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"A Novel Method For Spectrum Sensing In Cognitive Radio Networks Using Fractional GWO Single Bond CS Optimization" Review Paper

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Abstract: Cognitive Radio (CR) technology enables adaptive configuration of transmission parameters based on the operating environment and diverse Quality of Service (QoS) requirements, offering a pathway to energy-efficient wireless communications. Among the radio frequency (RF) components, the power amplifier (PA) constitutes a major contributor to energy consumption, particularly in medium- and long-range transmissions. Minimizing PA power consumption is therefore critical for realizing green radio systems. This study presents a mathematical formulation of total system power consumption at a CR transmitter with Class B PA and investigates optimization via parameter reconfiguration for multicarrier data transmission scenarios. Five nature-inspired (NI) metaheuristic algorithms Ant Lion Optimizer (ALO), Grasshopper Optimization Algorithm (GOA), Grey Wolf Optimizer (GWO), Moth Flame Optimization (MFO), and Whale Optimization Algorithm (WOA) are applied and compared based on multiple performance metrics. Simulation results indicate that WOA achieves superior performance in minimizing system power consumption while satisfying multiple QoS constraints, demonstrating its effectiveness for green cognitive radio design.

Index Terms **-** Cognitive Radio, Green Radios, Power Amplifier, Nature-Inspired Optimization, Multicarrier Transmission, Whale Optimization Algorithm, QoS Constraints, Energy Efficiency

I. Introduction

The exponential growth in wireless communication applications has significantly increased the demand for radio spectrum. However, a major challenge hindering the fulfillment of this demand is the limited availability of radio resources. According to the Federal Communications Commission (FCC), the core issue lies in the spatial and temporal under-utilization of spectrum by licensed users. Particularly in frequency bands below 3 GHz where non-line-of-sight propagation is more effective spectrum utilization ranges from as low as 15% to as high as 85%. The existing static spectrum allocation policy, which assigns specific frequency bands to licensed or Primary Users (PUs), has led to inefficient spectrum usage.

Cognitive Capability

Cognitive capability allows CR devices to perceive and adapt to environmental conditions such as spectrum occupancy and channel quality. This adaptability is achieved by monitoring both spatial and temporal variations in the radio environment while ensuring minimal interference to incumbent users. The cognitive cycle consists of four key functions:

Spectrum Sensing: Identifies vacant spectrum bands that can be accessed by SUs.

Spectrum Management: Selects the most appropriate channel based on user requirements and channel conditions.

Spectrum Sharing: Coordinates access among multiple CR users to ensure fair and efficient use of the selected spectrum.

Cognitive Decision Engine (CDE)

The CDE is a critical component in a CR system, enabling intelligent decision-making based on environmental awareness. Upon receiving inputs from its surroundings or the user, the CDE analyzes the situation (cognition), evaluates possible actions, and selects the most appropriate response (reconfiguration). Figure 1 illustrates the decision-making framework of the CDE, which will be elaborated upon in the following section.

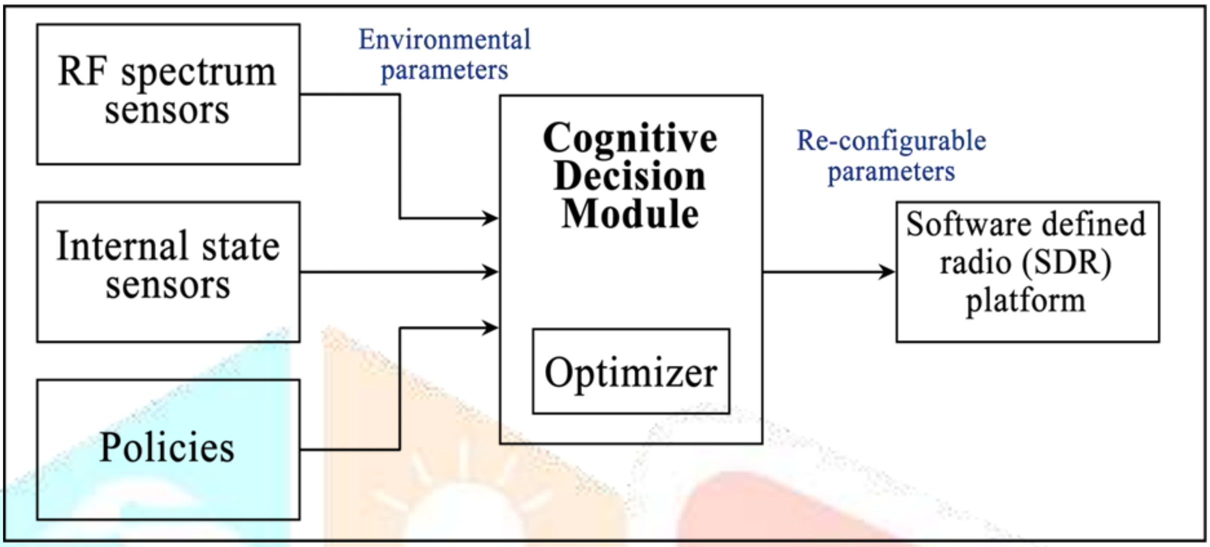

Figure -1 illustrates the decision-making framework of the CDE

Components of the Cognitive Decision Engine (CDE)

The Cognitive Decision Engine (CDE) is responsible for enabling the intelligent behavior of a Cognitive Radio (CR). It integrates several key components to support cognitive capability and system adaptability:

Radio Parameters for CDE Design

The radio parameters used in CDE design are categorized into two main types [12–13]:

Input (Environmental) Parameters: These include channel-specific information such as path loss, signal-to-noise ratio (SNR), and noise power. They also encompass internal metrics like battery status and service requirements.

Output (Transmission) Parameters: These tunable parameters are generated by the decision module to meet Quality of Service (QoS) requirements. Examples include transmit power, modulation type, symbol rate, bandwidth, frame size, and time-division duplexing ratios.

Need for Adaptive Spectrum Sensing

Spectrum sensing is a cornerstone function of dynamic spectrum access in cognitive radio networks (CRNs). Efficient sensing enables secondary users to detect the presence of primary users (PUs) and identify idle bands for opportunistic access, while minimizing interference.

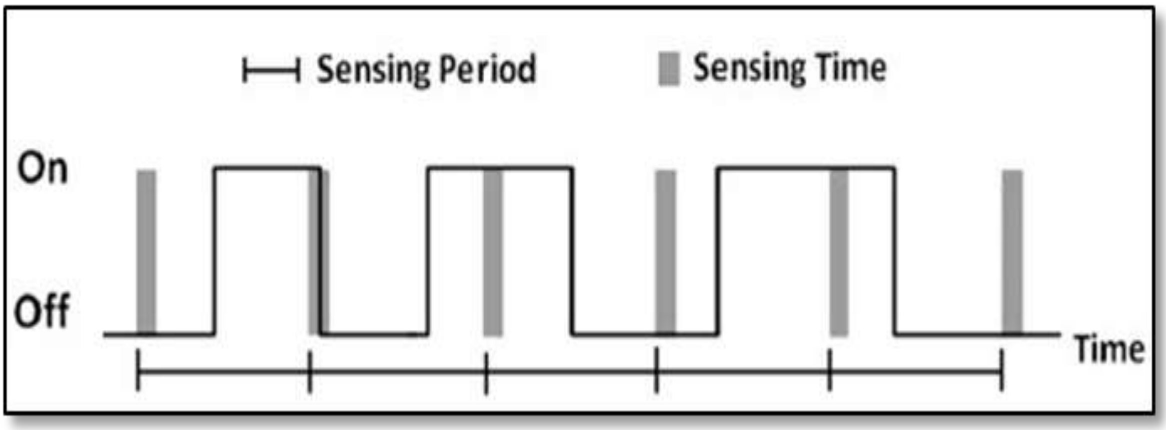

Figure 2: On- Off model of PU with the concept of sensing period and sensing time

II. Objective

The main objectives of this research are:

This thesis is focused on the adaptation of different parameters of a CR system so that the overall transmission and sensing performance of the system can be improved. As meta-heuristic algorithms offer numerous advantages over classical mathematical approaches, performance of these algorithms is investigated to solve the problem of parameter reconfiguration.

An optimization problem with multiple constraints is studied to reconfigure the transmission parameters for the data transmission scenario of a CR.

The objective is to minimize the total system power consumption at CR transmitter operating with class B PA while considering the constraints on total data rate, BER and ACI.

III. Literature Review

This chapter provides a comprehensive review of literature available on different meta-heuristic algorithms followed by the review of research published on parameter adaptation in cognitive radio systems. After a brief introduction in this section, the rest of the chapter is organized as: the novel work available on recently proposed meta-heuristic algorithms is discussed

Rajavel et al. (2025) proposed an energy-efficient relay selection framework for 5G cognitive radio networks. They leveraged CR networks and collaborative spectrum sensing to improve transmission performance. The framework addressed energy limitations for each SU and potential errors in secondary transmission, enhancing dynamic energy efficiency in 5G communication systems.

Farhi et al. (2025) introduced a novel method for spectrum sensing in cognitive radio networks using the Snake Optimizer (SO) along with reinforcement learning (RL). This meta-heuristic approach simulates snake cloning behavior to optimize resource allocation in CRNs. The integration of SO and RL demonstrated improved spectrum utilization and energy efficiency in CR networks.

Abdelbaset et al. (2024) introduced a deep learning-based spectrum sensing approach using Convolutional Neural Networks (CNNs). This method significantly advanced the precision of spectrum sensing, enabling more accurate identification of available spectrum bands for SU transmission.

Zaheer et al. (2024) focused on efficient resource allocation for 5G/6G cognitive radio networks. They aimed to maximize the throughput of the overall network considering multiple users under the umbrella of CR networks. Their work addressed the challenges of resource allocation in next-generation networks, emphasizing the importance of efficient spectrum utilization and interference management.

Rani and Sivakumar (2023) addressed efficient management of co-channel interference and radio resources in wireless communication systems through Radio Resource Management (RRM) strategies. These strategies control key parameters such as transmit power, data rate, error control coding, and user allocation to maximize spectrum utilization. One of the major challenges in spectrum management is the presence of unused spectrum segments, commonly known as spectrum holes. Cognitive Radio (CR) technology facilitates the identification and exploitation of these spectrum holes to improve overall network throughput. In this context, a novel hybrid optimization technique combining Grey Wolf Optimization (GWO) and Cuckoo Search (CS)—termed the Fractional GWO–CS Optimization model—is proposed. This model incorporates a Fractional Optimization Mechanism (FOM) that allows Secondary Users (SUs) to simultaneously perform periodic spectrum sensing and data transmission. The primary objective of the approach is to jointly optimize power spectral density (PSD), transmit power, and sensing bandwidth (SB) to achieve maximum energy efficiency.

A. Paraskevopoulos (2017) developed a CDE for IoT devices using a modified real-coded Biogeography-Based Optimization (RCBBO) integrated with a fuzzy decision-making process. Three mutation strategies — Gaussian (RCBBO-G), Levy (RCBBO-L), and Cauchy (RCBBO-C) were employed to improve population diversity and exploration ability. Simulation results demonstrated that RCBBO-based CDE outperforms the original BBO in fitness value and convergence speed, with the performance gap widening as the number of subcarriers increases.

You *et al.* (2017) proposed a CDE framework integrating fuzzy reasoning with an Improved Multi-Objective Artificial Bee Colony (IMOABC) algorithm. IMOABC was first used to generate a set of Pareto-optimal solutions under given channel conditions, after which fuzzy reasoning selected the solution best suited to user requirements. Enhancements such as reverse initialization, multidimensional evolution, integration of social and cognitive strategies, and external population maintenance were incorporated to improve search efficiency and preserve non-dominated solutions. A parallel hybrid coding strategy was also designed to further enhance optimization performance for CDE design.

P.H. Qi et al. (2016) addressed the constrained parameter adaptation problem in CR systems for minimizing power consumption. The problem was solved using the Biogeography-Based Optimization (BBO) algorithm, which employs a novel Habitat Suitability Index (HSI) to penalize solutions that fail to satisfy Quality of Service (QoS) constraints such as BER and data rate. Comparative analysis with Cuckoo Search Optimization (CSO) and Particle Swarm Optimization (PSO) demonstrated that BBO effectively reduces power consumption while maintaining QoS for different service types. However, achieving the optimal solution required a large number of generations, indicating a need for faster optimization techniques.

J. Heo (2014) observed that the primary user (PU) access pattern consists of alternating transmission and idle periods across multiple time slots. Consequently, sensing the PU at the start of every time slot is redundant and leads to unnecessary energy consumption. To model this behavior, probability density functions (PDFs) of the PU's busy and idle durations were derived using a Hidden Markov Model (HMM). The study aimed to maximize user satisfaction via a sigmoid-based objective function, which is achieved by optimizing the spectrum sensing interval to enhance secondary network throughput while reducing energy consumption. Optimal sensing intervals were derived for two cases: (i) when the current channel state is idle and (ii) when it is busy. Extensive simulations validated the high accuracy of the proposed approach and demonstrated significant energy savings.

IV. Methodology for Parameter Adaptation and Power Optimization in Cognitive Radio Networks

Green communication has become a critical concern in the telecommunication community. Mobile and wireless devices operating at high data rates face the challenge of high power consumption. Therefore, achieving energy-efficient operation in wireless communication systems has become essential. Reducing the carbon footprint through lower power consumption in wireless networks is also a social responsibility.

The major contributions and distinctions of the proposed methodology are:

To improve realism, the constraint of adjacent channel interference (ACI) caused by secondary user (SU) transmissions at primary user receivers (PU_Rx) is incorporated.

A novel penalty mechanism using an exponential function is adopted, which penalizes particles according to the extent of constraint violations.

The dimensionality of the parameter adaptation problem in this work is twice as large as that in . To handle this higher-dimensional and complex problem, the performance of recent, highly efficient nature-inspired (NI) algorithms—ALO, GWO, MFO, WOA, and GOA—is investigated. These algorithms have not been explored previously for this problem.

Opportunistic transmission by the CR network utilizing TV white space (TVWS) channels in the ultra-high frequency (UHF) band is considered, with channel occupancy data obtained from actual quantitative measurements reported in [110].

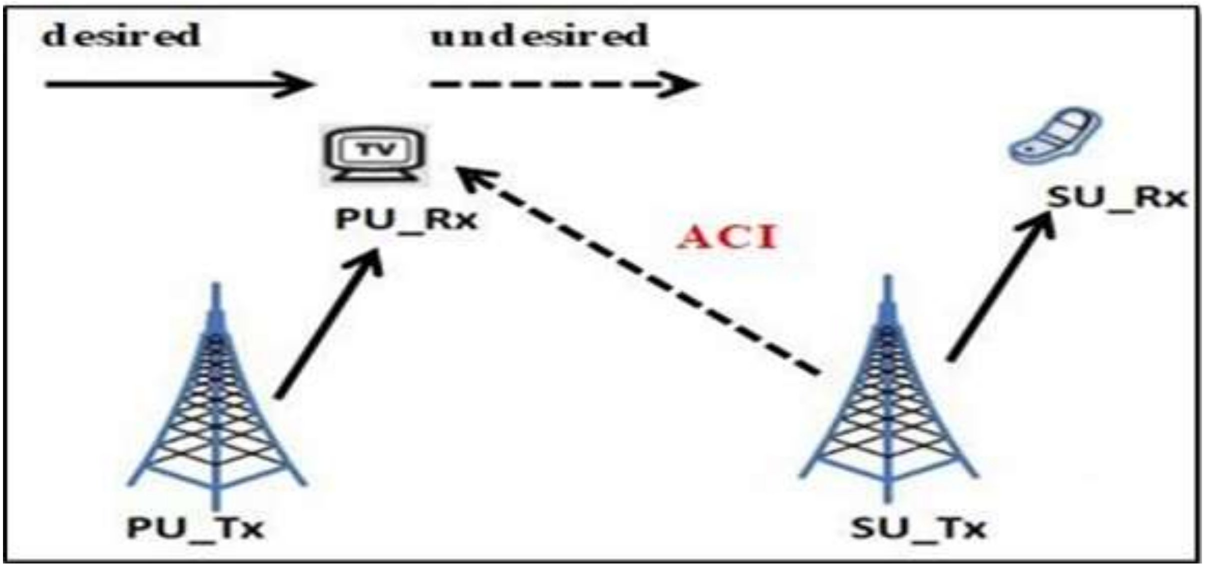

Figure 3: System model for a CR network

Data Rate Constraint:
The sum of the data rates for all subcarriers must exceed or equal the threshold data rate for the SU:

$$\sum_{k=1}^{K} DR_K \geq DR_{th}$$

Interference Power Constraint:
The total interference power, as a function of subcarrier-specific interference, must not exceed the maximum tolerable interference by the PU receiver:

$$\sum_{\{k=1\}}^{K} INT_K(d_k, P_k) \leq INT_{th}$$

Bit Error Rate (BER) Constraint:
The sum of the individual Bit Error Rates (BER) across all subcarriers must be less than or equal to the threshold BER for the system:

$$\sum_{K=1}^{K} BER_K \leq BER_{th}$$

Penalty Function and Constraint Handling
When employing a penalty function, the extent of constraint violation is used to penalize an infeasible solution. This ensures that feasible solutions are favored during the selection process.

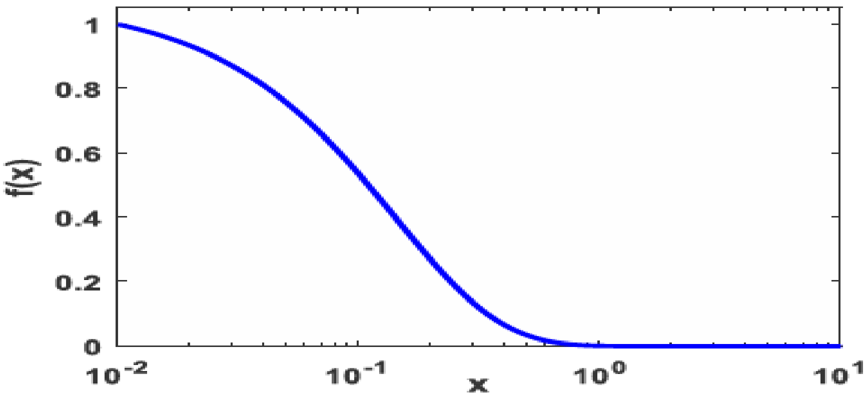

Figure 4: Penalty Function Response to Input Variation

V. RESULT ANALYSIS

Various parameter settings required for the cognitive radio (CR) based system model and the different metaheuristic algorithms are described in the following subsection

5.1 Simulation Settings

For the data transmission scenario, the threshold values are assumed as:
Bit Error Rate threshold: $\text{BER}_{th} = 10^{-6}$
Data rate threshold: $\text{DR}_{th} = 200$ Kbps [74]
Interference power threshold: $\text{INT}_{th} = 5 \times 10^{-12}$ W
The CR parameter adaptation for power consumption minimization is carried out in an OFDM-based multicarrier system comprising 64 subcarriers. The environmental parameters affecting secondary user (SU) transmission are:
Path loss: 75 dB
Noise floor: -90 dBm
The distance between the SU transmitter (SU_{Tx}) and the adjacent channel primary user receiver (PU_{Rx}) is assumed to be 1.5 km. The SU transmits over TVWS channel U-30 with:
Center frequency: 543.25 MHz
Channel bandwidth: 8 MHz

Algorithm	Parameter	Value
ALO [28]	Number of ants/antlions	40
	Maximum number of iterations	200
GOA [46]	Number of grasshoppers	40
	Maximum number of iterations	200
	Intensity of attraction, f	0.5
	Attractive length scale, l	1.5
	$c_{\max}$	1
	$c_{\min}$	0.00001
GWO [47]	Number of grey wolves	40
	Maximum number of iterations	200
MFO [29]	Number of moths/flames	40
	Maximum number of iterations	200
	Constant for logarithmic spiral, b	1
WOA [30]	Number of whales	40
	Maximum number of iterations	200
	Constant for logarithmic spiral, b	1

Table 1 Simulation Settings for ALO, GOA, GWO, MFO, and WOA

Simulation Results

The goal of the simulation is to achieve the optimal transmission parameters at the earliest possible iteration so that the secondary user (SU) can efficiently utilize the available white space whenever it needs to transmit. An ideal algorithm should not only provide the best solution corresponding to the highest fitness (or lowest power consumption) but also achieve it quickly, i.e., in fewer iterations. The optimal generation is defined as the iteration number at which convergence is achieved for a particular algorithm. The standard deviation (Std. Dev.) of this metric indicates the consistency in the processing time requirement of each algorithm. The computational complexity of an algorithm depends on the average number of function evaluations (AFE) needed to reach the optimal generation, calculated as the product of the population size and the optimal iteration number.

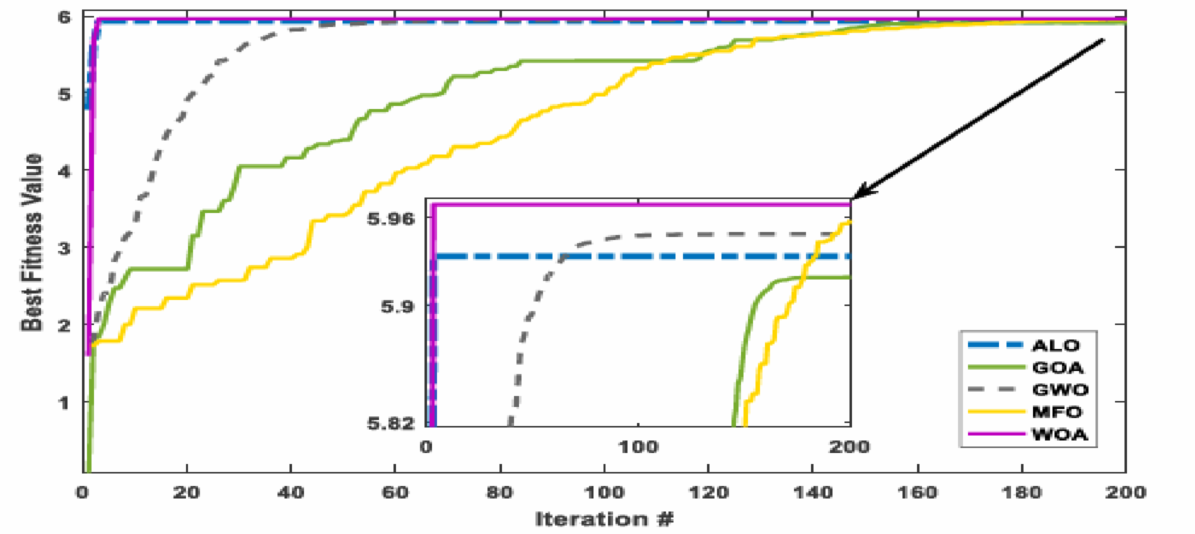

Figure 5: Convergence characteristics of fitness score for ALO, GOA, GWO, MFO

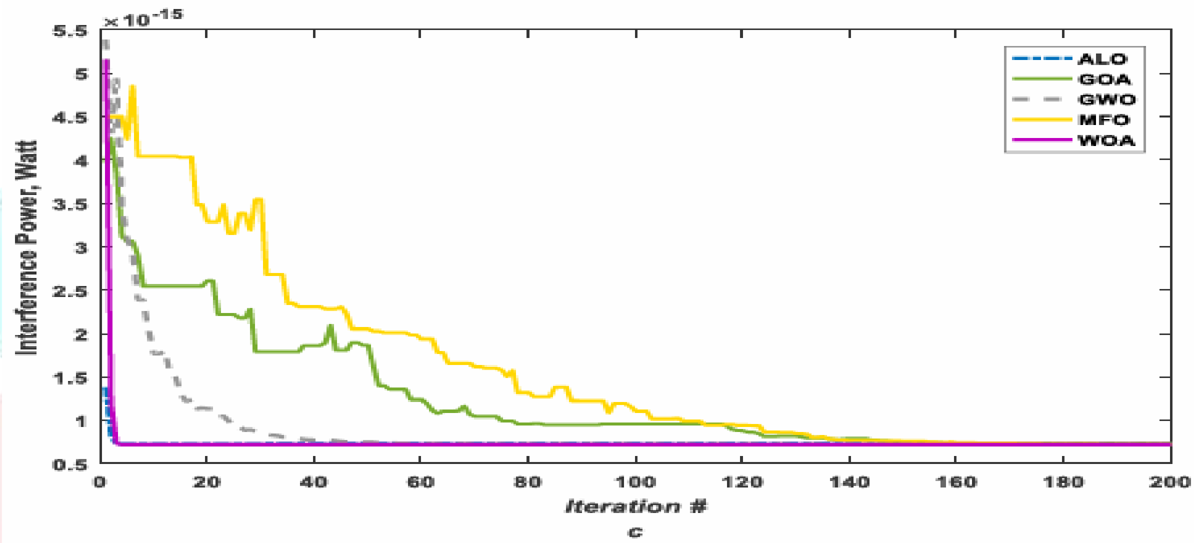

Figure 6: Convergence characteristics of (c) interference power (Watt) for ALO, GOA, GWO, MFO and WOA

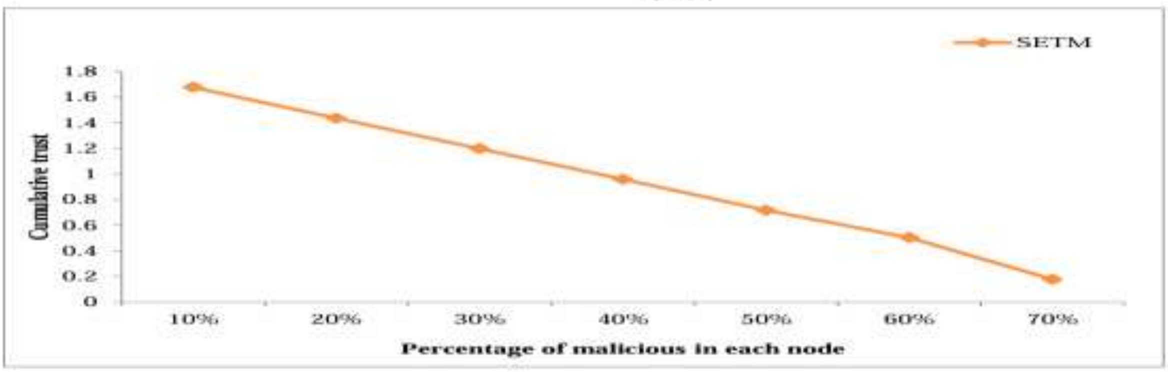

Figure Fig-7 Comparison of Cumulative Trust with the variation in the malicious behavior of SU

VI. Conclusions

Following are the key insights drawn from the work reported in this chapter:

WOA based CDE emerged as the best choice for realizing green communication as it provides the highest fitness value by offering the least power consumption.

It also serves as the best candidate for supporting real-time CR applications as it needs very few function evaluations (or iterations) to reach at an optimal solution. Therefore, WOA offers the least computational complexity.

WOA offers the highest percentage power saving of 74.70 % while satisfying different QoS requirements (BER, data rate and interference power) with a good amount of margin. It is also highly consistent and stable in its performance with lower standard deviation value obtained over the course of different Monte-Carlo trails.

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