Optimal Spectrum Sensing Framework for Cognitive Radio Networks

Won-Yeol Lee, *Student Member, IEEE,* and Ian. F. Akyildiz, *Fellow, IEEE*

***Abstract*—*Spectrum sensing* is the key enabling technology for cognitive radio networks. The main objective of spectrum sensing is to provide more spectrum access opportunities to cognitive radio users without interfering with the operations of the licensed network. Hence, recent research has been focused on the *interference avoidance* problem. Moreover, current radio frequency (RF) front-ends cannot perform sensing and transmission at the same time, which inevitably decreases their transmission opportunities, leading to the so-called *sensing efficiency* problem. In this paper, in order to solve both the interference avoidance and the spectrum efficiency problem, an optimal spectrum sensing framework is developed. More specifically, first a theoretical framework is developed to optimize the sensing parameters in such a way as to maximize the sensing efficiency subject to interference avoidance constraints. Second, in order to exploit multiple spectrum bands, spectrum selection and scheduling methods are proposed where the best spectrum bands for sensing are selected to maximize the sensing capacity. Finally, an adaptive and cooperative spectrum sensing method is proposed where the sensing parameters are optimized adaptively to the number of cooperating users. Simulation results show that the proposed sensing framework can achieve maximum sensing efficiency and opportunities in multi-user/multi-spectrum environments, satisfying interference constraints.**

***Index Terms*—Cognitive radio networks, spectrum sensing, sensing efficiency, interference avoidance, optimization, scheduling, cooperation.**

I. Introduction

TODAY'S wireless networks are characterized by a static spectrum assignment policy. Recently, due to the increase in spectrum demand, however, this policy is faced with the spectrum scarcity at particular spectrum bands. On the contrary, a large portion of the assigned spectrum is still used sporadically leading to under-utilization of the significant amount of spectrum [1]. The limited available spectrum and the inefficiency in spectrum usage make it necessary to develop a new communication paradigm to exploit the existing wireless spectrum opportunistically. Cognitive radio technology is proposed to solve these current spectrum inefficiency problems [2].

A cognitive radio is designed to be aware of and sensitive to the changes in its surrounding, which makes spectrum sensing an important requirement for the realization of cognitive radio networks. *Spectrum sensing* enables unlicensed users, referred to as *cognitive radio (CR) users*, to adapt to the environment by detecting unused spectrum portions without causing interference to the licensed network, referred to as the *primary network*.

The main objective of spectrum sensing is to provide more spectrum access opportunities to CR users without interference to the primary networks. Since cognitive radio (CR) networks are responsible for detecting the transmission of primary networks and avoiding interference to them, CR networks should intelligently sense the primary band to avoid missing the transmission of primary users. Thus, *sensing accuracy* has been considered as the most important factor to determine the performance of CR networks. Hence, recent research has been focused on improving the sensing accuracy for interference avoidance. In [3], three different detection methods are investigated: *matched filter detection*, *energy detection*, and *feature detection*. While the matched filter can perform coherent detection, energy detection is a non-coherent detection method that uses the energy of the received signal to determine the presence of primary signals. Feature detection exploits the inherent periodicity in the received signal to detect primary signals with a particular modulation type. In order to mitigate the multi-path fading and shadowing effects, cooperative detection methods among multiple CR users are proposed in [4], [5]. All these detection methods are based on the transmitter detection to determine if a signal from primary transmitter is locally present in a certain spectrum through the local observations of CR users. Unlike the transmitter detection, a direct receiver detection method considers the location of primary receivers by exploiting the local oscillator leakage power of the primary receiver [6].

Although all these efforts enable CR users to enhance the sensing accuracy, the hardware limitations of CR users introduce a new critical issue on spectrum sensing. Ideally, to avoid interference to the primary users, CR users should monitor the spectrum continuously through the radio frequency (RF) front-end. However, in reality, the RF front-end cannot differentiate between the primary user signals and CR user signals [7]. While feature detection is known to be capable of identifying the modulation types of the primary signal, it requires longer processing time and higher computational complexity [8]. With energy detection, mostly used in the spectrum sensing, CR users are not able to perform the transmission and sensing tasks at the same time. Thus, due to this hardware limitation, CR users necessitate a *periodic sensing* structure where sensing and transmission operations are performed in a periodic manner with separate observation period and transmission period. In this structure, CR users should stop their transmissions during the sensing time to

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prevent false alarms triggered by unintended CR signals.

This periodic sensing structure introduces the following design issues:

- *Interference avoidance:* Interference in CR networks depends on the sensing accuracy, which is determined by the observation time. However, in periodic sensing, CR users cannot sense the spectrum bands during the transmission time, which leads to the increase in interference. Thus, for the interference avoidance, both the observation time and the transmission time need to be considered in the periodic spectrum sensing method.
- *Sensing efficiency:* The main objective of CR networks is efficient spectrum utilization. Thus, the spectrum sensing functionality should provide more transmission opportunities to CR users. However, during the observation period, the transmission of CR users is not allowed, which inevitably decreases the transmission opportunities of CR users, leading to the so-called *sensing efficiency* issue.

As explained above, there is a tradeoff between interference and sensing efficiency. For interference avoidance, the observation time needs to be long enough to achieve sufficient detection accuracy, i.e., longer observation time leads to higher sensing accuracy, and hence to less interference. But as the observation time becomes longer, the transmission time of CR users will be decreased. Conversely, while a longer transmission time enhances the sensing efficiency, it causes higher interference due to the lack of sensing information. Hence, *observation time* and *transmission time* are the sensing parameters that mainly influence both the spectrum efficiency and interference avoidance. Thus, the proper selection of these sensing parameters is the most critical factor influencing the performance of CR networks.

Besides spectrum sensing parameters, there are two more crucial factors to be considered if the spectrum sensing method is applied to multi-spectrum/multi-user networks. Usually, CR users are allowed to exploit multiple spectrum bands. However, practically, CR users do not have enough sensing transceivers to sense all the available spectrum bands. In order to maximize the spectrum access opportunities of CR users subject to the transceiver constraint, a well-defined spectrum selection method is essential.

Furthermore, there exists a high spatial correlation among sensing data detected from different locations in CR networks since neighboring CR users are highly likely to be located in the same transmission range of the primary network. Cooperative sensing is the traditional approach to exploit this spatial correlation in multi-user networks by allowing CR users to exchange their sensing information. In cooperative sensing, the number of cooperating users affects the sensing accuracy, and hence the sensing parameters. Since the number of users varies over time, it is essential for CR networks to adaptively decide the optimal sensing parameters with varying number of users.

As mentioned above, spectrum sensing primarily requires the decision of the proper sensing parameters by considering both spectrum efficiency and interference avoidance. However, in multi-spectrum/multi-user network environments, the spectrum sensing method is required to provide additional functionalities such as spectrum selection and multi-user cooperation. Thus, a unified spectrum sensing framework needs to be developed to consider all possible network environments and define inter-operations of all functionalities.

Hence, in this paper, in order to solve both the interference avoidance and sensing efficiency problems, we develop an optimal sensing framework to maximize spectrum access opportunities considering interference and sensing resource limitations. More specifically, a theoretical framework is developed for the optimization of sensing parameters to maximize the spectrum efficiency subject to interference constraints in a single spectrum band. For multi-spectrum environments, based on the optimal sensing parameters, a novel sensing resource allocation method is developed to maximize the spectrum access opportunities of CR users. Finally, in order to exploit the sensing accuracy gain obtained by the multi-user cooperation, we propose an adaptive and cooperative decision method for the sensing parameters, where the transmission time can be optimized adaptively to the number of users.

The remainder of the paper is organized as follows. The system model used in this paper is presented in Section II. In Section III, we introduce a theoretical framework of the sensing parameter optimization including the detection and the interference models. Then, we describe spectrum selection and resource scheduling for the multi-spectrum sensing in Section IV. In Section V, we investigate how cooperation gain influences the sensing parameter optimization and propose an adaptive and cooperative sensing method to exploit the cooperation gain. Performance evaluation and simulation results are presented in Section VI. Finally, conclusions are presented in Section VII.

II. System Model

A. System Description

The design objective of CR networks is to exploit the best available spectrum bands. To achieve this goal, spectrum sensing needs to consider the requirements on the network architecture, terminal hardware capabilities, and the radio environment as explained below.

1) Network Architecture: In this paper, we assume CR networks have a centralized network entity such as a base-station in infrastructure-based networks. Ad hoc networks are assumed to have a cluster head node. This centralized network entity can communicate with all CR users within its coverage and decide the spectrum availability of its coverage.

There are two main reasons to adopt a centralized network architecture. The first reason is the receiver uncertainty problem. With the transmitter detection, CR networks cannot avoid interference at the nearby primary receivers since the transmitter detection relies only on local observations of CR users and does not consider the location information of the primary receivers [2]. Hence, in order to reduce the receiver uncertainty, CR networks require the base-station[1] to collect sensing information from CR users inside its coverage. The second reason is the limitation in sensing capabilities. All

[1]In the remainder of the paper we will use the term "base-station" to refer to the centralized network entity both in infrastructure-based networks and in ad hoc networks.

CR users have the same sensing cycles not to interfere with sensing operations, which means that CR networks should be synchronized to schedule the spectrum sensing. Thus, CR networks need to have the base-station to synchronize the scheduling.

2) CR User Requirements: Here, CR users are assumed to use energy detection for the spectrum sensing. Furthermore, CR users may have multiple software-defined radio (SDR) transceivers to exploit the multiple spectrum bands over wide frequency ranges by adjusting the operating frequency through software operations. Each transceiver can be used for the purpose of both transmission and sensing.

3) Radio Environment: In CR networks, all available spectrum bands are spread over a wide frequency range, and hence exhibit different characteristics. In this paper, CR networks are assumed to be aware of the following *a priori* spectrum information of primary networks:

- *Operating frequency range:* CR users are aware of the bandwidth and of the frequency range of the primary networks.
- *Minimum signal-to-noise ratio (SNR):* To determine the spectrum availability, CR users need statistical information on the received primary signals. The minimum SNR is the least signal level needed to decode the received signals, depending on the modulation type, channel coding and multiple access methods of primary user networks.
- *Primary user activity:* This is defined as the traffic statistics of the primary networks, which will be explained more in detail in Section II-B.
- *Interference constraint:* Since CR users cannot monitor the spectrum continuously, CR networks do not guarantee interference-free transmissions. Instead, CR networks exploit the interference constraint, which can be defined as either maximum interference level or maximum interference probability that primary networks can tolerate. Although the former is the most suitable for the objective of the opportunistic transmission, the latter is more practical since there is no practical way to measure the amount of the interference at the nearby primary receivers.

B. Primary User Activity Model

Since primary user activity is closely related to the performance of CR networks, the estimation of this activity is a very crucial issue in spectrum sensing. We assume that primary user activity can be modeled as exponentially distributed interarrivals. In this model, the primary user traffic can be modeled as a two state birth-death process with death rate α and birth rate β. An ON (Busy) state represents the period used by primary users and an OFF (Idle) state represents the unused period [9], [10]. Since each user arrival is independent, each transition follows the Poisson arrival process. Thus, the length of ON and OFF periods are exponentially distributed [11].

C. Optimal Spectrum Sensing Framework

In this paper we develop an optimal spectrum sensing framework, which is illustrated in Figure 1. The proposed framework consists of the *optimization of sensing parameters* in a single spectrum band, *spectrum selection and scheduling*, and an *adaptive and cooperative sensing* method.

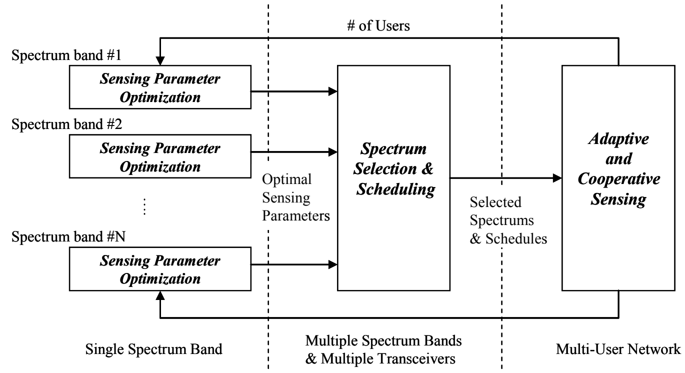

Fig. 1. The proposed optimal spectrum sensing framework.

The detailed scenario for the optimal sensing framework is as follows. According to the radio characteristics, base-stations initially determine the optimal sensing parameters of each spectrum band through the *sensing parameter optimization*. When CR users join the CR networks, they select the best spectrum bands for sensing and configure sensing schedules according to the number of transceivers and the optimized sensing parameters by using spectrum selection and scheduling methods. Then, CR users begin to monitor spectrum bands continuously with the optimized sensing schedule and report sensing results to the base-station. Using these sensing results, the base-station determines the spectrum availability. If the base-station detects any changes which affect the sensing performance, sensing parameters need to be re-optimized and announced to its CR users through the *adaptive and cooperative sensing*.

III. Sensing Parameter Optimization in a Single Spectrum Band

In the preceding discussions, we defined the *a priori* information for spectrum sensing and introduced the optimal sensing framework consisting of three functionalities, namely *sensing parameter optimization*, *spectrum selection and scheduling* for multiple spectrum bands, and *adaptive and cooperative sensing* in multi-user networks. In this section, we first propose a sensing parameter optimization method to maximize the spectrum efficiency subject to the interference constraint.

A. Problem Definition

Consider a typical sensing scenario in which a single CR user monitors a single spectrum band. The CR user alternately senses the spectrum and transmits data with observation time t_s and transmission time T. To determine these sensing parameters accurately, we need to consider the interference constraint and the sensing efficiency at the same time. Therefore, we introduce the following definitions:

Definition 1: The *interference ratio* T_I is the expected fraction of the ON state (i.e., the transmission time of primary networks) interrupted by the transmission of CR users, which will be derived in Eq. (13).

Definition 2: The *lost spectrum opportunity ratio* T_L is the expected fraction of the OFF state (i.e, idle time) undetected by CR users, which will be derived in Eq. (14).

Definition 3: The *maximum outage ratio* T_P is the maximum fraction of interference that primary networks can tolerate.

Definition 4: The *sensing efficiency* η is the ratio of the transmission time over the entire sensing cycle, defined as follows:

$$\eta = \frac{T}{T + t_s} \tag{1}$$

The objective of spectrum sensing is to achieve accurate detection probability as well as high sensing efficiency. Since both metrics are related to the sensing parameters T and t_s, the sensing parameter decision can be expressed as the optimization problem to maximize the spectrum efficiency satisfying interference constraint T_P as follows:

$$\begin{aligned} &\text{Find: } T^*, t_s^* \\ &\text{Maximize: } \eta = \frac{T}{T+t_s} \\ &\text{Subject to: } T_I \leq T_P \end{aligned} \tag{2}$$

where t_s^*,T^* are optimal observation and transmission times, respectively.

In the following subsections, we first explain a maximum a posteriori (MAP) based energy detection model, and then we propose an analytical interference model. Finally, we show how to optimize sensing parameters based on the MAP based energy detector and the interference model.

B. Maximum A Posteriori (MAP) Energy Detection for Spectrum Sensing

Due to the interference constraints in CR networks, spectrum sensing method needs to develop a more accurate detection scheme. Although a maximum a posteriori (MAP) detector is known to be optimal [12], a maximum likelihood (ML) detection has been widely used for the energy detection without considering the probabilities of ON and OFF states [5], [13], [9]. In this paper, we propose the MAP-based energy detection and its decision criterion based on the primary user activities.

When CR users observe the spectrum to detect the primary user activity, the received signal $r(t)$ takes the following form [14]:

$$r(t) = \begin{cases} n(t) & H_0 \\ s(t) + n(t) & H_1 \end{cases} \tag{3}$$

where H_0 represents the hypothesis corresponding to “no signal transmitted”, and H_1 to “signal transmitted”. $s(t)$ is the signal waveform, and $n(t)$ is a zero-mean additive white Gaussian noise (AWGN).

Assume the spectrum has bandwidth W and the primary user activities with death rate α and birth rate β. From the primary user activity model, we can estimate the *a posteriori* probabilities as follows [15]:

$$\begin{aligned} P_{on} &= \frac{\beta}{\alpha+\beta} \\ P_{off} &= \frac{\alpha}{\alpha+\beta} \end{aligned} \tag{4}$$

where P_{on} is the probability of the period used by primary users and P_{off} is the probability of the idle period. From the definition of MAP detection, the detection probability P_d and false alarm probability P_f can be expressed as follows:

$$P_d(\lambda) = Pr[Y > \lambda | H_1] P_{on} = \bar{P}_d \cdot P_{on} \tag{5}$$

$$P_f(\lambda) = Pr[Y > \lambda | H_0] P_{off} = \bar{P}_f \cdot P_{off} \tag{6}$$

where λ is a decision threshold of MAP detection.

Generally, the decision threshold, λ can be determined by the minimum probability of error decision rule as $f(\lambda|H_1)P_{on} = f(\lambda|H_0)P_{off}$ where $f(y|H_1)$ and $f(y|H_0)$ are probability density functions of the received signal through the occupied spectrum and the idle spectrum, respectively. This method minimizes the total error probabilities including false alarm and miss detection. However, in this method, sometimes one of the error probabilities may be greater than the other. In [9], to achieve the best tradeoff between false alarm and detection error, this decision rule is dynamically exploited by considering the interference constraint which is assumed to be equal to the detection error probability. However, in reality, the false alarm probability also affects the interference, which will be explained in Section III-C. Furthermore, in spectrum sensing, the detection of opportunities is as much important as that of the primary signals. Hence, instead of minimizing the total error probability, in this paper, we emphasize the balance of both error probabilities as follows:

$$P_{on} - P_d(\lambda) = P_f(\lambda) \tag{7}$$

This method enables balancing between the interference T_I and the lost spectrum opportunity T_L caused by the detection errors and the false alarms.

Based on the MAP detection model explained above, we derive the detection and false alarm probabilities of energy detection. In order to measure the energy of the received signal, the output signal of bandpass filter with bandwidth W is squared and integrated over the observation interval t_s. Finally, the output of the integrator, Y, is compared with a threshold, λ, to decide whether a licensed user is present or not. The output of the integrator in the energy detector is known as the Chi-square distribution [14]. However, if the number of samples is large, we can use the central limit theorem to approximate the Chi-square distribution as Gaussian distribution [13].

$$Y \sim \begin{cases} \mathcal{N}(n{\sigma_n}^2, 2n{\sigma_n}^4), & H_0 \\ \mathcal{N}(n({\sigma_n}^2 + {\sigma_s}^2), 2n({\sigma_n}^2 + {\sigma_s}^2)^2), & H_1 \end{cases} \tag{8}$$

where n is the number of samples, ${\sigma_n}^2$ is the variance of the noise, and ${\sigma_s}^2$ is the variance of the received signal $s(t)$. According to the Nyquist sampling theorem, the minimum sampling rate should be $2W$. Hence n can be represented as $2t_sW$ where t_s is the observation time.

From Eq. (5), (6), and (8), P_f and P_d in MAP-based energy detection can be derived in terms of the Q function as follows:

$$P_f(W, t_s, \alpha, \beta) = \frac{\alpha}{\alpha+\beta} \cdot Q(\frac{\lambda - 2t_s W {\sigma_n}^2}{\sqrt{4t_s W {\sigma_n}^4}}) \quad (9)$$

$$P_d(W, t_s, \alpha, \beta) = \frac{\beta}{\alpha+\beta} \cdot Q(\frac{\lambda - 2t_s W ({\sigma_s}^2 + {\sigma_n}^2)}{\sqrt{4t_s W ({\sigma_s}^2 + {\sigma_n}^2)^2}}) \quad (10)$$

From Eq. (9) and (10), we can see that each spectrum band has different detection and false alarm probabilities according to the spectrum information, α, β, and W, as well as the observation time t_s.

The decision threshold λ can be obtained by means of numerical methods. However, since λ is independent of the observation time t_s, it is not required to find optimal sensing parameters, T^* and t_s^*, which is explained in Appendix B.

C. Analytical Model for Interference

In order to optimize sensing parameters satisfying the interference constraint, we need to specify the relation between the interference ratio T_I and sensing parameters, as explained in Section III-A. Hence, we propose an analytical interference model as a function of primary user activities and detection statistics derived in Section III-B.

In periodic sensing, interference can be expected to occur in the following cases:

- *Interference on busy state sensing,* I_{on}*:* In this case, the spectrum band is busy, but the CR user does not detect the primary user signals and begins to transmit. As a result, interference can occur during the transmission period T, as shown in Figure 2(a).
- *Interference on idle state sensing,* I_{off}*:* Even though the spectrum band is idle and CR users detect it correctly, there still exists the possibility that a primary user activity may appear during the transmission period T, as shown in Figure 2(b).

As shown in Figure 2(a), the interference I_{on} has two different patterns according to the transmission time *T*. The left figure depicts the interference over the entire transmission period *T*. The right figure describes the interference in case there are one or more changes in primary user activities during *T*. From the primary user activity model explained in Section II-B, the probability that the spectrum band is busy during the entire transmission time *T*, can be obtained as $e^{-\alpha T}$, and the probability with one or more transition of primary user activities during T is $1 - e^{-\alpha T}$.

If *T* is relatively short, the spectrum state does not change during the transmission time *T*. Thus, the interference is highly likely to persist over the entire transmission period with probability $e^{-\alpha T}$, as shown in the left column of Figure 2(a). However, if *T* is long enough, busy and idle states occur alternately during *T* and hence, interference converges to $P_{on} \cdot T$ with probability $1 - e^{-\alpha T}$, as shown in the right column of Figure 2(a). Thus, the expected interference on the busy state sensing E[I_{on}] during the transmission time *T*, can be expressed as follows:

$$\begin{aligned} E[I_{on}] &= (P_{on} - P_d)(e^{-\alpha T} T + (1 - e^{-\alpha T}) P_{on} T) \\ &= P_{off} \bar{P}_f (\frac{\alpha}{\alpha+\beta} T e^{-\alpha T} + \frac{\beta}{\alpha+\beta} T) \end{aligned} \quad (11)$$

Similarly, in case of interference in the idle state, I_{off}, the interference only occurs when one or more primary user activities occur during the transmission time, which converges approximately to $P_{on} \cdot T$ with the probability $1 - e^{-\beta T}$, as shown in Figure 2 (b).

$$\begin{aligned} E[I_{off}] &= (P_{off} - P_f)(e^{-\beta T} \cdot 0 + (1 - e^{-\beta T}) P_{on} T) \\ &= P_{off}(1 - \bar{P}_f)(1 - e^{-\beta T}) \frac{\beta}{\alpha+\beta} T \end{aligned} \quad (12)$$

While the proposed models provide a close approximation in the expected interference over an entire transmission time range, they may show a finite approximation error when the transmission time T is shorter compared to the average busy time $1/\alpha$ or the average idle time $1/\beta$, which is the more realistic assumption in CR networks. For example, if $\alpha > \beta$ and $T < 1/\beta$, the interference in the idle state will be much greater than E[I_{off}] given in Eq. (12) since a higher primary user activity α is a more dominant factor in determining interference in the above short transmission time. This approximation error can be mitigated as the average interference free period, i.e., idle time in Figure 2(b), approaches the average busy time 1/α. As a result, the exponents α and β in Eq. (11) and (12) can be replaced with $\mu = \max(\alpha, \beta)$. By combining E[$I_{\text{on}}$] and E[$I_{\text{off}}$], we obtain the expected interference ratio T_I as follows:

$$\begin{aligned} T_I &= \frac{E[I_{on}] + E[I_{off}]}{T \cdot P_{on}} \\ &= \frac{\alpha}{\beta}[e^{-\mu T} \bar{P}_f + (1 - e^{-\mu T}) \frac{\beta}{\alpha+\beta}] \end{aligned} \quad (13)$$

In Eq. (13), the range of T_I is determined as $\frac{P_{off}}{P_{on}} \bar{P}_f \le T_I \le P_{off}$. When the interference limit T_P is greater than P_{off}, this spectrum band always satisfies the interference limit and can be used for CR transmission without any coordination of the sensing parameters. On the contrary, when the T_P is less than $\frac{P_{off}}{P_{on}} \bar{P}_f$, this spectrum band cannot be used since the interference constraint is always violated.

This model shows another advantage in balancing the interference and the lost spectrum opportunity. Using the proposed interference model, the expected lost spectrum opportunity T_L can be obtained as follows:

$$T_L = \frac{\beta}{\alpha}[e^{-\mu T} \bar{P}_f + (1 - e^{-\mu T}) \frac{\alpha}{\alpha+\beta}] \quad (14)$$

More details are given in Appendix A.

Since T_I and T_L have the duality characteristics of α and β, the interference and the lost spectrum opportunity can be balanced. From Eq. (14), we can see that the range of T_L is $\frac{P_{on}}{P_{off}} \bar{P}_f \le T_L \le P_{on}$, which shows a similar trend to that of T_I. Only the primary user activity factors can determine the difference.

D. Sensing Parameter Optimization

In this section, based on the proposed MAP-based energy detection and interference model, we show how to solve the sensing parameter optimization problem defined in the beginning of this section.

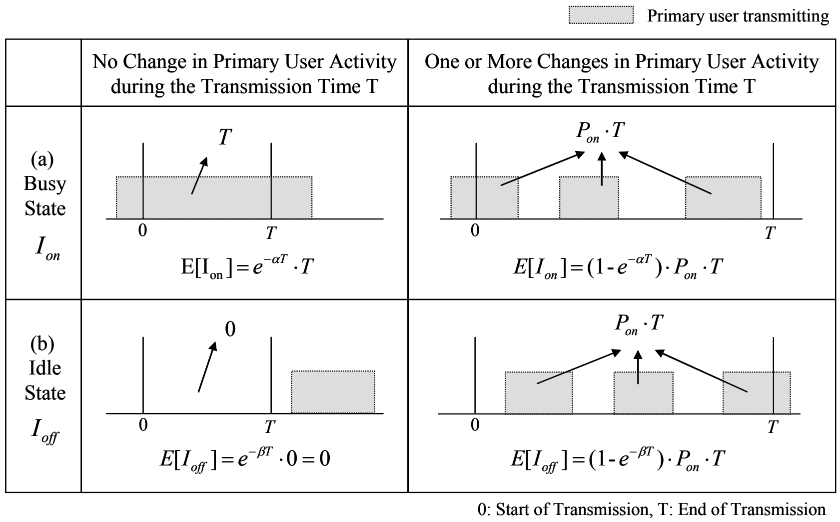

Fig. 2. Interference model in busy state and idle state sensings.

1) Observation Time: In order to solve the optimization problem, we first specify the relation between the false alarm probability $\bar{P}_f$ and the observation time t_s. Through the calculations given in Appendix B, t_s can be represented as follows:

$$t_s = \frac{1}{W \cdot \gamma^2}[Q^{-1}(\bar{P}_f) + (\gamma+1)Q^{-1}(\frac{P_{off}\bar{P}_f}{P_{on}})]^2 \tag{15}$$

where W is the bandwidth of the spectrum band and $\gamma = {\sigma_r}^2/{\sigma_n}^2$ represents the signal-to-noise ratio (SNR).

Since this function is the sum of two different inverse-Q functions, it is obvious that this is a monotonically decreasing function, as depicted in Figure 3.

2) Operating Region for Transmission Time: From the Eqs. (2) and (13), the transmission time T can have the following operating region:

$$\begin{aligned}\bar{P}_f &< \frac{\frac{T_P \cdot P_{on}}{P_{off}} - P_{on}(1-e^{-\mu T})}{e^{-\mu T}} \\ &= P_{on} - P_{on}(1 - \frac{T_P}{P_{off}})e^{\mu T} = \bar{P}_f(T)\end{aligned} \tag{16}$$

where $\bar{P}_f(T)$ is the boundary function of the operating region.

Since T_P is less than P_{off} as shown in Section III-C, $\bar{P}_f(T)$ is monotonically decreasing. In addition, $\bar{P}_f$ is bounded by $min(0.5, 0.5 \cdot \frac{T_{\text{on}}}{T_{\text{off}}})$ since the false alarm and detection error probabilities are assumed to be the same. Furthermore, from Eq. (16), we can see that the maximum *T* is bounded by $-\frac{1}{\mu} \cdot log(1 - \frac{T_P}{P_{\text{off}}})$, which means that if *T* is greater than this value, this spectrum band cannot satisfy the interference constraint T_P, regardless of $\bar{P}_f$.

Figure 3 shows the operating region given in Eq. (16) and the inverse function of Eq. (15), $\bar{P}_f(t_s)$. The operating region, which is illustrated in gray in Figure 3, is the area of $\bar{P}_f$ and T where the interference constraint T_P is always satisfied. The operating region and $\bar{P}_f(t_s)$ are used in determining the optimal sensing parameters T^* and t_s^*, which will be explained in the next subsection.

3) Optimization Procedure: The optimization problem defined in the beginning of this section is not easy to be solved numerically since the objective function and the constraints are combined with the false alarm probability $\bar{P}_f$. Instead, we introduce an iterative method to exploit $\bar{P}_f(t_s)$, the inverse function of Eq. (15) and $\bar{P}_f(T)$ given in Eq. (16).

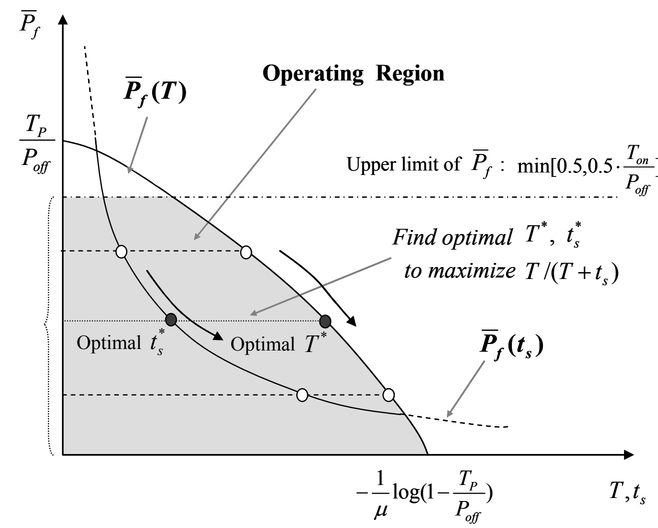

Fig. 3. The operating region of optimal transmission and observation times.

In Figure 3, we show how to find the optimized parameters. As shown in Figure 3, T and t_s have the same false alarm probability $\bar{P}_f$. Furthermore T, t_s and $\bar{P}_f$ should be placed inside the operating region in order to satisfy the interference constraints. Thus, this optimization can be simplified to the problem to find an optimal false alarm probability $\bar{P}_f$ to maximize the sensing efficiency, which can be easily obtained through an iterative numerical method. In this method, first, $\bar{P}_f$ is calculated according to the T using the boundary function $\bar{P}_f(T)$. According to the $\bar{P}_f$, t_s is obtained from Eq. (15), and then the spectrum efficiency is calculated using T and t_s. As depicted in Figure 3, by searching all possible transmission times T within the operating region, we can obtain an optimal $\bar{P}_f$ which provides a maximum sensing efficiency.

Figure 4 depicts the results of the numerical analysis on spectrum efficiency and sensing parameters where we can see that there exist optimal sensing parameters to maximize

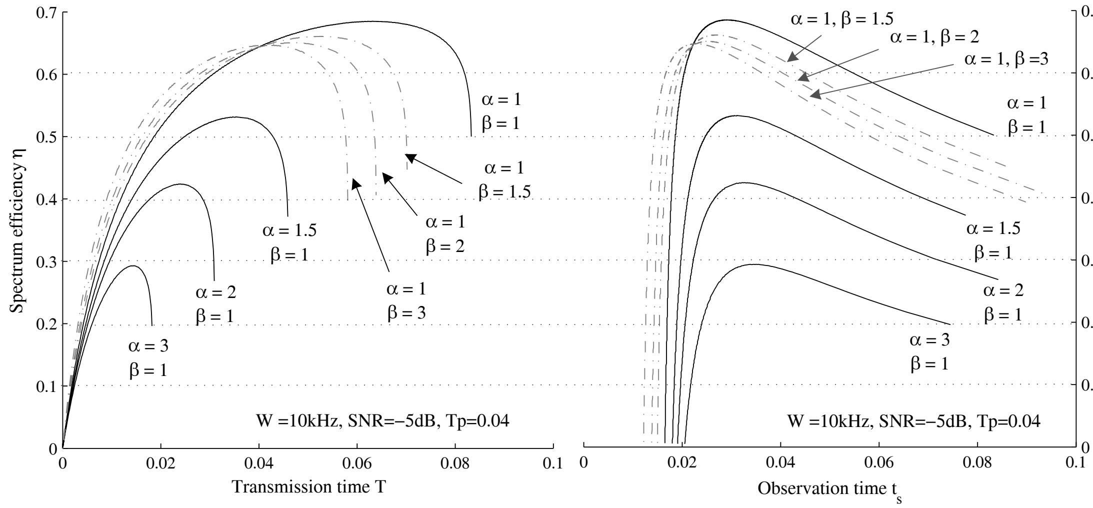

Fig. 4. The relation between spectrum efficiency and sensing parameters (transmission and observation times).

sensing efficiency. Furthermore, as shown in Fig 4, optimal sensing parameters and sensing efficiency are more sensitive to the changes of α than of β.

In this section, we proposed an MAP-energy detection and an analytical interference model for the periodic spectrum sensing. Then we derived optimal observation and transmission times, which maximizes the sensing efficiency under the interference constraint. In order to extend this optimization method to multi-spectrum/multi-user network environment, additional functionalities need to be developed, which will be explained in the following sections.

IV. Spectrum Selection and Scheduling for Spectrum Sensing on Multiple Spectrum Bands

In the previous section, we explained how to find the optimized parameters for single-band/single-user sensing. However, in reality, in order to mitigate the fluctuating nature of the opportunistic spectrum access, CR users are supposed to exploit multiple available spectrum bands showing different characteristics. To handle multiple spectrum bands, two different types of sensing strategies can be exploited: wideband sensing and sequential sensing. In *wideband sensing*, the sensing transceiver can sense multiple spectrum bands over a wide frequency range at a time. Although wideband sensing method requires only a single sensing transceiver, it uses identical observation and transmission times over multiple spectrum bands without considering their different characteristics, which cause the violation of interference limit. Furthermore, it requires a high-speed analog-to-digital (A/D) converter [3]. On the contrary, in *sequential sensing*, the sensing transceiver monitors only a single spectrum band at a time, which enables CR users to use sensing parameters adaptively to the characteristics of each spectrum band. However, CR users may not have enough transceivers to exploit all available spectrum bands, which leads to the spectrum selection and scheduling problems in multi-spectrum CR networks

Here we assume all CR users use sequential sensing. In the following subsections, we explain how to extend our proposed optimal sensing method to multiple spectrum bands.

A. Problem Definition

As explained in Section III, multiple spectrum bands have different optimal observation and transmission times according to their characteristics. If CR users are required to exploit all available spectrum bands, the number of sensing transceivers can be expressed as $\sum_{i\in A}\frac{t^*_{s,i}}{T^*_i+t^*_{s,i}}$ where A is a set of all available spectrum bands and $t^*_{s,i}$ and T^*_i represent optimal observation and transmission times of spectrum band i. However, since CR users generally have a finite number of transceivers, it is not practical to monitor all available spectrum bands. Hence, instead of exhaustive sensing, selective sensing is more feasible in CR networks. To select the spectrum bands properly under the sensing resource constraint, we introduce a new notion, *opportunistic sensing capacity* as follows:

Definition 5: The *opportunistic sensing capacity* $C^{\mathrm{op}}_{o,i}$ represents the expected transmission capacity of spectrum band i that CR users can achieve, which can be defined as follows:

$$C^{\mathrm{op}}_i = \eta_i \cdot \rho_i \cdot W_i \cdot P_{\mathit{off},i} \tag{17}$$

where η_i, W_i, and $P_{\mathit{off},i}$ represent the sensing efficiency, the bandwidth, and the idle state probability of the spectrum band i. ρ_i is the spectral efficiency of the spectrum band i (bit/sec/Hz) depending on the modulation and channel coding schemes. $\rho_i \cdot W_i$ represents how much transmission rate this spectrum band can support. In order to reflect the dynamic nature of spectrum bands in CR networks, $C^{\mathrm{op}}_{o,i}$ also consider the spectrum efficiency and the probability of the idle state.

Another practical sensing problem in multi-spectrum networks is that each spectrum band has different optimized sensing cycles $T^*_i + t^*_{s,i}$. Once spectrum bands are selected, the sensing transceiver is required to be scheduled for spectrum sensing. However, heterogeneous sensing cycles of each spectrum cause the collision of the sensing operations, which degrades the transmission capacity in CR networks. Thus, a novel sensing scheduling method needs to be developed to reduce the collisions of the sensing schedules.

B. Spectrum Selection for Selective Sensing

Since the number of sensing transceivers is finite, CR users require a selective sensing method to exploit multiple available spectrum bands, which show different capacities according to the spectrum characteristics. In order to consider the dynamic and heterogenous nature of underlying spectrum bands in CR networks, we propose a spectrum selection method to maximize *opportunistic sensing capacity* of CR networks, which can be expressed as the following optimization problem:

$$\begin{aligned} \text{Maximize: } & \sum_{i \in A} \eta_i \cdot \rho_i \cdot W_i \cdot P_{\mathit{off},i} \cdot x_i \\ \text{Subject to: } & \sum_{i \in A} \frac{t^*_{s,i}}{T^*_i + t^*_{s,i}} \cdot x_i \leq N_{sen} \end{aligned} \tag{18}$$

where A is a set of all available spectrum bands, N_{sen} represents the maximum number of transceivers for spectrum sensing, and $x_i \in \{0, 1\}$ represents the spectrum selection parameter. This optimization can be easily solved by the binary integer programming [16]. Once spectrum bands are selected, the transceiver is required to be scheduled for spectrum sensing, which is explained in the following subsection.

C. Sensing Scheduling for Multiple Spectrum Bands

The proposed spectrum selection method shows an ideal and theoretical sensing capacity bound of the sensing transceiver. However, in reality, it is impossible to assign multiple sensing tasks with different periods into one resource schedule without collision. If the sensing cycle is fixed over all multiple heterogeneous spectrum bands, the sensing efficiency will be surely degraded. Thus, in this section, we propose a practical approach for sensing scheduling on multiple spectrum bands. While traditional scheduling methods in wireless networks have explored how multiple users can access the wireless channel considering fairness and channel throughput, the proposed scheduling is focusing on how the sensing transceiver is scheduled to sense multiple spectrum bands satisfying optimal sensing cycles of each spectrum. In this paper, we assume the CR networks adopt a time-slotted sensing scheduling where a time slot is used as the minimum time unit of the observation time and the transmission time.

If multiple spectrum bands compete for the sensing slot at the same time, CR users determine one of the spectrum bands through the proposed sensing scheduling based on the *opportunity cost*. The *opportunity cost* is defined as the sum of the expected opportunistic sensing capacities of the spectrum bands to be blocked if one of the competing spectrum bands is selected. In the proposed method, the current time slot is assigned to the one of the competing spectrum bands to minimize the opportunity cost, referred to as the *least cost first serve (LCFS)* scheduling algorithm. The following equation explains how to assign the sensing slot to the best spectrum band j^* in the LCFS scheduling.

$$j^* = \arg\min_{j \in B} \left(t^*_{s,j} \sum_{i \in B, i \neq j} \rho_i W_i P_{\mathit{off},i} + \sum_{i \in B, i \neq j} t^{\mathrm{b}}_i \rho_i W_i P_{\mathit{off},i} \right) \tag{19}$$

where B is a set of competing spectrum bands and t^{b}_i is the blocked time of the spectrum band i. ρ_i, W_i, and $P_{\mathit{off},i}$ represent the spectral efficiency, the bandwidth, and the idle state probability of the spectrum band i, respectively. The first term represents the opportunity cost of spectrum band j. The second term represents the sum of the opportunistic capacities of the blocked spectrum bands during the past blocked time t^{b}_i. For the fair scheduling among competing spectrum bands, the proposed method considers not only the opportunity cost for the future sensing time but also the opportunistic capacity blocked in the past. Through these procedures, the LCFS algorithm assigns the current time slot to the spectrum band such a way as to minimize the sum of the opportunity cost and the blocked opportunistic capacity of other spectrum bands.

The detailed procedure for sensing scheduling is as follows. When a sensing cycle starts, CR users check the state of the current time slot. If the current time slot is already occupied by the other spectrum band, all competing bands go to the *blocked period*. When the time slot is available, CR users assign the current time slot to one of the competing spectrum bands. The rest of the spectrum bands should block their sensing operations to the next available time slot. When the *observation period* ends after the observation time t_s, the spectrum band goes to the *transmission period* and the current time slot is available to the other spectrum bands.

V. Adaptive and Cooperative Spectrum Sensing in Multiuser Networks

The most important and unsolved issue in spectrum sensing is a receiver uncertainty problem [2]. With the local observation, CR users cannot avoid the interference to the primary receivers due to lack of location information. Generally, a cooperative sensing scheme method is known to be more effective in mitigating the receiver uncertainty problem. In this section, we extend our proposed optimal sensing method to the multi-user environment and propose an adaptive and cooperative sensing, especially focusing on the functionalities of the base-station.

A. Problem Definition

Assume CR networks have a base-station. CR users sense spectrum bands at each location and report the sensing results to the base-station periodically. Then, the base-station decides the availability of the spectrum bands inside its coverage and allocates the available spectrum bands to the users. These sensing data have a spatial correlation which can be used to enhance the spectrum sensing accuracy through cooperation.

However, in order to exploit this cooperative gain, the base-station should consider the following issues. First, since the cooperative scheme can enhance the detection probability, the expected interference ratio is less than the originally estimated in the sensing parameter optimization, which means the optimal parameters are no longer valid. Second, the cooperation gain has the time-varying characteristic according to the number of users involved in the cooperation. Furthermore, the number of primary user activity regions will affect the cooperative gain. Considering all of the above issues, we propose an adaptive and cooperative sensing framework in the following subsections.

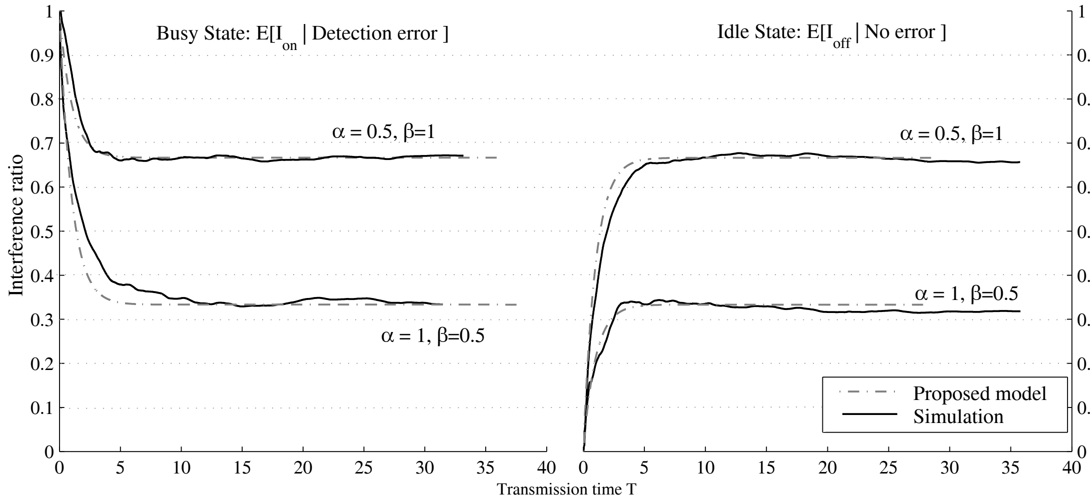

Fig. 5. Comparison between the proposed interference model and simulation results.

B. Availability Decision using Cooperative Gain

In traditional cooperative sensing, the spectrum band is decided to be available only if no primary user activity is detected out of all sensing data. Even if only one primary user activity is detected, CR users cannot use this spectrum band [5]. From this detection criterion, the cooperation gain of N sensing data is obtained by $\bar{P}_d^c = 1 - (1 - \bar{P}_d)^N$ where $\bar{P}_d^c$ and $\bar{P}_f^c$ are the cooperative detection and false alarm probabilities, respectively. While this decision strategy surely increases the detection probability, it increases the lost spectrum opportunities due to the increase in cooperative false alarm probability, $\bar{P}_f^c = 1 - (1 - \bar{P}_f)^N$.

Thus, we define a new cooperative gain for the decision of the spectrum availability. The number of detections follows the binomial distribution $\mathcal{B}(N, \bar{P}_d)$. Similarly, the number of false alarms also shows the binomial distribution $\mathcal{B}(N, \bar{P}_f)$. Thus, in order to determine the detection threshold N_{th} to balance between the detection error probability and the false alarm probability, we exploit the same strategy as explained in Section III-B.

$$P_{on}(1 - P_{bd}(N_{th})) = P_{off} \cdot P_{bf}(N_{th}) \tag{20}$$

where P_{bd} is the binomial cumulative distribution function (CDF) of the number of detections, and P_{bf} is the binomial CDF of the number of false alarms.

In order to use this cooperative scheme, all CR users should be located in the same primary user activity region. In other words, the spatial correlation of primary user activities at each location affects the performance of the cooperative sensing significantly. If there are multiple primary user activities, the base-station should calculate cooperative detection probability of each region separately. Then the cooperation gain is obtained as follows:

$$\bar{P}_d^c = 1 - \prod_{i=1}^{N_{corr}} (1 - \bar{P}_{d,i}^c) \tag{21}$$

$$\bar{P}_f^c = 1 - \prod_{i=1}^{N_{corr}} (1 - \bar{P}_{f,i}^c) \tag{22}$$

where N_{corr} is the number of the primary user activity regions in the CR network coverage. $\bar{P}_{d,i}^c$ and $\bar{P}_{f,i}^c$ represent the cooperative detection and false alarm probabilities of the primary user activity region i, respectively. In this case, only if none of the regions detects the primary signals, the spectrum is determined to be available, and hence the detection error probability and the false alarm probability are not the same any longer. For this reason, while the detection probability increases, the lost spectrum opportunity T_L increases due to the increase in the false alarm probability, which shows the same pattern to the traditional cooperation approach explained in Section V-B.

C. Sensing Parameter Adaptation

Through the proposed cooperative detection method explained above, both detection and false alarm probabilities can be improved as follows:

$$P_d^c = P_{on} \bar{P}_d^c = P_{on} \sum_{i=N_{th}}^{N} \binom{N}{i} \bar{P}_d{}^i (1 - \bar{P}_d)^{N-i} \tag{23}$$

$$P_f^c = P_{off} \bar{P}_f^c = P_{off} \sum_{i=N_{th}}^{N} \binom{N}{i} \bar{P}_f{}^i (1 - \bar{P}_f)^{N-i} \tag{24}$$

Since both detection and false alarm probabilities change, the optimal sensing parameters need to be re-optimized. However, the optimal observation time t_s^* is already considered for the false alarm probability of each user, which is used for the calculation of the cooperation gain. Hence, the cooperation gain only affects the transmission time T^*, which needs to be re-optimized using the Eq. (16). Usually the number of sensing data varies over time due to the user mobility and user transmission. Whenever it changes, the base-station re-optimizes the transmission time, which improves the transceiver utilization maintaining the same interference level as the non-cooperative sensing. Since the proposed method exploits the cooperation gain to reduce the sensing resources of the spectrum band, it enables CR users to have more spectrum access opportunities.

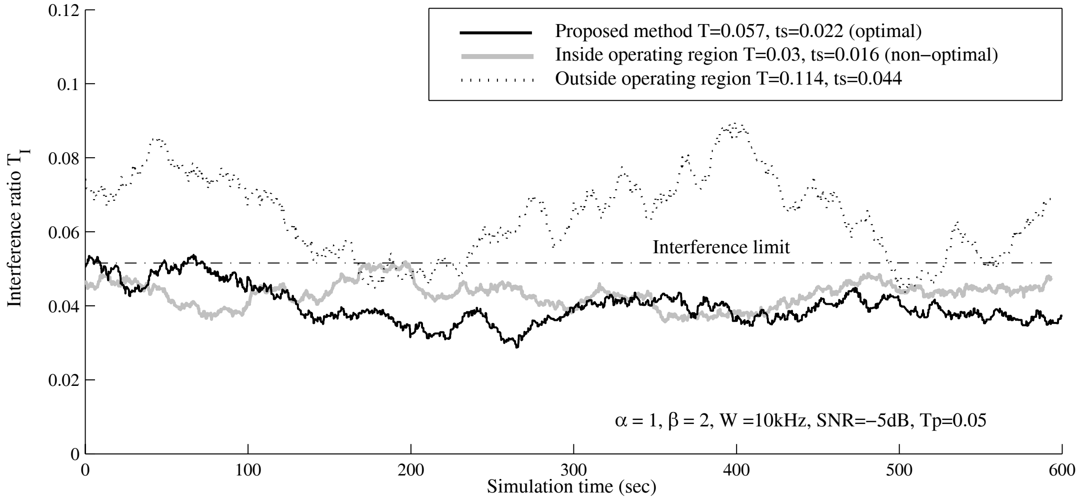

Fig. 6. The simulation results of the proposed optimal sensing in a single band: interference T_I.

TABLE I
SPECTRUM INFORMATION FOR SIMULATION.

Parameter	Low Opportunity										High Opportunity									
	Low Activity					High Activity					Low Activity					High Activity				
Spectrum #	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
α	0.2	0.3	0.4	0.3	0.8	1.5	2	1	1	2	0.2	0.8	0.7	1	0.3	4	3	2	3	5
β	0.4	0.6	0.5	0.9	1	4	5	2	5	3	0.1	0.1	0.2	0.7	0.2	1.5	2	1	3	2
SNR(dB)	-20	-15	-10	-5	0	-20	-10	-5	0	-15	-20	-10	-5	0	-15	-20	-10	-5	0	-15
BW(kHz)	250	100	70	40	10	250	100	70	40	10	250	100	70	40	10	250	70	100	40	10
$T_P(\%)$	0.03	0.05	0.04	0.02	0.01	0.05	0.01	0.04	0.02	0.03	0.05	0.01	0.03	0.02	0.04	0.05	0.04	0.01	0.03	0.02

VI. PERFORMANCE EVALUATION

In the previous sections, we developed the sensing parameter optimization scheme, spectrum selection, sensing scheduling, and the adaptive and cooperative sensing method. In this section, we present both analytical and simulation results on the performance of our proposed sensing framework.

A. Sensing Parameter Optimization in a Single Band

In order to evaluate the performance of the proposed optimal sensing algorithm explained in Section III, we implement the primary traffic generator based on the ON-OFF Poisson arrival model and measure the expected interference ratio T_I on various sensing parameters.

First, in Figure 5, our proposed interference model, given in Section III, is compared to the interference measurement through the simulations. In Figure 5, we can see the proposed interference model is valid for both busy and idle states.

Based on the optimal sensing parameters obtained from Section III, we simulate the periodic sensing procedure on the randomly generated primary user traffic. To demonstrate the optimality of the selected sensing parameters. we compare the optimal sensing parameters with two other non-optimal sensing parameter pairs selected from the operating region and the non-operating region, respectively. Figure 6 shows the moving average of the interference T_I measured in the simulations. While both optimal and non-optimal sensing parameters from the operating region satisfy the interference limit, optimal sensing parameters show a better sensing efficiency. In case of the sensing parameters obtained from the non-operating region, while sensing efficiency is the same as that of optimal parameters, they violate the interference constraint. In case of the sensing parameters obtained from the non-operating region, while sensing efficiency is the same as that of optimal parameters, they violate the interference constraint.

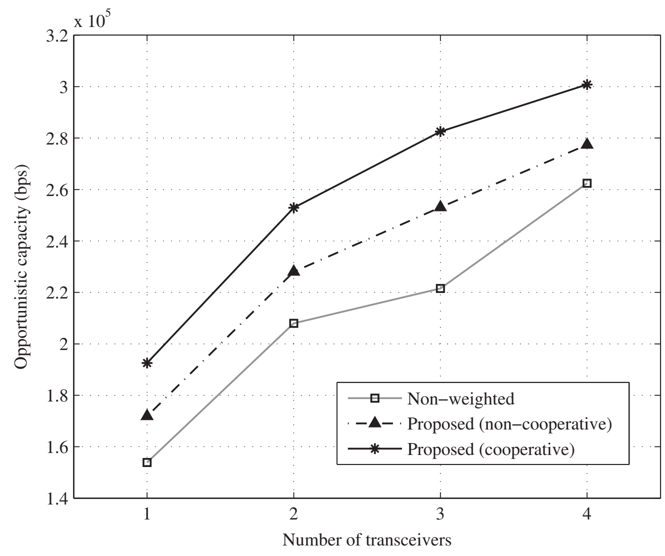

Fig. 7. The opportunistic capacity of the proposed spectrum selection.

B. Resource Allocation on Multiple Spectrum Band

For simulations of the spectrum sensing on the multiple spectrum bands, we first define on scenario of the spectrum

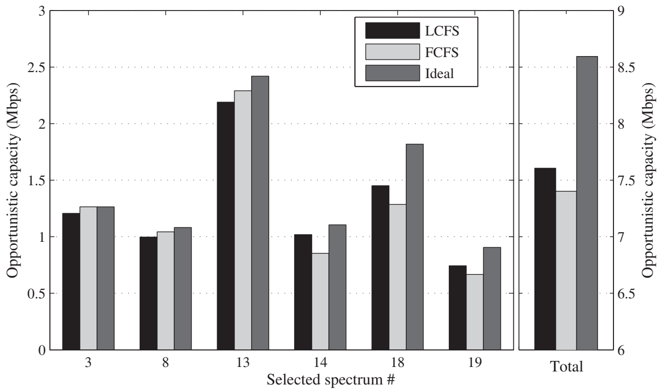

Fig. 8. The performance of the proposed sensing scheduling.

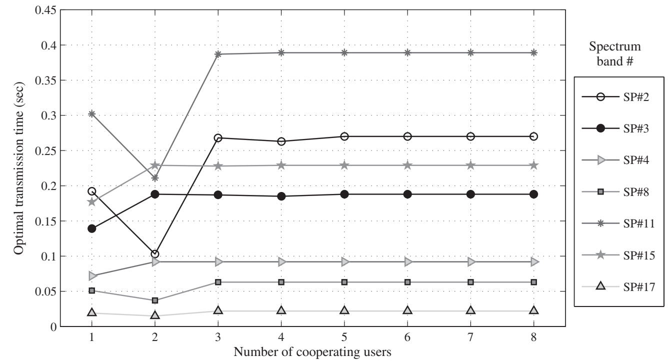

Fig. 9. The optimal transmission time in the proposed cooperative sensing.

environments. According to the primary user activity and the portions of opportunities on the spectrum band, we classify the available spectrum bands in 4 classes: *high-opportunity/high-activity*, *high-opportunity/low-activity*, *low-opportunity/high-activity*, and *low-opportunity/low-activity*. High-opportunity represents the spectrum bands with $P_{on} < P_{off}$ and low-opportunity represents the spectrum bands with $P_{on} > P_{off}$. High-activity represents the spectrum with $\alpha > 1$ or $\beta > 1$, and low-activity represents the spectrum with $\alpha < 1$ and $\beta < 1$. According to this classification, we generate the spectrum information as explained in Table I. In this simulation, we assume that the bandwidth efficiency $\rho = 1$ over all spectrum bands.

First, in Fig 7, the proposed spectrum selection method is compared to the non-weighted method, where spectrum bands are determined to maximize the number of selected spectrum bands. In this simulation, our selection algorithm shows more capacity than the non-weighted methods, since our method considers the potential opportunistic capacities as well as traffic activities.

For the spectrum bands chosen by our proposed selection method, we evaluate the performance of the proposed sensing scheduling algorithm and compare it with the ideal scheduling and with First Come First Serve (FCFS) scheduling. Here, we assume that the CR user has a single transceiver. The ideal scheduling is assumed to achieve the optimal sensing efficiency given in Section III. In FCFS scheduling, the time slot is assigned to the spectrum band with the longest blocked time. In Figure 8, we show the allocated capacity of each spectrum band. As shown in Figure 8, our LCFS scheduling provides higher capacity in total than that of the FCFS, since our LCFS method assigns the sensing slot to minimize the opportunity cost, as explained in Section IV-C. Although high capacity is emphasized in the LCFS method, the fairness in allocating sensing resources is maintained by exploiting the blocked capacities in the past, as shown in Figure 8.

C. Cooperative Sensing in Multi-User Networks

In order to investigate how the proposed optimal sensing algorithm works in the cooperative sensing, we simulate the adaptive and cooperative sensing method in the multi-user environment. First, we evaluate the proposed cooperative sensing gain in terms of optimal transmission time. In Figure 9, according to the number of cooperating users, we recalculate optimal transmission times of each spectrum band (#2, #3, #4, #8, #11, #15, #17) given in Table I. As depicted in Figure 9, the cooperation gain increases the optimal transmission time of the spectrum bands, which improves the sensing efficiency. As shown in Figure 9, as the number of users increases, T^{op} increases and is finally converged to $-\frac{1}{\mu}log(1-\frac{T_P}{P_{off}})$. Some of the spectrum bands show the degradation of the cooperation gain at the small number of users depending on the primary user activities. With the small number of cooperating users, our availability decision method given in Eq. (20) may increase both detection error and false alarm probabilities. In case of small number of users, therefore, the traditional approach given in Section V-B is recommended.

To evaluate the performance of the proposed cooperative sensing scheme, given in Section V-C, we use the same simulation explained in Section VI-A. Here we assume there are 4 cooperating users in the same primary user activity region. In Figures 10 and 11, we show the T_I and T_L measured through the simulation based on the re-optimized sensing parameters. Although the transmission time increases due to the cooperation gain, our adaptive and cooperative method maintains the interference limit. However, same sensing parameters without the cooperation lead to the violation of the interference limit. We also compare our proposed algorithm with the traditional cooperation approach, given in Section V-B. As shown in Figures 10 and 11, while the traditional approach satisfies the interference constraint with better spectrum efficiency, it shows much more lost spectrum opportunities due to the increase in the false alarm probability. In Figure 7, we show how the proposed adaptive and cooperative sensing method can improve the sensing capacity by simulating the proposed spectrum selection method, given in Section IV-B. From the Figure 7, we can see that the proposed cooperative sensing can improve the total sensing capacity since it increases the sensing efficiency of each spectrum band, i.e., the proposed cooperative sensing method enables the sensing transceiver to sense more spectrum bands without violation of the interference constraints.

VII. Conclusion

We introduced the optimal sensing framework for cognitive radio networks, which consists of three different functionalities. First, we proposed the sensing parameter optimization,

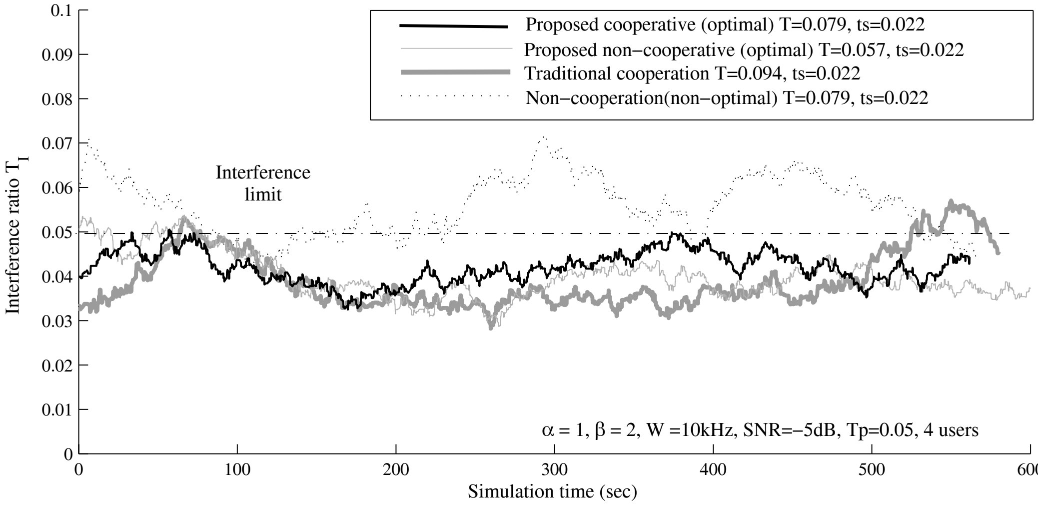

Fig. 10. The simulation results of the cooperative sensing method: interference T_I.

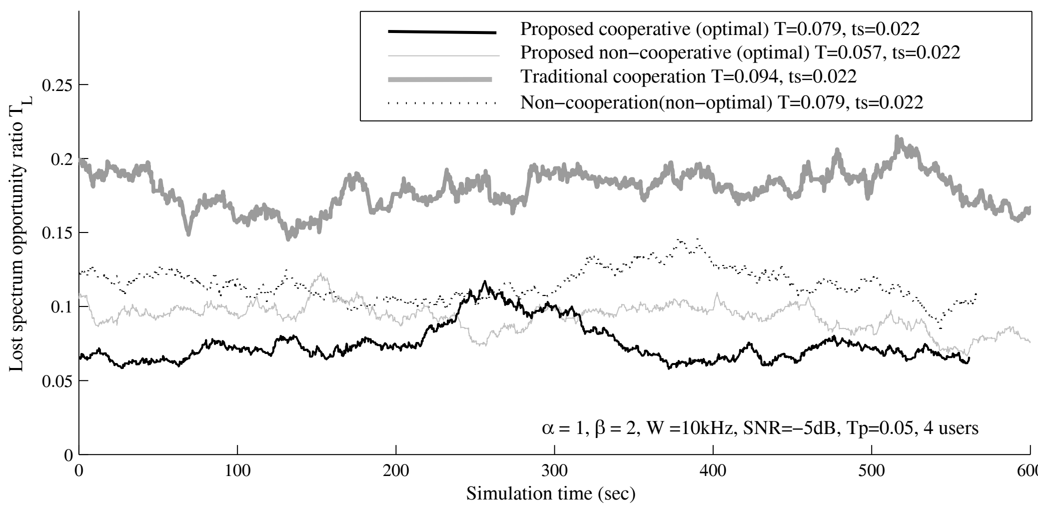

Fig. 11. The simulation results of the cooperative sensing method: lost opportunity T_L.

which leads to the optimal transmission and observation time to maximize the sensing efficiency satisfying the strict interference constraint of primary networks. Second, for the extension of multi-spectrum environment, we introduced a spectrum selection and scheduling algorithm based on the opportunistic capacity concept. Finally, we investigated how the cooperation sensing affects the performance of the proposed optimal sensing framework. In order to exploit the cooperative gain, we proposed an adaptive and cooperative sensing functionality mainly running on the centralized network entities such as a base-station. Furthermore, the simulation experiments show that the proposed sensing framework can achieve maximum sensing efficiency and opportunities in multi-user/multi-spectrum environments satisfying the interference constraints.

Appendix A
Calculation of the Lost Spectrum Opportunity

The lost spectrum opportunity T_L can be obtained by the same procedure explained in Section III-C. In case of idle state sensing, the false alarm can introduce the loss of opportunities during transmission period T. If T is short, the opportunity is highly likely to be lost over the entire transmission period. Conversely, if T is long enough, the lost spectrum opportunity converges to $P_{off} \cdot T$. Thus, the expected lost spectrum opportunity $E[L_{off}]$ can be obtained as follows:

$$\begin{aligned} E[L_{off}] &= P_f(e^{-\mu T}T + (1-e^{-\mu T})P_{off}T) \\ &= P_{off}\bar{P}_f(\frac{\beta}{\alpha+\beta}e^{-\mu T}T + \frac{\alpha}{\alpha+\beta}) \end{aligned} \tag{25}$$

where α and β represent the death and birth rates, respectively, and μ is $\max(\alpha,\beta)$. Similarly, the opportunity can be lost on busy state sensing only if there are one or more primary user activities during T, which converges approximately to the $P_{off} \cdot T$ as follows:

$$\begin{aligned} E[L_{on}] &= P_d(e^{-\mu T}\cdot 0 + (1-e^{-\mu T})P_{off}T) \\ &= (P_{on} - \bar{P}_f)(1-e^{-\mu T})\frac{\alpha}{\alpha+\beta}T \end{aligned} \tag{26}$$

Thus, the expected lost spectrum opportunity, T_L, can be obtained as follows:

$$\begin{aligned} T_L &= \frac{E[L_{on}] + E[L_{off}]}{T \cdot P_{off}} \\ &= \frac{\beta}{\alpha}[e^{-\mu T}\bar{P}_f + (1 - e^{-\mu T})\frac{\alpha}{\alpha + \beta}] \end{aligned} \tag{27}$$

Appendix B
Calculation of the Observation Time

Since we determine the threshold λ as the value to equalize both error probabilities, the detection error probability P_m can be represented as follows:

$$\begin{aligned} P_m &= P_{on}(1 - Q(\frac{\lambda - 2t_s W({\sigma_s}^2 + {\sigma_n}^2)}{\sqrt{4t_s W({\sigma_s}^2 + {\sigma_n}^2)^2}})) \\ &= P_{on}Q(\frac{2t_s W({\sigma_s}^2 + {\sigma_n}^2) - \lambda}{\sqrt{4t_s W({\sigma_s}^2 + {\sigma_n}^2)^2}}) \end{aligned} \tag{28}$$

From the false alarm probability P_f in Eq. (9), the threshold λ can be obtained as follows: From

$$\begin{aligned} \lambda &= \sqrt{4t_s W {\sigma_n}^4} Q^{-1}(\frac{P_f}{P_{off}}) + 2t_s W \\ &= \sqrt{4t_s W {\sigma_n}^4} Q^{-1}(\bar{P}_f) + 2t_s W \end{aligned} \tag{29}$$

Assume signal-to-noise ratio (SNR) $\gamma = {\sigma_s}^2/{\sigma_n}^2$. We can get another equation for threshold λ from the detection error probability P_m in Eq. (28) as follows:

$$\lambda = 2t_s W(\gamma + 1){\sigma_n}^2 - \sqrt{4t_s W}(\gamma + 1){\sigma_n}^2 Q^{-1}(\frac{P_{off}\bar{P}_f}{P_{on}}) \tag{30}$$

Since both equation should be the same, t_s can be represented as follows:

$$t_s = \frac{1}{W \cdot \gamma^2}[Q^{-1}(\bar{P}_f) + (\gamma + 1)Q^{-1}(\frac{P_{off}\bar{P}_f}{P_{on}})]^2 \tag{31}$$

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