Cooperative Study of the Gross Spectrum for Cognitive Radio Networks

Dr. S. Pradeep Gnanam
Head, PG &Research Dept of Computer science & Application
Joseph Arts & Science College

S. Udhayakumar
PG & Research Dept of Computer science
Joseph Arts & Science College

Abstract: **The numbers of applications that use industrial and scientific radio frequency bands (ISB) increases every day, which creates a problem with the interference of Wireless Sensor Networks (WSN) that generally operate at these frequencies. The Cognitive Radio Sensor Network (CRSN) has been proposed as a promising solution for this problem. However, since the sensor nodes are energy saving devices, low energy RF spectrum recognition methods are required for CRSN. To respond to this need, we propose a new cooperative group monitoring scheme for CRSN (CC4C). The CC4C is based on constant observation, so it is simple and fast. The results of the simulation show that the CC4C causes less time delay monitoring and provides significant energy savings compared to gross power detection schemes, as well as one level monitoring schemes that do not perform Robust Detection.**

Keywords: Cognitive Radio Sensor Networks, Spectrum of Sensitivity, Opportunistic access to radio frequency spectrum, Gross observation, Sequential monitoring .

I. INTRODUCTION

In recent years, demand for applications that use wireless communication has increased exponentially. Most of the wireless traffic is generated by people, resulting in highly dynamic spectral activity that changes significantly in space and time. This trend also affects the ISM bands where WSNs usually work. Since ISM bands are unlicensed, the WSNs in these bands meet their low requirements. However, with a significant increase in environmental disturbance, the efficient use of conventional WSNs is becoming increasingly difficult every day. CRSN has been proposed as a promising solution to mitigate interference and increase spectrum use.

CRSN is a distributed network of wireless cognitive radio node sensors that capture an event signal and jointly communicate their readings in dynamically accessible frequency bands in a multidirectional manner to finally meet the specific requirements of the application. [1]

The CRSN paradigm introduces opportunities for opportunistic spectrum access (OSA) to WSN. However, OSA comes with the extra weight of the spectrum. In the first years of the development of WSN, adding the obligation to monitor the spectrum to nodes with limited resources will not make sense.

However, wireless sensor nodes have experienced significant improvements over the years. The size of the memory has increased from several kilobytes to tens of megabytes, its processing capacities have increased from the 8-bit CPUs running in lower MHz 32-bit analog processors with dynamic clocks that can accelerate up to hundreds of

MHZ and reduce their energy consumption through new energy-saving schemes [2].

The viability of CRSN has been investigated by several investigators [1], [3], [4]. In general, it is accepted that WSN may need radio cognitive abilities in the near future. As a result, there has recently been an increase in the CRSN studies [5], [6].

The most important problem that must be addressed for the implementation of the CRSN is the development of energy efficient spectrum surveillance techniques. There is a lot of research on the spectrum in the literature. However, studies related to radio spectrum surveillance for CRSN are limited. In [7] an average access scheme is proposed, which includes spectrum sensors. However, it does not use multiple channels. If the channel is recorded, the sensors are waiting for the next option. In addition, the monitoring scheme is simplified and takes high values of SNR. [8] Proposes a spectrum monitoring scheme that aims to minimize energy consumption due to the spectrum sensors. However, the proposed scheme is not practical because it requires nodes to solve complex optimization problems in order to obtain optimal thresholds for observation. In [9] we have proposed a narrow band detection scheme, a CSS specially designed for CRSN. The idea was to use the correlation of environmental sensor readings to support cooperative spectrum decisions. In particular, we have developed a censorship scheme that recognizes only low correlation nodes to reduce redundancies in cooperative surveillance.

An important radio spectrum capture problem is to identify the most promising spectrum surveillance channels. Most of the existing solutions do not address this issue. Instead, they assume that the most promising channels are known or predetermined and focus on details of the specific detection scheme. PU activity patterns, however, have a significant impact on the spectrum sensor [10] [11] as the nodes have to perform the spectrum sensors again and again in different channels until an available channel is found. In the case of a regular CRN, nodes can afford to perform sensors sequentially until a free channel is detected. On the other hand, as the CRSN nodes are devices with limited energy consumption, it is imperative to keep monitoring time to a minimum.

Therefore, a mechanism must be created to assess the channels that are less likely to be occupied by the PU

For this purpose, several researchers have proposed two research methods. The first stage consists of an approximate sensor that is fast but cannot be very precise. It is used to find channels that are more likely to be available. As the drilling in the wall is not exactly in the second stage using a more precise fixed sensor circuit for the final decision. The alternative is to continue using different channel filters until an available channel is found. As the final monitoring requires more time to monitor and, therefore, more energy, the two-tier approach is usually more efficient in terms of energy.

The general approach in the two-step surveillance literature is to use energy detection as a coarse sensor method [12], [13], [14]. There are other approaches, but they are either specific to a PU network type such as LTE [15], or make some unrealistic assumptions as a predictable PU arrival process [16]. According to the best knowledge of the authors in the literature, a special spectrum control regime specifically developed for CRSN is not designed.

In this article we present a new thick sensor circuit, CC4C. In the next section, we will give you details about the work of CC4C. In Section III, we describe the details of our results evaluation and simulation. Finally, in Section IV, we present our concluding observations

II. EVALUATION AIR-BASED ASSESSMENT

A. Motivation for an approximate study: The cost of detection increases as the probability of increasing the PU of a channel. Suppose the probability that a channel is available at any time is ρ. Let E_s denote the energy consumed during the observation of a channel. Then the probability of finding a free band in imitation is $(1 - p)^{(i - 1)}$ p.

As the common and the blow are common, the total energy consumed is ι Es? It is, therefore, the expected $E_{\frac{t}{s}}$ energy consumption can be written as $E_{\frac{t}{s}} = E_s \sum^{\theta}_{i=1} (1 - p)^{(i - 1)}$ p. The sum is the expected value of the geometric distribution, so Ets = Es = p.

Therefore, the energy consumption expected for the observation is inversely proportional to the probability of deploying an available channel. This suggests that blind collection of sensation channels can have prohibitive energy costs, especially in the case of saturated spectrum. Another issue of the spectrum sensor is that the CR nodes have no means to determine whether the detected signal is a real PU signal or not. Therefore, even if the signal actually belongs to another CRN, it will be taken as PU activity. Given this and the expected increase in timely access to spectrum in the future, it is reasonable to assume that the spectrum will generally be overloaded to some extent. Therefore, CR nodes need a means to determine which channels are most likely to be available. For this, we offer a simple approximate sensor technique that provides approximate results for PU spectrum occupancy. Based on the results of this approximate detection, the nodes select the channels that are most likely to be available and the sensitivity to these channels.

For a thick sensor circuit to be viable, it must be simple, fast and energy efficient. Otherwise, only the recurrent capture will be more preferable. Our scheme is based on Consecutive Probability Ratio Test (SPRT). It is shown in [17] that for a false alarm (PF) and lost probabilities (PM), SPRT is the detector with the smallest average sample size. Therefore, consistent monitoring is very appropriate for rapid monitoring.

*B. Sequential detection motivation :*The basic idea of our SPRT-based spectral spectrum tracking scheme is that in the SPRT, the average number of samples required to detect PU depends on the SNR. As the SNR increases, PU detection can be done with fewer samples. So, if we want to detect a group of adjacent channels instead of a single channel, as the total number of active PUs in these channels increases, the total power of the PU signal increases. This means that the SNR increases with the number of active PUs.

Now think of a case in which each node performs this approximate broadband sequential detection in different channel bands.

It is clear that the average node that decides with the smallest number of samples has the most complete set of channels because the average SNR experienced by this node will be greater than the others. This is the main idea behind our approximate monitoring scheme. Next we present the theoretical details.

C. Theoretical Context : The SPRT has two threshold values, A and B the ratio of the probability probabilities of the samples obtained, y̸, formed as $\lambda = p(y|H_1) = p(y|H_0)$. A new sample is being tested, y̸k

while λ is between the upper (A) and the upper (B) threshold values. If the ratio falls below A, decide H_0. If it exceeds B ,H_1 is decided. Another alternative is to take

$\eta = In \left(\frac{P_y|(y|H_1)}{p\,(y|H_0)} \right)$ Then the lower and upper bounds will be α = ln (A) and b = ln (B).For the first time, we look at the following scenario. The received signal in both hypotheses,

$$H_0: y(t) = n(t)$$

$$H_1: y(t)=s(t)+n(t) \qquad (1)$$

where n (t) is the zero average, the white additive Gaussian noise with σ_η^1variability. s (t) is the combination of all the PU signals that are present across the broadband that we are trying to detect. We do not accept a special PU signal because the monitoring scheme must meet the detection criteria regardless of the specifications of the PU signal. Therefore, we analyze a common case in which it is assumed that all PU signals are a random Gaussian process with a zero average value and a variance a s2. In practical cases, most types of digital modulation have a zero average with a signal strength known as variation. In this way, our conjecture is significant.

Similar assumptions have been made about several previous works in the literature (eg, [18]). The first step in forming the SPRT is to calculate the thresholds for the desired PF $=\alpha$ and PM $= \beta$[19],

$$A \approx \left(\frac{\alpha}{1-\beta}\right) \text{and } B \approx \left(\frac{1-\beta}{\alpha}\right)$$

The first step in forming the SPRT is to calculate the thresholds for the desired values PF = α and PM = β [19],A ≈ β (1-α) and B≈ (1-αβ).One property of successive tests is that performance the criteria, that is. The requirements of FP and PM can always be met

if enough samples are taken However, the real the number of samples required to meet the criteria in each given species the time depends on the current SNR of the signal,

PM at any time depends on the current SNR. The expected number of samples for decision making, also called ERL, below H_0 and H_1 for a with PF = α and PM = β given as [19],

$$E\{N|H_0\} \approx \frac{1}{\sigma_0^2}\left[(1-\alpha)\left(\ln\frac{\beta}{1-\alpha}\right)^2+\alpha\left(\ln\frac{1-\beta}{\alpha}\right)^2\right] \quad (2)$$

$$E\{N|H_1\} \approx \frac{1}{\sigma_1^2}\left[\beta\left(\ln\frac{\beta}{1-\alpha}\right)^2+(1-\beta)\left(\ln\frac{1-\beta}{\alpha}\right)^2\right] \quad (3)$$

where $\sigma^2{}_0$ and $\sigma^1{}_2$ are the differences for a single sample in relevant hypotheses. Without loss of the ordinary, we Take the first sample, $\sigma_0^2 = Var(\eta(y|H_0)$and $\sigma_1^2 = Var(\eta(y1|H_1)$

$$\sigma_0^2 = Var(\eta(y_1|h_k)E = [(1n\{p(y_1|H_1)/p(y_1|H_0))^2|H$$

$$= 1n\left(\frac{\sigma_n^2}{\sigma_j^2}\right)\frac{\sigma_{j}^2-\sigma_n^2}{\sigma_j^2-\sigma_n^2} Var\,(y_1^2|H_k) \quad (4)$$

$\sigma_j^2 = \sum_{k=1}^{j}\sigma_{sk}^2 + \sigma_n^2$ *and* $\sigma_{sk}^2$is the received signal the power of PU k and j is the number of active PUs within the group of groups we make a rough feeling. Finall y, y_1^2 is a chi-square

$$Var(y_1^2) = 2Var\,(y_1|H_k) = \left\{\begin{Bmatrix}\sigma_n^2 under\, H_0 \\ 2\;\sigma_n^2 under H_1\end{Bmatrix}\right. \quad (5)$$

Distributed with As a result, when the number of active PUs in the sensor the broadband region is j, the ERL under the respective hypotheses are,

$$E\{N|H_0\} \approx \frac{1}{k_0}[(1-\alpha)a^2 - \alpha b^2 \quad (6)$$

$$E\{N|H_1\} \approx \frac{1}{k_1}[(\beta j a^2 + (1-\beta j)b^2 \quad (7)$$

Where $K_0 = \frac{\sigma_j^2-\sigma_n^2}{\sigma_j^2} 1n\left(\frac{\sigma_n^2}{\sigma_j^2}\right)$ *and* $\frac{\sigma_j^2-\sigma_j^2}{\sigma_n^2}$

denotes the value of AF when there is a total active PU of βJ of the group of channels detected, a and b are as defined in the beginning of this section. Eqn. 7 shows that ERL under H_1 depends on βj, which depends on the active PU number, we calculate βj as follow Let Z_0 be the sample area for which H_0 is resolved

$$Z_0 = \{y \in \mathbb{R}^\infty | \eta_N(y_1, \cdots, y_N) \le a\} = \cup_{n=1}^{\infty} Z_{0n} \quad (8)$$

where N is the number of samples taken to make the decision, or is the probability register and the probability ratio
test

$$Z_{0n} = \{y \in \mathbb{R}^n | N = n \text{ and } \eta_n(y_1, \cdots, y_n) \le a\} \quad (9)$$

Therefore, Z_0n is the area of the samples for which H0 is decide with n samples, that is,

$$\eta_n = \sum_{i=1}^{n}\left(\ln\frac{p(y|H_1)}{p(y|H_0)}\right)$$
$$= \ln(\sigma_n/\sigma_j)^n\left(\frac{(\sigma_j^2-\sigma_n^2)}{2\sigma_j^2\sigma_n^2}(y_1^2+\cdots+y_n^2)\right) \le a \quad (10)$$

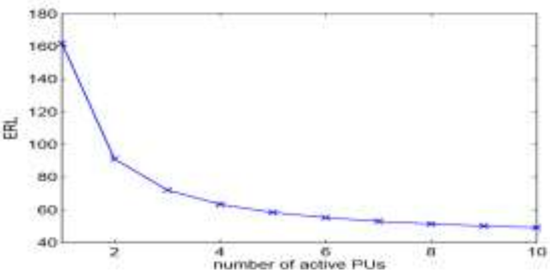

Fig. 1. Expected run length for various number of active PUs.

$$Z_{0n} = \left\{y \in \mathbb{R}^n | \sum_{k=1}^{n} y_k^2 \le r^2\right\} \quad (11)$$

$$r^2 = \frac{2\sigma_j^2\sigma_n^2}{(\sigma_j^2-\sigma_n^2)}\ln\left(a\left(\frac{\sigma_j}{\sigma_n}\right)^n\right) \quad (12)$$

We see that $Z_0{}^n$ is the region within the n-dimensional hyper here. $Z_0{}^n$ can also be represented in a spherical coordinate system measured at n with coordinates

$$r = \sqrt{y_1^2 + y_2^2 + \cdots y_n^2} \quad (13)$$

$$\theta_1 = \text{arccot}\left(\frac{y_1}{\sqrt{y_n^2 + y_{n-1}^2 + \cdots + y_2^2}}\right) \quad (14)$$

$$\cdots$$

$$\theta_{n-2} = \text{arccot}\left(\frac{y_{n-2}}{\sqrt{y_n^2 + y_{n-1}^2}}\right) \quad (15)$$

$$\phi = 2\,\text{arccot}\left(\frac{\sqrt{y_n^2 + y_{n-1}^2} + y_{n-1}}{y_n}\right) \quad (16)$$

Z_0n and Z_0m are mutually exclusive kits for m, therefore,and you can write as

$$\beta = \int_{Z_0} p(\bar{y}|H_1)d\bar{y} \tag{17}$$
$$- \sum_{n=1}^{\infty} \int_{Z_{0n}} \prod_{k=1}^{n} p(y_k|H_1)dy_k \tag{18}$$

Same

$$\alpha = \sum_{n=1}^{\infty} \int_{Z_{1n}} \prod_{k=1}^{n} p(y_k|H_0)dy_k \tag{19}$$

Where

Z_1 and Z_2 are Define similiry Z_0 and $Z_{0n\ ie.,}$ $Z_1 = \{\mathcal{Y} \in \mathbb{R}\infty | \lambda_\eta \geq B\} = \cup_{n=1}^{\infty} Z_{1n} = \{\lambda \in \mathbb{R}^n | N = n$

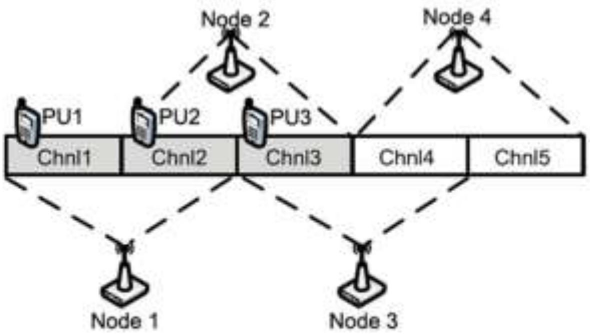

Fig. 2. A sample scenario depicting overlapped sensing idea to overcome near-PU problem.

Probability of permeability in the presence of an active PU f3j can be written as

where dVn = dy1dY2 ··· dYn is the differential volume element. In spherical coordinates, dVn can be written as

$$\beta_j = \sum_{n=1}^{\infty} \int_{Z_{0n}} (2\pi\sigma_j^2)^{-n/2} \exp\left(-\frac{1}{2\sigma_j^2} \sum_{k=1}^{n} y_k^2\right) dV_n \tag{20}$$

As found in (11), integral boundaries make up volume of the hyper sphere, therefore, integral in (20) cannot be written as

$$I(n) = \int_0^R \int_0^{2\pi} \int_0^{\pi} \cdots \int_0^{\pi}$$
$$(2\pi\sigma_j^2)^{-n/2} \exp\left(-\frac{1}{2\sigma_j^2} r^2\right) r^{n-1} \prod_{m=1}^{n-2} (sin\theta_m)^m d\theta_m d\phi dr$$
$$= (2\pi\sigma_j^2)^{-n/2} \int_0^R \exp\left(-\frac{1}{2\sigma_j^2} r^2\right) r^{n-1} dr \frac{2\pi^{n/2}}{\Gamma(n/2)} \tag{21}$$

r (·) is the gamma function given as r (x) = 1000 tX-le-tdt.We evaluate the definitive integral, we have,

$$I(n) = 1 - \frac{\Gamma\left(\frac{n}{2}, \frac{r^2}{2\sigma_j^2}\right)}{\Gamma\left(\frac{n}{2}\right)} \tag{22}$$

where r (a, x) = Ixoo ta-1e-tdt is the upper incomplete gamma function. Thus,

$$\beta_j = \sum_{n=1}^{\infty} I(n) = \sum_{n=1}^{\infty} 1 - \frac{\Gamma\left(\frac{n}{2}, \frac{r^2}{2\sigma_j^2}\right)}{\Gamma\left(\frac{n}{2}\right)} \tag{23}$$

By placing f3j in Eqn 7 we can obtain ERL for active j PU. The relationship between the expected execution length and the number of active PUs is shown in Figure 1 for PF = 0.01, PM = 0.01, an = 1 and as = 1, Le., Normalized Noise and SNR of 0 dB. As you can see clearly, the number of samples taken before making the decision gives us an approximate idea of how many of the channels in the sensitive broadband band are occupied.

*D. The problem of nearby PU:*CC4C has a weak point. Because it depends on the common SNR be an indicator of the amount of active PUs if one of the PU is too close to the secondary network, CC4C can

produce unwanted results For example, if PU in a group of the channels has twice the output power of another PU c another group of channels when only those two are active their respective groups of channels, means CC4C concludes that the PU group with the most power has a double number of the PU in this group where there is really only one active PU in each group

One way to overcome this problem is to use average methods We offer two average methods. One is to choose two nodes that are farther away from each other to perform

CC4C of the same group of channels, then collect the average of ERL informed by them. With the nodes selected in this way, PU which is close to one, will be further from the other

the average results of these two nodes will soften the effect of close to the problem of PU

Another method of averaging is the use of the previous method along with the selection of groups of channels in an overlapping manner. The idea is illustrated in a simplified case in figure 2 a total of five channels across the spectrum. Four knots CC4C group surveillance, each of which covers two channels, with an ERL superimposed channel for each channel is determined by averaging the ERL of the nodes that are running approximate sensor for this channel. For the example presented case if PU2 represents the near PU problem for node 2, node 1 will soften this effect as it is farther from PU and ERL of channel 2 is determined by averaging. The remaining problem is how to define the nodes They are further away from each other. Good convergence of

this would be using spectral correlation specimens of the nodes. Due to the probability of greater shading the objects between two nodes increase as the distance increases,correlation specimens to track the farthest the pairs of nodes are more likely to be closer to zero. However, exchanging thousands of samples with multiple nodes each time Spectrum report is done to calculate this correlation is not realistic The information is huge, the number of emissions is n 2, unless the total number of nodes is n + 1, it is also present channel (s) to transmit this information is not known from the capture spectrum is still not fulfilled. However, in the CRSN

Instead, we can use the idea we propose [9]. It should be used Correlations of environmental monitoring data instead of sharing Spectrum sensor data. Reading the sensors in the environment is already regularly sent to the sink as a normal operation of the CRSN. All the neighbors listen to these reports. Therefore, in the CRSN, the nodes can monitor continuously its correlation with its neighbors, which can be used as evaluation to determine nodes that are far from anyone other. This makes the CC4C a good thick sensor scheme for CRSN.

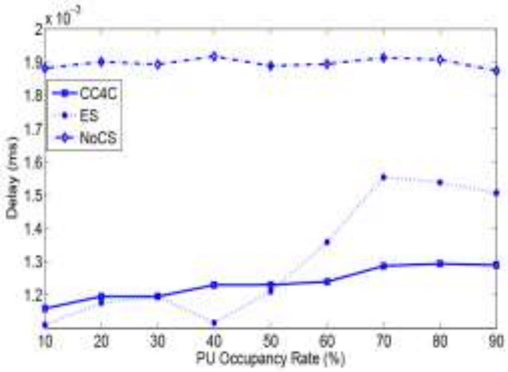

Fig. 3. Average delay vs PUs occupancy rate

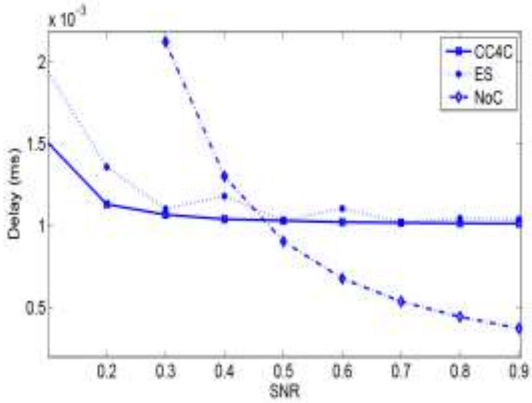

Fig. 4. Average delay vs SNR

II. IMPLEMENTATION EVALUATION CC4C

In this section, we present our results on the performance of the CC4C compared to the signaling schemes based on approximate signaling (ES). We do not include schemes that are specific to a particular type of PU, since these schemes will have additional information and will be specifically adapted to this PU, the comparison would not be fair. In the simulations, we use observation in two stages for both cases. We determine the threshold (and the number of samples for the case of ES) for the desired false alarm probability parameters, PFA = 0: 1 and probability of detection, PD = 0: 9.

The effectiveness of finalization is not the objective of this book, so the method chosen is not very important, provided that the same method of final touch is used in both compared schemes.

For both methods, we use energy detection with much stricter parameters, ie. PFA = 0:01 and PD = 0:99. We also include a case in which a coarse detection is not performed and the available channel is detected by repeated filtering of different channels until an available channel is found. We mark this case as NoCS in the figures.

In both cases CC4C and ES, if an available channel is not found at the end of the observation stage, we assume that the node that has transmission data must wait until the next observation round. We assume that for each 1 ms interval an observation cycle is performed (for example, LTE has an interval of 1 ms). We note that the delay due to the spectrum sensor is the interval between the beginning of the approximate detection and the moment when the node detects a transmission channel.

We use the parameters given in [20] for energy consumption. Namely, we use the energy consumed for the spectrum is Es = IrV ts, where Ir = 19: 7mA is the receive current, V = 3V is the supply voltage and ts is the total amount of time spent reading the spectrum, including both stages.We assume that the entire usable band has 40 channels.

The CC4C divides the spectrum into equally sized pieces and monitors approximately these pieces at the same time. To present a comparatively slow comparison, we assume that in the case of ES, multiple nodes make sudden changes simultaneously in different parts of the same size group. For both methods, we have received 8 nodes that perform an approximate monitoring at the same time every 5 channels. In each simulation, we use a range of 100 Spectrum Observation Circuits. We test the simulations 1000 times and present the average value of the results.

Figure 3 shows the delay due to observation patterns as the spectrum becomes full. We see the advantage that two-step monitoring schemes provide clarity. The one-step scheme causes up to 69.7% delay compared to CC4C. CC4C and ES have similar indicators with low levels of PU employment, but CC4C has fewer delays since the employment rate increases to an improvement of 20.75%.

Figure 4 provides a comparison of the delay to increase the SNR values. The one-step observation scheme is extremely low in the low SNR regions, so we had to increase the graph to see the difference between CC4C and ES. However, with the SNR increase, the one-stage circuit works better and, in fact, is more advantageous for SNR values greater than 0.5, ie -3 dB. This is expected because the number of required samples that meet the detection criteria decreases rapidly as the SNR increases. At approximately -3 dB, the required number of completion samples is so low that repetitive detection causes less delay. However, keep in mind that getting the desired results in high SNR regions is easy. In real-life scenarios, CRs typically operate in low SNR regions and the real challenge is to meet the monitoring requirements for SNR values below -20 dB. In this low SNR region, CC4C causes less delay compared to other circuits with up to 10.3% less delay compared to ES.

The comparison of energy consumption as an increase in the use of PU is shown in Figure 5. Here, too, there is a large difference between two-stage circuits and a one-stage scheme. The one-step scheme consumes 119.4% more energy than CC4C. ES also consumes more power than CC4C, up to 49.89% difference between the two circuits.

Figure 6 shows the energy consumption of the SNR increase. Again, the scheme of one level is implemented very poorly in the low SNR regions. CC4C works better than other schemes, allowing up to 85.95% conservation compared to ES.

III. CONCLUSIONS

An approximate spectrum monitoring scheme is presented for use in the two-stage spectrum observation method for CRSN, CC4C.The CC4C coincides with our previous proposal to fine-tune the CRSN, which completely forms a two-tier monitoring system, such as

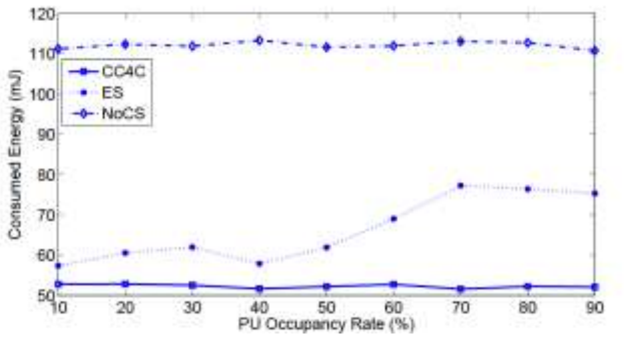

Fig. 5. Average energy consumption vs PUs occupancy rate

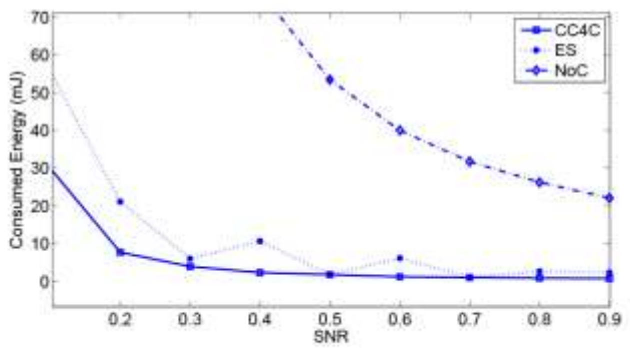

Fig. 6. Average energy consumption vs SNR

both methods use the correlations of the environmental readings of the sensor nodes and, once calculated for one, can be used by the other. The results of the simulation show that CC4C is significantly more energy efficient than other circuits. Comparing the delay due to the sensor spectrum, we see that the CC4C works best in the low SNR region where the observation requirements are the most difficult to achieve.

REFERENCES

[1] O. B. Akan, O. B. Karli, O. Ergul, "Cognitive Radio Sensor Networks," IEEE Network Magazine, vol. 23, no. 4, pp. 34-40, Jul-Aug. 2009

[2] L. Nachman, J. Huang, J. Shahabdeen, R. Adler, R. Kling, "IMOTE2: Serious Computation at the Edge," International Wireless Communica-tions and Mobile Computing Conference (IWCMC), pp.1118,1123, Aug. 2008

[3] H. G. Gog, K. H. Kwong, C. Shen, C. Michie, I. Andonovic, "CogSeNet: A Concept of Cognitive Wireless Sensor Network," IEEE Consumer Communications and Networking Conference (CCNC), pp.1-2, Jan. 2010

[4] G. Vijay, E. Bdira, M Ibnkahla "Cognitive approaches in Wireless Sensor Networks: A survey," 25th Biennial Symposium on Communications (QBSC), pp.177-180, May 2010

[5] B. Gulbahar, O.B. Akan, "Information Theoretical Optimization Gains in Energy Adaptive Data Gathering and Relaying in Cognitive Radio Sensor Networks," IEEE Transactons on Wireless Communications, vol.11, no.5, pp.1788-1796, May 2012

[6] H. Zhang, Z. Zhang, X. Chen, R Yin, "Energy Efficient Joint Source and Channel Sensing in Cognitive Radio Sensor Networks," IEEE Inter-national Conference on Communications (ICC), 2011, pp.1-6, 5-9 June 2011

[7] L. Stabellini, M. U. Javed, "Energy-Aware Spectrum Sensing in Cog-nitive Wireless Sensor Networks: A Cross Layer Approach," Wireless Communications and Networking Conference (WCNC), 2010 IEEE, pp. 1-6, 2010

[8] S. Maleki, A.Pandharipande, G. Leus, "Energy-Efficient Distributed Spec-trum Sensing for Cognitive Sensor Networks," IEEE Sensors Journal, vol.11, no.3, pp.565-573, Mar. 2011

[9] O. Ergul, O. B. Akan, "Energy-efficient Cooperative Spectrum Sensing for Cognitive Radio Sensor Networks," to appear in Proc. IEEE Sympo-sium on Computers and Communications (ISCC),, Jul. 2013

[10] J. Riihijarvi, J. Nasreddine, P. Mahonen, "Impact of Primary User Activity Patterns on Spatial Spectrum Reuse Opportunities," Wireless Conference (EW), 2010 European, pp.962-968, 2010

[11] K. W. Sung, S. L. Kim, J. Zander, "Temporal Spectrum Sharing Based on Primary User Activity Prediction," IEEE Transactions on Wireless Communications, vol. 9, no.12, pp.3848-3855, December 2010

[12] S. Maleki,A. Pandharipande, G. Leus, "Two-stage spectrum sensing for cognitive radios," IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP), pp.2946,2949, March 2010

[13] L. Ling, N. M. Neihart, S. Roy, D. J. Allstot, "A two-stage sensing technique for dynamic spectrum access," IEEE Transactions on Wireless Communications, vol.8, no.6, pp.3028,3037, June 2009

[14] Z. Li, H. Wang, J. Kuang, "A two-step spectrum sensing scheme for cognitive radio networks," International Conference on Information Science and Technology (ICIST), pp.694,698, 26-28 March 2011

[15] M, Abdelmonem, M. H. Ismail, M. S. El-Soudani, M. Nafie, "Coarse spectrum sensing for LTE systems," IEEE International Conference on Telecommunications (ICT), pp.116,121, 4-7 April 2010

[16] S.C. Chen, C.J Chang, R.H. Gau, "A two-phase and two-period spec-trum sensing scheme using high-layer information for cognitive radio networks," Computing, Communications and Applications Conference (ComComAp), pp.250,255, 11-13 Jan. 2012

[17] A. Wald, J. Wolfowitz, "Optimum character of the sequential probability ratio test," Ann. Math. Statist., no. 19, pp. 326-339.

[18] Y. C. Liang, Y. Zheng, E. C. Y. Peh, A. T. Hoang, "Sensing-Throughput Tradeoff for Cognitive Radio Networks," IEEE Transactions on Wireless Communications, vol.7, no.4, Apr. 2008.

[19] H. V. Poor, "An Introduction to Signal Detection and Estimation," SpringerVerlag, 2nd Ed., 1994. [20] R. Jurdak, A. G. Ruzelli, and G. M. P. O'Hare, "Radio Sleep Mode Op-timization in Wireless Sensor Networks," IEEE Transactions on Mobile Computing, vol.9, no.7, pp. 995-968, Jul. 2010.