Quality-of-Service in Cognitive Radio Networks with Collaborative Sensing

Caoxie Zhang, Xinbing Wang, Xinping Guan
Department of Electronic Engineering
Shanghai Jiao Tong University, China
Email: {zcx, xwang8,xpguan}@sjtu.edu.cn

Hsiao-Hwa Chen
Dept. of Engineering Science
National Cheng Kung Univ, Taiwan
Email: hshwchen@ieee.org

***Abstract*—Uncertain capacity in newly emerged Cognitive Radio Networks(CRN) renders specific performance analysis for the secondary users (SUs), particularly in the aspects of Quality-of-Service (QoS). The effective bandwidth concept is employed to analyze the SUs' performance. Considering the time-varying arrival and service process, we analytically obtain the QoS metrics, such as the approximated delay-violation probability and mean time delay. The accuracy of the approximation is demonstrated via simulation. With the extension to multiple secondary users, we then consider the inevitable sensing errors in CNR in a cross-layer framework, and introduce the promising collaborative sensing method among SUs. By integrating to upper link layer, we then study the collaborative gains in terms of mean time delay.**

I. Introduction

Cognitive Radio Networks (CRN) play important roles for alleviating the inefficient spectrum usage in coexistence with the licensed radios [1] and [2]. It is therefore important to investigate the performance of the cognitive secondary users (SUs). In order to meet with the increasing demands of delay-sensitive applications such as multimedia applications, the Quality-of-Service (QoS) metric appears to be a very desirable objective. For the QoS analysis in CRN, some unique characteristics include the uncertainty of the SUs' capacity due to the time-varying idle primary channel. We consider the CRN as one primary channel and multiple SUs adopting opportunistic spectrum access paradigm. By employing the large-deviation applied concept: effective bandwidth [3], we try to obtain the analytical forms of the QoS metrics, e.g., approximated delay-violation probability and mean time delay.

Meanwhile, we address that there are other main challenges in the design and analysis of CRN, such as primary user detection, also known as spectrum sensing [2], [12]. In this paper, we try to answer the impact of the spectrum sensing to the upper-layer QoS performance, e.g., mean time delay. Furthermore, it is reasonable to think that future un-licensed secondary users (SUs) equipped with intelligent techniques, therefore SUs should be able to cooperate within the networks for better exploitation of spatial diversity. This paper focuses on the collaborative sensing within the SUs [4]: explore better sensing reliability to the primary radios via simultaneous sensing at multiple locations. The increasing reliability could therefore benefit the SUs in two ways: (i) less interference to primary channels due to less missed detections, and (ii) more opportunities in utilizing the spectrum holes due to less false alarms.

The rest of the paper is organized as follows. Sec. II introduces the related works with our concern. Sec. III presents a preliminary on the simplest QoS modeling for one primary channel and one SU with perfect sensing. In Sec. IV, we extend to Cognitive Radio Networks for multiple secondary users. Sec. V deals with the collaborative sensing and study the collaborative gains from both the physical layer to link layer. Finally, Sec. VI concludes the paper.

II. Related Works

Effective bandwidth is abundantly researched in wire networks, such as ATM, for the QoS provisioning [3] and [5]. The asymptotic queue-overflow probability in a fluid queue model is approximated as exponential decaying under the large-deviation principle. The effective bandwidth used in ATM networks frequently assumes the service capacity to be constant. A time-varying service capacity is discussed in [3] to widen the application. Since the queue-overflow probability is equivalent to the delay-violation probability in the stationary state, it is more compelling to measure delay in real-time applications. [6] and [7] extended the concept of effective bandwidth to effective capacity in wireless fading channel, which is the dual of effective bandwidth. [8] applied the same QoS measures in analyzing 802.11 multihop networks. [9] proposed a cross-layer approach for wireless QoS metrics.

Meanwhile, the idea of collaborative sensing within the secondary radios was reported by [4] and [10]. The collaborative gains are also demonstrated experimentally in realistic scenarios by [11]. [13] proposed an in-band spectrum sensing algorithm for the still in draft IEEE 802.22, based on the same collaborative concept by clustering sensors.

The contribution of this paper lies in two aspects: (i) Quality-of-Service model is built to analyze the performance of the secondary users in the coexistence of primary users. The exponential decaying property of the delay-violation probability is also demonstrated via simulations; (ii) we propose the cross-layer optimization problem when considering the sensing errors in Cognitive Radio Networks. We show that the optimal policy would always offer collaborative gains with the increase of SUs under the OR-rule scheme.

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III. Preliminary on QoS in Cognitive Radio

We consider a continuous-time fluid model, i.e., the packet length is infinitely small, and each secondary user (SU) has a queue of an infinite buffer size. There is one primary channel and we initially consider only one SU with perfect sensing. The SU adopts opportunistic spectrum access paradigm, i.e., allows to transmit immediately after the primary channel becomes idle and refrains from transmission after the primary channel turns busy. Therefore, the primary channel process determines the service process of the SU. We assume the secondary service process to be a two-state ON/OFF Markov Modulated Process, which suggests the primary idle and busy period to be i.i.d. exponentially distributed. The exponential traffic modeling is worth of theoretic research because of the simplicity and near good fit for practical situations [15] and [16]. The arrival process for the SU can be a general stationary process. Let us denote the number of packets arrived in the SU's queue during $[0, t]$ by $A(t)$, and the maximum number of packets can be served during $[0, t]$ by $S(t)$. We then restate some applicable results obtained in the effective bandwidth research [3] and [5]. The "energy function" $\psi_{f(t)}(\theta)$ of a process $f(t)$, i.e., the asymptotic log moment generating function, is

$$\psi_{f(t)}(\theta) \quad = \quad \lim_{t\to\infty} \frac{1}{t} \log E[e^{\theta f(t)}] \tag{1}$$

The asymptotic exponential decaying rate of the stationary queue-overflow probability is

$$\lim_{B\to\infty} \frac{\log \Pr(Q(\infty) \geq B)}{B} = -\theta^* \tag{2}$$

if θ^* is the unique solution of

$$\psi_{A(t)}(\theta) + \psi_{S(t)}(-\theta) = 0 \tag{3}$$

where $Q(\infty)$ is the queue length at the stationary state. From (2), the approximation of $\Pr(Q(\infty) \geq B)$ could be arbitrary forms, e.g., $\alpha B^{-\beta} e^{-\theta^* B}$. However, we adopt the simplest form: the one-parameter exponential approximation as

$$\Pr(Q(\infty) \geq B) \approx e^{-\theta^* B} \tag{4}$$

Later simulations would demonstrate that (4) is rather accurate even for small queue bound B.

The delay of a packet is denoted here as the time the packet spends before the service. In the stationary state, the statics of the queue length and delay is governed by the following important equation

$$\Pr(Q(\infty) \geq B) = \Pr(D(\infty) \geq \lambda D_{\max}) \tag{5}$$

where λ is the average arrival rate, and $D_{\max}$ is the delay bound.[1] Therefore, the stationary delay-violation probability can be approximated by

$$\Pr(D(\infty) \geq D_{\max}) \approx e^{-\lambda \theta^* D_{\max}} \tag{6}$$

[1] (5) is suited for considerable generality, note this is the extension of Little's Law.

We then consider this model for the SU in the Cognitive Radio framework, and first investigate the service process of the SU. Under the opportunistic spectrum access paradigm, the service capacity of the SU becomes its transmission rate r when the primary channel is idle and capacity becomes 0 when the primary channel is busy. Therefore, we can consider the secondary service process on the primary channel state process. Since the busy and idle period of the primary channel are i.i.d. exponentially distributed, we assume the mean time to be one-parameter μ_0 and μ_1 respectively. The transition rate for the primary channel state is therefore $\frac{1}{\mu_0}$ (from busy to idle) and $\frac{1}{\mu_1}$ (from idle to busy), respectively, as can be seen in Fig. 1.

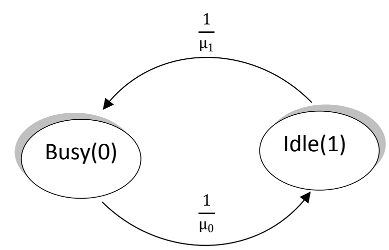

Fig. 1. State transition diagram of the primary channel.

The service process of the SU corresponds to a two-state ON/OFF Markov Modulated Process (MMP). Since the the "energy function" of the general two-state MMP is known, (47) in [3], we are then able to calculate the ON/OFF MMP as

$$\psi_{S(t)}(\theta) = \frac{r\theta - \frac{1}{\mu_0} - \frac{1}{\mu_1} + \sqrt{(r\theta - \frac{1}{\mu_0} - \frac{1}{\mu_1})^2 + \frac{4r\theta}{\mu_0}}}{2} \tag{7}$$

As for the practical modeling of the arrival process, we consider two frequently used arrival processes: constant arrival and Poisson bursty arrival. The constant arrival process can be used to model the continuous video data sent from the stream provider. The process is denoted by one parameter λ, the number of packets arrived per unit of time. For the Poisson bursty arrival, it can be used to model the data of web page browsed, i.e., the number of web page requests is modeled as Poisson process and the data of one web page is constant. We denote the Poisson arrival rate as $\frac{1}{\mu_2}$, and the number of packets for each arrival is a constant a. In these two cases, the "energy function" of each arrival process can be easily calculated as

$$\psi_{A_1(t)}(\theta) \quad = \quad \lambda\theta \tag{8}$$

$$\psi_{A_2(t)}(\theta) \quad = \quad \frac{1}{\mu_2}(e^{a\theta} - 1) \tag{9}$$

With the knowledge of the "energy function" for both arrival and service process, we can then obtain the exponential decaying rate. For the constant arrival process, the exponential decaying rate θ^* is solved from (3) as

$$\theta^* = \frac{\frac{r}{\mu_0} - \frac{\lambda}{\mu_0} - \frac{\lambda}{\mu_1}}{\lambda r - \lambda^2} \tag{10}$$

For the Poisson bursty arrival process, θ^* is difficult to obtain analytically. However, the monotonicity can be easily proved, thus the solution can be obtained through numerical binary search. Although we are unable to obtain the analytical decaying rate for the Poisson process, we come to a proposition for comparison as follow:

Proposition 1: With the same average arrival rate, the constant arrival process achieves better QoS performance (in terms of exponential decaying rate) than that of Poisson bursty arrival process.

Proof: Since the average rate is the same, $\lambda = \frac{a}{\mu}$. Notice that $\frac{e^{a\theta}-1}{a} \geq \theta$ ($a > 0$), therefore $\psi_{A_1(t)}(\theta) \leq \psi_{A_2(t)}(\theta)$. Observing that (i) $\psi_{A_1(t)}(\theta)$ and $\psi_{A_2(t)}(\theta)$ monotonically increase with $\psi_{A_1(t)}(0) = \psi_{A_2(t)}(0) = 0$, and (ii) $-\psi_{S(t)}(-\theta)$ monotonically increase with $\psi_{S(t)}(0) > 0$, we conclude that the decaying rate, which is the solution to $\psi_{A(t)}(\theta) = -\psi_{S(t)}(-\theta)$, satisfy: $\theta_1^* \geq \theta_2^*$. ■

Up to now, we have two QoS metrics: probabilities for queue-overflow and delay-violation. The exponential approximation for the tail probabilities therefore assumes that stationary distributions of the queue length and delay can be approximated as exponential distribution. The mean of the queue length and delay can be approximated as

$$E[Q] = \frac{1}{\theta^*} \quad \text{and} \quad E[D] = \frac{1}{\lambda\theta^*} \tag{11}$$

A. Simulated and Numerical Results for QoS metrics

In order to verify the QoS metrics proposed, we simulate the queue length distribution under the two cases of arrival processes. We present the analytical exponential approximation (4) to compare the simulated results. We make the average arrival rate for the two process to be equal. As can be seen from Fig. 2 , the approximations are very close to the simulations even for small value of the queue length bounds. In addition, for the constant arrival process, the decaying rate is higher than that of Poisson bursty process, which is also stated in Proposition 1.

The good approximation for the queue-overflow probability gives rise to good approximation for the delay-violation probability, as in (5), and therefore the approximations for the mean queue length and mean time delay are near accurate, in (11). In the following sections, we employ these metrics for the evaluations of QoS in Cognitive Radio Networks (CRN).

IV. QoS in CRN: Extending to Multiple Secondary Users

With the preliminary QoS metrics aforementioned for one SU, we extend to multiple SUs with perfect sensing of the channel. We assume there are N SUs and they compete for spectrum when the primary channel is idle. The contention scheme could adopt the back off scheme, as in IEEE 802.11. The maximum back off time could be different because of different pre-defined priority. The primary channel state again determines the service process of each SU i, i.e., under the contention rule, the idle channel will be utilized by SU i with a certain probability p_i. As for the primary state diagram,

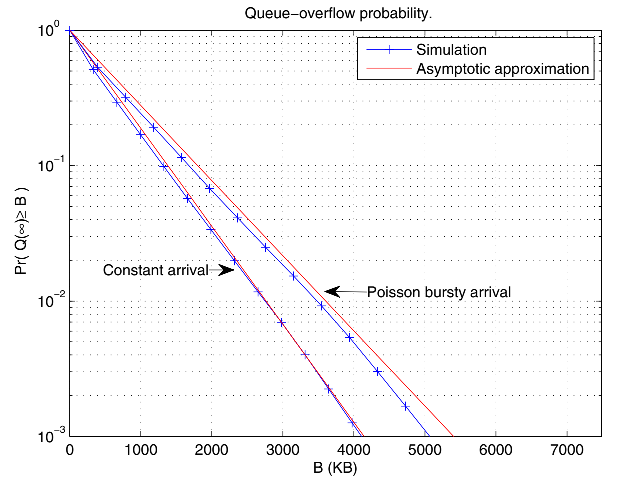

Fig. 2. Simulations and numerical results for the queue-overflow probability. (λ = 10 KB/s, r = 40 KB/s, μ_0 = 20 ms, μ_1 = 10 ms, μ_2 = 100 ms, a = 1 KB)

each idle state i corresponds to an effective service for SU i, with the capacity denoted as R_i. Fig. 3 illustrates the new state transition diagram for multiple SUs. Note that the sum

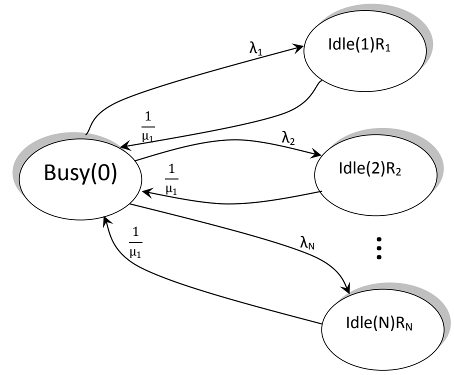

Fig. 3. Primary channel state diagram for multiple secondary users.

of probabilities $\{p_1, p_2, ..., p_N\}$ should satisfy the transition probability of the primary channel from the busy state to idle, i.e., $\sum_{i=1}^{N} p_i = \frac{1}{\mu_0}$.

It is not hard to calculate the new "energy function" of the service process for SU i from (7), as

$$\psi_{S_i(t)}(\theta) = \frac{R_i\theta - p_i - \frac{1}{\mu_1} + \sqrt{(R_i\theta - p_i - \frac{1}{\mu_1})^2 + 4p_iR_i\theta}}{2} \tag{12}$$

V. CRN with Collaborative Sensing

Based on the aforementioned QoS model, when analyzing the QoS performance, we should take into account of the inevitable sensing errors that secondary users have on the primary user. We need to consider two fundamental probabilities that represent the sensing reliability of the secondary networks: probabilities of detection and false alarm for sensing the existence of primary signals at one time. They are denoted as P_D and P_F respectively. We also assume the radio is sensing all the time while ignoring the sensing time, which might not be practical but simple enough for the theoretical analysis of maximum detection gains.

Our object is to guarantee the interference probability to the primary channel be less than a target value. Then with the opportunistic spectrum access paradigm and contention scheme, SU i, if successfully acquires the channel, would transmit immediately after they detect the channel is idle with its transmission rate R_i. The effective transmission rate, R_i^E, of each SU i (at its idle state) is defined as a maximizing problem:

$$\arg\max: \quad R_i^E = R_i(1-P_F) \tag{13}$$

$$s.t. \quad \frac{\mu_0}{\mu_0+\mu_1}(1-P_D) \leq P_{IF} \tag{14}$$

where P_{IF} is the target interference probability. (13) suggests the actual transmission rate is reduced by a factor due to failing to report the idle channel. And (14) suggests that the actual interference probability seen by the primary channel is modified by the channel occupancy level. By integrating the sensing errors in the effective transmission rate, we are then able to evaluate SU performance from upper-layer, e.g., delay performance.

One strategy to maximize (13) subject to (14) is to employ collaborative sensing between the SUs. Here we adopt a simple but practical collaborative scheme: SUs share their final 1-bit decisions by data fusion and use the OR-rule for final decision [4]. The OR-rule states that the primary is reported presence if at lease one SU report its presence. The OR-rule sensing scheme is decentralized, practical and efficient for medium and high SNR, see [11] and [13]. Other cooperative sensing scheme such as LQ-rule, [14] might be optimal but requires the knowledge of the primary signal statistics to obtain the centralized decision threshold.

Here we assume the SUs are in close proximity so that they would experience i.i.d. fading/shadowing and same average SNR. [2] By applying the OR-rule, the probabilities of detection and false alarm are

$$P_D = 1-(1-P_d(t))^N, \text{and} \quad P_F = 1-(1-P_f(t))^N \tag{15}$$

where $P_d(t)$ and $P_f(t)$ are the detection and false alarm probability for a SU to independently sense given the testing threshold t, and N is the number of the collaborative SUs. Although in practise, SUs could be far separate (different SNR) or densely deployed (strong correlation), and therefore with different detection probability $P_d(t)$, we can see (15) as a first step in the modeling of collaborative sensing. Returning to our optimization problem, obviously, the optimal policy for choosing the threshold is to let $\frac{\mu_0}{\mu_0+\mu_1}(1-P_D) = P_{IF}$, which can minimize P_F the most and therefore maximize R_i^E. However, it is not intuitive to answer whether R_i^E increases with N, since as N increases P_D and P_F both increase. We then come to a proposition:

[2]However we do not take into account of the correlation between the receiving signals, which suggests the radios network are not so dense.

Proposition 2: By choosing the optimal threshold policy: $\frac{\mu_0}{\mu_0+\mu_1}(1-P_D) = P_{IF}$, the effective rate R_i^E increases monotonically with the number of collaborative SUs N.

Proof: We simply present the outline of the proof. Fix the detection probability P_D, and we can find the false alarm probability P_F expressed by N. Take the first derivative of P_F with respect of N, and we would find that P_F decreases monotonically with the number N. Therefore, R_i^E increases monotonically with the number of collaborative SUs. ■

As we are confident on the collaborative gains, we move to more detailed scenarios. The one SU sensing probabilities, i.e., $P_d(t)$ and $P_f(t)$, are determined by the detection approaches, e.g., energy detection or feature detection, and wireless environment, e.g., shadowing or fading. Here we assume SUs adopt energy detection experiencing i.i.d. Rayleigh fading. We introduce the formulas for $P_d(t)$, ((4) in [4]) and $P_f(t)$, ((2) in [4]) as

$$\begin{aligned} P_d(t) &= e^{-\frac{t}{2}} \sum_{k=0}^{m-2} \frac{1}{k!}\left(\frac{t}{2}\right)^k + \left(\frac{1+\overline{\gamma}}{\overline{\gamma}}\right)^{m-1} \\ &\quad \times \left(e^{-\frac{t}{2(1+\overline{\gamma})}} - e^{-\frac{t}{2}} \sum_{k=0}^{m-2} \frac{1}{k!}\left(\frac{t\overline{\gamma}}{2(1+\overline{\gamma})}\right)^k\right) \end{aligned} \tag{16}$$

$$P_f(t) = \frac{\Gamma(m, \frac{t}{2})}{\Gamma(m)} \tag{17}$$

where m is the time-bandwidth product assumed to be an integer, $\overline{\gamma}$ is the average SNR under i.i.d. Rayleigh fading and $\Gamma(.)$ and $\Gamma(.,.)$ are complete and incomplete gamma functions [4].

Then we migrate to the upper link layer to analyze the delay performance. We consider a homogeneous case such that the arrival process for each SU i is constant with the same rate λ and the transmission rate $R_i = r$. Here we apply another QoS metric: mean time delay, in (11) The mean time delay for each SU i is same and can be obtained from (11) and (7) as

$$E[D_i] = \frac{R_i^E - \lambda}{\frac{R_i^E}{N\mu_0} - \frac{\lambda}{N\mu_0} - \frac{\lambda}{\mu_1}} \tag{18}$$

where R_i^E is the optimal effective transmission rate obtained in (13), which is also a function of N. We vary the arrival rate λ to look at the mean time delay $E[D_i]$ for each SU. As can be seen in Fig. 4, each SU's delay approaches to infinite when the arrival rate reaches to the maximum allowed arrival rate. In addition, with the increase of SUs ($N = 1, 2, 3, 5$), the delay increases because of the channel sharing. Here we take into account of the sensing errors, therefore the actual delay is larger than that of sensing error-free because of (i) inefficiency in utilizing channel and (ii) constraints on the interference on primary channel. The solid lines in the figures corresponds to independent non-collaborative sensing.

Then we investigate the collaborative gains. As can be seen in Fig. 4, the mean time delay for each SU in collaborative modes (dash lines) outperforms the non-collaborative mode under the same number of SUs. Note for $N = 1$, the delay

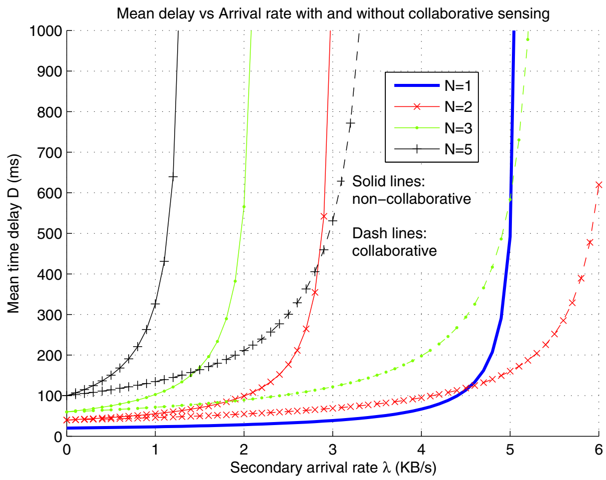

Fig. 4. Mean time delay for one SU vs secondary arrival rate with and without collaborative sensing under $P_{IF} = 0.1$. (Average SNR=10dB, primary occupancy level: $\frac{2}{3}$)

performance is the same. An interesting phenomenon appears when there are two SUs collaborating, even though sharing the channel would reduce each one's service capacity, the delay performance still outperforms to $N = 1$ when the arrival rate is larger than nearly 4.5 KB/S. This is because the two SUs collaborates in sensing could drastically reduce the false alarm probability so as to utilize the spectrum holes more efficiently.

VI. Conclusions

The effective bandwidth concept is applied in Cognitive Radio Networks to investigate the QoS performance of the secondary users. The secondary users adopt the opportunistic spectrum access paradigm with the back-off contention scheme. For the probabilities of the queue-overflow and delay-violation of SUs, the exponential approximation can be obtained analytically. The idle and busy period of the primary channel is modeled here as an two-state ON/OFF Markov Modulated Process. We show theoretically and analytically that the constant arrival process achieves better QoS performance than that of the Poisson bursty arrival process. The accuracy of the exponential approximation is demonstrated by the simulated queue length distribution. Therefore the QoS modeling is applicable for performance analysis.

We then consider the sensing errors in CRN. To maximize the effective transmission rate of SUs subject to required interference to primary channel, we introduce collaborative sensing between SUs. Collaborative gains under the OR-rule are shown to increase with the number of collaborative SUs. We finally show the collaborative gains from the QoS link layer under the i.i.d. Rayleigh fading.

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