On Energy-optimal Cooperation Strategy in Cognitive Radio Networks

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***Abstract*—Taking into account the overall energy consumption during consecutive processes of opportunistic spectrum access in cognitive radio networks, including sensing locally, reporting sensing results and transmitting data, etc., an energy efficient cooperation strategy is investigated in this paper. First, we formulate the energy-efficient cooperation problem for two special scenarios with SUs in different distribution ranges. By determining how many SUs to cooperate and which SUs to cooperate in the spectrum sensing, the overall sensing and transmitting energy is minimized. Based on the theoretic analysis, a low-complexity heuristic algorithm is proposed to find the most appropriate set of cooperative SUs corresponding to the minimal energy consumption. The simulation results show that the proposed algorithm can achieve a near-optimal performance.**

I. Introduction

With the rapid growth of wireless applications, spectrum resource is facing huge demands. However, most of the licensed spectrum is still largely under-utilized [1] because of the current spectrum allocation policy. Cognitive Radio (CR) technology [2] has been introduced as a potential solution to solve this conflict. Users in CR networks, secondary users (SUs), are allowed to utilize a licensed frequency band opportunistically when it is not being occupied by primary users (PUs). To avoid interfering communications of PUs, spectrum sensing plays a crucial role for SUs to detect PUs' presence. Among several sensing techniques, the energy detection [3] is adopted extensively with no need of any prior information of PUs.

By cooperative spectrum sensing, performance gain is achieved via diversity. However, cooperative sensing with a large number of SUs induces a lot of extra communication overhead. To reduce it, some researchers try to reduce the sensing time. In [6], Liang *et al.* consider a trade-off between the sensing time and the transmission time to maximize the throughput for a single user. In another work [7], Zhang *et al.* take the sensing time into account and allow SUs to report sensing measurements simultaneously instead of the round robin fashion, which reduces the reporting time and cuts down the sensing slot overhead.

Recently, several research works on energy-efficient spectrum sensing are published. In Wei and Zhang's work [8], a cluster-and-forward based spectrum sensing scheme is proposed to save energy. A related work for cognitive sensor networks is studied by Maleki *et al.* in [9] to minimize the energy consumption subject to the constraints on both detection probability and false alarm probability. In [10], Peh *et al.* shows that the optimal cooperative sensing performance is usually achieved by a group of SUs which have higher primary user's signal to noise ratio.

All of the above works just focus on the energy consumption of sensing and reporting processes. However, the performance of cooperative sensing influences the energy consumption of transmission process significantly. In our work, we investigate the cooperative sensing scheme which can reduce energy consumption both in finding transmitting opportunities (i.e. cooperative sensing) and in making use of those opportunities (i.e. transmitting after cooperative sensing). More specifically, when keeping the desired protection to PUs, reducing false alarm probability can cut down the energy consumption during transmitting; nevertheless, increasing the number of cooperative SUs to reduce transmitting energy consumption leads to more energy consumption of cooperative sensing. Therefore, we need to find out the most appropriate accuracy of the cooperative sensing to achieve the optimal energy efficiency for the entire communication process of SUs.

In this paper, we formulate the energy optimization problem and analyze the optimal cooperation strategy for the scenarios with the SUs in a narrow distribution range and a wide distribution range, respectively. The total energy consumption is considered during the opportunistic communications, including sensing locally, reporting sensing results and transmitting data. By determining how many SUs to cooperate, the minimal energy consumption can be achieved in the former scenario. In the latter one, the energy consumption is associated with not only how many SUs but also which SUs are involved in the

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cooperative sensing. We propose a low-complexity heuristic algorithm to find the most appropriate set of SUs corresponding to the minimal energy consumption. The simulation results show that the proposed algorithm can achieve a near-optimal performance.

The remainder of this paper is organized as follows. We summarize some important related work in Section II. The system model is introduced in Section III. In Section IV, the energy optimization problem is formulated. The cooperation strategies are investigated for the above two scenarios in Section V and Section VI, respectively. Following this, the simulation results are provided in Section VII. And in section VIII, the conclusions are stated.

II. Related Work

The scheme of cooperation in spectrum sensing was first proposed by Mishra *et al.* in [4]. Cooperation is an efficient approach to reduce the sensitivity requirements of individual CR equipments. With trust cooperation, CR equipments only need to be sensitive enough to deal with the nominal path loss. Furthermore, the effect of shadowing correlation on cooperative sensing has been studied via simulations. The results indicate that in a correlated fading environment, polling a few independent users is better than polling many correlated users. Another important result of cooperative sensing is that hard decision performs almost as well as soft decision in achieving performance gains.

While the cooperation mitigates the sensitivity requirements, it induces much extra overhead. Several works deal with this problem by optimizing sensing time. In [5] and [6], Liang *et al.* find the relation between (P_d, P_f) (where P_d is the detection probability and P_f is the false alarm probability) and the number of required samples in energy detection. This relation indicates the achievable throughput for CR networks is related with the length of required sensing time determined by the number of detection samples, because the lower the probability of false alarm (i.e. the longer the sensing time), the more spectrum opportunities can be discovered when it is available. In a length-fixed frame, more sensing time leads to less data transmission time. Thus, the sensing-throughput tradeoff problem is formulated mathematically and solved by finding the optimal sensing time.

Another work taking the sensing time into account is [7], in which the cooperative sensing scheme proposed by Zhang *et al.* combines not local decisions but pre-equalized sensing measurements from the sensor nodes using Maximum Ratio Combining (MRC). Since the conventional scheme of collecting sensing reports in a round robin fashion demands other secondary users remain silent when one SU reports its local decision, i.e. the time of collecting local decisions is proportional to the number of sensor nodes, the cooperative sensing scheme in [7] with MRC done automatically over the radio interface during the reporting process saves much time and the number of sensor nodes is no longer limited by the length of reporting duration.

Several research works on spectrum sensing with directly exploring energy efficiency are published recently. In [8], Wei and Zhang propose a cluster-and-forward based distributed spectrum sensing scheme. The clusters are formed dynamically; the cluster heads process information locally and send the local fusion center. Since broadcasting is an energy-expensive method if the secondary users are spread out in a wide area, this forwarding method requires less energy. Designing cluster range may be one possible extension of this work, since small clusters consume less power in local decision combination but lead to not only more long-range communications between cluster heads and fusion center but also more clustering overhead.

An energy-efficient distributed spectrum sensing scheme for cognitive sensor networks is proposed in [9], by Maleki *et al.*, which provides the basis for our analysis. To save energy, this scheme combines ideas of sleeping and censoring thresholds, the energy consumption in both spectrum sensing and reporting local decision is minimized. Besides the differences of coverage area as mentioned in [11], spectrum utilization, instead of spectrum detection, is the ultimate aim, which differs from that in sensor networks. Thus besides minimizing the energy consumption only in spectrum sensing process, the energy consumption of the transmission process should also be considered. Especially, the sensing accuracy does affect energy efficiency in finishing data transmission of secondary users, which is just what we treat deeply in this paper.

III. System Model

A. Network Model and Cooperative Sensing

We consider a secondary network which consists of N SUs and one fusion center (FC), as shown in Fig. 1. The secondary network seeks spectrum opportunities by cooperative sensing. Table I lists the notations of the basic parameters in this paper.

TABLE I
SYMBOL EXPLANATION

γ	signal-to-noise ratio (SNR)
λ	threshold of energy detection
P_d	detection probability of one SU
P_f	false alarm probability of one SU
Q_D	detection probability of cooperative spectrum sensing
Q_F	false alarm probability of cooperative spectrum sensing
C_s	energy consumed by spectrum sensing
C_r	energy consumed by reporting sensing information
C_t	energy consumed by transmission

Each SU adopts the energy detection as its spectrum sensing technique. As mentioned in [3], assume the i-th SU samples the received signal, calculates the accumulated energy over the observation time interval T_0, and then takes the normalized result as a decision statistic

$$D_i = \frac{1}{WN_0} \sum_{k=1}^{2u} x_i^2 [k] \tag{1}$$

where W is the width of the detected channel, N_0 is the power spectrum density of AWGN, $u = WT_0$, and $x_i[k]$ is the power of the k-th sample of the PU signal received by the i-th SU. The sampled power is combined by two parts as below.

$$x_i[k] = h[k]s_i[k] + n_i[k] \tag{2}$$

where $s_i[k]$ is the PU signal part in the sample and $n_i[k]$ is the noise part. Here, $h[k]$ is an indicator denoting whether the PU is presence.

Spectrum sensing is a binary hypothesis testing problem. For the i-th SU, the local decision rule is given as

$$\begin{cases} D_i \geq \lambda_i & H_1 : \text{PU presence} \\ D_i < \lambda_i & H_0 : \text{PU absence} \end{cases} \tag{3}$$

and D_i has approximately the following distribution [3]

$$D_i \sim \begin{cases} N\left(2u(\gamma_i+1), 4u(2\gamma_i+1)\right) & H_1 \\ N\left(2u, 4u\right) & H_0 \end{cases} \tag{4}$$

Based on the distribution, the false alarm probability and the detection probability can be written as

$$P_{f_i} = Pr\left(D_i \geq \lambda_i \mid H_0\right) = \frac{1}{2} erfc\left(\frac{\lambda_i - 2u}{2\sqrt{2u}}\right) \tag{5}$$

$$P_{d_i} = Pr\left(D_i \geq \lambda_i \mid H_1\right) = \frac{1}{2} erfc\left(\frac{\lambda_i - 2u(\gamma_i+1)}{2\sqrt{2u(2\gamma_i+1)}}\right) \tag{6}$$

A part of the N SUs report their sensing results to the FC, and the false alarm probability and the detection probability of cooperative spectrum sensing are given by

$$Q_F = 1 - \prod_{i=1}^{N} (1 - I(i)P_{f_i}) \tag{7}$$

$$Q_D = 1 - \prod_{i=1}^{N} (1 - I(i)P_{d_i}) \tag{8}$$

where $I(i)$ indicates whether the i-th SU has reported local sensing decision to FC.

B. The Basic Protocol Structure

Without delving into protocol details, we present here the basic protocol structure. We assume the channel is block fading. At the beginning of each block, every SU reports its received SNR γ_i of sensing channel in identical power, which is used by FC for calculating reporting energy consumption C_{r_i} when received SNR of reporting channel is determined. With information of pairs of (γ_i, C_{r_i}), FC chooses appropriate set of SUs to detect primary users' presence, the methods of which will be given in subsequent sections.

Every block includes several slots and each slot consists of sensing duration and data transmission duration. In sensing duration, selected SUs sense the channel and report their local sensing decisions to the FC to make final decision of spectrum occupancy. Once FC makes the final decision that this channel is available to secondary users, one of the SUs can exploit it. (Scheduling access of SUs is beyond our exploration in this paper and it has no effect on results of this work).

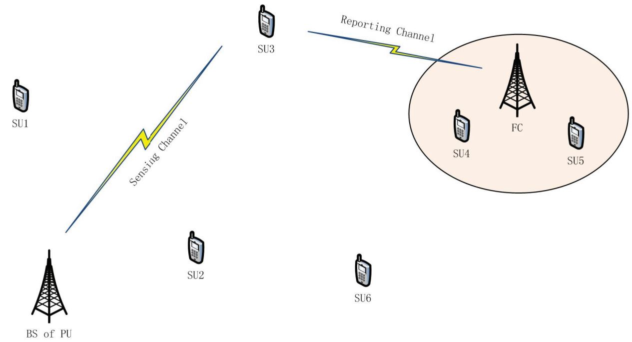

Fig. 1. Cooperative Sensing Structure in a Cognitive Radio Network

Define C_{SU} as the *efficient throughput* of the SU which transmits data at the interested channel. Consider the waste of spectrum opportunities by false alarm, the efficient throughput can be presented as

$$C_{SU} = (1 - Q_F)C \tag{9}$$

where C is the channel capacity, which is calculated by Shannon formula as

$$C = W \log\left(1 + \frac{GP_{tr}}{WN_0}\right) \tag{10}$$

where G is the path gain of the data transmission and P_{tr} is the transmit power of the SU.

IV. Problem Formulation

The objective of our work is to optimize the energy efficiency of SUs on the premise that the communications of PUs are protected effectively. The energy consumption of the CR system includes three parts. If the i-th SU has been chosen to participate in cooperative spectrum sensing, it implements the spectrum sensing independently first, which consumes the energy C_s. And then, it reports its local sensing results to the FC, which consumes energy C_{r_i}. When the final decision of the FC shows that the channel is available, the data transmission on the channel will consume energy C_t.

It is reasonable to assume that the signal processing energy C_s for each SU is identical, however, C_{r_i} for different SUs might be different from each other on account of different radio environments. Hence, from the very beginning of spectrum sensing to the end of transmission of the SU, the total energy consumption is given by

$$C_{total} = \sum_{i=1}^{N} I(i)(C_s + C_{r_i}) + (1-\delta)(1-Q_F)C_t \tag{11}$$

where δ is the active ratio of PUs from statistic information and $I(i)$ is an indicator to show whether the i-th user participate the cooperative spectrum sensing.

Let T denote the duration of a transmission slot. We use $T_t = (1-\delta)T$ to represent the average duration available to SUs. Because $C_t = TP_{tr}$, we can rewrite (11) as

$$C_{total} = \sum_{i=1}^{N} I(i)(C_s + C_{r_i}) + (1-Q_F)T_t P_{tr} \tag{12}$$

To minimize the total energy consumption C_{total} subject to the constraint that the detection probability of cooperative spectrum sensing should be not less than a predetermined value θ, the optimization problem can be formulated based on (12) as follows,

$$\begin{array}{ll} \min & \sum_{i=1}^{N} I(i)(C_s + C_{r_i}) + (1-Q_F)P_{tr}T_t \\ s.t. & Q_D \geq \theta \end{array} \tag{13}$$

From (9) and (10), it is derived that

$$P_{tr} = \frac{N_0 W}{G}\left[\exp\left(\frac{C_{SU}}{W(1-Q_F)}\right) - 1\right] \tag{14}$$

Substitute (14) into (13), the optimization problem is rewritten as

$$\begin{array}{ll} \min & \sum_{i=1}^{N} I(i)(C_s + C_{r_i}) + \\ & (1-Q_F)\frac{N_0 W}{G}[\exp(\frac{C_{SU}}{W(1-Q_F)}) - 1]T_t \\ s.t. & Q_D \geq \theta \end{array} \tag{15}$$

Associating (5) $\sim$ (10), the parameters being optimized are $\boldsymbol{\lambda}$ and $\mathbf{I}$, where $\boldsymbol{\lambda} = [\lambda_1, \lambda_2, \ldots, \lambda_N]$ denotes all secondary users' detection thresholds and $\mathbf{I} = [I(1), I(2), \ldots, I(N)]$ denotes whether each SU participates in cooperative sensing.

In the subsequent two sections, we will try to solve the above optimization problem. When secondary users distribute in a narrow range as described in Section V, it is reasonable to assume their reporting energy consumptions are identical and all SUs have the same received SNRs of the PU signal. In this case, the problem of selecting appropriate SUs degenerates into determining the appropriate number of SUs in cooperative spectrum sensing, and the optimal number can be derived for the minimum total energy consumption.

When secondary users distribute in a wide range as described in Section VI, the reporting energy consumptions and received SNRs of PU signal are not the same for different SUs, so we need to obtain the most appropriate set of SUs, i.e. the vector $\mathbf{I}$ as mentioned above. In this case, the optimization problem is a NP-hard problem, which can be solved by exhausting search, but it is too complex to implement in practise. Therefore, we propose a suboptimal heuristic algorithm instead.

V. Narrow Distribution Range Scenario

The first scenario is similar with that in [12], and as shown in Fig. 1, the distance between SU_4 and SU_5 is relatively small when compared with the distance from the primary transmitter to any of them. In this case, the received signal at each SU experiences almost identical path loss, so the SNRs γ_i of PU signal are i.i.d random variables with the same mean γ and all SUs can use the same threshold λ. The assumptions are reasonable because decorrelation distance is in the range of $120 \sim 200$ (m) in suburban areas [13], whereas the typical cell radius is 33 km [14].

Furthermore, all SUs will have nearly identical reporting energy consumptions C_r. Therefore, the original optimization problem (15) is transformed into

$$\begin{array}{ll} \min & K(C_s + C_r) + \frac{N_0 W T_t}{G}(1-Q_F)[\exp(\frac{C_{SU}}{W(1-Q_F)}) - 1] \\ s.t. & Q_D \geq \theta \end{array} \tag{16}$$

where $K = \sum_{i=1}^{N} I(i)$ denotes the number of cooperative SUs. And the parameters being optimized are transformed accordingly into the identical threshold λ and the number of non-zero elements of $\mathbf{I}$, i.e. K.

With the same λ and γ, the performance of sensing can be calculated by (7) and (8) as

$$Q_F = 1 - \left(1 - \frac{1}{2}erfc\left(\frac{\lambda - 2u}{2\sqrt{2u}}\right)\right)^K \tag{17}$$

$$Q_D = 1 - \left(1 - \frac{1}{2}erfc\left(\frac{\lambda - 2u(\gamma+1)}{2\sqrt{2u(2\gamma+1)}}\right)\right)^K \tag{18}$$

The parameters to be determined are the detection threshold λ and the number of SUs participating in cooperative spectrum sensing K. At first, for a given K, both the objective function and the constraint decrease monotonically with increasing λ, so the optimal threshold $\lambda^*(K)$ can be obtained when the equation is satisfied in the constraint, i.e.

$$1 - \left(1 - \frac{1}{2}erfc\left(\frac{\lambda - 2u(\gamma+1)}{2\sqrt{2u(2\gamma+1)}}\right)\right)^K = \theta \tag{19}$$

By solving the above equation, the optimal threshold $\lambda^*(K)$ for different K can be obtained as

$$\lambda^*(K) = 2\sqrt{2u(2\gamma+1)} \cdot erfc^{-1}(2 - 2\cdot \sqrt[K]{1-\theta}) + 2u(\gamma+1) \tag{20}$$

Based on the optimal λ for a given K, substituting $\lambda^*(K)$ into (16), the objective function becomes

$$\min_{K} \quad K(C_s + C_r) + \frac{N_0 W T_t}{G}(1-Q_F)[\exp(\frac{C_{SU}}{W(1-Q_F)}) - 1] \tag{21}$$

where

$$Q_F(K) = 1 - \left(1 - \frac{1}{2}erfc\left(\frac{\lambda^*(K) - 2u}{2\sqrt{2u}}\right)\right)^K \tag{22}$$

Let $C_{total}(K)$ denote this objective function in (21). The following lemma shows that the convexity of the objective function.

Lemma 1: The total energy consumption $C_{total}(K)$ is a convex function of K, where K is the number of cooperative users.

Proof: The total energy consumption $C_{total}(K)$ is composed of two terms. The former one is the energy consumption for spectrum sensing and reporting local sensing results. Its derivative is $(C_s + C_r)$, which is a positive constant. The latter term is the energy consumption for transmission of a SU. Although the expression of the derivative, denote as $g(K)$, is too complex to be analyzed, we can investigate from the network perspective. When there is no user to sense, the secondary system can not discover any spectrum opportunity, so $g(K) \to -\infty$ when $K \to 0$. If there are too many cooperative users, Q_f decreases only a little with the increasing K, $g(K) \to 0$ when $K \to \infty$. Because it is obvious that the gain of increasing cooperative users decreases, $g'(K) > 0$, so $g(K)$ is a monotonically increasing function of K from $-\infty$ to 0. Therefore, there is a unique K satisfying $C'_{total}(K) = (C_s + C_r) + g(K) = 0$. ∎

By the numerical searching, e.g. the steepest descent method, the optimal value of K can be obtained for minimizing the total energy consumption because of the convexity of the objective function. If the obtained optimal value is not an integer, compare the values of the objective function corresponding to the two closest integers, the one which achieves the smaller energy consumption is chosen as the optimal number of cooperative SUs K^*.

VI. Wide Distribution Range Scenario

When the location distribution of secondary users is in wide range, as shown in Fig. 1, $\mathrm{SU}_1 \sim \mathrm{SU}_6$, their received SNRs γ_i and reporting energy consumptions C_{r_i} are diverse due to different radio environments. In this case, the original optimization problem (15) cannot be simplified and this combination optimization problem is NP-hard. The worse-case computational complexity of its optimal algorithm (exhaustion algorithm) grows exponentially in the user number N as $O(2^N)$, which is too high to be acceptable in practical systems. Thus we propose a low-complexity heuristic algorithm for a sub-optimal solution.

The basic idea of the proposed algorithm is derived from two findings below:

- While demanding each participator in cooperative sensing to have the same detection probability, increasing the number of participators lead to not only each P_{f_i} reduce but also false alarm probability of cooperative sensing, Q_F. Thus energy consumption in data transmission duration will be cut down.
- Increasing the number of participators, the energy consumption in cooperative sensing duration accumulates.

Since each participator have effect on energy consumption both in cooperative sensing duration and data transmission duration, the algorithm choosing SUs of cooperation needs to take those two aspects into account simultaneously.

The procedure of the proposed heuristic algorithm is selecting the cooperative SUs one by one. If adding one more SU can decrease the total energy consumption, the SU corresponding to the minimal total energy consumption is selected. The procedure of calculating the energy consumption and adding another SU is repeated till the value of energy consumption can not be reduced any more. The pseudo-code of the proposed algorithm is presented in Algorithm 1, in which $C_{total}(\cdot)$ can be calculated via (15).

Algorithm 1 Appropriate Set of Cooperative SUs

```
C_min = ∞
S_1 = ∅; S_2 = {SU_1, SU_2, ··· , SU_N}
repeat
   C* = min_i C_total (S_1 ∪ {SU_i}), ∀i ∈ S_2
   i* = arg min_i C_total (S_1 ∪ {SU_i}), ∀i ∈ S_2
   if C_min > C* then
      C_min = C*
      S_1 = S_1 ∪ {SU_i*}; S_2 = S_2 \ {SU_i*}
   end if
until C_min ≤ C*
Output C_min as the minimal energy consumption.
Output S_1 as the set of cooperative users for sensing.
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The proposed algorithm is with the complexity of $O(N^2)$.

VII. Simulation Results

In this section, we verify the aforementioned analysis results via simulations. In a cognitive radio network with 10 SUs, the SUs have the same sensing energy consumption C_s, which is considered as a unit of energy. In the narrow distribution range scenario, the SNR of primary signal experienced by each SU is $5dB$ and their energy consumption C_r for reporting the local sensing results is set as 2 units of energy. In the wide distribution range scenario, the SNRs of primary signal are uniformly distributed during $-5dB \sim 5dB$ and the values of their reporting energy consumption are also uniformly distributed during $0 \sim 5$ units.

A. Simulation Verification for Narrow Distribution Range Scenario

The false alarm probability and the energy consumption in narrow distribution range scenario is shown in Fig. 2. In Fig. 2, C_1 is the energy consumption for cooperative sensing, which consists of the energy in both spectrum sensing and reporting sensing results, and C_2 is the energy consumption for data transmission. Due to the identical C_r, $C_1(K)$ increases linearly with the increasing K. $C_2(K)$ decreases dramatically only if Q_F can be reduced remarkably, otherwise it almost cannot be reduced anymore. Therefore, the sum of $C_1(K)$ and $C_2(K)$ decreases first and then increases with increasing K. By choosing the appropriate K, we can always obtain the minimal total energy consumption in this scenario.

B. Simulation Verification for Wide Distribution Range Scenario

In Fig. 3, two cooperative schemes are adopted as the baselines. One is the optimal performance achieved by the exhaustive enumeration method, and the other is the method that all the SUs participate in the cooperative sensing. It can be found that the total energy consumption is reduced with the increasing path gain. Comparing the minimum energy

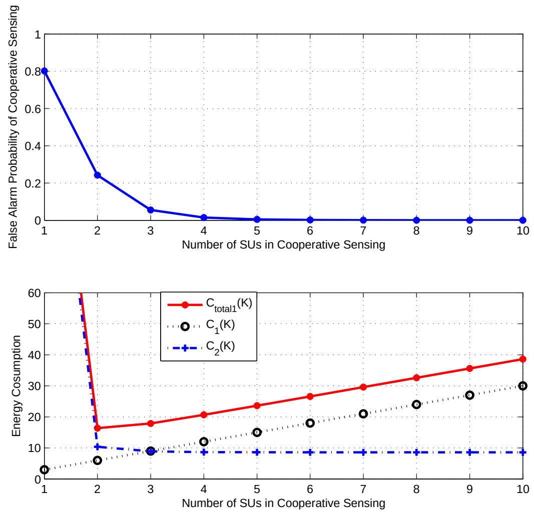

Fig. 2. False Alarm Probability Q_F and Energy Consumption for Narrow Distribution Range of SUs

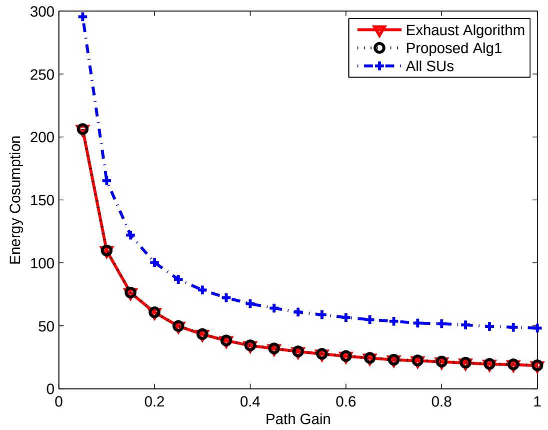

Fig. 3. Minimal Energy Consumption versus Path Gain for Different Cooperative Schemes

consumption with that of exhaustive enumeration algorithm, the proposed algorithm achieves the excellent performance and is almost the same with the optimal performance. Both the proposed algorithm and the optimal exhaustive enumeration algorithm are much better on energy efficiency than the performance when all SUs participate in cooperative sensing.

Fig. 4 shows the difference (i.e. the absolute error and the relative error) between the proposed algorithm and the optimal performance for 100 snapshots, in which the SNR of primary signal and the energy consumption of reporting is generated randomly. Compared with the optimal exhaustion algorithm, the proposed algorithm can also obtain the minimal energy consumption for almost every snapshots.

VIII. Conclusions

In this paper, an energy optimization problem is formulated for CR networks. The cooperation strategy is proposed for

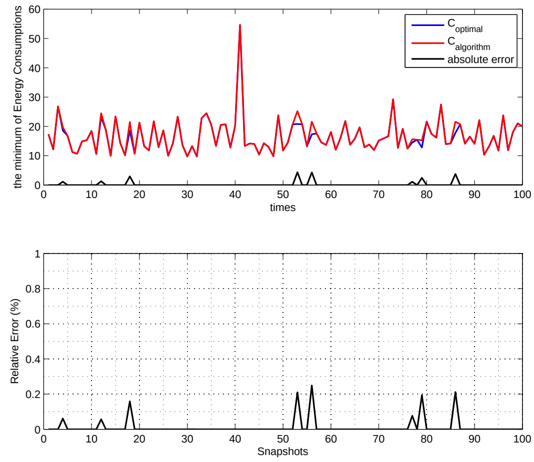

Fig. 4. Performance Comparison with Exhaustive Enumeration Method

balancing the energy tradeoff between using less energy for finding transmitting opportunities and using more transmitting opportunities to transmit data with less energy. The objective is to achieve the lowest energy consumption of the whole communication progress for CR networks, including sensing locally, reporting sensing results and transmitting data.

In the narrow distribution range scenario, the optimization problem is solved by the theoretic deduction and we discover that the minimal energy consumption can be achieved by choosing the appropriate number of cooperative SUs. In the wide distribution range scenario, a sub-optimal heuristic algorithm with low complexity is proposed to choose cooperative SUs. For diverse channel qualities, the proposed algorithm can identify the appropriate set of cooperative SUs and it achieves almost the same performance compared with the optimal exhaustive algorithm. Furthermore, the proposed cooperative strategy has much more energy efficiency compared with the conventional cooperative sensing with all SUs participating in cooperative spectrum sensing.

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