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ENERGY MINIMIZATION APPROACH FOR COOPERATIVE SPECTRUM SENSING IN COGNITIVE RADIO WIRELESS SENSOR NETWORKS

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Abstract
Cooperative spectrum sensing is a promising method for improving spectrum sensing performance in cognitive radio. Although it yields better spectrum sensing performance, it also incurs additional energy consumption that drains more energy from the sensor nodes and hence shortens the lifetime of sensor networks. This paper proposes energy minimization approach to reduce energy consumption due to spectrum sensing and sensed result reporting in a cooperative spectrum sensing. The approach determines optimal number of cooperative sensing nodes using particle swarm optimization. We derived mathematical lower bound and upper bound for the number of cooperative sensing nodes in the network. Then we formulate a constraint optimization problem and used particle swarm optimization to simultaneously optimize the two mathematical bounds to determine the optimal number of sensing nodes. Simulation results indicate viability of the proposed approach and show that significant amount of energy savings can be achieved by employing optimal number of sensing nodes for cooperative spectrum sensing. Performance comparison with conventional approach shows performance improvement of the proposed approach over the conventional method in minimizing spectrum sensing energy consumption without compromising spectrum sensing performance.

***Keywords*:** Cooperative Spectrum Sensing, Energy Consumption, Cognitive Radio, Wireless Sensor Networks

1. Introduction

Technological advancements in wireless communications and microelectronics have led to the widespread use of Wireless Sensor Networks (WSNs) in a wide variety of application areas. Wireless sensor network is a self-organizing ad hoc communication network characterized by constraint memory, power and computational resources. Proliferation of wireless sensor nodes and other wireless devices based on Bluetooth, Wi-Fi and ZigBee technologies have led to severe congestion in the usable unlicensed Industrial Scientific and Medical (ISM) spectrum band and hence pose operational challenges to the wireless devices. Federal communications commission report (FCC, 2003) revealed that many spectrum bands that are assigned to licensed users (primary users) for various wireless communication services are underutilized. Conventional policy of allocating spectrum bands to licensed users regardless of temporal and geographical variations has inadvertently contributed to the spectrum scarcity and hence necessitates the need for a paradigm shift from the static spectrum allocation policy to intelligent and dynamic spectrum access.

Cognitive radio (CR) has emerged as the viable technique for efficient utilization of spectrum holes by dynamically allocating the unoccupied licensed spectrum bands to unlicensed users referred to Secondary Users (SUs) in an agile manner without causing harmful interference to the Primary Users' (PUs) transmission (Mitola, 2000). To properly harness the potentials benefits of cognitive radio technology in WSN to improve spectrum utilization, a novel network paradigm of sensor nodes equipped with cognitive radio technology called cognitive radio wireless sensor network (CR-WSN) has emerged. A CR-WSN is a dispersed network of cognitive radio sensor nodes that dynamically utilized unused available spectrum bands to communicate sensed readings to satisfy application requirement(Mustapha *et al.*, 2016). CR-WSN networks is sought to be the most promising technology to address current and future challenges of spectrum scarcity in WSNs.

Spectrum sensing is the main fundamental function of CR to detect the presence or absence of primary users in a licensed spectrum band. Cooperative spectrum sensing (CSS) is identified as the feasible method that enhances sensing performance through exploration of multi-user sensing diversity(Salah *et al*., 2016). Performance of cooperative spectrum sensing is measured based on two important decision metrics, cooperative probability of detection $\bar{Q}_d$ and cooperative probability of false alarm $\bar{Q}_f$. It has been shown in (Pham *et al*., 2010) that, when the number of SUs increases, both the $\bar{Q}_d$ and $\bar{Q}_f$ increase. In addition, large number of SUs means more energy would be consumed for sensing the spectrum which is undesirable in sensor networks owing to the energy constraint of the nodes. Therefore, optimal number of sensing nodes (SUs) that satisfies both energy constraint of sensor nodes and spectrum sensing performance accuracy need to be determined.

This paper describes a method to minimize energy consumption for spectrum sensing in a cooperative spectrum sensing by determining optimal number of sensing nodes that satisfy both predefined $\bar{Q}_d$ and $\bar{Q}_f$thresholds using Particle swarm optimization (PSO).Energy minimization in CSS is formulated as constraint optimization problem and PSO technique is used to determine the optimal number of sensing nodes.

2. Materials and Methods

The network consists of N sensing nodes that are uniformly distributed in an area N_A of $L$by L square meters, each cognitive radio sensor node is equipped with a single transceiver that switches alternately from any of the available channels Ch_n. Also, each node used a dedicated control channel C_{tr} to exchange control information. It is assumed that at the initial stage all nodes have equal amount of energy.

2.1 Energy Detection Based Spectrum Sensing

Spectrum sensing is a key function in cognitive radio networks for achieving basic requirement of protecting primary user (PU)from harmful interference. Its main goal is to identify and access spectrum holes without compromising PUs' transmission. Energy detection is the optimum non-coherent technique that can be used to sense the channels to detect the existence of PUs' signals in the channels. The technique measures energy of the PU's signal waveform received over a specified observation time. The PU signal received at the SU is filtered by a Band-Pass Filter (BPF) to limit the noise bandwidth. This is followed by a squaring device which converts the analogue signals to discrete samples $N_o$and then passes to an integrator which determines the observation interval t as depicted in Figure 1.

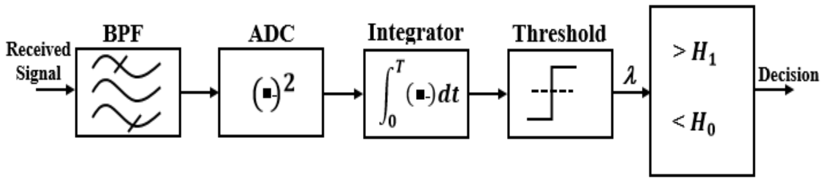


Figure 1: Block diagram of energy detection scheme

The energy of the received PU's signal waveform can be expressed as:

$$Y = \sum_{t=1}^{N_o} |y(t)|^2 \qquad (1)$$

To determine existence of PU's signal, the average energy of the observed signal samples which serves as test statistics is compared with a predefined threshold λ. If the value of the received signal energy is below the threshold $Y < \lambda$, then PU's signal is said to be absent and the channel is considered available, Otherwise, PU's signal is present and the channel is being occupied. PU signal detection problem can be formulated as binary hypothesis test and can be expressed as (Hojjati *et al*., 2017).

$$H_o: \quad x(t) \text{ (White space)}$$
$$H_1: z(t) + x(t) \text{ (Occupied)} \qquad (2)$$

where: $x(t)$ and $z(t)$ denote zero-mean Additive White Gaussian noise (AWGN) and the received signal waveform respectively. H_o denotes null hypothesis which indicates absence of PU's signal in the frequency band, while H_1 hypothesis indicates presence of PU's signals in the frequency band. Test statistics Y under hypothesis H_1 follows a non-central chi-square distribution $\sim \chi^2_{2\mu}(2\gamma_s)$, while test statistics Y in the case of hypothesis H_0 follows a central chi-square distribution $\chi^2_{2\mu}$. Thus, test statistics Y can be expressed as(Urkowitz, 1967).

$$Y \approx \begin{cases} \chi^2_{2\mu}\ , & H_0 \\ \chi^2_{2\mu}(2\gamma_s), & H_1 \end{cases} \tag{3}$$

where: $\gamma_s$denotes signal-to-noise ratio (SNR), 2μ denotes degree of freedom and μ denotes time bandwidth product given as $\mu = TB_w$. According to Nyquist sampling theorem, the number of received signal samples N_o can be represented as $N_o = 2TB_w$ in which the minimum sampling rate for the received signal is $2B_w$ (Lee and Akyildiz, 2008). Probability of detection P_d which indicates truly the presence of PU's signal in the considered spectrum band and probability of false alarm P_f which suggests presence of PU's signal in the considered channel when there is no PU's signal can be expressed as(Cheng *et al*., 2012).

$$P_d = P_r[Y > \lambda \backslash H_1] = \mathbb{Q}_\mu(\sqrt{2\gamma_s}, \sqrt{\lambda}) \tag{4}$$

$$P_f = P_r[Y > \lambda \backslash H_0] = \frac{\Gamma(\mu, \lambda/2)}{\Gamma(\mu)} \tag{5}$$

where: $\Gamma(a, x)$denotes upper incomplete gamma function, and $\mathbb{Q}_\mu(a, x)$ is the generalized Marcum Q-function.

2.2 Cooperative Spectrum Sensing

Although energy detection technique offers low implementation complexity and less computational requirement compared to other techniques which make it more attractive to resource constraint devices such as cognitive radio sensor node, its detection performance may be compromised by propagation impairments such as shadowing, interference, receiver uncertainty and multi-path fading as illustrated in Figure 2 (Akyildiz *et al*., 2011). Cooperative spectrum sensing is key enabling technique for combating the aforementioned wireless propagation impairment(Singh *et al*., 2012). The technique improves sensing performance through exploration of multi-users spatial sensing diversity in which each sensing node shares its local test statistics with other cooperative sensing nodes and collectively decides on existence of PU in the channel as illustrated in Figure 3. The important decision metrics ($\bar{Q}_d$ and $\bar{Q}_f$) which play vital roles in determining the occupancy or otherwise of a channel, must be within an acceptable range such that $\bar{Q}_d \geq Q_{dt}$ and $\bar{Q}_f \leq Q_{ft}$. Where Q_{dt} and Q_{ft} are the threshold for detection and false alarm probabilities which define the minimum acceptable detection probability P_d^{min} and the maximum tolerable false alarm probability P_f^{max} respectively.

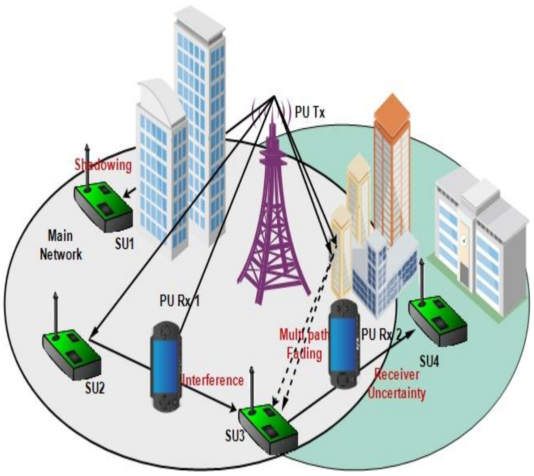


Figure 2: Illustration of propagation impairments

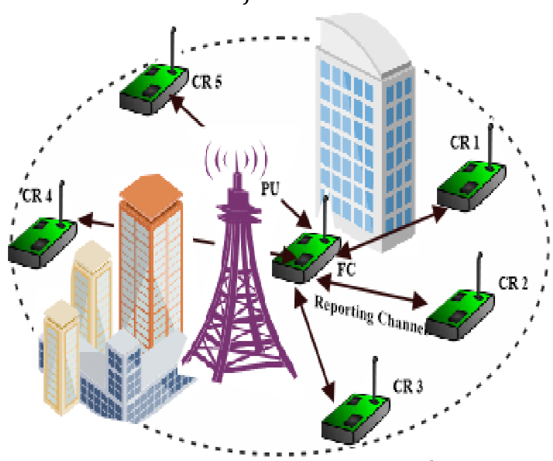


Figure 3: Cooperative spectrum sensing

In cooperative spectrum sensing, multiple sensing nodes are grouped and coordinated to efficiently share sensing results and collectively decide on the existence of PU in the spectrum band. each of the sensing node or some selected sensing nodes periodically sense the spectrum band and then share the sensing results with rest of the sensing nodes in the network to improve the spectrum sensing performance (Mustapha *et al*., 2015). A dedicated central entity (Fusion

Centre) coordinates the spectrum sensing and performs data fusion on sensing results received from either individual sensing node or group of sensing nodes to determine the presence or absence of PU. The fusion centre (FC) can be a base station or any of the sensing node among the sensing nodes in the network. Each of the sensing node individually senses the spectrum bands, decides on the existence of primary user or otherwise and then reports its decision to the FC for data fusion and final decision on spectrum band occupancy. It is assumed that channel between the sensing nodes and the FC is perfect since distance between them is assumed to be short. Similarly, fading statistics, noise and SNR are assumed to be the same for each of the sensing nodes. The FC employs "OR-rule" decision counting rule fusion to determine the channel occupancy. This means that final cooperative decision probabilities on the channel occupancy will indicate busy if at least one of the sensing node reports a decision of channel busy. Therefore, cooperative probability of detection $\bar{Q}_d$ and cooperative probability of false alarm $\bar{Q}_f$for n_s number of cooperative sensing nodes based on OR-rule are given as.

$$\bar{Q}_d = 1 - \prod_{i=1}^{n_s}(1 - p_{d,i}) = 1 - (1 - p_{d,i})^{n_s} \tag{6}$$

$$\bar{Q}_f = 1 - \prod_{i=1}^{n}(1 - p_{f,i}) = 1 - (1 - p_{f,i})^{n_s} \tag{7}$$

2.2.1 Lower Bound and Upper Bound for Cooperative sensing nodes

If Q_{dt} and $Q_{ft}$are the thresholds for cooperative detection and false alarm probabilities respectively and $p_{d,i}$ and $p_{f,i}$ are probabilities of detection and false alarm for the sensing nodes, then these relationships exist.

$$1 - \prod_{i=1}^{n_s}(1 - p_{d,i}) \geq Q_{dt} \leftrightarrow 1 - Q_{dt} \geq \prod_{i=1}^{n_s}(1 - p_{di}) \tag{8}$$

$$1 - \prod_{i=1}^{n_s}(1 - p_{f,i}) \leq Q_{ft} \leftrightarrow 1 - Q_{ft} \leq \prod_{i=1}^{n_s}(1 - p_{fi}) \tag{9}$$

This shows that to satisfy detection accuracy by maintaining acceptable sensing performance, the number of sensing nodes must be within the ranges of $[n_s^{min}, n_s^{max}]$.Thus, the mathematical lower bound for the minimum number of cooperative sensing nodes can be expressed as:

$$1 - (1 - p_{d,i})^{n_s^{min}} \geq Q_{dt}$$

$$1 - Q_{dt} \geq (1 - p_{d,i})^{n_s^{min}}$$

$$n_s^{min} = \frac{\log(1-Q_{dt})}{\log(1-p_{d,i})} \tag{10}$$

Similarly, the mathematical upper bound for the maximum number of cooperative sensing nodes can be expressed as:

$$1 - (1 - p_f)^{n_s^{max}} \leq Q_{ft}$$

$$1 - Q_{ft} \leq (1 - p_f)^{n_s^{max}}$$

$$n_s^{max} = \frac{\log(1-Q_{ft})}{\log(1-p_{f,i})} \tag{11}$$

Therefore, the number of cooperative sensing nodes must be within the range of:

$$n_s^{min} < n_s^* < n_s^{max} \tag{12}$$

2.2.2 Problem Definition

Performance of cooperative sensing is influenced by the number of cooperative sensing nodes, large number of cooperative sensing nodes leads to higher $\bar{Q}_d$, higher $\bar{Q}_f$, higher sensing and reporting energy consumption. While higher $\bar{Q}_d$ minimizes chances of interference to primary user, higher $\bar{Q}_f$increases chances of missing spectrum opportunity which leads to under-utilization of spectrum bands. Therefore, it is extremely important to find optimal number of cooperative sensing nodes that satisfies both energy constraint of sensor nodes and sensing performance accuracy defined by probability of detection and probability of false thresholds. The problem is formulated as constraint optimization problem to minimize energy cost due to spectrum sensing and sensing results reporting subject to sensing accuracy constraints. Thus, optimization problem is formulated as follows:

$$\min_{n_s} \quad E(n_s)$$

$$\text{Subject to: } \bar{Q}_d(n_s) \geq Q_{dt}$$

$$\bar{Q}_f(n_s) \leq Q_{ft}$$

Find: n_s^* such that

$$\frac{\log(1-Q_{dt})}{\log(1-p_{d,i})} \leq n_s^* \leq \frac{\log(1-Q_{ft})}{\log(1-p_{f,i})} \tag{13}$$

$$\bar{Q}_d(n_s) \geq Q_{dt} \text{ and } \bar{Q}_f(n_s) \leq Q_{ft}$$

Where: E is the network energy cost, n_s denotes number of cooperative sensing nodes, Q_{dt} and Q_{ft} are the target cooperative detection and false alarm probabilities respectively.

2.3 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an evolutionary computing technique inspired by social behavior of fish schooling and bird flocking. It is based on random search algorithms developed by Kennedy and Eberhart (Kennedy and Eberhart, 1997). The algorithm works by first creating a population of random particles based on search space defined by the optimization problem. During every generation u, each of the particles i in the randomly distributed population interact with one another, learn its best position $pBest$ and neighborhood's best position. The particle uses knowledge about its previous best position and the neighboring particles' best positions and move towards a better region for optimal solution, $gBest$. The particle velocity is limited to minimum velocity v_{min} and maximum velocity v_{max} to restrict movement within the search space.In every generation process, position x_i and velocity v_i of each particle i is updated based on Eqn. (13) and Eqn. (14), respectively.

$$v_{ij}(u+1) = v_{ij}(u) + c_1 r_1 \left(P_{bij}(u) - x_{ij}(u)\right) + c_2 r_2 \left(P_{gj}(u) - x_{ij}(u)\right) \tag{14}$$

$$x_{ij}(u+1) = x_{ij}(u) + v_{ij}(u+1) \tag{15}$$

Where $v_{ij}(u)$ denotes velocity of i-th particle in j-th dimension at u-th generation, $c_1 and c_2$ denote learning factors, c_1 denotes cognitive learning factor and c_2 denotes social learning factor, r_1 and r_2 denote uniformly distributed random numbers between the range of [0 1]. $P_{bij}(u)$ is the particle's i-th best position at dimension j-th in generation u-th and $P_{gj}(u)$ is the global best position found by the entire particles at j-th dimension in u-th generation. $x_{ij}(u)$ denotes position of i-th particle at dimension j-th in generation u-th.

2.3.1 Fitness Function

The algorithm is implemented at the base station which has no energy constraint. The BS runs the PSO to minimize the fitness function f and determine the optimal number of cooperative sensing nodes for the network. The main objective of the fitness function f is to simultaneously optimize mathematical upper bound for the number of cooperative sensing nodes f_1 and mathematical lower bound for the number of cooperative sensing nodes f_2 as given by:

$$f = \alpha x f_1 + (1-\alpha) x f_2 \tag{16}$$

$$\text{Subject to: } \bar{Q}_d \geq Q_{dt} \text{ and } \bar{Q}_f \leq Q_{ft}$$

Where: α is a constant used to weigh contribution of each of the sub-objective functions in the fitness function. f_1 and f_2 are the maximum and minimum number of cooperative sensing nodes in the network respectively given by:

$$f_1 = \frac{\log(1-Q_{ft})}{\log(1-p_{f,i})} \tag{17}$$

$$f_2 = \frac{\log(1-Q_{dt})}{\log(1-p_{d,i})} \tag{18}$$

If p_k is a set of particles such that $p_k = \{i_n | n = 1 \ldots\ldots\ldots N, i_n > 0 \; \& i_n < 1\}$represent set of possible values for the probabilities of detection and false alarm in the fitness functions f and S denotes swarm of the particles such that $S = \{x_1 \ldots, x_i \ldots\ldots, x_n\}$, then $x_i$indicates particle i with position $x_{i,n} \in p_k$. Also, if element of set $s_p = \{i_n, i_m\}$ denote the cooperative probability of detection $\bar{Q}_d$and the cooperative probability of false alarm $\bar{Q}_f$ respectively and $s_p \subseteq p_k$, then the corresponding value of $f$when $i_n \geq Q_{dt}$ and $i_m \leq Q_{ft}$ is the optimal number of the sensing node which would be between the minimum and the maximum number sensing nodes. The flowchart for the PSO is shown in Figure 4.

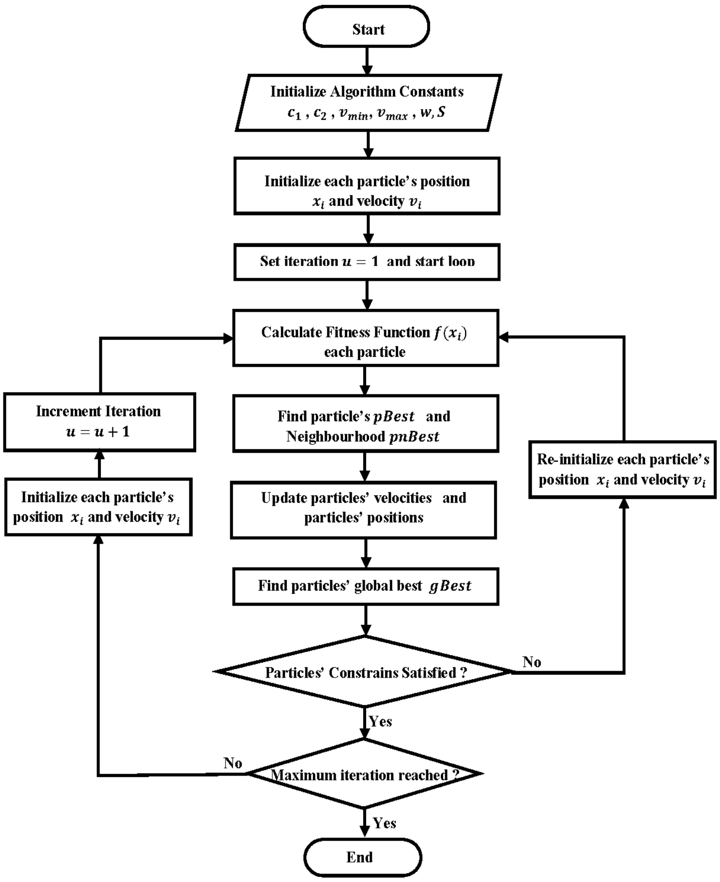


Figure 4: Flowchart for PSO used to determine the optimal number of cooperative sensing nodes

2.4 Energy Consumption for Cooperative Spectrum Sensing

Cooperative spectrum sensing energy consumption to detect vacant channels comprises energy consumption for sensing sets of channels and reporting local decisions as well as receiving final cooperative decisions. Energy consumption for spectrum sensing $\mathrm{E_{ss}}$ comprises energy consumption for listening over a channel and receiving N_o observation samples, as well as energy required to process the signal samples (modulation, signal shaping etc) and make local decision. It mainly depends on the sensing duration T and increases with increase in number of cooperative sensing nodes$\mathrm{n_s}$. Therefore, energy dissipated by sensing node for sensing spectrum band is given as:

$$\mathrm{E_{ss}}(n_s, \mathrm{T}) = \sum_{i=1}^{\mathrm{n_s}} (\mathrm{TE_{sr}} + \mathrm{E}_{sp})$$

$$= \sum_{i=1}^{\mathrm{n_s}} \left(\frac{N_o \mathrm{E}_{sr}}{2B_w} + \mathrm{E} \right) \quad (19)$$

Where: E_{sr} denotes circuit energy consumption of i-th sensing nodes for receiving N_o signal sample, E_{sp} denotes the energy cost for processing N_o signal samples and B_w is the bandwidth of the spectrum and $N_o = 2TB_w$. Energy consumption for reporting sensing results $\mathrm{E_{rr}}$ is the energy required to transmit B-bits of local decision to fusion centre and it mostly results from energy dissipated in running power amplifier and radio electronic circuitry of the node. It mainly depends on the packets to be transmitted, which is influenced by the Euclidian distance between the transceivers.

$$\mathrm{E_{rr}}(B, d_{i,j}) = \sum_{i=1}^{\mathrm{n_s}} B\left(E_e + E_a d_{i,j}^2\right) \tag{20}$$

Where: $d_{i,j}$ is the Euclidian distance between the FC and the sensing nodes, E_e denotes energy cost for running the radio electronics of the nodes and E_a denotes the energy cost for amplifying signal to be transmitted to FC so as to maintain acceptable level of SNR. Since the distance between sensing nodes and the FC is presumably short, the channel between them is assumed to follow Friis free space model with signal power attenuation of d^2 power loss(Kyperountas *et al*., 2007). The energy cost for receiving the B-bits packet of final cooperative decision broadcasted by the FC after performing decision is mainly determined by the number of bits in the packet and energy consumed for running the radio electronics circuitry. Therefore, energy consumption for receiving B-bits of broadcasted packet can be expressed as:

$$\mathrm{E}_{rx}(B) = \sum_{i=1}^{\mathrm{n_s}} BE_e \tag{21}$$

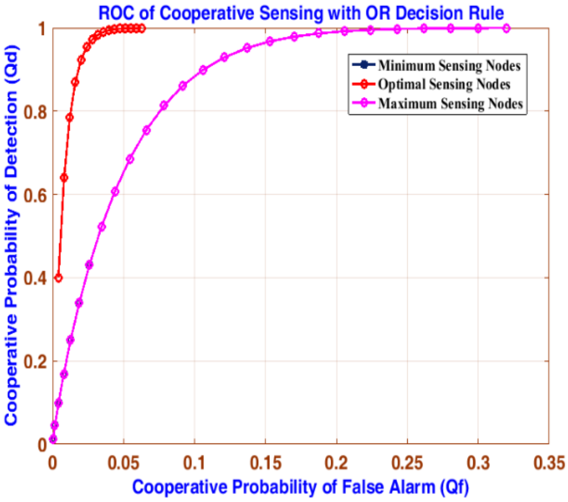
Therefore, energy consumption for cooperative channel sensing comprises energy consumption for sensing sets of channels, energy consumption for reporting local decision and energy consumption for receiving final cooperative decision given as:

$$\mathrm{E_{ts}} = \sum_{i=1}^{\mathrm{n_s}}\left(\left(\frac{N_o \mathrm{E}_{sr}}{2B_w} + \mathrm{E}_{sp}\right) + 2BE_e + BE_a d_i^2\right) \tag{22}$$

3. Results and Discussion

Simulation results are presented to validate the cooperative spectrum sensing energy consumption model and to evaluate the performance of the proposed scheme. The optimal number of cooperative sensing nodes is compared with the minimum number (mathematical lower bound) and maximum number (mathematical upper bound) of the cooperative sensing nodes. A network area N_A of $X = 90$ by $Y = 90$ square meters consisting of $N = 225$ stationary cognitive radio sensor nodes uniformly distributed is considered (Ibrahim Mustapha, 2014). Energy dissipated for spectrum sensing comprises of energy dissipated to tune the receiver circuit to the channel frequency $\mathrm{E}_{sr} = 40\ mW$ which is influenced by number of signal samples received during detection time t and energy dissipated for signal processing E_{sp} which is approximately given by ($\mathrm{E}_{sp} = \frac{2.1x17.4x10^{-3}}{250x10^3} = 150$ nJ/bit) based on data rate of 250 kbps, voltage 2.1V and current of 17.4mA as in (Maleki *et al*.,2009). Energy dissipated for reporting sensing result consists of energy cost for running the radio electronics of the sensing nodes at transmitting power of 20mW which is approximately $Ee = \frac{250kbps}{20mW} = 80$ nJ/bit and energy dissipated for amplifying the received signal at SNR 10 dB to be transmitted to FC is $E_a = 40.4$ pJ/bit/m^2. The number of received signal samples, signal bandwidth and sampling interval are set to$N_o = 50$, $B_w = 2.5\ MHz$and $T = \frac{N_o}{2B_w}$which is 1µs respectively.

Figure 5 compares the receiver operating characteristics (ROC) curves for minimum, optimal and maximum number of cooperative sensing nodes. For the minimum and maximum number of cooperative sensing nodes, the result indicates that cooperative probability of detection increases almost proportionally along with the cooperative probability of false alarm. But for the optimal number of cooperative sensing nodes, the result shows that both the cooperative probability of detection and cooperative probability of false detection, satisfy spectrum sensing accuracy of $\bar{Q}_d \geq Q_{dt}$ and $\bar{Q}_f \leq Q_{ft}$ i.e (0.98 ≥ 0.9 and 0.057 ≤ 0.1). This indicates the effectiveness of the proposed scheme which satisfied the spectrum sensing accuracy requirements. Figure 6 shows energy consumption for achieving cooperative probability of detection for the minimum, optimal and maximum number of cooperative sensing nodes, respectively. The result indicates that minimum number of cooperative sensing nodes consume least energy of $\mathrm{E_{ts}} = 40\ \mu J$ with maximum cooperative probability of detection of $\bar{Q}_d = 0.450$ which compromises the required detection threshold $(\bar{Q}\_d \geq Q\_dt)$. This means that PU detection accuracy would not be achieved with the minimum number of cooperative sensing nodes.On the other hand, cooperative probability of detection for the optimal and maximum number of sensing nodes satisfy the required detection performance of $\bar{Q}_d \geq Q_{dt}$. While the energy consumption for the maximum number of cooperative sensing nodesis$\mathrm{E_{ts}} = 480\ \mu J$ for $\bar{Q}_d = 0.97$, the energy consumption for the optimal number of cooperative sensing nodesis only $\mathrm{E_{ts}} = 250\ \mu J$ for $\bar{Q}_d = 0.97$ which is 48% less than the former. This means energy savings of 48% can be achieved by employing optimal number of cooperative sensing nodes for spectrum sensing. The result indicates that significant amount of energy can be saved while minimizing interference to primary user transmission.



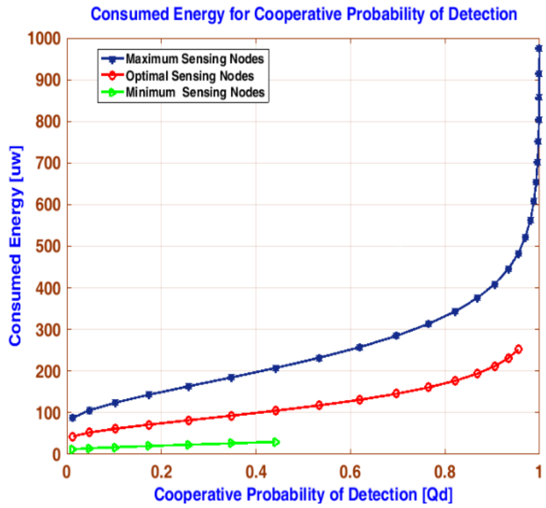


Figure 5: ROC of Cooperative Spectrum Sensing **Figure 6:** Consumed Energy for Cooperative Detection

Figure 7 compares the energy consumption for spectrum sensing, result reporting and total energy for the three cases, respectively. The result shows that spectrum sensing consumes much more energy than reporting sensing results. Also, significant amount of energy can be saved when the optimal number of cooperative sensing nodes is employed for cooperative sensing. The amount of saved energy is calculated as percentage of the difference between energy consumption when all sensing nodes participate in the spectrum sensing and energy consumption when only the optimal number of sensing nodes performed the spectrum sensing.

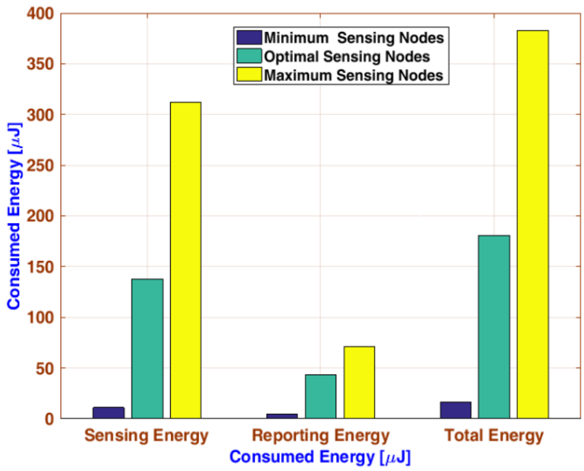


Figure 7: Consumed Energy for Sensing and Reporting Activities

It is determined that the amount of saved energy for spectrum sensing is much higher than the amount of energy savings for reporting results. This shows that even though the number of cooperative sensing nodes has significant effect on both the spectrum sensing and reporting energy consumptions, reporting energy consumption is very much influenced by the distance between the FC and sensing node. Figure 8 shows the energy consumption for sensing nodes. It is observed that energy consumption increases with the increase in number of sensing nodes for the case of maximum number and optimal number of cooperative sensing nodes, while for the minimum, it remains steady at a very low amount. This indicates that optimal number and maximum number of cooperative sensing nodes increases with increase in number of sensing nodes in the network, but the minimum number of sensing nodes is not influenced by number of nodes in the network. It also indicates that number of sensing nodes has significant effect on the energy consumption.

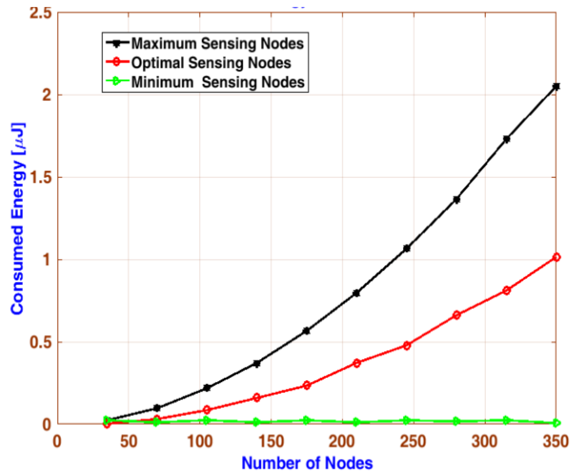
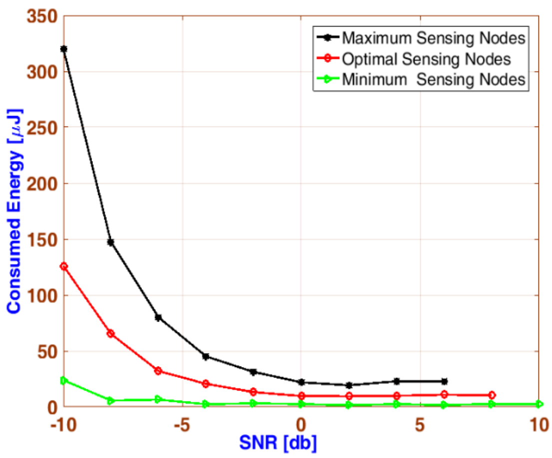


Figure 8: Consumed Energy for Sensing Nodes

Figure 9 reveals the influence of SNR on the consumed energy. It shows that in a relatively poor



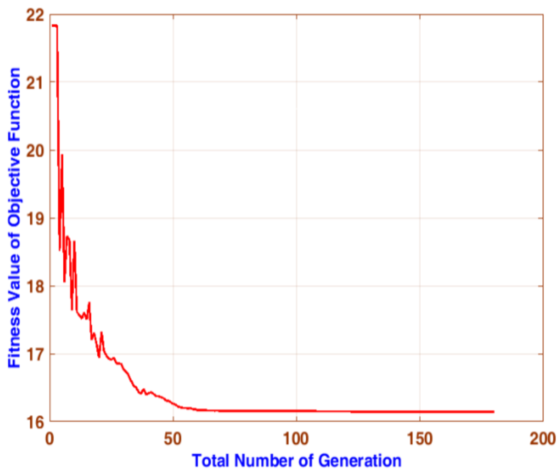


Figure 9: Consumed Energy against Number of Clusters

Figure 10: Fitness Function Convergence

channel condition of $SNR = -6\ dB$, maximum number of cooperative sensing nodes consume extremely high energy than the optimal and minimum number of cooperative sensing nodes. As the channel condition improves from $SNR = -6\ dB$to $SNR = 4\ dB$, the consumed energy decreases drastically. This indicates that when the channel condition is poor with low SNR, relatively high cooperative energy would be needed to satisfy the performance accuracy. The reverse is true, i.e. when the SNR value is high, only a small amount of cooperative energy is required to achieve high detection probability. Figure 10 shows convergence rate of the fitness function using PSO technique. The result indicates that PSO converges faster at generations of less than 50 and achieves optimal number of sensing nodes. This indicates that PSO can give better global minimum in the context of sensing nodes minimization.

4. Conclusion

A cooperative spectrum sensing scheme that minimizes spectrum sensing energy consumption while guaranteeing sensing accuracy has been described in this paper. The scheme employs PSO to determine the optimal number of cooperative sensing nodes that minimizes energy consumption and satisfies spectrum performance threshold. Numerical simulation results validate the effectiveness of the proposed scheme and indicate significant energy saving for spectrum sensing and for result reporting.

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