Adaptive Resource Allocation for Multiuser OFDM System Based on Modified Genetic Algorithm and Particle Swarm Optimization

by

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A thesis submitted in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE
IN
ELECTRICAL AND ELECTRONIC ENGINEERING

Department of Electrical and Electronic Engineering
BANGLADESH UNIVERSITY OF ENGINEERING AND TECHNOLOGY

September 2008

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ACKNOWLEDGEMENT

"All praises to Allah, the Almighty, the most gracious benevolent, without whose help, this work would not have been possible."

I would like to express my heartiest gratitude to my respected supervisor Dr. Satya Prasad Majumder, Professor, department of Electrical and Electronic Engineering (EEE), Bangladesh University of Engineering and Technology (BUET), Dhaka. I am highly grateful to him for his overall supervision, steadfast guidance, constructive criticism, helpful suggestions, persistent encouragement, invariable support and endless patience throughout the course of the research.

I convey my gratefulness to the department of EEE, BUET for providing me the opportunity to carry on my research work. I also express my whole hearted respect to Prof. Dr. Aminul Hoque, the Head, department of EEE, BUET, to Dr. Shah Alam, Associate Professor, department of EEE, BUET and Dr. M. A. Mottalib, the Head, department of CIT, IUT for providing their valuable time for assessment of my research work. I am also grateful to all of my respected teachers, colleagues and friends of my department for their selfless support and encouragement.

I am also indebted to Dr. Shafiul Alam, Associate Professor, department of APECE, Dhaka University, for necessary support and ingenious idea what he provided throughout the most important parts of my educational career.

Finally my heartiest thanks go to my parents, my brother, my wife and all the members of my entire family for their continuous supports and necessary advices.

ABSTRACT

Like other wireless systems, Orthogonal Frequency Division Multiplexing (OFDM) requires the proper allocation of the limited resources, like total transmit power and available frequency bandwidth, among the users to meet the users' service requirements. As a matter of fact, adaptive resource allocation is one of the most challenging tasks for multiuser OFDM systems. In this dissertation, two evolutionary approaches, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been applied for adaptive subcarrier and bit allocations to minimize the overall transmit power (margin adaptation) and to maximize the throughput (rate adaptation) of a multiuser OFDM system. Each user will be assigned a number of subcarriers. This allocation of subcarriers may be done through unconstrained or fairly scheduled approaches. The number of bits are then calculated according to channel state information and subcarrier arrangements. The transmit power level as well as bit rate for an OFDM symbol are evaluated through these subcarrier and bit information. Simulation results reveal that both the evolutionary approaches outperform the conventional static resource allocation schemes considerably both in unconstrained and constrained cases. The results further assert that both the algorithms can handle large allocation of subcarriers without significant performance degradation. However the performance of PSO has been found to be better than the GA in terms of execution time, simplicity and convergence.

The original versions of GA and PSO have been modified in different manners to provide further improvements. All these modified versions perform relatively better than the original versions. Furthermore the modification of PSO has been done by three different manners where all of them perform relatively better than the original PSO as well as the original and modified versions of GA. Finally all these modified versions have been compared with the existing algorithms. The comparison reveals the fact that the modified versions of PSO perform relatively much better results than the previously best algorithm for higher number of users.

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LIST OF IMPORTANT ABBREVIATIONS

2G	Second Generation mobile phone system (GSM, IS-95)
3G	Third Generation mobile phone system (systems using WCDMA)
4G	Fourth Generation mobile phone system
ADSL	Asymmetric Digital Subscriber Line
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BPSK	Binary Phase Shift Keying
CNIR	Carrier-to-Noise plus Interference Power Ratio
CoI	Carrier over Interference
CP	Cyclic Prefix
CSI	Channel State Information
DAB	Digital Audio Broadcasting
D-AMPS	Digital Advance Mobile Phone System.
DBPSK	Differential Binary Phase Shift Keying
DFT	Discrete Fourier Transform
DMT	Differential Modulation in Time Domain
DMF	Differential Modulation in Frequency Domain
DPSK	Differential Phase Shift Keying
DQPSK	Differential Quadrature Phase Shift Keying
DVB	Digital Video Broadcasting
EDGE	Enhanced Data Rates for GSM Evolution
FDM	Frequency-Division Multiplexing
FDMA	Frequency Division Multiple Access
FFT	Fast Fourier Transform
FM-PSO	First Modified Particle Swarm Optimization
(FM+SM)-PSO	First and Second Modified Particle Swarm Optimization
(FM+TM)-PSO	First and Third Modified Particle Swarm Optimization
(FM+SM+TM)-PSO	First, Second and Third Modified Particle Swarm Optimization
GA	Genetic Algorithm
GI	Guard Interval
GMSK	Gaussian Minimum-Shift Keying

GPRS	General Packet Radio Service
GSM	General System for Mobile Communication.
HDTV	High Definition Television
HiperLAN2	High Performance Radio Local Area Network
ICI	Intercarrier Interference
IDFT	Inverse Discrete Fourier Transform
IFFT	Inverse Fast Fourier Transform
ISI	Intersymbol Interference
ITU	International Telecommunication Union
LOS	Line of Sight
MARA	Margin Adaptive Resource Allocation
MC-CDMA	Multi-carrier Code Division Multiple Access
MGA	Modified Genetic Algorithm
MIMO	Multiple-Input Multiple-Output
OFDM	Orthogonal Frequency Division Multiplexing.
OFDMA	Orthogonal Frequency Division Multiple Access
PAPR	Peak-to-Average Power Ratio
PSO	Particle Swarm Optimization
QAM	Quadrature Amplitude Modulation
QPSK	Quadrature Phase Shift Keying
RA	Resource Allocation
RARA	Rate Adaptive Resource Allocation
SDMA	Space-Division Multiple Access
SER	Symbol Error Rate
SINR	Signal to Interference plus Noise power Ratio
SM-PSO	Second Modified Particle Swarm Optimization
(SM+TM)-PSO	Second and Third Modified Particle Swarm Optimization
SNR	Signal to Noise Ratio
TDD	Time Division Duplexing
TDM	Time-Division Multiplexing
TM-PSO	Third Modified Particle Swarm Optimization
UMTS	Universal Mobile Telecommunications System.
WLAN	Wireless Local Area Network
WiMAX	Worldwide Interoperability for Microwave Access

Chapter 1
INTRODUCTION

1.1 Introduction

With the basic trends of modem life, wireless as well as cellular technology has become an indispensable part of everyday life. Now a days people not only want to communicate but also want to exchange different sorts of information in remote locations. As thus, cellular technology is enhancing its features in different manners through its generations. Orthogonal Frequency Division Multiplexing (OFDM) is an ameliorated cellular technology for the next generation wireless systems. Different sorts of research has been done and also being done on it to make it appropriate for practical usage. In view of this, allocation of wireless resources in OFDM systems under multiuser scenario is definitely a challenging job for engineers. The resource allocation needs to optimize the usage of certain quantities like total transmit power and available bandwidth. This dissertation has tried to explore this research area though different existing and newly introduced algorithms. The optimization has been performed through evolutionary approaches which are certainly new in multiuser OFDM systems.

1.2 Basics of a Communication System

In the most fundamental sense, communication involves implicitly the transmission of information from one point to another through a succession of processes. The processes involve generation of a message signal, description of the message signal through a defined set of symbols, encoding of the symbols, transmission of the encoded symbols through communication channels, decoding and reproduction of original symbols and finally re-creation of the original message signal. All these features are encapsulated by defining three basic elements of a communication system, namely transmitter, channel and receiver as shown in the Fig. 1.2.1.

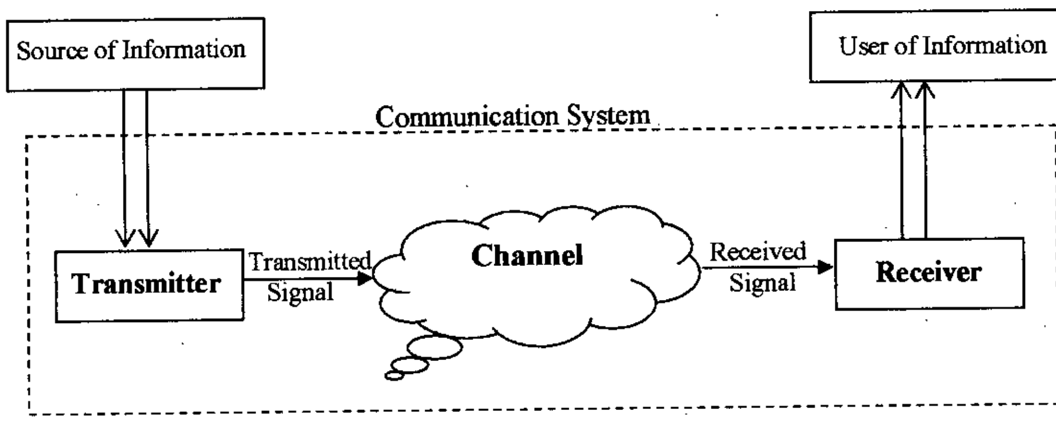


Fig. 1.2.1: Elements of a communication system

The transmitter is located at one point in space, the receiver is located at some other point in space separated from the transmitter, and the channel is the physical medium that connects them. The purpose of the transmitter is to convert of the message signal produced by the source of information into a form suitable for transmission over the channel. As the transmitted signal propagates along the channel, it is distorted due to the channel imperfections. Moreover, noise and interfering signals are added to the channel output with the result that the received signal is the corrupted version of the transmitted signal. The receiver has the task of operating on the received signal so as to reconstruct a recognizable form of the original message signal for a user. There are two basic modes of communication:

1. *Broadcasting*, which involves the use of a single powerful transmitter and numerous receivers that are relatively inexpensive to build. Here information bearing signals flow only in one direction.
2. *Point-to-point communication*, in which the communication process takes place over a link between a single transmitter and a receiver. In this case, there is a bidirectional flow of information-bearing signals, which requires the use of a transmitter and receiver at each end of the link.

The broadcasting mode of communication is exemplified by radio and television whereas the ubiquitous cellular systems provide the mean for one form of point-to-point communication.

1.3 Characteristics of Wireless Systems

Mobile cellular wireless systems operate under harsh and challenging channel conditions. The wireless channel is distinct and much more unpredictable than the wire-line channel because of factors such as multipath and shadow fading, Doppler Spread, and time dispersion or delay spread. These factors are all related to variability that is introduced by the mobility of the user and the wide range of environments that may be encountered as a result.

Multipath is a phenomenon that occurs when a transmitted signal is reflected by objects in the environment. These objects can be building, trees, hills or even cars. The reflected signals pass through different paths to reach the user's receiver. The result may be random signal fading due to the destructive reflections of signals on one another, which affectively can cancel some portion of the signal energy for brief periods of time. The degree of cancellations, or fading, depend on the delay spread of the reflected signals, as embodied by their relative phases, and their relative power.

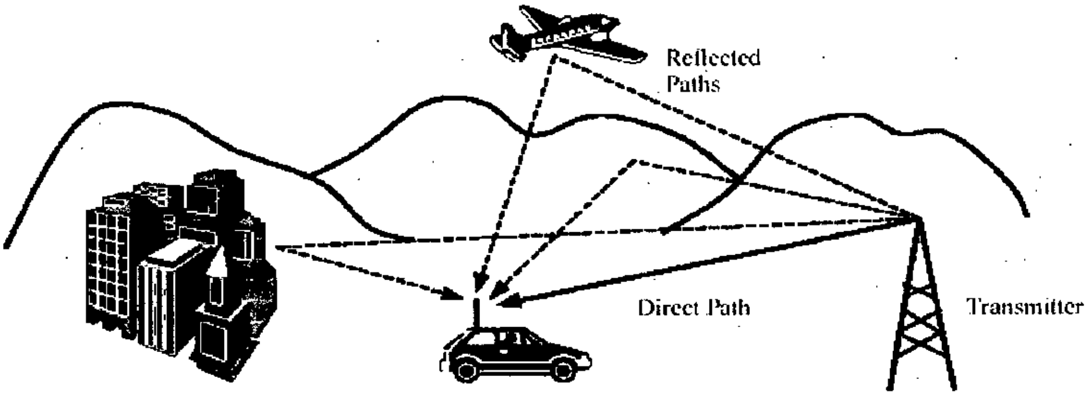


Fig. 1.3.1: Multipath Signals

Time dispersion represents distortion to the signal and is manifested by the spreading in time of the modulation symbols. This occurs when the channel is band-limited, or, in other words, when the coherence bandwidth of the channel is smaller than the modulation bandwidth. Time dispersion leads to intersymbol interference, or ISI, where the energy from one symbol spills over into another symbol, and as a result, the bit error rate (BER) is increased. Time dispersion can also lead to fading.

In many instances, the fading due to multipath might be frequency selective, randomly affecting a portion of the overall channel bandwidth at certain time. Frequency selective fading occurs when the channel introduces time dispersion and when the delay spread exceeds the symbol period. When there is no dispersion and delay spread is less than the symbol period, the fading will be flat, thereby affecting all frequencies in the signal equally. Flat fading can lead to deep fades of more than 30 decibels (dB).

Doppler spread describes the random changes in the channel introduced as a result of a user's mobility and the relative motion of objects in the channel. Doppler has the effect of shifting, or spreading, the frequency components of a signal. The coherence time of the channel is the inverse of the Doppler spread and is a measure of the speed at which the channel characteristics change. This in effect determines the rate at which fading occurs. When the rate of change of the channel is higher than the modulated symbol rate, fast fading occurs. Slow fading, on the other hand, occurs when the channel changes are slower than the symbol rate.

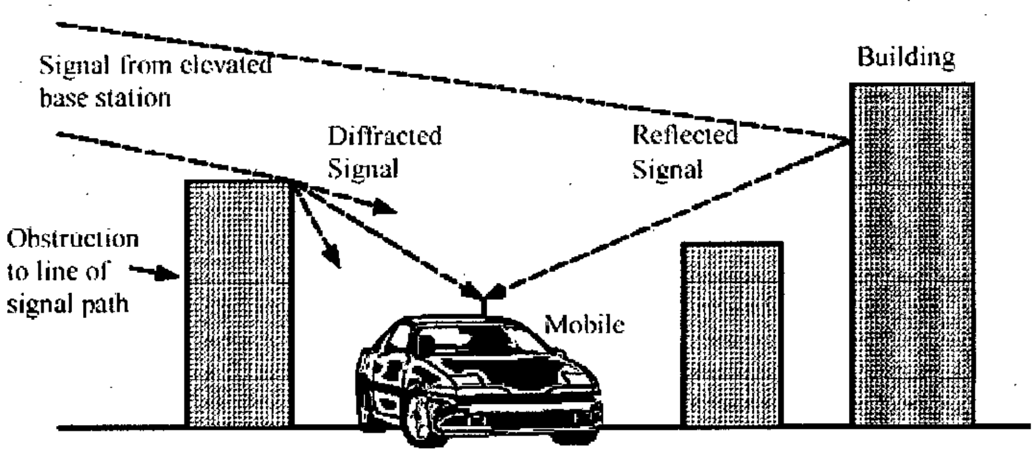


Fig. 1.3.2: Radio Propagation Effects

The statistics describing the fading signal amplitude are frequently characterized as either Rayleigh or Ricean. Rayleigh fading occurs when there is no line of sight (LOS) component present in the received signal. If there is a LOS component present, the fading follows a Ricean distribution. There is frequently no direct LOS path to a mobile, because the very nature of mobile communications means that mobiles can be in a building or behind one or other obstacles. This leads to Rayleigh fading but also results in a shadow loss. These conditions, along with the inherent variation in signal strength caused by changes in the distance between a mobile and cell site, result in a large dynamic range of signals, which can easily be as much as 70 dB.

In addition to the aforementioned channel impairments, spectrum is a scarce resource for wireless systems, and thus is reused within cellular systems. This means that the same frequencies are allocated to each cell, or to a cluster of cells, and are shared. This increases the overall system capacity at the expense of increased potential for interference within a cell and between cells as each channel is reused throughout the system. This generally results in cellular systems being interference-limited.

All modern mobile wireless systems employ a variety of techniques to combat the aforementioned effects. Some techniques are more effective than others, with the effectiveness depends on the air-interface and the system-architecture. As mobile systems were evolved from analog to digital, more sophisticated signal processing techniques have been employed to overcome the impairments in wireless environment. These techniques include equalization, channel or error-correction coding, spread-spectrum, interleaving and diversity.

Diversity has long been used to help mitigate the multipath-induced fading that results from users' mobility. The simplest diversity technique, spatial diversity involves the use of two or more receive antennae at the base station that are separated by some distance. The signals from the mobile generally follow separate paths to each antenna. This relatively low-cost approach yields significant performance improvement by taking advantage of the statistical likelihood that the paths are not highly correlated with each other. When one antenna is in a fade, the other one will generally not be.

1.4 A Brief History of Cellular Systems

Powered by enabling technologies, such as advanced digital signal processing and very large scale integrated circuits, wireless communication has been experiencing an explosive growth over the last decades. Cellular systems are one of the most successful wireless applications, having billions of subscribers all over the world. It owes its birth to Bell Laboratories, where the cellular concept was conceived in the 1970s [1]. Due to the fact that radio signal strength is waned with distance, the limited frequency bandwidth can be spatially reused, rendering the possibility of wide coverage over a large population.

The first generation (1G) of analog cellular systems include Advanced Mobile Phone Systems (AMPS), Nordic Mobile Telephone (NMT) and Total Access Communication Systems (TACS). AMPS had major deployments in North America, the Asia/Pacific region and Central and Latin America in 1980. NMT and TACS began their journey in Europe during the year 1979. AMPS adopted analog FM technology with frequency division multiple access (FDMA). With the introduction of second generation (2G) networks, the 1G phones were destined to become obsolete, as they were not adaptable to the new 2G standards and also had other drawbacks, such as their poor security due to the lack of encryption, and the fact that anyone with a receiver tuned to the right frequency could overhear the conversation. The 2G systems, adopted during early 1990s, started to use digital technologies and provided much higher communication capacity at an even lower cost. Due to the debate on the spectrum access technologies, three major 2G standards were born, namely IS-136, IS-95 in the United States and Global System for Mobile (GSM) in Europe. The 2G standards have high data rate versions, e.g. General Packet Radio Service (GPRS) and Enhanced Data rates for GSM Evolution (EDGE) for GSM, IS-136 high speed (IS-136HS) for IS-136, and IS-95 high data rate (IS-95 HDR) for IS-95 [2]. These improved 2G cellular systems had generally been referred to as 2.5G systems. The third and current generation of cellular systems includes wideband code division multiple access (WCDMA) and CDMA2000. The WCDMA frequency division duplex (FDD) and time division duplex (TDD) standards have been adopted in Europe and China, respectively, while CDMA2000 has been deployed in Korea and United States of America. With different spreading factors and modulation methods, WCDMA and CDMA2000 can support transmission rate up to several mega-bits per second. The next generation of wireless cellular systems is envisioned to be multicarrier-based for its efficient bandwidth usage [3] [4] [5].

1.5 Introducing the Fourth Generation of Wireless Communication

Research has recently begun for quite few years on the development of 4th generation (4G) mobile communication systems. The commercial rollout of these systems was likely to begin around 2008 – 2012. As such the 4G systems have already set out its expedition and are trying to put back the 3G technology. Many of the aims of 4G networks have already been published, however it is likely that they will be to extend the capabilities of 3G networks, allowing a greater range of applications, and improved universal access. Ultimately 4G networks should encompass broadband wireless services, such as High Definition Television (HDTV) (4 - 20 Mbps) and computer network applications (1 - 100 Mbps). This will allow 4G networks to replace many of the functions of WLAN systems. However, to cover this application, cost of service must be reduced significantly from 3G networks. The spectral efficiency of 3G networks is too low to support high data rate services at low cost. As a consequence one of the main focuses of 4G systems will be to significantly improve the spectral efficiency. In addition to high data rates, future systems must support a higher Quality Of Service (QOS) than current cellular systems, which are designed to achieve 90 - 95% coverage, i.e. network connection can be obtained over 90 - 95% of the area of the cell. This will become inadequate as more systems become dependent on wireless networking. As a result 4G systems are likely to require a QOS closer to 98 - 99.5%.

In order to achieve this level of QOS it will require the communication system to be more flexible and adaptive. In many applications it is more important to maintain network connectivity than the actual data rate achieved. If the transmission path is very poor, e.g. in a building basement, then the data rate has to drop to maintain the link. Thus the data rate might vary from as low as 1 kbps in extreme conditions, to as high as 20 Mbps for a good transmission path. Alternatively, for applications requiring a fixed data rate, the QOS can be improved by allocating additional resources to users with a poor transmission path. A significant improvement in spectral efficiency will be required in order for 4G systems to provide true broadband access. This will only be achieved by significant advances in multiple aspects of cellular network systems, such as network structure, network management, smart antennas, RF modulation, user allocation, and most importantly the resource allocation.

1.5.1 Features of 4G wireless systems

1. Support interactive multimedia, voice, video, wireless internet and other broadband services.
2. High speed, high capacity and low cost per bit.
3. Global mobility, service portability, scalable mobile networks.
4. Seamless switching, variety of services based on Quality of Service (QoS) requirements
5. Better scheduling and call admission control techniques.
6. Ad hoc networks and multi-hop networks.

1.5.2 Comparison between 3G Vs 4G

Table 1.5.1 Comparative features between 3G and 4G

	3G	4G
Frequency Band	1.8 - 2.5 GHz	2 - 8 GHz
Bandwidth	5-20 MHz	5-20 MHz
Data rate	Up to 2Mbps (384 kbps WAN)	Up to 20 Mbps or more
Access	Wideband CDMA	Multi-carrier - CDMA or OFDM(TDMA)
FEC	Turbo-codes	Concatenated codes
Switching	Circuit/Packet	Packet
Mobile top speeds	200 kmph	200 kmph

1.5.3 Introducing OFDM as main premise of 4G

Orthogonal Frequency Division Multiplexing (OFDM) is being considered the most promising transmission technique to support the fourth generation of wireless multimedia communications because of its dexterous performance in combating multipath fading as well as Inter Symbol Interference (ISI) and in the use of the available bandwidth. This scheme was proposed by Chang in 1966 for dispersive fading channels. During the early years of the evolution of OFDM systems, the efforts of Weinstein, Hirosaki, Peled, Ruiz et. al. have to be mentioned. OFDM has been widely adopted and implemented in wire and wireless communications, such as Digital Subscriber Line (DSL), European Digital Audio Broadcasting (DAB), Digital Video Broadcasting-Terrestrial (DVB-T) and its handheld version DVB-H, and IEEE 802.11a/g standards for Wireless Local Area Networks (WLANs) [6]-[7] etc. OFDM is very similar to the well-known and used technique of Frequency Division Multiplexing (FDM). OFDM uses the principles of FDM to allow multiple messages to be sent over a single radio channel. It is however in a much more controlled manner, allowing an improved spectral efficiency.

The system's operating principle is that the original bandwidth is divided into a high number of narrow subchannels, in which the mobile channel can be considered as non-dispersive. Hence no subchannel is required and instead of implementing a bank of subchannel modems, they can be conveniently put into service with the aid of simple Fast Fourier Transform (FFT).

1.6 Motivation towards the Objective of the Thesis

In light of the trends of future wireless communications and the significant growth of the subscriber population and penetration rate, radio resources, especially frequency spectrum would be far from adequate unless advanced technologies are developed to achieve a better efficiency of resource utilization. The traditional way of statically managing resources results in a waste of scarce spectrum and power, since a fixed margin is required to provide a good coverage and minimal required QoS everywhere. Therefore it is essential to control resource allocation and utilization in a way other than statically to achieve a higher spectral/power efficiencies and provide a better QoS while functioning under bandwidth and power restriction.

Recently, research and development of the OFDM have received considerable attention and have made a great deal of progress for the next generation wireless system due to its high data rate transmission capability with high bandwidth efficiency. OFDM is a wideband modulation scheme that is specifically able to cope up with the problems of the multipath reception. Wireless channels are of frequency selective fading type and time varying. OFDM converts the frequency selective fading channels into a number of flat fading channels and allows transmission without Inter Symbol Interference (ISI) with a low-complexity transceiver.

Multiuser OFDM adds multiple access to OFDM by allowing a number of users to share an OFDM symbol. Two classes of resource allocation schemes exist: fixed resource allocation [8] and dynamic resource allocation [9] [10] [11] [12]. Fixed resource allocation schemes, such as time division multiple access (TDMA) and frequency division multiple access (FDMA), assign an independent dimension, e.g. time slot or subchannel, to each user. A fixed resource allocation scheme is not optimal since the scheme is fixed regardless of the current channel condition. On the other hand, dynamic resource allocation allocates a dimension adaptively to the users based on their channel gains. Due to the time-varying nature of the wireless channel, dynamic resource allocation makes full use of multiuser diversity to achieve higher performance. Two classes of optimization techniques have been proposed in the dynamic multiuser OFDM literature: margin adaptive (MA) [12] and rate adaptive (RA) [9], [11]. The margin adaptive objective is to achieve the minimum overall transmit power given the constraints on the users' data rate or bit error rate (BER). The rate adaptive objective is to maximize each user's error-free capacity with a total transmit power constraint. These optimization problems are nonlinear and hence computationally intensive to solve. In [10], the nonlinear optimization problems were transformed into a linear optimization problem with integer variables. The optimal solution can be achieved by integer programming. However, even with integer programming, the complexity increases exponentially with the number of constraints and variables. Two rate adaptive optimization problems have been proposed by researchers. Recently, Jang and Lee proposed the rate maximization problem [9]. In [9], they proved that the sum capacity is maximized when each subchannel is assigned to the user with the best subchannel gain and power is then distributed by the water-filling algorithm. However, fairness is not considered in [9]. When the path loss differences among users are large, it is possible that the users with higher average channel gains will be allocated most of the resources, i.e. subchannels and power, for a significant portion of time. The users with lower average channel gains may be unable to receive any data, since most of the time the subchannels will be assigned to users with higher channel gains. In [11], Rhee and Cioffi studied the max-min problem, where by maximizing the worst user's capacity, it is assured that all users achieve a similar data rate. However, the max-min optimization problem can only provide maximum fairness among the users. In most wireless systems of interest, different users require different data rates, which may be accommodated by allowing users to subscribe to different levels of service. Viswanath, Tse, and Laroia discussed long-term proportional fairness resource allocation with "dumb" antennas. They pointed out that in multiuser systems, channel fading can be exploited as a source of randomness, i.e. multiuser diversity. However, in some scenarios, due to the limited scatters in the environment and slow channel variation, the dynamic range of channel fluctuation in the time scale of interest may be small.

In [13], Wong et al proposed iterative searching algorithm that applies Lagrangian relaxation for optimum multiuser subcarrier, bit and power allocation. The algorithm is close to the lower bound with the requirement of high and complex computation. The algorithm proposed in [14], however, over-simplifies the subcarrier allocation but could not fully utilize the multiuser diversity. In [15], an iterated water-filling algorithm is proposed; the algorithm can acquire similar performance as Wong's algorithm and avoids the computational complexity. Y. B. Reddy et al introduced Genetic Algorithm in resource allocation with significant improvements [16].

In this research work, evolutionary approaches have been applied through different proposed algorithms of resource allocation. To our best knowledge, adaptive resource allocation for OFDM systems based on Particle Swarm Optimization (PSO) method is still missing in the literature. In this literature, PSO is introduced as a promising technique of adaptive resource allocation for multiuser OFDM systems. The performance of PSO has been compared with the original and a modified Genetic Algorithm (GA). In the modified version, the convergence of the conventional GA has been improved by introducing fractional generation gap. The performance of the modified GA and PSO methods are also compared with some of the existing fixed and dynamic subcarrier and bit allocation schemes. Moreover, the original PSO has been modified in three different manners to improve the overall performance.

1.7 Problem Statement of the Thesis

This research work falls into two categories, the first one deals with the optimization of available resources' allocation with definite imposed constraints and the second one is mainly concerned with the topological aspect of the optimization techniques. For proper clarification of the first category, two conventional methods of OFDMA resource allocation have been deployed. Of the two methods, the margin adaptive approach minimizes the overall transmit power for a constant bit rate and overall bit error rate (BER). The second one, rate adaptive approach deals with the maximum throughput for a constant total power and BER. In this thesis, both the approaches have been deployed with the two mostly common evolutionary approaches, the Genetic Algorithm (GA) and the Particle Swarm Optimization (PSO). Actually OFDM system deals with immensely high data rate as well as large number of subcarriers. This research work reflects that evolutionary approaches can be efficiently applied to adaptive resource allocation without performance degradation. GA and PSO both have been applied for margin and rate adaptive allocation methods. For margin adaptive case, the power has been minimized in two cases, unconstrained scheduled allocation and fair scheduled allocation. In unfair scheduling, the subcarriers are allocated to the users according to the dynamic channel conditions by water-filling algorithms. This process does not follow proper fairness in scheduling in the sense that any of the users can even obtain no subcarrier at any particular case. This might give the optimum level of power allocation for a constant bit rate and BER but this is far away from the fairness in allocating the resources. On the other side, the fair scheduled allocation may not give optimum result but a constant fairness with a constant bit rate of individual user is preserved. In rate adaptive process also, both the unfair and fair scheduled approach have been deployed to maximize the total users' throughput and minimum user throughput for a constant transmit power. In every case, GA and PSO have been compared with each other either by slight or without modification. The comparative results reveal that PSO shows relatively better result than the genetic algorithm or even modified genetic algorithm in terms of simplicity, coding capability, computational resources, execution time and convergence.

Secondly, the research has been diverted towards the topological modification of GA and PSO. The GA has been slightly modified with the introduction of the concept of genetic gap between parent and child chromosomes. The PSO has been modified in three ways. Firstly the generation index has been apportioned into the position update equation to commence a concept of timing information. Secondly the weight inertia used in the velocity update equation has been made adaptive. This acclimatization is accompanied with the use of updated inertia constant by current generation index in each generation. The last amendment is the use of ring topology to search the global best value for each generation in PSO. The use of different topology other than straight through searching option reveals the search option more diversified.

1.8 Organization of the Thesis

The thesis is premised of five chapters. Chapter 1 has already given an idea on basic communication system, attributes of wireless environment, evolution of cellular systems from its origin and introducing OFDM in 4G. The chapter is finished by the preview of preceding researches and also by a brief review of the carried out research work of this dissertation.

Chapter 2 gives a detail description of OFDM systems, different multiple access techniques, resource allocation schemes of an OFDMA system and introductory discussion of Genetic Algorithm (GA) in addition to Particle Swarm Optimization (PSO).

Chapter 3 describes the proposed system models under diversified scenario. The diversity comes into the fact through various resource allocation schemes under either unconstrained or fair scheduled approach. The chapter also deals with different proposed algorithms along with their flowcharts.

Chapter 4 provides the numerical and comparative results of different systems proposed in chapter 3. This chapter also gives a clear comparison of proposed architectures with different existing ones. Chapter 5 concludes the dissertation by stating total outcome of the research work and by invoking the scopes of the future exploration.

Chapter 2

BASICS OF OFDM, MULTIPLE ACCESS, RESOURCE ALLOCATION AND OPTIMIZATION TECHNIQUES

2.1 Overview of OFDM

Orthogonal Frequency Division Multiplexing (OFDM) divides a communication channel into a number of equally spaced frequency bands. A subcarrier carrying a portion of the user information is transmitted in each band. Each subcarrier is orthogonal with every other subcarrier, differentiating OFDM from the commonly used frequency division multiplexing (FDM) [17].

OFDM has long been regarded as an efficient approach to combat the adverse effects of multipath spread. Its inherent multicarrier nature allows flexible frequency channel control so that the transmission power and constellation size can be adapted on every subcarrier to exploit the frequency-domain diversity and improve the attainable data rates [18]-[19]. In addition, if adaptive transmission is jointly optimized for all users in a multiuser OFDM environment, power or spectrum efficiency can be significantly enhanced because the multiuser diversity provides another degree of freedom for adaptation [20].

2.1.1 Preliminary concepts of orthogonality

Signals are orthogonal if they are mutually independent of each other. Orthogonality is a property that allows multiple information signals to be transmitted perfectly over a common channel and detected, without interference. Loss of orthogonality results in blurring between these information signals and degradation in communications. Many common multiplexing schemes are inherently orthogonal. Time Division Multiplexing (TDM) allows transmission of multiple information signals over a single channel by assigning unique time slots to each separate information signal. During each time slot only the signal from a single source is transmitted preventing any interference between the multiple information sources. Because of this TDM is orthogonal in nature. In the frequency domain most FDM systems are orthogonal as each of the separate transmission signals are well spaced out in frequency preventing interference. Although these methods are orthogonal, the term OFDM has been reserved for a special form of FDM. The subcarriers in an OFDM signal are spaced as close as is theoretically possible while maintain orthogonality between them. OFDM achieves orthogonality in the frequency domain by allocating each of the separate information signals onto different subcarriers. OFDM signals are made up from a sum of sinusoids, with each corresponding to a subcarrier. The baseband frequency of each subcarrier is chosen to be an integer multiple of the inverse of the symbol time, resulting in all subcarriers having an integer number of cycles per symbol. As a consequence the subcarriers are orthogonal to each other. Fig. 2.1.1 shows three subcarriers, which are orthogonal to each other.

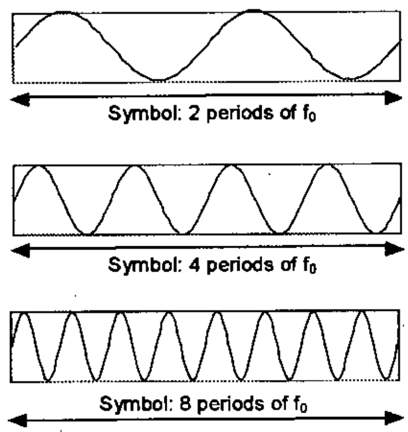


Fig. 2.1.1: Time domain construction of an OFDM signal.

Sets of functions are orthogonal to each other if they match the conditions in equation (2.1). If any two different functions within the set are multiplied, and integrated over a symbol period, the result is zero, for orthogonal functions. Another way of thinking of this is that if we look at a matched receiver for one of the orthogonal functions, a subcarrier in the case of OFDM, then the receiver will only see the result for that function. The results from all other functions in the set integrate to zero, and thus have no effect.

$$\int_0^T s_i(t)s_f(t)dt = \begin{cases} C & i=j \\ 0 & i \neq j \end{cases} \tag{2.1}$$

Equation (2.2) shows a set of orthogonal sinusoids, which represent the subcarriers for an unmodulated real OFDM signal.

$$s_k(t) = \begin{cases} \sin(2\pi k f_0 t) & 0 < t < T \quad k = 1, 2, \ldots M \\ 0 & otherwise \end{cases} \tag{2.2}$$

where f_0 is the subcarrier spacing, M is the number of subcarriers, T is the symbol period. Since the highest frequency component is Mf_0, the transmission bandwidth is also Mf_0. These subcarriers are orthogonal to each other because when we multiply the waveforms of any two subcarriers and integrate over the symbol period the result is zero. Multiplying the two sine waves together is the same as mixing these subcarriers. This results in sum and difference frequency components, which will always be integer subcarrier frequencies, as the frequency of the two mixing subcarriers has integer number of cycles. Since the system is linear we can integrate the result by taking the integral of each frequency component separately then combining the results by adding the two sub-integrals. The two frequency components after the mixing have an integer number of cycles over the period and so the sub-integral of each component will be zero, as the integral of a sinusoid over an entire period is zero. Both the sub-integrals are zeros and so the resulting addition of the two will also be zero, thus the frequency components are orthogonal to each other.

2.1.2 Frequency domain orthogonality

Another way to view the orthogonality property of OFDM signals is to look at its spectrum. In the frequency domain each OFDM subcarrier has a *sinc(x)*, *sin(x)/x*, frequency response, as shown in Fig. 2.1.2. This is a result of the symbol time corresponding to the inverse of the carrier spacing. As far as the receiver is concerned each OFDM symbol is transmitted for a fixed time (T_{FFT}) with no tapering at the ends of the symbol.

This symbol time corresponds to the inverse of the subcarrier spacing of $1/T_{FFT}$ Hz .This rectangular, boxcar, waveform in the time domain results in a sinc frequency response in the frequency domain. The sinc shape has a narrow main lobe, with many side-lobes that decay slowly with the magnitude of the frequency difference away from the centre. Each carrier has a peak at the centre frequency and nulls evenly spaced with a frequency gap equal to the carrier spacing.

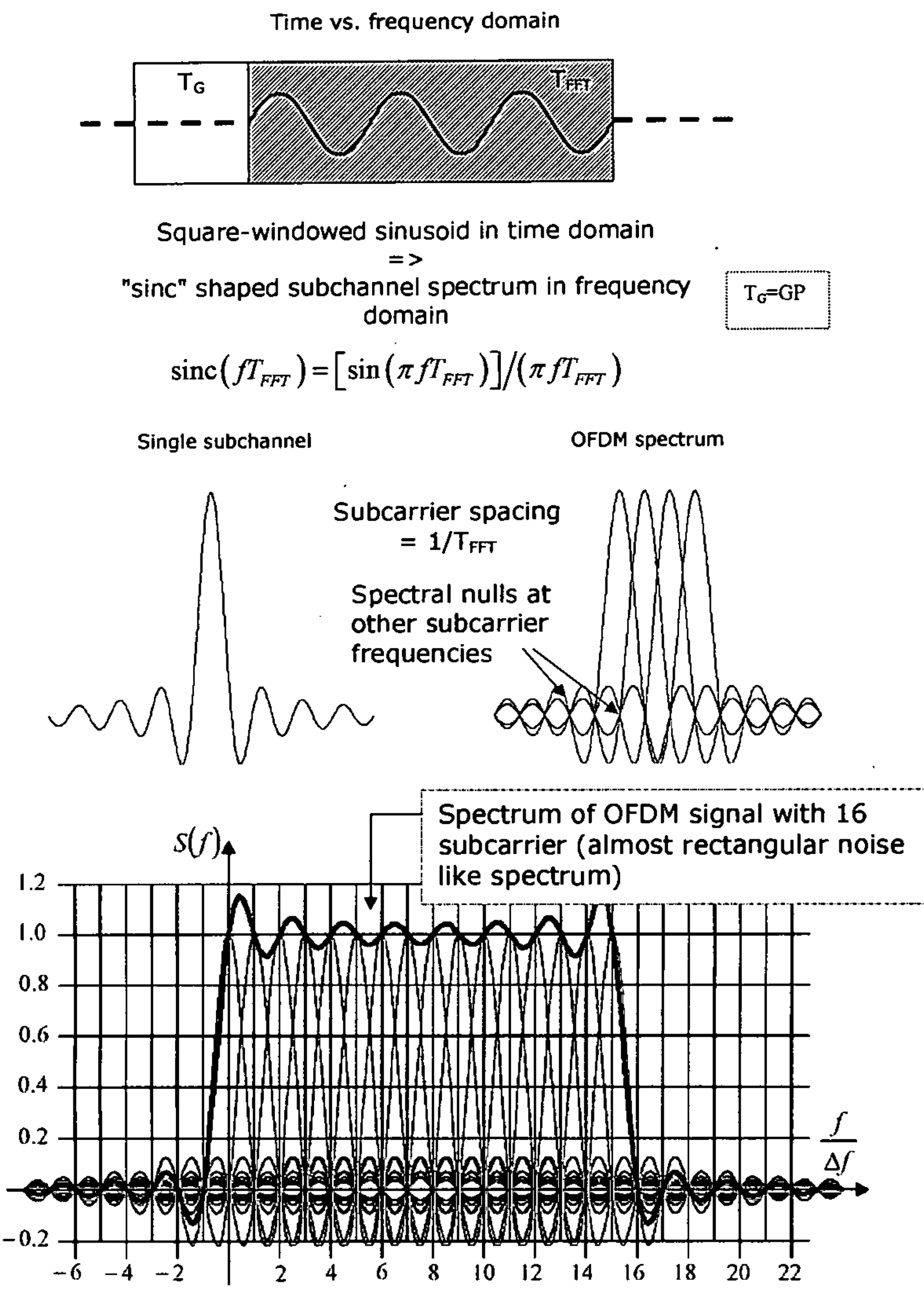


Fig. 2.1.2: Derivation and representation of OFDM spectrum

The orthogonal nature of the transmission is a result of the peak of each subcarrier corresponding to the nulls of all other subcarriers. When this signal is detected using a Discrete Fourier Transform (DFT) the spectrum is not continuous, but has discrete samples. If the DFT is time synchronized, the frequency samples of the DFT correspond to just the peaks of the subcarriers, thus the overlapping frequency region between subcarriers does not affect the receiver. The measured peaks correspond to the nulls for all other subcarriers, resulting in orthogonality between the subcarriers.

2.1.3 OFDM generation and reception

OFDM signals are typically generated digitally due to the difficulty in creating large banks of phase lock oscillators and receivers in the analog domain [19]. Fig. 2.1.3 shows the block diagram of a typical OFDM transceiver. The transmitter section converts digital data to be transmitted, into a mapping of subcarrier amplitude and phase. It then transforms this spectral representation of the data into the time domain using an Inverse Discrete Fourier Transform (IDFT). The Inverse Fast Fourier Transform (IFFT) performs the same operations as an IDFT, except that it is much more computationally efficient, and so is used in all practical systems. In order to transmit the OFDM signal the calculated time domain signal is then mixed up to the required frequency.

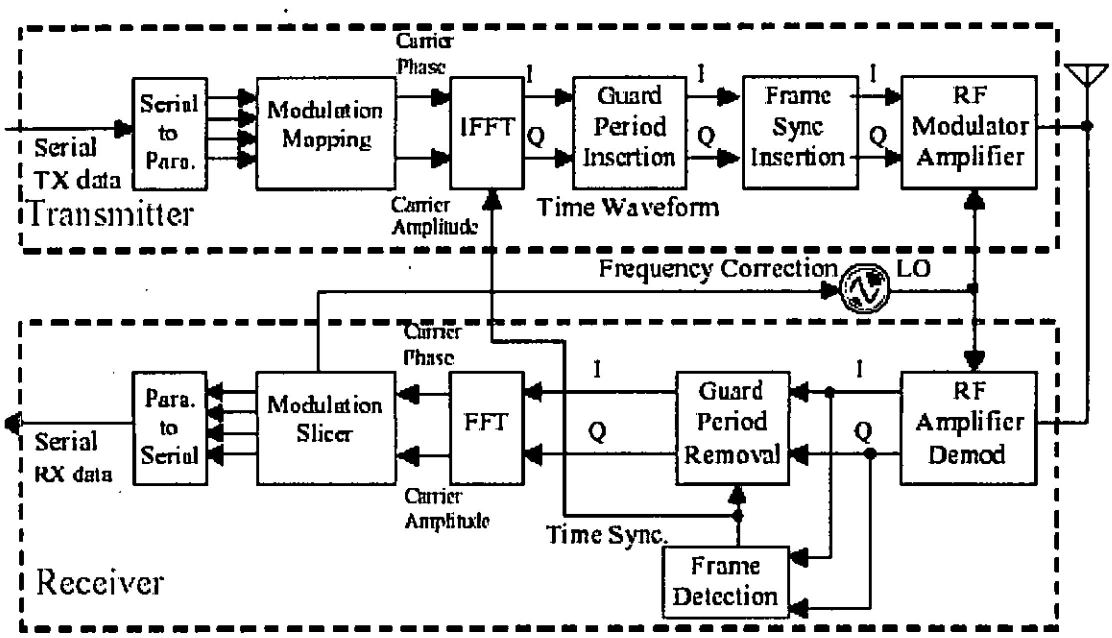


Fig. 2.1.3: Block diagram of a basic OFDM Transceiver

The receiver performs the reverse operation of the transmitter, mixing the RF signal to base band for processing, then using a Fast Fourier Transform (FFT) to analyze the signal in the frequency domain. The amplitude and phase of the subcarriers is then picked out and converted back to digital data.

2.1.3.1 Serial to parallel conversion

Data to be transmitted is typically in the form of a serial data stream. In OFDM, each symbol typically transmits 40 - 4000 bits, and so a serial to parallel conversion stage is needed to convert the input serial bit stream to the data to be transmitted in each OFDM symbol. The data allocated to each symbol depends on the modulation scheme used and the number of subcarriers. For example, for a subcarrier modulation of 16-QAM each subcarrier carries 4 bits of data, and so for a transmission using 100 subcarriers, the number of bits per symbol would be 400. For adaptive modulation schemes, the modulation scheme which is used on each subcarrier can vary and so the number of bits per subcarrier also varies. As a result the serial to parallel conversion stage involves filling the data payload for each subcarrier. At the receiver the reverse process takes place, with the data from the subcarriers being converted back to the original serial data stream. When an OFDM transmission occurs in a multipath radio environment, frequency selective fading can result in groups of subcarriers being heavily attenuated, which in turn can result in bit errors. These nulls in the frequency response of the channel can cause the information sent in neighboring carriers to be destroyed, resulting in a clustering of the bit errors in each symbol. Most Forward Error Correction (FEC) schemes tend to work more effectively if the errors are spread evenly, rather than in large clusters, and so to improve the performance most systems employ data scrambling as part of the serial to parallel conversion stage. This is implemented by randomizing the subcarrier allocation of each sequential data bit. At the receiver the reverse scrambling is used to decode the signal. This restores the original sequencing of the data bits, but spreads clusters of bit errors so that they are approximately uniformly distributed in time. This randomization of the location of the bit errors improves the performance of the FEC and the system as a whole.

2.1.3.2 Subcarrier modulation

Once each subcarrier has been allocated bits for transmission, they are mapped using a modulation scheme to a subcarrier amplitude and phase, which is represented by a complex In-phase and Quadrature-phase (IQ) vector [18]. Fig. 2.1.4 shows an example of subcarrier modulation mapping. This example shows 16-QAM, which maps 4 bits for each symbol. Each combination of the 4 bits of data corresponds to a unique IQ vector, shown as a dot on the figure. A large number of modulation schemes are available allowing the number of bits transmitted per carrier per symbol to be varied.

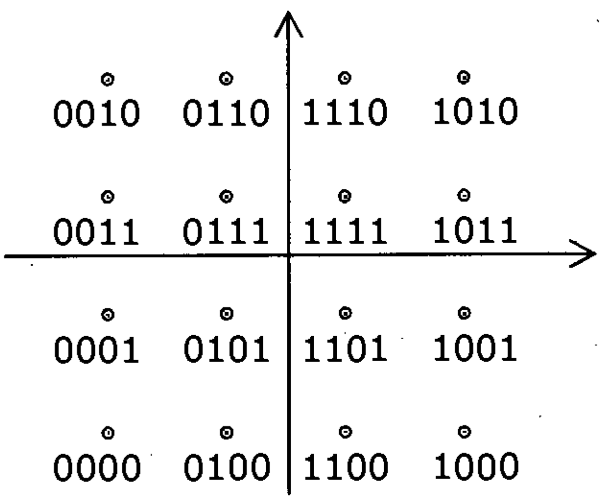


Fig. 2.1.4: Example IQ modulation constellation. 16-QAM, with gray coding of data to each location

Subcarrier modulation can be implemented using a lookup table, making it very efficient to implement. In the receiver, mapping the received IQ vector back to the data word performs subcarrier demodulation. During transmission, noise and distortion becomes added to the signal due to thermal noise, signal power reduction and imperfect channel equalization. Fig. 2.1.5 shows an example of a received 16-QAM signal with a SNR of 18 dB. Each of the IQ points is blurred in location due to the channel noise. For each received IQ vector the receiver has to estimate the most likely original transmission vector. This is achieved by finding the transmission vector that is closest to the received vector. Errors occur when the noise exceeds half the spacing between the transmission IQ points, making it cross over a decision boundary.

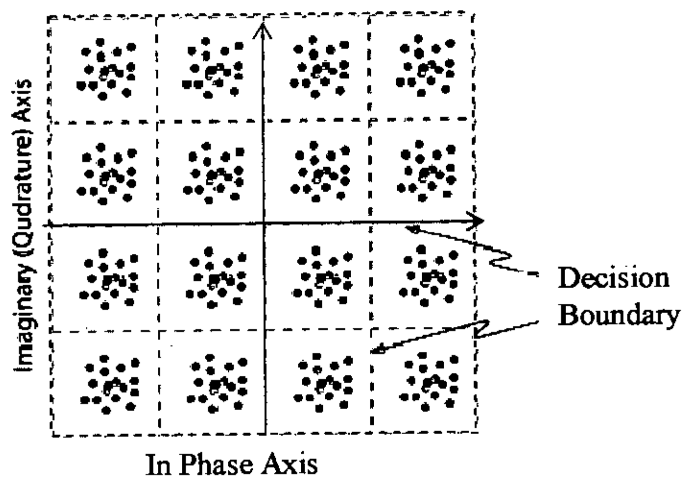


Fig. 2.1.5: IQ plot for 16-QAM data with added noise

2.1.3.3 Frequency to time domain conversion

After the subcarrier modulation stage each of the data subcarriers is set to an amplitude and phase based on the data being sent and the modulation scheme; all unused subcarriers are set to zero. This sets up the OFDM signal in the frequency domain. An IFFT is then used to convert this signal to the time domain, allowing it to be transmitted. Fig. 2.1.6 shows the IFFT section of the OFDM transmitter. In the frequency domain, before applying the IFFT, each of the discrete samples of the IFFT corresponds to an individual subcarrier. Most of the subcarriers are modulated with data. The outer subcarriers are unmodulated and set to zero amplitude. These zero subcarriers provide a frequency guard band before the Nyquist frequency and effectively act as an interpolation of the signal and allows for a realistic roll off in the analog anti-aliasing reconstruction filters.

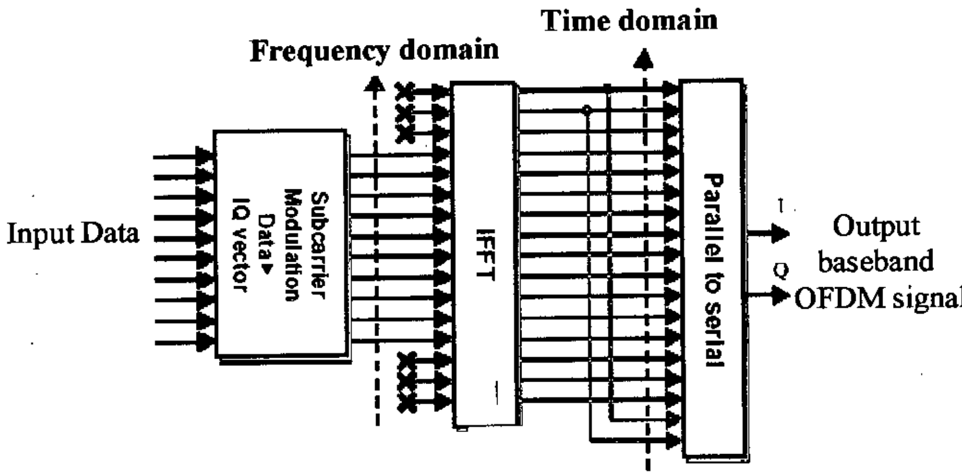


Fig. 2.1.6: OFDM generation, IFFT stage

2.1.3.4 RF modulation

The output of the OFDM modulator generates a base band signal, which must be mixed up to the required transmission frequency. This can be implemented using analog techniques or using a Digital Up Converter. Both techniques perform the same operation, however the performance of the digital modulation will tend to be more accurate due to improved matching between the processing of the I and Q channels, and the phase accuracy of the digital IQ modulator.

2.1.3.5 Guard period

For a given system bandwidth the symbol rate for an OFDM signal is much lower than a single carrier transmission scheme. For example for a single carrier BPSK modulation, the symbol rate corresponds to the bit rate of the transmission. However for OFDM the system bandwidth is broken up into N_c subcarriers, resulting in a symbol rate that is N_c times lower than the single carrier transmission. This low symbol rate makes OFDM naturally resistant to effects of Inter-Symbol Interference (ISI) caused by multipath propagation. Multipath propagation is caused by the radio transmission signal reflecting off objects in the propagation environment, such as walls, buildings, mountains, etc. These multiple signals arrive at the receiver at different times due to the transmission distances being different. This spreads the symbol boundaries causing energy leakage between them. The effect of ISI on an OFDM signal can be further improved by the addition of a guard period to the start of each symbol. This guard period is a cyclic copy that extends the length of the symbol waveform. Each subcarrier, in the data section of the symbol, (i.e. the OFDM symbol with no guard period added, which is equal to the length of the IFFT size used to generate the signal) has an integer number of cycles. Because of this, placing copies of the symbol end-to-end results in a continuous signal, with no discontinuities at the joins. Thus by copying the end of a symbol and appending this to the start results in a longer symbol time. Fig. 2.1.7 shows the insertion of a guard period.

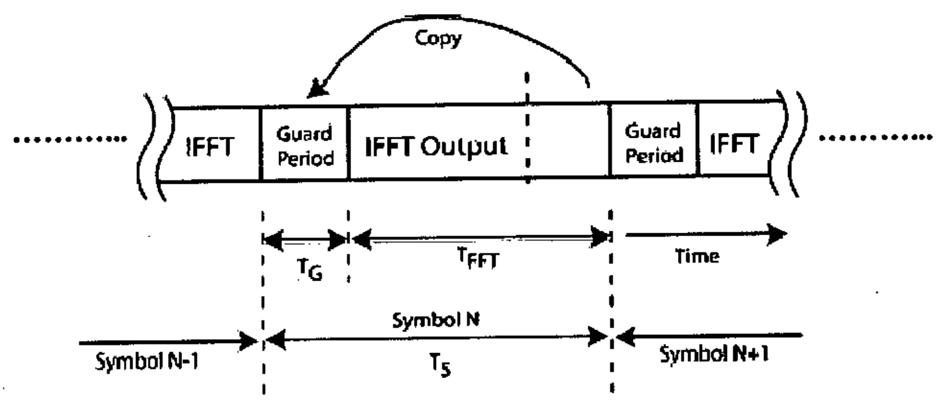


Fig. 2.1.7: Addition of a guard period to an OFDM signal

The total length of the symbol is $T_s=T_G+T_{FFT}$, where T_s is the total length of the symbol in samples, T_G is the length of the guard period in samples, and T_{FFT} is the size of the IFFT used to generate the OFDM signal. In addition to protecting the OFDM from ISI, the guard period also provides protection against time-offset errors in the receiver.

2.1.4 The OFDM system model

In the transmitter the incoming the data stream is grouped into blocks of N data symbols. These groups are called OFDM symbols and can be represented by a vector $x_m=[x_{o,m},x_{1,m},x_{2,m},\ldots\ldots\ldots,x_{N-1,m}]^T$. Next an IDFT operation is performed on each data symbol blocks and a cyclic prefix of length N_{cp} is added. The resulting complex baseband discrete time signal of the m^{th} OFDM symbol is

$$s_m(n) = \frac{1}{N}\sum_{k=0}^{N-1} x_{k,m} e^{j2\pi k(n-N_{cp})/N_c} \quad if \;\; n \in [0, N+N_{cp}-1] \qquad (2.3)$$
$$= 0 \qquad\qquad otherwise$$

n denotes the timing index.

The complete time signal $s(n)$ is given by

$$s(n) = \sum_{m=0}^{\infty} s_m(n - m(N+N_{cp})) \qquad (2.4)$$

In general the received signal is the sum of a linear convolution with the discrete channel impulse response $h(n)$ and the additive white Gaussian noise (AWGN), $w(n)$. In addition it is assumed that the transmitter and the receiver are perfectly synchronized. Based on the fact that the cyclic prefix is sufficiently longer to accommodate the channel impulse response, the linear convolution becomes circular one. Thus the received signal becomes

$$r(n) = \sum_{n=0}^{N_{cp}-1} h(\lambda)s(n-\lambda) + w(n) \qquad (2.5)$$

In the receiver the incoming sequence $r(n)$ is split into two blocks and the cyclic prefix associated with each block is removed. This results in a vector $r_m = [r(z_m), r(z_m+1), \ldots\ldots\ldots, r(z_m+N-1)]^T$ with $z_m = m(N+N_{cp}) + N_{cp}$. The received data symbol $y_{k,m}$ is given by

$$y_{k,m} = \sum_{n=0}^{N-1} r(z_m+n)e^{-2\pi kn/N} \qquad (2.6)$$

Substituting $r(n)$

$$\begin{aligned} y_{k,m} &= \sum_{n=0}^{N-1}\left(\sum_{\lambda=0}^{N_{cp}-1} h(\lambda)s_m(N_{cp}+n-\lambda)\right)e^{j2\pi kn/N} + \sum_{n=0}^{N-1} w(n+z_m)e^{j2\pi kn/N} \\ &= \sum_{n=0}^{N-1}\left(\sum_{\lambda=0}^{N_{cp}-1} h(\lambda)\frac{1}{N}\sum_{k=0}^{N-1} x_{k,m}e^{j2\pi k(n-\lambda)/N}\right)e^{-j2\pi kn/N} + w_{k,m} \end{aligned} \qquad (2.7)$$

where $w_{k,m} = \sum_{n=0}^{N-1} w(n+z_m)e^{-j2\pi kn/N}$

2.2 Overview of Multiple Access Techniques in OFDM Systems

Various multiple access schemes can be combined with OFDM transmission like Orthogonal Frequency Division Multiplexing- Time Division Multiple Access (OFDM-TDMA), Orthogonal Frequency Division Multiple Access (OFDMA), Multi Carrier-Code Division Multiple Access (MC-CDMA).

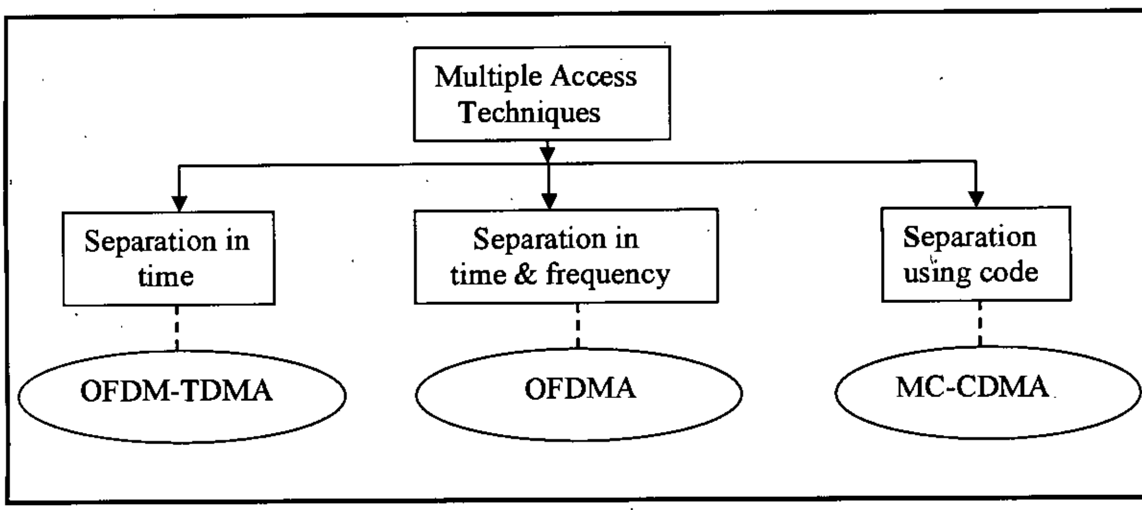


Fig. 2.2.1: Different multiple access schemes

2.2.1 OFDM-TDMA

In OFDM-TDMA, time slots in multiples of OFDM symbols are used to separate the transmission of multiple users as shown in Fig. 2.2.1. This means that all the used subcarriers are allocated to one of the users for a finite number of OFDM symbol periods. In WiMax, one of the allowed transmission mode uses OFDM-TDMA wherein the base station allocates the time-slots to the users for the downlink (DL) and uplink (UL) transmission.

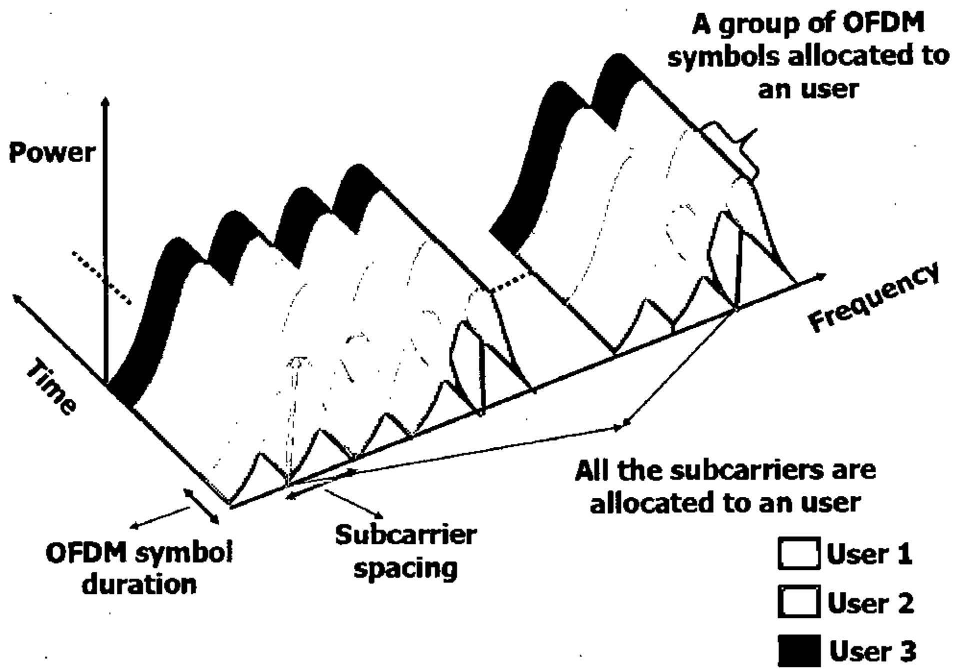


Fig. 2.2.2: Time-Frequency view of an OFDM-TDMA

2.2.2 OFDMA

Orthogonal Frequency Division Multiple Access (OFDMA) is a multi-user OFDM that allows multiple access on the same channel by forming subchannels with a group of subcarriers. OFDMA distributes subcarriers among users so all users can transmit and receive at the same time within a single channel on what are called subchannels. Subcarrier-group subchannels can be matched to each user to provide the best performance, meaning the least problems with fading and interference based on the location and propagation characteristics of each user. Different users transmit their signals through their mobile stations to the corresponding base-station. The base station then allocates the subcarriers to the corresponding users considering different conditions imposed on it. Fig. 2.2.2 shows K number of users are transmitting their signals and base station allocates their subcarrier into an OFDM signal according to different parametric conditions. This OFDM signal is magnified in Fig. 2.2.3.

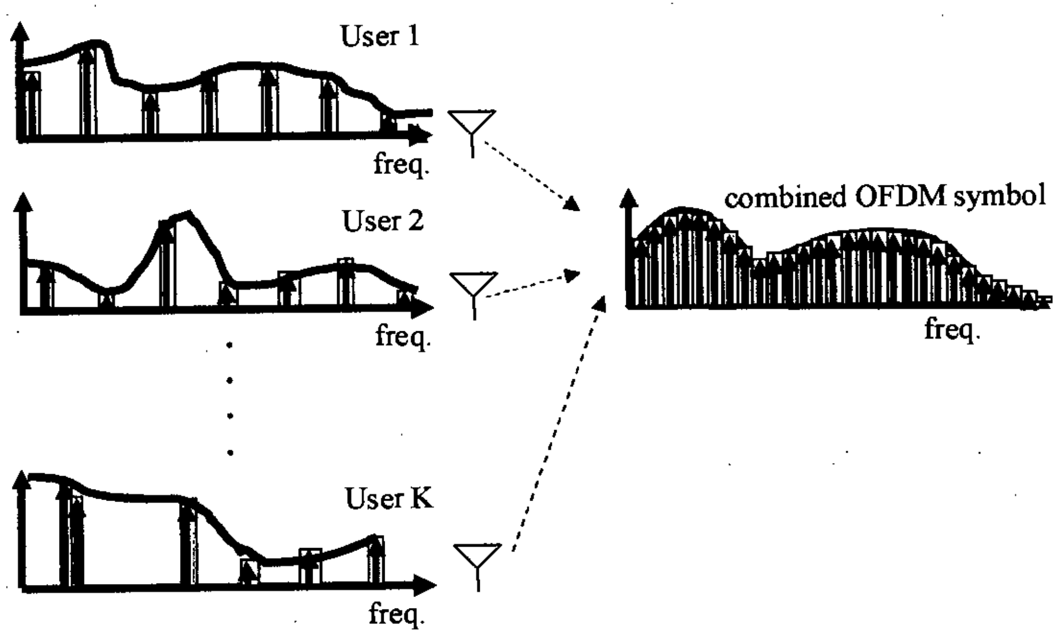


Fig. 2.2.3: Signals from multiple users form an OFDMA signal at the base station.

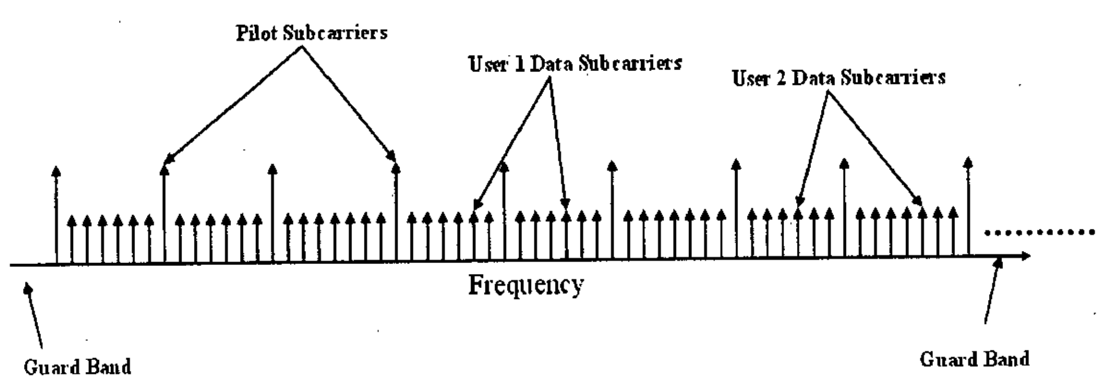


Fig. 2.2.4: Complete OFDMA signal at the base station.

In OFDMA systems, both time and/or frequency resources are used to separate the multiple users' signals. The time-frequency view of a typical OFDMA signal is shown in Fig. 2.2.4 for a case where 3 users are transmitting data. The users' signals are separated in time domain by using different OFDM symbols and/or by subcarrier domain. Thus both time and frequency resources are used to support multiuser transmission.

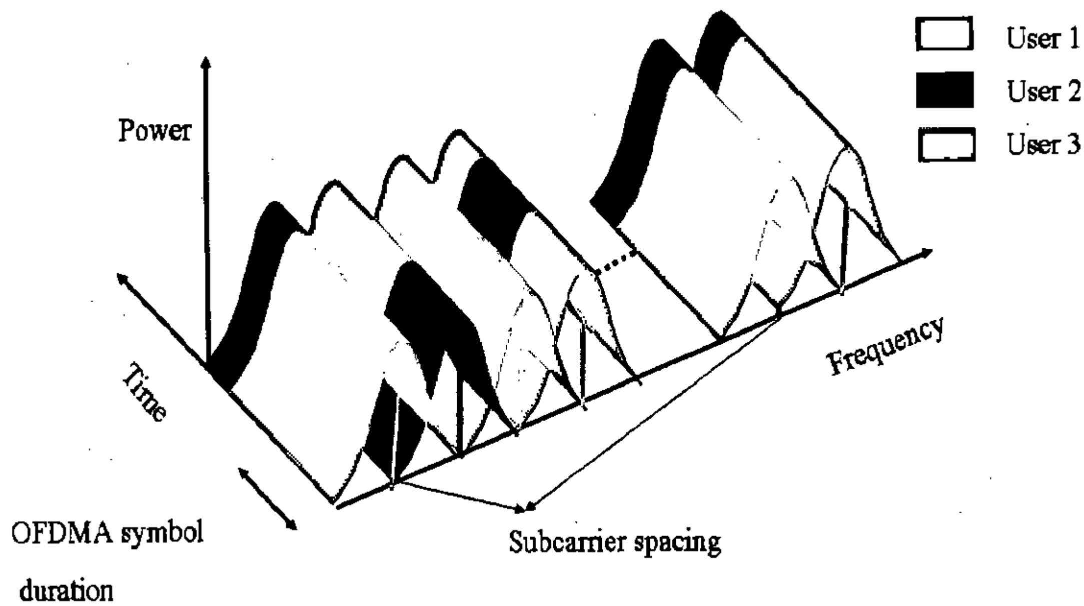


Fig. 2.2.5: Time-Frequency view of an OFDMA signal

2.2.3 MC-CDMA

In MC-CDMA systems, a data symbol is sent on multiple subcarriers by using a spreading code, which is different for multiple access users [21]. Multiple users' signals overlap in time and frequency domain but they can be separated at the receiver by using the knowledge of spreading codes. Thus MC-CDMA can be considered as a combination of OFDM and CDMA schemes resulting in benefits due to both these approaches.

2.3 Overview of Resource Allocation in OFDMA Systems

Channel-aware scheduling and resource allocation has become an essential component for high-speed wireless data systems. In these systems, the active users and the allocation of physical layer resources among them are dynamically adapted based on the users' current channel conditions and quality of service (QoS) requirements. The purpose of resource allocation at the base station is to allocate intelligently the limited resources, e.g. total transmit power and available frequency bandwidth, among users to meet users' service requirements. Channel-aware adaptive resource allocation has been shown to achieve higher system performance than static resource allocation, and is becoming more critical in current and future wireless communication systems as the user data rate requirements increase. To allocate the available resources among users, two methods, margin adaptive process [22] and rate adaptive [23] method are used.

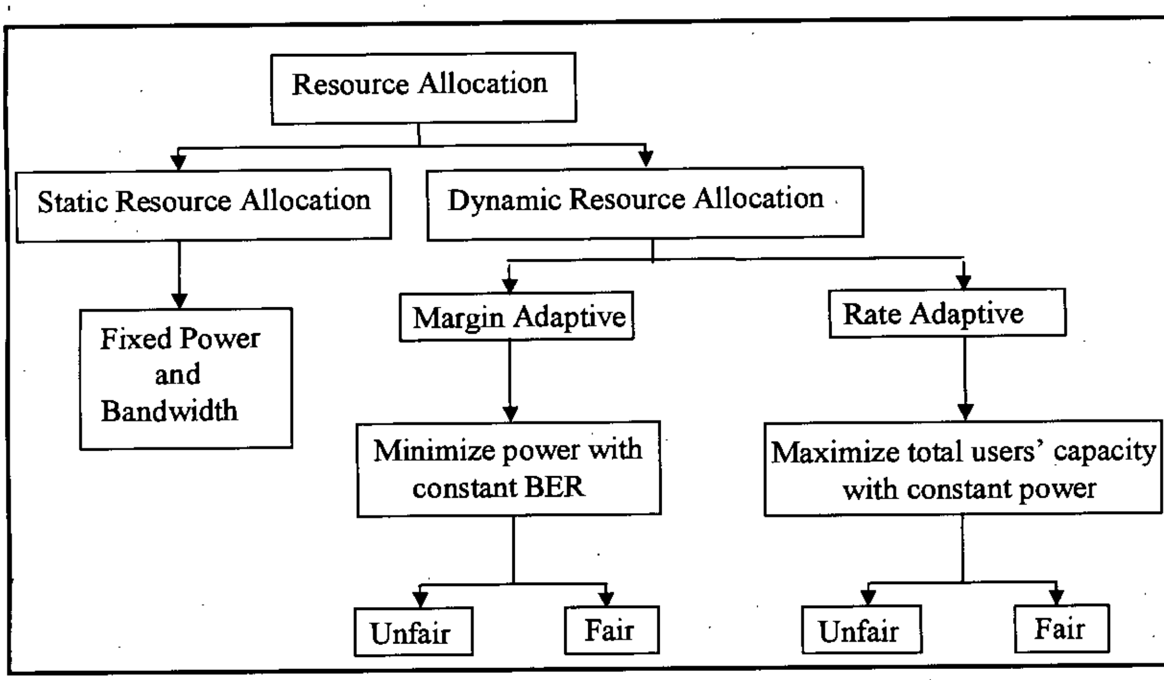


Fig. 2.3.1: Different schemes of OFDM resource allocation

2.3.1 Margin adaptive approach

Margin adaptive resource allocation [22] deals with the allotment of subcarrier, bit and power to a number of users where all users transmit in all the time slots. The system uses the given set of user data rates and bit error rate and attempts to minimize total transmit power. The minimum transmit power is obtained by

$$P = \sum_{n=1}^{N}\sum_{k=1}^{K}\frac{f(b_{n,k})}{\alpha_{n,k}^{2}} \qquad (2.8)$$

where P is the total transmit power, $b_{n,k}$ is the bite rate for kth user on the nth subcarrier, and $\alpha_{n,k}^2$ is the channel gain squared for nth subcarrier in addition to kth user and $f(.)$ is the required received power expressed by

$$f(b_{n,k}) = \frac{N_0}{3}[Q^{-1}(\frac{BER_n}{4})]^2(2^{b_{n,k}}-1)$$

Here N_0 stands for noise power spectral density and BER_n designates the bit error rate for nth subcarrier.

$Q(x)=\frac{1}{\sqrt{2\pi}}\int_x^{\infty} e^{-\frac{t^2}{2}}dt$ and here Q^{-1} denotes the inverse Q function.

In margin adaptive approach, the total transmit power is minimized for a constant overall bit error rate and as well as for a constant bit rate for each user. The margin adaptive resource allocation can also be viewed as minimizing bit error rate for a constant transmit power. Both the approaches assume constant bit rate for each user.

2.3.2 Rate adaptive approach

Rate adaptation [23] represents an algorithm that maximizes the total data rate of the multiuser OFDM system by adapting the transmit power for each user and each subcarrier. The total transmit power for the system is fixed and represented by

$$\sum_{k=1}^{K}\sum_{n=1}^{N} s_{k,n} = \bar{S} \tag{2.9}$$

where $\bar{S}$ is the total transmit power and $s_{k,n}$ is the transmit power for kth user and the nth subcarrier. Mathematically, the optimization problem considered in this approach is formulated as

$$R_k = \sum_{k=1}^{K}\sum_{n=1}^{N} \frac{\rho_{k,n}}{N}\log_2\left(1+\frac{p_{k,n}h_{k,n}^2}{N_0\frac{B}{N}}\right) \tag{2.10}$$

where K is the total number of users, N is the total number of subcarriers, N_0 is the power spectral density of additive white Gaussian noise, B is the total available bandwidth. $p_{k,n}$ is the power allocated for user k in the subcarrier n , $h_{k,n}$ is the channel gain for user k and subcarrier n, $\rho_{k,n}$ can only be the value of either 1 or 0, indicating whether subcarrier n is used by user k or not. The fourth constraint shows that each subcarrier can only be used by one user.

2.3.3 Unfair and fair scheduling

Fairness in scheduling can be introduced into a system by either of the two ways, fairness in data rate and fairness in using subcarriers. Fairness in data rate means a minimum amount of data rate has to be preserved for a particular user regardless any condition of the channel. Like the previous one, fairness in subcarrier sharing also signifies the fact that a minimum number of subcarriers have to be used for a particular user even at the worst condition. With proper fairness scheduling, the minimum power or maximum throughput does not reflect the optimum result but reveals a fair allocation of subcarriers to the corresponding user. The fairness index is defined as

$$\Im = \frac{\left(\sum_{k=1}^{K} \gamma_k\right)^2}{K \sum_{k=1}^{K} \gamma_k^2} \tag{2.11}$$

with the maximum value of 1 to be the greatest fairness case in which all users would achieve the same data rate or subcarriers. Here $k = 1,2, \ldots, K$ denotes user and $\{\gamma_i\}_{i=1}^{K}$ is a set of predetermined values which are used to ensure proportional fairness among users.

2.4 Introducing Genetic Algorithm & Particle Swarm Optimization in OFDM

The purpose of resource allocation at the base station is to intelligently allocate the limited resources, e.g. total transmit power and available frequency bandwidth among users to meet users' service requirements. Channel-aware adaptive resource allocation has been shown to achieve higher system performance than static resource allocation, and is becoming more critical in current and future wireless communication systems as the user data rate requirements increase. Furthermore, the subcarrier allocation problem to multiple users has many different permutations, thereby making the solution space very large. Unlike other algorithms, the evolutionary approaches can handle large solution space without any performance degradation. In this thesis, the subcarriers and bits are allocated to different users according to the dynamic channel state information through evolutionary approaches. Each user is allocated one or more subcarriers provided that one subcarrier can be used by only one user. The number of bits are then chosen according to the water filling algorithm i.e. the modulation schemes are selected in response of the channel state information of the corresponding user. The optimum arrangement of the users as well as subcarriers can be evaluated by one of the two evolutionary approaches, Genetic Algorithm (GA) or Particle Swarm Optimization (PSO).

2.4.1 Basics of genetic algorithm

A genetic algorithm (GA) is a search technique used in computing to find exact or approximate solutions to optimization and search problems. Genetic algorithms are categorized as global search heuristics. Genetic algorithms are a particular class of evolutionary algorithms that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover. Genetic algorithms are implemented as a computer simulation in which a population of abstract representations (chromosomes) of candidate solutions (individuals) to an optimization problem evolves toward better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached.

2.4.1.1 Population representation and initialization

GAs operate on a number of potential solutions, called a population, consisting of some encoding of the parameter set simultaneously. Typically, a population is composed of between 30 and 100 individuals, although, a variant called the micro GA uses very small populations, ~10 individuals, with a restrictive reproduction and replacement strategy in an attempt to reach real-time execution [24].

The most commonly used representation of chromosomes in the GA is that of the single-level binary string. Here, each decision variable in the parameter set is encoded as a binary string and these are concatenated to form a chromosome. The use of Gray coding has been advocated as a method of overcoming the hidden representational bias in conventional binary representation as the Hamming distance between adjacent values is constant [25]. Empirical evidence of Caruana and Schaffer [26] suggests that large Hamming distances in the representational mapping between adjacent values, as is the case in the standard binary representation, can result in the search process being deceived or unable to efficiently locate the global minimum. A further approach of Schmitendorgf et-al [27], is the use of logarithmic scaling in the conversion of binary-coded chromosomes to their real phenotypic values. Although the precision of the parameter values is possibly less consistent over the desired range, in problems where the spread of feasible parameters is unknown, a larger search space may be covered with the same number of bits than a linear mapping scheme allowing the computational burden of exploring unknown search spaces to be reduced to a more manageable level.

Whilst binary-coded GAs are most commonly used, there is an increasing interest in alternative encoding strategies, such as integer and real-valued representations. For some problem domains, it is argued that the binary representation is in fact deceptive in that it obscures the nature of the search [28]. In the subset selection problem [29], for example, the use of an integer representation and look-up tables provides a convenient and natural way of expressing the mapping from representation to problem domain.

The use of real-valued genes in GAs is claimed by Wright [30] to offer a number of advantages in numerical function optimization over binary encodings. Efficiency of the GA is increased as there is no need to convert chromosomes to phenotypes before each function evaluation; less memory is required as efficient floating-point internal computer representations can be used directly; there is no loss in precision by discretization to binary or other values; and there is greater freedom to use different genetic operators. The use of real-valued encodings is described in detail by Michalewicz [31] and in the literature on Evolution Strategies.

Having decided on the representation, the first step in the GA is to create an initial population. This is usually achieved by generating the required number of individuals using a random number generator that uniformly distributes numbers in the desired range.

2.4.1.2 The objective and fitness functions

The objective function is used to provide a measure of how individuals have performed in the problem domain. In the case of a minimization problem, the most fit individuals will have the lowest numerical value of the associated objective function. This raw measure of fitness is usually only used as an intermediate stage in determining the relative performance of individuals in a GA. Another function, the fitness function, is normally used to transform the objective function value into a measure of relative fitness. Thus $F(x) = g(f(x))$ where f is the objective function, g transforms the value of the objective function to a non-negative number and F is the resulting relative fitness. This mapping is always necessary when the objective function is to be minimized as the lower objective function values correspond to fitter individuals. In many cases, the fitness function value corresponds to the number of offspring that an individual can expect to produce in the next generation.

2.4.1.3 Selection

Selection is the process of determining the number of times a particular individual is chosen for reproduction and, thus, the number of offspring that an individual will produce. The selection of individuals can be viewed as two separate processes:

1) determination of the number of trials an individual can expect to receive, and
2) conversion of the expected number of trials into a discrete number of offspring.

The first part is concerned with the transformation of raw fitness values into a real valued expectation of an individual's probability to reproduce and is dealt with in the previous subsection as fitness assignment. The second part is the probabilistic selection of individuals for reproduction based on the fitness of individuals relative to one another and is sometimes known as sampling.

Types of selection methods

- Roulette Wheel Selection Methods
- Stochastic Universal Sampling

2.4.1.4 Crossover (Recombination)

The basic operator for producing new chromosomes in the GA is that of crossover. Like its counterpart in nature, crossover produces new individuals that have some parts of both parent's genetic material.

Types of crossover

- Single point crossover
- Multipoint crossover
- Uniform crossover

2.4.1.4.1 Single point crossover

The simplest recombination operator is that of single-point crossover.

Consider the two parent binary strings:

P_1 = 1 0 0 1 0 1 1 0, and

P_2 = 1 0 1 1 1 0 0 0.

If an integer position, *i*, is selected uniformly at random between 1 and the string length, *l* minus one *[1, l-1]*, and the genetic information exchanged between the individuals about this point, then two new offspring strings are produced. The two offspring below are produced when the crossover point *i = 5* is selected,

O_1 = 1 0 0 1 0 0 0 0, and

O_2 = 1 0 1 1 1 1 1 0.

This crossover operation is not necessarily performed on all strings in the population. Instead, it is applied with a probability P_x when the pairs are chosen for breeding.

2.4.1.4.2 Multipoint crossover

For multi-point crossover, m crossover positions, $k_i \in \{1, 2, \ldots\ldots\ldots, l\}$, where k_i are the crossover points and *l* is the length of the chromosome, are chosen at random with no duplicates and sorted into ascending order. Then, the bits between successive crossover points are exchanged between the two parents to produce two new offspring. The section between the first starting position and the first crossover point is not exchanged between individuals. This process is illustrated in Fig. 2.4.1.1.

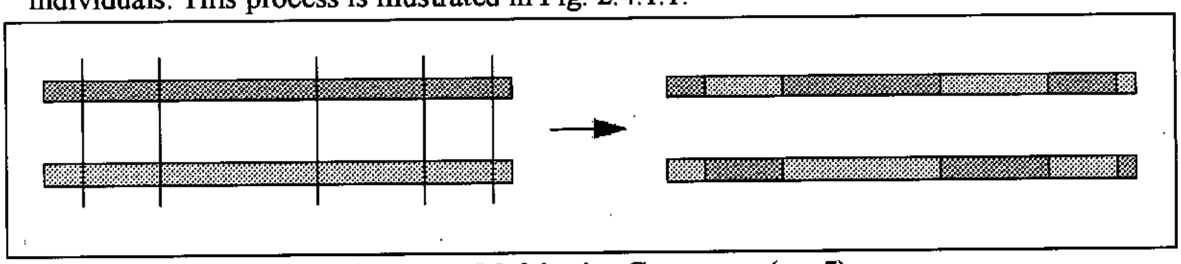


Fig. 2.4.1: Multipoint Crossover (m=5)

2.4.1.4.3 Uniform crossover

Single and multi-point crossover define cross points as places between loci where a chromosome can be split. Uniform crossover [18] generalizes this scheme to make every locus a potential crossover point. A crossover mask, the same length as the chromosome structures is created at random and the parity of the bits in the mask indicates which parent will supply the offspring with which bits. Consider the following two parents, crossover mask and resulting offspring:

P1 = 1 0 1 1 0 0 0 1 1 1

P2 = 0 0 0 1 1 1 1 0 0 0

Mask = 0 0 1 1 0 0 1 1 0 0

O1 = 0 0 1 1 1 1 0 1 0 0

O2 = 1 0 0 1 0 0 1 0 1 1

Here, the first offspring, O1, is produced by taking the bit from P1 if the corresponding mask bit is 1 or the bit from P2 if the corresponding mask bit is 0. Offspring O2 is created using the inverse of the mask or, equivalently, swapping P1 and P2. Uniform crossover, like multi-point crossover, has been claimed to reduce the bias associated with the length of the binary representation used and the particular coding for a given parameter set. This helps to overcome the bias in single-point crossover towards short substrings without requiring precise understanding of the significance of individual bits in the chromosome representation.

2.4.1.5 Mutation

In natural evolution, mutation is a random process where one form of a bit of a gene is replaced by another form to produce a new genetic structure. In GAs, mutation is randomly applied with low probability, typically in the range 0.001 and 0.01, and modifies elements in the chromosomes. Usually considered as a background operator, the role of mutation is often seen as providing a guarantee that the probability of searching any given string will never be zero and acting as a safety net to recover good genetic material that may be lost through the action of selection and crossover.

Binary mutation flips the value of the bit at the loci selected to be the mutation point. Given that mutation is generally applied uniformly to an entire population of strings, it is possible that a given binary string may be mutated at more than one point. With non-binary representations, mutation is achieved by either perturbing the gene values or random selection of new values within the allowed range.

mutation point

Original string - 0 0 $\boxed{0}$ 1 1 0 0 0 1 0

Mutated string - 0 0 $\boxed{1}$ 1 1 0 0 0 1 0

Fig. 2.4.2: Binary Mutation

2.4.1.6 Reinsertion

To maintain the size of the original population, the new individuals have to be reinserted into the old population. Similarly, if not all the new individuals are to be used at each generation or if more offsprings are generated than the size of the old population then a reinsertion scheme must be used to determine which individuals are to exist in the new population.

2.4.1.7 Termination of the GA

Because the GA is a stochastic search method, it is difficult to formally specify convergence criteria. As the fitness of a population may remain static for a number of generations before a superior individual is found, the application of conventional termination criteria becomes problematic. A common practice is to terminate the GA after a pre-specified number of generations and then test the quality of the best members of the population against the problem definition. If no acceptable solutions are found, the GA may be restarted or a fresh search initiated. GA can also be terminated by defining a variable which signifies the dynamic change for each generation. The dynamic change may be defined as a change of fitness value of the current generation from that of the previous generation. When the dynamic change declines than a predefined value then the GA is terminated.

2.4.1.8 Algorithm and flowchart of a simple GA

The algorithm as well as flowchart of a basic genetic algorithm is as follows

0 START : Create random population of **n** chromosomes
1 FITNESS : Evaluate fitness **f(x)** of each chromosome in the population
2 NEW POPULATION
- **0 SELECTION** : Based on **f(x)**
- **1 RECOMBINATION** : Cross-over chromosomes
- **2 MUTATION** : Mutate chromosomes
- **3 ACCEPTATION** : Reject or accept new one

3 REPLACE : Replace old with new population: the new generation
4 TEST : Test problem criterium
5 LOOP : Continue step 1 – 4 until criterium is satisfied

Fig. 2.4.3: Algorithmic structure of basic genetic algorithm

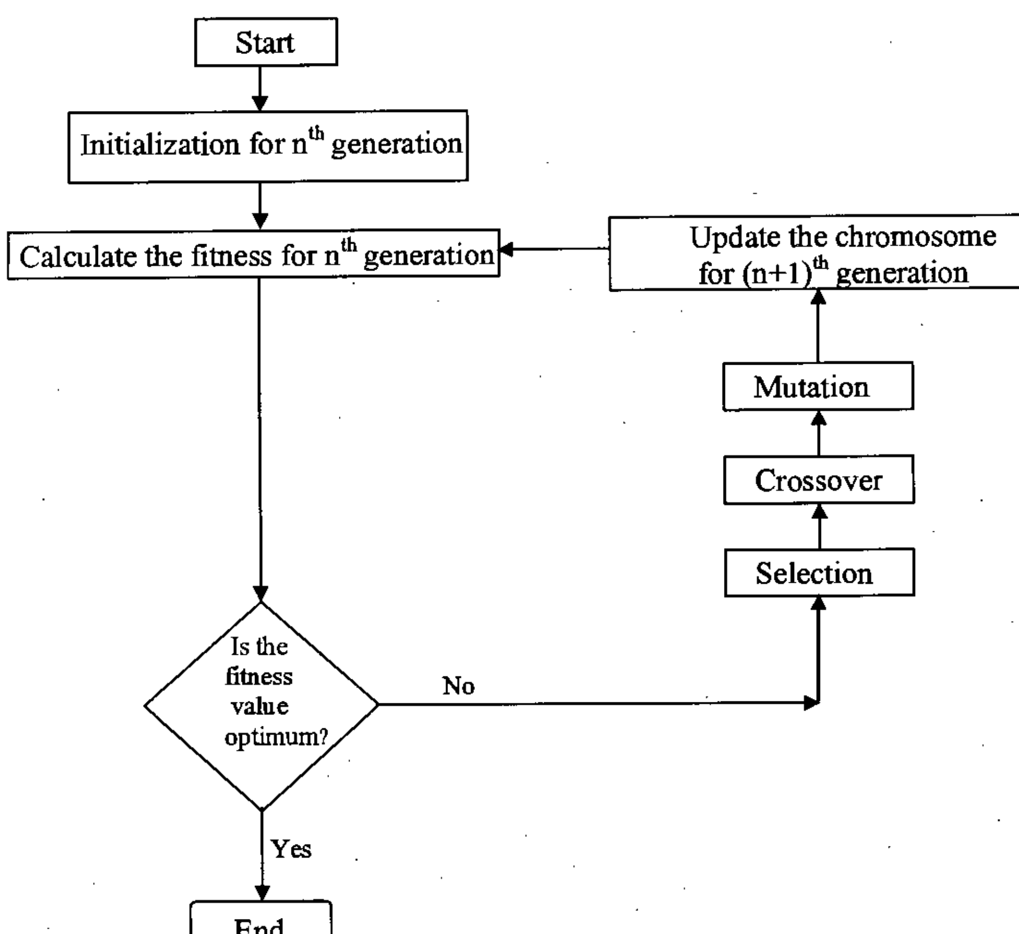


Fig. 2.4.4: Flowchart of basic genetic algorithm

2.4.2 Basics of particle swarm optimization

Particle swarm optimization (PSO) is one of the evolutionary computational techniques. Like the other evolutionary computation techniques, PSO is a population-based search algorithm and is initialized with a population of random solutions, called particles. Unlike in the other evolutionary computation techniques, each particle in PSO is also associated with a velocity. Particles fly through the search space with velocities which are dynamically adjusted according to their historical behaviors. Therefore, the particles have a tendency to fly towards the better and better search area over the course of search process. Since its introduction in 1995 by Kennedy and Eberhart, PSO has attracted a lot of attentions from the researchers around the world [32]-[38].

The original PSO algorithm is discovered through simplified social model simulation. The PSO algorithm works on the social behavior of particles in the swarm. Therefore, it finds the global best solution by simply adjusting the trajectory of each individual towards its own best location and towards the best particle of the entire swarm at each time step (generation).

The original PSO algorithm [32] can be described by

$$v_{id} = wv_{id} + c_1 rand()(p_{id} - x_{id}) + c_2 Rand()(p_{gd} - x_{id}) \tag{2.12}$$

$$x_{id} = x_{id} + v_{id} \tag{2.13}$$

where c_1 and c_2 are positive constants, w is the inertia weight and *rand()* and *Rand()* are two random functions in the range [0,1]; $X_i = (x_{i1}, x_{i2}, \ldots\ldots x_{iD})$ represents the i^{th} particle; $P_i = (p_{i1}, p_{i2}, \ldots\ldots p_{iD})$ represents the best previous position (the position giving the best fitness value) of the i^{th} particle; the symbol g represents the index of the best particle among all the particles in the population; $V_i = (v_{i1}, v_{i2}, \ldots\ldots v_{iD})$ represents the rate of the position change (velocity) for particle i. The best previous position, P_i and the best position among all the particles, P_g are designated as the local best (pbest) and global best (gbest) respectively.

Equation (2.12) & (2.13) are the equations describing the flying trajectory of a population of particles. Equation (2.12) describes how the velocity is dynamically updated and Equation (2.13) signifies the position update of the "flying" particles. Equation (2.12) consists of three parts. The first part is the momentum part. The velocity can't be changed abruptly. It is changed from the current velocity. The second part is the "cognitive" part which represents private thinking of itself - learning from its own flying experience. The third part is the "social" part which represents the collaboration among particles - learning from group flying experience. In Equation (2.12), if the sum of the three parts on the right side exceeds a constant value specified by user, then the velocity on that dimension is assigned to be $\pm V_{max}$, that is, particles' velocities on each dimension is clamped to a maximum velocity V_{max}, which is an important parameter, and originally is the only parameter required to be adjusted by users. Big V_{max} has particles have the potential to fly far past good solution areas while a small V_{max} has particles have the potential to be trapped into local minima, therefore unable to fly into better solution areas. Usually a fixed constant value is used as the V_{max}, but a well designed dynamically changing V_{max} might improve the PSO's performance.

2.4.2.1 Processing steps of PSO

- Initialize a population of N particles which signifies the random positions and velocities on D dimensions in the problem space.
- For each particle, evaluate the optimization fitness function in D variables.
- Compare particle's fitness evaluation with its *pbest*. If current value is better than *pbest*, then set *pbest* equal to the current value, and P_i equals to the current location X_i in D-dimensional space.
- Identify the particle in the neighborhood with the best success so far, and assign its index to the variable g.
- Change the velocity and position of the particle according to equation (2.12) and (2.13).
- Loop to step 2 until a criterion is met, usually a sufficiently good fitness or a maximum number of iterations.

2.4.2.2 Algorithm and flowchart of basic PSO

The algorithm as well as flowchart of a basic genetic algorithm is as follows

0 START : Create random swarm of **n** particles
1 FITNESS : Evaluate fitness **f(x)** of each particle in the population
2 NEW POPULATION
  0 : Calculate the local best value
  1 : Calculate the global best value
  2 : Update the position and velocity of the particle
3 REPLACE : Replace old with new population: the new generation
4 TEST : Test problem criterium
5 LOOP : Continue step 1 – 4 until criterium is satisfied

Fig. 2.4.5: Structure of Basic Particle Swarm Optimization

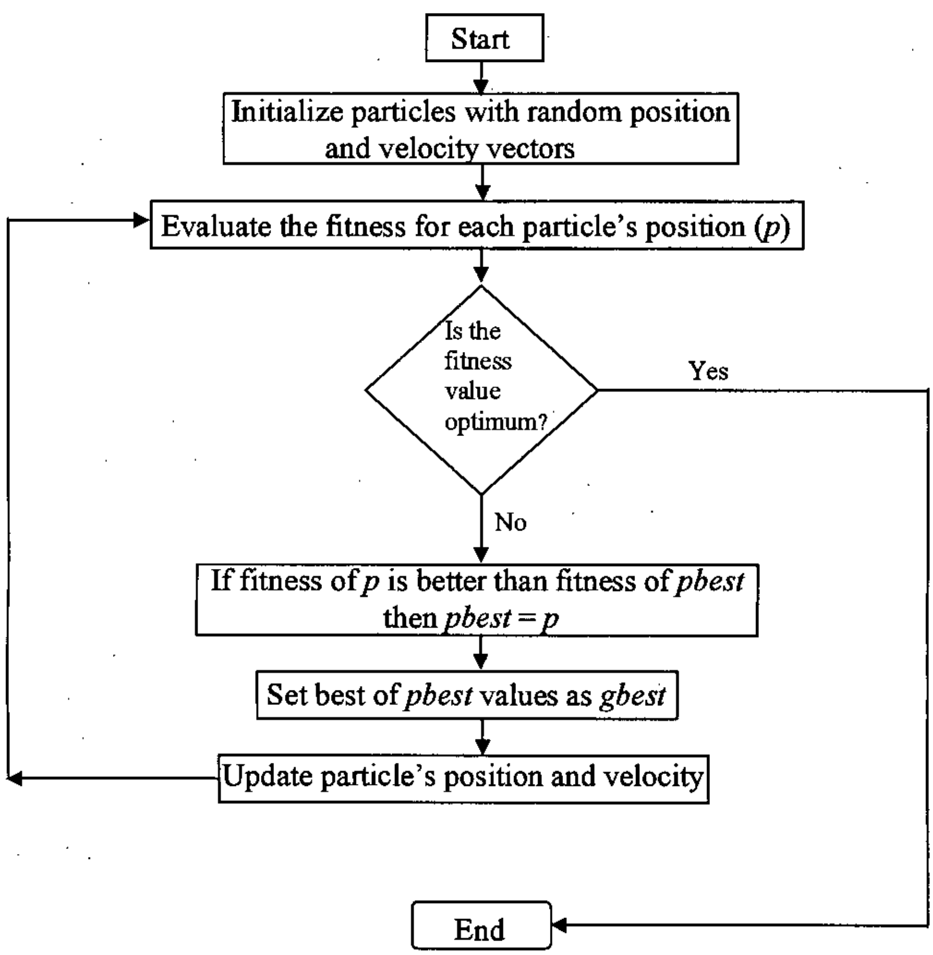


Fig. 2.4.6: Flowchart depicting the general PSO algorithm

Chapter 3

MODELING AND DESCRIPTION OF SYSTEM

In this chapter, the analytical expressions as well as structural view of used system models have been represented with necessary equations. The resource allocation schemes that have been used in this research work are given with necessary algorithms and flowcharts. The optimization system model of both GA and PSO have been presented with their modified versions along with their algorithms and corresponding flowcharts.

3.1 Structural Model Used in OFDMA Systems for Resource Allocation

Orthogonal Frequency Division Multiple Access (OFDMA) has recently received significant interest and has been adopted as one of the three physical layer modes in the IEEE wireless MAN standard 802.16-2004. In OFDMA the active subcarriers are divided into subsets of subcarriers termed as subchannels which are assigned to multiple users for simultaneous transmission. The subcarriers of each subchannel may not necessarily be adjacent. To maintain the orthogonality among the subcarriers in the uplink of OFDMA systems, the signals from all active users should arrive at the base station simultaneously. This is accomplished by an initial uplink synchronization called the ranging process by which the base stations adjust their transmission time instants and transmitted powers so that at the base station their ranging signals synchronize their mini-time slot boundary of the base station and have equal power. By means of the ranging process, the system compensates the near/far problems in large cells. Generally a ranging process can be categorized as initial ranging and periodic ranging. In this thesis, periodic ranging has been considered where transmitted power as well as the corresponding throughput has to be allocated to different users according channel state condition. Allocation of these available resources are accomplished after a certain period in a dynamic nature.

The basis of an OFDMA system in a particular cell in cellular structure has been shown in Fig. 3.1.1. Different users (say 10 users) reside over a particular hexagonal cell and always try to synchronize with the corresponding base station. The base station not only performs the initial synchronization but also allocates the available resources to the users for efficient and reliable transfer of data. For allocation of resources like power and throughput, the base station use to communicate with the available users with the help of forward and reverse transmission links (Fig. 3.1.2).

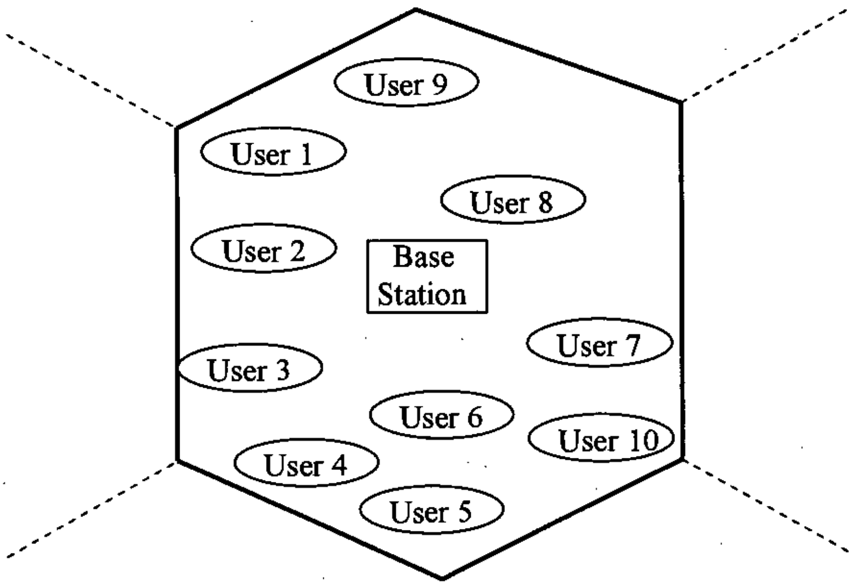


Fig. 3.1.1: Structural model of an OFDMA system in a particular cell for a cellular network

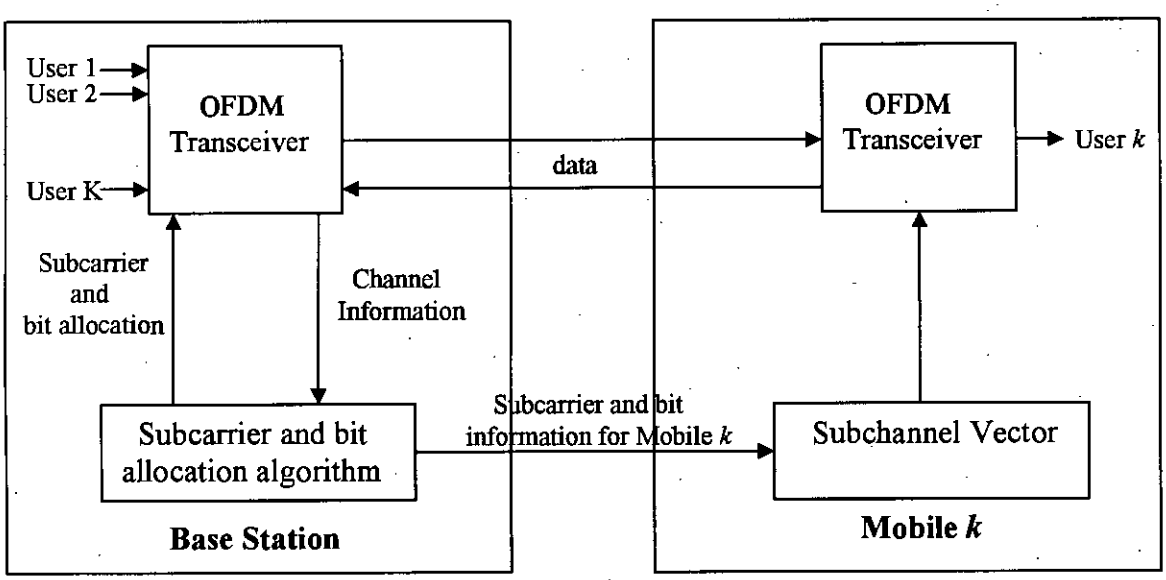


Fig. 3.1.2: Two-way communication between base station and a particular user

In the base station, all channel information is sent to the subcarrier and power allocation algorithm through feedback channels from all mobile users. The resource allocation scheme made by the algorithm is forwarded to the OFDM transceiver. The transceiver then selects different numbers of bits from different users to form an OFDM symbol. The resource allocation scheme is updated as fast as the channel information is amassed. In this research work, perfect instantaneous channel information is assumed to be available at the base station and only the broadcast scenario has been studied. It is also assumed that the subchannel and bit allocation information is sent to each user by a separate channel.

3.2 Basic OFDMA System Model

Let we consider the multiuser OFDM system having K $(k = 1, 2, \ldots, K)$ users and N $(n = 1, 2, \ldots, N)$ subcarriers. In the transmitter, the serial data from the users are fed into the subcarrier and bit allocation block which allocates bits from different users to different subcarriers. We assume that each subcarrier has a bandwidth that is much smaller than the coherence bandwidth of the channel and that the instantaneous channel gains on all the subcarriers of all the users are known to the transmitter. Using the channel information, the transmitter applies the combined subcarrier, bit, and power allocation algorithm to assign different subcarriers to different users and the number of bits/OFDM symbol to be transmitted on each subcarrier. Depending on the number of bits assigned to a subcarrier, the adaptive modulator will use a corresponding modulation scheme, and the transmit power level will be adjusted according to the combined subcarrier, bit, and power allocation algorithm. These subcarriers are grouped together into Q subchannels where each subchannel has $m = \dfrac{N}{Q}$ subcarriers. As a consequence, the system allots a subset of N subcarriers to a particular user and determines the number of bits per each assigned subcarrier on downlink transmission (Fig. 3.2.1).

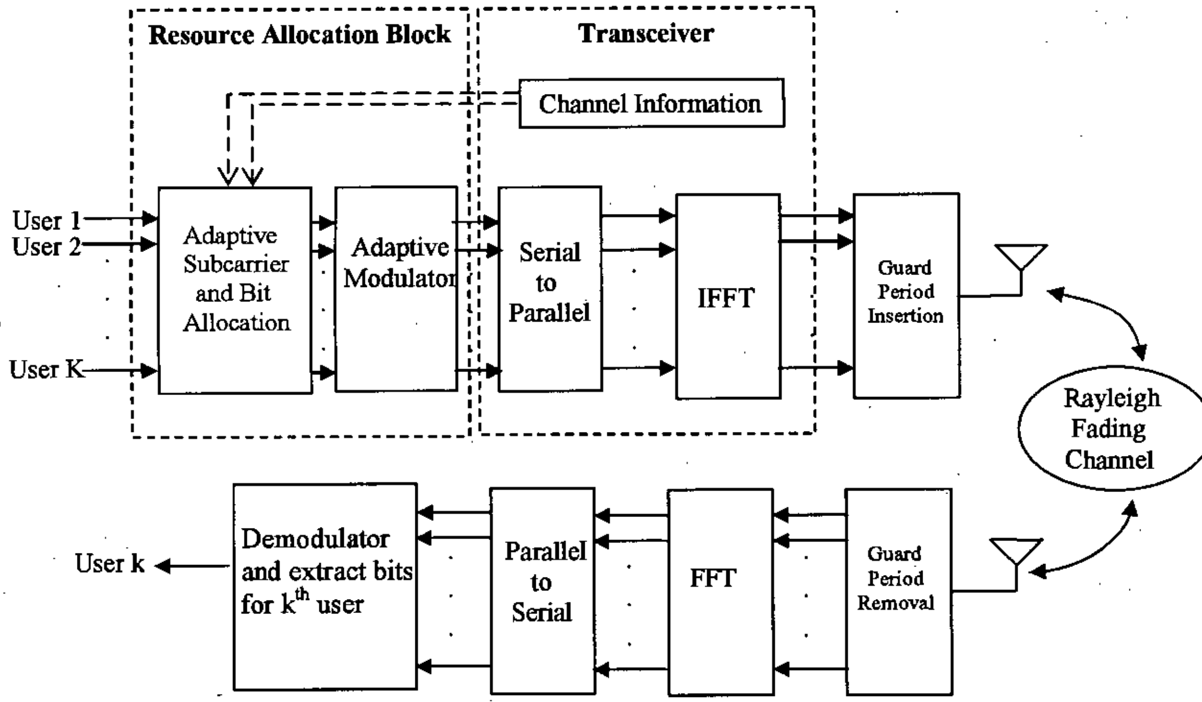


Fig. 3.2.1: Baseband transmission of a multiuser OFDM system

The complex symbols at the output of the modulators are transformed into the time domain samples by inverse fast Fourier transform (IFFT). Cyclic extension of the time domain samples, known as the guard interval, is then added to ensure orthogonality between the subcarriers, provided that the maximum time dispersion is less than the guard interval. The transmit signal is then passed through the Rayleigh fading channel to different users. We assume that the subcarrier and bit allocation information is sent to the receivers via a separate control channel. At the receiver, the guard interval is removed to eliminate the ISI, and the time samples of the k^{th} user are transformed by the FFT block into modulated symbols. The bit allocation information is used to configure the demodulators while the subcarrier allocation information is used to extract the demodulated bits from the subcarriers assigned to the k^{th} user. In the Rayleigh fading channel, different subcarriers will experience different channel gains. We denote by $|H|_{n,k}$ the magnitude of the channel gain (assuming coherent reception) of the n^{th} subcarrier as seen by the k^{th} user. We assume that the single-sided noise power spectral density (PSD) level N_0 is equal to unity for all subcarriers and is the same for all users.

3.3 Diversified Proposed Systems for Different Resource Allocation Schemes

The purpose of resource allocation at the base station is to intelligently allocate the limited resources, e.g. total transmit power and available frequency bandwidth among users to meet users' service requirements. Channel-aware adaptive resource allocation has been shown to achieve higher system performance than static resource allocation, and is becoming more critical in current and future wireless communication systems as the user data rate requirements increase. Furthermore, the subcarrier allocation problem to multiple users has many different permutations, thereby making the solution space very large. Unlike other algorithms, the evolutionary approaches can handle large solution space without any performance degradation. In this thesis, the subcarriers and bits are allocated to different users according to the dynamic channel state information through evolutionary approaches. Each user is allocated one or more subcarriers provided that one subcarrier can be used by only one user. The number of bits are then chosen according to the water filling algorithm i.e. the modulation schemes are selected in response of the channel state information of the corresponding user. The optimum arrangement of the users as well as subcarriers are evaluated by two evolutionary approaches. In this thesis work Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been deployed as the evolutionary methods. Considering the optimum usage of evolutionary approaches in multiuser OFDM systems, this thesis work has been diversified into two main category of its entity

- Application specific task in optimization of resource allocation
- Topological modification of PSO in optimization of resource allocation

The first one is the application of GA and PSO into two multiuser OFDM resource allocation schemes, namely margin adaptive allocation and rate adaptive allocation. Both the margin and rate adaptation schemes are evaluated by the original and modified versions of GA and PSO. Each of the algorithms is analyzed for unconstrained case as well as fair scheduled case. The second category is dealt with the topological modifications of these optimization techniques. The original versions are modified to obtain better results for either of the adaptation cases.

3.3.1 Application specific task in optimization of resource allocation

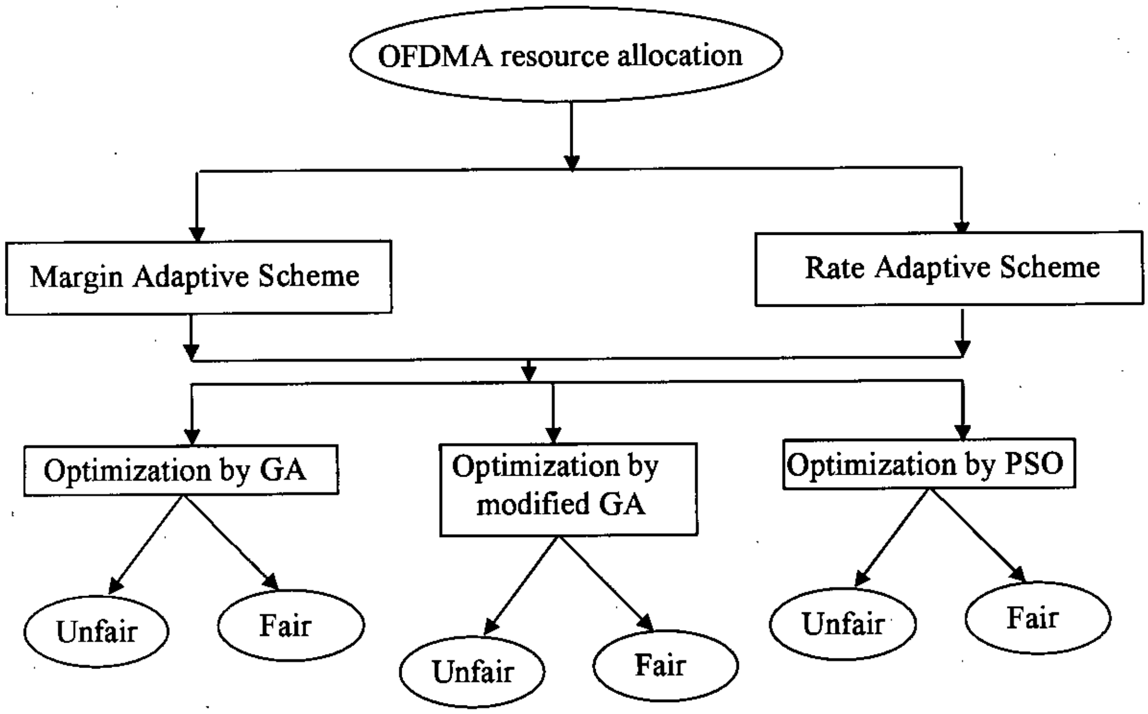


Fig. 3.3.1 Different proposed systems for resource allocations

During the first part of thesis, genetic algorithm (GA), modified GA and particle swarm optimization (PSO) have been applied in optimizing the transmit power for a constant bit error rate and in optimizing the bit rate for a definite amount of transmitting power. Both the optimizations are performed under unconstrained and fair scheduled approach.

3.3.1.1 Margin Adaptive (MA) resource allocation for multiuser OFDM systems

In margin adaptive resource allocation system the total transmitted power has to be minimized for the optimum arrangement of subcarriers and bits to the users with the constraints of bit error rate. In some cases, margin adaptive scheme concentrates on minimizing the overall bit error rate for a definite amount of transmitted power. For both the cases, the user data rate has to remain constant throughout the transmission period. In this thesis dissertation both the methods have been analyzed after defining a suitable fitness function for power as well as bit error rate optimization for the used multicarrier systems. The genetic algorithm and particle swarm optimization have been applied to optimize the overall requirement keeping the constraints intact. At first an appropriate fitness function has been derived for the used system model and then the initial population matrix as well as sub-initial populations have been affixed to start the evolutionary approaches.

3.3.1.1.1 Modeling of the fitness function for MA approach

Let $b_{n,k} \in \{0,1,2,.....,B\}$ signify the number of bits for n^{th} subcarrier and k^{th} user where B denotes the maximum number of information bits that can be transmitted by each subcarrier. R_k represents the number of bits that are needed to be transmitted in an OFDM system. Here $b_{n,k}$ determines the mode of adaptive modulation (i.e. BPSK, 16 QAM, 64 QAM or anything else). The system has been assumed to acquire channel state information through its dynamic channel estimation scheme. Let $|H|_{n,k}$ represents the channel gain for n^{th} subcarrier and k^{th} user. The required transmission power for the specified bit error rate at $b_{n,k}$ bits per symbol is given by [13],

$$p_{n,k} = \frac{f(b_{n,k})}{|H|^2_{n,k}} \tag{3.1}$$

In multiuser scenario, not more than one user is considered to share a particular subcarrier. Mathematically it is expressed as

$$\lambda_{n,k} = \begin{cases} 1 \ if \ b_{n,k} \neq 0 \\ 0 \ if \ b_{n,k} = 0 \end{cases} \tag{3.2}$$

We assume that the channel is ISI-free and has gain $|H|$. The probability of two-dimensional symbol error in QAM is closely approximated as

$$P_e = 4Q\left[\frac{d_{\min}}{2\sigma}\right] \tag{3.3}$$

where $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty e^{-\frac{t^2}{2}}dt$ and $d_{\min}$ is the minimum distance between QAM constellation points at the channel output and is given by

$$d^2_{\min} = d^2|H|^2 \tag{3.4}$$

where d is the distance between constellation points at the channel output.

We define a convenient quantity called SNR gap (or sometimes called normalized SNR) by

$$3\Gamma = \frac{d_{\min}^2}{4\sigma^2} \tag{3.5}$$

where $2\sigma^2$ is defined as the noise power. In QAM the number of bits to be transmitted is defined as

$$b = \log_2 M = \log_2(1 + \frac{SNR}{\Gamma}) \tag{3.6}$$

Here M denotes number of QAM levels and $SNR = \frac{P|H|^2}{2\sigma^2}$ where P defines total transmitted power. So from equation (1), the symbol error probability,

$$\begin{aligned} P_e &= 4Q\left[\frac{2\sqrt{3\Gamma}\sigma}{2\sigma}\right] \\ &= 4Q[\sqrt{3\Gamma}] \\ &= 4Q\left[\sqrt{3}\sqrt{\frac{SNR}{2^b - 1}}\right] \\ &= 4Q\left[\sqrt{3}\sqrt{\frac{P|H|^2}{2\sigma^2(2^b - 1)}}\right] \end{aligned} \tag{3.7}$$

So,

$$\begin{aligned} & Q\left[\sqrt{\frac{3P_{ind}|H|^2}{2\sigma^2(2^b - 1)}}\right] = \frac{1}{4}P_e \\ &\Rightarrow \sqrt{\frac{3P_{ind}|H|^2}{2\sigma^2(2^b - 1)}} = Q^{-1}\left(\frac{1}{4}P_e\right) \\ &\Rightarrow \frac{3P_{ind}|H|^2}{2\sigma^2(2^b - 1)} = \left[Q^{-1}\left(\frac{1}{4}P_e\right)\right]^2 \\ &\Rightarrow \frac{3P_{ind}|H|^2}{N_0(2^b - 1)} = \left[Q^{-1}\left(\frac{1}{4}P_e\right)\right]^2 \\ &\Rightarrow P_{ind} = \frac{N_0}{3|H|^2}\left[Q^{-1}\left(\frac{1}{4}P_e\right)\right]^2 \left(2^b - 1\right) \end{aligned} \tag{3.8}$$

Here Q^{-1} denotes the inverse Q function. This equation represents the fitness function for Margin Adaptive optimization problem. If we assume the symbol error rate as bit error rate for corresponding modulation scheme then the above equation can be approximated as

$$P_{ind} = \frac{N_0}{3|H|^2}\left[Q^{-1}\left(\frac{1}{4}BER\right)\right]^2 \left(2^b - 1\right) \tag{3.10}$$

So, the required total transmission power (P_{total}) can be written as follows

$$P_{total} = \sum_{n=1}^{N}\sum_{k=1}^{K}\frac{f(b_{n,k})}{H_{n,k}^2} \times \lambda_{n,k} \tag{3.11}$$

where, $$f(b_{n,k}) = \frac{N_0}{3}[Q^{-1}(\frac{BER_n}{4})]^2(2^{b_{n,k}}-1)$$

3.3.1.1.2 Setting of initial population of MA approach

The serial binary data from the transmitting side of different users are made into parallel and then mapped according to different modulation schemes like, BPSK, QPSK, 16 QAM, 64 QAM etc. The selection of modulation schemes ultimately decides the number of the bits to be transmitted. The subcarrier allocation to the different users are made into random and therefore this random selection is used to define the initial population. The number of bits for a particular subcarrier are then selected according to the water filling algorithm. This conventional algorithm reveals the fact that more bits are allocated to a subcarrier whose channel state information is good and vice-versa. So

$$\text{Initial population} = \begin{bmatrix} g_{1,1} & g_{1,2} & g_{1,3} & \cdots\cdots & g_{1,N} \\ g_{2,1} & g_{2,2} & g_{2,3} & \cdots\cdots & g_{2,N} \\ . & .. & & .. & .. \\ . & .. & & .. & .. \\ g_{Nind,1} & g_{Nind,2} & g_{Nind,3} & \cdots\cdots & g_{Nind,N} \end{bmatrix} \tag{3.12}$$

Here $g_{i,j}$ represents the random assignment of user to a particular subcarrier j for i^{th} chromosome.

The matrix of the random assignments of users reveals two another implicit initial populations, (which is defined as sub-initial populations) of channel state information and number of bits. The wireless channel has been assumed here as the quasi static. The channel state information at each subcarrier is generated randomly and subject to 'Rayleigh' distribution.

Rayleigh fading models assume that the magnitude of a signal that has passed through a transmission medium (also called a communications channel) varies randomly, according to a Rayleigh distribution. Rayleigh fading is a reasonable model when there are many objects in the environment that scatter the radio signal before it arrives at the receiver. The central limit theorem holds that, if there is sufficiently much scatter, the channel impulse response will be well-modelled as a Gaussian process irrespective of the distribution of the individual components. If there is no dominant component to the scatter, then such a process will have zero mean and phase evenly distributed between 0 and 2π radians. The envelope of the channel response will therefore be Rayleigh distributed.

Calling this random variable R, it will have a probability density function:

$$p_R(r) = \frac{2r}{\Omega} e^{-r^2/\Omega} \qquad (3.13)$$

where $\Omega = E(R^2)$

Then according to the Rayleigh distribution, the implicit channel matrix becomes –

$$\text{Channel matrix} = \begin{bmatrix} ch_{1,1} \; ch_{1,2} \; ch_{1,3} \; \cdots\cdots\cdots\cdots\cdots ch_{1,N} \\ ch_{2,1} \; ch_{2,2} \; ch_{2,3} \; \cdots\cdots\cdots\cdots\cdots ch_{2,N} \\ . \quad .. \quad .. \quad .. \\ . \quad .. \quad .. \quad .. \\ ch_{Nind,1} \; ch_{Nind,2} \; ch_{Nind,3} \; \cdots\cdots ch_{Nind,N} \end{bmatrix} \qquad (3.14)$$

where $ch_{i,j}$ represents the channel gain for a user to a particular subcarrier j for i^{th} chromosome.

The bits from the corresponding users are allocated to the subcarriers according to the conventional water-filling algorithm.

$$\text{Bit matrix} = \begin{bmatrix} b_{1,1} & b_{1,2} & b_{1,3} & \dots\dots\dots\dots\dots & b_{1,N} \\ b_{2,1} & b_{2,2} & b_{2,3} & \dots\dots\dots\dots\dots & b_{2,N} \\ . & .. & .. & & .. \\ . & .. & .. & & .. \\ b_{Nind,1} & b_{Nind,2} & b_{Nind,3} & \dots\dots\dots & b_{Nind,N} \end{bmatrix} \qquad (3.15)$$

where $b_{i,j}$ represents the number of bits for a user to a particular subcarrier j for i^{th} chromosome.

The bit and channel matrices are used to evaluate the total power for an OFDM symbol.

3.3.1.1.3 Unfair scheduling

The subcarrier, bit and power allocation problem for minimizing the total transmit power can be formulated as –

$$\arg\min_{b_{n,k}} \sum_{n=1}^{N}\sum_{k=1}^{K} \frac{f(b_{n,k})}{H_{n,k}^2} \times \lambda_{n,k} \qquad (3.16)$$

subject to

$$\sum_{k=1}^{K} \lambda_{n,k} = 1 \quad \text{for } n=1,\, 2,\, \dots\dots\dots,\, N \qquad (3.17)$$

$$\sum_{n=1}^{N}\sum_{k=1}^{K} \lambda_{n,k} = N \quad \text{for } b_{n,k} \in \{0,1,2,\dots\dots,B\} \qquad (3.18)$$

$$R_k = \sum_{n=1}^{N} b_{n,k} \quad \text{for k} = 1,\, 2,\, \dots\dots\dots,\, K \qquad (3.19)$$

3.3.1.1.4 Fair share scheduling

In fairly scheduled case, the problem has been formulated with the fact in mind that a minimum number of subcarriers have to be allocated to a particular user even at the worst scenario. The optimization problem for fair scheduled case can be formulated as –

$$\arg\min_{b_{n,k}} \sum_{n=1}^{N}\sum_{k=1}^{K} \frac{f(b_{n,k})}{H_{n,k}^2} \times \lambda_{n,k} \qquad (3.20)$$

subject to

$k_n \geq N_{\min}$, where k_n is the number of subcarriers for a particular user k

$$\sum_{k=1}^{K} \lambda_{n,k} = 1 \quad \text{for } n=1, 2, \ldots\ldots\ldots, N \tag{3.21}$$

$$\sum_{n=1}^{N} \sum_{k=1}^{K} \lambda_{n,k} = N \quad \text{for } b_{n,k} \in \{0,1,2,\ldots\ldots,B\} \tag{3.22}$$

$$R_k = \sum_{n=1}^{N} b_{n,k} \quad \text{for k} = 1, 2, \ldots\ldots\ldots, K \tag{3.23}$$

3.3.1.1.5 Use of the evolutionary approaches for optimization

Unlike other algorithms, the evolutionary approaches can handle large solution space without any performance degradation. Two most famous algorithms, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) can be efficiently used for optimization of two schemes of resource allocation.

3.3.1.1.5.1 Original genetic algorithm

Genetic algorithm is inspired by the mechanism of natural selection where stronger individuals are likely to be the winners in a competing environment. The continuing performance improvement of the computational system has made GA attractive for some types of optimization. As a matter of fact GA is very suitable for the optimization of bit and subcarrier allocation problem in multiuser OFDM system.

After the formation of the initial and corresponding sub-initial population according to different constraints, GA is used to evaluate the optimum arrangement of the users to the subcarriers. An algorithmic pseudo code has been formulated to evaluate this proposed margin adaptive algorithm.

```
ORIGINAL_GA(NIND, MAXGEN,NVAR,PRECI)

1. start
2. chrom ← initial_population(NIND, NVAR*PRECI)
3. gen ← 0
4. objV ← objfun(chrom)
5. while gen < MAXGEN
    a. FitnV ← ranking(objV)
    b. Selch ← select(chrom,FitnV) % For minimum
    c. Selch ← recombin(Selch,recombin_probability)
    d. Selch ← mut(Selch,mut_probability)
    e. ObjV ← objfun(Selch)
    f. gen ← gen + 1
6. end while
7. end
```

Fig. 3.3.2: Algorithmic pseudo-code of original GA

In this pseudo code, NIND, MAXGEN,NVAR,PRECI stand for number of individuals, maximum generation number, number of variables (here it designates the number o subcarriers for a particular OFDM system) and precision index. With the help of this values, the initial and sub-initial populations are generated by initial_population() function. The following table explains each of the used functions

Table 3.3.1 Parameter specification for original GA in margin adaptation

Functions	Explanation
objfun()	Evaluates the fitness value by fitness function
ranking()	Ranks the fitness values according to the requirements
select()	Performs selection procedure
recombin()	Performs recombination procedure
mut()	Performs mutation procedure

3.3.1.1.5.2 Modified genetic algorithm

GA has been modified slightly over the conventional one by setting a fractional value of the generation gap. The fractional generation gap ('GGAP' in the following pseudo code) helps to converge quickly by taking the good genes for the next generation.

```
MODIFIED_GA(NIND, MAXGEN, NVAR, PRECI,GGAP)

1. start
2. chrom ← initial_population(NIND, NVAR*PRECI)
3. gen ← 0
4. objV ← objfun(chrom)
5. while gen < MAXGEN
   a. FitnV ← ranking(objV)
   b. Selch ← select(chrom,FitnV,GGAP) % For minimum
   c. Selch ← recombin(Selch,recombin_probability)
   d. Selch ← mut(Selch,mut_probability)
   e. ObjVsel ← objfun(Selch)
   f. [chrom objV]=reins(chrom, Selch, ObjVsel)
   g. gen ← gen + 1
6. end while
7. end
```

Fig. 3.3.3: Algorithmic pseudo-code of modified GA

Table 3.3.2 Parameter specification for modified GA in margin adaptation

Functions	Explanation
objfun()	Evaluates the fitness value by fitness function
ranking()	Ranks the fitness values according to the requirements
select()	Performs selection procedure
recombin()	Performs recombination procedure
mut()	Performs mutation procedure
reins()	Reinserts new chromosomes

3.3.1.1.5.3 Particle swarm optimization

Particle swarm optimization (PSO) is one of the evolutionary computational techniques. Like the other evolutionary computation techniques, PSO is a population-based search algorithm and is initialized with a population of random solutions, called particles. The original PSO algorithm is discovered through simplified social model simulation.

ORIGINAL_PSO (NIND, MAXGEN, NVAR, C1, C2, WEIGHT, rand(), RAND())

1. start
2. chrom ← initial_population(NIND, NVAR*PRECI)
3. gen ← 0
4. objV ← objfun(chrom)
5. while gen < MAXGEN
    a. lbest ← local_bst(NIND, NVAR) % For minimum
    b. gbest ← global_bst(NIND, NVAR) % For minimum
    c. Calculate updated velocity and position
        i. $(v_{id})_{i,j} = w(v_{id})_{i,j} + c_1 rand()((p_{id})_{i,j} - (g_{id})_{i,j}) + c_2 Rand()((p_{gd})_{i,j} - (g_{id})_{i,j})$
        ii. $(g_{id})_{i,j} = (g_{id})_{i,j} + (v_{id})_{i,j}$
    d. gen ← gen + 1
6. end while
7. end

Fig. 3.3.4 Algorithmic pseudo-code of original PSO

In this pseudo code NIND, MAXGEN, NVAR, C1, C2, WEIGHT, rand(), RAND() represent number of individuals, maximum generation number, number of variables (here it designates the number o subcarriers for a particular OFDM system), constants, inertia weight and random variables respectively. Like GA, the initial population matrix has been formed along with its sub-initial population matrices. The following table signifies each of the commands.

Table 3.3.3 Parameter specification for PSO in margin adaptation

Functions	Explanation
objfun()	Evaluates the fitness value by fitness function
local_bst()	Finds the local best value for a particular generation
global_bst()	Finds the global best value for a particular generation

3.3.1.2 Rate Adaptive (RA) resource allocation for multiuser OFDM systems

3.3.1.2.1 Fitness function for RA approach

In rate adaptive resource allocation scheme, the throughput is maximized for a constant transmitted power level having a fixed amount of bit error rate. The fitness function used here for optimization is evolved from Shanon's theorem which signifies the fact of the maximum capacity of a dedicated channel. The fitness function for rate adaptive approach is –

$$R_k = \sum_{k=1}^{K}\sum_{n=1}^{N}\frac{\rho_{k,n}}{N}\log_2\left(1+\frac{p_{k,n}H_{k,n}^2}{N_0\frac{B}{N}}\right) \tag{3.24}$$

where K is the total number of users, N is the total number of subcarriers, N_0 is the power spectral density of additive white Gaussian noise, B is the total available bandwidth. $p_{k,n}$ is the power allocated for user k in the subcarrier n , $h_{k,n}$ is the channel gain for user k and subcarrier n, $\rho_{k,n}$ can only be the value of either 1 or 0, indicating whether subcarrier n is used by user k or not. The fourth constraint shows that each subcarrier can only be used by one user.

3.3.1.2.2 Setting of initial population for RA approach

The serial binary data from the transmitting side of different users are made into parallel and then mapped according to different modulation schemes like, BPSK, QPSK, 16 QAM, 64 QAM etc. The selection of modulation schemes ultimately decides the number of the bits to be transmitted. The subcarrier allocation to the different users are made into random and therefore this random selection is used to define the initial population. The number of bits for a particular subcarrier are then selected according to the water filling algorithm. This conventional algorithm reveals the fact that more bits are allocated to a subcarrier whose channel state information is good and vice-versa. So

$$\Rightarrow \text{Initial population} = \begin{bmatrix} g_{1,1} & g_{1,2} & g_{1,3} & \cdots & g_{1,N} \\ g_{2,1} & g_{2,2} & g_{2,3} & \cdots & g_{2,N} \\ . & .. & .. & & .. \\ . & .. & .. & & .. \\ g_{Nind,1} & g_{Nind,2} & g_{Nind,3} & \cdots & g_{Nind,N} \end{bmatrix} \qquad (3.25)$$

Here $g_{i,j}$ represents the random assignment of user to a particular subcarrier j for ith chromosome.

The matrix of the random assignments of users reveals two another implicit initial populations, (which is defined as sub-initial populations) of channel state information and number of bits. The wireless channel has been assumed here as the quasi static. The channel state information at each subcarrier is generated randomly and subject to 'Rayleigh' distribution.

Then according to the Rayleigh distribution, the implicit channel matrix becomes –

$$\text{Channel matrix} = \begin{bmatrix} ch_{1,1} & ch_{1,2} & ch_{1,3} & \cdots & ch_{1,N} \\ ch_{2,1} & ch_{2,2} & ch_{2,3} & \cdots & ch_{2,N} \\ . & .. & .. & & .. \\ . & .. & .. & & .. \\ ch_{Nind,1} & ch_{Nind,2} & ch_{Nind,3} & \cdots & ch_{Nind,N} \end{bmatrix} \qquad (3.26)$$

where $ch_{i,j}$ represents the channel gain for a user to a particular subcarrier j for ith chromosome.

3.3.1.2.3 Unfair scheduling

The subcarrier, bit and power allocation problem for minimizing the total transmit power can be formulated as –

$$\arg\min_{\rho_{n,k},p_{n,k}} \sum_{n=1}^{N}\sum_{k=1}^{K} \frac{\rho_{k,n}}{N} \log_2\left(1+\frac{p_{k,n}H_{k,n}^2}{N_0\frac{B}{N}}\right) \qquad (3.27)$$

subject to

$$\begin{aligned}
&\sum_{n=1}^{N}\sum_{k=1}^{K} p_{n,k} \le P_{total} \\
&p_{n,k} \ge 0 \ for\ all\ n,k \\
&\rho_{n,k} = \{0,1\} \ for\ all\ n,k \\
&\sum_{k=1}^{K} \rho_{n,k} = 1 \ for\ all\ n
\end{aligned} \qquad (3.28)$$

3.3.1.2.4 Fair share scheduling

In fairly scheduled case, the problem has been formulated with the fact in mind that a minimum number of subcarriers has to be allocated to a particular user even at the worst scenario. The optimization problem for fair scheduled case can be formulated as –

$$\underset{\rho_{n,k},p_{n,k}}{\arg\min} \sum_{n=1}^{N}\sum_{k=1}^{K} \frac{\rho_{k,n}}{N} \log_2\left(1+\frac{p_{k,n}H_{k,n}^2}{N_0\frac{B}{N}}\right) \qquad (3.29)$$

subject to

$k_n \ge N_{\min}$, where k_n is the number of subcarriers for a particular user k

$$\begin{aligned}
&\sum_{n=1}^{N}\sum_{k=1}^{K} p_{n,k} \le P_{total} \\
&p_{n,k} \ge 0 \ for\ all\ n,k \\
&\rho_{n,k} = \{0,1\} \ for\ all\ n,k \\
&\sum_{k=1}^{K} \rho_{n,k} = 1 \ for\ all\ n
\end{aligned} \qquad (3.30)$$

3.3.1.1.5 Use of the evolutionary approaches for optimization

For rate adaptation, the evolutionary approaches have been used in both unconstrained and constrained manner. Like margin adaptation, the evolutionary approaches can handle large solution space without any performance degradation in rate adaptation also. GA, with its original and modified version and PSO, with its original version have been deployed to optimize the throughput of an OFDM symbol.

3.3.1.1.5.1 Original genetic algorithm

```
ORIGINAL_GA(NIND, MAXGEN,NVAR,PRECI)

1. start
2. chrom ← initial_population(NIND, NVAR*PRECI)
3. gen ← 0
4. objV ← objfun(chrom)
5. while gen < MAXGEN
     a. FitnV ← ranking(objV)
     b. Selch ← select(chrom,FitnV) % For maximum
     c. Selch ← recombin(Selch,recombin_probability)
     d. Selch ← mut(Selch,mut_probability)
     e. ObjV ← objfun(Selch)
     f. gen ← gen + 1
6. end while
7. end
```

Fig. 3.3.5: Algorithmic pseudo-code of original GA

Table 3.3.4 Parameter specification for original GA in rate adaptation

Functions / Variables	Explanation
NIND	number of individuals
MAXGEN	maximum generation number
NVAR	number of variables (number of subcarriers)
PRECI	precision index
initial_population()	Initial population set
objfun()	Evaluates the fitness value by fitness function
ranking()	Ranks the fitness values according to the requirements
select()	Performs selection procedure
recombin()	Performs recombination procedure
mut()	Performs mutation procedure

3.3.1.1.5.2 Modified genetic algorithm

GA has been modified slightly over the conventional one by setting a fractional value of the generation gap. The fractional generation gap helps to converge quickly by taking the good genes for the next generation.

```
MODIFIED_GA(NIND, MAXGEN, NVAR, PRECI,GGAP)

1. start
2. chrom ← initial_population(NIND, NVAR*PRECI)
3. gen ← 0
4. objV ← objfun(chrom)
5. while gen < MAXGEN
    a. FitnV ← ranking(objV)
    b. Selch ← select(chrom,FitnV,GGAP) % For maximum
    c. Selch ← recombin(Selch,recombin_probability)
    d. Selch ← mut(Selch,mut_probability)
    e. ObjVsel ← objfun(Selch)
    f. [chrom objV]=reins(chrom, Selch, ObjVsel)
    g. gen ← gen + 1
6. end while
7. end
```

Fig. 3.3.6: Algorithmic pseudo-code of modified GA

Table 3.3.5 Parameter specification for modified GA in rate adaptation

Functions / Variables	Explanation
NIND	number of individuals
MAXGEN	maximum generation number
NVAR	number of variables (number of subcarriers)
GGAP	Generation gap
PRECI	precision index

initial_population()	Initial population set
objfun()	Evaluates the fitness value by fitness function
ranking()	Ranks the fitness values according to the requirements
select()	Performs selection procedure
recombin()	Performs recombination procedure
mut()	Performs mutation procedure
reins()	Reinserts new chromosomes

3.3.1.1.5.3 Particle swarm optimization

Particle swarm optimization (PSO) is one of the evolutionary computational techniques. Like the other evolutionary computation techniques, PSO is a population-based search algorithm and is initialized with a population of random solutions, called particles. The original PSO algorithm is discovered through simplified social model simulation.

ORIGINAL_PSO (NIND, MAXGEN, NVAR, C1, C2, WEIGHT, rand(), RAND())

1. start
2. chrom ← initial_population(NIND, NVAR*PRECI)
3. gen ← 0
4. objV ← objfun(chrom)
5. while gen < MAXGEN
    a. lbest ← local_bst(NIND, NVAR) % For maximum
    b. gbest ← global_bst(NIND, NVAR) % For maximum
    c. Calculate updated velocity and position
        i. $(v_{id})_{i,j} = w(v_{id})_{i,j} + c_1 rand()((p_{id})_{i,j} - (g_{id})_{i,j}) + c_2 Rand()((p_{gd})_{i,j} - (g_{id})_{i,j})$
        ii. $(g_{id})_{i,j} = (g_{id})_{i,j} + (v_{id})_{i,j}$
    d. gen ← gen + 1
6. end while
7. end

Fig. 3.3.7: Algorithmic pseudo-code of original PSO

Table 3.3.6 Parameter specification for PSO in rate adaptation

Functions	Explanation
NIND	number of individuals
MAXGEN	maximum generation number
NVAR	number of variables (number of subcarriers)
C1, C2	Constant
Rand(), rand()	Random variables
WEIGHT	Inertia weight
objfun()	Evaluates the fitness value by fitness function
local_bst()	Finds the local best value for a particular generation
global_bst()	Finds the global best value for a particular generation

3.3.2 Topological modification of PSO in optimization of resource allocation

3.3.2.1 First modified structure

Here the generation index has been introduced in the equation of position update. In the original PSO position update equation the previous position has just been added with the newly obtained velocity. But the generation information is missing here. As a consequence the timing information as well as the generation information should be introduced here in the velocity update equation. The modified update equations are as follows:

$$(v_{id})_{i,j} = w(v_{id})_{i,j} + c_1 rand()((p_{id})_{i,j} - (g_{id})_{i,j}) + c_2 Rand()((p_{gd})_{i,j} - (g_{id})_{i,j}) \qquad (3.31)$$

$$(g_{id})_{i,j} = (g_{id})_{i,j} + ((v_{id})_{i,j} . (gen)_{norm}) \qquad (3.32)$$

Here $(gen)_{norm}$ denotes normalized generation index.

FIRST_MODIFIED_PSO (NIND, MAXGEN, NVAR, C1, C2, WEIGHT, rand(), RAND())

1. start
2. chrom ← initial_population(NIND, NVAR*PRECI)
3. gen ← 0
4. objV ← objfun(chrom)
5. while gen < MAXGEN
    a. lbest ← local_bst(NIND, NVAR)
    b. gbest ← global_bst(NIND, NVAR)
    c. Calculate updated velocity and position
        i. $(v_{id})_{i,j} = w(v_{id})_{i,j} + c_1 rand()((p_{id})_{i,j} - (g_{id})_{i,j}) + c_2 Rand()((p_{gd})_{i,j} - (g_{id})_{i,j})$
        ii. $(g_{id})_{i,j} = (g_{id})_{i,j} + gen \cdot (v_{id})_{i,j}$
    d. gen ← gen + 1
6. end while
7. end

Fig. 3.3.8: Algorithmic pseudo-code of first modified PSO

3.3.2.2 Second modified structure

In conventional PSO, static inertia weight does not give the optimum result whereas the dynamicity in inertia weight makes the result closer to the optimum one. The dynamic nature has been introduced here by formulating an equation

$$Inertia\ weight = w\_max - (gen-1)*w\_dec \qquad (3.33)$$

where *w_max* is defined as the maximum possible value for inertia weight, *gen* stands for generation number and *w_dec* is calculated by

$$w\_dec=(w\_max-w\_min)/w\_step \qquad (3.34)$$

Here *w_min* and *w_step* stands for minimum and incremental rate of inertia weight respectively.

By linearly decreasing the inertia weight from a relatively large value to a small value through the course of the PSO run gives the best PSO performance compared with fixed inertia weight settings.

SECOND_MODIFIED_PSO (NIND, MAXGEN, NVAR, C1, C2, rand(), RAND())

---

1. start
2. chrom ← initial_population(NIND, NVAR*PRECI)
3. gen ← 0
4. objV ← objfun(chrom)
5. while gen < MAXGEN
    a. lbest ← local_bst(NIND, NVAR)
    b. gbest ← global_bst(NIND, NVAR)
    c. Calculate adaptive inertia weight
        i. *Inertia_weight,(I.A.) = w_max-(gen-1)*w_dec*
        ii. *w_dec = (w_max-w_min)/w_step*
    d. Calculate updated velocity and position
        i. $(v_{id})_{i,j} = I.A.\cdot(v_{id})_{i,j} + c_1 rand()((p_{id})_{i,j} - (g_{id})_{i,j}) + c_2 Rand()((p_{gd})_{i,j} - (g_{id})_{i,j})$
        ii. $(g_{id})_{i,j} = (g_{id})_{i,j} + gen\cdot(v_{id})_{i,j}$
    e. gen ← gen + 1
6. end while
7. end

Fig. 3.3.9: Algorithmic pseudo-code of second modified PSO

3.3.2.3 Third modified structure

The commonly used PSOs are either global version or local version of PSO. In the global version of PSO, each particle flies through the search space with a velocity that is dynamically adjusted according to the particle's personal best performance achieved so far and the best performance achieved so far by all the particles. In the local version of

PSO, each particle's velocity is adjusted according to its personal best and the best performance achieved so far within its neighbourhood. The neighbourhood of each particle is generally defined as topologically nearest particles to the particle at each side. The global version of PSO can also be considered as a local version of PSO with each particle's neighbourhood to be the whole population. Kennedy and Mendes tested PSOs with regular shaped neighborhoods, such as global version, local version, pyramid structure, star structure, 'small' structure, and von Neumann, and PSOs with randomly generated neighbourhoods. In this part of modification, the ring topology is used to find the global best value for any particle while updating its velocity. The particles are arranged on a ring-like network according to its index values in the initial population as shown in Fig. 3.3.10. Here n is the total number of particles in the swarm and k the index of particles, where $k = 1, 2, \ldots, n$. For any particle, neighbours are selected one from either side of it on the ring. For example, the neighbours of particle 1 are particles of index 2 and n (Fig. 3.3.10). The best guide for that particle is selected, based on the objective function, from the three, two neighbors and the particle itself. This distributed nature adds diversity to the particles while updating its positions and enables to search a wider region in the solution space rather than converging to a single point, P_g , as it happens in case of the global model.

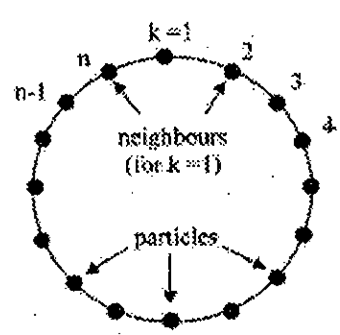


Fig. 3.3.10: Ring Topology

THIRD_MODIFIED_PSO (NIND, MAXGEN, NVAR, C1, C2, WEIGHT, rand(), RAND())

1. start
2. chrom ← initial_population(NIND, NVAR*PRECI)
3. gen ← 0
4. objV ← objfun(chrom)
5. while gen < MAXGEN
    a. lbest ← local_bst(NIND, NVAR)
    b. gbest ← global_bst_ring(NIND, NVAR)
    c. Calculate updated velocity and position
        i. $(v_{id})_{i,j} = w(v_{id})_{i,j} + c_1 rand()((p_{id})_{i,j} - (g_{id})_{i,j}) + c_2 Rand()((p_{gd})_{i,j} - (g_{id})_{i,j})$
        ii. $(g_{id})_{i,j} = (g_{id})_{i,j} + (v_{id})_{i,j}$
    d. gen ← gen + 1
6. end while
7. end

Fig. 3.3.11: Algorithmic pseudo-code of third modified PSO

3.4 Necessary Flowcharts of the Proposed Algorithms

The systems have been described along with their algorithmic pseudo code in the previous section. These proposed systems have been simulated by MATLAB 7.1. The flowcharts of all the proposed systems have been given in this section whereas the results are provided in the next chapter.

3.4.1 Flowcharts of application specific optimizations in resource allocation

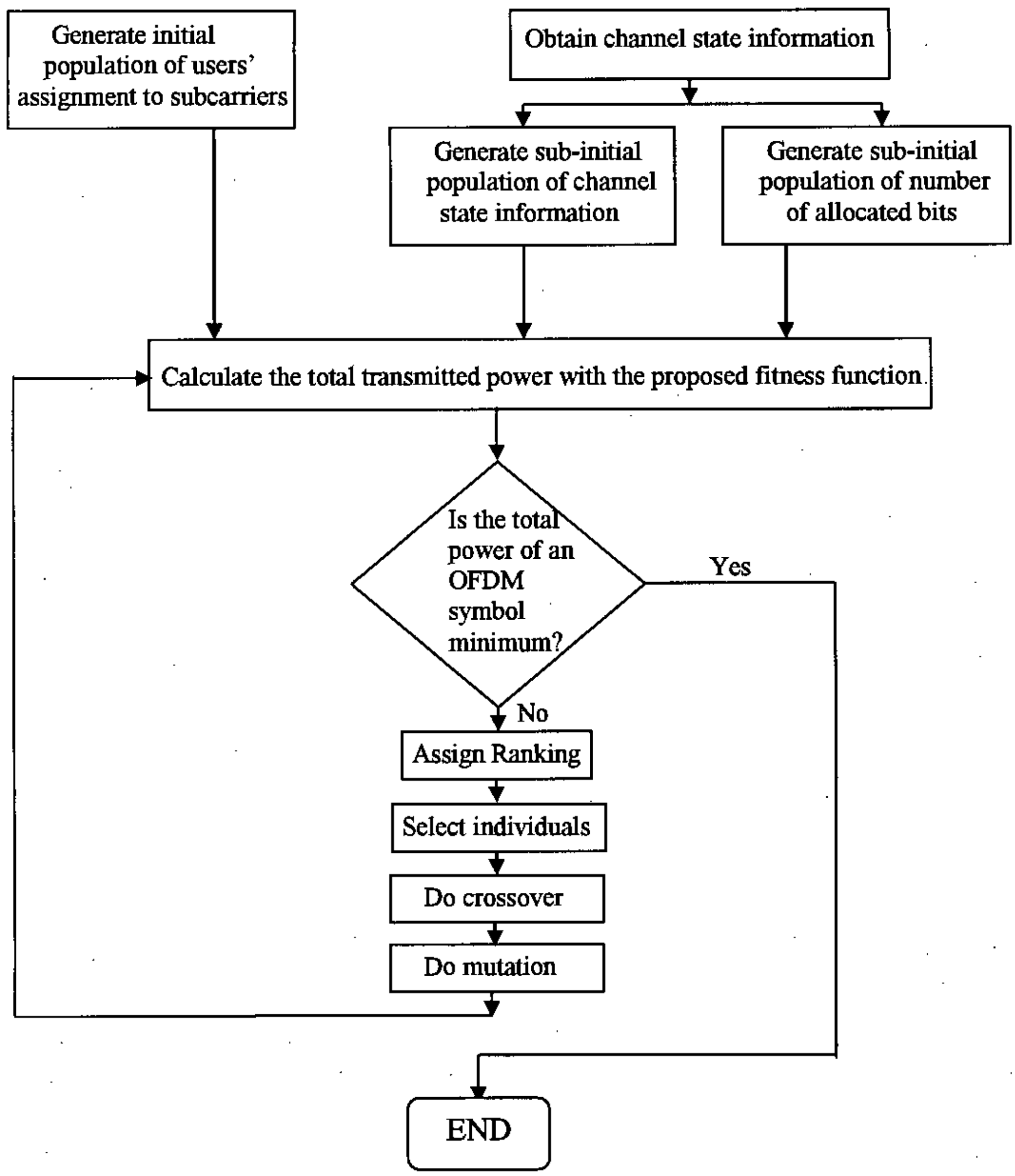


Fig. 3.4.1: Flowchart of the proposed algorithm with original structure of GA (Unfair Scheduling) for margin adaptive approach

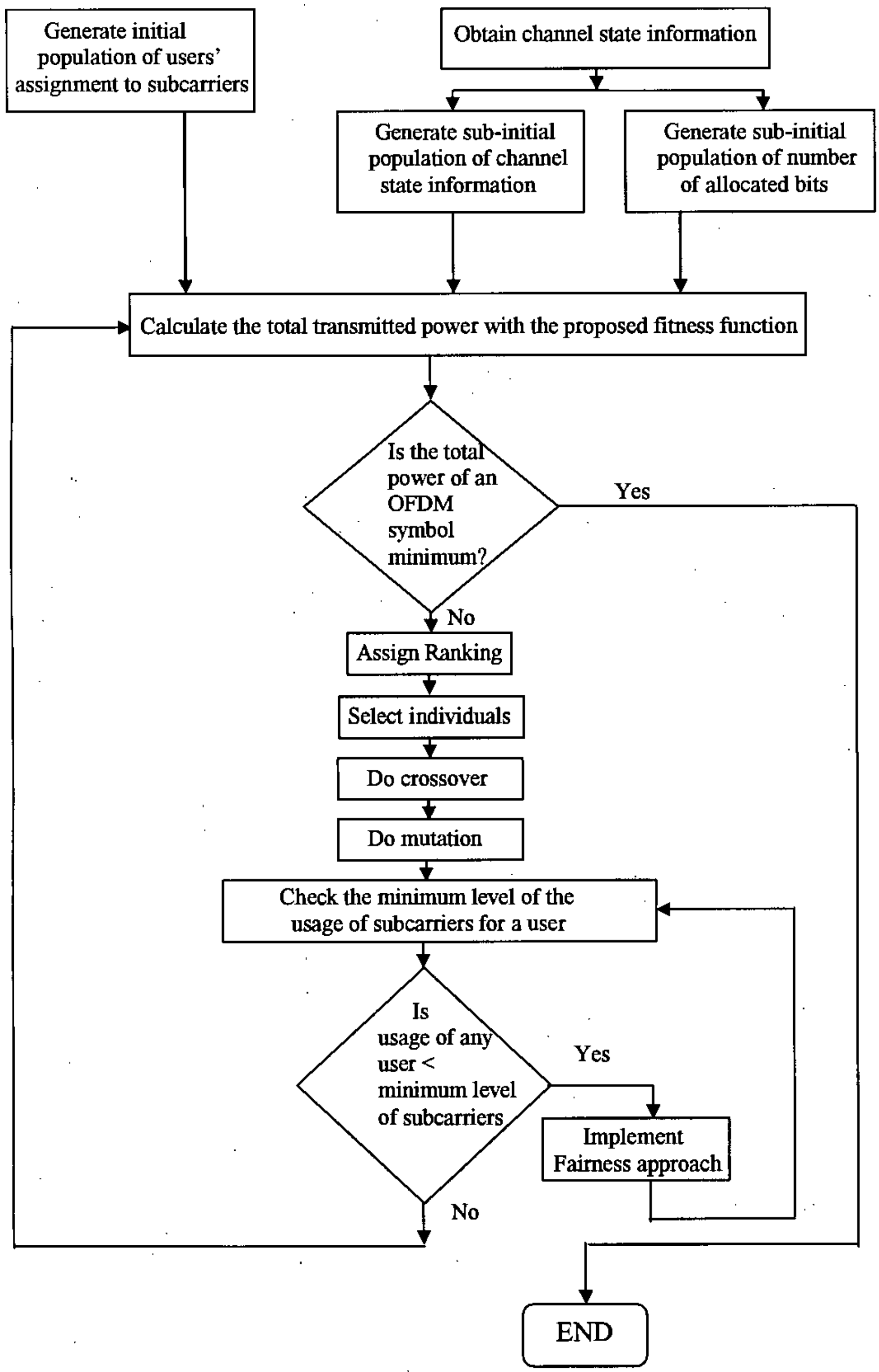


Fig. 3.4.2: Flowchart of the proposed algorithm with original structure of GA (fair Scheduling) for margin adaptive approach

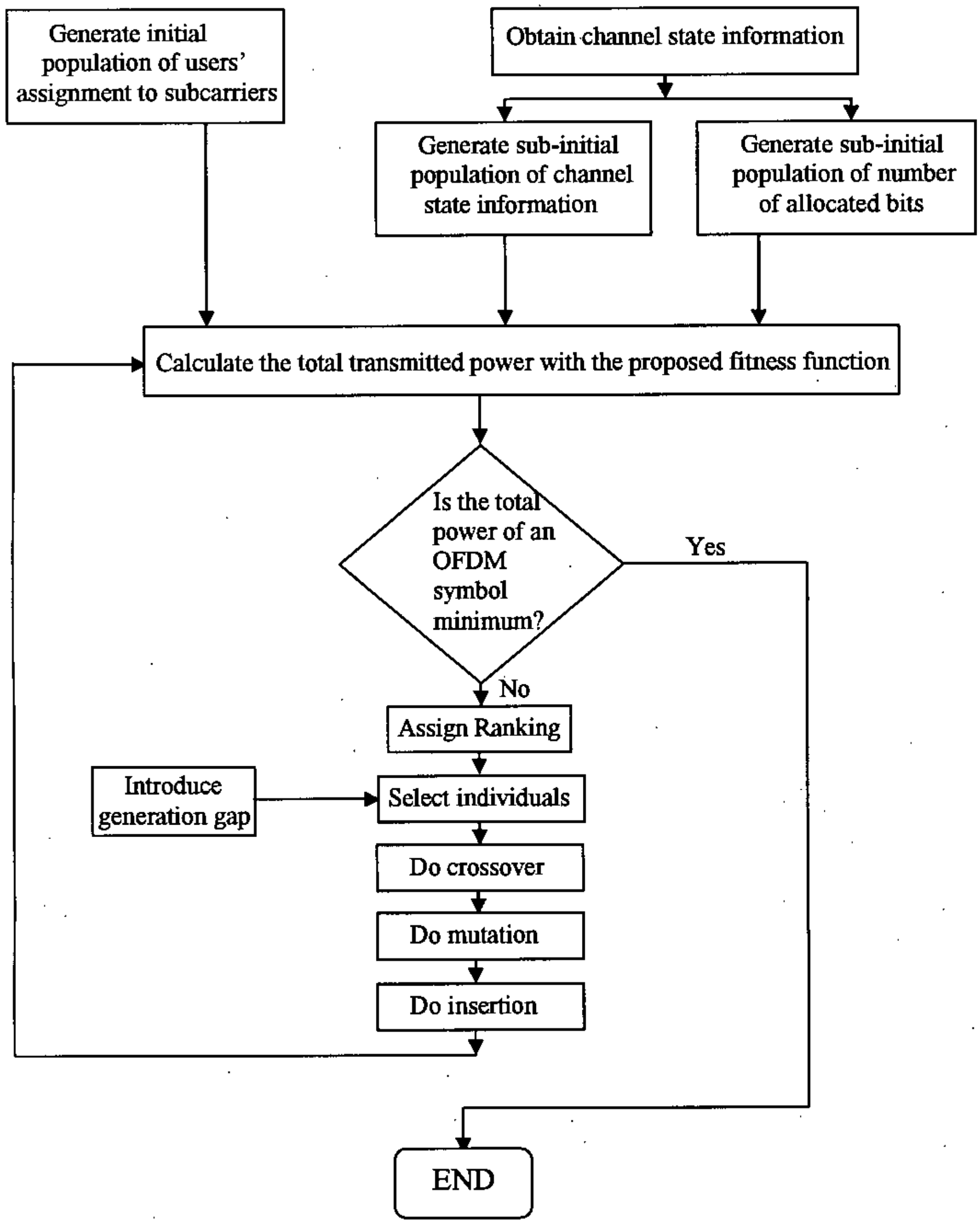


Fig. 3.4.3: Flowchart of the proposed algorithm with modified structure of GA (unfair Scheduling) for margin adaptive approach.

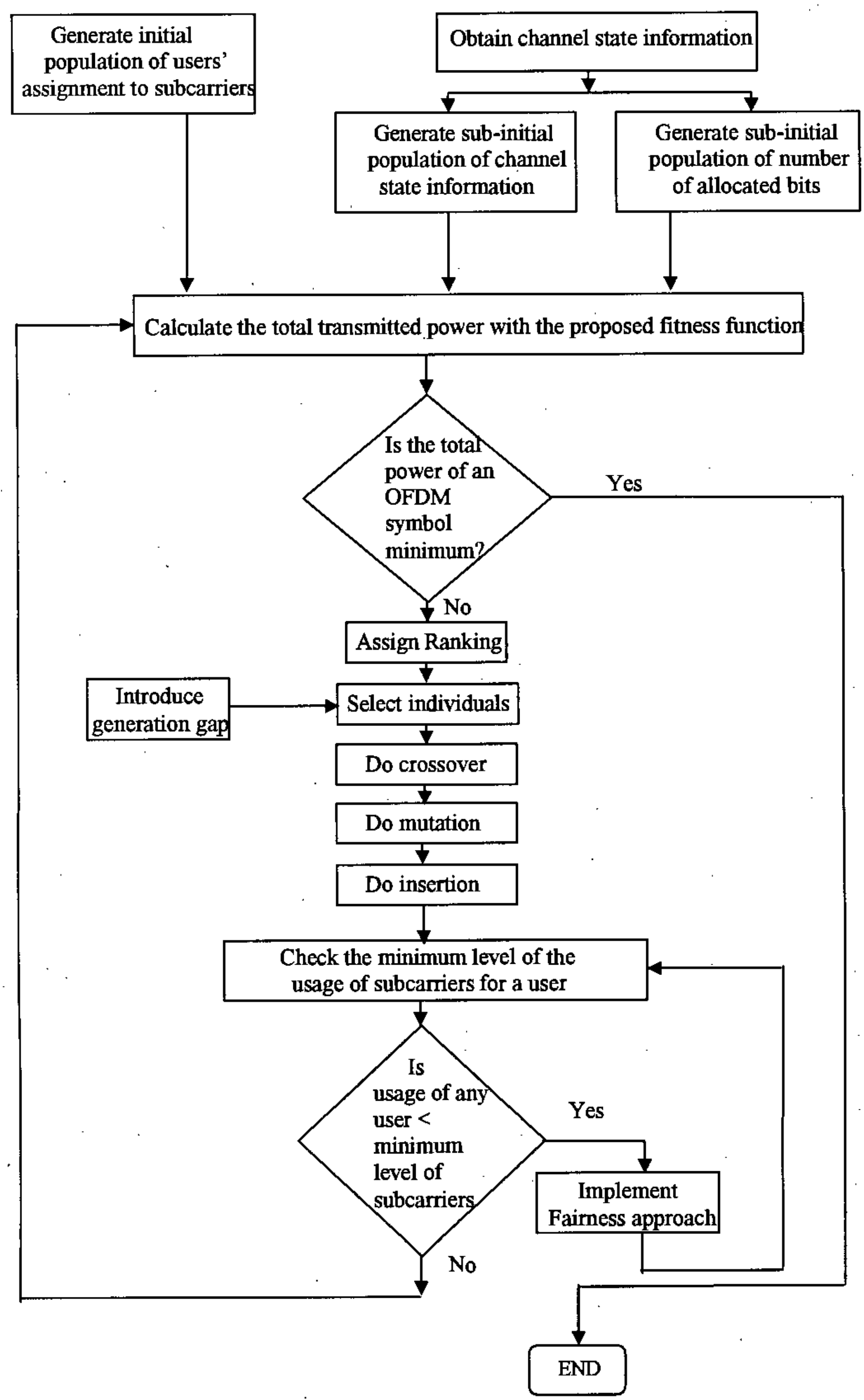


Fig. 3.4.4: Flowchart of the proposed algorithm with modified structure of GA (fair Scheduling) for margin adaptive approach

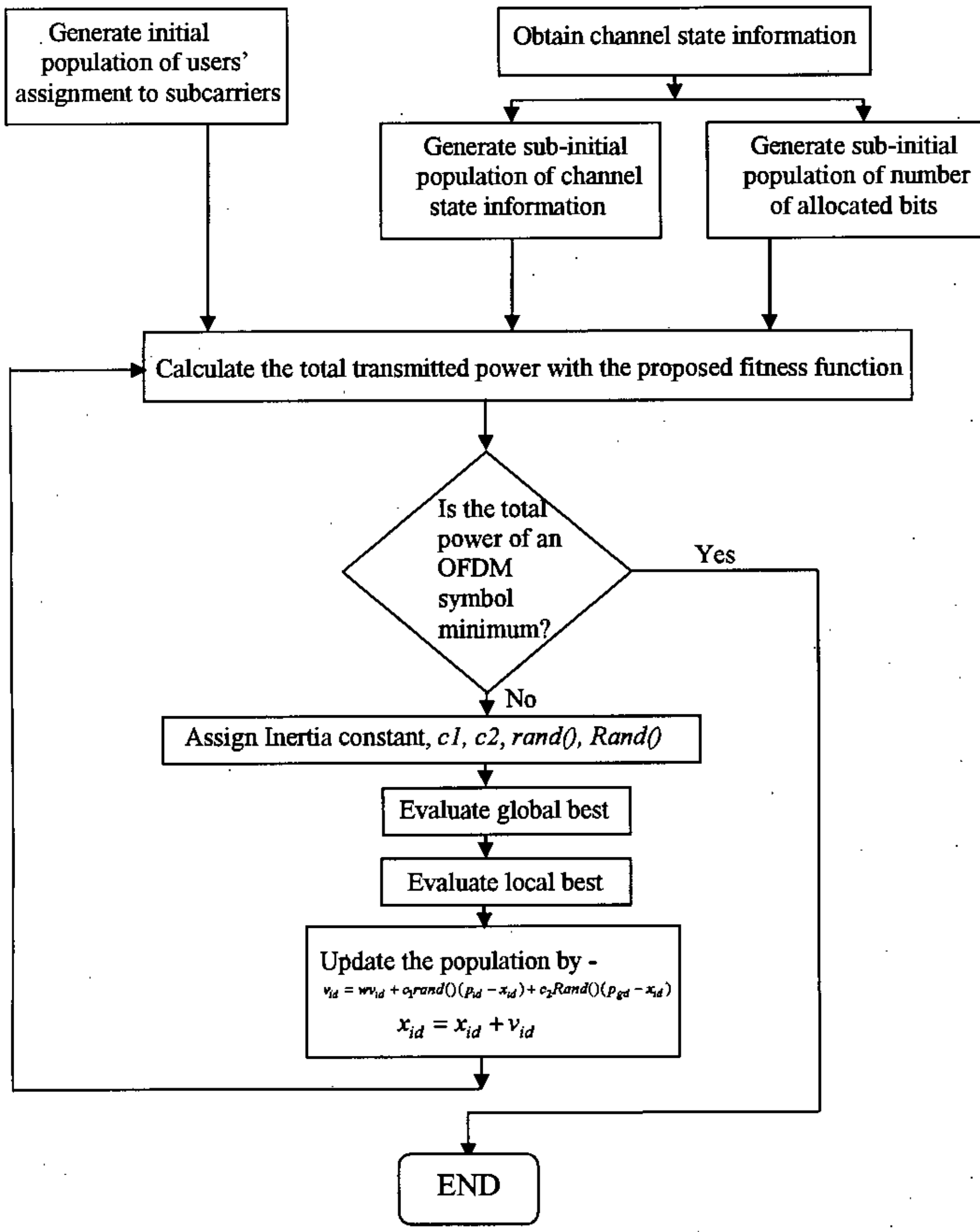


Fig. 3.4.5: Flowchart of the proposed algorithm with original structure of PSO (Unfair Scheduling) for margin adaptive approach

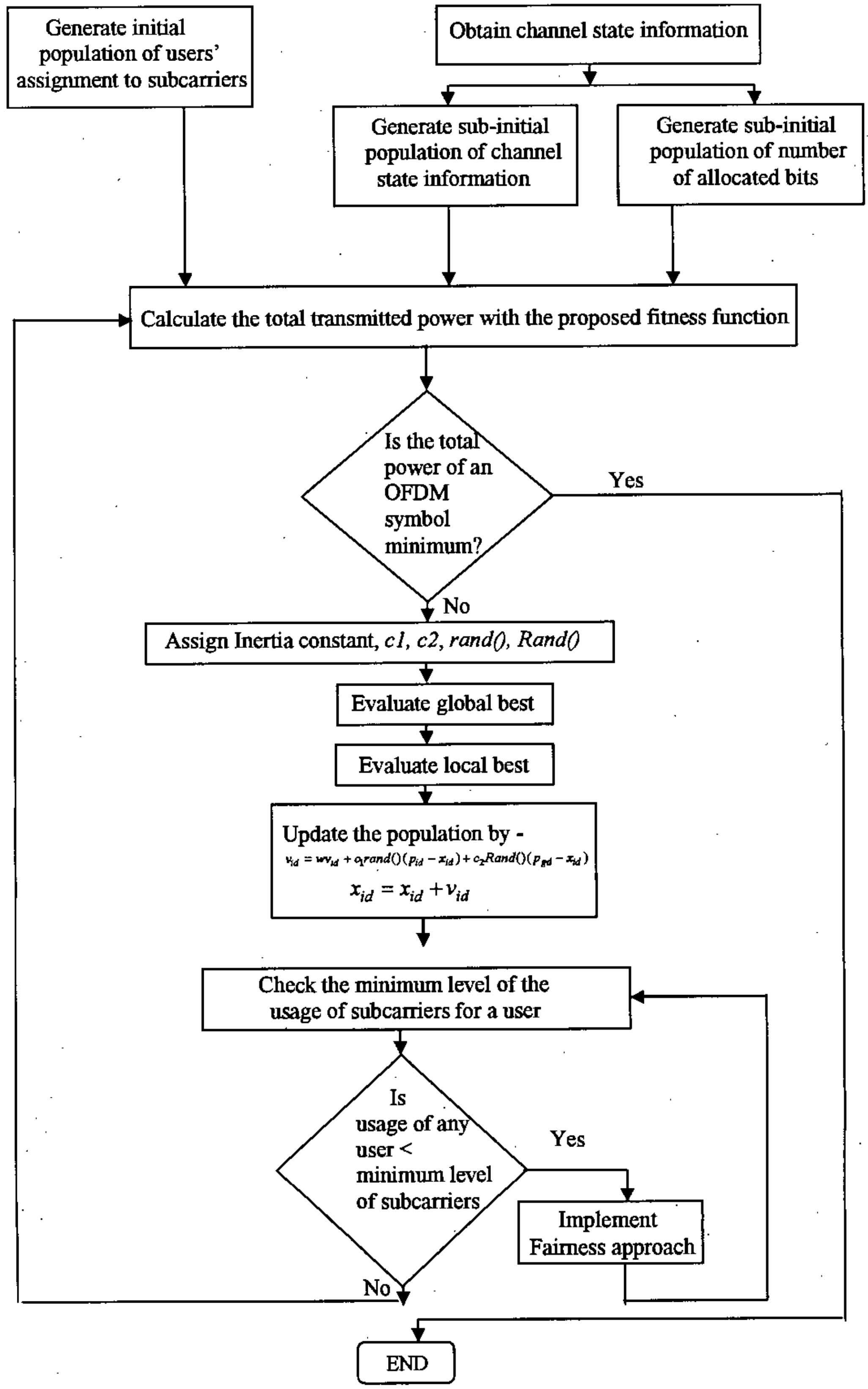


Fig. 3.4.6: Flowchart of the proposed algorithm with original structure of PSO (fair Scheduling)

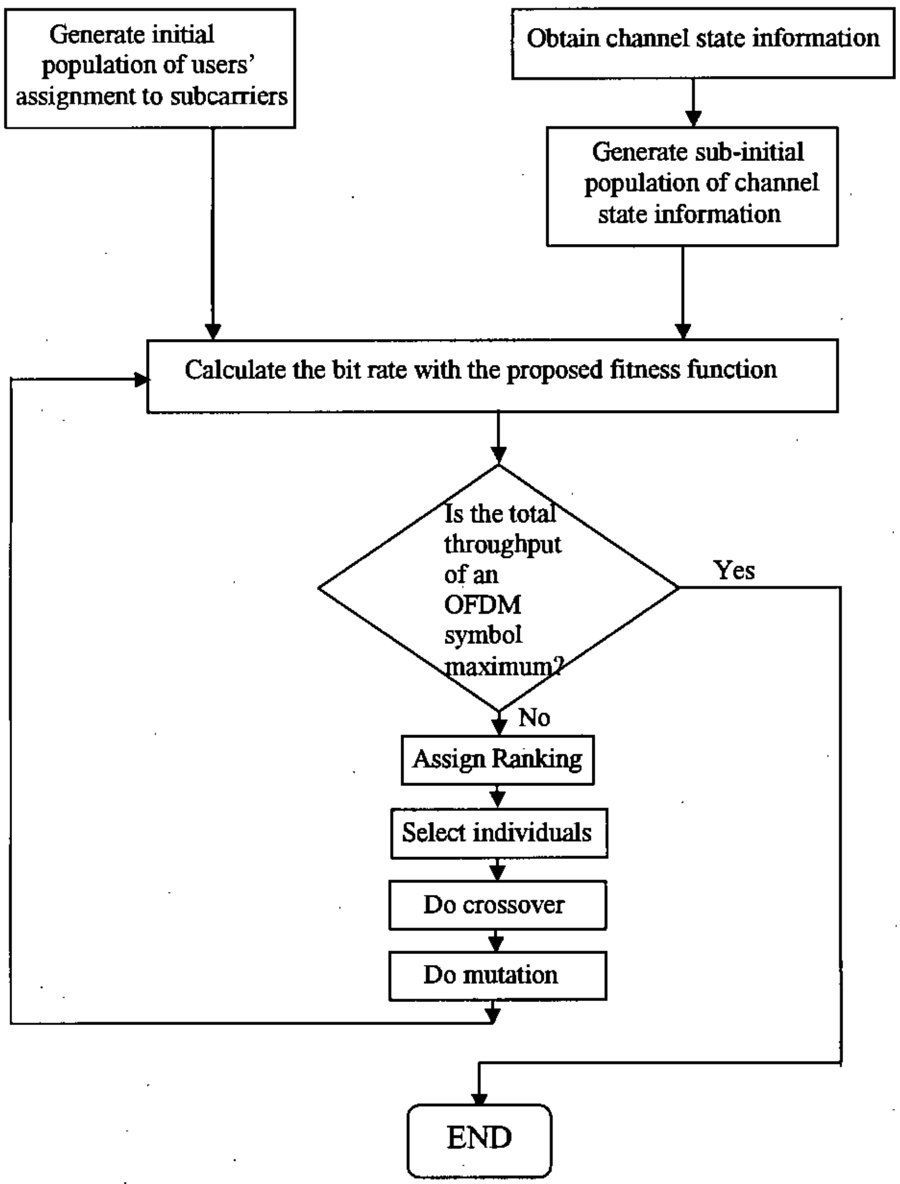


Fig. 3.4.7: Flowchart of the proposed algorithm with original structure of GA (Unfair Scheduling) for rate adaptive approach

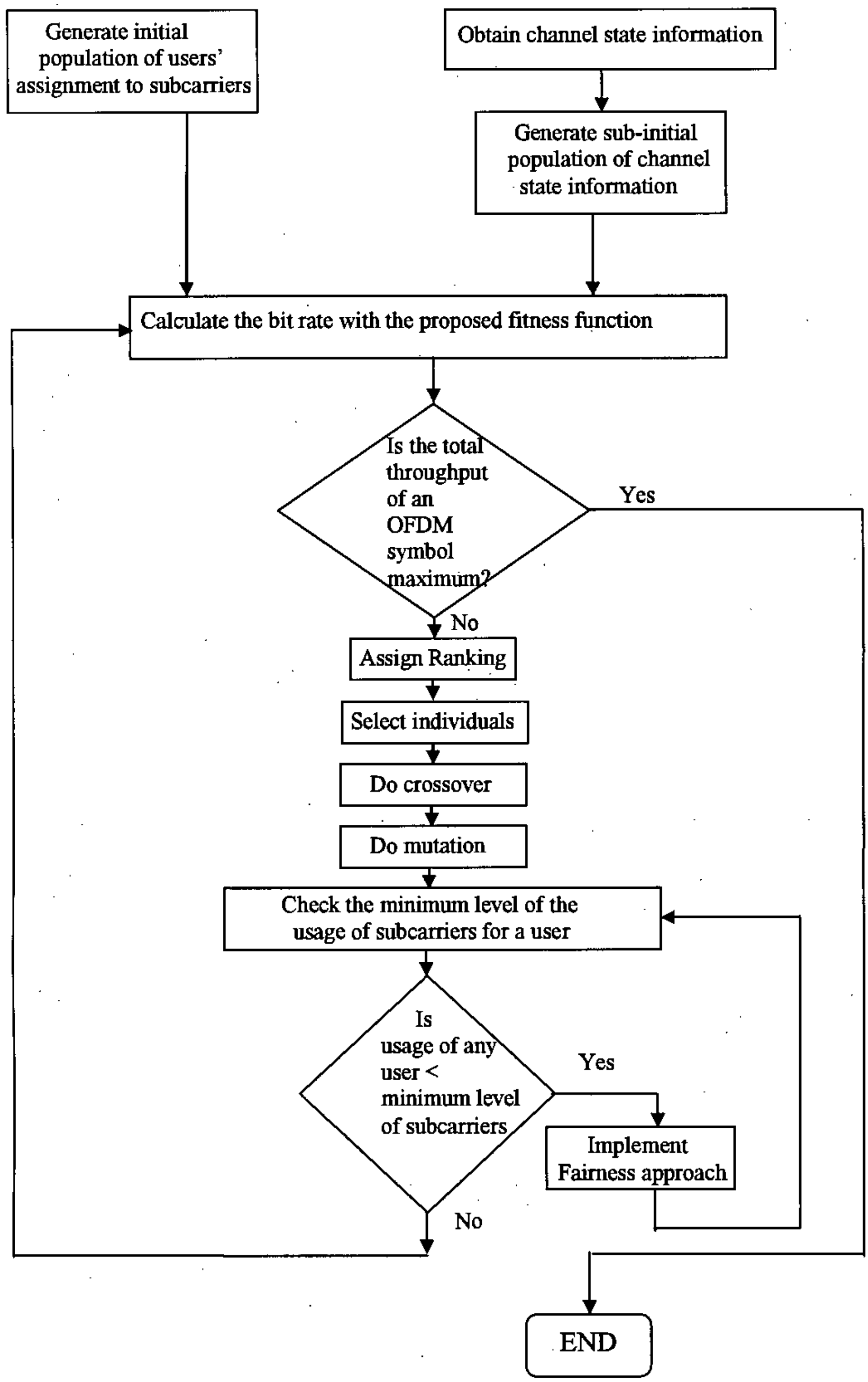


Fig. 3.4.8: Flowchart of the proposed algorithm with original structure of GA (fair Scheduling) for rate adaptive approach

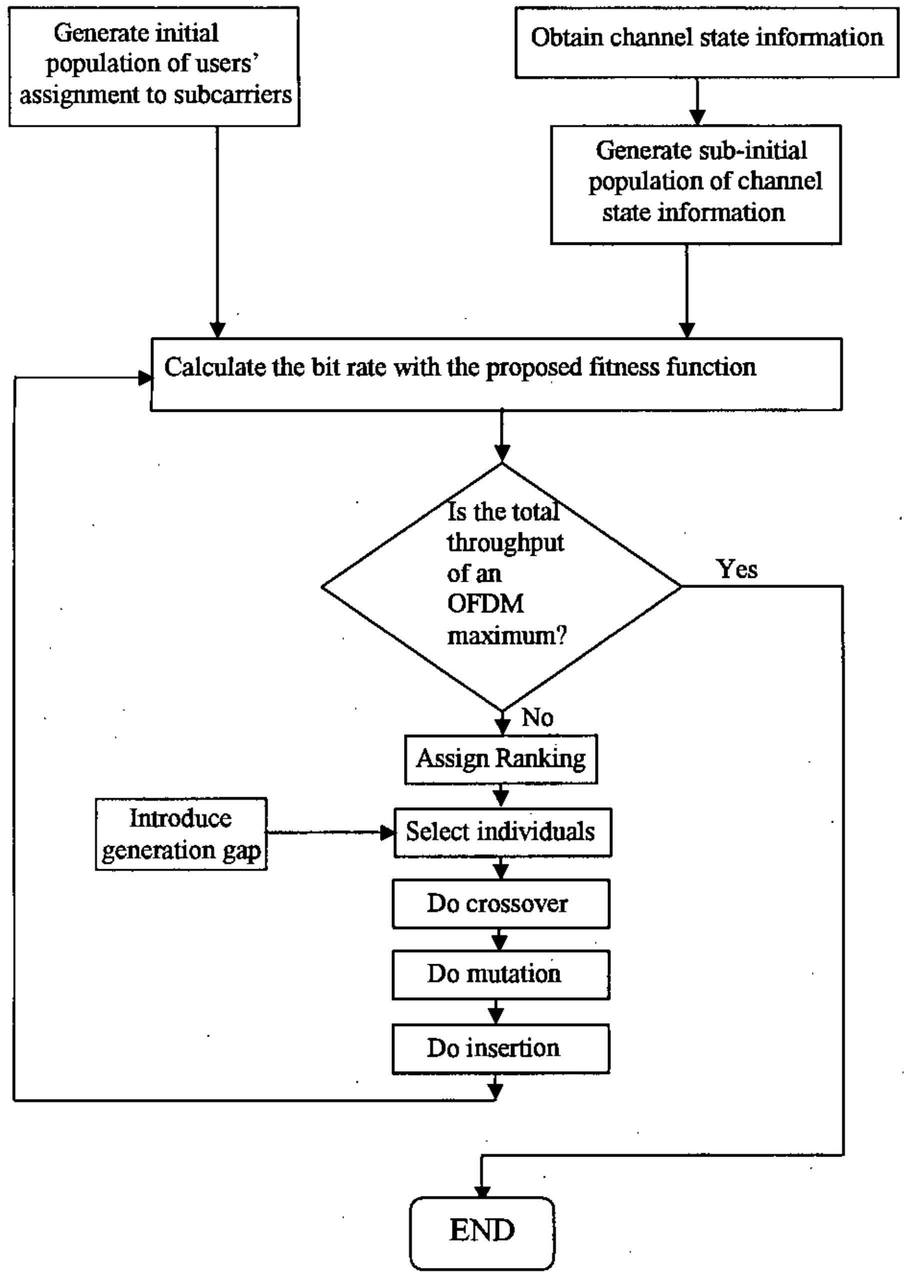


Fig. 3.4.9: Flowchart of the proposed algorithm with modified structure of GA (unfair Scheduling) for rate adaptive approach

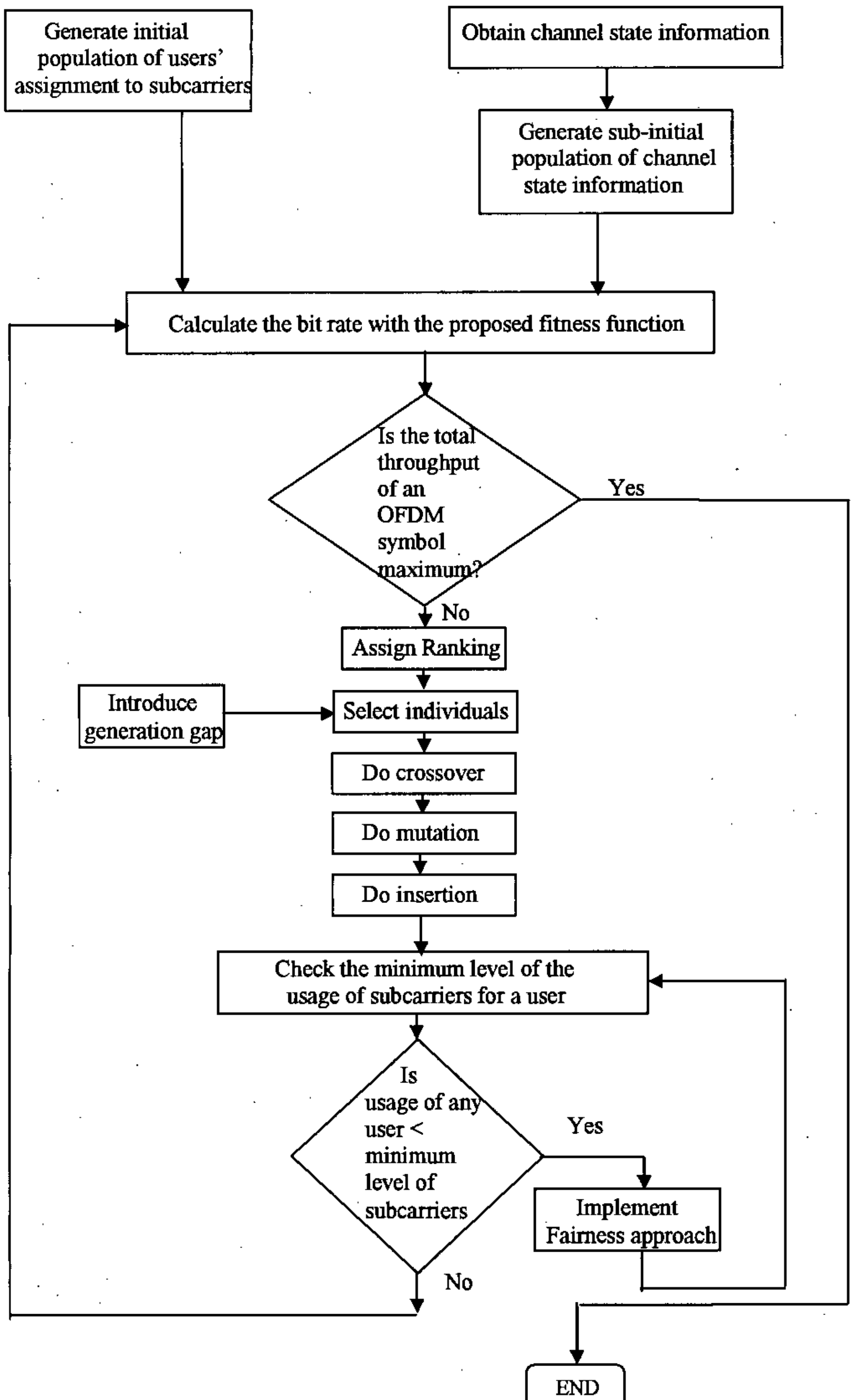


Fig. 3.4.10: Flowchart of the proposed algorithm with modified structure of GA (fair Scheduling) for rate adaptive approach

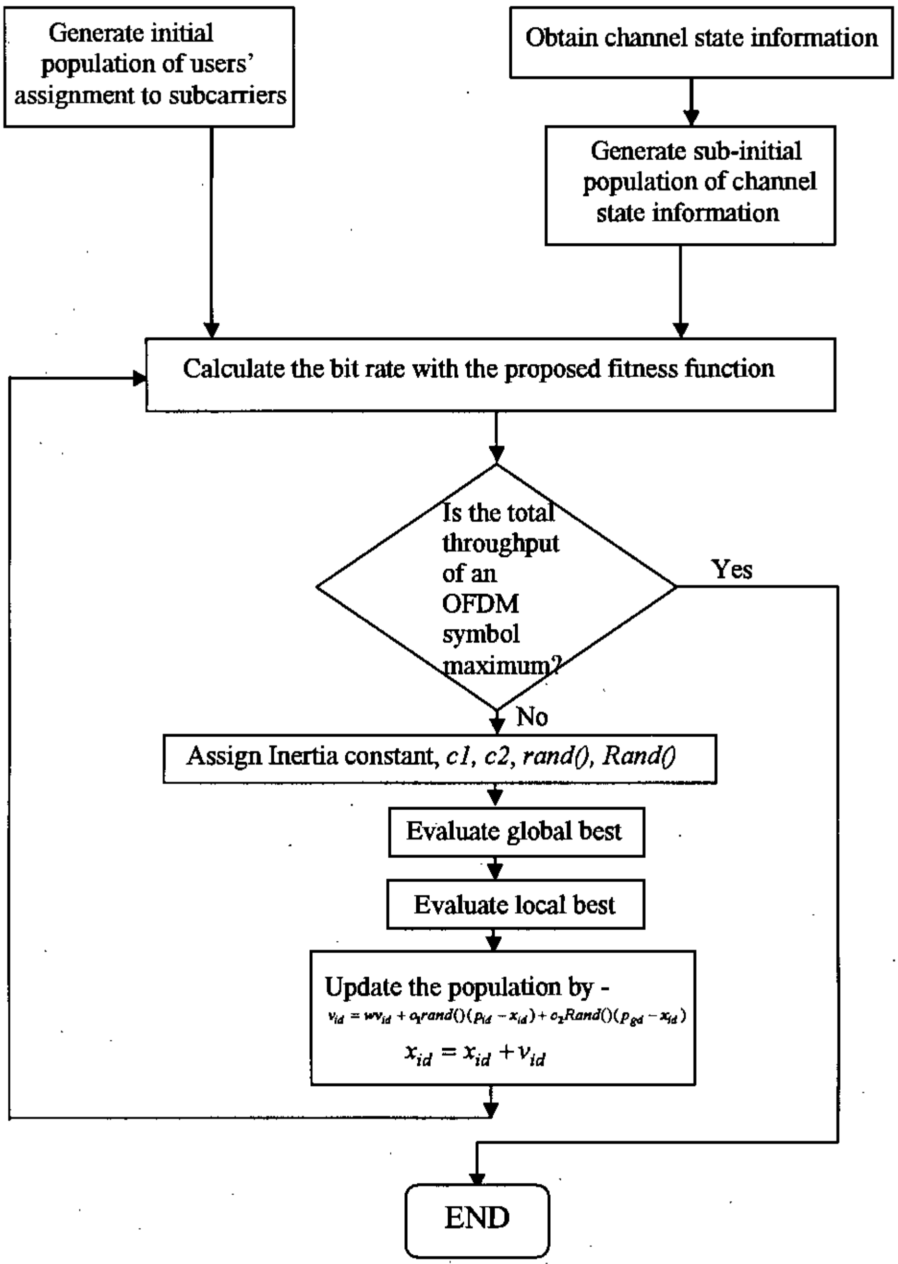


Fig. 3.4.11: Flowchart of the proposed algorithm with original structure of PSO (Unfair Scheduling) for rate adaptive approach

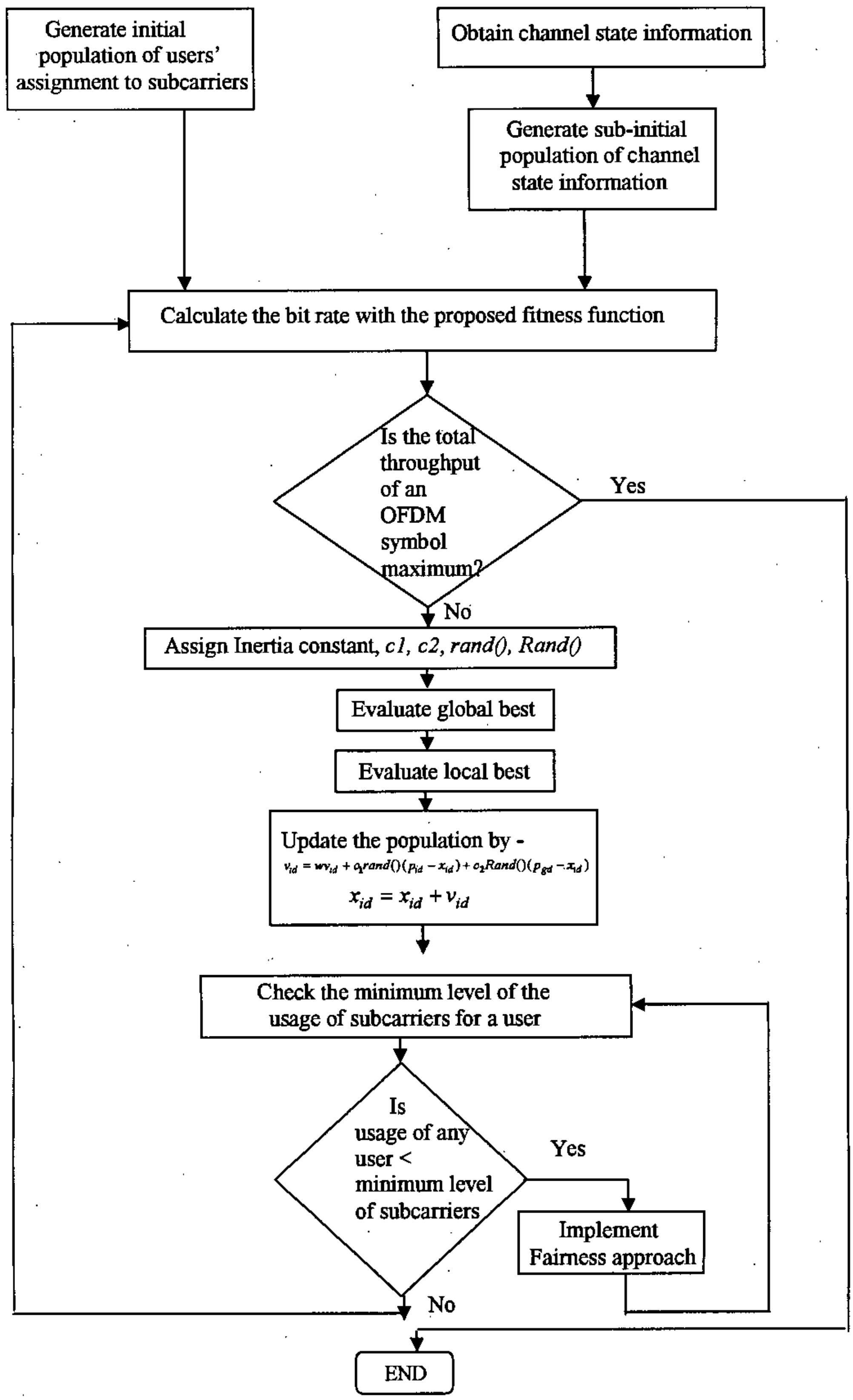


Fig. 3.4.12: Flowchart of the proposed algorithm with original structure of PSO (fair scheduling)

3.4.2 Flowcharts of topologically modified PSO in optimization of resource allocation

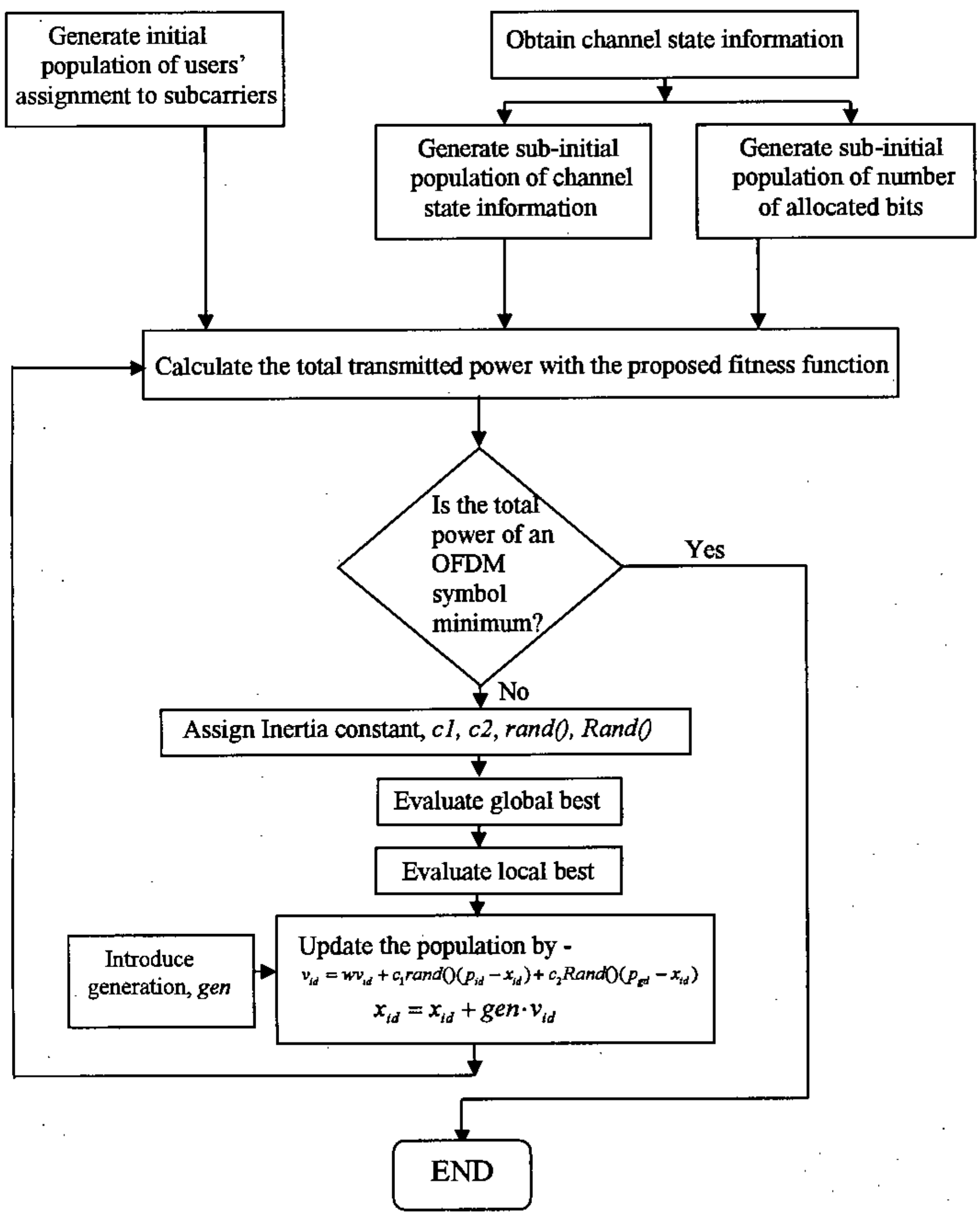


Fig. 3.4.13: Flowchart of the proposed algorithm with first modified structure of PSO (Unfair Scheduling) for margin adaptive approach

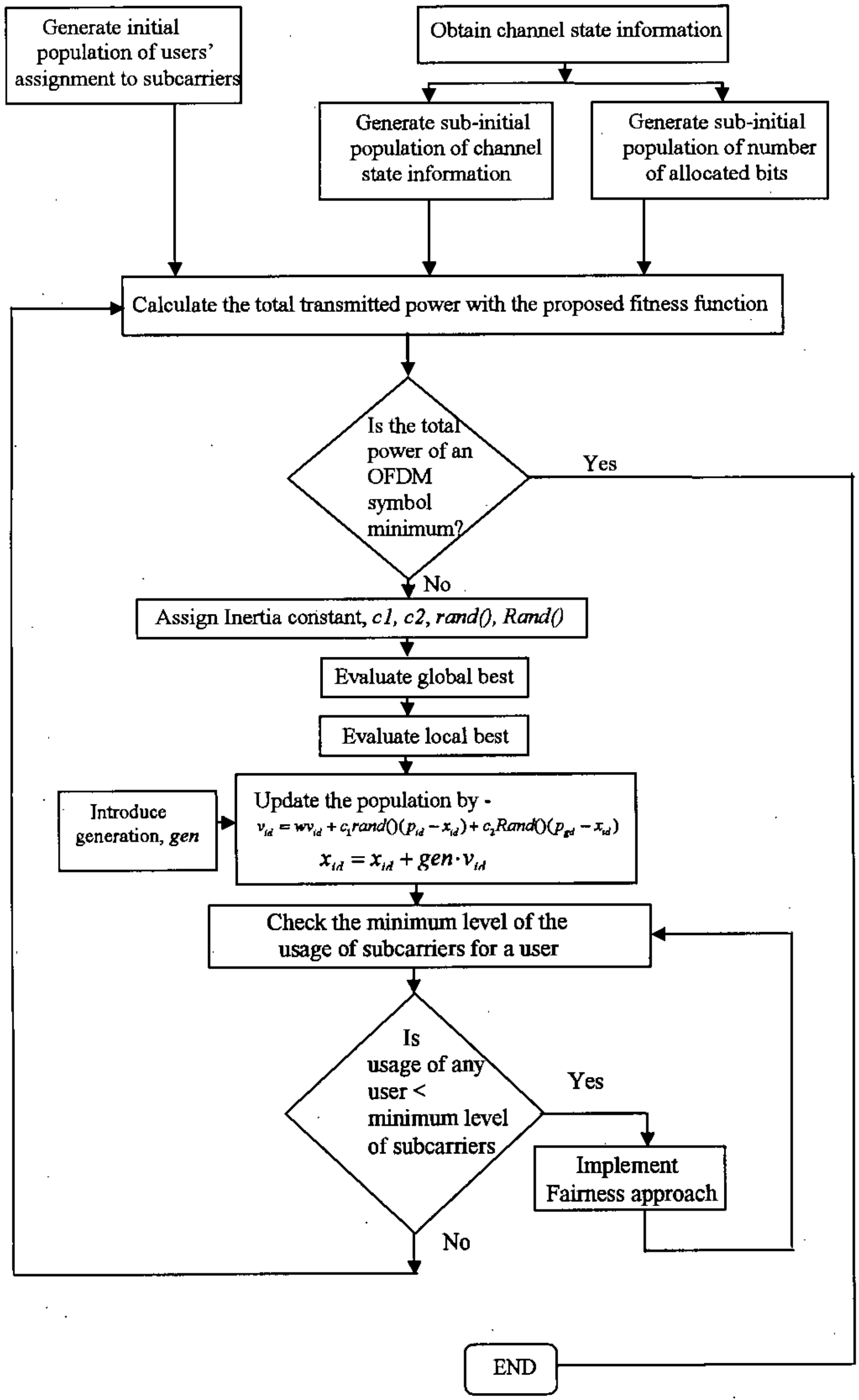


Fig. 3.4.14: Flowchart of the proposed algorithm with first modified structure of PSO (fair Scheduling) for margin adaptive approach

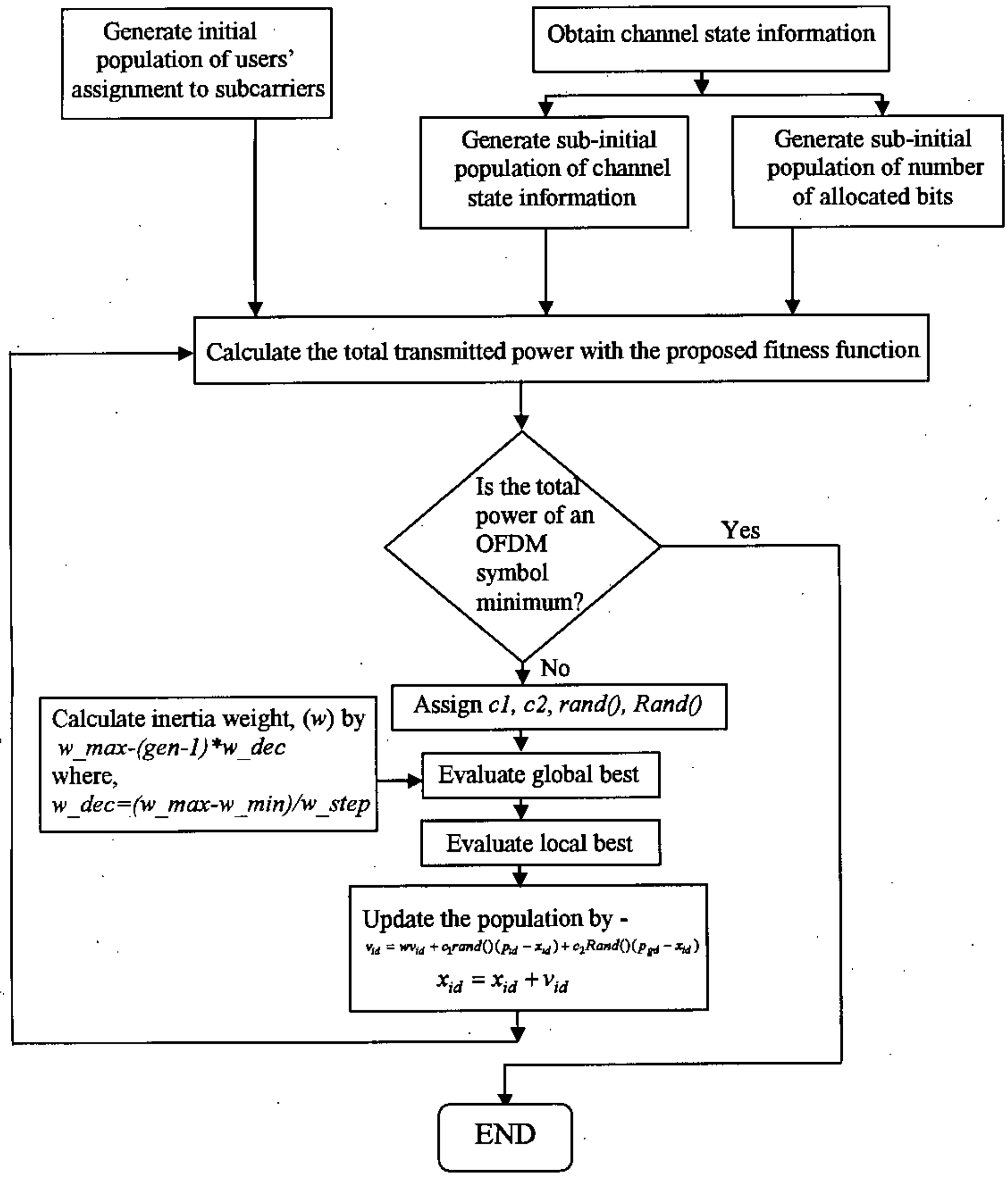


Fig. 3.4.15: Flowchart of the proposed algorithm with second modified structure of PSO (Unfair Scheduling) for margin adaptive approach

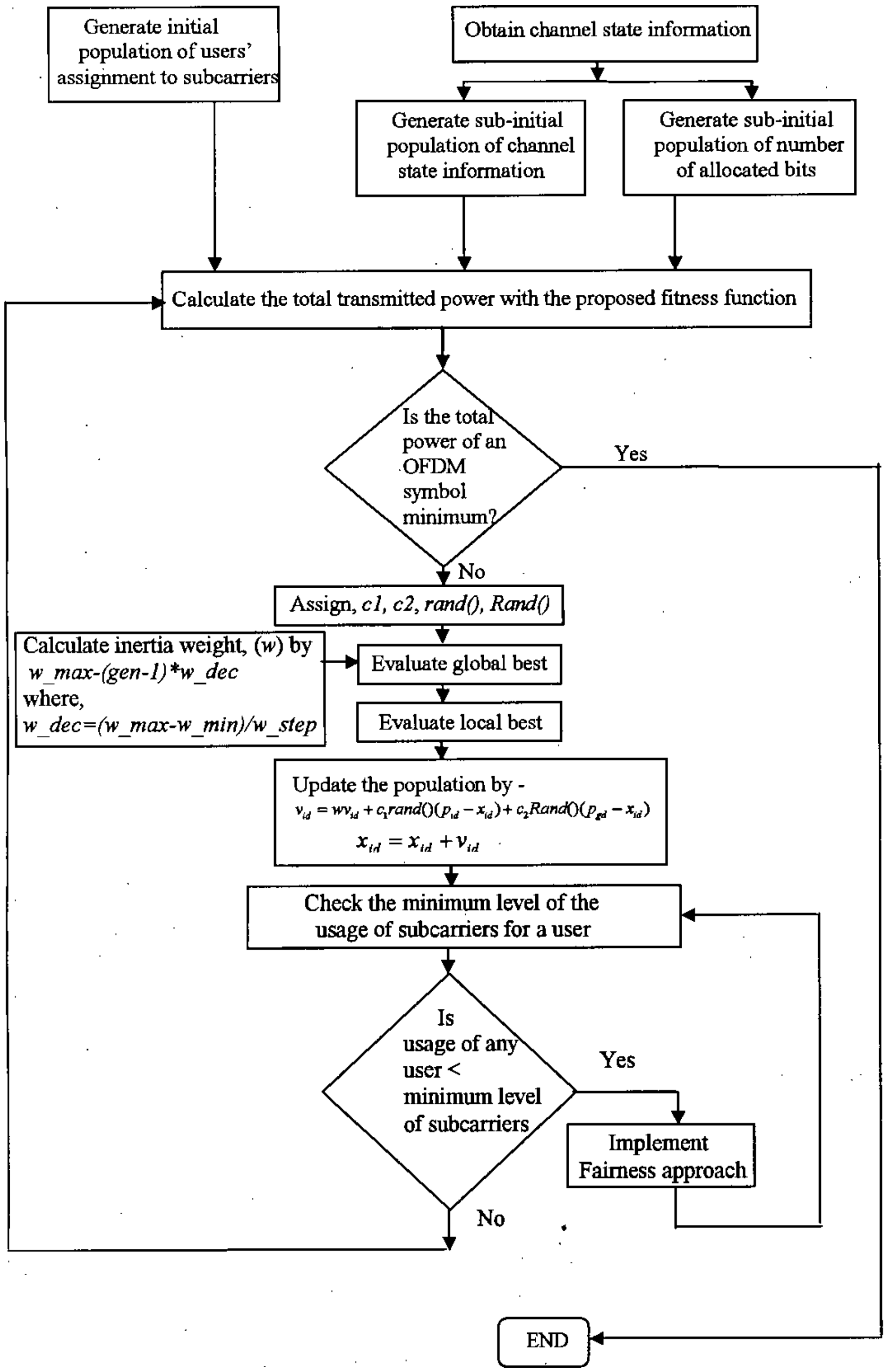


Fig. 3.4.16: Flowchart of the proposed algorithm with second modified structure of PSO (fair Scheduling) for margin adaptive approach

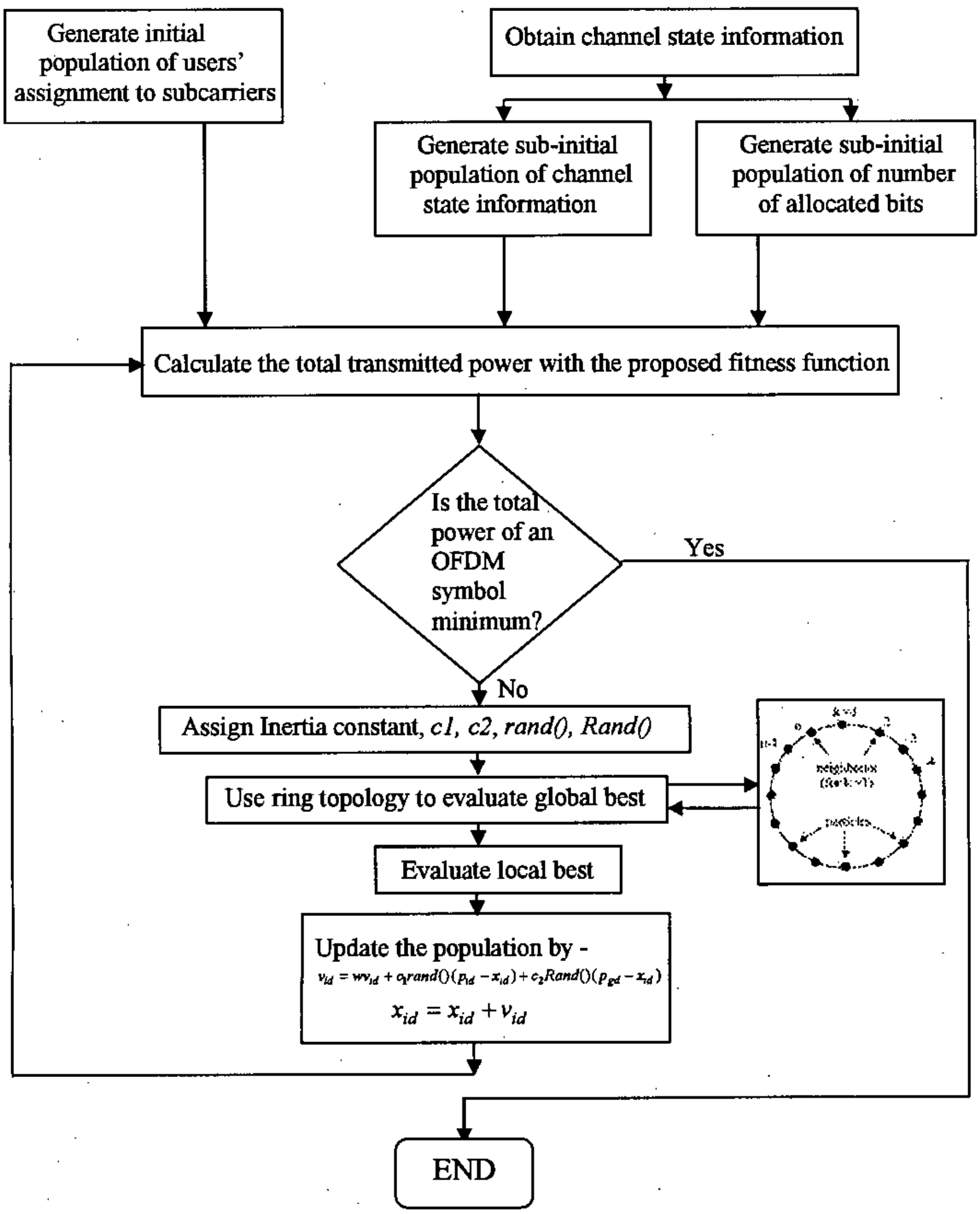


Fig. 3.4.17: Flowchart of the proposed algorithm with third modified structure of PSO (Unfair Scheduling) for margin adaptive approach

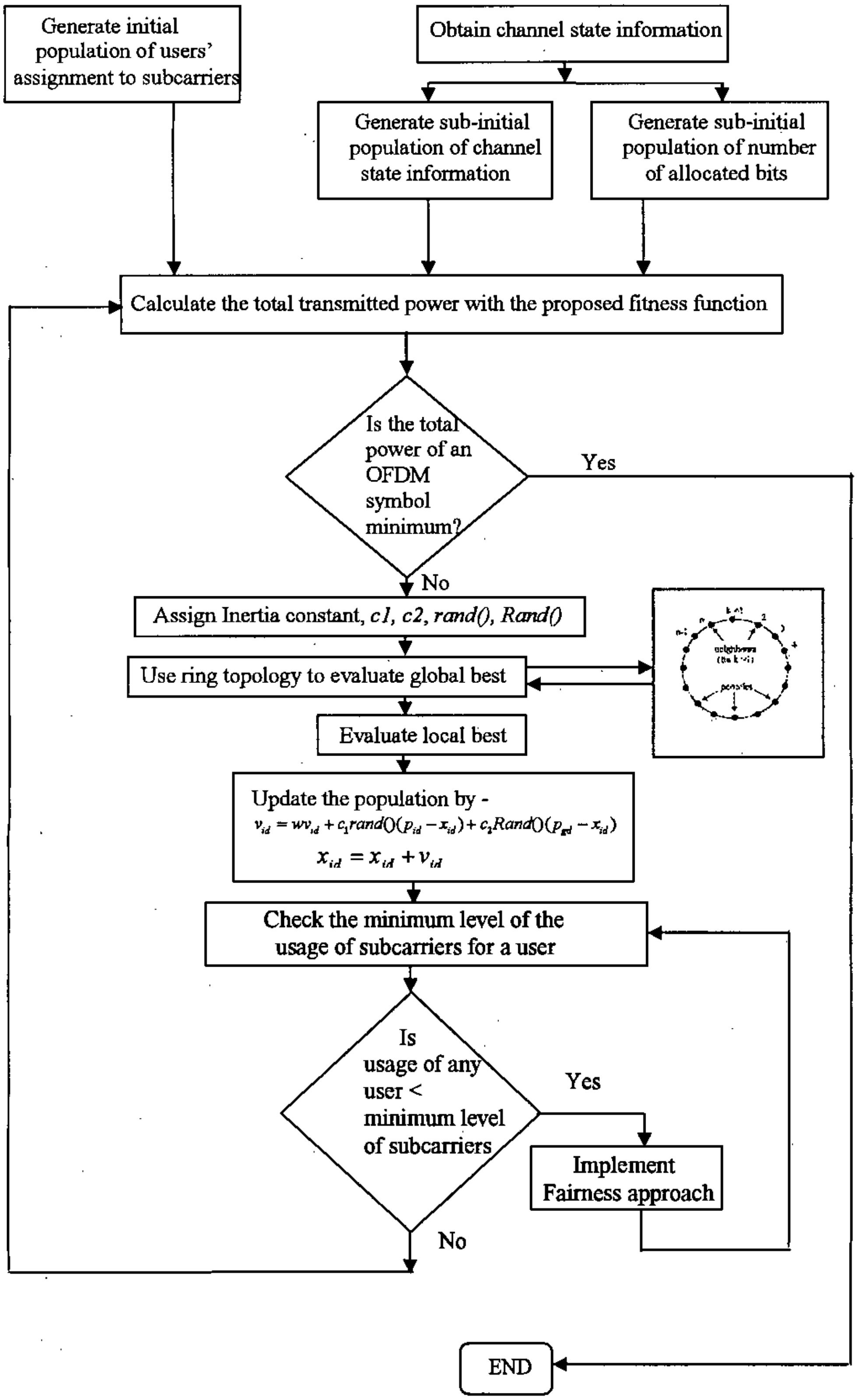


Fig. 3.4.18: Flowchart of the proposed algorithm with third modified structure of PSO (fair Scheduling) for margin adaptive approach

Chapter 4
RESULTS AND DISCUSSION

The performance of diversified resource allocation schemes in OFDMA systems have been analyzed in this chapter. OFDMA resources have been allocated with the help of different existing and modified evolutionary approaches. Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), the two evolutionary algorithms have been applied in this thesis to improve the overall performance of all the resource allocation methods. The use of PSO significantly perks up the system performance over GA by many factors. Further improvement has become possible by modifying both the algorithms. This encroachment has become more significant when the results have been compared with the existing ones.

4.1 Used Specification for Total System

4.1.1 Specification for multiuser OFDM system

In this thesis, all the simulations have been performed with MATLAB 7.1. A simulator has been created for this purpose which is used to allot the resources of OFDM systems though different optimizers. Except stated otherwise, all the simulations follow the specification of table 4.1.1.

Table 4.1.1 Parameters of multiuser OFDM simulator

Parameter	Value
Number of subcarriers (if otherwise not stated)	64
Number of users (if otherwise not stated)	2, 4, 6, 8
Channel	Rayleigh
Modulation scheme	no modulation (0 bits), QPSK (2 bits), 16 QAM (4 bits) and 64 QAM (6 bits)
Channel State Information	Known

4.1.2 Parameter setting for genetic algorithm & particle swarm optimization

In this section, genetic algorithm as well as the particle swarm optimization have been studied extensively to affix their operational parameters. If not otherwise stated, all the optimizers use the specifications of table 4.1.2.

Table 4.1.2 Parameters of GA, modified GA and PSO

GA		Modified GA		PSO	
Initial Population size	80	Initial Population size	80	Initial Swarm Size	25
Generations	0 to 100	Generations	0 to 100	Generations	0 to 100
Crossover	0.6	Crossover	0.6	C_1	1.5
Mutation	0.03	Mutation	0.03	C_2	1.5
		Generation Gap	0.8	Initial Inertia weight	0.8

The most important aspect in parameter setting is the settlement of the size of the initial population in genetic algorithm and particle swarm optimization. Fig. 4.1.1 & 4.1.2 represent the convergence curves (evaluated by GA & PSO) with different sizes of initial population and swarms. These curves are the simulated results in obtaining minimum transmit power.

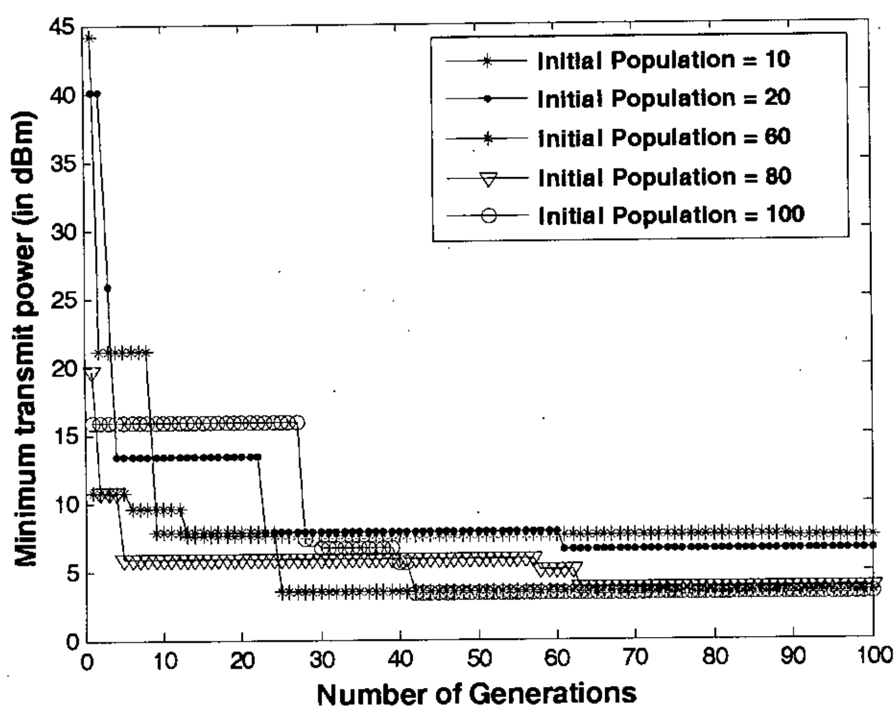


Fig. 4.1.1: Convergence curves of GA for different sizes of initial population.

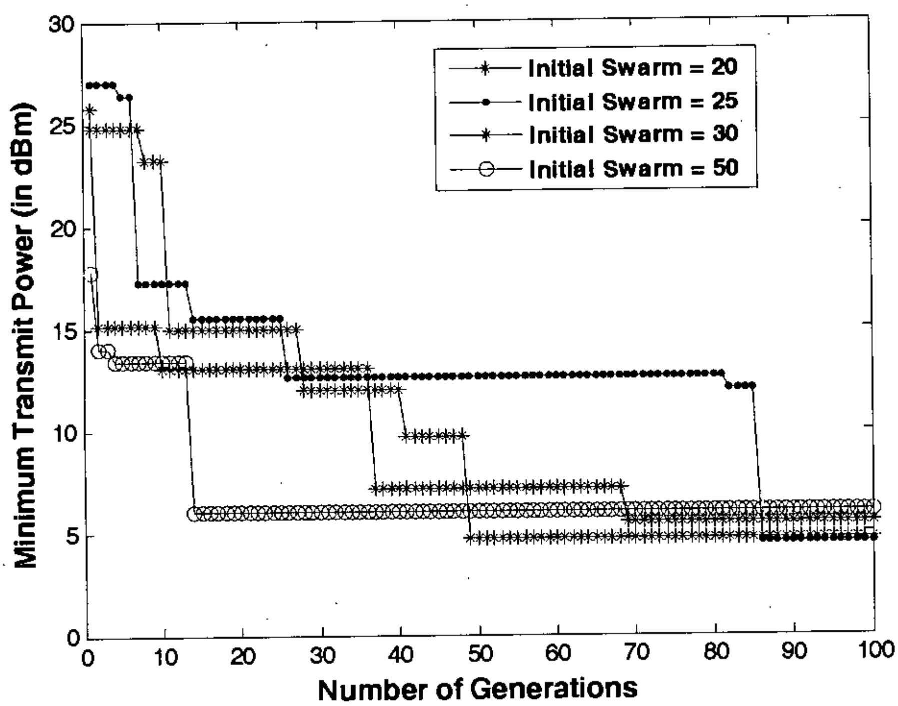


Fig. 4.1.2: Convergence curves of PSO for different swarm sizes.

Initial population size greater than 60 gives similar impact whereas its lower value gives few dBm higher than the original result (Fig. 4.1.1). Similar aspect is validated for modified version of GA also. But unlike GA, the low value of initial swarm size does not degrade the overall performance too much in PSO. So it is quite sufficient to take the value of 25 for initial size of swarm. This lowers the need of memory size as well as computational complexity for PSO.

4.2 Application Specific Task in Optimization of Resource Allocation

4.2.1 Margin adaptive approach

4.2.1.1 Margin adaptive approach by GA and modified GA

4.2.1.1.1 Minimum transmit power obtained by GA and modified GA using margin adaptive approach (unconstrained approach)

With the value of 80 for the initial population of the GA, the original GA along with the modified one has been used for simulation to allocate the resources for multiuser OFDM systems. The minimum power has been calculated with these algorithms for 10 times (Table 4.2.1). Both the algorithms have been simulated for 0 to 200 generations. It is clearly evident that modified version of GA converges to lower value compared with original GA (Fig. 4.2.1).

Table 4.2.1 Minimum transmit power evaluation by GA and modified GA*
(Unconstrained approach)

Margin Adaptive approach (Unconstrained approach)		
Run	**Minimum Transmit Power (in dBm) (By GA)**	**Minimum Transmit Power (in dBm) (By modified GA)**
1	4.862	4.748
2	5.048	5.351
3	4.549	5.459
4	5.9	4.751
5	5.347	5.272
6	4.625	4.601
7	5.738	5.001
8	4.94	4.980
9	6.207	5.321
10	6.628	4.931
Mean	**5.3844**	**5.0415**

*** Simulations have been run for an OFDMA system having 64 subcarriers & 4 users**

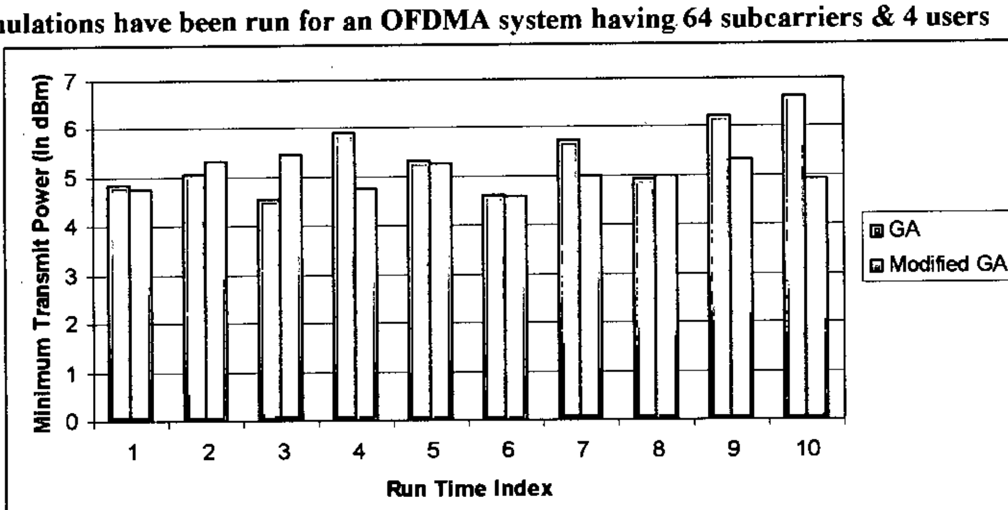


Fig. 4.2.1: Comparison between GA and modified GA in unconstrained margin adaptive approach

This statement is reflected through the mean value of the 10 outcomes which clearly signifies the fact that by introducing a concept of the generation gap between the parent and child population, the possibility of obtaining more optimum result is enhanced. The convergence curve for this method is given in Fig. 4.2.2.

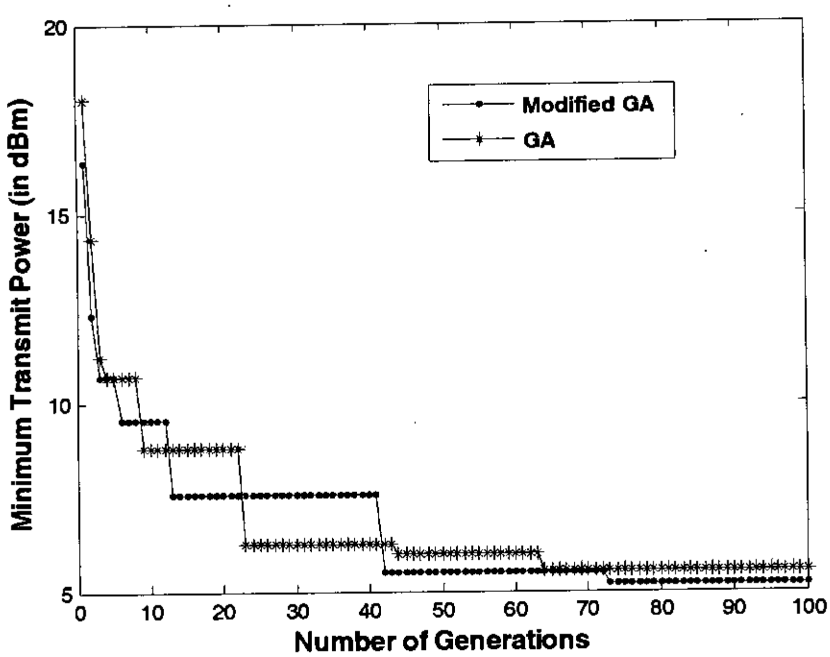


Fig. 4.2.2: Convergence curves of GA and modified GA for evaluating total transmit power (for a particular run time of each algorithm) [Unconstrained approach]

4.2.1.1.2 Minimum transmit power obtained by GA and modified GA using margin adaptive approach (fair scheduled approach)

With the previous affixed size of the initial population, two algorithms have been run again to allocate the resources for multiuser OFDM systems under fair scheduled approach. The fair scheduling has been introduced into the simulation with the fact that a minimum number of subcarriers have to be used for a particular user. The minimum power has been calculated with these algorithms for 10 times (Table 4.2.2). Both the algorithms have been simulated for 0 to 200 generations. Yet again it is clearly evident that modified version of GA converges to lower value compared with original GA (Fig. 4.2.3). The convergence curves are given in Fig. 4.2.4.

Table 4.2.2 Minimum transmit power evaluation by GA and modified GA* (Fair scheduled approach)

Margin Adaptive approach (Fair scheduled approach)		
Run	**Minimum Transmit Power (in dBm) (By GA)**	**Minimum Transmit Power (in dBm) (By modified GA)**
1	25.2113	23.1830
2	23.7787	21.4330
3	21.0987	22.6718
4	27.9440	25.7185
5	25.6760	22.7958
6	23.1860	23.3612
7	26.5640	23.5845
8	26.1073	23.3500
9	25.0021	22.7197
10	27.9812	25.4546
Mean	**25.2549**	**23.4272**

*** Simulations have been run for an OFDMA system having 64 subcarriers & 4 users**

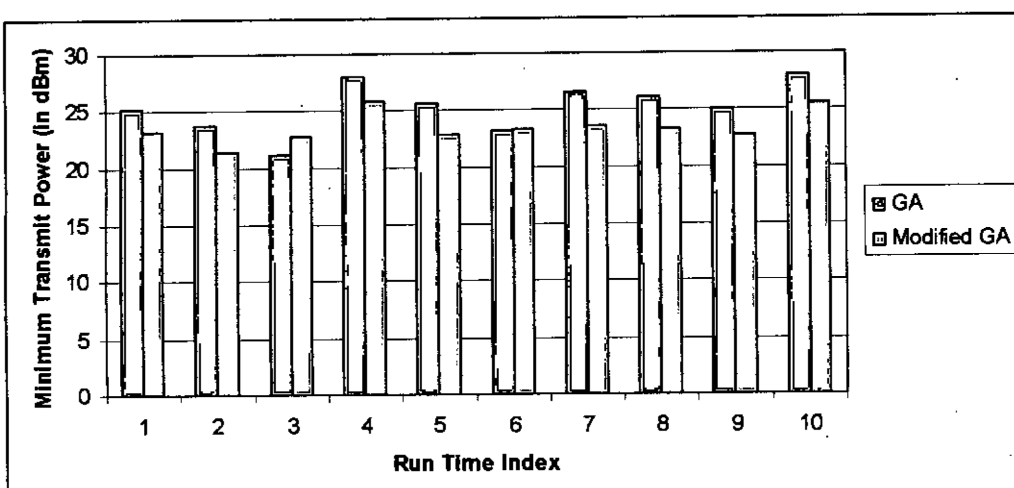


Fig. 4.2.3: Comparison between GA and modified GA in fair scheduled margin adaptive approach

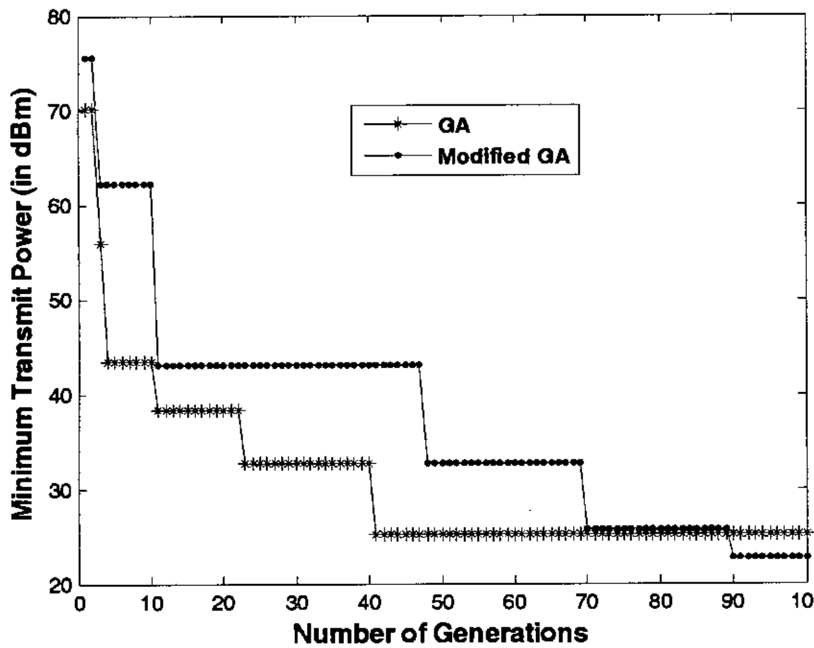


Fig. 4.2.4: Convergence curves of GA and modified GA for evaluating total transmit power (for a particular run time of each algorithm) [Fair scheduled approach]

4.2.1.1.3 Comparison between the unconstrained approach and fair scheduled approach for margin adaptive resource allocation scheme

In this section, a comparative feature has been depicted between unconstrained and fair scheduled margin adaptation.

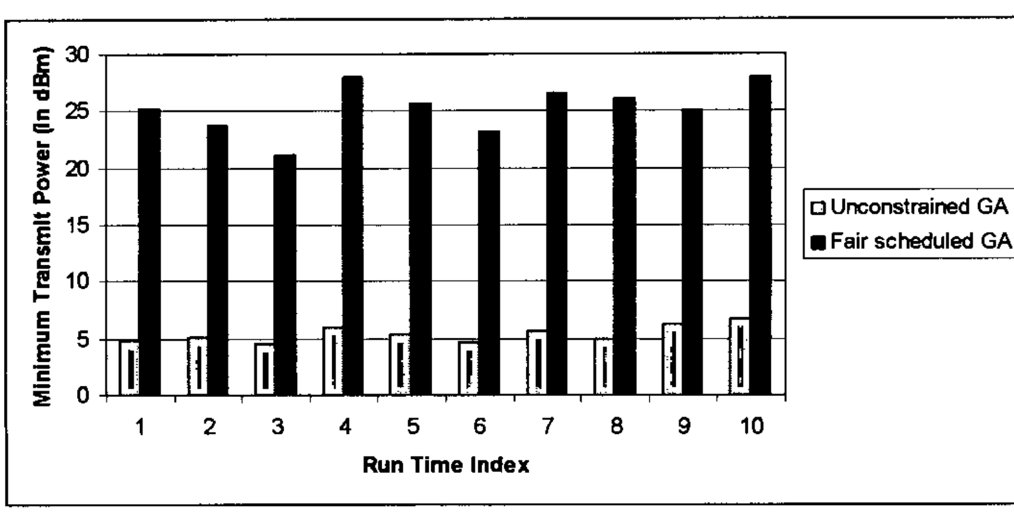


Fig. 4.2.5: Comparative results for unconstrained and fair scheduled GA in margin adaptation.

The optimum value for fair scheduled approach is several dBm higher than the unconstrained approach. This fact clearly reveals that the fair share scheduling does not give the optimum result in arrangement of users to the subcarriers. This statement are valid both for original and modified versions of GA. (Fig. 4.2.5 and Fig. 4.2.6)

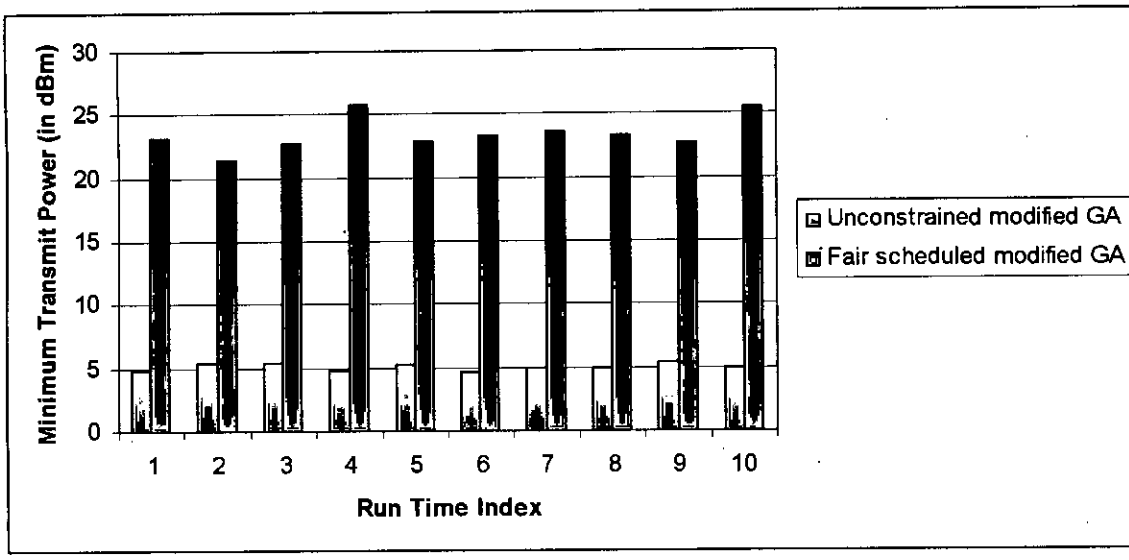


Figure 4.2.6 Comparative results for unconstrained and fair scheduled modified GA in margin adaptation.

4.2.1.2 Margin adaptive approach by PSO

4.2.1.2.1 Minimum transmit power obtained by PSO using margin adaptive approach (unconstrained approach)

Table 4.2.3 Minimum transmit power evaluation by PSO*(Unconstrained approach)

Run	**Minimum Transmit Power (in dBm) (By PSO)**
1	4.829
2	4.015
3	5.767
4	4.698
5	4.864
6	4.654
7	4.662
8	5.149
9	5.757
10	4.328
Mean	**4.8722**

***Simulations have been run for an OFDMA system having 64 subcarriers & 4 users**

With the affixed value of initial size, the PSO has been applied for simulation to allocate the resources for multiuser OFDM systems. The minimum power has been calculated with these algorithms for 10 times (Table 4.2.3). Fig. 4.2.7 represents the corresponding convergence curve for a particular run time.

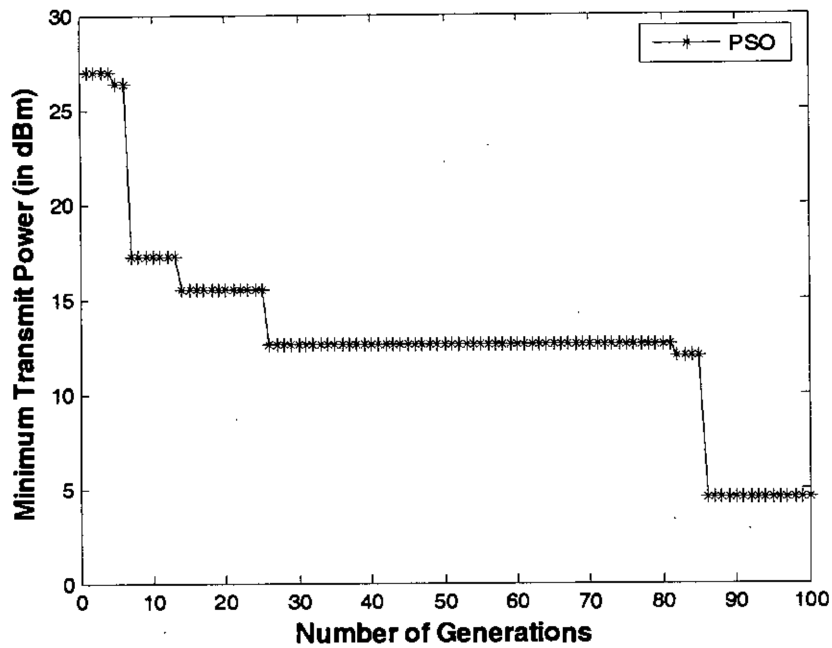


Fig. 4.2.7: Convergence curve of PSO for evaluating total transmit power (for a particular run time of each algorithm) [Unconstrained approach]

4.2.1.2.2 Minimum transmit power obtained by PSO using margin adaptive approach (fair scheduled approach)

Table 4.2.4 Minimum transmit power evaluation by PSO* (Fair scheduled approach)

Run Time	Minimum Transmit Power (in dBm)
1	19.2176
2	20.1876
3	18.8423
4	20.1525
5	20.0302
6	19.7645
7	19.3405
8	20.1003
9	19.5621
10	19.6709
Mean	**19.6869**

*** Simulations have been run for an OFDMA system having 64 subcarriers & 4 users**

The fairness in choosing the subcarriers has been introduced here also in the PSO algorithm. A minimum number of subcarriers has been affixed in fair sharing. The results and convergence curves are shown in table 4.2.4 and Fig. 4.2.8.

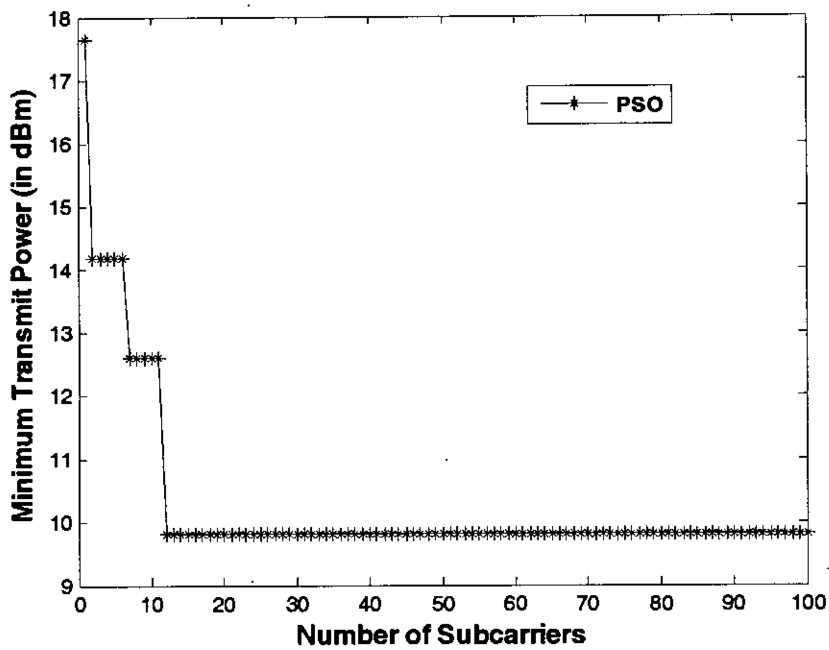


Fig. 4.2.8: Convergence curve of PSO for evaluating total transmit power (for a particular run time of each algorithm) [Fair scheduled approach]

4.2.1.2.3 Comparison between the unconstrained approach and fair scheduled approach for margin adaptive resource allocation scheme by PSO

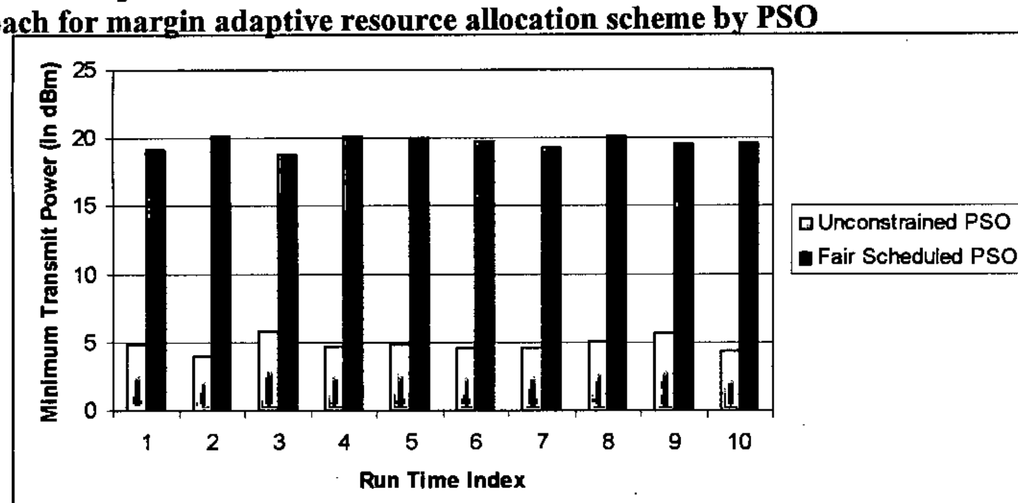


Fig. 4.2.9: Comparative results for unconstrained and fair scheduled PSO in margin adaptation

The fair shared algorithm clearly reveals that introducing fairness act as an obstacle in reaching the optimum level of the transmitted power. In the comparison Fig. 4.2.9, it is evident that the optimum level of power in fair scheduled approach is several dBm higher than that of unconstrained approach.

4.2.2 Rate adaptive approach
4.2.2.1 Rate adaptive approach by GA and modified GA

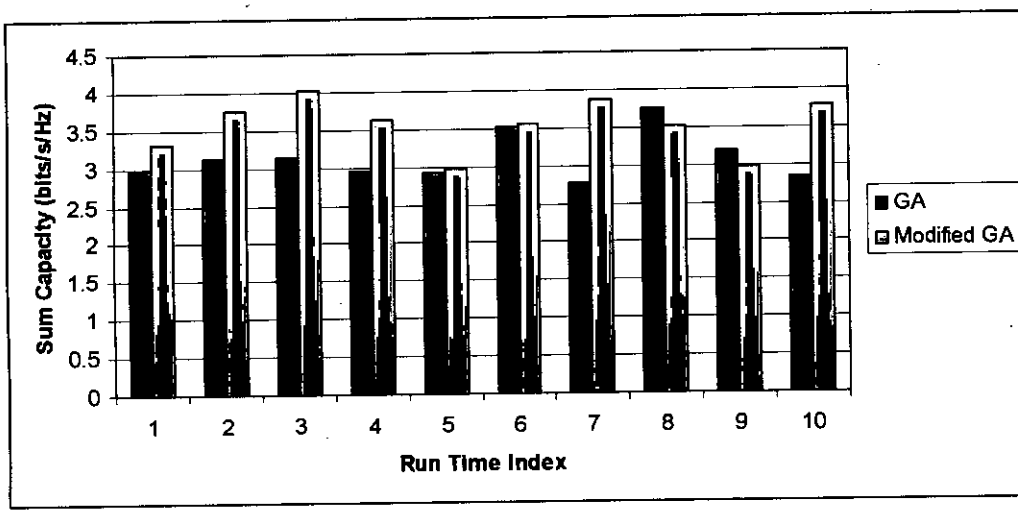
4.2.2.1.1 Maximum throughput obtained by GA and modified GA using rate adaptive approach (unconstrained approach)

In rate adaptive method, the throughput for an OFDMA system has been calculated for a constant transmitted power and for a specific bit error rate. The simulation parameters are the same as the previous section, i.e. the number of initial population, cross-over / mutation probability and so on. Additionally the total available bandwidth for rate adaptation is set to 1 MHz, the total transmit power at basestation is 1W and the AWGN power density is -80 dBW/Hz. Table 4.2.5 (along with Fig. 4.2.10) bestows bit rate for 10 time different times whereas Fig. 4.2.11 represents the corresponding convergence curve for a particular run time.

Table 4.2.5 Maximum throughput evaluation by GA and modified GA*
(Unconstrained approach)

Rate Adaptive approach (Unconstrained approach)		
Run	**Maximum Sum Capacity (in bits/s/Hz) (By GA)**	**Maximum Sum Capacity (in bits/s/Hz) (By Modified GA)**
1	2.98	3.33
2	3.12	3.75
3	3.14	4.02
4	2.95	3.62
5	2.92	2.98
6	3.51	3.56
7	2.78	3.87
8	3.76	3.51
9	3.19	2.98
10	2.83	3.78
Mean	**3.118 (≈ 3)**	**3.54 (≈ 4)**

*** Simulations have been run for an OFDMA system having 64 subcarriers & 4 users**



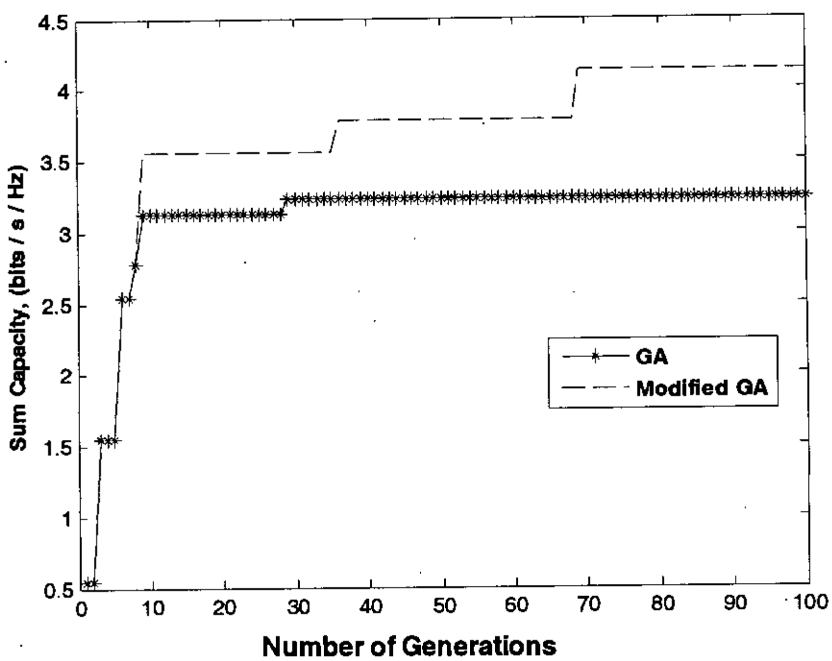


Fig. 4.2.11: Convergence curves of GA and modified GA for evaluating total throughput (for a particular run time of each algorithm) [Unconstrained approach]

4.2.2.1.2 Maximum throughput obtained by GA and modified GA using rate adaptive approach (fair scheduled approach)

Like all other algorithms, the fair scheduling has been introduced into the simulation with the fact that a minimum number of subcarriers have to be used for a particular user. The maximum bit rate has been calculated with these algorithms for 10 times (Table 4.2.6) for each of the algorithms. The convergence curves are shown in Fig. 4.2.13.

Table 4.2.6 Maximum throughput evaluation by GA and modified GA*
(Fair scheduled approach)

Rate Adaptive approach (Fair scheduled approach)		
Run	**Maximum Sum Capacity (in bits/s/Hz) (By GA)**	**Maximum Sum Capacity (in bits/s/Hz) (By Modified GA)**
1	2.01	2.67
2	1.89	2.12
3	1.9	1.84
4	2.2	1.97
5	2.18	2.56
6	1.78	2.45
7	2.24	2.39
8	1.56	2.58
9	1.78	2.79
10	2.31	2.71
Mean	**1.985 (≈ 2)**	**2.408 (≈ 2)**

***Simulations have been run for an OFDMA system having 64 subcarriers & 4 users**

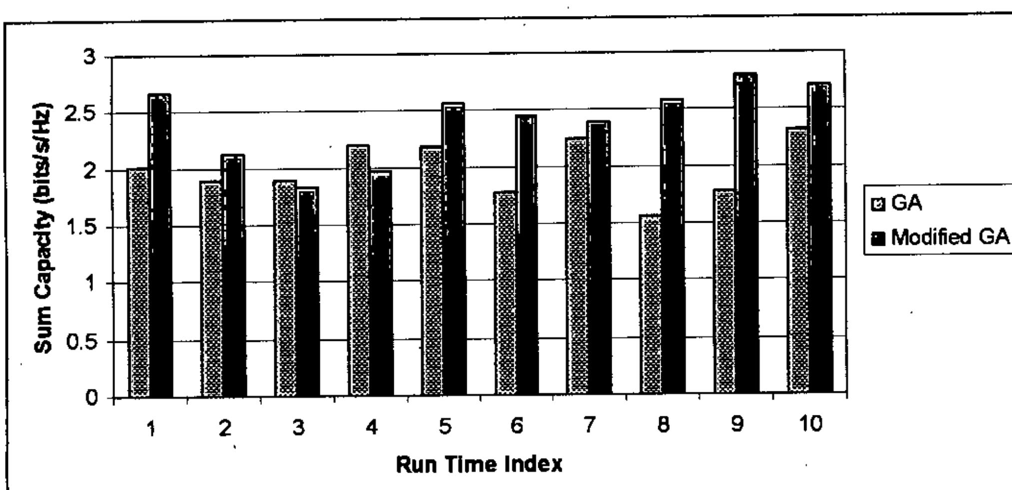
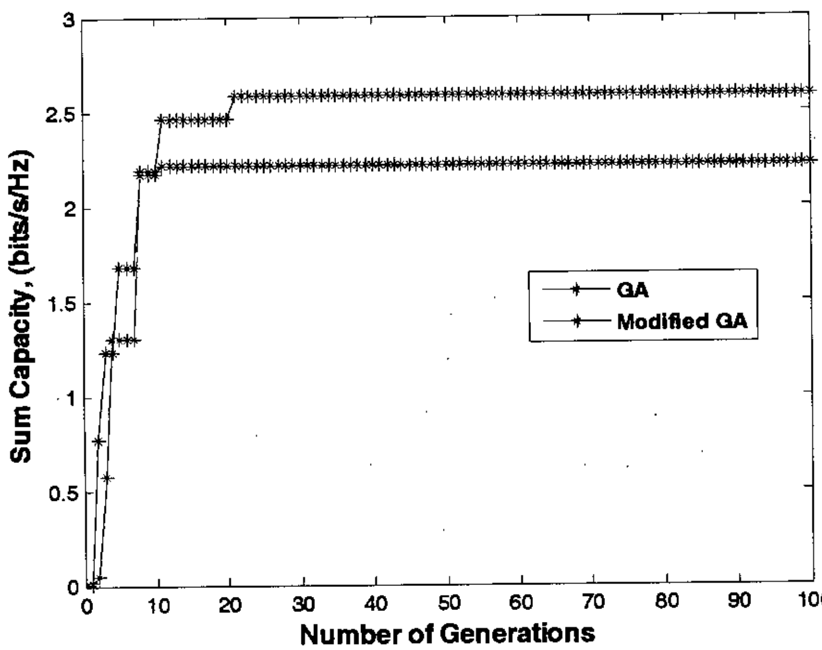


Fig. 4.2.12: Comparison between GA and modified GA in fair scheduled rate adaptive approach



throughput (for a particular run time of each algorithm) [Fair scheduled approach]

4.2.2.1.3 Comparison between the unconstrained approach and fair scheduled approach for rate adaptive resource allocation scheme

The comparative results reveal the fact that unlike unconstrained approach, with the introduction of the fairness in scheduling approach, the bit rate does not reach to the maximum value.

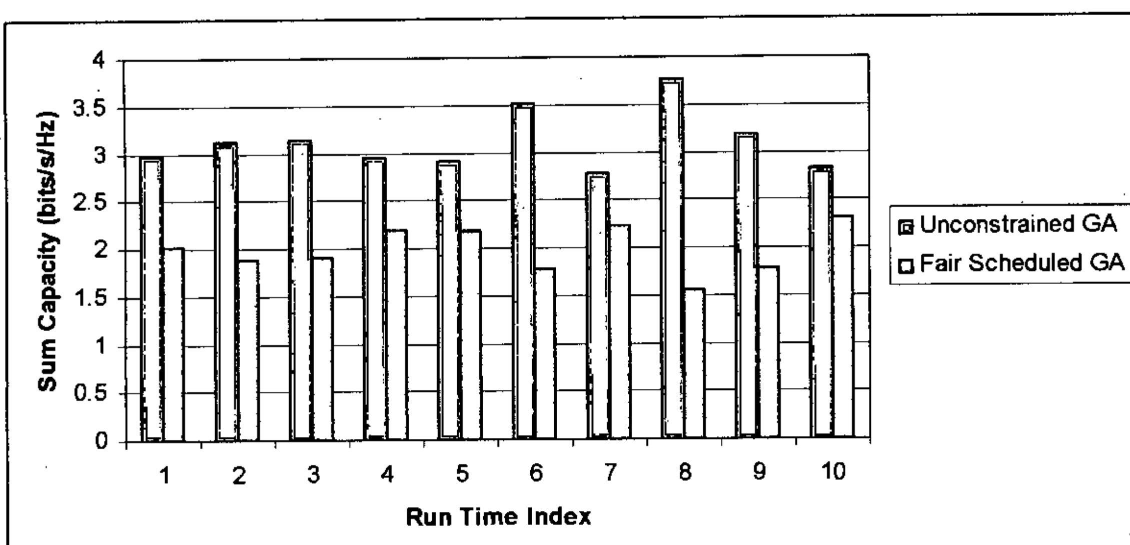


Fig. 4.2.14: Comparative results for unconstrained and fair scheduled GA in rate adaptation.

The fact is validated for both the original and modified versions of GA in Fig. 4.2.14 and 4.2.15. But another fact is that this deviation between the fair and unfair scheduling is not so prominent like that of margin adaptive approach.

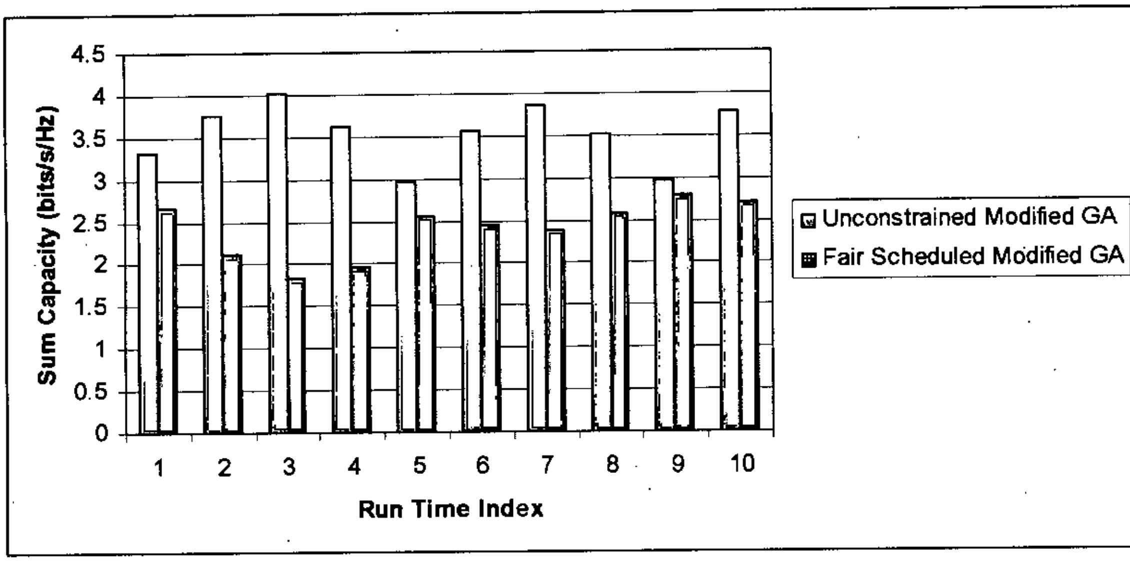


Fig. 4.2.15: Comparative results for unconstrained and fair scheduled Modified GA in rate adaptation.

4.2.2.2 Rate adaptive approach by PSO

4.2.2.2.1 Maximum throughput obtained by PSO using rate adaptive approach (unconstrained approach)

In this section, PSO has been applied in rate adaptive resource allocation in multiuser OFDM systems for unconstrained approach in selecting subcarriers. Table 4.2.7 calculates the maximum capacity of a particular OFDMA symbol for several times where the mean value is approximately 5 bits/s/Hz. Fig. 4.2.16 represents the convergence curve whereas Fig. 4.2.17 and 4.2.18 represent some comparative nature of the results with the variation of subcarriers and users. Fig. 4.2.17 shows that the maximum capacity increases with the increment of subcarriers for system of 4 users. Fig. 4.2.18 signifies the minimum user's capacity as a function of number of users for 3 systems having 3 sets of subcarriers. The figure reveals the fact that with the increment of users, minimum user's capacity gain decreases. Due to the effect of multiuser diversity, the more users in the system, the lower the probability that a given subchannel is in a deep fade for all users.

Table 4.2.7 Maximum throughput evaluation by PSO (Unconstrained approach)

Run	Maximum Sum Capacity (in bits/s/Hz) (By PSO)
1	4.56
2	4.22
3	4.21
4	4.78
5	4.45
6	4.72
7	4.44
8	4.49
9	4.71
10	4.89
Mean	**4.547 (≈ 5)**

* Simulations have been run for an OFDMA system having 64 subcarriers & 4 users

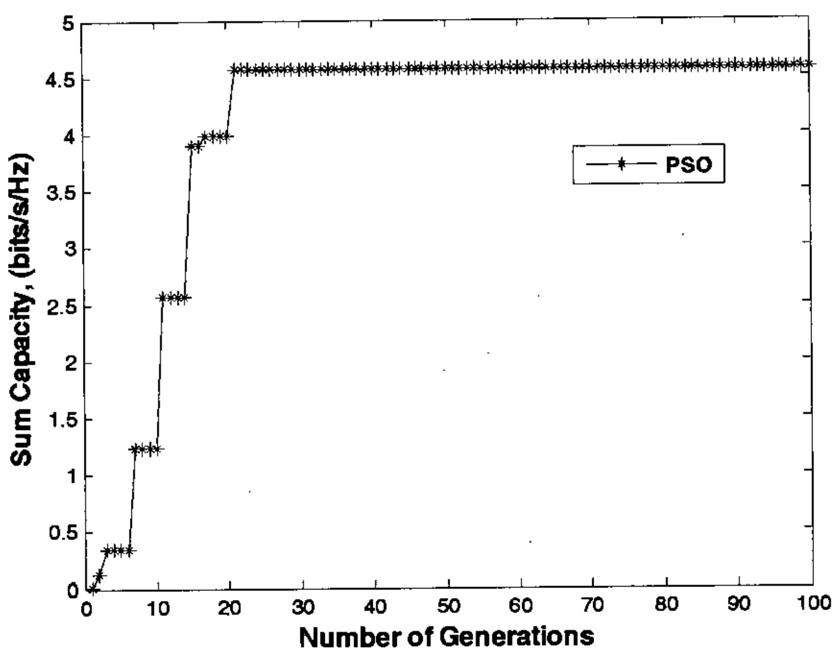


Fig. 4.2.16: Convergence curve of PSO for evaluating maximum throughput (for a particular run time of each algorithm) [Unconstrained approach]

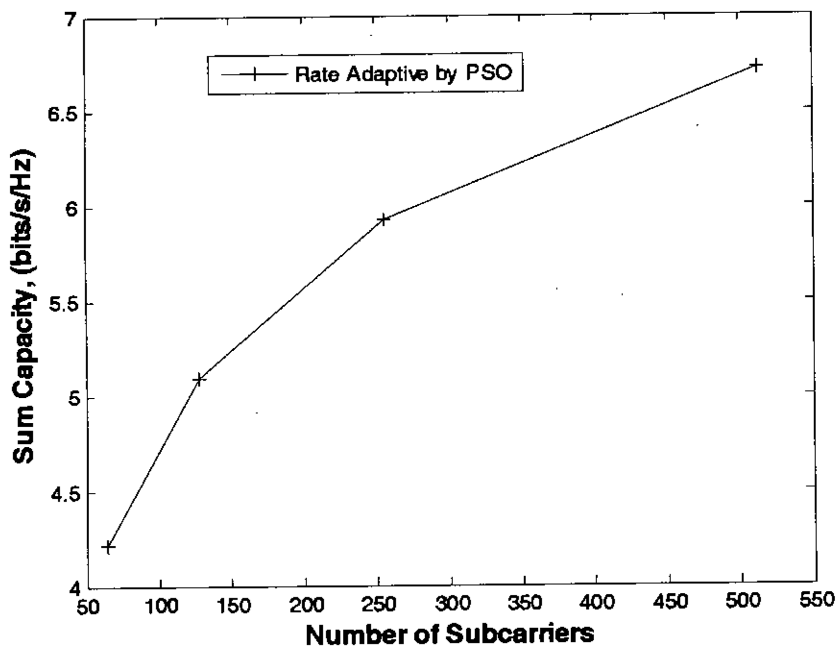


Fig. 4.2.17: Sum capacity for different number of subcarriers

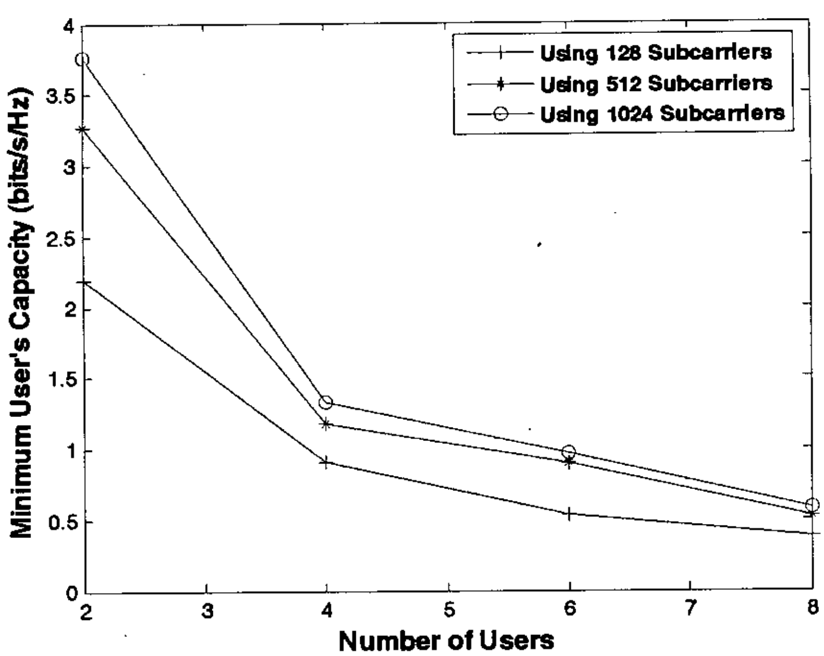


Fig. 4.2.18: Minimum user's capacity for different number of users

4.2.2.2.2 Maximum throughput obtained by PSO using rate adaptive approach (fair scheduled approach)

This section is more likely the reappearance of the previous section with slight modification in using constrained approach rather than the unconstrained one. The fairness has been deployed in the system considering a minimum threshold level in using subcarriers. Table 4.2.8 gives the maximum capacity for different run times. In comparison with table 4.2.7, the fairness approach gives less optimum value in choosing maximum capacity. Fig. 4.2.19 shows the convergence curve whereas the Fig. 4.2.20 and 4.2.21 correspond to the maximum capacity and minimum user's capacity as a function of number of subcarriers and number of users respectively. The curves signify that the maximum capacity in fairness approach is less than the unconstrained one whereas the minimum user's capacity is also affected with the introduction of fairness in scheduling. The second case is more prominent in the lower value of total users. For higher number of users this difference decreases significantly.

Table 4.2.8 Maximum throughput evaluation by PSO (Fair scheduled approach)

Run	Maximum Sum Capacity (in bits/s/Hz) (By PSO)
1	4.01
2	3.56
3	3.78
4	4.12
5	3.96
6	3.91
7	4.23
8	4.29
9	4.08
10	3.96
Mean	**3.99 (≈ 4)**

*** Simulations have been run for an OFDMA system having 64 subcarriers & 4 users**

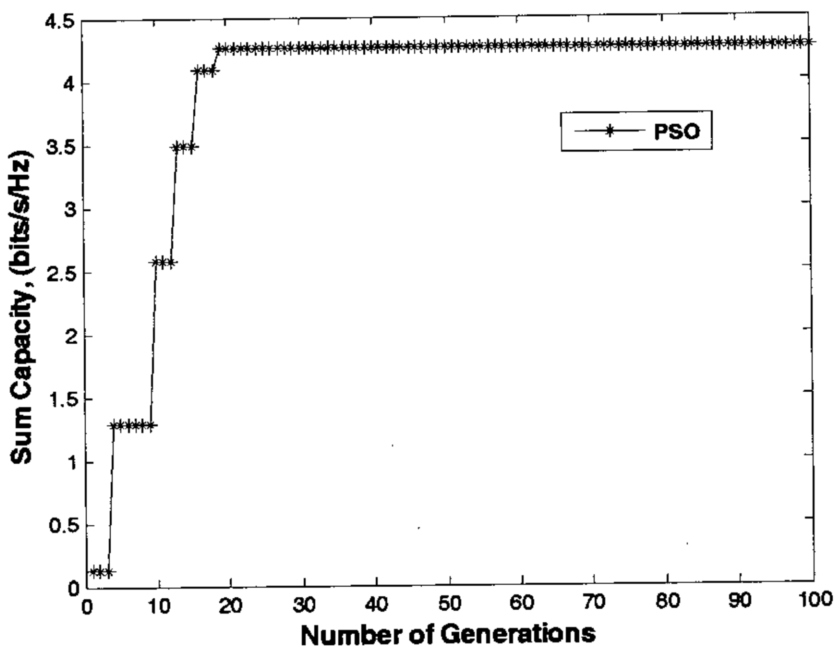


Fig. 4.2.19: Convergence curve of PSO for evaluating maximum throughput (for a particular run time of each algorithm) [Unconstrained approach]

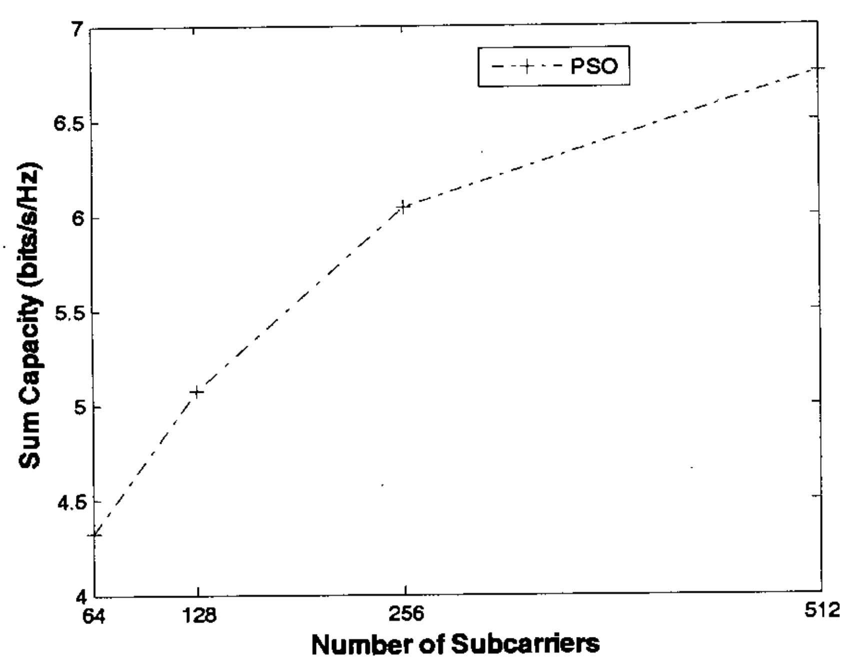


Fig. 4.2.20: Sum capacity for different number of subcarriers

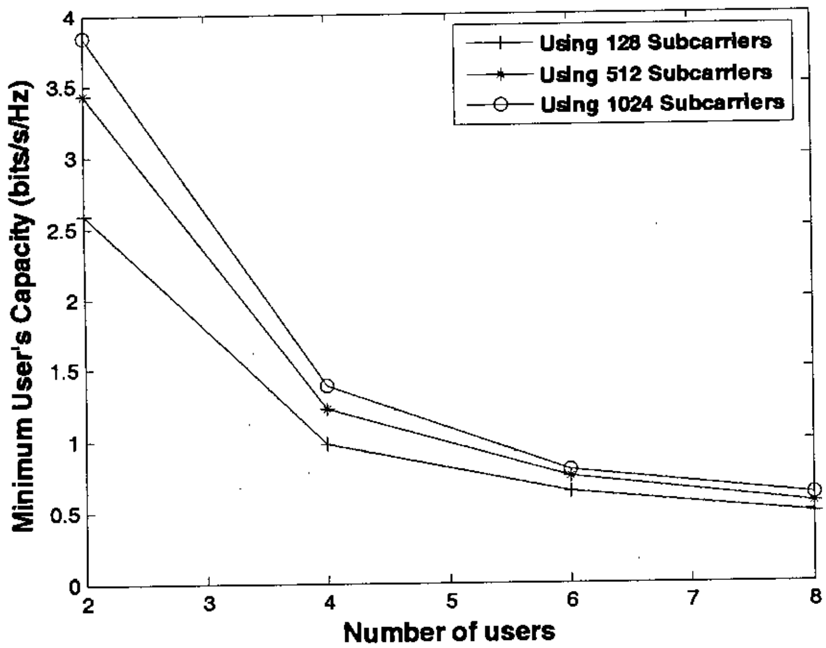


Fig. 4.2.21: Minimum user's capacity for different number of users

4.2.2.2.3 Comparison between the unconstrained approach and fair scheduled approach for rate adaptive resource allocation scheme by PSO

In comparison between the unconstrained and constrained approaches (in Fig. 4.2.22), the optimum level for rate adaptation is reached more prominently in unconstrained case. In fair scheduled case, as appalled conditioned subcarriers are allowed to carry bits for a specific user, definitely the maximum throughput declines from the optimum result.

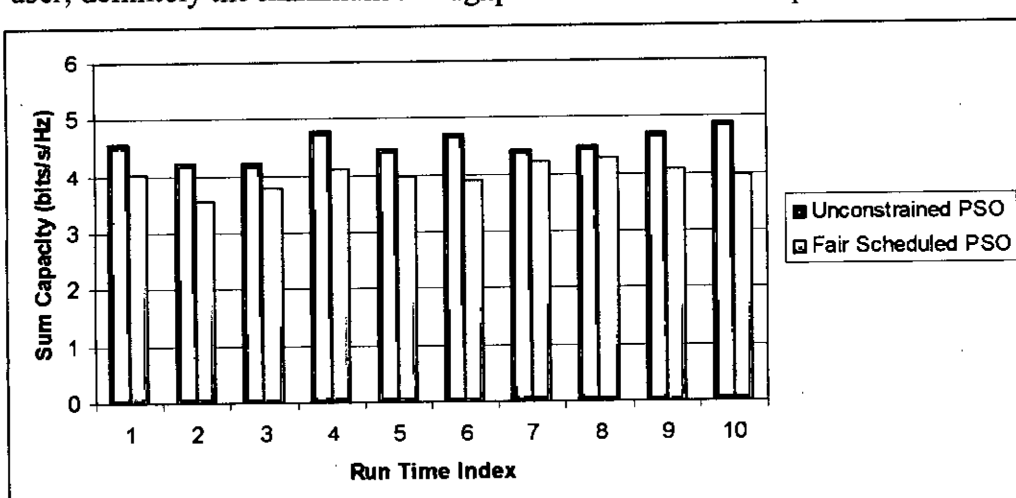


Fig. 4.2.22: Comparative results for unconstrained and fair scheduled PSO in rate adaptation

4.2.3 Performance comparison of GA, modified GA and PSO for all the proposed algorithms

4.2.3.1 Comparison in terms of the optimum value

In all the previous sections, the proposed algorithms have been simulated for few times for each of the cases. The mean value of each of the arrangements have been taken in this section to provide a clear idea amount the relative performances of the algorithms.

Table 4.2.9 Margin adaptive resource allocation (Unconstrained case)

Proposed Scheme	By MA (in dBm)
GA	5.3844
Modified GA	5.0415
PSO	4.8722

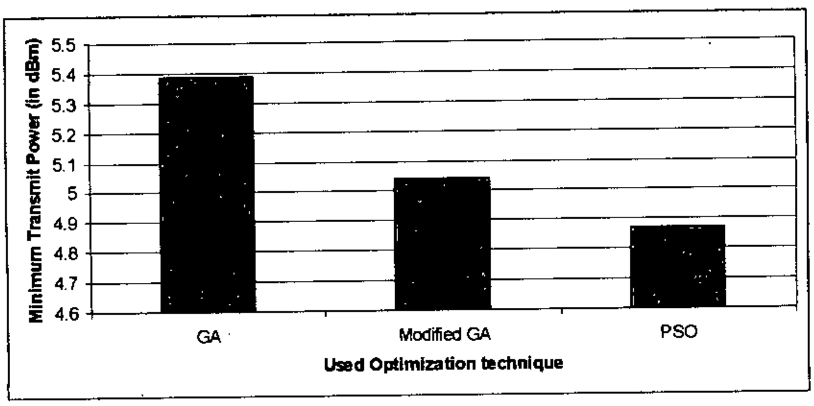


Fig. 4.2.23: Comparison among different margin adaptive unconstrained allocation

Table 4.2.10 Margin adaptive resource allocation (Fair scheduled case)

Proposed Scheme	By MA (in dBm)
GA	25.2549
Modified GA	23.4272
PSO	19.6869

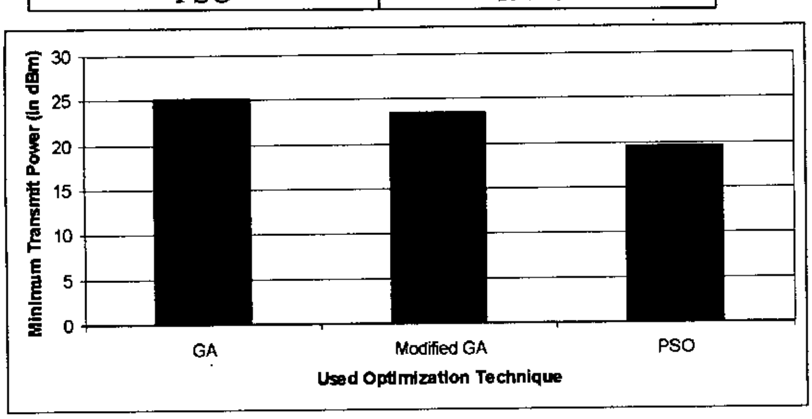


Fig. 4.2.24: Comparison among different margin adaptive fair scheduled allocation

Table 4.2.11 Rate adaptive resource allocation (Unconstrained case)

Proposed Scheme	By RA (in bits/s/Hz)
GA	3.118 (≈ 3)
Modified GA	3.54 (≈ 4)
PSO	4.547 (≈ 5)

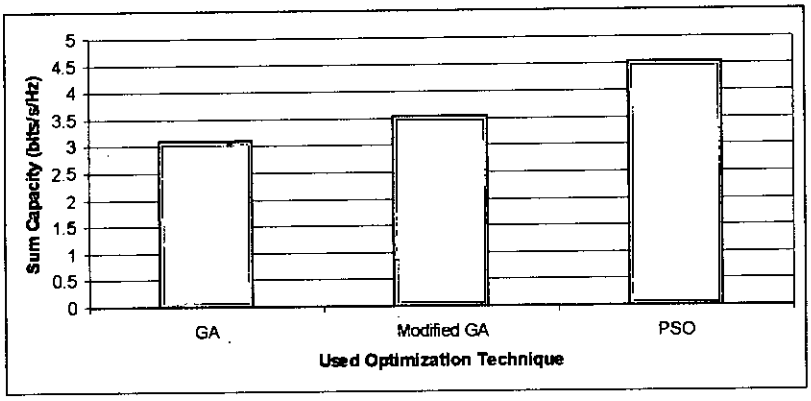


Fig. 4.2.25: Comparison among different rate adaptive unconstrained allocation

Table 4.2.12 Rate adaptive resource allocation (Fair scheduled case)

Proposed Scheme	By RA (in bits/s/Hz)
GA	1.985 (≈ 2)
Modified GA	2.408 (≈ 2)
PSO	3.99 (≈ 4)

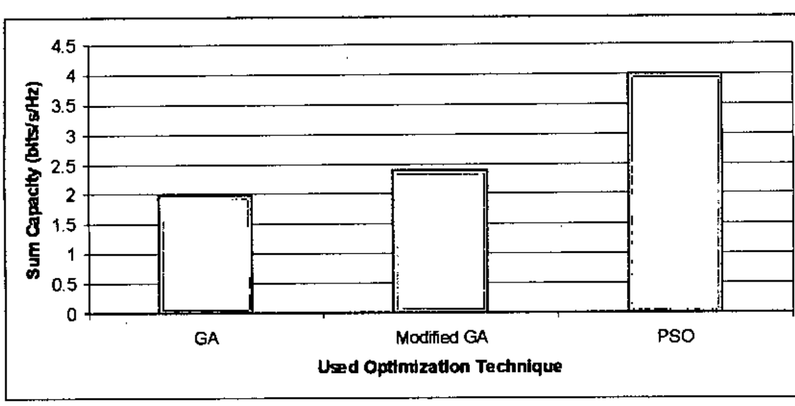


Fig. 4.2.26: Comparison among different rate adaptive fair scheduled allocation

From all the tables and figures in this subsection it is clearly evident that PSO performs the best among all the optimization algorithms. This is validated both for margin and rate adaptation cases. Even the difference between unconstrained and constrained system cannot alter this proclamation. Modified version of GA improves the result over its original version, but PSO perks up the optimum result quite significantly.

4.2.3.2 Comparison in terms of convergence

With these values of initial sizes of the algorithms, the modified GA and PSO have been used for simulation to allocate the resources for multiuser OFDM systems once again to sketch an impact of convergence. In Fig. 4.2.27, both the algorithms have been simulated for 0 to 200 generations. It is clearly evident that PSO converges to lower value compared with GA although the initial rate of convergence is higher for GA. The relative higher rate in initial convergence may be attributed to higher number of individuals in the population and hence higher number of function evaluated in one generation of GA, which is several times compared with that of PSO.

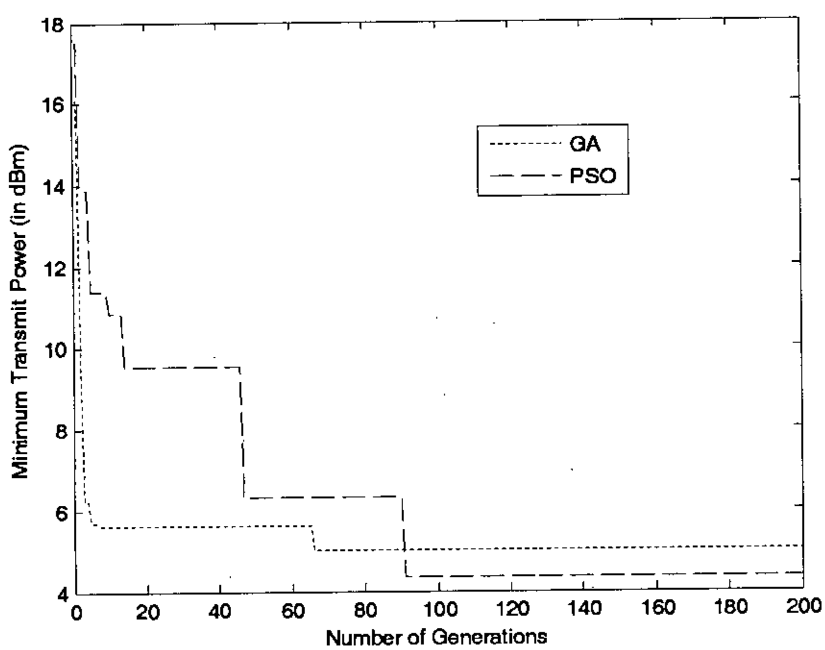


Fig. 4.2.27: Comparison of the convergence of GA and PSO

4.2.3.3 Comparison in terms of computational time

Although there are huge differences between GA and PSO in terms of internal operations to update the solutions, yet both of them are population-based and evaluate objective function and they try to optimize it. As such the number of function evaluated to achieve the target (objective function) value and corresponding central processing unit (CPU) execution time are considered as the performance metrics to carry out a comparative assessment between GA and PSO (in Table-4.2.13 and in Fig 4.2.28). Here in all the cases GA needs more time to converge than PSO although the number of generations for GA is sometimes lower than that of PSO. It is mainly due to the fact that GA needs more functions to evaluate to reach an optimum value whereas PSO needs to execute only two simple functions per generation for each swarm.

Table 4.2.13 Comparative performance measures of modified GA and PSO for a target value of 3.01 dBm*

	PSO			Modified GA		
Run	CPU execution time (s)	Number of generations	Number of functions evaluated	CPU execution time (s)	Number of generations	Number of functions evaluated
1	2.5428	66	1650	3.978	30	4320
2	2.2932	60	1500	12.8701	100	14400
3	1.2012	30	750	4.1184	32	4608
4	3.666	100	2500	8.2681	64	9216
5	2.7144	70	1750	4.0872	31	4464
6	3.6192	100	2500	12.9481	100	14400
7	1.1388	24	600	4.2744	32	4608
8	3.6972	100	2500	12.4021	95	13680
9	0.3276	6	150	1.1232	9	1296
10	1.6536	43	1075	4.9296	31	4464

***All the simulations have been carried out on a PC (Processor: Intel(R), Core(TM) 2 CPU, 1.73 GHz, RAM: 1022 MB).**

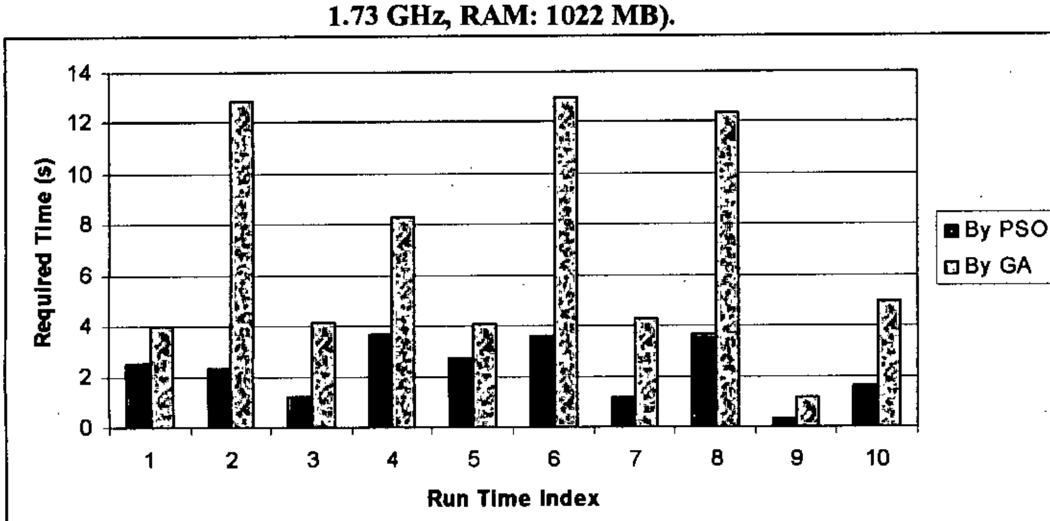


Fig. 4.2.28: CPU execution time for PSO and GA for a target value of 3.01dBm

4.3 Performance comparison of the proposed modified versions of PSO

4.3.1 First modification of PSO

Here the generation index has been introduced in the equation of position update. In the original PSO position update equation the previous position has just been added with the newly obtained velocity. But the generation information is missing here. As a consequence the timing information as well as the generation information should be introduced here in the velocity update equation. The modification clearly reveals that much more faster convergence is obtained here in the modified version. Two sets of convergence curves have been given in Fig. 4.3.1 and Fig. 4.3.2 for margin and rate adaptation approach respectively. For both the cases it is apparent that the modified version of PSO provides faster convergence than that of the original one.

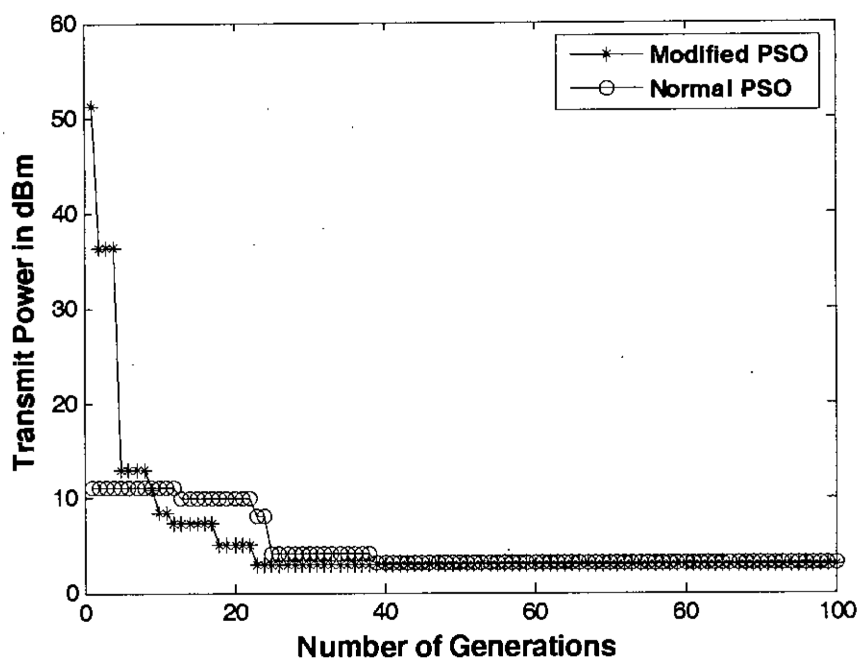


Fig. 4.3.1: Convergence curves of original and modified PSO (for Margin Adaptation)

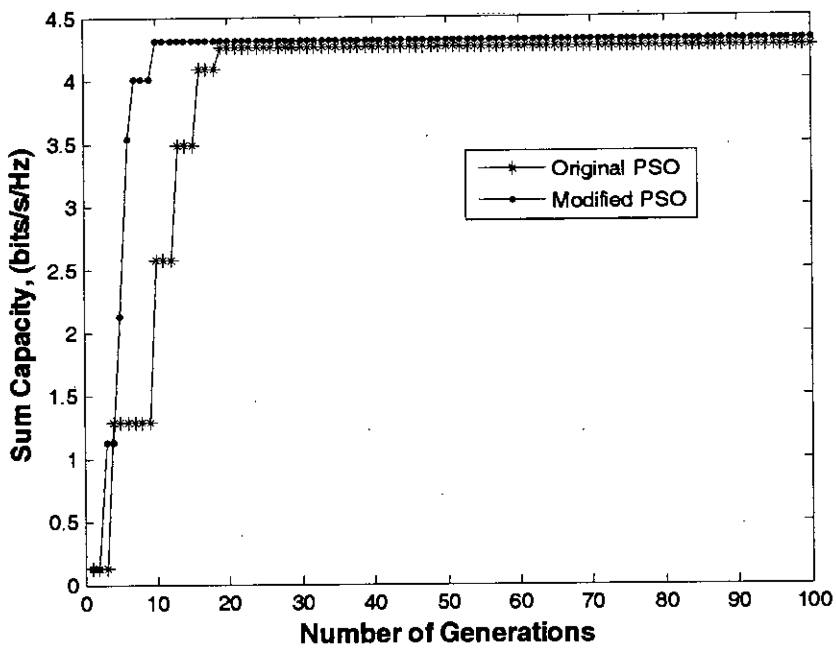


Fig. 4.3.2: Convergence curves of original and modified PSO (for Rate Adaptation)

4.3.2 Second modification of PSO

A large inertia weight (w) facilitates a global search while a small inertia weight facilitates a local search. By linearly decreasing the inertia weight from a relatively large value to a small value through the course of the PSO run gives the best PSO performance compared with fixed inertia weight settings.

Table 4.3.1 Comparison of power calculation using static and dynamic inertia weight (For Margin Adaptive approach)

Margin Adaptive approach	
Power Calculation Using Static Inertia Weight (in dBm)	**Power Calculation Using Dynamic Inertia Weight (in dBm)**
6.2567	3.4772
7.8892	4.4217
5.7088	3.3295
6.8486	3.7947
5.9896	5.4535
7.6657	4.2393
7.8121	2.7139
5.6677	3.7957
3.9179	2.9788
9.8576	2.9065
Mean = 6.7614	**Mean = 3.7111**

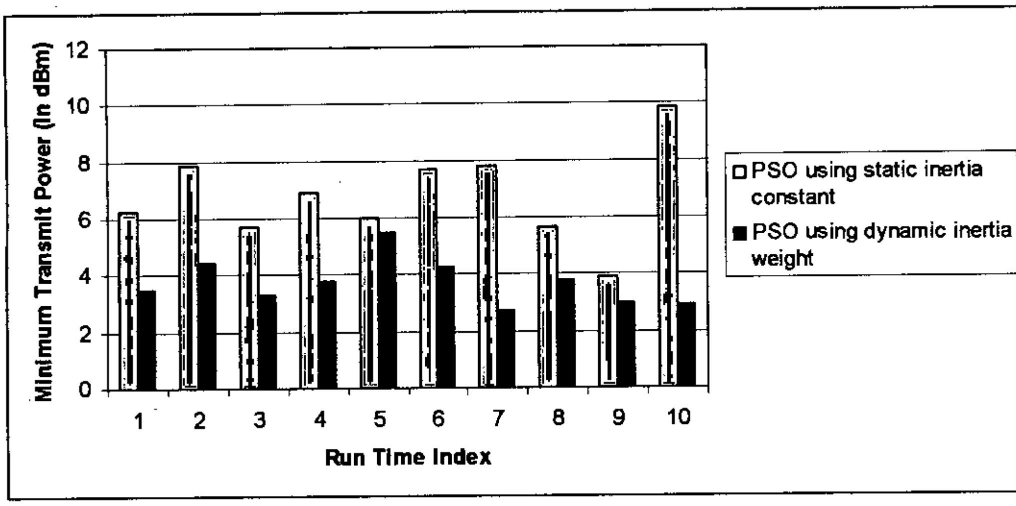


Fig. 4.3.3: Comparison between original PSO and modified PSO in margin adaptation (The PSO is modified by introducing dynamic inertia weight)

Table 4.3.2 Comparison of transmitted capacity calculation using static and dynamic inertia weight (For Rate Adaptive approach)

Rate Adaptive approach	
Sum Capacity Using Static Inertia Weight (in bits/s/Hz)	Sum Capacity Using Dynamic Inertia Weight (in bits/s/Hz)
1.8201	3.9087
1.7867	3.6712
2.6791	4.2341
1.8921	4.6751
1.6589	4.5431
2.1123	3.9976
1.8982	4.7896
2.0911	4.2389
2.1219	4.6754
1.7962	4.4786
Mean = 1.9857 (≈ 2)	**Mean = 4.3212 (≈ 4)**

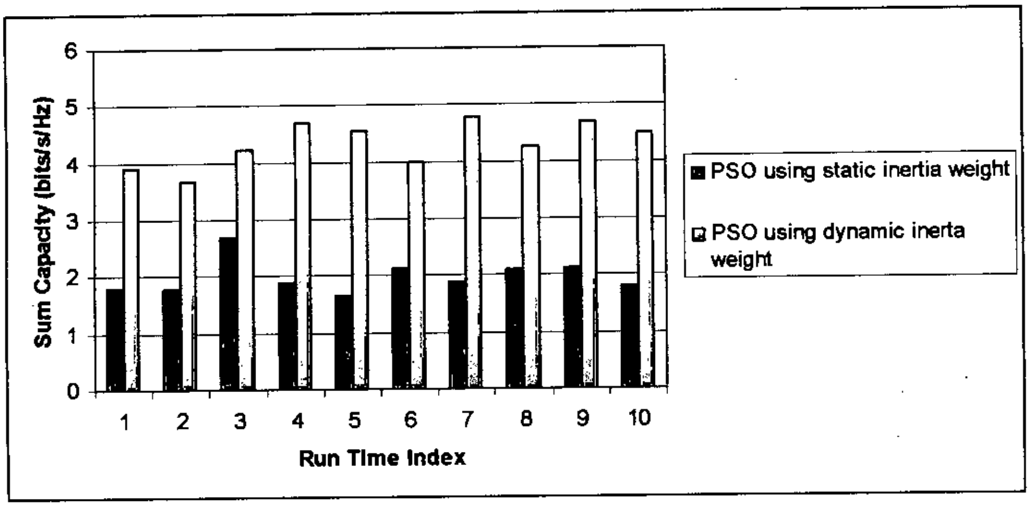


Fig. 4.3.4: Comparison between original PSO and modified PSO in rate adaptation (The PSO is modified by introducing dynamic inertia weight)

4.3.3 Third modification of PSO

The ring topology has been used here in search of global best value in each generation of the PSO. This modified version of PSO helps to find the global minima either maxima more efficiently. The principle reason behind this is the introduction of a global diversity of the swarms in each step of generation. As the searching process becomes more diversified, the probability of achieving the optimum result turns out to be more prominent. Table 4.3.3 as well as Fig. 4.3.5 reveals these facts.

Table 4.3.3 Power calculation by using ring topology and comparison with that of the original one (For Margin Adaptive approach)

Margin Adaptive approach	
Power Calculation Without Ring Topology (in dBm)	**Power Calculation Having Ring Topology (in dBm)**
3.7727	3.5695
3.2062	2.8543
3.6131	5.9559
3.0651	4.7227
3.4911	5.581
3.3293	3.4816
3.9871	5.2988
3.4391	7.6293
3.3666	2.7139
3.5617	2.9788
SD = 0.2691	**SD = 1.6289**

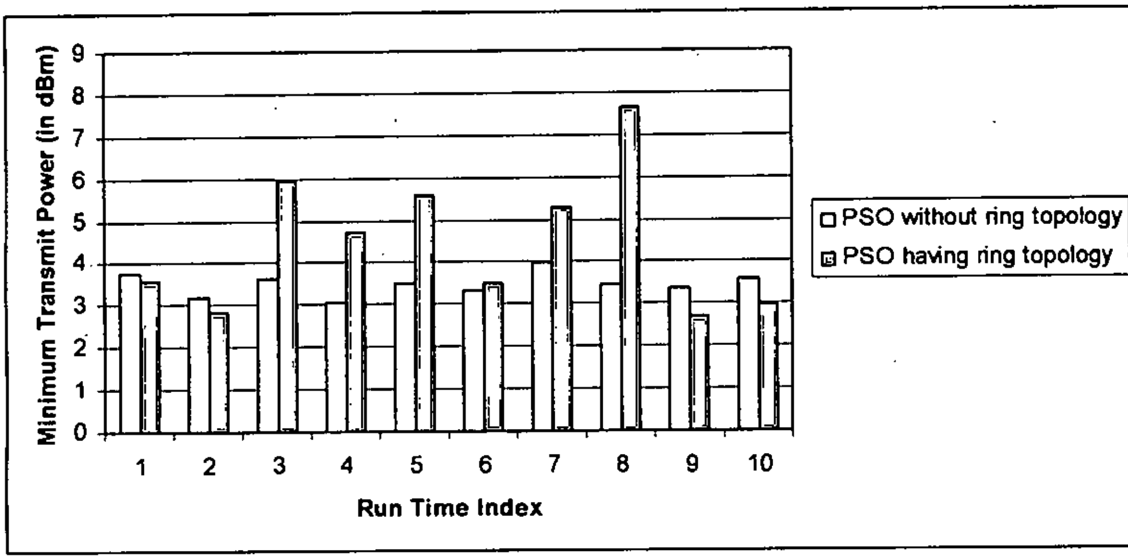


Fig. 4.3.5: Comparison between original PSO and modified PSO in margin adaptation (The PSO is modified by introducing ring topology in search of global best value)

Table 4.3.4 Power calculation by using ring topology and comparison with that of the original one (For Rate Adaptive approach)

Rate Adaptive approach	
Sum Capacity Without Using Ring Topology (in bits/s/Hz)	**Sum Capacity Using Ring Topology (in bits/s/Hz)**
4.4087	3.7087
4.6712	3.6712
4.3341	4.1341
4.6751	4.9751
4.5431	4.5431
4.4973	3.9976
4.7892	5.1296
4.3341	4.2389
4.6754	5.3754
4.4786 SD = 0.1576	4.9786 SD = 0.6129

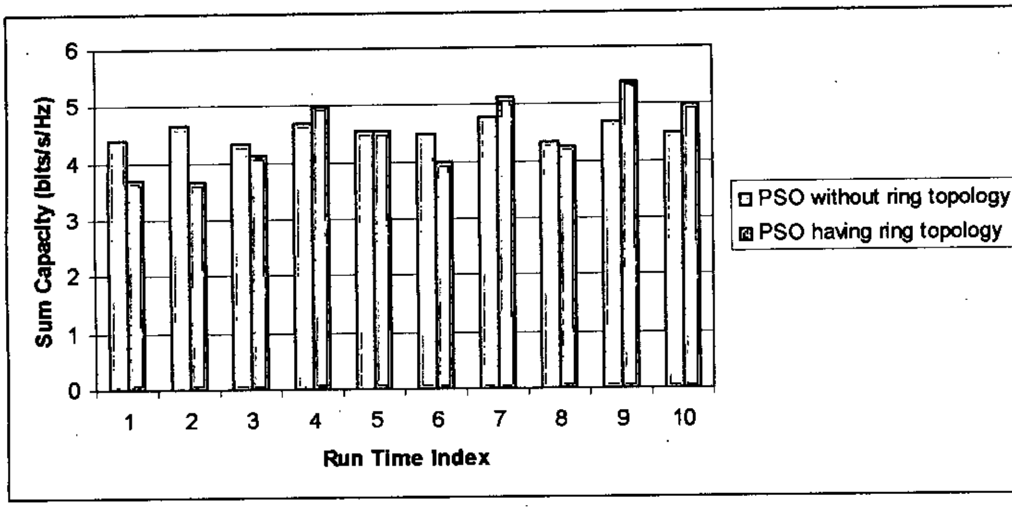


Fig. 4.3.6: Comparison between original PSO and modified PSO in rate adaptation (The PSO is modified by introducing ring topology in search of global best value)

4.4 Performance comparison of all the algorithms with the existing ones

The performance measure of subcarrier and bit allocation algorithms for real-time services in multiuser OFDM systems is the total transmit power required by all users on all subcarriers. The total transmit power, evaluated by different original and proposed algorithms have been compared in table 4.4.2. Fig. 4.4.1 and 4.4.2 clearly show the relative impact. All the algorithms are depicted in table 4.4.1.

Table 4.4.1 Introducing different algorithms with their abbreviations

TDMA	Time Division Multiple Access
FDMA	Frequency Division Multiple Access
GA	Genetic Algorithm
M-GA	Modified Genetic Algorithm
PSO	Particle Swarm Optimization
FM-PSO	First Modified Particle Swarm Optimization
SM-PSO	Second Modified Particle Swarm Optimization
TM-PSO	Third Modified Particle Swarm Optimization
(FM+SM)-PSO	First and Second Modified Particle Swarm Optimization
(SM+TM)-PSO	Second and Third Modified Particle Swarm Optimization
(FM+TM)-PSO	First and Third Modified Particle Swarm Optimization
(FM+SM+TM)-PSO	First, Second and Third Modified Particle Swarm Optimization

Table 4.4.2 Comparison among all the algorithms (proposed and existing ones) in calculating the total transmit power in margin adaptive approach*

Used Method / Algorithm	Total transmit power (in dBm) for 2 users	Total transmit power (in dBm) for 4 users	Total transmit power (in dBm) for 6 users	Total transmit power (in dBm) for 8 users
TDMA	6	12	19	26
FDMA	8.5	15.5	22.5	30
Wong's Algorithm	-2	0.5	7	13
Jang's Algorithm	6.5	16	28	45
GA	2.5	5	11	15
M-GA	2.5	4.5	9	13.5
PSO	3.5	5.5	8	10
FM-PSO	3.5	5	7.5	8.5
SM-PSO	3.5	4.5	7	8
TM-PSO	3.5	6	7.5	9
(FM+SM)-PSO	3.5	4.5	7	8
(SM+TM)-PSO	3.5	5	8	9
(FM+TM)-PSO	3.5	5.5	7.5	9
(FM+SM+TM)-PSO	3.5	4	7	8

* Simulations have been carried out for an OFDMA system having 64 subcarriers and Rayleigh fading channel

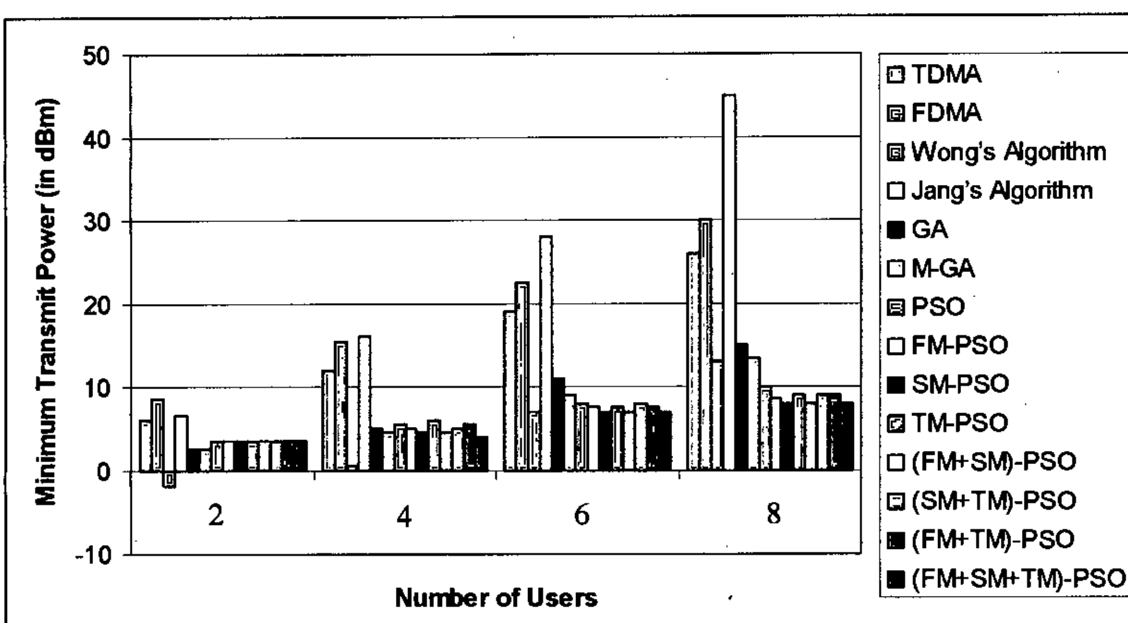


Fig. 4.4.1: Comparison among all the algorithms (proposed and existing ones) in calculating the total transmit power in margin adaptive approach

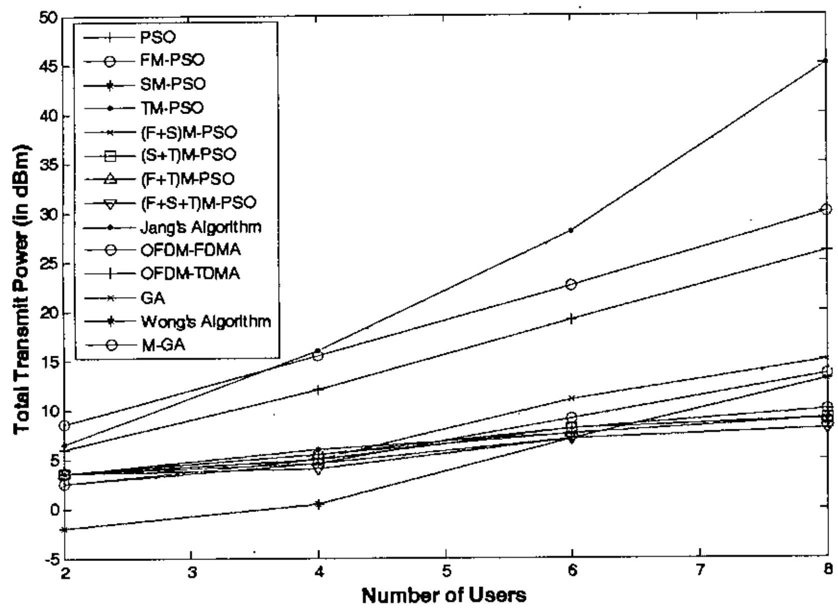


Fig. 4.4.2: Comparison of total transmit power calculated by all the existing and proposed algorithms

Fig. 4.4.2 gives a comprehensive view of performance all the algorithms. As this figure is apparently ambiguous to clarify the characteristics of the algorithms, this figure is sub divided into three divisions (Fig 4.4.3, Fig 4.4.4 and Fig 4.4.5) to have a clear aspect.

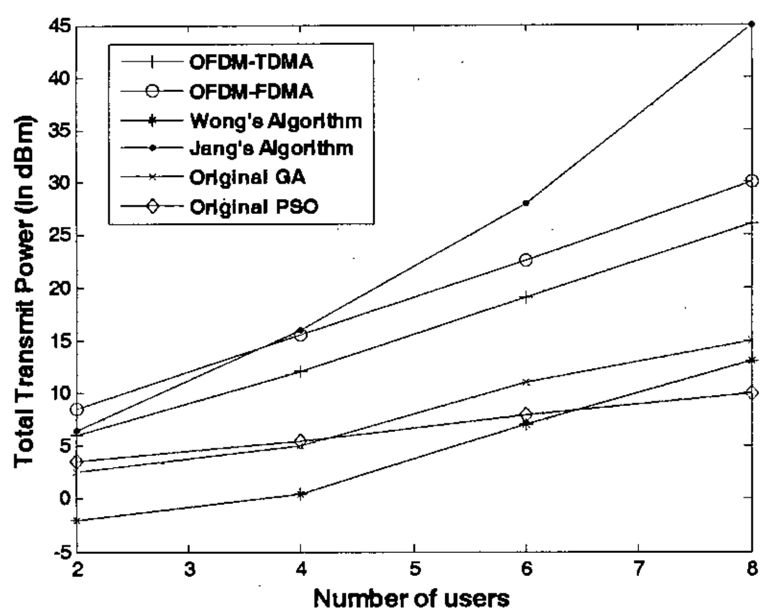


Fig. 4.4.3: Comparison of total transmit power calculated by different existing static and dynamic approaches along with the evolutionary approaches

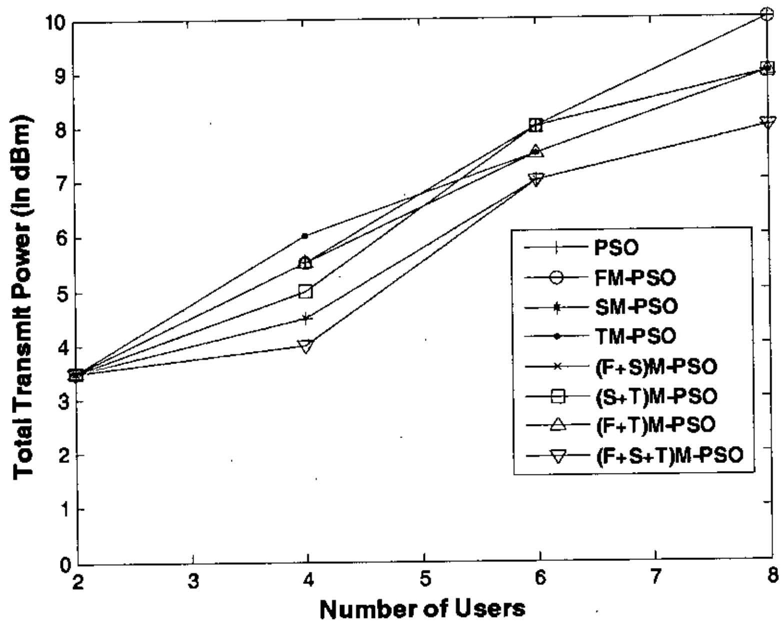


Fig. 4.4.4: Comparison of total transmit power calculated by PSO and different modified PSO

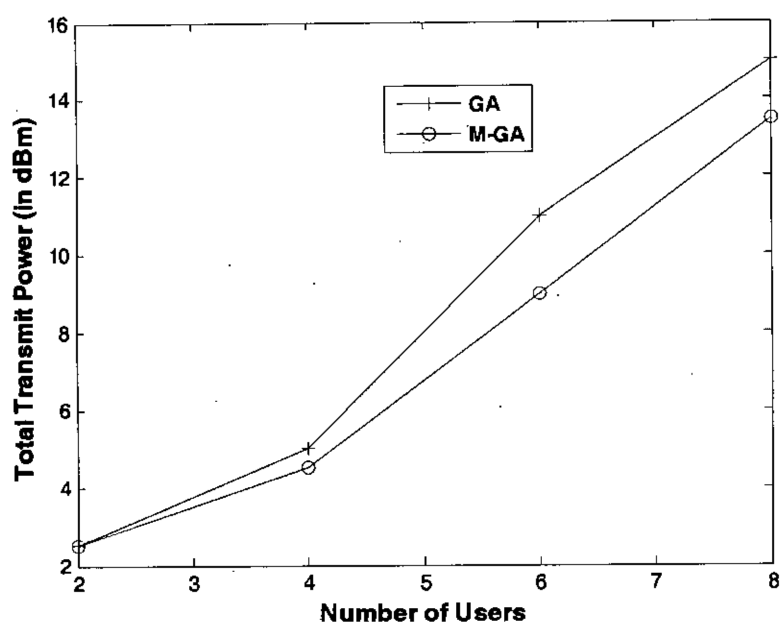


Fig. 4.4.5: Comparison of total transmit power calculated by GA and modified GA

This comparison clearly reveals several facts –

- All the proposed dynamic algorithms outperform the static ones (OFDM-FDMA, OFDM-TDMA) and Jang's dynamic algorithm. Although Wong's performance shows the optimum performance among all the static and dynamic algorithms for minimum number of users, yet its performance declines with the increment of the number of users. For large number of users, all the proposed and existing algorithms perform optimum.

- Among the dynamic allocation schemes, PSO along with all of its modified versions outperform the original and modified GA .
- The modified GA and modified PSO perform better than their original ones.
- The second modified version performs the best among all the modified versions of PSO.
- The third modified version performs the worst among all the modified versions of PSO and original PSO.
- Among the hybrid modified version, the hybrid of first and second modified versions of PSO outperform all proposed and existing static algorithms.

Besides of the calculation of total transmit power for different number of users, the total throughput can be evaluated for different number of users as well. As a matter of fact, the total throughput has been evaluated for different number of users by all the existing and proposed algorithms. (Table 4.4.3 and Fig. 4.4.6)

Table 4.4.3 Comparison among all the algorithms (proposed and existing ones) in calculating the total throughput in rate adaptive approach*

Used Method / Algorithm	Total throughput (in bits/s/Hz) for 2 users	Total throughput (in bits/s/Hz) for 4 users	Total throughput (in bits/s/Hz) for 6 users	Total throughput (in bits/s/Hz) for 8 users
GA	2	3	4	5
M-GA	2	4	5	7
PSO	3	5	6	8
FM-PSO	3	5	7	9
SM-PSO	3	5	7	9
TM-PSO	2	4	6	8
(FM+SM)-PSO	3	6	7	9
(SM+TM)-PSO	3	6	7	9
(FM+TM)-PSO	3	5	6	8
(FM+SM+TM)-PSO	3	6	7	9

*** Simulations have been carried out for an OFDMA system having 64 subcarriers and Rayleigh fading channel**

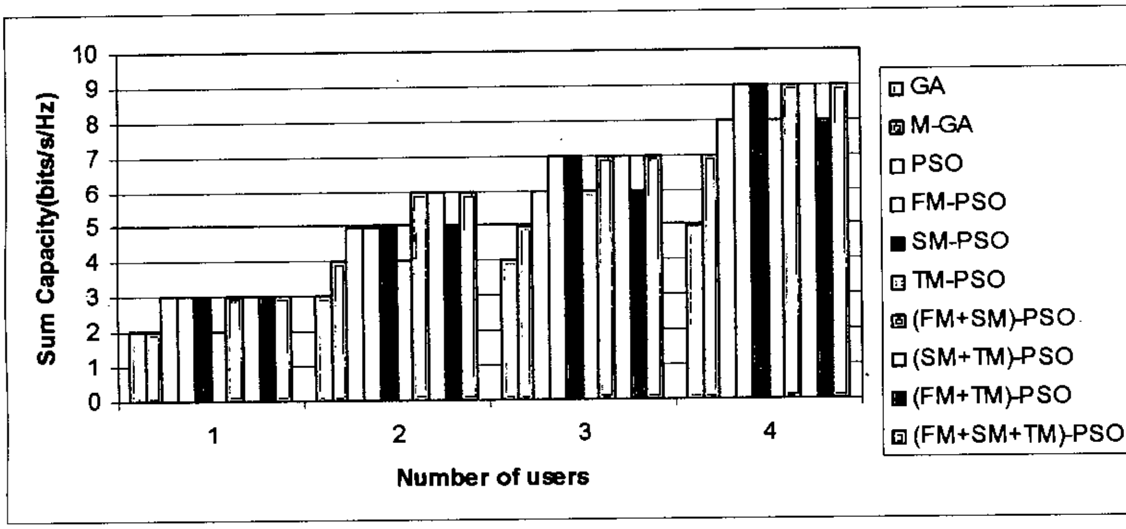


Fig. 4.4.6: Comparison among all the algorithms (proposed and existing ones) in calculating the total throughput in rate adaptive approach

This comparison also reveals some valuable facts –

- PSO and modified version of GA perform relatively better than the original version of GA.
- All the modified versions of PSO perform better than the original version of PSO.
- Among all the modifications, the second modified version as well as the final hybrid modified structure perform the best of all the algorithms.

From all the comparisons (both margin and rate adaptation), it is clearly evident that the PSO and its modified versions outperform all the existing static as well as dynamic algorithms.

Chapter 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

A central problem in OFDMA is rate and power allocation of users to subcarriers. Fixed resource allocation assigns a predetermined set of subc arriers to each user. Since the scheme is fixed regardless of the current channel condition, it is far from being optimal. Subcarriers which appear in deep fade to one user may be in good condition for others. That's why dynamic resource allocation assigns subcarriers adaptively to users according to the current channel conditions. In this literature, dynamic resource allocation has been analyzed under different scenario considering various practical and theoretical impacts. To allocate the available resources, the transmitter as well as the base station needs efficient optimization techniques. As OFDM deals with huge data rate, therefore the optimization has to deal with a large solution space. This research work has fully concentrated on evolutionary approaches for optimization because these stochastic processes can handle huge solution space without performance degradation. Moreover some of their results are comparable with other algorithms and this result has further been improved by slight modification over the original ones.

Actually this dissertation has focused on several points in OFDMA resource allocation. The first one has dealt with the application specific task of the evolutionary techniques. Here both Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been used to optimize the resources in margin and rate adaptation. GA has slightly been modified by introducing a concept of generation gap and reinsertion process. In margin adaptation, the total transmit power has to be minimized for a constant bit error rate and user data rate. On the other hand, rate adaptation deals with the maximization of the total throughput while maintaining a constant transmit power. Both the adaptation have clarified for unconstrained and fair scheduled cases. The unconstrained algorithm does not provide any restriction in choosing the number of subcarriers for a particular user whereas the fair scheduled approach confined a minimum number of subcarriers to a particular user. During the second phase, this research work concentrated on topological modifications of PSO. A type of modification was made in PSO by introducing generation information in position update equation. The second modification was done by using a dynamic inertia weight in velocity update equation. The last modification was performed by introducing a ring topology in search of globally best value for each generation.

From the result of the first phase of this dissertation it is evident that PSO provides a significant improvement over conventional and even the modified version of GA. In margin adaptation PSO gives the minimum result among three optimizers whereas in rate adaptation also, PSO provides the maximum value than GA and modified GA finally. For each iteration, PSO needs to update their position using two very simple equations whereas GA needs some procedures (like crossover, mutation, reinsertion) to update its value. As a whole, the performance obtained by PSO shows relatively better result than the other two algorithms in terms of simplicity, coding capability, computational resources, execution time. To compare the convergence between GA and PSO, it is apparent that GA shows initial higher rate of convergence whereas PSO provides better result in final converging capability. As such PSO can be defined as one of the effective means to optimize the allocated resources.

Furthermore the allocation schemes have been classified into unconstrained and fair scheduled approaches. The unconstrained algorithms provide more optimum result in either case whereas the fair scheduled subcarrier distribution prevails a fairness in affixing resources but loses the optimality in final result. In all the cases PSO performs the best among all the algorithms.

The second phase of the thesis mainly deals with the topological modification of PSO. All the modifications provide better result than original version of PSO. The key performance identifier for any system is the total transmit power required by all users. In view of this all the proposed algorithms have been compared with other existing algorithms. The comparison reveals the fact that dynamic resource allocations outperform the static ones. Among all the dynamic algorithms, Wong's performance provides the best result for lower number of users. But its performance declines with the increment of the number of users. All the evolutionary algorithms give comparable results with other algorithms. Among them the modified versions of PSO provide the best results in terms of optimality. The hybrid modified structures of PSO bestow even better result than

Wong's algorithm for higher number of users. As a matter of fact, the modified versions of PSO can be effectively applied in optimizing the allocated resources for multiuser OFDM systems.

5.2 Future Work

5.2.1 Extension of the current research

To the best of knowledge, PSO has not been deployed in multiuser OFDM resource allocation systems so far. This dissertation implemented PSO in different resource allocation schemes quite effectively and efficiently. The modification of PSO has further fructified its application oriented purpose. There are definitely future ideas which can be regarded as an extension of this research work.

a) The basic operations of GA like selection, crossover, mutation can be applied in PSO to update the position of the particles. This can enhance the system performance by combining the effect of initial higher rate convergence and final converging capability.

b) This research work has totally been concentrated on periodic ranging process, the same work can be done in initial ranging process also.

c) Multiple antenna provides the advantage of spatial diversity which ultimately improves the system performance as well. As such this work can be extended for Multiple Input Multiple Output (MIMO) OFDMA systems where resources can be optimized using these proposed algorithms. The use of channel coding can further increase the system performance. Convolutional code can be applied to the original system and the overall performance can be evaluated remaining the same structure.

5.2.2 Application of evolutionary approaches in other areas of OFDM

Evolutionary algorithms can also be applied in other sectors of wireless communications particularly in OFDMA systems.

- GA and PSO can be applied to solve the peak to average power ratio (PAPR) problem in OFDM. Here a contradictory situation has to be handled by maximizing bit rate and minimizing the non-linearity of the amplifier.
- In the case of antenna diversity, the higher number of antenna results in lower bit error rate. On the other hand, higher number of antenna results in huge complexity. So an optimum level has to be reached where an effective result can be obtained.
- GA and PSO can also be applied in the resource allocation of MC-CDMA systems and the comparison of this system can be drawn out with the OFDM systems.

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