Analytical Simulation and Performance Optimization for Spectrum Sensing in Cognitive Radio Networks

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Abstract —Dynamic spectrum allocation (DSA) solutions such as cognitive radio networks (CRNs) have been proposed as a key technology to exploit the frequency segments that are spectrally underutilized. In this paper, the performance of cooperative CRNs has been analyzed under two different operational modes, namely, constant primary user protection (CPUP) and constant secondary user spectrum usability (CSUSU). The CRN performance metrics have been selected to be the overall CRN capacity and the overall interference from CRN to the primary users under CPUP and CSUSU scenario, respectively. Computer simulations are invoked to evaluate the CRN performance with varying the sensing time as well as the number of cooperating users in the network and the observations have been presented. Finally, particle swarm optimization algorithm has been used to jointly optimize the sensing time duration and cooperation level of spectrum sensing in CRNs. The simulation results show that the CRN performance can be noticeably improved by applying suitable optimization algorithms.

Keywords- Cognitive radio; Spectrum sensing; Capacity; Interference; Optimization.

I. INTRODUCTION

The conventional approach of static spectrum allocation is very inflexible in the sense that frequency bands are exclusively licensed to radio operators and each technology has to operate within its assigned band. With the increasing demand of radio spectrum, it is becoming next to hard to find vacant bands to either deploy new technologies or to extend the existing ones. Furthermore, recent spectrum measurements, such as the one done by Spectrum Policy Task Force (SPTF) [1], reveal that there is obviously an inefficient use of the already-licensed spectrum segments. These observations were the trigger to start looking around for possible alternatives of dynamic allocation solutions. There was a significant juncture in wireless communications when J. Mitola introduced his terrific idea of the cognitive radio (CR) as an upgraded version of the conventional software defined radio (SDR) armed with a spectrum sensing capability over three degrees of freedom; time, frequency and space [2]. The CR technology is a means of opportunistic dynamic spectrum access to mitigate the spectrum underutilization phenomenon. The spectrum sensing is normally considered as a pure detection problem where the CR-assisted users have to scan a vast range of frequencies to observe any available 'white spaces' or 'holes' that are temporarily and spatially available for transmission. The CR-assisted users are classified as secondary users (SUs) competing with primary users (PUs) who are obviously, Licensees, or alternatively, users of existing technologies on unlicensed bands (e.g. IEEE802.11a) [3]. The SUs or CR users are allowed to utilize the frequency bands of the PUs when they are not currently being used but they should willingly and quickly vacate the band once a PU has been detected. This fast vacation is necessary to avoid causing harmful interference to the PUs who should maintain ubiquitous and uninterrupted accessibility. Therefore, the SUs are required to periodically monitor the PUs activities using fast and reliable detection/sensing algorithms.

In fading environments, spectrum sensing is challenged by some sort of uncertainty occurs as a result of inability to distinguish between the white spaces whether it is because of PU absence or because of deep fade. Thus, many cooperative spectrum sensing techniques have been proposed in the literature to overcome this issue and enhance the decision-making process of PU availability. The last decade has witnessed an increasing interest in the opportunistic spectrum access research. Some of which focused on the design of physical (PHY) layer where the main function is to reliably identify the white spaces across time, frequency and space. Different approaches have been proposed to perform this function such as direct spectrum sensing [4], geo-location and centralized database [5], probe method [6], licensed-receiver detection [7], and beacon signal incorporation [8]. Among these, the direct spectrum sensing has received more attention due its implementation simplicity and compatibility with the existing PU systems.

A brief overview of the different alternatives for local spectrum sensing, such as matched filter, cyclo-stationary detector, and energy detector, has been presented in [4].

The matched filter requires a prior knowledge of PU waveform which is practically not possible. The CR framework is initiated based on the idea of dealing with the PU signals as unknown signals. On the other hand, the cyclo-stationary detector can be used if some the PU features are available [9] but it has the disadvantage increased complexity and processing time. For cooperative spectrum sensing, there have been many proposals on how to combine the local measurements sent by the individual SUs to the central or distributed fusion center(s). These schemes can be classified as hard decision fusion (HDF) [10][11][12] or soft decision fusion (SDF) [13][14]. In HDF, the local sensors, or SUs, make their own judgments on the presence of a PU and their corresponding resultant 1-bit decisions are sent to the BS for fusion. These hard fusion schemes have the advantage of reduced traffic overhead as only one single bit needs to be reported to the BS from each SU. In contrast, the SDF schemes require the local sensors to report their measurements as raw data to the BS at which, this data will be fused to construct a final decision on the presence of PU(s). These soft schemes have shown better detection performance than HDF schemes [15] but they own the negative feature of the increased overhead due to the huge amount of reported data from the SUs to the BS. Another way to improve the sensing performance is to group the SUs into clusters and instruct them to send their 1-bit hard decisions to clusters' headers which will then forward there evaluations to the BS [16][17]. In this paper, the OR- and AND-rule HDF schemes are implemented at the common fusion center or BS due to their simplicity as well as to achieve a reduced traffic overhead. Overhead reduction is a crucial demand in CRNs whose main concern is achieving an efficient use of radio resources. HDF schemes require control channels from the SUs to the common BS with less bandwidth. In addition, the individual decisions of SUs are reported to the BS in an orthogonal manner and thus, achieving high level of multiplexing.

II. LOCAL SPECTRUM SENSING

In local sensing, each SU senses the spectrum within its geographical location and makes a decision on the presence of primary user(s) based on its own local sensing measurements.

A. Channel Sensing Hypotheses

Consider a SU in a cognitive radio system sensing a frequency band W and a the received demodulated signal is sampled at a sampling rate, f_s, then $f_s \geq W$. Hence, the sampled received signal, $X[n]$ at the SU receiver will have two hypotheses as follows

$$\begin{array}{lll} H_0: & X[n] = W[n] & \text{if the PU is absent} \\ H_1: & X[n] = W[n] + S[n] & \text{if the PU is present} \end{array} \quad (1)$$

where $n = 1, \ldots, K$; K is the number of samples. The noise $W[n]$ is assumed to be additive white Gaussian (AWGN) with zero mean and variance σ_w^2 . $S[n]$ is the primary user's signal and is assumed to be a random Gaussian process with zero mean and variance σ_s^2 . P_d and P_f are defined as the probabilities that the sensing SU algorithm detects a PU under H_0 and H_1, respectively. High detection probability is always required to ensure minimum level of interference to PUs whereas low probability of false alarm should be targeted to offer more chances for the SUs to use the scanned spectrum.

B. Statistical Model for Energy Detector

The energy detector (ED) is a well-known detector which can be utilized to detect unknown signals as it does not require a prior knowledge on the transmitted waveform. The EDs are implemented at the SUs' receivers. The decision statistic of the ED, T, is a random variable described by

$$T = \sum_{n=1}^{K} \left(X[n]\right)^2 \quad (2)$$

Under the common Neyman-Pearson (NP) criteria, the ED performance can be characterized by a resulting pair of (P_f, P_d) that is estimated as

$$P_f = P(T > \beta \mid H_0) = \int_{\beta}^{\infty} f_0(x)dx \quad (3)$$

$$P_d = P(T > \beta \mid H_1) = \int_{\beta}^{\infty} f_1(x)dx \quad (4)$$

where $f_0(x)$ and $f_1(x)$ are the probability density functions (PDFs) of Chi-square distributions with K degrees of freedom for the real-valued signal and noise under H_0 and H_1, respectively. Using the central limit theorem (CLT) and for large K (e.g. $K > 250$), the PDF of T under hypothesis H_0 can be approximated by a Gaussian distribution with mean $\mu_0 = K\sigma_w^2$ and variance $\sigma_0 = 2K\sigma_w^4$, and similarly, the PDF of T under hypothesis H_1 can also be approximated by a Gaussian distribution with mean $\mu_1 = K(\sigma_w^2 + \sigma_s^2)$ and variance $\sigma_1 = 2K(\sigma_w^2 + \sigma_w^2)^2$. Thus

$$P_f = Q\left(\frac{\beta - K\sigma_w^2}{\sqrt{2K\sigma_w^4}}\right) \quad (5)$$

$$P_d = Q\left(\frac{\beta - K\left(\sigma_w^2 + \sigma_s^2\right)}{\sqrt{2K\left(\sigma_w^2 + \sigma_s^2\right)^2}}\right) \quad (6)$$

where β is a particular detection threshold that tests the decision statistic and $Q(.)$ is the complementary distribution function of the Gaussian distribution.

C. Cognitive Radio Transmission Scenarios

In this paper, the performance of CR network is evaluated under two different operational modes, namely, the constant primary user protection (CPUP) and the constant secondary user spectrum usability (CSUSU) scenarios. The CPUP transmission mode is viewed from the Pus' perspective whereas CSUSU is viewed from SU's perspective. In CPUP scenario, the interference from Sus to PUs will be set to a specific level that is low enough to ensure ubiquitous and uninterruptable service for the active PUs. This scenario can be realized by fixing the probability of detecting PUs, P_d, at a satisfactory level while minimizing P_f as much as possible. In CSUSU scenario, the usability of unoccupied bands by Sus can be kept constant by setting P_f at a certain level while maximizing P_d. A summary for realizing CPUP and CSUSU transmission scenarios is formulated in TABLE I.

Now, let's express the detection and false alarm probabilities in terms of each other by eliminating the threshold detection β in (5) and (6) we can get

$$P_f = Q\left(Q^{-1}\left(\overline{P}_d\right)\left(1 + SNR_p\right) + SNR_p\sqrt{\frac{K}{2}}\right) \quad (7)$$

under CPUP scenario, and

$$P_d = Q\left(\frac{Q^{-1}\left(\overline{P}_f\right) - \sqrt{\frac{K}{2}}SNR_p}{\left(1 + SNR_p\right)}\right) \quad (8)$$

under CSUSU scenario, where $\overline{P}_d$ is the targeted probability of PU detection under CPUP, $\overline{P}_f$ is the targeted probability of false alarm under CSUSU and $SNR_p = \sigma_s^2 / \sigma_w^2$ is the signal-to-noise ratio of the PU.

TABLE I. A SUMMARY OF COGNITIVE RADIO NETWORK TRANSMISSION SCENARIOS AND PERFORMANCE OBJECTIVES

	Metric/procedure	**CPUP scenario**	**CSUSU scenario**
Metric 1	Interference to PU	Constant	Minimized
	How?	$P_d = \overline{P}_d$	Maximizing P_d

Metric2	Capacity of SU network	Maximized	Constant
	How?	Minimizing P_f	$P_f = \overline{P}_f$

III. COOPERATIVE SPECTRUM SENSING

The cooperative spectrum sensing aims to improve detection sensitivity at low signal-to-noise ratio (SNR) environments and tackle the so-called hidden terminal problem, where the PUs' activities might be shadowed from the local SU receiver(s) by any existing intermediate obstacles.

A. Cognitive Radio Network Deployment

The network deployed in this paper is based on IEEE 802.22 WRAN [18]. The WRAN base BS collects information on the PU activities from the SUs within its coverage area. Local SUs keep monitoring the presence of a PU, which is a TV broadcast station, and send their detection and false alarm probabilities to the base station for combining them into one overall final decision. In this scenario, it is assumed that the TV BS is far away from the WRAN BS and therefore, low SNR_p values are used where the later is the SNR of PU signal at the SU receiver. A simplified depiction of the IEEE 802.22 WRAN system deployment is shown in Fig. 1.

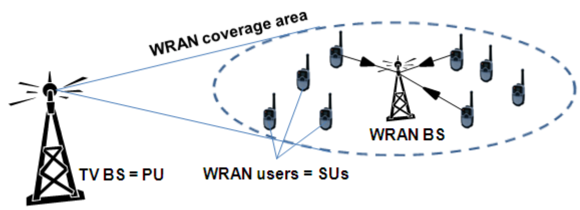

Figure 1. IEEE 802.22 WRAN system deployment.

B. Network Probabilities under CPUP and CSUSU Scenarios

At the SUs base station, all local sensing information are combined and merged into one final decision using Chair-Varshney fusion schemes [19][20]. Two fusion schemes are used in this work, namely, OR- and AND-rule. The total CRN (SU network) false alarm and detection probability formulas under CPUP and CSUSU scenarios can be then written as;

For CPUP-OR

$$P_f = 1 - \prod_{i=1}^{N}\left(1 - Q\left(\begin{array}{l} Q^{-1}\left(1-\left(1-\overline{P}_d\right)^{\frac{1}{N}}\right)\times\ldots \\ \left(1+SNR_{p,i}\right)+SNR_{p,i}\sqrt{\frac{K}{2}} \end{array}\right)\right) \quad (9)$$

, for CPUP-AND

$$P_f = \prod_{i=1}^{N} Q\left(Q^{-1}\left(\left(\overline{P}_d\right)^{\frac{1}{N}}\right)\left(1+SNR_{p,i}\right)+SNR_{p,i}\sqrt{\frac{K}{2}}\right) \quad (10)$$

, for CSUSU-OR

$$P_d = 1 - \prod_{i=1}^{N}\left(1 - Q\left(\frac{Q^{-1}\left(1-\left(1-\overline{P}_f\right)^{\frac{1}{N}}\right)-\sqrt{\frac{K}{2}}SNR_{p,i}}{\left(1+SNR_{p,i}\right)}\right)\right) \quad (11)$$

, and for CSUSU-AND

$$P_d = \prod_{i=1}^{N} Q\left(\frac{Q^{-1}\left(\left(\overline{P}_f\right)^{\frac{1}{N}}\right) - \sqrt{\frac{K}{2}}SNR_{p,i}}{\left(1 + SNR_{p,i}\right)}\right) \quad (12)$$

C. Formulation of Performance Objectives under CPUP and CSUSU Transmission Modes

Under CPUP, the CRN normalized capacity is considered as a performance indicator. The capacity of the CRN is maximized as much as possible by minimizing the total false alarm probability of the network. Under CSUSU, the quantum interference from the SU network to the PU is taken into account. Here, the interference is minimized by maximizing the probability of detecting the PU. In WRAN systems, each frame consists of one sensing slot (t_s) plus one data transmission slot (T_f - t_s), where T_f is the total frame duration.

1) *Normalized capacity under CPUP transmission scenario:* There are two cases for which the SUs network might operate at the PU's licensed band: first when the PU is inactive and the SUs successfully declare that there is no PU. In this case, the normalized capacity of the WRAN system is represented as [21]

$$C_0 = \left(1 - \frac{t_s}{T_f}\right)\left(1 - P_f\right)P(\mathrm{H}_0) \quad (13)$$

where $P(\mathrm{H}_0)$ is the probability that the PU is inactive in the frequency band being sensed. The other case is when the PU is active but the SUs fail to detect it. The normalized capacity is then given by

$$C_0 = \left(1 - \frac{t_s}{T_f}\right)\left(1 - P_d\right)P(\mathrm{H}_1) \quad (14)$$

where $P(\mathrm{H}_1)$ is the probability of the PU being active in the frequency band of interest. Obviously, $P(\mathrm{H}_0)$ + $P(\mathrm{H}_1)$ = 1. The objective of this research is to determine the optimal sensing time for each frame such that the SUs network capacity is maximized. Consequently, this objective can be formed as an optimization problem described as follows:

$$max\, C = \left(1 - \frac{t_s}{T_f}\right)[\left(1 - P_f\right)P(\mathrm{H}_0) + \left(1 - P_d\right) P(\mathrm{H}_1)] \quad (15)$$

subject to: $0 < t_s \le T_f$, and

$P_d \ge \overline{P}_d$ under CPUP or $P_f \le \overline{P}_f$ under CSUSU.

Since P_d should be set large enough to protect the PU under CPUP scenario, the second term in (18) can be ignored as $P(H_1)$ can also be assumed small as we are interested to maximize the throughput of SUs in absence of PU. Thus, the normalized capacity (C_{norm}) can be written as

$$C_{norm} = \left(\frac{T_f - t_s}{T_f}\right)(1 - P_f) \quad (16)$$

2) Quantum interference under CSUSU transmission scenario: The interference to PU is caused by the SU when it mistakenly declares that there is no PU exists in the vicinity. The SU will then start transmitting for (T_f - t_s) out of the total frame duration, T_f, causing interference to the miss-detected PU(s). The probability of miss-detecting the PU is (1 - P_d). The quantum interference (IQ) is a measure defined as the amount of interference suffered by PU when it is miss-detected by the sensing SU(s). Thus, the quantum interference (IQ) from SU to PU under CSUSU transmission scenario can be expressed as

$$IQ = \left(\frac{T_f - t_s}{T_f}\right)(1 - P_d) \quad (17)$$

IV. Simulation Results of Individual Parameters

A. Detection Sensitivity and Processing-Cooperation Analysis

In this section, the performance of local and cooperative spectrum sensing is evaluated in terms of detection sensitivity, processing amount, and cooperation gain. The detection sensitivity of the local energy detector-based spectrum sensor is analyzed. The detection sensitivity is defined as the minimum SNR_p at which a SU should still be able of detecting the PU signal. The detection sensitivity is analyzed versus the required number of samples required to achieve certain detection or false alarm probability. High detection sensitivity means that the SNR_p is low enough to detect weak PU signals. On the other hand, increasing the number of samples leads to increase the amount of local processing at the SU sensor and it also increases the sensing time which will cause a reduction in the SU transmission time for a given frame duration and sampling frequency. Thus, increasing the detection sensitivity and reducing the required number of samples of PU signal to achieve a specific detection of false alarm probability are both crucial factors to ensure a satisfactory spectrum sensing performance at the stage of SU receiver. As shown in Fig. 2, the detection sensitivity can be improved by increasing the number of samples needed to achieve a targeted probability of detection under CPUP scenario. It is also clear that number of samples has to be again increased in order to increase the probability of detection, say from 0.6 to 0.9, for specific detection sensitivity. Fig. 3 shows similar observations under CSUSU scenario where reducing the probability of false alarm, say from 0.4 to 0.1, with particular detection sensitivity requires an increase in the number of processing samples. Thus, for the two cases in Fig. 2 and Fig. 3, the number of samples needs to be increased in order to improve the detection sensitivity at a specific detection probability and false alarm probability, respectively. Let's now raise a question; how can we reduce the number of samples in Fig. 2 and Fig. 3? The answer is that the amount of local processing can be reduced by cooperating more SUs. This answer is substantiated in Fig. 4; as shown, the detection sensitivity is improved (minimum manageable SNR_p is reduced) by increasing the cooperation level between SUs from 1 (no cooperation) to 20 SUs while maintaining the detection and false alarm probabilities at arbitrary fixed rates of 0.9 and 0.1, respectively. In addition, it is observable that after a certain level of cooperation, there is noticeable improvement in the sensitivity-processing relationships as their curves will not differ much (e.g. after 20 cooperated SUs). So, the SUs cooperation is highly needed as it offers a quite better improvement in the sensitivity-processing relationship. However, this cooperation should not exceed a certain level after which there will be no benefit but instead; it will increase the amount of reported decisions from the SUs to the central BS and hence increase the traffic overhead unnecessarily. For instance, if the CRN topology of interest contains N users, the optimal performance is not achieved by collaborating all the N users but instead, a certain fraction of it, k, where $k < N$. This explained in detail in section 4.4. Fig. 5 depicts the direct relationship of required number of samples versus number of cooperative users. Again, we can observe that the number of processing samples can be reduced by increasing the number of cooperative users. Also, at a specific number of cooperative users, increasing P_d or decreasing P_f requires more samples to be processed.

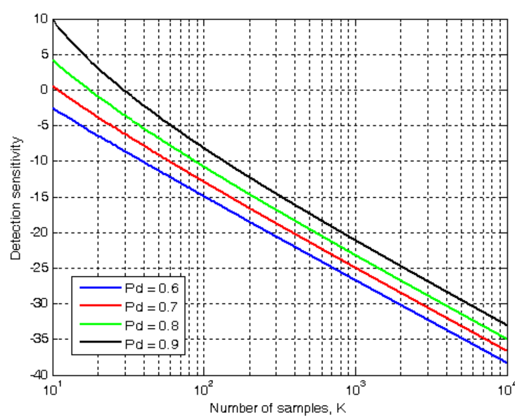

Figure 2. Detection sensitivity versus number of samples under CPUP scenario

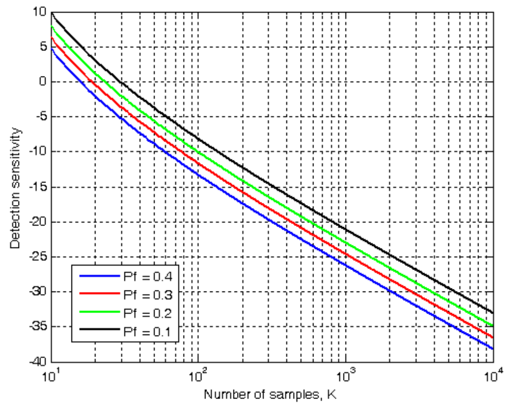

Figure 3. Detection sensitivity versus number of samples under CSUSU scenario

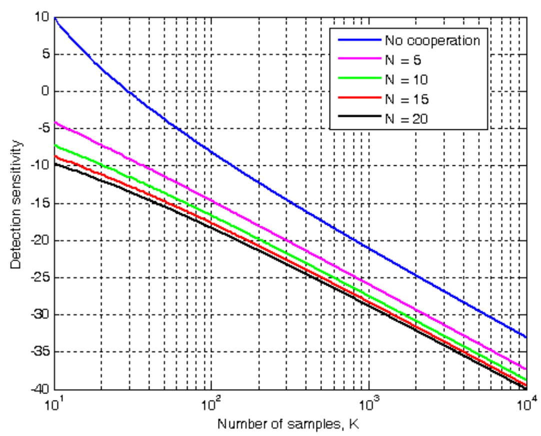

Figure 4. Detection sensitivity versus number of samples with different number of samples
(P_d = 0.9 and P_f = 0.1)

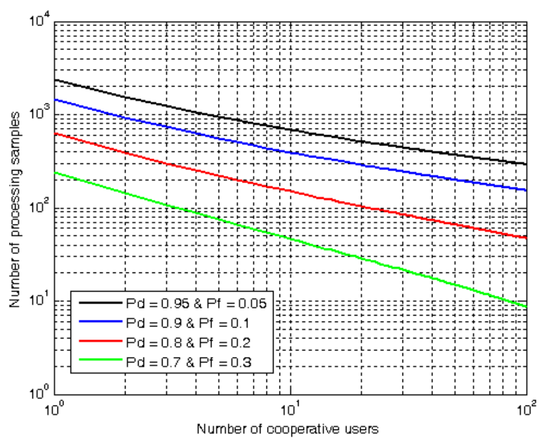

Figure 5. Number of processing samples versus number of cooperative users (SNR_p = -10 dB).

B. Sensing Time Optimization

Indeed, short sensing slots should be always aimed as it results in longer data transmission slot and therefore, higher capacity. However, shortening t_s might affect the reliability of PU detection and then cause interference. Computer simulations have been performed to analyze the performance under CPUP and CSUSU scenarios. Let's first consider the local sensing case; the WRAN frame duration was set to 100 ms and the one-side bandwidth of PU bandpass signal is assumed to be 3MHz. The SNR_p is set to -20 dB. Fig. 6 shows that there is an optimal sensing time at which the throughput is maximized under CPUP. This optimal sensing time increases if higher level of PU protection (P_d increases) is targeted. It is also clear that, in general, the capacity decreases with increasing P_d. Under CSUSU, Fig. 7 shows that at a targeted low interference level, say $IQ = 0.1$, the higher the P_f the longer the sensing time required to achieve this protection level. Furthermore, the interference decreases if the capacity is scarified by increasing P_f. Let's now consider the cooperative sensing where all SUs have the same SNR_p at their receivers, Fig. 8 shows that the normalized capacity increases by increasing the number of collaborating users under CPUP using either OR- or ANR-rule. However, this will be explored more lately. Fig. 9 presents the great wining of cooperating sensing where the optimal sensing time required to maximize the network capacity decreases with increasing the number of collaborating SUs. Under CSUSU, OR- and ANR-rule show similar results as shown in Fig. 10 and Fig. 11, respectively. At sector A in both figures, to achieve a specific low interference level (e.g. IQ = 0.1), cooperating more users reduce the sensing time required. This is also observable at sector B where at a specific sensing time (e.g. 15 ms), the interference decreases with increasing the number of cooperating users. However, this reduction becomes less critical after exceeding a certain number of cooperating users. Therefore, there will be a great saving in measurements processing if certain SUs are considered for fusion rather than all.

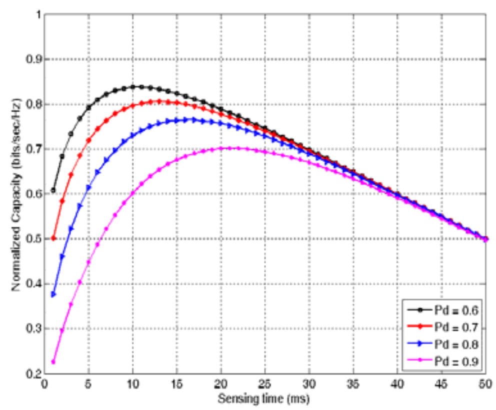

Figure 6. Normalized capacity versus sensing time for local sensing under CPUP scenario.

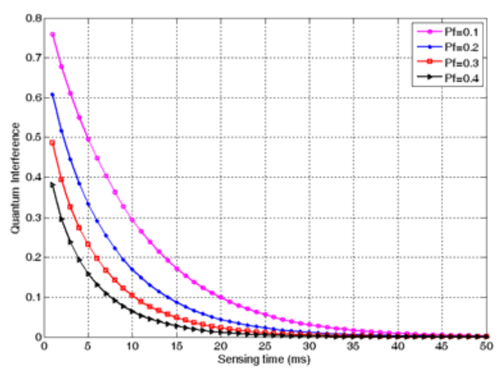

Figure 7. Normalized capacity versus sensing time for local sensing under CSUSU scenario.

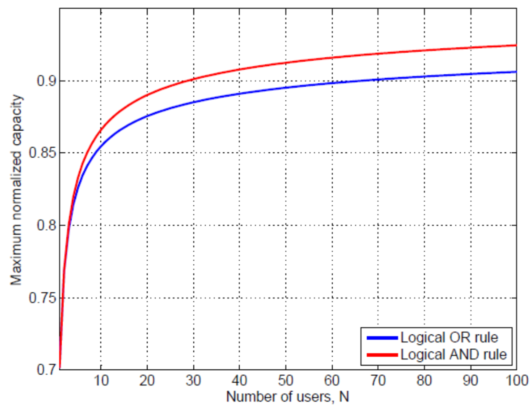

Figure 8. Maximum achieved normalized capacity versus number of collaborated users under CPUP scenario.

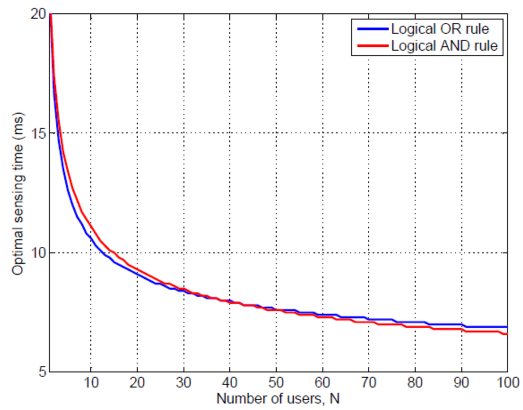

Figure 9. Optimal sensing time versus number of collaborated users under CPUP scenario.

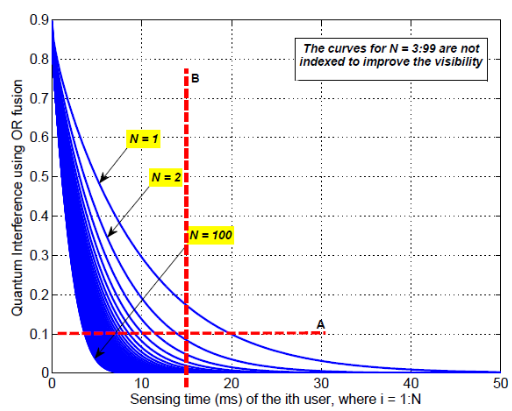

Figure 10. Quantum Interference versus sensing time with different number of users using OR-rule fusion scheme under CSUSU scenario.

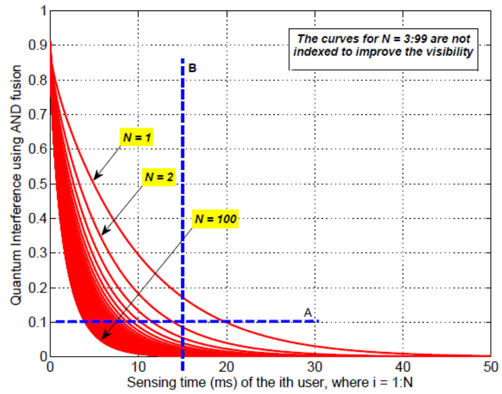

Figure 11. Quantum Interference versus sensing time with different number of users using AND-rule fusion scheme under CSUSU scenario.

C. Optimization of Number of Collaborated Secondary Users

In the previous section, the SNR_p was assumed to be fixed for all cooperating users in the network. Here, we are testing the network performance when varying the SNR_p values for different users. The sensing algorithm is implemented by cooperating the SUs with higher SNR_p values first and to monitor the performance metrics with increasing the cooperation level. Fig. 12 shows that the maximum capacity under CPUP is achieved by cooperating a certain number of users (k) rather than cooperating all users in the network for N = 50, 100, 150 and 200 SUs. Fig. 13 presents this finding clearly where cooperating k out of N SUs provides higher capacity than cooperating all the N SUs. Fig. 14 shows a similar finding where under CSUSU, the interference is minimized by cooperating a certain number of users rather than cooperating all the users in the network. Fig. 15 again shows how cooperating k out of N SUs provides lesser interference.

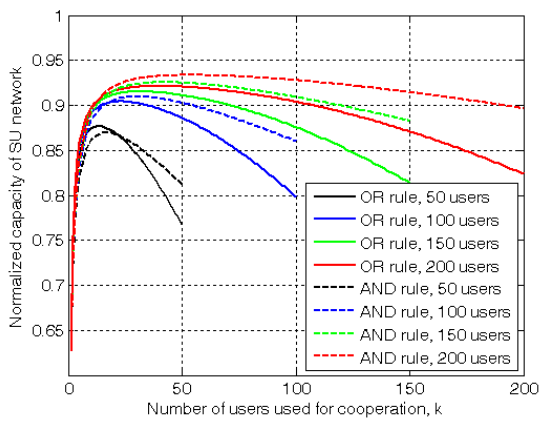

Figure 12. Normalized capacity versus variable fraction (k) of different total number of users (N = 50, 100, 150, or 200) under CPUP scenario.

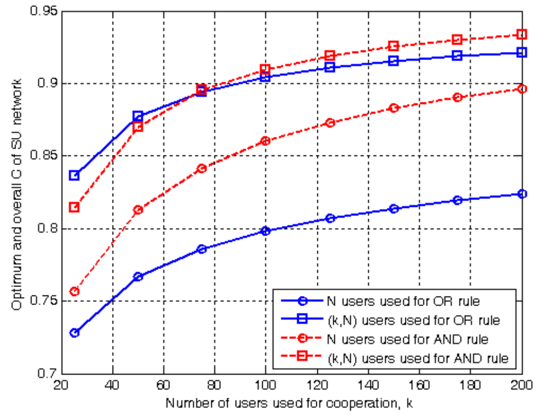

Figure 13. Optimum and overall normalized capacity versus variable fraction (k) of different total number of users under CPUP scenario.

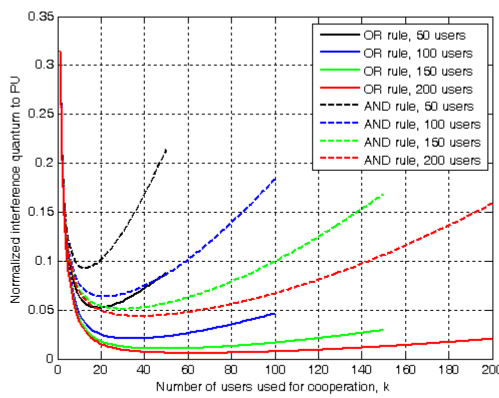

Figure 14. Normalized capacity versus variable fraction (k) of different total number of users (N = 50, 100, 150, or 200) under CSUSU scenario.

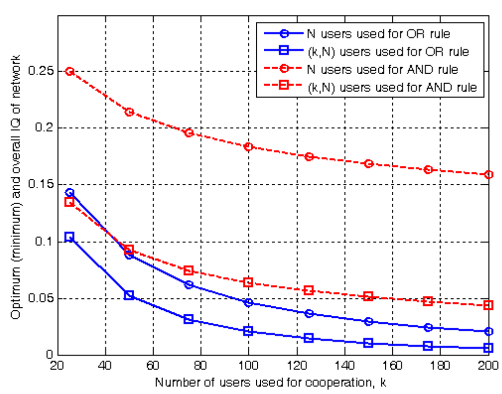

Figure 15. Optimum and overall normalized capacity versus variable fraction (k) of different total number of users under CSUSU scenario.

V. Joint Optimization of Sensing Parameters

A. Particle Swarm Optimization

Particle swarm optimization (PSO) is a population-based stochastic optimization technique inspired by social behavior of bird flocking or bees. The PSO mechanism is initialized with a population of random solutions and searches for optima by updating generations [22][23][24]. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (best fitness) it has achieved so far. This value is called *pbest*. Another "best" value tracked by the particle swarm optimizer is the best value obtained so far by any particle in the neighbours of the particle. This location is called *lbest*. The best value ever in the whole search space is called as the global best (*gbest*). The particle swarm optimization concept involves, at each time step, changing the velocity (accelerating) of each particle towards its *pbest* and *lbest* locations. This particle movement is governed by the equation of motion given by

$$V_{(n+1)} = w.V_{(n)} + C_1.(lbest - X_{(n)}) + C_2.(gbest - X_{(n)})$$
$$X_{(n+1)} = X_{(n)} + V_{(n+1)} \qquad (18)$$

where w is the weight inertia, C_1 is the self-confident coefficient and C_2 is the confident in other coefficients. These two parameters together with the swarm size are the PSO's intrinsic control parameters that can be analyzed to achieve better performance for a given problem. Fig. 16 shows the next displacement calculation for a particle in the swarm.

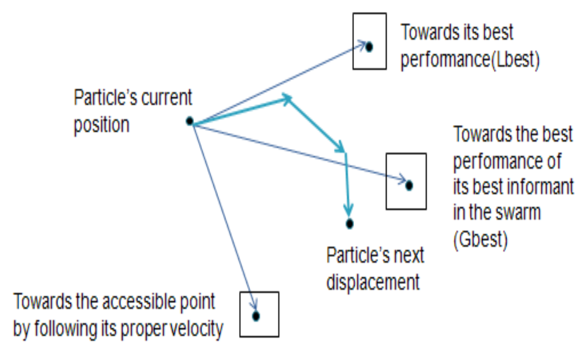

Figure 16. The next-displacement scenario for a swarm particle.

B. Joint Optimization of Sensing Time and Cooperation Level Using PSO-Algorithm

In this section, the CRN optimization problem is defined and modelled using a PSO-based algorithm. The PSO is used to simultaneously search for the optimal sensing time and cooperation level that maximize the CRN throughput. Fig. 17 shows 30 swarm particles (not all appear) randomly distributed on the 2-dimensional throughput surface that is a function of sensing time and cooperation level. The probability of detection is set to 0.9 and CRN contains 50 SUs. The CRN frame duration is set to 100 msec. It is clear that maximum capacity that is the surface peck value is achieved at a specific sensing time and number of cooperated SUs. The PSO algorithm finds the optimal sensing time and cooperation level as 2.795 msec out of 100 msec and 9 cooperated SUs out of a total of 50 available SUs. Fig. 18 shows the improvement of average fitness over the number of PSO iterations. The optimization process is to be performed every cyclic period of frame duration. It is assumed that the channel condition does not change much within two successive frame durations.

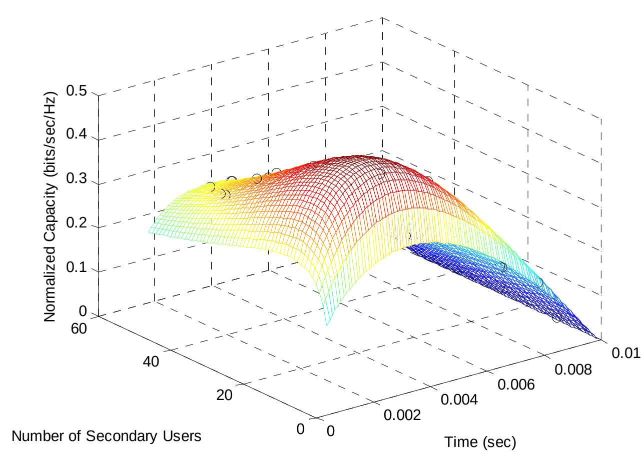

Figure 17. Normalized capacity as a function of sensing time and number of secondary users.

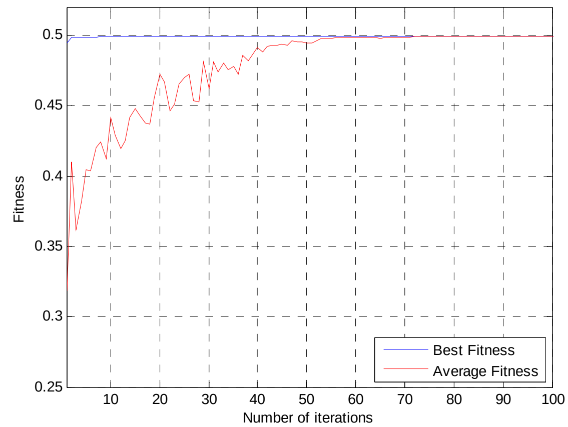

Figure 18. Performance of PSO-based algorithm implemented at the central base station of CRN.

In fact, this model can be easily used to include several sensing and design parameters such as frame duration and local thresholds. Furthermore, this optimizing problem becomes more challenging in fading environment as the throughput surface would not appear as smooth as shown in Fig 17. In future, we will be working on extending this optimization problem to multi-dimensional optimization problem of several realistic sensing and design parameters.

CONCLUSION

In this paper, the optimum CRN performance was defined as the maximum CRN capacity and the minimum CRN interference to the PU under the CPUP and CSUSU, respectively. The simulation results showed that under CPUP, there is an optimal sensing time at which the CRN capacity is maximized. While under CSUSU, cooperating all SUs will not significantly improve the network performance. This observation was under the assumption of a fixed SNR_p for all SUs. When varying SNR_p, the simulation results shows that the optimum performance of the CRN is achieved by cooperating a certain number of users with the highest SNR values rather than cooperating all the available SUs of CRN. Finally, a PSO-based algorithm has been implemented at the CRN base station to jointly optimize the sensing time as well as the cooperation level between the SUs so that the CRN performance is maximized. The PSO-based algorithm can be further improved to include more sensing and design parameters for better system identification. Optimizing the CRN performance is considered as a real-time optimization problem which is repeated every cycle of frame duration assuming that the channel condition does not change much within this period.

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