PARAMETRIC OPTIMIZATION OF MULTICARRIER SYSTEM USING METAHEURISTIC TECHNIQUES

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DECLARATION

I Ashmeet Kaur hereby, declare that the work presented in this thesis entitled **"Parametric Optimization of Multicarrier System Using Metaheuristic Techniques"** in fulfillment of the requirement for the award of degree of Masters of Engineering submitted at, Electronics and Communication Engineering Department, Thapar Institute of Engineering & Technology, Patiala is an authentic record of work carried out under supervision of Dr. Surbhi Sharma (Associate Professor, Electronics and Communication Engineering Department) form July 2016 to July 2018.

The matter presented in this has not been submitted either in part or full to any other university or institute for the award of any other degree.

Date: 13 - July 2018

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It is certified that the above statement made by the student is correct to the best of my knowledge and belief.

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ABSTRACT

In this work, Parametric Optimization of Multicarrier System using Metaheuristic Techniques has been carried out employing different optimization techniques namely Particle Swarm Optimization (PSO), BAT Algorithm, Differential Evolution (DE) and Wind Driven Optimization (WDO). Best value of transmission parameters is obtained for a system comprising of 32 and 64 subcarriers. Multi-objective optimization involves solving parameter adaptation problem with three and five objectives that is solved using weighted sum approach. All the simulations are carried out in MATLAB, in order to compare all the four algorithms on the basis of average fitness value and average transmission parameters. Solving multi-objective optimization problem involving three conflicting objectives i.e. minimize BER, minimize transmit power and maximizing throughput while the problem involving five objectives involves two additional objectives i.e. minimizing of interference and maximizing spectral efficiency. To find effective optimization scheme, all algorithms are compared with the help of convergence characteristics and decision results for diverse modes.

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LIST OF ABBREVIATIONS

CR	Cognitive Radio
CRN	Cognitive Radio Networks
IoT	Internet of Things
PSO	Particle Swarm Optimization
DE	Differential Evaluation
WDO	Wind Driven Optimization
SDR	Software Defined Ratio
AI	Artificial Intelligence
CBR	Case-Based Reasoning
HMM	Hidden Markov Model
EA	Evolutionary Algorithm
BER	Bit Error Rate
H2H	Human to Human
M2M	Machine to Machine
ISM	Industrial, Scientific and Medical
FCC	Federal Communications Commission
CIoT	Cognitive Internet of Things
QoS	Quality of Service
DSA	Dynamic Spectrum Access
SU	Secondary Users
PU	Primary Users
QGA	Quantum Genetic Algorithm
CSGC	Color Sensitive Graph Coloring
SAA	Spectrum Allocation Algorithm
RCBBO	Real-Coded Biogeography-Based Optimization
BBO	Biogeography-Based Optimization
OFDM	Orthogonal Frequency-Division Multiplexing
CDE	Cognitive Decision Engine
SNR	Signal to Noise Ratio
QPSK	Quadrature Phase Shift Keying
QAM	Quadrature Amplitude Modulation

CHAPTER-1

INTRODUCTION

Advancement of communication technology has made incredible growth in wireless communication. This growth has rapidly increased the use of wireless devices, leading to spectrum scarcity. Congestion of spectrum is caused due to increase in number of users which leads to increase in spectrum traffic. Spectrum can be accurately and successfully exploited for providing opportunistic access to cognitive users in licensed bands. Communication technology is moving towards adapting the cognitive radio network into Internet of Things (IoT). To achieve this, spectrum sensing task should be followed by real time tuning of transmission parameters so that the objectives of minimum transmit power, minimum bit error rate, maximum throughput, minimum interference and maximum spectrum efficiency could be achieved for different service types. In this thesis, we have done comparative performance analysis of four evolutionary algorithms i.e. Particle Swarm Optimization (PSO), BAT algorithm, Differential Evolution (DE), Wind Driven Optimization (WDO) for the parameter tuning problem in CR network.

1.1 DEFINITION OF COGNITIVE RADIO

Cognitive Radio (CR) is a new technology of wireless communication system for proper utilization of frequency spectrum. The problem is not the shortage of available spectrum but it is that the available bands are not properly used. J. Mitola in 1999 [25], introduced the concept of cognitive radio. Cognitive radio is an intelligent radio which detects underused spectrum avoiding occupied signals. Cognitive radio is development of Software Defined Ratio (SDR) which is combination of software and hardware. SDR is a radio transceiver which allows parameters like modulation type, output power and frequency range to be modified by software. CR allows users to access the spectrum assigned to licensed bands unless there is interference by unlicensed bands. The spectrum sharing is where these two licensed and unlicensed bands share a spectrum without interfering.

1.2 NETWORK ARCHITECTURE

The CRNs is categorized into primary users and secondary users. Licensed users are primary users while unlicensed users are secondary users. So we need certain technology in which unlicensed users can use licensed spectrum band without any disturbance. To operate the devices without interference a flexible spectrum management is needed. Hence, CRNs varies according to the spectrum weather it is authorized and unauthorized. Coexistence of cognitive radio with primary networks gives arise to some challenges:

- **Avoid Intervention:** use of spectrum without interference by secondary.
- **Quality of Service:** CR should support quality of service.

Cognitive radio technology as a dynamic access technology which enables the use of available spectrum licensed and unlicensed users.

1.3 COGNITIVE RADIO ENGINE

Cognitive engine is a decision making module in cognitive radio. Information collected by sensors is useful only if it is developed into knowledge. In wireless systems various techniques are available for the implementation of cognitive engine. Bayesian network is a powerful learning technique based in Baye's theorem. It uses past experience to enhance future decisions. Expert systems are successful in some applications of AI [2].

- Neutral Networks provide a means for signal and modulation detection and classification. These networks are not suitable for problems which require process explanation.
- Case-Based Reasoning (CBR) systems provide learning and feedback to improve their performance. This approach is a black-box which gives little insight into the system and processes involved.
- The Hidden Markov Models (HMM) is a processing instrument that uses past data to help predict future actions an implementation of Baye's law. This method demands case data base of reasonable size and quality which is expensive for large data bases.
- Fuzzy logic deals with uncertainty in decision making, analysis and potential in problem solving areas. Learning capability and memory is not found in fuzzy systems.
- Evolutionary Algorithm (EA) the problem of optimizing a radio is more complex than many search and optimization algorithms can handle. It offers a significant amount of power and flexibility.

1.4 COGNITIVE RADIO PARAMETERS

Decision making engine is formed by combining several techniques, to enable efficient communication. To accomplish best throughput by as yet looking after BER adaptive modulation technique are used in PHY layer of hardware to monitor the power and modulation. The value of frame length is also estimated by environment research on frame length adaptation. Specific goals are performed by these techniques. A single parameter influences different techniques in different ways, by using multiple techniques and create a trade off. The job of CR is to combine these, adaptive technique, based on specific objective of system CR input environment scenario and output the adaptive scenario.

Inputs play a major role in the CR control systems. Quality and quantity of inputs effects the decision made by AI method. External sensors received data from environement which is primary feature of CR and is input to the system. Output decision depends on the input received. Enviromently sensed data received by the system using an external sensor is used to create this model [2].

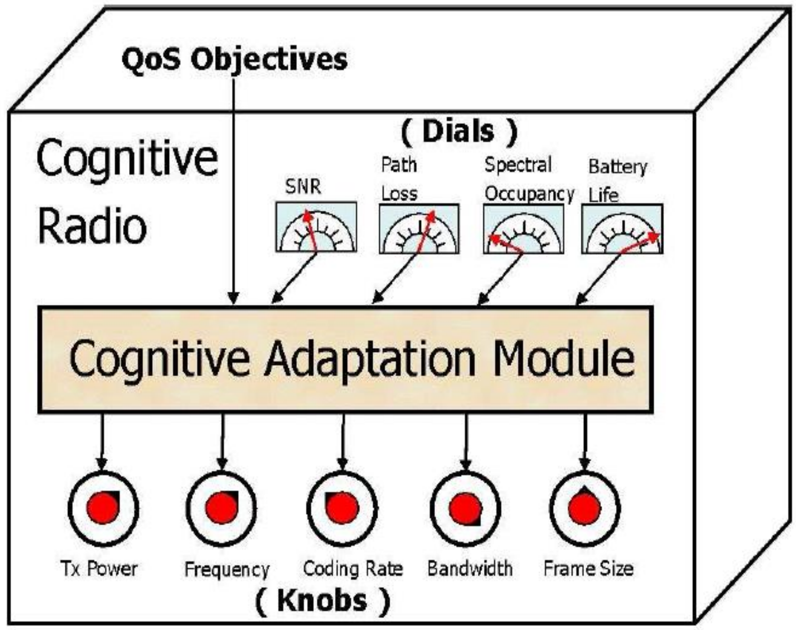

Figure 1.1: Cognitive Radio

1.4.1 Decision variables

Input to AI methods are used to make decision variables which can be controlled by the system. These variables represent the transmission parameters that can be controlled by the system. Different decision variable are applied to the fitness function in the virtual wireless environment and achievement of operation goals is estimated. This scalar approximation and the environmental data determine the operation of system in performance objective. The input of the system are the guides for determining the fate of the system. They provide the means to take decisions for output. Transmission parameters can be manipulated to provide the lowest possible BER.

1.4.2 Parameters of Cognitive Radio

Cognitive engine is a decision making module in cognitive radio. Software defined ratio to which decision is send. The control parameters, environmental parameters and objectives are inputs to the fitness function. A scalar score is provided by these fitness functions which estimate the achievement of the given objectives. Transmission parameters must be available in which CR has to use generating CR functions. Software radio components are controlled by the transmission parameters. A unique list of parameters is possessed for radios which are developed for different reasons and application.

The list of parameters to generate a fitness function is shown in Table 1.1

Table 1.1: Transmission Parameter

Parameter Name	Description
Power Transmit	Rare power of transmission
Type Modulation	Kind of modulation format
Index of Modulation	Number of sings for given modulation scheme
Bandwidth	Data of transmission signal in Hertz
Channel Coding Rate	Coding rate of channel
Size of Frame	Amount of transmission frame in bytes
Time Division Duplexing	Percentage of transmit time
Symbol Rate	Number of signs per second

1.4.2.1 Fitness Objective

Various desirable objectives are to be achieved in wireless communications environment. Five objectives for the fitness function are defined here to guide the system to an optimal state. These objectives are given in Table 1.2.

Table 1.2: Five Objectives Parameter

Objective Name	Description
Minimizing Bit Error Rate	Enhance the general BER of the transmission environment.
Maximizing Throughput	Increment the general data throughput transmitted by the radio.
Minimizing Power Consumption	Reduce the amount of power consumed by the system.
Minimizing Interference	Decrease the radio interference contributions.
Maximizing Spectral Efficiency	Improve the efficient use of the frequency spectrum.

Wireless communication emphasis on minimizing the BER and improving communication quality, it means minimizing the errors in relation to the amount of bits being sent. Maximize the throughput and minimize power consumption objective introduce, analysis trade-off between minimizing BER, maximizing throughput, and minimizing power consumption.

Minimizing interference objective can be achieved by avoiding interference and spectrum with high noise flow. Maximize spectral efficiency objective would help to use available space by more transmission signals. A weighted, aggregate sum approach has been used where every goal gets a weight speaking to its significance. We chose this strategy due to the straightforwardness of execution inside the genetic algorithm procedure and control capacity that this technique gives to the framework.

1.4.2.2 Multi-Objective Fitness Functions

The multi-objective fitness functions describe and represent the logical techniques which can be used to generate a fitness function. To generate an accurate fitness function we must overcome challenges.

Problem Statement

Presentation of multi-objective fitness function problem trying to determine correct mapping of a set of m parameters to a set of N objectives, can be defined as below:

$$\vec{y} = (f_1(\vec{x}), f_2(\vec{x}), f_3(\vec{x}), \dots f_N(\vec{x})) \tag{1}$$

Subject to,

$$\vec{x} = (x_1, x_2, x_3, \dots x_m) \epsilon\, X \tag{2}$$

$$\vec{y} = (y_1, y_2, y_3, \dots y_N) \epsilon\, Y \tag{3}$$

where, x is the set of decision variables, X is the parameter space, y is the set of objectives and Y is the objective space and $f_i(x)$ represents the fitness function for a single objective. The aim of multi-objective evolution algorithm is to get a single fitness function, $f\,(x)$, taking all objectives and parameters.

The objectives under consideration in this thesis might conflict with each other in real world. Due to the single parameter, transmit power, minimizing BER and minimizing power simultaneously creates a conflict affecting each objective differently.

1.4.3 Environment Measurements

The surrounding environment characteristics are informed to the system by environmental measurements. These qualities incorporate interior data about the radio working state, and outside data speaking to the remote channel condition. Decision by the cognitive controller is made according to this information. They can be classified into two categories.

1. Environment variables: these are primary inputs to the fitness function.

2. Parameters of environment: these are checked by the system and helps in decision making. i.e., at the point when battery is worked it diminishes blow determined limit, the framework may modify the weighting on the target capacities in order to give a higher weighting on the limit control utilization objective. These parameters are given in Table 1.3.

Table 1.3: Environment Parameter

Parameter Name	Description
Path Loss	Measure of signal degradation lost due to the channel way attributes.
Noise Power	Estimate in decibels of the noise power.
Battery Life	Evaluated vitality left of the noise power.
Power Consumption	Power utilization of current design
Spectrum Information	Spectrum occupancy data.

1.5 INTERNET OF THINGS

The Internet of Things (IoT) portrays correspondence Human to Human (H2H) as well as Machine to Machine (M2M) without the need of human impedance [23]. The idea of Internet of Things has pulled in the consideration of specialists and academicians all over the world. The mission behind the same is to extend the Internet connectivity to a large number of things or devices. These devices provide the environmental information about spectral resources and exploit the wireless communication to send the information to or from the internet. Such services were earlier used using unlicensed ISM band that has now become overexploited and congested. Presently used allocation policy for spectrum is static in nature that assigns a particular band to each primary or licensed user. The studies by FCC have regarded this type of spectrum allocation as inefficient. At any given time and space, main part of the licensed spectrum is unoccupied or underused for most of the times such as licensed bands for TV broadcasting, resulting in substantial spectrum wastage.

Cognitive Internet of Things (CIoTs) are achieved when IoT is integrated with cognitive radio technology. The universal objects based on CR- IoTs concept, are the future that would empower savvy choices to accomplish whenever, wherever obstruction free and on-request benefits. The main function of cognitive radio technology is decision making i.e. to reach at some autonomous decision for a set of transmission parameters.

1.6 METAHEURISTIC ALGORITHMS

In artificial intelligence, an Evolutionary Algorithm (EA) is a part of evolutionary computation. It is non specific population based metaheuristic optimization algorithm. An EA is based on biological evolution, such as reproduction, mutation, recombination, and selection. Applicant answers for the enhancement issue assume the part of people in a population, and the wellness work decides the nature of the arrangements. Evolution of the population then takes place after the repeated application of the above operators.

Developmental calculations regularly perform evaluated answers for a wide range of issues since they preferably don't make any supposition about the hidden wellness scene. Systems from transformative calculations used to the demonstrating of organic development are for the most part constrained to investigations of microevolutionary procedures and arranging models in view of cell forms. In most genuine uses of EAs, computational many-sided quality is a not connected factor.In actuality, this computational many-sided quality is because of wellness work assessment. Wellness estimation is one of the answers for evacuate this trouble. Be that as it may, apparently straightforward EA can take care of troublesome issues; in this way, there might be no immediate connection between calculation many-sided quality and issue many-sided quality.

A metaheuristicis an abnormal state issue free algorithmic structure that gives an arrangement of rules or systems to create heuristic improvement calculations. Properties of metaheuristic are [3]:

- Metaheuristics are methodologies that guide the search procedure. The objective is to effectively investigate the search space so as to discover near ideal arrangements.
- Techniques which constitute metaheuristic algorithms go from basic neighborhood look techniques to complex learning forms.
- Metaheuristic algorithms are surmised and non-deterministic.
- Metaheuristics are not issue particular.

In this manner Metaheuristic algorithm can be utilized to take care of complex issues. Following systems are utilized as a part of this thesis [25]:

- **Particle Swarm Optimization (PSO)**

The PSO is a developmental calculation procedure created by Kennedy and Eberhart. It is enlivened by the social conduct and movement elements of bird flocking or fish schooling. Not at all like the GA, the fundamental PSO calculation has no hybrid and transformation administrators. In PSO, a populace of potential arrangements (called particles) is made which are arbitrarily disseminated over the hunt space with arbitrary speed.

- **BAT Algorithm**

Xin-She Yang developed the BAT algorithm, which is a metaheuristic bio-inspired algorithm. BAT, when chase the prey, decrease the loudness and increase the rat e of ultra-sonic sound.

- **Differential Evolution (DE)**

The DE is a stochastic, population based optimization algorithm created by Storn and Price. The key distinction between the DE and the GA/PSO is in the instrument for producing new solutions. The DE, in comparison with GA/PSO, produces another arrangement by combining a few arrangements with the hopeful arrangement. The population in the DE develops through repeated cycles of crossover, mutation and selection which are not quite the same as the ones utilized as a part of the GA.

- **Wind Driven Optimization (WDO)**

WDO depends on air flow. It is figured using Newton's second law of development, twist blows from high weight locale to low weight areas, altering the ponderousness of weight

Metaheuristic algorithms, for example, particle swarm optimization, firefly algorithm and agreement seek are presently ending up ground-breaking techniques for taking care of numerous extreme improvement issues. These algorithms are driven from the conduct of organic frameworks and additionally physical frameworks in nature. For instance, molecule swarm advancement was created in light of the swarm conduct of winged animals and fish [7, 8], while recreated tempering depended on the toughening procedure of metals.

1.7 ORGANISATION OF THE THESIS

In chapter 2, the research paper are discussed which help in building a general understanding about the cognitive radio. It gives the brief knowledge about the work done by the researchers till date and scope of improvements.

In chapter 3, multiobjective optimization problem is solved by using different bio-inspired mataherics techniques like particle swarm optimizaton, BAT algorithm, differential evolution and wind driven optimization for three different transmission paramters by using weighted sum approach for 32 and 64 subcarriers and observed best algorithm in terms of avreage fitness value.

In chapter 4, multiobjective problem is solved for five different transmission parameters for four different algorithms which are BAT algorithm, wind driven optimization, particle swarm optimization and differential evolution, from different type of sevices to get a best optimization technique along with results.

In chapter 5, the conclution of work done and its future scope is shown.

CHAPTER-2

LITERATURE SURVEY

Tim R. Newman (2006) *et al.* [4] in “Cognitive Engine Implementation for Wireless Multicarrier Transceivers,” this paper introduces a Genetic Algorithm (GA) driven, cognitive radio decision engine that decides the ideal radio transmission parameters for single and multicarrier system. Deciding the suitable radio parameters given a dynamic remote channel condition is the essential element of cognitive radios. GA are intended to choose the ideal transmission parameters by scoring a subset of parameters and advancing them until the ideal value is reached. In spite of the fact that there have been usage of GA based single carrier cognitive radio engines, the execution of these algorithms has not been thoroughly analyzed nor have the fitness function utilized by the algorithms. An arrangement of precise single and multi carrier fitness function for GA implementations that totally control the development of the algorithm. The performance results come about outline the exchange offs between the convergence time of the GA and the size of the GA search space.

Xiaobo Tan (2012) *et al.* [5] in “A genetic-based cognitive link decision algorithm for OFDM system,” an enhanced genetic algorithm based decision making module was proposed. The basic decision making module gathers the natural data and QoS necessities of the radio and afterward delivers connect arrangement for the radio based on the enhanced genetic algorithm. New crossover and mutation were introduced with quicken merging rate of the genetic algorithm. A novel population initialization technique was proposed to diminish the time of accomplishing the ideal choice. Simulations and discussion showed the efficiency of the basic decision making module, and this examination work displayed its significance of upgrading the decision speed that is of essential request in cognitive decision making application.

Priyanka Rawat (2016) *et al.* [6] in “Cognitive radio for M2M and Internet of Things: A survey,” this paper overviews novel methodologies and discussions about research challenges related to the utilization of cognitive radio innovation for internet of things. This paper displays a general foundation on cognitive radio and internet of things with some potential applications. the review is not quite the same as existing surveys in that we center around late advances and continuous research headings in cognitive radio with regards to machine to machine and internet of things. CR solution that address bland issues of IoT including developing difficulties of autonomicity, scalability, energy efficiency, heterogeneity as far as client capabilities, environment and so on. The arrangements are supported by taxonomy of various CR approaches. This paper expects to help new analysts entering the area of CR and IoT by giving a thorough review on ongoing advances.

Ian F. Akyildiz (2006) *et al.* [7] in “NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey,” the present wireless systems are describe by a fixed spectrum strategy. However, a vast segment of the appointed spectrum is utilized sporadically and geological varieties in the usage of allocated spectrum range. The restricted accessible spectrum and the inefficiency in the spectrum, require another correspondence worldview to abuse the current wireless spectrum opportunites. This new systems paradigm referee to as neXt generation networks, Dynamic Spectrum Access (DSA) and cognitive radio networks.

Minho Jo (2013) *et al.* [8] in “Selfish Attacks and Detection in Cognitive Radio Ad-Hoc Networks,” cognitive radio is a technology intended to help unlicensed clients to use the maximum accessible authorized bandwidth. Cognitive radio has gathered the attention of researchers. Therefore a little research has been finished with respect to security in cognitive radio, while considerably more research has been done on spectrum sensing and allocation issues. A selfish cognitive radio hub can possess all or part of the assets of various channels, restricting other cognitive radio hubs from getting to these assets. Selfish cognitive radio assaults are a genuine security issue since they essentially corrupt the execution of an intellectual radio system. In this article we distinguish another egotistical assault compose in cognitive radio ad-hoc networks and propose a simple and productive selfish cognitive radio assault recognition strategy, called COOPON, with multichannel assets by agreeable neighboring subjective radio hubs.

Ding Xua (2014) *et al.* [9] in “Ergodic capacity and outage probability optimization for secondary user in cognitive radio networks under interference outage constraint,” cognitive radio systems where a secondary customer coincides with a primary user. The impedance outage constraint is associated with secure the fundamental transmission. The power partition issue to mutually enlarge as far as possible and point of confinement the power outage probability of the SU, subject to the typical transmit control basic and the impedance power outage impediment, is considered. Expect that the perfect learning of the snappy channel state information of the block interface between the SU transmitter and the PU beneficiary is available at the SU, the perfect power allocation strategy is then proposed. Moreover, to manage more practical conditions, we furthermore expect only the block associate channel scattering is known and decide the looking at perfect power allocation system. Wide propagation happens are given to affirm the ampleness of the proposed methodology. It is shown that the proposed systems achieve high ergodic point of confinement and low power outage probability in the meantime, while enhancing as far as possible just prompts altogether higher power outage probability. It is in like manner showed that the SU execution isn't degraded due to fragmentary learning of the block interface CSI if tight transmit control basic is associated.

Supreet Singh (2017) *et al.* [10] in “Performance analysis of spectrum sensing techniques over TWDP fading channels for CR based IoTs,” the execution of range distinguishing techniques in excess of two wave diffused power (TWDP) obscuring channels has been explored for CR based IoT contraptions. The ubiquitous things in perspective of IoTs with mental capacities are the future that would enable sharp decisions to achieve at whatever point, wherever, check free and on-ask for benefits. A new close edge verbalizations in regards to Marcum-Q limit and Whittaker work for the range area probability over TWDP obscuring channels have been gathered for different recognizing frameworks. The verbalizations are then used to enhance as far as possible for IoT sensor center points depicting the perfect direct of recognizing over TWDP channels. The screw up probability and receiver operating characteristic twists have been plotted and the working point and compelling estimations of breaking point for perfect execution have been perceived. The execution loss of standard essentialness area, cyclo stationary based recognition acknowledgment and facilitated filtering discoverer has been destitute down. The explanatory results subsequently got are endorsed through montecarlo generations.

Zhijin Zhao (2009) *et al.* [11] in "Cognitive Radio Spectrum Allocation using Evolutionary Algorithms," cognitive radio has been regarded as a promising technology to improve spectrum utilization significantly. In this letter, spectrum allocation model is presented firstly, and then spectrum allocation methods based on genetic algorithm, Quantum Genetic Algorithm (QGA), and particle swarm optimization, are proposed. To decrease the search space we propose a mapping process between the channel assignment matrix and the chromosome of GA, QGA, and the position of the particle of PSO, respectively, based on the characteristics of the channel availability matrix and the interference constraints. Results show that our proposed methods greatly outperform the commonly used color sensitive graph coloring algorithm.

Jamal Elhachmi (2016) *et al.* [12] in "Cognitive radio spectrum allocation using genetic algorithm," this paper presents the problem formulation, development, and use of a robust dynamic genetic algorithm for channel allocation in cognitive radio. This approach offers an efficient way to access available spectrum for both primary and secondary users. The proposed dynamic genetic algorithms based on the new sophisticated crossover and mutation operators ensure the validity of channels and the fast convergence to the best solution in a highly dynamic environment. Compared with existing methods, simulation results demonstrate that our approach algorithm produces satisfactory results with reduced network interference and enhance efficiently the spectrum throughput.

Timothy R. Newman (2018) *et al.* [13] in "Population Adaptation for Genetic Algorithm-based Cognitive Radios," genetic algorithms are most appropriate for optimization issues including huge search spaces. The issue space experienced while enhancing the transmission parameters of a cognitive radio for a given wireless condition and set of execution goals can turn out to be restrictively substantial because of the high number of parameters and their numerous conceivable qualities. Ongoing exploration has shown that Genetic algorithms are a reasonable usage system for cognitive radio engine. As the time required for the Genetic algorithms to go to a solution substantially increments as the framework complexity develops. In this paper, we display a populace adjustment strategy for genetic algorithms that exploits the data from past perception cycles so as to lessen the time required to achieve an ideal choice, in order to reduce the time required to reach an optimal decision.

Usama Mehboob (2016) *et al.* [14] in "Genetic algorithms in wireless networking: techniques, applications, and issues," wireless access technology is ending up progressively ordinary because of the simplicity of task and establishment of unethered remote media. The plan of wireless systems networking is demanding due to the highly active environmental condition that makes parameter optimization a complex task. GAs are notable for their momentous sweeping statement and flexibility and have been connected in a wide assortment of settings in wireless networks. This paper, give a far reaching overview of the utilizations of GAs in wireless systems for both a composition and design, give a wide extending overview of GA.

Federico Marini (2015) *et al.* [15] in "Particle swarm optimization (PSO). A tutorial," swarm-based algorithms developed as a great group of optimization techniques, inspired by the aggregate behavior of social creatures. In particle swarm optimization the arrangement of applicant solutions for the enhancement issue is characterized as a swarm of particles which may move through the parameter space characterizing directions which are driven by their own particular and neighbors' best exhibitions. The capability of particle swarm optimization for taking care of different sorts of optimization issues in chemo metrics is appeared through a broad portrayal of the algorithm and by methods for chose worked cases in the fields of flag distorting, estimation hearty PCA arrangements and variable choice.

Kotha Srinivasa Reddya (2015) *et al.* [16] in "An approach for FIR filter coefficient optimization using differential evolution algorithm," a hardware efficient finite impulse response filter design using differential evolution and common sub expression elimination algorithm. With the DE algorithm, first found a set of filter coefficients which reduced number of signed power of two terms without compromising on quality of the filter response. After obtaining coefficients, applied common sub expression elimination algorithm, and determined the hardware cost in terms of adders. The filters were designed using DE for various word lengths, and the same were implemented in transposed direct form structure.

S. D. Chavan (2013) *et al.* [17] in "An Overview on Particle Swarm Optimization: Basic Concepts and Modified Variants," Particle swarm optimization is stochastic optimization algorithm enlivened by behavior of bird swarm searching for the nourishment. PSO is another, intense canny swarm intelligence based algorithm utilized for discovering ideal solution for complex issues. It can be altered to bunches of different adaptations to build speed of convergence and diversity. PSO variations are found to build its execution and enhance the capacity to fathom an extensive variety of streamlining issues. This paper focus is on traditional PSO, its control parameters and adjusted forms.

Lamiaa Khalid (2010) *et al.* [18] in "Emerging cognitive radio technology: Principles, challenges and opportunities," because of the expanding interest for new wireless services and applications and in addition the expanding number of wireless clients, the accessible spectrum is winding up progressively. Therefore, the Federal Communications Commission (FCC) has been researching better approaches to deal with the radio frequency resources. Cognitive radio innovation is an inventive radio outline reasoning which intends to expand range use by abusing unused and under-used range in progressively evolving conditions. The fundamental thought is to give unlicensed clients a chance to utilize authorized frequencies, if they can ensure least impedance saw by the primary licensed clients. However, permitting opportunistic utilization of the wireless spectrum makes new issues, for example, tranquil conjunction with different wireless technologies and also understanding the impact of interference that every one of these systems can make.

Nitasha Soni (2014) *et al.* [19] in "Study of Various Crossover Operators in Genetic Algorithms," genetic algorithms are the populace based search and optimization method that copy the procedure of natural evolution. Execution of genetic algorithms principally relies upon kind of genetic operators – Selection, Crossover, Mutation and Replacement utilized as a part of it. Distinctive crossover and mutation operators exist to take care of the issue that includes huge populace size. Case of such an issue is travelling sales representative issue, which is having a large set of solution. In this paper we will talk about various crossover operators that assistance in taking care of the issue.

Andson Balieiro (2014) *et al.* [20] in "A multi-objective genetic optimization for spectrum sensing in cognitive radio," cognitive radio has risen as a promising answer for the issue of range underutilization. In CR, spectrum sensing is a key element. It empowers the secondary client to recognize spectrum gaps and guarantee non-interference to primary communication. Spectrum sensing has its own particular difficulties, for example, revelation of chances for transmission and detecting overhead. High sensing overhead may disable spectral efficiency as the radio is for the most part utilized for recognizing essential clients, instead of transmitting information. Then again, a less successive detecting may bring about obstruction to PU, because of the deferral in the identification of the PU' s return and can prompt loss of transmission openings. Consequently, it is of vital significance to streamline the detecting time frames for every essential direct keeping in mind the end goal to boost the quantity of transmission openings and diminish the detecting overhead caused.

Narwant S. Grewal (2017) *et al.* [21] in “A Linear Mutually Coupled Parallel Dipole Antenna Array Failure Correction Using Bat Algorithm,” the issue of mutually coupled dipole antenna array cluster disappointment has been comprehended utilizing bat algorithm by altering just the amplitude excitation of good exhibit components. The component disappointment causes the debasement of side-flap control level to an inappropriate level. A fitness work is figured to acquire the distinction between debased side-projection design and estimated side-flap design, and an adaptable approach utilizing bat calculation is utilized to limit this capacity. Numerical cases of single and different component disappointment revision under common coupling conditions are talked about to demonstrate the capacity of this proposed approach.

Xin-She Yang (2010) *et al.* [22] in “A New Metaheuristic Bat-Inspired Algorithm,” metaheuristic algorithm, for example article swarm optimization, firefly algorithm and harmon seek are presently winding up great techniques for taking care of numerous extreme optimization issues. Metaheuristic strategy, the Bat Algorithm, based on the echolocation behavior of bats. We likewise plan to join the benefits of existing calculations into the new bat algorithm. After a point by point definition and clarification of its usage, we will then contrast the proposed algorithm and other existing algorithms, including GA and PSO. Reproductions demonstrate that the proposed calculation appears to be much better than different calculations, and further examinations are additionally talked about.

Athanasios Paraskevopoulos (2017) *et al.* [23] in “Cognitive Radio Engine Design for IoT Using Real-Code Biogeography-Based Optimization and Fuzzy Decision Making,” the internet of things worldview extends the present internet and empowers communication through machine to machine. CR Systems have gotten much attention throughout the recent decade, in light of their capacity to adaptably adjust their transmission parameters to their environment condition. Current innovation patterns are moving to the flexibility of cognitive radio systems into IoT. The assurance of the fitting transmission parameters for a given wireless channel environment is the primary component of a cognitive radio engine. For wireless multicarrier handsets, the issue turns out to be high dimensional because of the expansive number of decision variables required. Evolutionary algorithms are appropriate strategies to tackle the previously mentioned issue. CR engine for wireless multicarrier handsets utilizing Real-Coded Biogeography-Based Optimization (RCBBO). The CR engine additionally utilizes a fuzzy decision maker for acquiring the best traded off solution. RCBBO utilizes a mutual operator keeping in mind the end goal to enhance the assorted variety of the populace and improve the investigation capacity of the first BBO algorithm. In addition, RCBBO is more effective when connected to high dimensional issues in instances of multicarrier framework.

Muhammad Waheed (2009) *et al.* [24] in “Cognitive Radio Parameter Adaptation in Multicarrier Environment,” Transmission parameter adjustment in a dynamic multicarrier condition is a testing errand for cognitive radio. Therefore, a novel adjustment strategy that utilizations binary ant colony optimization streamlining to improve the cognitive radio parameters given an arrangement of targets. Simulation comes about demonstrate that proposed technique performs superior to anything genetic algorithm based adjustment strategy as far as convergence speed and converged fitness values. The proposed technique gives a superior answer for the parameter adjustment issue and gives higher fitness value in less number of iterations.

Pyari Mohan Pradhan (2014) *et al.* [25] in “Comparative performance analysis of evolutionary algorithm based parameter optimization in cognitive radio engine: A survey,” One of the essential highlights of the cognitive radio engine is to adjust the parameters of radio to satisfy certain goals in a time varying wireless environment. To satisfy the goal, six evolutionary algorithms are utilized for improving the predefined fitness functions in the radio environment. The execution of genetic algorithm, particle swarm optimization, differential evolution, bacterial foraging optimization, artificial bee colony optimization and cat swarm optimization algorithm in various modes of operation. Every algorithm is tried in single and multicarrier communication system keeping in mind the goal to recognize the benefit of multicarrier communication system in wireless environment. The spectral interference brought by the cognitive user into the primary user’s band and that brought by the primary user into the cognitive user’s band are additionally explored. The execution of various algorithm are compared using convergence characteristics and four factual measurements.

Anabel Martinez-Vargas (2013) *et al.* [26] in “Comparing particle swarm optimization variants for a cognitive radio network,” it is perceived that static spectrum allocation policy as of now utilized as a part of most nations has prompted a inefficient utilization of spectrum. It implies that accessible spectrum is underutilized over certain bands while in others stay scarce. In cognitive radio technology is proposed to reuse bands to take care of the issue of spectrum scarcity and utilize the restricted spectrum resource. This exhibits the application and execution correlation of three variations of PSO to be specific Binary Particle Swarm Optimization (BPSO), Socio Cognitive Particle Swarm Optimization (SCPSO) and derivation 0 of every a cognitive radio network. The aim for maximizing the sum throughput for the quantity of optional connections that can be conceded in the cognitive radio network within the sight of essential connections under interference imperatives.

Dervis Karaboga (2004) *et al.* [27] in "A Simple and Global Optimization Algorithm for Engineering Problems: Differential Evolution Algorithm," differential evolution algorithm is another heuristic approach essentially having three points of interest; finding the true global minimum regardless of the initial parameter values, quick convergence and utilizing few control parameters. DE algorithm is a populace based algorithm like genetic algorithms utilizing comparative operation; crossover, mutation and selection. This work has contrasted the execution of DE algorithm with that of some other surely understood forms of genetic algorithm. In reproduction examines, De Jong's test capacities have been utilized. From the recreation comes about, it was watched that the convergence speed of DE is significantly superior to genetic algorithms. In this way, DE algorithm is by all accounts a promising methodology for designing improvement issues.

Meigin Tang (2016) *et al.* [28] in "Energy efficient power allocation in cognitive radio network using co-evolution chaotic particle swarm optimization," the exchange off amongst utility and energy utilization in Orthogonal Frequency Division Multiplexing (OFDM) based cognitive radio network is examined. Energy efficiency issue is vital in the field of CR network, where the utility is maximized and the energy consumption is limited in such a CR networks. Since the exchange off between them has been paying more considerations, this examination condenses the power allocation as an optimization issue that boosts the energy effectiveness by means of another energy efficiency metric characterize. The figured issue is an extensive scale non-convex issue, which is extremely hard to comprehend. This paper introduce an enhanced PSO algorithm to solve the difficult large-scale optimization. Given the weak convergence of the first PSO around local optima, an enhanced rendition that consolidates the chaos theory is proposed, where chaos theory can enable PSO to scan for arrangements around the personal and global bests. Furthermore, to accelerate the convergence procedure when looking with such an extensive scale optimization, the first issue is decayed into various little ones by utilizing the convolutionary system, and afterward divide-and-conquer technique is utilized to avoid producing infeasible solutions. Simulations exhibit that the proposed convolution chaotic PSO needs fewer number of iterations and can accomplish more energy efficiency than alternate calculations.

Iztok Fister Jr. (2013) *et al.* [29] in "A Hybrid Bat Algorithm," swarm intelligence is a great procedure proper to optimization. This paper, exhibit another swarm intelligence algorithm which depends on the bat algorithm. BAT algorithm has been hybridized with differential evaluation systems. This hybridization indicated exceptionally encouraging outcomes on standard benchmark capacities and furthermore fundamentally enhanced the first bat algorithm.

Zhao Junhui (2012) *et al*. [30] in “Parameter adjustment based on improved genetic algorithm for cognitive radio networks,” multi- objective parameter alteration assumes an essential part in enhancing the execution of the CR system. In present we focus on the GA to accomplish parameter optimization in CR, while general GA dependably fall into premature convergence. From that point, this paper proposed a linear scale transformation to the fitness of individual chromosome, which can lessen the effect of exceptional individuals exiting in the early evolution iterations and guarantee rivalry between people in the last evolution iterations. This paper additionally presents a adaptive crossover and mutation probability algorithm into parameter adjustment, which can guarantee the diversity and convergence of the populace. Two applications are connected in the parameter adjustment of CR, one application inclines toward the bit error rate and another favors the bandwidth. Simulation comes about demonstrate that the enhanced parameter adjustment algorithm converge to the global optimal solution fast without falling into premature convergence.

Saeed Motiian (2011) *et al.* [31] in “Particle Swarm Optimization of power allocation in cognitive radio system with interference constraints,” CR is utilized for improvement of spectrum efficiency. Although numerous works have been accomplished on the power allocation of cognitive radio, limited efforts have considered evolutionary algorithms. The issue in the cognitive radio systems where interference constraints are characterized for insurance of quality of service (QoS) for both primary and secondary clients. Utilities characterized as elements of the signal-to-interference-plus-noise ratio are matched for every secondary client who meets Nash's axioms. The area of utilities that meets the requirements is non-convex. It is conceivable to make simplifications, to produce a convex region, and after that utilization regular convex optimization ways to deal with get a solution. PSO does not need such improvements and accordingly its outcomes are better than those of the convex optimization techniques. PSO is an evolutionary algorithm in view of social intelligence, used in numerous optimization issues. PSO is a global optimizations algorithm that does not require the target work be differentiable as required in optimization techniques

Nadine Abbas (2015) *et al.* [32] in “Recent advances on artificial intelligence and learning techniques in cognitive radio networks,” CR plays a major role towards taking care of the exploding traffic demand over wireless systems. A cognitive radio hub detects the environment, breaks down the outdoor parameters, and after that settles on choices for dynamic time- frequency space asset allocation and management to enhance the use of the radio spectrum. The cognitive radio is normally joined with artificial intelligence and machine-learning strategies so that a versatile and insightful allocation is accomplished. This paper initially displays the cognitive radio networks, resources, objectives, constraints, and challenges. It presents artificial intelligence and machine-learning systems and stresses the part of learning in cognitive radios. At that point, a study on the best in class of machine-learning procedures in cognitive radios is introduced. The literature review is composed in view of various artificial intelligence techniques such as fuzzy logic, genetic algorithms, neural networks, game theory, reinforcement learning, support vector machine, case-based reasoning, entropy, and artificial bee colony algorithm. This paper likewise examines the cognitive radio execution and the learning challenges anticipated in cognitive radio applications.

Nitin Sharma (2017) *et al.* [33] in "Simultaneous Power and Sub-channel Allocation in Interference Limited OFDM-Based Cognitive Radio Network with Quality of Service Considerations," the consistently expanding interest for radio spectrum we are not ready to accomplish complete efficiency in using the spectrum. The spectrum itself being confined can just suit set number of clients. In this manner, it is exceptionally basic to productively use it. Cognitive radio is seen as a critical component for improving spectral efficiency. In this paper we center around apportioning assets to SU which coincide with PU in OFDM based cognitive radio networks. Simultaneous power and subchannel distribution for each SU is considered with the intend to maximize the aggregate throughput, additionally expected to augment the power proficiency of framework and all the while keeping a beware of aggregate obstruction caused to PUs. The adaptable rate interest for each SU is viewed as and henceforth classified as real time and non real time SU. The issue is explained utilizing non- dominant arranging genetic algorithm. The outcomes obtained are compared and existing arrangement and optimal solution.

Si Chen (2009) *et al.* [34] in "Efficient spectrum utilization via cross-layer optimization in distributed cognitive radio networks," a novel spectrum allocation approach for disseminated cognitive radio systems are fit for detecting the prevailing environmental conditions and consequently adjusting its working parameters in order to upgrade system and system execution. Utilizing this innovation, our proposed approach improves every individual remote gadget and its single-jump communication joins utilizing the halfway working parameter and natural data from nearby gadgets inside the remote system. Expecting stationary remote hubs, all remote correspondence joins utilize non-adjacent symmetrical recurrence division multiplexing keeping in mind the end goal to empower dynamic range get to (DSA). The proposed approach will endeavor to at the same time limit the bit mistake rate, limit out-of-band interference, and maximize general throughput utilizing a multi- objective fitness function. GAs are utilized to play out the real streamlining. A few helping forms have likewise been contrived to make the approach more productive and vigorous. Such methodology can lessen BER by a request of extent.

Zikri Bayraktar (2013) *et al.* [35] in "The Wind Driven Optimization Technique and its Application in Electromagnetics," another sort of nature- inspired global optimization approach in light of atmospheric movement is presented. The proposed WDO strategy is a populace based iterative global optimization algorithm for multi-dimensional and multi-modular issues with the possibility to actualize limitations on the inquiry area. At its center, a population of imperceptibly little air packages explores over a N-dimensional inquiry space following Newton's second law of movement, which is additionally used to portray the movement of air distributes the world's air. Contrasted with comparable particle based algorithms, WDO utilizes extra terms in the speed refresh condition giving vigor and additional degrees of flexibility to adjust. Alongside the hypothesis and phrasing of WDO, a numerical report for tuning the WDO parameters is introduced. WDO is additionally connected to three electromagnetic advancement issues, including the combination of a direct radio wire cluster, a twofold sided fake attractive channel for WiFi applications, and an E- shaped microstrip patch antenna. These cases propose that WDO can, now and again, out-perform other surely understood systems, for example, PSO, GA or DE and that WDO is appropriate for issues with both discrete and constant esteemed parameters.

CHAPTER-3

MULTIOBJECTIVE OPTIMIZATION PROBLEM WITH THREE OBJECTIVES

The fundamental part of cognitive engine is that it reconfigures the radio parameters to outfit the best execution for a predefined set of objectives and limitations. In CR system, the input to the cognitive decision module are various environmental parameters like path loss, noise power, etc that are assumed to be available and transmission parameters like transmit power, modulation index, modulation type, etc act as a decision variables. This activating signal is send to Software Defined Radio (SDR) stage which quickly changes its designs according to the configured variables. The RF sensors will detect the channel attributes and inside state sensors interfaced with CDE, will contribute towards Signal to Noise Ratio (SNR), noise power and current battery level. These parameters will be further optimized using various bio-inspired optimization techniques.

3.1 OPTIMIZATION OF OBJECTIVE FUNCTIONS FOR CR NETWORK

Objective or fitness function should empower the system to achieve one ideal arrangement of parameters. Since the goal in a wireless environment are, multiple in number, so the issue of CR engine design can be figured as a multi-objective optimization problem [46].

3.1.1 Objective function for Minimization of Bit Error Rate

To minimize the bit error rate or to obtain an error free signal is one of the most important objective for any communication system. Bit error rate is impacted by transmit power, modulation type, noise power and so on. The fitness function (converted to maximization problem) is made inside a output range [0, 1] and is characterized as:

$$f_{minBER} = 1 - \frac{log_{10}(0.5)}{log_{10}(P_{avBER})} \tag{4}$$

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

$$P_{avBER} = \frac{1}{K}\sum_{i=1}^{K} BER\ (M_i, E_b/N) \tag{5}$$

where, M_i,E_b/N is the modulation level, $BER\ (M_i, E_b/N)$ is the bit SNR of the i^{th} subcarrier. In this work, we suppose the possible modulation types to be B/QPSK and M-QAM.

The following equations represent the BER probability of M-PSK and M-QAM modulation in AWGN channel.

$$BER_{B/QPSK} = \frac{1}{log_2 M_i} erfc\left[\sin\left(\frac{\pi}{M_i}\right)\sqrt{log_2 M_i \frac{\mathrm{E_b}}{N}}\right]$$
$$BER_{MQAM} = \frac{2\left(\sqrt{M_i}-1\right)}{\sqrt{M_i}log_2 M_i} erfc\left[\sqrt{\frac{3\, log_2 M_i}{2(M_i-1)}\left(\frac{E_b}{N}\right)}\right] \tag{6}$$

where, erfc(.) is the complementary error function.

3.1.2 Objective function for Minimization of Power Consumption

For any communication system, power must be utilized ideally. Consumption of power must be, minimum for all the tasks. The objective function for power consumption minimization is given as:

$$f_{minP} = 1 - \sum_{i=1}^{K} \frac{P_i}{KP_{max}} \tag{7}$$

where, P_i corresponds to the transmit power for the i^{th}subcarrier and P_{max} is the maximum allowed power for the subcarrier.

3.1.3 Objective function for Maximization of Throughput

Throughput of the system can be enhanced by influencing the average modulation level of the system to be maximum. This is because, for the OFDM system the overall throughput is impacted by the symbol rate of each one of the subcarriers. Thus the objective function for maximization of information throughput is given as:

$$f_{maxTPT} = \frac{\frac{1}{K}\sum_{i=1}^{K} log_2 M_i - 1}{log_2 M_{max} - log_2 M_{min}} \tag{8}$$

where, M_i is the modulation level of i^{th} subcarrier, M_{max} and M_{min} are the maximum and minimum allowed modulation levels of the system.

3.2 FITNESS EVALUATION USING WEIGHTED SUM APPROACH

The calculation of the ideal value for each of the above functions will result in a set of local solutions in place of a global solution. Different approach have been used in the literature to solve an optimization problem having fitness function. One of the approach is utilizing weighted sums that use to consolidate different single objective functions into one aggregate multiple objective function. This approach for M objectives is given as [11]:

$$f = \sum_{i=1}^{M} w_i f_i \tag{9}$$

where, w_i is the weight of i^{th} objective that satisfies the following constraints:

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

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

$$w_1 + w_2 + \dots + w_M = 1 \tag{10}$$

Multiple-objective fitness function of this cognitive radio system, with three objectives, is given in (11). These weight values will conclude the search direction for the optimization algorithms.

$$f = w_1 f_{minBER} + w_2 f_{minP} + w_3 f_{maxTPT} \tag{11}$$

The different scenarios observed by communication channel for different weights are given in Table 3.1. These weights are assigned on the premise that the device entitled for email services known as Mode 1 needs lower BER, while Mode 2 for lower power consumption and Mode 3 for higher throughput are required for voice and video services respectively.

Table 3.1: Weight scenarios for different service types

Service Type	**Requirement**	w_1	w_2	w_3
Mode 1	Minimize BER	0.8	0.15	0.05
Mode 2	Minimize Power	0.05	0.8	0.15
Mode 3	Maximize Throughput	0.15	0.05	0.8

3.3 EVOLUTIONARY OPTIMIZATION TECHNIQUES

Particle Swarm Optimization (PSO), BAT Algorithm, Differential Evolution (DE) and Wind Driven Optimization (WDO) are generally used metaheuristic optimization techniques owing to their simplicity and flexibility and wide range of applicability. This section provides pseudo code for designing PSO, BAT, DE and WDO based CDE. Dimensionality of the problem issue turns out to be high with increase in number of subcarriers.

3.3.1 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is influenced by the social and cooperative behavior of different species. Each particle is assumed to have two characteristics: a position (x_i) and velocity(v_i). It moves around in the search space and remembers the best position (having best objective function value) it has attained so far, called its personal best [15]. The particles communicate information about good position to each other and alter their individual positions and velocities according to (12) and (13) respectively.

$$v_i(t+1) = wv_i(t) + c_1r_1[L_i(t) - x_i(t)] + c_2r_2[g(t) - x_i(t)] \quad (12)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (13)$$

Where, $c_1 \geq 0, c_2 \leq 4$ & $r_1, r_2 \in [0,1]$ and $x_i(t+1)$ is the position and $v_i(t+1)$ is the velocity of i^{th} particle in $(t+1)$ iteration, w is the inertia or momentum term that prevents the particle from drastically changing direction. c_1 is called the cognitive component-t, that accounts for the tendency of particles to return to their own previously found best position L_i and personal best position P_i. c_2 is the social component which guides the particle towards the global best position g of the whole swarm i.e. . The pseudo code for PSO based CDE is given in Algorithm 1.

1. Initialization: Set parameters

   $$w_{min}, w_{max}, c_1, c_2, maxite, swarm\ size(N),$$
   $$no\ of\ subcarriers(K)$$

   Real value encoding for transmission power and modulation levels of K subcarriers,

   a) Initialize the position for each of the N particles, $x_i(0) \forall\ i \in 1{:}N$
   b) Initialize this initial position as the best position of the particles $p_i(0) = x_i(0)$
   c) Calculate the fitness of each particle and if $f(x_j(0)) > f(x_i(0))\ \forall\ i \neq j$, initialize the global best as $g = x_j(0)$
2. set iteration as $ite = 1$
3. $w = w_{max} - ite * (w_{max} - w_{min})/maxite$
   a) Change the particle velocity according to equation (12)
   b) Change the particle position according to equation (13)
   c) Evaluate the fitness of the particle $f(x_i(t+1))$
   d) if $f(x_i(t+1)) \geq f(p_i)$, update the personal best : $p_i = x_i(t+1)$
   e) if $f(x_i(t+1)) \geq f(g)$, update the global best : $g = x_i(t+1)$
4. If $ite \leq maxite; ite = ite + 1$ and go to step 3. At the end of iterative process, the best solution is g.
   a) Return the best transmit power for K subcarriers
   b) Return the best modulation level for K subcarriers

Algorithm 1: Pseudo Code for Multi-objective PSO

3.3.2 BAT Algorithm

The BAT Algorithm (BAT), introduced by Xin-She Yang in 2010 [38], is an extremely proficient metaheuristic bio-motivated algorithm. This algorithm is gotten from the echolocation guideline of BAT and has been effectively connected in late improvement issues as examined in [39]. BAT tend to diminish the clamor and increment the rate of discharged ultrasonic sound when they pursue the prey. The pseudo code for BAT Algorithm [40] is given below

1. Initialize the random population of bats with dimensionality D and population size N.
2. For each iteration, all bats are assigned a random frequency value that controls its range and speed as:

$$f_i = f_{min} + (f_{max} - f_{min})\beta \tag{14}$$

Where $\beta \in [-1,1]$ is a random number having uniform distribution. f_{min} and $f_{max}$are minimum and maximum possible frequencies.

3. Position x_i and velocity v_i in d-dimensional search space for each bat are updated during each iteration as:

$$v_i^{t+1} = v_i^t + (x_i^t - best)f_i$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{15}$$

$best$ is the global best solution obtained after evaluating fitness for all N bats.

4. If $(rand > r_i)$, generate a local solution around the selected best solution by applying random walk as given below

$$x^t = best{+}\in A^t \tag{16}$$

Where $\varepsilon \in [-1,1]$ and A^t is the average loudness of all the bats.

5. Accept the new solution and update loudness and pulse rate for each bat in successive iterations as in (17) such that loudness $A_i$decreases and pulse rate r_i increases only when

$$(rand < A_i and\ f(x_i) is\ better\ than\ f(best))$$

$$A_i^{t+1} = \alpha A_i^t$$

$$r_i^{t+1} = r_i^0[1 - \exp(-\gamma t)] \tag{17}$$

where α and β are the constants

6. Rank the bats and find the current best bat, $best$.
7. Repeat till the termination criterion is satisfied.

Algorithm 2: Pseudo Code for Multi-objective BAT

3.3.3 Differential Evolution

Differential Evolution (DE) improvement was created by R. Stron and K. Cost in 1995 [41]. In this, a populace of arbitrary factors is presented and existing arrangements are joined to produce new arrangements. After development of parent (target) vector $x_{i,G}$ $(i = 1,2, \dots . n_p)$ where n_p is the population size and dimensionality of every molecule is taken as D, following three activities are expected to perform [16]:

i) **Differential Mutation:** In this stage two arbitrary factors $x_{r2,G}$ and $x_{r3,G}$ are driven from the populace $x_{ri,G}$ and their distinction is increased with a scale factor F (positive real number), and latter added to another arbitrarily chose component, $x_{r1,G}$. Thus mutant vector, $v_{i,G+1}$ is produced by transforming each parent.

$$v_{i,G+1} = x_{r1,G} + F\left(x_{r2,G} - x_{r3,G}\right) \forall\, i = 1,2, \dots \dots n_p \tag{18}$$

ii) **Differential Crossover:** It mixes two populations on the basis of crossover probability (CR) and to obtain a trail vector $u_{ji,G+1}$ as given below:

$$\begin{aligned} u_{ij,G+1} &= v_{i,G}\ if\ randb(j) < CR\ or\ j = I_{rand} \\ &\quad x_{ji,G+1}\ if\ randb(j) > CR\ or\ j \neq I_{rand} \end{aligned} \tag{19}$$

Where $randb(j) \sim U[0,1]$ and I_{rand} is random integer form $[1,2 \dots . . D]$.

iii) **Evaluation and Selection:** The objective function value of trial and target vector were compared. The next generation depends on highest value target, then a new population is generated, and the complete process starts again.

$$\begin{aligned} x_{i,G+1} &= u_{i,G+1}\ if\ f(u_{i,G+1}) \geq f(x_{i,G}) \\ x_{i,G+1} &= x_{i,G}\ otherwise \end{aligned} \tag{20}$$

3.3.4 Wind Driven Optimization

The WDO gets motivation from the air. In the environment, twist blows trying to adjust the awkwardness of weight. It blows from high weight region to low weight region at a speed. Contingent upon the above examination, some hypothetical suppositions are figured in determination of the WDO calculation. The beginning stage of WDO calculation is Newton's second law of movement, which is utilized to give exact outcomes to the examination of environmental movement in the Lagran gain portrayal [37].

$$\rho\vec{\alpha} = \sum \vec{F}_i \tag{21}$$

Where $\vec{\alpha}$ is the acceleration, ρ is the air density for an infinitesimal air parcel, and $\vec{F_i}$ are all the forces acting on the air parcel. In order to let air pressure establish the equation relationship with the air parcel's density and temperature, the ideal gas law is given by

$$P = \rho RT \tag{22}$$

where, P is the pressure, R is the universal gas constant and T is the temperature. The combination of forces like gravitational force ($\vec{F}_G$), pressure gradient force ($\vec{F}_{PG}$), Coriolis force ($\vec{F}_C$), and friction force ($\vec{F}_F$). The physical equations of the above mentioned forces are as follows:

$$\vec{F}_G = \rho\delta V\vec{g}, \tag{23a}$$

$$\vec{F}_{PG} = -\nabla P\delta V, \tag{23b}$$

$$\vec{F}_C = -2\Omega \times \vec{u}, \tag{23c}$$

$$\vec{F}_F = -\rho\alpha\vec{u}, \tag{23d}$$

where δV is finite volume of the air, $\vec{g}$ represents the gravitational acceleration, ∇P represents the pressure gradient, Ω is rotation of the Earth, $\vec{u}$ represents the velocity vector of the wind, and α is the friction coefficient. Put the value of 23a, 23b, 23c and 23d into (21). Thus we get

$$\rho\frac{\Delta\vec{u}}{\Delta t} = (\rho\delta V\vec{g}) + (-\nabla P\delta V) + (-2\Omega \times \vec{u}) + (-\rho\alpha\vec{u}), \tag{24}$$

where, the acceleration $\vec{\alpha}$ in (21) is rewritten as $\vec{\alpha} = \frac{\Delta\vec{u}}{\Delta t}$; for simplicity, set $\Delta t = 1$; for an infinitesimal air parcel, set $\delta V = 1$, which simplifies (24) to

$$\rho\Delta\vec{u} = (\rho\vec{g}) + (-\nabla P) + (-2\Omega\sim\vec{u}) + (-\rho\alpha\vec{u}) \tag{25}$$

form (22), the density ρ can be written in terms of the pressure; thus (25) can be rewritten as

$$\nabla\vec{u} = \vec{g} + \left(-\nabla P\frac{RT}{P_{cur}}\right) + \left(\frac{-2\Omega\times\vec{u}RT}{P_{cur}}\right) + (-\alpha\vec{u}), \tag{26}$$

Where P_{cur} is the pressure of present location, it is assumed in the WDO algorithm that velocity and position of the air parcel are changing at each iteration. Thus, $\Delta\vec{u}$ can be written as $\Delta\vec{u} = \vec{u}_{new} - \vec{u}_{cur}$, where $\vec{u}_{new}$ represents the velocity in next iteration and $\vec{u}_{cur}$ is the velocity at the current iteration. $\vec{g}$ and ∇P are vectors, they can be written in terms of direction and magnitude as $\vec{g} = |g|(0 - x_{cur}), -\nabla P = |P_{opt} - P_{cur}|(x_{opt} - x_{cur})$, P_{opt} is the optimum pressure point that has been found so far, x_{opt} is the optimum location that has been found so far, and x_{cur} is the current location; updating (26)

$$\vec{u}_{new} = (1-\alpha)\vec{u}_{cur} - gx_{cur} + \left(\frac{RT}{P_{cur}}\left|P_{opt} - P_{cur}\right|\left(x_{opt} - x_{cur}\right)\right) + \left(\frac{-2\Omega\times\vec{u}RT}{P_{cur}}\right) \quad (27)$$

Finally, there are three additional substitutions needed. Firstly, the influence of the Coriolis force $(\Omega \times \vec{u})$ is replaced by the velocity influence from another dimension $\vec{u}_{cur}^{other\ dim}$. Secondly, all the coefficients are combined together; that is $c = -2RT$. Thirdly, in some cases where the pressure is extremely large, the updated velocities are too large to become meaningless and the efficiency of the WDO algorithm will be reduced. So the actual pressure value is replaced by rank among all air parcels based on their pressure values, the resulting equation of updating the velocity can be described as in (26), and the equation of updating the location can be described as in (27):

$$\vec{u}_{new} = (1-\alpha)\vec{u}_{cur} - gx_{cur} + \left(RT\left|1-\frac{1}{i}\right|\left(x_{opt} - x_{cur}\right)\right) + \left(\frac{c\vec{u}_{cur}^{other\ dim}}{i}\right),$$

$$\vec{x}_{new} = \vec{x}_{cur} + (\vec{u}_{new} \times \Delta t), \quad (28)$$

where, i is the ranking among all air parcels and $\vec{x}_{new}$ represents the new location for the next iteration. WDO is similar to other nature-inspired optimization algorithms, but compared to other optimization algorithms, the code of WDO is more simple and easy to implement; it has less few control variables that need adjustment.

3.4 RESULTS AND DISCUSSIONS

In this proposed Multicarrier System, we are considering 32 and 64 subacrrier. The transmit power of each subcarrier goes in the vicinity of 1 and 25.6 dBm with a determination of 0.1 dBm. Large search space is given by aggregate of 247 value of transmit power and the four modulation types used, B/QPSK and 16/32 QAM with comparing modulation level (M) as 2, 4, 16 and 32 respectively for 32 subcarrier and 2, 4, 16, and 64 for 64 subcarrier system. Noise floor of the system is considered as 0 dBm. The attenuation values for each sub-channel take after the Rayleigh distribution and are created autonomously. The pdf of Rayleigh distribution is given by:

$$f(x) = \frac{x}{\sigma^2} e^{\left(\frac{-x^2}{2\sigma^2}\right)}, \quad x \geq 0 \quad (26)$$

where σ^2 is called fading envelope of Rayleigh distribution. The proposed system model simulations are carried out in MATLAB in order to compare the performance of four algorithms for different modes. Average fitness score, modulation level, transmit power and BER are the metrics for performance comparison of the four engines. The population size is 30 and number of iterations are 1000. $c_1 = c_2 = 2, maxite = 1000, w_{max} = 0.9, w_{min} = 0.9$ for PSO. Initial loudness, initial pulse emission rate, minimum frequency, maximum frequency and constant are $A_i^0 = r_i^0 = 0.5, f_{max} = 2, f_{min} = 0$ for BAT, Scaling factor $F = 0.7$ and crossover probability $CR = 0.3$ for DE and the coefficient $RT = 3$ in gaslow, gravitational constant $g = 0.2$, coriolis effect $c = 0.4$, maximum allowed speed $maxV = 0.3$ for WDO respectively based engine. Channel attenuation is calculated with parameter $\sigma^2 = 0.5$.

Average fitness value obtained for particle swarm optmization, BAT algorithm, differential evolution and wind driven optimization based CDE for four different transmission parameters in a multicarrier system are given in Table 3.2. The average value for BER in terms of MHz lower, transmit power in terms of lower and modulation level in terms of bits per symbol is higher for given algorithms. These results are obtained after averaging 1000 montecarlo stimulation results obtained for each mode. Also the number of iterations required to reach the optimal generation or getting convergedfor both the engines is quite small as compared to previous works [10].

Table 3.2: Optimized Average Fitness Value For Various Metaheristic Techniques For Three Modes

		Average Fitness Value							
MODE	**# of SC**	**PSO**		**BAT**		**DE**		**WDO**	
		MEAN	**S.D**	**MEAN**	**S.D**	**MEAN**	**S.D**	**MEAN**	**S.D**
1	**32**	0.8756	0.0126	0.9334	0.0043	0.9385	0.0043	**0.9399**	**0.0097**
	64	0.8602	0.0105	0.9055	0.0048	0.9369	0.0028	**0.9395**	**0.0112**
2	**32**	0.8624	0.0261	0.9407	0.0123	0.9629	0.0094	**0.9756**	**0.0034**
	64	0.8363	0.0433	0.8502	0.0183	0.9523	0.0066	**0.9569**	**0.0087**
3	**32**	0.8678	0.0855	0.9083	0.2522	0.9142	0.0267	**0.9576**	**0.0077**
	64	0.7234	0.0622	0.8865	0.0225	0.8875	0.1502	**0.9499**	**0.0085**

3.4.1 Optimization of Average Fitness Values

The optimization average fitness value is obtained using the simutaion parameters given in previous section and tabulated in Table 3.2. from this table, it is clear that WDO outperforms other optimization techniques for all modes. The comparison of the convergence characteristics of WDO, DE, BAT and PSO based CDE for the average fitness values for different transmission scenarios is given in Figure 3.1-3.3 for all subcarriers.

From the convergence characteristics shown in Figure 3.1 - 3.3 and from Table 3.2 , it is conclude that WDO performs superior than DE, BAT and PSO based CDE design in all types of services.

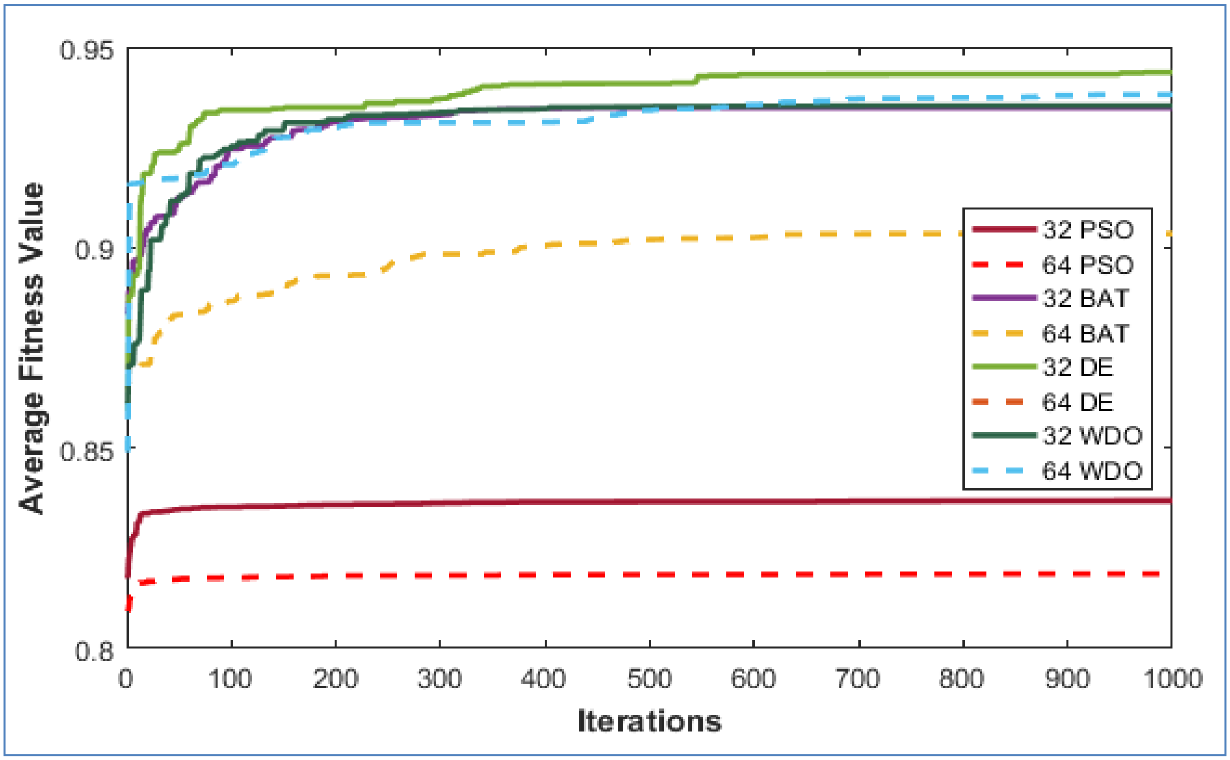

Figure 3.1: Convergence characteristics for average fitness value for Mode-1

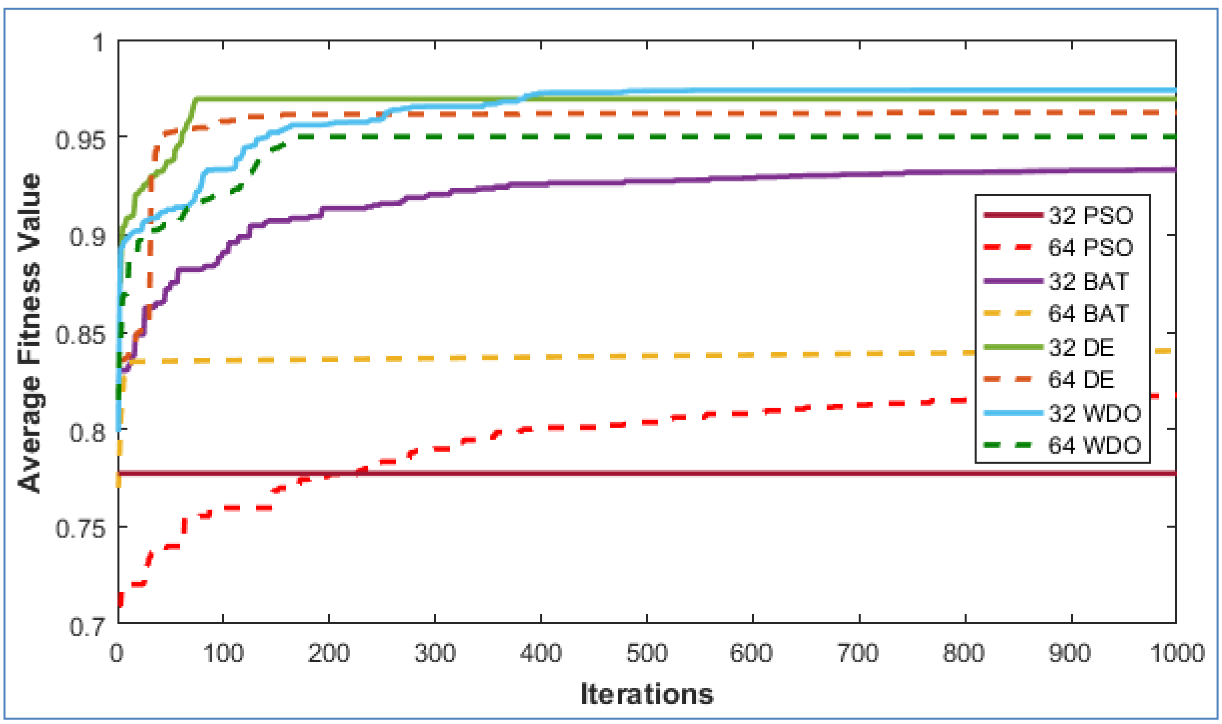

Figure 3.2: Convergence characteristics for average fitness value for Mode-2

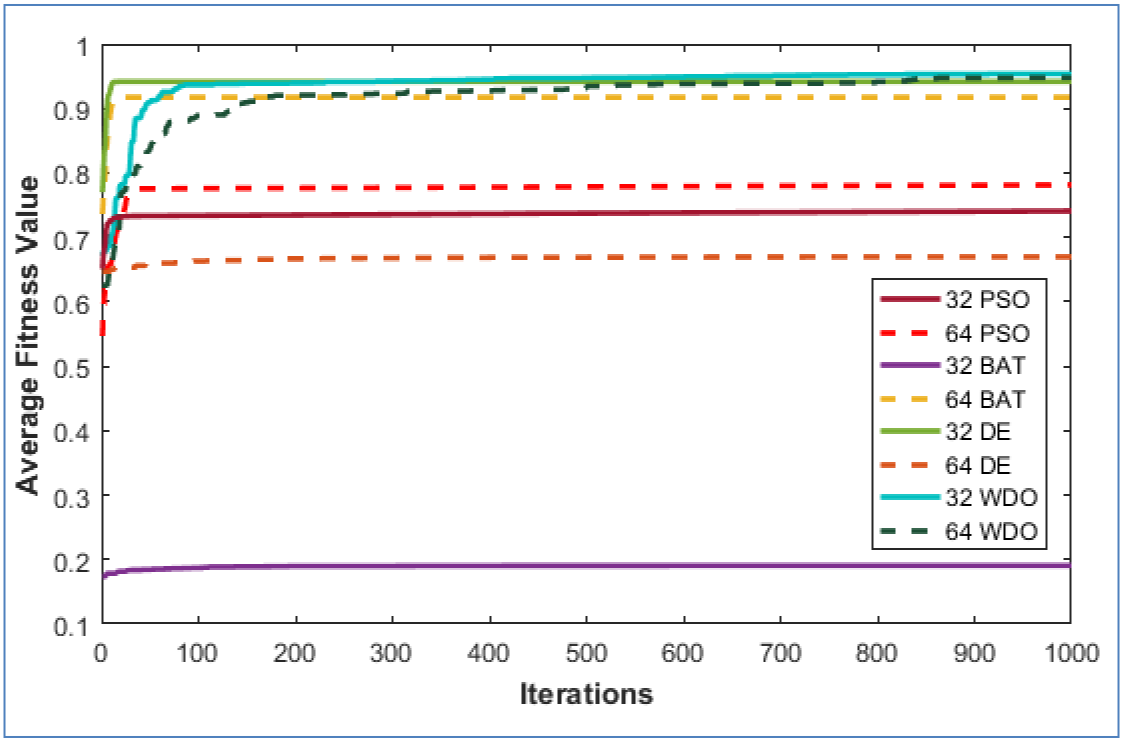

Figure 3.3: Convergence characteristics for average fitness value for Mode-3

3.4.2 Optimization of Average Transmission Parameters

Form Table 3.3 - Table 3.4 and Figure 3.4 - 3.6 gives the decision results obtained which show that WDO performs better than other optimization techniques for different objective function. Figure 3.4 shows the minimium BER for Mode-1, Figure 3.5 shows the minimium power for Mode-2 and Figure 3.6 shows the maximum throughput for Mode-3.

- **32 Subcarrier**

Table 3.3: Optimized Average Transmission Parameters For Various Metaheristic Techniques For Three Modes (32 Subcarrier)

Average Transmission Parameters (32 Sub-carrier)					
Modes	**Parameters**	**Algorithms**			
		PSO	**BAT**	**DE**	**WDO**
Mode-1	**Transmit Power**	12.0822	15.2275	15.1290	7.2022
	Modulation Index	13.8238	15.1289	14.3449	8.5341
	BER	0.0377	2.7183e-07	1.7001e-05	0.0049
Mode-2	**Transmit Power**	12.7908	19.0663	1.1450	1.0141
	Modulation Index	15.3664	19.6907	28.8125	30.6836
	BER	0.0340	1.1172e-07	0.1513	0.1323
Mode-3	**Transmit Power**	14.2261	9.0187	14.5394	17.7297
	Modulation Index	27.2055	28.8926	31.0625	31.6057
	BER	0.0551	0.0118	0.0388	0.0187

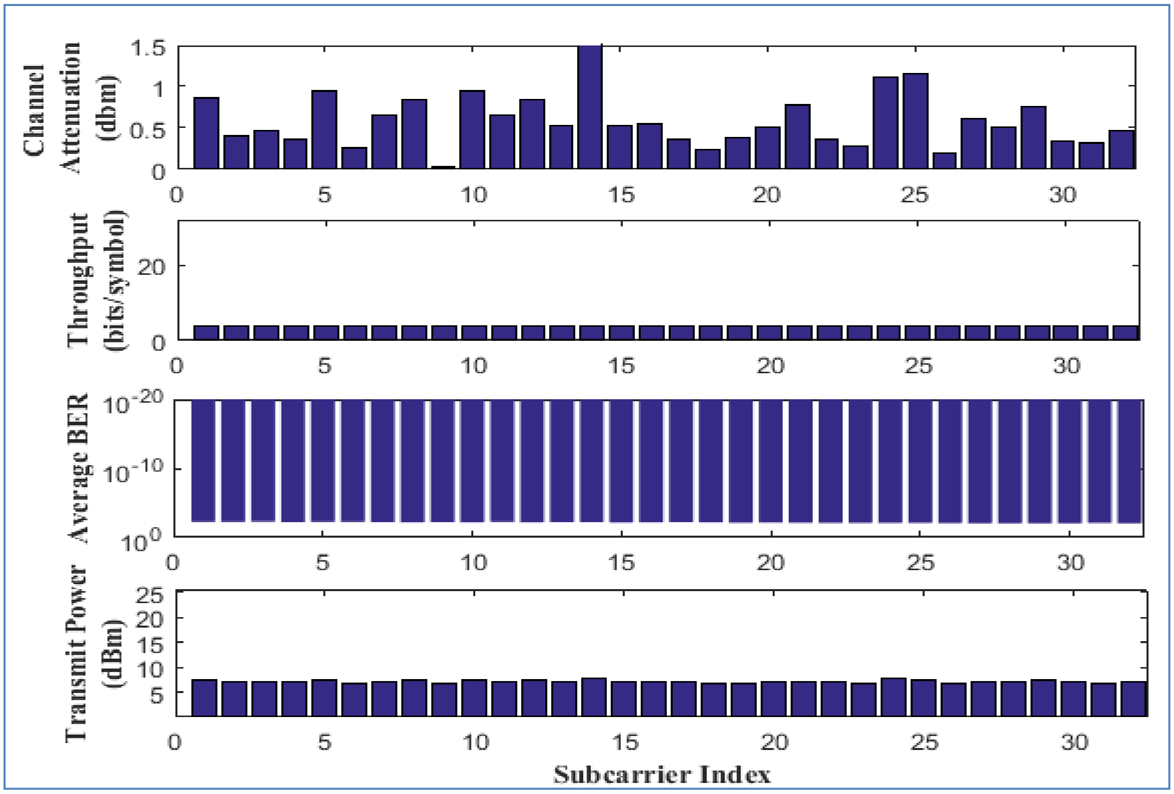

Figure 3.4: WDO based decision results for Mode-1 (32 Subcarrier)

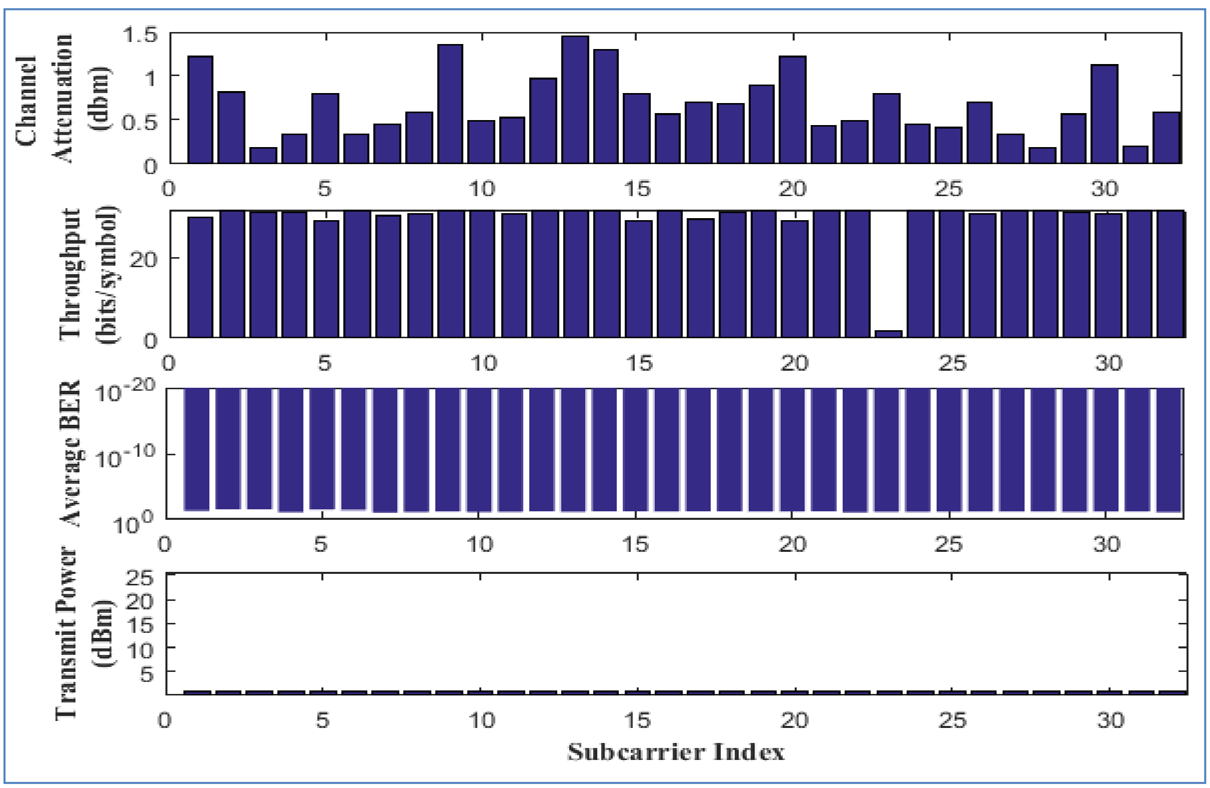

Figure 3.5: WDO based decision results for Mode-2 (32 Subcarrier)

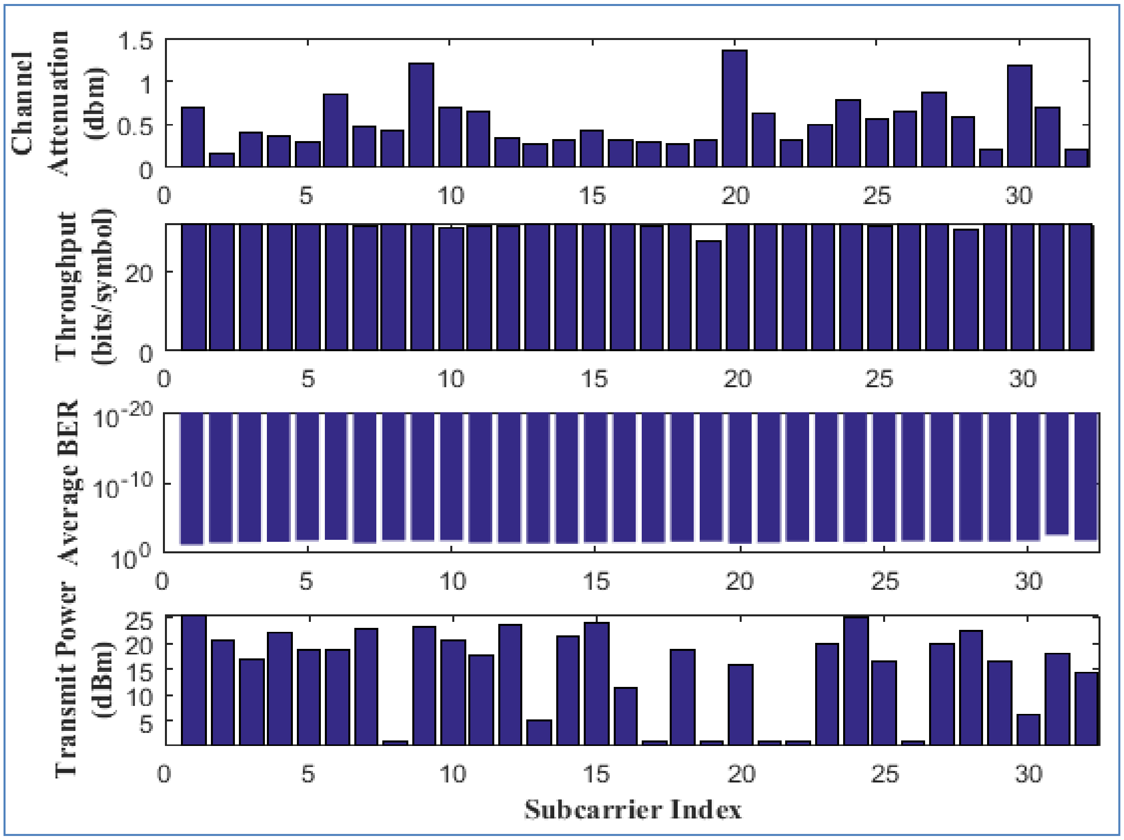

Figure 3.6: WDO based decision results for Mode-3 (32 Subcarrier)

- **64 Subcarrier**

Table 3.4: Optimized Average Transmission Parameters For Various Metaheristic Techniques For Three Modes (64 Subcarrier)

Average Transmission Parameters (64 Sub-carrier)					
Modes	**Parameters**	**Algorithms**			
		PSO	**BAT**	**DE**	**WDO**
Mode-1	**Transmit Power**	15.3402	12.2589	7.0348	7.0267
	Modulation Index	25.0095	22.9311	16.5594	9.1599
	BER	5.8001e-06	0.0402	0.0085	0.0092
Mode-2	**Transmit Power**	1.3029	13.1178	17.5820	19.6679
	Modulation Index	54.5262	22.7841	7.7427	53.9909
	BER	0.1674	0.0328	3.8399e-06	1.5788e-06
Mode-3	**Transmit Power**	15.1182	13.5030	8.7085	3.2047
	Modulation Index	60.3188	37.7765	48.4950	60.1666
	BER	0.0684	0.0468	0.0242	0.1095

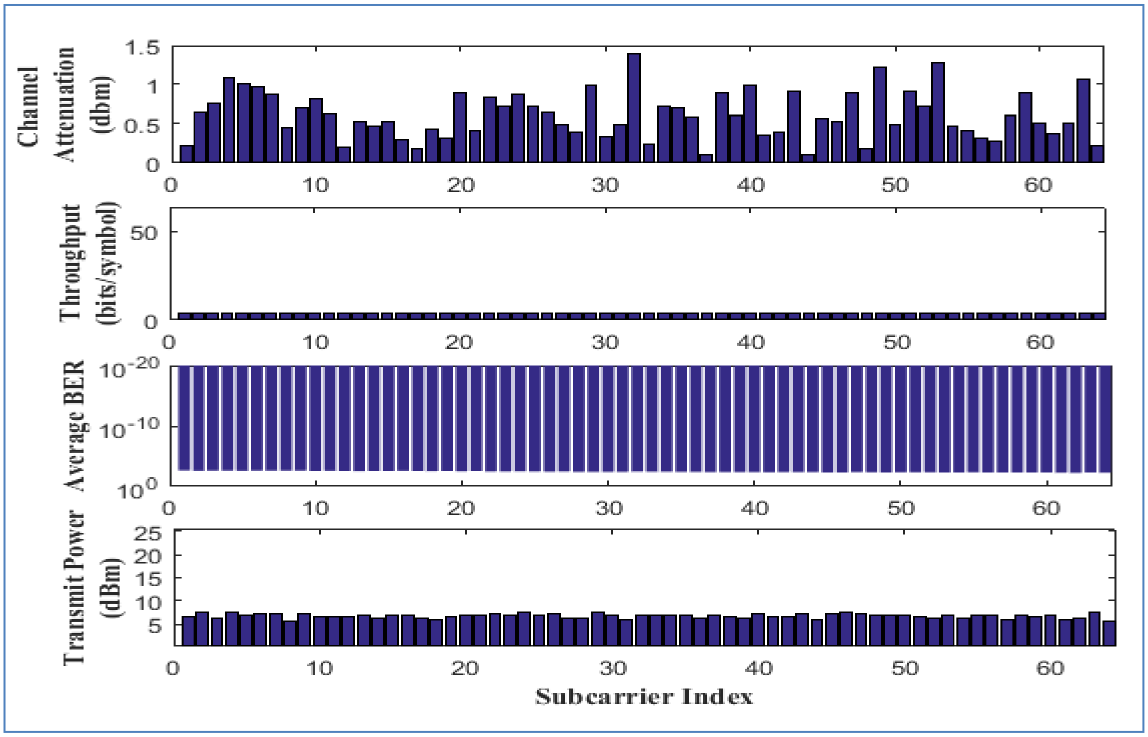

Figure 3.7: WDO based decision results for Mode-1 (64 Subcarrier)

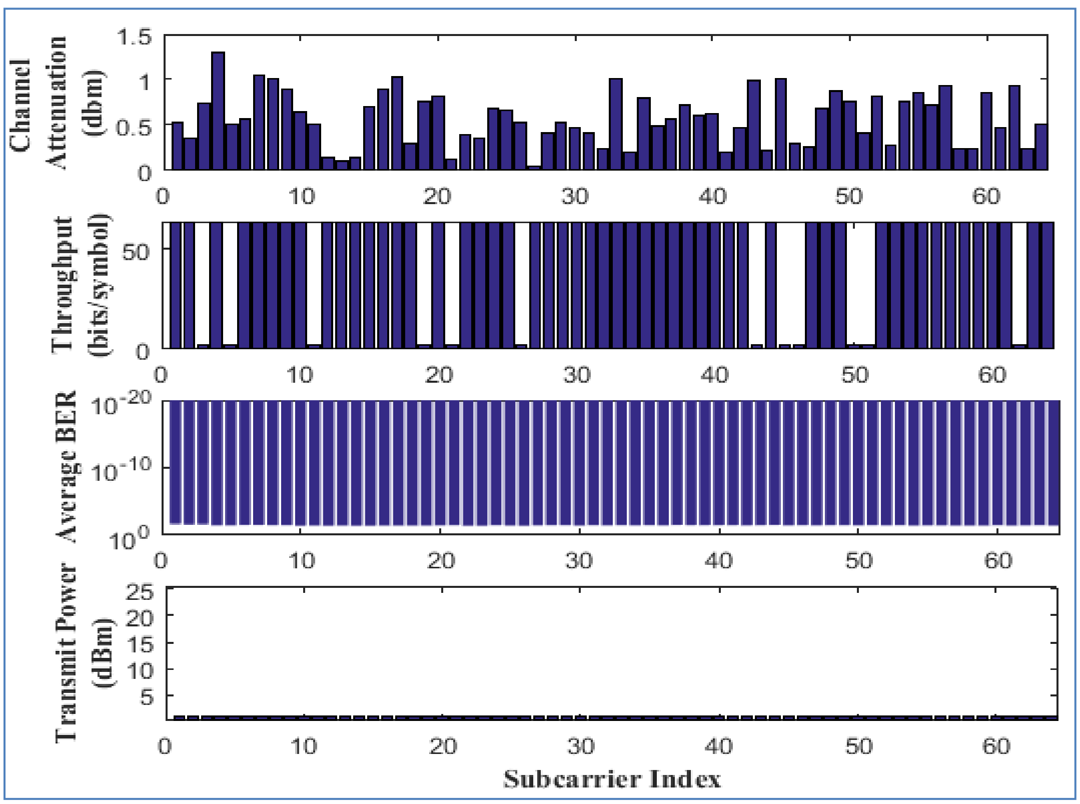

Figure 3.8: WDO based decision results for Mode-2 (64 Subcarrier)

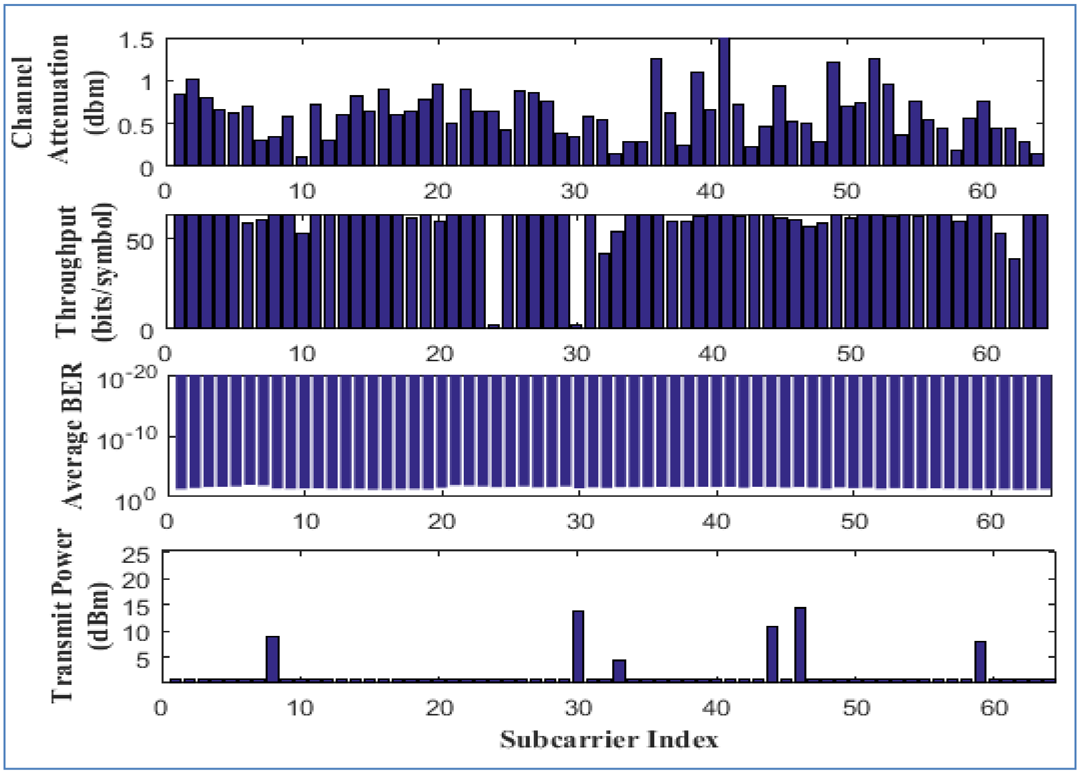

Figure 3.9: WDO based decision results for Mode-3 (64 Subcarrier)

From these convergence characteristics form Figure 3.1-3.3 and decision results form Figure 3.4-3.9 we can concluded that WDO based CDE is able to perform better than particle swarm optimization, BAT algorithm and differential evolution for all types of service scenarios. For the Mode 1, BER is much lower for all the subcarriers but at the cost of high transmit power while in Mode 2, the transmit power is much lower leading tohigher BER. Similarly for Mode 3, the throughput is maximized by increasing the modulation level of all subcarriers while maximizing transmit power and BER. Table 3.3 it is evident that that WDO performs better than other optimization techniqes for 32 and 64 subcarrier, OFDM sceme therfore figure 3.4-3.6 representents the decision results for WDO scenarios.

CHAPTER-4

MULTIOBJECTIVE OPTIMIZATION PROBLEM WITH FIVE OBJECTIVES

In this chapter, we have extended the previous work done in chapter 3, by introducing two new objectives function which is interference and spectral efficiency. We have used this objective function to minimize the interference and maximizing the spectral efficiency. With the help of previous three objectives and these two objectives we will achieve best optimization results. The bio-inspired optimization techniques have been taken like particle swarm optimization, differential evaluation, BAT algorithm and WDO (which is also discussed in chapter 3) for 32 and 64 subcarriers.

4.1 OBJECTIVE FUNCTION FOR CR NETWORKS

Objective or fitness function should enable the system to reach one optimal set of parameters. Since the objectives in a wireless environment are different in number, the issue of CR engine design can be figured as a multi-objective optimization problem. The different objective functions [8-9] are discussed in detail in next subsections.

4.1.1 Objective function for Minimization of Interference

Minimizing the interference is main goal in frequency band. Transmission parameters such as time division duplex, power and bandwidth percentage determine the amount of interference caused by SU transmission. Fitness function for the minimization of interference given as:

$$f_{minI} = 1 - \frac{\sum_{i=1}^{L}[(P_i \times B_i \times TDD_i) - (P_{min} \times B_{min})]}{L(P_{max} \times B_{max} \times 100)} \tag{29}$$

Where B_i is the bandwidth and TDD_i is the time division duplex for i^{th} subcarrier while B_{min} and B_{max} are minimum and maximum bandwidth values.

4.1.2 Objective function for Maximization of Spectral Efficiency

Maximizing spectral efficiency means maximizing the quantity of information that can be transmitted over a given bandwidth so that given band of frequency is utilized. As this objective is associated directly to BW and amount of information transmitted.

$$f_{maxS} = \frac{\sum_{i=1}^{L} \frac{M_i \times R_{S,i} \times B_{min}}{M_{max} \times R_{S,max} \times B_i}}{L} \tag{30}$$

Where $R_{S,i}$ and $R_{S,max}$ is the symbol rate for i^{th} subcarrier and maximum symbol rate respectively.

4.1.3 Objective function for Minimization of Power Consumption

CR environment may have maximum weighting on power minimization consumption. Therefore objective function for power consumption minimization is given as:

$$f_{minP} = 1 - \sum_{i=1}^{L} \frac{P_i}{KP_{max}} \tag{31}$$

where P_i corresponds to the transmit power for the i^{th} subcarrier and P_{max} is the highest allowed power for the subcarrier.

4.1.4 Objective function for Minimization of Bit Error Rate

Bit error rate is influenced by transmit power, noise power, modulation type etc. The fitness function for minimization of Bit error rate (converted to maximization problem) is defined as:

$$f_{minBER} = 1 - \frac{log_{10}(0.5)}{log_{10}(P_{avBER})} \tag{32}$$

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

4.1.5 Objective function for Maximization of Throughput

The good quality of information received at receiver is known as throughput. Maximizing throughput is valuable in a variety of services. For the OFDM system, the overall throughput is influenced by the modulation level of each of the subcarriers. Thus the objective function for maximization of throughput is given as:

$$f_{maxTPT} = \frac{\frac{1}{L}\sum_{i=1}^{L} log_2 M_i - 1}{log_2 M_{max} - log_2 M_{min}} \tag{33}$$

where, M_i is the modulation level of i^{th} subcarrier, M_{max} and M_{min} are the maximum and minimum allowed modulation levels of the system.

4.2 FITNESS FUNCTION EVALUATION USING WEIGHT SUM APPROACH

The calculation of the optimal value for each of the given functions will bring a set of local keys in place of a global key. Different works have been reported in the literature to solve an optimization problem having more than one fitness function. One of the approach is using weighted sums that allow us to combine different single objective functions into one aggregate multiple objective function.

Multiple-objective fitness function of this cognitive system, considering above five objectives, is given below. These weight values will decide the search direction for the optimization algorithms.

$$f = w_1 f_{minBER} + w_2 f_{minP} + w_3 f_{maxTPT} + w_4 f_{minI} + w_5 f_{maxS} \quad (34)$$

The different scenarios or service types observed by communication channel with reference to required application along with the weight values are given in Table 4.1. These weights are assigned based on experimentation technique as higher objective function value is achieved corresponding to these weights.

Table 4.1: Weight Scenarios for Different Service Types

Transmission Scenario		w_1	w_2	w_3	w_4	w_5
Mode 1	**Minimize Power**	0.75	0.05	0.05	0.10	0.05
Mode 2	**Minimize BER**	0.05	0.8	0.05	0.05	0.05
Mode 3	**Maximize Throughput**	0.05	0.05	0.8	0.05	0.05
Mode 4	**Minimize Interference**	0.10	0.05	0.05	0.75	0.05
Mode 5	**Minimize Spectral Efficiency**	0.05	0.05	0.35	0.15	0.4

4.3 PROBLEM FORMULATION

In this work, multicarrier OFDM CR system is considered having 32 and 64 number of sub-carriers. Performance of WDO, BAT, DE and PSO is tested on five different transmission scenarios given in Table 4.2. The attenuation values for each sub-channel follow the Rayleigh distribution and are generated independently. Large search space is provided by five different transmission parameters whose range is shown in Table 4.2.

Table 4.2: Range of Transmission Parameters

Transmission Parameter	**Minimum Value**	**Maximum Value**
Power	1 dBm	25.6 dBm
Modulation Index	2	256
Bandwidth	2 MHz	32 MHz
TDD	25%	100%
Symbol Rate	125 Ksps	1 Msps

The population size and maximum number of iterations are taken as 30 and 1000 respectively, while algorithm specific stimulation parameters are given in Table 4.3.

Table 4.3: Simulation Parameters

S.No.	Name of Parameter	Value
Particle Swarm Optimization		
1	Acceleration Factor (c_1 and c_2)	2
2	Inertial Weight (w_{min})	0.4
3	Inertial Weight (w_{max})	0.9
BAT Algorithm		
1	Initial Loudness $\left(A_i^0\right)$	0.5
2	Initial Pulse emission rate $\left(r_i^0\right)$	0.5
3	Minimum frequency (f_{min})	0
4	Maximum frequency (f_{max})	2
5	Constant ($\alpha = \beta$)	0.9
Differential Evolution		
1	Scaling Factor (F)	0.7
2	Crossover probability (CR)	0.3
Wind Driven Optimization		
1	RT Cofficient (RT)	3
2	Gravitational Constant (g)	0.2
3	Coriolis Effect (c)	0.4
4	Maximum Speed ($maxV$)	0.3

4.4 SIMULATION RESULTS AND DISCUSSIONS

Fitness values obtained for WDO, PSO, BAT and DE based CDE for the four different transmission scenarios in a multicarrier system are given in Table 4.4. Besides this, average transmit power of all the subcarriers in dBm, average modulation level in bits/symbol, average bandwidth in MHz, time division duplex percentage in (%) and average symbol rate in symbols per sec obtained at the last iteration for four, the algorithms are tabulated in Table 4.4. These results are obtained after averaging 1000 montecarlo simulation results obtained for each mode.

4.4.1 Convergence Characteristics

From the convergence characteristics shown in Figure 4.1-4.5 and the results given in Table 4.4, it can be concluded that WDO algorithm performs superior than DE, BAT and PSO for CDE design in all types of service scenarios. Using the various parameters and ranges defined in table 4.4 we have obtained average fitness value for varying number of iterations for 32 and 64 subcarrier. Figure 4.1-4.5 shows the plot for different modes.

Table 4.4: Average Results Obtained for PSO, BAT, DE and WDO

		Average Fitness Value							
MODE	**# of SC**	**PSO**		**BAT**		**DE**		**WDO**	
		MEAN	**S.D**	**MEAN**	**S.D**	**MEAN**	**S.D**	**MEAN**	**S.D**
1	**32**	0.8559	0.0293	0.9121	0.0322	0.9287	0.0109	**0.9293**	**0.0024**
	64	0.8355	0.0393	0.8814	0.0276	0.8960	0.0219	**0.9185**	**0.0047**
2	**32**	0.7859	0.0130	0.8719	0.0096	0.8732	0.0063	**0.8740**	**0.0052**
	64	0.7806	0.0182	0.8627	0.0063	0.8669	0.0111	**0.8701**	**0.0075**
3	**32**	0.7856	0.0342	0.8337	0.0793	0.8418	0.1258	**0.9495**	**0.0044**
	64	0.7571	0.0352	0.7832	0.0917	0.8018	0.1154	**0.9305**	**0.0174**
4	**32**	0.9081	0.0158	0.9249	0.0294	0.9387	0.0045	**0.9538**	**0.0143**
	64	0.8872	0.0071	0.9158	0.0258	0.9271	0.0029	**0.9447**	**0.0144**
5	**32**	0.6226	0.0754	0.6544	0.0965	0.6615	0.1209	**0.6721**	**0.0381**
	64	0.5986	0.0672	0.6143	0.0392	0.6360	0.0788	**0.6476**	**0.0327**

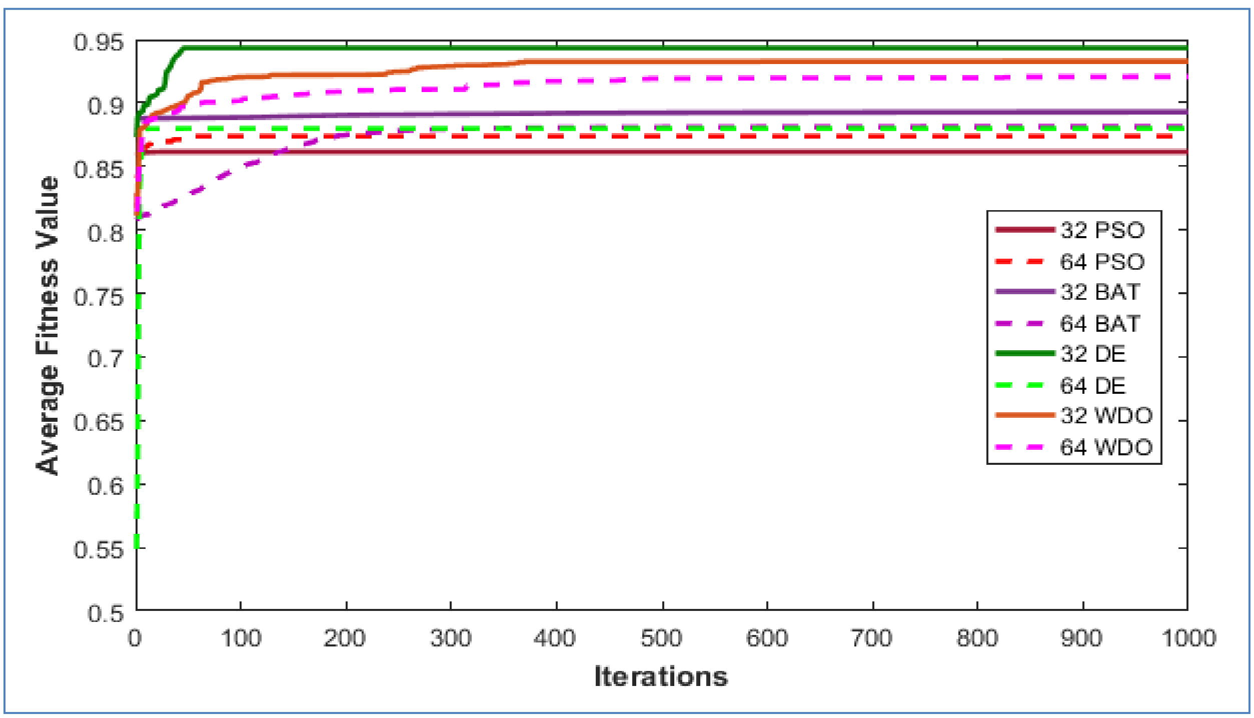

Figure 4.1: Convergence characteristics of fitness value for Mode-1

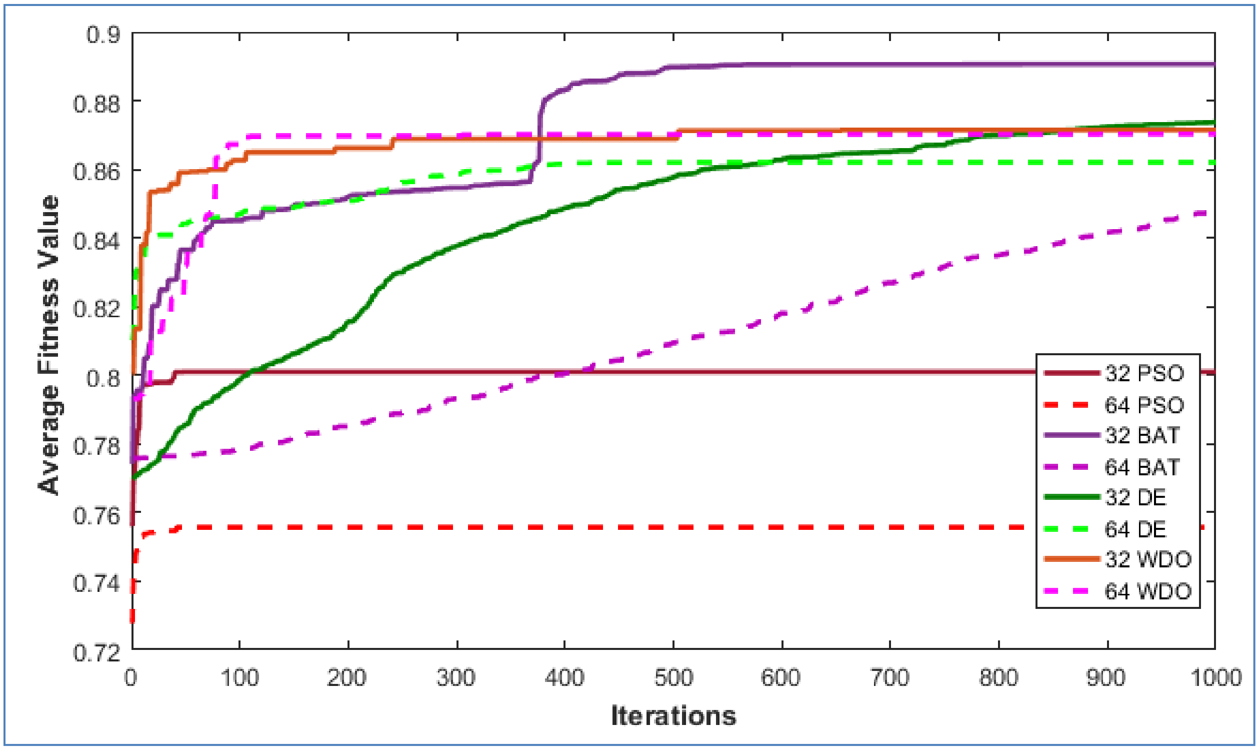

Figure 4.2: Convergence characteristics of fitness value for Mode-2

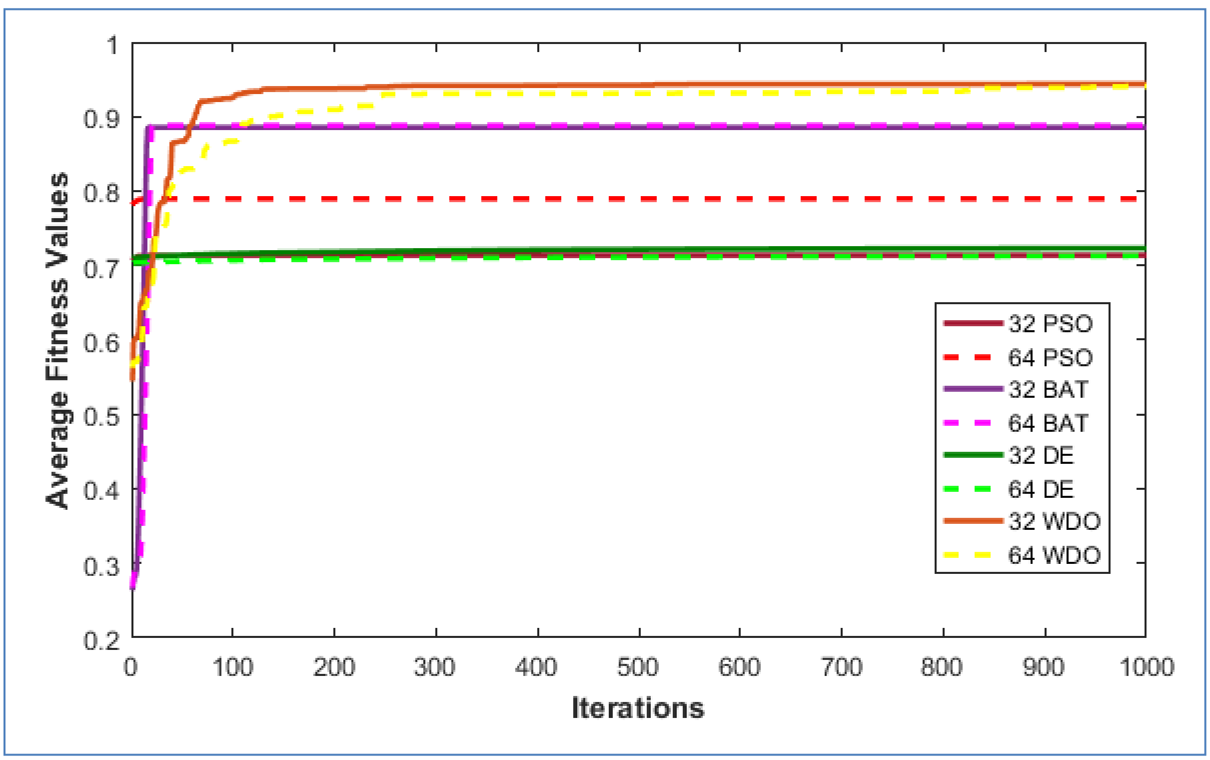

Figure 4.3: Convergence characteristics of fitness value for Mode-3

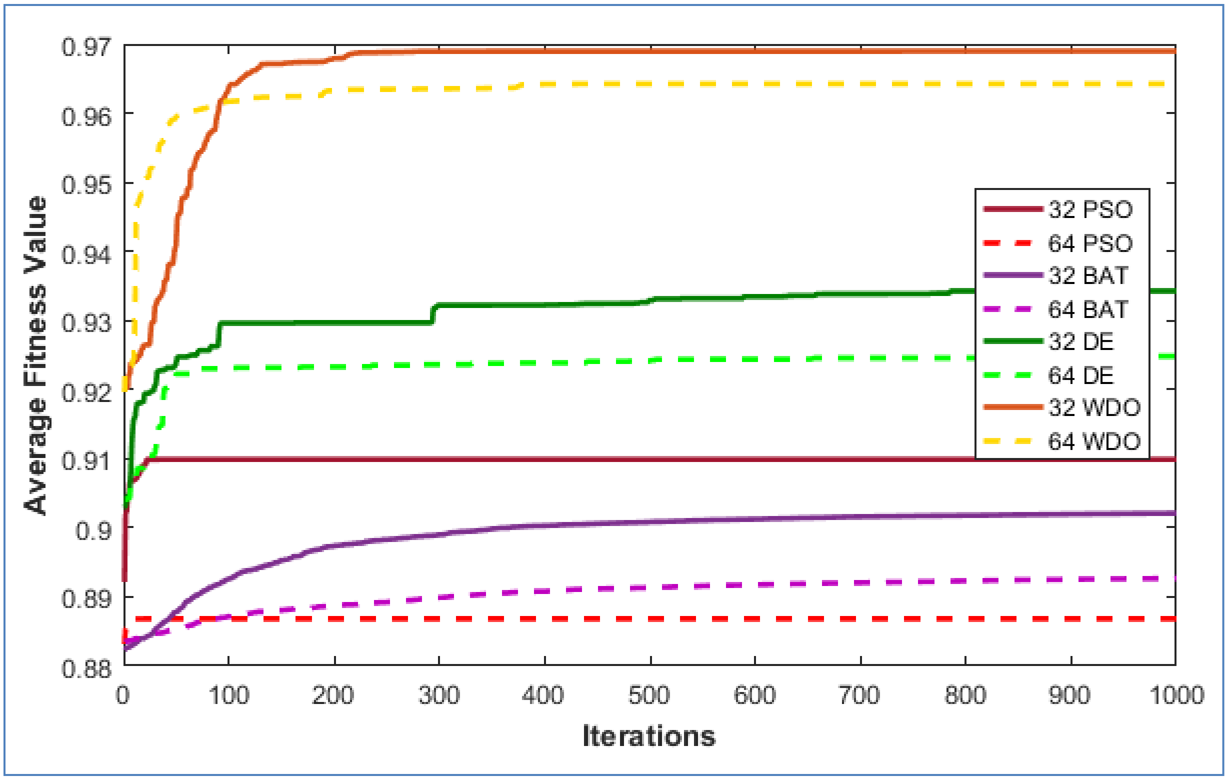

Figure 4.4: Convergence characteristics of fitness value for Mode-4

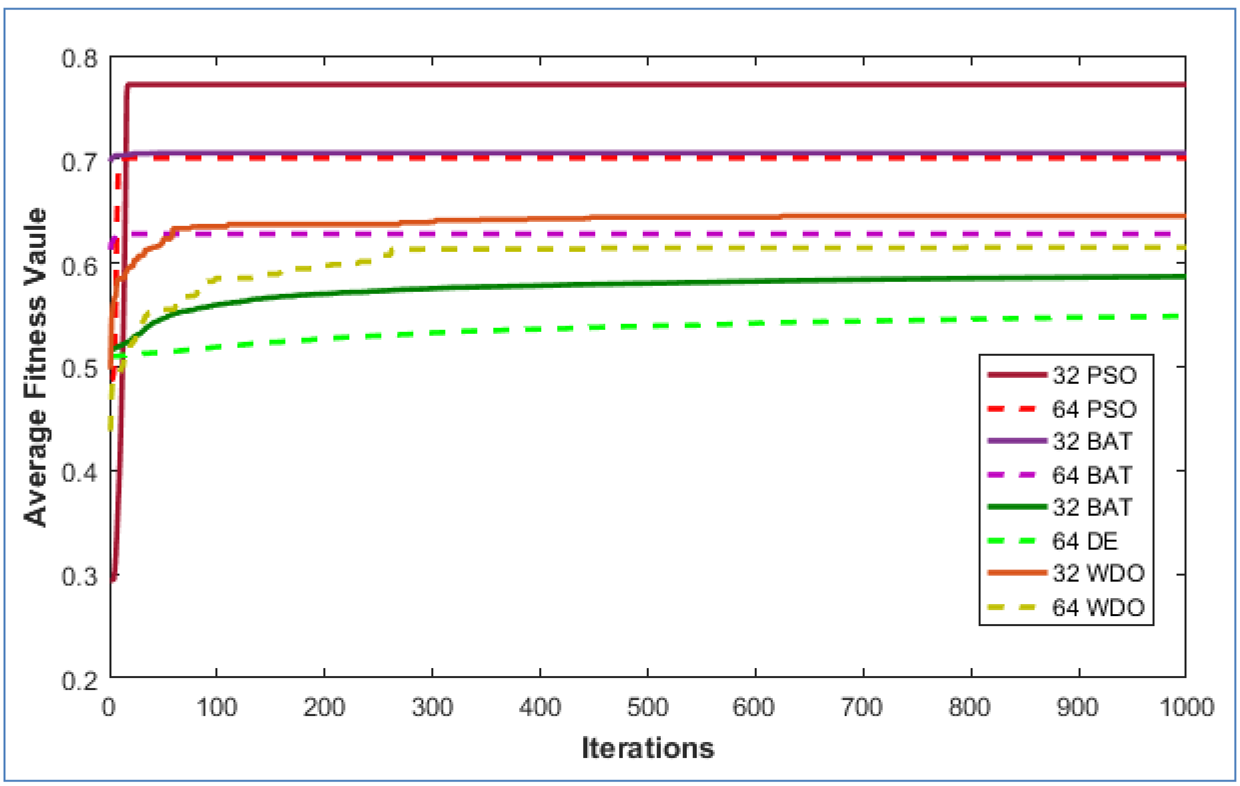

Figure 4.5: Convergence characteristics of fitness value for Mode-5

4.4.2 Optimized Decision Variables

The results of decision variables obtained at WDO based CDE for transmit power, average modulation level, average bandwidth, time division duplex percentage and average symbol rate is plot in Figure 4.6-Figure 4.15 for different subcarriers.

In Table 4.5 and Table 4.6 we have shown the average mean values and average transmission parameters for all metaheristic optimization techniques along with different types of service for 32 subcarrier and for 64 subcarrier. In figure 4.4 and 4.11, it is shown for minimize power consumption for Mode-1, figure 4.7 and 4.12 is for maximize throughput, figure 4.8 and 4.13 is for minimizing BER, figure 4.9 and 4.14 is for minimize interference and figure 4.10 and 4.15 is for maximize spectral efficiency.

- **32 subcarrier**

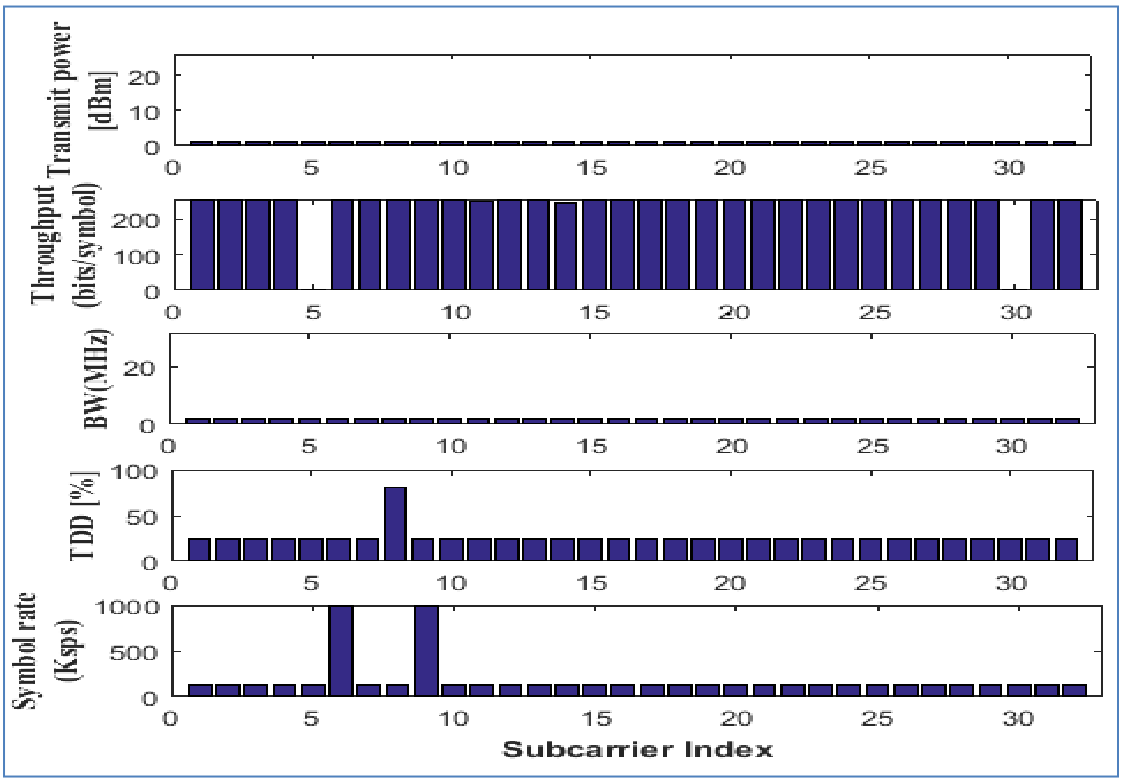

Figure 4.6: WDO based decision results for Mode-1 (32 Subcarrier)

Table 4.5: Optimized Average Transmission Parameters for Various Metaheristic Techniques for Five Mode (32 Subcarrier)

Average Transmission Parameters (32 Sub-carrier)					
Modes	**Parameters**	**Algorithms**			
		PSO	**BAT**	**DE**	**WDO**
MODE-1	**Transmit Power**	13.5508	3.6276	1.0307	1
	Throughput	155.4411	75.9193	165.5125	217.0642
	Bandwidth	18.9734	4.6816	10.4375	2.5782
	Time Division Duplex	70.5082	59.9197	62.7344	25.6286
	Symbol Rate	623.6916	807.7858	685.5469	206.9020
MODE-2	**Transmit Power**	14.5091	18.2603	20.1892	18.1051
	Throughput	153.2400	6.8334	78.9319	19.3637
	Bandwidth	16.5567	28.4130	13.0956	14.0549
	Time Division Duplex	74.1687	57.5582	57.4959	34.5228
	Symbol Rate	542.9921	765.1685	605.7722	159.9695
MODE-3	**Transmit Power**	13.5302	13.6784	11.7617	1.7044
	Throughput	125.2217	229.0125	157.2586	253.6703
	Bandwidth	16.1609	25.9063	3.5561	4.8946
	Time Division Duplex	74.9433	73.0469	59.3887	37.7462
	Symbol Rate	565.4461	633.5938	900.8420	464.3269
MODE-4	**Transmit Power**	11.3581	9.3453	1.0371	4.0312
	Throughput	103.7576	92.0398	191.8363	236.1510
	Bandwidth	16.0392	3.0424	2.8131	4.5313
	Time Division Duplex	61.9380	46.9523	28.8535	56.1924
	Symbol Rate	603.8296	762.1187	501.2358	663.6719
MODE-5	**Transmit Power**	10.3512	12.9835	13.1436	1.4046
	Throughput	207.5813	219.5279	113.8989	186.0207
	Bandwidth	13.5313	16.1778	2.3752	3.1190
	Time Division Duplex	67.6563	59.6777	59.3745	34.8431
	Symbol Rate	611.7188	619.6053	963.3283	563.6027

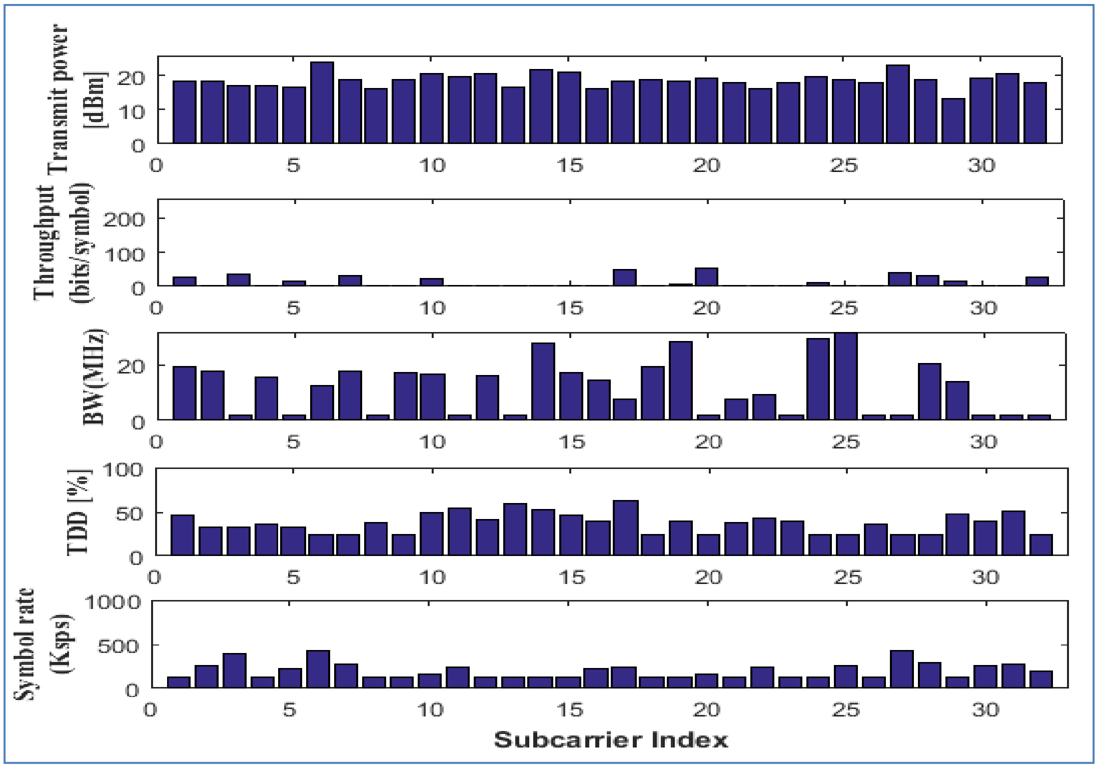

Figure 4.7: WDO based decision results for Mode-2 (32 Subcarrier)

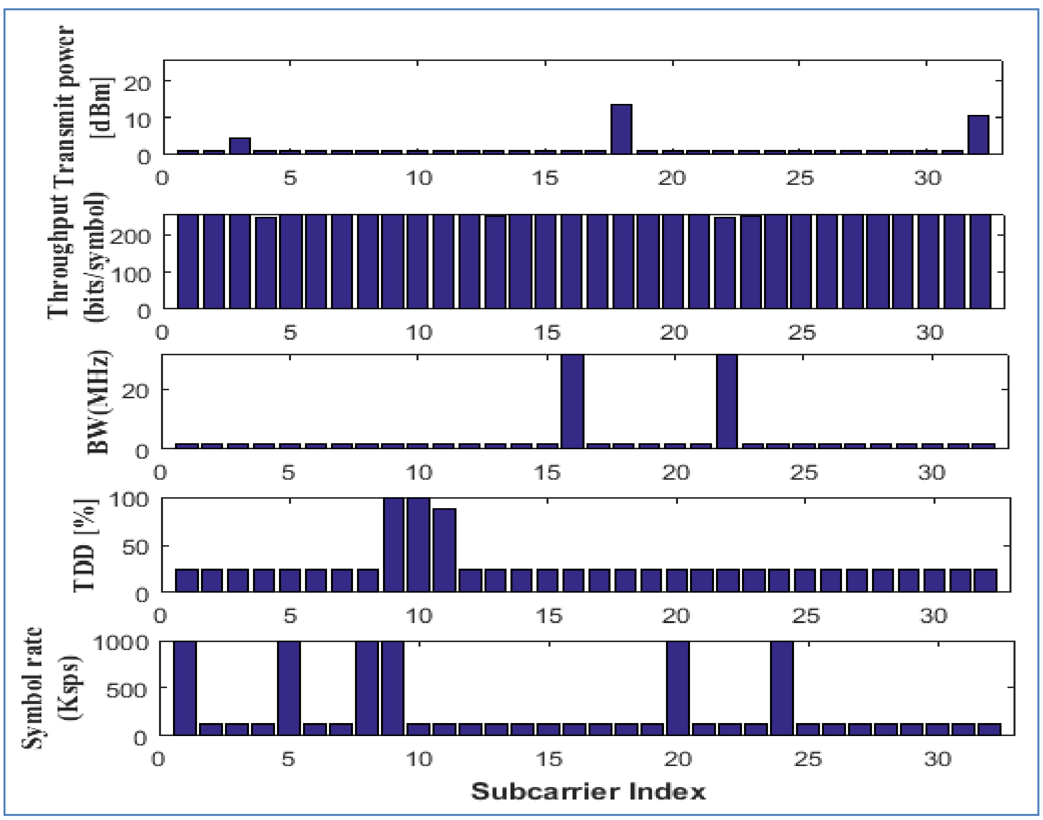

Figure 4.8: WDO based decision results for Mode-3 (32 Subcarrier)

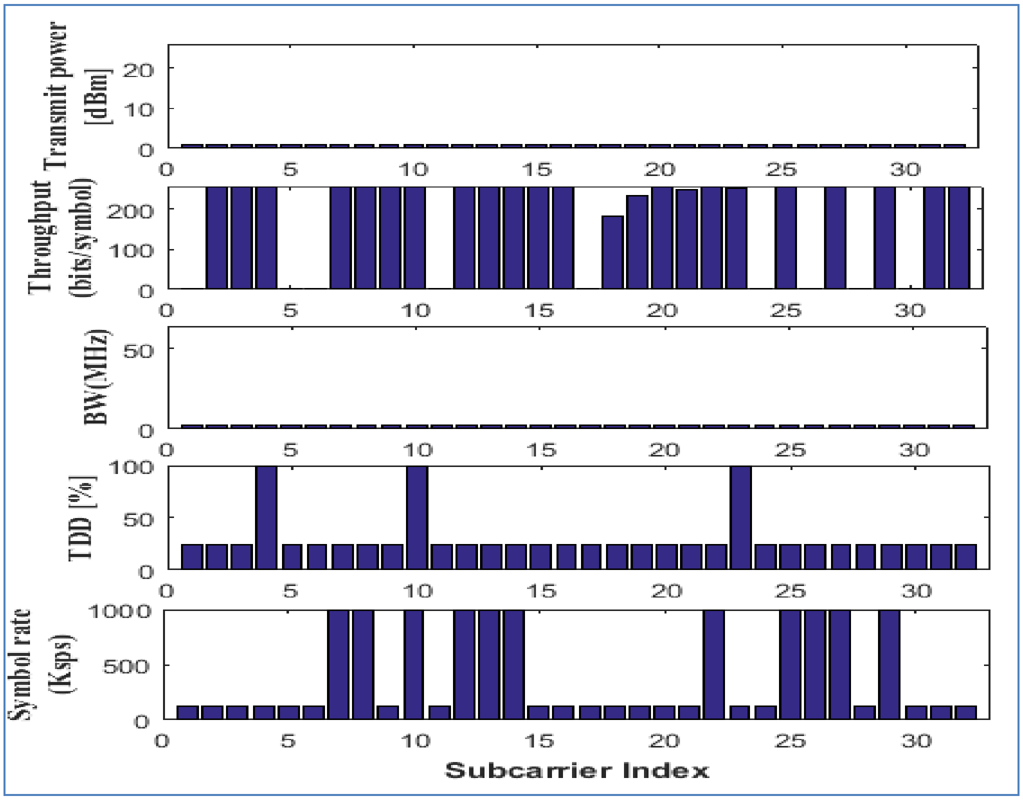

Figure 4.9: WDO based decision results for Mode-4 (32 Subcarrier)

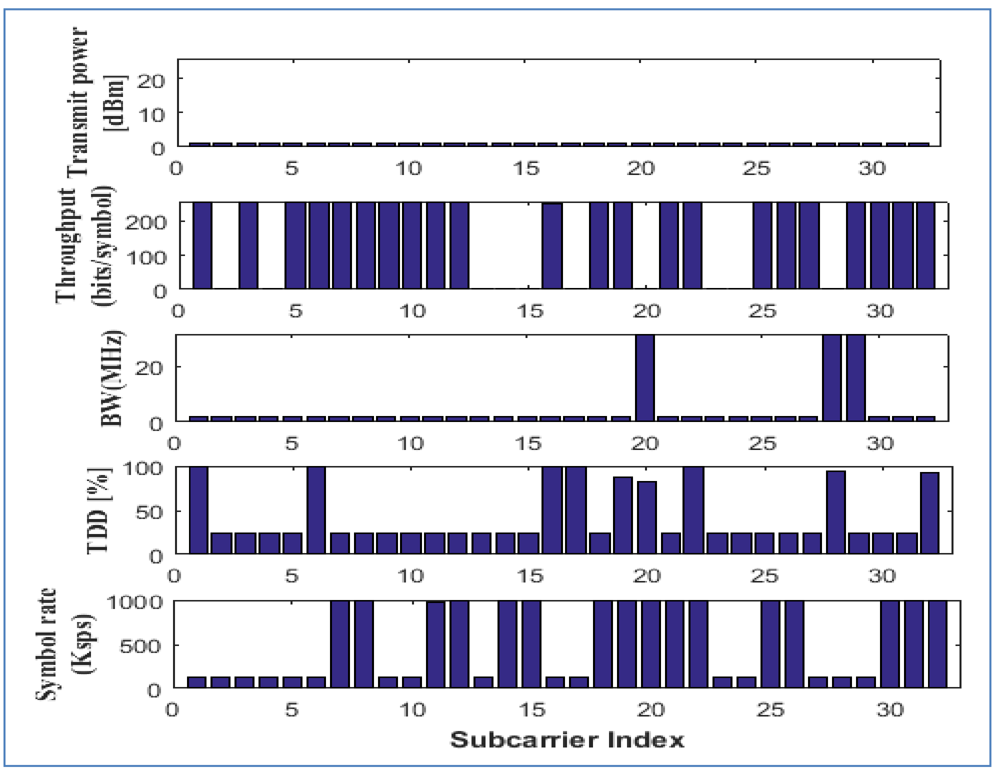

Figure 4.10: WDO based decision results for Mode-5 (32 Subcarrier)

- **64 Subcarrier**

Table 4.6: Optimized Average Transmission Parameters for Various Metaheristic Techniques for Five Mode (64 Subcarrier)

Average Transmission Parameter (64 Sub-carrier)					
Modes	**Parameters**	**Algorithms**			
		PSO	**BAT**	**DE**	**WDO**
MODE-1	**Transmit Power**	12.8570	4.1993	1.9635	1.0146
	Throughput	64.1060	64.7836	111.9867	175.3263
	Bandwidth	15.5905	21.9650	9.0298	4.0940
	Time Division Duplex	71.9552	60.9013	47.7442	25.9855
	Symbol Rate	447.5552	644.6556	371.8533	174.1901
MODE-2	**Transmit Power**	13.0570	17.6691	16.7460	17.3346
	Throughput	177.2781	58.0904	10.6023	20.2001
	Bandwidth	16.5727	28.9084	38.0491	21.5169
	Time Division Duplex	62.2822	62.7677	77.8406	33.0866
	Symbol Rate	561.5028	584.5914	663.3309	137.7335
MODE-3	**Transmit Power**	12.8680	14.0864	10.9614	2.1882
	Throughput	95.3176	218.2969	136.0125	243.8655
	Bandwidth	18.0587	37.7469	19.0078	14.6032
	Time Division Duplex	66.2449	78.5547	61.3056	42.2121
	Symbol Rate	564.1159	619.9219	679.7579	603.5457
MODE-4	**Transmit Power**	10.9375	8.8625	1.5273	7.1929
	Throughput	21.2381	95.6853	165.1500	194.9296
	Bandwidth	18.2083	12.1227	5.4056	9.6282
	Time Division Duplex	59.2938	55.1055	29.6288	62.3113
	Symbol Rate	633.0783	633.8206	391.9853	717.1003
MODE-5	**Transmit Power**	12.7576	15.2917	10.9800	2.4342
	Throughput	196.8656	168.9366	145.4598	167.8355
	Bandwidth	32.2250	20.2075	13.8860	7.8464
	Time Division Duplex	67.1875	64.3459	62.8458	34.2608
	Symbol Rate	625.3906	590.0191	751.4251	576.5090

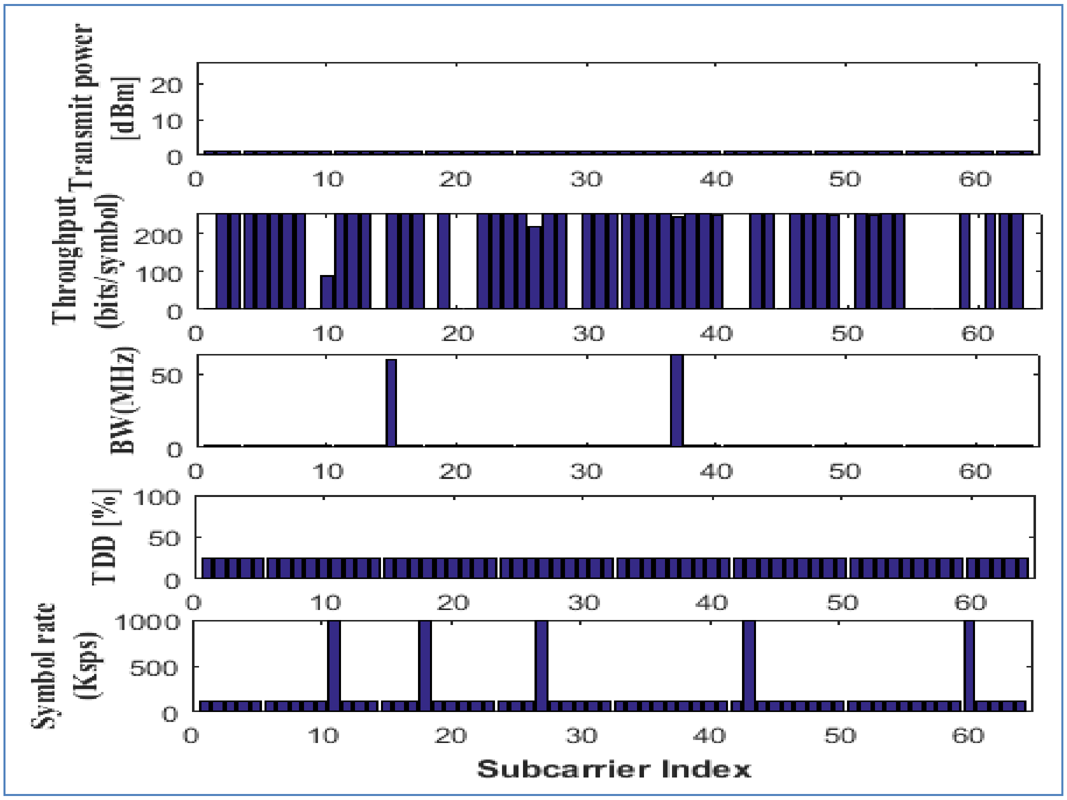

Figure 4.11: WDO based decision results for Mode-1 (64 Subcarrier)

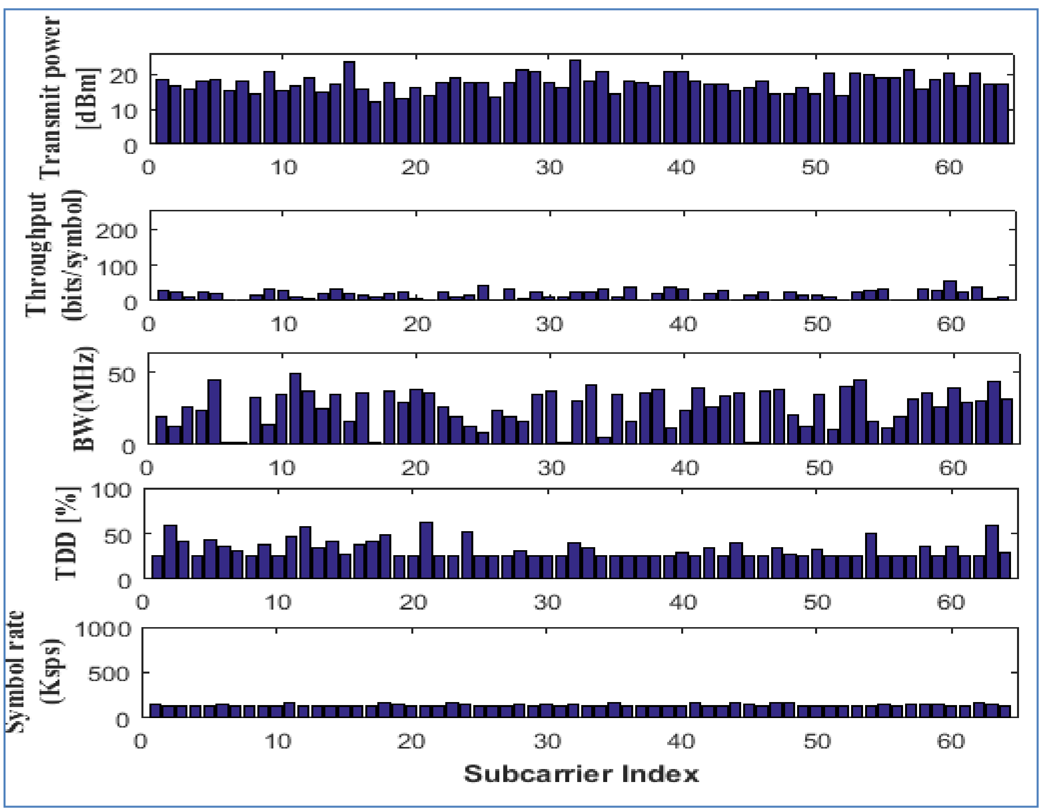

Figure 4.12: WDO based decision results for Mode-2 (64 Subcarrier)

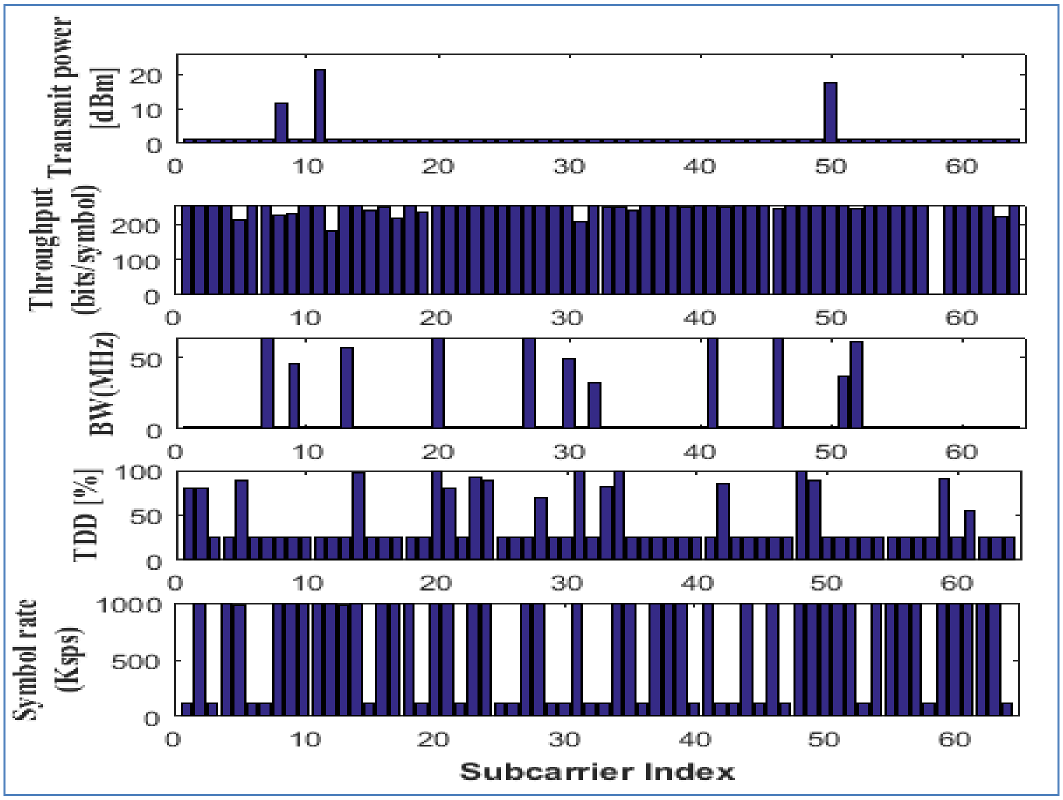

Figure 4.13 WDO based decision results for Mode-3 (64 Subcarrier)

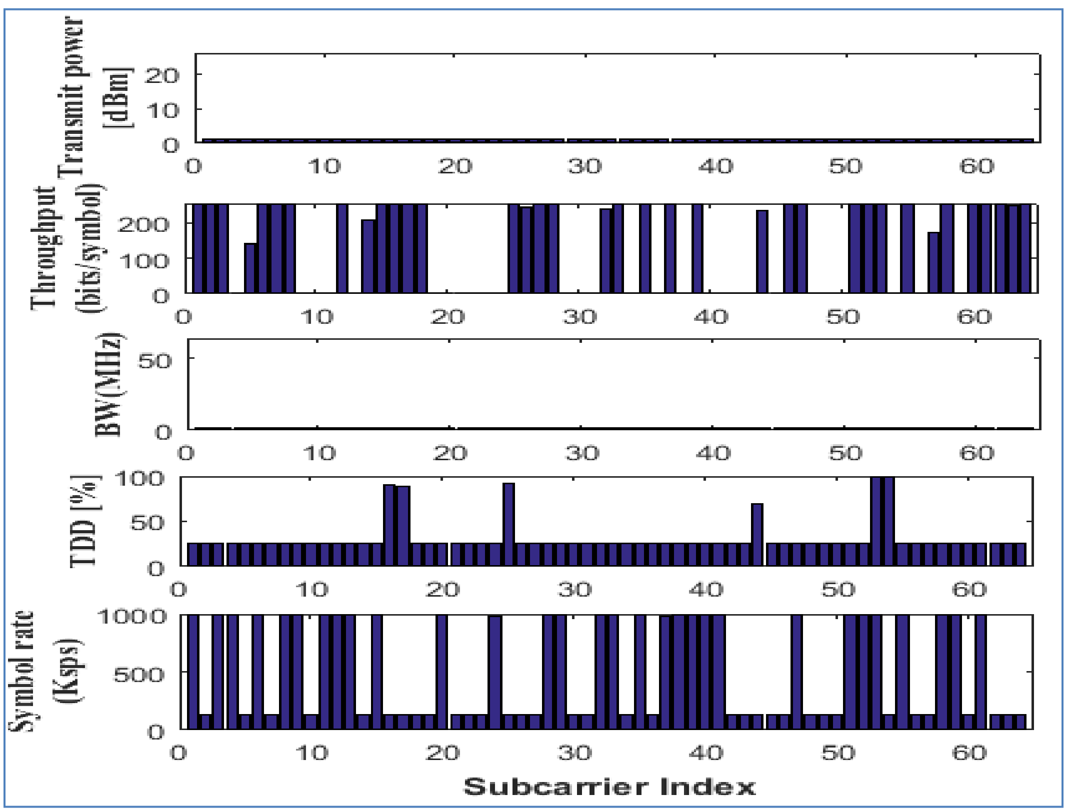

Figure 4.14: WDO based decision results for Mode-4 (64 Subcarrier)

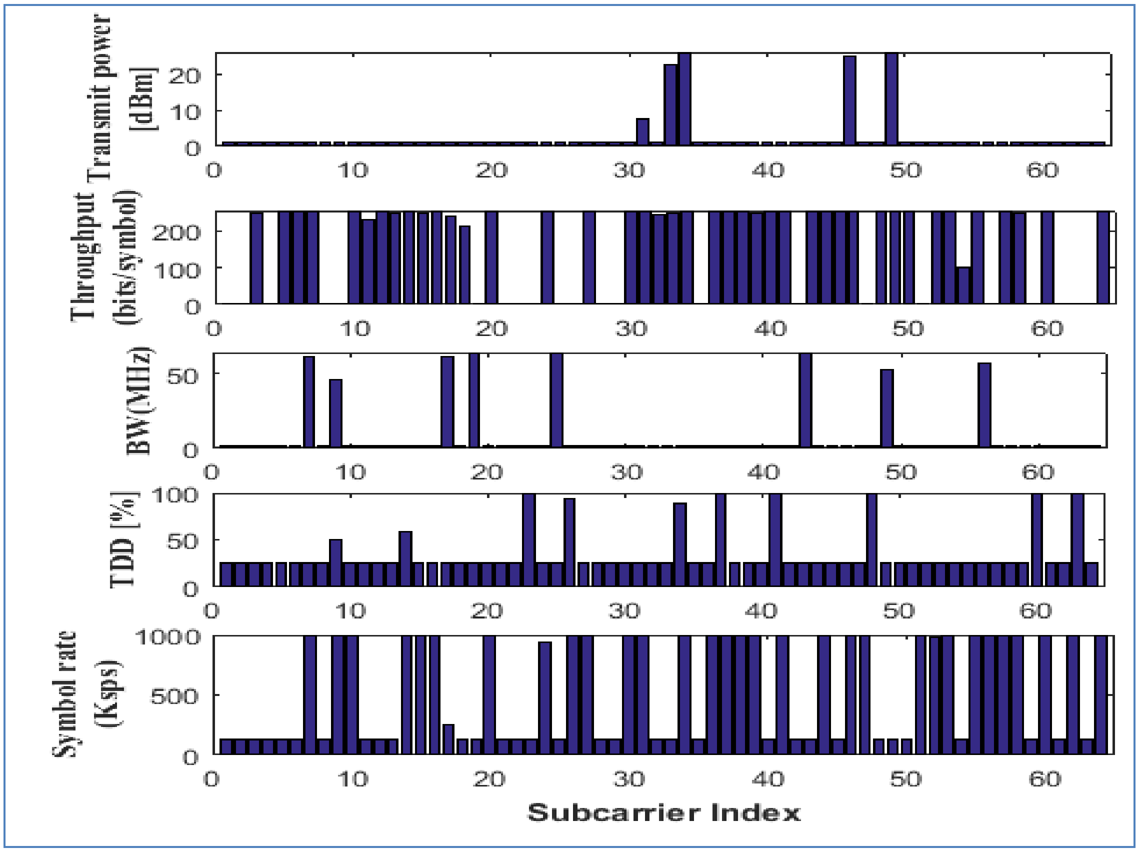

Figure 4.15: WDO based decision results for Mode-5 (64 Subcarrier)

CHAPTER-5

CONCLUSION AND FUTURE SCOPE

5.1 CONCLUSION OF THE WORK DONE

In this thesis, we have conjoined CDE with bio-inspired optimization algorithms to optimize various transmission parameters. The most important fundamental requirement of communication system includes utilization of spectrum efficiency and provides good quality of service. Therefore to improve the utilization of spectrum, we maximized the spectral efficiency and to improve the good quality of service, we minimized the BER and power consumption. Further, the role of interference has also been taken into account and therefore we have formulated different objective function to minimize the interference and maximize throughput. The optimal qresult shown in term of transmission parameters in different modes has been obtained. Weighted sum approach has been used to reach at one optimal solution while satisfying multi-objective optimization for Wind Driven Optimization, particle swarm optimization, differential evolution and BAT algorithm. The performance of PSO, BAT, DE and WDO based CDE is compared for the three and five transmission scenarios. Optimum value of different transmission parameters obtained by four algorithms has been formulated. The main aim of report work is to increase the fitness value and the convergence speed for the decision engine when the CR has to support multicarrier system. From simulation results, it is observed that the Wind Driven Optimization (WDO) based cognitive decision module outperforms particle swarm optimization, BAT algorithm and differential evolution in terms of overall fitness function and the optimal values of the transmission parameters.

5.2 FUTURE SCOPE

The applicability of evolutionary algorithms as optimization techniques has become quite promising to solve different engineering problems. In the literature, problem of parameter adaptation in cognitive radio is also solved using these techniques. Future work will explore more such advanced and efficient optimization algorithms with several enhancements to the existing CR model with improved optimization technique with more parameters.

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