Meta-heuristic Optimization based Parameter Adaptation in Cognitive Radio Systems

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This work is dedicated to my lifelines:

Father - S. Ajmer Singh

Mother - Smt. Balbir Kaur

Husband - Er. Yadwinder Singh

Brother - Ajaybir Singh

Certificate

I, **Avneet Kaur** hereby certify that the thesis entitled, "**Meta-heuristic Optimization based Parameter Adaptation in Cognitive Radio Systems**", which is being submitted by me to the Department of Electronics and Communication Engineering, Thapar Institute of Engineering and Technology, Patiala for the award of the degree of Doctor of Philosophy in Electronics and Communication Engineering, is a bonafide research work carried out by me under the supervision of Associate Prof. (Dr.) Surbhi Sharma and Assitant Prof. (Dr.) Amit Mishra. The contents presented in this thesis have not been in part or fully submitted to any other university for the award of the degree.

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This is to certify that the above statement made by the candidate is correct and true to the best of our knowledge and belief.

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Abstract

Cognitive Radio (CR) has emerged as an enabling technology to dynamically use the unused or underused spectrum, thereby increasing the spectral efficiency. The task of adapting or reconfiguring the system parameters is of utmost importance to enhance the overall performance of the CR system. In CR based system, the decision engine is an important module that not only embeds the features of observation and cognition of the radio but also responsible for parameter adaptation.

As meta-heuristic algorithms offer numerous advantages over classical mathematical approaches, the performance of these algorithms is investigated to design an efficient CR system that possesses the ability:

- To adapt the transmission parameters for efficiently minimizing the power consumption, bit error rate and adjacent channel interference while maximizing the throughput of a secondary user (SU).
- To maximize the number of transmission opportunities for a SU by optimizing the sensing period of a licensed channel.
- To improve the reliability of a physical layer based sensing by enhancing the probability of detection of a licensed user using cooperative spectrum sensing (CSS) scheme.

In this research work, the performance of various parameter-less meta-heuristic techniques such as ant lion optimizer (ALO), grey wolf optimizer (GWO), grasshopper optimization algorithm (GOA), moth flame optimization (MFO) and whale optimization algorithm (WOA) is investigated to reconfigure the transmission parameters for minimizing the total system power consumption at CR transmitter (CR_Tx) operating with Class B power amplifier. A simple system model is considered where one primary transmitter communicates with a primary receiver on a TV band. Upon finding this band as vacant, i.e. on the occurrence of TV white space, SU_Tx communicates with the secondary receiver in an interweave manner. A mathematical formulation of total system power consumption is shown and the problem is solved for data transmission scenario with constraints on data rate, bit error rate and adjacent channel interference. Simulation results show the effectiveness of WOA in minimizing the system power consumption by parameter adaptation in a multicarrier CR system while satisfying different QoS constraints.

Further, the application of ALO, GWO, MFO, WOA and Jaya algorithm is investigated to reconfigure the parameters for various transmission scenarios of a CR based IoT device. In each scenario, different user requirement, i.e. an IoT application and radio's battery level are considered. Constrained multi-objective optimization problem is solved by employing the weighted sum method where each weight vector emphasizes different communication objective such as minimize power consumption, minimize bit error rate and maximize throughput. The constraints for ACI and total transmit power of a SU are incorporated into a given problem by using a novel exponential penalty function.

After adapting the transmission parameters, the performance of a MAC layer based sensing is improved by optimizing the sensing period of a licensed channel. The recently proposed Jaya algorithm is employed to maximize the number of transmission opportunities for a SU while constraining the sensing overhead and interference time within a user-defined limit using a penalty function. Jaya algorithm is found to achieve quick convergence and better optimal value; making it a preferable choice for real-time applications.

This thesis also focuses on improving the detection performance of a physical layer based sensing. CSS is an effective technique to improve the probability of detection of a primary user. The performance of CSS can be enhanced by optimizing the weight vector of the observation statistics obtained from different SUs at the fusion center. A novel integrated technique, i.e. opposition based grey wolf optimizer (OBGWO) is proposed and tested on several benchmark problems by comparing its performance with existing algorithms: MFO, GWO and sine cosine algorithm. It is observed that OBGWO provides better solutions and improved convergence characteristics when compared with these techniques. Further, the performance investigation of these algorithms is done for optimizing the weight vector of a CSS scheme that improves the detection probability of a PU. OBGWO scheme is then employed to study the effect of variation in the number of secondary users, sensing channel noise and control channel noise on the proposed CSS model.

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List of Abbreviations

ABC	Artificial bee colony
ACI	Adjacent channel interference
ACO	Ant colony optimization
ALO	Ant lion optimizer
ANN	Artificial neural network
BBO	Biogeography based optimization
BER	Bit error rate
BFO	Bacterial foraging optimization
BPSK	Binary phase shift keying
BPSO	Binary particle swarm optimization
CBS	Case based system
CDE	Cognitive decision engine
CR	Cognitive radio
CS	Cuckoo search
CSO	Cat swarm optimization
CSS	Cooperative spectrum sensing
DE	Differential evolution
DSA	Dynamic spectrum access
DTV	Digital television
EA	Evolutionary algorithm
EA-ABC	Efficient adaptive artificial bee colony
EGC	Equal gain combining
FA	Firefly algorithm
FC	Fusion centre
FSS	Fish school search
GA	Genetic algorithm
GOA	Grasshopper optimization algorithm
GWO	Grey wolf optimizer
ICA	Imperialistic competitive algorithm
IMOABC	Improved multi-objective artificial bee colony

IoT	Internet of Things
JA	Jaya algorithm
MABC	Modified artificial bee colony
MAC	Media access control
MACO	Mutated ant colony optimization
MATLAB	Matrix laboratory
MDC	Modified deflection coefficient
MFO	Moth-flame optimization
MOBFO	Multi-objective bacteria foraging optimization
MOCSO	Multi-objective cat swarm optimization
MOGA	Multi-objective genetic algorithm
MOOP	Multi-objective optimization
MOPSO	Multi-objective particle swarm optimization
MRC	Maximal ratio combining
NDC	Normal deflection coefficient
NI	Nature-inspired
NSGA-II	Non dominated sorting genetic algorithm-II
OBGWO	Opposition based grey wolf optimizer
OBL	Opposition based learning
OFDM	Orthogonal frequency division multiplexing
PA	Power amplifier
PAPR	Peak-to-average power ratio
PSO	Particle swarm optimization
PU	Primary user
QAM	Quadrature amplitude modulation
QoS	Quality of service
QPSK	Quadrature phase-shift keying
RBS	Rule-based system
RCBBO	Real-coded biogeography-based optimization
RF	Radio frequency
SA	Simulated annealing
SCA	Sine-cosine algorithm
SDC	Soft decision combining

SDR	Software-defined radio
SFLA	Shuffled frog leaping algorithm
SLC	Square law combining
SU	Secondary user
TDD	Time-division duplex
TVWS	TV white spaces
UHF	Ultra-high frequency
WOA	Whale optimization algorithm

List of Symbols

P_k	Power radiated corresponding to k^{th} subcarrier
DR_k	Data rate corresponding to k^{th} subcarrier
BER_k	BER corresponding to k^{th} subcarrier
INT_k	ACI caused by k^{th} Subcarrier of SU's band into the adjacent PU's band
INT_{th}	Maximum interference power tolerable by PU receiver
DR_{th}	Threshold value for data rate
BER_{th}	Threshold value for bit error rate
d_k	Spectral distance between k^{th} subcarrier of SU and central frequency of adjacent PU channel
B	Bandwidth of the adjacent PU band
$L(D)$	Path loss in dB for distance D between PU and SU
P_T	Total power transmitted by SU_Tx
$\bar{\eta}$	Average efficiency for class B power amplifier
$\dot{P}_{max}$	Maximal output power of a power amplifier
P_c	Total system power consumption of SU transmitter (SU_Tx)
P_{avBER}	Average BER of K subcarriers of cognitive OFDM system
M_{max}	Maximum allowed modulation level
SR_{max}	Maximum allowed symbol rate
P_{max}	Maximum allowed power for the subcarrier
M_k	Modulation level of k^{th} subcarrier
SR_k	Symbol rate of k^{th} subcarrier
w	Weight vector
x_i	Signal received at i^{th} SU
h_i	Complex channel gain between i^{th} SU and PU
$s(k)$	Signal transmitted by PU
$a(k)$	Complex additive white Gaussian sensing noise
n_i	Zero mean Gaussian variable
δ	Variance of control channel noise
σ	Variance of sensing channel noise

P_f	Probability of false alarm
P_d	Probability of detection
P_{md}	Probability of miss-detection
P_e	Total error probability
γ_G	Test threshold

List of SCI Publications

1. Avneet Kaur, Surbhi Sharma, Amit Mishra, "Nature-inspired optimization algorithms assisted realization of green communication via Cognitive radio: A comparison study", *IET Communications*, 12(19), pp. 2511 – 2520, 2018.
2. Avneet Kaur, Surbhi Sharma, Amit Mishra, "Performance optimization of cognitive decision engine for CR-based IoTs using various parameter-less meta-heuristic techniques", *Arabian Journal for Science and Engineering*, 44, pp. 9499-9515, 2019. doi:10.1007/s13369-019-03787-w.
3. Avneet Kaur, Surbhi Sharma, Amit Mishra, "Sensing period adaptation for multi-objective optimization in Cognitive radio using Jaya algorithm", *IET Electronics Letters*, 53 (19), pp. 1335 – 1336, 2017.
4. Avneet Kaur, Surbhi Sharma, Amit Mishra, "Nature-inspired optimization algorithms based adaptation of transmission parameters in CR based IoTs", *Wireless Personal Communications*, vol. 108, pp. 2517-2540, 2019.doi: 10.1007/s11277-019-06536-2.
5. Avneet Kaur, Surbhi Sharma, Amit Mishra, "A novel Jaya-BAT algorithm based power consumption minimization in cognitive radio network", *Wireless Personal Communications*,108, pp. 2059-2075, 2019.doi:10.1007/s11277-019-06509-5.

Other Publications:

1. Ashmeet Kaur, Avneet Kaur and Surbhi Sharma, "PSO based multiobjective optimization for parameter adaptation in CR based IoTs", in *4th IEEE International Conference on Computational Intelligence & Communication Technology (CICT)*, Ghaziabad, India, 2018.
2. Avneet Kaur, Ashmeet Kaur and Surbhi Sharma, "Cognitive decision engine design for CR based IoTs using differential evolution and bat algorithm", in *5th IEEE International Conference on Signal Processing and Integrated Networks*, Noida, India, 2018.

Chapter 1
Introduction

1.1 Cognitive Radio Technology

A tremendous rise in the applications of wireless communication technology has prompted the increased spectrum demand. However, the great barrier faced for this demand is the inadequacy of radio resources. Research by the Federal Communications Commission (FCC) has proved that the major factor behind this scarcity is the spatial or temporal under-utilization of the spectrum by the licensed users [1]. Non-line-of-sight radio propagation is favored in bands below 3 GHz and the efficiency of spectrum usage varies between 15% - 85% in these bands [2]. The present used spectrum allocation policy is static that assigns a particular band to each licensed or primary user (PU) and has resulted in spectrum under-utilization [3].

Cognitive radio (CR) technology has received remarkable attention to alleviate the apparent shortage of available spectrum. Motivated by the studies of FCC that highlighted about inefficient utilization of a major part of the licensed spectrum, the idea of CR was proposed by Joseph Mitola in the late 1990s [4]. This technology allows the unlicensed or secondary users (SUs) to dynamically search for idle spectrum bands and allow them to operate in the underused parts of the spectrum, thereby increasing the spectral efficiency while avoiding any interference to PUs [5-6].

"*Cognitive radio is described as an intelligent wireless communication system that can adjust and reconfigure itself as per the surrounding environment so that the requirements of end-user are satisfied*". Cognition and re-configuration are important capabilities responsible for making CR an intelligent device [7]. These capabilities are explained below in detail:

Cognitive capability

It provides the spectrum awareness in terms of spectral occupancy, channel conditions etc. and is achieved by capturing the spatial and temporal variations present in the environment while avoiding any interference to other users. The complete cognitive cycle is formed when the following tasks are performed by the radio [8]:

- ***Spectrum sensing:*** determines the portions of the spectrum available for opportunistic usage.
- ***Spectrum management:*** selects the best available channel as per the end user's requirement.

• ***Spectrum sharing:*** provides unbiased spectrum scheduling by coordinating access to the selected channel among coexisting CR users.

• ***Spectrum mobility:*** involves vacating the channel when a licensed user becomes active and moving smoothly to another unused channel.

Re-configurability

It enables dynamic programming of the device by adjusting the operating parameters on the fly without any change in hardware components. CR device can be programmed to transmit and receive on different frequencies and its hardware design can support various transmission access technologies. Operating frequency, transmission power, modulation scheme and channel coding are some of the parameters that can be reconfigured according to the user needs, present environmental factors and previous experiences [9]. The module which combines the characteristics of observation, cognition and reconfiguration is called cognitive decision engine (CDE) [10] and is described in the following section.

1.2 Cognitive Decision Engine

CDE is an integral part of CR which helps the radio to respond in an intelligent manner according to its operating environment. After receiving input from the environment/user (observation), CR analyzes the situation and classifies it to determine a suitable response for stimulus (cognition) and gives the decision (re-configuration). The decision making framework of the CDE module is shown in Figure 1.1 and is explained in detail along with the components' description in the next section.

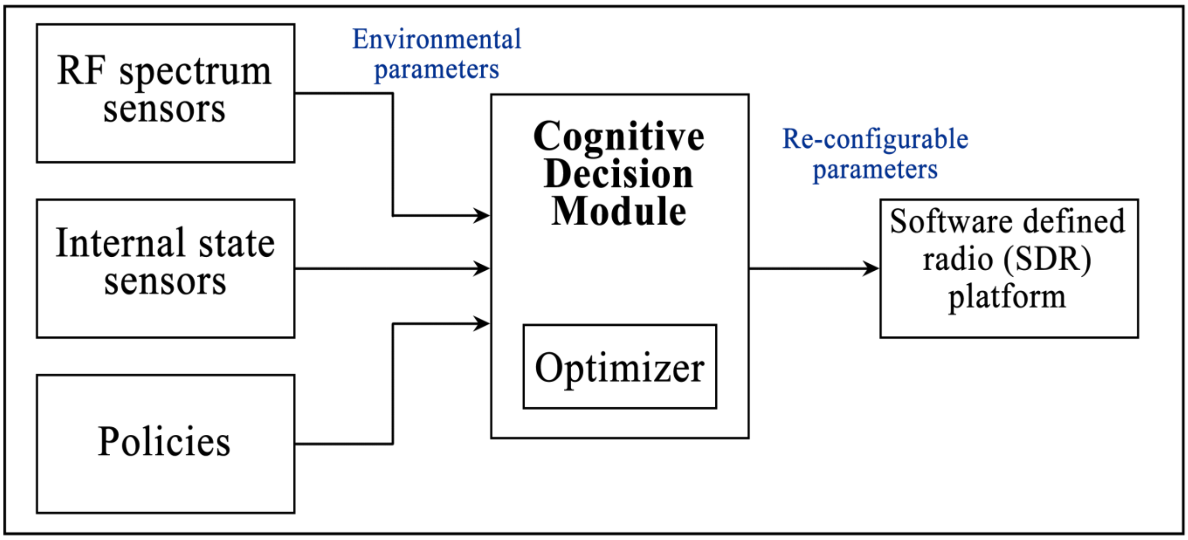


Figure 1.1: Decision-making framework for CR with CDE

1.2.1 Components of CDE

The components that help in building the cognitive capability and achieve CR operation are explained below [11]:

Sensors: Spectrum sensing module comprises of RF sensors and internal state sensors. RF sensors sense the radio environment and channel characteristics such as path loss, noise power, interference power etc. On the other hand, internal state sensors are responsible for capturing the information about the current service requirement of the user and the radio's battery level.

Policy engine: Policies are the regulations defined by the government which confine the actions of CR and must be considered during decision making. The policy engine ensures that the transmission parameters returned by the optimization process are legal with respect to the local regulatory restrictions.

Decision module: The decision-making component of the CDE analyses the information received from sensors and further decides the required actions. If optimization is required, the decision module will provide the optimization goals (such as high throughput or low power consumption) to the optimizer. It also provides the time limit and stopping criteria to achieve these goals.

Optimizer: An optimizer provides the optimal set of transmission parameters that will maximize the performance for given environmental conditions and user-oriented information.

Hence, the decision-making module combines the information provided by sensors and takes an autonomous decision according to the present environmental scenario. The decision is in the form of reconfigurable parameters which are sent to the radio realized as software-defined radio (SDR). After this, SDR changes its configurations as per the decision results of the decision-making module.

1.2.2 Radio parameters for CDE design

Radio parameters for CDE are classified into environmental and transmission parameters [12-13] as described below:

Input or environmental parameters: Environmental parameters are the radio parameters that inform the CR about path loss, channel attenuation, noise power, signal-to-noise ratio (SNR) etc. through RF sensors. The information from internal state sensors about the radio's battery level and service type required by the user also acts as an input parameter.

Output or transmission parameters: Transmission parameters act as reconfigurable or tunable parameters of CR, generated by the decision module to meet the quality of service (QoS) requirements of the user in the present operating environment. Transmit power, modulation level, bandwidth, symbol rate, size of a transmission frame in bytes, time division duplex percentage are examples of transmission parameters.

As the *input variables* depend on environmental conditions and user requirements, these are considered to be static for the present scenario. Therefore, transmission parameters, also called *decision variables* need to be optimized in order to achieve specified objectives and QoS requirements of the end-user. In other words, CDE should be able to adjust the transmission parameters according to the environmental information. The specific objectives can be bit error rate (BER) minimization, power consumption minimization, interference minimization or throughput maximization. The optimal set of transmission parameters can be obtained using various available techniques as discussed in the following section.

1.2.3 Various techniques for parameter adaptation in CDE

Numerous techniques have been proposed in the literature to obtain the transmission parameter adaptation in CDE and are explained as follows:

Rule-based system (RBS) [14]: It is the simplest technique and its performance depends on the set of offline rules defined by the user. RBS comprises the following elements:

- Rule base: It contains a list of permanent rules.
- Inference engine (IE): This engine is responsible for inferring the information and taking actions on the basis of input parameters and the defined rule base.

The performance accuracy of this system is decided by the underlying rule base and RBS is unable to perform well during undefined situations. It might return inappropriate responses if the domain is not perfectly understood.

Case-based system (CBS) [15-16]: This system relies on using past cases and their solutions to solve the current similar problem. The case base stores previous actions and based on the input received from sensors, a suitable solution to the new problem is found from the case database. One of the key issues of CBS is that its performance relies on previous cases. It also requires a large amount of memory to store the history of cases and these cases would rise quickly as the system runs. In the actual scenario, if inaccurate responses of the CBS are saved, the error may propagate onto the new cases.

Artificial neural networks (ANN) [11, 17]: Neural network is inspired by the biological nervous system and is formed by interconnected neurons to form the network. Each artificial neuron produces a single output value by collecting input from other neurons. The output depends on the weights and activation functions. The adaptive weights are adjusted until the output of the network approximates the desired value. The accuracy and performance of an algorithm depends on the data used for training the model along with the initial parameters and attributes. Some of the disadvantages of this approach are summarized below:

- ANN requires large training data and prior knowledge of the environment. If the network size is large, training for the neural network can be slow.
- The problem of over-fitting arises when the developed model is not general. The network might get over-trained which means it is trained exactly to respond to only one type of input.

Machine learning (ML) [18]: ML algorithms are computationally expensive requiring long training time and a large number of samples to train the model before its application to real-time decision making. The computational and storage requirements increase rapidly with the number of training vectors. Different kernel functions are used to map the input vector space to feature space. Support vector machine (SVM) offers a unique solution since it deals with convex optimization problems, unlike neural networks that provide multiple solutions associated with local minima. A learning engine based on SVM is proposed in [19] to realize the core function of a CR, i.e. intelligence.

Meta-heuristic algorithms: These algorithms possess high convergence speed, ease of applicability and capability to solve non-convex, non-linear, multi-dimensional or highly complex optimization problems [20]. The optimization process using meta-heuristic algorithms starts with the generation of a set of random solutions. These initial solutions are then modified over a certain number of iterations. These algorithms differ from each other by the mechanism involved in updating or modifying the solutions. Over the last two decades, meta-heuristic techniques have gained wide popularity among researchers and academicians. These have been successfully applied in the literature to solve the parameter adaptation problem for CDE. Meta-heuristic algorithms that have been employed for optimizing the CDE design include:

- Genetic algorithm [21]
- Particle swarm optimization (PSO) [22]
- Artificial bee colony (ABC) algorithm [23]
- Ant colony optimization (ACO) [24]

- Simulated annealing (SA) [25]
- Biogeography based optimization (BBO) [26]
- Cat swarm optimization (CSO) [13]

The detailed discussion of the advantages of meta-heuristic algorithms, different mechanisms involved in the optimization process for these algorithms and their classification based on the population size is provided in the next section.

1.3 Meta-heuristic Algorithms

Algorithms with stochastic components were often referred to as heuristic in the past, though the recent literature tends to refer to them as meta-heuristic. Loosely speaking, heuristic means to find or to discover by trial and error. Here *meta-* means beyond or higher level, and meta-heuristics (*higher-level search)* generally perform better than simple heuristics.

1.3.1 Advantages of meta-heuristic algorithms

Meta-heuristic algorithms offer numerous advantages [27-28] that are listed below:

Simplicity: Meta-heuristics are fairly simple as they are inspired by simple physical phenomena, animal behavior or evolutionary process. Scientists find it easy to simulate these simple natural concepts. Besides, these algorithms follow a common framework that involves the creation of random solutions that are enhanced or evolved iteratively. The only difference among different algorithms lies in the criteria adopted to improve the solution set.

Flexibility: Meta-heuristics can be applied to a wide range of disciplines without any special change in the algorithm's structure as they consider problems as black boxes. For the optimization process, the nature of the problem is not the concern as it is based only on the provided inputs and received outputs. The designer only needs to know how to represent his problem for solving it using these algorithms.

Derivation free mechanism: Meta-heuristic approaches involve a derivation-free mechanism, unlike gradient-based optimization methods. The problem is optimized stochastically, starting with the generation of random solution(s) and there is no need to calculate the derivative of search spaces to find the optimum. These are highly suitable for real-world problems having unknown or expensive derivative information.

Local optima avoidance: As meta-heuristic algorithms are stochastic in nature, they possess superior abilities to escape local optima and explore the entire search space extensively. Real-world problems have unknown and complex search space with a large number of local optima. Therefore, these algorithms are a good solution to solve such challenging optimization problems. The stochastic nature of meta-heuristic algorithms offers higher chances to avoid local optima as compared to deterministic methods. Although there is no guarantee that a very accurate approximation of the global optimum is obtained, the chances to obtain a better solution are increased when the meta-heuristic is run several times.

1.3.2 Mechanisms involved in the optimization process with meta-heuristic algorithms

The optimization process is divided into two conflicting objectives of ***exploration*** and ***exploitation*** [29-30] where improvement in one results in the degradation of another. An appropriate balance between these two results in a very accurate approximation of the global optimum.

Exploration: This phase involves the broad investigation of the promising areas of search space, thereby avoiding the local solutions. Exploration is achieved by an abrupt and stochastic change to the candidate solutions which move globally, thereby improving their diversity. For example, a high probability of crossover in GA is the main exploration mechanism. Similarly, inertia weight in PSO emphasizes exploration by maintaining the tendency of particles towards their previous direction.

Exploitation: After undergoing enough exploration, solutions undergo gradual change and move locally. This phase is called exploitation which is the local search ability of an algorithm around the promising regions that are obtained in the exploration phase. The candidate solutions should undergo less sudden change and must do a local search. For instance, in GA, mutation operators bring exploitation by causing slight random changes and search locally around the candidate solutions. The low inertia rate in PSO causes low exploration and a high tendency towards the personal best solutions obtained, thereby allowing particles to converge towards the best solution instead of moving around the search space. Meta-heuristic algorithms require the search agents to move smoothly from exploration to exploitation phase using different adaptive mechanisms.

1.3.3 Classification of meta-heuristic algorithms

Meta-heuristics are classified into the following two categories:

Individual or single solution based: These algorithms create a single solution and improve it over the course of iterations [31]. Therefore, such optimization techniques require $1 \times T$ number of function evaluations where T is the maximum number of iterations. As only one solution is involved, the computational cost is also low. But these algorithms suffer from premature convergence, i.e. the stagnation of an optimization technique to some local optima, which prevents it from converging towards the global optimum. Tabu search [32] and simulated annealing [33] are well-known algorithms that belong to this family. The optimum value obtained at the end of each iteration is perturbed which is considered as the starting point for the next iteration.

Population-based: These algorithms involve the initialization of a set of candidate solutions that exchange information among themselves and improve them over the course of iterations [31]. Population-based algorithms possess high local optima avoidance and are more reliable in exploring the search space and exploiting the global optimum. However, the requirement for large function evaluations and high computational cost are the two major drawbacks of these techniques. A large number of swarm intelligence based algorithms such as PSO [34], ABC [35], DE [36], bat algorithm [37], cuckoo search (CS) and firefly algorithm (FFA) [38] fall in this category. Wind-driven optimization (WDO) [39], gravitational search algorithm (GSA) [40] and colliding bodies optimization (CBO) [41] are some of the population-based techniques inspired from the physical phenomenon. The application of meta-heuristic algorithms can be found in numerous domains of science and engineering. These algorithms have also been applied for parameter adaptation in CR networks [21-26, 50-51], antenna array synthesis [42], fault-tolerant clustering in wireless sensor networks [43], peak-to-average power ratio (PAPR) reduction in orthogonal frequency division multiplexing (OFDM) systems [44] etc.

According to the No Free Lunch (NFL) theorem [45], there is no single algorithm among meta-heuristics that can find the best optimal solution for all types of optimization tasks. An algorithm that shows very promising results for a particular problem may show poor performance when applied to some other set of problems. Therefore, search for advanced, new or hybrid optimization techniques and their application to different domains is an open research area. Hence, extensive research has been carried out in this field to propose new meta-heuristic techniques and to enhance the capability of existing techniques.

Meta-heuristic techniques offer numerous advantages over conventional optimization methods. Hence, in this thesis, the task of adapting the transmission and sensing parameters is carried out using recently proposed meta-heuristic algorithms. The performance of ant lion optimizer (ALO) [28], grasshopper optimization algorithm (GOA) [46], grey wolf optimizer (GWO) [47], moth flame optimization (MFO) [29], whale optimization algorithm (WOA) [30], sine cosine algorithm (SCA) [102] and Jaya algorithm [103] is explored to find an optimal solution to the parameter reconfiguration problem in CR systems. These algorithms are highly efficient and possess excellent exploration and exploitation features. Another motivation for using these algorithms comes from the fact that these techniques are either free from any algorithm-specific parameters or have very few control parameters that need to be tuned at the user end.

This encourages the application of meta-heuristic techniques to not only reconfigure the transmission variables but also to optimize different sensing parameters like sensing period, sensing overhead time, number of spectrum utilization opportunities for a SU etc. In the next section, the need for an adaptive spectrum sensing scheme is highlighted and the meta-heuristic based approach to optimize the sensing period is discussed.

1.4 Need for Adaptive Spectrum Sensing

Spectrum sensing is a key requirement for dynamic spectrum access based CR networks [48]. An efficient spectrum sensing enables periodic detection of PU's presence and discovery of the available bands for SU transmission. The sensing task by SU aims at finding the transmission opportunities and avoiding the interference to transmissions done by PU. The sensing process involves two-layer mechanisms given below:

Physical (PHY) layer-based: It emphasizes on efficient detection of PU's status to identify the spectrum opportunities for a SU. Energy detection, matched filter and feature detection are some of the well-known techniques for physical layer based sensing [49]. In other words, PU's presence or absence is known from any of the PHY- layer based detection methods.

Media access control (MAC) layer-based: This sensing mechanism determines the sensing periodicity of the spectrum, i.e. when the SU has to sense the licensed channel [50]. The sensing process consists of sampling the licensed channel at regular time instants. PU's behavior, in terms of MAC layer based sensing, is represented by the ON-OFF model as shown in Figure 1.2.

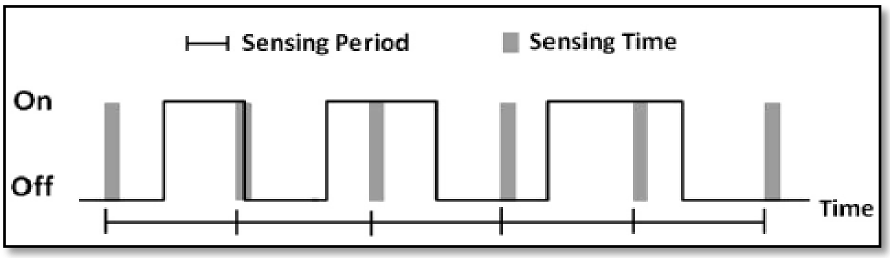


Figure 1.2: On- Off model of PU with the concept of sensing period and sensing time

Sensing period and sensing time (shown in Figure 1.2) are two important metrics for the periodic sensing scheme. The sensing period is an interval between two detection instances and greatly impacts the sensing efficiency of a CR system. The choice of a physical layer based sensing method determines the time required for sensing. After sensing the licensed channel during sensing time, the SU determines its availability for use. If any idle channel is found upon periodic sensing, it becomes a new spectrum opportunity to be utilized by an unlicensed user. Hence, SU can transmit opportunistically if a licensed channel is in OFF state, i.e. no PU is currently transmitting.

As shown in Figure 1.3, when sensing is less frequent or the sensing period is long, it results in the loss of transmission opportunities by SU or there is a rise in the number of missed opportunities [51]. A missed opportunity is that duration when the licensed channel was inactive (OFF state), but it was not discovered by SU. Also, PU activity ($ON\ state$) is not detected due to long sensing period. Even though the sensing overhead is smaller, PU communication can incur some transmission collisions from the SU (interference to the PU). Moreover, the transmission collisions not only result in interference to PU but also require more SU retransmissions that lead to more energy wastage [52].

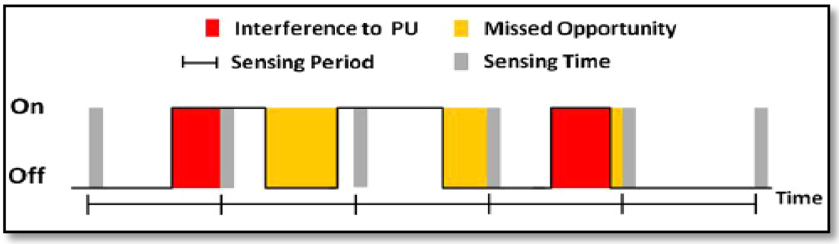


Figure 1.3: Large sensing period leading to missed opportunities and interference to PU

Contrarily, reduction in the sensing period value or higher sensing frequency leads to redundant sensing as SU will perform sensing even when there is no variation in the channel's state as shown in Figure 1.4. In other words, it will result in higher sensing overhead, which is the time duration for which SU must stop data transmission to measure the licensed channel's availability. It compromises the spectral efficiency of SU as most of the time is consumed in PU's detection, instead of transmitting data.

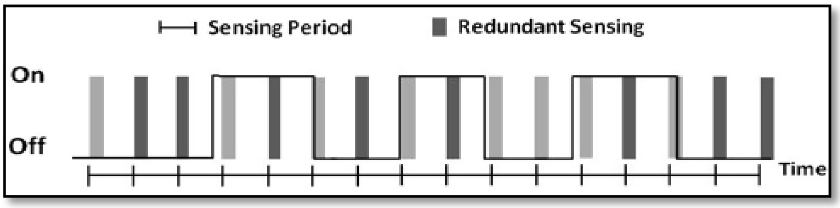


Figure 1.4: Redundant sensing leading to high overhead

Therefore, an efficient designing of a periodic sensing scheme involves the selection of an appropriate value of sensing period which balances the tradeoffs among sensing overhead, spectrum utilization and interference to PUs. Application of advanced meta-heuristic techniques can provide an intelligent adaptation of sensing period that can be more effective for real CR systems. An optimization goal is to adjust the *sensing period* to increase the number of spectrum utilization opportunities while constraining the *sensing overhead* and *interference time* within user-defined limits. In this way, an efficient MAC layer based sensing is achieved.

In order to enhance the performance of PHY-layer based sensing, the idea of cooperative spectrum sensing (CSS) is introduced [53]. The detailed discussion of the need for CSS scheme, its types and different data fusion methods used for CSS is given in the next section.

1.5 Need for Cooperative Spectrum Sensing

Shadowing, multipath fading, noise uncertainty and the presence of obstacles lead to the most challenging problem of hidden PU that degrades the detection performance of SU [54]. In such a case, unwanted interference is caused by SU to PU's transmission as the former is unable to distinguish between faded PU's signal and white space. The impact of these issues can be mitigated to a greater extent by the CSS technique.

CSS involves the number of SUs and the sensing results of different SUs are combined to enhance the sensing reliability for efficient detection of PUs. CSS involves the exploitation of the spatial diversity offered by different secondary users as each SU experiences a separate channel between PU and itself [54]. Individual SUs perform the task of energy detection based spectrum sensing and send the local observations to the fusion centre (FC) which fuses all the decisions to deduce about the absence or presence of PU. In other words, cooperative sensing can solve the hidden node problem by decreasing the probabilities of miss-detection and false alarm. Although, CSS offers a cooperative gain in terms of improved detection performance, that comes at the cost of incurring cooperation overhead.

1.5.1 Classification of CSS

The cooperative spectrum sensing is broadly classified into two categories:

Centralized CSS: It involves one central entity termed as FC that coordinates the following three-stage process [55]:

- FC chooses the frequency band of interest and all cooperating SUs are directed to tune to that licensed channel in order to perform individual sensing. *The sensing channel* is a physical point-to-point link between PU transmitter and each cooperating SU for detecting the PU's presence.

- Reporting of sensing results to the FC is done by all cooperating SUs through *reporting or control channel*. This channel provides a physical point-to-point link between each SU and the FC.
- Locally sensed information received by FC is combined to determine the presence of PU. The final decision is then shared with cooperating SUs.

Distributed CSS: For this type of sensing, FC is not required to make a unified decision. SUs exchange information among themselves and reach a combined decision about PU's presence.

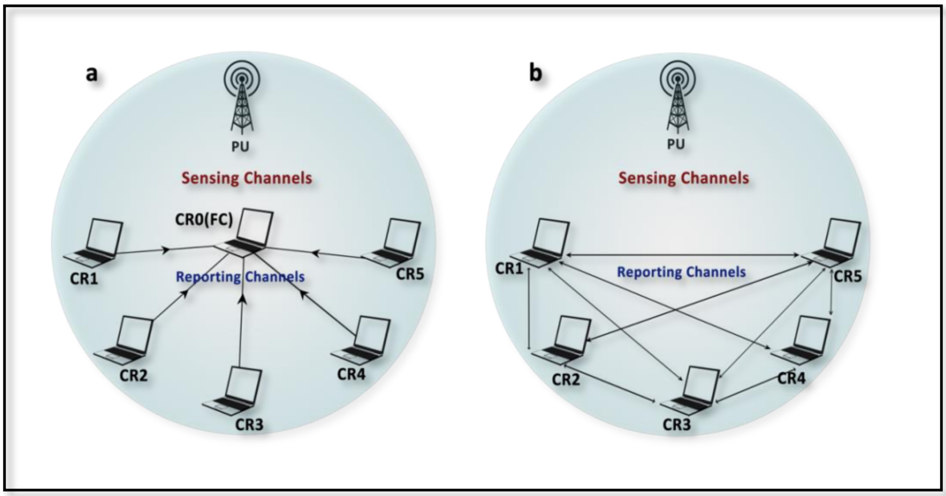


Figure 1.5: Different models of CSS a) Centralized b) Distributed

1.5.2 Data fusion in CSS

Data fusion is an important element of CSS and is defined as a process of combining local sensing observations for hypothesis testing. Data fusion in the CSS scheme is classified into hard combining and soft combining [53-56].

Hard combining: Each SU senses the band independently and sends a one-bit binary decision to the FC. PU's presence (H_1) is indicated by bit '1' and absence (H_0) is depicted by bit '0'. Linear fusion rules (OR rule, AND rule and MAJORITY rule) are used to combine the local decisions in order to obtain the cooperative decision.

- **OR rule**: According to this rule, a decision is taken in favor of PU's presence; even if a single SU sends the bit '1', i.e. the global decision at FC: $u = 1$ if $u_i = 1$ for any i, where u_i is the local decision of the i^{th} SU and u is the combined decision made by the FC.

- **AND rule**: In this rule, a decision is taken in favor of the hypothesis H_1 if all SUs send bit '1', i.e. the combined decision at FC: $u = 1$ if $u_i = 1 \; \forall \; i$.
- **'K'-out-of-'M' rule**: It is also referred to as majority rule that needs at least half of the SUs to send bit '1'. In other words, FC takes a decision in favor of the hypothesis H_1 when 'K' out of 'M' SUs send bit '1'.

Soft Combining: In this technique, each SU sends the exact observation value to the FC instead of concluding at a certain decision. Selection combining (SC), maximal ratio combining (MRC), square-law combining (SLC), equal gain combining (EGC) and meta-heuristic algorithm based weighted combining scheme are some of the techniques that have been adopted for the soft combination of test statistics.

The information fusion framework of linear CSS shown in Figure 1.6 can be divided into the following three phases:

- **Local sensing**: Different CRs use spectrum sensing method (preferably energy detection) to detect the PU signal and locally process the sensed information.
- **Information fusion**: Local sensing information of CRs is weighed linearly by FC employing certain intelligent optimization techniques such as meta-heuristic algorithms.
- **Global decision**: The information processed by FC is compared with a certain threshold and an ultimate decision about PU's presence or absence is made.

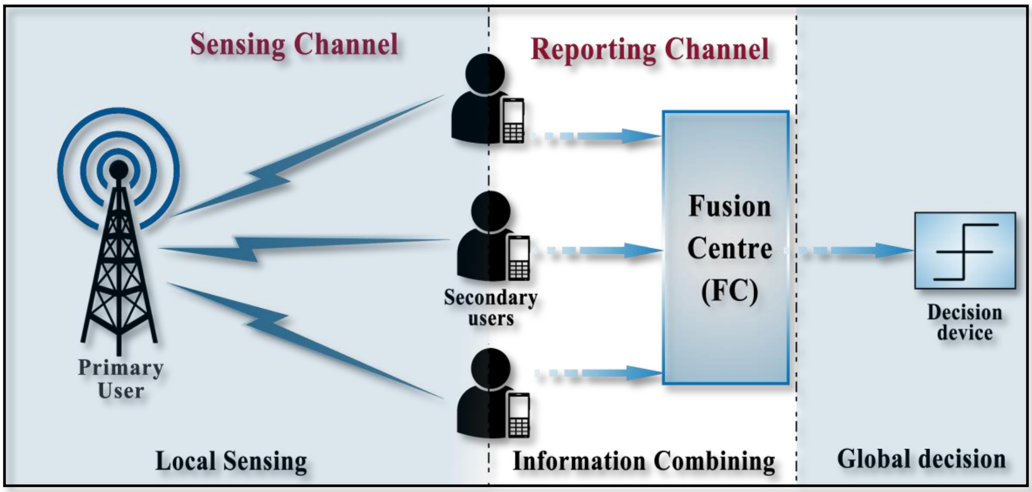


Figure 1.6: Fusion framework for a CSS scheme

It is found that the detection performance of soft combining methods is superior to hard combining schemes. Therefore, our research work is focused on optimizing the performance of a weighted soft combination of local statistics from multiple nodes at the FC, using meta-heuristic algorithms.

1.6 Organization of the Thesis

The work in this thesis has been organized into seven chapters. The contents of all the chapters are briefly described below:

Chapter One presents the background theory of CR, different usage paradigms of CR and various artificial intelligence techniques proposed in the literature for CDE design. Further, the concept of sensing period is discussed and the importance of optimizing its value for efficient spectrum sensing is highlighted. The fundamentals of the CSS scheme, its types and data fusion methods are also presented.

Chapter Two provides a comprehensive literature survey of different techniques for adaptation of transmission parameters in a CR system. Besides, the literature available on various sensing period adaptation methods and optimization of the CSS scheme is introduced.

Chapter Three describes the mathematical formulation of total system power consumption at CR transmitter with a Class B power amplifier (PA). Reconfiguration of transmission parameters is carried out to obtain the least power consumption. The performance of recently proposed nature-inspired optimization algorithms is explored to solve the power consumption minimization problem for a multicarrier CR system subjected to different QoS constraints.

Chapter Four focuses on the multi-objective optimization problem of adapting the transmission parameters of a CR based Internet of things (IoT) system. Advanced meta-heuristic algorithms are tested to solve the parameter adaptation problem for CDE design. Simulation results are analyzed, compared and plotted for different transmission scenarios.

Chapter Five presents the sensing period adaptation scheme for a licensed channel employing the Jaya algorithm. A novel objective function is introduced that maximizes the number of transmission opportunities while constraining the sensing overhead and interference time within user-defined value.

Chapter Six introduces a novel algorithm proposed in this work, called Opposition based Grey wolf optimizer (OBGWO). OBGWO is an extension of GWO employing the concept of an opposition based learning (OBL) scheme. The proposed algorithm is tested on different benchmark functions and applied to enhance the performance of the CSS scheme. The weight vector of observation statistics received from different SUs is optimized to increase the probability of detection of a licensed user.

Chapter Seven summarizes the conclusions drawn from the research and outlines the possible extension of this work in the future.

Chapter 2
Literature Survey

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 in Section 2.1. Existing research work related to the adaptation of transmission parameters employing various meta-heuristic techniques is reviewed in Section 2.2. Literature review on parameter reconfiguration for power consumption minimization in order to realize green radios is presented in Section 2.3. Section 2.4 summarizes the literature available on the optimization of the sensing period for implementing the adaptive spectrum sensing scheme. In Section 2.5, a literature review based on the weight optimization of CSS has been presented. Section 2.6 provides a review of the latest literature available on CR based IoT systems. Limitations of the existing literature are put forth in Section 2.7. Further, the objectives and research contributions of this thesis are provided in Section 2.8 and Section 2.9 respectively.

2.1 Literature Survey based on different Meta-heuristic Algorithms

This section provides the literature review of recent meta-heuristic algorithms that have been employed for parameter adaptation in this thesis.

S. Mirjalili [28] proposed a novel ant lion optimizer (ALO) algorithm. ALO is a nature-inspired (NI) technique that is inspired by the hunting mechanism of ant-lions. The algorithm is tested on a set of 19 mathematical functions and is compared with seven well-known algorithms in literature: BA, CS, FA, FPA, GA, PSO and SMS (States of Matter Search). Results show the superiority of ALO in terms of improved exploration and exploitation abilities, local optima avoidance and high convergence rate. Classical engineering problems of gear train design, three-bar truss design and cantilever beam design are solved using ALO. Finally, ALO is employed to solve the challenging constrained and real-world problems of optimizing the shapes of two ship propellers.

MFO algorithm is a NI paradigm proposed by Mirjalili [29] and is inspired by the navigation method adopted by moths known as transverse orientation. The spiral convergence of moths towards artificial lights is mathematically modeled to perform optimization. MFO algorithm is compared with other well-known algorithms (PSO, GSA, BA, FPA, SMS, GA and FA) on a set of 19 test cases that comprise of unimodal, multi-modal and composite functions. MFO is found to show high exploitation for unimodal functions, good exploration for multi-modal problems and provides a proper balance between exploration and exploitation for composite test functions. Further, 7 real engineering test problems: welded beam design, gear train design, three-bar truss design, pressure vessel design, cantilever design, I-beam design, and tension/compression spring, 15-bar truss, and 52-bar truss design are solved to investigate the superiority of MFO. MFO is then applied to show its competency in solving highly constrained and expensive optimization problems of marine propeller design.

In [46], the authors proposed GOA that is inspired by the swarming behavior of grasshoppers for solving different optimization problems. Repulsive and attractive forces between grasshoppers were mathematically modeled where repulsion allows exploration of search space by grasshoppers, whereas attraction enables exploitation of the promising regions. First of all, GOA is tested on unimodal, multi-modal, composite, and CEC2005 test functions. It is found to outperform several other algorithms in literature: PSO, SMS, BA, FPA, CS, GA, DE and GSA. The competency of GOA is then tested to find the optimal shape for cantilever beam, 3-bar truss and 52-bar truss design problems. The results of these applications validate the advantage of GOA in solving real-world problems having unknown search spaces.

S. Mirjalili et al. [47] developed GWO which is a NI and swarm intelligence based meta-heuristic algorithm. It mimics the hunting mechanism and leadership hierarchy of grey wolves. Three mechanisms: prey search, prey encirclement and attack of prey are mathematically modeled while leadership hierarchy is simulated via alpha, beta, delta, and omega wolves. The performance of GWO is benchmarked on a set of benchmark functions and results are compared with PSO, GSA, DE, Evolutionary Programming (EP) and Evolution Strategy (ES). GWO provides highly competitive results as compared to these algorithms. GWO is also employed to solve classical engineering design problems of tension/compression spring, welded beam, and pressure vessel. The real problem in the domain of optical engineering is also solved using GWO and all these experiments show the effectiveness of GWO in solving various constrained and unconstrained optimization problems.

WOA is a NI meta-heuristic, proposed by S. Mirjalili and A. Lewis [30] that simulates the social behavior of humpback whales. It is inspired by their bubble-net hunting strategy and three operators are adopted to model the prey search, prey encirclement, and bubble-net foraging behavior. WOA is tested using 29 mathematical optimization problems and 6 structural design problems of a welded beam, tension/compression spring, pressure vessel, 15-bar truss, 25-bar truss and 52-bar truss. Optimization results validate the competitiveness of WOA over other existing meta-heuristic algorithms (PSO, GSA and DE) as well as conventional approaches (Fast Evolutionary Programming (FEP) and Evolution Strategy with Covariance Matrix Adaptation (CMA-ES)).

S. Mirjalili [102] proposed a novel population-based optimization algorithm called SCA to solve different optimization problems. It involves the random generation of initial candidate solutions and a mathematical model based on sine and cosine functions is used. This model allows the fluctuation of candidate solutions towards or outwards the best solution. It also involves the generation of several random variables that adapt themselves to emphasize exploration and exploitation of the search space. The abilities of convergence, exploitation, exploration and local optima avoidance are first tested on a set of unimodal, multi-modal, and composite functions. In order to verify the superiority of results obtained with SCA, its performance is compared with PSO, BA, FA, FPA and GSA. To verify the performance of SCA in solving constrained optimization problems with unknown search spaces, the cross-section of the aircraft's wing was effectively optimized by SCA.

R.V. Rao [103] proposed a simple optimization technique called the Jaya algorithm (JA) that effectively solves a variety of constrained and unconstrained problems. JA is tested on 24 constrained and 30 unconstrained benchmark problems and the results were compared with existing techniques (GA, PSO, DE, BC, BBO, Homomorphous mapping (HM), heat transfer search (HTS), Teacher learning based optimization (TLBO), adaptive segregational constraint handling evolutionary algorithm (ASCHEA), simple multi-membered evolution strategy (SMES). Results prove that the Jaya algorithm performs satisfactorily for solving constrained optimization problems. Statistical analysis done also supports the performance superiority of this algorithm.

2.2 Literature survey based on the adaptation of transmission parameters for solving the multi-objective optimization problem in a CR system

This section briefly discusses the existing literature on the generalized concepts of the cognitive radios followed by the application of meta-heuristic techniques for CDE design.

In [2], the authors proposed Cognitive radio as an opportunistic access method which resolves the problem of limited spectrum availability and inefficient spectrum usage. An overview of CR technology is provided and the unique challenges involved in the next generation networks are presented. The concepts of spectrum mobility, spectrum sensing, spectrum handoff and spectrum sharing were introduced.

The authors discussed key operations and principles of a CR network in [57] along with the challenges and opportunities for this network. Different techniques for spectrum sensing, i.e. matched filtering, energy detection, waveform based sensing and cyclostationary feature detection along with cooperative detection were reviewed. Authors also addressed the issue of spectrum management, spectrum sharing and spectrum mobility.

T.R. Newman [58] formulated different objective functions that represent the relationship between transmission and environmental parameters for a CR system. The problem for CDE design is solved using a weighted sum approach that aggregates the objective functions and the overall fitness value is controlled by the value of weight coefficients. The problem is solved using two different techniques i.e., GA and RBS. GA is found to provide more flexibility and a user-friendly interface for adjustment of system parameters. RBS has a lower memory requirement for storing the cases and provides solutions very fast. The convergence speed of GA is enhanced by adopting a new adaptive population initialization method known as seeding. It biases the population of present iteration towards the best solutions obtained in the last run. The seeding approach improves performance as long as the environment is not changed significantly.

A comprehensive survey of different bio-inspired approaches and their application in the field of CR networks is presented in [59]. CR networks are found to efficiently handle the challenges of distributed and heterogeneous network architecture, dynamic spectrum access and rising complexity. Research work available on the application of ACO and PSO for spectrum sensing, spectrum sharing, resource allocation and path routing was reviewed. Further, the problem of downlink power allocation for multi-user OFDMA based CRN is solved using ACO and PSO algorithms.

In [60], the authors studied opportunistic radio (OR) and presented the decision-making framework under MatLab environment. The framework comprises the steps of: flow of context information (derived from the capability of a device, preference of a user, and application requirement) as an input to CDE; case-based reasoning for filtering of context and multi-objective genetic algorithm (MOGA) based optimization for reasoning engine. The stability of the reasoning engine based on GA is checked via simulations. Test platform based on Ettus Universal Software Radio Peripheral (USRP) hardware and the GNU Radio is set up for performing an experimental study.

T.R. Newman *et al*. [21] proposed GA based CDE that provides the optimal set of reconfigurable parameters for single and multicarrier CR systems. Different fitness functions were presented and optimized using the weighted sum method. Re-configuration of the set of transmission variables i.e., transmit power and modulation level for different transmission modes is done. Each scenario involves a primary objective with 80% weighting and two secondary goals with much lower weighting. GA has the disadvantage of getting stuck at local optimal solution and it takes nearly 500 iterations to converge to the best value.

In [22], parameter adaptation for a multicarrier CR system was obtained using PSO as a decision making algorithm. The multi-objective optimization (MOO) problem was solved for four different modes of operation. The authors had compared the performance of a real coded version of the PSO algorithm with the GA-based method. Higher stability and fitness value are obtained using this method as compared to the conventional GA approach.

Chen et al. [61] solved the problem of adapting the transmission parameters in a dynamic wireless channel for a multicarrier CR system. The cross-entropy (CE) method efficiently finds the near-optimal solution in a vast search space and its application is investigated to optimize the transmission parameters for a given set of objectives. From the simulation results, it was concluded that the proposed method outperforms the conventional PSO algorithm in terms of convergence time and fitness value.

In [23], authors compared the performance of GA, PSO and ABC algorithms for designing the cognitive radio engine. Three transmission modes: emergency mode, multimedia mode and low power modes are evaluated and interference constraints for PU and SU are considered. Results obtained via simulations are compared in terms of mean optimal fitness and mean computation time. Performance investigation done for all the modes reveals that ABC based CDE is a better choice than GA and PSO-based approaches.

N. Zhao *et al*. [24] proposed a novel mutated ant colony optimization (MACO) algorithm for solving the CDE design problem with 10 number of subcarriers. Four different scenarios: Low power mode, multimedia mode, emergency mode, and balanced mode are considered with the application of a weighted sum method to optimize the overall objective function. The mutation mechanism in MACO helps in local minima avoidance, thereby making its performance better than the conventional ACO algorithm. Simulations were performed by setting the value of evaporation rate ρ for MACO to 0.8, 0.85 and 0.9 respectively. Fitness scores obtained corresponding to MACO with $\rho = 0.9$ surpass the values obtained with GA and ACO.

K. Kaur *et al.* [25] proposed SA based CDE for adapting the transmission parameters in a CR system. These parameters were optimized to satisfy different QoS requirements of the user such as minimizing transmit power, bit error rate and interference power while maximizing throughput and spectral efficiency. Different transmission parameters i.e., transmit power, bandwidth, modulation level, time division duplexing and symbol rate were optimized to satisfy different objectives. SA based CDE provided better fitness scores than GA based system but computation time and the number of generations needed by SA are comparatively higher. Therefore, SA based CDE is a favorable choice only when the optimization task is not time-bound and it is not suitable for real time applications where the decision process needs to be quite fast.

The above-mentioned work is extended in [26] in which the authors adopted a BBO technique for solving the optimization problem in a single carrier CR system. Migration and mutation are the two mechanisms employed in BBO to search the global optimum value. These mechanisms are further controlled by immigration and emigration rates. A comparative study of BBO and GA in different scenarios revealed that the fitness scores obtained using BBO are better than those obtained for conventional GA based CDE.

In [62], the authors formulated the MOO problem of CDE design and solved it by proposing a hybrid architecture of PSO and case database. The application of a hybrid approach resulted in fast decision-making when unknown wireless situations are faced. It also endows the radio with learning ability and provides an appropriate balance between exploration and exploitation features. A binary version of the PSO algorithm employing time-varying inertial weights called IBPSO was adopted and its performance comparison was done with other optimization techniques: Simple Genetic algorithm (SGA), original BPSO and simulated annealing genetic algorithm (SAGA). Simulation results validate the superiority of hybrid architecture for providing a better fitness value and lower average time consumption.

X. Tan *et al.* [63] solved the problem of cognitive link decision for an OFDM system with 32 sub-channels by proposing a modified version of GA i.e., Non-dominated Sorting Genetic Algorithm II (NSGA-II). The seeding approach was adopted along with new crossover and mutation techniques which help together in accelerating the convergence rate of decision-making module. The work lacks the consideration of spectral interference constraints for PU and SU.

P.M. Pradhan *et al*. [13] tested and compared the performance of six evolutionary algorithms: ABC, GA, DE, BFO, PSO and CSO for solving the CDE design problem. The problem is aimed at parameter adaptation to optimize certain communication objectives for a single and multi-carrier based CR system. These objectives are formulated in terms of predefined fitness functions which correspond to minimize power consumption (for low power mode), minimize bit error rate (for emergency mode) and maximize throughput (for multimedia mode). The spectral interference introduced by SU and PU is also considered.The performance of different algorithms is compared in terms of optimal fitness value, optimal generation, optimal computation time and total number of function evaluations. From the average and standard deviation values of these metrics, it was concluded that CSO algorithm is a fair choice to realize efficient CDE.

The authors proposed a solution to the problem of an overcrowded frequency spectrum in the form of distributed optimizer for cognitive radio sensor networks (CRSNs) in [64]. A sensor node is composed of CR unit and works as a SU by sensing the white spaces of PUs. The authors adopted NSGA-II based distributed optimizer for simultaneously optimizing five different fitness functions. Simulation results validate that NSGA-II based implementation of distributed optimizer results in minimum convergence time and fewer iterations to reach an optimal solution as compared to GA and SA. These factors also contribute to minimizing the energy requirement of the sensor nodes.

P.M. Pradhan *et al.* [65] proposed an efficient design of an OFDM based CR system with 16 sub-channels employing multi-objective cat swarm optimization (MOCSO) algorithm. The fitness sharing concept is utilized which spreads the non-dominated candidates along the Pareto front. Performance comparison of MOCSO-fs is done with multi-objective particle swarm optimization (MOPSO-fs), NSGA-II and multi-objective bacteria foraging optimization (MOBFO). BER, throughput and power consumption form important performance measures that are optimized simultaneously and a fuzzy-based approach is adopted to obtain a compromised solution on the Pareto front. The stability of the obtained results is checked through detailed statistical analysis.

In [66], the authors adopted the MOO approach that jointly minimizes transmit power and maximizes the throughput of an OFDM based CR system while considering the errors introduced due to imperfect spectrum sensing. The problem is subjected to the constraints of interference power on both SU and PUs, QoS constraints in terms of BER for SU, transmit power budget and the maximum number of allocated bits per subcarrier. Closed-form expressions are obtained for the optimal bit and power allocations per SU subcarrier. The proposed approach was found to perform superior to single-objective optimization approaches without any additional complexity.

In [10], the authors proposed a surrogate model based CDE for optimizing the performance of IEEE 802.11 links. The present state and network configuration are taken as input and prediction about the QoS parameter is done by CDE. The engine steers the network towards an optimal set of parameters. The proposed CDE when applied to two realistic interference scenarios, outperformed the case for which the decision engine was not deployed.

X. You *et al*. [67] proposed CDE that combines fuzzy reasoning with an improved multi-objective artificial bee colony (IMOABC) algorithm. First of all, IMOABC was applied to find a set of Pareto optimal solutions for certain channel conditions. After this, fuzzy reasoning is employed to select the best solution that satisfies the needs of the user. The concepts of reverse initialization, multidimensional evolution, integration of social and cognitive strategies, setting of the external population in order to save the non-dominated solutions and recording newly generated solutions were incorporated to improve the performance of IMOABC. The effectiveness of this algorithm was proved by testing it on a set of benchmark problems. A parallel hybrid coding strategy was designed to increase the search efficiency of IMOABC and it was incorporated to solve the CDE problem.

In [68], CDE design for IoT device is carried out using a modified real-coded biogeography-based optimization (RCBBO) method. This optimization approach is integrated with a fuzzy decision process to obtain the best solution. Three different mutation strategies i.e., Gauss mutation (RCBBO-G), Levy mutation (RCBBO-L) and Cauchy mutation (RCBBO-C) were adopted to improve the population diversity and increase the exploration ability of the original BBO algorithm. RCBBO based CDE is found to provide better results than original BBO in terms of convergence rate and fitness value. The performance difference between RCBBO and BBO becomes more evident as the number of subcarriers is increased.

The authors proposed an adaptive resource allocation algorithm for a CR system in [**127**] that is based on modified PSO. It involves both GA and PSO's updating processes that helps in overcoming the PSO's disadvantages and keep only its advantages. Simulation results showed that the modified PSO has high flexibility and better performance than PSO for resource allocation in three different communication scenarios.

2.3 Literature Survey based on Adaptation of Transmission Parameters for Solving Power Consumption Minimization Problem

Power consumption is a significant issue for many mobile and wireless devices, especially those operating at a higher data rate. The recent trends in the domain of wireless communication indicate a shift towards green communication for the next generation networks. The need for an energy-efficient operation was highlighted by the authors in [69] and the various techniques required for the power optimization of future 5G networks were surveyed.

As the Power amplifier consumes the major portion of energy in RF circuits, the need for high efficiency, broadband and linear PAs was put forth in [70]. Different works proposed in the literature for designing wideband PAs and oscillators were also reviewed.

A. He *et al*. [71] formulated the analytical model for minimizing the system power consumption under the rate constraints for a multichannel communication system. Numerical algorithms were developed to find optimal and sub-optimal solutions. Simulation results showed that significant power saving can be achieved for a four-channel system using proposed power allocation schemes i.e., ~55% with Class A PA and ~20% with Class B PA. The usage of sub-optimal algorithms had also resulted in a considerable reduction of computational complexity. The proposed framework is also expected to perform well for MIMO systems that are widely used in new wireless standards.

A. He *et al*. [72] proposed an energy minimization framework for delay insensitive applications such as file or email transfer employing CR technology. Unlike conventional adaptive modulation, CR is shown to not only adjust the modulation, coding and radiated power but also the device characteristics (e.g., PA characteristics) in order to operate the radio in an energy-efficient way. Considerable energy savings of up to 75% along with throughput improvement are achieved as compared to conventional adaptive modulation.

In [73], the authors extended the work done in [72] and demonstrated the application of CR to optimize the power consumption of a multiple-input multiple-output (MIMO) system under the constraints of the sum rate. The influence of partial channel state information and channel correlation at the transmitter is considered while solving the constrained optimization problem. Significant power savings of ~75% were obtained for a 4×4 MIMO system with Class A PA as compared to conventional power allocation schemes. It is concluded that the application of suboptimal heuristic algorithms that are computationally efficient helps in achieving the power savings that are comparable to the exhaustive search algorithm.

P.H. Qi *et al*. [74] formulated the constrained parameter adaptation problem for minimizing the power consumption in CR. It is solved by employing the Biogeography based optimization (BBO) algorithm which uses a novel habitat suitability index (HSI) evaluation method to introduce penalty to the particles which do not satisfy QoS constraints of BER and data rate. Comparative performance analysis of BBO with CSO and PSO revealed that BBO effectively minimizes the power consumption of a CR system while satisfying the QoS requirements for different service types. Even though BBO gives better results, but the number of generations required to obtain the optimal value are very large. Therefore, a better optimization technique that can find an optimal solution in few iterations is required.

2.4 Literature Survey based on Optimization of Sensing Period for CR system

Adaptation of the sensing period is an important requirement to enhance the sensing efficiency of CR systems. The selection of an appropriate sensing period involves balancing the tradeoff among interference to PUs, spectrum utilization and sensing overhead.

H. Kim *et al.* [75] highlighted the two issues related to MAC-layer based sensing, i.e. in which order to sense the licensed channels and how often to sense them for checking their availability for use. The problem of maximizing the discovery of spectrum opportunities by adapting the sensing period and minimizing the delay to find the available channel was addressed. A technique to estimate the channel-usage pattern is also proposed. The proposed sensing period adaptation strategy leads to efficient detection of spectrum opportunities with smaller channel switching delay that ranges from 0.08 to 0.35 seconds. Up to 22% more opportunities were discovered than the previous sensing approaches which do not involve adaptation of sensing period.

In [76], the authors proposed a proactive channel access mechanism for dynamic spectrum networks. The disadvantage of a conventional reactive technique that relied on the sense-and-adapt approach is highlighted. The reactive approach causes disruption as the SU cannot predict the future status of a PU channel. The proactive scheme adopted by SU utilizes the PU traffic model and the past channel histories to make a prediction about future spectrum availability. From the simulation and testbed results, it was revealed that a proactive scheme employing different channel selection and switching techniques reduces the interference to PUs by 30% and throughput jitters at SU are also decreased significantly.

Authors in [48] proposed an adaptive sensing period (ASP) algorithm for efficient MAC layer sensing by automatic adjustment of sensing period for an ON/OFF channel usage model of PU. 15~20% more opportunities were utilized than the Fixed Sensing Period (FSP) algorithm. Simulation results prove that performance is not steady when different channels are sensed with the FSP method but the ASP method always gives stable performance regardless of the number of channels.

In [77], the authors addressed an opportunistic spectrum access (OSA) scheme adopted by slotted SU. It uses periodic communication protocol and overlays over an unslotted primary network whose channel is modeled as two-state ON/OFF continuous-time Markov chain (CTMC), under the constraints of energy consumption and interference. The interference constraint is obtained as the average temporal overlap between PU and SU and the energy consumption constraint depends on the sensing period. The optimal values of sensing period and transmission time are obtained and the closed-form solutions with low computational cost are derived.

K.W. Choi (2010) [78] implemented the novel adaptive spectrum sensing scheme that avoids unnecessary sensing by proposing a decision-making algorithm that used a partially observable Markov decision process (POMDP). This framework decides among sensing, channel switching and data transmission at each decision epoch. The objective of the problem under consideration is maximizing the channel utilization while minimizing the collision probability. Results show that the proposed scheme is robust to fast variations in PU state.

In [79], authors considered a multichannel CR network with one slotted SU that can access non-time-slotted On/Off CTMC modeled multiple PU channels simultaneously. Authors proposed selective sensing and selective access (SS-SA) mechanisms to maximize channel utilization by SU while limiting the energy consumption and interference it causes to PUs.

In [80], the authors proposed a mathematical optimization scheme that targets at maximizing the throughput of SUs, while optimizing the sensing interval for certain PU channel in order that the transmission delay of cognitive transmission is reduced. The novelty of this work lies in the consideration of delay caused by retransmission of incorrectly received SU data along with the delay induced by a busy period of PU and spectrum sensing overhead.

H. He *et al.* [81] developed a new adaptive spectrum sensing method that improves the throughput of SUs as compared to the non-adaptive scheme. This novel scheme takes into account the wireless channel variations and needs no prior knowledge about the statistics of PU activity. The sensing duration is adjusted at the beginning of each time frame in accordance with Channel state information of the time-varying channel and previous sensing results. This adaptive sensing mechanism can be used even when the channel model of the Primary network is unknown. Numerical results show that there is a remarkable improvement in system throughput as compared to the non-adaptive spectrum sensing scheme.

A novel scheme that optimizes the sensing interval and maximizes the SU's throughput while sufficiently protecting the PU was studied in [82]. If a large fraction of the busy period of PU is interfered by SU transmission, then it results in useless transmission which potentially degrades the QoS of PUs. The authors suggested that the busy period of PU that is impaired more than the per-transmission interference ratio (PTIR) undergoes primary transmission failure (PTF). The effect of sensing interval on PTIR and PTF is also studied. The probability of PTF is derived in terms of sensing interval that maximizes the throughput of SUs for the required value of PTIR. Performance analysis showed that PU can be protected in a better way with the proposed approach by introducing the aforementioned constraints of PTIR and PTF.

In [83], the authors observed that the PU access pattern consists of a series of transmission periods and alternating idle periods that last for certain time slots. Therefore, sensing the PU at the start of every time slot is redundant as it leads to energy wastage. PDFs of PU's busy and idle state durations were derived using a hidden Markov model (HMM). The objective is to maximize the level of user satisfaction using a sigmoid function. The objective is achieved by exploring spectrum sensing techniques that increase the secondary network throughput and reduce energy consumption while optimizing the sensing interval. Optimal sensing interval is derived for two cases: i) assuming the current channel state to be idle, ii) assuming the current channel state to be busy. Extensive simulations were performed to study the impact of system parameters on a spectrum sensing interval. Results confirm the high accuracy achieved for the proposed scheme along with reduced energy consumption.

An adaptive sensing period optimization technique for CR Networks based on MOGA is proposed in [50]. In this letter, the proposed scheme is aimed at maximizing the spectrum opportunities while minimizing the sensing overhead and maintaining its value below the user-defined upper bound. A Pareto strategy is adopted to evaluate the solutions and the dominance evaluation function forms the basis of optimization. Performance evaluations are done for different simulation scenarios that differ in the tolerable values of user-defined sensing overhead and the number of PU channels (3, 6 and 9). The proposed scheme was found to outperform the case of a fixed sensing period and the method proposed in [75]. The superiority of the evolutionary process lies in the fact that the sensing period is adjusted according to the usage pattern of a PU channel. It is different from the method proposed in [75] that adapts the sensing period by estimating the average channel behavior, which may not involve significant variations. This work is extended by the authors in [51] where a detailed analysis of adaptive sensing optimization scheme for CR networks based on a MOGA is presented. The proposed technique was found to outperform the non-optimized schemes by up to 90%.

The authors introduced the concept of simultaneous PU sensing and data transmission in [83]. SU transmitter senses the PU signal and transmits data signals at the same time by spatial resource division. The concept of "TranSensing" employing a two-stage algorithm (TSA) was proposed which adaptively uses spatial resources. It includes a multi-antenna system supporting self-interference cancellation and antenna isolation.

In [84], authors proposed different spectrum sensing schemes that increase the network throughput, spectrum efficiency and channel utilization. Different channel scenarios are considered i.e., Single SU with Single and Multiple Channels (SSSC and SSMC), Multiple SUs with Single and Multiple Channels (MSSC and MSMC) in order to guarantee effective and integrated research. A separate sensing scheme is adopted for each scenario e.g. optimal sensing period to increase the network throughput for SSSC, a novel sensing technique to reduce the search time for SSMC, partial CSS scheme for MSMC, and setting a spectrum pool in the FC to record the channel states for MSMC. The proposed method not only causes the SUs to access the white spaces efficiently but also allows transmission at low power under the constraints of interference temperature.

In [49], the authors presented the random periodic spectrum sensing scheme for CRNs. The sensing period and transmission time for PUs and SUs is presented in a general form as a random variable and sensing errors were considered. The sensing period is optimized to maximize the rewards generated by the channel using Markov analytical model.

2.5 Literature Survey based on the Optimization of CSS Scheme

In [54], the authors introduced CSS as an efficient technique to increase the detection performance of CR networks by exploiting the spatial diversity of different SUs. Different overheads involved in obtaining cooperative gain were also reviewed. Various cooperation models, data fusion methods, sensing techniques, user selection approaches and hypothesis testing involved in CSS were discussed. Research challenges and unresolved problems associated with CSS were identified.

The performance of CSS employing energy detection in CR networks is studied by authors in [53]. Multiple Cognitive units collaborate to detect the spectrum holes using energy detection such that the detection performance is optimized in an efficient manner. The half-voting rule is found to be optimal in order to minimize the total error probability. A fast spectrum sensing algorithm for a large network is proposed that needs a lesser number of cognitive radios while satisfying a given error bound.

The weight vector for a linear CSS was optimized in [85] using PSO. The authors found that usage of PSO based CSS scheme provides stability and efficiency. It provides a higher probability of detection than the modified deflection coefficient (MDC)-based method for the same false alarm probability.

SDF based CSS scheme for CR network based on GA is proposed in [86] to optimize the weight vector. For a given probability of false alarm, GA based SDF approach was found to perform superior and achieves higher detection probability as compared to conventional SDF techniques (NDC, MDC, MRC and EGC) and hard-decision fusion (HDF) based OR combining scheme.

Authors extended this work in [87] by adopting PSO algorithm as a promising technique to optimize the weight coefficients. This method was compared with GA, NDC and MRC based approaches through computer simulations which validate the advantage of the adopted method over all other SDF approaches.

M. Akbari *et al*. [88] also proposed the use of PSO to optimize the weight vector and reduce the total sensing decision error at soft data fusion (SDF) center of a centralized CR network. Sensing measurements are received from different cooperative SUs and the weight vector applied to these measurements is optimized. The proposed technique is compared with the conventional GA based evolutionary approach, EGC, MRC and Normal deflection coefficient (NDC) based schemes. The effect of varying the number of cooperative SUs on the detection performance has also been investigated for PSO based scheme. Simulation results confirm the advantage of PSO over the GA-based method and conventional EGC and MRC schemes in terms of detection and convergence performance.

X. Liu and X. Tan [89] proposed a CSS method based on weight fusion to enhance the sensing performance and reduce the interference to PU. The sensing period is first optimized for reducing interference and increasing the spectrum access. After that, the joint optimization algorithm for sensing time slots and the number of cooperative SUs is formulated for wideband CSS. It resulted in the achievement of maximal throughput for CR during each period. After this, the water-filling principle is used to decrease the search time for free channels. Significant enhancement in throughput and sensing performance of CR is achieved by employing the proposed optimization approach.

P.M. Pradhan *et al*. [90] optimized the performance of CSS scheme using recently developed MOCSO. The concept of fitness sharing spreads the non-dominated candidates along the Pareto front. The performance of MOCSO-fs is compared with MOPSO-fs, NSGA-II and MOBFO. In addition to this, a fuzzy-based mechanism is adopted to find a compromised solution on the non-dominated front. The weights assigned to each SU and the global decision threshold are optimized to enhance the detection probability and reduce the probability of false alarm.

M. Akbari and M. Ghanbarisabagh [91] proposed an evolutionary optimization based imperialistic competitive algorithm (ICA) SDF-based technique for proper selection of the weighting coefficients of each SU in the CSS scheme. Extensive comparisons were done with GA, PSO, MDC, NDC, and MRC based methods. Simulation results showed that the proposed scheme outperformed all other SDF-based methods. ICA- assisted method showed faster convergence and lower complexity.

A novel efficient adaptive artificial bee colony (EA-ABC) algorithm was presented by the authors in [92] which comprise mechanisms of adaptive mutation, optimal tracking and guaranteed convergence. EA-ABC showed superior performance than ABC, PSO and modified PSO algorithms when tested on five different benchmark functions. Performance is measured in terms of fitness value and convergence rate. This algorithm is then applied to CSS in order to determine the optimal weight vector. The proposed algorithm resulted in efficient sensing and spectrum utilization with an enhanced probability of detection and reduced false alarm probability.

F. Azmat *et al.* [93] utilized three different bio-inspired techniques i.e. PSO, firefly algorithm (FFA) and fish school search (FSS) to obtain the optimal weighting vectors at FC for CSS. Highly realistic signals are considered that suffer from non-linear distortion caused by the PAs. Numerical results showed that the performance of bio-inspired techniques exceeds the conventional weighted linear combining (WLC) scheme as these techniques ensure a higher probability of detection and guarantee conflict free spectrum allocation. FFA is found to be more powerful for solving noisy and non-linear optimization problems as it has auto-regulating exploration and exploitation capabilities.

Y. Hei *et al.* [94] investigated the different scenarios for MIMO CSS optimization with single or multiple antennas at PU and SU. By optimizing the weight values assigned to the received signals from different SUs, the probability of detection was optimized for a given false alarm probability. Simulation results showed that the sensing performance can be significantly increased with the usage of multiple antennas. GA was found to offer efficient and stable results while different crossover operators for GA were employed to discover their effect on sensing performance.

In [95], the authors introduced a novel spectrum sensing scheme that alternatively chooses either a single or double threshold energy detection approach on the basis of an estimated SNR value of each channel. A better tradeoff between throughput and sensing performance was achieved as compared to the previous approaches that rely on energy detection mechanism with purely one or two threshold levels.

The authors reviewed the soft and hard decision fusion methods adopted at the FC to discover the state of PU in [96]. The performance of a soft decision fusion scheme was found superior to the hard combination of decisions. But this performance difference comes at the cost of increased overhead and additional bandwidth requirement for soft fusion schemes. Therefore, the authors introduced a semi-soft decision fusion approach that provides a better tradeoff between bandwidth requirement and sensing performance. In this scheme, each CR sends a one or two-bit local decision data to the FC. The final decision is then taken by FC on the basis of received data by estimating the global test statistic, which is then compared to a certain threshold value. Closed-form expressions for average bandwidth cost associated with the proposed scheme were derived. The performance of the semi-soft fusion scheme approached the soft fusion approach while remarkably reducing the control channel bandwidth.

M. Li *et al.* [97] investigated the multiband CSS problem in a CR network that focused on maximizing the total throughput under the constraints of interference to PUs by jointly optimizing the decision threshold and weight vector. A novel modified artificial bee colony (MABC) algorithm is investigated to deal with this problem. Simulations are done to validate the superiority of MABC over other intelligent evolutionary algorithms i.e., GA, PSO, ABC and EA-ABC for solving different classical benchmark functions and optimizing the performance of multiband CSS system.

In [56], the authors surveyed different information combining methods for CSS. Various hard fusion rules such as OR, AND, K out of N rule and quantized hard combining scheme were discussed along with different soft combining methods i.e., SC, MRC, SLC, EGC and evolutionary algorithm (EA) based combining. DE, PSO, GA, ABC, BFO and CSO are six EAs investigated by the authors for this problem. Detection probability has been maximized by employing these techniques for a specific probability of false alarm. Simulation results demonstrate that EAs perform superior to other statistical techniques by reducing the time and computational complexity by a high margin. Consistency of the results obtained by EAs was assessed using various statistical tests. CSO emerged as the most promising EA to optimize the parameters of CSS.

In [98], the authors integrated PSO with the golden section search (GSS) technique and proposed the PSO-GSS method which possesses a powerful search ability to solve the multiband CSS optimization problem. Constrained optimization problem to maximize the aggregate throughput with constraints on total interference, sub-band utilization and sub-band interference is solved while optimizing sensing time, weight coefficients and decision threshold. The weight vector and decision threshold is optimized using PSO, while GSS searches for the optimal sensing time. Theoretical analysis is also performed to study the impact of varying different parameters on aggregate throughput. Simulation results revealed that the PSO-GSS method is more suitable than GA, PSO and ABC algorithms to solve the multiband CSS optimization problem.

The authors investigated energy-efficient CSS in CRN with QoS provisioning in [99]. SU's transmit power and sensing time are jointly optimized to maximize the EE. Another algorithm is proposed that maximizes the EE under the constraint of the required amount of spectrum efficiency (SE). It is found that strengthening the protection of PU leads to the decline of energy efficiency.

In [100], the authors proposed a novel improved technique namely, shuffled frog leaping algorithm (SFLA) which is motivated by the theory of distance movement. This approach fuses the sensing results obtained from multiple nodes, thereby improving the detection reliability for CSS. The performance of a modified SFLA based CSS framework is compared with conventional SFLA and MDC methods using simulations. The improved SFLA was found to perform superior to all other methods by offering a higher detection probability.

Jaglan [101] introduced a trained artificial neural network (ANN) based spectrum sensing model at FC which achieves considerable improvement in detection performance and reduction in false alarm rate as compared to the existing schemes. It was found that as the number of SUs was increased, the proposed scheme successfully maintains the required detection performance, thereby effectively dealing with the scalability of a CRN. The scheme showed robustness when tested against security attacks done by malicious users and inadvertent errors occurring at SUs.

2.6 Literature Survey on Cognitive Radio based Internet of Things Systems

Cognitive Internet of Things (CIoTs) is a new research paradigm focused on the potential applications of CR technology in Internet of Things (IoTs) domain. Several review papers available in this field which motivate the work done on CIoTs in this thesis are discussed below:

In [130], authors introduced a new network paradigm, named cognitive Internet of Things (CIoT) that empowers the current IoT with a “brain” for high-level intelligence. A comprehensive definition for CIoT is presented that is inspired by the human cognition process. Based on this definition, an operational framework of CIoT is provided, which characterizes the fundamental cognitive tasks. Then, the key enabling techniques involved in the cognitive tasks are addressed in detail. Also, the design of proper performance evaluation metrics, research challenges and open issues ahead are discussed.

In [112], the authors highlighted the number of potential IoT applications such as smart and green cities, logistics, aeronautics etc. In order to support these diverse applications and the number of heterogeneous connected devices, CR is adjudged as a key empowering technology for IoT. Authors surveyed novel approaches and research challenges related to the use of CR for machine-to-machine and IoT.

The need of CR networks for IoTs is highlighted in [113], along with the discussion of potential applications, architectures and frameworks of CR based IoT systems. Authors envisioned that different versions of IoT are meaningless if IoT objects are not equipped with CR capability. Numerous applications of CR based IoTs in the field of healthcare, in-home applications, smart grid, smart cities and internet of vehicles are discussed. Open issues, research challenges and future directions for CR-IoT networks are also presented.

In [131], the authors surveyed the frameworks and design factors for CR-based IoT. Reviews of recent spectrum sensing and sharing approaches along with their selection criteria are presented in this survey. Furthermore, the survey explores the integration of newly emerging technologies such as blockchain and ML, with the CR-based IoT systems. Finally, the survey highlights some emerging challenges and concludes with suggesting future research directions and open issues.

2.7 Limitations of the Existing Studies

On the basis of the literature survey discussed in Section 2.2-2.5, certain limitations and research gaps are founds in the existing studies as discussed below:

- The optimal power allocation approaches for OFDM based CR networks reported in [105-109, 128] do not consider the circuit aware energy-efficient operation. The work in [22-26] is focused on parameter adaptation using MOO with power consumption minimization as one of the objectives. It does not emphasize the power consumption by circuit components such as filters, PAs, front end mixers etc. The approaches used for energy-efficient power allocation like water filling algorithm and Lagrange's formulation [71] involve certain complex transformations and assumptions to get sub-optimal solutions. The existing methods are incapable to provide an effective and economical solution to a problem with higher dimensionality and larger constraints. Though the power consumption optimization problem is addressed in [74] using a meta-heuristic algorithm, it involves the usage of a less efficient discrete version of BBO.
- Transmission scenarios reported in [13, 22-25] focused only on the end-user requirement without giving any due concern towards the radio battery level.
- IoT is an emerging paradigm and CR acts as an enabling technology to support IoT applications. The research work in this field is still at a preliminary stage and the parameter adaptation for CR-IoT systems is not widely explored.
- System models assumed in [24] and [13] support the multicarrier transmission with only 10 and 16 number of subcarriers respectively. If the number of subcarriers is large, there is a

need for some highly efficient meta-heuristics which are capable of solving large dimensionality problems.

- Existing work related to MAC layer based sensing using meta-heuristic optimization technique is limited and appeared only in [50-51] where GA has been used to optimize the sensing period. As GA involves selection, crossover, mutation etc. along with time-consuming coding-decoding mechanism, the processing time required to find the optimum sensing period is quite large for GA. This is a serious concern for delay-sensitive CR applications. There is a need to study some simple yet efficient meta-heuristic algorithms to optimize the sensing period for a licensed channel.
- The work reported in [50-51] used only the constraints for sensing overhead but not for the interference time which can be of great concern if the licensed channel application has higher intolerance towards interference.
- The existing work to optimize the sensing performance employing CSS lacks the application of a highly efficient meta-heuristic algorithm. The required algorithm must have fast processing speed and capability to provide a higher probability of detection for a licensed channel. Apart from this, the effect of varying the number of cognitive users, sensing channel noise and control channel noise, on the detection performance of a licensed channel is not well explored.

Based on the literature survey and limitations of the existing work, formulated research objectives for this thesis are given in the next section.

2.8 Objectives of the Thesis

1. Design an efficient Cognitive decision engine optimizer for adaptation of transmission parameters in a multicarrier system.
2. To propose a multi-objective optimization scheme for adaptive sensing period in Cognitive radio network.
3. To evaluate the performance of an optimization algorithm assisted Cooperative spectrum sensing scheme.

2.9 Research Contributions based on the above Objectives

Based on the formulated objectives, the main contribution of this thesis is to employ meta-heuristic algorithms for efficiently reconfiguring the transmission and sensing parameters of CR system. The contributions of this thesis are listed below:

***Contribution 1*:**

- **To minimize the total system power consumption at CR transmitter operating with Class-B power amplifier.**
- **Performance evaluation of various meta-heuristic algorithms for reconfiguring the transmission parameters of the proposed multicarrier CR system.**

In order to achieve this contribution, a mathematical formulation of total system power consumption at CR transmitter with Class B PA is obtained. Optimization for the proposed system has been done by parameter reconfiguration for data transmission scenario employing NI optimization techniques, i.e. ALO, GOA, GWO, MFO and WOA. Total system power consumption minimization is formulated as an optimization problem while considering three different constraints of BER, adjacent channel interference (ACI) and data rate. A novel penalty introduction mechanism using exponential function has been adopted which penalizes the particles as per the extent of violation of these constraints.

Simulation results show that WOA effectively minimizes the system power consumption by parameter adaptation in multicarrier CR system, while satisfying different QoS constraints.

Contribution 2:

- **To solve the constrained multi-objective optimization problem by reconfiguring the transmission parameters of CR based IoT system.**
- **Performance evaluation of parameter-less meta-heuristic algorithms, i.e. ALO, GWO, MFO, WOA and JA for solving this problem.**

A CDE optimizer is proposed to solve the multi-objective optimization problem for a CR based IoT network. Simultaneous optimization of three communication objectives, i.e. minimize power consumption, minimize bit error rate and maximize throughput; while considering two QoS constraints of transmission power and ACI is carried out. Five different modes of operation for CR-IoT device are considered based on the application that device has to support along with the battery level of the radio. Inspired by the efficient exploration and exploitation abilities of recently proposed ALO, GWO, MFO, WOA and Jaya algorithm, the application of these techniques has been investigated for solving the proposed MOO problem. To the best of author's knowledge, none of these techniques is investigated so far for solving this problem.

MFO algorithm provides the best solution for minimize power consumption and maximize throughput scenarios while WOA emerges as the best candidate for minimize BER mode.

Contribution 3:

- **To propose a constrained optimization scheme for adaptation of sensing period in CR system.**
- **Performance evaluation of JA and GA to solve the proposed optimization problem.**

An optimum value of sensing period is obtained in order to maximize the discovery of spectrum opportunities while maintaining the sensing overhead and interference time within user defined value. A novel objective function evaluation method is proposed that introduces penalty for the violation of constraints. JA is found to provide better optimal values for different parameters as compared to GA. As JA offers smaller processing time requirement, it emerges as a suitable choice for real-time CR applications.

Contribution 4:

- **To propose an efficient meta-heuristic algorithm for optimizing the performance of CSS scheme.**
- **Comparative performance analysis of the proposed algorithm with other existing algorithms for optimization of CSS scheme.**

A novel algorithm called Opposition based Grey wolf optimizer (OBGWO) is proposed that is an enhancement of GWO employing the concept of opposition based learning (OBL). The proposed technique is tested on different benchmark functions in order to prove its effectiveness over MFO, SCA and GWO.

Application of OBGWO is investigated to enhance the performance of CSS scheme by optimizing the weight vector that maximizes the probability of detection of PU. Simulation results show that OBGWO not only offers higher detection probability but also converges faster as compared to GWO, SCA and MFO algorithms. OBGWO scheme is then employed to study the effect of variation in number of cognitive users, sensing channel noise and control channel noise for the proposed CSS model.

Chapter 3

Parameter Adaptation for Power Consumption Minimization in a Multicarrier CR System

CR technology enables adaptation of transmission parameters according to the operating environment and different QoS requirements. This feature can be applied to realize green radios as recent research trends are focused on improving the energy efficiency of wireless communication systems. A power amplifier (PA) is found to consume a major portion of energy in RF circuits for medium and long-range transmissions. Therefore, minimizing PA power consumption is one of the major challenges to realize green radios. In this chapter, a mathematical formulation of total system power consumption at CR transmitter with Class B PA is shown and its optimization is done by parameter reconfiguration for data transmission scenario employing recently proposed NI optimization techniques. The performance of ant lion optimizer (ALO), grasshopper optimization algorithm (GOA), grey wolf optimizer (GWO), moth flame optimization (MFO) and whale optimization algorithm (WOA) is compared in terms of different performance metrics. Simulation results show the effectiveness of WOA in minimizing the system power consumption by parameter adaptation in a multicarrier CR system while satisfying different QoS constraints.

3.1 Introduction

Green communication has become a matter of great concern in the telecommunication community. Mobile and wireless devices operating at large data rates have a serious issue of higher power consumption [72-74]. Therefore, an energy-efficient operation of wireless communication systems has become a need of the hour [104]. Decreasing the carbon footprint by reducing power consumption in wireless networks is also our social responsibility. Though the PA is a crucial element of CR transmitters, it consumes a large portion of energy in radio frequency (RF) circuits for medium and long-range transmissions. A broadband linear PA with high efficiency is required as the transmitter needs to operate at different frequency ranges for CR applications [73].

None of the optimal power allocation approaches for OFDM based CR networks reported in [105-109, 128] considers the circuit aware energy-efficient operation. Most of the existing works on parameter adaptation as discussed in [22-26], focused on multi-objective optimization with power consumption minimization as one of the objectives. These works do not emphasize the power consumption by circuit components such as filters, power amplifiers, front end mixers etc. Earlier used approaches for energy-efficient power allocation like water filling algorithm and Lagrange's formulation [74] involve certain complex transformations and assumptions to get sub-optimal solutions. The work reported in [109] uses 'throughput per joule metric' and involves the parameter programming based transformation of non-convex objective function into a convex problem. These approaches are unable to offer an effective and economical solution for a problem with higher dimensionality and larger constraints. Hence, there is a need for an efficient methodology that must be able to address the issue of reduction in system-level power consumption along with the consideration of power consumption at the circuit level components. In this chapter, an attempt has been made to propose an efficient method to reduce the total power consumption of a CR system.

Although Qi *et al.* addressed the power consumption optimization problem in [74] using a meta-heuristic algorithm, i.e. a discrete version of BBO. However, the system model proposed in this chapter and the problem-solving approach is significantly different. The major contributions and differences of the proposed methodology are as follows: (i) In order to make the system model more realistic, the constraint of adjacent channel interference (ACI) caused by SU transmission at PU receiver (PU_Rx) is considered (ii) A novel penalty mechanism using exponential function has been adopted which penalizes the particles as per the extent of violation of constraints. (iii) The dimensionality of the parameter adaptation problem in the present work is two times higher than the system model reported in [74]. In order to solve such a higher dimensional and complex problem, the performance of recently proposed and highly efficient NI algorithms, i.e. ALO, GWO, MFO, WOA and GOA is investigated. Also, none of these techniques has been explored before to study the aforementioned problem. (iv) Opportunistic transmission by CR network utilizing TV white space (TVWS) channels in Ultra high frequency (UHF) band is considered, the channel occupancy data for which was obtained from the actual quantitative analysis reported in [110].

3.1.1. Need for parameter-less meta-heuristics

The issue of setting the initial values of control parameters for any optimization algorithm is crucial for its good performance. The control parameters significantly determine the efficiency of the search and the quality of solutions obtained. Considering this fact, the recent research efforts are focused on developing algorithm-specific parameter-less techniques that add to the algorithm's simplicity and minimization of efforts at the user end. The motivation of using ALO, GWO, GOA, MFO and WOA comes from the fact that these algorithms have already been tested on a suite of benchmark functions for their effectiveness over classical algorithms in [28-30, 46-47]. Apart from this, there is no available literature related to the performance comparison of these five techniques together for any real-world problem. Moreover, these algorithms are simple to apply and require either none or very few algorithm-specific parameters. Therefore, there is no need to carefully tune the parameters as required for conventional techniques such as GA, PSO etc. Meta-heuristic techniques used in this work involve the generation of random numbers in a certain range to update the parameters at various steps. This is unlike the classical techniques where parameter values need to be fixed a priori.

3.2 System Model and Problem Formulation

In the system model shown in Figure 3.1, opportunistic access of TVWS frequency bands by SU is considered. Periodic sensing of licensed channels is performed by SU transmitter (SU_Tx) in order to identify the white spaces. On finding a certain TV channel as vacant, SU decides to transmit on it with 'K' number of subcarriers such that the received power at another PU_Rx operating on an adjacent channel, i.e. ACI doesn't exceed a certain threshold value. An alternative approach to explore and exploit TV white spaces by using a location-specific TVWS database as presented in [111].

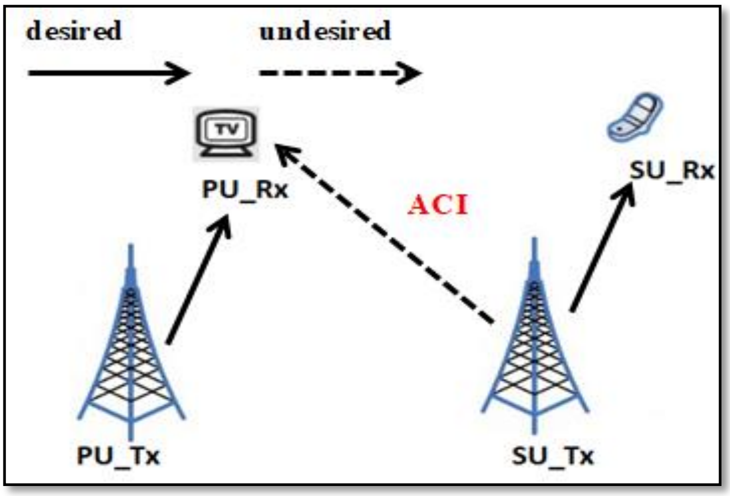


Figure 3.1: System model for a CR network

The problem for minimization of power consumption in an OFDM based multicarrier CR system under the constraints of data rate, BER and interference power can be formulated as:

$$minimize\ \ P_c \tag{3.1}$$

$$subject\ to \qquad \sum_{k=1}^{K} DR_k \geq DR_{th},$$

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

$$\frac{1}{K}\sum_{k=1}^{K} BER_k \leq BER_{th} \tag{3.2}$$

where P_c is the total system power consumption of SU_Tx and P_k, DR_k and BER_k are the power radiated, data rate and BER corresponding to k^{th} subcarrier respectively. $\mathrm{DR_{th}}$, $\mathrm{BER_{th}}$ and $\mathrm{INT_{th}}$ are the threshold values of data rate, BER for SU and maximum interference power tolerable by PU_Rx respectively. INT_k is the ACI caused by k^{th} subcarrier of SU's band into the adjacent PU's band being sensed to be occupied and represented as [66]:

$$INT_k(d_k, P_k) = 10^{-0.1L(D)} P_k T_s \int_{\mathrm{d_k}-\frac{\mathrm{B}}{2}}^{\mathrm{d_k}+\frac{\mathrm{B}}{2}} \mathrm{sinc}^2\{\mathrm{T_s f}\}\,\mathrm{df} \tag{3.3}$$

d_k is the spectral distance between k^{th} subcarrier of SU and central frequency of adjacent PU channel. B represents the bandwidth of an adjacent PU band. $L(D)$ is the path loss in dB for distance D between PU and SU. T_s is the symbol duration of an OFDM symbol of SU.

$P_T = \sum_{k=1}^{K} P_k$ is considered as the total power transmitted by an OFDM transmitter. The total system power consumption (P_c) is related to average efficiency of PA ($\bar{\eta}$) and power radiated (P_T) as follows [71]:

$$P_c = \frac{P_T}{\bar{\eta}} \tag{3.4}$$

Average efficiency ($\bar{\eta}$) for Class B PA is related to its maximum efficiency (η_{max}) and radiated power (P_T) as [71] :

$$\bar{\eta} = \ \eta(P_T) = \left(\frac{P_T}{\dot{P}_{max}}\right)^{\alpha} \eta_{max} \tag{3.5}$$

where $\dot{P}_{max}$ is the maximal output power of PA. For class B PA, $\alpha = 1/2$ and η_{max}= 0.785. The power consumption P_c is given by:

$$P_c = \frac{\dot{P}_{max}{}^{1/2}}{\eta_{max}} (P_T)^{1/2} \tag{3.6}$$

The constrained optimization problem for power consumption minimization represented in (3.1) with constraints given by (3.2) can be converted into an unconstrained objective function by introducing a penalty term. Therefore, the objective function F (to be maximized) for this problem can be formulated as:

$$maximize\ F$$

$$F = (P_{c,max} - P_c) \times \frac{1}{1+f\left(\frac{DR_{obt}}{DR_{th}}\right)} \times \frac{1}{1+f\left(\frac{BER_{th}}{BER_{obt}}\right)} \times \frac{1}{1+f\left(\frac{INT_{th}}{INT_{obt}}\right)} \tag{3.7}$$

where $P_{c,max}$ is the maximum power consumption of the system in case all the sub-carriers transmit at maximum power. A penalty is introduced when any of the constraints is violated. The term $f(.)$ is a novel exponential penalty function shown in Figure 3.2 and defined as follows:

$$f(x) = ab^x \tag{3.8}$$

where a and b are real numbers chosen such that $f(1) = 0.001$ and $f(0.01) = 0.99$.

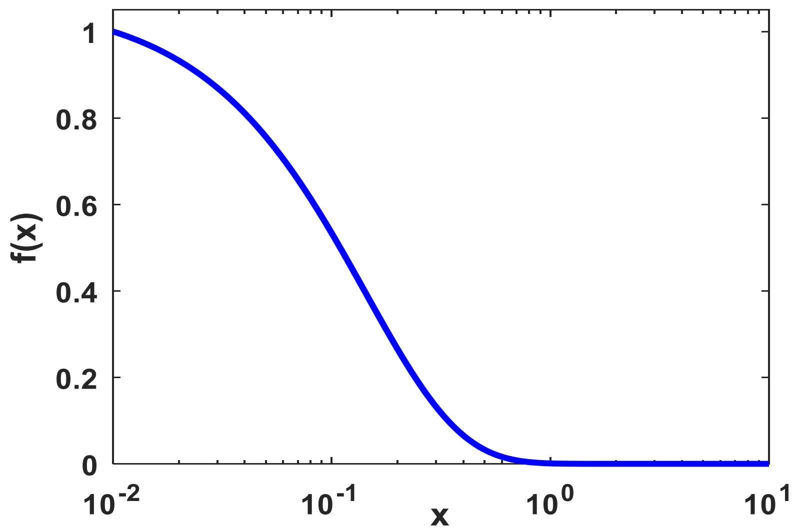


Figure 3.2: Variation of a penalty with input

While using a penalty function, the amount of constraint violation is used to punish or penalize an infeasible solution so that feasible solutions are favored by the selection process. BER_{obt}, DR_{obt} and INT_{obt} are the actual bit error rate, data rate and interference power obtained respectively corresponding to the certain set of transmit power values and modulation levels for all the subcarriers. If any particle violates the constraints given in (3.2) such as BER_{obt} (INT_{obt}) is more than BER_{th} (INT_{th}) or DR_{obt} is less than DR_{th}, a penalty function will reduce the objective (fitness) function value for the respective particle in an algorithm. As the algorithm will progress towards higher fitness function value, the solution obtained at the end not only provides minimum power consumption but also meets all the QoS constraints.

3.3 Meta-heuristic Algorithms used for Parameter Reconfiguration to Minimize the Total Power Consumption of a CR System

A detailed description of five different algorithms employed for the parameter adaptation problem along with their pseudo-codes is provided in this section.

a) Ant lion optimizer [28]**:** This algorithm is inspired from the foraging behavior of larvae of ant-lions. Their favorite prey is ants and they dig the cone-shaped pits in the sand that act as traps for ants. ALO algorithm mimics the interaction between ants and ant-lions. Different steps are involved in hunting such as: random walk of agents, entrapment of ants in the trap, building traps, catching prey and rebuilding traps. All these steps are explained below:

Step 1: Random walk of agents

Ants move stochastically in nature over the search space while searching for food and their movement can be modeled as a random walk as follows [28]:

$$X(t) = [0, cumsum(2r(t_1 - 1), cumsum(2r(t_2 - 1) \ldots \ldots cumsum(2r\left(t_{\max\_iter} - 1\right))] \quad (3.9)$$

where the cumulative summation is obtained through $cumsum$, $\max\_iter$ is the maximum number of iterations and $r(iter)$ is given as:

$$r(iter) = \begin{cases} 1 \; if \; rand > 0.5 \\ 0 \; if \; rand \; \leq 0.5 \end{cases} \quad (3.10)$$

Four different matrices store the position of ants, fitness of ants, position of ant-lions and fitness of ant-lions. The location of ants corresponds to the decision variables of the problem. The following equation enables the random walk by ants implemented in (3.9) to be within the boundaries of search space:

$$X_d^{iter} = \frac{(X_d^{iter} - A_d) \times (D_d^{iter} - C_d^{iter})}{(B_d - A_d)} + C_d^{iter} \quad (3.11)$$

$iter$ is the current iteration, A_d and B_d are the minimum and maximum random walk by ant taken in d^{th} dimension. For each iteration, C_d^{iter} and D_d^{iter} are the minimum and maximum limits for d^{th} dimension respectively.

Step 2: Trapping in antlion's pits

Ant lion's traps effect the random walk of ants as defined by vectors C and D given by (3.12). For the d^{th} dimension, lower and upper boundary of random walk by ant is adjusted around the selected ant lion, j.

$$C_d^{iter} = Antlion_j^{iter} + C_d^{iter-1}$$

$$D_d^{iter} = Antlion_j^{iter} + D_d^{iter-1} \quad (3.12)$$

Step 3: Building trap

A roulette wheel operator is used for selecting ant-lions based on their fitness. This step provides a higher probability of catching the ants by ant-lions.

Step 4: Trapping in ant-lion's pit

Ant-lions shoot sand outwards in order to slide ants towards them. This is modeled by reducing the lower and upper limit of random walk of ants by factor I as follows:

$$C^{iter} = \frac{C^{iter}}{I}$$

$$D^{iter} = \frac{D^{iter}}{I} \quad (3.13)$$

where $I = 10^{\frac{z*iter}{Max\_iter}}$, z is a parameter that varies between 1 and 6 and adjusts the accuracy level of exploitation. Max_iter is the maximum number of iterations.

Step 5: Catching prey and rebuilding the pit

This step is simulated through the following equation.

$$Antlion_j^{iter} = Ant_i^{iter} \qquad if\ f(Ant_i^t) > f\left(Antlion_j^t\right) \quad (3.14)$$

$Antlion_j^{iter}$ and Ant_i^{iter} is the location of j^{th} antlion and i^{th} ant at $iter^{th}$ iteration.

Step 6: Elitism

Through elitism, the best solution (ant-lion) is maintained and each ant is assumed to randomly walk around selected ant-lion by a roulette wheel $RW_{antlion}$ and elite RW_{Elite} together as follows:

$$Ant_i^{iter} = \frac{RW_{antlion}^{iter} + RW_{Elite}^{iter}}{2} \quad (3.15)$$

where $RW_{antlion}^{iter}$ is the random walk around the ant-lion selected by the roulette wheel, RW_{Elite}^{iter} is the random walk around the elite and Ant_i^{iter} is the position of i^{th}ant at the $iter^{th}$ iteration.

Algorithm 1 Pseudo code for ALO

for *run=1:30*
Initialize population size and maximum no. of iteration, Max_iter. *Define the upper and lower bounds for* d *dimensions.*
Initialize first the population of ants and ant-lions randomly
Calculate the fitness of ants and ant-lions using Eq. (3.7)
Find the best ant-lion and assume it as the elite (determined optimum)
while (Ite $\leq$ ***maxite)***
for *every ant*
Select an ant-lion using a Roulette wheel
Update C and D using equations Eq. (3.13)
Create a random walk and normalize it using Eqs. (3.9) and (3.11)
Update the position of ant using (3.15)
end for
Calculate the fitness of all ants
Replace an ant-lion with its corresponding ant if it becomes fitter (Eq. (3.14))
Update elite if an ant-lion becomes fitter than the elite
end while
Return elite which corresponds to the transmission parameters of 'K' *subcarriers.*
end for

b) Grasshopper optimization algorithm [46]**:** This algorithm mimics the swarming behavior of grasshoppers in nature, the mathematical model for which is given below.

Potential solutions for a given problem are represented by the position of grasshoppers in a swarm. The position of i^{th} grasshopper is given as [46]:

$$X_i = S_i + G_i + A_i \tag{3.16}$$

where S_i, G_i and A_i indicate social interaction, gravity force and wind advection respectively. Social interaction S_i between grasshoppers is the main component given as:

$$S_i = \sum_{\substack{j=1 \\ j\neq i}}^{N} s(d_{ij})\widehat{d_{ij}} \tag{3.17}$$

where d_{ij} is the distance between i^{th} and j^{th} grasshoppers calculated as $d_{ij} = |x_j - x_i|$ and $\widehat{d_{ij}} = \frac{x_j - x_i}{d_{ij}}$ is the unit vector from i^{th} to j^{th} grasshopper. The s function with general input parameter r defining a social force is obtained as $s(r) = fe^{\frac{-r}{l}} - e^{-r}$, where f denotes the intensity of attraction and l is the attractive length scale. Components G and A can be calculated for i^{th} grasshopper as follows:

$$G_i = -g\widehat{e_g} \tag{3.18}$$

$$A_i = u\widehat{e_w} \tag{3.19}$$

where g is a gravitational constant, u is a constant drift, $\widehat{e_g}$ and $\widehat{e_w}$ are the unit vectors towards the earth's centre and in the direction of wind respectively. Absence of G component is assumed and wind direction is always towards the target $\widehat{T_d}$. In order to enable exploration and exploitation at the different stages of optimization, the above model needs to be equipped with some special parameter (c here) as follows:

$$X_i^d = c\left(\sum_{\substack{j=1 \\ j\neq i}}^{N} c\,\frac{ub_d - lb_d}{2}\, s(|x_j - x_i|)\,\frac{x_j - x_i}{d_{ij}}\right) + \widehat{T_d} \tag{3.20}$$

$$\text{where} \quad c = cmax - \frac{iter(cmax - cmin)}{Max\_iter} \tag{3.21}$$

Parameter 'c' balances the exploration and exploitation of the swarm along with reducing the attraction, repulsion and comfort zones between the grasshoppers. Here, $cmax = 1$, $cmin = 0.00001$, $iter$ is current iteration and Max_iter is the total number of iterations. The first term in (3.20) considers the position of other grasshoppers and implements their interaction. ub_d, lb_d and $\widehat{T_d}$ are upper bound, lower bound and the best solution found so far in the d^{th} dimension respectively. The pseudo-code for GOA is given below:

Algorithm 2 Pseudo-code for GOA

for *run=1:30*
Initialize the swarm X_i $(i = 1,2,\dots,n)$. Define the upper and lower bounds for d dimensions.
Initialize $cmax$, $cmin$, *and maximum number of iterations,* Max_iter
Calculate the fitness of each search agent
T*=the best search agent*
While *(*$l <$ *Max number of iterations)*
Update c using Eq. (3.21)
for *each search agent*
Normalize the distances between grasshoppers in [1,4]
Update the position of the current search agent by equation (3.20)
Bring the current search agent back if it goes outside the boundaries
end for
Update T *if there is a better solution*
$l = l + 1$
end while
Return T *which corresponds to the transmission parameters of* K *subcarriers*
end for

c) Grey wolf optimizer [47]**:** This algorithm is inspired from the grey wolves' leadership hierarchy and their hunting mechanism.

Social hierarchy of grey wolves: Alphas (α) are the leader male and female wolves that are the most dominant and take an important decision of hunting and managing the pack. Betas (β) are the wolves at the second level that act as subordinates to alphas in decision making and command the other lower-level wolves as well. Omegas are the wolves at the lowest rank that have to agree to the commands of dominant wolves. The wolves except for alpha, beta and omega are called deltas (δ) that dominate the omegas but have to bow to alphas and betas. Various mechanisms involved during hunting are modeled mathematically as follows:

Step 1: Prey Encirclement

Encircling the prey during hunt can be mathematically modeled as [47]:

$$\vec{D} = |\vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t)| \tag{3.22}$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}.\vec{D} \tag{3.23}$$

where $\vec{X}$ is a position vector of potential solutions (wolves) and $\overrightarrow{X_p}$ represents the position vector of prey. t represents the current iteration and coefficient vectors are represented by $\vec{A}$ and $\vec{C}$. These vectors are obtained as:

$$\vec{A} = 2\vec{a}.\overrightarrow{r_1} - \vec{a} \tag{3.24}$$

$$\vec{C} = 2.\overrightarrow{r_2} \tag{3.25}$$

where $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ are randomly generated vectors in the range [0,1] and $\vec{a}$ is decreased linearly from 2 to 0 as the iterations progress. Eq. (3.22) and (3.23) allow updating the position of a grey wolf around the prey in any random direction of search space.

Step 2: Hunting mechanism

It is assumed that the α, β and δ wolves have a better idea about the prey location and form the first three best solutions $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$ and $\overrightarrow{X_\delta}$ respectively. The position of other search agents is updated randomly according to these best solutions as follows:

$$\overrightarrow{D_\alpha} = |\overrightarrow{C_1}.\overrightarrow{X_\alpha} - \vec{X}|, \overrightarrow{D_\beta} = |\overrightarrow{C_2}.\overrightarrow{X_\beta} - \vec{X}|, \overrightarrow{D_\delta} = |\overrightarrow{C_3}.\overrightarrow{X_\delta} - \vec{X}| \tag{3.26}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}.\overrightarrow{D_\alpha}, \quad \overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}.\overrightarrow{D_\beta}, \overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}.\overrightarrow{D_\delta} \tag{3.27}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1+\vec{X}_2+\vec{X}_3}{3} \tag{3.28}$$

where $\overrightarrow{C_1}$, $\overrightarrow{C_2}$ and $\overrightarrow{C_3}$ represent random vectors and $\vec{X}$ is the location of a present solution.

Step 3: Search for prey and attacking the prey

Searching the prey forms an exploration phase where the wolves are modeled to diverge from the prey in order to find fitter prey for$|A| > 1$. Similarly, $|A| < 1$ enables wolves to attack towards the prey. The value of C is randomly chosen between 0 and 2 to enable the exploration process during the last iterations and thus avoids any possibility of entrapment at a local optimum. Grey wolves attack the prey when it stops moving, for which the value of a is decreased from 2 to 0.

Algorithm 3 Pseudo-code for GWO

for *run=1:30*
Initialize population size and maximum no. of iterations, Max_iter.
Define X_α *=the best search agent*
X_β*=the second-best search agent*
X_δ*=the third best search agent*
while *(t < maximum number of iterations)*
for *each search agent*
Update the position of current search agent using Eq.(3.28)
End for
Update the upper and lower bounds for d *dimensions.*
Initialize the grey wolf population X_i *(i = 1, 2, ..., n)*
Initialize a, A and C
Calculate the fitness of each search agent
X_α*=the best search agent*
Update a, A and C.
Calculate the fitness of all search agents.
Update X_α, X_β *and* X_δ
t=t+1
end while
return X_α *which corresponds to the transmission parameters of* K *subcarriers*
end for

d) Moth-flame optimization algorithm [29]**:** This algorithm is inspired from the transverse orientation of moths that is the navigation mechanism adopted by them. These insects travel in a straight line at night for long distances by keeping a fixed angle with respect to the moon. But maintaining a similar angle with the human-made artificial lights that are extremely close as compared to the moon, leads to useless and deadly spiral paths resulting in the trapping of moths. Moths form the potential solutions of the problem and their positions in hyper-dimensional space represent the problem's variables. Both moths and flames are considered as solutions, with the only difference that moths move around the search space acting as actual search agents, while flames represent the best position of moths obtained so far. Each moth searches and updates the corresponding flame on finding a better solution, thus never losing its best solution. Moths mainly update their position using logarithmic spiral S defined as [29]:

$$S(M_i, F_j) = D_i . e^{bt} . \cos(2\pi t) + F_j \quad (3.29)$$

where D_i is the distance of the i^{th} moth (M_i) from the j^{th} flame (F_j) and calculated as $D_i = |F_j - M_i$. t is generated randomly in the range [-1,1] and decides the closeness of the moth's next position w.r.t. flame. $t = -1$ and $t = 1$ represent the closest and farthest position of moth to flame respectively. b is a constant that defines the shape of a logarithmic spiral. This spiral movement ensures exploration and exploitation of search space as it not only allows the moths to fly in space between flames but around the flames also. One of the matrices in an algorithm always holds the n (total number of moths) recent best solutions found so far.

In order to enhance exploitation, t is taken in the range $[r, 1]$ where r is the convergence constant that is linearly decreased from -2 to -1 causing accelerated convergence over the course of iterations. This allows the moths to exploit the corresponding flames more accurately. For every iteration, after updating the flame list, each moth changes its position using only one corresponding flame. A specific flame is not assigned to all the moths in order to avoid trapping at a local optimum solution. Best and the worst flames are used by the first and the last moths in order to update their positions.

Exploration is enhanced by changing the sequence of flames based on the best solutions obtained so far. In order to increase the exploitation around the best solution, the number of flames is decreased adaptively over the course of iterations as follows:

$$No\_flames = round\left(N - l * \frac{N-1}{T}\right) \quad (3.30)$$

where l is the current iteration, N is the maximum number of flames and T indicates the maximum number of iterations. The gradual decline in the number of flames balances exploration and exploitation of the search space.

Algorithm 4 Pseudo-code for MFO algorithm

for run=1:30

Initialize population size and maximum no. of iterations, $\boldsymbol{maxite}$*. Define the upper and lower bounds for* d *dimensions.*

while (Ite$\leq$ $\boldsymbol{maxite}$***)***

$flame\ no = round(N - ite * (N - 1)/maxite)$

Initialize matrix M holding population of moths (potential solutions) with real value encoding for transmission parameters

Calculate objective function value using (3.7) for each solution and store the corresponding aggregate fitness function value in array OM.

$\boldsymbol{If\ ite = 1}$

$F = sort\ (M)$ *% F is the matrix holding flame positions*

$OF = sort(OM)$ *%* OF *is the array holding flame's fitness*

else

$F = sort(M_{ite-1}, M_{ite})$

$OF = sort(OM_{ite-1}, OM_{ite})$

end

$a = -1 + Ite * ((-1)/maxite)$ *%* a *is linearly decreased from* -1 *to* -2.

for i=1:N

for j=1:d

$b = 1$ *% constant for defining the shape of spiral*

$t = (a - 1) * rand + 1;$ *% random number generated in range [-1,1]*

$D_i = |F_j - M_i|$*% distance of the* i^{th} *moth for the* j^{th} *flame*

$M_i = D_i * e^{bt} * cos(2\pi t) + F_j$*% update the position of moths*

end

end

At the end of iterative process, best flame position corresponds to the transmission parameters of K *subcarriers.*

end for.

e) Whale optimization algorithm [30]**:** This algorithm is inspired from the social behavior and bubble-net hunting strategy observed in only humpback whales. These whales are intelligent creatures that prefer to hunt krills or small fishes close to the sea's surface. Mathematical modeling for WOA involves the following mechanisms:

Step 1: Prey Encirclement

These creatures encircle the prey on recognizing its location. Target prey is assumed to be the current best solution and the search agents update their position towards the best search agent. This behavior is represented by the following equations [30]:

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}.\vec{D} \tag{3.31}$$

$$\vec{D} = |\vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t)| \tag{3.32}$$

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{3.33}$$

$$\vec{C} = 2.\vec{r} \tag{3.34}$$

where $\overrightarrow{X_p}$ and $\vec{X}$ are the position vectors of the optimal solution obtained so far and the position vector of whales respectively for the t^{th} iteration, $\vec{A}$ and $\vec{C}$ are the coefficient vectors and '.' denotes an element-by-element multiplication. $\vec{a}$ is linearly decreased from 2 to 0 as the iterations progress (in both exploration and exploitation phases) and r is a random number in [0,1].

Step 2: Bubble-net attacking method (exploitation phase)

It involves the following two approaches:

- **Shrinking encircling mechanism**: This behavior is achieved by decreasing the value of $\vec{a}$. $\vec{A}$ is randomly generated in the interval [-a, a] and $\vec{a}$ is reduced from 2 to 0 over the course of iterations. So, fluctuations in the range of $\vec{A}$ are also decreased by $\vec{a}$. If a random value for $\vec{A}$ is set in the range [-1,1], then the new position of a whale can be defined anywhere in between its original position and the current best agent's position.
- **Spiral updating position**: In order to mimic the spiral movement between the prey and the whale following equation is used:

$$\vec{X}(t+1) = \overrightarrow{D'}.e^{bl}.\cos(2\pi l) + \overrightarrow{X_p}(t) \tag{3.35}$$

$\overrightarrow{D'} = |\overrightarrow{X_p}(t) - \vec{X}(t)|$ denotes the distance of the whale from the prey which is the best solution found so far. b is a constant quantity that defines the shape of the logarithmic spiral, l is a random number in [-1,1] and '.' is an element-by-element multiplication. Humpback whales simultaneously swim around the prey within a shrinking circle and spiral-shaped path as well. To update the position of whales, 50-50% probability is taken for both the methods as follows:

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X_p} - \vec{A}.\vec{D} & if\ p < 0.5 \\ \overrightarrow{D'}.e^{bl}.\cos(2\pi l) + \overrightarrow{X_p}\,(\mathrm{t}) & if\ p \geq 0.5 \end{cases} \tag{3.36}$$

where p is a random number in [0,1]. Depending on the value of p, WOA is able to switch between either a spiral or circular movement. The next step involves random searching for prey by humpback whales that is an exploration phase.

Step 3: Search for prey

In the exploration phase, the position of a whale is updated randomly. $|\vec{A}|\geq 1$ emphasizes exploration phase, i.e. when $\vec{A}$ value is greater than 1 or less than -1, the search agents are forced to move away from the reference whale and allow WOA algorithm to perform global search as given below:

$$\vec{D} = |\vec{C}.\vec{X}_{rand} - \vec{X}| \tag{3.37}$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A}.\vec{D} \tag{3.38}$$

Algorithm 5 Pseudo code for WOA

for run=1:30
Initialize population size and maximum no. of iterations, $maxite$. Define the upper and lower bounds for d dimensions.
Initialize the whales population X_i (i = 1, 2, ..., n)
Calculate the fitness of each search agent
X=the best search agent*
while *(t < maximum number of iterations)*
for *each search agent*
Update a, A, C, l, and p
if1 *(p<0.5)*
if2 *(|A| < 1)*
Update the position of the current search agent by the Eq. (3.31)
else if2(|A|≥ 1)
Select a random search agent (X_{rand})
Update the position of the current search agent by the Eq. (3.38)
end if2
elseif1 *(p ≥0.5)*
Update the position of the current search by the Eq. (3.35)
end if1
end for
Check if any search agent goes beyond the search space and amend it
Calculate the fitness of each search agent
Update X if there is a better solution*
t=t+1
end while
return ***X**** which corresponds to the transmission parameters of K subcarriers
end for

The common pseudo-code for ALO, GOA, GWO, MFO and WOA to solve the problem under consideration is given in Algorithm 6:

Algorithm 6 Pseudo-code for maximization of objective function using ALO/GOA/GWO/MFO/WOA

Initialization:
 *Population size, **N= 40** and the maximum number of iterations,* $\boldsymbol{maxite}$ ***=200.***
 Initialize random population of particles encoding transmit power, $P_k \in [\mathbf{0}, \mathbf{15}]$ *and modulation level* $M_k \in (\mathbf{2}, \mathbf{4}, \mathbf{16}, \mathbf{32})$ *for **K=64** subcarriers.*
 Set lower bound, $LB = \{LB_1, LB_2, \ldots . LB_d\}$ *and upper bound* $UB = \{UB_1, UB_2, \ldots . UB_d\}$ *for d-dimensional particle.*
 Initialize the parameters corresponding to the optimization algorithm ALO/GOA/GWO/MFO/WOA.
 $\boldsymbol{while\ ite \leq maxite}$
 for N=1:40
 Calculate BER, Data rate, interference power and power consumption P_c *corresponding to* N^{th} *particle.*
 Obtain objective function value corresponding to each potential solution from (3.7).
 Check for the best particle in population and update the position of N^{th} *particle as per the procedure given in Algorithm 1-5.*
 end for
 $ite = ite + 1$
 End while
 return (*the optimal value of transmission parameters)*

3.4 Results and Discussion

Various parameter settings required for the CR based system model and different algorithms are given in the following subsection.

3.4.1 Simulation settings

For the data transmission scenario, the threshold values are assumed as: $\mathrm{BER_{th}} = 10^{-6}$, $\mathrm{DR_{th}} = 200\ Kbps$ [74] and $\mathrm{INT_{th}} = 5 \times 10^{-12}$ W. CR parameter adaptation for power consumption minimization in an OFDM based multicarrier system comprising of 64 sub-carriers is carried out. Path loss and noise floor acting as environmental parameters for SU transmission are taken as 75 dB and -90 dBm respectively. The distance between SU_Tx and adjacent channel PU_Rx is assumed as 1.5 Km. We considered the usage of TVWS channel no. U-30 with center frequency 543.25 MHz and channel bandwidth of 8 MHz for SU transmission. PU_Rx is assumed to be operating on the adjacent channel U-29 at 535.25 MHz (occupied TV channel). The channel occupancy data was obtained from the quantitative analysis done at Pune, India as reported in [110].

The range for transmit power of each subcarrier is 0-15 dBm with a resolution of 0.1dBm. Four modulation types are considered: BPSK, QPSK, 16 QAM and 32 QAM. The symbol rate is assumed to be 10 $Ksps$. Each particle (ant/ antlion/ grasshopper/ grey wolf/ moth/ whale) encodes (real value encoding) the transmit power and modulation level of K subcarriers. Population size and the maximum number of iterations are common control parameters for all the algorithms and taken as 40 and 200 respectively.

Table 3.1 Simulation settings for ALO, GOA, GWO, MFO and WOA

Algorithm	**Parameter**	**Value**
ALO [28]	Number of ants/ant lions	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
	$cmax$	1
	$cmin$	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 defining shape of logarithmic spiral, b	1
WOA [30]	Number of whales	40
	Maximum number of iterations	200
	Constant for defining shape of logarithmic spiral, b	1

3.4.2 Simulation Results

It is required that the optimal value of transmission parameters is achieved at the earliest so that the SU is able to utilize the white space efficiently whenever it needs to transmit. Moreover, we need an algorithm that not only provides the best solution corresponding to the highest fitness or lowest power consumption but should also be obtained at the earliest. Therefore, our preference would be for an algorithm that provides quick convergence or reaches at an optimal solution in very few iterations. *Optimal generation* is the value of an iteration number at which the convergence is achieved for a particular algorithm. Standard deviation (Std. Dev.) of this metric tells about the consistency in processing time requirement of each algorithm.

Computational complexity of each algorithm depends on the average number of function evaluations (AFE) needed to reach the optimal generation. It equals the product of population size and the optimal iteration number.

Table 3.2 depicts the mean and Standard deviation values of the fitness score (F), power consumption (P_c) and optimal generation along with AFEs obtained from 30 Monte-Carlo simulation trials of each algorithm.

Table 3.2 Mean and standard deviation values for fitness score, power consumption and optimal generation

Algorithm	Fitness score (F)		Power consumption, dBm		Optimal generation		AFE
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
ALO	5.9338	0.0558	25.1175	0.0558	4	1	160
GOA	5.9203	0.0211	25.1279	0.0229	NC*	-	-
GWO	5.9491	1.1151e-04	25.1022	1.1164e-04	166	**7**	6640
MFO	5.9588	0.0082	25.0925	0.0082	NC*	**-**	-
WOA	**5.9691**	**0.0000**	**25.0822**	**0.0000**	**4**	**0**	**160**

NC*- Not converged

Highest fitness score of 5.9691 is offered by WOA with a standard deviation of 0.0 which means this algorithm is very competitive and shows high consistency in providing an optimal solution. The other metric for the performance comparison is an optimal generation number at which the convergence is achieved. It was observed that in all the 30 independent runs, convergence for WOA was achieved in only 4 iterations which are very low as compared to about 200 iterations required by the BBO algorithm in [74]. Therefore, the computational complexity of WOA is found to be smaller.

Though the average optimal generation number for ALO is also 4 but it varies between 3 and 5 making ALO relatively less stable in terms of convergence speed. MFO and GOA are not able to converge in 200 iterations and keep on improving the fitness value at each successive generation for most of the runs. GWO also required a large number of iterations to reach at an optimal value. Standard deviation value for the optimal generation in case of GWO is also higher to eliminate its candidature amongst top performers.

The fitness score for MFO is quite close to that obtained with WOA but the former is unable to reach at an optimal solution quickly, making it the worst performer in terms of convergence speed. Convergence characteristics for the fitness (objective function) value and power consumption for all the algorithms are shown in Figure 3.3 and Figure 3.4 respectively. Magnified view of the curves at final iterations is provided in the inset which clearly shows that

ALO and GWO converged at local optimal solution while GOA and MFO require a large number of iterations to converge.

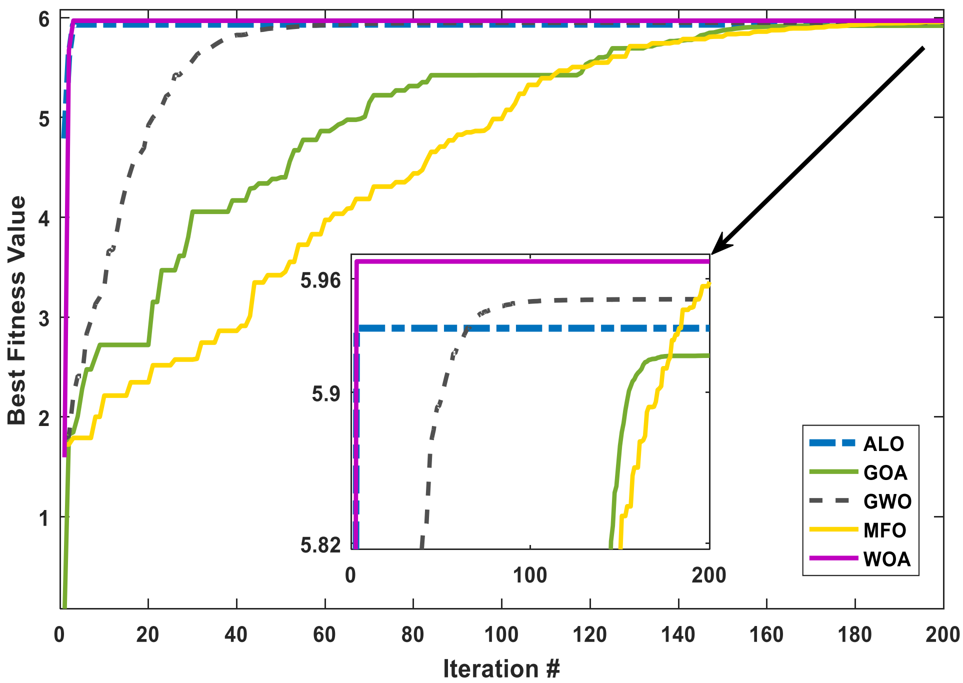


Figure 3.3: Convergence characteristics of fitness score for ALO, GOA, GWO, MFO and WOA

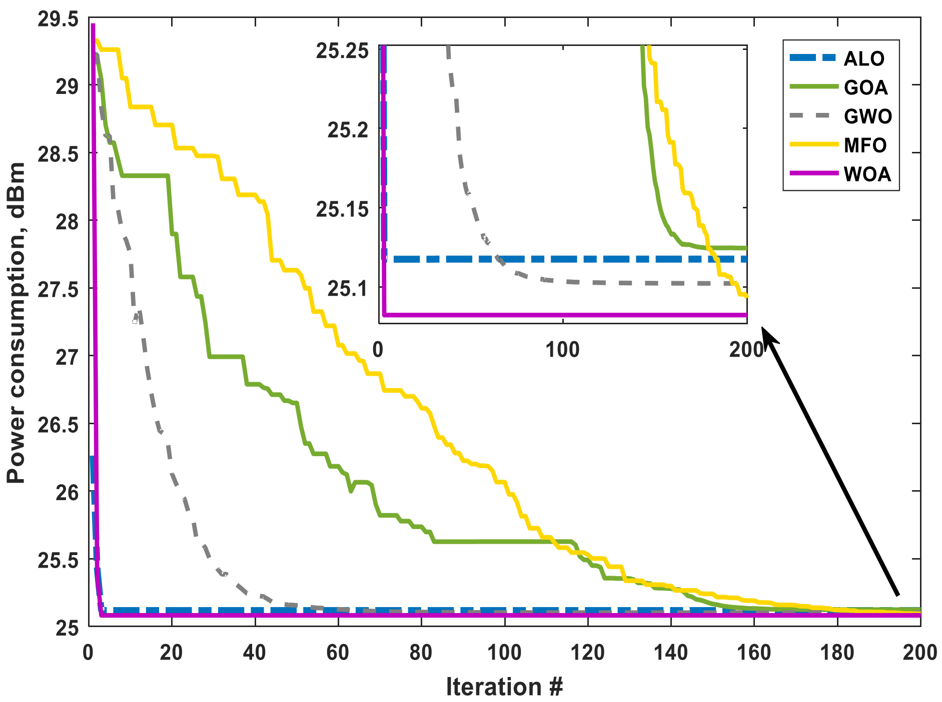


Figure 3.4: Convergence characteristics of power consumption (dBm) for ALO, GOA, GWO, MFO and WOA

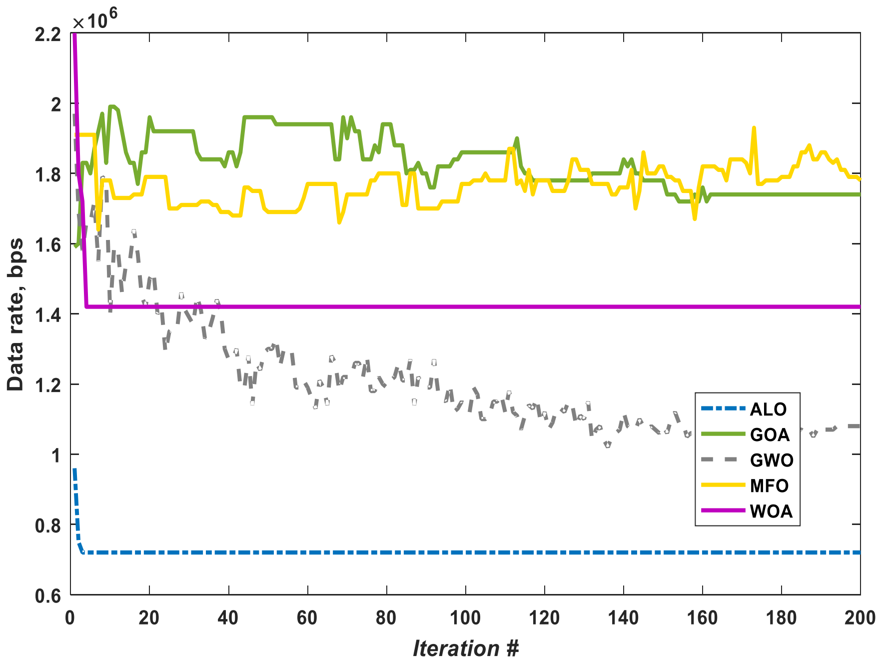
Mean and standard deviation values of different QoS metrics, i.e. BER, data rate and interference power obtained using all the algorithms are tabulated in Table 3.3.

Table 3.3 Mean and standard deviation values for BER, data rate and interference power

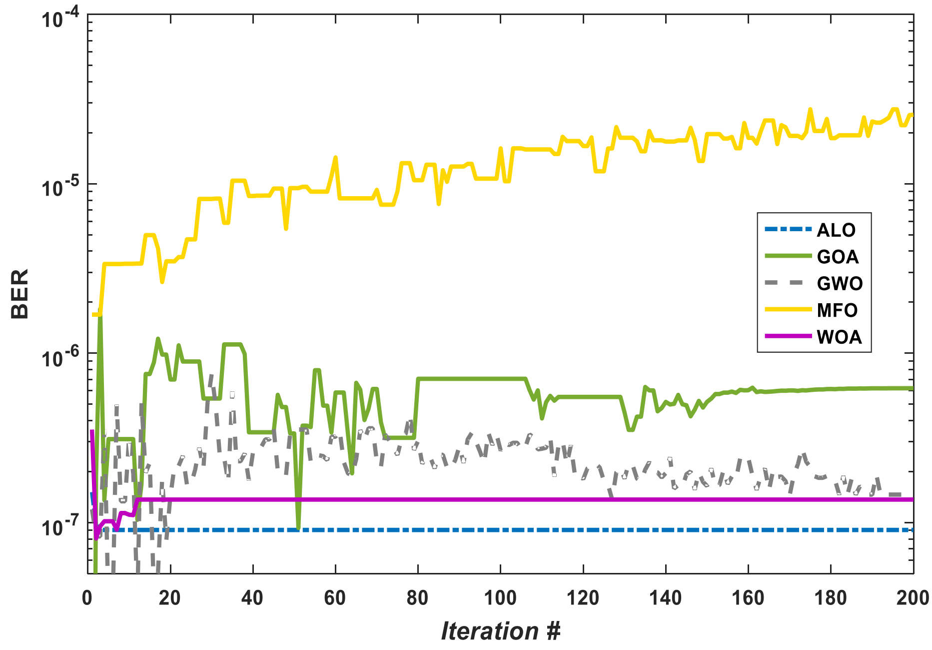
Algorithm	BER		Data rate ($Kbps$)		Interference power ($Watt$)	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
ALO	0.9909 e-07	9.1785e-09	681.00	34.140	0.0744e-14	2.0991e-17
GOA	6.0239e-07	8.9142e-08	1762.00	142.66	0.0739e-14	7.9831e-18
GWO	1.4873e-07	4.4781e-08	1072.00	100.09	0.0727e-14	3.9052e-20
MFO	2.2963e-05	6.0191e-06	1783.00	103.93	0.0728e-14	2.9147e-18
WOA	1.2782e-07	1.4095e-08	1427.00	48.086	0.0725 e-14	0.0000

Though the average data rate obtained with MFO is quite large but its standard deviation value is also large along with the highest BER obtained. The standard deviation of data rate for WOA is higher than ALO only and quite acceptable. Therefore, WOA performs best among other algorithms for minimizing power consumption while satisfying the requirements for BER, data rate and interference power.

The convergence characteristics for different QoS metrics for all the algorithms are shown in Figure 3.5. Convergence graphs for interference power are quite similar to that of power consumption owing to the dependency of both (interference power and power consumption) on only transmit power whereas BER and data rate depend not only on transmit power but modulation levels also.



a



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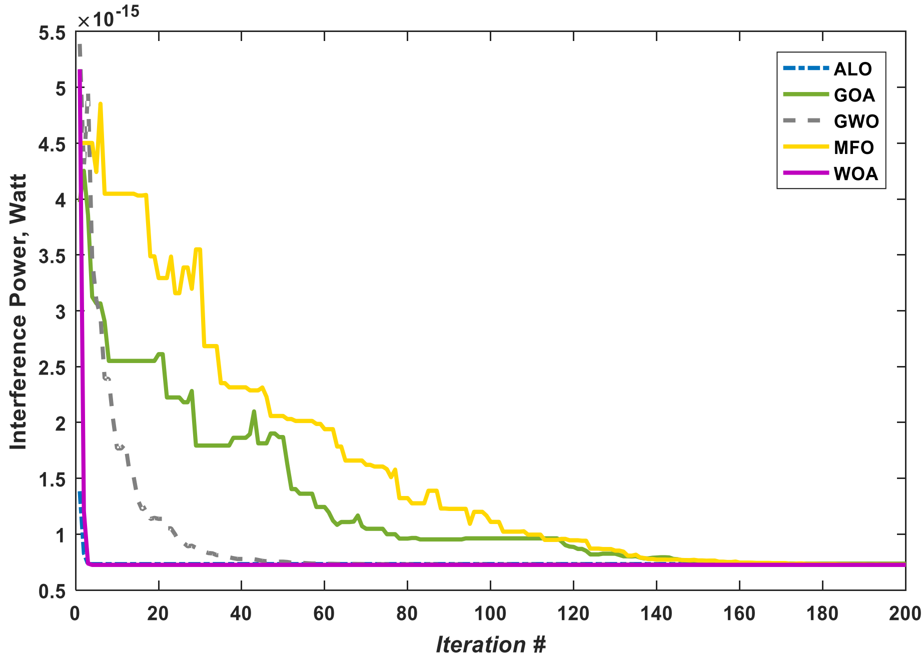

c

Figure 3.5: Convergence characteristics of (a) data rate (bps) (b) BER (c) interference power (Watt) for ALO, GOA, GWO, MFO and WOA.

It is observed that different QoS metrics are satisfied by all the algorithms with a good amount of margin while WOA is able to quickly achieve the desired objective of reducing the power consumption along with satisfying the requirements for data rate, BER and interference power. Therefore, WOA based optimizer is the best candidate to obtain an energy-efficient operation employing parameter reconfiguration ability of CR as is demonstrated by the percentage power-saving characteristics in Figure 3.6. Percentage power saving is calculated as:

$$\%\, power\ saving = \frac{(P_{c,max} - P_c)}{P_{c,max}} \times 100 \tag{3.39}$$

where $P_{c,max}$ and P_c are in $Watt$.

WOA based optimizer for CDE provides 74.70 % of power-saving which is the highest among all other algorithms, thus proving its efficacy in achieving the desired objective of constrained minimization of power consumption in very few iterations.

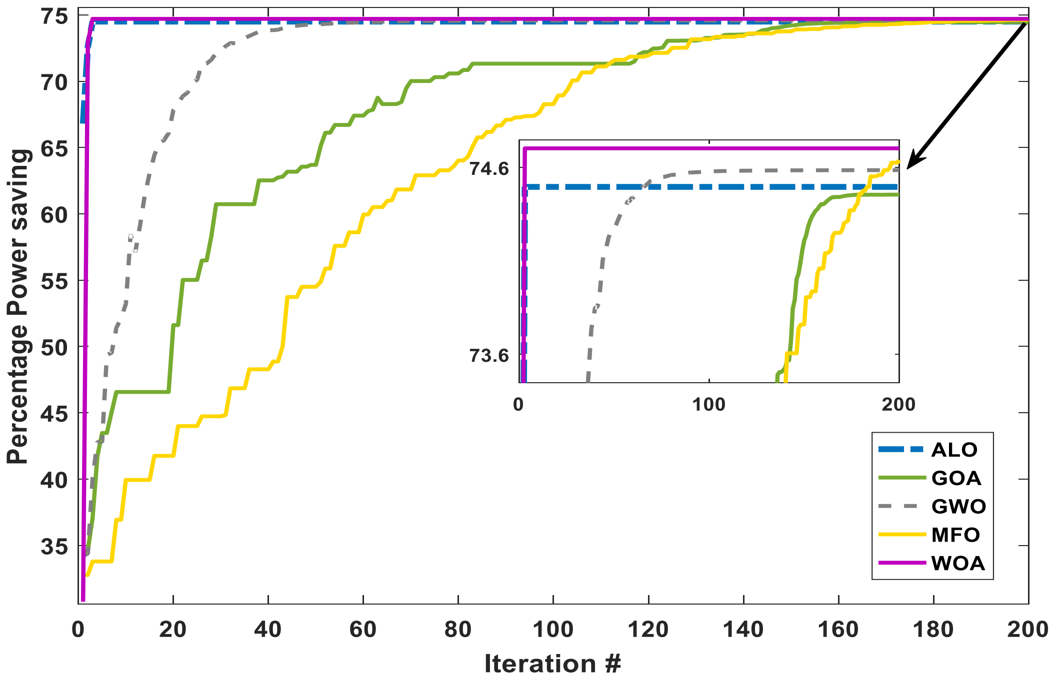

Figure 3.6: Convergence characteristics of percentage power saving for ALO, GOA, GWO, MFO and WOA

3.5 Conclusion

In this chapter, a NI optimization algorithm assisted methodology is proposed to reduce the system power consumption via CR considering Class B PA operation at CR transmitter. A novel penalty function based mechanism is introduced to evaluate an objective function value considering three different QoS constraints of data rate, BER and ACI. Comparative performance analysis of five different algorithms, i.e. ALO, GOA, GWO, MFO and WOA for constrained optimization, is done on the basis of fitness score and convergence speed.

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.
- Both ALO and GWO converged to a local optimal solution, thus offering lower fitness value while GOA and MFO have slower convergence and are unable to reach at an optimal solution even in 200 iterations.

Chapter 4

Performance Optimization of Cognitive Decision Engine for CR-Based IoTs using various Parameter-Less Meta-Heuristic Techniques

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Future communication technology will be comprised of ubiquitous objects based on the Internet of Things (IoTs) with cognitive capabilities. These devices would enable intelligent decisions in order to achieve any-time, any-place, on-demand and interference-free services. In this chapter, performances of recently proposed optimization algorithms are investigated for the problem of parameter reconfiguration in CR based IoT system. Five different transmission scenarios are taken into consideration each supporting different user requirement and radio battery level. It is a challenging task to determine the optimal value of transmission parameters for a multicarrier system with high dimensionality. But meta-heuristic optimization techniques offer an efficient and simple solution to the aforementioned problem. Performance investigation of ant lion optimizer (ALO), grey wolf optimizer (GWO), Jaya algorithm (JA), moth flame optimization (MFO) and whale optimization algorithm (WOA) is done and an optimal solution obtained for each transmission scenario is reported. All these techniques either have few or no algorithm-specific parameters or reach at an optimal solution without the need of any control-parameter-setting specialist, thereby reducing the complexity of an algorithm.

4.1 Introduction

Currently deployed smart networks operate in the license exempted Industrial Scientific Medical (ISM) band with WiFi, ZigBee and Bluetooth as the prominent technologies used for these networks. As these technologies co-exist in a small physical space, it results in performance degradation due to interference and limited throughput. With a large number of IoT connected devices, the demand for free spectrum resources has arisen tremendously and is unable to cope up with the current dedicated spectrum assignment. This necessitates the emergence of smart IoT devices with cognitive capabilities [112]. CR technology has emerged as a promising technique to handle a large number of connected devices in the future IoTs. Therefore, the current technology trends are shifting towards embedding the cognitive ability into these devices and handling them in a highly flexible, reliable and scalable manner by offering secondary access to TVWS. It has led to a new research paradigm called Cognitive Internet of Things (CIoTs) which is focused on the potential applications of CR technology in the Internet of Things (IoTs) domain

[113]. The periodic sensing of an environment by CR based IoT device should be followed by altering the operating parameters in order to adapt as per the changing environmental conditions and user demands. This parameter reconfiguration as per QoS requirements and decision making for an optimal set of transmission parameters is supported by a module called as CDE. In this chapter, CDE is designed to meet the multiple objectives in five different transmission scenarios for an OFDM based CR-IoT system.

Multicarrier modulation technique such as OFDM is a preferred candidate for CR systems as it provides good flexibility and computational efficiency on a subcarrier by subcarrier basis. Unfortunately, multicarrier systems offer higher dimensionality which makes the adaptation or reconfiguration task even more challenging due to an increase in the number of transmission variables to be optimized. Solving such a large dimensionality problem requires a highly efficient meta-heuristic technique with excellent exploration and exploitation features. System models assumed in [24] and [13] support a multicarrier transmission with only 10 and 16 number of subcarriers respectively. Determination of optimal parameter values is rather easy for these systems (because of lower dimensionality) as compared to the model reported in this chapter with 64 number of subcarriers. As the complexity of problems keeps on rising, there is a need for some better, highly efficient and intelligent approach [114]. Therefore, we have investigated the performance of recently proposed efficient meta-heuristic approaches such as ALO, GWO, MFO, WOA and JA to solve the parameter reconfiguration problem for different transmission scenarios of a CR-IoT system. Transmission scenarios reported in [13, 22-25] focused only on the end-user requirement without giving any due concern towards the radio battery level. We have considered different modes of operation for a CR-IoT device where CDE evaluates the transmission parameters according to the application supported by the IoT device and the current battery level of the radio (high or low).

4.2 System Model and Problem Formulation

The proposed system model for a CR based IoT network is shown in Figure 4.1. We have selected an interweave model for opportunistic access of TVWS frequency bands by CR based IoT device, i.e. a SU. After finding a vacant TV channel through sensing technique, SU decides to transmit its data on this channel with K number of subcarriers provided that the received power at primary user receiver (PU_Rx) operating on an adjacent channel, i.e. ACI doesn't exceed a certain threshold value.

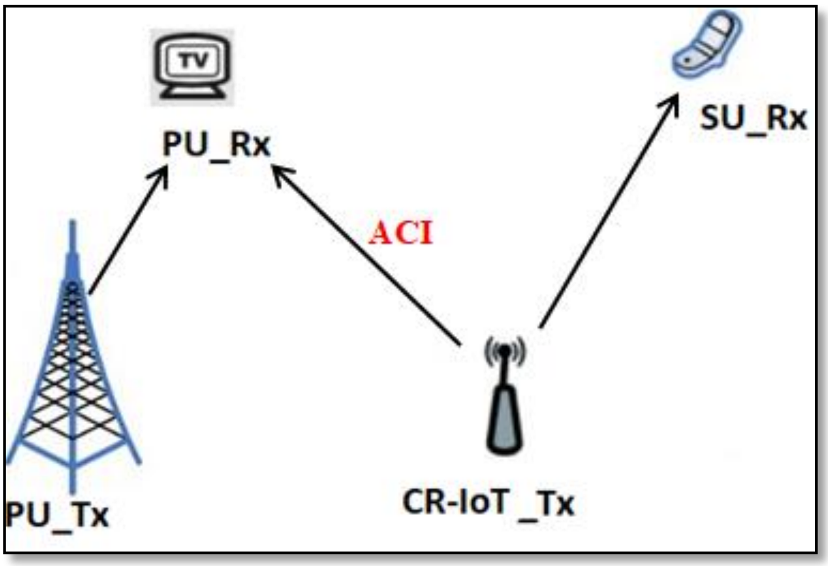


Figure 4.1: System model for a CR based IoT network

Some of the important requirements to support IoT applications include: higher QoS, adaptability and re-configurability. There is a need for some advanced algorithms to deal with features such as high flexibility and re-configurability. The use of opportunistic radio resources can provide efficiency as well as reliability [112]. IoT devices should have the ability to scan their environment and reconfigure themselves. RF sensors and internal state sensors shown in Figure 4.2, are responsible for sensing the environmental parameters and user requirements respectively. CDE module reaches some autonomous decision for the set of transmission parameters on the basis of sensed information. Consequently, the decision is sent as an actuating signal to SDR which adjusts the output parameters in order to obtain the optimal performance. The SDR based platform is selected due to its ability to support the operation and adaptability of the CR-IoT device across different TVWS frequency bands along with the usage of different radio protocols and modulation techniques.

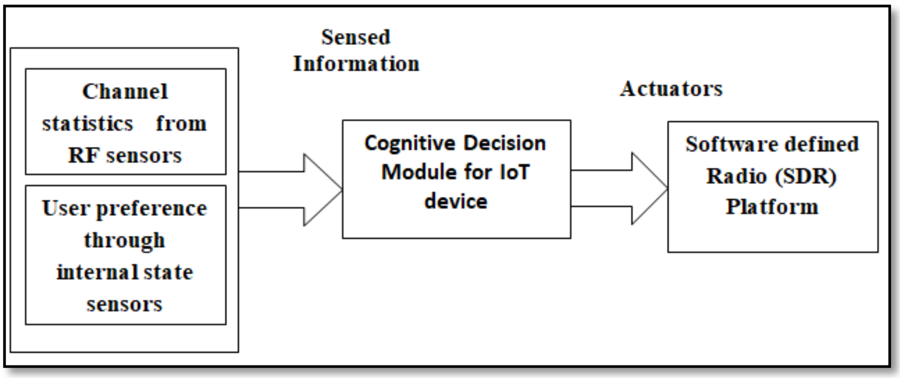


Figure 4.2: Interface of a CDE Module for IoT device with sensors and SDR

In order to make the system model more realistic, the presence of path loss and ACI caused by SU transmission is considered which resulted in interference power constraints at the PU receiver. These assumptions were missing in the work reported in [22-25] where an AWGN channel was assumed and interference constraints were simply ignored.

Minimizing BER, minimizing power consumption and maximizing throughput are the primary objectives for emergency mode (e.g. email transmission), low power mode (e.g. voice transmission) and multimedia mode (e.g. video transmission) respectively. The objective functions [13, 22-25] for the above operating modes when SU employs a multicarrier transmission with K subcarriers are given below:

1. Objective function for minimization of BER

To minimize the BER or to obtain an error-free signal is one of the most important goals for any communication system. BER is influenced by transmit power, modulation type, noise power etc. The fitness function (converted to maximization problem) of this objective is created within an output range [0, 1] and is defined as [13]:

$$f_{minBER} = 1 - \frac{log_{10}(0.5)}{log_{10}(P_{avBER})} \tag{4.1}$$

where P_{avBER} is the average BER of K subcarriers of a cognitive OFDM system. This average is normalized to the worst possible BER of 0.5.

2. Objective function for minimization of power consumption

For any communication system, power must be used optimally. Consumption of power should be minimum for all the tasks. The objective function for power consumption minimization is given as [13]:

$$f_{minP} = 1 - \sum_{k=1}^{K} \frac{P_k}{KP_{max}} \tag{4.2}$$

where P_k corresponds to the transmit power for the k^{th} subcarrier and P_{max} is the maximum allowed power for the subcarrier.

3. Objective function for maximization of throughput

The amount of correct information received at the receiver provides the throughput of the system. It can be improved by making the average modulation level and symbol rate of the system to be maximum. This is because for an OFDM system the overall throughput is influenced by the symbol rate of each subcarrier. Thus the objective function for maximization of throughput of the system is given by:

$$f_{maxTPT} = \frac{\frac{1}{K}(\sum_{k=1}^{K}(log_2 M_k)*SR_k)}{(log_2 M_{max})*(SR_{max})} \tag{4.3}$$

where M_k and SR_k are modulation level and symbol rate of k^{th} subcarrier, M_{max} and SR_{max} are the maximum allowed modulation level and the symbol rate of the system.

INT_i is the ACI caused by i^{th} subcarrier of SU's band into adjacent PU's band that it has sensed to be occupied and given by Eq. (3.3) in Chapter 3. The ACI at PU_Rx operating on an adjacent channel shouldn't exceed a certain threshold INT_{th} for all the services, i.e.

$$\sum_{i=1}^{K}\left(INT_k(d_k, P_k)\right) \leq INT_{th} \tag{4.4}$$

$P_T = \sum_{i=1}^{K} P_i$ is the total transmit power for SU_Tx which should remain below a certain threshold value P_{th}, i.e.

$$\sum_{k=1}^{K} P_k \leq P_{th} \tag{4.5}$$

For any mode or service type, one of the objectives is selected as primary and others are treated as secondary. There are several techniques available in the literature to solve such problems with multiple fitness functions. One of these techniques is a weighted sum approach [115] which is adopted in this work. This approach assigns a higher weight to the primary objective and lower weight values to all the secondary objectives. In general, the weighted sum approach for M objective functions is defined as [115]:

$$F = \sum_{i=1}^{M} w_i f_i \tag{4.6}$$

where w_i and f_i are the weight value and fitness value respectively corresponding to i^{th} objective function and F is the aggregate or overall fitness function. The weight value w_i is subjected to the following two constraints [63]:

$$W = [w_1, w_2, w_3, \dots \dots w_M]$$

$$w_i > 0, i = 1,2, \dots M$$

$$\sum_{i=1}^{M} w_i = 1 \tag{4.7}$$

Based on the type of various modes of operation and battery levels, the assigned weight values are listed in Table 4.1. These weights are chosen on the basis of few trial and error simulations aimed at getting higher objective function value.

Table 4.1 Weight values for different transmission scenarios of CR-IoT device

Transmission scenario	Mode of operation	w_1	w_2	w_3
I	Low power mode [13]	0.1	0.8	0.1
Battery level- High				
II	Multimedia [13]	0.1	0.1	0.8
III	Emergency [13]	0.8	0.1	0.1
Battery level- Low				
IV	Multimedia	0.2	0.4	0.4
V	Emergency	0.65	0.3	0.05

Performance Metric**:** Objective function, F (to be maximized) based on the weighted sum approach with interference and transmission power constraints is given by (4.8). A penalty function $f(.)$ is introduced when the interference or transmission power constraint is violated. The selected penalty function term automatically reduces the fitness value for a candidate solution which violates the constraints.

$$max.\ F = \left((w_1 f_{minBER} + w_2 f_{minP} + w_3 f_{maxTPT}) \times \frac{1}{1+f\left(\frac{INT_{th}}{INT_{obt}}\right)} \times \frac{1}{1+f\left(\frac{P_{th}}{P_T}\right)} \right) \tag{4.8}$$

INT_{obt} is the actual interference power obtained corresponding to the certain set of transmit power and modulation levels for all the subcarriers.

If a selected particle violates the constraint, i.e. INT_{obt} (P_T) is more than $INT_{th}(P_{th})$, the penalty term will reduce the objective (fitness) function value for that particle. In other words, penalty function penalizes an infeasible solution so that only feasible solutions are favored by the selection process.

4.3 Meta-heuristic Optimization Algorithms used for Adaptation of Transmission Parameters of a CR-IoT system

A brief overview and pseudo codes for ALO, GWO, MFO and WOA techniques employed for the parameter adaptation in CR based IoT network is provided in Section 3.3 of Chapter 3. This section describes the Jaya algorithm and the common pseudo code for all the algorithms to solve the parameter adaptation problem.

Jaya Algorithm [103]: It is a robust optimization technique proposed to solve different constrained and unconstrained optimization problems. The name 'Jaya' is a Sanskrit word which means 'victory'. During the exploration, JA always tries to reach the best solution (i.e. gets closer to success) and avoids the worst solution by moving away from it, thus avoiding the failure. JA is very simple as the solution is modified using only one equation in a single phase [116]. It shuns the requirement of cautious initialization of algorithm-specific parameters as needed for conventional optimization approaches.

Let $g(x)$ be the function to be optimized, D is the total number of design parameters, i.e. $(d = 1, 2, \dots \dots D)$ and N is the population size with $n = 1,2, \dots \dots N$. If $x_{d,n}^{i}$ is the value of d^{th} variable corresponding to the n^{th} candidate during i^{th} iteration, then its value is updated as:

$$X_{d,n}^{i} = x_{d,n}^{i} + \mu_{1,d}^{i}\left(x_{d,best}^{i} - \left|x_{d,n}^{i}\right|\right) - \mu_{2,d}^{i}\left(x_{d,worst}^{i} - \left|x_{d,n}^{i}\right|\right) \qquad (4.9)$$

where $x_{d,best}^{i}$ and $x_{d,worst}^{i}$ are the values of the d^{th} parameter for the best and worst solutions respectively. $X_{d,n}^{i}$ is the updated value of $x_{d,n}^{i}$ and $\mu_{1,d}^{i}$ and $\mu_{2,d}^{i}$ are the random numbers for d^{th} variable at i^{th} iteration lying in the range of [0,1]. The term $\left(x_{d,best}^{i} - \left|x_{d,n}^{i}\right|\right)$ implies that the solution attempts to come close to the best solution and the term $\left(x_{d,worst}^{i} - \left|x_{d,n}^{i}\right|\right)$ shows that the solution tries to avoid the worst solution. $X_{d,n}^{i}$ is accepted only if the objective function value corresponding to it is better than that obtained with the previous solution [117]. For each iteration, the input values are the updated values obtained during the last generation.

Algorithm 1 Pseudo Code for Jaya Algorithm (JA)

for run=1:30
Initialize population with size (N) *and maximum no. of iterations,* $\boldsymbol{max\_ite}$.
Define the upper and lower bounds for D *dimensions.*
while *(t < maximum number of iterations)*
Calculate the objective function value for each potential solution.
Identify the best and worst solutions from the entire population.
Alter all the solutions based on best and worst solutions as per Eq (4.9)
If $X_{d,n}^{i} > x_{d,n}^{i}$
accept the new solution
else
Reject the new solution and keep the old one as it is.
end if
t=t+1
end while
return $\boldsymbol{x_{best}}$ which corresponds to the transmission parameters of Ksubcarriers
end for

Algorithm 2 provides the common pseudo-code for ALO, GWO, MFO, JA and WOA to solve the multi-objective optimization problem defined by Eq. (4.8).

Algorithm 2 Pseudo code for maximization of the objective function using ALO/Jaya/GWO/MFO/WOA

Start computing the algorithm run time.

Initialization:

Population size, ***N =40*** *and the maximum number of iterations,* $\boldsymbol{maxite}$ ***=1000.***

Initialize random population of particles encoding transmit power P_i*; modulation level* M_i *and symbol rate* SR_i *for* ***K=64*** *subcarriers.*

Set lower bound, $LB = \{LB_1, LB_2, \ldots. LB_d\}$ *and upper bound* $UB = \{UB_1, UB_2, \ldots. UB_d\}$ *for* d*-dimensional particle.*

Initialize the parameters corresponding to the optimization algorithm ALO/GWO/JA/MFO/WOA.

while $\boldsymbol{ite \leq maxite}$

for N=1:40

Obtain three objective function values corresponding to each potential solution from Eq. (4.1)-(4.3).

Calculate the ACI obtained at PU receiver, INT_{obt} *corresponding to* N^{th} *particle.*

Obtain the overall fitness function value considering penalty evaluation using Eq. (4.8).

Check for the best particle in population and update the position of N^{th} *particle.*

end for

ite = ite + 1

End while

return (*the optimal value of transmission parameters and the computation time).*

4.4 Results and Discussion

Various parameter settings done for the CR based system model and different algorithms are given in the following subsection.

4.4.1 Simulation settings

The threshold values for SU transmission power and ACI at PU_Rx for all the transmission scenarios are taken as, $\mathrm{P_{th}} = 5\ W$ and $\mathrm{INT_{th}} = 5 \times 10^{-12} W$ respectively. Path loss and noise floor act as environmental parameters for SU transmission and taken as $75\ dB$ and $-90\ dBm$ respectively. Each subcarrier is assigned a random attenuation value in the range 0-1 in order to simulate a dynamic channel. The range for transmit power of each subcarrier is $5 - 250\ mW$ with an increment of $0.5\ mW$ [24]. Five modulation types considered are BPSK, QPSK, 16 QAM, 32 QAM and 64 QAM with symbol rate lying in the range 125-1000 $Ksps$.

The distance between SU_Tx and adjacent channel PU receiver is taken as 1.5 Km. We considered the usage of TVWS channel No. U-30 with center frequency 543.25 MHz and the channel bandwidth of 8 MHz for SU transmission. PU_Rx is assumed to be operating on the adjacent channel U-29 at 535.25 MHz (occupied TV channel). This channel occupancy data was obtained from the quantitative analysis done at Pune, India as reported in [110].

In this chapter, a comparison of five algorithms is carried out for the parameter adaptation in an OFDM based multicarrier CR-IoT system. Each algorithm is run for 30 independent trials for five different modes of operation. A particle (ant/ant-lion/grey-wolf/moth/whale) encodes (real value encoding) the transmit power, modulation levels and symbol rates of K subcarriers. Population size and the maximum number of iterations (stopping criteria) are common control parameters for all the algorithms and taken as 40 and 1000 respectively.

4.4.2 Simulation results

In order to compare the different optimization techniques, five different weight settings depicted in Table 4.1 are tested. Each weight scenario emphasizes a particular objective and is suitable for different CR based IoT applications. The criteria adopted for performance comparison is optimal fitness (or objective) function value, optimal iteration number and the algorithm processing time requirement (in seconds). The algorithm that provides better trade-off for these criteria is chosen as the best candidate for a particular mode. The processing time requirement for an algorithm decides the ***time complexity*** for that algorithm.

a) Transmission scenario: I (Low power mode)

This scenario supports low power applications such as voice transmission over CR network. Table 4.2 summarizes the mean, best, worst and standard deviation of the best fitness value, optimal iteration number and optimal processing time requirement obtained after 30 independent simulation trials for low power mode.

Table 4.2 Comparative results of mean, best, worst and standard deviation of the fitness value and optimal iteration number for transmission scenario I

Algorithm		ALO	GWO	MFO	WOA	Jaya
Fitness value	Mean	0.8672	0.9303	0.9449	0.9395	0.6957
	Best	0.8678	0.9339	0.9503	0.9563	0.7388
	Worst	0.8668	0.9248	0.9368	0.8692	0.645
	Std. dev.	3.75e-04	0.0026	0.0043	0.0252	0.0298
Optimal iteration number	Mean	243	NC*	497	359	28
	Best	218	NC*	355	286	7
	Worst	263	NC*	578	466	63
	Std. dev.	15	NC*	93	52	18
Processing time (in seconds)	Mean	120.012	3.8366	3.6743	3.5729	2.221
	Best	109.6	3.5898	3.5815	3.4814	2.1758
	Worst	165.6	3.9146	3.8682	3.7834	2.3367
	Std. dev.	17.1106	0.3979	0.1082	0.1022	0.0548

NC*- Not Converged

It is found that the highest average fitness value is achieved for MFO algorithm which is significantly greater than the fitness values obtained with other techniques. Though the number of iterations needed by MFO to reach at an optimal value is larger than ALO, WOA and JA schemes, the fitness value of MFO becomes higher than all the other algorithms after few iterations as shown in Figure 4.3.

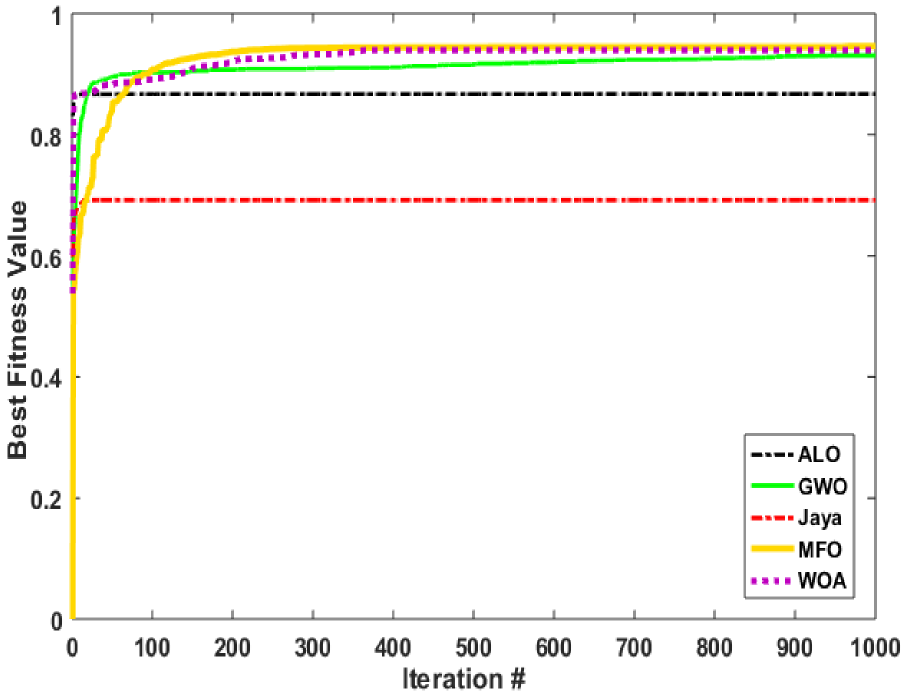


Figure 4.3: Convergence characteristics of the best fitness value in low power mode

The decision-maker can thus opt for a lesser number of iterations as stopping criteria if the SU application is delay-sensitive. From the processing time requirement given in Table 4.2, it was found that MFO needs lesser time than ALO and GWO to complete 1000 iterations whereas the time to reach an optimal iteration will be far less, making this algorithm suitable for timely adaptation of network.

Table 4.3 presents the average value of three objective functions: f_{minBER}, f_{minP} and f_{maxTPT}; transmission parameters: Transmit power, modulation level and symbol rate for 64 subcarriers along with QoS parameters: BER and interference power.

Table 4.3 Average values of transmission and performance metrics for transmission scenario I

Algorithm	f_{minBER}	f_{minP}	f_{maxTPT}	**Average transmit power, (mW)**	**Average throughput, ($bits/sec$)**	**Average symbol rate, ($Ksps$)**	**Average BER**	**Average interference power, ($Watt$)**
ALO	0.8045	0.9800	0.0279	5.0115	2.7120	135.3932	0.0288	3.6309e-15
GWO	0.7861	0.9744	0.6912	6.4041	33.9063	859.3481	0.0392	4.6923e-15
MFO	0.7384	0.9800	0.8709	5.0000	57.6910	928.9048	0.0707	3.6259e-15
WOA	0.7925	0.9777	0.7813	5.5810	51.4890	851.8683	0.0394	4.0364e-15
Jaya	0.7579	0.7295	0.3760	67.0855	38.9245	544.6010	0.0358	4.7560e-14

MFO algorithm gives the best-compromised solution offering the lowest transmit power value and satisfying other objectives as well. JA performs the worst as it gets trapped at a local optimal solution while GWO and WOA give tough competition to MFO offering higher fitness values. Convergence characteristics of the transmit Power (averaged over all the subcarriers) are shown in Figure 4.4.

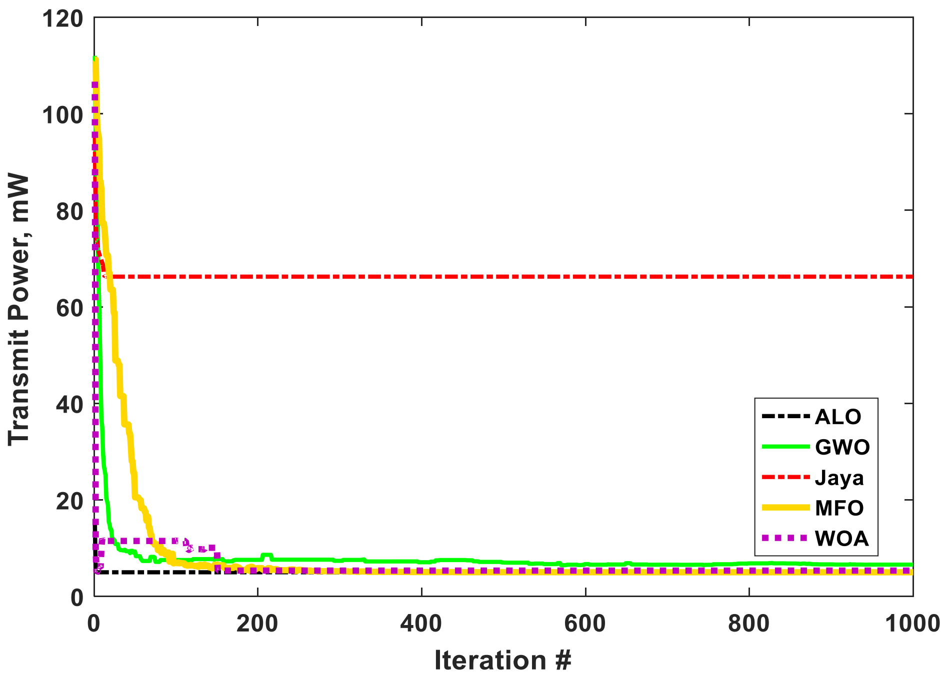


Figure 4.4: Convergence characteristics of the average transmit power in low power mode

b) Transmission scenario: II (Service: Multimedia mode & Battery level: High)

In this transmission mode, CR-IoT device with a high battery level should support higher throughput in order to support multimedia applications such as video transmission. Mean, best, worst and standard deviation values of the optimal fitness and optimal generation obtained by all the algorithms simulated for this scenario are given in Table 4.4.

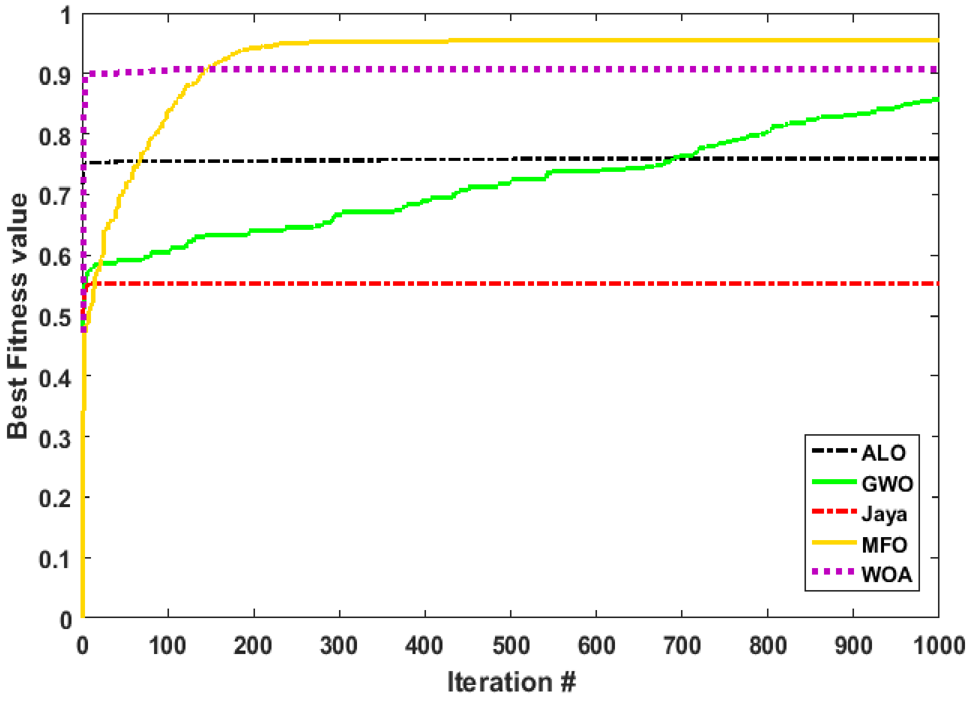
Table 4.4 Comparative results of mean, best, worst and standard deviation of the fitness value and optimal iteration number for transmission scenario II

Algorithm		ALO	GWO	MFO	WOA	Jaya
Fitness value	Mean	0.7596	0.8517	**0.9594**	0.9412	0.5356
	Best	0.7626	0.889	0.9695	0.9786	0.5788
	Worst	0.7561	0.8151	0.9452	0.9176	0.4845
	Std. dev.	0.0028	0.021	0.0074	0.0224	0.034
Optimal iteration number	Mean	767	NC*	505	336	24
	Best	754	NC*	430	273	15
	Worst	784	NC*	560	420	35
	Std. dev.	14	NC*	44	77	7
Processing time (in seconds)	Mean	172.7151	3.9989	3.7258	3.5739	2.2018
	Best	157.3129	3.5973	3.6438	3.3948	2.1515
	Worst	206.1861	4.7531	4.0672	3.9686	2.3094
	Std. dev.	18.2894	0.3712	0.1538	0.211	0.0514

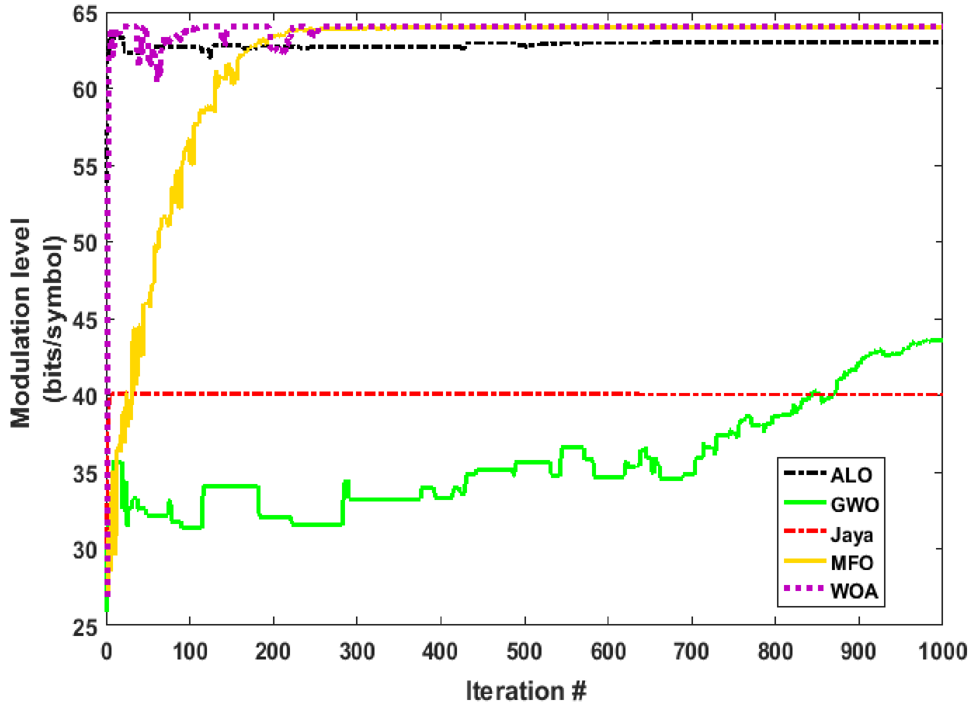
NC*- Not Converged

In this transmission scenario, MFO algorithm performs significantly better than the other algorithms by offering higher fitness value. Though the optimal number of iterations needed by MFO to reach at the best value is larger as compared to WOA and Jaya but it was found that the later get struck at a local optimal solution, while GWO does not converge in 1000 iterations and keeps on improving the best fitness value for each successive iteration.

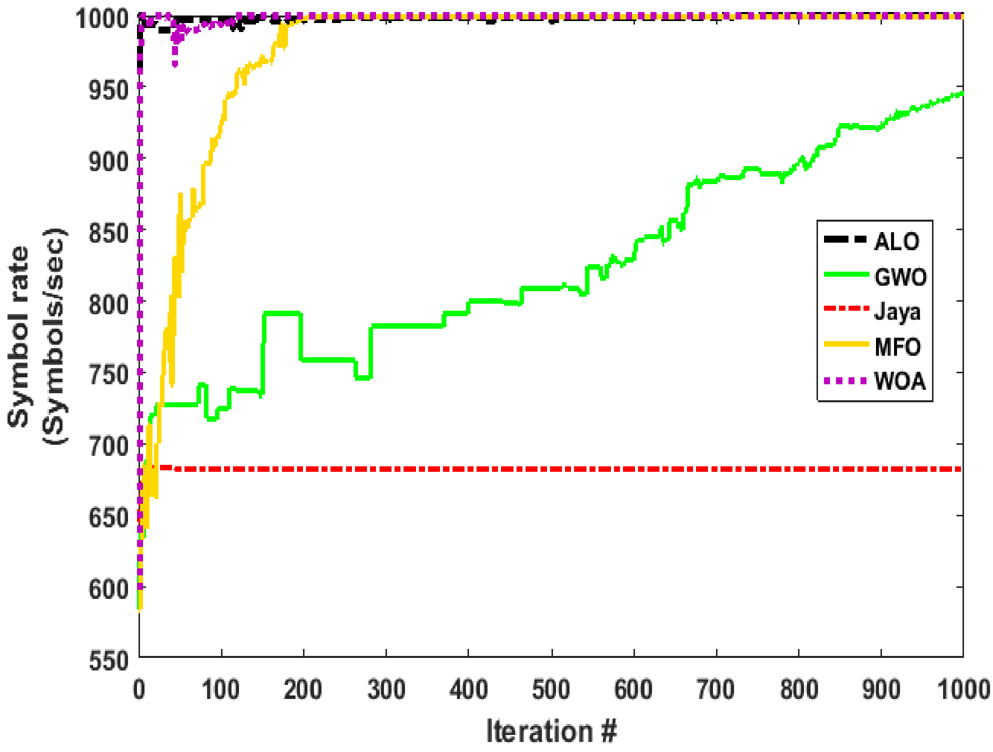
Similar to low power mode, it was observed from the convergence characteristics that after a few hundred iterations, the best fitness value for MFO becomes higher than the other algorithms as shown in Figure 4.5(a). The processing time required to complete 1000 iterations by MFO is also found to be tolerable for real-time adaptation of CR network. Therefore, MFO emerges as the best candidate for obtaining an optimal solution for the multimedia mode of transmission. Convergence characteristics for the average modulation level and symbol rate are shown in Figure 4.5(b) and 4.5(c) respectively.



(a)



(b)



(c)

Figure 4.5: Convergence characteristics of the a) best fitness value b) modulation level c) symbol rate for multimedia mode

The average values of different transmission and performance metrics obtained for transmission scenario II are given in Table 4.5.

Table 4.5 Average values of transmission and performance metrics for transmission scenario II

Algorithm	f_{minBER}	f_{minP}	f_{maxTPT}	Average transmit power, (mW)	Average throughput, $(bits/sec)$	Average symbol rate, $(Ksps)$	Average BER	Average interference power, $(Watt)$
ALO	0.9760	0.2246	0.9977	193.8606	63.5000	999.6995	9.0125e-13	1.4028e-13
GWO	0.8217	0.9068	0.8477	23.2960	45.5564	946.0531	0.0206	1.6644e-14
MFO	0.7811	0.8682	0.9932	32.9427	63.6109	997.2656	0.0422	2.6162e-14
WOA	0.8549	0.6938	1	76.5572	64	1000	0.0094	5.4111e-14
Jaya	0.7906	0.5631	0.5078	108.3160	40.5818	678.9072	0.0198	7.7363e-14

c) Transmission scenario: III (Service: Emergency mode & Battery level: High)

In this mode, the user application demands lower BER which depends on modulation format, transmission power and channel attenuation value for each subcarrier. Various performance metrics obtained for fitness value, optimal generation and processing time are given in Table 4.6.

Table 4.6 Comparative results of mean, best, worst and standard deviation of the fitness value and optimal iteration number for transmission scenario III

Algorithm		ALO	GWO	MFO	WOA	Jaya
Fitness value	**Mean**	0.9025	0.8895	0.883	**0.9052**	0.8253
	Best	0.9134	0.8959	0.8902	0.9145	0.8355
	Worst	0.8939	0.8725	0.8678	0.8906	0.8194
	Std. dev.	0.007	0.007	0.0082	0.0063	0.0047
Optimal iteration number	**Mean**	547	NC*	NC*	409	41
	Best	503	NC*	NC*	218	9
	Worst	624	NC*	NC*	535	102
	Std. dev.	50	NC*	NC*	96	32
Processing time (in seconds)	**Mean**	161.979	3.9539	3.6069	3.5593	2.2721
	Best	156.5238	3.8128	3.3365	3.4865	2.2109
	Worst	170.8433	3.2623	3.9436	3.6565	2.3564
	Std. dev.	5.1377	0.1458	0.1952	0.0533	0.0489

NC*- Not converged

Figure 4.6 and Figure 4.7 show the convergence characteristics of fitness value and BER respectively for all the algorithms, obtained corresponding to the transmission scenario III. It was found that the highest fitness value is obtained corresponding to WOA. Therefore, WOA emerges as the best candidate solution for transmission scenario III and offers a good compromise for all the three objectives and lower time complexity as well.

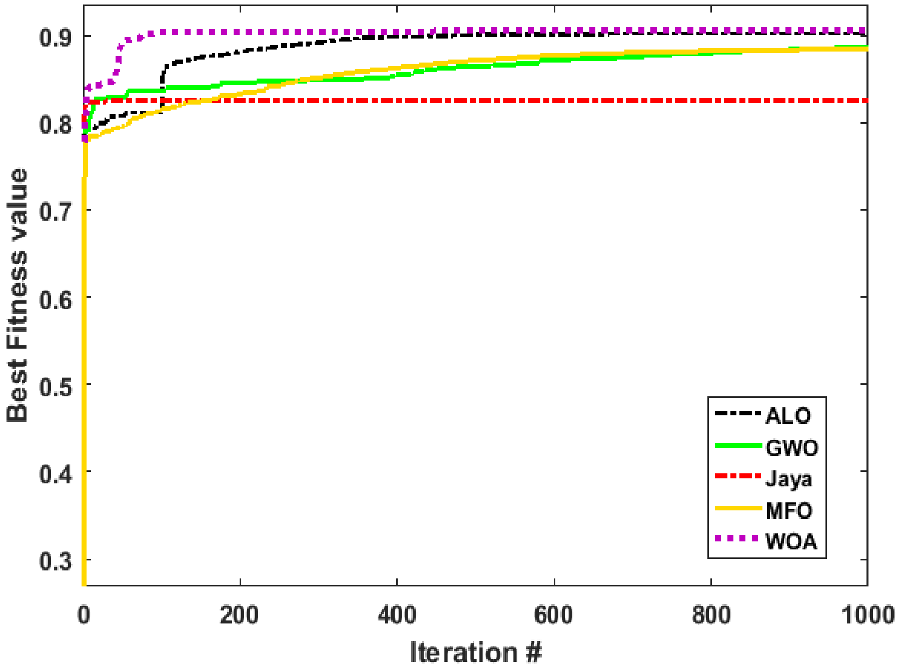


Figure 4.6: Convergence characteristics of the best fitness value for emergency mode

The average values of different transmission and performance metrics are given in Table 4.7.

Table 4.7 Average values of transmission and performance metrics for transmission scenario III

Algorithm	f_{minBER}	f_{minP}	f_{maxTPT}	Average transmit power, (mW)	Average throughput, $(bits/symbol)$	Average symbol rate, $(Ksps)$	Average BER	Average interference power, $(Watt)$
ALO	0.9541	0.7166	0.6195	70.8545	29.9969	783.6357	3.8700e-07	4.8377e-14
GWO	0.8951	0.8259	0.3429	43.5259	13.7544	577.5052	0.0016	3.2217e-14
MFO	0.9359	0.7662	0.5967	58.4402	34.3097	832.2361	6.0951e-05	4.3565e-14
WOA	0.9616	0.7770	0.5984	55.7544	16.2871	924.7312	6.2287e-08	4.2142e-14
Jaya	0.8726	0.6046	0.3811	107.8765	24.3170	567.1240	2.1141e-05	7.9047e-14

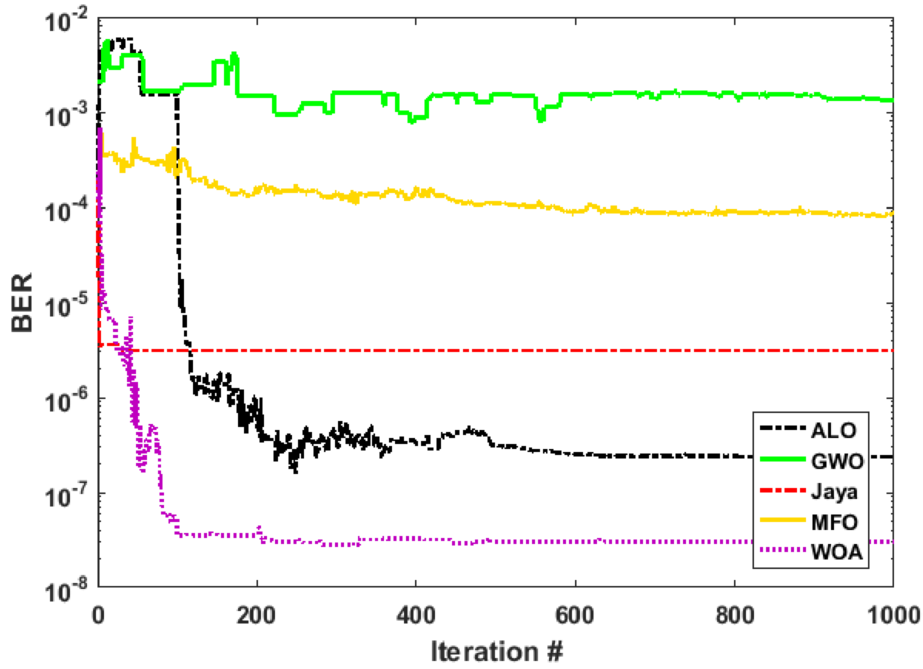


Figure 4.7: Convergence curve of the BER value for emergency mode

d) Transmission scenario: IV (Service: Multimedia mode & Battery level: Low)

This transmission scenario demands higher throughput but with lower transmit power. Statistical results for fitness value, optimal generation and processing time requirement are tabulated in Table 4.8.

Table 4.8 Comparative results of mean, best, worst and standard deviation of the fitness value and optimal iteration number for transmission scenario IV

Algorithm		ALO	GWO	MFO	WOA	Jaya
Fitness value	Mean	0.8287	0.8606	**0.9226**	0.8862	0.606
	Best	0.8362	0.8781	0.9399	0.928	0.6373
	Worst	0.8154	0.849	0.9012	0.8667	0.5698
	Std. dev.	0.0084	0.01	0.013	0.0209	0.0233
Optimal iteration number	Mean	727	NC*	353	431	39
	Best	673	NC*	315	283	13
	Worst	770	NC*	402	572	98
	Std. dev.	43	NC*	33	75	29
Processing time (in seconds)	Mean	167.0129	3.9157	3.6497	3.1968	2.3025
	Best	157.0023	3.7701	3.5325	3.0976	2.2509
	Worst	186.259	4.0851	3.8316	3.4729	2.4285
	Std. dev.	9.2042	0.1087	0.1255	0.1292	0.0668

NC*- Not converged

Figure 4.8 shows the convergence characteristics of the fitness value obtained for all the algorithms in multimedia mode with a low battery level. Similar to the convergence characteristics obtained for transmission scenario II, it was found that the highest fitness value is obtained for MFO along with a tolerable value of processing time requirement.

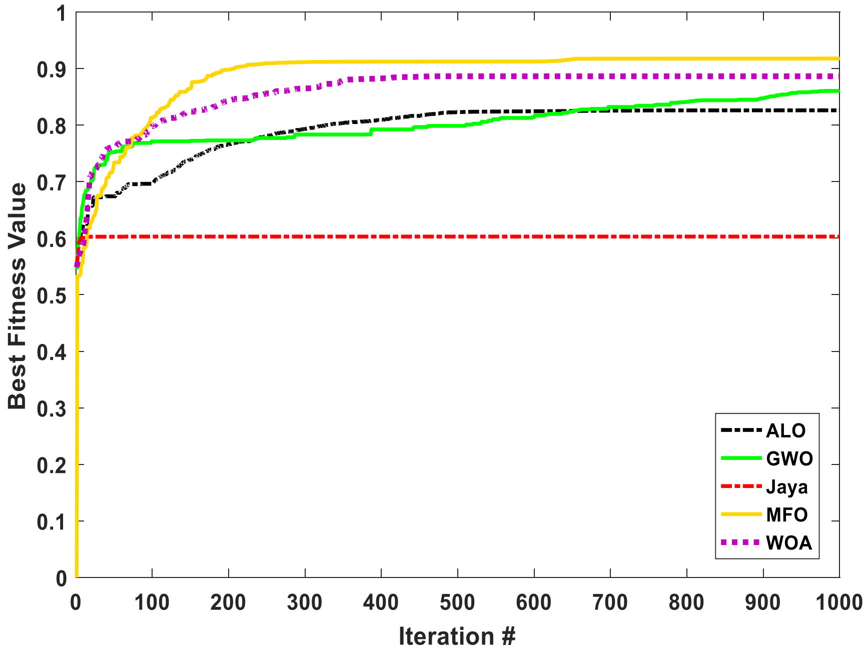


Figure 4.8: Convergence curve of the fitness value for multimedia mode at low radio battery level

The average values of different transmission and performance metrics for transmission scenario IV are given in Table 4.9.

Table 4.9 Average values of transmission and performance metrics for transmission scenario IV

Algorithm	f_{minBER}	f_{minP}	f_{maxTPT}	Average transmit power, (mW)	Average tpt. $(bits/sec)$	Average symbol rate, $(Ksps)$	Average BER	Average interference power, $(Watt)$
ALO	0.9102	0.7245	0.8918	68.8686	46.8189	977.9086	4.9409e-04	5.3710e-14
GWO	0.8069	0.9546	0.7830	11.3483	41.9536	898.3857	0.0277	8.3453e-15
MFO	0.7532	0.9664	0.9635	8.3890	61.9803	984.9560	0.0605	5.8547e-15
WOA	0.8512	0.7931	1	51.7234	64	1000	0.0095	3.0039e-14
Jaya	0.7701	0.6749	0.4559	80.2992	39.4457	626.7979	0.0277	5.8178e-14

e) Transmission scenario: V (Service: Emergency mode & Battery level: Low)

In this transmission mode, the application demands lower BER and low radio battery level, thereby indicating that transmit power must be lower. Simulation results obtained for the fitness value, optimal generation and computation time are given in Table 4.10. From the convergence characteristics shown in Figure 4.9, it was found that WOA offers the highest fitness value after a few hundred iterations.

Table 4.10 Comparative results of Mean, best, worst and standard deviation of the fitness value and optimal iteration number for transmission scenario V

Algorithm		ALO	GWO	MFO	WOA	Jaya
Fitness value	**Mean**	0.8995	0.9036	0.865	**0.9236**	0.779
	Best	0.9048	0.9088	0.871	0.9263	0.7962
	Worst	0.8955	0.8957	0.8548	0.9108	0.7588
	Std. dev.	0.0035	0.004	0.0047	0.0046	0.0129
Optimal iteration number	**Mean**	733	NC*	NC*	462	86
	Best	663	NC*	NC*	365	55
	Worst	776	NC*	NC*	549	128
	Std. dev.	36	NC*	NC*	61	35
Processing time (in seconds)	**Mean**	164.551	3.8067	3.4538	3.4443	2.5786
	Best	155.7613	3.6065	3.2759	3.2241	2.5174
	Worst	209.3314	3.4076	4.048	4.0036	2.7165
	Std. dev.	16.1273	0.2548	0.2405	0.2957	0.0705

NC*- Not converged

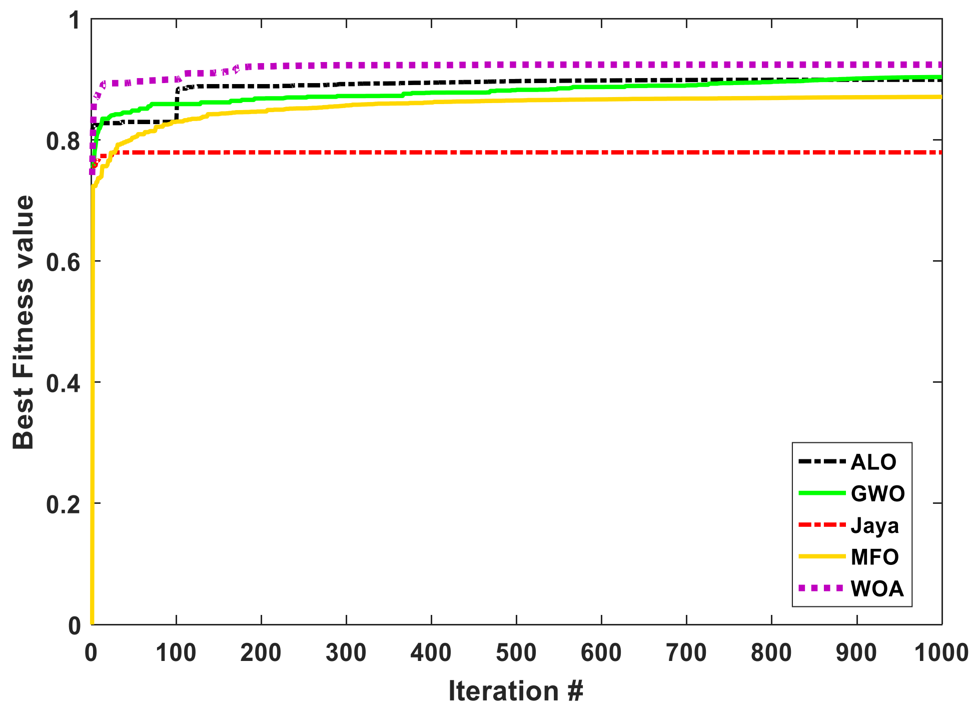


Figure 4.9: Convergence curve of the fitness value for emergency mode at low radio battery level

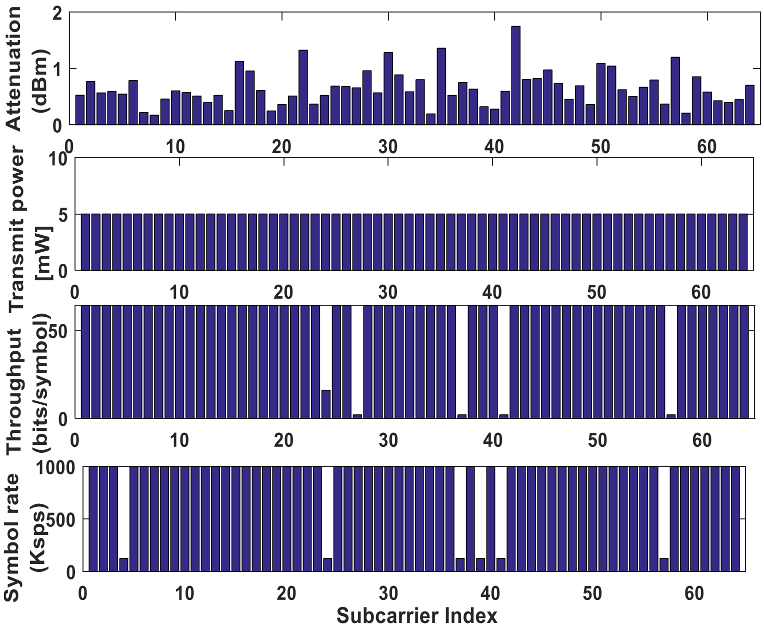
JA gets trapped at some local optimal value whereas GWO and MFO do not converge in 1000 iterations. ALO algorithm requires a substantial number of iterations to reach an optimal value. Therefore, WOA comes out as the best solution for the applications demanding lower BER at low radio battery power level as it offers the highest fitness value and smaller processing time requirement.

The average values of different transmission and performance metrics are shown in Table 4.11.

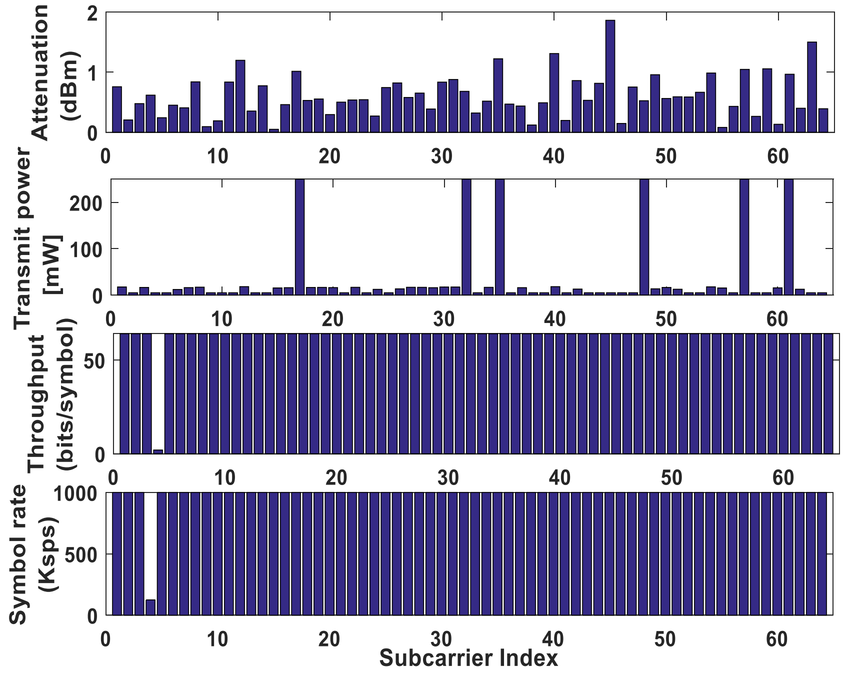
Table 4.11 Average values of transmission and performance metrics for transmission scenario V

Algorithm	f_{minBER}	f_{minP}	f_{maxTPT}	Average transmit power, (mW)	Average Tpt. $(bits/symbol)$	Average symbol rate, $(Ksps)$	Average BER	Average interference power, $(Watt)$
ALO	0.9567	0.8948	0.1672	26.2881	10.9232	303.0490	1.5665e-07	2.0765e-14
GWO	0.8939	0.9133	0.2565	21.6800	10.8406	488.6054	0.0017	1.5604e-14
MFO	0.8549	0.9402	0.5457	14.9548	29.5205	799.5639	0.0085	1.1367e-14
WOA	0.9645	0.8958	0.5585	26.0395	11.3211	962.8084	4.1843e-09	1.9385e-14
Jaya	0.8433	0.6408	0.3544	98.6927	25.8443	555.2345	9.4887e-04	7.2266e-14

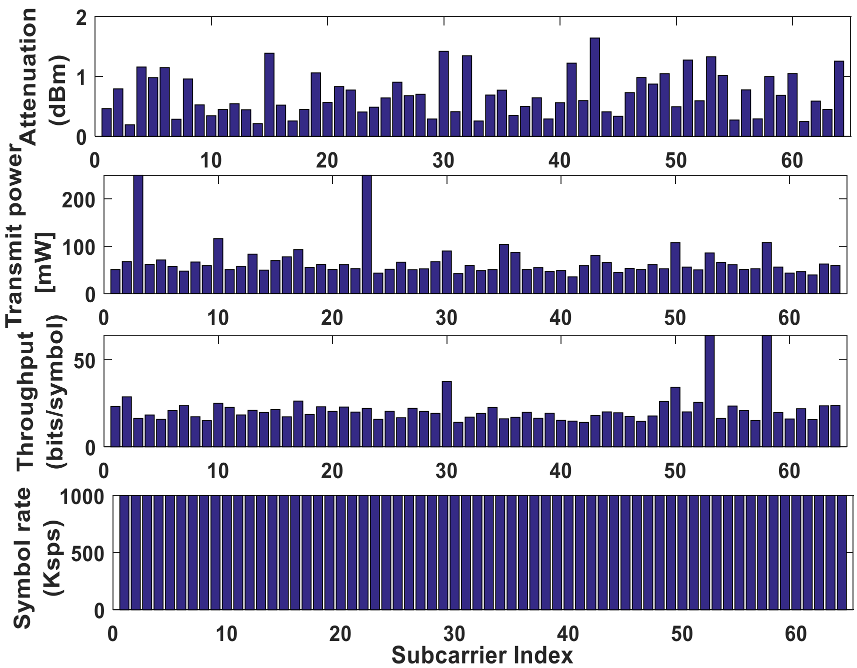
Decision results: The optimized values of transmission parameters obtained for transmission scenario I and II correspond to the MFO algorithm and shown in Figure 4.10(a)-(b) respectively, while the best solution obtained for transmission scenario III corresponds to WOA and is depicted in Figure 4.10(c).



(a)



(b)



(c)

Figure 4.10: Decision results for (a) transmission scenario I (b) transmission scenario II (c) transmission scenario III

From these decision results, it is found that the transmit power for all the subcarriers has the least value for transmission scenario I which corresponds to the low power mode. Similarly, for transmission scenario II each subcarrier has higher throughput and symbol rate in order to support multimedia mode while for transmission scenario III, lower BER is obtained with higher transmit power and lower throughput.

4.5 Conclusion

This chapter brings out the comparative performance analysis of five optimization algorithms: ALO, GWO, JA, MFO and WOA for parameter adaptation in CR based IoT system. Five different transmission scenarios are considered and each scenario supports different user requirement and radio battery level. The exponential penalty function is introduced to penalize the particles that do not satisfy the QoS constraints for transmission power at SU_Tx and ACI caused by SU transmission at PU_Rx. Simulation results show that the MFO algorithm gives the best solution to minimize power consumption and maximize throughput scenarios while WOA emerges as the best candidate for minimizing BER mode.

Chapter 5

Sensing Period Adaptation in CR Using Jaya Algorithm

Adaptation of the sensing period for a licensed channel is one of the key requirements to maximize the utilization of transmission opportunities by a SU. In this chapter, a novel objective function evaluation method is formulated for sensing period optimization in CR. A recently introduced optimization technique, namely Jaya Algorithm has been used for achieving the optimum value of sensing period in order to maximize the discovery of spectrum opportunities while maintaining the sensing overhead and interference time within a user-defined value. This multi-objective optimization problem involving different constraints is solved using an objective function that introduces the penalty for the violation of constraints. Simulation results show that the proposed scheme leads to quick adaptation and efficient discovery of spectrum opportunities as compared to GA while satisfying the different QoS constraints. Therefore, JA emerges as a better choice for sensing period adaptation in real-time CR applications.

5.1 Introduction

A secondary user (SU) can access the licensed spectrum when any PU is in an idle state or with power and interference constraints provided that it does not cause performance degradation to the PU network. Sensing the spectrum status is one of the crucial elements to identify the spectrum opportunities [129]. Spectrum sensing technology involves physical layer and MAC- layer based sensing. Different PHY-layer detection methods such as energy detection, matched filter and feature-based detection can provide a desirable level of detection quality. MAC layer sensing is concerned about scheduling the sensing of PU channels, i.e. the time instants when the SUs have to sense the licensed channel.

It is essential to optimize the *sensing period* which determines the frequency at which the sensing occurs for each channel such that the number of spectrum opportunities is maximized with minimum incurred sensing overhead. If a shorter sensing period is adopted, many transmission opportunities will be discovered and the PU return can be quickly detected by a SU. However, a SU will spend a lot of time sensing instead of transmitting which has a negative impact on the spectrum utilization. However, using less frequent sensing may result in the interference to PU due to delay in the immediate detection of PU reappearance.

Existing work related to MAC layer based sensing using meta-heuristic optimization technique is limited and appeared only in [50-51] where Pareto based strategy with GA has been used to optimize the sensing period. GA involves different stages such as selection, crossover, mutation etc. along with the time consuming coding-decoding mechanism for binary-coded GA. This results in the requirement of larger processing time to find the optimum sensing period using GA, which is a serious concern for delay-sensitive CR applications. Also, it is not always assured that the global optimum value could be reached with GA.

The above-stated limitations of GA motivate the use of a simple, highly efficient and newly proposed technique, i.e. Jaya algorithm for sensing period adaptation. JA has a strong potential to solve the constrained and unconstrained optimization problems. R.V. Rao [103] applied JA on 24 constrained and 30 unconstrained benchmark problems and compared its performance with other well-known optimization algorithms such as GA, PSO, DE, ABC, BBO etc. From Friedman's rank test based statistical analysis, JA has been found to secure the first rank for the 'best' and the 'mean' solutions for all the 24 constrained benchmark problems. Similarly, the performance of this algorithm is found to be better when investigated on 30 unconstrained benchmark functions.

In general, the optimization schemes require some algorithm-specific parameters that need careful tuning at the user end. On the contrary, JA needs the common control parameters only and provides the optimum results in comparatively less number of function evaluations. It shuns the requirement of cautious initialization of algorithm-specific parameters as needed for GA such as crossover and mutation rates, choice of selection technique etc. This algorithm is quite simple as the solution is updated in only one step based on the 'best' and 'worst' positions of the whole population [103]. Moreover, the optimization problem proposed in this chapter has very low dimensionality as it requires adapting the sensing period of a single channel.

The above discussion justifies the application of JA as a simple meta-heuristic technique to solve the sensing period adaptation problem. The research work of this thesis is focused on the application of parameter-less meta-heuristics for parameter adaptation in CR systems. In a similar context, JA is being explored for the very first time to solve the problem of sensing period adaptation and its performance is compared with GA. Some of the novel contributions of this chapter are discussed below:

A novel penalty function is introduced for handling the constraint violation that affects the overall fitness function value. This constraint handling approach is easier to apply as compared to the Pareto strategy and dominance concept [50-51]. Moreover, it is important to consider the interference time constraint if a licensed channel application has higher intolerance towards interference. Therefore, the interference time constraint that was earlier missing in [50-51], is considered here along with the sensing overhead constraint.

5.2 Formulation of Objective Function

A single PU channel as shown in Figure 5.1 is considered, the ON (1) and OFF (0) duration of which follows an exponential distribution with mean uniformly distributed in the range [0.5, 5.5]. Periodic sampling of PU channel state is done with sensing period x_i in order to discover the maximum number of PU OFF (0) states that are transmission opportunities for a SU.

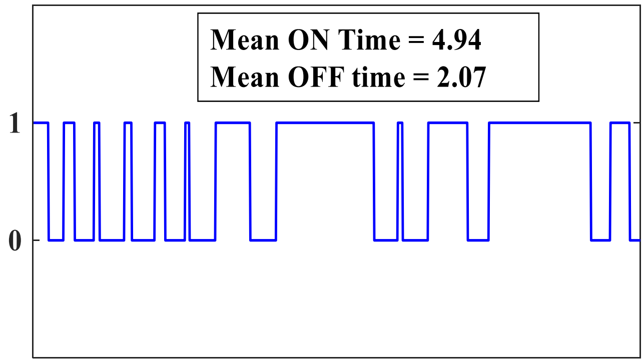


Figure 5.1: PU ON-OFF channel model

A novel fitness function evaluation method is proposed as given in (5.1) where Opp is the number of spectrum opportunities discovered by a SU. Ov_{obt} is the sensing overhead obtained, means the time spent on sensing the spectrum and INT_{time_obt} is the time for which interference is caused to the PU. Ov_{tar} and INT_{time_tar} are the target overhead and interference duration selected as 20s and 5s respectively. The increase in overhead and interference time above their target value will impact (decrease) the overall fitness function value because of the nature of $h(.)$ function.

$$F = (Opp) \times h\left(\frac{Ov_{tar}}{Ov_{obt}}\right) \times h\left(\frac{INT_{time\_tar}}{INT_{time\_obt}}\right) \tag{5.1}$$

$h(.)$ is a penalty function to introduce punishment to the fitness value if a constraint is violated and given as:

$$h(a) = \frac{1}{1+exp(-l(log(a)-m))} \tag{5.2}$$

l and m are real numbers chosen such that $h(1) = \alpha$ and $h(1/2) = \beta$, where α is chosen close to but smaller than 1 while β is larger than but close to 0. As shown in Figure 5.2, when $a > 1$, $h(a) \approx \alpha$ while for $a < 1$, $h(a) \ll \alpha$.

The optimization problem for N candidate solutions can be formulated as:

$$max\ F\ (x_i) \qquad i = 1,2, \dots, N$$

$$\text{subject to} \quad Ov_{obt}(x_i) \leq Ov_{tar}\ ,\ INT_{time\_obt}\ (x_i) \leq INT_{time\_tar} \tag{5.3}$$

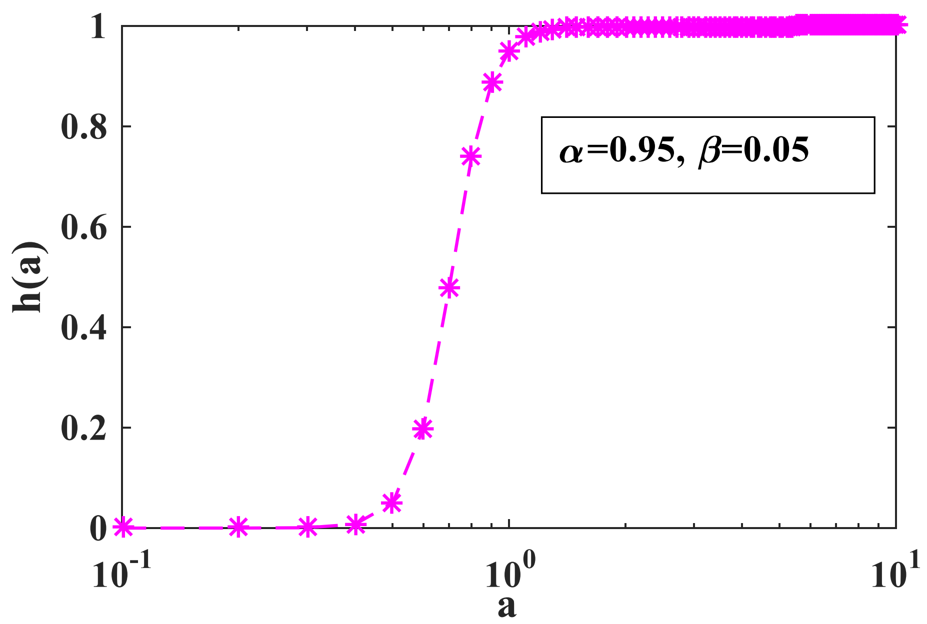


Figure 5.2: Variation of the penalty with input

In order to maximize the objective function defined by (5.3), JA and GA based adaptation of the sensing period is done as described in the next section.

5.3 Jaya Algorithm and Genetic Algorithm based Adaptation of a Sensing Period

a) Jaya algorithm-based optimization

Jaya algorithm explores the search space in an attempt to become victorious. It always tries to reach the best solution (gets closer to success) and avoids the worst solution by moving away from it, thus avoiding the failure [116-117]. The solution is modified using only one equation given in step 2(c) of Algorithm 1.

X_i^{t+1} is the modified solution at $(t+1)^{th}$ iteration and x_i^t is the i^{th} particle at the previous iteration. μ_1^t and μ_2^t are random numbers in range [0,1]. $x^{best}$and x^{worst} are the best and worst sensing period values discovered so far.

Algorithm 1 Jaya algorithm based adaptation of the sensing period
Step 1. Initialization: Initialize population (potential solutions) of sensing periods $\boldsymbol{x} \in (\mathbf{0}, \mathbf{10})$ with Population size, $\boldsymbol{N}$ **=15** and set the maximum number of iterations as $\boldsymbol{maxite}$. **Step 2.** set $\boldsymbol{ite} = \mathbf{1}$ a) Calculate objective function value for each solution from (5.1). b) Identify the best and worst solutions from **the** entire population. c) Alter all the solutions based on best and worst solutions as: $\boldsymbol{X_i^{t+1} = x_i^t + \mu_1^t\left(x^{best} - \lvert x_i^t \rvert\right) - \mu_2^t\,(x^{worst} - \lvert x_i^t \rvert)}$ **Step 3.** $\boldsymbol{If}$ Objective function value for X_i^{t+1} is better than the value associated with x_i^t, then Accept the new solution and replace it with the old one. $\boldsymbol{else}$ Reject the new solution and keep the old one as it is. **Step 4.** $\boldsymbol{If\ ite \leq maxite}$**;** $\boldsymbol{ite}$ **=** $\boldsymbol{ite}$ **+ 1 and go to step 2(a).** At the end of the iterative process, an optimal sensing period value is represented by $\boldsymbol{x^{best}}$.

b) GA based optimization

GA is a population-based meta-heuristic proposed by Holland [118] and based on the theory of natural evolution and survival of the fittest. Reproduction, crossover and mutation are the three operators used to enhance the fitness of candidates over the course of iterations. Reproduction involves the selection of the fittest candidates that are chosen as parents to generate new off-springs. Crossover involves the swapping between two parents to produce two new off-springs [119]. Arithmetic crossover operator [120] is used for real coded GA that linearly combines two parents and produces two off-springs as follows:

$$Offspring1 = a * Parent1 + (1-a) * Parent2$$

$$Offspring2 = (1-a) * Parent1 + a * Parent2$$

where a is a random number lying between 0 and 1.

These offsprings are genetically modified by mutation operation to form the next generation of the population. The mutation mechanism introduces a perturbation that is a random number in the range of 0–1 to the new offsprings [121] and provides better candidates. The pseudo-code for adaptation of the sensing period using GA is given below:

Algorithm 2 Genetic algorithm based adaptation of a sensing period

Step 1. Initialization
Random parent population of sensing periods with size $\boldsymbol{N = 15}$ *is initialized. Set maximum number of iterations,* $\boldsymbol{maxite}$*. Crossover rate: 0.8.*
Step 2. $\boldsymbol{for\ ite = 1; ite \leq maxite; ite++; do}$
Evaluate the fitness of N *individuals from (5.1)*
Rank selection of $N/3$ *best individuals.*
Retain three best off-springs as elites
$\boldsymbol{for}\ i = 1; i \leq 6; i++;\ do$
Select two parents from $N/3$ *fitter individuals using rank selection.*
Crossover these parents using arithmetic crossover, and resulting two children are generated.
end for
Mutate these off-springs with mutation rate: 0.01
Combine the elites with newly generated off-springs and the required population size is restored.
Step 3. (Replacement)
Replace the old population with off-springs generated at step 2 and repeat the same for '$\boldsymbol{maxite}$*' times.*
Step 4. (Termination)
$\boldsymbol{end\ for}$
Return the best value of sensing period

Computational complexity of an algorithm refers to how the consumption of some resources increases with the size of the input. Time is the most commonly encountered resource and time complexity is related to the number of steps an algorithm takes to solve the problem.

Time Complexity of GA in terms of big 'O' notation: In each iteration, GA involves mutation mechanism with complexity: $c(m)$, crossover and selection operations with associated complexity: $c(c)$ and $c(s)$ respectively. If $c(f)$ is the complexity for evaluating the fitness function given by (5.1), the overall time complexity of GA with population size 'N' and the number of generations 'ite' is measured as [132]: $O(ite * N * [\, c(m) + c(c) + c(s) + c(f)])$.

Time Complexity of JA in terms of big 'O' notation: The main operations involved for JA and their associated complexity is given as:

1) Evaluating the fitness value from (5.1) involves the complexity of $c(f)$.
2) Finding the best and the worst positions from the population with size 'N' involve 'N'number of steps each.
3) Updating the position of the whole population based on the best and the worst positions with $(N * d)$ operations in each generation, where d is the number of variables. Here, $d = 1$ since our problem involves adapting the sensing period value of a single channel.

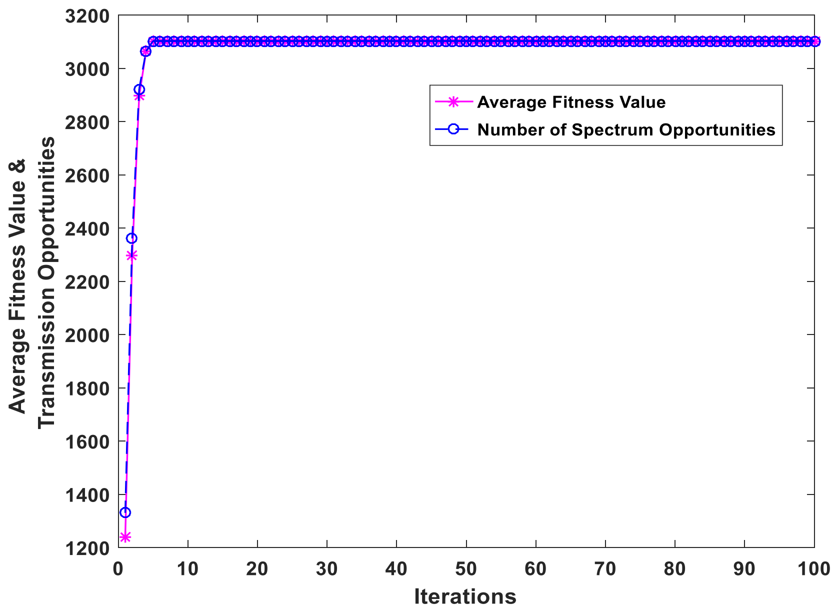
Therefore, the overall time complexity of JA is given as: $O(ite * [\,N * c(f) + 2 * N + N * d]) \approx O(ite * N * c(f))$.

Some meta-heuristics need a few hundred iterations (with a big computational effort for each iteration) to gain good results, others need several million iterations (with only a tiny computational effort for each iteration). Therefore, a better way to measure the time complexity and compare different algorithms is to measure their CPU run time.

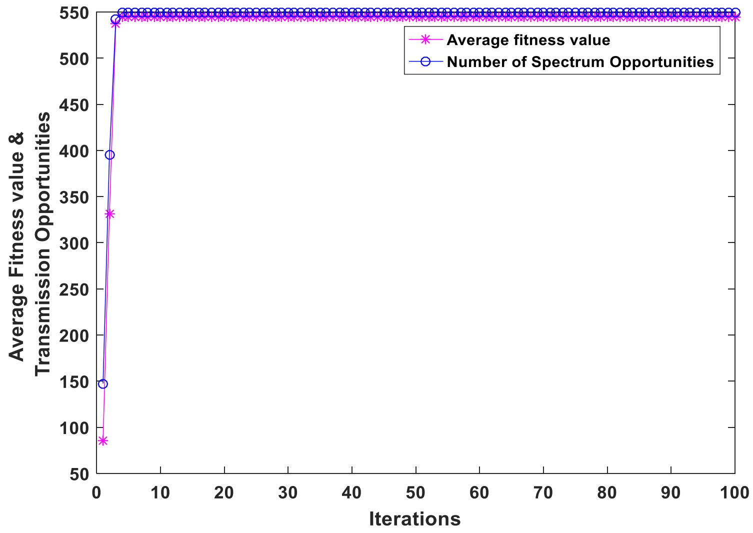
5.4 Results and Discussion

Population size and the maximum number of iterations for both the algorithms are assumed as 15 and 100 respectively. Convergence characteristics of different sensing metrics for JA based adaptation of the sensing period are presented in this section. Figure 5.3 shows the convergence characteristics of mean fitness score (evaluated from (5.1)) and the average number of transmission opportunities (Opp) discovered by N potential solutions using both the algorithms.

The average fitness value is lower than Opp for the first few iterations when the constraints are not satisfied and later on approaches the value of Opp. It is found that the fitness score is better for JA based optimizer than the GA based approach. The number of spectrum opportunities discovered by JA far exceed the opportunities obtained using GA.



(a)



(b)

Figure 5.3: Convergence graph of a) Jaya Algorithm b) Genetic Algorithm for average fitness value and average number of transmission opportunities

Optimum values obtained for different parameters at the end of convergence for both the algorithms are given in Table 5.1.

Table 5.1 Optimum values of different parameters for JA and GA based adaptation of sensing period

Parameter	Optimum Value	
	JA	GA
Optimal generation	5	3
Sensing period (s)	0.1	0.6040
Average fitness value	3102.5	544.7
Average number of spectrum opportunities	3103	549
Average sensing overhead (s)	20	3.4143
Average interference time (s)	1	5.6
Average processing time (s)	6.83	19.54

It is found that GA gets converged to some local optimum value in only three iterations while the JA provides an optimal solution at the fifth iteration. Although GA required a lower number of iterations to reach convergence, JA involves only one step updation of solutions. On the other hand, GA involves certain steps (e.g. selection, crossover, mutation) to obtain a new population. Therefore, the processing time required for JA is lower as compared to GA as is evident from the values of average time taken to complete 100 iterations. Therefore, the computational complexity associated with JA is found to be lower than GA.

The constraints for sensing overhead are followed by both the algorithms, whereas GA is found to violate the interference time constraint. Figure 5.4, Figure 5.5 and Figure 5.6 represent the convergence characteristics for sensing period, sensing overhead and interference time respectively.

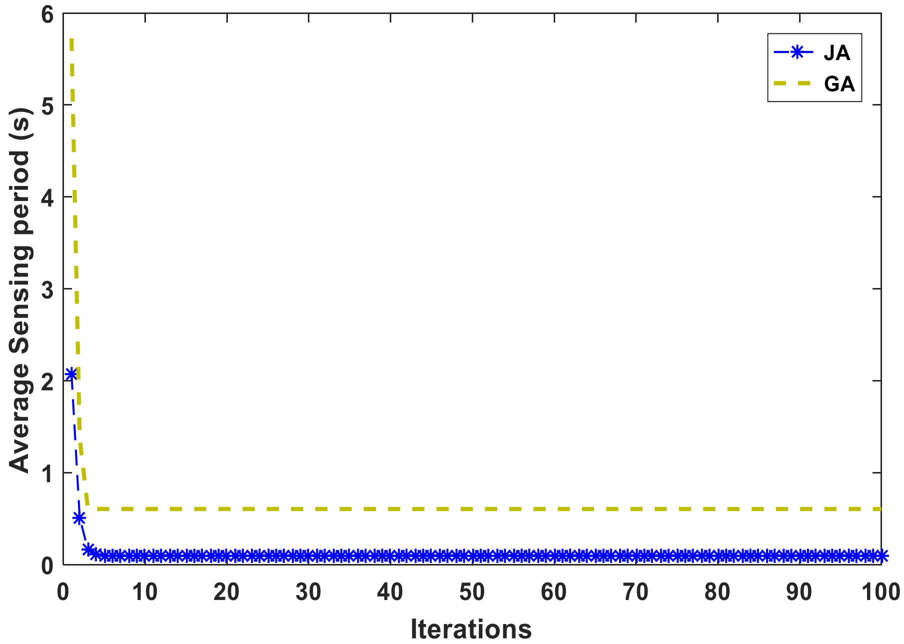


Figure 5.4: Convergence characteristics of average sensing period

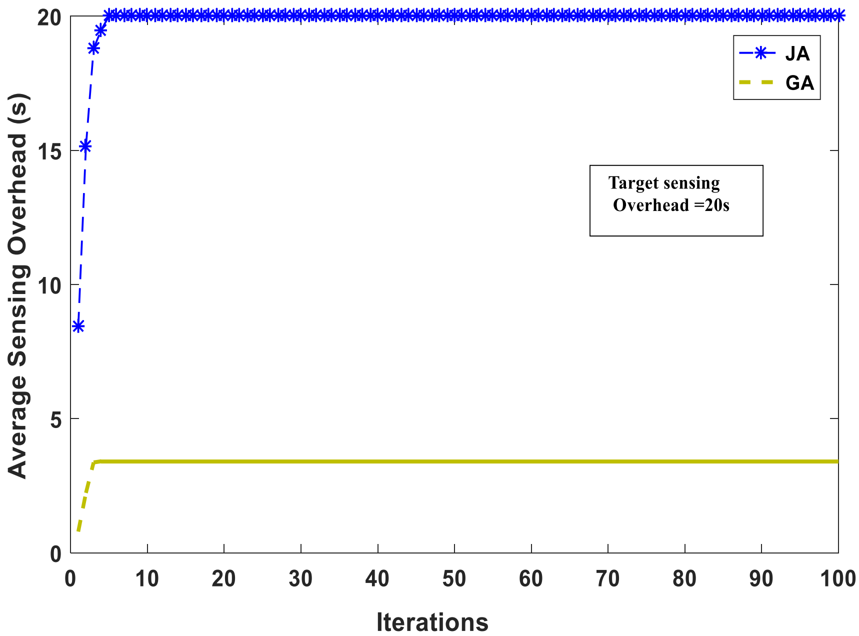


Figure 5.5: Convergence characteristics of average sensing overhead

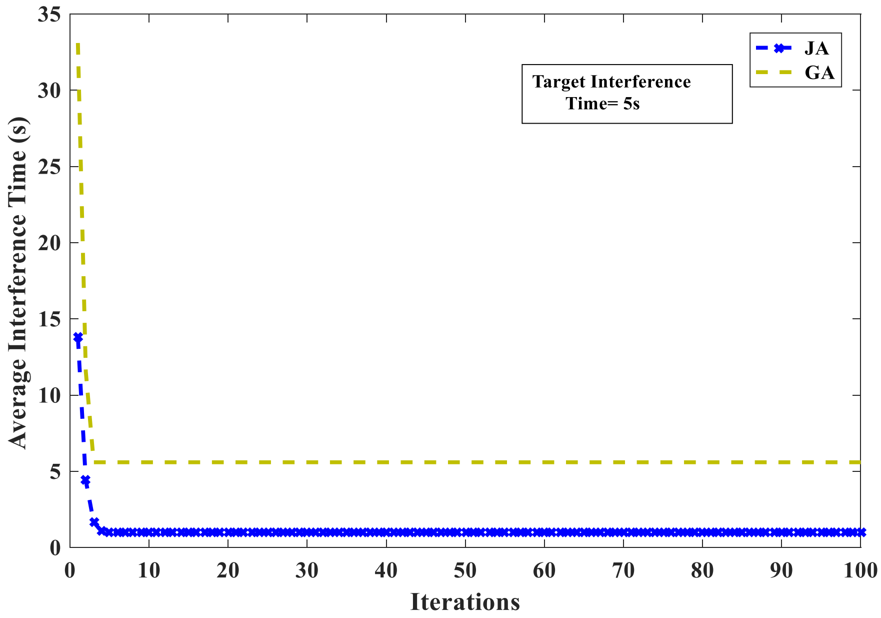


Figure 5.6: Convergence characteristics of average interference time

From the convergence characteristics of different parameters and the optimal values obtained for these parameters, it can be concluded that JA performs far better than GA based approach to optimize the sensing period value.

5.5 Conclusion

In this chapter, a novel objective function evaluation method for sensing period optimization problem using Jaya algorithm is proposed that takes into account different user-defined constraints. JA provides quick convergence and better optimal value as compared to the classical GA based optimization. Therefore, JA emerges as a suitable choice for sensing period adaptation in real-time CR applications.

Chapter 6

Performance Evaluation of an Optimization Algorithm Assisted Cooperative Spectrum Sensing Scheme

A novel integrated technique, namely Opposition based Grey wolf optimizer (OBGWO) is proposed in this chapter and its application is demonstrated for optimizing the weight vector of the cooperative spectrum sensing (CSS) scheme in the CR system. The proposed technique improves the search ability of the grey wolf optimizer (GWO) by integrating it with the concept of opposition based learning (OBL). Further, the competence of OBGWO is tested on seven benchmark functions and its performance is compared with other existing meta-heuristic techniques. Simulation results demonstrate that OBGWO provides better solutions and improved convergence characteristics when compared with GWO, SCA and MFO algorithms. Subsequently, the proposed scheme is applied to weight vector optimization for CSS and it results in a higher probability of detection for a given probability of false alarm.

6.1 Introduction

CSS has emerged as a very promising solution to increase the reliability of the sensing process in which different CR units perform individual sensing and collaborate later to give a final decision about the occupied/unoccupied status of the frequency spectrum under consideration [54]. Cognitive users report their individual or local sensing results to a central entity called fusion center (FC) through reporting channels after performing individual sensing via a sensing channel. These results are combined at FC and a final decision is taken, thereby enabling cooperation and exploitation of spatial diversity of different CRs [56]. Each CR experiences different channels between PU and itself. Therefore, combining the sensing information of different SUs results in improved chances of PU detection.

The detection performance of the soft combining approaches is found superior to the hard combining techniques [56]. In [85], the authors proposed a PSO algorithm based CSS mechanism and it resulted in a higher probability of detection than the modified deflection coefficient (MDC)-based method for the same probability of false alarm. This is because the MDC approach offers a sub-optimal solution while the application of meta-heuristic algorithms is found to offer a better optimal solution. As meta-heuristics offer numerous advantages like high convergence speed, ease of applicability and capability to solve non-convex, non-linear, multi-dimensional or highly complex optimization problems, there are several works reported in the literature such as in [88-90] where the probability of PU's detection is enhanced by optimizing the weight vector employing certain meta-heuristic techniques.

In this chapter, the performance of recent meta-heuristics algorithms: GWO, MFO and SCA is tested along with the newly proposed technique namely, OBGWO for finding the optimal weight vector which maximizes the probability of detection for a CSS scheme. In order to exploit the strengths of CSS along with meta-heuristic techniques, we have considered the weighted CSS model using soft data fusion technique and the weight vector is optimized using these meta-heuristics.

6.2 System Model for CSS and Problem Formulation

The spectrum sensing framework for CSS [56,122] shown in Figure 6.1 is divided into two stages:

1. Sensing stage: This is the first stage in which 'M' number of SUs sense the PU's occupation status on a licensed channel. The binary hypothesis test for spectrum sensing at i^{th} SU and at k^{th} time instant is given below [56]:

$$x_i(k) = \begin{cases} a_i(k) & i = 1,2,\dots\dots.., M \quad H_0 \\ h_i s(k) + a_i(k) & i = 1,2,\dots\dots.., M \quad H_1 \end{cases} \tag{6.1}$$

$k = 1, 2, 3 \dots\dots N$ is the sample index. H_0 is the null hypothesis that represents the absence of PU and H_1 is an alternative hypothesis that represents the presence of PUs. $x_i(k)$ is the signal received at i^{th} SU. h_i is the complex channel gain between PU and i^{th} SU that accommodates the effects of fading, channel shadowing etc. It is assumed to remain constant for i^{th} SU during sensing time. $s(k)$ is the signal transmitted by PU and $s(k) = 0$ when there is no PU transmission. $a_i(k)$ is the complex additive white gaussian sensing noise, i.e. $a_i(k) \sim \mathcal{CN}(0, \sigma_i^2)$ and variances are collected into a vector $\sigma = [\sigma_1^2, \sigma_2^2, \dots\dots.., \sigma_M^2]^T$ where T is a matrix transpose. Noise $a_i(k)$ and PU signal $s(k)$ are independent of each other.

For each SU, observation statistics u_i is calculated as the summation of received energy over the detection period of N samples as follows:

$$u_i = \sum_{k=0}^{N-1} |x_i|^2 \qquad i = 1,2,\dots\dots. M \tag{6.2}$$

where N is the size of observation vector or number of samples and x_i is the sampled received signal.

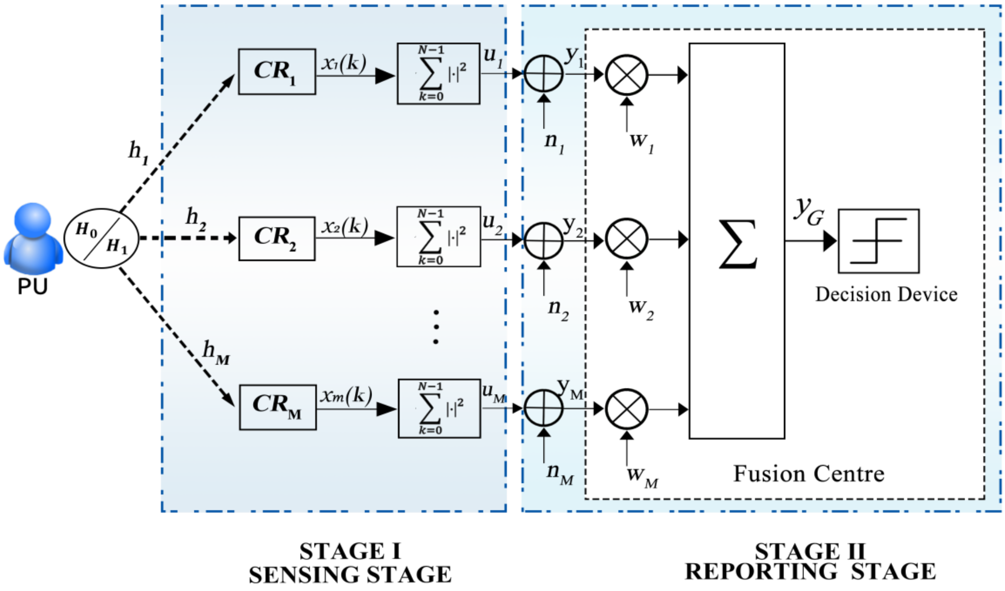


Figure 6.1: System model for a weighted SDF-based CSS

2. **Reporting stage:** This is the second stage of CSS in which SUs direct their locally sensed statistics towards FC. The summary statistics $\{u_i\}$ is transmitted to FC via control or reporting channel and denoted as [85]:

$$y_i = u_i + n_i, \qquad i = 1,2, \dots \dots M \tag{6.3}$$

where the noise $\{n_i\}$ is zero-mean Gaussian variable with variance $\{\delta_i^2\}$ and $\delta = [\delta_1^2, \delta_2^2, \dots \dots .., \delta_M^2]^T$. The test statistic $\{u_i\}$ is directly transmitted to FC via a dedicated control channel. As y_i is obtained at FC, a global test statistic y_G is calculated as follows [85]:

$$y_G = \sum_{i=1}^{M} w_i y_i = w^T y \tag{6.4}$$

where $w = [w_1, w_2, \dots \dots w_M]^T$ is the weight vector assigned at FC; $(w_i \geq 0)$ and $y = [y_1, y_2 \dots \dots . y_M]^T$.

Probability of false alarm (P_f) is the probability of a SU declaring about PU's presence on a particular frequency when the spectrum is actually free. In other words, $P_f = P\{decision = H_1 | H_0\}$ and given by [92]:

$$P_f = Q\left(\frac{y_G - N\sigma^T w}{\sqrt{w^T \Sigma_{H_0} w}}\right) \tag{6.5}$$

where $Q(x)$ is the complementary error function and defined as $Q(x) = \int_{x}^{+\infty} \frac{1}{\sqrt{2\pi}} exp^{\frac{-t^2}{2}} dt$, $\sum_{H_0} = 2N\ diag^2(\sigma) + diag\ (\delta)$ and $diag\ (.)$ is a diagonal matrix.

Probability of detection (P_d) represents the probability of a SU declaring about PU's presence on the said frequency when the spectrum is truly occupied by the PU, i.e. $P_d = P\{decision = H_1|H_1\}$. Therefore, it is required that the detection probability should be large.

$$P_d = Q\left(\frac{\gamma_G - (N\sigma + E_s h)^T w}{\sqrt{w^T \sum_{H_1} w}}\right) \tag{6.6}$$

where $\sum_{H_1} = 2N\ daig^2(\sigma) + diag\ (\delta) + 4E_s diag(h) diag(\sigma)$, $E_s = \sum_{k=0}^{N-1} |s(k)|^2$ and $h = [|h_1|^2,\ |h_2|^2, \dots \dots |h_M|^2]^T$.

Probability of miss-detection (P_{md}) represents the probability of not detecting the PU signal when the licensed user is actually present, i.e. $P_{md} = 1 - P_d = P\{decision = H_0|H_1\}$

Therefore, the *total error probability* (P_e) is the sum of probabilities of false alarm and miss detection, i.e. $P_e = P_f + P_{md}$.

Test threshold γ_G in terms of required P_f is obtained from (6.5) as follows:

$$\gamma_G = N\sigma^T w + Q^{-1}(P_f)\sqrt{w^T \sum_{H_0} w} \tag{6.7}$$

If a linear rule is considered at FC with a test threshold γ_G, we have

$$y_G \underset{H_0}{\overset{H_1}{\gtrless}} \gamma_G \tag{6.8}$$

Substituting (6.7) into (6.6), following equation is obtained:

$$P_d = Q\left(\frac{Q^{-1}\left(P_f \sqrt{w^T \sum_{H_0} w}\right) - E_s h^T w}{\sqrt{w^T \sum_{H_1} w}}\right) \tag{6.9}$$

where maximum P_d is obtained for a given P_f and maximizing P_d is same as minimizing the function $\mathcal{F}(w)$ as follows:

$$\mathcal{F}(w) = \frac{Q^{-1}\left(P_f \sqrt{w^T \sum_{H_0} w}\right) - E_s h^T w}{\sqrt{w^T \sum_{H_1} w}} \tag{6.10}$$

Therefore CSS optimization problem can be formulated as:

$$\min \mathcal{F}(w)$$
$$\text{s.t. } 0 \le w_i \le 1, i = 1,2, \ldots., M \text{ and}$$
$$\sum_{i=1}^{M} w_i = 1 \quad (6.11)$$

To minimize $\mathcal{F}(w)$, a new algorithm namely OBGWO is proposed that optimizes the weight vector (w) and solves the problem of the hidden primary user.

6.3 Proposed meta-heuristic algorithm (OBGWO) and other techniques to solve the weighted CSS optimization problem

SCA, MFO, GWO and OBGWO have been employed to solve the aforementioned problem of optimizing the performance of the CSS scheme. This section gives a detailed description of the proposed integrated meta-heuristic, i.e. OBGWO algorithm. A brief overview of SCA is also provided while MFO and GWO are already discussed in Section 3.3 of Chapter 3.

a) Sine cosine algorithm (SCA)

SCA [102] is a global optimization technique based on two trigonometric functions. It utilizes sine and cosine functions to update the candidate solutions as shown below:

$$X_i = \begin{cases} X_i + c_1 \times \sin(c_2) \times |c_3 G_i - X_i| & \text{if } c_4 < 0.5 \\ X_i + c_1 \times \cos(c_2) \times |c_3 G_i - X_i| & \text{if } c_4 \ge 0.5 \end{cases} \quad (6.12)$$

X_i is the current solution, G_i is the destination solution, $|.|$ indicates the absolute value and c_1-c_4 are the random variables. c_1 is responsible for balancing the exploration and exploitation and determines the area of the next solution.

$$c_1 = a - iter * \frac{a}{Max\_iter} \quad (6.13)$$

where a is constant, Max_iter is the maximum number of iterations and $iter$ is the current iteration. c_2 decides how far the solution's movement should be towards or outwards the destination. c_3 provides random weight for G_i in order to emphasize $(c_3 > 1)$ or deemphasize $(c_3 < 1)$ the effect of desalination in defining the distance. Parameter c_4 is a random number in [0, 1] and is responsible for equally switching between sine and cosine components.

b) Proposed Opposition based Grey wolf optimizer (OBGWO)

Opposition based optimization**:** This paper presents an enhanced version of GWO that combines the OBL [123] strategy with conventional GWO and name the integrated version as OBGWO. The leadership hierarchy mechanism in GWO helps in advancing towards exploitation of search space but the algorithm lacks good exploration feature in some cases and it fails to find the global optimal solution. OBGWO overcomes this problem by offering a better exploration of search space and generating more accurate solutions.

OBL improves the performance of meta-heuristic algorithms by generating the opposite position of a current candidate solution in the search space [124]. Simultaneous checking of the opposite solution will increase the algorithm's chance to start with a fitter solution. Consequently, it will reduce the computation time of an algorithm by decreasing the distance between the initial guess and an optimal solution. Consider a multidimensional space in which the position of a current solution x is given as $x = [x_1, x_2 \ldots\ldots, x_n] \in R^n$, where $x_j \in [l_j, u_j]$. l_j and u_j are the lower and upper bounds for j^{th} dimension. The opposite point $\bar{x} = [\bar{x}_1, \bar{x}_2, \ldots\ldots \bar{x}_n]$ is obtained as [123]:

$$\bar{x}_j = u_j + l_j - x_j, \qquad j = 1,2, \ldots \ldots n \tag{6.14}$$

As OBL helps in searching for a solution in the opposite direction to the present solution, it results in faster convergence as the solution approaches closer to the optimal value. The pseudo-code for the proposed OBGWO algorithm is given below:

Algorithm 1 Pseudo code for OBGWO
Step I: Initialization stage Initialize the random population, i.e. X with P potential solutions Compute the opposite population $\bar{X}$ as: $\bar{x}_{ij} = u_i + l_i - x_{ij} \qquad i = 1,2, \ldots \ldots P$ and $j = 1,2, \ldots., n$ where x_{ij} and $\bar{x}_{ij}$ represent the j^{th} point of the i^{th} solution of X and the corresponding opposite solution $\bar{X}$. The new population of best P solutions is constructed from the union of two populations ($X \cup \bar{X}$). **Step II: Updation Stage** First three best solutions : $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$ and $\overrightarrow{X_\delta}$ are determined after selecting the best P solutions. Solutions of X are updated by GWO and their fitness is computed. Similarly, opposite population $\bar{X}$ is computed and fitness function is evaluated for each $\bar{X}$. P best solutions are selected from $\bar{X} \cup X$ based on the fitness function values and these particles form the initial population for next iteration.

The flowchart showing different stages of OBGWO is illustrated in Figure 6.2.

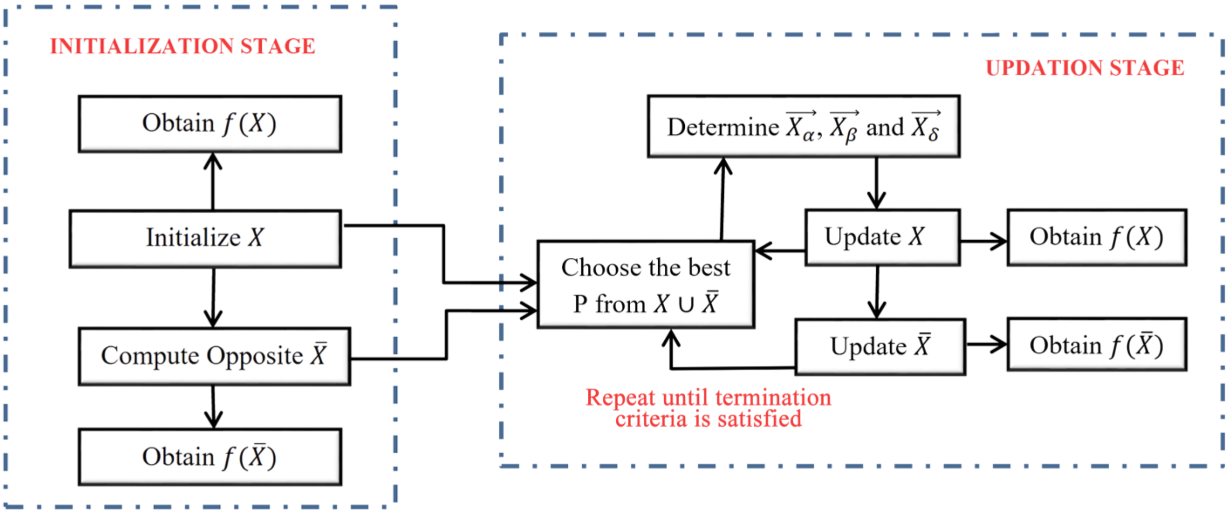


Figure 6.2: Flowchart for OBGWO algorithm

6.4 Benchmark Functions

In order to prove the competence of the proposed integrated algorithm, seven different benchmark functions are solved. Although there are numerous benchmark problems available but there is no agreed set of test functions that validates the new optimization techniques. In this work, we have chosen a set of seven test functions ($f_1 - f_7$) [125-126] with a wide range of dimensions and varied complexities. Table 6.1 provides dimensionality, search domain and global optimal solution for these benchmark problems.

6.5 Results and Discussion

The discussion of simulation results is divided into two sections, where section 6.5.1 is focused on performance comparison of OBGWO with other algorithms for benchmark problems while the results obtained for the CSS optimization problem are given in Section 6.5.2.

6.5.1 Results for Benchmark Problems

Simulation settings: The performance of MFO, SCA, GWO and OBGWO is investigated for seven different benchmark problems. Simulation is run for 1000 iterations and 30 such Monte-Carlo trials are performed for each case. Population size is taken as 20 for all the cases. The value of constant for defining the shape of a logarithmic spiral, $b = 1$ for MFO [29] while there are no algorithm-specific parameters needed for other algorithms.

Table 6.1 Dimensionality, search domain and global optima for different test functions

S. No.	Test Function	Dimensionality	Search domain	Global Minima
1.	ACKLEY $f_1(x) = -20\exp\left[-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right] - exp\left[\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right] + 20 + e$	30	[-100,100]	0
2.	EASOM $f_2(x) = -\cos(x_1)\cos(x_2)\, exp[\,(x_1-\pi)^2 - (x_2-\pi)^2]$	2	[-100,100]	-1
3.	GRIEWANK $f_3(x) = \sum_{i=1}^{D}\frac{x_i^2}{4000} - \prod_{i=1}^{D}\cos\frac{x_i}{\sqrt{i}} + 1$	30	[-600,600]	0
4.	RASTRIGIN $f_4(x) = 10D + \left[\sum_{i=1}^{D} x_i^2 - 10\cos(2\pi x_i)\right]$	30	[-5.12,5.12]	0
5.	ROSENBROCK $f_5(x) = \sum_{i=1}^{D-1}[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	10	[-2.048,2.048]	0
6.	SPHERE $f_6(x) = \sum_{i=1}^{D} x_i^2$	10	[-5.12,5.12]	0
7.	ZAKHAROV $f_7(x) = \sum_{i=1}^{D} x_i^2 + \left(\sum_{i=1}^{D} 0.5ix_i^2\right)^2 + \left(\sum_{i=1}^{D} 0.5ix_i^2\right)^4$	10	[-5,10]	0

Simulation Results: The algorithms are compared on the basis of mean, minimum, maximum and standard deviation of the fitness values obtained from 30 independent Monte-Carlo trials as shown in Table 6.2. The convergence characteristics of four algorithms obtained for all the test functions are represented in Figure 6.3. The discussion of results is given below:

It is found that OBGWO is quite competitive as it performs either superior or comparable to other algorithms in solving the minimization problems and offers a better optimal solution for the majority of cases. All algorithms are found to stuck at some local optimum value for test function f_1. The mean and minimum values obtained with OBGWO for the test functions $f_2 - f_7$ are found to be the best among all the algorithms. The least standard deviation value obtained for all the cases shows that OBGWO is having relatively high stability, thus showing robustness and consistency in its performance. On the other hand, MFO is found to have the highest standard deviation value for $f_2 - f_7$ which shows that it is not much consistent over the course of different Monte-Carlo trials. The magnified view of convergence characteristics shown in Figure 6.3

illustrates that OBGWO is able to reach an optimal value in fewer iterations as compared to other algorithms for all the cases.

Table 6.2 Performance comparison of MFO, SCA, GWO and OBGWO for different test functions

Test function	**Algorithm**	**Mean**	**Minimum**	**Maximum**	**Std. dev.**
f_1 **Ackley**	**MFO**	8.8818e-16	8.8818e-16	8.8818e-16	0.0000
	SCA	8.2146e-128	3.3089e-146	1.6428e-126	3.6735e-127
	GWO	8.8818e-16	8.8818e-16	8.8818e-16	0.0000
	OBGWO	8.8818e-16	8.8818e-16	8.8818e-16	0.0000
f_2 **Easom**	**MFO**	-1	-1	-1	0.0000
	SCA	-0.9988	-0.9998	-0.9939	0.0014
	GWO	-1.0000	-1.0000	-1.0000	3.5481e-07
	OBGWO	-1.0000	-1.0000	-1.0000	2.4953e-07
f_3 **Griewank**	**MFO**	0.0264	0.0000	0.0887	0.0227
	SCA	4.1826e-04	0.0000	0.0084	0.0019
	GWO	0.0026	0.0000	0.0074	0.0036
	OBGWO	4.5685e-04	0.0000	0.0074	0.0017
f_4 **Rastrigin**	**MFO**	0.2487	0.0000	0.9950	0.4420
	SCA	0.0000	0.0000	0.0000	0.0000
	GWO	0.0000	0.0000	0.0000	0.0000
	OBGWO	0.0000	0.0000	0.0000	0.0000
f_5 **Rosenbrock**	**MFO**	0.0089	2.0258e-09	0.0391	0.0112
	SCA	7.7700e-04	3.5114e-05	0.0023	7.1392e-04
	GWO	3.6971e-07	3.7442e-08	1.1522e-06	3.0839e-07
	OBGWO	5.6805e-07	4.3201e-09	3.9301e-06	9.0148e-07
f_6 **Sphere**	**MFO**	2.1901e-202	1.1230e-217	4.2653e-201	0.0000
	SCA	4.1457e-15	1.6914e-23	7.3198e-14	1.6303e-14
	GWO	4.9407e-324	0.0000	9.8813e-324	0.0000
	OBGWO	0.0000	0.0000	0.0000	0.0000
f_7 **Zakharov**	**MFO**	6.5929e-10	3.4694e-14	7.0465e-09	1.7103e-09
	SCA	6.1660e-13	1.9010e-17	6.1383e-12	1.4927e-12
	GWO	1.9255e-54	1.6825e-61	3.8415e-53	8.5887e-54
	OBGWO	8.0846e-63	4.8203e-69	5.8080e-62	1.6556e-62

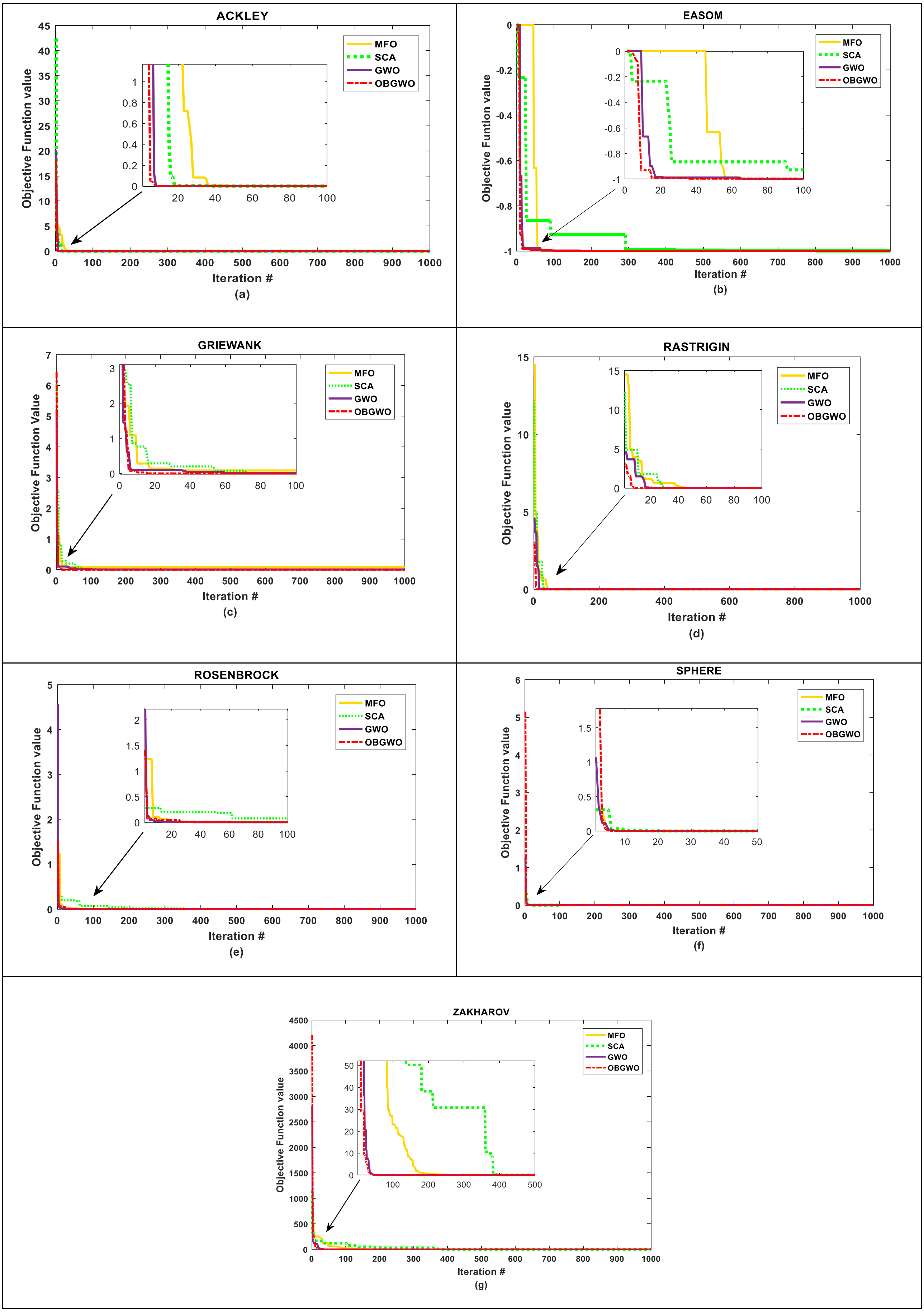


Figure 6.3: Convergence characteristics of different algorithms for benchmark problems

Therefore, it can be concluded from the above comparative performance analysis that the proposed integrated approach, i.e. OBGWO performs better than GWO, SCA and MFO algorithms for optimizing the variety of benchmark problems. In the following section, we have evaluated the strength and competence of OBGWO by applying it to optimize the weight vector of local observations from different SUs to obtain an efficient CSS system.

6.5.2 Results for a weighted CSS optimization problem

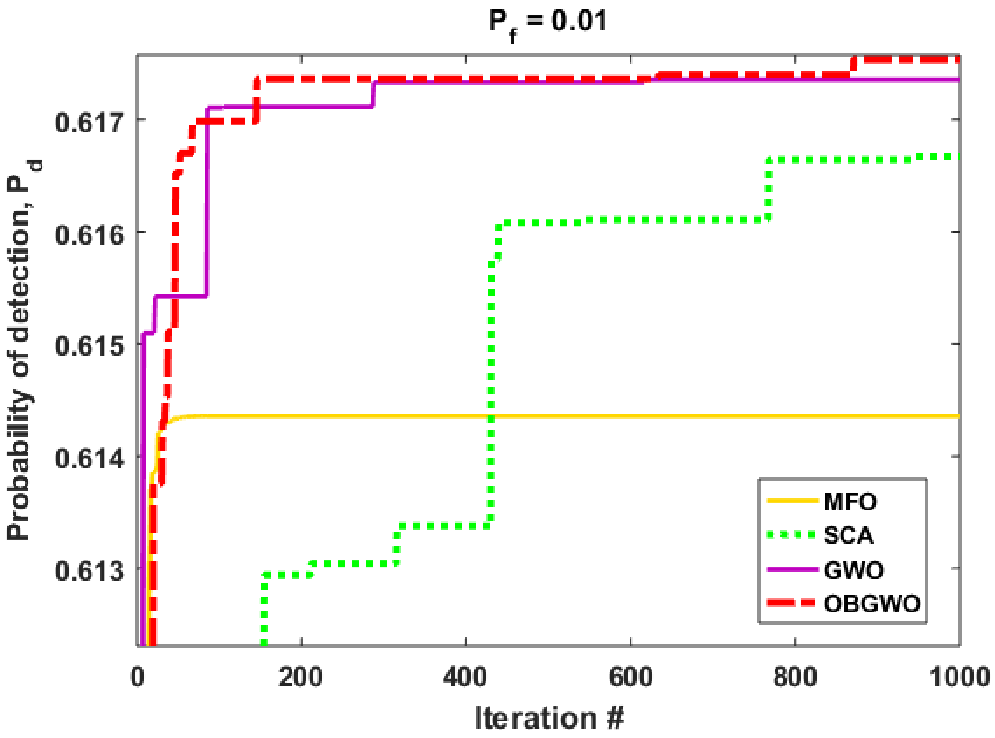
The problem for CSS is aimed at optimizing the weight vector value that will result in maximization of the probability of detection P_d or minimizing the objective function $\mathcal{F}(w)$ given by Eq. (6.10).

Assumptions: A CR system with 'M' SUs is considered where each SU performs independent spectrum sensing. For simplicity, the transmitted primary signal is assumed as $s(k) = 1$ and N is taken as 20. $\sigma = \delta = [1\ 1\ 1\ 1\ 1\ 1\ ]^T$, $M = 6$ and the received signal to noise ratios (SNR) at different SUs are $-3.7, -3.4, -6.4, -5.2, -9.5$ and -3.3 in dB [92]. Performance comparison of OBGWO with other existing techniques is done and the population size is taken as 20 for all the algorithms. The maximum number of iterations are assumed as 1000 and 30 Monte-Carlo runs are performed for each case. Mean, minimum, maximum and standard deviation values of P_d along with mean fitness value and mean probability of error obtained from 30 independent cases are reported in Table 6.3.

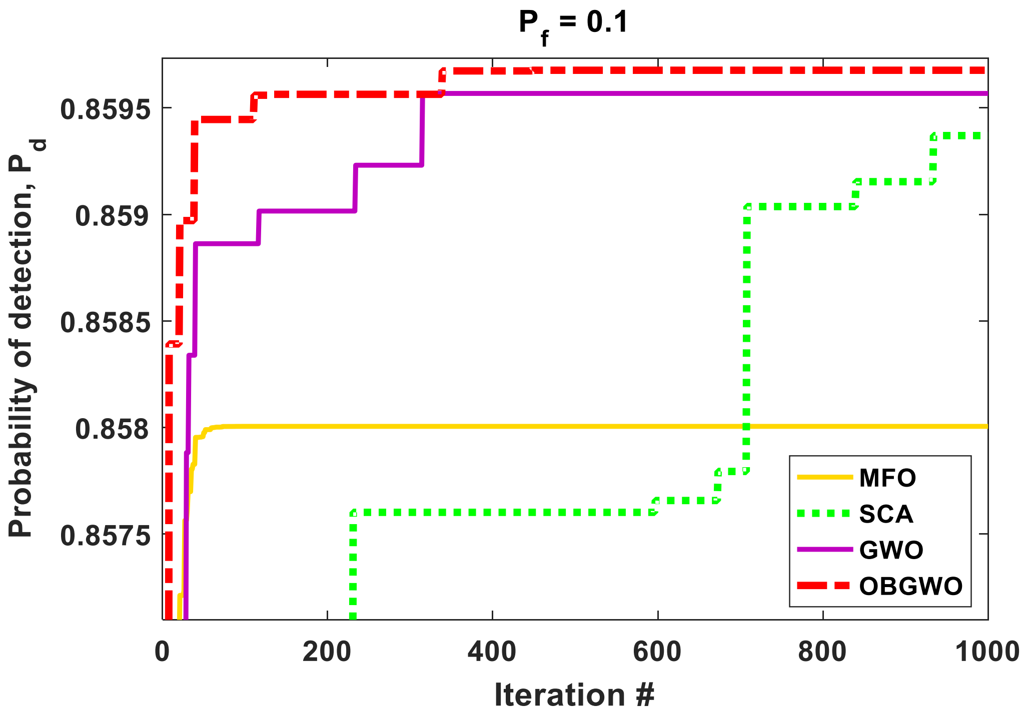
Table 6.3 Statistical results for the probability of detection, fitness value and the probability of error under different false alarm probabilities

Algorithm	**Probability of detection, P_d**				**Mean fitness value, $\mathcal{F}(w)$**	**Probability of error, P_e**
	Mean	**Minimum**	**Maximum**	**Std. dev.**		
Probability of false alarm, $P_f = 0.01$						
SCA	0.6166	0.6158	0.6175	4.7232e-04	-0.2966	0.3934
MFO	0.6162	0.6177	0.6187	0.0030	-0.2954	0.3938
GWO	0.6173	0.6172	0.6175	9.0749e-05	-0.2985	0.3927
OBGWO	0.6175	0.6174	0.6176	1.0307e-05	-0.2988	0.3925
Probability of false alarm, $P_f = 0.1$						
SCA	0.8594	0.8588	0.8597	2.4897e-04	-1.0775	0.2406
MFO	0.8588	0.8552	0.8598	0.0015	-1.0751	0.2412
GWO	0.8596	0.8594	0.8597	1.2079e-04	-1.0784	0.2404
OBGWO	0.8597	0.8596	0.8598	4.6353e-05	-1.0790	0.2403
Probability of false alarm, $P_f = 0.2$						
SCA	0.9202	0.9197	0.9205	2.4343e-04	-1.4065	0.2798
MFO	0.9201	0.9177	0.9206	9.5644e-04	-1.4055	0.2799
GWO	0.9204	0.9203	0.9205	7.8079e-05	-1.4080	0.2796
OBGWO	0.9205	0.9205	0.9205	2.2489e-05	-1.4085	0.2795

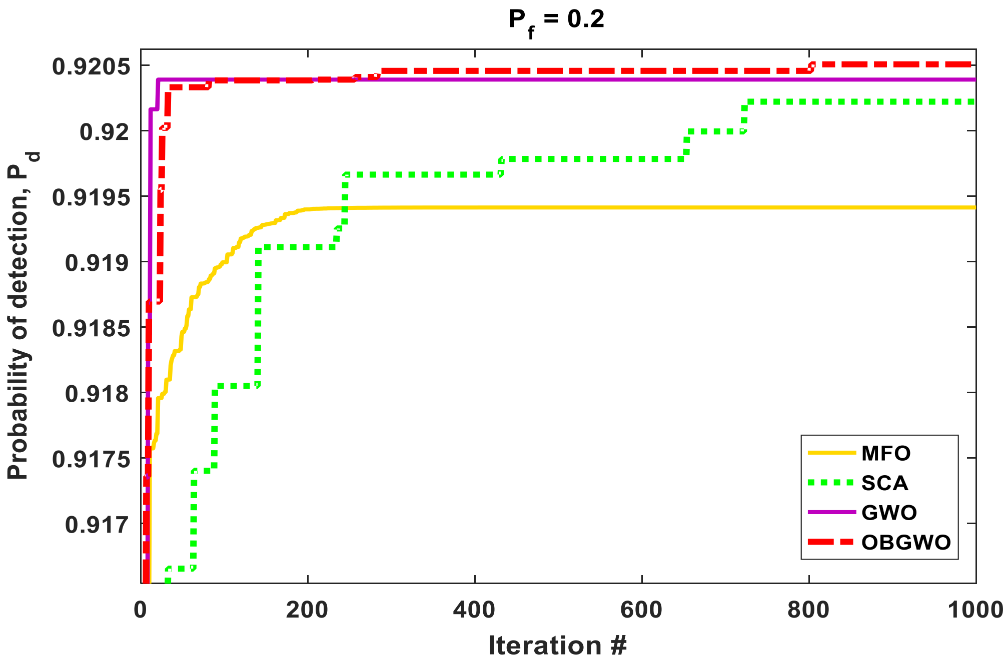
It can be observed that the value of P_d for OBGWO is significantly higher than the other algorithms and it is quite stable in its performance as it offers the least standard deviation value among all other algorithms. The convergence characteristics of the probability of detection (P_d) for different values of probability of false alarm (P_f) are shown in Figure 6.4(a)-(c).



(a)



(b)



(c)

Figure 6.4: Probability of detection $\mathrm{P_d}$ when the probability of false alarm (a) $\mathrm{P_f} = 0.01$ (b) $\mathrm{P_f} = 0.1$ (c) $\mathrm{P_f} = 0.2$ and $\mathrm{M} = 6$

The value of P_d for OBGWO surpasses the other algorithms in the first few hundred iterations for all the cases. This shows that OBGWO not only offers higher detection probability but also faster convergence as compared to GWO, SCA and MFO algorithms. The convergence characteristics of fitness value $\mathcal{F}(w)$ and total error probability P_e for the case $P_f = 0.1$ and $M = 6$ are demonstrated in Figure 6.5 and Figure 6.6 respectively.

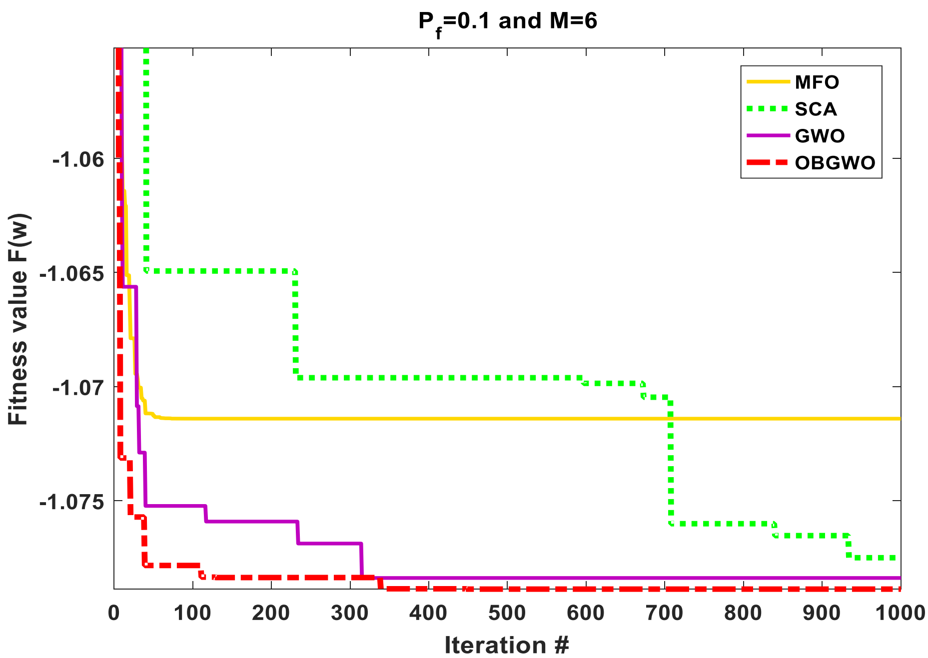


Figure 6.5: Fitness value obtained for the case $\mathrm{P_f} = 0.1$ and $\mathrm{M} = 6$

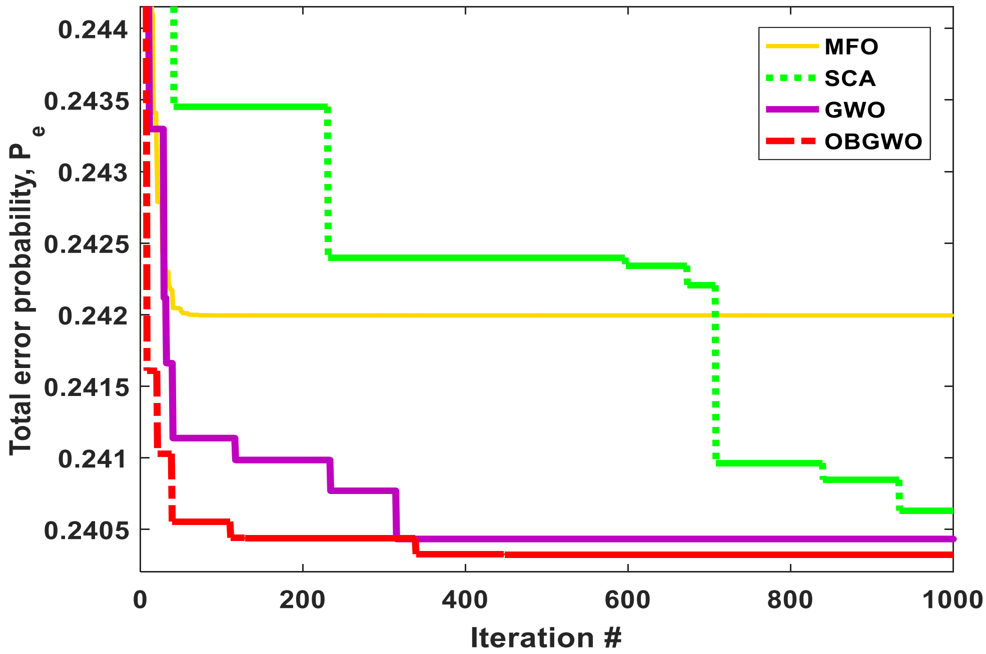


Figure 6.6: Total error probability obtained for the case $\mathrm{P_f} = 0.1$ and $\mathrm{M} = 6$

The objective function value ($\mathcal{F}(w)$) and total error probability (P_e) obtained for OBGWO is found to be least among all other techniques. Therefore, OBGWO emerges out as an appropriate choice to realize an efficient CSS scheme.

Further, the following experiments are conducted to demonstrate the performance of OBGWO and study the impact of variation of certain system parameters.

Case 1: Effect of variation in the number of SUs (M)

The performance of OBGWO is analyzed by varying the number of cooperating users: $M = 2, 3, 6$ and 10. Figure 6.7 shows the complementary ROC curves which depict the probability of misdetection ($P_{md} = 1 - P_d$) versus probability of false alarm (P_f).

Single sample SNRs at each SU along with sensing and control channel noise for different number of SUs are provided in Table 6.4.

Table 6.4 Single sample SNRs at each SU, sensing channel noise (σ) and control channel noise (δ) for different number of SUs (M)

Number of SUs, M	SNR (in dB)	Sensing channel noise, σ	Control channel noise, δ
2	$[-3.7, -5.2]$	$[1\ 1]^T$	$[1\ 1]^T$
3	$[-3.7, -5.2, \ -3.4]$	$[1\ 1\ 1]^T$	$[1\ 1\ 1]^T$
6	$[-3.7, -5.2, -3.4, -6.4, -9.5, -3.3]$	$[1\ 1\ 1\ 1\ 1\ 1]^T$	$[1\ 1\ 1\ 1\ 1\ 1\ ]^T$
10	$[\ -3.7, -5.2, -3.4, -6.4, -9.5, -3.3, -4.3, -3.3, \ -2.5$ and $-6.9]$	$[1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1]^T$	$[1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1]^T$

It is found that by increasing the number of secondary users, there is an improvement in the value of the probability of detection and the problem of hidden PU is solved.

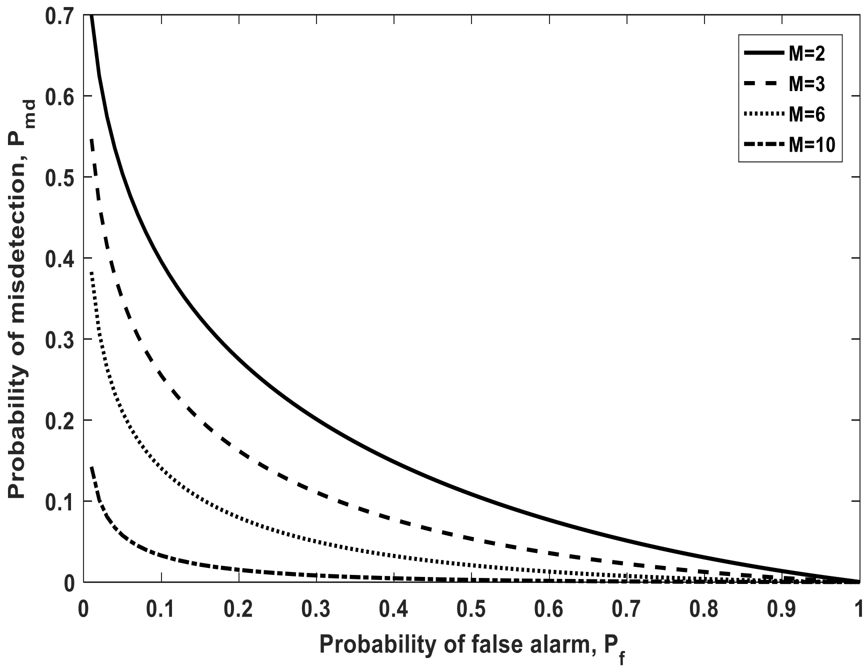


Figure 6.7: Probability of misdetection v/s probability of false alarm for different number of cooperating users

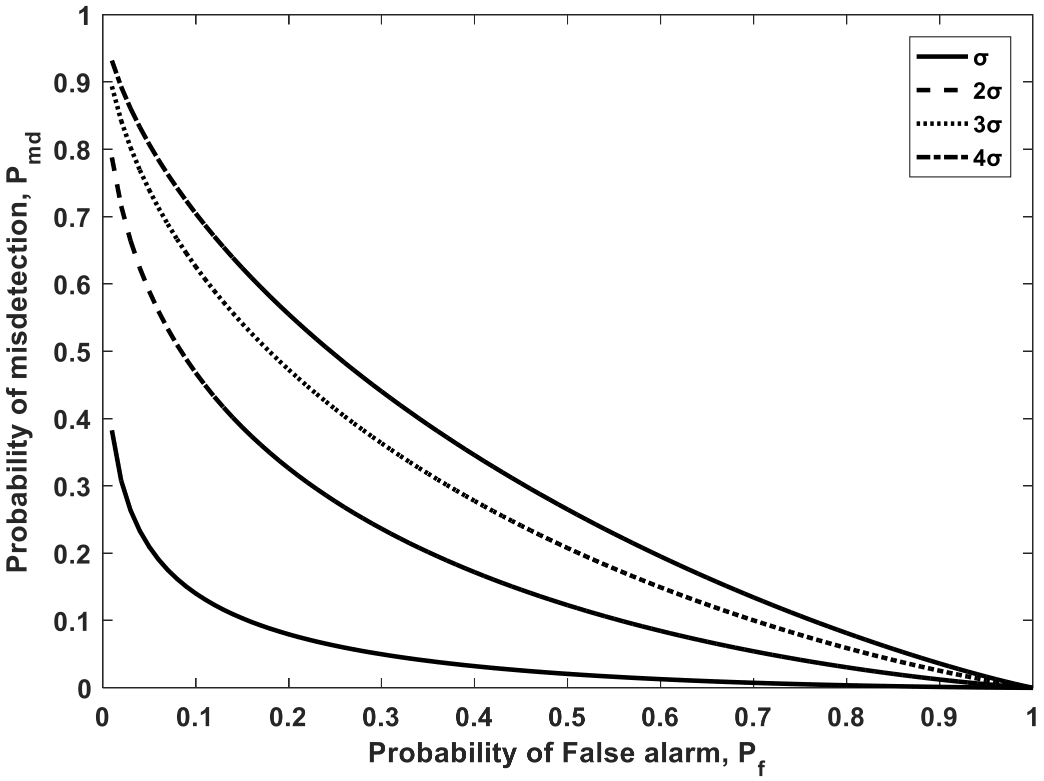
Case 2: Effect of variation in noise level

a) Variation in sensing channel noise (σ)

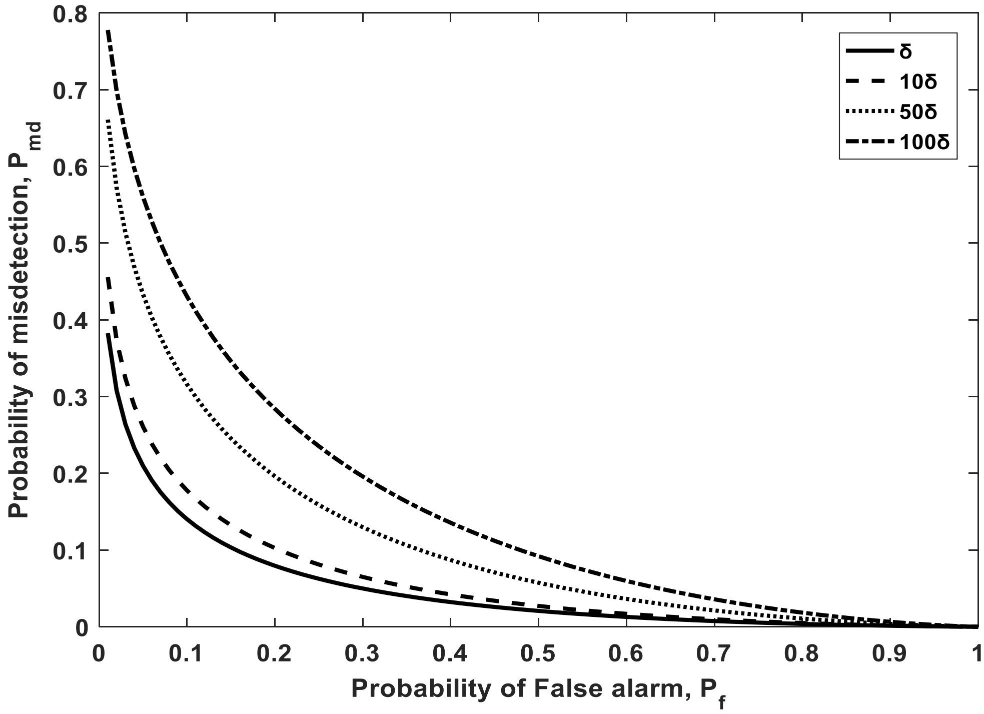
Assumptions: $M = 6$, noise levels, $\sigma = \delta = [1\ 1\ 1\ 1\ 1\ 1]^T$ and single sample SNRs at individual nodes are $[-3.7, -5.2, -3.4, -6.4, -9.5, -3.3]$ in dB.

Figure 6.8(a) shows the plot of P_{md} versus P_f for different values of sensing noise: σ, 2σ, 3σ and 4σ employing OBGWO. It is found that the probability of detection degrades considerably with a small increase in the value of sensing noise. It shows that detection performance is highly sensitive to variation in sensing noise.

b) Variation in control channel noise ($\boldsymbol{\delta}$) Performance of OBGWO is investigated for different values of control channel noise, i.e. δ, 10δ, 50δ and 100δ. The number of cooperating users and individual SNR received at each of them is considered same as taken for the previous case 2(a). Figure 6.8(b) shows the plot of P_{md} versus P_f. It is found that when control channel noise is changed by a large factor, the degradation in the probability of detection is not that high.



(a)



(b)

Figure 6.8: Probability of misdetection v/s probability of false alarm for different values of (a) sensing channel noise (b) control channel noise.

From these experiments, it can be concluded that the detection performance is greatly sensitive to changes in sensing channel noise as compared to variations in control channel noise. This fact encourages the idea of using several SUs to improve the sensing performance of a CR system.

6.6 Conclusion

An appropriate choice of the weighting co-efficients in CSS scheme is a major challenge and the choice of an algorithm that optimizes these coefficients is crucial to the efficient detection performance of a CR system. In this chapter, a highly efficient algorithm namely, OBGWO is proposed and employed for optimizing the weight vector of the CSS system. This algorithm is the integrated version of OBL concept and GWO technique, developed with an aim to generate promising candidate solutions that help in achieving global optimum efficiently. Simulation results indicate that the proposed technique outperforms GWO, SCA and MFO algorithms for solving various benchmark problems as well as for optimizing the weight vector of the CSS scheme by providing higher probability of detection. OBGWO scheme is then employed to study the effect of variation in number of cognitive users, sensing channel noise and control channel noise for the proposed CSS model.

Chapter 7
Conclusion and Future Scope

7.1 Conclusion

CR is a promising technology to overcome the challenge of additional spectrum requirement posed by rising wireless applications. 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. The mathematical formulation of total system power consumption is probed and its optimization is done by employing recently proposed NI optimization techniques: ALO, GOA, GWO, MFO and WOA. Simulation results show that WOA not only efficiently minimizes the system power consumption through parameter adaptation but also satisfies different QoS constraints for a CR system.

Further, the adaptation of transmission parameters by CDE is carried out for a multicarrier CR based IoT system employing ALO, GWO, MFO, WOA and JA. The multi-objective optimization problem is dealt with the weighted sum method along with the constraints for ACI and total transmit power. Five different transmission scenarios are considered each supporting different user requirement and radio battery level. MFO algorithm provides the best solution for minimizing power consumption and maximizing throughput scenarios while WOA emerges as the best candidate for minimizing BER mode.

Adaptation of the sensing period for MAC layer based sensing of a licensed channel is realized using the Jaya algorithm. The numbers of transmission opportunities for a SU are maximized while constraining the sensing overhead and interference time within a user-defined limit through penalty function. Jaya algorithm outperforms the conventional GA to achieve a better optimal value of different parameters with smaller processing time requirement; thereby emerging as a preferable choice for real-time CR applications.

A novel integrated meta-heuristic algorithm, OBGWO is proposed and tested on different benchmark problems. Its performance is also compared with other existing techniques: SCA, GWO and MFO. The utility of OBGWO is investigated to enhance the performance of the CSS scheme by optimizing the weight vector that maximizes the probability of detection of PU. Simulation results show that OBGWO not only offers higher detection probability but also converges faster as compared to GWO, SCA and MFO algorithms. Consequently, OBGWO scheme is employed to study the effect of variation in the number of cognitive users, sensing channel noise and control channel noise for the proposed CSS model.

7.2 Future Scope

- The search for advanced or hybrid meta-heuristic optimization techniques is an open research area.
- The problem of CDE design can be studied for other smart networks such as home area networks, smart grids etc. through advanced meta-heuristic schemes.
- Advanced meta-heuristic optimization techniques can be investigated for transmission parameter adaptation to realize green radios that support different transmission modes with the application of highly efficient PAs such as Doherty PA.
- Sensing period adaptation can be extended to a multi-channel system employing hybrid or advanced optimization techniques.
- The idea of energy harvesting based CSS with meta-heuristic techniques has not been explored yet and has a wider scope to probe in.

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