Energy Consumption Control in Cooperative and Non-cooperative Cognitive Radio using Variable Spectrum Sensing Sampling

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***Abstract*—In cognitive radio (CR) network, the concept of energy-efficient design is very important considering the costly energy consumption that may limit its implementation, especially in battery-powered devices. In these networks, significant part of the energy is consumed in the energy detector during spectrum sensing to detect the presence and absence of the primary user (PU). In this paper, we investigated the reduction of energy consumption in two scenarios: the non-cooperative scenario and the cooperative scenario by reducing the number of sensed samples. We also explained the optimisation criteria for improving energy consumption by controlling the number of sensed samples, and the detection probability in both scenarios. The performance of energy detection system was evaluated in AWGN and Rayleigh fading channels. The simulation results show that in non-cooperative scenario at E_b/N_o of 10 dB, 50% and 46% of the energy consumed in the detection was saved when the number of sensed samples was reduced by 50% with acceptable loss in detection probability of 5% and 12% in AWGN and Rayleigh channel respectively. In cooperative scenario, the result shows that increasing the number of cognitive users (CU) reduced the average energy consumption per sensor and improved the detection probability.**

***Index Terms*—Cognitive Radio; Cooperative Sensing; Energy Detection; Energy Consumption.**

I. INTRODUCTION

With the rapid growth of wireless services, scarcity of spectrum resources has become the bottleneck of its development [1]. Cognitive radio (CR) is commonly defined as a radio system that adapts its operating parameters (e.g., power, carrier frequency, bandwidth, modulation and coding) according to the knowledge of its environment. CRs allow unlicensed secondary users (SUs) to access spectrum bands that are temporarily not used by licensed primary users (PUs). These temporary vacant channels are known as spectrum holes [2]. One of the main challenges in CR networks is the high consumption of energy, especially in battery-powered terminals. The CR networks consist of three stages: first, the sensing stage that senses the presence and absence of PU by using any one of the sensing techniques; second, the transmission stage that reports the local decision of sensing to the fusion centre (FC) and third, the decision stage that makes the final decision about the presence and absence of PU. Two scenarios of spectrum sensing are used in CR networks, which are the non-cooperative and the cooperative. In the non-cooperative scenario, single CRs are used to sense the activity of PU, while in the cooperative scenario multiple CRs are used to sense the spectrum. When the CR network is shadowed or in severe multipath fading, it cannot detect the presence of the PU. The primary transmission undergoes a harmful interference since the channel access is allowed while PU is still in operation; thus, cooperative scenarios are used to address this issue [3]. In this paper, the energy saving is performed in the sensing stage using the non-cooperative and cooperative scenario and the energy detection technique.

A lot of work has been done to improve energy consumption in sensing stage. Sequential sensing as an approach in making decision to reduce the average number of sensors has been studied comprehensively in [4-7]. A truncated sequential sensing technique is employed in [8] to reduce the sensing time of CR network where many thresholds are used. These thresholds are determined such that certain false alarm probability P_f and detection probability P_d are obtained. Optimising the number of sensing users is another approach to improve energy consumption in CR networks. This is related to the fact that any reduction in the number of sensing users leads to a reduction in all the preceding stages. In [9-10], the energy consumption is reduced using a minimum number of CUs that satisfy the pre-set thresholds on the detection accuracy. In [9], an energy efficiency optimisation problem is formulated by reducing the number of sensing CUs to a minimum possible limit, keeping the predefined constraints on the false-alarm and detection probabilities to a satisfactory limit. In [10], the minimum number of sensing CUs that satisfies two constraints on detection and false-alarm probabilities is mathematically formulated. In [11], the CUs are divided into non-disjoint subsets in a way that only one subset senses the spectrum while the other subsets stay in a low power mode. The energy minimisation problem is formulated as a network lifetime maximisation problem with the constraints of the correct detection probability. In [12], an algorithm that divides the CUs into subsets is proposed such that only the subset that has the lowest cost function and guarantees the desired detection accuracy is chosen. The desired detection accuracy depends on two thresholds, namely the false alarm and the detection probabilities, while the cost function is defined by the total energy consumption. In [13], a combination of censoring and truncated sequential sensing is presented to improve energy consumption.

In this paper, we investigated the amount of energy saving that can be achieved when the number of sensed spectrum samples is reduced during the detection process and the corresponding deterioration in detection probability of the energy detector in both the non-cooperative and the cooperative CR network.

II. ENERGY DETECTION BASED SPECTRUM SENSING

Energy detection is considered as one of the widely used spectrum sensing techniques due to its simplicity as it does not need any information about the structure of the PUs signals. However, it needs information about the noise variance to correctly perform the detection. In CR networks, the SU checks the spectrum allocated to PU, and when it detects the absence of PU transmission, it starts to transmit the data to its receiver. The received samples at CU receiver are [3]:

$$Y(n) = h_{ps}\theta X_p(n) + W(n) \tag{1}$$

where $X_p(n)$ is the signal of the PU with transmitted power P_p, h_{ps} is the channel gain between PU and SU, θ is the PU activity indicator, and it can take one out of the two values as given in equation (2). $W(n)$ is the Additive White Gaussian Noise (AWGN) at the CU receiver.

$$\theta = \begin{cases} 0 & for \quad H_0 \, hypothesis \\ 1 & for \quad H_1 \, hypothesis \end{cases} \tag{2}$$

when the PU is active. The active PU is referred to as hypothesis H_1, while the inactive PU is referred to as hypothesis H_0. The false alarm and detection probabilities are evaluated by comparing the detector decision metric with a pre-set threshold λ. The decision metric DMED is defined by the energy of the captured samples during the observation window t.

$$DMED = \frac{1}{N}\sum_{n=1}^{N}|Y(n)|^2 \tag{3}$$

where N is the number of sensing samples $N = tF_s$, where F_s is the sampling frequency. The probabilities of false alarm and detection are evaluated by:

$$P_f = P_r(DEMD > \lambda | H_0) \tag{4}$$

$$P_d = P_r(DEMD > \lambda | H_1) \tag{5}$$

III. THE PROPOSED ENERGY SAVING SCHEME

Energy consumption in sensing stage of CR can be improved by reducing the number of sensed samples since it reduces the amount of computations performed by energy detector before producing a decision. This approach also leads to a reduced time required in sensing and it can be very useful if the sensing reliability of the cognitive radio network is kept to a satisfactory level. The sensing reliability is defined by the maximum probability of detection (specifies that a detector makes a correct decision that a channel is occupied H_1) and the minimum probability of false alarm (a false alarm event occurs when the detector assumes H_1; when the correct decision is H_0) [14]. Figure 1 shows the process of selecting the samples we followed when the spectrum sensing includes 50%, 33%, and 25% of the overall spectrum samples, where the selected samples are marked by black colour. As shown in the Figure1 (a), 50% sensing is done by sensing only even (or odd) numbered samples i.e the process is done to over all spectrum bands starting from the first sample by sensing one sample and skipping (not sensing) to the next sample. The 33% sensing is done by sensing one sample and skipping (not sensing) to the two next samples, and so on for the 25% sensing. To calculate the amount of energy consumption achieved by the cognitive user C_j, we use the procedure followed in [13]:

$$C_j = NC_{sj} + (1-\rho_i)C_{tj} \tag{6}$$

where C_{sj} and C_{tj} are the energy consumed by the j-th radio in sensing sample and transmission per bit, respectively, ρ_j is the average censoring rate, and N is the number of sensed samples. As we calculate the amount of energy consumption in sensing stage only, equation (6) is reduced to:

$$C_j = NC_{sj} \tag{7}$$

where C_j is the energy consumed by j-th CU, and C_{sj} is the energy consumption per sample. As stated in [13] and [15], C_{sj} is fixed and depends only on the sampling rate and energy consumption of the sensing module. When P_d is decreased, C_s is increased since the energy detector will produce false decision, leading to repeating the sensing. According to this discussion, C_{sj} can be written as:

$$c_{sj} = \begin{cases} C_{sa} & if \;\; P_d = 1 \\ C_{sa} + C_{sa}(1-P_d) & if \;\; P_d \neq 1 \end{cases} \tag{8}$$

We can note that when $P_d = 1$, Equation (9) becomes $C_j = NC_{sa}$, considering that a sensor used by CU is based on IEEE 802.15.4/ZigBee radios. The sensing energy for each decision consists of two parts: The energy consumption involved in listening over the channel and making the decision and the energy consumption of the signal processing part for modulation, signal shaping etc. The number of samples per detection interval used in our simulation was chosen to be 5 according to [16]. This interval corresponds to a detection time of 1µs. Considering the typical circuit power consumption of ZigBee is approximately 40 mW, the energy consumed for listening is approximately 40 nJ. Therefore, we conclude that energy consumption per sample is 40 nJ/5 =8nJ. Thus, C_{sa} =8 nJ was used.

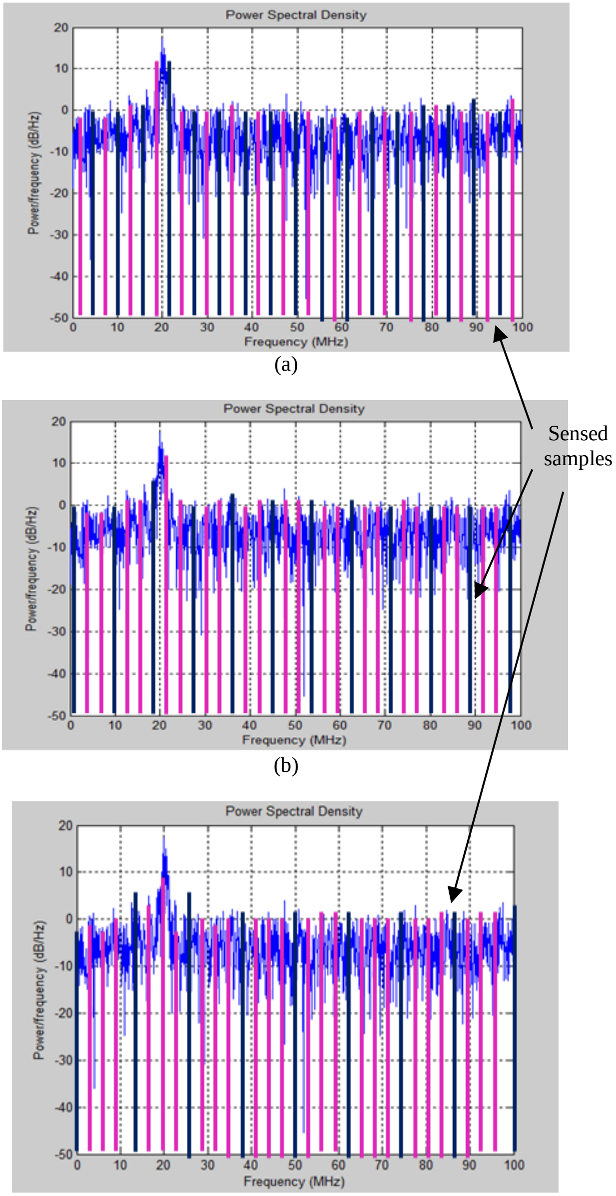

Figure 1: The selection of spectrum sensing samples
(a) 50% sensing, (b) 33% sensing, (c) 25% sensing

IV. SIMULATION RESULTS AND DISCUSSION

This section presents the simulation results of energy detector performance and energy consumption of the non-cooperative and the cooperative CR when the number of sensed sample was reduced. The three cases of sample reduction shown in Figure1 are considered: These are sensing 50% of the samples, sensing 33% of the samples, and sensing 25% of the samples. The simulation parameters used are shown in Table 1. The system performance was tested under AWGN and Rayleigh multipath fading channels. In the last channel, the multipath fading was verified with path delays starting from one to six path delays for “ITU indoor channel model” as shown in Table 2 [17].

Table 1
Simulation Parameters

Parameter Name	Value
Bit rate	2 Mbps
Carrier frequency	20 MHz
Modulation type	QPSK (PU signal)
Probability of false alarm	10-3
Spectrum band	(0 – 100) MHz
Sampling frequency	200 MHz
Bits per symbol	2
Samples per symbol	100

Table 2
Multipath Fading Properties Of Itu Indoor Channel Model

Tap	Relative delay (ns)	Average power (dB)	Doppler spectrum
1	0	0	flat
2	50	-3.0	flat
3	110	-10.0	flat
4	170	-18.0	flat
5	290	-26.0	flat
6	310	-32.0	flat

A. Non-Cooperative Senario

Figure 2 and 3 shows the performance curves of energy consumption of CU and P_d versus E_b/N_o with sensing ratio as parameter in AWGN channel, respectively.

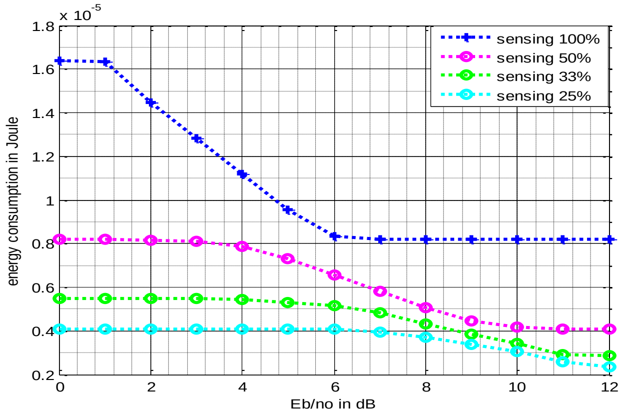

Figure 2: Energy consumption versus E_b/N_o in AWGN channel.

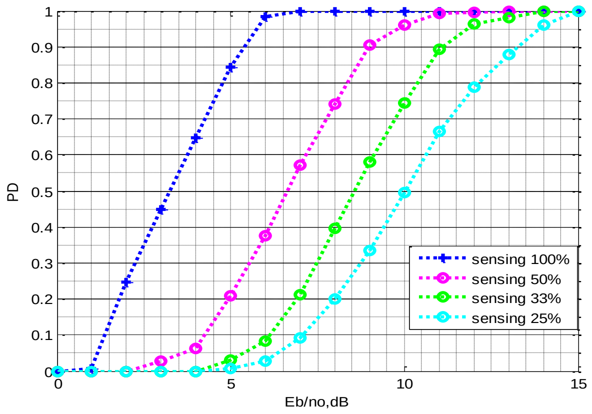

Figure 3: P_d versus E_b/N_o in AWGN channel.

In Figure 2, it can be seen that the energy consumption decreases as E_b/N_o increases since less number of sensing samples is required by CU in sensing process to detect the PU signal when E_b/N_o is high. For example, at E_b/N_o equals to 10 dB, the energy consumption reduced by 50%, 60% and 63% for sensing ratio values 50%, 33% and 25% respectively. In Figure 3, it can be seen that the detection performance improves as E_b/N_o is increased. It also shows that P_d increases when the number of sensed samples is increased. For example, when E_b/N_o is 10 dB, P_d reduces from 1 when the sensing ratio is 100% to 0.96 , 0.75 and 0.5 for sensing ratio values 50% , 33% and 25% respectively.

Figure 4 and 5 shows the performance curves of energy consumption and P_d versus E_b/N_o with sensing ratio as the parameter in Rayleigh multipath fading channel, respectively. In Figure 4, it can be seen that similar behaviour is obtained as in Figure 2 (AWGN channel). For instance, when E_b/N_o is 10 dB, the energy consumption is reduced by 46%, 57% and 62% when we reduced the number of sensed samples to 50%, 33% and 25% respectively. However, if we compare the numeric values of the obtained energy consumption as in Figure 2, we notice that the energy consumption increases. For example, when E_b/N_o is 10 dB, the energy consumption in Rayleigh channel increases by 4%, 3% and 1% for sensing ratio values 50%, 33% and 25 % respectively as compared to that in AWGN.

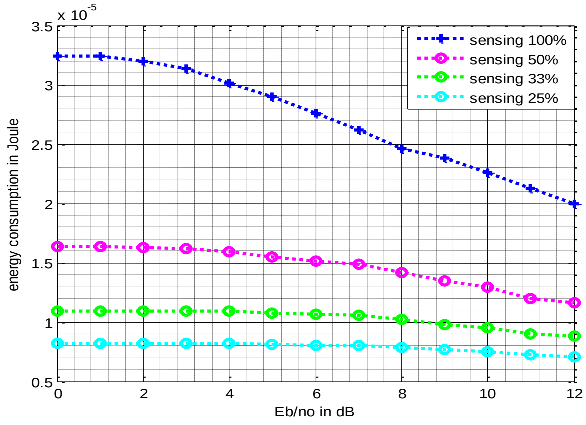

Figure 4: Energy consumption versus E_b/N_o in Rayleigh multipath fading channel.

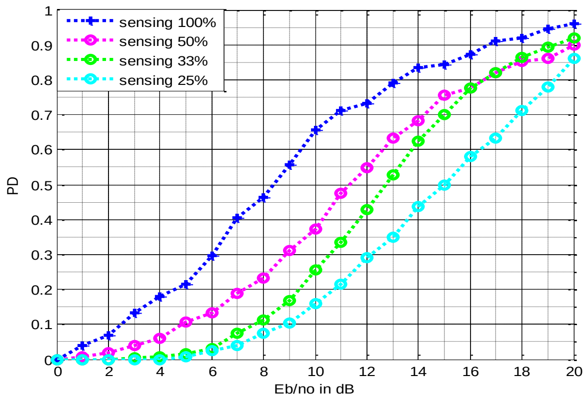

Figure 5: P_d versus E_b/N_o in Rayleigh multipath fading channel.

In the Rayleigh multipath channel, although an improvement is gained in energy consumption by reducing the number of sensed samples (50%, 33% and 25%) as compared to the case of sensing ratio 100%, a significant reduction in P_d occurs, as shown in Figure 5. We observe in this figure that high P_d values (more than 0.9) could not be reached unless E_b/N_o is increased to around 20 dB due to the severe effect of multipath fading. Numerically, at E_b/N_o equals 10 dB, P_d in Rayleigh channel is decreased from 0.65 in 100% sensing case to 0.35, 0.25 and 0.15 for sensing ratio values 50%, 33% and 25% respectively. The figure also shows that energy consumption is almost constant even if E_b/N_o is increased for sensing ratio values of 33% and 25%, respectively. This is due to the impact of high degradation in P_d values. However, the effect of fading can be minimised by using cooperative cognitive radio.

B. Cooperative Senario

This section shows the performance curves of energy consumption and P_d versus E_b/N_o with the number of CUs and sensing ratio as parameters. The number of CUs has changed to take the values: 1, 2, 4, and 6. The scenarios considered for multipath fading are as follows: in single CU scenario, the CU suffers from multipath fading, in two CUs scenario, only one CU suffers from multipath fading, in four and six CUs only two CUs suffer from multipath fading. Figure 6 and 7 show the average energy consumption per sensor versus E_b/N_o with sensing ratios of 100% and 50% respectively. In Figure 6, it can be seen that the average energy consumption per user decreases when E_b/N_o increases, and this reduction is increased as the number of CUs increases since they will share the statistics about PU existence which will increase the overall detection probability. For example, when E_b/N_o is 6 dB, and when we compare with single CU, the average energy consumption per sensor reduces to 33%, 42%, and 43 % when the number of CUs are 2, 4, and 6 respectively. It is clear that a significant improvement in the average energy consumption per sensor is obtained when we switch from single CU to two and four CUs. However, further increase in the number of CU will not produce further improvement, especially at high E_b/N_0 values due to the fact that the P_d already have high values, and the increase in CUs number will add very small fractions to Pd value. In Figure 7, it can be seen that similar behaviour to that in Figure 6 is obtained because the number of sensed samples is reduced by 50% although more reduction of energy consumption. When we compare to Figure 6 (sensing ratio 100%), at E_b/N_o of 6 dB, the energy consumption is reduced by 38%, 40%, and 45% when the number of CUs is increased to 2, 4, and 6 respectively.

Figure 8 and 9 show the performance curves of the average probability of detection P_d versus E_b/N_o with sensing ratio 100%, and 50% respectively. Figure 8 shows P_d for single CU and 4 CUs when sensing ratio 100%. It can be seen that the detection performance is improved in 4 CUs case as compared to single CU case. For example, at E_b/N_o of 10 dB, P_d is increased from 0.75 in single CU to 0.87 in 4 CUs. The same discussion mentioned in Figure 7 is also valid here, i.e. when the number of sensed samples is reduced, this leads to a decrease in the detection probability in single CU, but in 4 CUs the reduction in P_d is very small. Numerically, at E_b/N_o

equals 10 dB and when comparing with Figure 8 (100% sensing ratio), P_d is decreased hugely from 0.75 to 0.6 in single CU, while in 4 CU P_d is decreased slightly from 0.87 to 0.83.

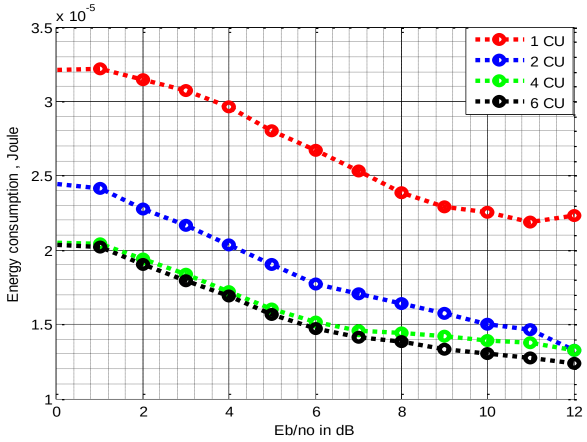

Figure 6: Energy consumption versus E_b/N_o in Cooperative scenario, sensing ratio=100%

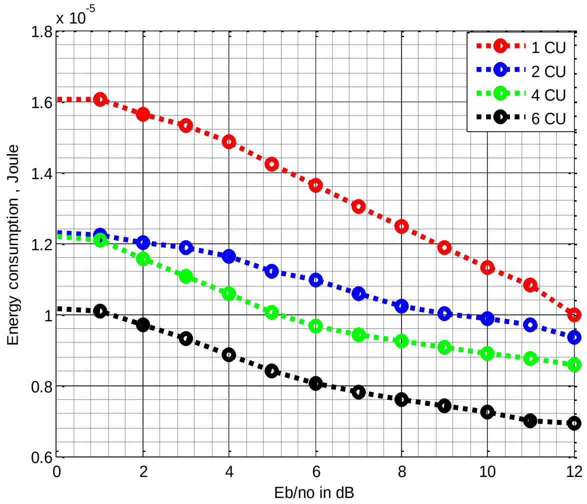

Figure 7: Energy consumption versus E_b/N_o in Cooperative Scenario, sensing ratio 50%

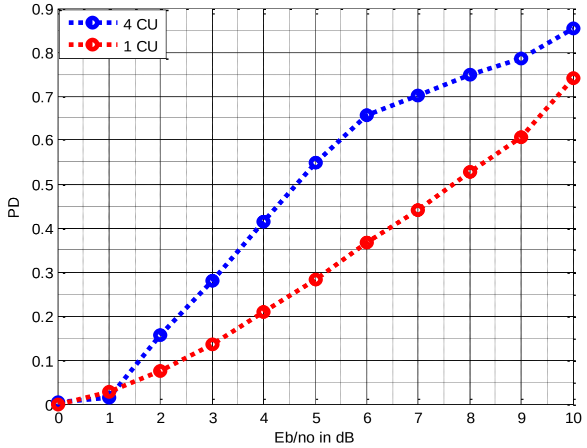

Figure 8: P_d versus E_b/N_o in Cooperative scenario sensing ratio 100%

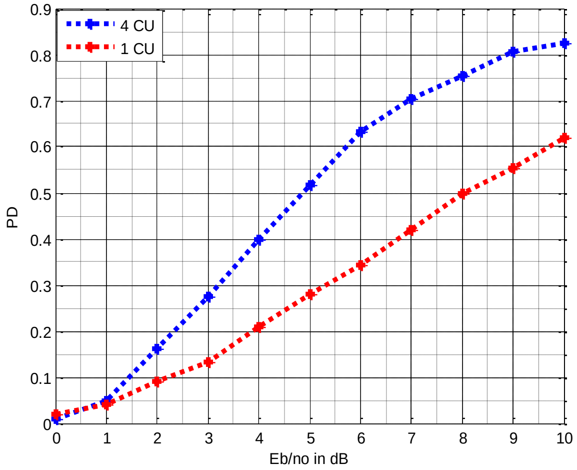

Figure 9: P_d versus E_b/N_o in Cooperative scenario sensing ratio 50%

V. CONCLUSION

This paper discussed an efficient method to improve energy consumption in CR networks in two scenarios: the non-cooperative scenario and cooperative scenario by reducing the number of sensed samples and evaluating the impact of that improvement on receiver operating characteristics. We conclude that in the non-cooperative scenario, reducing the number of sensed samples can achieve more than 40% reduction in energy consumption at high signal to noise ratio values with acceptable loss in detection probability. The sensing ratio that fulfill this optimisation process is not less than half the number of samples in standard spectrum sensing algorithms in both AWGN and Rayleigh fading channels. In cooperative scenario, the conclusion that can be drawn is that the average energy consumption per sensor is reduced and the detection probability is improved as the number of CU is increased up to a certain number after which no further improvements are obtained. The best performance in terms of reduced energy saving and high detection probability can be obtained when we set the number of users to four, using sensing ratio of 50%.

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