Chapter 12
Computation of Performance Parameters in Multi-Service Cognitive Radio Networks

Hongbing Lian
University of Texas at Dallas, USA

Andras Farago
University of Texas at Dallas, USA

ABSTRACT

In this chapter the authors consider a cognitive cellular network that allows secondary (cognitive) users to access the bandwidth that is left over by the primary users. Furthermore, the authors allow multiple traffic classes in the system. The analysis of such a network is complicated by the fact that the secondary users face a randomly changing available capacity to serve their demands. The authors start with the multi-class Call Admission Control (CAC) model for existing Primary Radio Network (PRN). Then the authors propose a multi-class CAC model for Cognitive Radio Network (CRN) with different call blocking and call dropping thresholds for different class of services. The authors build up their analytical models for PRN and CRN based on Markov chain. The PRN works as if there is no interference from CRN. But the CRN needs to sense the status of PRN and to utilize the unused channels left by PRN. So the CRN is dependent on the PRN traffic load. The authors use a multi-dimensional Markov chain to model the CRN status under the condition of certain channels unused by the PRN. The authors can get the stationary distributions over all possible states of PRN and CRN. The Quality of Service (QoS) performance parameters for CRN, such as blocking probability, call dropping probability, and channel utilization can be derived from the obtained stationary distributions. Using it, the authors calculate the QoS performance parameters for multi-service cognitive radio network.

INTRODUCTION

Based on the report of the Federal Communication Commission (FCC, 2003), the current static spectrum policy, which only allows licensed operations on the spectrum for cellular networks, causes severe underutilization of the spectrum. The network using licensed spectrum is called primary radio network (PRN). For example, the mobile cellular network (MCN) is one kind of primary radio network. The users of the primary network are called primary users (PUs). The inefficient usage of the existing spectrum can be improved through opportunistic access to the
licensed bands without interfering with the existing primary users. As next generation networks, the cognitive radio networks (CRNs) are designed to provide the capability to use or share the unused spectrum in an opportunistic manner. The users who use secondary networks, like the cognitive radio networks (CRNs), are secondary users (SUs).

The call admission control (CAC) is an important functionality to ensure the quality of service (QoS). For easier reading, we list the used acronyms in the section of Key Terms and Definitions.

CAC has been investigated intensely for traditional mobile cellular networks (MCN) (Choi et al. 2000) (Kwon et al., 1998) (Xiao et al., 2000). Typical policies in multi-class networks are complete sharing (CS), complete partitioning (CP), threshold, etc. Choi et al. (2000) presented a centralized CAC for mobile cellular network (MCN). Kwon et al. (1998) proposed a distributed CAC. Xiao et al. (2000) gave an optimal CAC solution using semi-Markov decision process (SMDP). All these CAC analyses are for PRNs, like mobile cellular network (MCN). Very little of CAC analysis exists for cognitive radio network (CRN) (Huang et al., 2009; Zhu et al., 2007; Wang et al., 2009). Huang et al. (2009) analyzed a CAC for CRN with simulation for a total of 6 channels. Zhu et al. (2007) analyzed a CAC for CRN with single class primary users and single class secondary users. Wang et al. (2009) analyzed the network selection problem when there are multiple networks with spared spectrum. In this chapter we investigate a call admission control (CAC) scheme for multi-service cognitive radio network (CRN). We adopt a Markov chain model to describe the procedure of the proposed CAC and spectrum handoff strategy. The quality of service (QoS) requirements, such as call blocking probability, call dropping probability, and spectrum utilization are evaluated for each service class. This CAC allows us to control the call blocking probability and the call dropping probability. This CAC scheme has the flexibility to allow the tradeoff between call dropping and call blocking, according to QoS requirements. Our CAC scheme can also adjust priorities for different service classes. We model the CAC scheme with a Markov chain model and obtain the stationary distribution of the number of SUs calls. Then we show how to apply the result in deriving an explicit expression of QoS for each class of SUs calls.

The remainder of the chapter is organized as follows: Section II presents the system model of multi-class CAC for cognitive radio network and the detailed Markov chain model analysis of secondary users (SUs) in stationary state. Section III analyses QoS such as call blocking probability and call dropping probability. Section IV presents numerical and simulation results. Finally, section V concludes the chapter.

**MULTICLASS CAC MODEL FOR COGNITIVE RADIO NETWORK**

Currently, Mobile Cellular Networks (MCNs) are using fixed/licensed spectrum bands. Most of the allocated spectrum bands are observed to be underutilized. All these existing radio networks are called primary radio networks (PRNs). The users that have exclusive license to use certain spectrum bands in PRNs are the primary users (PUs). The (temporarily) unused spectrum bands in PRNs are called “spectrum holes.” Cognitive Radio Network (CRN) is a promising technology that can identify and exploit the spectrum holes. Cognitive Radio Networks are designed to work with primary radio networks (PRNs). The users in CRNs using the spectrum holes left by PRNs are the secondary users (SUs).

**Analysis of PRNs with One Class Service**

The existing PRNs work just like there is no CRN. So there are no hardware or software changes required for PRNs. But CRNs need to work with PRNs, and the CRNs’ performance analysis depends on the traffic statistics of PRNs. Therefore, we need to analyze PRNs first. We can model