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Effective Capacity Optimization for Cognitive Radio Network Based on Underlay Scheme in Gamma Fading Channels

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***Abstract*—As fundamental spectrum sensing and access techniques in cognitive radio networks (CRN) matured in last decade, the satisfaction of quality-of-service (QoS) demands for cognitive users (CU) has attracted lots of research attention. In this paper, we study how the delay QoS requirements affect the dynamic spectrum access (DSA) strategy on network performance. We first treat the delay-QoS in interference constrained cognitive radio network by applying the *effective capacity* theory, focusing on the dominant DSA scheme: *underlay*. We show that the roles that the transmit-power/interference-power constraints play in optimizing CUs' throughput vary significantly with the delay QoS requirements. Performance analysis and numerical evaluations are provided to demonstrate the effective capacity of CRN based on underlay scheme, taking into consideration the impact of delay QoS requirements and other related parameters.**

I. Introduction

The increasing density of competing wireless communication requirements makes the cognitive radio (CR) playing a central role in future communication systems. Since there is only a finite amount of the spectrum resource, the remaining spectrum is being exhausted and it leads to the spectrum scarcity problem. It is reported in recent studies by the FCC, that there are vast temporal and spatial variations in the usage of he allocated spectrum, which can be as low as 15% [1]. So the frequency bands are often idle in many areas, and inefficiently used.

While CR can improve the overall spectrum efficiency, transmission from cognitive devices can create harmful interference to primary users (PU). This motivates researches to maximize the throughput of a CR network while maintaining performance of the coexistent PUs.

Previously, the cognitive users (CUs) can only transmit when detecting spectrum holes, particular frequency bands that are not concurrently used by any PUs. Some recent studies have extended the cognitive protocols to allow both users (primary and secondary) to transmit simultaneously in the same frequency band [2]. In these protocols, the CUs are assumed to be willing to relay the PU's information.

The main challenge for the cognitive users is to control their interference levels to guarantee their own quality of service requirements by transmitting at the desired rates and limiting the delay experienced by the data in the buffers [3].

Recently, the problem of quality-of-service (QoS) satisfaction demands for cognitive users has attracted lots of research attention. The functions of cognition radio networks have been broadened such that the CUs can not only detect the transmission opportunities under the specific DSA approach, but also cognitively adapt the dynamic spectrum access strategies to the QoS requirements and the channel variations. Among several DSA schemes, underlay based spectrum sharing is the dominant scheme in cognitive networks. In the underlay scheme [4, 5], the CUs are allowed to use the PUs' spectrum even when PUs are active, but need to confine the interference power to a tolerable level. In [4], optimal power allocation policies were derived, which can optimize the ergodic and outage capacities of CRNs under the PU outage constraint. The joint bandwidth and power allocation was considered in [5], and the optimal resource allocation schemes are investigated under all possible combinations of the average/peak transmit and interference power constraints. However, the previous work could not well meet the requirements on QoS constraints in CRNs, thus the developed schemes may cause performance degradation for CUs.

In this paper, an efficient resource allocation scheme is developed with statistically guaranteed delay QoS for the underlay DSA scheme to achieve maximum capacity. The concept of effective capacity proposed in [6] is applied, it is defined as the maximum constant arrival rate that can be supported by the given time-varying service process.

The rest of this paper is organized as follows. The system model and assumptions are presented in Section II. The concept of the statistical delay QoS requirements is discussed in Section III. Section IV is divided into two subsections, where, the effective capacity and optimal resource allocation are studied, respectively. Performance analysis and numerical results are presented in Section V. Section VI concludes the paper.

II. Network Model And Assumptions

A typical CRN model is assumed [7], in which a cognitive wireless network coexisting with a primary wireless network by sharing B Hz spectrum band is considered. In which, a primary user and a cognitive user try to access this spectrum band. It is assumed that there is no direct signalling between the primary and cognitive networks. The cognitive network includes a CU transmitter $\mathbf{T}_{SX}$ and a CU receiver $\mathbf{R}_{SX}$. The primary network includes a PU transmitter $\mathbf{T}_{PX}$ and a PU receiver $\mathbf{R}_{RX}$. The primary transmitter adjusts its transmit power S_p based only on its own transmission requirements, while the secondary transmitter transmits with variable power S_s and should not exceed a maximum value of S_s^m. All channel power gains are assumed to be stationary and ergodic independent random processes. These system gains are grouped in the vector $G = [g_{ss}, g_{sp}, g_{pp}, g_{ps}]$, where g_{ij}, $i, j \in \{s, p\}$ represents the power fading of the channel between the transmitter i to the receiver j. All channel power gains are assumed to be independent and identically distributed ($i.i.d.$), and follow the *Gamma* probability density function (pdf), with the same mean μ. The Gamma distribution has been considered as an adequate model to characterize wireless channel fading such as slow fading (shadowing) or even fast fading [8, 9]. It has been observed that this distribution fits the experimental data [8]. The corresponding pdfs for $f_{g_{ss}}$, $f_{g_{sp}}$, $f_{g_{pp}}$, and $f_{g_{ps}}$, are given as

$$f_X(x) = \frac{x^{a-1}e^{-x/b}}{\Gamma(a)b^a}; \qquad x \geq 0, \tag{1}$$

where a is known as the shape parameter of the distribution, and b is the scale parameter. Without loss of generality, it is assumed that scale parameter $b = 1$. The average $\mathbb{E}[X] = ab = \mu$, and $\mathbb{V}ar[X] = ab^2 = \mu$. The background noise at both receivers are modeled as AWGN independent zero-mean Gaussian random variables with variance σ_s^2 and σ_p^2 respectively. For all the used abbreviations below, the common subscripts s and p refer to the cognitive user and primary user respectively, while the superscripts $\{0, 1\}$ and $*$ refer to the state number and optimal value respectively. The maximum interference at the primary receiver should be kept below a threshold value I^{th}. This value is a system parameter which can be specified by the primary network operator or by the spectrum regulator. Small scale variations are assumed in this paper, where other variations such as distance path loss dependent or shadowing impacts are considered as background or/and interference constraint.

In this paper, resource allocation schemes will be developed taking into account the statistical delay QoS guarantees. As mentioned above, in the underlay scheme, the secondary user is required to always satisfy the interference constraint. Therefore, even in circumstances when the primary user is not transmitting, the cognitive user has to adjust its transmission power based on the interference threshold constraint. Consequently, the derived resource allocation schemes should not be only a function of system gain vector G, but also will be varied with different QoS requirements. In order to clearly illustrate the concept, it is assumed that each frame at the data link layer of the CU transmitter has the same time duration, denoted by T. The frames are stored at the transmit buffer and split into bit-streams at the physical layer. The CU transmitter employs adaptive modulation and power control based on the statistical QoS constraint and the system gain vector G, which can be perfectly derived by the CU transmitter.

The factors that will impact the resource allocation of the cognitive network include: (1) the average transmit and interference power constraints; (2) the statistical delay QoS requirement; (3) the primary network activities; (4) the DSA strategy used by the cognitive network; and (5) the interference caused by the PU transmitter on the cognitive network. The existing literatures studied the underlay strategy, while the primary network activities are ignored. In this paper, the PUs' spectrum-occupancy probability is taken into consideration even for the underlay strategy. It is assumed that the primary network will choose whether to use the spectrum or not at the beginning of each frame. As the spectrum-occupancy status of the primary network can be viewed as the two hypothesis test from the CU's perspective, the probability that the primary network does not occupy the spectrum is denoted as P_i (idle probability), and the probability that the spectrum is occupied as P_b (busy probability). These probabilities are assumed to be fixed during the frame interval.

III. Optimal Resource Allocation For Underlay Scheme

In this section, an optimal resource allocation for the underlay scheme is proposed under given statistical delay QoS guarantee determined by the QoS exponent θ. When the CU applies the underlay scheme, the spectrum sensing is not needed, and the CU can use the whole frame duration for transmission with adjusted transmit power no matter whether the primary network occupies the spectrum or not. The cognitive network with the underlay scheme has two system states for each frame, which are listed as follows:

- **State** 0: The channel is idle, *i.e.*, it is not occupied by the primary network, with a probability P_i.
- **State** 1: The channel is busy, *i.e.*, it is currently used by the primary network, with a probability P_b.

The service rates of these two states are denoted as R^0 and R^1 at CU, respectively. Based on Shannon information theory, the achievable service rates of the two system states can be written as

$$R^0 = TB\log_2\left(1 + \frac{g_{ss}S_s^0}{\sigma_s^2}\right) \tag{2}$$

$$R^1 = TB\log_2\left(1 + \frac{g_{ss}S_s^1}{g_{ps}S_p + \sigma_s^2}\right), \tag{3}$$

where S_s^0 and S_s^1 are the transmit power of the CU transmitter when the spectrum is idle and busy, respectively.

A. Effective Capacity for Underlay scheme

The effective capacity denoted by $E_C(\theta)$, is defined as the maximum constant arrival rate that can be supported by the time-varying service process under a given QoS exponent θ [6]. If the service rate $R[t]$ is time-uncorrelated, $E_C(\theta)$ can be represented by [6]

$$E_C(\theta) = -\frac{1}{\theta}\log\mathbb{E}[e^{-\theta R[t]}]. \tag{4}$$

As the PU active probability is taken into consideration, the solution of the effective capacity of (4) can be found as [10, 11]

$$E_C(\theta) = -\frac{1}{\theta}\log\left(\rho(\mathbf{P}\cdot\mathbf{D})\right), \tag{5}$$

where $\mathbf{D}$ is a diagonal matrix given by $\mathbf{D} = diag\Big[d_1(\theta), d_2(\theta)\Big] = \Big[\mathbb{E}[e^{-\theta R^0}], \mathbb{E}[e^{-\theta R^1}]\Big]$, and $\rho(\cdot)$ function is the *spectral radius* of a matrix, which is defined as the maximum of the absolute values of its *eigenvalues*, *i.e.*, $\rho(A) \overset{def}{=} \max_i(|\omega_i|)$, ω_i's are the eigenvalues. $\mathbf{P}$ in (5) denotes the transition probability matrix. As the primary network independently selects whether to access the spectrum or not at the beginning of each frame, the two system states are time-uncorrelated and thus the entries of the transition probability matrix can be written as

$$\begin{cases} p_{00} = p_{10} = P_i, \\ p_{01} = p_{11} = P_b. \end{cases} \tag{6}$$

Since the transition probability matrix $\mathbf{P}$ has a unit rank, the spectral radius of matrix $(\mathbf{P}\cdot\mathbf{D})$ can be easily calculated by

$$\rho(\mathbf{P}\cdot\mathbf{D}) = trac(\mathbf{P}\cdot\mathbf{D}) = P_i\mathbb{E}[e^{-\theta R^0}] + P_b\mathbb{E}[e^{-\theta R^1}]. \tag{7}$$

Substituting (7) into (5), the effective capacity can be obtained as

$$E_C(\theta) = -\frac{1}{\theta}\log\left(P_i\mathbb{E}[e^{-\theta R^0}] + P_b\mathbb{E}[e^{-\theta R^1}]\right). \tag{8}$$

Statistically, if X and Y are two independent *Gamma* distributed random variables with parameters μ_1 and μ_2, respectively, then, $Z = \frac{X}{Y}$ is a *Beta Prime* distributed random variable with parameters μ_1 and μ_2 [12]. Let us define a new random variable $Y = (g_{ps}S_p + \sigma_s^2)/S_s^1$, since all power gains are assumed to be Gamma distribution, Y is also Gamma distributed with mean μ_2. The *pdf* of Y can be expressed as

$$f_Y(y) = \frac{y^{\mu_2-1}e^{-y}}{\Gamma(\mu_2)}, \tag{9}$$

where $\mu_2 = \frac{(\mu_1 S_p + \sigma_s^2)}{S_s^1}$. Then, the *pdf* of the random variable Z has the following Beta Prime distribution function

$$f_Z(z) = \frac{z^{\mu_1-1}(1+z)^{-\mu_1-\mu_2}}{\beta(\mu_1,\mu_2)}, \tag{10}$$

where $\beta(\mu_1, \mu_2)$ is the Beta function, and $\mu_1 = \mu$ is the mean value of power channel gains as it is assumed above. Substituting (2) and (3) in (8), we get

$$\begin{aligned} E_C(\theta) = -\frac{1}{\theta}\log\Bigg(&P_i\mathbb{E}\Bigg[e^{-TB\theta\log_2\left(1+\frac{g_{ss}S_s^0}{\sigma_s^2}\right)}\Bigg] \\ &+P_b\mathbb{E}\Bigg[e^{-TB\theta\log_2\left(1+\frac{g_{ss}S_s^1}{g_{ps}S_p+\sigma_s^2}\right)}\Bigg]\Bigg), \end{aligned} \tag{11}$$

which can be written as

$$E_C(\theta) = -\frac{1}{\theta}\log\left[P_i\mathbb{E}_x\left[\left(1+\frac{x}{\gamma}\right)^{-\alpha}\right] + P_b\mathbb{E}_z\left[(1+z)^{-\alpha}\right]\right], \tag{12}$$

where, $\mathbb{E}_x$ and $\mathbb{E}_z$ is the average value with respect to the random variable X and Z defined in (1) and (10), respectively, $\gamma = \frac{\sigma_s^2}{S_s^0}$, and $\alpha = (TB\theta/\ln 2)$ can be named as the normalized QoS exponent. It can characterize the statistical delay QoS requirement since it is only a function of θ.

By evaluating (12), a closed form result can be obtained as in (13),

$$\begin{aligned} E_C = -\frac{1}{\theta}\log\Bigg[&P_i\Bigg(\frac{\Gamma(\alpha-\mu_1)}{\Gamma(\alpha)}(\gamma)^{\mu}\ {}_1F_1(\mu_1; 1+\mu_1-\alpha; \gamma) \\ &+\frac{\Gamma(\mu_1-\alpha)}{\Gamma(\mu_1)}(\gamma)^{\alpha}\ {}_1F_1(\alpha; 1+\alpha-\mu_1; \gamma)\Bigg) \\ &+P_b\left(\frac{\Gamma(\alpha+\mu_2)\Gamma(\mu_1+\mu_2)}{\Gamma(\alpha+\mu_1+\mu_2)\Gamma(\mu_2)}\right)\Bigg], \end{aligned} \tag{13}$$

where the function ${}_1F_1$ is called Confluent Hypergeometric function of first kind, defined as [13]:

$${}_1F_1(a,b,z) = \sum_{n=0}^{\infty}\frac{(a)_n}{(b)_n}\frac{z^n}{n!}, \tag{14}$$

where
$(a)_n = a(a+1)(a+2)\cdots(a+n-1);\ n \neq 0,$ and $(a)_0 = 1$, and $\mu_1 = \mu$.

The above integrations are expressed in terms of gamma function and hypergeometric function. Some properties of these functions listed in [13] are used to obtain a simplified expression as below

$$E_C(\theta) = -\frac{1}{\theta}\log\Big[P_iC_{i1}f_1(x) + P_iC_{i2}f_2(x) + P_bf_3(y)\Big], \tag{15}$$

where:
$C_{i1} = \Gamma(\alpha-\mu_1)/\Gamma(\alpha), \quad C_{i2} = \Gamma(\mu_1-\alpha)/\Gamma(\mu_1);$
$f_1(x) = \gamma^{\mu}\ {}_1F_1(\mu_1; 1+\mu_1-\alpha; \gamma)$
$f_2(x) = \gamma^{\alpha}\ {}_1F_1(\alpha; 1+\alpha-\mu_1; \gamma),$
$f_3(y) = (\Gamma(\alpha+\mu_2)\Gamma(\mu_1+\mu_2))/(\Gamma(\alpha+\mu_1+\mu_2)\Gamma(\mu_2)),$

where the dummy variables x, y correspond to the variables S_s^0, S_s^1 which are embedded in the variables γ and μ_2, respectively.

B. Optimal Power Allocation for Underlay scheme

Now, the objective is to find the optimal power allocation (S_s^0, S_s^1) to maximize the effective capacity of the cognitive network subject to the upper bounded transmit and interference powers. Therefore, from (15), an expression for the optimal effective capacity for the cognitive network channel can be formulated and the optimization problem can be written as follows

$$\begin{aligned} &\underset{x,y}{\textbf{maximize}} - \frac{1}{\theta}\log\Big[P_i\left(C_{i1}f_1(x) + C_{i2}f_2(x)\right) + P_bf_3(y)\Big] \\ &S.t. \qquad 0 \leq P_ix + P_by \leq S_s^m \\ &\qquad\qquad P_i\mathbb{E}[g_{sp}x] + P_b\mathbb{E}[g_{sp}y] \leq I^{th}. \end{aligned} \tag{16}$$

The optimization variables x, y are again equivalent to S_s^0, S_s^1 respectively. They are not only a function of the system gain vector G, but also a function of the QoS exponent θ. Because the CU transmitter usually has an upper bounded transmit power S_s^m, the CU transmitter should satisfy transmit power constraint, which appears in the first constraint in (16). In the same time, since the transmissions of the cognitive network will interfere the primary network, in order to protect the QoS of the primary network, the average interference power constraint is in the second constraint of (16). Now, by using the fact that the function $\log(z)$ is a monotonically increasing function of z, the solution to the maximization problem (16) can be mapped to the following minimization problem

$$\begin{aligned} &\underset{x,y}{\textbf{minimize}} \quad \frac{1}{\theta}\Big[P_i\left(C_{i1}f_1(x)+C_{i2}f_2(x)\right)+f_3(y)\Big] \\ &S.t. \quad\quad 0 \le P_i x + P_b y \le S_s^m \\ &\quad\quad\quad\quad P_i\mathbb{E}[g_{sp}x]+P_b\mathbb{E}[g_{sp}y] \le I^{th}. \end{aligned} \tag{17}$$

Using Lagrangian optimization approach, the corresponding optimal power allocation can be written as in (18) and (19) (The details are omitted for the lack of space).

$$\begin{aligned} &\Bigg[C_{i1}\mu_1(\gamma)^{\mu_1+1}\left({}_1F_1(\mu_1;1+\mu_1-\alpha;\gamma)+\frac{\gamma\,{}_1F_1(1+\mu_1;2+\mu_1-\alpha;\gamma)}{1+\mu_1-\alpha}\right) \\ &+C_{i2}\alpha(\gamma)^{\alpha+1}\left({}_1F_1(\alpha;1+\alpha-\mu_1;\gamma)+\frac{\gamma\,{}_1F_1(1+\alpha;2+\alpha-\mu_1;\gamma)}{1+\alpha-\mu_1}\right)\Bigg] \\ &=\sigma_s^2\theta(\lambda+\nu\mu_1). \end{aligned} \tag{18}$$

$$\begin{aligned} &(\mu_2^*)^2\frac{\Gamma(\alpha+\mu_2^*)\Gamma(\mu_1+\mu_2^*)}{\Gamma(\alpha+\mu_1+\mu_2^*)\Gamma(\mu_2^*)}\Big(\Psi(\alpha+\mu_2^*)+\Psi(\mu_1+\mu_2^*) \\ &-\Psi(\alpha+\mu_1+\mu_2^*)-\Psi(\mu_2^*)\Big)=\theta(\mu_1 S_p+\sigma_s^2)(\lambda+\nu\mu_1). \end{aligned} \tag{19}$$

The function Ψ in (19) is known as polygamma function and defined as [13]

$$\Psi(z)=\int_0^\infty \frac{t^m e^{-zt}}{e^t-1}dt. \tag{20}$$

The optimal value μ_2^* in (19) is the value of μ_2 corresponding to S_s^{*1}, *i.e.*, $\mu_2^*=(\mu_1 S_p+\sigma_s^2)/S_s^{*1}$.

Unfortunately, there is no closed form solutions for power allocation, because the inverse hypergeometric function, *i.e.*, ${}_1F_1^{-1}(a;b;z)$ is not known up until now. Furthermore, the inverse function of both Gamma, $\Gamma^{-1}(\cdot)$, and Polygamma $\Psi^{-1}(\cdot)$ can only be found numerically. Therefore, by solving (18) and (19) numerically, one can find optimal solutions for both S_s^{*0} and S_s^{*1}.

In (18) and (19), $\gamma=\frac{\sigma_s^2}{S_s^{*0}}$, and the multipliers, λ and ν are the optimal Lagrangian multipliers that satisfy the constraints in (17).

IV. Numerical Results and Performance Analysis

In this section, numerical results are presented to evaluate the performance of the proposed power allocation strategies. In the calculation, the frame duration is set to $T = 50ms$, the sampling frequency $B = 100K$symbol/s, and the probability of the channel to be idle is set to $P_i = 0.2$ as a target value. Other parameters are listed in the corresponding figures.

First, the convergency of the proposed algorithm is evaluated. Fig. 1 shows the iterative method for determining the optimal Lagrangian multipliers. The maximum secondary transmit power is set to $10dBw$, *i.e.*, $S_s^m = 10W$ and the interference threshold and the primary transmit power are set to $0dBw$, and $S_p = 10dBw$, respectively. The QoS exponent $\theta = 0.001$. As shown in Fig. 1, the Lagrangian multipliers can quickly converge to their optimal values when choosing a dynamic step size.

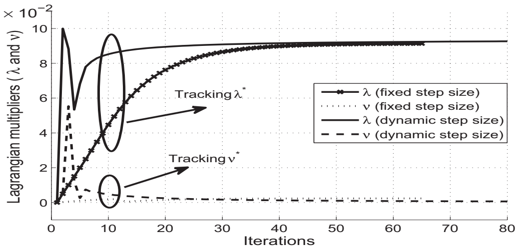

Fig. 1. Tracking the optimal Lagrangian multipliers. $I^{th} = 0dBw$, $S_p = 10dBw$, $S_s^m = 10dBw$, and $\theta = 10^{-3}$

Fig. 2 presents the normalized effective capacity as a function of the QoS exponent θ. From the figure, it can be observed that the QoS exponent θ plays a critically important role in the maximum throughput of the cognitive network. When θ is small (*i.e.*, the QoS constraint is loose), the cognitive network can realize higher throughput. On the contrary, when θ is large (*i.e.*, the QoS constraint is stringent), the cognitive network can only support lower arrival rates.

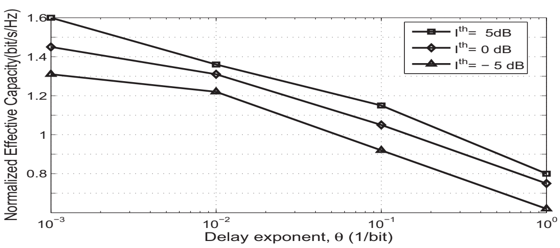

Fig. 2. Normalized effective capacity versus exponent delay. $S_s^m = 10dBw$

Higher P_i means the cognitive transmitter assumes that the channel is idle with a higher probability. The CU exploits the situation and transmits with a higher power level, which in turn, gains more capacity. While at lower P_i, the cognitive transmitter assumes the channel is busy with a higher probability (since $P_b = 1 - P_i$) and thus, it reduces the transmit power to comply with the interference constraint.

The interference threshold I^{th} also has a significant impact on the performance. In order to evaluate the impact of I^{th}, Fig. 3 shows the normalized effective capacity versus I^{th} with different QoS exponent θ. It can be noted that the effective capacity improves with increasing of I^{th}. This can be easily understood since a higher I^{th} means the PU receiver can tolerate higher interference. Consequently, the CU transmitter can use higher transmit power and thus achieve better performance.

The transmit power of the primary network S_p is another crucial parameter that affects the performance of the cognitive network. Fig. 4 shows the effective capacity versus

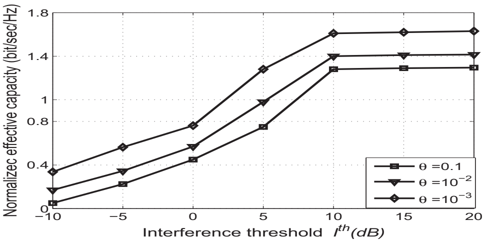

Fig. 3. Normalized effective capacity versus interference threshold for different θ.

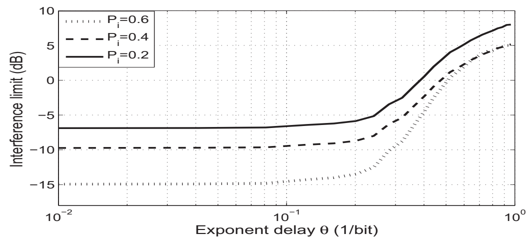

Fig. 5. Interference power threshold versus exponent delay for various PUs' spectrum-occupancy probability, $S_s^m = S_p = 10W$.

the transmit power of the primary user S_p with different QoS exponent θ. It can be observed that the performance of the cognitive network degrades as S_p increases. This is because that a higher S_p will cause more severe interference to the CU receiver. Therefore, the CU transmitter needs to transmit with a higher power to overcome this negative impact. However, as shown in Fig. 4, when the QoS exponent is small (*i.e.*, $\theta = 10^{-3}$), the performance loss is not obvious. On the contrary, the performance of the cognitive network degrades more dramatically when the QoS exponent is large (*i.e.*, $\theta = 0.1$). The reason for this observation is that a small θ denotes loose QoS requirement and the power allocation becomes water-filling, thus the power resource can be more efficiently utilized. However, large θ means stringent QoS requirement, which results the cognitive network transmit with constant rate. Therefore, more power is used to overcome the more serious interference caused by larger S_p and the upper bounded power resource is less efficiently utilized.

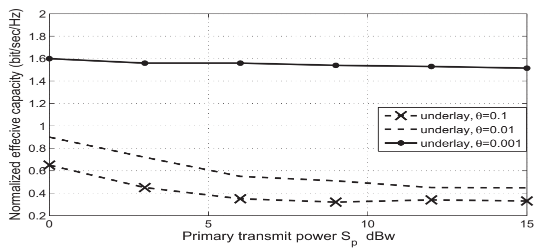

Fig. 4. Normalized effective capacity versus primary transmit power with different θ, $P_i = 0.2$.

Fig. 5 shows the interference power versus θ under different spectrum-idle probabilities (P_i). It is shown that the interference power increases with the increase of θ, and decreases with the increase of (P_i). It is reasonable that when θ increases, the CU transmitter will transmit with higher power to meet the more stringent QoS requirement, leading to higher interference to PU.

V. CONCLUSIONS

In this paper, the concept of effective capacity is investigated and the optimal resource allocation for the underlay DSA scheme is developed. The impact of the delay-QoS constraint on the network performance is investigated taking into account the PUs' spectrum-occupancy probability. Closed form for the effective capacity is derived. Optimal power allocation to achieve the maximum effective capacity is also obtained in implicit forms. The cognitive user can support higher throughput in loose QoS constraint and vice versa. Numerical results are presented to give more interesting observations and insights.

REFERENCES

[1] Federal Communications Commission, "Spectrum policy task force," *Rep. ET Docket*, , no. 02-135, Nov. 2002.

[2] C. Cordeiro, K. Challapali, D. Birru, and N. Shankar, "IEEE 802.22: The first worldwide wireless standard based on cognitive radio," *First IEEE Int. Symp. New Frontiers in Dynamic Spectrum Access Networks*, pp. 328–337, Nov 2005.

[3] D. Qiao, M. Gursoy, and S. Velipasalar, "Energy efficiency of fixed-rate wireless transmissions under queueing constraints and channel uncertainty," *In Proceedings of IEEE GLOBECOM*, pp. 24–29, Nov 2009.

[4] X. Kang, Y. Liang, A. Nallanathan, H. Garg, and R. Zhang, "Optimal power allocation for fading channels in cognitive radio networks: ergodic capacity and outage capacity," *IEEE TR. on Comm.*, vol. 8, no. 2, pp. 940–950, Feb 2009.

[5] X. Gong, S. Vorobyov, and C. Tellambura, "Optimal bandwidth and power allocation for sum ergodic capacity under fading channels in cognitive radio networks," *IEEE TR. on Signal Process.*, vol. 59, no. 4, pp. 1814–1826, Apr 2011.

[6] D. Wu and R. Negi, "Effective capacity: A wireless link model for support of quality of service," *IEEE Trans. Wireless Commun.*, vol. 2, no. 4, pp. 630–643, Jul 2003.

[7] X. Kang, Y. Liang, H. Garg, and L. Zhang, "Sensing-based spectrum sharing in cognitive radio networks," *IEEE TR. on Veh. Technol.*, vol. 58, no. 8, pp. 4649–4654, Oct 2009.

[8] F. Ramos aand V. Kontorovitch and M. Lara, "High order fading distributions in nakagami wireless channels," *in Proc. IEEE Vehicular Technology Conf.*, pp. 564–568, Apr. 2007.

[9] S. Al-Ahmadi and H. Yanikomeroglu, "On the approximation of the generalized distribution by a gamma distribution for modeling composite fading channels," *IEEE Tran. on Wireless Communications,*, vol. 9, no. 2, pp. 706–713, 2010.

[10] C. Chang, "Stability, queue length, and delay of deterministic and stochastic queueing neyworks," *IEEE TR. on Automatic Control.*, vol. 39, no. 5, pp. 913–931, May 1994.

[11] C. chang, *Performance Guarantees in Commucation Networks*, Springer, London, 2000.

[12] S. Kotz, N. Jonhnson, and N. Balakrishnan, *Continuous Univariate Distributions: Models and applications*, vol. 2, John Wiley and Sons, 2nd edition edition, 2000.

[13] F. Olver, D. Lozier, R. Boisvert, and C. Clark, *NIST Handbook of Mathematical Functions*, Cambridge University Press, 2010.