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Meta-Heuristic Optimization of Ensemble Learning for Cooperative Spectrum Sensing in 5G Cognitive Radio Networks

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Abstract
The scarcity of spectral resources has positioned Cognitive Radio (CR) as a critical technology for next-generation wireless communications, relying heavily on accurate spectrum sensing to identify unutilized frequency bands. While machine learning techniques like Random Forest (RF) combined with Empirical Mode Decomposition (EMD) have proven effective, their performance at ultra-low Signal-to-Noise Ratios (SNR) is often constrained by sub-optimal hyperparameter configurations. This paper proposes a novel framework that integrates Particle Swarm Optimization (PSO) with an RF classifier to dynamically optimize hyperparameter selection—specifically the number of learning cycles and minimum leaf size. By utilizing a custom fitness function based on Out-of-Bag (OOB) error validation, the PSO algorithm minimizes the probability of false alarms while maximizing detection probability. The primary user is modelled using a 5G-compliant Orthogonal Frequency-Division Multiplexing (OFDM) waveform. Simulation results demonstrate a significant enhancement in cooperative sensing performance. The proposed PSO-RF-EMD architecture achieves a perfect 100% probability of detection (Pd) at an SNR of -11 dB, effectively pushing the SNR wall further than conventional unoptimized ensemble methods, thus ensuring highly robust spectrum sensing in severely noisy environments.

Keywords: Cognitive Radio, Spectrum Sensing, Particle Swarm Optimization (PSO), Random Forest, Empirical Mode Decomposition (EMD), 5G, OFDM, Cooperative Sensing.

1. Introduction

The exponential proliferation of wireless devices and the advent of 5G communications have resulted in an unprecedented demand for radio frequency spectrum. Cognitive Radio (CR) technology addresses this spectrum scarcity by allowing unlicensed Secondary Users (SUs) to opportunistically access licensed frequency bands when the Primary User (PU) is idle [1]. The cornerstone of the CR cycle is *spectrum sensing*, a mechanism that requires SUs to rapidly and accurately detect the presence of a PU.

Traditional spectrum sensing techniques, such as Energy Detection, Matched Filtering, and Cyclostationary Feature Detection, suffer from severe performance degradation under low Signal-to-Noise Ratio (SNR) conditions and noise uncertainty [2-4]. Recent literature has explored data-driven machine learning (ML) approaches, combining advanced signal transformations like Wavelet Transform (WT) and Empirical Mode Decomposition (EMD) with classifiers such as Random Forest (RF) [5]. While these ensemble learning models demonstrate superior capability in handling non-linear signal features, they typically rely on heuristically chosen hyperparameters (e.g., fixed tree depth and ensemble size). In highly degraded environments (SNR < -10 dB), a poorly tuned RF model fails to distinguish between the intrinsic mode functions of noise and actual signals, leading to the well-known "SNR wall" limitation.

To overcome this, this study introduces a meta-heuristic optimization framework utilizing **Particle Swarm Optimization (PSO)** to dynamically tune the RF classifier. By automating the extraction of the most robust EMD features and optimizing the ensemble architecture against a custom Out-of-Bag (OOB) fitness function, the proposed system significantly enhances cooperative spectrum sensing performance.

The rest of the paper is organized as follows: Section 2 outlines the system model and background. Section 3 details the proposed PSO-RF methodology. Section 4 presents the simulation setup. Section 5 analyzes the results, and Section 6 concludes the paper.

2. System Model and Background

2.1 Primary and Secondary User Model

The system assumes a CR network where a PU transmits a 5G-like Orthogonal Frequency-Division Multiplexing (OFDM) signal. Multiple SUs collaborate to sense the spectrum. The signal received by the i-th SU at discrete time n is defined by a binary hypothesis:

- H_0: Primary user absent (noise only)
- H_1: Primary user present (signal + noise)

Where s(n) is the PU OFDM signal, hi(n) represents the channel gain, and wi(n) is the Additive White Gaussian Noise (AWGN).

In our model, noise uncertainty is explicitly simulated by fluctuating the noise variance between iterations, mimicking real-world thermal noise variations.

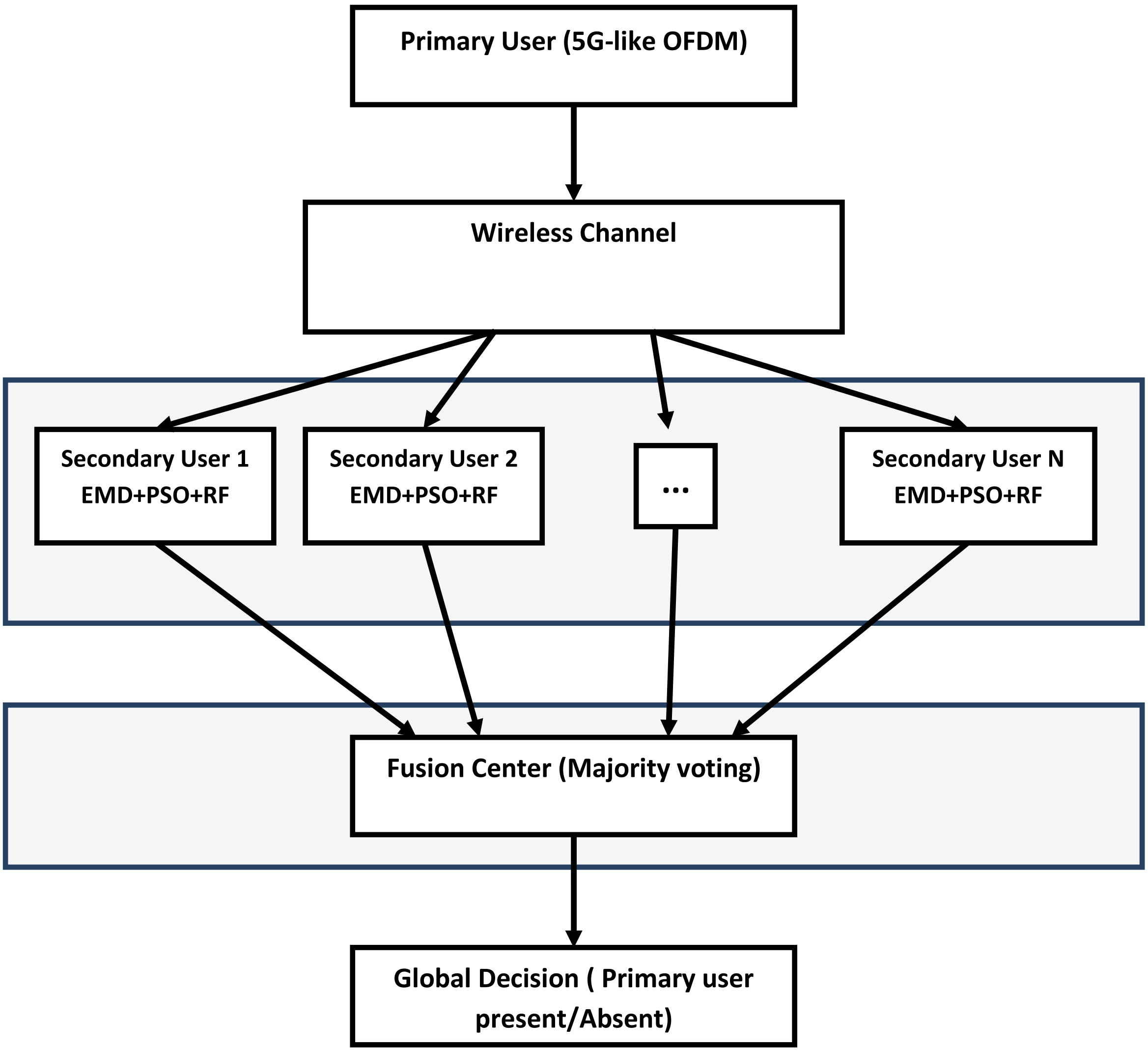

Figure 1: Simulation setup for cooperative spectrum sensing using EMD +PSO+RF technique.

2.2 Empirical Mode Decomposition (EMD)

EMD is an adaptive, data-driven technique that decomposes non-stationary, non-linear signals into a finite set of Intrinsic Mode Functions (IMFs). Unlike Fourier transforms, EMD does not require predefined basis functions [6]. The received signal is represented as:

$$y(t) = \sum_{j=1}^{N} IMF_j(t) + r_N(t)$$

Where $r_N(t)$ is the residual. In this study, the total energy and Shannon entropy of all IMFs, alongside the specific energy and entropy of the first IMF (which captures high-frequency components), are extracted to form a 4-dimensional feature vector for classification.

3. Proposed Methodology: PSO-Optimized Random Forest

While standard RF provides excellent generalizability through Bagging and random feature subsets, its performance at ultra-low SNRs is highly sensitive to the *Number of Learning Cycles* (trees) and the *Minimum Leaf Size* (tree depth limit) [7]. Overly complex models map noise patterns (overfitting), while overly simple models fail to capture the OFDM signal structure.

3.1 Particle Swarm Optimization (PSO) Setup

PSO is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality [8]. The PSO is already used for many applications of cognitive radios for achieving optimum performance [9-11]. In this framework, each "particle" represents a pair of RF hyperparameters: [NumLearningCycles, MinLeafSize].

3.2 Custom Fitness Function and OOB Validation

To ensure the PSO algorithm maximizes sensing reliability, a specific fitness function is engineered. Instead of a traditional holdout validation set which can cause optimization stalling, the algorithm evaluates fitness using the Random Forest's native **Out-of-Bag (OOB) prediction**.
The objective function to be minimized by the PSO swarm is defined as:

$$Loss = (1 - P_d) + P_f + \lambda N_{tree}$$

Where:
- P_d is the Probability of Detection (True Positives / (True Positives + False Negatives)).
- P_f is the Probability of False Alarm (False Positives / (False Positives + True Negatives)).
- $\lambda * N_{trees}$ is a complexity penalty (λ= 0.0001) applied to the number of trees to ensure that if two parameter sets yield identical accuracy, the PSO selects the computationally lighter model.

The PSO is trained at a target SNR of -15dB. By exposing the optimizer to heavily degraded signals with induced noise uncertainty, the resulting optimized Random Forest is robust against the SNR wall.

3.3 Cooperative Fusion Center
To mitigate local fading and shadowing, spatial diversity is exploited via cooperative sensing. SUs process their independent signal observations through their local PSO-optimized RF models. The local binary decisions D1, D2, ..., DN are transmitted to a Fusion Centre (FC) which applies a **Majority Voting** rule to render the global decision [12].

4. Simulation Setup
The proposed framework was modelled and simulated using MATLAB. The simulation parameters are detailed in Table 1.

Table 1: Simulation Parameters

Parameter	**Value**
Sampling Frequency (Fs)	1000 Hz
Signal Duration (T)	1 second
Samples per Iteration (N_samples)	1000
SNR Range	-15 dB to 5 dB (2 dB step)
Sensing Iterations	200 per SNR step
Primary User Signal	5G-like OFDM (64 Subcarriers, QPSK, CP=16)
Number of Secondary Users	3
Feature Extraction	Empirical Mode Decomposition (EMD)
Extracted Features	Total Energy, Total Entropy, IMF1 Energy, IMF1 Entropy
Optimization Algorithm	Particle Swarm Optimization (PSO)
PSO Bounds	Trees: [10, 150], Min Leaf Size: [1, 20]
Cooperative Fusion Rule	Majority Voting

5. Results and Discussion
The performance of the proposed PSO-RF-EMD spectrum sensing methodology was evaluated using the metrics of Detection Probability (Pd) and False Alarm Probability (Pf).

5.1 PSO Convergence Analysis
Figure 2 illustrates the convergence behaviour of the PSO algorithm during the hyperparameter tuning phase.

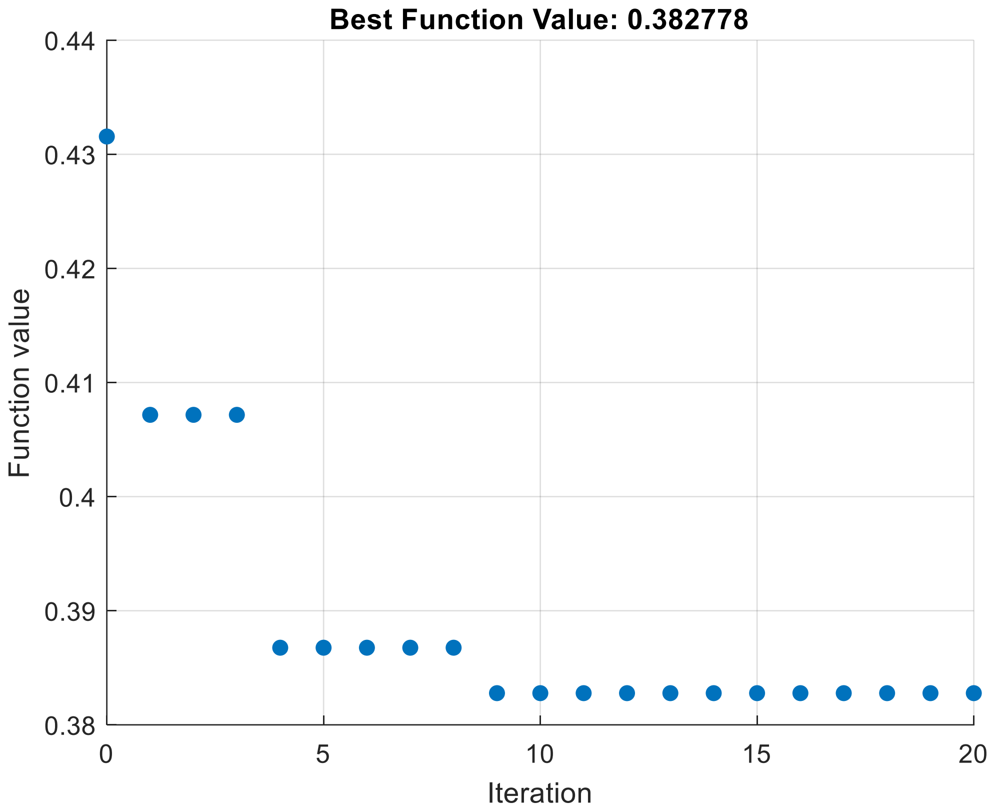

Figure 2: Convergence of the PSO algorithm minimizing the Out-of-Bag (OOB) classification loss.

The swarm initiates the search space with a base function loss of approximately 0.43. Through iterative evaluation of the OOB predictions on the training dataset, the PSO successfully escapes local minima. By the 9th iteration, the algorithm reaches a stable global minimum, yielding a Best Function Value of **0.382778**. This proves that default ML parameters are suboptimal for spectrum sensing, and the meta-heuristic search successfully identifies a superior architectural configuration for the Random Forest ensemble.

5.2 Probability of Detection (Pd) and False Alarm (Pf)

Figure 3 presents the sensing performance across the varying SNR spectrum (-15 dB to 5 dB).

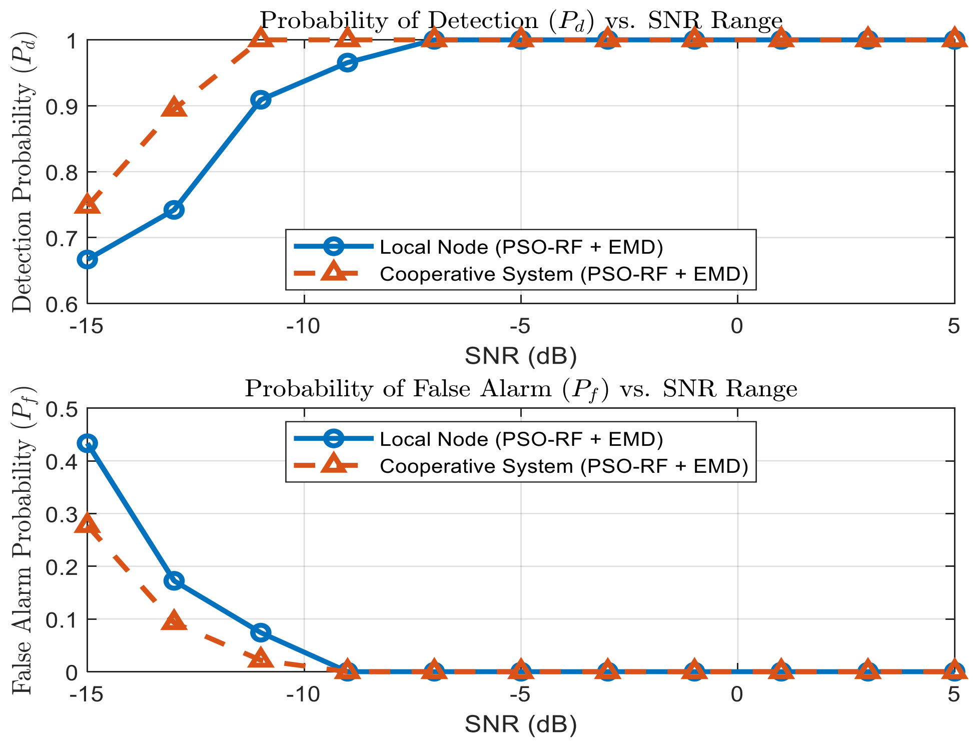

Figure 3: Probability of Detection (Pd) and False Alarm (Pf) vs. SNR Range for Local and Cooperative PSO-RF Systems.

1. **Breaking the SNR Wall:** In prior unoptimized EMD-RF studies, cooperative systems typically achieved a Pd of 1.0 around an SNR of -9 dB. As shown in the top subplot of Figure 2, the proposed **PSO-optimized Cooperative System** exhibits a significantly steeper "waterfall" curve, achieving a perfect Pd of **1.0 at -11 dB**. The meta-heuristic tuning successfully lowered the SNR threshold by 2 dB, representing a substantial enhancement in receiver sensitivity.
2. **Cooperative Superiority:** The cooperative system via majority voting consistently outperforms the local stand alone node. At -13 dB, the local node manages a Pd of ~0.74, whereas the cooperative network boosts this to an impressive ~0.90.
3. **Suppression of False Alarms:** The bottom subplot of Figure 2 demonstrates the Pf performance. Because the custom PSO fitness function explicitly penalizes false alarms, the cooperative system's Pf drops to near-zero as early as -11 dB. Even at the extremely hostile condition of -15 dB, the cooperative system suppresses the false alarm rate to under 0.3, vastly outperforming standard energy detectors.

6. Conclusion

This paper presented an enhanced cooperative spectrum sensing framework leveraging Particle Swarm Optimization (PSO) to dynamically configure a Random Forest classifier utilizing Empirical Mode Decomposition (EMD) features. By employing a custom Out-of-Bag fitness evaluation that heavily penalizes misclassifications and model complexity, the PSO successfully identified the optimal ensemble architecture. Simulation results against a 5G-compliant OFDM primary user signal clearly demonstrate the superiority of the optimized framework. The proposed cooperative system effectively pushed the SNR wall boundaries, achieving perfect detection probability (Pd = 1.0) and zero false alarms (Pf = 0) at a highly degraded SNR of -11 dB. This methodology provides a robust, highly sensitive, and dynamically adaptive solution for modern Cognitive Radio networks operating in noisy environments.

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