

## Article

# A Crowd Cooperative Spectrum Sensing Algorithm Using a Non-Ideal Channel

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**Abstract:** Spectrum sensing is the prerequisite of the realization of cognitive radio. So it is a significant part of cognitive radio. In order to stimulate the SUs to sense the spectrum, we combine the incentive mechanism of crowd-sensing with cooperative spectrum sensing effectively, and put forward a crowd cooperative spectrum sensing algorithm with optimal utility of secondary users (SUs) under non-ideal channel which we define SUs' utility expectation functions related to rewards, sensing time and transmission power. Then, we construct the optimization problem of maximizing the utilities of SUs by optimizing the sensing time and the transmission power, and prove that this problem is a convex optimization problem. The optimal sensing time and transmission power are obtained by using the Karush-Kuhn-Tucker (KKT) conditions. The numerical simulation results show that the spectrum detection performance of algorithm, which we put forward, is improved.

**Keywords:** cognitive radio; spectrum sensing; crowd sensing; detective probability

## 1. Introduction

In recent years, mobile data services have developed rapidly, and the demand for wireless spectrum resources is growing. Therefore, the technology of cognitive radio was invented. Spectrum sensing, which is an important part of cognitive radio, is aimed to sense whether the primary user (PU) occupies a specific frequency spectrum resource at a specific time in a particular location. Because of the existence of path loss and shadow effect, there is a large error in single detection problem. Cooperative spectrum sensing can solve this problem [1].

There are five hard-decision fusion methods for cooperative spectrum sensing, including “and” fusion, “or” fusion, voting fusion, maximum posterior probability fusion and Bayesian fusion [2]. Soft-data fusion schemes like square law selection fusion, maximal ratio combination fusion, square law combining fusion and selection combining are analyzed in [3]. The selection of SUs will influence the performance of spectrum sensing. In [4], SUs are selected by the size of the signal-to-noise ratio. SUs need to send the signal-to-noise ratio to base station for selecting, but it will increase the data overhead of the SUs. The dynamic selection of SUs in sensing system is studied, and a distributed sensing compensation method is put forward to solve the problem in [5]. Game theory is also applied to spectrum sensing, and the rewards of SUs are related to the reporting results. SUs will get higher rewards if their results are correct, otherwise, they will get lower rewards [6]. Because the communication between SUs and base station mostly adopts wireless communication, there must be error codes and packet loss. In [7], this phenomenon is analyzed, and the accuracy of data fusion is also calculated. All the papers above assume that the SUs are willing to participate in the sensing. In [8,9], reputation mechanism is considered in the cooperative spectrum sensing. While the smartphones have been popular, the robust spectrum sensing and cloud-based architecture has been studied, [10–12]. The spectrum assignment methods are also studied in [13–15]. In [16], how the selection of SUs can

influence the performance of spectrum sensing is analyzed. However, because the SUs will not take part in the sensing without some rewards, a certain mechanism is needed to stimulate the SUs.

Crowd sensing is a method of collecting samples, and the main way is to collect samples by using intelligent equipment. Crowd sensing incentive mechanism is a mechanism for recruiting and stimulating the people involved in sensing. This mechanism can be divided into monetary incentive mechanism and non-monetary incentive mechanism [17]. At present, most of the research is monetary incentive mechanism. In [18], the game theory is applied to crowd sensing incentive mechanism, and the economic model of crowd sensing application is studied to improve the quality of sensing data. In [19], the task assignment problem of sensitive service quality is studied, the rewards of participants are related to the quality of sensing data. To ensure that the tasks are completed, each task can be completed by more than one participant. In order to reduce the social cost, a task participant cooperation mechanism is designed [20]. Participants in this mechanism are interrelated, so it is easy for participants to cooperate, and the sensing cost can be reduced. However, the above literatures do not concretely translate the crowd sensing into some applications.

In cognitive radio network, the SUs need to sense the spectrum to judge whether the primary user (PU) occupies a specific frequency spectrum resource. In order to stimulate the SUs to take part in the cooperative spectrum sensing, we need to combine the crowd sensing incentive mechanism with the cooperative spectrum sensing. The contributions of this paper are summarized as follows:

- (1) Under non-ideal channel, we propose a system model which combines crowd sensing incentive mechanism with cooperative spectrum sensing, and define SU's utility expectation function which considers the SUs' sensing time and transmission power at the same time.
- (2) We construct an optimization problem about the SU's utility expectation, and prove that the optimization problem is a convex optimization problem. We obtained the optimal solution by using KKT conditions.

This paper is organized as follows. In Section 2, we introduce the system model. In Section 3, we propose a cooperative spectrum-sensing algorithm based on crowd sensing incentive mechanism under non-ideal channel with the optimal SUs' utilities. The numerical simulation results and comparisons are given in Section 4, and finally, we draw the conclusions in Section 5.

## 2. System Model

The system model is shown in Figure 1.  $M$  SUs are evenly distributed within the coverage of base station. The base station releases the channel to be sensed and reward information. After SUs finish the sensing, they send the sensing results to the base station, and the base station fuse all the results.

SUs use energy detection for spectrum sensing. The detection probability of SU  $i$  is given by [21]:

$$p_i = Q((Q^{-1}(p_f) - \sqrt{t_i f_s \gamma_i}) / \sqrt{2\gamma_i + 1}), \quad (1)$$

where  $p_f$  is the target probability of false alarm, and  $\gamma_i$  represents the signal-to-noise ratio of SU  $i$ .  $t_i$  indicates the sensing time.  $t_i f_s$  indicates the sampling points, and it can be written as  $n_i$ . The sampling frequency is a constant value. Function  $Q$  is expressed as:

$$Q(x) = \frac{1}{2\pi} \int_x^\infty e^{-y^2/2} dy. \quad (2)$$

Take  $p(u_1)$  as the probability of the existence of the PU, and take  $p(u_0)$  as the probability that the PU does not exist. So the correct sensing probability of SU  $i$ ,  $p_i^c$ , and the incorrect sensing probability of SU  $i$ ,  $p_i^e$ , are given by:

$$p_i^c = p(u_1)p_i + p(u_0)(1 - p_f), \quad (3)$$

$$p_i^{in} = p(u_1)(1 - p_i) + p(u_0)p_f, \quad (4)$$

If the PU exist, the sensing result is 1, otherwise, the result is 0. When SUs sends the results of sensing to the base station, error codes will occur. So the correct probability of the results which is received by the base station from SU  $i$  is given by:

$$p_i^{rc} = p_i^c(1 - p_e) + p_i^{in}p_e, \quad (5)$$

and the incorrect probability is given by:

$$p_i^{rin} = p_i^c p_e + p_i^{in}(1 - p_e), \quad (6)$$

where  $p_e$  is the transmission error rate. Assuming that SUs use 2DPSK modulation, the error rate of the receiver using non-coherent demodulation is  $p_e = \frac{1}{2}e^{-r}$  [22], where  $r$  indicates the signal-to-noise ratio of SUs signals received by base station.

In this paper, we adopt voting fusion method for data fusion. First set a threshold  $m$ . A hypothesis will be true if more than  $m$  SUs support this hypothesis. The detection probability and false alarm probability of voting fusion is expressed by:

$$p_D = \sum_{j=m}^M \sum_{\sum u_i=j} \prod_i (p_i)^{u_i} (1 - p_i)^{1-u_i}, \quad (7)$$

$$p_F = \sum_{j=m}^M \sum_{\sum u_i=j} \prod_i (p_f)^{u_i} (1 - p_f)^{1-u_i}, \quad (8)$$

where  $u_i$  indicates the sensing result of SU  $i$ . When threshold  $m = M/2$ , the performance of fusion is optimum [21].

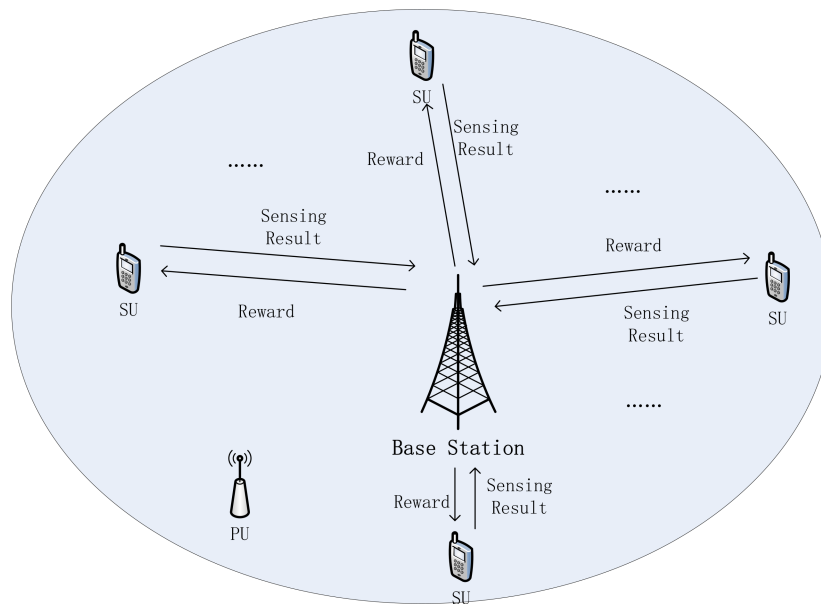


Figure 1. System scenario.

### 3. Utility Optimal Algorithm

The base station first releases information about the channel to be sensed, the correct reward  $k$  and incorrect reward  $k'$  for the SUs. The SUs optimize the sensing time and signal transmission power to obtain the optimal utility expectation of the SUs according to the utility expectation formula. If the utility expectation is greater than 0, the SU would execute the sensing and send its sensing result to the base station. After the data fusion, the base station will offer the rewards to SUs in accordance with

the correctness of the decision received, if the result of SU  $i$  is the same with the result of the fusion decision, SU  $i$  can get the correct reward  $k$ , otherwise the reward is  $k'$ . The reward expectation of SU  $i$  is given by:

$$\text{re}_i = k \cdot p_i^{rc} + k' \cdot p_i^{rin}. \quad (9)$$

The utility expectation of SU  $i$  can be expressed by:

$$\begin{aligned} \text{utility}_i &= \text{re}_i - c \cdot t_i - c_s \cdot s_i \\ &= k \left\{ [p(u_1)p_i + p(u_0)(1 - p_f)](1 - p_e) + [p(u_1)(1 - p_i) \right. \\ &\quad \left. + p(u_0)p_f]p_e \right\} + k' \left\{ [p(u_1)p_i + p(u_0)(1 - p_f)]p_e + \right. \\ &\quad \left. [p(u_1)(1 - p_i) + p(u_0)p_i](1 - p_e) \right\} - c \cdot t_i - c_s \cdot s_i \end{aligned} \quad (10)$$

where  $s_i$  indicates the signal transmission power of SU  $i$ .  $c$  and  $c_s$  represent the cost of unit sensing time and the cost of unit transmission power, respectively.

In order to improve the efficiency of spectrum sensing, a SU will not take part in the spectrum sensing if the detection probability is less than 0.5, because the sensing result does not have reference value. Hence a SU will take part in the spectrum sensing when the detection probability is greater than 0.5. It is known from the properties of Q function that if the detection probability is greater than 0.5, the argument of the Q function in (2) is less than 0, i.e.,

$$\frac{Q^{-1}(p_f) - \sqrt{t_i f_s} \gamma_i}{\sqrt{2\gamma_i + 1}} < 0. \quad (11)$$

The goal of this paper is that the SU can obtain the optimal utilities by optimizing the sensing time and the transmission power, and the optimization problem can be expressed as follows:

$$P1 : \quad \min_{\{t_i, s_i\}} (-\text{utility}_i) \quad (12)$$

$$s.t. \quad -t_i + \frac{1}{f_s} \cdot \left( \frac{Q^{-1}(p_f)}{\gamma_i} \right)^2 < 0, \quad (13)$$

$$-s_i < 0, \quad (14)$$

where the constraint condition (13) is derived from (11), and (14) indicates that the transmission power of the SU is greater than 0.

As long as the optimization problem is proved to be a convex optimization problem, the optimal sensing time and transmission power can be obtained through the KKT conditions [23].

**Proposition 1.** *Optimization problem P1 is a convex optimization problem.*

The proof is given in Appendix A.

Set  $X_i = (t_i, s_i)$ , and  $h_k(X_i) < 0, k = 1, 2$  represents 2 constraints on convex optimization problem. We define the Lagrangian equation as follows:

$$L_i = -\text{utility}_i + \sum_{k=1}^2 \mu_k h_k(X_i). \quad (15)$$

Thus, the KKT condition for the convex optimization problem is given by:

$$\frac{\partial L_i}{\partial X_i} = 0, \quad (16)$$

$$\mu_k \geq 0 \quad k = 1, 2, \quad (17)$$

$$h_k(X_i) < 0 \quad k = 1, 2. \quad (16)$$

According to (15), we can get  $\mu_k = 0, k = 1, 2$ . Hence (14) can be expressed by:

$$\begin{cases} \frac{\partial(\text{utility}_i)}{\partial t_i} = \frac{1}{2}(k - k')(1 - 2p_e) \left[ \frac{\gamma_i}{2\sqrt{4\pi\gamma_i + 2\pi}} (t_i f_s)^{-1/2} e^{-m^2/2k} \cdot b_i - \frac{c_i}{f_s} \right] - c = 0 \\ \frac{\partial(\text{utility}_i)}{\partial s_i} = -\frac{1}{n}(k - k')(p_i - p_f) e^{-s_i/n} - c_s = 0 \end{cases}. \quad (18)$$

The optimal sensing time and emission power can be obtained by solving Equation (17).

In summary, the algorithm of crowd cooperative spectrum sensing is as follows (Algorithm 1):

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**Algorithm 1** Crowd Cooperative Spectrum Sensing Algorithm under Non-Ideal Channel.

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1: for all SUs do
2:   Solve the Equations (17) and get the optimal sensing time  $t_i$  and emission power  $s_i$ ;
3:   Calculate the  $\text{utility}_i$  according to (10);
4:   if  $\text{utility}_i > 0$ 
5:     SU  $i$  take part in the spectrum sensing and send the result to the base station;
6:     The base station receives the sensing result  $R_i$  from SU  $i$ ;
7:   end if
8: end for
9: The base station fuses the results from SUs and gets the fusion result  $R$ ;
10: for all SUs participating in the sensing do
12:   if  $R = R_i$ 
13:     SU  $i$  gets correct reward  $k$ ;
14:   else
15:     SU  $i$  gets incorrect reward  $k'$ ;
16:   end if
17: end for

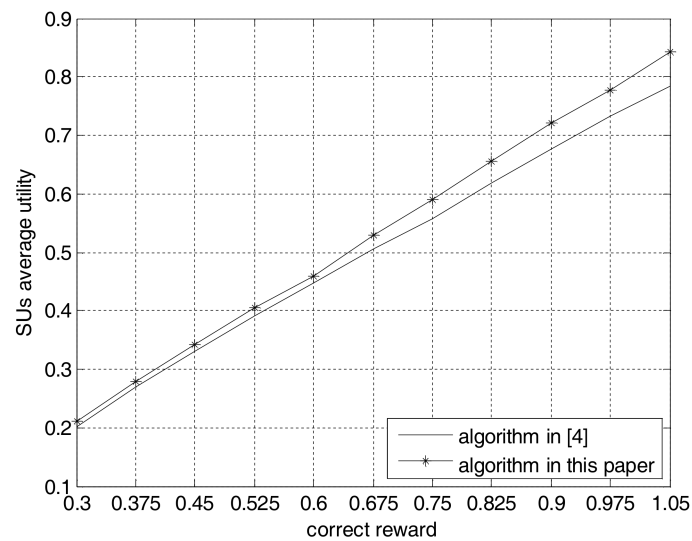
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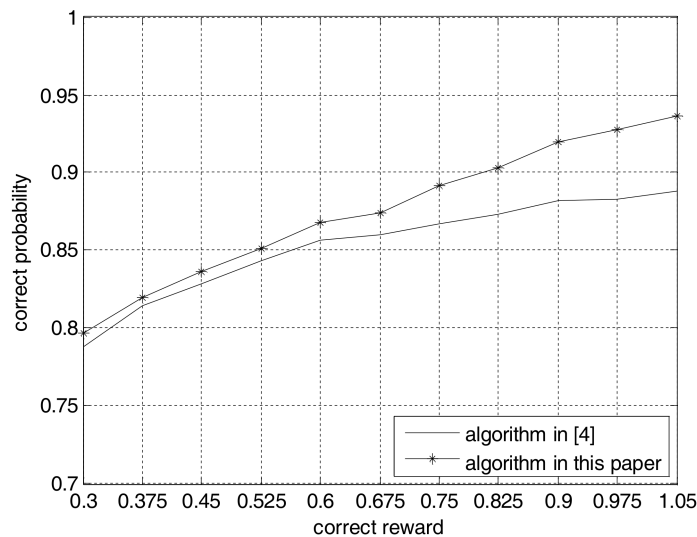
#### 4. Computer Simulations

In this paper, we simulate the correct detection probability and the SUs' average utility with MATLAB R2012a, and compare the simulation results with the results of [4]. In the simulation scenario, 6 SUs are randomly distributed in the circle with a radius of 100 m. The coordinate of the PU is (0,0), and the base station's coordinate is (200,200) m. The sampling frequency of the SU  $f_s$  is set to 10 kHz. The sensing time cost  $c$  is set to 0.1 per millisecond, and the transmission power cost  $c_s$  is set to 0.01 per milliwatts. The incorrect reward  $k'$  is 1/10 of the correct reward  $k$ , and the target false alarm probability of SUs is set to 0.1. The transmission of signal is based on the empirical path loss model in large scale fading, and the fading coefficient is 2.5. The transmission power of the primary user is 40 mW, and the program runs 3000 times to get the average values.

Figures 2 and 3 show the changes in the average utility and correct sensing probability of SUs with the reward  $k$ . In Figure 2, the SUs average utility of the algorithm increases with remuneration, and is greater than of the comparison algorithm. The reason is that this algorithm is a utility expectation optimal algorithm. By maximizing the sensing time and signal transmission power, the utilities expectation of the SUs get the maximum value. However, the contrast algorithm did not consider the SUs' sensing time and transmission power, so the detective probability and error rate cannot be changed which means it can not get the optimal values. Therefore, the average utility of the SUs is greater than the contrast algorithm. From Figure 3, it can be seen that the correct probability of sensing is also increasing with the reward, and the correct probability of this algorithm is higher than that of the contrast algorithm. The reason is that with the increase of the reward, the number of people involved in sensing will increase, which can improve the correct probability. Because the average utility of this algorithm is greater than the contrast algorithm, the number of people involved in the sensing will be more than the contrast algorithm, so the correct probability is higher than the contrast algorithm.



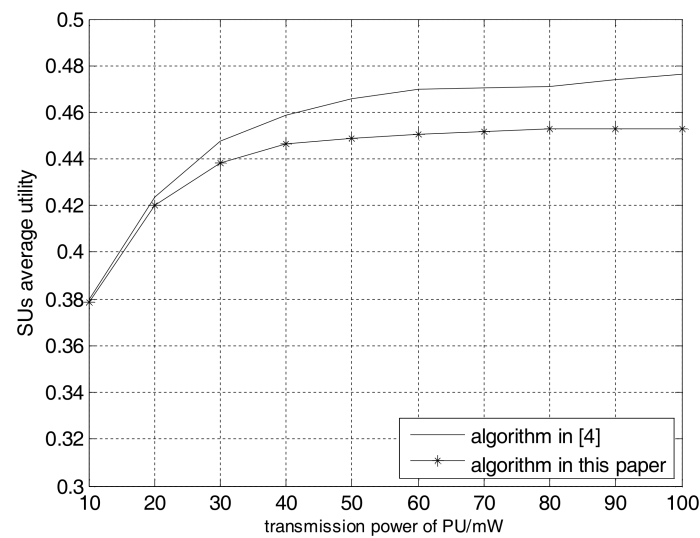
**Figure 2.** The change of the SUs average utility with the correct reward.



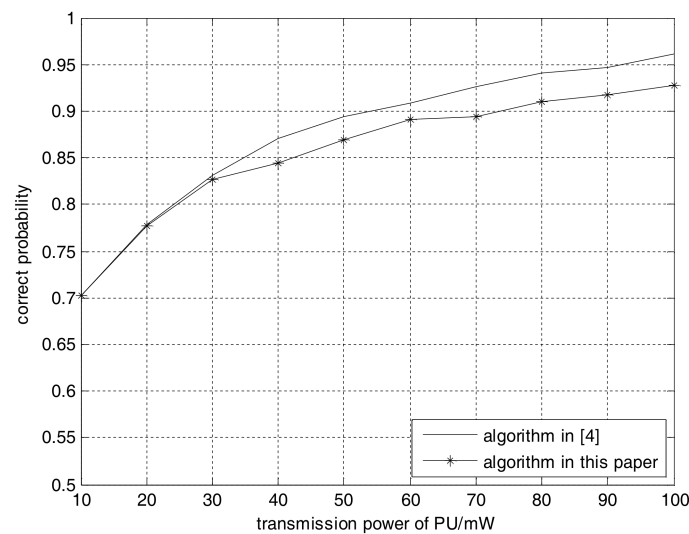
**Figure 3.** The change of the correct probability with the correct reward.

Figures 4 and 5 represent the changes in the average utility and correct probability of the SUs with the transmission power of the PU, and the reward  $k$  is set to 0.6. In Figure 4, the two curves are beginning to grow more clearly, and then more slowly. The reason is that when the transmission power of the PU is low, the SUs' acceptance of signal-to-noise ratio is low, the detection error is large, so the utilities are low. With the promotion of the power of the PU, the accuracy of the SUs is improved, so the utilities of the SUs are also improved. Because the reward  $k$  is constant, when the detection probabilities increase, the utilities of the SUs are close to the maximum utility that can be obtained, so the curves are relatively gentle behind. In can be seen from Figure 4 that the secondary user's average utility of this algorithm is greater than that of the contract algorithm. The reason is that this algorithm is a utility expectation optimal algorithm. By maximizing the sensing time and signal transmission power, we can get the maximum utility expectations of the SUs, so the average utility of the SUs is higher than that of the contrast algorithm. From Figure 5, we can see that two curves increase monotonously with the transmission power of the primary users. The correct probability of the algorithm is greater than that of the contrast algorithm. The reason is that the secondary user

utility of the algorithm is higher than that of the contrast algorithm, so the number of participants is more, and the probability of correctness is higher.



**Figure 4.** The change of the SUs average utility with the transmission power of PU.



**Figure 5.** The change of the correct probability with the transmission of PU.

## 5. Conclusions

We apply the crowd sensing incentive mechanism to cooperative spectrum sensing under non-ideal channel, and propose a cooperative spectrum sensing algorithm based on crowd sensing incentive mechanism under non-ideal channel with the optimal SUs' utilities. First, the utility expectation function of the SUs is set up, and the maximum utility expectation is obtained by optimizing the sensing time and signal transmission power. The base station compares the received SUs judgment results with the fusion decision results, if the same, the secondary users can get a higher reward, otherwise the reward is low, so as to stimulate the SUs' sensing initiative and the performance of spectrum sensing is improved. Finally, the simulation shows that while the utility of the SU is getting the optimal value, the accuracy of spectrum sensing is also improved. The key insight of our algorithm is that spectrum sensing and crowd sensing incentive mechanism can be combined to stimulate the SUs and improve the sensing performance.

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## Appendix A

Proof for Proposition 1: It is obvious that the feasible domain of the optimization problem  $P1$  is a convex set, and then we prove that the objective function is a convex function.

The necessary and sufficient condition for a function to be a convex function is that the Laplace operator is not less than 0 [23], i.e.,

$$\Delta(-utility) \geq 0 \quad (A1)$$

For the sake of simplicity, without losing the generality, we set  $p(u_1) = p(u_0) = 0.5$ , i.e., the probability of the existence of the main user is 0.5. (10) can be simplified as follows:

$$utility_i = 0.5 \cdot [(k - k')(p_i - 2p_i p_e + 2p_f p_e + 1 - p_f)] - c \cdot t_i - c_s \cdot s_i. \quad (A2)$$

So the Laplace operator of the objective function can be expressed as follows:

$$\Delta(-utility_i) = \frac{\partial^2(-utility_i)}{\partial t_i^2} + \frac{\partial^2(-utility_i)}{\partial s_i^2}. \quad (A3)$$

First calculate  $\frac{\partial^2(-utility_i)}{\partial t_i^2}$ , and we can get:

$$\frac{\partial^2(-utility_i)}{\partial t_{ji}^2} = \frac{1}{2}(k - k')(1 - 2p_e)(\frac{1}{2} \cdot s \cdot (t_i f_s)^{-3/2} e^{-m^2/2} + m \cdot s \cdot (t_i f_s)^{-1/2} e^{-m^2/2} \frac{-\frac{1}{2}(t_i f_s)^{-1/2} \gamma_i}{\sqrt{2\gamma_i + 1}}), \quad (A4)$$

where

$$m = \frac{Q^{-1}(p_f) - \sqrt{t_i f_s} \gamma_i}{\sqrt{2\gamma_i + 1}}, \quad s = \frac{1}{2} \cdot \frac{\gamma_i}{\sqrt{4\pi\gamma_i + 2\pi}}.$$

Because the signal-to-noise ratio  $\gamma_i$  is positive and therefore  $s > 0$ . Because  $(t_i f_s)^{-3/2} \cdot e^{-m^2/2} > 0$ , so  $-\frac{1}{2} \cdot s \cdot (t_i f_s)^{-3/2} \cdot e^{-m^2/2} < 0$ , i.e.,  $m \leq 0$ . So

$$m \cdot s \cdot (t_i f_s)^{-1/2} \cdot e^{-m^2/2} \cdot \frac{-\frac{1}{2}(t_i f_s)^{-1/2} \cdot \gamma_{ji}}{\sqrt{2\gamma_{ji} + 1}} > 0. \quad (A5)$$

According to the definition and (5), we can get  $k - k' > 0$  and  $p_e \leq 0.5$ . So

$$\frac{\partial^2(-utility_i)}{\partial n_{ji}^2} \geq 0. \quad (A6)$$

Then calculate  $\frac{\partial^2(-utility_i)}{\partial s_i^2}$ , and we can get:

$$\frac{\partial^2(-utility_i)}{\partial s_i^2} = \left(\frac{pl}{n}\right)^2 (k - k')(p_i - p_f) e^{-s_i \cdot pl/n}, \quad (A7)$$

where  $n$  indicates noise power, and  $pl$  indicates path loss. Set target false alarm probability  $p_f$  less than 0.5. Because  $\frac{1}{n^2} \cdot e^{-s_i/n} > 0$ , we can get:

$$\frac{\partial^2(-utility_i)}{\partial s_i^2} \geq 0. \quad (A8)$$



Thus, we can get:

$$\Delta(-utility_i) = \frac{\partial^2(-utility_i)}{\partial t_i^2} + \frac{\partial^2(-utility_i)}{\partial s_i^2} \geq 0. \quad (A9)$$

Hence objective function is a convex function. Optimization problem *P1* is a convex optimization problem. Proof complete.

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