal solution. Chen and Huang (2015) also designed a distributed and imitative spectrum-access mechanism with incomplete network information based on achieving an efficient spectrum utilization, which also provides fairness across the pool of SUs.

However, the traditional dual-hop network scheme with a cognitive relay explored by most researchers has the following shortcomings: First, the SU data flow must be consistent with the PU data flow. It means that the network provides only one-way communication. Second, the transmission range is still limited by the dual-hop relay methodology. Inspired by Shoukry *et al.* (2014), we investigated how a triple-hop relay scheme solves these problems. Shoukry *et al.* (2014) designed new protocols based on a CRN with a source, two half-duplex relays, and a destination, which maximize the average rate and constraints of the average delay. However, it still cannot solve the data flow direction problem. Wang *et al.* (2013) investigated power allocation for DF transmissions with multi-hop relaying.

Meanwhile, a non-orthogonal scheme, encompassing superposition coding (SC), can be used to handle the two-receiver case. Orthogonal channels can eliminate interference during transmissions, so the conventional method takes advantage of the orthogonal channels to implement frequency division multiplexing. However, this cannot achieve the highest available transmission rate for certain levels of reliability (Vanka *et al.*, 2012b). Superposition coding is a non-orthogonal scheme that achieves high capacity on a broadcast channel. Vanka *et al.* (2012a) suggested that SC can provide substantial gains in spectral efficiencies over such orthogonal schemes as time division multiplexing (TDM). Kaneko *et al.* (2014) proposed a novel SC scheme to enhance the users' throughput and fairness across the pool of users. Elgendi *et al.* (2014) introduced a multicast scheme based on SC to transmit scalable video-coded signals.

In this paper, we consider a DF-based cooperative triple-hop network with a cognitive relay scheme by jointly allocating two types of resources: power and time. To the best of our knowledge, no attempt resembling joint optimization for a triple-hop network has been carried out in the literature to date.

The contributions of this paper are listed as follows:

We propose a new cooperative triple-hop network scheme using the SC technique. Unlike previous investigations, which considered only dual-hop scenarios, our scheme achieves time-division duplex (TDD) communication for SUs. From that, we formulate a resource allocation problem to maximize the throughput and transmission range subject to the power constraints.

The optimal policy for time and power allocation is obtained by proving that the objective function is a concave function. Karush–Kuhn–Tucker (KKT) conditions are introduced to achieve the solution.

Simulation results are presented and analyzed to investigate the performance of the proposed scheme. The results show that SUs' throughput is significantly increased, and PUs' transmission range is also enlarged, compared to the existing methods.

2 System and channel models

Consider a DF triple-hop cooperation system where PUs and SUs share the same spectrum band in a given environment and work in an underlay model. SUs periodically sense the spectrum, intelligently detect the spectrum that is available, and then simultaneously communicate over the spectrum along with PUs. For simplicity, we assume perfect spectrum sensing, perfect accuracy of recoding at relays, and that false alarm probabilities and missed probabilities can be neglected.

The system consists of two source-destination pairs: a primary source P_1, a primary destination P_2, a secondary source S_1, and a secondary destination S_2. S_1 and S_2 are both DF cognitive relays for the primary system.

As shown in Fig. 1, d_1, d_2, d_3, and d_4 are the distances of P_1–S_1, S_1–S_2, S_1–P_2, and S_2–P_2, respectively. To guarantee the PU transmission rates, SU selection is critical, and has been studied by many

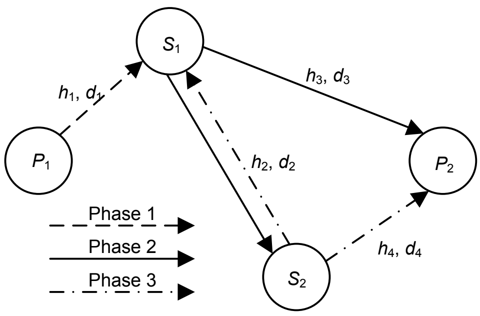

Fig. 1 System model

researchers (Li *et al.*, 2013).

Let x_1, x_2, and x_3 be the signal vectors transmitted by P_1, S_1, and S_2, respectively. Let h_1, h_2, h_3, and h_4 be the channel coefficients of their corresponding links. The study assumes that all links undergo Rayleigh flat fading. Thus, we have

$$|h_i|^2 = 1/d^{v_i},\ 0 \le i \le 5, \tag{1}$$

where v_i is the path loss coefficient and d_i is the distance. The additive white Gaussian noise (AWGN) for all links is modeled as a complex Gaussian variable with zero mean and variance σ_i^2. The channel gain can be formulated as $\gamma_i=|h_i|^2$, and all the coefficients remain static within the three-phase transmission.

In phase 1, P_1 broadcasts the signal x_1. Assume that only S_1 receives the signal. x_1 would be considered by S_2 and P_2 as an irrelevant signal and thus be ignored. P_2 can hear the primary information from P_1, S_1, and S_2. Since the signals are transmitted using the same codebooks (Shin and Kim, 2011), they can be combined with maximum ratio combining (MRC). Assume that P_2 does not ignore the signal from P_1, whose strength is always weaker than that of the signal from S_1 and S_2.

The signal received by S_1 can be expressed as

$$y_{P_1-S_1}^{(1)} = h_1\sqrt{p_1}x_1 + n_{S_1}, \tag{2}$$

where n_{S_1} denotes the Gaussian noise received by S_1, p_1 denotes the transmission power of P_1, and the superscript '1' denotes phase 1. Then, S_1 decodes x_1 and keeps it in memory for the next phase.

In phase 2, superposition coding is introduced to handle the two-receiver situation (Vanka *et al.*, 2012b). S_1 re-encodes x_1, and superposes it with its own signal x_2, which needs to be transmitted to S_2. The power would be distributed to x_1 and x_2 in specific ratios. The coding result is (Vanka *et al.*, 2012a)

$$X = \sqrt{\alpha P}x_1 + \sqrt{(1-\alpha)P}x_2,\ \alpha \in (0,1]. \tag{3}$$

S_1 broadcasts the weighted linear composite signal X, where α denotes the ratio of power to transmit the signal x_1, and the remaining $1-\alpha$ power is assigned to the secondary signal x_2. The signal received from S_2 and P_2 can be expressed respectively as follows:

$$y_{S_1-S_2}^{(2)} = h_2\left[\sqrt{\alpha p_2}x_1+\sqrt{(1-\alpha)p_2}x_2\right] + n_{S_2},\ \alpha \in (0,1], \tag{4}$$

$$y_{S_1-P_2}^{(2)} = h_3\left[\sqrt{\alpha p_2}x_1+\sqrt{(1-\alpha)p_2}x_2\right] + n_{P_2},\ \alpha \in (0,1], \tag{5}$$

where P_2 denotes the transmission power of S_1.

To extract signals x_1 and x_2 from the received signal $y_{S_1-S_2}^{(2)}$, a successive interference cancellation (SIC) procedure (Li *et al.*, 2011) is introduced into the scheme: S_2 will first decode x_1 and treat the desired signal x_2 as an interference. The signal-to-noise ratio (SNR) of x_1 is

$$\mathrm{SNR}_{x_1}^{(2)} = \frac{h_2\sqrt{\alpha p_2}}{h_2\sqrt{(1-\alpha)p_2} + n_{S_2}}. \tag{6}$$

After that, S_2 subtracts the decoded interference x_1 from $y_{S_1-S_2}^{(2)}$ and obtains the signal

$$\mathrm{SNR}_{x_2}^{(2)} = h_2\sqrt{(1-\alpha)p_2}x_2 + n_{S_2},\ \alpha \in (0,1]. \tag{7}$$

SNR of x_2 is

$$\frac{h_2\sqrt{(1-\alpha)p_2}}{n_{S_2}}. \tag{8}$$

Finally, S_2 decodes the desired message x_2 from the interference-free signal.

In phase 3, S_2 re-encodes x_1, and superposes the desired signals x_3 and x_1. Then S_2 broadcasts the signal. S_1 and P_2 subsequently receive

$$y_{S_2-S_1}^{(3)} = h_2\left[\sqrt{\beta p_3}x_1 + \sqrt{(1-\beta)p_3}x_3\right] + n_{S_1},\ \beta \in (0,1], \tag{9a}$$

$$y_{S_2-P_2}^{(3)} = h_4\left[\sqrt{\beta p_3}x_1 + \sqrt{(1-\beta)p_3}x_3\right] + n_{P_1},\ \beta \in (0,1], \tag{9b}$$

where β denotes the ratio of power to transmit x_1, and p_3 denotes the transmission power of S_2.

S_1 and S_2 both send the signal x_1 to P_2, and the signals $y_{S_1-P_2}^{(2)}$ and $y_{S_2-P_2}^{(3)}$ can be combined by MRC. The SNR of the primary signal received by P_2 is

$$\mathrm{SNR}_{P_2} = \frac{\beta\gamma_4 p_3}{(1-\beta)\gamma_4 p_3 + \sigma^2} + \frac{\alpha\gamma_3 p_2}{(1-\alpha)\gamma_3 p_2 + \sigma^2}. \tag{10}$$

P_2 treats x_3 and x_2 as interferences, and decodes x_1 from the combined signal $y_{S_2-P_2}^{(3)}$. S_1 decodes x_3 through the SIC procedure, just like S_2 does in phase 2. It is observed that S_1 and S_2 can transmit a signal to each other during the transmission. Thus, S_1 and S_2 form a TDD communication system.

3 Performance analysis

3.1 Equation analysis of constraints

Assuming that PUs are working, the primary source P_1 transmits signal x_1 to the primary destination P_2. Thus, the throughput of the primary system is

$$\overline{R}_{P_1-P_2} = \log_2\left(1 + \frac{\gamma_0 p_1}{\sigma^2}\right). \tag{11}$$

PU spectrum sharing is allowed under the condition that SUs can help PUs achieve the target rate $\overline{R}_p$. If $\overline{R}_{P_1-P_2} < \overline{R}_P$, P_2 would seek relays from nearby nodes to improve the throughput by sending out a request-to-cooperate (RTC) signal (Lu and Wang, 2014). P_1 would respond to it with an acknowledge-to-cooperate (ATC) signal. When RTC and ATC signals are both received, SUs are able to estimate the transmission rate in each phase.

Let $R_{S_1}^{(1)}$, $R_{S_2}^{(2)}$, and $R_{P_2}^{(3)}$ denote the primary transmission rate received by S_1, S_2, and P_2 in phases 1, 2, and 3, respectively. The throughput of the primary system can be calculated as

$$\overline{R}_{P_1-P_2} = \min(R_{S_1}^{(1)}, R_{S_2}^{(2)}, R_{P_2}^{(3)}) \ge \overline{R}_P. \tag{12}$$

Let δ, ε, and $1-\delta-\varepsilon$ denote the ratios of time spent in phases 1, 2, and 3, respectively. Thus, the corresponding throughputs are

$$R_{S_1}^{(1)} = \delta\log_2\left(1 + \frac{\gamma_1 p_1}{\sigma_{S_1}^2}\right),\ \delta \in (0,1), \tag{13}$$

$$R_{S_2}^{(2)} = \varepsilon\log_2\left[1 + \frac{\alpha\gamma_2 p_2}{(1-\alpha)\gamma_2 p_2 + \sigma^2}\right],\ \varepsilon \in (0,1), \tag{14}$$

$$\begin{aligned} R_{P_2}^{(3)} = (1-\delta-\varepsilon)\log_2\Bigg[1 &+ \frac{\beta\gamma_4 p_3}{(1-\beta)\gamma_4 p_3 + \sigma^2} \\ &+ \frac{\alpha\gamma_3 p_2}{(1-\alpha)\gamma_3 p_2 + \sigma^2}\Bigg],\ \delta + \varepsilon \in (0,1). \end{aligned} \tag{15}$$

When SUs discover that the primary target rate can be achieved by cooperation, they will broadcast a confirm-to-cooperate (CTC) signal to identify their presence. If the CTC signal is received by PUs, the SUs are permitted to share the spectrum band; otherwise, they will remain silent.

3.2 Optimization of time and power allocation

In this section, to maximize the secondary throughput R_{cn}, we derive the joint optimization of δ, ε, α, and β:

$$\begin{aligned} R_{\mathrm{cn}} &= R_{S_1-S_2}^{(2)} + R_{S_2-S_1}^{(3)} \\ &= \varepsilon\log_2\left[1 + \frac{(1-\alpha)\gamma_2 p_2}{\sigma^2}\right] \\ &\quad + (1-\delta-\varepsilon)\log_2\left[1 + \frac{(1-\beta)\gamma_2 p_3}{\sigma^2}\right]. \end{aligned} \tag{16}$$

Therefore, the optimization problem can be formulated as

$$(\delta^*, \varepsilon^*, \alpha^*, \beta^*) = \arg\max_{\delta,\xi,\alpha,\beta} R_{\mathrm{cn}} \tag{17}$$

subject to

$$\begin{cases} R_{S_1}^{(1)} = \delta \log_2\left(1+\dfrac{\gamma_1 p_1}{\sigma^2}\right) \geq \overline{R}_p, \\ R_{S_2}^{(2)} = \varepsilon \log_2\left[1+\dfrac{\alpha\gamma_2 p_2}{(1-\alpha)\gamma_2 p_2+\sigma^2}\right] \geq \overline{R}_p, \\ R_{P_2}^{(3)} = (1-\delta-\varepsilon)\log_2\left[1+\dfrac{\beta\gamma_4 p_3}{(1-\beta)\gamma_4 p_3+\sigma^2}\right. \\ \qquad \left. +\dfrac{\alpha\gamma_3 p_2}{(1-\alpha)\gamma_3 p_2+\sigma^2}\right] \geq \overline{R}_p, \\ (\delta,\varepsilon,\delta+\varepsilon)\in(0,1),\ \alpha\in(0,1],\ \beta\in[0,1). \end{cases} \tag{18}$$

According to Eq. (16), $R_{\text{cn}}(\delta)$ is a monotonically decreasing function of δ. Thus, the optimal δ can be derived from Eq. (16):

$$\delta^* = \delta_{\min} = \frac{\overline{R}_p}{\log_2\left(1+\dfrac{\gamma_1 p_1}{\sigma^2}\right)}. \tag{19}$$

Considering the other time variable ε, the first- and second-order derivatives of ε are

$$\begin{cases} R_{\text{cn}}{}'(\varepsilon) = \left\{ \lg\left[1-\dfrac{p_2}{\sigma^2}\gamma_2(\alpha-1)\right] \right. \\ \qquad \left. -\lg\left[1-\dfrac{p_3}{\sigma^2}\gamma_2(\beta-1)\right]\right\}\dfrac{1}{\lg 2}, \\ R_{\text{cn}}{}''(\varepsilon) = 0. \end{cases} \tag{20}$$

Thus, R_{cn} is a linear and monotonic function of ε. Along with increasing ε, whether R_{cn} will increase or decrease will depend on the sign of $R_{\text{cn}}'(\varepsilon)$. In other words, with α and β being constants, ε^* can be confirmed as

$$\varepsilon^* = \begin{cases} \varepsilon_{\max}, & R_{\text{cn}}{}'(\varepsilon) \geq 0, \\ \varepsilon_{\min}, & R_{\text{cn}}{}'(\varepsilon) < 0. \end{cases} \tag{21}$$

Then, to optimize the power variables α and β, R_{cn} should be proved as a concave function first. The Hessian matrix of R_{cn} is

$$\boldsymbol{H}(R_{\text{cn}}) = \begin{bmatrix} \dfrac{\partial^2 R_{\text{cn}}}{\partial\alpha^2} & \dfrac{\partial^2 R_{\text{cn}}}{\partial\alpha\partial\beta} \\ \dfrac{\partial^2 R_{\text{cn}}}{\partial\alpha\partial\beta} & \dfrac{\partial^2 R_{\text{cn}}}{\partial\beta^2} \end{bmatrix}, \tag{22}$$

where

$$\frac{\partial^2 R_{\text{cn}}}{\partial\alpha^2} = \frac{-\left(\dfrac{p_2}{\sigma^2}\right)^2 \varepsilon\gamma_2{}^2}{\lg 2\cdot\left[\dfrac{p_2}{\sigma^2}\gamma_2(\alpha-1)-1\right]^2}, \tag{23}$$

$$\frac{\partial^2 R_{\text{cn}}}{\partial\beta^2} = \frac{-\left(\dfrac{p_3}{\sigma^2}\right)^2 \gamma_2{}^2(\delta+\varepsilon-1)}{\lg 2\cdot\left[\dfrac{p_3}{\sigma^2}\gamma_2(\beta-1)-1\right]^2}, \tag{24}$$

and

$$\frac{\partial^2 R_{\text{cn}}}{\partial\alpha\partial\beta} = 0. \tag{25}$$

For $p_2/\sigma^2>0$, $p_3/\sigma^2>0$, $\varepsilon\in(0, 1)$, $\alpha\in(0, 1]$, it could be derived that

$$\frac{\partial^2 R_{\text{cn}}}{\partial\alpha^2} < 0, \tag{26}$$

and

$$\frac{\partial^2 R_{\text{cn}}}{\partial\beta^2} < 0. \tag{27}$$

By definition, the result whereby the Hessian matrix of R_{cn} is negative definite can be obtained from the reasoning process above.

According to Boyd and Vandenberghe (2004), R_{cn} is a strictly concave function when the Hessian matrix of R_{cn} is negative definite.

KKT conditions are used to optimize the concave objective function R_{cn} (Luo and Yu, 2006). The corresponding Lagrange function is

$$\begin{aligned} L(\varepsilon,\alpha,\beta) &= \varepsilon\log_2\left[1+\frac{(1-\alpha)\gamma_2 p_2}{\sigma^2}\right] \\ &+(1-\delta^*-\varepsilon)\log_2\left[1+\frac{(1-\beta)\gamma_2 p_3}{\sigma^2}\right] \\ &+\lambda\left\{\varepsilon\log_2\left[1+\frac{\alpha\gamma_2 p_2}{(1-\alpha)\gamma_2 p_2+\sigma^2}\right]-\overline{R}_p\right\} \\ &+\mu\left\{(1-\delta^*-\varepsilon)\log_2\left[1+\frac{\beta\gamma_5 p_3}{(1-\beta)\gamma_5 p_3+\sigma^2}\right]-\overline{R}_p\right\}, \end{aligned} \tag{28}$$

where λ, $\mu\geq 0$ are the Lagrange multipliers. The KKT conditions are given by

$$\begin{cases} \lambda\left\{\varepsilon\log_2\left[1+\dfrac{\alpha\gamma_2 p_2}{(1-\alpha)\gamma_2\mathrm{P}_2+\sigma^2}\right]-\overline{R}_P\right\}=0, \\ \mu\left\{(1-\delta^*-\varepsilon)\log_2\left[1+\dfrac{\beta\gamma_4 p_3}{(1-\beta)\gamma_4 p_3+\sigma^2}\right.\right. \\ \quad \left.\left.+\dfrac{\alpha\gamma_3 p_2}{(1-\alpha)\gamma_3 p_2+\sigma^2}\right]-\overline{R}_P\right\}=0, \\ \partial L(\varepsilon,\alpha,\beta)/\partial\varepsilon^*=0, \\ \partial L(\varepsilon,\alpha,\beta)/\partial\alpha^*=0, \\ \partial L(\varepsilon,\alpha,\beta)/\partial\beta^*=0. \end{cases} \tag{29}$$

According to Eq. (15), $\alpha(\beta)$ is a function that depends on β, and it is monotonically decreasing. For $\beta_{\max}$=1, the new lower bound of α can be determined as

$$\alpha_{\min}=\alpha(\beta_{\max}). \tag{30a}$$

Similarly, $\beta(\alpha)$ is a decreasing function of α, and thus

$$\beta_{\min}=\beta(\alpha_{\max}). \tag{30b}$$

Narrowing the boundaries of variables can improve the accuracy and efficiency of solving Eq. (28).

4 Simulation results

In this section, various numerical simulation results are presented to verify the theoretical derivation of the proposed scheme and the resource allocation scheme by comparing the results with those of both an optimized dual-hop network (Shin and Kim, 2011) and a conventional triple-hop network (Liu, 2009).

The optimized dual-hop network is a two-phase, time-sharing system. In phase 1, P_1 sends x_1 to S_1. In phase 2, S_1 superposes x_1 with x_2, and then sends it to P_2. The transfer time and power are optimized by using the Lagrangian multiplier method.

The conventional triple-hop network is a member of the multi-hop network. Its transfer process is a three-phase, time-sharing process with the same transfer time (Fig. 2). In phase 1, P_1 sends x_1 to S_1. In phase 2, S_1 sends x_1 to S_2. In phase 3, S_2 sends x_1 to P_2. During this period, S_1 and S_2 send x_2 and x_3 to each other by SC, respectively. The conventional

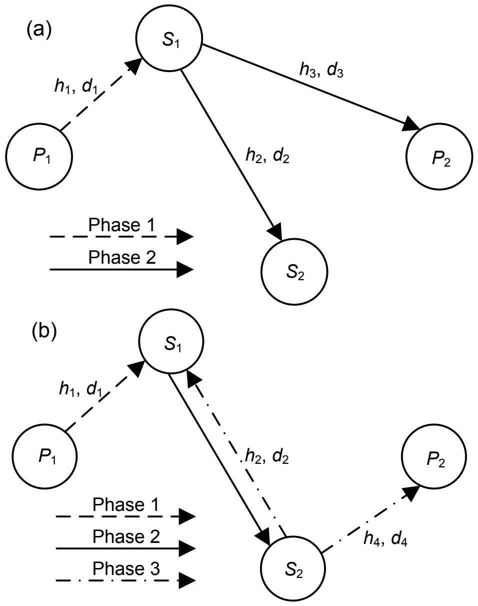

Fig. 2 Comparative system models of an optimized dual-hop network (a) and a conventional triple-hop network (b)

triple-hop network can be extended to multi-hop (four or more hops) networks easily. However, it can neither be optimized because the parameters are fixed, nor obtain the diversity gain.

The simulated network system consists of a pair of SUs, named S_1 and S_2, and a pair of PUs, named P_1 and P_2. Similar to Shin and Kim (2011) and Lu *et al.* (2013), we assume the path loss coefficient v=4, p_1/σ^2=8 dB, p_2/σ^2=10 dB, p_3/σ^2=10 dB, and $\overline{R}_P=0.6$.

The medium-scale algorithm is used to solve the parameter optimization problem. According to the simulation results, the error would be less than 10^{-3} in 400 iterations. A 2.4 GHz core processor computer can generally obtain the results in a second.

To illustrate the secondary throughput in which P_2 is in a different location, we assume that the locations of P_1, S_1, and S_2 are fixed, and their coordinates are (0, 0), (0, 1), and (0, 2), respectively.

In Fig. 3, the impacts of P_2's coordinates on the transmission are investigated where the primary system can achieve the target rate. Compared with a dual-hop network, the triple-hop network can transmit data for a longer distance, and the proposed scheme can enlarge the transmission coverage without increasing the number of hops.

Fig. 4 shows the secondary throughput as a function of P_2's coordinates with other parameters being fixed. A dual-hop network can achieve a high throughput. However, the curve declines rapidly with the increase in the transmission distance. The triple-hop network curve is relatively flat. However, the throughput is low when P_2 is close to P_1. The proposed scheme inherits the advantages of the first two networks.

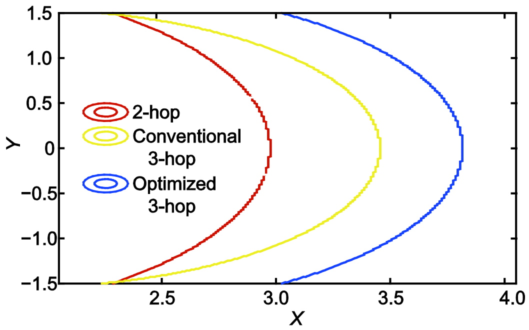

Fig. 3 Transmission range for P_2 to receive a signal

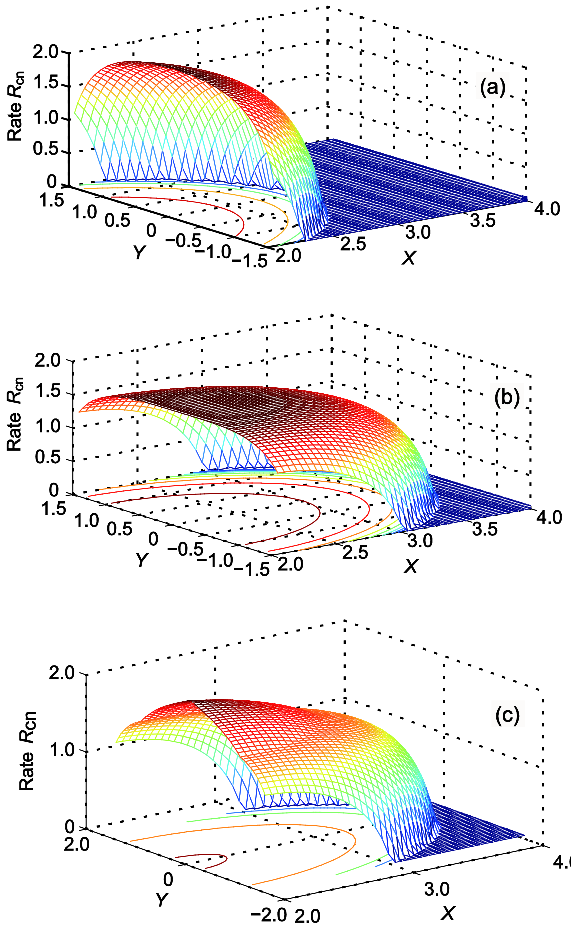

Fig. 4 Value of R_{cn} versus different locations of P_2 of dual-hop (a), conventional triple-hop (b), and optimized triple-hop (c)

Fig. 5 further shows the secondary throughput R_{cn} as a function of the distances P_1 and P_2 under the scenarios of two different path loss coefficients: case 1 (C1 v=3) and case 2 (C2 v=4). It can be found that the performance of the proposed scheme improves when increasing the value of v. More bottlenecks appear as the loss coefficient increases. However, the optimization can be used to alleviate the problem.

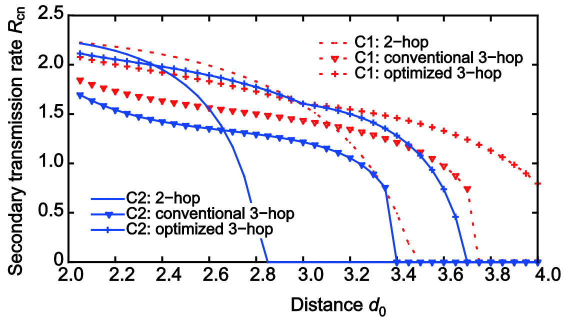

Fig. 5 Comparisons of R_{cn} in case 1 (C1 v=3) and case 2 (C2 v=4)

From Figs. 2, 3, and 4, we can see that after a series of optimizations, the communication system has improved with respect to the transmission range, secondary system throughput, and fading resistance, as a result of introducing the KKT conditions. The wireless resources can be considered having been used properly.

Consider a new transmission scenario with new constraints, which may occur in actual applications. For the secondary system throughput of two directions (S_1–S_2 and S_2–S_1), there may be floors and ceilings for $R^{(2)}_{S_1-S_2}$ and $R^{(3)}_{S_2-S_1}$, respectively. In this circumstance, $R^{(2)}_{S_1-S_2}$ and $R^{(3)}_{S_2-S_1}$ would be subject to

$$\begin{cases} R^{(2)}_{S_1-S_2} \in \left[\overline{R}^{\text{floor}}_{x_2}, \overline{R}^{\text{ceiling}}_{x_2}\right], \\ R^{(3)}_{S_2-S_1} \in \left[\overline{R}^{\text{floor}}_{x_3}, \overline{R}^{\text{ceiling}}_{x_3}\right]. \end{cases} \tag{31}$$

With the constraints of $R^{(2)}_{S_1-S_2}$ and $R^{(3)}_{S_2-S_1}$, the secondary transmission rate R_{cn} may be influenced, while whatever the constraints are, R_{cn} must be in a specific range. Fig. 5 compares the maximum and minimum values of R_{cn} (v=4). According to Fig. 6, the mean ratio for the maximum and minimum values of R_{cn} is 84%. Since the gap between the upper and lower bounds is relatively small, the constraints of $R^{(2)}_{S_1-S_2}$ and $R^{(3)}_{S_2-S_1}$ have little influence on R_{cn}.

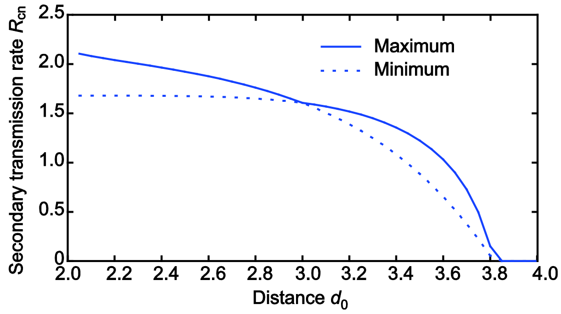

Fig. 6 Comparison of the maximum and minimum values of R_{cn}

5 Conclusions

We have investigated the throughput and transmission range optimization for a triple-hop network with cognitive relay, and then proposed a cooperative TDD communication system, in which SUs act as relays to assist PUs in achieving the target transmission rate. The designated objective is to expand the transmission range of the primary system by triple-hop relay, maximize the throughput of the secondary systems, and implement TDD communication between the SUs. To solve the problem, we also introduced the KKT conditions to optimize time and power allocation during the transmission process. Meanwhile, the SC technique was used to handle the two-receiver case. Simulation results were presented to prove the theoretical design concept. Under the given conditions, the transmission distance was increased by 11%, and the secondary throughput was improved by 14%.

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