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An Efficient Hybrid Optimization-Based Particle Swarm Optimization & Genetic Algorithm For Cooperative Spectrum Sensing In Cognitive Radio Networks

Jitendra Kumar Mishra[1], Bhagwat kakde[2]

[1]Department of Electronics & Communication, Madhyanchal Professional University, Bhopal, India.

[2]Department Electronics & Communication, Madhyanchal Professional University, Bhopal, India.

Abstract

Emerging communication devices need an effective resource allocation approach in wireless communication systems. Cognitive radio networks minimize the bottleneck problem of spectrum scarcity in wireless communication. In wireless communication systems, cognitive radio networks provide the principle of unused licenced spectrum utilization. The cognitive radio network system process accesses spectrum without interfering with the licenced user. The diversity of spectrum sharing and sensing of cognitive radio networks are gaining much attention in wireless communication systems. This paper proposed an efficient hybrid optimization algorithm for the sensing of spectrum without interference. The proposed hybrid optimization algorithm encapsulates particle swarm optimization and genetic algorithms. The objective of the proposed algorithm is to collect information about spectrum on a local level and allocate global units using particle swarm optimization. The diversity of proposed algorithms influences the performance of cognitive radio networks. The proposed algorithm simulates various parameters in terms of throughput using MATLAB tools. The proposed algorithm compares existing algorithms for spectrum sensing and dynamic resource allocation in cognitive radio networks. According to the results, the proposed algorithm outperforms the existing cognitive radio network algorithms by 3–5%.

Keywords: - CRN, Spectrum Sensing, PSO, GA, Sharing, Dynamic Allocation

Introduction

The crowd of wireless communication networks faces a problem of data blockage and congestion. Traffic congestion degrades the quality of service and reliability of networks. Spectrum is licenced and underutilized, resulting in a spectrum scarcity bottleneck in wireless communication networks. radio networks (CRN) provide the solution to underutilization of spectrum in wireless communication. The cognitive radio networks utilise the spectrum of licenced users without interfering with the system [1,2,3]. The management of resource allocation in cognitive radio networks is dynamic and efficient, in contrast to conventional resource allocation in wireless communication systems. The growth of emerging devices or communication models such as 5G, 6G, and the Internet of Things adopts the dynamic allocation of resources. The management of cognitive radio networks impacts the performance of radio spectrum in wireless communication systems. Based on the number of users and the sensing technology utilized, cooperative spectrum approaches may be divided into two major types[3,4,5,6]. There are two forms of cooperative spectrum sensing based on quantity: single user and multiuser. The hidden terminal problem is most common in single user cooperative spectrum sensing, but multiuser cooperative spectrum sensing works well. Multiuser cooperative spectrum sensing is an effective solution to the signal fading and shadow problem. Cooperative spectrum sensing is further classified based on the technology used to sense the network [7,8,9]. These are distributed, centralized, and relay-assisted. The secondary users are in responsible of making the ultimate decision in distributed cooperative spectrum sensing. There is no shared infrastructure, and detection is performed by the SUs. Each SU detects the spectrum in the same frequency range and records the data. The SUs exchanges their findings with one another. In the event of a centralized approach, however, the sensing results collected by each SU are forwarded to a central fusion center. The fusion center makes the final decision in this method. The fusion center's decision is based on the observations received from the SUs. Spectrum sensing is the major factor in cognitive radio networks. Sensing plays a vital role in the detection of vacant spectrum in networks. The conventional approach to spectrum detection is compromised by poor detection rate and complex methods such as matched filter cyclo-stationary detection. The problem of detection and performance of conventional detection of spectrum demands a new approach to spectrum sensing and sharing. The reported survey suggests that many authors apply optimization algorithms in cyclo-stationary detection and matched filters. The applied optimization algorithm increases the complexity of detection and the performance of the system is poor. The complexity of algorithms reduces the productivity of cognitive radio networks. Thus, this paper proposes a hybrid optimization algorithm for the sensing of spectrum in cognitive radio networks. The proposed algorithm encompasses particle swarm optimization and genetic algorithms. The particle swarm optimization applies at the end of the decision system of the secondary user (SU). The genetic algorithm collects the local free spectrum for the processing of fusion centres [10,11]. The final processing of the algorithm is called hybrid optimization. The main objective of this paper is to improve the detection probability, accuracy, and efficiency of cognitive radio networks through the proposed algorithm. The second objective is the efficiency of energy using the proposed algorithm. The rest of the article is organised as in Section II: related work, in Section III: description of proposed methodology, in Section IV: experimental analysis, and in Section V: conclusion of the work and direction of future work.

II. Related Work

The tireless efforts of various authors of algorithm design and model formulation in cognitive radio networks have culminated in their supremacy in wireless communication systems. The design models and algorithms increase the engagement of spectrum sensing, energy efficiency, and many other factors of cognitive radio networks. The major contributions of the authors are described here. In this [1] author present a cloud sharing-decision mechanism, cognitive radio networks, a new wireless network optimization technique has been devised. As major performance measures, spectrum usage, power consumption, and exposure were all optimized. Our solution surpasses the conventional architecture by 4.8 percent, 7.3 percent, and 4.3 percent in terms of network power consumption, spectrum utilization, and global exposure, respectively. In this [2] author Create a CRN using CSS and IWOA (Improved Whale Optimization Algorithm). In our job, several cooperating secondary users are supplied for the support of the primary users. Delay, delivery ratio, energy usage, impartiality index, and performance factors are used to calculate assessment measures. The proposed method has a 95.36 percent accuracy rate. In this [3] author includes five contributions: real-world behaviour of licensed users, performance metrics for spectral mobility, a suggestion for an RGB conversion algorithm based on the threshold level, feedback in the classifier, and a system for determining the channels with the highest availability based on priorities and scores In each of the five criteria, the suggested model outperforms the other strategies, according to the results of this examination. In this [4] author seeks to perform an in-depth assessment on recent SS technologies and recent 5G-enabling technologies in the context of 5G development. The classification of SS techniques is done, and SS surveys and associated studies on SS techniques that are important to 5G networks are evaluated. Discussions on the concerns and obstacles in the current implementation of SS and CR, as well as the measures to promote efficient 5G advancement, are performed for a comprehensive survey. In this [5] author reduce the average number of decisions while preserving detection performance, we present an energy-efficient virtual cooperative spectrum sensing system based on the sequential 0/1 fusion rule. Numerical simulations show that theoretical analysis is accurate and that virtual cooperative spectrum sensing with the sequential 0/1 fusion rule is efficient. In this [6] author strives to find the highest detection probability possible. In spectrum sensing, detection probability is important. The presence or absence of primary users must be detected on the channel. The channel usage efficiency will improve if the detection probability is enhanced. Other state-of-the-art methods are compared to the suggested method. The findings suggest that cognitive radios may effectively leverage MRFO for spectrum sharing. In this [7] author suggest a unique Multi-Objective Modified Multi-Objective In the subject of spectrum sensing in a cognitive radio network, which is a key paradigm in wireless communication technology, the Grey Wolf Optimization method is developed to handle the multi-objective optimization problem. The simulation results suggest that the proposed MOMGWO outperforms the existing methods in terms of Pareto front quality. In this [8] author focuses on the problem of Secondary transmitters are supplied by the RF signal emitted by primary broadcasts in a mobile energy-harvesting cognitive radio network. One of the important findings reveals that under an energy-deficit scenario, the number of reports received at the FC can be utilized to calculate the optimal range of final decision criteria. In this [9] author propose MU detection in networks, a blockchain-based technique. Through cryptographic keys, a MU can readily be distinguished from a trustworthy person utilizing this strategy. The effectiveness of the suggested method is evaluated using MATLAB simulations. As a result, this approach can be used to validate participating users in the spectrum sensing process in the CRN for IoTs. In this [10] author proposed the dragonfly optimization algorithm and the adaptive threshold method, an efficient optimized spectrum sensing technique for cognitive radio networks has been developed. When compared to traditional spectrum sensing systems such as linear support vector machine and particle swarm optimization models, the proposed approach outperforms them in terms of detection accuracy and efficiency. In this [11] author propose the mean EE optimization problem of cognitive radio systems for mathematical structure computation, as well as a wireless multiple-access channel function for determining the presence of principal users. The simulation results reveal that the improved EE given in this work delivers much more when compared to others with similar detection performance. In this [12] author using the MOACO model and the double Q learning model, offers a hybrid model for jamming mitigation and energy monitoring. The comparison with the genetic algorithm and another meta heuristic method that improves network lifespan, residual energy, and lifetime parameters is shown in the experimental analysis. In this [13] author propose an evaluation is based on metrics of similarity between the SUs, which are chosen based on the clustering process's goal. The sensing message from a set of SUs is shared with their cluster chiefs, who then share it with the FC for a final decision. In comparison to traditional clustering techniques, the proposed approach achieves the maximum energy and performance efficiency. In this [14] author suggest the architecture has been evaluated in both the presence and absence of prime users, with the goal of increasing the network's capacity and data throughput. Furthermore, the simulation results show that the best solution is found for each subordinate user in the entire network, taking into account capacity, spectrum sharing, data rate, and interference. In this [15] author examines the aforementioned problem and proposes an adaptive resource allocation strategy for secondary users in terms of channel and power allocation. The proposed research also demonstrates the simulation's performance in terms of energy efficiency up to 8.25 × 105 bits/Joule. In this [16] author present a localized clustering system with the goal of improving stability, scalability, spectrum management efficiency, and lowering communication overhead. In the CRN, we compare the performance of our protocol to that of rival protocols. Finally, we give an analysis and simulation of our protocol, as well as a way for dealing with cluster dynamics. In this [17] author proposed an Energy detection-based spectrum detection has been proposed for this effort, which is based on the Adaptive Threshold Spectrum Energy Detection technique. The simulated subsequent diagnostic effect on the likelihood increases as the SNR is increased. The decrease in frequency detection is equated to a decrease in frequency detection. In this [18] author provide the various solution methods some structure, significance, and meaning, a complete examination of the popular strategies created for addressing RA problems in CRN is conducted. As a result, the solution models are grouped and/or classed based on a few key characteristics, with their strengths and limitations highlighted. In this [19] author focuses on vacancy detection through spectrum sensing in the radio spectrum and cloud computing secondary user assignment. In this study, spectrum sensing was approached in two ways: overlay and interweave spectrum allocation. Certain performance indicators, such as throughput augmentation and waiting time minimization, are used to compare the two approaches. In this [20] author propose difficulties of next-generation IoT networks will continue to include lowering total network latency and increasing throughput without compromising reliability. Coexistence of networks running on various frequencies is one viable option. The key issues, however, are data bandwidth support and spectrum availability. As a result, CRN are the best existing technology to address all of these difficulties for IoT, WSN, 5G, and beyond coexistence.

III. Proposed Methodology

The proposed algorithm for efficient resource allocation in cognitive radio networks is described in three segments. In the first segment, we describe the system model of cognitive radio networks; in the second segment, we describe the particle swarm optimization and genetic algorithms; in the third segment, we describe the hybrid optimization algorithm for resource allocation in cognitive radio networks.

1st segment system model

The system model of cognitive radio networks, consider primary user station (PUS) and secondary user station (SUS) each one. Consider the system model of K^{th} secondary user(SU) communicating with SUS and PUS in uplink and downlink respectively. The paring of primary user and secondary user in same frequency range lie in worst case scenario. The spectrum of primary user station divided into N sub-channels each have same bandwidth with no spectrum sensing error. Also neglect the mutual interference of secondary user. The resource allocation of using hybrid optimization algorithm for all secondary users fall into various service region. The figure 1 system mode of cognitive radio networks

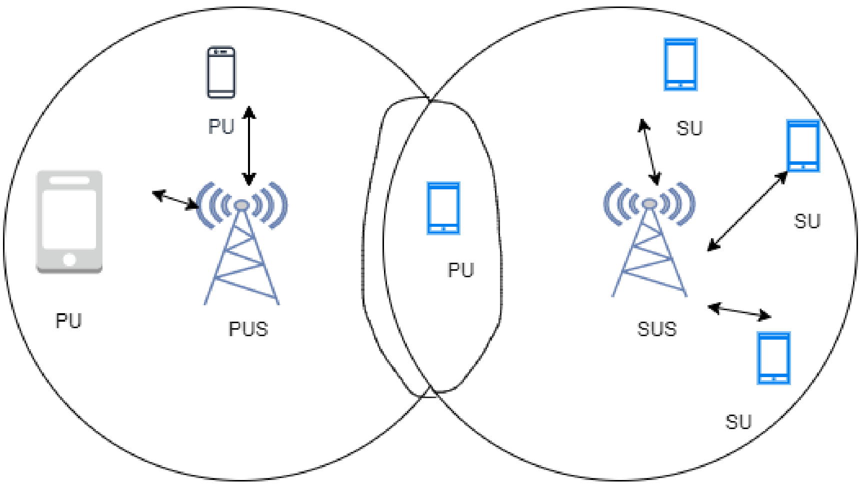

Figure 1 cognitive radio network with same pair of frequency in line of primary users.

2nd segment Optimization Algorithm

The role of optimization is very important in efficient sensing of spectrum in cognitive radio networks. The major challenge to select efficient optimization algorithm for sensing of spectrum for secondary users in wireless communication. The spectrum sensing is non-convex optimization problem so various approach are used for the process of sensing such as dynamic programming, graph theory, heuristic function, machine learning and swarm-based optimization algorithms. In this paper applies two algorithms genetic algorithm and particle swarm optimization for efficient selection of spectrum and resources for cognitive radio networks. The particle swarm optimization and genetic algorithm encapsulates in single units and formed hybrid optimization algorithm for sensing of spectrum in cognitive radio networks.

Genetic Algorithm

A genetic algorithm is a robust search approach for solving optimization problems in complicated space that is primarily based on the process of evolution and natural genetics. In GA, a parameter is represented by a gene, and the parameter set to optimise is represented by a chromosome. Chromosomes are examined based on the fitness function to identify the best option. The following are the key elements of GA:

• Population size: The population size, which specifies the number of people in each generation, is a factor that influences convergence speed performance. A large population size generates divergence, whereas a small population size may fail to cover the whole search space.

• Crossover: Crossover is the process through which a group of genes switches across two chromosomes to create a new population. A cross probability performs the crossover operation, which directly influences the performance of GA.

• Mutation: Mutation is the process by which one or more genes in an arbitrary chromosome are reversed. The mutation procedure is carried out based on a mutation probability that typically ranges between 0.001 and 0.1.

• Fitness function: The fitness function is the operation that determines whether the fitness of each chromosome is represented as a solution measured in specific genes or not. There are trade off parameters to optimise in various performance targets. Under specific constraint constraints, the optimum solution is the one with the highest fitness value among all potential chromosomes [21].

Particle Swarm Optimization (PSO)

The PSO algorithm, developed by Kennedy and Eberhart in 1995 [20], is based on the social behaviour of a group of fish and birds. PSO employs the behaviour of these social groups, also known as the swarm intelligence algorithm. This method searches the space of an objective function, modifying the trajectories of individual agents, termed particles, as these trajectories form piecewise routes in a quasi-stochastic fashion. Each particle in the PSO algorithm operates on its own information as well as group knowledge and has two basic characteristics: location and velocity. During several iterations, the particles share information about the optimal placements and adjust their individual velocities and positions based on the knowledge gained about the optimum places. The method converges to the optimal solution of the objective function after a sufficient number of iterations [22].

3rd Segment Hybrid Optimization

The main objective of the cognitive radio networks is to detect the presence of primary users accurately. We proposed cooperative spectrum sensing model using hybrid optimization algorithm. the main aim of hybrid optimization algorithm is estimate optimal weight vector of network. Now the fitness function is formulated of the objective function that is $f(x) = \frac{1}{u}$. The processing of generation function defined as

$$\emptyset i + 1 = \mu \phi i(1 - \phi i) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .. (1)$$

Here ∅ is a random number between intervals [0,1] and μ ∈ [0,4] is constant.

The processing of particle swarm optimization (PSO) algorithm faces a problem of global optimization in cognitive radio networks, so apply genetic algorithm to control the iteration and minimize the deficiency of particle swarm optimization. The position of particle can be regarded as the genes and the production of genes as constraints of fitness. Now the selection process of hybrid optimization describes as

$$\begin{cases} \mathrm{Pr(Xi)} = \dfrac{\mathrm{g(xi)X\ exp\ (-h(xi))}}{\sum_{j=1}^{N}(\mathrm{g(xj)X\ exp\ (-h(xj)}} \\ \mathrm{g(Xi)} = \dfrac{1}{\mathrm{exp\ (-SNRi)}} \\ \mathrm{h(Xi)} = \dfrac{1}{\mathrm{m}}\sum_{j=1}^{N} |\mathrm{g(xi)} - \mathrm{g(xj)}| \end{cases} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$$

Here g(Xi) and h(Xi) represent the degree of odder level

The subgroup of particle colon convergence population defined as

$$\mathrm{Var\{Ui\}} = \frac{1}{\mathrm{N}}\sum_{i=1}^{N}\left(\mathrm{fi(t)} - \mathrm{f'(t)}\right) \dots\dots\dots\dots\dots\dots\dots\dots\dots (3)$$

Now define the mutation operator for average fitness constraints function of particles

$$\mathrm{X_i^*} = \mathrm{xi} + \mathrm{cE(0,1)} \dots\dots\dots\dots\dots\dots\dots\dots\dots.. (4)$$

Where c denotes the length of mutation and E(0,1) is mutation operator

After the mutation estimates the similarity of particles

$$\mathrm{sim(Xi,Xj)} = 1 - \frac{|\quad |\mathrm{Xi} - \mathrm{Xj}| \quad |}{\mathrm{MaxXi, Xj} \in \mathrm{Xc}\{|\mathrm{Xi} - \mathrm{xj}|\}} \dots\dots\dots\dots\dots\dots\dots\dots (5)$$

After the similarity estimation of particle finally assign the weight to available spectrum and allocate to secondary users.

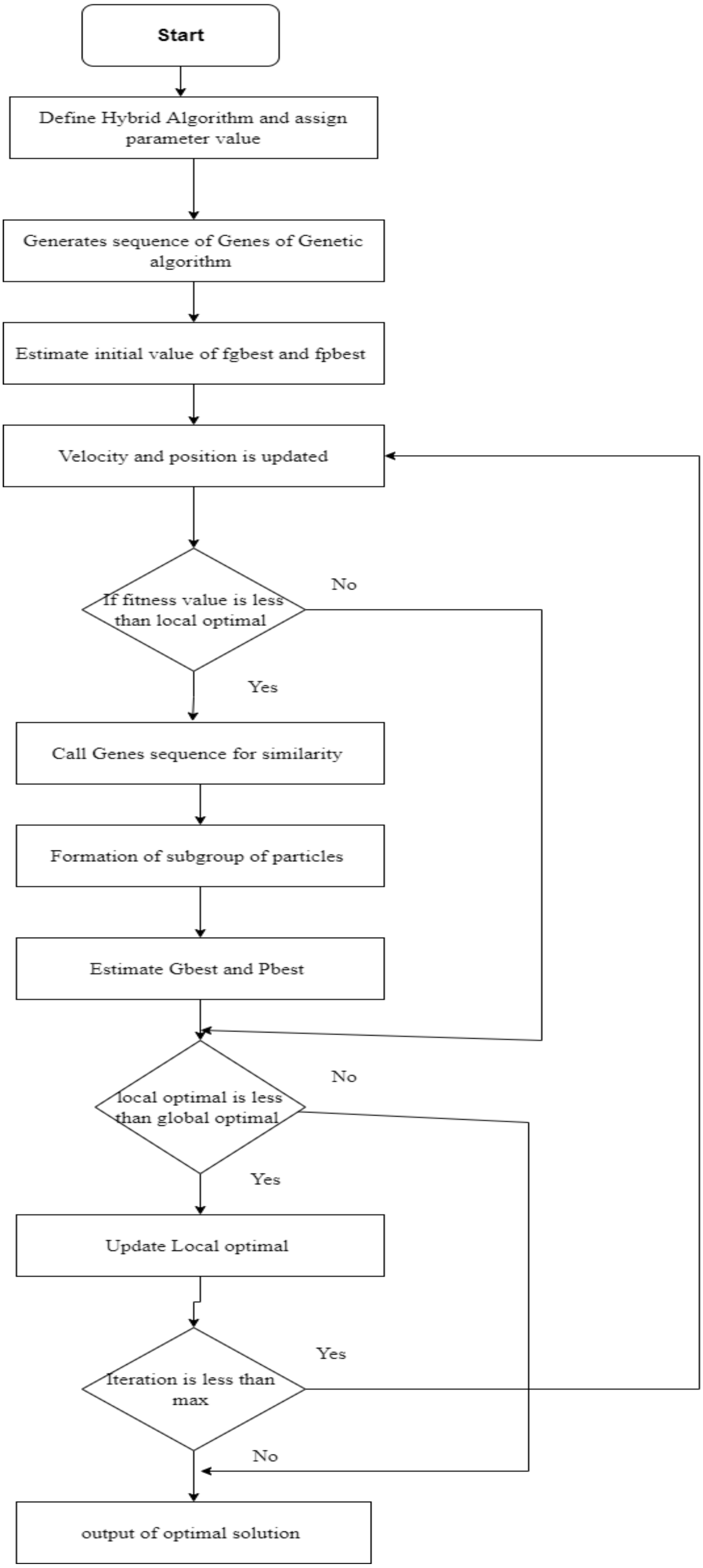

Figure 2 proposed process block of hybrid optimization algorithm for cognitive radio networks

IV. Experimental Analysis

To validate the proposed hybrid optimization algorithm in cognitive radio networks. The process of simulation carried over on MATLAB software, windows 10 with I7 processor, 16GB RAM. The parameter of cognitive radio set is 8, sample rate of sensing spectrum is 100 and noise and sensing variance randomly generated [18,19,20]. The simulation parameters and value mention in Tabel 1

Table 1 simulation parameters of cognitive radio networks

Parameters	Value
PUS radius	1000m
SUS radius	1000m
Primary User (PU)	1
Secondary User (SU)	5
PU Bandwidth	1.5MHz
PU Sub-channel	12
Sub-Channel bandwidth	125KHz
PU accommodated channels	CH6 &10
PUS coordinator	(-1500,0)
SUS coordinator	(0,0)
X coordinator of SU	300m
Y coordinator of SU	200m
Distance between each SU	300m

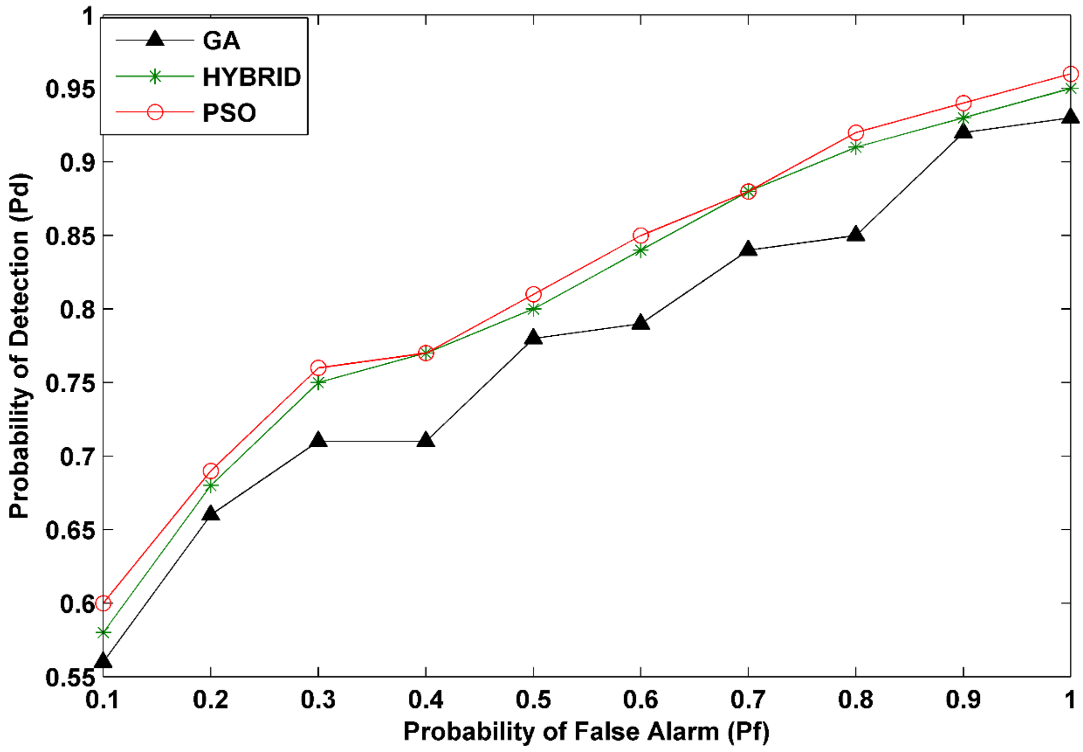

Fig 3: Probability of Detection (Pd) vs Probability of False Alarm (Pf) for M=10.

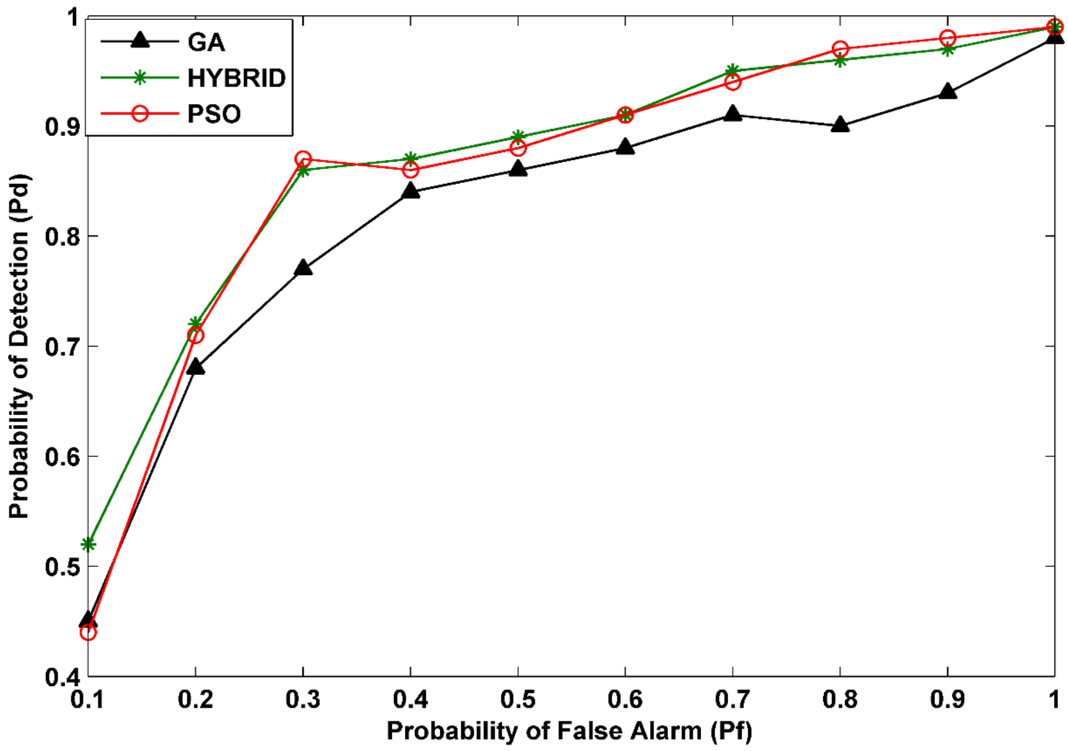

Fig: 4 Probability of Detection (Pd) vs Probability of False Alarm (Pf) for M=15.

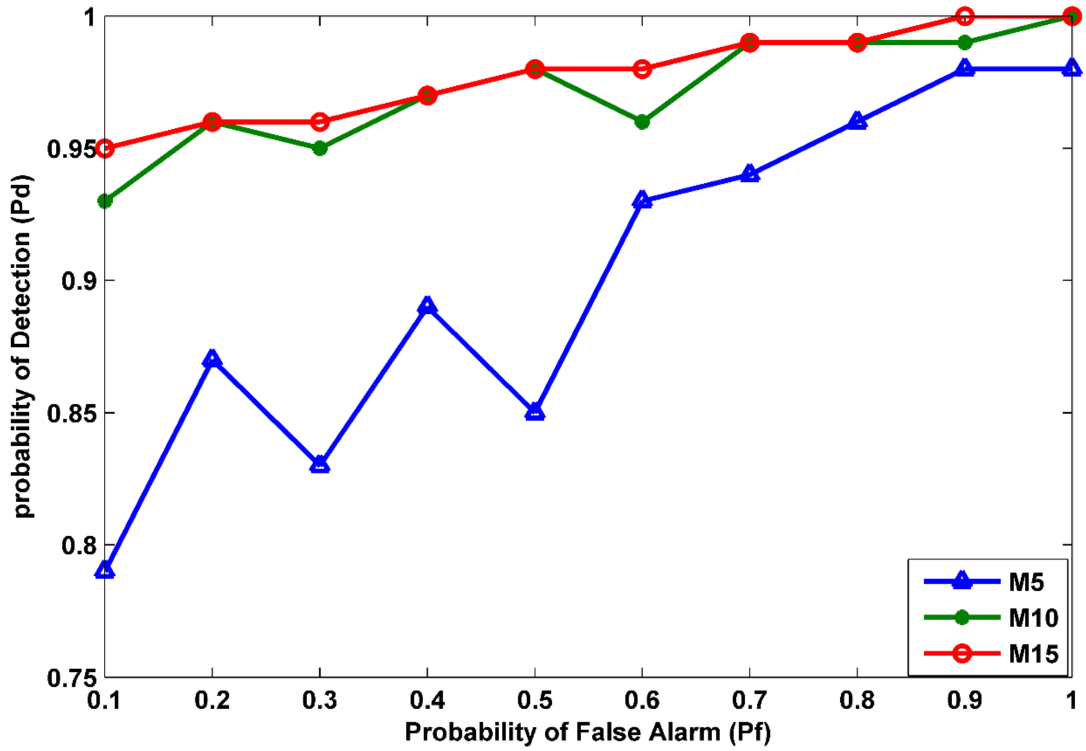

Fig : 5 Probability of Detection (Pd) vs Probability of False Alarm (Pf) for SNR = -4dB.

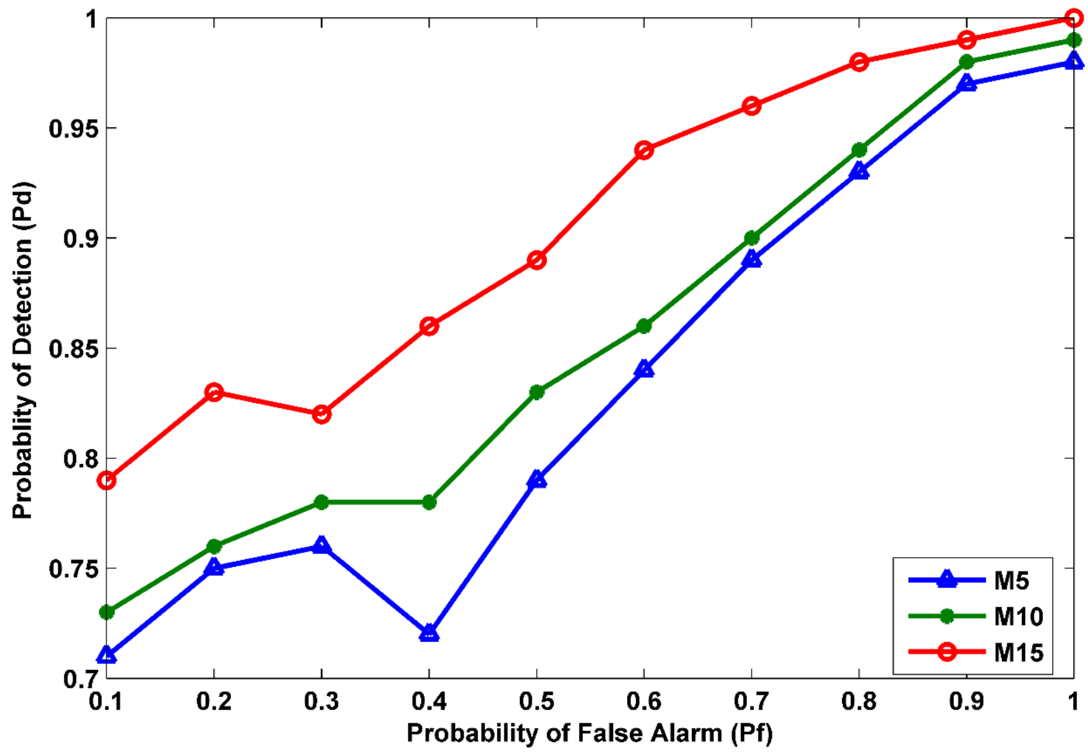

Fig : 6 Probability of Detection (Pd) vs Probability of False Alarm (Pf) for SNR = -0.5 dB.

V. Conclusion & Future Scope

The objective of this paper is to optimise the sensing parameters of cognitive radio networks. This paper employed hybrid optimization algorithms using particle swarm optimization and genetic algorithms. In the processing of hybrid optimization algorithms, genetic algorithms modify the selection of particles using genetic algorithms. The mutation operator of a genetic algorithm increases the similarity of particles. The improved rate of particles increases the sensing rate of spectrum in primary users. The proposed work is done with a single PU in mind, although multi-objective functions for many PUs will be addressed in future work. The MATLAB 2018 simulation results show that the proposed approach effectively got the best value of sensing duration, detection threshold, and transmission power for the hybrid optimization issue, which includes opportunistic throughput, interference, and energy efficiency. The proposed algorithm performance is evaluated qualitatively by verifying the findings and comparing them to the performance metrics acquired by the PSO and GA algorithms. When compared to existing algorithms, the proposed algorithm outperforms them in terms of detection probability, false rate, and efficiency of transmission. As a result, when compared to previous optimization algorithms, the proposed method has demonstrated high-quality coverage and convergence for the genetic algorithm.

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