



# **Throughput Optimization in Cooperative Communications using Evolutionary Algorithms**

Abhishek Singh<sup>1</sup>, Ashish Raman<sup>2</sup>, Deepti kakkar<sup>3</sup>

M.tech Student, Department of ECE, N.I.T Jalandhar, Punjab, India<sup>1</sup>

Assistant Professor, Department of ECE, N.I.T Jalandhar, Punjab, India<sup>2</sup>

Assistant Professor, Department of ECE, N.I.T Jalandhar, Punjab, India<sup>3</sup>

**ABSTRACT:** This paper illustrates the results of the throughput of Secondary User (SU) in cognitive radios under cooperative scenario with the use of evolutionary algorithms in the presence of additive white Gaussian (AWGN) noise. In this work, the performance of half-voting and OR fusion rule is studied in terms of  $P_d$  Vs  $P_f$  curves. OR fusion rule is found to be most suitable in cooperative scenario. Then, Particle Swarm Optimization (PSO) and Biogeography Based Optimization (BBO) algorithms are implemented using OR fusion rule to enhance the throughput of cognitive users by taking in to account the protection of primary (licensed) users. The probability of detection is set to 0.9 for protection purpose. Simulations results in terms of co-operations shows that PSO performs better initially but as numbers of co-operations increases PSO performance degrades.

**KEYWORDS:** Throughput, Evolutionary Algorithms, Fusion rules, Optimization

## **I.INTRODUCTION**

In recent years, cognitive radio (CR) has emerged as a promising paradigm for exploiting the spectrum opportunity, which is restricted by the current rigid spectrum allocation scheme, to solve the spectrum scarcity problem [1-2]. Different spectrum sensing techniques are available for sensing primary users (PUs) signals. They can be broadly classified in to three categories: matched filter detection, cyclostationary detection and energy detection [19]. Energy detection is widely adopted because of lower complexity than other two schemes and priori knowledge of signal is also not required. Spectrum sensing depends upon two probabilities namely detection probability ( $P_d$ ) and false alarm probability ( $P_f$ ) [5]. Detection probability is related to probability of correctly detecting the presence of PUs, whereas false alarm probability is related to incorrect detection of PUs when it is absent [4]. Many research works are proposed to improve the performance metrics of detection probability and false alarm probability. However, PSO is addressed for sensing-throughput trade-offs problem under cooperative scenarios using various hard combination fusion schemes [3]. Optimization performance of cooperative sensing in terms of number of cooperative users is performed using constant detection rate (CDR) and constant false alarm rate [4]. But, there is no consideration for throughput of CUs. The work in [5] focuses on the optimization of sensing-throughput tradeoffs using iterative algorithms. In this paper, PSO and BBO algorithms are implemented to achieve the same objective. Both the algorithms are performed over OR fusion schemes.

The Paper is organized as follows: Section-II denotes the system model and other performance metrics. A BBO and PSO algorithms are discussed in section III and IV respectively. Section 5 covers the methodology used by proposed work. However, the section VI and section VII include results and conclusions respectively.

## **II.SYSTEM MODEL**

This study focuses on PUs signals with AWGN at CUs. We assume that both noise and PUs signal are independent. The basic model for energy detector shown in fig 1, consists of noise filter, square law device and integrator as [6];

# International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

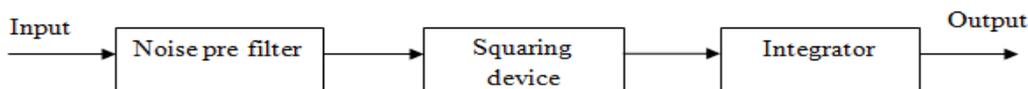


Fig..1 Energy Detection

The output signal is compared against a particular threshold to decide whether the signal is present or not. Threshold is decided depending upon statistical properties of Output(O/p). In the cooperative detection, secondary users receive the transmitted signals and calculate signal/energy power. After performing detection, individual hard decisions are sent to a fusion centre for decision combining using some fusion rules. The  $P_f$  is related to  $P_d$ , number of observation samples (N) and SNR ( $\gamma$ ) as follows [5];

$$P_f = Q\{(Q^{-1}(P_d))\sqrt{1 + 2\gamma} + \gamma\sqrt{N}\} \quad (1)$$

The number of observation samples for sensing is related to  $P_d$  and  $P_f$  [5] under energy detection by:

$$N = \frac{1}{\gamma^2} \{Q^{-1}(P_f) - (Q^{-1}(P_d))\sqrt{1 + 2\gamma}\}^2 \quad (2)$$

The cooperative model taken into consideration is shown in Fig.2 [18];

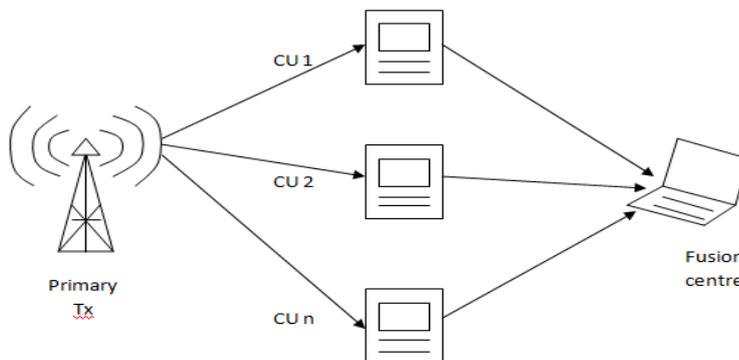


Fig. 2 Cooperative Environment

In fig.2, CU1, CU2, ..... CUN are cognitive users providing individual sensing decisions which are then combined at the fusion centre using various fusion rules such as OR, AND, and Half-voting.

### A.Hard decision fusion rules

The fusion centre implements n-out-of-M rule if at least n local decisions indicate the presence of PUs. The probability of detection at fusion centre assuming uncorrelated decisions is given by [6-7]

$$P_d = \sum_{k=n}^M \binom{M}{k} P_{d,i}^k (1 - P_{d,i})^{M-k} \quad (3)$$

#### 1) Logical and-rule

In this rule, if all the decisions sent to the fusion centre are one, then the final decision made by the combiner is one. The performance evaluation using this fusion rule is computed by setting  $n=M$  in above equation as [6];

# International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

$$P_{d, \text{and}} = P_{d,i}^M \quad (4)$$

## 2) Logical or-rule

The final decision made by the fusion centre is one if any one of the decision is one. The performance evaluation using this fusion rule is computed by setting  $n=1$  in above equation as [7];

$$P_{d, \text{or}} = 1 - (1 - P_{d,i})^M \quad (5)$$

## 3) Logical majority rule

If half or more of the local decisions at the fusion centre is one, then the final decision made by the combiner is one and obtained by setting  $n=M/2$  in above equation as [6];

$$P_{d, \text{h.v.}} = \sum_{M/2}^M \binom{M}{k} P_{d,i}^k (1 - P_{d,i})^{M-k} \quad (6)$$

where  $P_{d,i}$  is the detection probability of  $i^{\text{th}}$  branch of the cooperation and  $M$  is the number of cooperative users

## B. Throughput-Sensing problem criteria

The CUs first sense the PUs signal and transmits the data if later is absent. The CUs are allocated time frames for both sensing and transmission period. In the end on detecting PUs signal, CUs need to vacate the channel for primary user protection.

The frame structure for CUs is as follows [3]

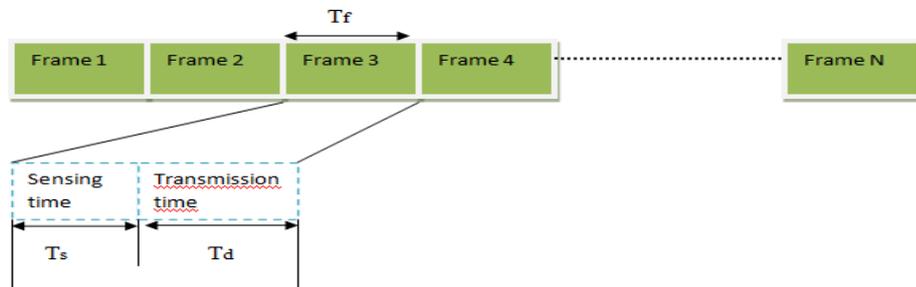


Fig.3 Frame Structure

where  $T_f$ : Frame duration  
 $T_s$ : Sensing time  
 $T_d$ : Data transmission time

Fig.3 describes that a frame duration is divided in to two phases: Sensing phase and transmission phase. The transmission phase contributes to the throughput of cognitive users.

The throughput of the CUs is generated under two conditions, as reported in [8]: First scenario indicates the absence of PU signal and no false alarm is generated by CU. The throughput in this case is given by [3];

$$R_0(T_s) = \frac{T_f - T_s}{T_f} (1 - P_f) C_0 \quad (7)$$

Second scenario states that PU is not detected by CU even if it is present. The throughput for this case is as follows [3];

$$R_1(T_s) = \frac{T_f - T_s}{T_f} (1 - P_f) C_1 \quad (8)$$



# International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

$C_0$  :denotes throughput of CU in PU absence

$C_1$  :denotes throughput of CU operating in the presence of PU

The net achievable throughput of the system is represented as [9];

$$R(T_s) = P(H_0)R_0(T_s) + P(H_1)R_1(T_s) \quad (9)$$

Where  $P(H_1)$  is the probability of PU being active and  $P(H_0) = 1 - P(H_1)$

The problem criterion can be fixed as follows: To maximize the value  $R(T_s)$  above such that  $P_d$  never goes below 0.9 for PU protection, numerically it can be shown as;

$$\max R(T_s) \text{ such that } P_d > 0.9 \text{ wrt FCC guidelines}$$

Assuming  $P(H_1)$  considerably small  $< 0.2$  [9] and  $C_0 > C_1$ , eqn. (9) simplifies to

$$\max R(T_s) = P(H_0)R_0(T_s) = P(H_0) \frac{T_f - T_s}{T_f} (1 - P_f) C_0 \quad (10)$$

## III. BIO-GEOGRAPHY BASED OPTIMIZATION

Biogeography-Based Optimization (BBO) is a global optimization algorithm developed by Dan Simon in 2008 and is inspired by mathematical models of biogeography by Robert MacArthur and Edward Wilson. Biogeography is the study of distribution of species in nature over time and space; that is the immigration and emigration of species between habitats [16]. Each possible solution is an island and their features that characterize habitability are called suitability index variables (SIV) [21]. The fitness of each solution is called its habitat suitability index (HSI) and depends on many features of the habitat. High-HSI solutions tend to share their features with low-HSI solutions by emigrating solution features to other habitats. Low-HSI solutions accept a lot of new features from high-HSI solutions by immigration from other habitats [20].

### A. BBO operators

**Migration:** The BBO migration strategy in which we decide whether to migrate from one region to other or not [22]. The migration rates of each solution are used to probabilistically share features between solutions. BBO migration is used to change existing habitat. Migration in BBO is an adaptive process [16].

**Mutation:** Mutation is a probabilistic operator the randomly modifies a solution feature. The purpose of mutation is to increase habitat among the population [21]. For low value solutions, mutation gives them a chance of enhancing the quality of solutions, and for high fitness value solutions, mutation try to improve the value as compared to the previous value [20].

### B. Limitations of GA over BBO:

- 1) Genetic algorithms cannot ensure finding a global optimum; they usually give a good approximation [13].
- 2) Genetic algorithms can take a long time to converge and are also not easy to implement [17].
- 3) Genetic algorithms do not scale well with complexity [15]. That is, where the number of elements which are exposed to mutation is large there is often an exponential increase in search space size.

## IV. PARTICLE SWARM OPTIMIZATION

PSO is an evolutionary algorithm which is population based and designed keeping in view the social behavior of flock of birds [10-11]. Each solution is represented by a particle and the particles are grouped into swarm. Each particle moves toward best optimal solutions with every iterations by learning from past experiences and surroundings. Due to its simplicity, high convergence rate, and searching capability, PSO has been deployed to many optimization problems [12]. After achieving the required output or number of iterations, process terminates.



# International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

Two fundamental equations which are the essence of PSO representing position and velocity of the particle at any instant  $t+1$  are [10]

$$V(t + 1) = WV(t) + C_1(P_1 - X(t)) + C_2(P_g - X(t)) \quad (11)$$

$$X(t + 1) = X(t) + V(t + 1) \quad (12)$$

where  $P_1$  and  $P_g$  are local best of particle and global best of the swarm respectively.

For a particle with  $n$ -dimensions, vector  $X$  and vector  $V$  can be represented as  $X=(x_1, x_2, \dots, x_n)$ ,  $V=(v_1, v_2, \dots, v_n)$  and  $P=(p_1, p_2, \dots, p_n)$ .  $V(t)$  ensures that all the particles are in the right direction without any sudden change whereas  $2^{nd}$  and  $3^{rd}$  terms in eqn. (11) measures the performance of particle relative to its past performance and neighbor performance

## V. METHODOLOGY

The basic optimization flow using BBO and PSO algorithm is as follows: Firstly, the performances of decision fusion rules such as OR and Half-Voting are compared in terms of their  $P_d$  Vs  $P_f$  plots. The rule with better system performance i.e. smaller value of  $P_f$  and larger value of  $P_d$  is then used in the optimization environment to optimize the throughput (T) of SUs. The optimization parameters for both PSO and BBO such as swarm size, mutation probability, weight factors, and learning factors are defined. Then solutions are randomly initialized for BBO with random positions and zero initial velocities in case of PSO. Based on the migration rate, the features of solutions are updated and mutation if desired is applied in BBO. The positions of particles are updated in terms of velocity vectors in PSO. This process continues until the desired output or termination condition is achieved. Finally, the results are compared to conclude the performances of both evolutionary algorithms.

Table.1 Parameters of BBO

Parameters	Values
E <sub>max</sub>	1
I <sub>max</sub>	1
Population size	75
Mutation probability	0.04
No. of iterations	75
Target $P_d$	0.9
$P_f$	$\leq 0.3$
Elite solutions	2
Min. samples(N <sub>min</sub> )	5
Max. samples(N <sub>max</sub> )	320

Table. 2 Parameters of PSO

Parameters	Values
Number of particles	75
Number of iterations	75
Learning factors C1 and C2	0.8
W <sub>max</sub>	0.44
W <sub>min</sub>	0.4
Target $P_d$	0.9
Min. samples(N <sub>min</sub> )	5
Max. samples(N <sub>max</sub> )	320

# International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

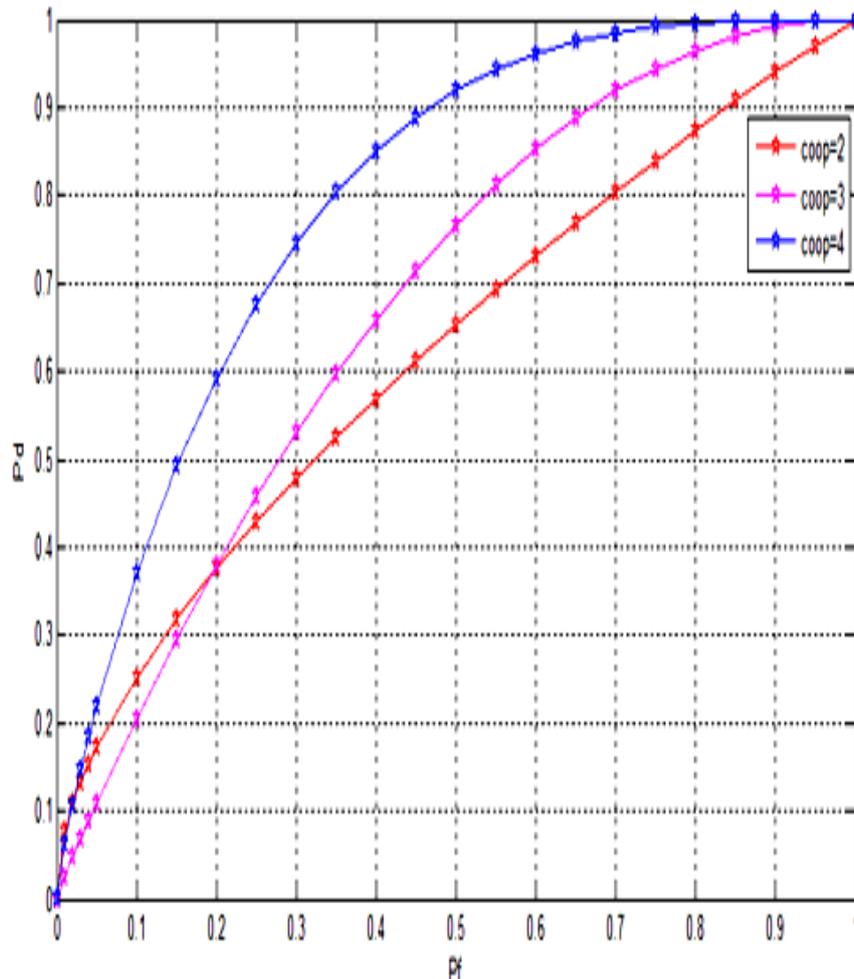
The value of parameters used for BBO and PSO algorithm are indicated in table 1 and table 2 respectively. These values are used for designing the framework of optimization process.

## VI.RESULTS AND DISCUSSIONS

Based on the boundary condition given in table 1 and 2, all the simulation has been performed on MATLAB under nakagami-m fading environment with AWGN, with  $P_f \leq 0.3$  and  $P_d = 0.9$ . Using the formula for OR fusion rule as given in equation (5), simulation is carried out.

Fig.5. shows the  $P_d$  Vs  $P_f$  curve for AWGN channel with half voting Fusion rule for different number of co-operations (2, 3 and 4).

Fig.6. shows the  $P_d$  Vs  $P_f$  curve for AWGN channel with OR Fusion rule for different number of co-operations.



## International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

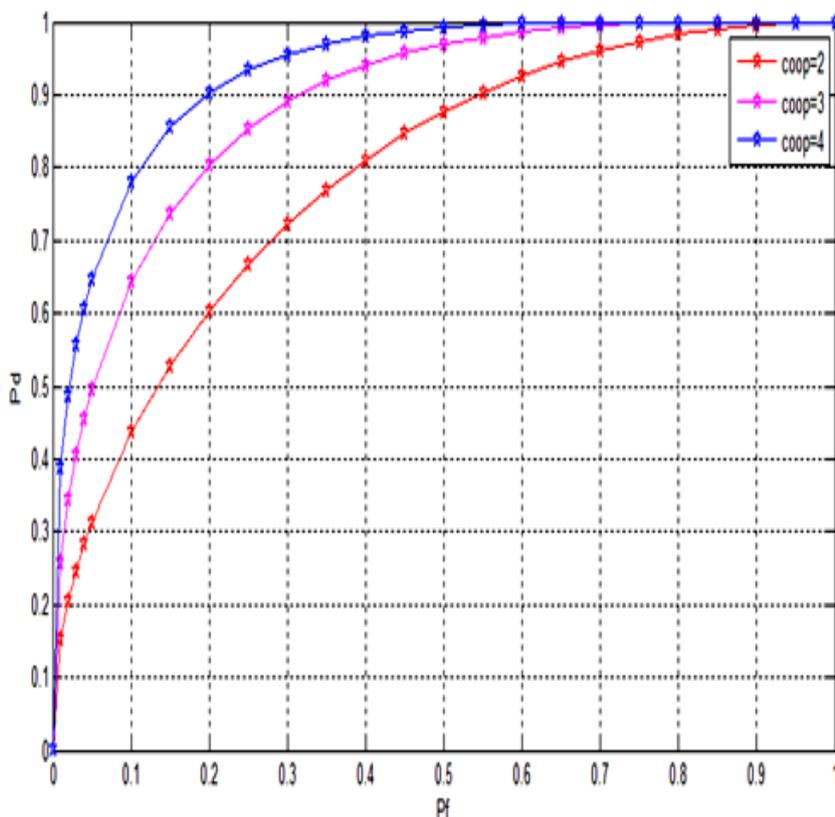


Fig.5  $P_d$  Vs  $P_f$  curve for AWGN channel with rule Half voting fusion rule

Fig.6.  $P_d$  Vs  $P_f$  curves for AWGN channel with OR fusion

From fig.5 and fig.6, it is seen that ROC curves for both fusion rules shift toward left side with increase in number of cooperation indicating an improvement in system performance. But the shift in case of OR fusion rule is more as compared to half-voting rule. For 4 cooperation case, targeted detection probability ( $P_d$ ) of 0.9 is achieved at  $P_f=0.2$  in case of OR fusion rule and at  $P_f=0.45$  in case of half-voting rule. A smaller value of  $P_f$  denotes that OR fusion rule is more suitable as compared to Half-Voting rule. The table.3 is formed using eqn. (2) and (10). The value of throughput for OR fusion rule with different number of cooperation is shown in table 3.

Table. 3 Throughput for OR Fusion Rule (as calculated from fig.6)

Number of cooperations (C)	Number of samples (Nmin)	Avg snr(in dB)	Detection probability ( $P_d$ )	False alarm probability ( $P_f$ )	Throughput (T)
2	4	2	0.9	0.32	0.6715
3	5	2	0.9	0.20	0.7875
4	6	2	0.9	0.15	0.8340
5	7	2	0.9	0.07	0.9096

# International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 10, October 2014

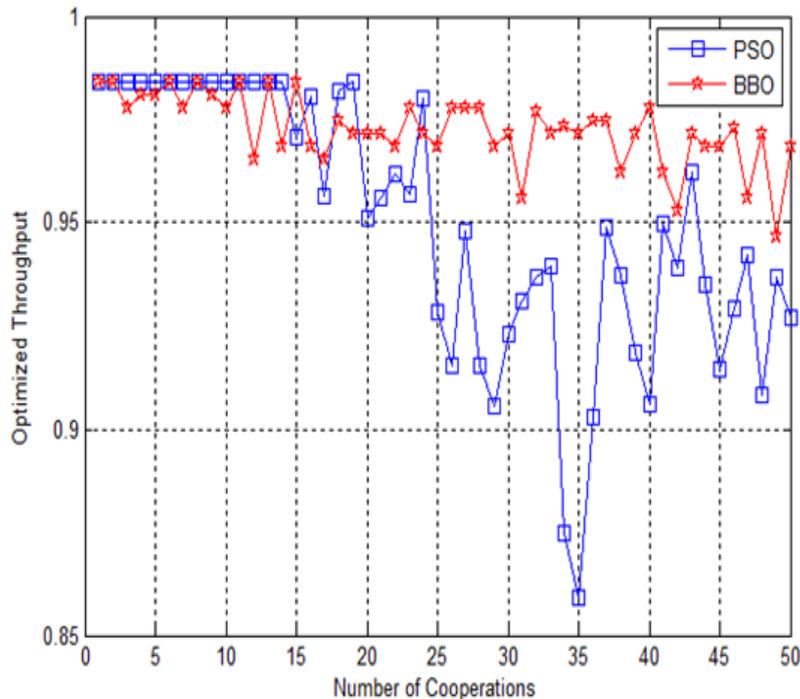


Figure.7 Comparison of BBO and PSO in terms of Cooperations

Fig.7 shows the throughput of the SUs with respect to cooperation for both PSO and BBO. Simulation results shows that both optimization algorithms provides better results as compared to non-optimized throughput values as given in table 3. There is an improvement of 8% in SU throughput for 4 cooperations. Among BBO and PSO, PSO is dominant initially but its performance deteriorates as the number of cooperations increases.

## VII.CONCLUSION

With the help of this paper, we study the performance of the BBO and PSO algorithms for throughput optimization of the cognitive users in cooperative scenario case using OR fusion rule and comes at the conclusion that these evolutionary algorithms perform better than non-optimized (normal) case and results in higher achievable throughput. The performance of the PSO algorithm in terms of number of co-operations is dominant initially but as the number of co-operations increases, BBO performance remains steady whereas PSO performance degrades.

## REFERENCES

- [1] S. Haykin, "Cognitive radio: brain-empowered wireless communications," IEEE Journal on Selected Areas in Communications, vol. 23, pp. 201-220, 2005.
- [2] Q. Zhao and B. M. Sadler, "A survey of dynamic spectrum access: signal processing, networking, and regulatory policy," IEEE Signal Processing Magazine, vol. 24, pp. 79-89, May 2007.
- [3] Rozeha A. Rashid, A. Hadi Fikri A. Hamid, N. Faisal, M. Adib Sarijari, Rozaini A. Rahim, Alias Mohd "Optimal User Selection for Decision Making in Cooperative Sensing IEEE symposium on wireless and technology application" sept 2012
- [4] Edward Peh and Ying-Chang Liang, "Optimization for Cooperative Sensing in Cognitive Radio Network", WCNC , Hong Kong, vol. 58, no. 9, pp. 11-15, 2007
- [5] E.C.Y. Peh, Y.C. Liang, Y. L. Guan and Y. Zeng, "Optimization of Cooperative Sensing in Cognitive Radio Networks: A Sensing-Throughput Tradeoff View", IEEE Trans. On Vehicular Technology, vol. 58, no. 9, 2009
- [6] Md. Shamim Hossain , Md. Mahabubur Rahman, Md. Ibrahim Abdullah and Mohammad Alamgir HossainHard , "Combination Data Fusion for Cooperative Spectrum Sensing in CognitiveRadio" vol.2, pp. 811-818, 2012
- [7] Spyros Kyperountas, Neiyer Correal, Qicai Shi "A Comparison of Fusion Rules for Cooperative Spectrum Sensing in Fading Channels". EMS Research, Motorola



ISSN (Print) : 2320 – 3765  
ISSN (Online): 2278 – 8875

# International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

**Vol. 3, Issue 10, October 2014**

- [8] Yiyang Pei, Anh Tuan Hoang, Ying-Chang Liang, "Sensing-Throughput Tradeoff in Cognitive Radio Networks: How Frequently Should Spectrum Sensing be Carried Out?," IEEE 18th International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC, pp. 1-5, Athens, 3-7 Sept. 2007.
- [9] Y.-C. Liang, Y. Zeng, E. C. Y. Peh, and A. T. Hoang, "Sensingthroughput tradeoff for cognitive radio networks", IEEE Trans. Wireless Commun., vol. 7, no. 4, pp. 1326-1337, 2008.
- [10] J. Kennedy, and R. C. Eberhart, "Particle swarm optimization", Proc. IEEE International Conference on Neural Networks, Australia, vol. 4, pp. 1942-1948, 1995.
- [11] J. Kennedy and R. C. Eberhart, Swarm Intelligence, Morgan Kaufman Publishers, California, 2001.
- [12] C. Mendis, S. M. Guru, S. Halgamuge, and S. Fernando, "Optimized Sink node Path using Particle Swarm Optimization", 20th International Conference on Advanced Information Networking and Applications, IEEE computer society, vol.2, pp. 5, 2006
- [13] Prasanna A. Lohe and D.D.Patil, "Enhancement of Digital X-Ray Image by Combining the Genetic Optimization and Watershed Transformation Technique", IJESIT, vol. 2, no. 1, 2013
- [14] Khaled Ben Letaief and Wei Zhang, "Cooperative Communications for Cognitive Radio Networks", IEEE Trans. Wireless Commun., vol. 97, no. 5, 2009
- [15] en.wikipedia.org/wiki/Genetic\_algorithm
- [16] Dan Simon, "Biogeography-Based Optimization", IEEE Trans. on Evolutionary Computation, vol. 12, no. 6, 2008
- [17] Mittu Mittal and Gagandeep, "Comparison between BBO and Genetic Algorithm", IJSETR, vol. 2, no. 2, pp. 284-293, 2013
- [18] Lu Lu\*, Xiangwei Zhou, Uzoma Onunkwo and Geoffrey Ye Li, "Ten years of research in spectrum sensing and sharing in cognitive radio", EURASIP Journal on Wireless Communications and Networking 2012, 2012:28 doi:10.1186/1687-1499-2012-28
- [19] Nan Zhao, Fei Richard Yu, Hongjian sun, Arumugam Nallanathan, "Energy-efficient cooperative spectrum sensing schemes for cognitive radio networks", EURASIP Journal on Wireless Communications and Networking 2013, 2013:120 doi:10.1186/1687-1499-2013-120
- [20] H. Ma, D. Simon, Biogeography-based optimization with blended migration for constrained optimization problems, in: Genetic and Evolutionary Computation Conference, Portland, OR, pp. 417-418, July 2010.
- [21] V. Panchal, P. Singh, N. Kaur, H. Kundra, "Biogeography based satellite image classification", International Journal of Computer Science and Information Security vol. 6, no. 2, pp. 269-274, 2009.
- [22] R. Rarick, D. Simon, F.E. Villaseca, B. Vyakaranam, "Biogeography-based optimization and the solution of the power flow problem", in: IEEE Conference on Systems, Man, and Cybernetics, San Antonio, Texas, pp. 1029-1034, 2009.