

Spectrum Efficient Cognitive Radio Sensor Network for IoT with Low Energy Consumption

Pravin Jaronde¹, Dr. Archana Vyas², Dr. Mahendra Gaikwad³

¹Department of Electronics and Telecommunication
G H Raisoni University
Amravati, India

Department of Information Technology
G H Raisoni College of Engineering
Nagpur, India
pravin.jaronde@raisoni.net

²Department of Electronics and Telecommunication
G H Raisoni University
Amravati, India
archana.vyas@ghru.edu.in

³Department of Information Technology
G H Raisoni College of Engineering
Nagpur, India
mahendra.gaikwad@raisoni.net

Abstract—Cognitive Radio Sensor Networks (CRSNs) have emerged as a promising solution for efficient utilization of the limited frequency spectrum. One of the key challenges in CRSNs is achieving spectrum efficiency by avoiding interference and maximizing the use of the available spectrum. Particle Swarm Optimization (PSO) techniques have been widely used to optimize the spectrum allocation and improve the spectrum efficiency of CRSNs. In this paper the study provides an overview of the research on spectrum efficiency in CRSNs using PSO techniques and also discussed the key parameters that affect the spectrum efficiency, such as the swarm size, sensor's threshold and maximum number of iterations and highlights the importance of identifying the optimal combination of these parameters. This paper also emphasizes the need for further research and development in this area to improve the efficiency and effectiveness of PSO-based optimization techniques for CRSNs and to adapt them to various real-world scenarios. Achieving spectrum efficiency in CRSNs is critical for enabling effective wireless communication systems and improving the overall utilization of the available frequency spectrum.

Keywords—Cognitive Radio Sensor Network; Particle Swarm Optimization; Frequency spectrum; Spectrum efficiency; Spectrum scarcity.

I. INTRODUCTION

All Cognitive Radio (CR) is an advanced wireless communication technology that enables intelligent and dynamic access to the radio frequency spectrum [3]. It utilizes cognitive capabilities, such as spectrum awareness, adaptive decision-making, and interference mitigation, to optimize spectrum utilization and improve overall communication efficiency. CR technology holds great potential for improving spectrum utilization and addressing the increasing demand for wireless communication services. By enabling dynamic access to underutilized spectrum, CRs can enhance network capacity, improve reliability, and foster innovation in wireless communication systems. Cognitive networks consist of two types of users: Primary Users (PU) and Secondary Users (SU). PUs are the licensed or authorized users of the spectrum. They hold exclusive rights to specific frequency bands, they have priority access to the spectrum and are protected from harmful

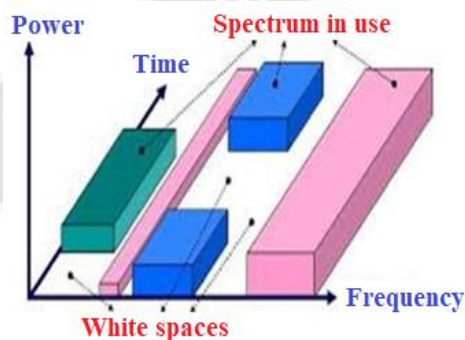


Figure 1. Spectrum hole

interference caused by SUs. SUs also known as cognitive users, are the unlicensed or opportunistic users of the spectrum. These users are equipped with CR devices having capabilities to sense, adapt, and access spectrum bands not used by PUs as a spectrum hole shown in figure 1.

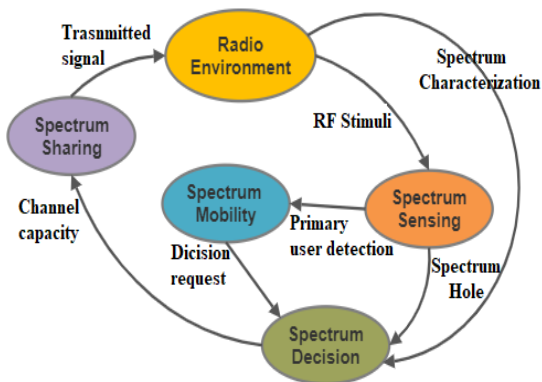


Figure 2. Cognitive cycle

SUs opportunistically utilize spectrum bands that are unused or underutilized by PUs, maximizing spectrum efficiency and capacity. The concept of cognitive networks revolves around SUs intelligently and dynamically accessing spectrum resources while ensuring co-existence and minimal disruption to PUs. By allowing SUs to opportunistically access underutilized spectrum, cognitive networks [22,27,30] aim to improve spectrum utilization, alleviate congestion, and enhance overall wireless communication efficiency. The four crucial functions of CR for managing the spectrum are spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility. The cognitive cycle depicted in figure 2, illustrates the sequence of these functions in CR operation.

A. Spectrum Sensing

The fundamental function of CR is spectrum sensing that involves detecting and analyzing the spectral environment to identify the availability and occupancy of frequency bands. Spectrum sensing techniques [17] are used in CR systems to detect and analyze the presence or absence of PU signals in a specific frequency band. These techniques play a vital role in identifying available spectrum opportunities for SUs. Figure 3 shows some unique spectrum sensing techniques:

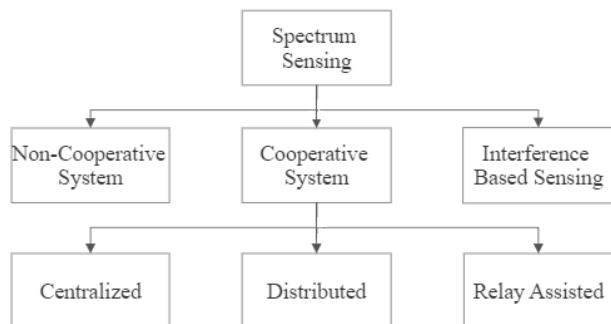


Figure 3. Spectrum sensing techniques

Energy detection is a fundamental and widely used spectrum sensing technique. It measures the received signal's energy and compares it to a predetermined threshold. Energy detection [5,6,18,19] is suitable for detecting wideband signals and can be

applied in various environments. However, it is susceptible to noise uncertainty and requires careful threshold selection to balance false alarms and missed detections. Matched filter detection correlates the received signal with a known template waveform or signal pattern. It exploits knowledge of the PU's waveform and maximizes the detection of signal-to-noise ratio (SNR). Matched filter detection is particularly effective for detecting signals in Additive White Gaussian Noise (AWGN) channels. However, it requires accurate understanding of PU's waveform, which can be a limitation in practice. [10] Cyclostationary feature detection leverages the cyclostationary properties present in many communication signals. It examines the cyclic statistics of the received signal, such as cyclic autocorrelation or cyclic spectrum. By detecting the presence of cyclostationary features, this technique can differentiate between PU signals and noise. Cyclostationary feature detection is especially useful in distinguishing between signals with similar energy levels or in the presence of interference. Pilot-based sensing utilizes known pilot signals inserted by PUs. SUs exploit these pilots to estimate channel characteristics and detect the presence of PUs. By measuring the quality of received pilot signals, SUs can infer the presence of PU activity. Pilot-based sensing offers robustness against noise and interference but relies on the availability of pilot signals. Cooperative sensing involves collaboration among multiple CRs to improve sensing performance. SUs share their sensing results and combine them to make more accurate decisions. Cooperative sensing mitigates fading, shadowing, and noise effects, enhancing the reliability of spectrum sensing. It also enables the detection of PUs that may be hidden or difficult to sense by an individual CR.

B. Problem Statement

Use Energy consumption is a critical issue in CRNs because of the Dynamic Spectrum Access (DSA) nature of these networks [28,29]. In CRNs, the radio devices need to constantly monitor the radio environment to detect available spectrum opportunities, which requires significant energy consumption. Additionally, the radio devices need to rapidly switch between different frequency bands and adjust their transmission power and modulation schemes, which further increases energy consumption. Energy consumption in CRNs can be particularly problematic in battery-powered devices, such as wireless sensor nodes or mobile devices, where energy is a limited resource. Excessive energy consumption can lead to reduced network [23] lifetime, increased maintenance costs, and reduced network performance. Moreover, the energy consumption problem is even more complex in CRSNs, where the cognitive capabilities of the radio devices are combined with the sensing capabilities of the sensor nodes. In CRSNs, the sensor nodes need to sense the physical environment and transmit the sensed data to the CR devices, which then need to process and transmit the data to the

network. This additional sensing and data processing can further increase energy consumption in CRSNs. Therefore, reducing energy consumption in CRNs and CRSNs is a critical research problem that needs to be addressed to enable sustainable and energy efficient wireless networks. Researchers are exploring various approaches to mitigate the energy consumption problem in CRNs, such as energy-efficient scheduling, power control, and spectrum sensing techniques, as well as new hardware and communication protocols that are optimized for energy efficiency.

This paper is arranged in the explained order. Section 1 basics of spectrum sensing in CRN, literature review in detail is exposed in section 2, proposed methodology for achieving energy optimization in section 3, the result analysis of spectrum efficiency is given in section 4. The outcomes of research work carried out is concluded in section 5.

II. LITURATURE REVIEW

In 2008, Mohanty studied [1] that explored the current state of research, unresolved affairs, and advancements in spectrum management within CRNs. This paper primarily centered on the diverse spectrum management functions in CRNs gives the varying Quality of Service (QoS) [24,25] requirements posed by different applications utilizing CRNs, the introduction of novel network paradigms brings forth latest innovative confrontation due to the charismatic character of the present spectrum. The study highlighted that by employing DSA techniques and heterogeneous wireless architectures, CRs have the potential to offer uninterrupted roaming capabilities and high bandwidth, thereby catering to the increasing demands in various applications. In [2], a thorough survey was conducted on spectrum sensing, covering various methodologies for detecting available spectrum. They introduced the multi-dimensional concept of spectrum sensing and investigated the statistical modelling of PU behavior considering different network traffic models. In [4], the authors presented a comprehensive overview of the research progress and advancements made in spectrum sensing and spectrum sharing methods for CRs over the past 10 years. As licensed communication have preference and requires protection through various access schemes, implementing CRs to improve spectrum utilization efficiency becomes challenging. SUs need to accurately estimate the availability of PUs using spectrum sensing methods. In [5], the authors conducted a study on the performance of energy detection in both AWGN and fading channels for an unknown transmitted signal. The analysis focused on the application of energy detection in the context of CR technologies and ultra-wideband systems. In [6] the energy detection exhibits limitations in low SNR environments. The authors introduced the concept of the "SNR wall," which represents the minimum SNR level below which authentic prediction becomes impossible using energy detection, even

with a long channel observation time. By determining the status of the "SNR wall," the effects of small modelling uncertainties on performance can be quantified. In a subsequent study [7], the authors propose utilizing cross-correlation to enhance the energy detector sensitivity. They mathematically quantify the "SNR threshold" and demonstrate its proportionality to the level of noise uncertainty. In a cross-correlation system, mathematical equations are developed to express the detection performance using pertinent system characteristics. Compared to a standard energy detector, faster detection is achievable using cross-correlation. The authors demonstrate that their proposed cross-correlation system can meet sensing specifications without any prior knowledge of the signals to be detected by employing approximations and IEEE 802.22 requirement parameters. Furthermore, [8] examines using a Receiver Operating Characteristic (ROC) curve the trade-off between sensing precision and complexity. The authors investigate how energy and Maximum Minimum Eigenvalue (MME) detectors are affected by signal bandwidth and observation bandwidth. Gardner conducted an extensive survey in [9] that covers fifty years of research on cyclostationary, providing a comprehensive bibliography. The survey includes literature from various languages that have significantly contributed to the field. The traditional stochastic approach represents signals as stochastic processes, whereas the second technique does statistical analysis using time series and temporal functions, replacing ensemble averages with infinite time series averaging. In [10], For OFDM-based CRNs, a straightforward multi-cycle-based cyclostationary sensing technique is provided. The algorithm consists of three steps, with test statistics formulated as the ratio of two quadratic cyclic autocorrelation functions. In [11], introduced a spectrum sensing technique called the cyclo-energy detector, which combines both cyclostationary and energy detection. While SU are sending, this detector seeks to detect the spectrum. The main test statistic makes use of an analysis of the PU signal's cyclostationary nature. In [12], Researchers investigate a thorough framework for implementing SDR-based CR with dynamic access and waveform creation flexibility. The authors propose a unified framework, referred to as the Spectrally Modulated Spectrally Encoded (SMSE) framework, which enables the generation and implementation of dynamic waveforms in CR. However, in [13], the SMSE framework is expanded upon by the authors, who introduce a Soft Decision SMSE (SDSMSE) approach to enhance the decision-making process. This extension combines the benefits of both underlay and overlay CR paradigms. The authors derive the probability of error in different test cases within an AWGN channel, demonstrating its suitability for CR applications. In [14], On an SDR platform, the SMSE cognitive-centric overlay waveform is implemented and tested. The CR multi-carrier transmission waveform generation over non-contiguous frequency bands is

made easier by the SMSE architecture. The non-contiguous Orthogonal Frequency-Division Multiplexing (OFDM) transmission using the SMSE approach is implemented, showcasing the CRs ability to dynamically adjust parameters such as bandwidth and the number of subcarriers based on the analytic framework. Real-time video transmission by SUs without interfering with PUs was shown by the authors. In [15], the analysis focuses on path loss effects in a cognitive relay network with multiple antenna terminals and cognitive relays employing the amplify-and-forward technique. The interference from the primary transmitter to the secondary receiver as well as from the secondary transmitter to the primary receiver is taken into account in the study. To evaluate system performance, analytical equations for end-to-end outage probabilities are developed. The [16] examines the simultaneous transmission of energy and information, highlighting the trade-off between reliable information transmission and energy transmission in the presence of noise. This trade-off is characterized by a coding theorem and a capacity-energy function, which are computed for different fading channels.

III. PROPOSED METHODOLOGY

The proposed methodology for energy and spectrum-efficient CRSNs involves several key steps aimed at improving the energy and spectrum efficiency of these networks. Firstly, the methodology proposes the use of a cooperative spectrum sensing technique that combines multiple sensing nodes to improve the accuracy of spectrum sensing while minimizing the energy consumption. This technique involves sharing information between the sensing nodes to make more informed decisions about the availability of spectrum bands for communication. Secondly, the methodology proposes the use of a DSA scheme that allows the CRSNs to access the available spectrum bands in an energy efficient manner. Thirdly, the methodology proposes the use of PSO mechanism to reduce energy consumption during idle periods. This involves putting the nodes into a low-power sleep mode when they are not actively sensing or communicating, and waking them up only when necessary.

A. Steps of Proposed Methodology

- **Step1: Network Formation** - A network topology is formed by deploying a set of CR sensor nodes in the sensor field. The sensor nodes are equipped with CRs which are capable of sensing and exploiting spectrum opportunities.
- **Step2: Spectrum Sensing** - The CRs of the sensor nodes sense the available spectrum bands and identify the unused spectrum bands. This is done using spectrum sensing techniques such as energy detection,

matched filtering, cyclostationary detection, and wavelet-based detection.

- **Step3: Spectrum Decision** - After sensing the available spectrum, the CRs make a decision on which spectrum bands to use based on spectrum utilization criteria. The decision is based on factors such as the QoS requirements of the application, the energy efficiency of the network, and spectrum availability.
- **Step4: Spectrum Access** - Once the CRs make a spectrum decision, they access the selected spectrum bands and start transmitting data.
- **Step5: Power Management** - The CRs of the sensor nodes use power management techniques to reduce energy consumption. This includes techniques such as power control, power scheduling, and power-efficient [26,31,32] routing.
- **Step6: Spectrum Handoff** - When the available spectrum bands become congested or unavailable, the CRs perform spectrum handoff to switch to a different spectrum band.
- **Step7: Data Aggregation** - The CR sensor nodes collect data from the sensor field and aggregate the data to reduce the amount of data transmitted. This reduces energy consumption and improves spectrum efficiency.
- **Step8: Data Transmission** - The CR sensor nodes use a transmission protocol to transmit the aggregated data to the sink node. The transmission protocol is designed to optimize energy consumption and spectrum utilization.
- **Step9: Energy Harvesting** - The CR sensor nodes use energy harvesting techniques to harvest energy from the environment. This includes techniques such as solar energy harvesting, kinetic energy harvesting, and RF energy harvesting.
- **Step10: Network Optimization** - The network is optimized based on energy and spectrum efficiency criteria. This includes optimizing the network topology, the transmission protocol, the power management techniques, and the spectrum sensing and decision algorithms.

B. Energy Efficiency and Spectrum Efficiency

The Energy efficiency in CRSNs refers to the ability of the network to operate and perform its functions while consuming minimal energy. This is achieved by optimizing the use of energy resources, reducing energy wastage, and minimizing unnecessary energy consumption. In CRSNs, energy efficiency is critical because these networks typically operate in energy-constrained environments where the nodes have limited energy resources.

The energy consumption of CRSNs is primarily influenced by the sensing, communication, and processing activities of the network nodes. These activities consume energy and can quickly deplete the energy resources of the nodes, limiting the network's functionality and lifespan. Therefore, to achieve energy efficiency in CRSNs, various techniques and strategies can be employed, such as optimizing the transmission power levels of the nodes, reducing the number of sensing nodes, using cooperative sensing techniques, and implementing sleep mode mechanisms to reduce idle energy consumption. Additionally, energy harvesting techniques can be used to supplement the energy requirements of the CRSNs by converting ambient energy sources such as solar, thermal or kinetic energy into electrical energy. By implementing these techniques and strategies, energy consumption in CRSNs can be significantly reduce, and the lifespan and functionality of the network can be improved, enabling their practical deployment and usage in various applications.

TABLE I. NETWORK PARAMETERS

Parameters	Values for Energy Efficient	Values for Spectrum Efficient
Number of samples (N)	1000	1000
Sampling frequency (fs)	1e6	1e6
Carrier frequency (fc)	2.4e9	2.4e9
Max. transmit power (Pmax)	1	1
Noise variance (sigma2)	0.01	0.01
False alarm probability (Pfa)	NA	0.1
Number of sensors (K)	NA	5

IV. RESULT ANALYSIS

The result analysis of spectrum efficient in CRSNs is critical for evaluating the performance of the network and identifying areas for improvement. The analysis typically involves measuring the efficiency of spectrum utilization, the detection probability, and the interference to PUs. The performance metrics can be obtained from simulations or experiments conducted in real-world settings. The analysis may also involve comparing the performance of different algorithms or techniques used for spectrum sensing and resource allocation. Additionally, the analysis can provide insights into the trade-offs between different performance metrics, such as the trade-off between detection probability and interference to PUs, which can inform the design of more efficient and effective CRSNs. Overall, result analysis is a crucial step in the development and optimization of spectrum efficient in CRSNs.

The proposed system can be divided into two approaches, the first approach is energy optimization using genetic algorithm and second approach is spectrum efficient in CRSN using PSO techniques. Final result analysis can be observed in various test cases of both the approach.

A. Test Cases for energy optimization using Genetic Algorithm

Energy Optimization

The fitness value vs. generation graph shows how the fitness value changes over time as the genetic algorithm based on population size = 5,10,20,30,40 and max generation = 10,20,40,60,80 as shown in figure 4.1, 4.2, 4.3, 4.4, 4.5 respectively. The graph typically starts with a randomly generated population of candidate solutions and shows how the fitness value improves over time as the genetic algorithm selects and evolves better solutions.

Initial Parameters

```
%% Parameters
N = 1000; % Number of samples
fs = 1e6; % Sampling frequency
fc = 2.4e9; % Carrier frequency
Pmax = 1; % Maximum transmit power
sigma2 = 0.01; % Noise variance
```

CASE-1 :- 'PopulationSize', 5, 'MaxGenerations', 10,

```
Command Window
Optimization terminated: maximum
number of generations exceeded.
Optimized results:
Transmit power = 0.698849
Decision threshold = 0.342989
>>
```

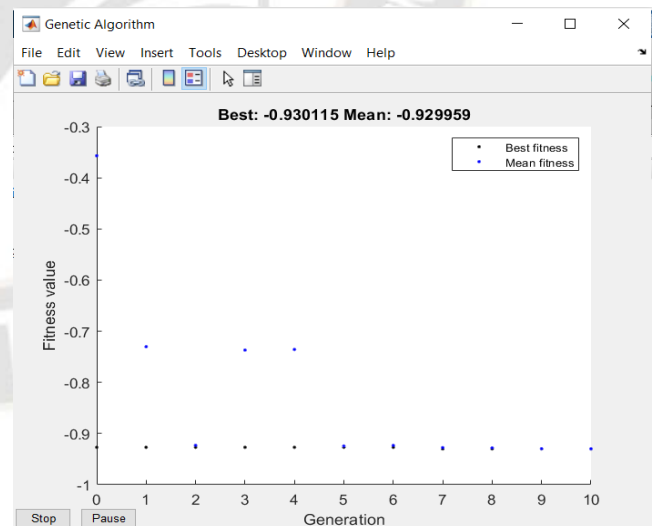


Figure 4.1: fitness value vs. generation with best fitness value of population size = 5

CASE-2 :- 'PopulationSize', 10, 'MaxGenerations', 20,

CASE-4 :- 'PopulationSize', 30, 'MaxGenerations', 60,

```
Command Window
Starting parallel pool (parpool)
using the 'local' profile ...
connected to 4 workers.
Optimization terminated: maximum
number of generations exceeded.
Optimized results:
Transmit power = 0.157404
Decision threshold = 0.160502
```

```
Command Window
Optimization terminated: maximum
number of generations exceeded.
Optimized results:
Transmit power = 0.021834
Decision threshold = 0.032174
```

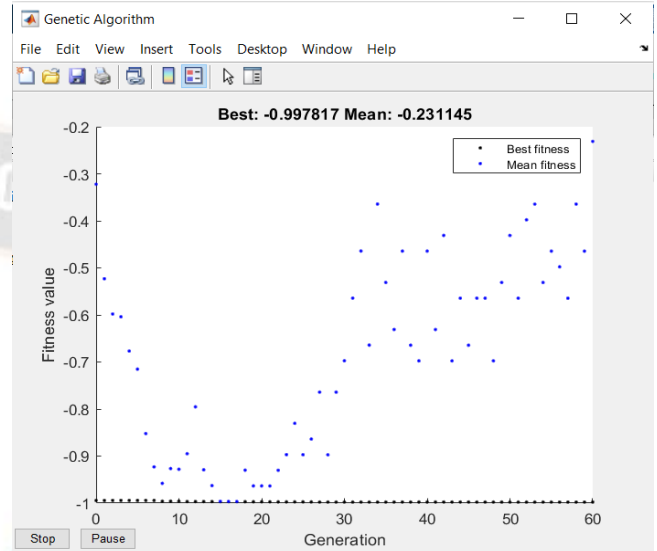
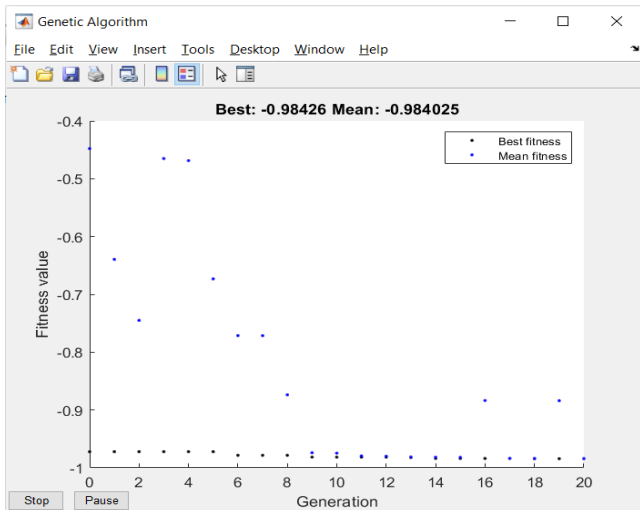


Figure 4.2: fitness value vs. generation with best fitness value of population size = 10

Figure 4.4. fitness value vs. generation with best fitness value of population size = 30

The graph typically starts with a randomly generated population of candidate solutions and shows how the fitness value improves over time as the genetic algorithm selects and evolves better solutions.

CASE-3 :- 'PopulationSize', 20, 'MaxGenerations', 40,

CASE-5 :- 'PopulationSize', 40, 'MaxGenerations', 80,

```
Command Window
Optimization terminated: maximum
number of generations exceeded.
Optimized results:
Transmit power = 0.019049
Decision threshold = 0.029003
```

```
Command Window
Optimization terminated: maximum
number of generations exceeded.
Optimized results:
Transmit power = 0.000041
Decision threshold = 0.010540
```

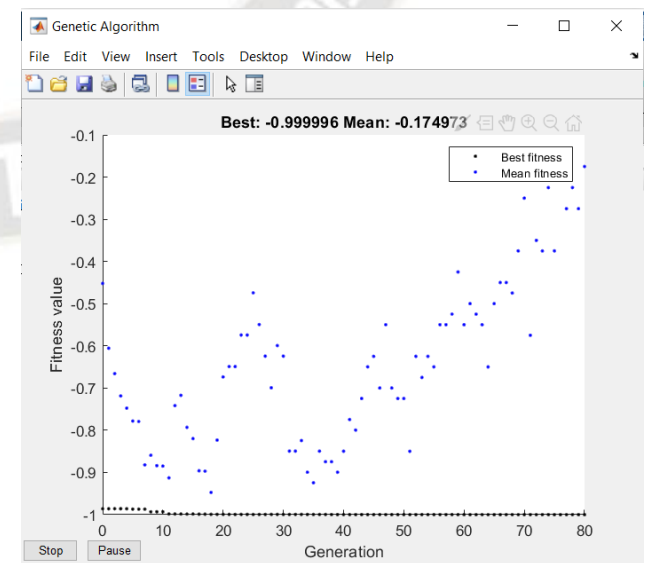
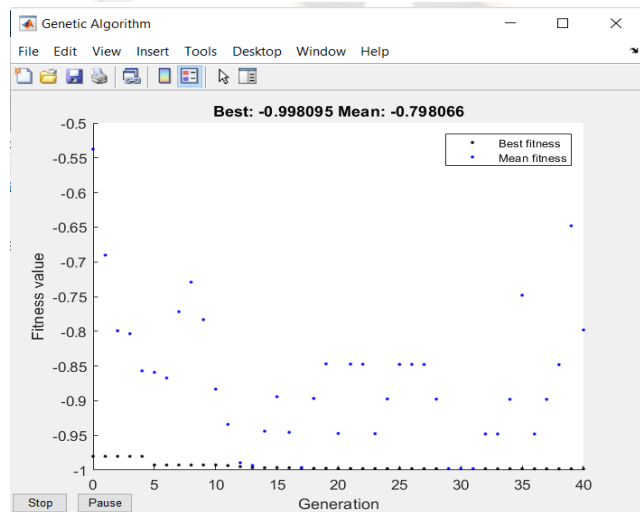


Figure 4.3. fitness value vs. generation with best fitness value of population size = 20

Figure 4.5. fitness value vs. generation with best fitness value of population size = 40

Overall, the fitness value vs. generation graph provides a visual representation of the genetic algorithm's optimization progress, which can be useful for understanding the performance of the algorithm and for optimizing its parameters.

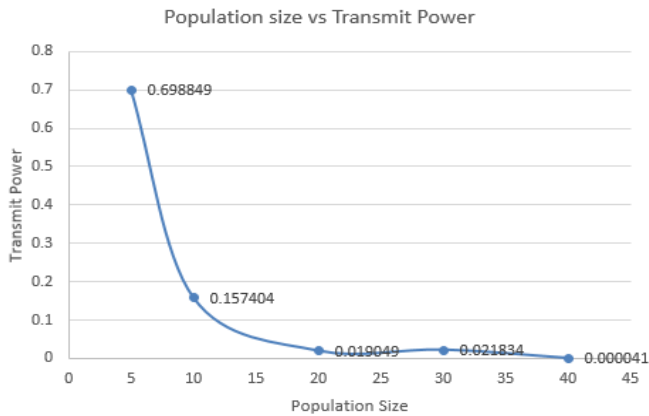


Figure 4.6. Graph between Population Size vs Transmit Power

In this work energy optimization in CRSNs using genetic algorithms, the population size vs. transmit power graph figure. 4.6 is a plot that shows the relationship between the population size and the transmit power level of the network. It shows how many potential solutions are considered and improved upon during each algorithm iteration. Although a greater population size may produce better results, it also raises the algorithm's cost of computing. The transmit power level is another important parameter in CRSNs. It represents the amount of power used by the network to transmit data from the sensors to the base station. A higher transmit power level can increase the signal strength and improve the network's performance, but it also consumes more energy.

The population size vs. transmit power graph in figure. 4.6 can be used to explore the trade-off between the computational cost of the genetic algorithm and the energy consumption of the network. A larger population size can improve the quality of the solutions found by the genetic algorithm, but it also requires more computational resources. On the other hand, a higher transmit power level can improve the network's performance, but it also consumes more energy.

The graph can show how changes in the population size affect the energy consumption of the network at different transmit power levels. It can also show how changes in the transmit power level affect the quality of the solutions found by the genetic algorithm at different population sizes.

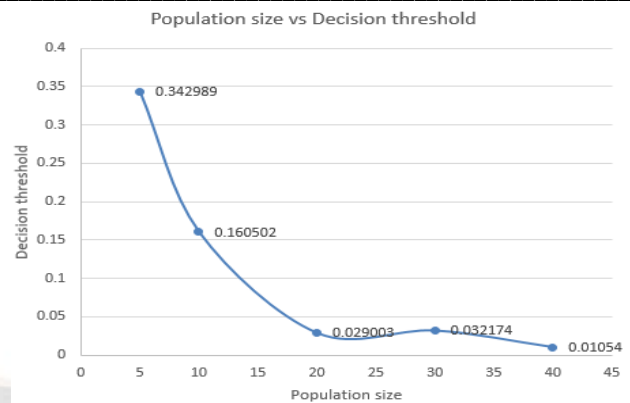


Figure 4.7. Graph between Population Size vs Decision Threshold

The population size vs decision threshold graph can be used to explore the trade-off between the computational cost of the genetic algorithm and the energy consumption of the network. It can show how changes in the population size affect the decision threshold level of the network and how this, in turn, affects the energy consumption of the network. The graph in figure. 4.7 can also show how changes in the decision threshold level affect the quality of the solutions found by the genetic algorithm at different population sizes. A higher decision threshold level can improve the network's energy efficiency by reducing the number of transmissions required to successfully transmit data, but it can also lead to more packet losses and reduced network performance. The Max Iterations Vs Transmit Power graph can be used to explore the trade-off between the computational cost of the genetic algorithm and the energy consumption of the network. It can show how changes in the maximum number of iterations affect the network energy consumption at different transmit power levels.

The graph in figure. 4.8 can also show how changes in the transmit power level affect the quality of the solutions found by the genetic algorithm at different maximum iteration values. A higher transmit power level can improve the network's performance, but it also consumes more energy. The maximum number of iterations can affect the quality of the solutions found by the genetic algorithm, with a higher maximum number of iterations potentially leading to better solutions but also increasing the algorithm computational cost.

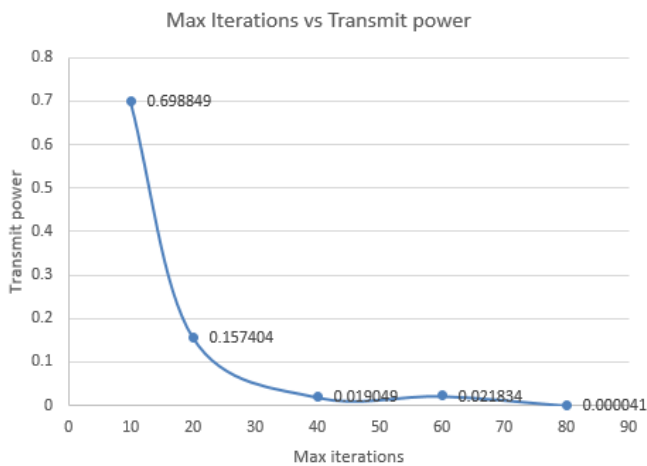


Figure 4.8. Graph between Max Iterations Vs Transmit Power

The Max Iterations Vs Decision Threshold graph can be used to explore the trade-off between the computational cost of the genetic algorithm and the energy consumption of the network. It can show how changes in the maximum number of iterations affect the decision threshold level of the network and how this, in turn, affects the network energy consumption.

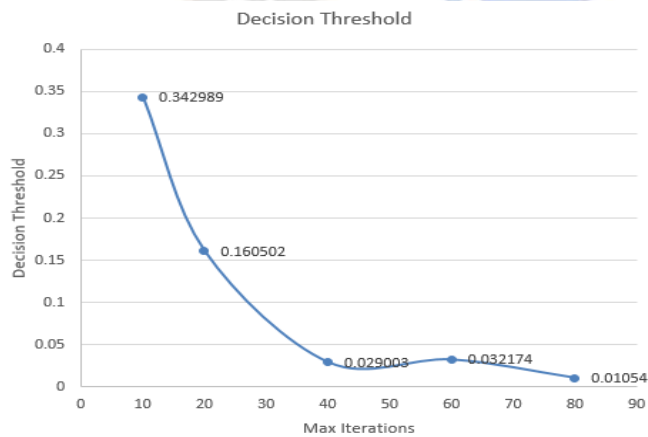


Figure 4.9. Graph between Max Iterations Vs Decision Threshold

The graph in figure. 4.9 can also show how changes in the decision threshold level affect the quality of the solutions found by the genetic algorithm at different maximum iteration values. A higher decision threshold level can improve the network's energy efficiency by reducing the number of transmissions required to successfully transmit data, but it can also lead to more packet losses and reduced network performance.

The maximum number of iterations can affect the quality of the solutions found by the genetic algorithm, with a higher maximum number of iterations potentially leading to better solutions but also increasing the computational cost of the algorithm.

B. Spectrum Efficient in CRSN using PSO techniques

Spectrum Efficient

Initial Parameters

```
%% Parameters
N = 1000; % Number of samples
fs = 1e6; % Sampling frequency
fc = 2.4e9; % Carrier frequency
Pmax = 1; % Maximum transmit power
sigma2 = 0.01; % Noise variance
Pfa = 0.1; % False alarm probability
K = 5; % Number of sensors
L = 1; % Number of samples per sensor
```

CASE-1 :- 'SwarmSize', 10, 'MaxIterations', 10

```
Command Window
Optimization ended: number of iterations
exceeded OPTIONS.MaxIterations.
Optimized results:
Sensor 1 threshold = 0.173808
Sensor 2 threshold = 0.450699
Sensor 3 threshold = 0.515040
Sensor 4 threshold = 0.155194
Sensor 5 threshold = 0.406756
```

CASE-2 :- 'SwarmSize', 20, 'MaxIterations', 20

```
Command Window
Optimization ended: number of iterations
exceeded OPTIONS.MaxIterations.
Optimized results:
Sensor 1 threshold = 0.858649
Sensor 2 threshold = 0.812796
Sensor 3 threshold = 0.427627
Sensor 4 threshold = 0.895182
Sensor 5 threshold = 0.741248
```

CASE-3 :- 'SwarmSize', 30, 'MaxIterations', 30

```
Command Window
Optimization ended: relative change in the objective value
over the last OPTIONS.MaxStallIterations iterations is less
than OPTIONS.FunctionTolerance.
Optimized results:
Sensor 1 threshold = 0.336743
Sensor 2 threshold = 0.119752
Sensor 3 threshold = 0.347795
Sensor 4 threshold = 0.375291
Sensor 5 threshold = 0.777407
```

CASE-4 :- 'SwarmSize', 40, 'MaxIterations', 40

```
Command Window
Optimization ended: relative change in the objective value
over the last OPTIONS.MaxStallIterations iterations is less
than OPTIONS.FunctionTolerance.
Optimized results:
Sensor 1 threshold = 0.463847
Sensor 2 threshold = 0.831092
Sensor 3 threshold = 0.584023
Sensor 4 threshold = 0.264338
Sensor 5 threshold = 0.904654
```


CASE-5 :- 'SwarmSize', 50, 'MaxIterations', 50

```

Command Window
Optimization ended: relative change in the objective value
over the last OPTIONS.MaxStallIterations iterations is less
than OPTIONS.FunctionTolerance.
Optimized results:
Sensor 1 threshold = 0.892244
Sensor 2 threshold = 0.993216
Sensor 3 threshold = 0.306804
Sensor 4 threshold = 0.682677
Sensor 5 threshold = 0.361387
    
```

The Swarm Size [20,21] vs Sensor's Threshold graph figure 4.10 is a visualization of the relationship between the two key parameters, swarm size and sensor's threshold, in a CRSN that uses PSO techniques to achieve spectrum efficiency. The graph usually has the swarm size on the x-axis and the sensor's threshold on the y-axis. Each point on the graph represents a combination of these two parameters, and the color or shading of the point indicates the spectrum efficiency achieved at that point. Similarly, increasing the sensor's threshold can improve spectrum efficiency by reducing interference, but beyond a certain point, it can also lead to decreased efficiency due to underutilization of the available frequency bands.

Therefore, the optimal combination of swarm size and sensor's threshold can be identified by finding the point on the graph that corresponds to the highest level of spectrum efficiency. This can be done through a process of experimentation and optimization, using PSO or other optimization techniques, to identify the most efficient parameters for the specific CRSN and application.

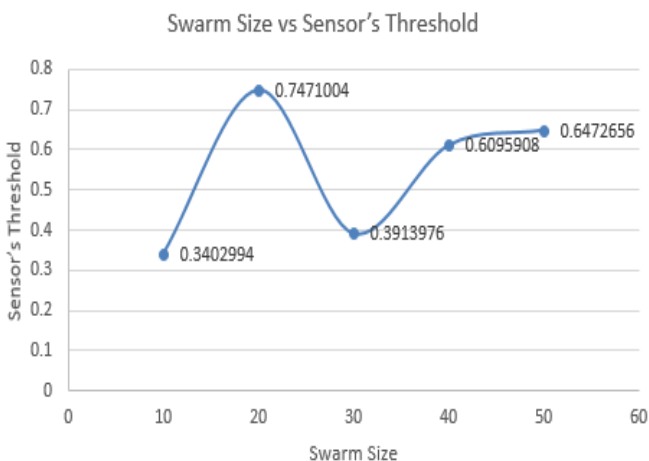


Figure 4.10. Graph between Swarm Size vs Sensor's Threshold

V. CONCLUSION

Spectrum sensing plays a crucial role in the successful deployment of Energy Efficient CR networks. It is important to intelligently use battery energy and to maximize the network life by designing energy-efficient CRN.

In this paper, Energy Efficiency of the CRN is maximized to enable green wireless network by exploring various methods. Energy Efficient CR network can be achieved by increasing the

energy efficiency in already existing network and in future networks by harvesting energy. Performance of Energy Efficient CR network has been studied in terms of throughput, energy efficiency, Spectrum Efficiency, Outage Probability, Capacity, Observation and Transmission duration. Therefore, CR network has been made energy efficient using spectrum sensing technique in this work. Energy and spectrum efficient CRSNs are critical for the success of future Internet of Things (IoT) applications. CRSNs can enable efficient and reliable wireless communication while conserving energy, which is essential for battery-powered devices and applications with limited energy resources. To achieve energy and spectrum efficiency in CRSNs, researchers have explored various techniques such as DSA, CR, and sensor fusion. DSA enables the efficient use of spectrum resources by dynamically allocating unused frequencies to communication nodes. CR technology allows communication nodes to sense the radio environment and adapt to change in the network to optimize energy consumption and network performance. Sensor fusion allows CR devices to combine information from multiple sensors to make better decisions and reduce energy consumption. Efficient energy consumption in CRSNs can be achieved by designing energy-efficient communication protocols, optimizing the transmission power and modulation schemes, and using energy-efficient hardware. The energy and spectrum efficient CRSNs are crucial for the success of IoT applications. By enabling efficient and sustainable wireless communication, CRSNs can help drive the growth and adoption of IoT applications across a wide range of industries.

Overall, PSO-based spectrum efficient CRSNs have the potential to greatly improve the utilization of the available frequency spectrum and enhance the performance of wireless communication systems. Further research and development in this area are needed to improve the efficiency and effectiveness of PSO-based optimization techniques for CRSNs and to adapt them to various real-world scenarios.

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