Statistical QoS Driven Power and Rate Allocation over Rayleigh Fading Cognitive Radio Links

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Abstract. In this paper, we propose a statistical Quality-of-Service (QoS) driven power and rate allocation scheme over wireless Rayleigh fading cognitive radio links. Specifically, we consider the scenario that one secondary link coexists with one primary link by sharing particular portions of the spectrum. Our proposed power and rate allocation scheme aims at maximizing the system effective capacity, which can be seen as the maximum arrival rate supported by the secondary link subject to a given statistical delay QoS constraint. In this work, we not only take into account the average transmit and interference power constraints for the secondary link, but also consider the influence from the transmission of the primary link to the effective capacity of the secondary link. Simulation results show that, (1) the effective capacity of the secondary link decreases when the statistical delay QoS constraint becomes stringent; (2) given the QoS constraint, the effective capacity of the secondary link varies with the interference power constraint and the SNR of the primary link.

Keywords: Cognitive radio, power allocation, statistical QoS guarantees, effective capacity.

1 Introduction

Cognitive radio is a promising yet challenging technology to solve wireless-spectrum underutilization problem caused by the traditional static spectrum allocation strategy [1] [2]. Spectrum sharing (underlay) and spectrum access (overlay) are two available methods for the secondary users (SUs) to dynamically utilize the spectrum which belongs to the primary users (PUs). Because the former method allows the SU to use the spectrum occupied by the PUs subject to a interference constraint, which can increase the spectrum utilization more obviously than the latter one, it has attracted a great deal of research attention.

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In the spectrum sharing networks, power and rate allocation is a critical problem to improve the capacity of the secondary link and some researches have been investigated. In this context, [3] and [4] are two fundamental researches. In [3], the optimal power allocation, which aims at maximizing the ergodic capacity of the secondary link over the additive white Gaussian noise (AWGN) channel under a received power constraint, is obtained. [4] considered different fading channel model, derived the corresponding optimal power allocation strategies, and evaluated the corresponding ergodic capacity of the secondary link. Based on the two fundamental researches, some investigations arise in recent years [5]-[10]. In [5] and [6], the authors analyzed the ergodic, outage, and delay-constrained capacities, respectively, and obtained the corresponding power allocation schemes under the block Rayleigh fading channel. In [7], the author considered the ergodic sum capacity of fading cognitive multiple-access and broadcast channels, respectively, and derived the corresponding TDMA structures as well as the power allocation scheme.

In the above researches, Quality of Service (QoS) guarantee related to the queue delay, which is important for the secondary link, is not integrated into the power and rate allocation. Effective capacity, which can be seen as the maximum arrival rate supported by the system, is an efficient tool to guarantee the statistical delay QoS of the system [11] [12]. The authors in [13] and [14] analyzed the effective capacity of the secondary link subject to different transmit and interference power constraints over the fading channel and obtained the corresponding optimal power allocations.

However, in these existing works, the influence of the transmissions implemented by the primary link, which is an important factor for the secondary link, does not take into consideration. In order to overcome the above problem and guarantee the statistical delay QoS for the SU, in this paper we consider the scenario that one secondary link coexists with one primary link by sharing particular portions of the spectrum and propose a statistical Quality-of-Service (QoS) driven power and rate allocation scheme, which aims at maximizing the effective capacity of the secondary link subject to a given statistical delay QoS constraint over the Rayleigh fading channel. We not only take into account the average transmit and interference power constraints for the secondary link, but also consider the influence from the transmissions of the primary link to the effective capacity of the secondary link. Moreover, we also derive the close-form of the optimal power and rate allocation strategy, which can maximize the effective capacity of the secondary link subject to our constraints.

The rest of this paper is organized as follows. Section 2 presents the system model. Section 3 introduces the concept of effective capacity. Section 4 develops the optimal power and rate allocation scheme based on the effective capacity introduced in Section 3. Simulation results are given in Section 5. The paper concludes with Section 6.

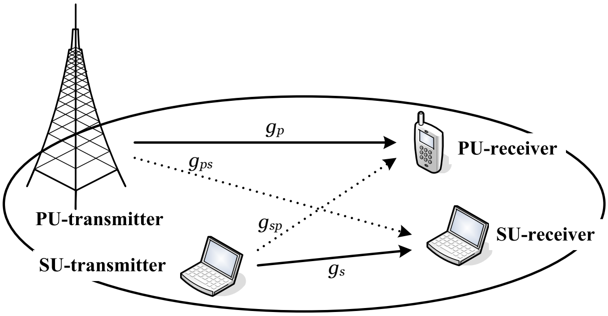

Fig. 1. The scenario that the secondary link coexists with the primary link

2 System Model

We consider the scenario that one secondary link coexists with one primary link by sharing a particular portions of the spectrum, as shown in Fig. 1. Each link consists of one transmitter and one receiver, respectively. The total spectrum bandwidth is denoted by B. The additive noise at the PU and SU receivers are modeled as zero-mean Gaussian random variables with the same variance N_0B, where N_0 denote the noise power spectral density.

We assume that the upper-protocol-layer packets are divided into frames, which have the same time duration denoted by T_f, at the datalink layer, as shown in Fig. 2. The discrete-time channel gains between the PU transmitter and PU receiver, the SU transmitter and SU receiver, the PU transmitter and SU receiver, as well as the SU transmitter and PU receiver are denoted by $g_p[i]$, $g_s[i]$, $g_{ps}[i]$, and $g_{sp}[i]$, respectively, and we define the system channel gain vector denoted by $\mathbf{G}[i] \stackrel{\Delta}{=} [g_s[i], g_p[i], g_{ps}[i], g_{sp}[i]]$, where i is the time index of the frame. We assume that the four channel gains are stationary, ergodic, independent, and block fading processes, which represent that the gains are invariant within a frame, but vary from one frame to another. Moreover, we assume that the channels gains described above all obey the same exponential distribution with mean a, so that their probability density functions (pdf) can be written as:

$$f_x\left(g_x\right) = ae^{-ag_x},\ g_x \geq 0;\ x \in \left\{s, p, ps, sp\right\}. \tag{1}$$

Throughout this paper, we assume that the maximal average transmit power of the SU transmitter is $P_{\rm av}$, the maximal average interference power that the PU receiver can tolerate is $Q_{\rm av}$, and the PU transmitter transmits data packets to the PU receiver with the constant transmit power $P_{\rm p}$. Besides, we assume that the channel state information (CSI) $\mathbf{G}$ can be perfectly estimated by the PU and SU receivers and reliably fed back to the SU transmitter without delay. We also assume that the datalink-layer buffer size of the SU transmitter is infinite.

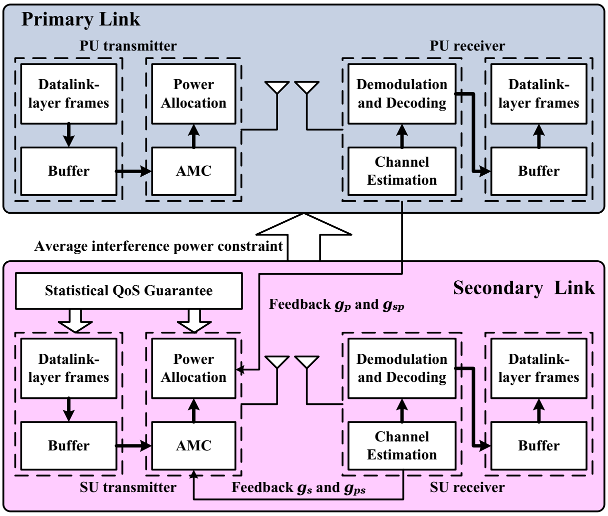

Fig. 2. The system model with statistical QoS guarantee

3 Effective Capacity

Delay QoS guarantee plays a critically important role in the wireless communication systems. However, the deterministic delay QoS guarantee will most likely result in extremely conservative guarantee. For example, in a Rayleigh or Ricean fading channel, the lower bound of the capacity that can be deterministically guaranteed is zero, which implies that the delay QoS guarantee is infinite. This conservative guarantee is clearly useless. Therefore, we need to use the statistical version to satisfy the delay constraint of the system.

The effective capacity, which is first proposed in [11], is an efficient tool to statistically guarantee the delay QoS of the system. The effective capacity is a dual concept of effective bandwidth [15]. In the effective bandwidth theory, the distribution of queue length process $Q(t)$ converges to a random variable $Q(\infty)$, which can be written as

$$-\lim_{x\to\infty}\frac{\log\left(\Pr\left\{Q\left(\infty\right)>y\right\}\right)}{y}=\theta, \tag{2}$$

where y is the queue length threshold and θ is a critically important role for statistical delay QoS guarantee called QoS exponent. The smaller θ is, the looser the QoS guarantee is, and the larger θ is, the more stringent the QoS guarantee is. inspired by the effective bandwidth, the effective capacity can be defined as the maximum constant arrival rate that a given service service process can support in order to guarantee a QoS requirement specified by θ.

Assume that the sequence $\{R\left[i\right], \; i=1,2,\cdots\}$ is a discrete-time stationary and ergodic stochastic service process and the partial sum of the service process is $S\left[t\right] \triangleq \sum_{i=1}^{t} R[i]$. Assume that the Gartner-Ellis limit of $S[t]$, which can be expressed as

$$\Lambda_{\mathrm{C}}\left(\theta\right) = \lim_{t\to\infty} \frac{1}{t} \log\left(\mathbb{E}\left\{e^{\theta S[t]}\right\}\right), \tag{3}$$

exists and is a convex function which is differentiable for all real θ. Therefore, the effective capacity of the system, denoted by $\mathrm{E_C}(\theta)$, is

$$\mathrm{E_C}\left(\theta\right) \triangleq -\frac{\Lambda_{\mathrm{C}}\left(-\theta\right)}{\theta} = -\lim_{t\to\infty} \frac{1}{\theta t} \log\left(\mathbb{E}\left\{e^{-\theta S[t]}\right\}\right), \tag{4}$$

where $\theta > 0$. If the sequence $\{R\left[i\right], \; i=1,2,\cdots\}$ is an uncorrelated process, the effective capacity can be reduced to

$$\mathrm{E_C}\left(\theta\right) = -\frac{1}{\theta} \log\left(\mathbb{E}\left\{e^{-\theta R[i]}\right\}\right). \tag{5}$$

In this paper, we aim at maximizing the effective capacity of the secondary link when the SU transmitter is subject to the given power constraints.

4 Optimal Power and Rate Allocation with Statistical QoS Guarantees

In this section, we will derive the optimal power and rate allocation, which can maximize the effective capacity subject to the average transmit and interference power constraints.

Since the channel power gains, which are g_s, g_p, g_{sp}, and g_{ps}, respectively, have been assumed to be block fading in section 2, the instantaneous service rate $R[i]$ of the secondary link during the frame i is

$$\begin{aligned} R[i] &= T_f B \log_2\left(1 + \frac{g_s[i]\mu\left(\theta, \mathbf{G}[i]\right) P_{\mathrm{av}}}{g_{ps}[i]P_{\mathrm{p}} + N_0 B}\right) \\ &= T_f B \log_2\left(1 + \frac{g_s[i]\mu\left(\theta, \mathbf{G}[i]\right) \overline{\gamma}_s}{g_{ps}[i]\overline{\gamma}_p + 1}\right), \end{aligned} \tag{6}$$

where $\overline{\gamma}_s$ and $\overline{\gamma}_p$ are the average Signal-to-Noise Ratio (SNR) at the SU and PU transmitters, respectively, and $\mu\left(\theta, \mathbf{G}[i]\right)$ is the power allocation policy of the secondary link, which are the functions of both QoS exponent θ and system channel gain vector $\mathbf{G}[i]$. In the following discussions, we omit the discrete time-index i for simplicity.

As the SU transmitter must be subject to a upperbounded average transmit power P_{av}, the power allocation policy $\mu\left(\theta, \mathbf{G}[i]\right)$ need to satisfy

$$\mathbb{E}_{\mathbf{G}}\left\{\mu\left(\theta, \mathbf{G}\right)\right\} \le 1. \tag{7}$$

In order to protect the data transmissions of the primary link, the transmit power of the SU transmitter must satisfy the average interference power constraint imposed by the PU receiver, which can be written as

$$\mathbb{E}_{\mathbf{G}}\left\{g_{sp}\mu\left(\theta,\mathbf{G}\right)\right\} \le \rho, \tag{8}$$

where ρ is the ratio of the average transmit power and average interference power and can be expressed as $\rho = P_{\text{av}}/Q_{\text{av}}$.

Our objective is to maximize the effective capacity of the secondary link subject to the constraints shown in (7) and (8). The mathematical description of our optimization problem can be written as

$$\begin{aligned}&\max_{\mu(\theta,\mathbf{G})}\left\{-\tfrac{1}{\theta}\log\left(\mathbb{E}\left\{\mathrm{e}^{-\theta T_f B\log_2\left(1+\frac{g_s\mu(\theta,\mathbf{G})\overline{\gamma}_s}{g_{ps}\overline{\gamma}_p+1}\right)}\right\}\right)\right\},\\ &\text{s.t.}\ \begin{cases}E_{\mathbf{G}}\left\{\mu\left(\theta,\mathbf{G}\right)\right\} \le 1,\\ E_{\mathbf{G}}\left\{g_{sp}\mu\left(\theta,\mathbf{G}\right)\right\} \le \rho.\end{cases}\end{aligned} \tag{9}$$

Because the function $\log(x)$ is a monotonically increasing function of x, the solution to the maximization problem shown in (9) is the same with the one for the minimization problem, which can be expressed as

$$\begin{aligned}&\min_{\mu(\theta,\mathbf{G})} E\left\{\left[1+\tfrac{g_s\mu(\theta,\mathbf{G})\overline{\gamma}_s}{g_{ps}\overline{\gamma}_p+1}\right]^{-\beta}\right\},\\ &\text{s.t.}\ \begin{cases}E_{\mathbf{G}}\left\{\mu\left(\theta,\mathbf{G}\right)\right\} \le 1,\\ E_{\mathbf{G}}\left\{g_{sp}\mu\left(\theta,\mathbf{G}\right)\right\} \le \rho,\end{cases}\end{aligned} \tag{10}$$

where β is the normalized QoS exponent and can be written as

$$\beta = \frac{\theta T_f B}{\log(2)}. \tag{11}$$

It is clear that the objective function in (10) is strictly convex and the constraints in (7) and (8) are both linear with respect to $\mu\left(\theta,\mathbf{G}\right)$. Therefore, the minimization problem has a unique optimal solution. We try to derive the optimal solution by using the Lagrangian optimization method [17]. The Lagrangian function, denote by $\mathcal{L}\left(\mu\left(\theta,\mathbf{G}\right),\lambda,\xi\right)$, can be expressed as

$$\begin{aligned}\mathcal{L}\left(\mu\left(\theta,\mathbf{G}\right),\lambda,\xi\right) = E&\left\{\left[1+\tfrac{g_s\mu(\theta,\mathbf{G})\overline{\gamma}_s}{g_{ps}\overline{\gamma}_p+1}\right]^{-\beta}\right\}\\ &+\lambda\left[E_{\mathbf{G}}\left\{\mu\left(\theta,\mathbf{G}\right)\right\}-1\right]\\ &+\xi\left[E_{\mathbf{G}}\left\{g_{sp}\mu\left(\theta,\mathbf{G}\right)\right\}\le\rho\right],\end{aligned} \tag{12}$$

where λ and ξ are the nonnegative Lagrangian multipliers. Differentiating the Lagrangian function given by (12) and setting the derivative equal to zero, we have

$$\begin{aligned}\tfrac{\partial L(\mu(\theta,\mathbf{G}),\lambda,\xi)}{\partial\mu(\theta,\mathbf{G})} &= \lambda+\xi g_{sp}\\ &-\beta\tfrac{g_s\bar{\gamma}_s}{g_{ps}\bar{\gamma}_p+1}\left[1+\tfrac{g_s\mu(\theta,\mathbf{G})\bar{\gamma}_s}{g_{ps}\bar{\gamma}_p+1}\right]^{-\beta-1}=0.\end{aligned} \tag{13}$$

Therefore, the optimal power and rate allocation policy, which can maximize the effective capacity of the secondary link, can be expressed as

$$\mu^{\text{opt}}(\theta, \mathbf{G}) = \begin{cases} \frac{\beta^{\frac{1}{1+\beta}}}{\Gamma^{\frac{\beta}{1+\beta}}(\lambda+\xi g_{sp})^{\frac{1}{1+\beta}}} - \frac{1}{\Gamma}, & \Gamma\beta \geq \lambda + \xi g_{sp} \\ 0, & \Gamma\beta < \lambda + \xi g_{sp} \end{cases} \tag{14}$$

where Γ is

$$\Gamma = \frac{g_s \overline{\gamma}_s}{g_{ps}\overline{\gamma}_p + 1}. \tag{15}$$

λ and ξ are determined such that the average transmit and interference power, which are shown in (7) and (8), respectively, are equal to 1 and ρ, respectively, i.e.,

$$\begin{aligned} &\int_{g_s}\int_{g_p}\int_{g_{sp}}\int_{g_{ps}} \mu^{\text{opt}}(\theta, \mathbf{G}) f_{ps}(g_{ps}) f_{sp}(g_{sp}) \\ &\qquad f_p(g_p) f_s(g_s)\, dg_{ps}\ dg_{sp}\ dg_p\ dg_s = 1 \end{aligned} \tag{16}$$

and

$$\begin{aligned} &\int_{g_s}\int_{g_p}\int_{g_{sp}}\int_{g_{ps}} g_{sp}\mu^{\text{opt}}(\theta, \mathbf{G}) f_{ps}(g_{ps}) f_{sp}(g_{sp}) \\ &\qquad f_p(g_p) f_s(g_s)\, dg_{ps} dg_{sp} dg_p dg_s = \rho. \end{aligned} \tag{17}$$

In [12], the author analysis the effective capacity of one wireless fading link, which contains one transmitter and one receiver, and obtained the optimal power and rate adaptive policy. In this fundamental work, the author found that the optimal policy converges to the water-filling and total channel inversion when $\theta \to 0$ and $\theta \to \infty$, respectively. Now we will check whether our derived optimal power and rate allocation policy $\mu(\theta, \mathbf{G})$ also has the same property. When $\theta \to 0$, $\mu(\theta, \mathbf{G})$ becomes

$$\lim_{\theta \to 0} \mu^{\text{opt}}(\theta, \mathbf{G}) = \begin{cases} \frac{1}{\lambda+\xi g_{sp}} - \frac{1}{\Gamma}, & \Gamma \geq \lambda + \xi g_{sp} \\ 0, & \Gamma < \lambda + \xi g_{sp} \end{cases} \tag{18}$$

which is just the water-filling formula [16]. When $\theta \to \infty$, we have

$$\lim_{\theta \to \infty} \mu^{\text{opt}}(\theta, \mathbf{G}) = 0, \tag{19}$$

which is the same conclusion as in [16] that the power allocation of the total channel inversion over Rayleigh fading channel is always zero. Therefore, we can conclude that the optimal power and rate allocation policy also has the same property as described in [12], i.e., when the QoS constraint becomes loose, the optimal power policy of the secondary link converges to the water-filling scheme and the effective capacity equals to the ergodic capacity, on the other hand, when the QoS constraint gets stringent, the optimal policy converges to the total channel inversion scheme and the transmission rate of the secondary is zero.

In our derived optimal power and rate allocation policy, not only the statistical delay QoS constraint is considered, but also the influence from the PU transmitter to the SU receiver is taken into consideration. When $g_{ps} \to 0$, the optimal policy $\mu(\theta, \mathbf{G})$ becomes

$$\lim_{g_{ps}\to 0} \mu^{\text{opt}}(\theta, \mathbf{G}) = \left[\frac{\beta^{\frac{1}{1+\beta}}}{(g_s\bar{\gamma}_s)^{\frac{\beta}{1+\beta}} (\lambda + \xi g_{sp})^{\frac{1}{1+\beta}}} - \frac{1}{g_s\bar{\gamma}_s} \right]^+ \tag{20}$$

which converges to the power allocation scheme obtained in [13]. Moreover, if we assume that $\theta \to 0$ and $g_{ps} \to 0$ simultaneously, our obtained optimal policy becomes

$$\lim_{\substack{\theta\to 0\\ g_{ps}\to 0}} \mu^{\text{opt}}(\theta, \mathbf{G}) = \begin{cases} \frac{1}{\lambda+\xi g_{sp}} - \frac{1}{g_s\overline{\gamma}_s}, & g_s\overline{\gamma}_s \geq \lambda + \xi g_{sp} \\ 0, & g_s\overline{\gamma}_s < \lambda + \xi g_{sp} \end{cases} \tag{21}$$

which is the same as the power allocation scheme derived in [4] and [6]. Therefore, we can conclude that, if the statistical delay QoS constraint become loose and the channel power gain between the PU transmitter and the SU receiver is small, our derived policy $\mu(\theta, \mathbf{G})$ will maximize the ergodic capacity of the secondary link subject to the average transmit and interference power constraints, and the power policy is only the functions of g_s and g_{sp}, but is unrelated with g_p and g_{ps}.

5 Simulation Results

Observe our optimization problem and the derived optimal power and rate allocation policy, which are shown in (9) and (14), respectively, the maximal average transmit power of the SU transmitter, the transmit power of the PU transmitter, and the maximal average interference power are the critically important parameters that will impact the effective capacity of the secondary link. Therefore, in this section, we will analyze how the effective capacity of the SU link varies with the three parameters mentioned above through simulation. As described in [12], the optimal power allocation policy $\mu^{\text{opt}}(\theta, \mathbf{G})$ depends on the frame duration T_f and the spectrum B through the normalized QoS exponent β. In our simulation, we set the frame duration $T_f = 2$ ms and the bandwidth $B = 10^5$ Hz. The other system parameters are detailed respectively in each of our simulation figures.

First, we evaluate the impact of the maximal average interference power to the normalized effective capacity of the second link, which is defined as the effective capacity divided by T_f and B. In this scenario, we set the average SNR at the SU transmitter $\overline{\gamma}_s = 0$ dB and the SNR at the PU transmitter $\overline{\gamma}_p = 0$, respectively. As describe in (8), the maximal average interference power Q_{av} can be reflected by the normalized average interference coefficient ρ, we vary ρ instead of changing Q_{av}. Fig. 3 presents the normalized effective capacity of the secondary link under different QoS exponents and normalized average interference coefficients. The

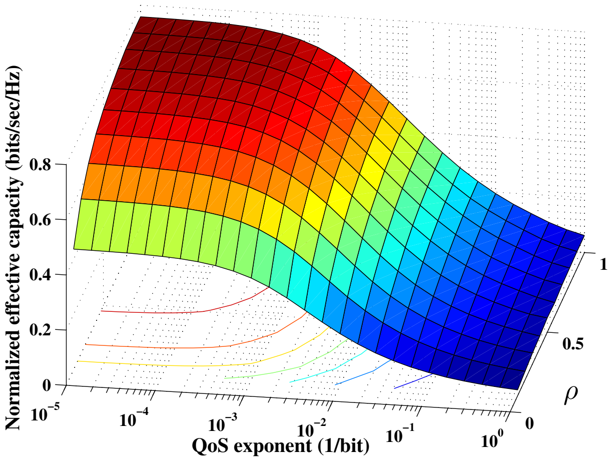

Fig. 3. The effective capacity of the secondary link when the transmit power of the PU transmitter varies

simulation result shows that, under any given normalized average interference coefficient ρ, the normalized effective capacity of the secondary link decreases while increasing the QoS exponent θ, which is the same as the results presented in [12]. Such observation can be explained as, when θ is small, the statistical delay constraint is loose, thus the traffic can be arrived with higher rate, but the statistical delay constraint will get stringent while increasing θ, which results that the secondary link can only support lower traffic arrival rate. The simulation result also shows that, under any given QoS exponent θ, the normalized effective capacity increases as the normalized average interference coefficient ρ increases. The reason for such phenomenon is that, the larger ρ implies that the PU receiver can tolerate more interference power. Therefore, the SU transmitter can use more power for the transmission even when the channel power gain between the SU transmitter and the PU receiver is larger compared with the scenario under smaller ρ, which leads to the improvement of the effective capacity of the SU link.

Second, we analyze the impact of the transmit power of the primary link to the effective capacity of the secondary link. As shown in the Eq. (6), the PU transmit power can be reflected by the SNR $\overline{\gamma}_p$ at the PU transmitter, the larger the transmit power is, the larger $\overline{\gamma}_p$ is. In this scenario, we set the average SNR at the SU transmitter $\overline{\gamma}_s = 0$ dB and the normalized average interference coefficient $\rho = 0.2$. The SNR at the PU transmitter $\overline{\gamma}_p$ varies from 0 dB to 10 dB. Fig. 4 shows the normalized effective capacity of the secondary link under different QoS exponents and SNRs of the PU transmitter. From the simulation result, we can observe the similar phenomenon as shown in Fig. 3, i.e., given the SNR $\overline{\gamma}_p$, the normalized effective capacity decreases as the QoS exponent θ increases. The explanation for this observation is the same with that mentioned above. Moreover, we also find that, given the QoS exponent θ, the normalized

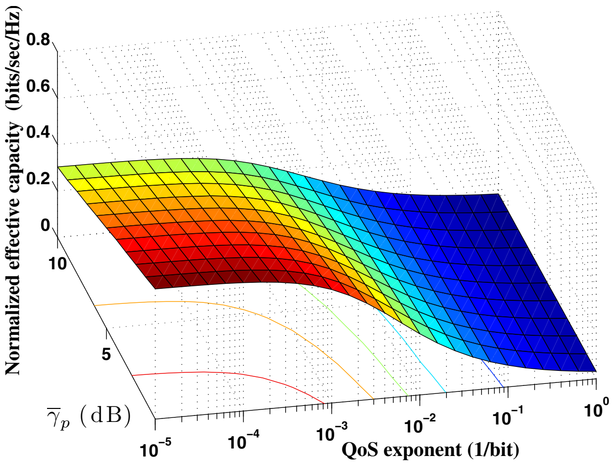

Fig. 4. The effective capacity of the secondary link when the ratio of the maximal interference power and the average transmit power varies

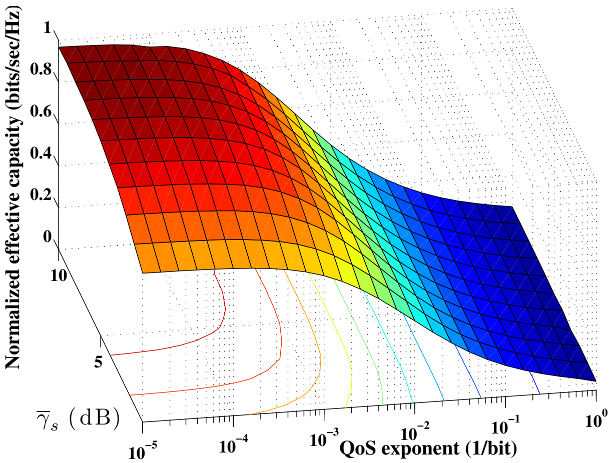

Fig. 5. The effective capacity of the secondary link when the transmit power of the SU transmitter varies

effective capacity of the secondary link decreases when we increase the SNR $\overline{\gamma}_p$. This is because that larger $\overline{\gamma}_p$ implies larger PU transmit power $P_{\rm p}$, which will result in a lower signal-to-interference plus noise ratio (SINR) Γ at the SU receiver as shown in Eq. (15). Therefore, under the given channel power gain g_{ps} between the PU transmitter and the SU receiver, the channel capacity and the maximal traffic arrival rate that can be supported by the secondary link will be reduced as $\overline{\gamma}_p$ increases, which lead to the decreasing tendency of the normalized effective capacity.

Finally, we evaluate the impact of the transmit power of the secondary link to its normalized effective capacity. As shown in the Eq. (6), the transmit power used by the secondary link can be reflected by the maximal average SNR $\overline{\gamma}_s$ at the SU transmitter. The larger the transmit power is, the larger $\overline{\gamma}_s$ is. In this scenario, we set the SNR at the PU transmitter $\overline{\gamma}_p = 0$ dB and the normalized average interference coefficient $\rho = 0.5$. The maximal average SNR at the SU transmitter $\overline{\gamma}_s$ varies from 0 dB to 10 dB. Fig. 5 presents the normalized effective capacity of the secondary link under different QoS exponents and maximal average SINRs of the SU transmitter. From the simulation result, we can also find that, under the given $\overline{\gamma}_s$, the normalized effective capacity decreases when the statistical delay QoS constraint becomes stringent, which is the same with the observations shown in Fig. 3 and Fig. 4. From the simulation result, we can also observe that, when we increase the maximal average SINR $\overline{\gamma}_s$, the normalized effective capacity of the secondary link also increases. The reason is that larger $\overline{\gamma}_s$ implies that the SU transmitter uses larger transmit power, which causes a larger SINR Γ as shown in Eq. (15). Therefore, under the given channel power gains g_s and g_{sp} as well as the SNR $\overline{\gamma}_p$, the maximal traffic arrival rate that can be supported by the secondary link will increase as $\overline{\gamma}_s$ increases, which improves the normalized effective capacity. Furthermore, we can also observe that the normalized effective capacity is nearly a constant when $\overline{\gamma}_s \geq 5$ dB. Such phenomenon is caused by the maximal average interference power constraint, which is reflected by ρ. As described in section 2, ρ is the ratio of the maximal average interference power Q_{av} and the maximal average power P_{av}. Since Q_{av} is unchanged in this scenario, a larger P_{av} (or $\overline{\gamma}_s$) will cause a smaller ρ, which represents a more strict interference power constraint. Therefore, although the SU transmitter are allowed to use larger power for its transmission, the maximal average interference power constraint prevents the SU transmitter from utilizing larger power, which keeps the normalized effective capacity of the secondary link nearly the same.

6 Conclusion

In this paper, we proposed a statistical Quality-of-Service (QoS) driven power and rate allocation scheme over wireless Rayleigh fading cognitive radio links in the scenario that one secondary link coexists with one primary link by sharing particular portions of the spectrum. Our derived power and rate allocation policy can maximize the effective capacity of the secondary link subject to both the average transmit power and average interference power constraints. In this work, we also considered the impact of the transmission of the primary link to the secondary link. Simulation results show that: (1) the effective capacity of the secondary link decreases when the statistical delay QoS constraint becomes stringent; (2) given the QoS constraint, the effective capacity of the secondary link increases as the average interference power constraint becomes looser, but decreases when the PU transmit power increases; (3) given the QoS constraint, the effective capacity of the secondary link will be improved with looser average transmit power constraint, but the effective capacity cannot be further increased with continuously increasing the transmit power because the average interference constraint will become more strict when the average interference power is unchanged.

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