Spectrum sensing and power efficiency trade-off optimisation in cognitive radio networks over fading channels

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Abstract: Multiple secondary users can cooperate to increase the reliability of spectrum sensing in cognitive radio (CR) networks. However, the total transmission power grows approximately linearly with the number of cooperative secondary users. This study proposes a new approach to optimise the trade-off between sensing reliability and power efficiency in cooperative CR networks over fading channels. The authors assume K cooperative secondary users each collect N samples during the sensing time. The proposed approach is based on dividing the spectrum sensing into two phases. In the first phase, the authors use only n1 of N samples (n1 ≤ N), to check the channels state, then k of K cooperative secondary users (k ≤ K), which are in deeply faded channels are discarded. The authors call this n1 a check point of the sensing time. The spectrum sensing with relatively less-faded channels are continued during the second phase. Therefore there is a check point at which the sensing time can be optimised in order to maximise the probability of detection and the power efficiency. Several experiments are carried out to test the performance of the proposed approach in terms of probability of detection and power efficiency. The obtained results show that the proposed approach enhances the probability of detection and shortens the optimal sensing time. Moreover, it improves the overall power efficiency.

1 Introduction

One of the major challenges in design of wireless networks is the use of the frequency spectrum. Recent measurements by Federal Communications Commission (FCC) show that 70% of the allocated spectrum is in fact not utilised [1]. Spectrum utilisation can be improved significantly by allowing a secondary user (SU) to utilise a licensed band when the primary user (PU) is absent. Cognitive radio (CR) has been proposed as a promising technique for future wireless communication systems [2–4]. CR is able to fill in spectrum holes and serve its users (secondary users) without causing harmful interference to the licensed user (PU). To do so, the CR must continuously sense the spectrum it is using in order to detect the reappearance of the PU. Once the PU is found to be active, the SU is required to vacate the channel. Therefore spectrum sensing is of significant importance in CR networks. Moreover, periodic sensing is essential where the SU has to be aware of the channel status at all times. This is achieved by using a frame structure as in [5, 6]. In this structure, each frame consists of a sensing period and a transmission period. At the end of each sensing period, the SU transmission starts when the licensed channel is idle. Otherwise, the SU will wait until the next frame to sense the licensed channel again.

There are two important parameters associated with spectrum sensing: probability of detection and probability of false alarm. From the PUs perspective, the higher the probability of detection, the better protection it will have from the SU. However, from the secondary user’s perspective, the lower the false alarm probability, the more secondary transmission opportunities it will have. Therefore a better sensing quality can be obtained by using a longer sensing period or, large number of samples.

Cooperative communications refer to the class of techniques, where the benefits of multiple-input–multiple-output (MIMO) techniques are gained through sharing information between multiple cooperating terminals in a wireless networks. Wireless relay networks that employ cooperative diversity have sometimes been referred to as virtual MIMO systems [7, 8]. Multiple secondary users can cooperate to increase the reliability of spectrum sensing. The key challenge of spectrum sensing is the detection of weak signals in noisy channels with a large probability of detection. CR sensing performance can be improved using secondary users cooperation where users share their spectrum sensing measurements. Having multiple cooperating users increases diversity by providing multiple measurements of the signal and thus guarantees a better performance at low signal-to-noise ratio (SNR). It also provides a possible solution to the hidden-terminal problem.
that arises because of shadowing or severe multipath fading environments [9, 10].

From the above discussion it is clear that, increasing the number of cooperative secondary users will increase the number of collected samples during the sensing time and this will improve the reliability of spectrum sensing in terms of probability of detection. On the other hand, the more the collected samples during the sensing time, the more the power would be consumed. Thus, there exists a trade-off between power consumption (power efficiency) and probability of detection; we can obtain higher probability of detection but we need to consume more power instead. The authors in [11, 12], considered the trade-off between the sensing quality and the achievable throughput. The spectrum sensing duration and the achievable throughput trade-off in a cooperative CR network over Nakagami fading conditions was introduced in [13]. However, none of these papers have examined the trade-off between probability of detection and power efficiency in cooperative CR networks. Therefore it is of great interest to consider this trade-off in this paper.

In this paper, we first study the trade-off between sensing quality in terms of probability of detection and power efficiency. Then we propose a new approach to optimise the trade-off between probability of detection and power efficiency in cooperative CRs over fading wireless channels. The basic idea of the proposed approach can be explained as follows; assume K cooperative secondary users each collect N samples during the sensing time. The proposed approach is based on dividing the spectrum sensing into two phases. In the first phase, we use only n1 of N samples, (n1 ≤ N) to check the channels state, then K of K secondary users, (k ≤ K) which are in deeply faded channels are discarded. We call this n1 a check point of the sensing time. The spectrum sensing with relatively less-faded channels are continued during the second phase. Therefore there is a check point at which the sensing time can be optimised in order to maximise the probability of detection and improve the power efficiency.

The remainder of this paper is organised as follows; Section 2 presents the general system model for spectrum sensing. The relation between probability of detection and probability of false alarm is also established in this section. Section 3, presents the energy detection over Rayleigh fading channels. Spectrum sensing based on hard-decision fusion is explained in Section 4. In Section 5 we explain the sensing-power efficiency trade-off. The proposed approach is used to optimise this trade-off is also presented in this section. Simulation results and discussion are given in Section 6. Finally, conclusions are drawn in Section 7.

2 General system model for cooperative spectrum sensing

In this section, the general model for spectrum sensing is presented. Then we introduce the energy detection scheme and analyse the relationship between the probability of detection and the probability of false alarm.

2.1 Cooperative spectrum sensing

The critical challenging issue in spectrum sensing is the hidden-terminal problem, which occurs when the SU is shadowed or in severe multipath fading. To address this problem, multiple secondary users can cooperate in spectrum sensing [9, 10]. Therefore cooperative spectrum sensing can greatly improve the probability of detection in Rayleigh fading channels [14, 15]. In general, cooperative spectrum sensing can be performed as shown in Fig. 1. Each SU performs its own local spectrum sensing measurements independently and then makes a binary decision on whether the PU is present or not. Then all of the secondary users forward their decisions to a common receiver, R0. The common receiver fuses the SU decisions and makes a final decision to infer the absence or the presence of the PU.

In this paper we consider a CR network with K cooperative secondary users as shown in Fig. 1. Spectrum sensing is performed periodically every N samples, which is the total number of samples for each SU. The spectrum sensing problem at the ith SU is modelled as a binary hypothesis test to determine the absence or the presence of the PU. Let H0 denote the absence of the PU and H1 designate the presence of the PU. Spectrum sensing is to decide between the following two hypotheses

\[ H_0 : y_i(n) = w_i(n), \quad \text{for } i = 1, \ldots, K, \]

\[ H_1 : y_i(n) = h_i(n)s(n) + w_i(n) \]

where y_i(n) is the received signal at the ith SU, s(n) represents the PUs signal samples which are independently and identically distributed (i.i.d.) with zero mean and variance \(E[|w_i(n)|^2] = \sigma_w^2\), w_i(n) is the additive white Gaussian noise, and h_i(n) is the complex channel gain of the sensing channel between the PU and the ith SU. When the channel is non-fading, h_i(n) is constant during the sensing process. On the other hand, when the channel is fading, h_i(n) is constant during the sensing process. On the other hand, when the channel is fading, h_i(n) includes multipath and fading effects [15]. It is assumed that noise samples are i.i.d. with zero mean and variance \(E[|w_i(n)|^2] = \sigma_w^2\). It is also assumed that the channel gain in average is 1. Denote \(\gamma = \sigma_s^2/\sigma_w^2\) as the received SNR of the PU measured at the secondary receiver of interest, under the hypothesis H1.

Generally, two probabilities are of interest for indicating the performance of a sensing algorithm; probability of detection, \(P_d\), which defines the probability of the sensing algorithm correctly detecting the presence of primary signal under hypothesis H1; and probability of false alarm, \(P_f\), which defines the probability of the sensing algorithm falsely declaring the presence of primary signal under hypothesis H0. Obviously, for a good detection algorithm, the probability of detection should be as high as possible whereas the probability of false alarm should be as low as possible.
2.2 Energy detection over non-fading channels

The spectrum sensing algorithm considered in this paper is the energy detection algorithm [16] because of its relatively low computational complexity, ease of implementation and the fact that it does not require any prior information about the PUs signal. Once the signal \( y_t \) has been collected, the \( i \)th SU computes its energy; the test statistic for the energy detector is given as [12]

\[
T(y_t) = \frac{1}{N} \sum_{n=1}^{N} |y_t(n)|^2
\]  

(2)

Under hypothesis \( H_0 \), the test statistic \( T(y_t) \) is a random variable whose probability density function (PDF) \( p_0(x) \) is a \( \mathcal{N}^2 \) with \( 2N \) degrees of freedom for complex valued case [12]. The energy detection is performed by measuring the energy of the received signal \( y_t(n) \) in a fixed bandwidth \( W \) over an observation or sensing time window \( T_s \). If \( e_i \) is the \( i \)th SU detection threshold, the probability of false alarm, \( P_{fa} \), is given by

\[
P_{fa}(e_i, T_s) = \text{Prob}(T(y_t) > e_i | H_0) = \int_{e_i}^{\infty} p_0(x) \, dx
\]  

(3)

where \( P_{fa} \) denotes the false alarm probability of the \( i \)th SU in its local spectrum sensing. Under hypothesis \( H_1 \), let \( p_1(x) \) represent the PDF of the test statistic \( T(y_t) \). For a chosen threshold \( e_i \), the probability of detection, \( P_{det} \), is given by

\[
P_{det}(e_i, T_s) = \text{Prob}(T(y_t) > e_i | H_1) = \int_{e_i}^{\infty} p_1(x) \, dx
\]  

(4)

where \( P_{det} \) denotes the probability of detection of the \( i \)th SU in its local spectrum sensing. From the central limit theorem, we can approximate the probabilities of detection and false alarm as follows [12]; for a large \( N \), \( T(y_t) \) can be approximated as a Gaussian random variable with mean

\[
H_0; \mu_0 = \sigma_w^2
\]  

and variance

\[
H_0; \sigma_w^2 = \frac{1}{N} \left[ E|w(n)|^4 - \sigma_w^4 \right]
\]  

(5)

\[
H_1; \mu_1 = (\gamma + 1)\sigma_w^2
\]  

and variance

\[
H_1; \sigma_1^2 = \frac{1}{N} \left[ E|s(n)|^4 + E|w(n)|^4 - (\sigma_s^2 - \sigma_w^2)^2 \right]
\]  

(6)

If we consider circularly symmetric complex Gaussian (CSCG) noise case and for the primary signal \( s(n) \), we consider the complex phase shift keying (PSK) modulated signal; the probabilities of false alarm and detection can be approximated, respectively, as follows

\[
P_{fa}(e_i, T_s) = Q\left(\sqrt{N}\left(\frac{e_i}{\sigma_s^2} - 1\right)\right)
\]  

(7)

\[
P_{det}(e_i, T_s) = Q\left(\sqrt{N}\left(\frac{e_i}{\sigma_w^2} - \gamma - 1\right)\right)
\]  

(8)

where \( Q(\cdot) \) is the complementary distribution function of the standard Gaussian, and given as

\[
Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} \exp\left(-\frac{t^2}{2}\right) \, dt
\]  

(9)

It is clear that, \( P_{fa} \) in (7) is independent of SNR since under \( H_0 \) there is no primary signal present. It is also clear from (8) that, for a large number of samples, \( N \) it is more likely to detect a signal with higher probability of detection.

If the decision is \( H_0 \) when there is a PU present, it is called missed detection and its probability is called missed probability of detection, \( P_{md} \), which can be written as

\[
P_{md}(e_i, T_s) = 1 - P_{det}(e_i, T_s)
\]  

(10)

Equation (8) can be rewritten in terms of detection threshold as

\[
\left(\sqrt{N}\frac{e_i}{\sigma_w^2} - 1\left(\frac{e_i}{\sigma_w^2} - \gamma - 1\right)\right) = Q^{-1}(P_{md})
\]  

(11)

where \( P_{md} \) is the \( i \)th SU target probability of detection. Using (7) this threshold is related to the probability of false alarm as follows

\[
\left(\sqrt{N}\left(\frac{e_i}{\sigma_s^2} - 1\right)\right) = Q^{-1}(P_{fa})
\]  

(12)

For a target probability of detection, \( P_{det} \), the probability of false alarm is related to the target probability of detection as follows

\[
P_{fa} = Q\left(\sqrt{2\gamma + 1}\left(Q^{-1}(P_{det}) - \sqrt{N}\gamma\right)\right)
\]  

(13)

Note \( N \) is the maximum integer not greater than \( T_s \times f_w \), where \( f_w \) is the received signal sampling frequency. In a similar way, the probability of detection for a target probability of false alarm is given by

\[
P_{det} = Q\left(\frac{1}{\sqrt{2\gamma + 1}} \left(Q^{-1}(P_{fa}) - \sqrt{N}\gamma\right)\right)
\]  

(14)

3 Energy detection over Rayleigh fading channels

In this section, we derive the average probability of detection over Rayleigh fading channels [15]. Note that the probability of false alarm, however, remains the same under any fading channel since it is considered for the case of no signal transmission and as such is independent of SNR [14]. When the channel is varying because of fading effects, the previously given equations for probability of detection represents the probability of detection conditioned on the instantaneous SNR. Therefore by averaging the conditional probability of detection over the SNR fading distribution, we can find the expressions in closed-form of probability of
detection in fading channels [15].

\[ P_{\text{d},\text{fading}} = \int_{\gamma} Q\left(\sqrt{2B\gamma}, \sqrt{\gamma}\right)f_{\gamma}(x)\,dx \]  

(15)

where \( B \) is the time-bandwidth product and \( f_{\gamma}(x) \) is the probability of distribution function of SNR under fading. Under Rayleigh fading, the signal amplitude follows a Rayleigh distribution. In this case, the SNR follows an exponential PDF

\[ f(\gamma) = \frac{1}{\bar{\gamma}} \exp\left(-\frac{\gamma}{\bar{\gamma}}\right) \]  

(16)

where \( \bar{\gamma} \) is the average SNR. Therefore in Rayleigh fading, a closed-form formula for probability of detection over Rayleigh fading channels may be obtained as follows

\[ P_{\text{d, Ray}, \text{fading}} = \exp\left(-\frac{\varepsilon_i}{2(1+\gamma)}\right) \left[1 + \frac{1}{B\gamma}\right]^{B-1} \]

\[ \times \left[1 - \frac{\Gamma(\gamma, (\varepsilon_i/2)/2)}{\Gamma(B-1)}\right] \]

\[ + \frac{\Gamma(B-1, (\varepsilon_i/2)/2)}{\Gamma(B-1)} \]  

(17)

where \( \Gamma(\cdot) \) is the gamma function.

4 Spectrum sensing based on hard-decision fusion

In cooperative spectrum sensing, all secondary users identify the availability of the PU independently. Each SU makes a binary decision based on its local spectrum sensing and then forwards one bit of the decision to the common receiver as in Fig. 1. Let \( d_i \) represent the local spectrum sensing result of the \( i \)th SU. The value of \( d_i \) for \( i = 1, \ldots, K \), can be given as follows

\[ d_i = \begin{cases} 0 & \text{The SU infers the absence of the PU} \\ 1 & \text{The SU infers the presence of the PU} \end{cases} \]  

(18)

Once the decision is made by each SU, there are different rules available for making the final decision on the presence of the PU [17]. At the common receiver, all 1-bit decisions are fused together according to the following logic rule

\[ R_c = \sum_{i=1}^{K} d_i \begin{cases} 0 & \L \Rightarrow H_0 \\ 1 & \L \Rightarrow H_1 \end{cases} \]  

(19)

Equation (19) demonstrates that the common receiver infers the presence of PU signal, that is \( H_1 \), if at least \( L \) out of \( K \) secondary users inferring \( H_1 \). Otherwise, the common receiver decides the absence of PU signal, that is, \( H_0 \).

4.1 Logic-OR rule

The common receiver infers the presence of the PU signal when there exists at least one SU that has the local decision \( H_1 \). Therefore the OR rule corresponds to the case of \( L = 1 \), that is \( R_c \geq 1 \). Otherwise, there is no PU signal. Assuming that all decisions are independent, the probability of detection and probability of false alarm of cooperative spectrum sensing based on the OR rule is given, respectively as

\[ P_d = 1 - \prod_{i=1}^{K} (1 - P_{d_i}) \]  

(20)

\[ P_f = 1 - \prod_{i=1}^{K} (1 - P_{f_i}) \]  

(21)

4.2 Logic-AND rule

The common receiver infers the presence of the PU signal if all decisions say that there is a PU. It can be seen that the AND rule corresponds to the case of \( L = K \). The probability of detection and probability of false alarm of cooperative spectrum sensing based on the AND rule is given, respectively as,

\[ P_d = \prod_{i=1}^{K} P_{d_i} \]  

(22)

\[ P_f = \prod_{i=1}^{K} P_{f_i} \]  

(23)

4.3 Majority rule

This decision rule is based on majority of the individual decisions of SU. If half or more of the decisions say that there is a PU signal, the final decision declares that there is a PU. The probability of detection and probability of false alarm can be obtained as in [12]. It can be seen that the OR rule is very conservative for the secondary users to access the licensed band of the PU. As such, the chance of causing interference to the PU is minimised as will be shown in results and discussion section.

5 Sensing-power efficiency trade-off and the proposed approach

In this section, we study the fundamental trade-off between sensing quality in terms of probability of detection and power efficiency then we discuss how the sensing time can be optimised in order to maximise the probability of detection and the power efficiency.

5.1 Problem formulation

For a CR network with \( K \) cooperative secondary users each collects \( N \) samples during the sensing time. The received \( K \times N \) data matrix \( \mathbf{D} \) is represented as

\[ \mathbf{D} = \begin{bmatrix} y_{1,1} & y_{1,2} & \ldots & y_{1,N} \\ y_{2,1} & y_{2,2} & \ldots & y_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ y_{K,1} & y_{K,2} & \ldots & y_{K,N} \end{bmatrix} \]  

(24)
As mentioned before, to improve the probability of detection we have to increase the number of collected samples during the sensing process, this can be achieved by increasing the number of cooperative secondary users. Generally, the larger the number of cooperative secondary users, the more the samples we collect during the sensing process, the higher the probability of detection but the more power would be consumed during the spectrum sensing process. Thus, there exists a trade-off between power consumption and probability of detection on spectrum sensing; one gets higher probability of detection but has to consume more energy instead.

5.2 Proposed approach

The proposed approach is based on dividing the spectrum sensing into two phases. In the first phase, we use only $n_1$ of $N$ samples, $n_1 \leq N$ to check the channels state; we call this $n_1$ a check point of the sensing time. Then $k$ of $K$ cooperative secondary users, ($k \leq K$) which are in deeply faded channels are discarded. Thus, after the check point, there are only $K-k$ secondary users employed for $N-n_1$ samples. Equation (25) shows the received data matrix under this new approach. It is clear from (25) that, after sensing $n_1$ samples of $K$ cooperative secondary users, the proposed approach selects $k$ of cooperative secondary users, which are considered to be more faded than others, to discard. Therefore discarding the cooperative secondary users with faded channel increases the overall power efficiency as explained next. See (25)

$$D = \begin{bmatrix}
    y_{1,1} & \cdots & y_{1,n_1} & y_{1,n_1+1} & \cdots & y_{1,N-1} & y_{1,N} \\
    \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
    y_{K-2,1} & \cdots & y_{K-2,n_1} & y_{K-1,n_1+1} & \cdots & y_{K-1,N-1} & y_{K-1,N} \\
    y_{K-1,1} & \cdots & y_{K-1,n_1} & y_{K-1,n_1+1} & \cdots & y_{K-1,N-1} & y_{K-1,N} \\
    y_{K,1} & \cdots & y_{K,n_1} & y_{K,n_1+1} & \cdots & y_{K,N-1} & y_{K,N}
\end{bmatrix}$$  \hspace{1cm} (25)

Let $N \times P$ is the required power for each secondary user. Therefore the power required for the sensing process using $K$ cooperative secondary users will be $K \times N \times P$. To explain how the proposed approach improve the overall power efficiency, consider first the case of discarding one SU ($k = 1$), after $n_1$ samples of sensing; this saves $(N-n_1) \times P$ in power. Now, if $k$ cooperative secondary users are chosen to be discarded after $n_1$ samples of sensing, we can save $k \times (N-n_1) \times P$ in power compared to that $K \times N \times P$ for all $N$ samples from $K$ cooperative secondary users. Power efficiency is proportional to the energy saved during the sensing process by discarding the deeply faded secondary users. That is, power efficiency should be an indicator of how much energy could be saved compared to the sensing of whole samples of all $K$ cooperative secondary users. Therefore we may represent the power efficiency $\eta_p$ as follows

$$\eta_p(n, k) = \frac{k \times (N-n_1)}{K \times N} \hspace{1cm} (26)$$

Fig. 2 shows the power efficiency $\eta_p$ against the number of samples, using $K = 8$ and $N_{max} = 200$ for different values of $k$. It is clear from this figure that, the power efficiency decreases as more numbers of samples are utilised. On the other hand, the power efficiency improved when discarding more secondary users, changing $k$ from 1 to 6. Also for a given number of $k$, the power efficiency is improved when less number of samples $n_1$ is employed before the check point. However, the probability of detection increases when more number of samples is employed. This trade-off can be optimised by finding the optimum sensing time for the proposed CR network.

5.3 Optimum sensing time

What we want now is to derive a target function to determine the optimal sensing time that jointly maximises the probability of detection and minimises the power consumption under given parameters. As there is a trade-off between the probability of detection and power efficiency,
the target function can be defined as

$$T_f(n_1, k) = (1 - \beta) \times P_d + \beta \times n_p(n_1, k)$$  \hspace{1cm} (27)$$

where $0 \leq \beta \leq 1$. As explained above, $P_d$ is proportional to the number of sensing samples $N$, whereas $n_p$ decreases as more number of samples are employed; thus, the constant $\beta$ controls the overall level of this target function as well as it controls this target function to have a maximum point. There are two extreme cases as follows:

1. $\beta \to 0$; The probability of detection is regarded as the more important factor. Therefore more number of samples are favourable to maximise the target function.
2. $\beta \to 1$; Power efficiency is regarded as more important than the probability of detection.

Therefore there may exist some range for $\beta$ at which the optimal sensing time could be found. It would be varied by other parameters, such as probability of false alarm, the size of the data matrix, and so on.

Fig. 3 presents the target function over non-fading channels for different values of $\beta$ using $K = 2$, $N = 400$, and $P_c = 0.1$. From this figure it is clear that, the target function has a maximum point at $n_1 = N$ for $\beta \leq 0.1$ and at $n_1 = 0$ for $\beta \geq 0.4$. It is clear also that, the optimum check point $n_1$ which maximises the target function tends to have small value for large values of $\beta$. For example, at $\beta = 0.2$ the optimal sensing time occurs at $n_1 = 300$ samples, whereas at $\beta = 0.3$ the optimal sensing time occurs at $n_1 = 100$ samples. However, from (27), increasing the value of $\beta$ will reduce the probability of detection. We must also note that, the range of $\beta$ to make the target function have a maximum point is altered if we change the above mentioned parameters.

Another focus to be set in this target function is how to obtain $P_d$. In this target function, the threshold value to calculate $P_d$ is obtained by fixing $P_c$. From (12), the threshold $\varepsilon$ is defined as

$$\varepsilon = \left( \frac{\Omega^{-1}(P_c)}{\sqrt{N}} + 1 \right) \sigma_w^2$$  \hspace{1cm} (28)$$

Therefore by using this target function, we can obtain the optimum value of check point, $n_1$. Also, we can conclude the optimal number of discarded secondary users for given number of check point.

6 Simulation results and discussion

In this section, several experiments are carried out to test the performance of the proposed approach in terms of probability of detection and power efficiency. The simulation parameters are summarised in Table 1.

It was demonstrated in [15] that, the detection performance showed significant degradation under Rayleigh fading scenario. Therefore under Rayleigh fading conditions, it becomes even more important to continue with less-faded channels (discarding the deeply faded channels) to maintain a certain level of performance.

A fundamental parameter determining the quality of detection is the average SNR, which mainly depends on the PUs transmitted power as well as its distance to the secondary users. Since our goal is to achieve optimum sensing time over the proposed approach, let us assume the following scenario, where the averages SNR of two secondary users have big differences. This scenario shows an environment in which one SU is experiencing rather severe fading, whereas the other is in a better condition. The average SNR values of the first and second secondary users are 5 and $-15$ dB, respectively.

Two different schemes are used to discard the secondary users. In the ‘first’ scheme, the secondary users are randomly discarded from the CR network. Whereas the ‘second’ scheme select the secondary users with the highest signal strength to keep tracking the activity of the PU and discarding the users with the lowest signal strength. The ‘second’ scheme requires additional feedback information to report the signal strength.
Fig. 4 shows the target function over Rayleigh fading channels against number of samples at different values of $\beta$ using the first scheme.

Fig. 5 shows the above results when we consider the second scheme, in which the SU is discarded according to the signal strength. It is noticeable that the overall level and maximum points of target functions are higher than those of Fig. 4. The target function for this scheme reaches its maximum point much earlier than the first scheme shown in Fig. 4.

Fig. 6 presents a comparison between probability of detection of first and second schemes. It is clear that the probability of detection of the second scheme has much higher value than of the first scheme, where it saturates approximately to 1 at $n_1 = 40$ samples compared to $n_1 = 100$ samples when we used the first scheme.

Table 2 shows the detailed comparisons of the target function for the two schemes. We can observe that, the second scheme based on the signal strength achieves the best performance. Not only the target function reaches its maximum point earlier but also it achieves higher performance. Therefore by using the proposed approach with the second scheme, the overall power efficiency is improved whereas maintaining good probability of detection.

Figs. 7 and 8 present the total average energy against number of samples using first and second schemes, respectively. From these two figures, one can see that there indeed exists an optimal sensing time to minimise the total energy consumption for spectrum sensing. Therefore there is a check point at which the sensing time can be optimised in order to maximise the probability of detection as shown in Fig. 6 and improve the power efficiency as shown in Figs. 7 and 8.

7 Conclusion

In this paper we proposed a new approach to optimise the trade-off between sensing quality and power efficiency in cooperative CR networks over fading channels. The
The proposed approach is based on discarding the secondary users which are in deeply faded channels. Two different schemes were proposed to discard the secondary users. In the first scheme, the secondary users are randomly discarded. Whereas the second scheme selecting the secondary users with the highest signal strength to keep tracking the activity of the PU and discarding the users with the lowest signal strength. It has been shown that the proposed approach with the second scheme improves the overall power efficiency whereas maintaining good probability of detection and shortens the optimal sensing time.

8 References