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Research paper

Energy efficient spectrum sensing for cognitive radio network using artificial bee colony algorithm

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Abstract

In this paper Artificial Bee Colony (ABC) algorithm based optimization of energy efficiency for spectrum sensing in a Cognitive Radio Network (CRN) is implemented. ABC algorithm which is an efficient optimization technique is used for optimizing energy efficiency function derived for cognitive users, where energy efficiency function is derived as the dependency on spectrum sensing time and the transmission power. Energy efficiency optimized by ABC is compared with Particle Swarm Optimization (PSO) based technique. Simulation results shows that with ABC it is able to achieve more energy efficient spectrum sensing as compared to PSO optimized with a margin of 33% efficiency over PSO.

Keywords: *Cognitive Radio Network; Artificial Bee colony; Particle Swarm Optimization; Energy Efficiency.*

1. Introduction

Radio spectrum is a limited natural resource and an expensive one [4], because of the wide spread growth in the wireless communication there happens to be scarcity of this radio spectrum but according to the published report from FCC it was seen that only 6% of the total radio spectrum was utilized and the rest was unutilized or under-utilized [5]. It raised the eye brows of the researcher around the world. With 4G technology there has been improvement in the spectrum usage as compared to 3G but still there is need of effective spectrum utilization, specially to Indian Mobile scenario where the rapidly increasing number of users will lead to scarcity of spectrum. Experts point out that, Indian Mobile will face the problem of spectrum shortage in the near future. For improving the spectrum utilization rate there is the need of Dynamic spectrum access specially cognitive radio network [9].

Cognitive Radio Network has the ability to grasp the knowledge of surrounding radio environment and intelligently access the authorized frequency spectrum in an efficient manner so as to improve the overall frequency spectrum utilization. Cognitive Radio working is such that it detects the idle spectrum and makes it available for cognitive users for proper spectrum utilization. So this ability makes the cognitive radio an effective choice for dynamic spectrum access in order to make spectrum utilization efficient one. In the Figure 1 for different channels frequency spectrum has been shown, for each channels some of the frequency spectrum is vacant while some are in use. The one which is vacant is termed as spectrum holes.

Figure 1 shows a description of spectrum holes which is actually the vacant channel that has not been used by primary users. Cognitive Radio Users (CRU) make use of these spectrum holes for opportunistic access.

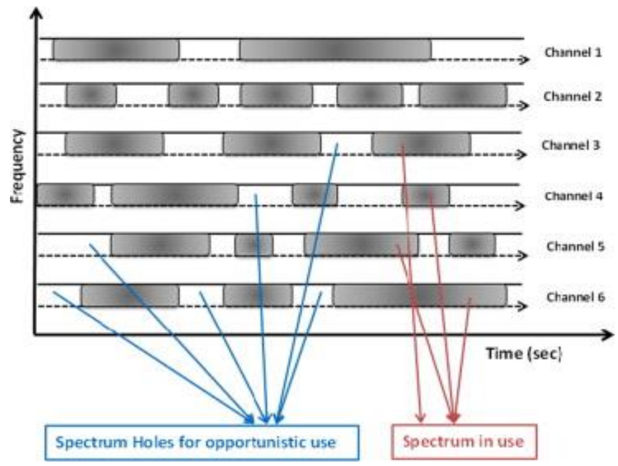

Fig. 1: Spectrum Holes [20].

Scarcity of Spectrum is one aspect of the problem associated with the radio spectrum, another one is the energy efficiency of radio spectrum. Energy efficiency is important aspect in order to reduce environmental pollution and wastage of natural resources. With the extended usage time of mobile phones, carbon di oxide and electromagnetic radiations emissions have adverse environmental impact. So while designing the system keeping the consideration of environmental impact is an important criteria. And improving energy efficiency of the system becomes an important aspect so as to reduce the environmental impact. In this paper, main consideration is over energy efficiency optimization using two best metaheuristic approaches (PSO and ABC) and comparing their results to find out the better one. Energy efficiency in general can be represented as ratio of throughput and the total power.

With most of the research work focused on increasing the spectrum sensing efficiency so as to increase the overall throughput. As compared to other communication devices Cognitive Radio devices requires additional energy because it performs periodic sensing. The accuracy of sensing result also effects the energy consumption. In order to increase the accuracy of sensing transmission time decreases and it eventually decreases overall throughput. So probable solution is cooperative spectrum sensing which increases the accuracy without decreasing overall throughput, but it will cause an additional energy consumption due to extra sensing time and delay. And also extra energy consumption by Co-operative spectrum sensing for reporting the result to the fusion center. So dedicated research work is required with focus on increasing the energy efficiency of CR devices, which are all battery powered.

2. Energy efficiency optimization function

For obtaining optimization function of energy efficiency, spectrum sensing working is needed to be considered.

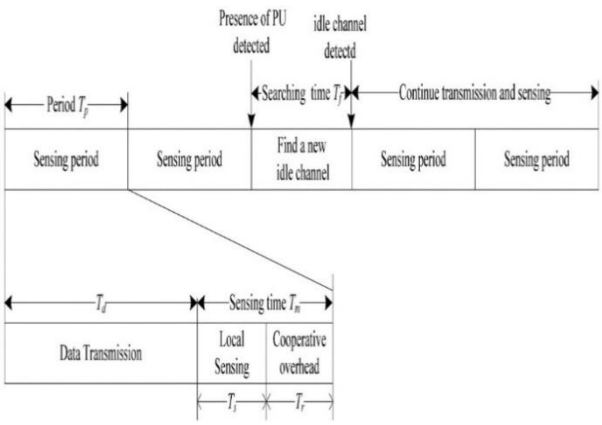

Fig. 2: The Periodic Cooperative Spectrum-Sensing Model [22].

Primary users or licensed users are the one that owns frequency spectrum in a channel. A vacant or idle channel indicates that a primary user is not using a particular spectrum in a channel, which can be utilized by a CR user. So, spectrum sensing starts with the sensing of vacant channel. Once the vacant channel has been detected, secondary users can transmit data on this channel and can perform periodic sensing in this channel. T_p which is subdivided into T_d and T_m, data transmission and sensing time respectively. Sensing time is further divided as local sensing T_s and cooperative overhead T_r. For every sensing period, first the data transmission takes place for a period of T_d, there after primary user detection is been done so as to prevent any kind of interference with the PU.If the channel is detected vacant, CRU will again perform the same process for the sensing period T_p. But if the PU is been detected during the sensing time T_m, CRU need to immediately vacate the channel and search for new vacant channel left from L-1 channels during searching time T_f. Since in this considered scenario CRUs are performing co-operative spectrum sensing, so for exchanging the signaling info among the CRUs a cooperative overhead time T_r is used.

For Optimization, single secondary user is considered based on overlay mode. And the following assumptions have been made:

- Channel frame sensed is accompanied by white gaussian noise.
- Vacant channel follows a negative probability of exponential distribution with parameters r.
- Occupied channel follows a negative probability of exponential distribution with parameters k.

So, probability of busy channel and idle channel can be summarised as in equation (1) and (2):

$$q_{on} = \frac{k}{r+k} \tag{1}$$

$$q_{off} = \frac{r}{r+k} \tag{2}$$

where q_{on}, q_{off} represents probability of busy channel and idle channel respectively. Spectrum sensing performance is measured with the help detection probability q_d, false alarm probability q_f [24]. Probability of false alarm is the measure of spectrum holes which are misclassified as busy channel. Greater the value of q_f lesser will be the opportunistic spectrum access. For the sensed signal x(n), Cognitive Radio (CR) users have two hypotheses [10] expressed in equation (3).

$$\begin{cases} \mathrm{H}_0 : x(n) = w(n) \\ \mathrm{H}_1 : x(n) = hs(n) + w(n) \end{cases} \tag{3}$$

Here *h* is the channel gain which is 0 for the hypothesis H_0 and 1 for the hypothesis H_1, *n =1,2,.....M; M* is the number of samples. *w(n)* is the noise assumed to be independent and identically distributed circularly symmetric complex gaussian with zero mean and variance $E\left[\left|w(n)\right|^2\right] = \sigma_w{}^2$.*s(n)* is the primary or licensed signal, if a channel is occupied by the primary signal then that channel is termed as busy channel. *s(n)* is assumed to be independent and identically distributed random with zero mean and variance $\sigma_s{}^2$.

With the help of q_{on}, q_{off} probability of detection and probability of false alarm can be formulated as:

$$\mathrm{q_d}(\gamma,t) = q_d(\gamma,t)q_{on} \tag{4}$$

$$\mathrm{q}_f(\gamma,t) = q_f(\gamma,t)q_{off} \tag{5}$$

2.1 Energy efficiency function using throughput and power

Secondary users' throughput based on channel capacity *C*, sensing time *t*, frame length T_p is given by equation (6):

$$R(\gamma,T_p,t) = \frac{C\left[1-q_f(\gamma,t)\right]q_{off}(T_p-t)}{T_p} \tag{6}$$

Transmission power, sensing power and the circuit consumption power all are need to be considered in a real system. Let q_s be the sensing power. Transmission power is expressed as $q_t \le q_{t,max}$,here $q_{t,max}$ is the maximum transmission power. Circuit consumption power is denoted as q_c . Using above denoted power terminologies, total power can be denoted by equation (7):

$$Q_{Total} = \frac{(tq_s + q_c + (T_p - t)q_t)}{T_p} \tag{7}$$

2.2 Optimization model for Energy efficiency

Energy efficiency optimization can be modeled as shown in equation (8):

$$\max_{t,q_t} \frac{C\left[1-q_f(\gamma,t)\right]q_{off}(T_p-t)}{(tq_s + q_c + (T_p - t)q_t)} \tag{8}$$

$$\text{s.t.}\quad q_{t,\min} \le q_t \le q_{t,\max}$$
$$1 \le t \le T_p$$

where $C = \log_2(1 + g\, q_t / \sigma_n^2)$ and therefore

$$\max_{t,q_t} \frac{\log_2(1 + g\, q_t / \sigma_n^2)\left[1 - q_f(\gamma, t)\right] q_{off}(T_p - t)}{(t q_s + q_c + (T_p - t) q_t)}$$
$$\text{s.t}\quad q_{t,\min} \le q_t \le q_{t,\max} \quad (7)$$
$$1 \le t \le T_p$$

3. Optimization Alternatives (PSO and ABC)

Existing conventional methods of optimization incorporate high complexity and are unpreferable for constrained optimization problem, these methods are preferred only when the parameters are known. But in the real world scenario the problems involve unknown parameters. For such problems we have stochastic approach such as hill climbing, random optimization, simulated annealing, computational intelligence algorithm which includes evolutionary computing such as genetic algorithm, swarm intelligence, genetic programming, and evolutionary programming. PSO and ABC are the examples of swarm intelligence. Swarm Intelligence has recently gained popularity because of its ease of implementation, better computational efficiency, and high quality of solution. ABC is a metaheuristic algorithm with efficient computational ability and simple implementation.

It is used in various real world problems involving unknown parameters. A comparative study of ABC with other swarm intelligence is done in [26], where the comparative results showed that ABC is better than some of the other swarm intelligence algorithms. Related works associated with ABC are discussed below:

- ANN trained with ABC to maximize the accuracy and minimize the number of connections in ANN is discussed in the article [12].
- ABC for computational biology for prediction of protein structures [21].
- Improved ABC for navigation map for mobile robots [19].
- Article [14] discussed the upgraded ABC for constrained optimization problem.

PSO stands for particle swarm optimization based on the behavior of swarms, PSO is a powerful optimization tool used for both scientific and engineering use. It is popular because of its ease of implementation irrespective of hardware and software. Data like binary, integer, float etc. can be optimized using PSO at a faster convergence speed. Some of the PSO based optimization works are:

- PSO based wireless sensor networks discussed in [13], where PSO showed better performance with respect to QoS and faster convergence time as compared to analytical methods
- PSO for vehicle scheduling with additional mechanism of using global-local optimal information ratio.
- Comparison of discrete PSO with polynomial time-bounded algorithm, binary PSO, simulated annealing and reduced variable neighborhood algorithms is done in [23].

3.1. Artificial bee colony (ABC) algorithm

Inspired by the behavior of honeybee swarms for searching food sources and implementing the similar searching process for finding an optimal solution by simulating the honeybee swarms' behavior of searching food sources with maximum nectar amount, ABC algorithm is a Meta-Heuristic algorithm. Its sound like very complicated but it is a simple algorithm [16-18].

In this method food sources searched by honey bees represents appropriate solutions for the optimization problem.

$$Y_i = (y_{i1}, y_{i2}, y_{i3}, \ldots\ldots y_{iD}) \quad (8)$$

Above equation (8) describes the ith food source where D is the number of dimensions for the optimization problem. Associated fitness value of the appropriate solution for the optimization problem is represented by the nectar amount of the food source [21]. There are three categories of honey bee swarms known as:

- Employed bees(n_e)
- Onlooker bees(n_o)
- Scout bees(n_s)

The employed bees perform global searching for new food source after which they transfer the information with respect to nectar amount to the onlooker bees; the onlooker bees select one employed bee with the help of roulette wheel selection and then perform local searching of better food source among the selected food sources. within a predefined limit of trials if the selected food source doesn't improve then that food source will be abandoned and the employed bee whose food source is abandoned becomes a scout bee and the scout bee makes a random search so as to find the new one in order to replace the abandoned one. With this particular step during optimization process the local optima can be effectively be avoided.

ABC algorithm starts by randomly generating n_s number of possible solutions, with the help of equation (9) stated as:

$$y_{ij} = y_{ij\min} + rand \times (y_{ij\max} - y_{ij\min}) \quad (9)$$

y_{ij} represents j^{th} dimension parameter of a possible solution, upper and lower bounds of dimension j is represented by $y_{ij\max}, y_{ij\min}$ respectively, *rand* generates random number between 0 and 1.

Searching is initiated by scout bees looking for food source and the information regarding nectar amount is collected by employed bee which is then shared with the onlooker bees, after information has been shared, the employed bees come back to their food sources $Y_i = (y_{i1}, y_{i2}, y_{i3}, \ldots\ldots y_{iD})$ from which they have derived benefit in their earlier visit. After this process they select new food sources $w_i = \{w_{i1}, w_{i2}, w_{i3}, \ldots\ldots w_{iD}\}$ and estimate the nectar amount with the help of the equation (10):

$$w_{ij} = y_{ij} + 2(\phi_{ij} - 0.5)(y_{ij} - y_{kj}) \quad (10)$$

Here j=1, 2…..d, where 'd' represents the optimization problem's dimension, i=1,2,……N_s. And ϕ_{ij} is the random number within the range [0,1]. k indicates random index number which is different from i. Once the employed finishes its work, then the onlooker bee selects the food source based on the value P_i which is the probability with respect to the selected food source, calculated by the equation (11) [19].

$$P_i = \frac{fit_i}{\sum_{i=1}^{N_s} fit_i} \quad (11)$$

Brief description about ABC algorithm is shown under:

The ABC Algorithm

1. Initialize maximum population N, dimension D, maximum iterations k_{max}, and lower limit and upper limit x_{min} , x_{max}
2. Initialize x_i randomly: $x_{\min} \le x_i \le x_{\max}$ And i: 1,2,3,…N

3. Evaluate c of x_i
4. Iteration $k = 1$, $t = 0$, $L = 100$
5. While $(k \le k_{\max})$ do

   Select $s \neq i$ and ϕ_i $where$ $-1 \le \phi_i \le 1$

   Select random food source x_{ij} and generate new food v_{ij} using s and ϕ_i

6. $$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{sj}) \; where$$
   $$s \in [1,2,...,N] \; and \; j \in [1,2,..D]$$
7. $$f_{vi} = 1/(1 + f_i(x_n)) \; if \; c_{vi} = 0$$
   $$f_{vi} = 1 + |(f_i(x_n))| \; if \; c_{vi} < 0$$
8. $$if \;\; f_{vi} > f_{xi} \; then$$
   $$v_{ij} = x_{ij}$$
   $$g = cv$$
   $$end \; if$$
9. $$if \;\; f_{vi} < f_{xi} \; then$$
   $$t = t + 1$$
   $$end \; if$$
10. Calculate probabilities for a new solution
    $$P_i = \frac{fit_i}{\sum_{i=1}^{N_s} fit_i}$$
11. Produce new solution v_i for onlookers using value of P_i and existing solutions x_i
12. Record g and v_i
13. Repeat step 9 to 18 for onlookers v_i
14. $$if \;\; \max(t) \ge L \; then$$
    $$Calculate \; the \; scout \; bees \; position$$
    $$x_i^j = x^j_{\min} + rand[0,1](x^j_{\max} - x^j_{\min})$$
    $$end \; if$$
    $$k = k + 1$$
    $$end \; while$$
15. Global optimum = g

3.2. Particle swarm optimization (PSO) algorithm

PSO is a sociologically inspired algorithm based on the sociological behavior associated with flocking mechanism such as birds and fish school.[1].The algorithm maintains a population of particles, where each represents the possible solution to an optimization problem. An PSO algorithm is characterized by basic three functions x_i (the current position of the particle), v_i (The current velocity of the particle. Here the particles move within the search space with changeable velocity and keeps the track of the best position it has achieved so far called as p_{best}, best position corresponds to the best solution for the optimization problem. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called g_{best}. Each particle modifies its position using its current position, velocities & the distance between the current position. One of the drawbacks associated with the previous version of PSO was the lack of mechanism which can control the magnitudes of the velocities that can pose the danger of swarm explosion and divergence [3]. So, to rectify, now the particles' velocities are summed up together to get v_{max}. For any condition in a particular dimension if the acceleration exceeds v_{max} then the velocity on that dimension is limited to v_{max}. The v_{max} value is user specified. The original version of PSO makes use of 1 and 2 for velocity and position update. c_1 and c_2 are constants referred as cognitive and social parameters respectively and r_1 and r_2 are random numbers between [0,1]. Now for the d dimensional optimization problem velocity and the position is expressed as in equation (12) and equation (13)[1][6]:

$$v_{id}(t+1) = v_{id}(t) + c_{1_{id}} r_{1_{id}} (p_{bestid}(t) - x_{id}(t)) + c_{2_{id}} r_{2_{id}} (g_{bestid}(t) - x_{id}(t)) \tag{12}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t) \tag{13}$$

But this modification alone didn't prove sufficient because PSO algorithm is good in exploration in global scale but poor in exploitation on local scale because of the inability to adjust the velocity step size so as to continue the search with better exploitation. So now for d dimensional search space velocity and position are updated as shown in equation (14) and equation (15) [24]:

$$v_{id}(t+1) = w(t)v_{id}(t) + c_{1_{id}} r_{1_{id}} (p_{bestid}(t) - x_{id}(t)) + c_{2_{id}} r_{2_{id}} (g_{bestid}(t) - x_{id}(t)) \tag{14}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t) \tag{15}$$

Compared to equation (13) in equation (15), additional term introduced is $w(t)$ referred as inertia weight, which effects the way by which previous velocities impacts the current velocity. Inertia weight helps in resolving the problem of tradeoff between exploration and exploitation ability of swarm. Large values of $w(t)$ helps in global exploration i.e. exploring the areas of search space which has not been encountered yet. Whereas smaller values encourage local exploration i.e. exploiting the current search space. So, a preferable value of $w(t)$ can give desired balance between exploration and exploitation ability of the PSO, thus improving the efficiency of the algorithm.

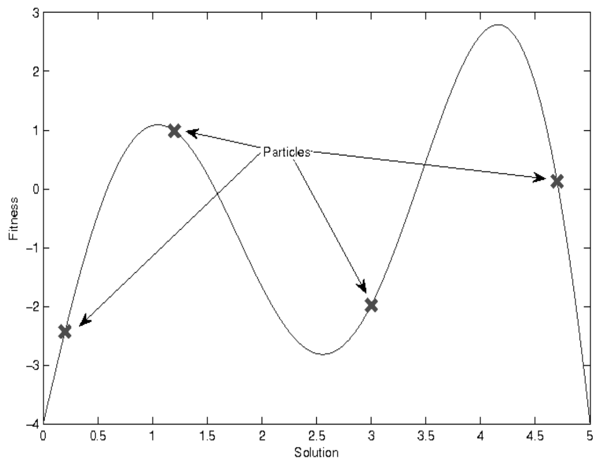

Fig. 4: Initial PSO State.

A simple PSO coding is represented by [16]:
For every particle
{
Activate particle
}

Repeat these for max or min value
{
For every particle
{
Calculate actual value
If actual value is better than p_{best}
{
Fix p_{best} = current actual value
}
If p_{best} is better than g_{best}
{
Fix g_{best} = p_{best}
}
}
For each particle
{
Calculate particle Velocity
Use gbest and Velocity to validate particle Data
}

3. Simulation Results

With the help of MATLAB based simulation results, the dependency of energy efficiency of spectrum sensing on transmitted power and sensing time can be interpreted. Figures 5, Figure 6 & Figure 7 shows the graphical representation of comparison made for ABC and PSO based energy efficiency optimization for spectrum sensing. Following considerations have been made for the simulation based result:
Bandwidth (B)=3MHz; Frame time (T_p)=20ms; q_{off}=0.7;
P_c=0.01w; g=0.1(Since large value of 'g' results in high value of SNR_{MRC} but low value of SNR, so an optimum value of 'g' is desired.

4.1 Graphical representation of energy efficiency optimized with the help of ABC and PSO

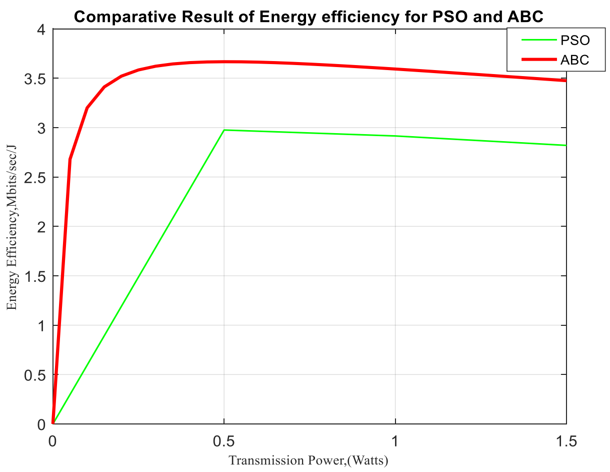

Fig. 5: Energy Efficiency Dependency for Varying Transmission Power.

Figure 5 gives the comparative study of Energy efficiency optimized by PSO and ABC for varying transmission power. For both PSO and ABC if we see the energy efficiency dependency on transmission power it is clear that for low value of q_t as the value of q_t increases energy efficiency also
increases, whereas after some threshold value if transmission power increases the energy efficiency decreases slowly. If we compare between PSO and ABC then ABC optimized energy efficiency has better dependency on varying transmission power.

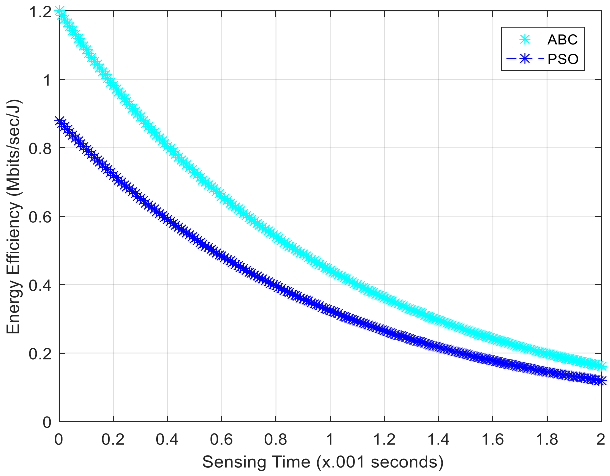

Fig. 6: Energy Efficiency Dependency for Varying Sensing Time.

Figure 6 shows the dependence of energy efficiency for varying sensing time with q_t=0.2w, graphical representation shows that increase in sensing time would decrease the energy efficiency, Therefore, sensing time optimization is required to obtain the tradeoff between sensing time duration and energy efficiency. In this paper energy efficiency is optimized with respect to transmission power and sensing time, from the simulation results it is clear that ABC optimized energy efficiency of spectrum sensing gives better value as compared to PSO.

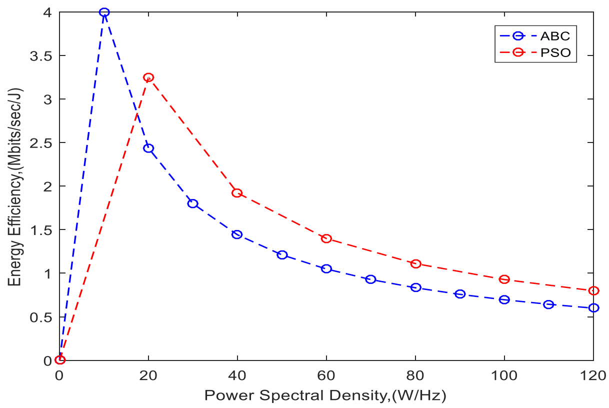

Fig. 7: Energy Efficiency Dependency for Varying Power Spectral Density.

As discussed for transmission power, in a similar way energy efficiency value increases to a peak with the increase in power spectral density (PSD) value after that there is steep decrease in its value for increase in PSD as shown in Figure 7. It is because for small value of PSD the power of SU is less than q_{tmax}, so with the increase in PSD power of SU also increases. Thus, energy efficiency increases with the increase in PSD but when the power of SU reaches q_{tmax}, it will not increase resulting in the decrease in the value of energy efficiency.

4.2. Tabular comparison between ABC and PSO for energy efficient spectrum sensing

Table 1: Comparative Study of PSO and ABC

S.No	Optimization Technique	Peak EE(Mbits/sec/J) for varying sensing time	Peak EE(Mbits/sec/J) for varying Transmission Power	Simulation Time(secs)
1	ABC	1.2	3.6	7.08
2	PSO	0.9	3	4.3

From the Table 1 percentage effectiveness of ABC on the grounds of Energy Efficiency with respect to sensing time is evaluated as

33% more as compared to PSO whereas for transmission power variation, ABC optimized energy efficiency is 20% more efficient than PSO.

4. Conclusion

In this paper for global optimization of energy efficiency for spectrum sensing in a cognitive radio network is considered. For that firstly an energy efficiency function for spectrum sensing dependent on sensing time and transmission power is derived and then the ABC algorithm has been used for its optimization. The results are compared with another powerful metaheuristic optimization technique i.e. PSO. Simulation results shows the effectiveness of ABC in obtaining optimum energy efficiency for a varying sensing time and transmission power with 33% and 20% more effective in respective sensing time and transmission power, because ABC has better exploitation for local search as compared to PSO.

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