Optimal Channel Selection and Power Control over D2D Communications Based Cognitive Radio Networks

Ya Gao(✉), Wenchi Cheng, Zhiyuan Ren, and Hailin Zhang

State Key Laboratory of Integrated Services Networks,
Xidian University, Xi'an 710071, China
gaoya@stu.xidian.edu.cn, {wccheng,zyren,hlzhang}@xidian.edu.cn

Abstract. We develop the joint optimal channel selection and power control scheme for video streaming with D2D communications in cognitive radio networks. In particular, we build the virtual queue model to evaluate the delays experienced by various streaming, which reflects the video distortion. To minimize the video distortion, we formulate an optimization problem, which is proved to be a quasi-convex optimization problem. Using the hypo-graph form, we convert the original problem into an equivalent convex optimization problem, solving which we can derive the joint channel selection and power control scheme in D2D communications based cognitive radio networks. The extensive simulation results obtained validate our developed joint channel selection and power control scheme. We also show that our developed scheme can significantly increase the average peak signal-to-noise ratio (PSNR) as compared with the existing research works.

Keywords: Cognitive radio networks · D2D communication · Channel selection · Power control · Video distortion · Convex optimization

1 Introduction

The evolving fifth generation (5G) wireless networks are envisioned to provide higher data rates, reduce end-to-end delay, improve the quality of experience (QoE) of mobile users, and mitigate the interference. This motivates the innovation of new communication paradigms. *Cognitive radio networks*, allowing secondary users (SUs) to spectrum share or time share the idle licensed spectrum with primary users (PUs), can efficiently increase the spectrum efficiency in frequency-domain and time-domain [1]. *D2D communications*, which enable data exchange directly between two mobile users (called *D2D pair*) in

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proximity bypassing base station (BS) or core network, can increase the spectrum efficiency in space-domain [2]. As a result, employing D2D communications in cognitive radio networks can significantly increase the spectrum efficiency in frequency/time/space-domain. Therefore, cognitive radio network coexisting with D2D communications, as a promising, but challenging, technical approach, has been paid much research attention.

The authors of [3] analyzed the engineering insights useful for system design in the D2D communications with cognitive radio assistance. The authors of [4] proposed a cognitive spectrum access in D2D-enabled cellular networks. Most of these works concentrate on how to improve the network performance by employing D2D communication in cognitive radio networks. However, for realtime video streams, the delay-sensitive traffic imposes new challenges for D2D communications based cognitive radio networks. To guarantee realtime transmission for delay-sensitive traffic, it is necessary to take the video distortion into account for D2D communications based cognitive radio networks.

To remedy the above deficiencies, in this paper we propose the joint optimal channel selection and power control scheme for video streaming over D2D communications based cognitive radio networks. Applying the "M/G/1 queues with vacations" theory, we build the virtual queue model to evaluate the delays experienced by various streaming. Then, we formulate the distortion minimization problem subject to the required capacity constraints and power constraints, which is proved to be a quasi-convex problem. Adopting the hypo-graph form, we convert the original problem into an equivalent convex problem. We develop the Lagrange-dual method to derive the joint optimal channel selection and power control scheme. The extensive simulation results obtained validate our proposed joint channel selection and power control scheme and show the better performance than the existing research works.

The rest of this paper is organized as follows. Section 2 shows the system model for the considered D2D communications based cognitive radio networks. Section 3 formulates the video distortion minimization, converts the original optimization problem into a strict convex optimization problem and solves the problem by developing primal-dual method. Section 4 simulates and evaluates our proposed channel selection and power allocation scheme. The paper concludes with Sect. 5.

2 The System Model

2.1 Network Model

We consider the D2D communications based cognitive radio network model as shown in Fig. 1, which consists of a number of important components described as follows. PUs, the traditional cognitive primary nodes, communicate with other terminals through the BS. SUs implement D2D communications with each other, forming D2D pairs. Both PUs and SUs share the same bandwidth B which is licenced to PUs. There are M channels in the cognitive radio networks. The PUs can only occupy their assigned channels. From the perspective of SUs, there is

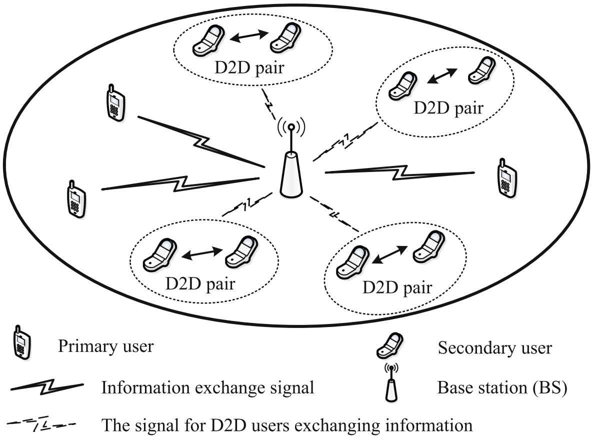

Fig. 1. The network model.

no need to differentiate different PUs on one channel. Therefore, we reduce the PUs on one channel into one aggregate PU. As a result, there are two sets of users on each channel: one aggregate PU and several SUs.

As transmitters, SUs take their actions of channel selection and power allocation for each packet. We denote the channel selection strategy of SU_i, $(1 \leq i \leq N)$ as $\boldsymbol{\alpha}_i = [\alpha_{i1}, \alpha_{i2}, \ldots, \alpha_{iM}]$, where $\alpha_{ij} \in [0,1]$ represents the probability of SU_i to choose channel j for transmission. Hence, we have $\sum_{j=1}^{M} \alpha_{ij} = 1$.

Let $\boldsymbol{P}_i = [P_{i1}, P_{i2}, \ldots, P_{iM}]$ denote by the power allocation of SU_i on each channel j $(1 \leq j \leq M)$. Due to D2D nodes' power-consumption constraints [2], each secondary user needs to satisfy an individual power constraint $\sum_{j=1}^{M} P_{ij} \leq P_i^{\max}$, where $P_i^{\max}$ is the maximum power constraint for SU_i.

2.2 Channel Model

Let x_i denote by the stream bit rate of SU_i, and $\mathcal{C}_{ij}$ denote by the "capacity". According to the channel selection strategy, the stream bit rate of SU_i over channel j is $\alpha_{ij} x_i$. Clearly, for each channel j, the stream bit rate of SU_i cannot exceed the channel capacity

$$\alpha_{ij} x_i \leq \mathcal{C}_{ij}. \tag{1}$$

The interference-limited network model is adopted. Hence, the channel capacity of channel j selected by SU_i can be written as the global and nonlinear functions of the transmit power $\boldsymbol{P}$ and channel conditions, which is given as follows:

$$\mathcal{C}(\boldsymbol{P}) = B \log_2 \left[1 + K \cdot \mathrm{SINR}(\boldsymbol{P})\right]. \tag{2}$$

Here, the parameter $K = (-1.5/\ln \mathrm{BER})$, where BER represents the required bit-error rate. The signal-to-interference-plus-noise ratio (SINR) from SU_i to the receiving node using channel j can be expressed as follows:

$$\mathrm{SINR}_{ij} = \frac{G_{jj} P_{ij}}{\sum\limits_{k \neq j} \sum\limits_{h \neq i} G_{kj} P_{hk} + n_j}, \tag{3}$$

where G_{kj} is the path gain from the transmitter on channel k to the receiver on channel j and n_j represents the additive Gaussian noise power (for the receiver of channel j). With proper spreading gain, G_{jj} is much larger than G_{jk}, $k \neq j$. Hence, $K \cdot \mathrm{SINR}$ is much larger than 1. In this high SINR regime, the attainable rate of SU_i on channel j can be closely approximate to $\mathcal{C} \simeq B \log_2(K \cdot \mathrm{SINR})$ [5].

2.3 Virtual Queue Model

The packet arrival process is modeled as a Poisson process with average packet arrival rate λ_j^{PU} and λ_{ij} respectively for the PU and SU_i on channel j. Note that the aggregation of Poisson processes in the same channel is still Poisson. The packets of the competing users are physically waiting in their buffer locally. For each channel j, Fig. 2 depicts N physical queues Q_{ij} for SU_i with the arrival rate λ_{ij}, a physical queue for PU_j with the arrival rate λ_j^{PU}, and a virtual queue $\tilde{Q}_j$ of channel j with the arrival rate of $\sum_{k=1}^{N} \lambda_{kj} + \lambda_j^{\mathrm{PU}}$. Since $\alpha_{ij} x_i$ represents the stream bit rate of SU_i over channel j, the arrival rate of SU_i can be determined by $\lambda_{ij} = {}^{\alpha_{ij} x_i}/_{L_i}$, where L_i is the average packet length of SU_i. The ARQ protocol is considered to decrease packet errors. The service time of the physical queue users can be modeled as a geometric distribution. We adopt the M/G/1 model for the traffic description of physical queues. Based on the well-known P-K formula [6], the first and second moments of the service time of SU_i using channel j can be derived as follows:

$$\begin{cases} \mathbb{E}[X_{ij}] = \frac{L_i}{\mathcal{C}_{ij}(1 - P_{ij}^{\mathrm{err}})}; \\ \mathbb{E}[X_{ij}^2] = \frac{L_i^2 (1 + P_{ij}^{\mathrm{err}})}{\mathcal{C}_{ij}^2 (1 - P_{ij}^{\mathrm{err}})^2}, \end{cases} \tag{4}$$

where P_{ij}^{err} is the packet error rate of SU_i over channel j.

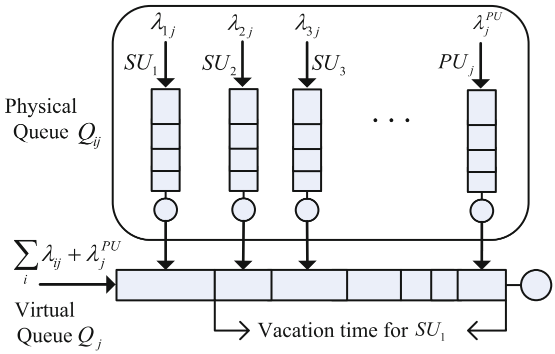

Fig. 2. The queuing process and the virtual queue.

For channel j, one SU can be allowed to transmit data on it at the same time. All the packets from different SUs on channel j form the virtual queue $\tilde{Q}_j$, as shown in Fig. 2. Given that the service time of SUs $\mathbb{E}[X_{ij}]$ are identically distributed (i.i.d), the virtual queue $\tilde{Q}_j$ is modeled as "M/G/1 queues with Vacations [7]". From the perspective of SU_i, at the end of its service time, the transmitter goes on a "vacation". In this "vacation" time, another user can send its traffic. In physical queues, we assume that a packet will join into the virtual queue once it arrives. Hence, the total delay is the service time in physical queue. Note that the total delay in physical queue becomes the service time in virtual queue. The service time in virtual queue is thus the service time in physical queue. Consequently, the end-to-end delay in virtual queue is the service time in physical queue plus the waiting time in virtual queue. The expectation of the vacation time $\mathbb{E}[V_{ij}]$, waiting time $\mathbb{E}[W_{ij}]$, and end-to-end delay $\mathbb{E}[D_{ij}]$ of SU_i using channel j can be derived as follows:

$$\begin{cases} \mathbb{E}[V_{ij}] & = \sum_{k=1,k\neq i}^{N} \frac{\mathbb{E}[X_{kj}^2]}{2\mathbb{E}[X_{kj}]} + \frac{\mathbb{E}[X_j^{PU\,2}]}{2\mathbb{E}[X_j^{PU}]}; \\ \mathbb{E}[W_{ij}] & = \frac{\lambda_{ij}\mathbb{E}[X_{ij}^2]}{2(1-\lambda_{ij}\mathbb{E}[X_{ij}])} + \mathbb{E}[V_{ij}]; \\ \mathbb{E}[D_{ij}] & = \mathbb{E}[X_{ij}] + \mathbb{E}[W_{ij}]. \end{cases} \tag{5}$$

Let P_{ij}^{loss} represent the probability of packet loss for SU_i sending packets through channel j. For video streaming, P_{ij}^{loss} can be determined by the probability that the video session violated its play-out deadline d_0, i.e., $P_{ij}^{\text{loss}} = \Pr(\mathbb{E}[D_{ij}] > d_0)$. Based on the work of [8], we have:

$$\Pr(\mathbb{E}[D_{ij}] > d_0) = \rho_{ij} \exp\left(-\frac{\rho_{ij} d_0}{\mathbb{E}[D_{ij}]}\right), \quad \rho_{ij} < 1, \tag{6}$$

where ρ_{ij} represents the normalized loading of SU_i using channel j, which is confirmed as $\rho_{ij} = \lambda_{ij}\mathbb{E}[X_{ij}]$. Since the normalized loading $\rho_{ij} < 1$ leads to a bounded delay $\mathbb{E}[D_{ij}]$ [6], which is expected for the video streaming, we can obtain:

$$\alpha_{ij} x_i < \mathcal{C}_{ij}(1 - P_{ij}^{\text{err}}), \tag{7}$$

where $\mathcal{C}_{ij}(1 - P_{ij}^{\text{err}})$ can be regarded as the achievable capacity under $\rho_{ij} < 1$. By contrast, Eq. (1) is a more relaxed constraint. Hence, we use Eq. (7) as the rate constraint.

2.4 Video Distortion Model

As a measurement of wireless video quality, an additive model to capture video distortion is used [9]. The overall Mean-Squared-Error (MSE) distortion consists of two types of distortions: the distortion caused by signal compression D_{com} and the distortion caused by transmission errors D_{err}. We can calculate the overall MSE as follows:

$$D_{\text{all}} = D_{\text{com}} + D_{\text{err}}. \tag{8}$$

The distortion D_{com} is determined by the compressed method, which can be approximated by:

$$D_{\text{com}} = \frac{\theta}{R - R_0} + D_0, \tag{9}$$

where R is the video stream bit rate, which is equivalent to $\alpha_{ij} x_i$. The parameters θ, R_0 and D_0 depend on the encoded sequence as well as the encoded structure. Note that θ, R_0 and D_0 can be estimated by nonlinear regression. Hence, they are assumed constants in this paper. Likewise, D_{err} can be modeled by a linear function with respect to packet error rate P^{err} and probability of packet loss P^{loss} as follows:

$$D_{\text{err}} = \sigma[P^{\text{err}} + (1 - P^{\text{err}})P^{\text{loss}}], \tag{10}$$

where σ is a constant.

3 Video Distortion Minimization

To minimize the total distortion of SUs, in this section we first formulate the video distortion minimization problem. Then, we develop the primal-dual method to solve the video distortion minimization problem.

3.1 Problem Formulation

Let $\boldsymbol{\alpha} = [\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, \ldots, \boldsymbol{\alpha}_N]^T$ and $\boldsymbol{P} = [\boldsymbol{P}_1, \boldsymbol{P}_2, \ldots, \boldsymbol{P}_N]^T$ denote by the total channel selection and power control strategies across all the SUs. The video distortion minimization problem can be formulated as follows:

$$\boldsymbol{P1}: \min_{(\boldsymbol{\alpha}, \boldsymbol{P})} \sum_{i=1}^{N} \sum_{j=1}^{M} \boldsymbol{\alpha}^T D_{\text{all}} \tag{11}$$

subject to:

$$\begin{cases} \alpha_{ij} x_i < \mathcal{C}_{ij}(1 - P_{ij}^{\text{err}}), \forall i, j; & (12) \\ \sum_{j=1}^{M} \alpha_{ij} = 1, \alpha_{ij} \in [0, 1], \forall i; & (13) \\ \sum_{j=1}^{M} P_{ij} \leq P_i^{\max}, P_{ij} \geq 0, \forall i; & (14) \\ \mathcal{C}(\boldsymbol{P}) = B \log_2 \left[1 + K \cdot \text{SINR}(\boldsymbol{P})\right], \forall i, j. & (15) \end{cases}$$

The objective function in Eq. (11) is set to minimize the total weighted video distortion for all SUs. The weight is channel selection probability $\boldsymbol{\alpha}$. The decision variables are $\boldsymbol{\alpha}$ and $\boldsymbol{P}$. The constraint Eq. (12) makes sure that the stream bit rate for SU_i using channel j cannot exceed the achievable capacity of channel j.

The constraints Eqs. (13) and (14) ensure the feasibility of channel selection and power control. The constraint Eq. (15) indicates the calculation of the capacity of channel j.

It is clear the constraints Eqs. (12)–(14) are convex functions. Because the $K \cdot \text{SINR}$ is much larger than 1, the constraint Eq. (15) can be approximated to $\mathcal{C}(\boldsymbol{P}) = B\log_2[K \cdot \text{SINR}(\boldsymbol{P})]$, which can be further converted into a nonlinear concave function through a log transformation, leading to a critical convexity property [5]. Next, we prove the convexity of the objective function Eq. (11). We first rewrite the objective function Eq. (11) as follows:

$$\min_{(\boldsymbol{\alpha},\boldsymbol{P})} \sum_{i=1}^{N}\sum_{j=1}^{M} \alpha_{ij}(D_0 + \sigma P_{ij}^{\text{err}}) + \frac{\theta\alpha_{ij}}{\alpha_{ij}x_i - R_0} + \sigma(1 - P_{ij}^{\text{err}})\alpha_{ij}\rho_{ij}\exp\left(-\frac{\rho_{ij}d_0}{\mathbb{E}[D_{ij}]}\right).$$

Theorem 1. *The objective function of this Video Distortion Minimization problem is a quasi-convex problem.*

Proof. It is easy to prove that the first term $\alpha_{ij}(D_0 + \sigma P_{ij}^{\text{err}})$, the second term $\frac{\theta\alpha_{ij}}{\alpha_{ij}x_i - R_0}$ and the multiplication $\alpha_{ij}\rho_{ij} = \frac{\alpha_{ij}^2 x_i}{\mathcal{C}_{ij}(1-P_{ij}^{\text{err}})}$ of the third term in the objective function are all convex. We denote $f = \rho_{ij}d_0 = \frac{\alpha_{ij}x_i d_0}{\mathcal{C}_{ij}(1-P_{ij}^{\text{err}})}$, checking its Hessian matrix, we can obtain:

$$\frac{\partial^2 f}{\partial \alpha_{ij}^2} \cdot \frac{\partial^2 f}{\partial P_{ij}^2} - \left[\frac{\partial^2 f}{\partial \alpha_{ij} P_{ij}}\right]^2 = -\left[\frac{x_i d_0 B}{\mathcal{C}_{ij}^2 P_{ij}(1 - P_{ij}^{\text{err}})\ln 2}\right]^2 \leq 0. \tag{16}$$

Therefore, the numerator of the exponent is concave. For the denominator of the exponent $E[D_{ij}]$, the first derivative with respect to $\mathcal{C}_{ij}$ and the Hessian matrix are shown as follows:

$$\frac{\partial \mathbb{E}[D_{ij}]}{\partial \mathcal{C}_{ij}} = \frac{-L_i\left[\alpha_{ij}^2 x_i^2 + 2\mathcal{C}_{ij}(1 - P_{ij}^{\text{err}})(\mathcal{C}_{ij} - \alpha_{ij}x_i)\right]}{2\mathcal{C}_{ij}^2[\mathcal{C}_{ij}(1 - P_{ij}^{\text{err}}) - \alpha_{ij}x_i]^2} \leq 0, \tag{17}$$

$$\frac{\partial^2 \mathbb{E}[D_{ij}]}{\partial \alpha_{ij}^2} \cdot \frac{\partial^2 \mathbb{E}[D_{ij}]}{\partial \mathcal{C}_{ij}^2} - \left[\frac{\partial^2 \mathbb{E}[D_{ij}]}{\partial \alpha_{ij}\partial \mathcal{C}_{ij}}\right]^2 = \frac{L_i^2 x_i^2(1 + P_{ij}^{\text{err}})}{\mathcal{C}_{ij}^3} \geq 0. \tag{18}$$

The Hessian matrix of $\mathbb{E}[D_{ij}]$ is semipositive. Hence $\mathbb{E}[D_{ij}]$ is convex with respect to α_{ij} and $\mathcal{C}_{ij}$. Note that $\mathbb{E}[D_{ij}]$ is nonincreasing of $\mathcal{C}_{ij}$. Meanwhile, $\mathcal{C}_{ij}$ is concave. As a result, $\mathbb{E}[D_{ij}]$ is convex with respect to α_{ij} and P_{ij}. Since the numerator $\rho_{ij}d_0$ is concave, and the denominator $\mathbb{E}[D_{ij}]$ is convex, the function $\exp(-\frac{\rho_{ij}d_0}{\mathbb{E}[D_{ij}]})$ is quasi-convex. Consequently, the objective function is quasi-convex. ■

In the objective function, the first term, second term and the multiplication of the third term are all convex. To make the primal objective function strictly convex, we just need to make the exponent part convex. For this reason, auxiliary variable t is introduced. We apply the hypo-graph form to replace the quasi-convex function as follows:

$$t\mathbb{E}[D_{ij}] - \rho_{ij} \leq 0,\ t \geq 0. \tag{19}$$

The Eq. (19) is strictly convex. Consequently, the optimization problem $\boldsymbol{P1}$ can be equivalently converted to the optimization problem $\boldsymbol{P2}$ as follows:

$$\boldsymbol{P2}: \min_{(\boldsymbol{\alpha},\boldsymbol{P},t)} \sum_{i=1}^{N}\sum_{j=1}^{M} \alpha_{ij}(D_0 + \sigma P_{ij}^{\text{err}}) + \frac{\theta\alpha_{ij}}{\alpha_{ij}x_i - R_0} + \sigma(1 - P_{ij}^{\text{err}})\alpha_{ij}\rho_{ij}\exp(-d_0 t)$$

subject to the constraints Eqs. (12)–(15) and (19).

It is clear that $\boldsymbol{P2}$ is a strict convex optimization problem because the objective function and the constraints are all convex.

3.2 Lagrange-Dual Method

We utilize the Lagrange-dual method to develop a solution algorithm for the video distortion minimization problem. We first define the Lagrangian function for the video distortion minimization problem $\boldsymbol{P2}$ in Eq. (20), where κ_1, κ_2, and κ_3 are the Lagrange multipliers associated with the problem's constraints.

$$\begin{aligned} L = \sum_{i=1}^{N}\sum_{j=1}^{M}\Big[\alpha_{ij}(D_0 + \sigma P_{ij}^{\text{err}}) + \tfrac{\theta\alpha_{ij}}{\alpha_{ij}x_i - R_0} + \sigma(1 - P_{ij}^{\text{err}})\alpha_{ij}\rho_{ij}\exp(-d_0 t)\Big] \\ + \sum_{j=1}^{M}\kappa_1\left(\alpha_{ij}x_i - \mathcal{C}_{ij}(1 - P_{ij}^{\text{err}})\right) + \sum_{i=1}^{N}\kappa_2\left(\sum_{j=1}^{M}P_{ij} - P_i^{\max}\right) \\ + \sum_{i=1}^{N}\sum_{j=1}^{M}\kappa_3\left(t\mathbb{E}[D_{ij}] - \rho_{ij}\right). \end{aligned} \tag{20}$$

Since the optimization problem $\boldsymbol{P2}$ is strictly convex, the duality gap is zero. We use gradient projection method to solve the Lagrange problem. In order to expand the Lagrange function, we replace ρ_{ij} and $\mathbb{E}[D_{ij}]$ in L with their expressions in Sect. 2. As the Lagrange function is differentiable, the gradients of L with respect to the Lagrange multipliers are obtained as

$$\begin{cases} \frac{\partial L}{\partial \kappa_1} = \alpha_{ij}x_i - \mathcal{C}_{ij}(1 - P_{ij}^{\text{err}}); \\ \frac{\partial L}{\partial \kappa_2} = \sum_{j=1}^{M} P_{ij} - P_i^{\max}; \\ \frac{\partial L}{\partial \kappa_3} = \sum_{i=1}^{N}\sum_{j=1}^{M}\left[t\left(\frac{L_i(2\mathcal{C}_{ij} - \alpha_{ij}x_i)}{2\mathcal{C}_{ij}[\mathcal{C}_{ij}(1-P_{ij}^{\text{err}}) - \alpha_{ij}x_i]} + \mathbb{E}[V_{ij}]\right) - \frac{\alpha_{ij}x_i}{\mathcal{C}_{ij}(1-P_{ij}^{\text{err}})}\right]. \end{cases} \tag{21}$$

By applying the gradient projection method, the Lagrange multipliers are calculated iteratively as follows:

$$\kappa_1(s+1) = \left[\kappa_1(s) + \nu\frac{\partial L}{\partial \kappa_1}\right]^+, \tag{22}$$

where $\nu > 0$ is the gradient step size, s represents the gradient numbers, and $[\cdot]^+$ denotes $\max(0,\cdot)$. The remaining Lagrange multipliers κ_2 and κ_3 are obtained iteratively using similar equations.

Taking the derivation of L with respect to α_{ij}, P_{ij} and t, setting the results to zero, respectively, we can obtain Eq. (23), where α_{ij} and P_{ij} can be numerically solved in the next section.

$$\begin{cases} \frac{\partial L}{\partial \alpha_{ij}} = \sum_{i=1}^{N}\sum_{j=1}^{M}\Big\{D_0 + \sigma P_{ij}^{\text{err}} - \frac{\theta R_0}{(\alpha_{ij}x_i - R_0)^2} + \frac{2\alpha_{ij}x_i\exp(-d_0 t)}{\mathcal{C}_{ij}(1-P_{ij}^{\text{err}})} + \kappa_1 x_i - \frac{\kappa_3 x_i}{\mathcal{C}_{ij}(1-P_{ij}^{\text{err}})} \\ \quad + \frac{\kappa_3 t x_i L_i (1+P_{ij}^{\text{err}})}{2[\mathcal{C}_{ij}(1-P_{ij}^{\text{err}}) - \alpha_{ij}x_i]^2}\Big\} = 0, \\ \frac{\partial L}{\partial P_{ij}} = \sum_{i=1}^{N}\sum_{j=1}^{M}\frac{B}{P_{ij}\ln 2}\Big\{-\frac{\sigma\alpha_{ij}^2 x_i}{\mathbb{C}_{ij}^2}\exp(-d_0 t) - \kappa_1(1-P_{ij}^{\text{err}}) + \frac{\kappa_3\alpha_{ij}x_i}{\mathbb{C}_{ij}^2(1-P_{ij}^{\text{err}})} \\ \quad + \kappa_3 t L_i \frac{2\mathbb{C}_{ij}(1-P_{ij}^{\text{err}})\alpha_{ij}x_i - 2\mathbb{C}_{ij}^2(1-P_{ij}^{\text{err}}) - \alpha_{ij}^2 x_i^2}{2\mathbb{C}_{ij}^2[\mathbb{C}_{ij}(1-P_{ij}^{\text{err}}) - \alpha_{ij}x_i]^2}\Big\} + \kappa_2 = 0, \\ t^* = -\frac{1}{d_0}\log\Big\{\frac{\kappa_3}{d_0\sigma x_i\alpha_{ij}^2}\Big[\frac{L_i(2\mathcal{C}_{ij} - \alpha_{ij}x_i)}{2[\mathcal{C}_{ij}(1-P_{ij}^{\text{err}}) - \alpha_{ij}x_i]} + \mathbb{E}[V_{ij}]\mathcal{C}_{ij}\Big]\Big\}. \end{cases} \tag{23}$$

4 Numerical Results

In this section, we evaluate the performance of our proposed joint optimal channel selection and power allocation scheme. We set the bandwidth $B = 10\,\text{MHz}$, the packet length $L_i = 1\,\text{Kbits}$, delay deadline $d_0 = 0.5\,\text{s}$, the transmit power constraint $P_i^{\max} = 0.1\,\text{W}$, the bit-error-rate $\text{BER} = 10^{-3}$, the noise power $n_j = -104\,\text{dB}$, and the parameters for distortion model $D_0 = 0.38$, $\theta = 2.53\,\text{kbps}$ and $R_0 = 18.3\,\text{kbps}$, respectively. The path gain G_{kj} is determined by the relative physical distance d_{kj} from the transmitter of channel k to the receiver of the channel j, i.e., $G_{kj} = d_{kj}^{-\beta}$, where β is the path loss. In our simulation, we set $d_{jj} = 10\,\text{m}$, $d_{jk} = 100\,\text{m}$ $(j \neq k)$ and $\beta = 4$.

First, we simulate the network with two SUs (a D2D pair) and three channels (i.e., $N = 2$ and $M = 3$), to show the results using simple network such that our model can be clearly understood. The initial channel selection and power control are set to be $\alpha_{ij} = 1/3$ and $P_{ij} = 30\,\text{mW}$ $(1 \leq i \leq 2$ and $1 \leq j \leq 3)$, respectively. The packet error rate for SUs across all the channels are $P_{11}^{\text{err}} = 0.11$, $P_{12}^{\text{err}} = 0.08$, $P_{13}^{\text{err}} = 0.15$, $P_{21}^{\text{err}} = 0.05$, $P_{22}^{\text{err}} = 0.12$ and $P_{23}^{\text{err}} = 0.01$. We set the required stream bit rates of SU_i $x_1 = 840\,\text{kbps}$ and $x_2 = 960\,\text{kbps}$, respectively. The normalized loadings of PU_j are set to be $\rho_1 = 0.25$, $\rho_2 = 0.35$ and $\rho_3 = 0.15$ respectively, and the second moment normalized loadings are set to be $\rho_j^2 = 1 \times 10^{-4}$.

Figures 3 and 4 depict the optimal channel selection and power allocation scheme for SU_1 and SU_2 across all the channels. As shown in Figs. 3 and 4, the probability for SU_1 choosing channel 2 is $\alpha_{12} = 0.83$, which is bigger than choosing the other channels. The probability for SU_2 choosing channel 2 is $\alpha_{22} = 0.07$, which is smaller than choosing the other channels. Meanwhile, the power allocation of SU_1 for channel 2 is $P_{12} = 53.63\,\text{mW}$, which is bigger than the other channels. The power allocation of SU_2 for channel 2 is $P_{22} = 4.98\,\text{mW}$,

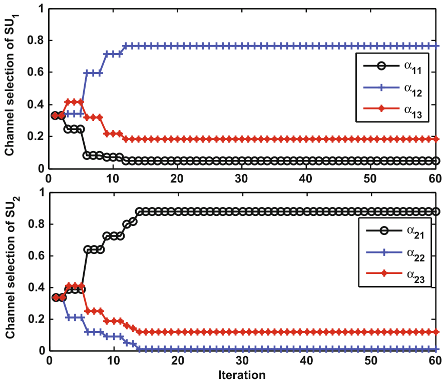

Fig. 3. Optimal channel selection.

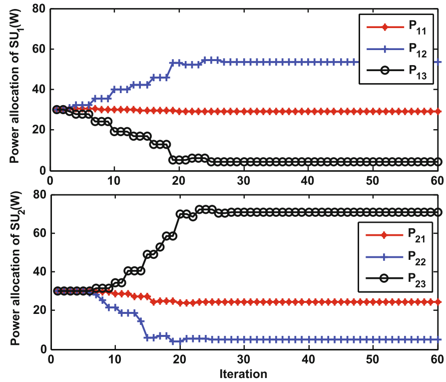

Fig. 4. Optimal power allocation.

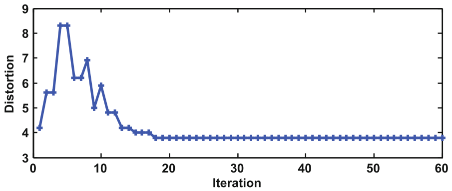

Fig. 5. Video distortion versus iterations.

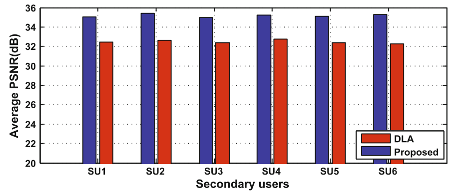

Fig. 6. Comparison with DLA.

which is smaller than the other channels. This is due to the reason that channel capacity is limited, thus channels with smaller packet error rate and lighter traffic loadings are assigned more data traffic and transmit power. Figure 5 plots the overall video distortion of all the applications. The overall video distortion (MSE) converges to 3.80, which is equivalent to the peak signal-to-noise ratio of 42.33 dB. As compared with DLA algorithm in [10] whose utility function cannot converge to a steady state, our algorithm can achieve a better performance.

Next, we consider the network with six SUs and ten channels. We set the bandwidth $B = 1$ MHz and simulate 100 times with different channel states (i.e. packet error rate) as well as the normalized loadings and calculate the average PSNR for the traffics from six SUs. We compare our proposed scheme with DLA algorithm. The comparison results depicted in Fig. 6 show that our joint scheme can achieve a better performance than the DLA algorithm.

5 Conclusion

In this paper, we studied the video distortion minimization problem in D2D communications based cognitive radio network by jointly optimize the channel selection and power control scheme.We first evaluated the delays experienced by various streaming. Then, we formulated the video distortion minimization problem. Using the hypo-graph form, we equivalently converted the original quasi-convex problem into a strict convex optimization problem, solving which, we derived the joint channel selection and power control scheme. The extensive simulation results obtained showed the better performance than the existing research works.

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