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# Efficiency-Accuracy Trade-off for Spectrum Sensing in Cognitive Network

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*Abstract*—**Spectrum sensing is the first and foremost step in cognitive radio technology, where sensing efficiency and accuracy cannot be simultaneously optimized. Tradeoff between the two metrics is represented by sensing duration and sensing period, which are among the most important parameters in spectrum sensing. Aiming at maximize overall available spectrum opportunity, an efficiency-accuracy tradeoff is proposed with interference to licensed user under specified threshold. Based on Neyman-Pearson criterion, joint optimal mathematical model is established and closed-form expressions are derived. Optimal sensing parameters can be obtained and simulation results verified our proposed scheme.**

***Keywords- Cognitive networks; Spectrum sensing; Neyman-Pearson Criterion; Sensing duration; Sensing period; Missed Detection Rate.***

## I. INTRODUCTION

With the rapid developments of wireless industry, available spectrum resources are nearly running out. But demands towards high speed data transmission never rested, leading to spectrum crisis in many fields. Several investigations conducted by Federal Communication Committee in the past ten years reveals that the so called spectrum crisis is indeed spectrum paradox [1-4]. The reason lies in that traditional, fixed spectrum allocation scheme, which renders available spectrum exhausted and heavily underutilized, i.e., more than 70% of the allocated spectrum are idle in terms of time and frequency [5]. Cognitive radio offers a promising future for solving the dilemma of spectrum paradox and has been widely acknowledged by researchers, industry professionals, and academics since it came into being in 2000[6-7]. Spectrum sensing is the first and foremost step of cognitive radio networks, fast and efficient discovery of spectrum holes rely considerably on spectrum sensing. It is noticeable that interference constraint is also an important factor when opportunistically accessing licensed channel authorizing originally to primary user [8]. The sensing procedure includes continuous monitoring, soft or hard decision (cooperative sensing) and finally conclusion of being opportunity or not [9-10]. PHY layer sensing is not enough for better sensing performance and MAC layer should be involved in sensing issue in order to accurately determine the spectrum hole. Current literature mainly focus on single objective optimization in determining sensing parameters such as sensing duration, sensing periods and combining rules (cooperative sensing) [11-12]. Joint optimization is seldom mentioned in few literatures except in that of [13-15]. The authors of [13] proposed a joint optimal sensing method to maximize throughput of secondary user under the constraint of detection probability and further works in [14] gives a more general case of multiple channel scenario. In [15], based on Maximum A Posteriori (MAP) criterion, an optimal sensing framework is proposed to obtain maximal opportunities in terms of transmission time for secondary user.

This paper investigates the tradeoff between accuracy and efficiency of local spectrum sensing based on energy detection (ED). In order to suits a variety of application environments, renewal processes is introduced to model the traffic behavior of primary user. Sensing parameters of sensing duration and sensing periods are jointly optimized to reach the goal of maximize spectrum opportunity under the constraints of interference to primary users, i.e., in terms of missed detection probability. Neyman-Pearson criterion is employed to get the decision threshold, but we fixes missed detection rate instead of constant false alarm rate widely used in literature[16-20] and textbooks. Closed form expression of sensing time and periods are derived and simulation results validate our proposal.

The rest of the paper is organized as follows: in the second section, general energy detection model is reviewed and Neyman-Pearson criterion is introduced to obtain optimal decision threshold. Section III gives traffic model of primary user and joint parameter optimization model is established, followed by a tradeoff between sensing accuracy and sensing efficiency. We conduct simulation in section IV and conclude our work in section V.

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## II. NEYMAN-PEARSON BASED ENERGY DETECTION IN SPECTRUM SENSING

### *A. General Energy Detection Framework*

The energy detection based spectrum sensing problem in cognitive radio can be formed as a binary detection problem, or rather hypothesis testing problem, where $H_0$ means primary user is absent and $H_1$ corresponds to the opposite side. So, the sensing problem is to differentiate the two hypotheses below:

$$y(t)=\begin{cases} n(t) & H_0 \\ h*x(t)+n(t) & H_1 \end{cases} \tag{1}$$

Where $x(t)$ is the transmitting signal wave of primary user with central frequency $f_c$ and bandwidth W. $h$ is the channel gain between the transmitter and secondary user, and $h*x(t)$ represents the received signal strength at the radio front-end of secondary user. $n(t)$ is Additive White Gaussian Noise with zero means and variance $\sigma_n^2$ [21-23]. Furthermore, we assume transmitting signal is also zero-mean and $\sigma_n^2$ .variance. Usually, to remove out-band noise and normalized noise variance, received signal is first pre-filtered by ideal band pass filter with transfer function:

$$H(f)=\begin{cases} \dfrac{2}{\sqrt{N_0}}, & |f-f_c|\le W \\ 0, & |f-f_c|\le W \end{cases} \tag{2}$$

According to principle of energy detection, the output of pre-filter is then squared and integrated over sensing time, noted as $\tau$ to produce a measure of energy of received signal waveform. The overall block diagram can be summarized as follows:

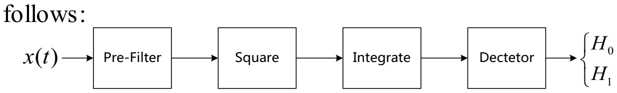


Figure 1. Band-pass processing method of energy detection

According to Fig.1, the test statistics of energy detector is dealt with in a band pass fashion and one can also tackle it in a low-pass way. Furthermore, not matter which aforementioned method is employed, the processing progress is analogue and not easy to implement. In practical, we prefer to handle discrete samples obtained by the sampling law of Nyquist [24-27]. For the sake of simplicity, we assume the sample rate is 2W and total number of samples is $N=2W\tau$. It is proved that both band pass and low pass method are equivalent and both lead to the same results if only energy metrics is concerned [28-31]. So, the discrete processing method can be profiled as follows:

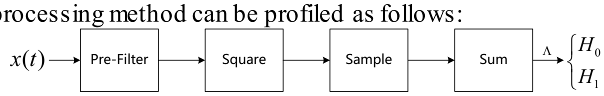


Figure 2. Energy detection: equivalent discrete case

Then we carry on our work. The energy detection method can be translated into:

$$y(k)=\begin{cases} n(k) & H_0 \\ h*x(k)+n(k) & H_1 \end{cases} \quad k\in\Omega=\{1,2,3,\cdots,N\} \tag{3}$$

### *B. Energy detection based on Neyman-Pearson Criterion*

Typically, samples of received signal waveform (noise or signal of primary user plus noise) forms a vector, namely, $\vec{y}=[y(1),y(2),\cdots y(N)]$, each of its element is an outcome of (3). According to the principle of Neyman-Pearson criterion, we now define likelihood ratio function (LRF):

$$L(\vec{y})=\frac{f(\vec{y},H_1)}{f(\vec{y},H_0)} \tag{4}$$

Where $f(\vec{y},H_1)$ and $f(\vec{y},H_0)$ are probability density function of energy detector of channel being busy and being idle, respectively. The LRF reveals the probability ratio of channel being busy over being idle for every possible $\vec{y}$ [32]. Based on above assumption, all the elements of $\vec{y}$ are Gaussian distributed, the energy detection distribution can be obtained:

$$\Lambda\sim\begin{cases} N(0,\sigma_n^2 I) & H_0 \\ N(0,(h^2\sigma_s^2+\sigma_n^2)I) & H_1 \end{cases} \tag{5}$$

Where $I$ is unit vector. Now the LRF can be obtained:

$$L(\vec{y})=\frac{\dfrac{1}{2\pi(h^2\sigma_s^2+\sigma_n^2)^{N/2}}\exp[-\dfrac{1}{2\pi(h^2\sigma_s^2+\sigma_n^2)}\sum_{i=1}^{N}y^2(i)]}{\dfrac{1}{(2\pi\sigma_n^2)^{N/2}}\exp[-\dfrac{1}{2\pi\sigma_n^2}\sum_{i=1}^{N}y^2(i)]} \tag{6}$$

According to Neyman-Pearson criterion, given specific missed detection rate, the best decision threshold is

$$\begin{cases} L(\vec{y})>\lambda_{LPR}\rightarrow H_1 \\ L(\vec{y})<\lambda_{LPR}\rightarrow H_0 \end{cases} \tag{7}$$

Where $\lambda_{LPR}$ is threshold value of LPR and can be obtained by:

$$P_M=\int_{\{\vec{y}:L(\vec{y})<\lambda_{LPR}\}} f(\vec{y},H_1)d\vec{y} \tag{8}$$

Substitute (7) into (6) and we get the decision area of $H_1$:

$$L(\vec{y})=\frac{\dfrac{1}{2\pi(h^2\sigma_s^2+\sigma_n^2)^{N/2}}\exp[-\dfrac{1}{2\pi(h^2\sigma_s^2+\sigma_n^2)}\sum_{i=1}^{N}y^2(i)]}{\dfrac{1}{(2\pi\sigma_n^2)^{N/2}}\exp[-\dfrac{1}{2\pi\sigma_n^2}\sum_{i=1}^{N}y^2(i)]}>\lambda_{LPR} \tag{9}$$

Perform some mathematical processing, we get:

$$\begin{aligned}\Lambda&=\sum_{i=1}^{N}y^2(n)>[2\ln\lambda_{LPR}-N\ln\sigma_n^2+N\ln(h^2\sigma_s^2+\sigma_n^2)][\frac{\sigma_n^2}{h^2\sigma_s^2}(h^2\sigma_s^2+\sigma_n^2)]\\ &=[2\ln\lambda_{LPR}-N\ln\sigma_n^2+N\ln(1+h^2\sigma_s^2/\sigma_n^2)](1+h^2\sigma_s^2/\sigma_n^2)\sigma_n^2/h^2\sigma_s^2\\ &=[2\ln\lambda_{LPR}-N\ln\sigma_n^2+N\ln(1+\gamma)](1+\gamma)/\gamma=V_{th}\end{aligned} \tag{10}$$

Where $V_{th}$ is the decision threshold of energy detection. The relationship of threshold value between LRF and ED is

$[2\ln\Theta - N\ln\sigma_n^2 + N\ln(1+\gamma)](1+\gamma)/\gamma = V_{th}$ .
According to basic probability theory, one can easily get the distribution of $\Lambda$:

$$\Lambda \sim \begin{cases} \chi_N^2(\sigma_n^2) & H_0 \\ \chi_N^2(h^2\sigma_s^2+\sigma_n^2) & H_1 \end{cases} \quad (11)$$

Where the $\chi_N^2(\cdot)$ is the non-central chi-square distribution with freedom N. Then the missed detection rate is:

$$\begin{aligned} P_M &= P(Y<V_{th},H_1) = \\ &P(\frac{Y}{h^2\sigma_s^2+\sigma_n^2} > \frac{V_{th}}{h^2\sigma_s^2+\sigma_n^2}, H_0) \\ &= F_{\chi^2,N}(\frac{V_{th}}{\sigma_n^2(1+\gamma)}) \end{aligned} \quad (12)$$

Where $F_{\chi^2,N}(\cdot)$ is the cumulative density function of central chi-square distribution with freedom N. Given specific missed detection rate $P_M^{th}$, decision threshold of N-P based ED is obtain by:

$$V_{th}^* = (1+\gamma)\sigma_n^2 F_{\chi^2,N}^{-1}(P_M^{th}) \quad (13)$$

Based on (13), missed detection rate can also be obtained:

$$P_F = \bar{F}_{\chi^2,N}(\frac{V_{th}^*}{\sigma_n^2}) = \bar{F}_{\chi^2,N}[(1+\gamma)F_{\chi^2,N}^{-1}(P_M^{th})] \quad (14)$$

Fig.3 presents the characteristic of Neyman-Pearson based energy detection.

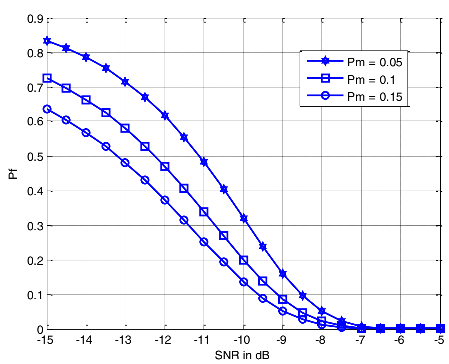


Figure 3. Characteristic of Neyman-Pearson based Energy Detection

## III. SYSTEM MODEL

### *A. Traffic Model of Primary User*

Without losing generality, we assume primary traffic obey alternative renewal process instead of Poisson process, which can be indicated as below:

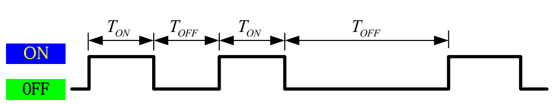


Figure 4. Renewal process based primary traffic model

Suppose primary user randomly appear (ON) and after a busy time interval disappeared (OFF) again, let $T_{ON}, T_{OFF}$ be random variables represent the ON time interval and OFF time interval, respectively. Then time interval sequence $\{T_{ON}^n\}_{n=1}^{\infty}$ and $\{T_{OFF}^n\}_{n=1}^{\infty}$ represents the realization of $T_{ON}, T_{OFF}$, respectively, whose means are $\lambda_{ON}^{-1}, \lambda_{OFF}^{-1}$, respectively. Let $W_0^i = 0, W_n^i = \sum_{j=1}^n T_i^j,\ \ n\ge 1, i\in\Omega=\{ON,OFF\}$ and $X^i(t)=\sup\{n: W_n^i \le t\}, i\in\Omega=\{ON,OFF\}$ ,then according to stochastic theory[33-34], $X^i(t), i\in\Omega=\{ON,OFF\}$ forms Poisson process. Construct new time interval sequence $\{T_{RP}^n\}_{n=1}^{\infty}$,where $T_{RP}^n = T_{ON}^n + T_{OFF}^n, \forall n \in \mathbb{N} = \{1,2,3,\cdots\}$ . Let $W_0 = 0, W_n = \sum_{j=1}^n T_{RP}^n,\ \ n\ge 1$ , then the $\{T_{RP}^n\}_{n=1}^{\infty}$ forms a new stochastic process:

$$X(t) = \sup\{n: W_n \le t\} \quad (15)$$

Based on renewal theory, $X(t)$ is an alternative renewal process, whose renewal interval is $T_{RP}$ . Assume $T_{ON}, T_{OFF}$ are exponentially distributed, the probability density function of $T_{RP}$ is the convolution of $f_{ON}(t)$ and $f_{OFF}(t)$:

$$f_{RP}(t) = \int_0^{+\infty} f_{ON}(\tau) f_{OFF}(t-\tau)d\tau = f_{ON}(t)\otimes f_{OFF}(t) \quad (16)$$

Where

$$f_i(t) = \begin{cases} \frac{1}{\lambda_i}\exp(-\frac{t}{\lambda_i}) & t\ge 0 \\ 0 & t<0 \end{cases} \quad i\in\Omega=\{ON,OFF\} \quad (17)$$

Then the probability density function of $T_{RP}$ is:

$$f_{RP}(t) = \begin{cases} \frac{\lambda_{OFF}\lambda_{ON}}{\lambda_{OFF}-\lambda_{ON}}[\exp(-\frac{t}{\lambda_{ON}}) - \exp(-\frac{t}{\lambda_{OFF}})] & t>0 \\ 0 & t\le 0 \end{cases} \quad (18)$$

The derivation of $f_{RP}(t)$ is prepared for later use in section B.

### *B. Joint Parameter Optimization Model*

The parameter optimization of spectrum sensing is a tradeoff between sensing accuracy and sensing efficiency. In fact, such an attitude towards spectrum sensing leads to a multi-objective optimization problem. Referring to [16] [17] and [18], we formulate our sensing duration and period tradeoff problem as follows:

$$\begin{aligned} \eta(\tau,T) = &\frac{T-\tau}{T} * \frac{\lambda_{OFF}}{\lambda_{OFF}+\lambda_{ON}} * (1-P_C) \\ &* F_{\chi^2,N}[(1+\gamma)F_{\chi^2,N}^{-1}(P_M)/\sigma_n^2)] \end{aligned} \quad (19)$$

Where $P_C$ is collision possibility of cognitive user and primary user, so $(1-P_C)$ is the probability of safely completing data transmission. Fig.5 illustrates the possible collision cases, where $\xi$ is the number of collision occurred during transmission of secondary user. Then the corresponding optimization model is:

$$(\tau^*, T^*) = \arg\max_{\forall \tau, T \in \Re^+} \eta(\tau, T)$$
$$= \arg\max_{\forall \tau, T \in \Re^+} \{\frac{T-\tau}{T} * \frac{\lambda_{OFF}}{\lambda_{OFF}+\lambda_{ON}} * (1-P_C) \quad (20)$$
$$*F_{\chi^2,N}[(1+\gamma)F^{-1}_{\chi^2,N}(P_M)/\sigma_n^2)]\}$$
$$s.t. \begin{cases} P_M \le P_M^{th} \\ T-\tau > 0 \end{cases}$$

Till now, $P_C$ is yet not presented. Based on the result of $f_{RP}(t)$ derived in section A, $P_C$ can be obtained by means of calculating the probability of collision.

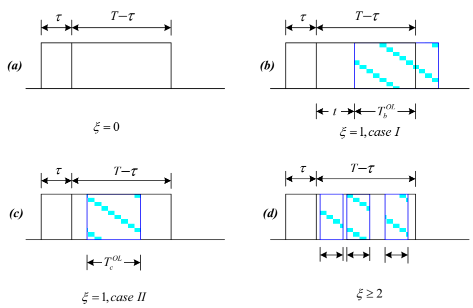


Figure 5. Possible primary-secondary user collision when secondary user access spectrum hole

It's easy to see that only sub-figure (a) is the desirable probability of $(1-P_C)$:

$$\xi = 0 \Leftrightarrow RES(T_{RP}) < T-\tau \quad (21)$$

Where $RES(T_{RP})$ is residual life of renewal interval of $T_{RP}$, according to [35], we have :

$$(1-P_C) = P(\xi = 0) = P\{RES(T_{RP}) < T-\tau\} \quad (22)$$

The probability of residual life of renewal life is [35]:

$$F_{RES}(t) = [1-F_{RP}(t))]/E(T_{RP}) = \bar{F}_{RP}(t)/E(T_{RP}) \quad (23)$$

So we have:

$$1-P_C$$
$$= \bar{F}_{RP}(t)/E(T_{RP}) \quad (24)$$
$$= \int_{T-\tau}^{\infty} \frac{\lambda_{OFF}\lambda_{ON}}{\lambda_{OFF}-\lambda_{ON}}[\exp(-\frac{t}{\lambda_{ON}}) - \exp(-\frac{t}{\lambda_{OFF}})]dt \;/(\lambda_{ON}^{-1}+\lambda_{OFF}^{-1})$$
$$= \frac{(\lambda_{OFF}\lambda_{ON})^3}{\lambda_{OFF}^2-\lambda_{ON}^2}[\exp(-\frac{T-\tau}{\lambda_{ON}}) - \exp(-\frac{T-\tau}{\lambda_{OFF}})]$$

Now the final optimization model can be formed as follows:

$$(\tau^*, T^*) = \arg\max_{\forall \tau, T \in \Re^+} \eta(\tau, T)$$
$$= \arg\max_{\forall \tau, T \in \Re^+} \{\frac{T-\tau}{T} * \frac{\lambda_{OFF}}{\lambda_{OFF}+\lambda_{ON}} * \frac{(\lambda_{OFF}\lambda_{ON})^3}{\lambda_{OFF}^2-\lambda_{ON}^2} \quad (25)$$
$$*[\exp(-\frac{T-\tau}{\lambda_{ON}}) - \exp(-\frac{T-\tau}{\lambda_{OFF}})]$$
$$*F_{\chi^2,N}[(1+\gamma)F^{-1}_{\chi^2,N}(P_M)/\sigma_n^2)]\}$$
$$s.t. \begin{cases} P_M \le P_M^{th} \\ T-\tau > 0 \end{cases}$$

### C. *Trade-off between sensing accuracy and sensing efficiency*

Since accuracy and efficiency cannot be obtained, tradeoff needs to be made to find the optimal results of spectrum opportunity. From optimal model above, we now carry on to get the final optimal sensing parameters.

For the multi-objective optimization problem, one can first fixes one parameter and get the first optimal value, then fixes the second parameter to get the second optimal value. Such a deed is not pervasive in solving every similar problem but it works well with us since optimal value can be obtained with whole positive real numbers and optimal pair of values surely exists. We now perform derivate with respect to $\tau$ and $T$, respectively:

$$\begin{cases} \frac{\partial}{\partial \tau}\eta(\tau,T) = [-\frac{1}{T} + \frac{T-\tau}{\lambda_{OFF}}]\exp(-\frac{T-\tau}{\lambda_{OFF}})F_{\chi^2,N}[(1+\gamma)F^{-1}_{\chi^2,N}(P_M)/\sigma_n^2)]P_{OFF} \\ \frac{\partial}{\partial T}\eta(\tau,T) = (\frac{\tau}{T^2} - \frac{T-\tau}{\lambda_{OFF}T})\exp(-\frac{T-\tau}{\lambda_{OFF}})F_{\chi^2,N}[(1+\gamma)F^{-1}_{\chi^2,N}(P_M)/\sigma_n^2)]P_{OFF} \end{cases} \quad (26)$$

The maximal value can be got by letting both of (26) be 0. Then we have:

$$\begin{cases} \frac{\partial}{\partial \tau}\eta(\tau,T) = [-\frac{1}{T} + \frac{T-\tau}{\lambda_{OFF}}]\exp(-\frac{T-\tau}{\lambda_{OFF}})F_{\chi^2,N}[(1+\gamma)F^{-1}_{\chi^2,N}(P_M)/\sigma_n^2)]P_{OFF} = 0 \\ \frac{\partial}{\partial T}\eta(\tau,T) = (\frac{\tau}{T^2} - \frac{T-\tau}{\lambda_{OFF}T})\exp(-\frac{T-\tau}{\lambda_{OFF}})F_{\chi^2,N}[(1+\gamma)F^{-1}_{\chi^2,N}(P_M)/\sigma_n^2)]P_{OFF} = 0 \end{cases} \quad (27)$$

By solving equations of (27), one can get the optimal sensing duration and sensing periods.

## IV. NUMERICAL RESULTS

Based on the proposed tradeoff scheme, we conduct our simulation with Matlab 2010a. In order to show clearly the scheme effect, spectrum opportunity is set relatively larger to offer more spectrum holes for secondary access. Simulation parameters are set below in Table 1.

TABLE I. SIMULATION PARAMETER SETTING

| Parameter | Value |
|---|---|
| $\lambda_{ON}^{-1}$ | 200 |
| $\lambda_{OFF}^{-1}$ | 600 |
| $P_M$ | 0.1 |
| $W$ | $10KHz$ |
| $\sigma_n^2$ | 1 |
| $\gamma$ | $-10$ |

Fig.6 illustrates the spectrum opportunity secondary user can get with various spectrum sensing duration. The curve is gradually increasing first and then starts to decrease, so maximal value does exist. For this scenario, the optimal value lies between 3 and 5, according to different sensing periods. For different sensing periods, optimal sensing duration is not the same, but the optimal points do exist.

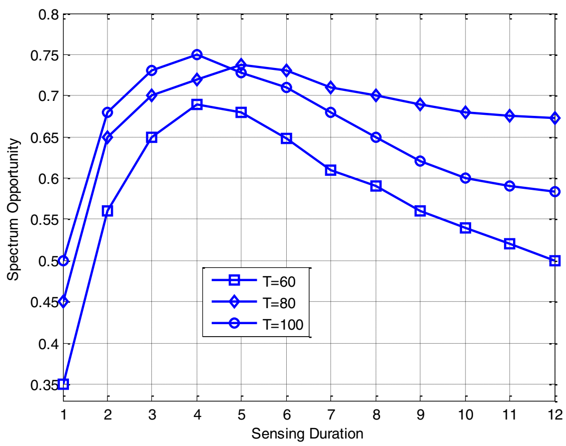


Figure 6. Spectrum opportunity with various sensing duration

Fig.7 gives the spectrum opportunity secondary user can get with various spectrum sensing periods and the peak points appears between 120 and 160, according different sensing duration. The curve of this figure is somewhat similar to that of Fig.6, the reason of this is we always consider one variable by means of fixing another.

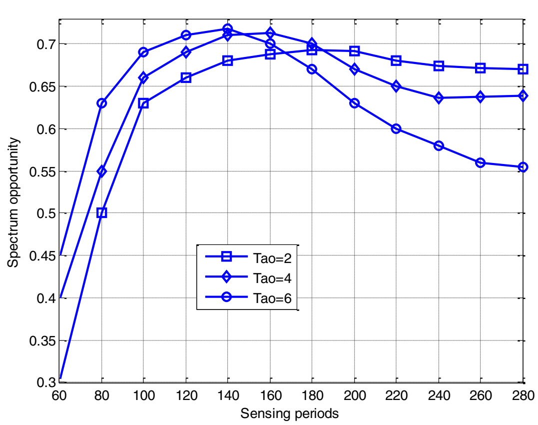


Figure 7. Spectrum opportunity with various sensing periods

Fig.8 and Fig.9 present the joint optimal results with various SRN ration at the radio front-end of secondary user and missed detection rate, respectively. From this figure, we can safely arrive at the conclusion that given received signal strength and interference constraints, one can get the optimal sensing parameters for energy detection based on Neyman-Pearson criterion.

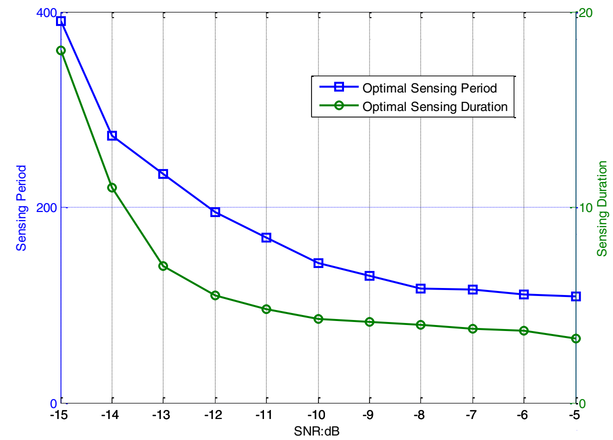


Figure 8. Optimal sensing parameter optimization with different SNR

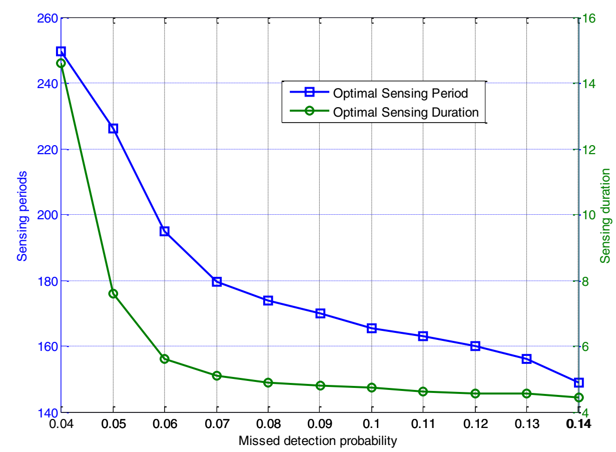


Figure 9. Optimal sensing parameter optimization with different missed detection rate

## V. CONCLUSION

Spectrum sensing aims to find spectrum holes as much as possible, as fast as possible and as reliable as possible. Unfortunately, these metrics are contradictive with each other, partially improve one metric always results in performance degeneration of other metrics. This paper is the very instance of such conclusion. Based on Neyman-Pearson criterion, this paper models the spectrum sensing problem to be a joint optimization problem. Tradeoff is performed in setting sensing duration and sensing period to reach a maximal spectrum opportunity for secondary users. Future works includes complexity analysis of proposed tradeoff scheme and other performance metrics optimization.

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