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Adaptive Threshold Optimization for Energy Detection-Based Spectrum Sensing in Cognitive Radio Networks Using Swarm Intelligence

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Abstract

Modern communication networks require efficient spectrum utilization to satisfy the low-latency and high-reliability requirements of next-generation wireless systems. However, the rapid growth of connected devices has intensified traffic congestion, increasing the demand for efficient spectrum sensing in Cognitive Radio Networks (CRNs). The conventional Energy Detection Method (EDM) relies on fixed decision thresholds, limiting its effectiveness under dynamic wireless conditions. This study investigates Swarm Intelligence (SI)-based threshold optimization for spectrum sensing by comparatively evaluating the Artificial Bee Colony (ABC) and Firefly Algorithm (FFA) in a multi-fusion center environment. Three experimental configurations with different swarm population sizes were investigated to evaluate the robustness and consistency of both optimization techniques. The optimized thresholds obtained using ABC and FFA were compared with the conventional EDM in terms of probability of detection (Pd), probability of false alarm (Pf), and average optimization time. The experimental results demonstrate that both swarm intelligence algorithms improve spectrum sensing performance over the conventional EDM by enabling adaptive threshold optimization. Among the investigated approaches, the ABC algorithm achieved a more balanced trade-off between probability of detection and false alarm, whereas the FFA exhibited stronger detection capability at the expense of a slightly higher false alarm rate while requiring a lower average optimization time than the ABC algorithm. These findings demonstrate that swarm intelligence provides an effective optimization framework for adaptive spectrum sensing and supports more reliable dynamic spectrum access in CRNs.

Keywords: Cognitive Radio Network (CRN), Spectrum Sensing, Communication Network, Swarm Intelligence (SI), Firefly Algorithm (FFA), Artificial Bee Colony Algorithm (ABC), Fusion Center (FC), Energy Detection Method (EDM).

I. INTRODUCTION

CRNs have emerged as a promising solution for enhancing spectrum utilization in wireless communication systems. A fundamental component of CRNs is spectrum sensing, which involves detecting unused or underutilized frequency bands in the radio spectrum . By identifying such opportunities, cognitive radios can dynamically access available channels, thereby improve network efficiency by reducing interference among users. Common spectrum sensing techniques include the Energy Detection Method, Cyclostationary Detection, and matched filter detection. Among these, the Energy Detection Method is widely used due to its simplicity and effectiveness in identifying signal energy across spectrum bands; therefore, it is adopted as the primary sensing technique in this study. Discussing the CRN environment, it has CRN router devices, local and central fusion centers, unlicensed users or secondary users, commonly known as cognitive users, licensed users or primary users, primary user emulators or attackers, licensed channels, and unlicensed channels . CRN architecture can be designed as per the requirements of a particular region or depending upon the usage and demand of users connected to the base stations in that region. Allotment of frequencies and placement of FCs can vary according to the needs of the situation and scenario .

The allotment of frequency bands for primary and secondary users depends on the specific architecture and the regulatory policies in place . Primary and secondary users can share the same frequency band sometimes, but secondary users must not operate with higher power users using unlicensed bands. There may be allocation of bands for primary and secondary users depending on the region, country, or on other criteria . Like based on the base stations, the architecture of the CRN can also vary. In some cases, there may be separate base stations for primary and secondary users, while in other cases, a single base station can serve both primary and secondary users .

A fusion center (FC) is a node or hub in the CRN that collects and fuses data from multiple sources, such as CRN router devices or base stations, for decision-making, spectrum sensing, and managing and controlling the overall network. The number of fusion centers needed in a CRN depends on factors such as the size of the network, the number of sensors or base stations, the complexity of the network tasks, and the processing capabilities of the nodes . In some CRN architectures, there may be multiple fusion centers distributed throughout the network, each responsible for a specific task or region. For example, in a hierarchical CRN architecture, there may be multiple levels of fusion centers, with each level responsible for aggregating and processing data from sensors or base stations in a specific geographic area . In other CRN architectures, a centralized fusion center may be present that collects and processes all data from the network. Fig. 1 shows the CRN environment with FC placement. In this case, the processing and communication requirements of the centralized fusion center can be a significant challenge, especially for large networks.

Therefore, the number of fusion centers in a CRN environment can vary significantly, and the specific number of fusion centers required for a given CRN design depends on

various factors and the network's specific requirements. Fig. 2 shows the placement of multiple FCs in different regions in a CRN environment.

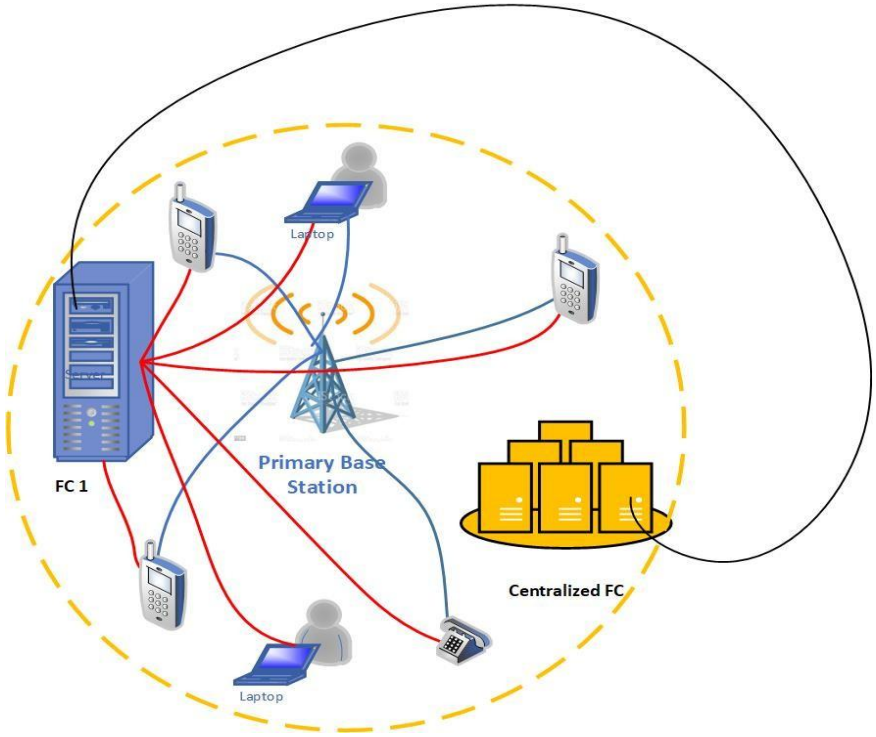


Fig. 1: Fusion Center Placement in CRN

Despite these achievements, conventional CRNs face challenges in meeting the stringent requirements of 5G networks, including ultra-low latency, high reliability, and efficient spectrum management. As wireless networks continue to grow in scale and complexity, traditional reactive approaches to spectrum measurement are proving insufficient. Therefore, researchers are increasingly exploring the integration of artificial intelligence techniques to improve CRN performance. Approaches based on machine learning and collective intelligence show great potential for improving spectrum measurement, resource allocation, and decision-making in dynamic network environments.

In this work, we investigate the application of Swarm Intelligence (SI) techniques to optimize spectrum sensing process in CRNs operating within a communication network environment. Specifically, the performance of two widely used swarm intelligence algorithms the ABC Algorithm and the FFA are analyzed and compared. These

algorithms are particularly suitable for such scenarios due to their strong local search capability and efficient exploration of large solution spaces. The study assumes a single base station operating environment and evaluates how these algorithms can reduce network congestion and sensing latency during spectrum detection.

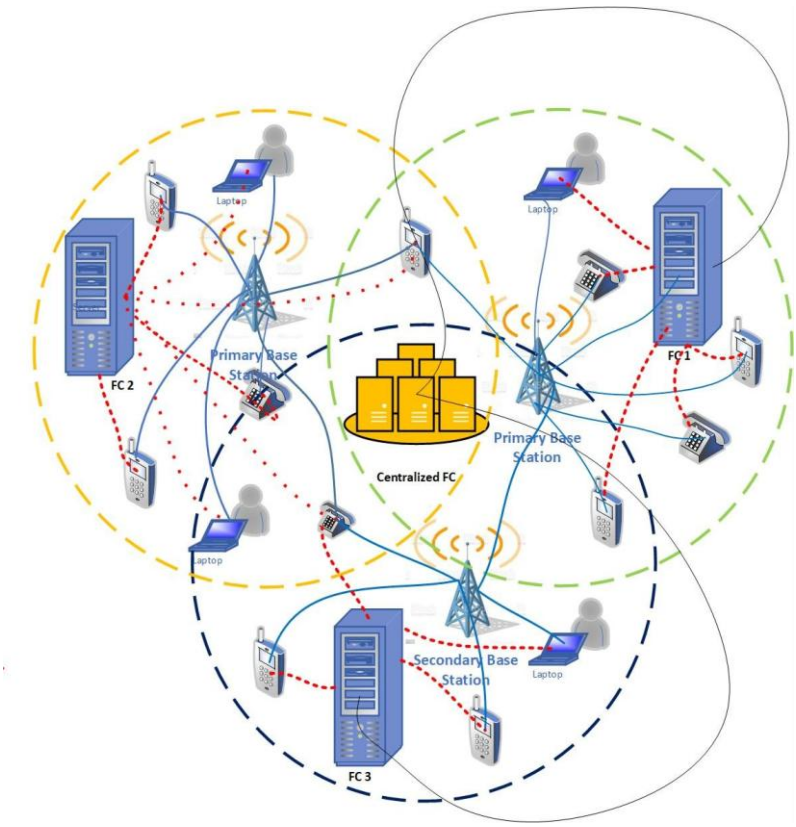


Fig. 2: Multiple Fusion Centers Placement in Different Regions in CRN

The ABC and FFA were selected due to their efficient search capabilities, fast convergence towards optimal solutions, and ability to effectively explore the search space. These characteristics make them suitable for adaptive threshold optimization in Energy Detection-based spectrum sensing. An optimal threshold can improve probability of detection while reducing sensing latency.

The remainder of this paper is organized as follows. Section I describes the architecture of cognitive radio networks and the experimental model used in this study. Subsections further discuss the allocation of licensed and unlicensed frequency channels and the placement of the Fusion Centre within the CRN environment. Section II is the literature study of using SI techniques for optimization in communication domain. Section III presents the implementation of conventional and swarm intelligence algorithms for spectrum sensing. Experimental evaluation and comparative analysis of results is

provided in Section IV. Finally, Section V concludes the study and outlines potential directions for future research.

II. BACKGROUND

EDM is not intelligent enough to explore and sense the white spaces keeping in view, the signal to noise ratio (SNR), channel fading, shadowing effects, interference from neighboring users, hidden primary user problem and so many other factors. Conventional EDM for SS in CRN performs well in small search spaces. On modern communication like 5G and beyond, where spectrum is dense and search space is wide , this EDM doesn't perform accurately. And due to noise and other distortion factors, sometimes it misjudges and miscalculate the energy, making wrong decisions and causing delays in the allocation of the spaces . Many researchers have worked on improving the conventional EDM strategy to perform spectrum sensing well on 5G and beyond networks. Mostly the focus has kept on improving the threshold calculation ignoring other factors that effects the sensing results. Implementation of different algorithms and techniques to enhance the detection and sensing process has been discussed in Table 1, a few researched improvements are highlighted.

Technique	Strategy	Improvement
Adaptive and dynamic Threshold	Threshold changes according to noise/SNR and updated continuously instead of remaining fixed. .	Proposed higher Probability of detection at the same Probability of false alarm.
Noise Estimation-Based ED	Estimates noise power first, then computes the threshold .	Typically improves low-SNR detection by adapting the threshold.
SNR Estimation-Based ED	Uses estimated SNR to adapt the threshold .	Usually compared by segmentation/detection quality rather than a fixed Pd improvement.

Table 1: Performance Improvements Achieved by Existing Energy Detection Methods

Several researchers have tried blending Artificial Intelligence (AI) based solutions including rule-based, Machine Learning (ML) and SI for optimization as well. A good literature is discussed in Table 2 to show some well-known AI approaches used to improve conventional EDM.

AI-Based Technique	Strategy	Improvement
ANN, LSTM, GNN, CNN and SVM.	A survey on nonlinear decision boundary instead of fixed threshold using AI for SS in CRN.	Analysis claims measurable performance improvement.
Naïve Bayes (NB)	Probabilistic learning using energy features, ignoring the threshold factor .	Moderate improvement has been achieved.
Deep Reinforcement Learning (DRL/RL)	Learns adaptive sensing and decision policy .	Claims to achieve 20% improvement depending on scenario.

Table 2: Performance Improvements Achieved by Using AI for Energy Detection

Although ML and Deep Learning techniques have moderately improved the performance of conventional methods, they often require extensive training data and computational resources . Metaheuristic Swarm Intelligence (SI) techniques provide a training-free optimization framework . SI is capable of adaptively optimizing the detection threshold with comparatively lower computational complexity. Some of the highlighted research is discussed in Table 3.

SI Technique	Application in CRN	Reported Improvement
Particle Swarm Optimization (PSO)	Double-threshold energy detection/cooperative spectrum sensing	Improved probability of detection and spectrum sensing performance with high computational overhead.
Particle Swarm Optimization (PSO)	In-band spectrum sensing optimization .	Enhanced high sensing probability and moderate searching time with a high trade-off for probability of false detection.
Artificial Bee Colony (ABC)	Energy-efficient spectrum sensing .	Improved energy efficiency factor by achieving fast convergence time compared to PSO with higher computational delay. Proved to be 20% more efficient than PSO but no discussion about the comparison with the conventional methods.
Grey Wolf Optimization (GWO)	IRS-assisted spectrum sensing optimization .	Moderate enhancement achieved in sensing reliability and spectrum utilization by improving intelligent

SI Technique	Application in CRN	Reported Improvement
		reflecting surface not focusing on EDM.
Whale Optimization Algorithm (WOA)	Energy-efficient CRN optimization .	Improved energy efficiency and overall network performance.

Table 3: Performance Improvements Achieved by Using SI for Energy Detection

Other SI techniques are also implemented for optimization of different factors than spectrum sensing, like resource searching and allocation process in CRN and 5G-SON . In , sharing spectrum in CRNs using Improved ABC with fuzzy logic has been experimented, the proposed strategy improved the convergence speed and secondary user throughput but lack the optimization of the sensing process. Similarly, ML and Intelligent decision-making techniques have been used by the authors of for spectrum sensing in 5G and beyond, study has shown improvement in the performance, but EDM was not considered for the work. Reviews on using recent AI techniques and deep learning have been made in on spectrum sensing, the work also didn't mention the use of SI or meta-heuristic methods on the specific domain. The paper , discusses about the comparative analysis of conventional SS methods and AI-based methods, proving that AI-based methods are more accurate but lacks the comparison of other factors like probability of detection and false alarm detection rate.

Several other studies have explored optimization techniques for CRNs with varying objectives and limitations. A bio-inspired collaborative spectrum sensing and allocation approach utilizes swarm intelligence and game theory to ensure fair and efficient spectrum usage, although it suffers from high computational complexity and scalability issues. Similarly, a modified FFA-based joint spectrum and power allocation scheme enhances throughput while controlling interference, though at the cost of increased computational complexity. Hybrid approaches, such as the integration of ABC with FFA for spectrum handoff , improve channel switching efficiency but introduce implementation challenges due to their complexity. The hybrid PSO-GSA model improves energy-efficient spectrum sensing and transmission power, yet its evaluation is limited to comparisons with only a few existing algorithms. In this paper, authors introduced an efficient joint spectrum and power allocation in cognitive radio networks using a modified firefly algorithm. The model used to maximize the throughput of secondary users while ensuring that the interference to primary users remains below a certain threshold, the technique faced congestion due to overhead, and performance was slow. Another hybrid model combining Firefly Optimization with Double Q-learning

enhances energy efficiency and network capacity, although it lacks comprehensive benchmarking beyond Ant Colony Optimization. An improved FFA-based cooperative resource allocation method achieves better convergence time compared to several algorithms but focuses solely on convergence without addressing latency in advanced networks. The dragonfly optimization-based adaptive threshold model dynamically adjusts sensing thresholds based on channel conditions; however, it lacks comparison with other adaptive techniques. A Real-Coded Firefly Algorithm-based cognitive radio engine improves spectrum allocation efficiency while maintaining QoS yet does not compare with non-optimization-based systems. Furthermore, a Differential Evolution-based method for detecting PUE attacks effectively identifies malicious users but raises concerns regarding its applicability to other attack types. More recently, a hybrid approach combining firefly, genetic, and ant colony optimization techniques for TV white space networks achieves improved spectrum utilization and reduced interference, though at the expense of increased computational complexity and scalability challenges.

Authors in explained the division of SI algorithms into two different areas, local searching area and the global searching area, and ABC and FFA are among the most widely used SI techniques and are famous for their local searching expertise. Motivated by these advantages, the present work investigates the ABC and Firefly Algorithm FFA for threshold optimization in Energy Detection-based spectrum sensing. Existing ABC-based spectrum sensing studies have primarily focused on improving convergence speed, energy efficiency and computational performance. Comparatively limited attention has been given to enhancing the detection performance of EDMs, particularly in terms of probability of detection and adaptive threshold optimization. The Firefly Algorithm has also received very limited attention for Energy Detection-based spectrum sensing specifically. Owing to their strong local search capability and attraction-based optimization mechanism, ABC and FFA are investigated as an alternative threshold optimization technique for spectrum sensing using EDM in CRN.

III. Working of ABC and FFA for Spectrum Sensing

The SI algorithms with respect to speed and latency handling in modern communication networks, can be quite effective because these algorithms involve many agents that can often parallelize well, allowing them to be run on multiple processors or even distributed across multiple computers. This can result in significant speed improvements over traditional optimization algorithms. However, the latency of SI algorithms can be more challenging to control . Because these algorithms involve many agents that interact with each other and with their environment, there can be significant communication overhead between agents. This can lead to increased latency and slower convergence times, especially in large-scale problems. To address this issue, researchers have developed several strategies for improving the speed and latency of SI algorithms. For example, some algorithms use heuristics to reduce the communication overhead

between agents, while others use adaptive algorithms that dynamically adjust the number of agents based on the problem size and complexity. While swarm intelligence algorithms can be effective for optimizing complex problems, their speed and latency characteristics depend heavily on the specific algorithm and problem being considered. As with any optimization algorithm, it is important to carefully consider the trade-offs between speed and scalability when selecting a swarm intelligence algorithm for a particular application .

A. Firefly Algorithm for Spectrum Sensing in CRN

The firefly algorithm is a metaheuristic algorithm that works based on the flashing behaviour of fireflies. Where each firefly represents a potential solution to the problem, and the intensity of light emitting by the fireflies represents the ranking of solutions towards the best solution . Fig. 3 shows the convergence mechanism of FFA to the most attractive one. This is the most important factor to observe that how fast a swarm converges towards the best solution.

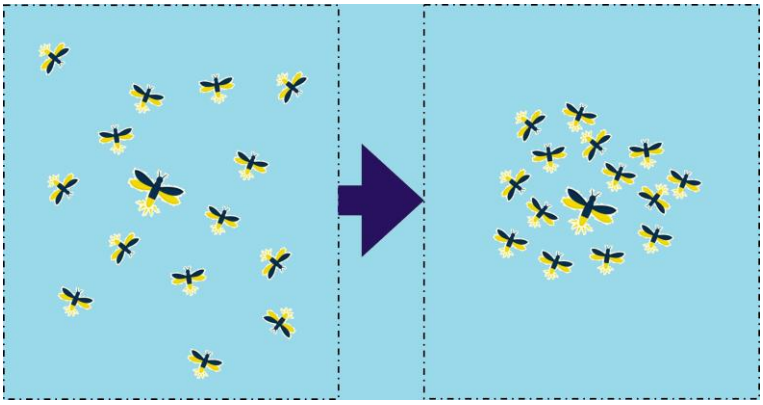


Fig. 3: Convergence of Fireflies towards the Brightest Firefly

The spectrum sensing process begins when FC sends out a firefly to the cognitive radio environment in its local region. This firefly acts as an agent and senses the presence of signals over the spectrum bands using EDM as objective function and report its findings back to the FC. The FC collects these reports to analyze the data and decide about the availability of bands in a particular region. There is a population of fireflies, each of which represents a potential solution to the objective function for finding available spectrum . The algorithm then iteratively updates the positions of these fireflies based on their attractiveness to the brighter fireflies in the population. In the case of spectrum sensing, the attractiveness of a firefly is measured by the level of probability gathered through EDM. The higher the probability, higher would be the attractiveness of the agent firefly, sensing the spectrum. Fireflies with the best data are considered the brightest, and they will attract other fireflies towards them. Once all the

fireflies converge, the FC will determine the availability of spectrum in that region. FC then communicates with other FC to exchange information about their respective regions. In this way, the FFA helps to optimize the spectrum sensing process in CRN allowing the algorithm to identify and utilize available white spaces of the radio spectrum. Implementation of the Firefly Algorithm for spectrum sensing using EDM in CRN could be seen in Fig. 4.

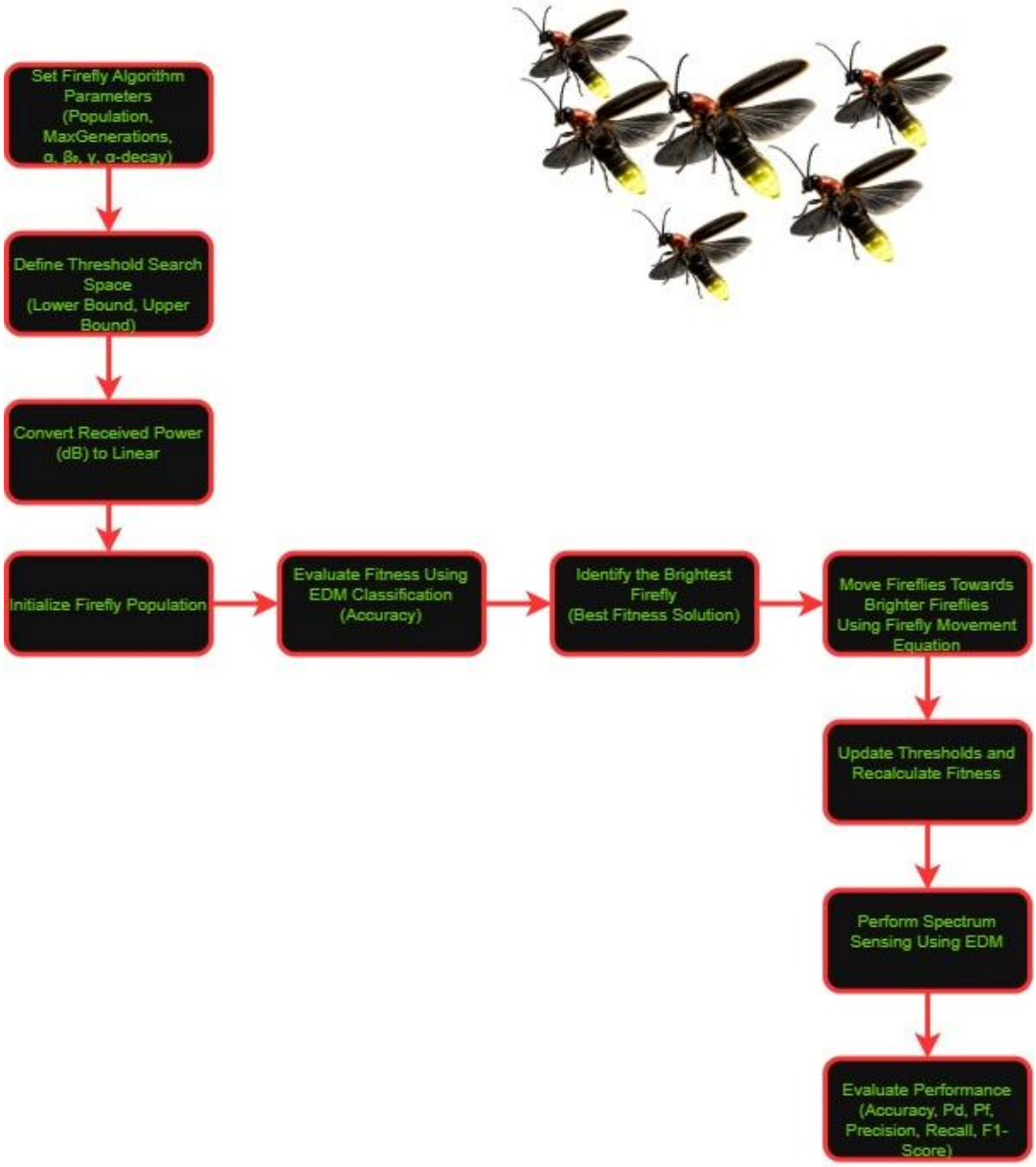


Fig. 4: Workflow of FFA for Spectrum Sensing in CRN

B. Artificial Bee Colony Algorithm for Spectrum Sensing in CRN

ABC is a metaheuristic SI technique inspired by the foraging behaviour of honeybees. It consists of three types of bees: employed bees, onlooker bees, and scout bees, where each type performs a specific role in searching for the optimal solution [8]. In the context of spectrum sensing in CRNs, the ABC algorithm is employed to optimize the detection threshold of the EDM, which serves as the objective function. Fig. 5 shows the working environment of the ABC algorithm for convergence towards best solution.

To evaluate the effect of the swarm population on spectrum sensing performance, three experimental settings were considered with colony sizes of 20, 30, and 50 bees, while maintaining a fixed maximum of 50 iterations. Each bee represents a candidate detection threshold within the search space defined by the minimum and maximum linear power values of the CASS spectrum dataset. The fitness of each candidate solution was evaluated using the Composite Detection Fitness (CDF) of the EDM, searching time for optimal result to reduce latency and the average performance obtained from the three settings was used for the final comparative analysis.

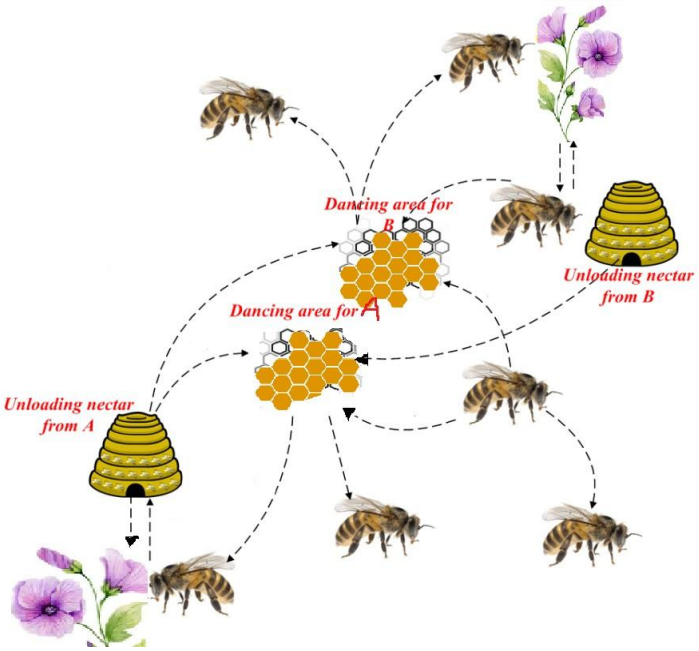


Fig. 5: Convergence of Bees towards the Most Attractive Bee

In Fig. 6 it is shown that the implementation of the ABC Algorithm for spectrum sensing using EDM in CRN could be broken down into mentioned steps.

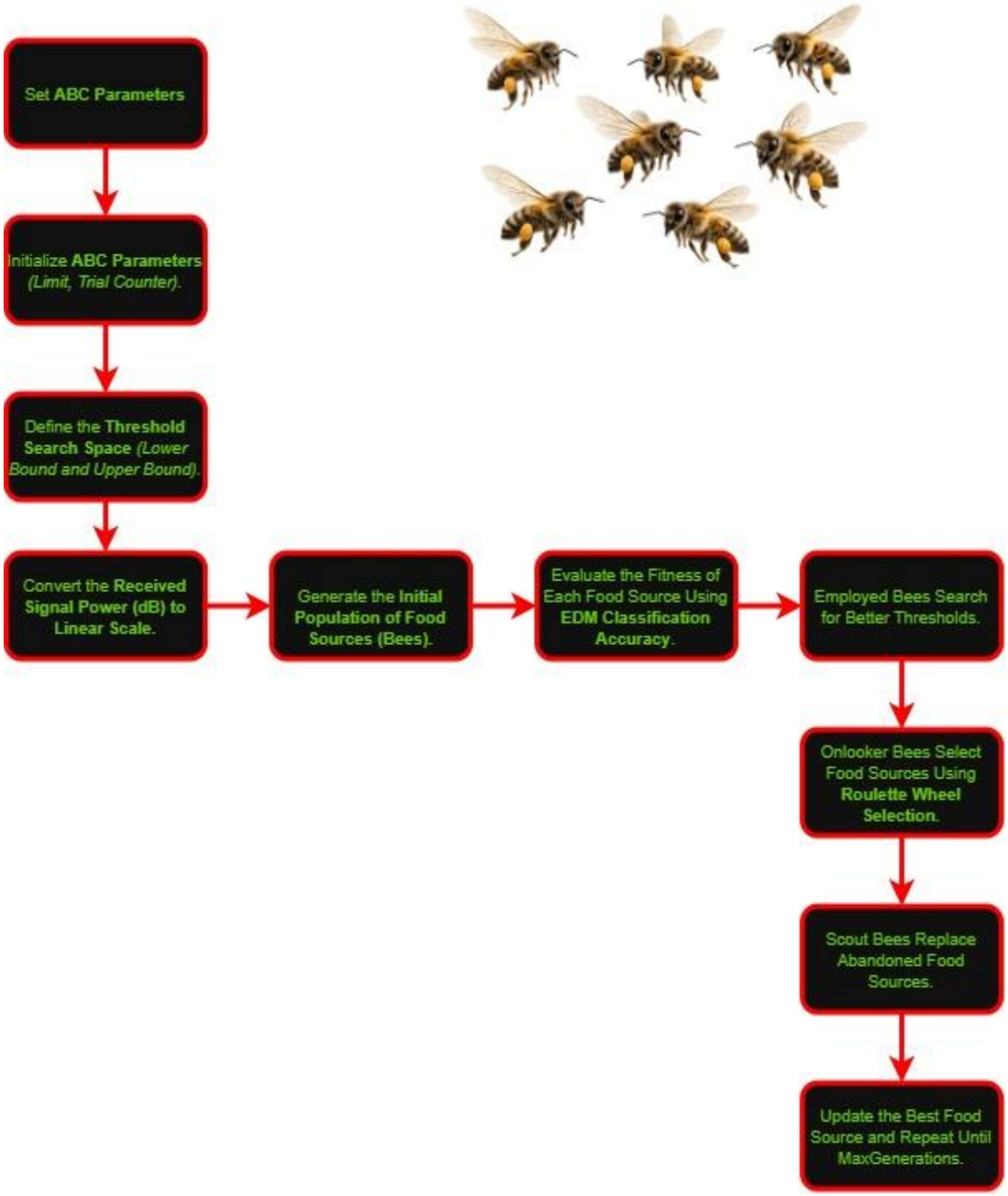


Fig. 6: Workflow of ABC for Spectrum Sensing in CRN

C. Comparing Performance of FFA and ABC Algorithm

To evaluate and compare the search time for latency reduction and overall performance improvement, both algorithms were executed for the population size representing the number of individual agents (Fireflies or Bees). Searching for the optimal detection threshold, where each agent corresponds to a potential solution. Increasing the population size allows a greater number of candidate solutions to be explored simultaneously, thereby improving the exploration capability of the search space. To investigate the influence of population size on optimization performance, three experimental settings were considered using 20, 30, and 50 agents, while keeping the maximum number of iterations fixed at 50. The average performance obtained from these three settings was used for the final comparison between the ABC-optimized EDM and FFA-optimized EDM.

IV. EXPERIMENTAL SETUP AND RESULTS

The execution of the experiments has been performed on the publicly available CASS Spectrum Dataset. The dataset has 31 features including: received signal power (power_dB), the status of primary user presence or absence (PU_Presence) labelled as '1' for present and '0' for absent. PU_signal_strength, Frequency_band, Freuqency_bin, spectral_entropy, dominant_frequency, phase_stability, confidence and so on. Both the SI algorithms were executed to optimize the energy detection threshold considering Energy Detection Method as an objective function of the swarms. Different optimization parameter settings were evaluated to perform the experiments. The objective function was based on detection probability (Pd), false alarm probability (Pf) and execution times. The most relevant features are power_dB and PU_presence status. Firstly, to detect the energy of a signal applying EDM, power was converted from dB to linear power. Using the following formula in Eq.1.

$$P = 10^{Power\ dB/10} \qquad Eq.1$$

Where,

P is the received signal power in linear scale and Power dB is the power of received signal in dB. EDM was applied on the dataset to calculate the decision variable that is initial detection threshold. Using Eq.2:

$$\lambda 0 = \mu(P) + k\sigma(P) \qquad Eq.2$$

Where,

$\lambda 0$ is the initial threshold, $\mu(P)$ is the mean of the received linear power, $\sigma(P)$ is the standard deviation and k is the scaling constant which can be 0.5, 1, 1.5 or 2. For

experimenting, here k is taken as 1, as it provides a balanced initial threshold value. After the calculation of the threshold value, probability of detection and probability of false alarm is derived. The probability of detecting the presence of a Primary User is calculated by Eq.3:

$$P_d = \frac{TP}{TP+FN} \qquad Eq.3$$

Where,
TP is the number of true detected PU and FN is the number of false PU detection.

The probability of false declaration of a PU is present when the channel is idle, it is calculated by Eq.4:

$$P_f = \frac{FP}{FP+TN} \qquad Eq.4$$

Where,
FP is the number of false alarms and TN is the number of correctly identified idle channels. The workflow of the proposed methodology can be seen in Fig. 7.

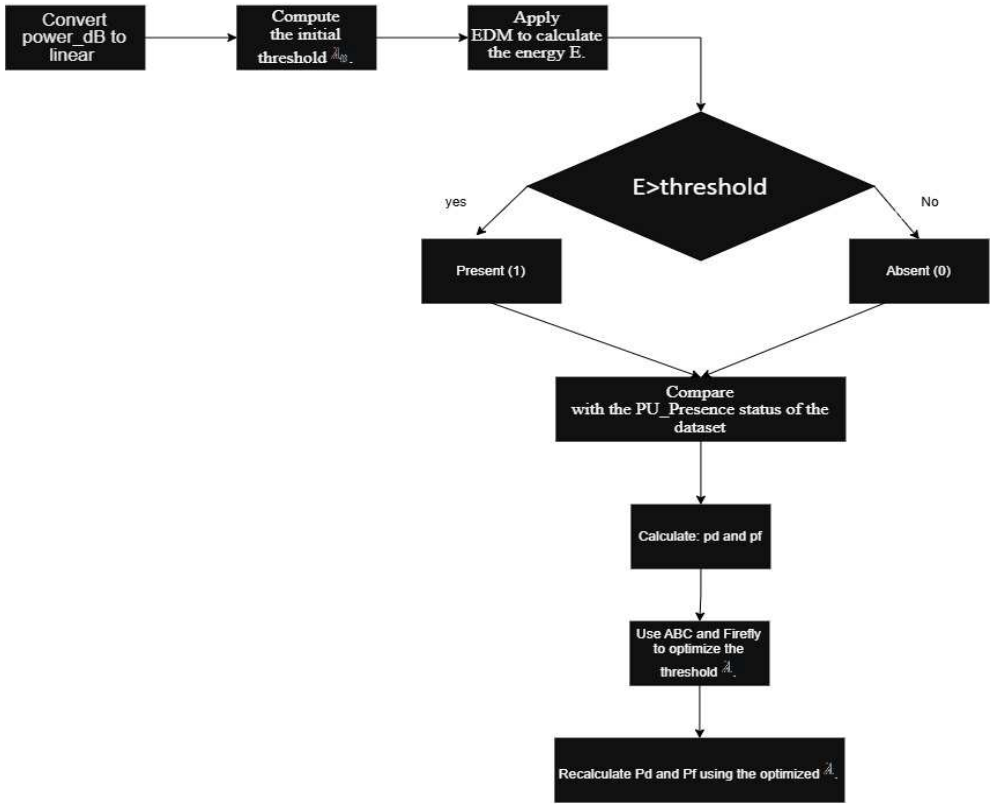


Fig. 7: Workflow of Proposed Methodology

Step 1: Data preprocessing
The CASS spectrum dataset was loaded in python environment and pre-processed using Pandas for subsequent analysis.

Step 2: Feature Selection
Only the required features for the calculation of EDM, were selected at this stage. Like, power_dB and PU_Presence. Remaining features will be used for further model analysis.

Step 3: Power Conversion
Energy Detection operates in linear energy, not in dB. Power values were converted using the formula mentioned in Eq.1.

Step 4: Initial Threshold
Baseline threshold was calculated using Eq.2.

Step 5: Dataset statistics
Signal distribution was performed to understand the search space for the bees and fireflies using the prebuilt min, max, mean and standard deviation functions in python.

Statistic	Value
Minimum Power	1.054×10^{-9}
Maximum Power	9.968×10^{-5}
Mean Power	8.908×10^{-6}
Standard Deviation	1.928×10^{-5}

Table 4: Signal Distribution

This analysis identified the search space within which the optimal threshold could be determined that the threshold values can exist in this range, calculated in Table 4.

A. Conventional EDM calculation
EDM is the classical method Eq.5 used to detect the presence of a signal in CRNs. For every received signal,

If
$$P_{linear} \geq \lambda \qquad Eq.5$$

PU is detected. Otherwise, No PU is detected.

The detection process is based on the following binary hypothesis model:

H0: Primary User is absent
H1: Primary User is present

The decision rule is expressed as

$$\text{If } \mathbf{P_{linear}} \geq \boldsymbol{\lambda}, \text{ then } \hat{\mathbf{H}} = \mathbf{H_1} \text{ (Primary User is present).}$$
$$\text{If } \mathbf{P_{linear}} < \boldsymbol{\lambda}, \text{ then } \hat{\mathbf{H}} = \mathbf{H_0} \text{ (Primary User is absent).}$$

where:

- $P_{\text{linear}}$is the received signal power in the linear domain.
- $\lambda$is the detection threshold.
- H_0denotes the absence of the Primary User.
- H_1denotes the presence of the Primary User.

In the CASS spectrum dataset, the performance of signal occupancy using conventional EDM and the ground truth labels was evaluated using confusion matrix. The confusion matrix consists of the following for outcomes, Table 5:

TP	True Positives	The Primary User (PU) is present, and the detector correctly identifies the channel as occupied.
FP	False Positives	The Primary User is absent, but the detector incorrectly declares the channel as occupied. This event is referred to as a false alarm.
TN	True Negatives	The Primary User is absent, and the detector correctly identifies the channel as idle
FN	False Negatives	The Primary User is present, but the detector fails to detect it and incorrectly declares the channel as idle. This event is referred to as a missed detection.

Table 5: Confusion Matrix Parameters

	Actual PU Present	**Actual PU Absent**
Predicted PU Present	TP = 117	FP = 102
Predicted PU Absent	FN = 393	TN = 388

Fig. 8: Confusion Matrix of EDM

The Probability of Detection (P_d) and Probability of False Alarm (P_f) were computed and compared to quantitatively assess the detector's performance from this confusion matrix (Fig. 8) using the formula mentioned in Eq.3 and Eq.4.

The performance of conventional EDM for the detection of signal's energy shows inefficient results using a fixed threshold derived from the mean linear power of the received signals is achieved by using this method. Although the detector demonstrated moderate the Pd was only 22.94%, indicating that a significant proportion of primary user transmissions remained undetected. Furthermore, the Pf of 20.82% suggests that the fixed threshold was unable to reliably distinguish between occupied and white spaces. These findings highlight the limitations of a static threshold under varying spectrum environments and motivate the use of intelligent optimization techniques to determine an adaptive detection threshold.

B. Proposed ABC-Based Energy Detection

ABC algorithm is employed to optimize the threshold of the conventional EDM. Instead of using a fixed threshold, the ABC algorithm searches for an optimal threshold that maximizes the detection performance while minimizing false alarms.

To investigate the effect of the optimization parameters on the performance of the ABC algorithm, three experimental settings with different colony sizes were considered. These settings were selected to evaluate the robustness of the optimization process under varying search efforts while maintaining the same objective function and dataset. Table 4 summarizes the parameter configurations used in this study.

The optimization process consists of the following sequential stages.

Step 1: Initialization of Bee Population

A population of artificial bees was independently executed for each parameter setting of 20, 30 and 50 colony size. Each bee represents a candidate energy detection threshold (λ) within the minimum and maximum linear power values obtained from the dataset.

Step 2: Fitness Evaluation

The fitness of each bee is evaluated by applying the corresponding threshold to the EDM. The predicted spectrum occupancy is compared with the ground truth labels, and the CDF is used as the fitness value, Eq.6.

$$CDF = F1 \times (1 - Pf) \qquad Eq.6$$

Step 3: Selection of the Best Threshold

The threshold corresponding to the highest fitness value is identified using argmax function, as the current best solution and is preserved for subsequent optimization.

Step 4: Employed Bee Phase
In this phase, for each bee:

1. *Take its current threshold.*
2. *Generate a neighbouring threshold.*
3. *Evaluate the new threshold.*
4. *If the new threshold has better fitness, replace the old threshold.*
5. *Otherwise, keep the original threshold.*

The neighbouring threshold is generated using the standard ABC, Eq.7.

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \qquad Eq.7$$

where:

- x_{ij}= current threshold of bee i
- x_{kj}= threshold of a randomly selected bee k
- ϕ_{ij}= random number in $[-, 11]$
- v_{ij}= new candidate threshold

If the new threshold produces a higher fitness, it replaces the old threshold; otherwise, the original threshold is retained. This greedy selection mechanism allows employed bees to progressively improve candidate solutions while maintaining valid thresholds within the predefined search space. After employed bee phase, the best bees are selected.

Step 5: Onlooker Bee Phase

1. Calculate the probability of selecting each bee based on its fitness.
2. Bees with higher fitness have a higher probability of being selected.
3. Each onlooker bee selects a food source (threshold).
4. It generates a neighbouring threshold.
5. If the new threshold is better, it replaces the old threshold.

The onlooker bees do not search randomly. Instead, they preferentially choose bees with higher fitness using roulette-wheel selection, where the probability of selecting bee i is done, Eq.8.

$$P_i = \frac{Fitness_i}{\sum_{j=1}^{N} Fitness_j} \qquad Eq.8$$

Step 6: Scout Bee Phase
If a threshold fails to improve after a predefined number of iterations, the corresponding bee is converted into a scout bee. The scout abandons the stagnated solution and randomly generates a new threshold within the search space to maintain population diversity.

Step 7: Iterative Optimization
The employed bee, onlooker bee, and scout bee phases are repeated for a fixed number of 50 iterations until the stopping criterion is satisfied or the maximum number of iterations is reached.

Step 8: Determination of the Optimal Threshold
Upon completion of the optimization process, the threshold associated with the highest fitness value is selected as the optimal detection threshold.

Step 9: Performance Evaluation
The optimized threshold is applied to the conventional Energy Detection Method. A confusion matrix is generated, and the evaluation metrics, including Probability of Detection (P_d) and Probability of False Alarm (P_f) are computed. These results are subsequently compared with those obtained using the conventional EDM to quantify the improvement achieved through ABC optimization. Confusion matrix in Fig. 9, Fig. 10 and Fig. 11 is showing the results of actual and predicted values using ABC.

The ABC algorithm was initialized with a randomly generated bee population within the search space defined by the minimum and maximum linear power values of the CASS spectrum dataset. To evaluate the effect of colony size on optimization performance, three experimental settings with different colony sizes (20, 30, and 50 bees) were considered while keeping the maximum number of iterations fixed at 50. Each bee represented a candidate detection threshold, and its fitness was evaluated using the fitness (CDF) of the EDM. The parameter settings used in this study are summarized in Table 6.

Setting	**Colony Size**	**Maximum Iterations**
S1	20	50
S2	30	
S3	50	

Table 6: ABC Parameter Settings

S1, Bees = 20:

Method	Probability of Detection (Pd)	Probability of False Alarm (Pf)	Optimization Time (sec)
ABC (S1)	26.47%	22.86%	5.61

Table 7: Performance Evaluation of ABC, S1

	Actual PU Present	Actual PU Absent
Predicted PU Present	TP = 135	FP = 112
Predicted PU Absent	FN = 135	TN = 378

Fig. 9: Confusion Matrix of ABC on S1

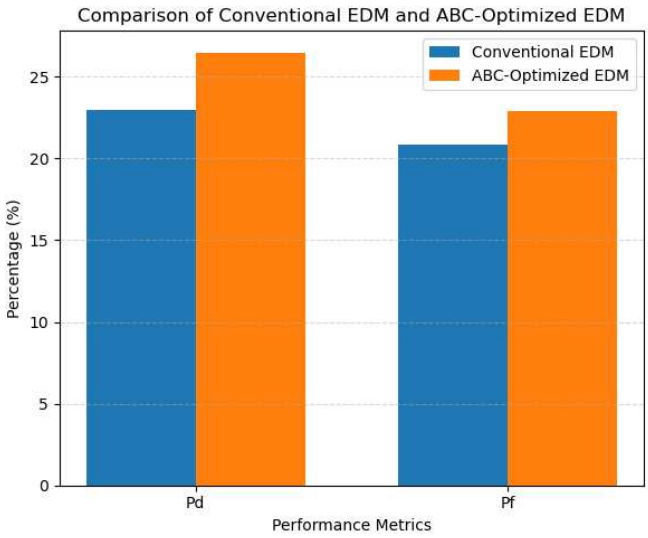


Fig. 10: Comparison of Conventional EDM and ABC-based Method, S1

S2, Bees = 30:

ethod	Probability of Detection (Pd)	Probability of False Alarm (Pf)	Optimization Time (sec)
ABC (S2)	58.04%	55.71%	8.44

Table 8: Performance Evaluation of ABC, S2

	Actual PU Present	Actual PU Absent
Predicted PU Present	TP = 424	FP = 391
Predicted PU Absent	FN = 86	TN = 99

Fig. 11: Confusion Matrix of ABC on S2

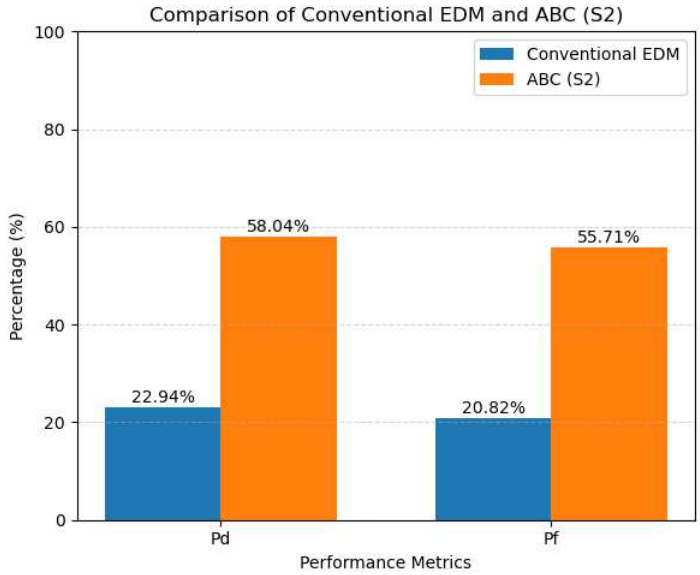


Fig. 12: Comparison of Conventional EDM and ABC-based Method, S2

S3, Bees = 50:

Method	Probability of Detection (Pd)	Probability of False Alarm (Pf)	Optimization Time (sec)
ABC (S3)	76.47%	72.04%	14.92

Table 9: Performance Evaluation of ABC, S3

	Actual PU Present	Actual PU Absent
Predicted PU Present	TP = 390	FP = 353
Predicted PU Absent	FN = 120	TN = 137

Fig. 13: Confusion Matrix of ABC on S3

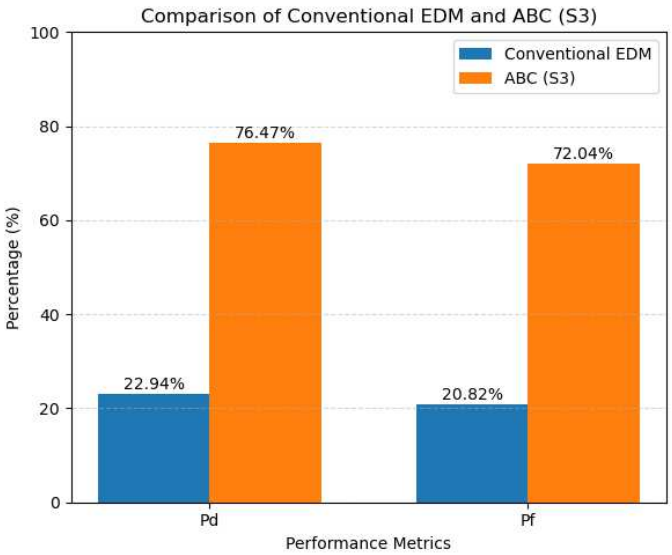


Fig. 14: Comparison of Conventional EDM and ABC-based Method, S3

Setting	Colony Size	Pd (%)	Pf (%)	Average Optimization Time (sec)
S1	20	26.47	22.86	10.06
S2	30	58.04	55.71	
S3	50	76.47	72.04	

Table 10: Performance Evaluation of ABC-based EDM with different parametric settings

The performance of the proposed ABC-based EDM was evaluated using the optimized threshold obtained after the iterative optimization process. The predicted spectrum occupancy was compared with the ground-truth labels contained in the CASS spectrum dataset.

Based on the confusion matrix, Pf and Pd were computed in Table 7, Table 8 and Table 9 to assess the effectiveness of the proposed detector.

The performance obtained using the optimized threshold is subsequently compared with the conventional EDM to quantify the improvement achieved through ABC optimization. After completing the optimization process, the best threshold identified by the bee colony was applied to classify the spectrum occupancy of the CASS dataset.

The ABC-optimized EDM achieved an improvement in spectrum sensing performance across all three experimental settings. Increasing the colony size from 20 to 50 bees resulted in only a marginal improvement in the overall fitness value. However, the probability of detection increased with larger colony sizes, indicating enhanced sensitivity in detecting occupied spectrum. This improvement was accompanied by an increase in the probability of false alarm, demonstrating the trade-off between detection capability and false alarm performance. Overall results indicate that increasing the colony size substantially affecting the detection and false alarm characteristics. Therefore, the average performance obtained from the three experimental settings was considered for the final comparison with the conventional EDM and the Firefly Algorithm.

Although the observed improvements are modest, the results demonstrate that the ABC algorithm can effectively optimize the decision threshold without altering the underlying EDM. The optimization process provides a data-driven threshold selection strategy instead of relying on a fixed mean-energy threshold. This optimized threshold serves as a stronger baseline for comparison with other swarm intelligence algorithms, that is FFA, which will be evaluated using the same experimental setup to determine the most effective optimization technique for spectrum sensing in cognitive radio networks.

Performance Metric	**Conventional EDM**	**ABC-Optimized EDM (Average)**	**Improvement**
Probability of Detection (Pd)	22.94%	53.66%	+30.72%
Probability of False Alarm (Pf)	20.82%	50.20%	+29.38%

Table 11: Comparison of EDM with ABC (Average)

This comparison in Table 11, clearly shows that increasing the colony size substantially improves Pd, but also significantly increases the False Alarm Rate (Pf).

C. Proposed FFA-Based Energy Detection

FFA is employed to optimize the decision threshold of the conventional EDM. Unlike the fixed threshold used in the conventional approach, the Firefly Algorithm iteratively searches for the optimal threshold by exploiting the attraction behaviour among fireflies. Like ABC, each firefly represents a candidate energy detection threshold, and its brightness corresponds to the fitness of that threshold. Fireflies with lower brightness move toward brighter fireflies, allowing the algorithm to converge toward an optimal threshold that improves spectrum sensing performance. The optimization process consists of the following sequential stages.

Step 1: Initialization of Firefly Population

A population of fireflies is randomly generated within the search space bounded by the minimum and maximum linear power values of the CASS spectrum dataset. Each firefly represents a candidate decision threshold.

Step 2: Fitness Evaluation

Each firefly's threshold is applied to the EDM. The resulting predictions are compared with the ground-truth labels, and the corresponding fitness (brightness) value is computed for each firefly.

Step 3: Identification of the Brightest Firefly

The firefly with the highest fitness value is identified as the brightest firefly and represents the current best threshold solution.

Step 4: Firefly Movement

Each firefly is attracted toward brighter fireflies according to the Firefly Algorithm movement rule. The movement is influenced by the attractiveness between fireflies, the Euclidean distance separating them, and a random exploration component.

The position (threshold) of each firefly is updated using Eq.9:

$$x_i^{new} = x_i + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j - x_i\right) + \alpha(rand - 0.5) \qquad Eq.9$$

where:

- x_i= current threshold of firefly i
- x_j= threshold of a brighter firefly j
- β_0= initial attractiveness
- γ= light absorption coefficient

- r_{ij}= Euclidean distance between fireflies
- α= randomization parameter
- rand = random number in $[0, 1]$

Step 5: Brightness Update
After movement, each new threshold is evaluated using the EDM. If the updated threshold produces a higher fitness value, the firefly's brightness is increased accordingly.

Step 6: Iterative Optimization
The movement and brightness update processes are repeated for a predefined number of generations until the stopping criterion is satisfied or the maximum number of iterations is reached.

Step 7: Determination of the Optimal Threshold
After the final iteration, the threshold associated with the brightest firefly is selected as the optimal decision threshold. After completing the iterative optimization process, the firefly with the highest fitness value is identified as the optimal firefly. The threshold associated with this firefly is selected as the optimal decision threshold for EDM.

Step 8: Performance Evaluation
The optimized threshold is applied to the EDM to classify spectrum occupancy. Confusion matrix can be seen in Fig. 15, Fig. 17 and Fig. 19 and the performance metrics including P_d and P_f are calculated in Table 12, Table 13 and Table 14. Graphs can be seen in Fig. 16, Fig. 18 and Fig. 20. These results are then compared with those obtained using the conventional EDM and ABC-optimized EDM.

S1, Fireflies = 20:

Method	**Probability of Detection (Pd)**	**Probability of False Alarm (Pf)**	**Optimization Time (sec)**
FFA (S1)	70.00%	65.92%	5.77

Table 12: Performance Evaluation of FFA, S1

	Actual PU Present	Actual PU Absent
Predicted PU Present	TP = 357	FP = 153
Predicted PU Absent	FN = 323	TN = 167

Fig. 15: Confusion Matrix of FFA, S1

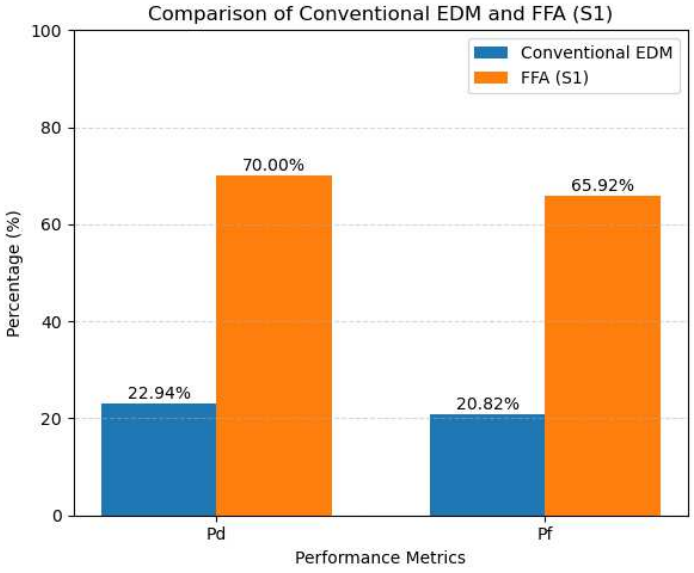


Fig. 16: Comparison of conventional EDM and FFA-based Method, S1

S2, Fireflies = 30:

Method	Probability of Detection (Pd)	Probability of False Alarm (Pf)	Optimization Time (sec)
FFA (S2)	57.20%	53.01%	7.78

Table 13: Performance Evaluation of FFA, S2

	Actual PU Present	Actual PU Absent
Predicted PU Present	TP = 378	FP = 112
Predicted PU Absent	FN = 375	TN = 135

Fig. 17: Confusion Matrix of FFA, S2

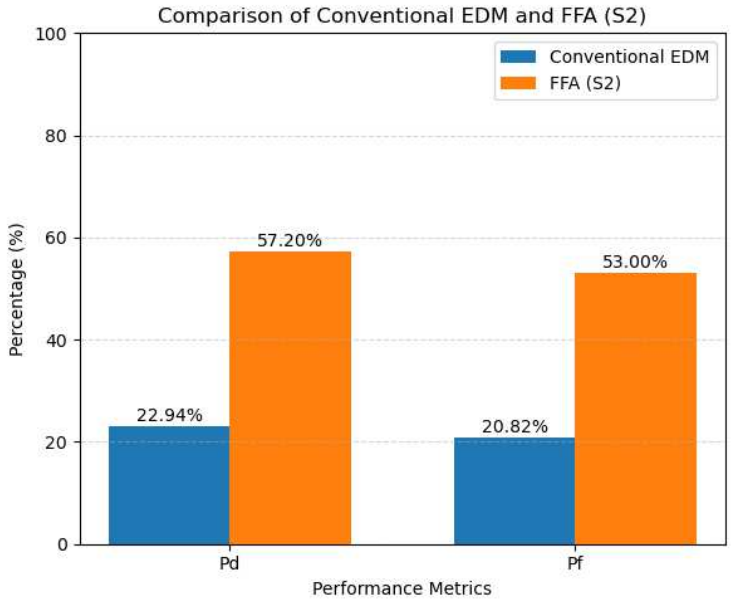


Fig. 18: Comparison of conventional EDM and FFA-based Method, S2

S3, fireflies = 50:

Method	Probability of Detection (Pd)	Probability of False Alarm (Pf)	Optimization Time (sec)
FFA (S3)	67.90%	64.69%	13.21

Table 14: Performance Evaluation of FFA, S3

	Actual PU Present	Actual PU Absent
Predicted PU Present	TP = 346	FP = 317
Predicted PU Absent	FN = 164	TN = 173

Fig. 19: Confusion Matrix of FFA, S3

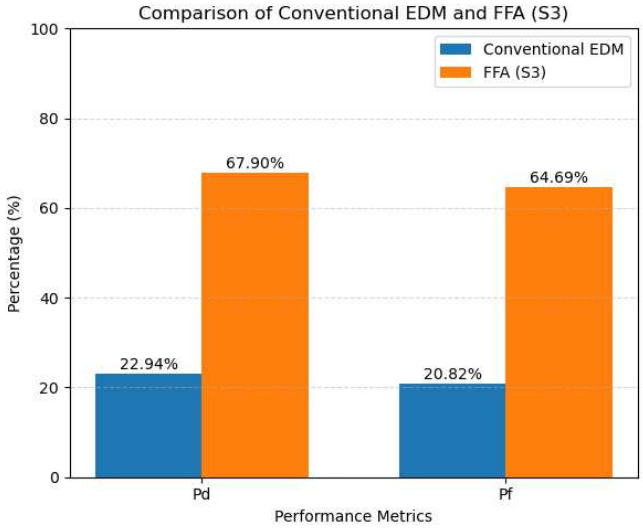


Fig. 20: Comparison of conventional EDM and FFA-based Method, S3

Setting	Colony Size	Pd (%)	Pf (%)	Optimization Time (sec)
S1	20	70.00	65.92	8.92
S2	30	57.20	53.01	
S3	50	67.90	64.69	

Table 15: Performance Evaluation of FFA-based EDM with different parametric settings

The FFA was initialized with a randomly generated population of fireflies within the search space defined by the minimum and maximum linear power values of the CASS spectrum dataset. To evaluate the effect of population size on optimization performance, three experimental settings like the ABC, with different firefly population sizes (20, 30, and 50 fireflies) were considered while keeping the maximum number of iterations fixed at 50. Each firefly represented a candidate detection threshold, and its brightness (fitness) was evaluated using the CFD of the EDM.

Metric	Conventional EDM	ABC-Optimized EDM (Average)	FFA-Optimized EDM (Average)
Probability of Detection (Pd)	22.94	53.66	65.03
Probability of False Alarm (Pf)	20.82	50.20	61.20
Average Optimization Time (sec)	--	10.06	8.92

Table 16: Comparative Performance Evaluation of Conventional EDM, ABC-Optimized EDM, and FFA-Optimized EDM

The average results presented in Table 16 demonstrate that both SI-based optimization techniques outperform the conventional EDM in terms of overall spectrum sensing performance. The FFA exhibited a slightly higher probability of detection, whereas the ABC maintained a marginally lower probability of false alarm, providing a comparatively balanced trade-off between detection capability and false alarm performance. These findings indicate the effectiveness of SI for adaptive threshold optimization in CRNs.

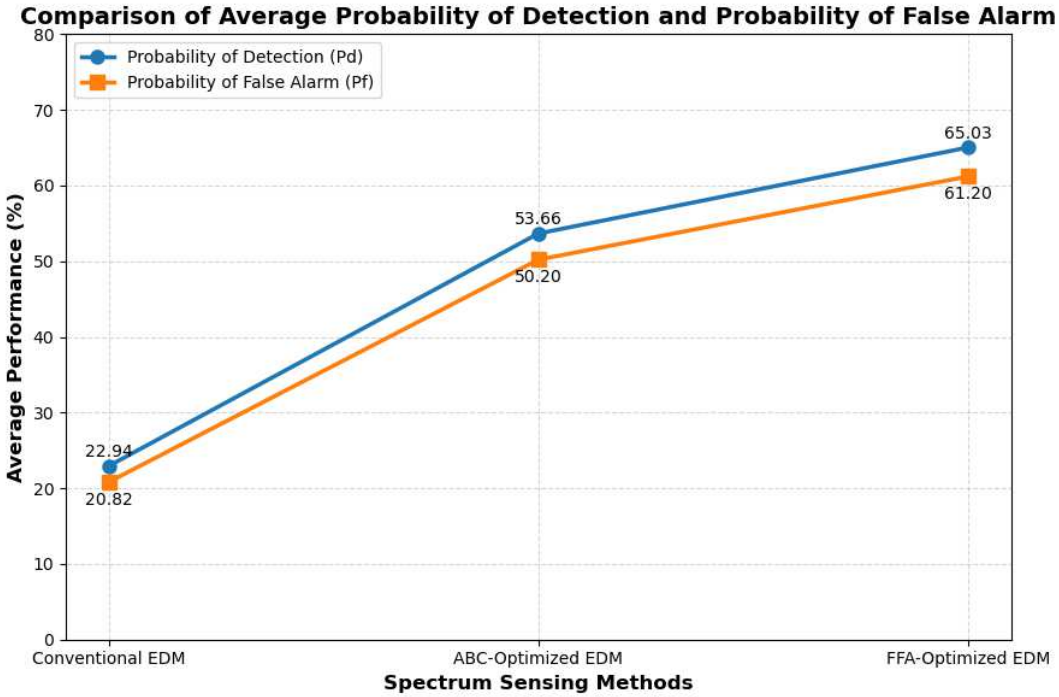


Fig. 21: Comparison of the average Pd and Pf) achieved by Conventional EDM, ABC-Optimized EDM, and FFA-Optimized EDM.

Fig. 22 compares and displays the average performance of the conventional method with the ABC-optimized and FFA-optimized EDM across all evaluation metrics. And the significant improvement is evident.

V. CONCLUSION

This paper presented the implementation of Swarm Intelligence (SI) techniques for threshold optimization in a Cognitive Radio Network (CRN) environment with multiple Fusion Centers (MFCs). The Artificial Bee Colony (ABC) and Firefly Algorithm (FFA) were employed as optimization techniques, while the conventional Energy Detection Method (EDM) was used as the objective function for spectrum sensing. The optimized thresholds obtained from both algorithms were utilized to determine the presence or absence of primary users on the spectrum and were compared with the conventional EDM.

To evaluate the performance of both algorithms, three different parameter settings consisting of 20, 30, and 50 agents, each with a fixed maximum of 50 iterations, were investigated. The average results obtained from these settings were used for comparative evaluation. The experimental results showed that the conventional EDM achieved a probability of detection (Pd) of 22.94%, whereas the ABC-optimized EDM and FFA-optimized EDM improved the Pd to 53.66% and 65.03%, respectively. Although both optimization techniques resulted in a higher probability of false alarm than the conventional EDM, the ABC algorithm maintained a comparatively lower false alarm rate than the FFA, providing a better trade-off between detection capability and false alarm performance. And the FFA achieved a slightly lower average optimization time than the ABC algorithm. The findings demonstrate that Swarm Intelligence-based threshold optimization can effectively enhance spectrum sensing in Cognitive Radio Networks by improving detection performance while maintaining acceptable false alarm characteristics. Furthermore, increasing the swarm population from 20 to 50 agents resulted in only marginal performance improvements, indicating that smaller swarm sizes can achieve comparable detection performance with lower computational overhead. Future work may investigate hybrid Swarm Intelligence approaches, adaptive optimization strategies, and Machine Learning-based techniques to further improve the efficiency, robustness, and adaptability of spectrum sensing for next-generation wireless communication networks.

Declarations

Author contributions

S.S.Z wrote the manuscript, prepared the figures and performed the experiments.
S.M.N.M contributed to writing Introduction and Literature part and formatted the final draft.
M.A supervised the idea and contributed to writing the overall manuscript.
All the authors reviewed the manuscript.

Data availability

Publicly available in a repository:
CASS data is deposited into the Kaggle database and is available at the following URL: https://www.kaggle.com/datasets/ajithdari/cass-spectrum-dataset

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Ethics, Consent to Participate, and Consent to Publish declarations: not applicable.

References

[1] S. S. Zehra, M. Magarini, R. Qureshi, S. M. N. Mustafa and F. Farooq, "Proactive approach for preamble detection in 5g-nr prach using supervised machine learning and ensemble model," *Scientific reports,* 2022.

[2] M. R. Valanarasu and A. Christy, "Comprehensive survey of wireless cognitive and 5G networks," *Journal of Ubiquitous Computing and Communication Technologies (UCCT),* 2019.

[3] W. S. H. M. W. Ahmad, N. A. M. Radzi and F. Samidi, "5G technology: Towards dynamic spectrum sharing using cognitive radio networks," *IEEE access,* 2020.

[4] B. Kathiriya and D. Keraliya, "OPTIMIZATION-BASED SPECTRUM SENSING IN CRN FOR EFFECTIVE UTILIZATION OF AVAILABLE CHANNEL," *International Journal on "Technical and Physical Problems of Engineering"(IJTPE),* 2020.

[5] K. B. Letaief and W. Zhang, "Cooperative communications for cognitive radio networks," *Proceedings of the IEEE,* 2009.

[6] A. Kumar, S. Pandit, P. Thakur and G. Singh, "Optimization of fusion center parameters with threshold selection in multiple antenna and censoring-based cognitive radio network," *IEEE Sensors Journal,* 2022.

[7] A. Sufyan, K. B. Khan, O. A. Khashan, T. Mir and U. Mir, "From 5G to beyond 5G: A comprehensive survey of wireless network evolution, challenges, and promising technologies," *Electronics,* 2023.

[8] P. a. S. T. a. K. M. a. N. A. Chithaluru, "An enhanced energy-efficient fuzzy-based cognitive radio scheme for IoT," *Neural Computing and Applications,* 2022.

[9] J. Lorincz, I. Ramljak and D. Begu, "A survey on the energy detection of OFDM signals with dynamic threshold adaptation: Open Issues and Future Challenges," *Sensors,* 2021.

[10] Y. Arjoune, Z. El Mrabet, H. El Ghazi and A. Tamtaoui, "Spectrum sensing: Enhanced energy detection technique based on noise measurement," in *2018 IEEE 8th annual computing and communication workshop and conference (CCWC)*, 2018.

[11] J. Talukdar, B. Mehta, K. Aggrawal and M. Kamani, "Implementation of SNR estimation based Energy Detection on USRP and GNU Radio for Cognitive Radio Networks," in *017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, 2017.

[12] M. Falco, A. Pagano and D. Croce, "AI-driven spectrum sensing: An in-depth meta-analysis of trends, challenges and opportunities," *Computer Networks,* 2025.

[13] M. T. Ahmed, M. Haque, Y. Sugiura and T. Shimamura, "Machine learning approach to energy detection based spectrum sensing for cognitive radio networks," *IEEJ Transactions on Electrical and Electronic Engineering,* 2025.

[14] A. Mehrabian, M. Sabbaghian and H. Yanikomeroglu, "RL-based hyperparameter selection for spectrum sensing with CNNs," *IEEE Transactions on Communications,* 2024.

[15] C. Chen, P. Zhang, H. Zhang, J. Dai, Y. Yi, H. Zhang and Y. Zhang, "Deep learning on computational-resource-limited platforms: A survey," *Mobile Information Systems,* 2020.

[16] A. Benmachiche, M. Derdour, M. S. Kahil, M. C. Ghanem and M. Deriche, "Adaptive hybrid PSO--APF algorithm for advanced path planning in next-generation autonomous robots," *Sensors,* 2025.

[17] F. Mohammed and M. Deriche, "A two-threshold cooperative spectrum sensing algorithm using swarm intelligence," *2013 Computing, Communications and IT Applications Conference (ComComAp),* 2013.

[18] R. A. Rashid, A. H. F. B. A. Hamid, N. Fisal, S. K. Syed-Yusof, H. Hosseini, A. Lo and A. Farzamnia, "Efficient in-band spectrum sensing using swarm intelligence for cognitive radio network," *Canadian Journal of Electrical and Computer Engineering,* 2015.

[19] G. Eappen and T. Shankar, "Energy efficient spectrum sensing for cognitive radio network using artificial bee colony algorithm," *Int J Eng Technol,* 2018.

[20] V. Srivastava and B. Prasad, "IRS assisted spectrum sensing in cognitive radio network with grey wolf optimization," *Physical Communication,* 2024.

[21] J. Ramkumar and R. Vadivel, "Whale optimization routing protocol for minimizing energy consumption in cognitive radio wireless sensor network," *network,* 2021.

[22] P. Mishra and N. Dewangan, "Survey on optimization methods for spectrum sensing in Cognitive radio network," *Int. J. New Technol. Res,* 2015.

[23] K. Sultan, "Efficient Spectrum Sharing in Cognitive Radio Networks With NOMA Using Computational Intelligence," *Applied Computational Intelligence and Soft Computing,* 2025.

[24] P. Pant and N. Srivastava, "AI-Enhanced Spectrum Sensing Cognitive Radio Networks: Revolutionizing 5G and Beyond," *IETE Journal of Research,* 2025.

[25] N. El-haryqy, Z. Madini and Y. Zouine, "A review of deep learning techniques for enhancing spectrum sensing and prediction in cognitive radio systems: approaches, datasets, and challenges," *International Journal of Computers and Applications,* 2024.

[26] N. El-haryqy, Z. Madini and Y. Zouine, "AI-Enhanced Spectrum Sensing Cognitive Radio Networks: Revolutionizing 5G and Beyond," *International Journal of Computers and Applications,* 2024.

[27] F. Azmat, Y. Chen and N. Stocks, "Bio-inspired collaborative spectrum sensing and allocation for cognitive radios," *Iet Communications,* 2015.

[28] A. Tounsi and M. Babes, "An efficient joint spectrum and power allocation in cognitive radio networks using a modified firefly algorithm," *International Journal of Communication Networks and Distributed Systems,* 2017.

[29] M. K. Devi and K. Umamaheswari, "Modified Artificial Bee Colony with firefly algorithm based spectrum handoff in cognitive radio network," *International Journal of Intelligent Networks,* 2020.

[30] G. Eappen and T. Shankar, "Hybrid PSO-GSA for energy efficient spectrum sensing in cognitive radio network," *Physical Communication,* 2020.

[31] J. Sharma, S. K. Patel and V. Patle, "Hybrid Firefly Optimization with Double Q-learning for Energy Enhancement in Cognitive Radio Networks".

[32] H.-x. Xing, H. Wu, Y. Chen and K. Wang, "A cooperative interference resource allocation method based on improved firefly algorithm," *Defence Technology,* 2021.

[33] S. Jothiraj, S. Balu and N. Rangaraj, "An efficient adaptive threshold-based dragonfly optimization model for cooperative spectrum sensing in cognitive radio networks," *International Journal of Communication Systems,* 2021.

[34] N. A. Saoucha, "Cognitive Radio Engine Based on Real-Coded Firefly Algorithm," in *2021 International Conference on Recent Advances in Mathematics and Informatics (ICRAMI)*, 2021.

[35] R. a. B. N. a. M. N. a. A. S. Batool, "Detection of primary user emulation attack using the differential evolution algorithm in cognitive radio networks," *Applied Sciences,* 2022.

[36] J. B. Mach, K. K. Ronoh and K. Langat, "Improved spectrum allocation scheme for TV white space networks using a hybrid of firefly, genetic, and ant colony optimization algorithms," *Heliyon,* 2023.

[37] S. S. Zehra, R. Qureshi, K. Dev, S. Shahid and N. A. Bhatti, "Comparative analysis of bio-inspired algorithms for underwater wireless sensor networks," *Wireless Personal Communications,* 2021.

[38] W. R. Ghanem, M. Shokair and M. I. Desouky, "An improved primary user emulation attack detection in cognitive radio networks based on firefly optimization algorithm," in *2016 33rd National Radio Science Conference (NRSC)*, 2016.

[39] G. Eappen and T. Shankar, "Hybrid PSO-GSA for energy efficient spectrum sensing in cognitive radio network," *Physical Communication,* 2020.

[40] N. A. Saoucha, K. Ghanem and B. Benmammar, "On applying firefly algorithm for cognitive radio networks," in *2014 IEEE 21st Symposium on Communications and Vehicular Technology in the Benelux (SCVT)*, 2014.