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A Novel Particle Swarm Optimization for Channel Allocation in OFDM Based Cognitive Radio Networks

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ABSTRACT: It has become increasingly apparent that bandwidth scarcity is an issue as wireless communications advance. Alternatively, spectrum sensing techniques are used to detect licensed users. A spectrum sensor can detect energy, matched filters, and cyclostationary features. There are, however, some drawbacks to these methods. Energy detector performance is affected by noise power uncertainty. Every primary user needs a dedicated receiver for matched filter spectrum sensing. Computational effort and observation time are required for cyclo-stationary feature detection. Spectrum use is determined using particle swarm optimization (PSO), an algorithm for determining the best frequency allocation and highest accuracy. Using PSO operations, this paper proposes an improved energy detection method compared to conventional energy detection methods. Detecting energy and using the PSO channel allocation technique to detect fading channels is also mathematically described.

Keywords: Cognitive Radio, Energy Detection, Match Filtery.

1. INTRODUCTION

Wireless communication that uses cognitive radio (CR) allows a transceiver to detect which communication channels are in use and which are not. After leaving an occupied channel, the transceiver immediately switches into an empty one. Radiofrequency (RF) spectrum is used more efficiently with these capabilities. Point process models and random fields can be used to analyze various statistics related to network connectivity. In addition, distributions may be assigned to primary users and CRN nodes based on the application being developed. Using collaborative localization techniques, such estimation is technically straightforward. As long as propagation models are also appropriately modelled, spectrum models can help improve both spectrum sensing and spectrum usage.

Radio technology that learns radio environments and changes transmission parameters is called cognitive radio, also called smart radio [1]. Transmitters, Matched Filters, Energy, and other techniques can all be used to detect spectrum holes. The spectrum management problem arises after the correct frequency is sensed [2]. A device should, therefore, be able to change its operating parameters automatically whenever a licensed user is not using certain bands during a certain period [3].

Since wireless devices have become more prevalent due to the development of technology, wireless networks have become more popular [4]. To ensure better use of frequency bands, spectrum detection techniques are available. PUs are detected via spectrum detection techniques. Furthermore, with these techniques, the SU benefits from the voids in the spectrum if no PU is present [5]. CRNs with wireless access points should not interfere with each other [6]. Secondary users change channels to avoid interfering with primary users [7, 8]. Secondary users should be provided with the most

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appropriate channel to pass through gaps in the frequency band. Analyzing the optimal channel between the available spectrum bands requires consideration of several parameters and transmission characteristics of secondary users [9].

Cognitive radio relies heavily on sensing, as discussed above. Several factors complicate the sensing process. There is a possibility that the SNR is very low (below -20dB) as a first factor. In addition, wireless signals are affected by fading and multipath. Coherent detection methods can be unreliable due to fading (can be as great as 10dB), and signal power can fluctuate dramatically due to multipaths (up to 10 dB) while multipaths are unknown. Also, noise power uncertainty (noise power uncertainty) and non-Gaussian noise can affect the level of noise/interference. Noise uncertainty occurs from either receiving devices or environmental sources. Receiver noise uncertainty occurs from receiving devices, while environment noise uncertainty occurs from the environment [10–12]. As a result of the uncertainty that arises from noise, obtaining an accurate noise power in practice is extremely challenging (virtually impossible).

1.1 OFDM FOR COGNITIVE RADIO

Asymmetric frequency division multiplexing, or OFDM, can be understood as Multi-carrier modulation that uses closely spaced orthogonal subcarriers to modulate data split into chunks. There is no mutual interference between orthogonal subcarriers. It is, therefore, extremely useful for the transmission of high-bit-rate data. Transmissions at high data rates are plagued by inter-symbol interference (ISI) caused by time dispersion of pulses. OFDM modulates data into overlapping orthogonal subcarriers in a low-rate manner. The number of subcarriers used in this splitting increases the duration of the symbol, reducing the ISI as a result of multipathing. A cognitive radio system should use OFDM for transmission [13]. OFDM is suitable for CR-based transmission systems due to its features and capabilities. CR systems require spectral efficiency, which OFDM provides. Due to the close spacing and overlap of the subcarriers, interference is not caused.

Adaptability and flexibility are also advantages of OFDM. CR system can be dynamically aided by the subcarriers depending on the environment. FFT, a digital signal processing tool, can be used to implement OFDM through digital signal processing.

2. LITERATURE REVIEW

Researchers have investigated resource allocation issues for cluster-based helpful multicast using OFDM frameworks [14]. The group proposes a more efficient bunching scheme to increase the framework aggregate rate. The selection of bunch heads is based on optional clients (SUs) with great channel conditions, while others select which bunch to be a part of. In the second stage of the group sorting process, the information is sent to the group heads by the optional base station (BS) and not to the cluster members by the bunch heads.

When unauthorized users access a frequency group in a structured way through cognitive radio, band effectiveness increases [15]. Domains that are free or white spaces are evaluated for the primary user (PU) and then vacated by them when and where it is specified. It is not yet necessary to remove all unauthorized secondary users from the domain requested by the requested customer to improve its normal use [16]. An engaging atmosphere is the goal of real-time CR [17]. Customer approvals are given to PUs, and secondary approvals are given to CRUs. The PU sits on the range and allows CR users to use it. A CR user must acquire data about the radio environment to maintain a strategic distance from the obstructions in the PU [18]. CRU bands spend a lot of time and energy collecting data about usage by checking their total transmission capacity. PU signal-to-noise ratio (SNR) was used to select the CRU detection type

Cognitive radio (CR) reduces the underutilisation of the radio spectrum. To effectively exploit the electromagnetic spectrum, CR is a challenging technology. CR specifies wireless designs that don't have predetermined channels for transmission. A high spectral resolution is required to detect the spectrum holes with spectrum sensing (SS). We have compared the validity and accuracy of our technique with those of other existing techniques in our paper, and the results show that ours is superior [19].

According to the authors [20], a centralized cognitive radio network is optimized to minimize a particular sensor unit's detection, false alarm, and error probability (SU). It must minimise error probability to maximize detection probability and minimize false alarms.

3. PARTICLE SWARM OPTIMISATION (PSO)

Swarm intelligence is the basis of PSO's evolutionary algorithm. A process inspired by biological analogies. Real-valued functions are defined in a given space, and their goal is to find the global optimum of those functions [21]. As the swarm searched for food, it was inspired by this behaviour. Originally introduced by Kennedy and Eberhart in 1995, this concept has since become widely accepted. Eberhart was an electrical engineer, and Kennedy was a psychologist. Social dynamics determine the movement patterns of insects, birds, and fish. Consider the food-searching behavior of fish. Fish in a shoal are small particles representing solutions to the search space in the fish's search space. A process of optimization is involved in searching for food. Each shoal member competes with the others and shares the information with partners so that they can find the best solution.

Neither birds nor fish search for food alone but work in collections (herds or groups). Information is shared among group members, according to the observation. Behavioural patterns are influenced by group behaviour. Simulating the simplified social system led to the development of the PSO, which is robust to nonlinear optimisation problems [13]. The PSO algorithm is simpler and better than conventional algorithms because fewer calculations are performed, reduced time and convergent solutions are produced more quickly.

Artificial Life and Evolutionary Algorithms are closely related to PSOs. A swarm-based searching process is based on a position-velocity model. Swarm members each represent a potential "solution". The position and velocity of each particle are used to characterize it.

Position and velocity are the characteristics of each particle. Using avail function or fitness value, fitness values are determined for each particle based on its position and velocity.

Due to its various advantages and disadvantages, the PSO algorithm is limited to certain applications. Only a few parameters must be determined, and it has an extremely efficient global search algorithm. The refinement stage of the search is slow, and local searches are weak. It is easy to use and not affected by parameter scaling [22], [23].

Continuous variable problems are best solved using the PSO algorithm. Artificial Neural Networks have been developed using it. Image processing and fuzzy logic are two areas in which these networks are trained [24]. Power distribution optimization can be achieved with this technology. In addition, biomechanics and biochemistry system identification and shape and size optimization are also used.

According to the algorithm's processing, synchronous and asynchronous PSOs fall into two basic categories. Parallel evaluation of particles is the first step of synchronous PSO, followed by comparison. All particles can start at the same time for iterations. Asynchronous PSO evaluates and compares each particle separately. Evaluating a particle again is unnecessary if it is already determined to fit, saving calculation time.

b) **The PSO parameters** [21]

1. **Initial Population:** Randomly generated particles make up the population.
2. **Population Size:** A swarm's number should be determined by its accuracy and computational performance (based on the tradeoff between the two).
3. **Swarm:** Populations or particles that move randomly.
4. **Search Space:** The algorithm computes the solution within this variety of all possible solutions.
5. **Number of Iterations:** Fitness value converges to an optimal solution after the maximum number of steps.
6. **Inertia weight:** An algorithm's convergence is controlled by its inertia weight, which must be carefully chosen. It is possible to fail convergence if the inertia weight is too high or too low. A binary hypothesis can be used to determine whether a cognitive radio contains the primary signal.

Hypothesis 0 (H_0): There is no primary signal.

Hypothesis 1 (H_1): There is no primary signal.

Assume that S is the transmitted signal. The $n^{th}(n = 1, 2, 3, \ldots..)$ sample of $y(n)$ for a complex signal with real S_r and imaginary S_i than $= S_r + j, +S_i$ It is given as follows:

$y(n) = \{n(n), \ 0 \leq n \leq N-1$ idle & @ $x(n) + n(n) \ 0 \leq n \leq N-1$ busy &)-1

And $x(n) = h \ s(n)$ a noise sample with a zero mean is referred to as $n(n) = nr(n) + jni(n)$ The channel gain is given by h, and $n(n)$ is the compound noise.

$E(w(n)\} = 0$ and variance $2^2_{\sigma w}$ (Var [n(n)]= $2^2_{\sigma w}$) I,e gN(0, $2^2_{\sigma w}$) $2^2_{\sigma w}(Var(n(n)] = 2^2_{\sigma w} \quad i, e\ gN(0,\ 2^2_{\sigma w}$ It is possible to write Equation 1 as follows:

$$y(n) = ex(n) + n(n) \tag{1}$$

Where $\theta = 0$ for H_0 and $\theta' = 1$ for H_1 Therefore, the signal model H_1 can be assumed as:

H1:y(n)={(n(n),& 1≤n≤no-1@x(n)+n(n) & no≤n≤N)

$$H_1 : y(n) = (n(n), \ \& \ 1 \leq n \leq no - 1@x(n) + n(n) \ \& \ no \ \leq n \leq N) \tag{2}$$

A comparison of the threshold value and the received signal's SNR value can be used to determine the primary signal for CR systems [3].

As a result of the Nyman-Person Criterion, a probability density function can be defined for binary hypothesis models y H is $f_y\ H(x)$where $H \in H_0,\ H_1\}$

Following are the metrics that define energy detector performance based on the above test statistics:

False alarm probability Pf**:** When H_0 is true, the Probability of determining the signal exists is $Pf = Pr[\Lambda > \lambda\,(H_0]$ Based on the assumption that λ is the detection threshold.

Missed detection probability Pmd**:** Taking into account the chance that H_1 is true, the likelihood of the signal being absent is high, i.e., $pmd = Pr[\Lambda < \lambda\,(H_1]$

Detection probability Pd**:** The likelihood of determining a signal's presence increases when it is true, i.e.,$Pd = Pr(\Lambda > \lambda\,(H_1\,]$And thus, $Pd = 1 - pmd$. To determine how well an energy detector performs, it is necessary to assess its statistical properties Λ. A signal and noise model is essential for obtaining the statistical properties. A binary hypothesis system can measure the detector's sensitivity using ROC curves. A plot of Pd (or Pmd) versus Pf as threshold varies on the ROC curve is shown in Derivations of Pd and Pf for Different Channel Models [2]. Based on the assumption that noise n(t) is a bandpass signal, we can represent the noise using a low pass signal:

$$n\,(t) = n_i\,(t)\,cos2\pi ft - n_q\,(t) \quad sin2\pi ft \tag{3}$$

Assuming N_0 is the noise signal with bandwidth (BW), then n(t) is the noise signal with PSD N_0, the noise signal n(t) can be represented by two components, n_i and n_q, which represents the noise of the low pass signal, the energy of the noise for a period of T, having capacity $BW/2$ and a power spectral density of $2N_0$ for low pass signals

$$E = \int_0^T n(t)^2 dt \tag{4}$$

$$E = \int_0^T n(t)^2 dt = \frac{1}{2}\int_0^T \; [n_i(t)^2 + n_q(t)^2\;]dt \tag{5}$$

The likelihood of AWGN being detected and the likelihood of false alarms being detected [2]. The Probability of H_1 being selected is given by P_d, whereas P_{fa} is given by the possibility of a false alarm when H_0 is selected. P_d and P_{fa} can also be defined as follows if the threshold value is selected:

P_d and P_{fa} It can also be defined as follows, assuming that the threshold value is chosen:

$$P_d = P(Y > \kappa|H_1\,)$$

$$P_{fa} = P(Y > \kappa|H_0\,)$$

Using their PDFs, P_{fa} This can be expressed as follows:

$$P_{fa} = \int_{\kappa}^{\infty} f_Y\,(y)\,dy$$

quations and formulae should be typed in Mathtype, and numbered consecutively with Arabic numerals in parentheses on the right hand side of the page (if referred to explicitly in the text). They should also be separated from the surrounding text by one space. (1)

4. RESULT SIMULATION

Signal detection is illustrated in this paper by showing the relationship between probabilities of detection (P_d), false alarms (P_{fa}), and signal-to-noise ratio (SNR). Monte Carlo simulations calculate detector performance and validate metrics, receiving operating characteristic curves. Figure 1 shows the Probability of the detection with the $P_{fa} = 0.01$ and quantity of Monte Carlo models =1000 for different SNR (dB) values. A higher SNR increases the chance of finding.

Based on Figure 2, the null and alternative hypotheses become less strongly supported as the SNR increases. As a result, false alarms increase detection odds. Increasing the number of false alarms increases the Probability of detecting one spectrum sensing method over another. When using conventional energy detection methods, there is an increase in false alarm probability of 5%; for the AWGN Channel, it is 1.8 times higher, and for the Rayleigh Channel, it is 0.8 times higher. With cyclic prefix-based spectrum sensing, the AWGN Channel can be improved by 1.48 times and the Rayleigh Channel by 1.36 times with a 5% false alarm rate increase.

Figure 3 shows complementary ROC curves for AWGN and Rayleigh fading channels according to the different SNR values for local spectrum sensing. Increased SNR decreases the likelihood of detecting AWGN and Rayleigh fading channels if a fixed probability of false alarm is provided.

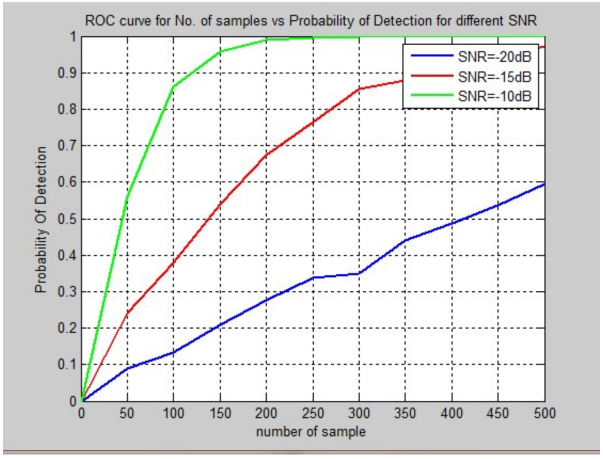

FIGURE 1. **Probability of detection versus number of samples.**

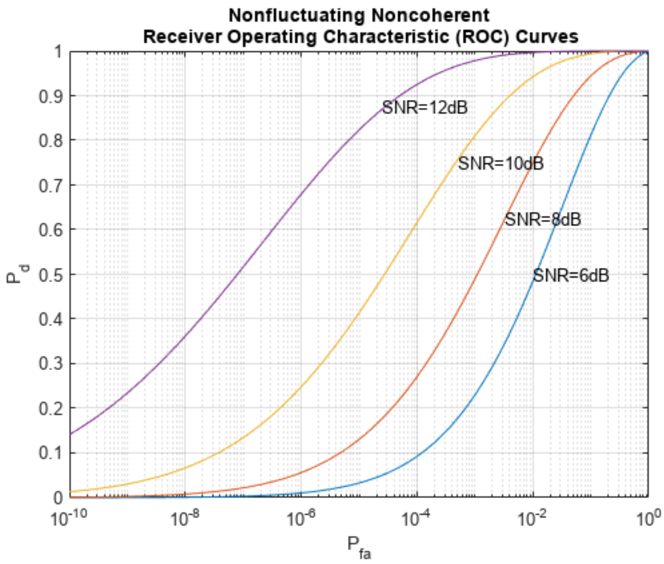

FIGURE 2. **Probability of detection versus Probability of false alarm (P_{fa}) using PSO.**

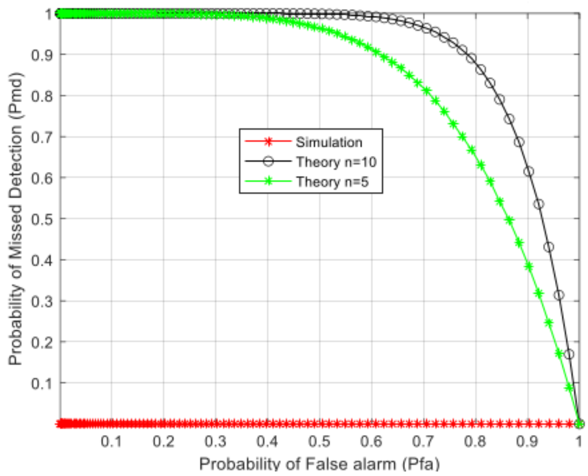

FIGURE 3. **Complementary ROC curves under AWGN for local spectrum sensing using PSO.**

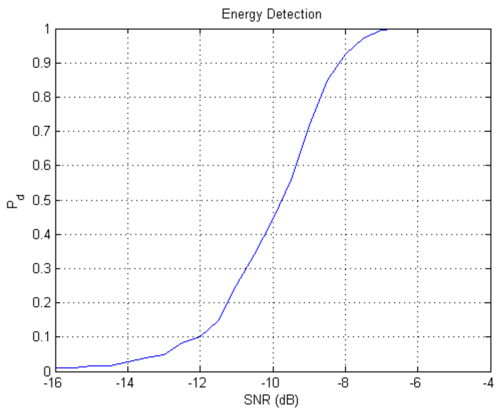

FIGURE 4. **Energy detection using wiener filter.**

Spectrum sensing method performance improves when the SNR increases, as shown in Figure 4. SNR increases by 5 dB, increases the Probability of detection for AWGN Channels by 0.8 times, and squaring operations increase the Probability by 0.7 times for Rayleigh Channels by 0.8 times. An improvement of 0.4 times is observed on the AWGN Channel, 0.3 times on the Rayleigh Channel, and 0.7 times on energy detectors.

5. CONCLUSION

This paper discusses particle swarm optimization (PSO) and energy-based spectrum sensing techniques. The Energy Detection method is implemented using two operations. A ROC curve and a Probability of detection versus SNR plot were used to evaluate Spectrum Sensing performance. Spectrum sensing based on cyclic prefixes is the most effective method for fading channels and low signal-to-noise ratios. The proposed operation improves indicators of conventional energy performance. Spectrum sensing based on cyclic prefixes is the most effective method for fading channels and low signal-to-noise ratios.

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CONFLICTS OF INTEREST

The author declares no conflict of interest.

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