Resource Allocation in Downlink OFDMA Systems: An Evolutionary Approach

THESIS

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CERTIFICATE

This is to certify that the thesis entitled "**Resource Allocation in Downlink OFDMA Systems: An Evolutionary Approach**" and submitted by **Mr. Nitin Sharma** ID No. **2007PHXF414P** for award of Ph.D. degree of the Institute, embodies original work done by him under my supervision.

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ABSTRACT

A downlink wireless system features a centralized basestation communicating to a number of users physically scattered around the basestation. The purpose of resource allocation at the basestation 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. Adaptive resource allocation in a multichannel downlink system is more challenging because of the additional degree of freedom for resources, but offers the potential to provide higher user data rates. Multiple channels can be created in the frequency domain using multiple carrier frequencies, a.k.a. multicarrier modulation (MCM), or in the spatial domain with multiple transmit and receive antennas, also known as multiple-input multiple-output (MIMO) systems. This thesis aims to study the system performance, e.g. total throughput and/or fairness, in multiuser multicarrier and multiuser MIMO systems with adaptive resource allocation, as well as low complexity algorithms that are suitable for cost-effective real-time implementations in practical systems.

First contribution of this thesis is the use of Particle Swarm Optimization (PSO), a stochastic optimization technique, for sub-channel allocation in downlink of OFDMA systems followed by power allocation using water filling algorithm. In PSO aided subchannel allocation the search and subchannel allocation is performed simultaneously as compared to traditional methods where the subchannels are first sorted in accordance of their gains and then allocation is performed. This significantly reduces the complexity of PSO aided allocation. This fact makes PSO aided subchannel allocation a suitable choice for practical wireless systems like WiMAX (802.16e) where the convergence rate plays a very important role as the wireless channel changes rapidly.

The second contribution to this thesis is a novel genetic algorithm adaptive resource allocation in MIMO OFDM systems. We impose a set of proportional fairness constraints to assure that each user can achieve a required data rate, as in a system with quality of service guarantees. With the proposed algorithm, the sum capacity can

be distributed fairly and flexibly among users. Since the optimal solution to the constrained fairness problem is extremely computationally complex to obtain, we propose a suboptimal algorithm that separates subchannel allocation and power allocation. In the proposed algorithm, subchannel allocation is first performed using novel Genetic Algorithm, assuming an equal power distribution. An optimal power allocation algorithm then maximizes the sum capacity while maintaining proportional fairness.

Finally, we present a joint solution to subchannel, bit and power allocation problem for downlink of MIMO OFDM systems. Using SVD, the MIMO fading channel of each subchannel is transformed into an equivalent bank of parallel Single Input Single Output (SISO) sub-channels. To achieve the capacity bound, one must solve a multiuser subchannel allocation and the optimal bit allocation jointly. We propose the use of Non-dominated Sorting Genetic Algorithm (NSGA) – II, which is a Multi-Objective Genetic Algorithm (MOGA), for joint allocation of bits and subchannels, in the downlink of MIMO OFDMA system. NSGA – II is intended for optimization problems involving multiple conflicting objectives. Here the two conflicting objectives are Rate Maximization and Transmit Power Minimization.

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LIST OF ACRONYMS

3GPP	3^{rd} Generation Partnership Project
AA	Antenna Array
ACO	Ant Colony Optimization
ANN	Artificial Neural Network
AWGN	Additive White Gaussian Noise
BC	Broadcast Channel
BD	Block Diagonalization
BER	Bit error rate
BFA	Best Fit Algorithm
BLAST	Bell Laboratories Layered Space-Time Architecture
BS	Base Station
CDMA	Code Division Multiple Access
CSI	Channel State Information
CSMA	Carrier Sense Multiple Access
D-BLAST	Diagonal Bell Laboratories Layered Space-Time Architecture
DE	Differential Evolution
DFT	Discrete Fourier Transform
DPC	Dirty Paper Coding
EA	Evolutionary Algorithm
EP	Evolutionary Programming

ExS	Exhaustive Search
ES	Evolutionary Strategies
FDD	Frequency Division Duplex
FDM	Frequency Division Multiplexing
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
GA	Genetic Algorithm
GP	Genetic Programming
GSA	Gravitation Search Algorithm
IEEE	Institute of Electrical and Electronics Engineers
ICI	Inter-Carrier Interference
i.i.d	Identically Independent Distributed
IFFT	Inverse Fast Fourier Transform
ISI	Inter-Symbol Interference
LoS	Line of Sight
LTE	Long Term Evolution
MA	Margin Adaptive
MAC	Multiple Access Channel
MAI	Multiple Access Interference
MF	Matched Filter
MIMO	Multiple Input Multiple Output
ML	Maximum Likelihood
MMSE	Minimum Mean Square Error

MOGA	Multi-Objective Genetic Algorithm
MQAM	M-ary Quadrature Amplitude Modulation
MRRC	Maximal Ratio Receiver Combining
MS	Mobile Station
MSE	Mean Square Error
MU	Multi-User
MUD	Multiuser Detection
NP	Non-deterministic Polynomial time
NP-C	Non-deterministic Polynomial time Complete
NPGA	Niched Pareto Genetic Algorithm.
NSGA	Non-Dominated Sorting Genetic Algorithm.
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency Division Multiple Access
PBIL	Population Based Incremental Learning (PBIL)
P_c	Probability of Crossover
PIC	Parallel interference cancellation
P_m	Probability of Mutation
PSO	Particle Swarm Optimization
QAM	Quadrature amplitude modulation
QoS	Quality of Service
QPSK	Quadrature Phase Shift Keying
RA	Rate Adaptive
RF	Radio frequency

RMS	Root-Mean-Squared
SBX	Simulated Binary Crossover
SDMA	Space Division Multiple Access
SIC	Successive Interference Cancellation
SIR	Signal to Interference Ratio
SINR	Signal-to-Interference plus Noise Ratio
SISO	Single Input Single Output
SNR	Signal-to-Noise Ratio
SPs	Successive Projections
STVC	Spatio-Temporal Vector Coding
SU	Single-User
SVD	Singular Value Decomposition
TDD	Time Division Duplex
TDMA	Time Division Multiple Access
UL	Uplink
V-BLAST	Vertical Bell Laboratories Layered Space-Time
VEGA	Schaffer's Vector Evaluated Genetic Algorithm
WF	Water Filling
WiMAX	Worldwide Interoperability for Microwave Access
WSN	Wireless Sensor Network
ZF	Zero-Forcing

List of Symbols

$\min f(\bullet)$	the minimum value of the function $f(\bullet)$
$\max f(\bullet)$	the maximum value of the function $f(\bullet)$
$\arg\min_{x} f(x)$	the value of x (argument) that minimizes $f(\bullet)$
$\arg\max_{x} f(x)$	the value of x (argument) that maximizes $f(\bullet)$
$\mathbf{\Theta}$	empty set
∞	infinity
$\in$	belongs to
$\subset$	subset of
$\cup$	Union of sets
$\cap$	Intersection of sets
$(\bullet)^{\dagger}$ or $(\bullet)^{H}$	(superscript only) conjugate transpose of a vector or matrix
$\lVert\bullet\rVert_{F}$	Frobenius norm
$\det(\bullet)$	determinant of a matrix
$\mathrm{tr}(\bullet)$	Trace of a matrix
$\mathrm{diag}(\bullet)$	diagonal matrix with the elements in the main diagonal given by $(\bullet)$
$\mathrm{rank}(\bullet)$	Rank of Matrix
$\mathbf{I}$	Identity Matrix
$\forall$	for all
$\sum_{i=1}^{n} x_i$	sum over i: i=1, 2,…,n = $(x_1+x_2+\ldots+x_n)$
$\sum_{i=1}^{n} x_i$	product over i: i=1, 2,…, n = $(x_1x_2\ldots x_n)$
$\lvert\bullet\rvert$	Modulus of $(\bullet)$
f_c	Carrier frequency
B_c	Coherence bandwidth
T_c	Coherence time

$h(t,\tau)$	Impulse response of channel
$\bar{\tau}$	mean excess delay
σ_τ	root mean squared (rms) delay spread
$I_0(\bullet)$	Modified Bessel function
M_T, M_R	Number of transmit and receive antenna respectively
Q	total number of paths in space (i.e., from different angles of arrival)
β_q	Corresponding fading coefficient
$\boldsymbol{\alpha}^{Rx}\left(\theta_q^{Rx}\right)$	Array responses for arrival angle
$\boldsymbol{\alpha}^{Tx}\left(\theta_q^{Tx}\right)^T$	Array responses for departure angle
θ_q^{Rx}	Arrival angle
θ_q^{Tx}	Departure angle
$\mathbf{n}$	Noise vector
N_o	Noise power spectral density

Chapter-1
Introduction

1.1. Introduction

The advent of new generation of communication technologies has ushered in an era of high data rates and better reliability. The next generation wireless communication systems are expected to provide data services with rate requirements ranging from a few Kbit/s up to several Mbits/s. The reliability expected of these systems is also very high. According to Shannon [Sha48] for such a reliable, high data rate transmission the bandwidth required is also very high. Due to scarcity of frequency spectrum, these systems also need to be extremely efficient in terms of the spectrum usage.

High data rate wireless systems with very small symbol periods usually face unacceptable Inter-Symbol Interference (ISI) because of multipath propagation and their inherent delay spread. As applications move to higher and higher data rates over wireless channels, ISI becomes more of a problem. The interference goes from being identified as fading to frequency selective fading (when delay spread t_{d} exceeds the bit time) as the data rate increases in multipath environment. The multipath components begin to interfere with later symbols, resulting in irreducible error floors.

Orthogonal frequency division multiplexing (OFDM) is the extension of the frequency division multiplexing (FDM) technique. The use of orthogonal subchannels allows the subchannels' spectra to overlap. Due to the orthogonality it is possible to recover the individual subchannels' signals despite the overlapping spectra and thus there is no need of guard bands as in FDM. OFDM is essentially a type of multicarrier modulation scheme. OFDM works on the concept of dividing a given high-bit-rate data stream into several parallel lower bit-rate streams. Each bit stream is then modulated on separate carriers often called subchannels, or tones. In FDM each subchannel needs a separate pair of matched filters at the transmitter and the receiver to make it possible to eliminate the inter-carrier interference (ICI). OFDM eliminate or minimize ISI by making the symbol time large enough to ensure that the channel induced delays are an insignificant fraction of the symbol duration.

The idea of using orthogonal subchannels was suggested more than 40 years ago [FL61, Cha66, Sal67] but in practice it was not used for a long time mostly due to its complexity. Simple OFDM-based transceivers can be efficiently implemented using the Fast Fourier Transform (FFT). Since with OFDM the channel transfer function of each subchannel becomes non-frequency-selective, sophisticated equalization structures are not needed [NP00, LL05, FKKC06]. Moreover, OFDM system can be used to provide rate flexibility and services with different rate requirements by allocating variable number of subchannels to a given radio link [LL05].

At the physical layer, Multiple Input Multiple Output (MIMO) technologies have received increasing attentions in the past decades [CLC10, ASC11, CLL11, PB10, HK10, LTC10]. Many broadband wireless networks have now included the MIMO option in their protocols. Compared to Single Input Single Output (SISO) system, MIMO offers better resistance against fading. In addition, the greater diversity can potentially lead to a multiplicative increase in capacity.

Equipped with multiple antennas at the transmitter and receiver, MIMO systems fully utilize the spatial dimension to improve the transmission reliability and/or the system throughput. Huge multiplexing gains can be achieved by transmitting multiple data streams separated in space over the same radio channel [Tel95, FG98]. In this way, high spectral efficiency values can be achieved without requiring additional frequency resources [FGH05, MK06, DSK$^+$06]. The Base Station (BS) can transmit data streams to different Mobile Stations (MSs) sharing the same radio resource in space. Such a sharing of radio resource in space which adds a spatial component in the multiple access schemes is called as Space Division Multiple Access (SDMA) [LR99, Tre02, PNG03]. The multiple antenna systems employed at the BS and MSs are usually called as Antenna Arrays (AAs). The individual antennas of the AAs are termed AA elements [LR99, Tre02].

The rest of this chapter presents a brief review of the existing literature and parallel work within the scope of the thesis.

1.2. Adaptive modulation for SISO fading channels

Information theory was introduced by Shannon in [Sha48], where he derived the general theory on reliable communication and, in particular, the capacity of the additive white Gaussian (AWGN) channel. In [Sha49], Shannon also showed that the capacity-achieving power allocation for a time-invariant spectrally shaped channel corresponds to a water-filling (WF) distribution [CT91]. Since Shannon capacity is the maximum data rate that a communication system can achieve with near zero error probability, the data rate achieved in a practical system is inevitable lower than the Shannon capacity due to the limitation of channel bandwidth and signal power. In other words, Shannon capacity is generally used as an upper bound on the achievable data rate in a real system.

The capacity of time-varying frequency-flat fading channels with full Channel State Information (CSI) was later analyzed by Goldsmith and Varaiya in [GV97], where they demonstrated that the Shannon capacity for a fading channel can be achieved by varying both the transmission rate and the power [GV97]. Caire and Shamai [CS99] showed that variable-rate variable-power coding schemes are not needed to achieve the capacity of this channel, and a simple single codebook scheme with dynamic power allocation may be a more viable solution, when the power allocation is of the WF type. In, the low Signal-to-Noise Ratio (SNR) case, adaptive systems yields both higher capacity and a lower complexity than non-adaptive transmission that do not exploit channel knowledge at the transmitter [GV97, CS99].

However, in high SNR case, the gain obtained from WF is reduced to zero. These capacity results can also be extended to the under spread (delay spread much smaller than the coherence time) time-variant frequency-selective case with multi-carrier modulation, where the optimal solution is WF over time and frequency [TV05].

However, it was shown in [CG01] that, for a large class of modulation techniques and general fading distributions keeping the rate or power the adaptive modulation to be constant achieves near optimal performance. Thus, even by using only one or two degrees of freedom in adaptive modulation can yield similar spectral efficiency obtained by utilizing all degrees of freedom.

For flat-fading SISO with more practical constraints, a large number of adaptive modulation schemes have been proposed [Hay68, Cav72, AK94, Vuc91, USMH98, WS95, GC97, GC98, VG03]. Practical adaptive transmission schemes with CSI feedback were first proposed by Hayes [Hay68] and Cavers [Cav72]. Hayes, in [Hay68] proposed an adaptive scheme in which the transmission power was varied in accordance with the CSI while maintaining a fixed target quality of service (QoS). On the other hand, in Cavers scheme [Cav72] the transmission symbol rate was varied while maintaining a fixed transmit power. After almost 20 years of inactivity, several proposals were made to adapt, e.g. the constellation size [USMH98, WS95], or the coding rate or scheme [AK94, Vuc91] in accordance with the instantaneous channel conditions.

Goldsmith and Chua in [GC97] proposed an optimal uncoded variable-rate variable power using M-ary Quadrature Amplitude Modulation (MQAM) modulation in order to maximizing spectral efficiency (bps/Hz) subject to the constraints of average power and Bit Error Rate (BER) requirements. It was shown in [GC97] that the same power adaptation can be used for both the capacity optimal transmission scheme [GV97] and the adaptive MQAM [GC97]. It was also shown in [GC97] that there was a constant gap between the channel capacity and the maximum efficiency of adaptive MQAM which is a simple function of the target BER. It is important to note that, in one of the first studies on dynamic power allocation for discrete subchannel in [Kal89] similar results were obtained for the case of wired multitone channel. Therein the WF was performed over a time-invariant wired multitone channel instead of a flat-fading time-variant channel. The variable rate variable power MQAM technique was further extended to the case of coded modulation in [GC98, VG03], resulting in further reduction in the gap to the capacity.

All the optimal adaptive loading algorithms proposed in [GC97, Kal89] were based on the assumption of continuous rate allocation implying infinite granularity in constellation size over subchannels or fading states. However, practical systems, no such continuous constellations are available. An optimal discrete bit and power loading algorithm was proposed by Hughes-Hartogs [HH87]. Therein an iterative approach to obtain the optimal power allocation to each subchannel was patented. Later Chow et al. in [CCB95] presented one of the first faster algorithms compared to the Hughes-Hartogs approach, with the aim to minimize the transmit power. Therein, the approach was to start with an equal power distribution and then alter this distribution in order to reach the required rate. These algorithms were originally developed for wired (twisted pair lines) frequency selective channels employing multicarrier modulation. However, these adaptive loading principles can be applied to wireless communication employing OFDM modulation. In general, adaptive loading algorithms employ different modulation and coding scheme for each OFDM subchannel based on their corresponding SNR.

Apart from these fully adaptive schemes, there exist two special cases for the power distribution in OFDM systems. In the first case, the transmit power is simply distributed statically. As the attenuation values might differ strongly, the resulting SNR per subchannel varies, too. These varying SNR's motivate the idea to adapt the modulation types solely, referred to as adaptive modulation. Given a certain target BER, for each modulation type a SNR range can be obtained. Then for each subchannel the modulation type is simply adapted according to the SNR ranges. An excellent, in depth discussion of adaptive modulation for multi-carrier systems is given in [KH00].

The second specific approach to power loading is to vary the transmit power exclusively while considering an OFDM system with a single modulation type. This has been suggested by Hunziker et al. in [HD03]. As the throughput is fixed in such a case (for each OFDM symbol the same number of bits is transmitted), the objective is to minimize the BER subject to a total transmit power budget. Since the transmit power is varied whereas only one modulation type is available, the respective optimization problem becomes a non-linear, continuous problem. The authors obtain an analytical expression for the BER of each bit in an OFDM symbol depending on the subchannel attenuations and the transmit power per subchannel. Then, using the Lagrange multiplier technique, they obtain an expression for the optimal power allocation, assuming perfect channel knowledge at the transmitter.

Fading channels, common in wireless systems, are a particularly hostile environment for reliable communications and can adversely affect achievable capacity. The transmitted signal is scattered, in a time-varying manner, along the transmission path resulting in random fluctuations in the received power level, or fading. Until recently, the fading in a wireless communication channel was considered as an adverse phenomenon. This is due to the fact that the BER in fading channel is significantly higher than in a non-fading AWGN channel [Skl97a, Pro01, Skl97b]. Such disadvantages make the design of a digital communication system over a wireless channel more challenging and interesting compared to the design for a traditional AWGN channel. An effective way to mitigate the adverse effects of fading is to apply diversity techniques. The basic idea of all diversity techniques is to send separate copies of the same information over multiple independently faded paths in order to increase reliability and the probability of successful transmission.

Time diversity (e.g., channel coding) is obtained via the interleaving of coded symbols over transmission blocks, whereas frequency diversity is achieved from multipath combining by using, e.g. the rake receiver or the equalizer. Multiple antennas at the receiver and/or the transmitter have traditionally been used to provide space or spatial diversity, i.e. redundancy across independently fading antennas [Gol06, Pro01, TV05]. Typically, several types of diversity can be combined and incorporated in wireless systems to further improve the overall performance of the systems.

In case perfect CSI is available at transmitter and the receiver, high system throughput can be achieved by exploiting multiuser (MU) diversity [KH95, KH97]. This is achieved by the adaptive allocation of resources among multiple users, transmitting at a high rate when the channel is good and vice versa [KH95, RC03, WCLM99]. By taking the variance of channel fading, interference scenario and traffic load into account, adaptive resource allocation yields higher system performance than fixed resource allocation, and is becoming more important in wireless communication systems while the user data rate requirements keep increasing. The purpose of the resource allocation is to allocate the limited resources, e.g. total transmit power, available time slot and frequency bandwidth, to users to meet the users' QoS requirements, e.g. data rate and delay. However, The problem of resource allocation in OFDM systems is an nondeterministic polynomial time (NP) hard combinatorial optimization problem [WSEA04] with non-linear constraints. It involves both continuous variables and binary variables. Such an optimization problem is called a mixed binary integer programming problem and such type of problems might even be nondeterministic polynomial time complete (NP-C) problems.

For single-antenna systems, the optimum strategy for maximizing the capacity is to allow only the user with the best instantaneous channel gain to transmit at any time [KH95, KH97, CV93]. This extends straightforwardly to the frequency-selective fading channel as well. It has been shown that the total capacity is maximized when each subchannel is assigned to the user with the highest channel gain and the transmit power is then distributed according to the WF algorithm WF over time and frequency [TV05, CV93]. However, such approach does not ensure any fairness among users, because it always selects users supporting the highest data rate and may leave out users with bad channel conditions, typically located at the cell edge. Similarly, discrete loading algorithms, such as the Hughes-Hartogs algorithm [HH87], can be applied to single antenna systems to maximize the spectral efficiency.

Another useful optimization criterion is to find an optimal subchannel, bit and power allocation to minimize the total transmission power while satisfying a minimum rate constraint per user [WCLM99]. This is, however, a far more complicated combinatorial problem with integer constraints. Wong et al. [WCLM99] reformulated the original problem as a convex problem with relaxed non-integer constraints, and provided a close-to-optimal allocation algorithm based on the achieved lower bound solution.

From the above discussion it follows that three different metrics can be considered for the optimization of practical systems: Maximizing the data rate for a given power budget and a target BER (called the bit rate maximization problem (RA)) [Kal89], minimizing the transmit power for a certain given rate and a target BER (called the margin maximization problem (MA)) [CCB95] and minimizing the BER for a given bit rate and power budget [FH96].

1.3. Multiple Antenna System

The use of multiple transmit and receive antennas, as shown in Fig.1.1, opens a new dimension (i.e. antenna or spatial domain) that has previously been unnoticed. Winters et al. [Win84, Win87] in their pioneering work proposed the use of SDMA to boost up the capacity of wireless communication systems. In addition to this capacity advantage, communication over multi-antenna channels presents two main practical advantages with respect to traditional communication over single antenna channels. These gains are usually referred to as diversity and multiplexing gains. A brief review of the gains available in a MIMO system is given in the following:

Diversity leads to improved link reliability by rendering the channel "less fading" and by increasing the robustness to co-channel interference. Diversity gain is obtained by transmitting the data signal over multiple (ideally) independent fading dimensions in time, frequency, and space and by performing proper combining in the receiver. Spatial (i.e., antenna) diversity is particularly attractive as compared to time or frequency diversity, as it does not incur any expenditure in transmission time or bandwidth, respectively. Diversity can be employed in the communication link to combat channel fading. In [Jak75] it was shown that multiple receiver antennas can be used to exploit the spatial diversity. The transmission reliability can be significantly improved by optimally combining the signals received from multiple antennas. Further, multi-antenna systems can even suppress co-channel interference thanks to additional degree of freedom in the spatial domain [RPK87, Win84]. Space-time coding [TSC98] realizes spatial diversity gain in systems with multiple transmit antennas without requiring channel knowledge at the transmitter.

Spatial multiplexing yields a linear (in the minimum of the number of transmit and receive antennas) capacity increase, compared to systems with a single antenna at one or both sides of the link, at no additional power or bandwidth expenditure [Tel95, Fos96]. Spatial multiplexing can be obtained by decomposing the wide band MIMO channel into parallel narrow band channels and multiplexing different data streams onto these channels. The corresponding gain is available if the propagation channel exhibits rich scattering and can be realized by the simultaneous transmission of independent data streams in the same frequency band. The receiver exploits differences in the spatial signatures induced by the MIMO channel onto the multiplexed data streams to separate the different signals, thereby realizing a capacity gain.

However, the SNR associated with each of these parallel narrow band channels depends on the singular values of the MIMO channel matrix. In capacity analysis this should be considered by assigning a relatively low rate to these channels. However, practical signaling strategies for these channels will usually exhibit poor performance, and require powerful channel coding techniques to be employed. As an alternative, channel gains can be coherently combined using beamforming, which provides a very robust channel with high diversity gain.

Moreover, it is not necessary that the antennas be used purely for multiplexing or diversity. Some of the space-time dimensions can be used for diversity gain, and the remaining dimensions used for multiplexing gain. A fundamental design question in MIMO systems arises as a consequence of this: should the antennas be used for diversity gain, multiplexing gain, or both?

The diversity/multiplexing tradeoff or, more generally, the tradeoff between data rate, probability of error, and complexity for MIMO systems has been extensively studied in the literature [Gol06], from both a theoretical perspective as well as in terms of practical space-time code designs [FKKC06, PNG03, ZT03]. Some of previous works have primarily focused on block fading channels with receiver CSI only. When full CSI is available at both transmitter and receiver the tradeoff is relatively straightforward: antenna subsets can be first grouped to obtain diversity gain and then the multiplexing gain corresponds to the new channel with reduced dimension because of grouping. In case of block fading model with CSI at the receiver only, as the blocklength grows asymptotically large, both full diversity gain and multiplexing gain can be achieved simultaneously with reasonable complexity by encoding diagonally across antennas [Fos96]. Diagonal Bell Laboratories Layered Space-Time Architecture (D-BLAST) is an example of this type of encoding. On the other hand if blocklength is finite it is not possible to achieve full diversity and multiplexing gain simultaneously, in such a case a tradeoff between these two gains occurs. Authors in [SGGP99, ZT03] proposed a simple characterization of this tradeoff for the case of block fading channels with M_T transmit, M_R receive antennas' and blocklength $T \geq M_T + M_R - 1$ in the limit of asymptotically high SNR. The diversity and multiplexing gains can also be adapted in accordance to channel conditions. Specifically, when channel states are poor more number of antennas can be used to provide diversity gain, whereas use more antennas for multiplexing when channel state is good. Investigation has been carried out on adaptive techniques that can change antenna uses to trade off diversity and multiplexing depending on current channel conditions [HP05].

In summary, MIMO technologies provide the diversity and multiplexing opportunities to improve communication reliability and spectral efficiency [FG98]. A theoretical study on the tradeoff between diversity and multiplexing of MIMO systems was presented in [SGGP99], and a practical algorithm on the switching between diversity and multiplexing was proposed in [HP05].

Thus when combined with advanced signal processing and coding techniques, MIMO systems can be used to provide higher data rates and/or more robust communications. The multiple antennas in the Uplink (UL) enable spatial separation of the signals from the different users, and hence, allow several users to simultaneously communicate with the BS. By mid-nineties this concept was transferred to point-to-point communication with multiple antennas at both the transmitter and the receiver [FG98, Tel95, Tel99]. It was noticed that SDMA with single transmit antennas is in fact similar to point-to-point MIMO communications without CSI at the transmitter, i.e. users/antennas cannot co-operate. This resulted in large potential for the use of the angular or space domain to convey multiple independent data streams from a single user (SU) to the BS. However, as stated earlier, in MIMO communications, the signals transmitted from co-located antennas can still be separated at the receiver provided that the scattering environment is rich enough. A Minimum Mean Square Error (MMSE) receiver with Successive Interference Cancellation (SIC) was shown to be an information theoretically optimal solution for both SDMA with single transmit antennas and MIMO without CSI [TV05].

1.4. Point-to-point MIMO communications

Point-to-point (SU) MIMO communication involves a BS supporting only one MS as shown in Fig.1.1. The research on point-to-point MIMO communications was pioneered by Telatar [Tel95, Tel99] and Foschini [FG98, Fos96]. Foschini considered the case where the CSI of the MIMO channel is only available at the receiver and not at the transmitter. For such a case, he also proposed a capacity achieving transmission architecture called the Bell Labs space-time architecture (BLAST) in [Fos96].

In addition to the analysis without any CSI at the transmitter, Telatar [Tel95, Tel99] showed that with perfect CSI at the transmitter, the MIMO channel can be decomposed in to parallel, non-interfering SISO subchannels using Singular Value Decomposition (SVD) of the channel matrix. The number of parallel subchannels or data streams, also known as singular value channels (SV channels) or known as Eigenmode channels, is dictated by the rank of the MIMO matrix. The maximum rank is given by minimum of transmit and receive antennas. Assuming R denotes the rank of channel matrix and a MIMO channel is decomposed R parallel independent channels, an R-fold dada rate increase can be achieved by multiplexing different data onto different channels in comparison with the SISO system. The optimal capacity achieving transmission is then carried out by pre (transmit precoding) and post processing (receiver shaping) each stream with the right and left singular vectors of the channel matrix, respectively. Optimal transmit power allocation is achieved via WF algorithm [CT91] over the parallel SISO subchannels with gains corresponding to the Eigen-values of the channel matrix [Tel95, Tel99]. Furthermore, the capacity-optimal transmission strategy requires a Gaussian codebook with continuous rate allocation among the parallel subchannels [CT91, Tel95, Tel99].

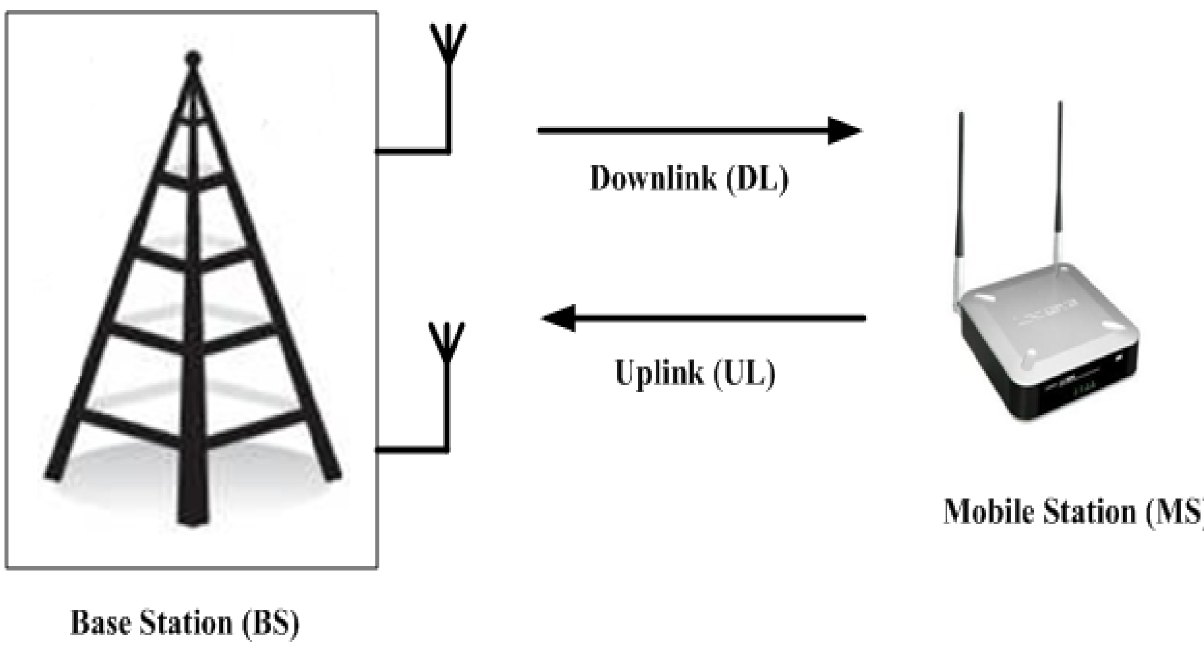


Figure 1.1: Point to Point MIMO System

Extensions of the MIMO capacity to multipath channels were provided in [RC98a]. The SVD based transmission is very similar to the OFDM system, where the frequency selective (multipath) channel is transformed into a set of parallel independent subchannels. In [RC98a] a spatio-temporal vector-coding (STVC) communication structure was suggested as a means for achieving MIMO channel capacity. Moreover, joint WF over space and frequency was sown to be capacity optimal power allocation for a MIMO OFDM [RC98a, CT91]. This achieves the capacity of the frequency selective MIMO channel as the number of subchannels approaches infinity [RC98a]. An overview of the Shannonian capacity limits of MIMO channels is provided in [GJJV03]. In [GJJV03], it was shown that for SU systems the capacity under perfect CSI at the transmitter and receiver is relatively straightforward and predicts that capacity grows linearly with the number of antennas. However, diverting from the perfect CSI assumption makes the capacity calculation much more difficult and the capacity gains are highly dependent on the nature of the CSI, the channel SNR, and the antenna element correlations. Other general overviews on MIMO communications are included in [PGNB04, STT+02, GSS+03, SBL+87, VY03] As mentioned above, the MIMO capacity depends heavily on the available channel knowledge at both the receiver and the transmitter, the signal-to-noise-plus-interference ratio (SINR) and the underlying channel properties, e.g., the correlation between the antenna elements. The large capacity gains associated with MIMO channels are based on the assumption that each transmit-receive antenna pair experiences independent identically distributed (i.i.d.) fading. This can be only achieved in a rich scattering environment [GJJV03]. MIMO transmission and the capacity available in non-ideal conditions, e.g. correlated fading channels, were studied in [CFGV02, CTKV02, TLV05]. In [CFGV02] it was shown that degenerate channel phenomena, called “keyholes” may arise under realistic assumptions which have zero correlation between the entries of the channel matrix and yet only a single degree of freedom. Decorrelation is therefore not a guarantee of BLAST performance. Authors in [TLV05] used random matrix theory to obtain analytical characterizations of the capacity of correlated multiantenna channels. Herein it was shown how antenna correlation impacts the tradeoffs among power, bandwidth, and rate.

For MIMO OFDM systems, Bölcskei et al. [BGP02] analyzed the influence of physical parameters such as the amount of delay spread, cluster angle spread, and total angle spread, and system parameters such as the number of antennas and antenna spacing on ergodic capacity and outage capacity. It was shown in [BGP02] that, in the MIMO case, unlike the SISO case, delay spread channels may provide advantages over flat fading channels not only in terms of outage capacity but also in terms of ergodic capacity. Therefore, MIMO delay spread channels will in general provide both higher diversity gain and higher multiplexing gain than MIMO flat-fading channels.

Thus it can be concluded that the optimal transceiver design with ideal CSI at the transmitter is rather simple [Tel95, Tel99], the case without CSI at the transmitter is less straightforward. In general, multiple antennas can be used for increasing the amount of diversity or the number of spatial multiplexing dimensions in wireless communication systems [Pro01]. There is a large amount of different techniques available in literature designed for extracting the maximal diversity gain or the maximal spatial multiplexing gain of a channel.

Based on the original BLAST scheme by Foschini [Fos96], several other spatial multiplexing schemes were proposed in [BGP02, BTT02, FGVW99]. Authors in [BTT02] proposed a coding/decoding scheme matched to a “vertical” BLAST (V-BLAST) architecture; every code had its words evenly split among the transmit antennas. The subcodes so transmitted by each antenna were decoded in sequence so as to cancel the spatial interference while a final decoding step was performed on the whole code. Herein, the behavior of zero-forcing (ZF) and MMSE BLAST was also examined by comparing their error probabilities with those resulting from optimum, i.e., maximum-likelihood (ML), processing.

In [FGVW99] a simplified space–time communication processing method was presented. The user’s bit stream was mapped to a vector of independently modulated equal bit-rate signal components that were simultaneously transmitted in the same band. A detection algorithm similar to multiuser detection (MUD) was employed to detect the signal components in AWGN. It was proved that for a large number of antennas, a more efficient architecture can offer no more than about 40% more capacity than the simple architecture presented.

Different multi-antenna schemes aiming at maximizing the available diversity have been proposed in [Ala98, HM00, NTSC98, TJC99a, TJC99b, TSC98]. Alamouti [Ala98] proposed a simple but elegant space-time coding technique, which turned out to be optimal from both the diversity and multiplexing perspectives for the case with two transmit and one receive antennas. It was also shown in [Ala98] that using two transmit antennas and one receive antenna the scheme provides the same diversity order as maximal-ratio receiver combining (MRRC) with one transmit antenna, and two receive antennas**.** Later, in [TJC99a] the Alamouti scheme was generalized to orthogonal designs with any number of transmit antennas. Unlike the Alamouti scheme, the coding structure from the orthogonal design [TJC99a], while indeed achieving the full diversity order, reduces the achievable spatial multiplexing gain. Further, the best tradeoff between the decoding delay and the number of transmit antennas was also presented [TJC99a] and it was shown that many of the codes presented were optimal in this sense as well. Zheng and Tse in [ZT03] showed that a part of the diversity and multiplexing gains can be obtained simultaneously. Furthermore, they characterized the optimal diversity–multiplexing tradeoff achievable by *any* scheme and used it to evaluate the performance of many existing schemes. Since then, several trade-off optimal space-time codes have been proposed in the literature. See, for example, [BRV05, DV05, GCD04], and the references therein.

In real systems it is often difficult to get perfect CSI at the transmitter. It is possible to achieve full CSI at the transmitter in Time Division Duplex (TDD) systems, where the reciprocal UL and Downlink (DL) channels are time-multiplexed on the same physical wireless channel [GSS$^+$03, SBL$^+$87]. The transceiver can extract the CSI from the information received in the current time slot and the same CSI can be used for transmission in the next time slot. This is possible as long as the TDD frame length is shorter than the channel coherence time. In general, this can be guaranteed in low mobility environments for practical system parameters [LGF05]. However, in high mobility environments, the CSI quickly becomes outdated as the terminal velocity increases due to a time delay between the estimation of the channel and the transmission of the data. Normally, CSI is obtained through channel estimation, by sending known training symbols to the receiver**.** A channel estimate always contains some noise along with the real channel. Training based channel estimation schemes, the losses due to estimation errors and the pilot overhead were studied in [HH03]. It was shown in [HH03] that, when the training and data powers are allowed to vary, the optimal number of training symbols is equal to the number of transmit antennas—this number is also the smallest training interval length that guarantees meaningful estimates of the channel matrix. However, when the training and data powers are instead required to be equal, the optimal number of symbols may be larger than the number of antennas. Furthermore, the impact of the errors in channel estimates at both the transmitter and the receiver on the capacity was studied in [YG06a]. Optimizing the transmitter with noisy channel estimates is still largely an unresolved research problem. However, a few solutions exist where it has been proposed to use worst case design criteria to guarantee robust performance for any realization of the actual and estimated channels, e.g. worst-case mean square error (MSE) precoder design [GL06, VGL03], or to combine robust beamforming with space-time coding [PPP+06].

In frequency division duplex (FDD) systems, in order to have full CSI at the transmitter it is required to have a dedicated feedback channel from the terminal(s). This, however, results in a massive overhead due to the large number of channel coefficients which need to be quantized and sent back to the transmitter over a limited bandwidth feedback channel. Hence, a dedicated feedback is impractical for FDD systems with any mobility. In cases where some statistical information only is available about the MIMO channel (distribution, mean, covariance) at the transmitter, the transmission strategy must be designed in accordance to the statistical information instead of the instantaneous information [RC03, GJJV03, JG04, JG05a, JB04a, JB04b, SM03, TLV06, VM01, JG04, ZG03]. It was shown in [RC03, GJJV03, JB04a, JB04b, SM03,VM01, JG04, ZG03] that for FDD based system the capacity-achieving eigenvectors should correspond to the eigenvectors of the statistical covariance matrix of the channel. Expectedly this finding is so similar to the solution with instantaneous channel information at the transmitter

[Tel95, Tel99]. However, the optimal power allocation in the transmit directions requires the use of numerical techniques and resemble WF with consideration to inter-stream interference due to non-orthogonal transmission [JG04, JB04a, TLV06, VM01].

Authors in [JG04, JSO02, LJ05, VP06, XZG04] proposed to couple the statistical beamforming with space–time block codes as a mechanism to improve the reliability of system with statistical or noisy channel information

A large number of solutions exist in literature for a FDD system which utilizes a very low rate feedback from the receiver to transmitter. A simple solution is to select a subset of transmit antennas in order to maximize the available rate (RA) or to minimize the power (MA) with fixed user rate requirements [HL05, HSP01], or to switch between spatial multiplexing and transmit diversity following instantaneous channel conditions (rank, correlation between antennas, etc.) [HP05, LH05a]. Another solution proposed in [CH05, LH05b,LHS03, MSAE03] is to report an index of a transmission strategy (precoder) which matches best with the instantaneous channel state. The idea is to choose a transmit precoder from a finite set of predefined precoding matrices known at both the receiver and the transmitter end. Kim and Skoglund [KS07] characterized the diversity-multiplexing tradeoff in MIMO channels with quantized CSI at the transmitter.

1.5. Multiuser MIMO communications

The capacity region for the Gaussian multiple access channel (MAC), i.e. the UL (Fig.1.2) channel with multiple users/transmitters and a single receiver, has been known for quite a while [Gal85]. The capacity region of MIMO MAC is achieved by successive decoding [CT91] (also known as SIC). Following the pioneering work on the use of multiple receive antennas in the UL by Winters [Win84, Win87, WSG94], the scalar Gaussian MAC capacity region was extended to ISI [CV93] and MIMO channels in [Tel99, YRBC04].

MIMO broadcast channel (BC) structure is similar to that of MIMO MAC (with the communication direction being reversed as shown in Fig.1.3). Surprisingly, the capacity-related problems in MIMO BC turn out to be much harder than those in MIMO MAC. The capacity region for the Gaussian degraded BC has been also known for more than thirty years [CT91, Cov72]. The degraded BC channel implies that the Gaussian channel has a scalar input and scalar outputs, i.e. a single-antenna transmitter and several receivers. For such a case, the capacity region is achieved by using superposition coding at the transmitter and interference subtraction at the receivers [CT91, Cov72]. However, for the non-degraded BC channel, where the transmitter has a vector input, i.e. multiple transmit antennas, the superposition coding no longer achieves the capacity.

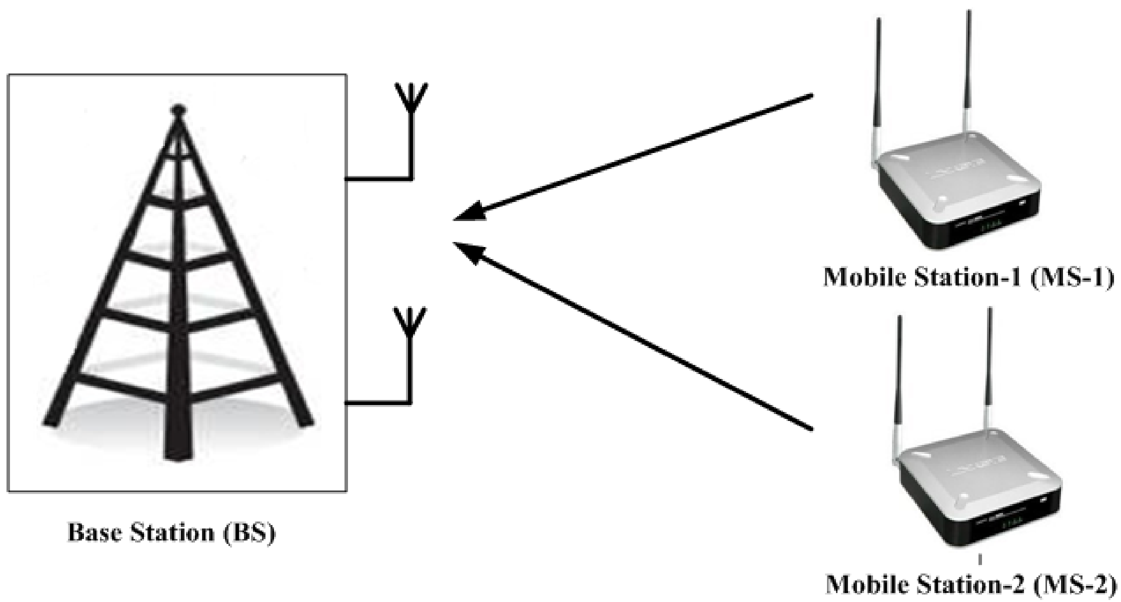


Figure 1.2: Multiuser MIMO MAC (Uplink)

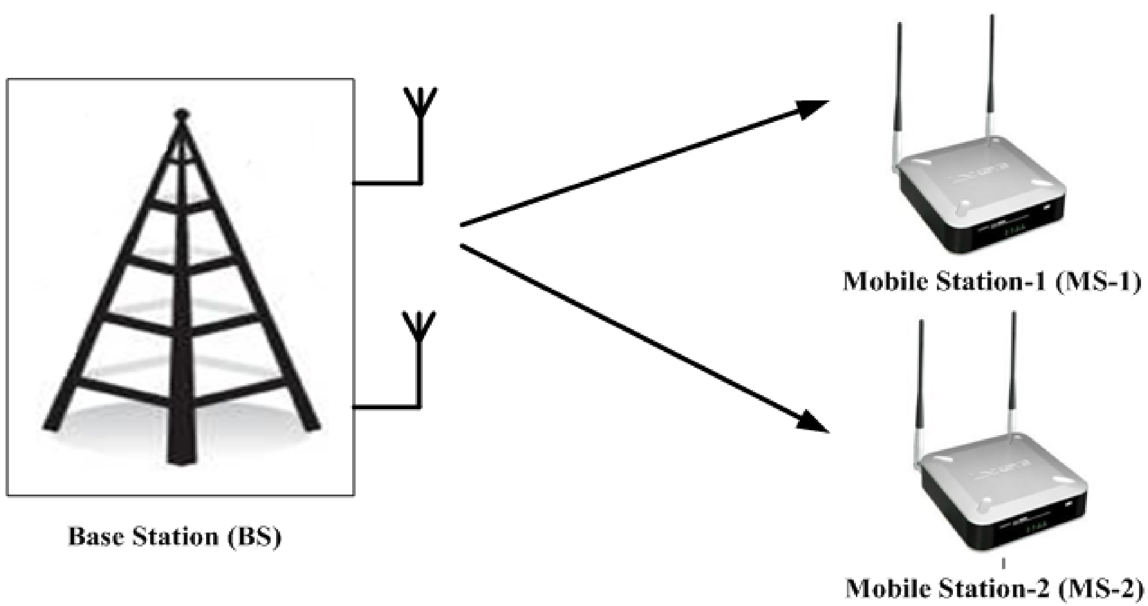


Figure 1.3: Multiuser MIMO Broadcast (Downlink)

The foundation for the information theoretic studies on the capacity of the non-degraded Gaussian MIMO BC channel was laid in Costa's landmark paper [Cos83], where he studied the capacity of a BC channel with both AWGN and additive Gaussian interference, and where the interference is non-causally known at the transmitter but not at the receiver(s). Costa [Cos83] concluded that the effect of the interference can be completely cancelled out at the transmitter by using specific precoding called dirty paper coding (DPC). Consequently, the capacity is identical to the case when the interference was known also at the receivers. However, unlike MIMO MAC, the DPC rate region is non-convex, making most optimization problems over the DPC rate region very difficult to solve.

Caire and Shamai [CS03] investigated the achievable throughput (sum rate) of a generally nondegraded broadcast Gaussian channel where the transmitter has multiple antennas and the receivers have one antenna each, subject to the assumption that the channel is perfectly known to all terminals. Therein, they proposed the use Costa's precoding for transmitting over the MIMO BC. They compared DPC with Sato's cooperative upper bound [Sat78] for the case of two users with single-antenna receivers and demonstrated that DPC achieves the sum capacity. However, because DPC is difficult to implement in real systems, a practical precoding techniques based on DPC was also proposed in [CS03]. ZF-DPC exploits the DPC principle, which is a nonlinear suboptimal implementation of DPC. For any given user, the ZF part completely suppresses interference caused by subsequently encoded users while the DPC coding is applied to the previously encoded users. In other word, any interference caused by data stream $j > i$ on each data stream i is forced to zero by pre-subtraction at the transmitter. Due to the pre-subtraction of interference, the transmit power of ZF-DPC increases, which may not be feasible in practical implementation. However, this strategy was shown to be asymptotically optimal for both high and low SNR regions. The proposals in [CS03] sparked off a number of new studies [VJG03, VT03, YC04], where the results of [CS03] were generalized to any number of users and an arbitrary number of receive antennas.

The duality between the DPC region for the MIMO BC and the capacity region of the MIMO MAC was established in [VJG03, VT03]. This duality allows expressing the capacity region of the Gaussian BC in terms of the Gaussian MAC, and vice versa. It was also shown that this duality extends to fading channels. In both these research the reciprocity of the UL and DL channels [Tel99] combined with the previously established duality between the scalar Gaussian BC and MAC [JVG04] was utilized. It was also shown that due to the MAC-BC duality, the sum-rate capacity of the MIMO BC is equal to the sum-rate capacity of the dual MAC with sum power constraint. Unlike for DPC region, the MIMO MAC rate maximization can be formulated as a concave function of the covariance matrices, for which efficient numerical algorithms exist. Therefore, the DPC-MAC duality allows the DPC region to be found using standard convex optimization techniques [GBY06, Stu99]. Furthermore, the explicit transformations of transmit covariance matrices from MAC to BC and vice versa were demonstrated in [VJG03]. A somewhat different approach in order to obtain the results in [VJG03, VT03] was used in [YC04]. Herein, the sum-rate optimal precoding structure was shown to correspond to a decision-feedback equalizer. In addition, the results in [YC04] laid the foundation for the studies on the more general case with arbitrary convex input constraints [WSS06, Yu06a, YL07].

Yu [Yu06a] established a connection between the duality approach [VJG03, VT03] and the decision-feedback approach [YC04], and generalized UL-DL duality to BC channels under arbitrary linear covariance constraints, e.g. per-antenna power constraints. It is shown that the UL-DL duality between a BC and a MAC can be derived as a special case of the minimax duality. It was also shown that the minimax expression for the sum capacity of the BC channel is a more general expression than UL-DL duality. The original DL optimization problem with linear covariance constraints was transformed into a dual UL minimax optimization with uncertain noise. The sum capacity result of [Yu06a] was extended to the entire BC capacity region with per-antenna power constraints in [YL07]. The DPC region was finally shown to be indeed the capacity region of the entire non-degraded Gaussian MIMO BC by Weingarten et al. [WSS06]. This result proved the conjecture of the DPC optimality which was already reported in

[TV03, VKS+03]. The capacity region for MIMO BC was characterized under a wide range of input constraints, accounting, as special cases, for the total power and the per-antenna power constraints. In general, it was shown that obtained results apply to any input constraint such that the input covariance matrix lies in a compact set of positive semidefinite matrices. For that purpose, a new notion of an enhanced channel was introduced. Using this enhanced channel, the Bergmans' proof [Ber74] was modified to provide converse for the capacity region of an aligned and degraded Gaussian vector BC channel. Thus, [WSS06] parallels the work on the sum capacity and the capacity region with linear covariance constraints reported in [Yu06a, YL07].

Even though the sum capacity and any point on the boundary of the MIMO BC capacity region can be computed by any standard interior point convex optimization technique [GBY06, Stu99], there exists a few methods in the literature that propose iterative computation of the sum capacity [CJL07, JRV+05, Yu06b] or any point on the boundary [KC06, VVH03] without explicitly using convex optimization techniques. Based on the iterative WF algorithm for MIMO MAC [YRBC04], Jindal et al. [JRV+05] proposed a sum power iterative WF algorithm for Gaussian MIMO BC. This simple algorithm exploits the structure of the dual sum power MAC problem and provides the optimum transmission policies for the MAC, which can easily be mapped to the optimal BC policies by the MAC-BC transformation [VKS+03]. An alternative approach based on dual decomposition was proposed by Yu in [Yu06b]. Herein, the BC channel was first transformed into a sum-power constrained Gaussian vector MAC, for which an iterative-WF based algorithm was proposed to compute its sum capacity. The main feature of this algorithm [Yu06b] was a dual decomposition approach that decouples the sum-power constraint. Despite being less complex than the standard interior point solutions, the convergence of these algorithms can be rather slow, especially for a large number of users. Codreanu et al. in [CJL07] proposed a random user pairing technique which was shown to greatly improve the convergence of the iterative WF algorithm. The key idea of the algorithm [CJL07] was to iteratively maximize the sum capacity for randomly selected pairs of users, while considering the other users' signals as noise. Viswanathan et al. in [VVH03] proposed a steepest descent method which makes it possible to calculate the weighted rate sum for a given set of weights, i.e. to find any point on the boundary of the BC capacity region [VVH03]. The algorithm was used to determine potential capacity enhancements to a cellular system through known-interference cancellation. Both the circuit data scenario in which each user requires a constant data rate in every frame and the packet data scenario, in which users can be assigned a variable rate in each frame so as to maximize the long-term average throughput, were considered. Further, the ZF beamforming technique was generalized to the multiple receive antennas case and was used as the baseline for the packet data throughput evaluation [VVH03].

The iterative WF approach was also later extended to a more general case with weighted rates by Kobayashi and Caire [KC06]. A simple iterative WF algorithm for the weighted rate sum maximization in the Gaussian MIMO BC (or MIMO MAC under sum-power constraint) was proposed in [KC06]. Jindal and Goldsmith [JG05b] analyzed the asymptotic gains from the optimal DPC compared to the SU capacity with Time Division Multiple Access (TDMA) in a MIMO BC multiple-antenna broadcast channel. They showed that, the sum capacity of a MIMO BC, achievable using DPC, is at most min(M_T; K) times larger than the maximum achievable sum rate using TDMA, where M_T is the number of transmit antennas (BS antennas) and K is the number of users. This bound applies at any SNR and for any number of receive antennas (M_R), and also generalizes to frequency-selective and time-selective channels. For Rayleigh-fading channels, the bound tightens to max (min (M_T/M_R,K),1) at high SNR, for a large number of transmit antennas, or for a large number of users. As a conclusion, the highest DPC gain is achieved with a large number of users, and when the ratio of transmit and receive antennas is high. On the other hand, the DPC gain converges to unity for both low and high SNRs when the number of receive antennas is higher than or equal to the number of transmit antennas. Furthermore, they demonstrated that transmit beamforming always performs better than or equal to the TDMA, and its achievable rate is upper bounded by the DPC rate.

1.6. Resource allocation for multiuser MIMO systems

MU MIMO OFDM systems benefit from the combined frequency and space domain freedom as well as MU diversity. Moreover, allowing intracell bandwidth reuse by means of SDMA is an advantage of multi-antenna systems over other systems. It greatly enhances the spectrum efficiency if the bandwidth is shared by spatially separable users. However, a major challenge for wireless communication systems is how to allocate resources among users across the space (including different cells), frequency and time dimensions with different system optimization objectives. In MIMO OFDM systems, this leads to an Orthogonal Frequency Division Multiple Access (OFDMA) solution with a three-dimensional subchannel and power allocation problem, i.e. how many subchannels should be allocated to each user in different dimensions. The problem remains unresolved for a large variety of optimization criteria, especially when combined with practical modulation and coding schemes [LZ06].

The problem of resource allocation in MU MIMO OFDM systems is more difficult to solve due to the following reasons. First of all, CCI caused by subchannel reuse makes the optimization problem combinatorial and non-convex. Adapting the transmission of one user affects the interference of other co-channel users, which in turn affects the optimal transmission schemes for all users. Second, the achievable signal-to-interference ratio (SIR) is a function of the set of users that share the subchannel. In order to maximize system capacity while maintaining sufficient SIR, it is required to identify optimal sets of co-channel users for every subchannel based on their spatial correlations and power distributions. Third, MIMO OFDM systems are able to multiplex the users in both the space and frequency domains. As a result, it is required to identify which dimension should be occupied by which set of users. Finally, QoS requirements impose additional constraints on the optimization problem.

For a single-cell MU MIMO system, the optimal sum capacity achieving allocation of resources across different dimensions (users, space, frequency) is given by the actual sum rate capacity of the frequency-selective MIMO BC as discussed in [VJG03, WSS06, YC04]. However, the computation of the sum capacity achieving covariance matrices requires solving the convex optimization problem in dual MAC and transforming the solution back to BC [VJG03]. Especially for frequency selective case with OFDM, the computational complexity becomes very high with increase in number of subchannels, users and antennas. Therefore, sub-optimal but less complex allocation techniques [CS03, TB03, TUBN06] are required.

MU diversity for the dirty paper approach with ZF-DPC was studied by Tu and Blum in [TB03], where they proposed a greedy scheduling algorithm for the selection of users and their encoding order for maximizing the sum rate. The greedy user selection and ordering algorithm combined with ZF-DPC was shown to have a sum rate very close to the capacity. Tejera et al. [TUBN06] investigated different subchannel allocation methods with the aim to maximize the sum rate of the MU MIMO BC with reduced complexity. They extended the sub-optimal ZF-DPC with single-antenna users from [CS03] to a more general case with multiple receive antennas per user. Moreover, the greedy approach was extended for the case of multiple receive antennas and it was utilized for allocating user beams on different subchannels in the space and frequency domains. Through simulation it was show that this technique tightly approaches the performance of the optimum solution that is; complexity reduction comes at almost no cost in terms of sum capacity.

The sum rate maximizing solutions can occasionally result in a very non-uniform rate allocation between users, leaving some of the users with no subchannels allocated at all. Therefore, other transmitter design criteria should be considered in order to guarantee, for example, fairness or the instantaneous QoS for all users. The symmetric or balanced capacity providing absolute fairness between users becomes an important performance metric for delay constrained applications [LJ06, SVL05]. The weighted symmetric capacity refers to the situation where the weighted user rates are equal, while their rates belong to the boundary of the capacity region [LJ06]. This enables the system to control the rates assigned to users that belong to distinct service priority classes. An iterative algorithm aiming at finding the weighted symmetric capacity for MIMO BC with a sum power constraint was proposed in [LJ06]. In addition, the difference between the symmetric and sum capacity, termed the fairness penalty, was studied in [LJ06]. While in [SVL05], the MAC and BC balanced capacities of wireline multiple access networks were computed and compared for an arbitrary number of users.

The capacity achieving schemes generally require very complex nonlinear precoding based on the DPC [VT03, WSS06]. Therefore, it is required to develop less complex transmission techniques, which may be suboptimal. Linear beamforming [God97a, God97b], also known as SDMA, is a sub-optimal transmission strategy which enables the spatial separation of several concurrent users. Channel gains can be coherently combined using beamforming, which provides a very robust channel with high diversity gain. Each user stream is encoded independently and spread over multiple antennas by a beamforming weight vector. Mutual interference between multiple streams is controlled or even completely eliminated by the proper selection of weight vectors. Adaptive beamforming when employed at the transmitter end is known as precoding. The weights applied to a transmitted signal are usually organized in a vector, known as a precoding vector [Gol06, PNG03, SSH04, MBQ04, JUN05, BHV06, Rap99, LTC10]. Thus, the BS is able to multiplex the signals intended for different MSs on the same subchannel, separating different signals in space through precoding. However, unlike the sum-rate capacity of MIMO BC using the DPC, the sum rate achieved by optimal beamforming cannot be written as a convex optimization problem [SH07].

Therefore, the throughput comparison between the DPC and beamforming is computationally intensive, especially for a large number of users. In spite of its sub-optimality, beamforming combined with a proper grouping of users has been shown to have the same asymptotic sum-rate as the DPC, when the number of users approaches infinity [SH05, SH07, YG06b]. This is due to a MU diversity effect [KH95, KH97, CV93], i.e. the probability of finding a set of close-to-orthogonal users with large channel gains increases for a large number of users.

Authors in [TJ05, TUBN05, B$^+$06, TUBN06], considered multiple antennas at the receivers side. Therein, the vectors containing the beamforming weights were used at the transmitter side during SDMA grouping as well at the receiver AAs. Block Diagonalization (BD) [SSH04] with transmit-receive cooperation was used as linear precoding in [TJ05]. In [TUBN05, B$^+$06, TUBN06], SVD based adaptive beamforming was carried out at the receiver side and was accounted for at the transmitter side by the null space Successive Projections (SPs). DPC techniques were then used in a way similar to [CS03]. Authors in [DS04a, DS05], through simulations, proved that the combination of group capacity as grouping metric with Best Fit Algorithm (BFA) as SDMA grouping algorithm, can achieve sum rate up to 87% of the value achieved by the DPC. The results were reconfirmed through independent investigation carried out by authors in [MK06] and [FGH07]. The authors in [FGH07], used a projection-based group capacity in contrast to the conventional group capacity employed in [DS05, MK06]. It was found that, SDMA algorithm based on projection based group capacity is less complex as compared to the one based on conventional group capacity.

In general, the solution for any sub-optimal allocation problem can be divided into two phases. Firstly, a set of users is selected for each orthogonal dimension (frequency/subchannel, time). Secondly, the transceiver is optimized for the selected set of users per orthogonal dimension. The optimal SDMA grouping is a difficult non-convex combinatorial problem with integer constraints [SH05, SH07, YG06b]. Consequently, finding the optimal solution requires an exhaustive search (ExS) over the entire user set which is computationally prohibitive for a large number of users.

Several scheduling algorithms based on, e.g. best user selection, largest Eigen value selection and greedy user/beam selection, have been proposed for DL beamforming, e.g. in [YG06b, Maz05, MK04, PSS05, ZCL05, DS05].

Dimic and Sidiropoulos [DS05] utilized the sub-optimal greedy user selection algorithm from [TB03] for the ZF beamforming with single antenna receivers. Yoo and Goldsmith [YG06b] also used the greedy algorithm with an additional semi-orthogonality test between users and showed that the performance of the ZF beamforming with sub-optimal user selection is still asymptotically optimal. Since the performance of the ZF beamforming is always inferior to optimal linear beamforming, the result in [YG06b] proves the asymptotic optimality of linear beamforming in general.

Often, the allocation problems have been addressed for systems with users having a single receive antenna. When the users are equipped with multiple receive antennas, receiver antenna coordination further enhances the data rates.

The signal space of each user has multiple dimensions, allowing for multiple beams to be allocated per user. Therefore, the receiver signal space has to be considered when selecting the optimal sets of users, as well as the dimension and orientation of the signal subspace used by each selected user, for each orthogonal dimension. This further complicates the optimization problem. Since the transmitter vectors, and, thus, the corresponding receiver vectors at each user are affected by the set of selected users, it is impossible to know the actual receiver structure at the transmitter before the final beam allocation. An apparent candidate for a smart initial guess of the receiver matrix is the optimum SU receiver that is the left singular vectors of the user channel matrix. This decomposes the system into a MIMO BC with virtual single-antenna users with corresponding channel gains. The Eigen values of the equivalent channel matrices of each user are sorted and at most M_T beams providing the maximum sum rate are selected for the transmission at any time instant. This type of approach has been taken by the author of this thesis, as well as in related works such as [YG06b, PSS05]. It was demonstrated in [YG06b] that, for large number of users the performance penalty from non-coordination reduces. Thus, it can be concluded that antenna coordination is not requisite for achieving the asymptotically optimal sum rate.

There are several instances available in literature where low complex sub-optimal solutions were adopted in order to solve the general MIMO OFDMA resource allocation problem [WCLM99, LZ06, CC07, LCL+07, PLC04, SS04, WML01, ZL04, ZL05, SCA+06, FGH07, HMT04]. The relaxation may involve, for example, ZF transmission which allows separate beamformer design and power allocation, reducing the complexity of the problem [CC07]. Grouping users according to their spatial separability or compatibility (their channels are spatially uncorrelated) for maximizing the system throughput is another way adopted for simplification of the resource allocation problem in MIMO OFDMA systems [SS04, ZL05, SCA+06, FGH07].

Several researchers have recognized the importance of the availability CSI at the transmitter for MU MIMO BC channels [SH05, JG05b, HMT04, Jin06, VTL02, KG05]. Hochwald and Marzetta [HMT04] studied the MU diversity gains achievable from MIMO channels in absence of CSI at transmitter using simple user scheduling method based on TDMA. It was shown in [HMT04] that, in such a scenario, the scheduling gains (MU diversity) decrease rapidly with the increase in number of antennas. The reason for reduced MU diversity was shown to be the reduction in mutual information fluctuation between the channels of different users. In contrast to the point-to-point MIMO capacity, where the transmitter CSI availability only affects the SNR offset to the capacity and not the multiplexing gain [Tel95, Tel99], both the multiplexing gain and the rate achievable from the MU MIMO BC are greatly affected by the level of CSI available at the transmitter. Jindal [Jin06] demonstrated that the throughput of the MU MIMO DL with linear transmit beamforming becomes saturated with imperfect or noisy transmitter CSI. This is due to increased MU interference. However, full multiplexing gain can be achieved if the quality of CSI is increased linearly as a function of SNR [Jin06].

Random opportunistic beamforming and nulling is a simple but remarkable limited feedback strategy for MIMO DL channels [SH05, VTL02]. Multiple random orthonormal beams are formed at the BS, and multiple users are simultaneously scheduled on these beams. Each user reports the channel quality metric, i.e. SINR for the strongest beam(s), and the users with the highest instantaneous metric value are scheduled at a time. The opportunistic transmission strategy relies on the fact that with a large number of users, the probability of finding a set of nearly orthogonal users with high channel gains is high [SH05, VTL02]. This has been shown to achieve asymptotically the performance of linear beamforming [VTL02] and to have the same capacity scaling obtained with perfect CSI using the DPC [SH05, SH07] as the number of user's approaches infinity. However, it may result in very poor performance from both the capacity and fairness point of views, when applied in a system with a low or medium number of users. Therefore, the transmitter CSI is important for systems with a low to moderate number of users, and especially with a large number of transmit antennas [Jin06].

In a realistic network with multiple users, the assumption of having full CSI from all users may be overly optimistic. This is due to the excessive overhead required for providing the transmitter with instantaneous CSI. The combination of opportunistic beamforming for the initial user selection from a finite user set and the use of supplementary CSI feedback for the selected users has been proposed in [CTAL07, KG05] allowing for improved optimization of linear transmit and receive beamformers at the BS and MSs, respectively. It was shown in [CTAL07], co-authored by the author of this thesis, that the supplementary CSI for the selected users greatly improves the performance of the opportunistic beamforming, especially for a low number of users.

1.7. Open Problems

The key challenge faced by future wireless communication systems is to provide high-data-rate wireless access at high QoS. Combined with the facts that spectrum is a scarce resource and propagation conditions are hostile due to fading (caused by destructive addition of multipath components) and interference from other users, this requirement calls for means to radically increase spectral efficiency and to improve link reliability. MIMO wireless technology seems to meet these demands by offering increased spectral efficiency through spatial multiplexing gain, and improved link reliability due to antenna diversity gain. MIMO communication systems have been attracting considerable research attention from both academia and industry. Topics of research include channel modeling, capacity limits, coding, modulation, receiver design and multi-user communication. In this section, some open problems and important aspects for investigation are discussed. From an implementation viewpoint practical MIMO systems present a plethora of challenges in such areas as synchronization, channel estimation, training, power consumption, complexity reduction and efficiency. From the review of the resource allocation strategies in previous sections it is clear that a considerable number of proposals have already been suggested.

However, there are still open problems which could be characterized as follows:

1. Combined channel covariance information and channel mean information: capacity under transmitter channel distribution information and perfect receiver channel state information is unsolved under combined channel covariance information and channel mean information distribution model even with a single receive antenna. With perfect Receiver channel state information and transmitter channel distribution information capacity is not known under the channel covariance information model for completely general (i.e. non-separable) spatial correlations. Capacity bounds, for almost all cases with channel distribution information at receiver only are required to be investigated.

2. Most results for channel distribution information only at either the transmitter or receiver are for ergodic capacity. Capacity versus outage has proven to be less analytically tractable than ergodic capacity and contains an abundance of open problems to be addressed.

3. There are a large number of suboptimal resource allocation strategies, which follow the most varied approaches to solve the resource allocation problem. This complicates their comparison and a model is required in order to identify the main elements of the resource allocation strategies and to help classifying and comparing them.

4. For the case of MIMO BC with perfect receiver channel state information and transmitter channel distribution information, capacity is only known when the channels of all users have the same distribution. When this condition is not met, however, little is known regarding the capacity.

5. Since perfect CSI is rarely possible, a study of capacity with channel distribution information at both the transmitter(s) and receiver(s) for both MACs and BCs is of great practical relevance.

6. In order to reduce complexity suboptimal SDMA algorithms are usually employed. An important issue which requires attention is to determine whether such methods are capable of achieving near optimal capacity.

7. DPC is a very powerful capacity-achieving scheme, but because of high complexity, it appears to be practically infeasible. Thus, non-DPC MU transmission schemes for the DL MIMO systems are also of practical relevance. In addition, performing DPC (or some variant) with imperfect transmitter channel state information or transmitter channel distribution information is still challenging.

8. In literature, a large number of resource allocation schemes have been proposed for the case of DL single antenna MU OFDM/OFDMA systems. However, most of these studies had one crucial limitation of heavy computational complexity, which makes them impractical for real-time implementations. Thus, in recent years, many algorithms have been proposed to reduce the implementation complexity [HZ06], [AMH+08]. However, most of these initial studies either tried to maximize the throughput or minimize the total transmit power. The fairness among users was not considered in any of these algorithms.

The problem of maximizing total system capacity with a proportional fairness constraint was first proposed in [SAE05], which was later extended in [HZ06], [DK07]. The complexity of fair resource allocation algorithm in [SAE05] was further reduced in [WSEA04] through relaxation in fairness constraint. A low complexity algorithm based on [SAE05] was proposed in [WSEA04] and was shown to achieve higher spectrum efficiency than the algorithm in [SAE05]. Furthermore, a priority-based sequential scheduling criteria [HZ06] was shown to obtain even higher spectrum efficiency than those achieved in [SAE05, WSEA04] at the cost of severely losing affecting fairness among users. However, all these traditional algorithms for DL resource allocation either adhere to enhance user fairness or to enhance system capacity. In many applications, fairness and capacity should be considered simultaneously. Thus it is important to study the possibility of developing low complexity solutions which can maintain fairness among users without sacrificing the system efficiency significantly

9. Although many dynamic resource allocation algorithms [LZ06, PLC04] have been proposed to adaptively allocate radio resources to users in MIMO OFDMA systems, these algorithms seldom consider user fairness or do not have a flexible control on the data-rate distribution. As a result, it becomes important to develop low complexity proportional fair algorithms for MIMO OFDMA systems.

10. In order to achieve the capacity bound, one must solve a MU subchannel allocation, optimal power allocation and the optimal bit allocation jointly. The computational cost for finding the optimal solution is exponential with respect to the number subchannels and polynomial with respect to the number of users. In [KPL06] it was shown that this problem can be solved sub-optimally by separating Subchannel, Power and Bit Loading. Thus it becomes important to investigate possibility of developing low complexity optimal solutions for joint subchannel, power and bit allocation.

1.8. Contents and Contributions of the Thesis

This thesis consists of eight chapters, whose contents and contributions are briefly described in this section. In this chapter, a framework for suboptimal resource allocation strategies intended for MIMO OFDMA systems was discussed. This provided some insight into the overall problem of maximizing the sum rate of the system, the problem complexity, the component subproblems and their interdependencies. With help of this framework several suboptimal resource allocation strategies have been put together in Table 1.1 and Table 1.2 and have been discussed in Section 1.3.

Assumptions in the Thesis

- *Perfect CSI for all MSs available at the BS*: When the instantaneous channel gains, also called the CSI, are known perfectly at both the transmitter and the receiver, the transmitter can adapt its transmission strategy (rate and/or power) relative to the instantaneous channel state. Thus user CSI plays a crucial role in order to exploit MU diversity in MU wireless communication systems.

In this thesis, we assume that users are capable of perfectly estimating and sending their channel information to the BS. However, the amount of feedback information increases the overhead of the system. Moreover in MIMO systems where each user's channel is represented by a matrix the overhead may become very large. Techniques like limited feedback [CH05, LW05] or channel prediction [SAE03, WFHE04] can be used in order to reduce the amount of feedback overhead.

- *Continuous Shannon channel capacity formula as a measure of system sum rate*:

The capacity of a channel, denoted by C, is the maximum rate at which reliable communication can be performed, without any constraints on transmitter and receiver complexity. The Shannon capacity, which is a continuous function, is used as the user throughput in this thesis. However, in practical systems, because of different modulation and coding schemes, user data rates assume discrete values. The continuous Shannon capacity formula, however, provides an upper bound on the achievable throughput. Moreover it simplifies the analysis of adaptive resource allocation. To model the SNR degradation similar to real scenarios, a SNR gap can be included in the Shannon capacity formula [CDEF95a, CDEF95b]. This gap is widely used in digital subscriber line standards [DC96, AEK01].

- *Single cell environment*: In this thesis, resource allocation in a single cell environment is considered. Hence, interference because of other cells is not modeled. However, when the users are at the cell edges, interference due to other cells is not negligible as it may significantly affect the user SINR. In order to schedule users lying at cell edges or during soft handover, BS cooperation or static frequency planning techniques can be used. There are several instances where researchers have proposed resource allocation for multi-cell environment or considering inter-user interference [YGC02, ZL04]. Resource allocation in multi-cell environment is usually much more complex to solve as compared to single cell environment. The resource allocation algorithms proposed in this thesis can be used for users with AWGN dominating other-cell interference.

- *Flat power spectrum density mask*: The transmit power budget available at the BS is usually limited by a power spectrum density mask. Due to the limitation of bandwidth, multiple standards may co-exist within the same frequency range. In order to minimize the interference to nearby systems, the transmit power allowed for every communication system is usually limited to maximum value by a power spectrum density mask defined by the standards. In order to reduce complexity, in this thesis, we assume a flat power spectrum density mask. Separate power constraints for different subchannels can be added in problem formulation in order to incorporate a non-flat power spectrum density mask.
- *Infinitely backlogged user queues*: The aim of resource allocation proposed in this thesis is to maximize the sum rate considering various constraints. The user queues are assumed to be infinitely backlogged. In other words, whenever a user is scheduled for transmission, that user always has some data to transmit. However in actual scenarios the amount of data a user needs to transmit is limited, but there always exist a subset of users who require an opportunity to transmit there data. Hence, the resource allocation algorithms proposed in this thesis can be used to transmit the data of these active users.

1.9. Organization of the Thesis

Fundamentals of Multicarrier wireless communication systems are discussed in Chapter 2. Chapter starts with the discussion on types of wireless propagation models and describes how the wireless channel is different from wired channels. The use of OFDM and MIMO OFDM to counter the adverse effects of wireless channels are then discussed briefly. Concept of adaptive modulation to use the bandwidth effectively is also discussed briefly.

Chapter 3 presents the concepts of Evolutionary Algorithms (EAs) in optimization. Various EAs are discussed in brief. Finally the use of single objective and multiobjective Genetic Algorithms (GAs) in solving engineering optimization problems is discussed.

First contribution of this thesis is presented in Chapter 4, where we have proposed the use of Particle Swarm Optimization (PSO), a stochastic optimization technique, for subchannel allocation in DL of OFDMA systems followed by power allocation using WFA. In PSO aided subchannel allocation the search and subchannel allocation is performed simultaneously as compared to traditional methods where the subchannels are first sorted in accordance of their gains and then allocation is performed. This significantly reduces the complexity of PSO aided allocation. This fact makes PSO aided subchannel allocation a suitable choice for practical wireless systems like Worldwide Interoperability for Microwave Access (WiMAX) and Third Generation Partnership Project Long Term Evolution (3GPP LTE) where the convergence rate plays a very important role as the wireless channel changes rapidly.

In Chapter 5, we present a novel GA adaptive resource allocation in MIMO OFDM systems. We impose a set of proportional fairness constraints to assure that each user can achieve a required data rate, as in a system with quality of service guarantees. With the proposed algorithm, the sum capacity can be distributed fairly and flexibly among users. Since the optimal solution to the constrained fairness problem is extremely computationally complex to obtain, we propose a suboptimal algorithm that separates subchannel allocation and power allocation. In the proposed algorithm, subchannel allocation is first performed using novel GA, assuming an equal power distribution. An optimal power allocation algorithm then maximizes the sum capacity while maintaining proportional fairness.

In Chapter 6, we present a joint solution to subchannel, bit and power allocation problem for DL of MIMO OFDM systems. Using SVD, the MIMO fading channel of each subchannel is transformed into an equivalent bank of parallel SISO subchannels. To achieve the capacity bound, one must solve a MU subchannel allocation and the optimal bit allocation jointly. We propose the use of Non-dominated Sorting Genetic Algorithm (NSGA) – II, which is a multi-objective Genetic Algorithm (MOGA), for joint allocation of bits and subchannels, in the DL of MIMO OFDMA system. NSGA – II is intended for optimization problems involving multiple conflicting objectives. Here the two conflicting objectives are Rate Maximization and Transmit Power Minimization.

In Chapter 7, we summarize the contributions of this thesis. Future research topics are discussed in Chapter 8.

Chapter-2

Fundamentals of Multicarrier Wireless Communication

2.1. Introduction

The wireless propagation channel constrains the information communication capacity between a transmitter and a receiver. The design of a wireless communication system's coding, modulation, signal processing schemes and multiple access schemes is based on the channel models. Unlike the wired channel, the wireless channel can vary from LoS to one that is severely obstructed by buildings, mountains, etc. Due to multiple propagation paths, the received signal is a composite of multiple delayed and attenuated copies of the transmitted signal. In addition, the wireless channel is time variant due to the motion of the mobile users or the changes in the surroundings. Typically, there are two types of propagation models: large-scale propagation loss and small-scale multipath fading model. Large-scale propagation loss is caused by path loss and shadowing, which usually fluctuates slowly and can be compensated by power control. Small-scale multipath fading, or simply fading, characterizes the variation of the received signal strength, which is caused by the constructive or destructive effects of the multiple paths depending on the time varying path attenuation and delay.

2.1.1. Large-Scale Propagation Loss

Both theoretical and measurement-based propagation models indicate that the average received signal power decreases logarithmically with distance in outdoor or indoor radio channels [Rap99]. The average large-scale path loss ($\overline{P}_L$) for an arbitrary Transmitter-Receiver (T-R) separation (*d*) is expressed as a function of distance by using a path loss exponent *n*. That is,

$$\overline{P}_L(d) \propto \left(\frac{d}{d_0}\right)^n \tag{2.1}$$

or

$$\overline{P}_L(d)_{dB} = \overline{P}_L(d_0)_{dB} + 10n\log\left(\frac{d}{d_0}\right) \tag{2.2}$$

where n is the path loss exponent which indicates the rate at which the path loss increases with distance, d_0 denoting the close-in reference distance which is determined from measurements close to the transmitter, and d is the T-R separation.

The model in equation.2.1 and equation.2.2 does not consider the fact that the surrounding environmental clutter may be vastly different at two different locations having the same T-R separation. Measurements have shown that at any value of d, the path loss $P_L(d)$ at a particular location is random and distributed log-normally about the mean distance-dependent value $\overline{P}_L(d)$). That is,

$$P_L(d)_{dB} = \overline{P}_L(d)_{dB} + \chi_\sigma = \overline{P}_L(d_0)_{dB} + 10n\log\left(\frac{d}{d_0}\right) + \chi_\sigma \tag{2.3}$$

where χ_σ is a zero-mean Gaussian distributed random variable (in dB) with standard deviation σ (also in dB). This phenomenon is referred to as log-normal shadowing.

2.1.2. Small-Scale Multipath fading

In this subsection, we will describe the characteristics of the wireless channels subject to multipath fading. The three most important effects of the small-scale fading are [Rap99, Pro01, Suz77]:

- Rapid changes in signal strength over a small travel distance or time interval;
- Random frequency modulation due to varying Doppler shifts on different multipath signals; and
- Time dispersion caused by multipath propagation delays.

Assume that $s_b(t)$ is the baseband signal to be transmitted and f_c is the carrier frequency. The corresponding Radio Frequency (RF) signal transmitted over the wireless channel can be written as

$$s(t) = \mathrm{Re}\left\lfloor s_b(t)e^{j2\pi f_c t} \right\rfloor \tag{2.4}$$

Let $\rho_l(t)$ and $\tau_l(t)$ denote the amplitude and the propagation delay for the l^{th} path. Then, the received bandpass signal is given by

$$r(t) = \sum_l \rho_l s(t - \tau_l(t))$$

$$= \mathrm{Re}\left\{\left[\sum_l \rho_l e^{-j2\pi f_c(t)\tau_l(t)} s_b(t-\tau_l(t))\right]\right\} e^{j2\pi f_c(t)} \quad (2.5)$$

where the AWGN is ignored for simplicity. It is apparent from equation.2.5 that the equivalent baseband signal is

$$r_b(t) = \sum_l \rho_l e^{-j2\pi f_c(t)\tau_l(t)} s_b(t-\tau_l(t)) \quad (2.6)$$

It can be concluded from equation.2.6 that the multipath channel can be regarded as a time-variant finite impulse response (FIR) system. We have

$$r_b(t) = s_b(t) \otimes h(t,\tau) \quad (2.7)$$

where

$$h(t,\tau) = \sum_l \rho_l e^{-j2\pi f_c(t)\tau_l(t)} \delta(t-\tau_l(t)) \quad (2.8)$$

is the impulse response of the channel at time t to an impulse input applied at time $t-\tau$. In most wireless communication systems, the total number of multipath is usually very large. According to the central limit theorem [Pro01], the time-variant impulse response $h(t,\tau)$ may be modeled as a complex-valued Gaussian random process in the t variable.

When the modulated symbol duration is much greater than the largest path delay, all the paths cannot be resolved. In this case, all the frequencies in the transmitted signal bandwidth will go through almost the same random attenuation and phase shift. This is known as flat fading and the channel impulse response is expressed as

$$h(t,\tau) = \alpha(t) e^{j\varphi(t)} \delta(\tau) \quad (2.9)$$

On the other hand, when the propagation delay is larger than the symbol duration, the frequency components in the transmitted signal will go through different attenuations and phase shift along the different path delays. This is called frequency-selective fading. In such a channel, some of the multipath can be resolved and the channel can be expressed as

$$h(t,\tau) = \sum_{l=1}^{L} \alpha_l(t) e^{j\varphi_l(t)} \delta(\tau-\tau_l(t)) \quad (2.10)$$

where L is the number of resolvable paths.

In equation.2.9 and equation.2.10, $\alpha(t)$ is the channel gain and $\varphi(t)$ is the channel phase shift. When there is no LoS, $\alpha(t)$ will be Rayleigh distributed with

$$f_\alpha(\alpha) = \frac{\alpha}{\sigma^2} e^{-\frac{\alpha^2}{2\sigma^2}} \tag{2.11}$$

where $2\sigma^2$ is the time average power of the received signal before envelope detection given the transmitted signal strength is unity.

When there is a direct path (case of Line of Sight (LoS)), $\alpha(t)$ will be of Rician distribution with

$$f_\alpha(\alpha) = \frac{\alpha}{\sigma^2} e^{-\frac{\alpha^2 + A_d^2}{2\sigma^2} I_0 \frac{\alpha + A_d}{\sigma^2}} \tag{2.12}$$

where A_d is the amplitude of the dominant path and $I_0(\bullet)$ is the modified Bessel function of the first kind and zero-order. When $A_d \to 0$, the Rician distribution degenerates to a Rayleigh distribution.

Delay spread and coherence bandwidths are the parameters that describe the time dispersive nature of the channel in a local area. The *mean excess delay* is the first moment of the power delay profile and is defined to be

$$\bar{\tau} = \frac{\sum_l \alpha_l^2 \tau_l}{\sum_l \alpha_l^2} \tag{2.13}$$

The root mean squared (rms) delay spread (σ_τ) is the square root of the second central moment of the power delay profile and is defined to be

$$\sigma_\tau = \sqrt{\overline{\tau^2} - \left(\bar{\tau}\right)^2} \tag{2.14}$$

where

$$\overline{\tau^2} = \frac{\sum_l \alpha_l^2 \tau_l^2}{\sum_l \alpha_l^2} \tag{2.15}$$

The coherence bandwidth is a range of frequencies over which two frequency components have strong potential for amplitude correlation. If the coherence bandwidth is defined as the bandwidth over which the frequency correlation function is above 0.9, then the coherence bandwidth (B_c) is approximately [Lee89]

$$B_c = \frac{1}{50\sigma_\tau} \quad (2.16)$$

Likewise, Doppler spread and coherence time are parameters which describe the time varying nature of the channel in a small-scale region. Doppler spread is defined as the largest frequency shifts of the various paths of the multipaths in the wireless communication channel. If we assume that the channel is wide sense stationary, the Doppler power spectrum $D(f)$ of a mobile channel for an omni-directional mobile antenna and the received plane wave with uniformly distributed arrival angle can be given by

$$D(f) = \frac{a}{\pi f_d \sqrt{1 - \left(\frac{f - f_c}{f_d}\right)^2}} \quad (2.17)$$

where a is a constant and f_d is the maximum Doppler spread. If the receiver and transmitter are in relative motion with constant speed, the received signal will be subjected to a constant frequency shift called Doppler spread. The Doppler spread is given as

$$f_d = \frac{v}{c} f_c \quad (2.18)$$

where v is the velocity at which a mobile is moving, f_c is the carrier frequency and c is the velocity of light.

Coherence time T_c is a statistical measurement of the time duration over which the channel impulse response is essentially invariant, and quantifies the similarity of the channel response at different times. In other words Coherence time is measure of the expected time duration during which the channel response is approximately constant. Coherence time is also defined as the inverse of the Doppler spread. That is,

$$T_c = \frac{1}{f_d} \quad (2.19)$$

To summarize,

- Frequency selective fading occurs if the bandwidth of the transmitted signal (B_s) is large compared with coherent bandwidth of the channel (B_c), that is $B_s > B_c$. In other words the symbol duration, T_s is less than the delay spread of the channel T_d. Under these circumstances, the channel's output signal that arrives at the receiver will include multiple versions of the transmitted signal, which are faded and delayed in time, resulting in ISI problem. As such, different frequency components of the transmitted signal would then undergo different degrees of fading. This channel effect can be avoided by transforming the wideband signal into parallel narrowband signals with bandwidth smaller the channel's B_c.

- Frequency dispersion results from different frequencies propagating at different speeds. It smears the signal spectrum in the frequency domain. Also, because of time selectivity the rate of the variation in signal is higher than the rate at which the channel can be accurately estimated. This can be taken care of by considering CSI inaccuracy.
- Large distance propagation attenuates the received signal strength. Thus, it reduces the rate at which the data can be transmitted by limiting modulation schemes which can be used. The adoption of cooperative relay technologies combats large scale fading.

Fig.2.1 shows the graphical representations of the mean delay and toot mean squared delay spread. When the channel delay dispersion is greater than the signal reciprocal bandwidth, i.e., the symbol duration $T_s << \tau_{rms}$, the transmitted train of symbols overlaps at the receiver. This phenomenon is known as ISI which is illustrated in Fig.2.1.

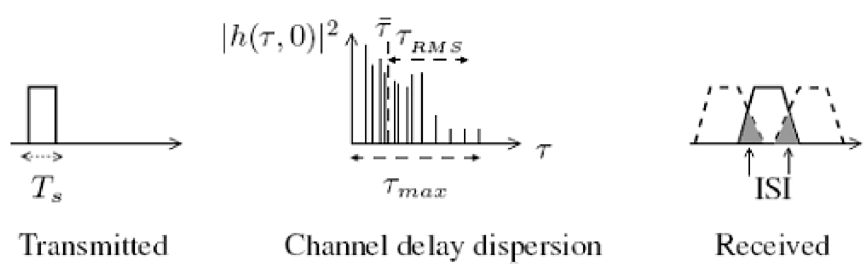


Figure 2.1: Wireless channel effect: delay dispersion

The coherence bandwidth B_c measures the spectral width over which the channel is considered frequency flat. Note that the frequency selectivity is relative to the transmitted signal bandwidth. In particular, if the channel's B_c is less than the transmitted signal bandwidth, the channel distorts the received signal at selected frequencies, as shown in Fig.2.2. On the other hand, the channel does not affect the received signal, if its B_c is greater than the transmitted signal bandwidth.

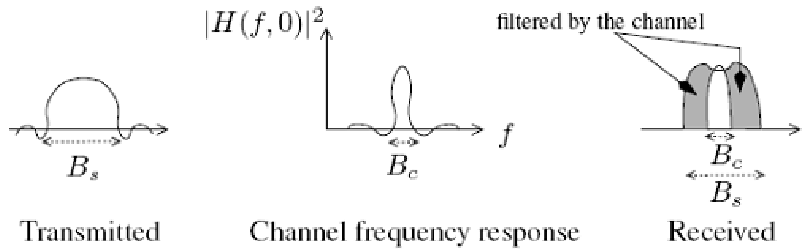


Figure 2.2: Wireless channel effect: frequency selectivity

2.2. Orthogonal Frequency Division Multiplexing

Based on the discussions in the previous section it is clear that, the channel impairments significantly degrade the performance of Broadband wireless access networks. Doelz et al. [DHM57] in 1957 first proposed the concept of parallel data transmission over dispersive channels. Later, Chang [Cha66] and Saltzberg [Sal67] in 1960s, proposed the concept of OFDM. In these papers, a new concept of simultaneous transmission of signals over a band limited channel while eliminating ICI and the ISI was presented. Since, the early OFDM schemes required large number of sinusoidal subchannel generators both at the transmitter and receiver; their use was limited to military applications. However, Weinstein and Ebert [WE71] in 1971 suggested the use of Discrete Fourier Transform (DFT) matrix for the OFDM modulation and demodulation processes. The use of DFT matrix significantly reduces the implementation complexity of OFDM.

OFDM is basically FDM scheme, utilized as a digital multicarrier modulation method. Similar to any other modulation technique, multicarrier technologies try to approach the channel's capacity. For specific channel condition and network architecture, one of the available techniques may perform better than others. The multicarrier transmission is selected among others as a promising technique for future communication due to:

- Robustness against frequency selectivity for high speed data communication.
- Maturity through the research and development for wireless LAN and terrestrial digital video transmission [HP03].

FDM first appeared in 1950s [HP03], however its implementation required multiple analog RF modules in each transceiver that made FDM impractical [LL05]. Recently, the implementation of FFT and FDM ability in mitigating the channels ISI brought FDM back under the limelight. While FDM's major advantage is eliminating the ISI effect, it does not eliminate the ICI that rises due to closely packed multicarriers. Alternatively, data symbols can be modulated on orthogonal multiple carriers to reduce ICI, which is termed OFDM [CMS02].

High-data-rate communications are limited not only by noise but often more significantly by the ISI due to the time dispersive nature of the wireless channels. Multi-carrier modulation divides a broadband channel into narrowband subchannels. OFDM uses a large number of closely-spaced orthogonal narrowband subchannels instead of a single wideband carrier to transport data. The data is divided into several parallel data streams or channels, one for each subchannel. In an OFDM system, a single data-stream is transmitted over lower data rate subchannels as a coded quantity at each carrier frequency in the same bandwidth. OFDM is easy to implement and efficient in dealing with multi-path. OFDM is robust against narrowband interference and frequency selective fading.

Generally, the effects of ISI are negligible as long as the delay spread is significantly smaller than the symbol duration. This implies that the symbol rate of communication systems is practically limited by the channel's memory. For high data rate transmission where symbol rates exceed this limit, some sort of mechanisms is required to combat the effects of ISI [FK03].

OFDM is considered as an extremely promising solution for supporting high-data-rate transmission in future broadband wireless communication systems. The key concept in OFDM is to split a wide band signal into several orthogonal narrow band signals for transmission. In other words, instead of transmitting a volume of bits over short time duration and on a wide frequency band, it is transmitted over long time duration and on several narrow frequency bands. This allows us to design a system supporting high data rates while maintaining symbol durations much longer than the channel's delay spread. By doing so, each subchannel experiences almost a flat fading, and the detrimental effects of the multipath channels are reduced to a multiplication of each subchannel by a complex transfer factor. A schematic diagram of an OFDM system is shown in Fig.2.3.

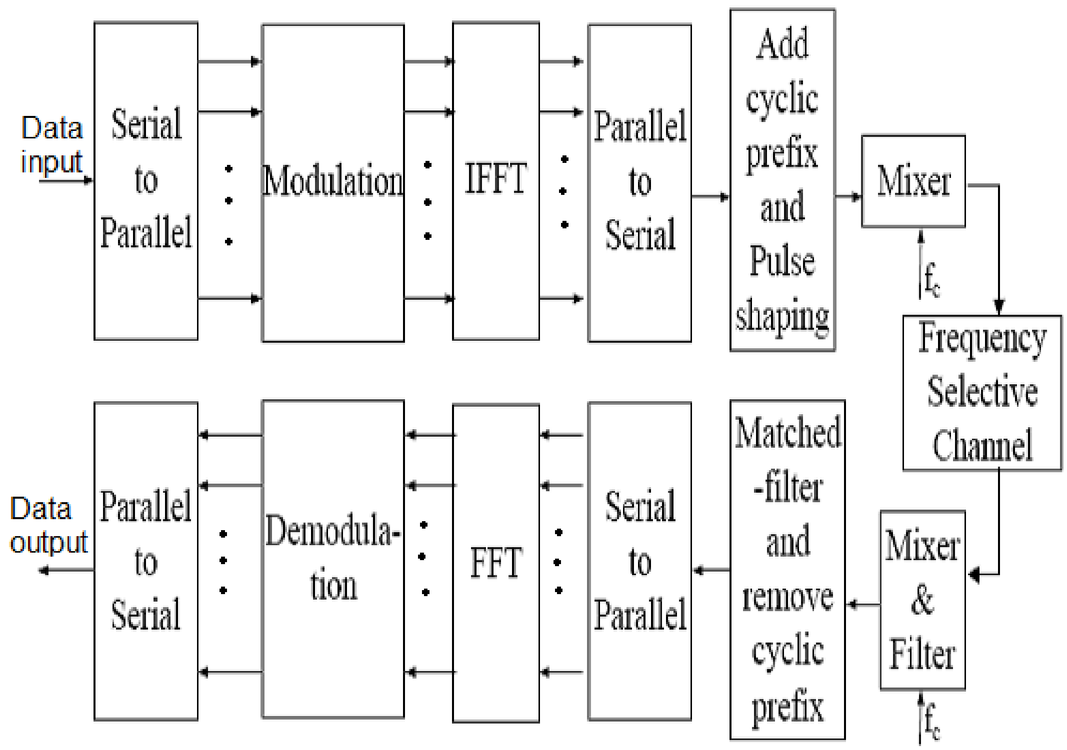


Figure 2.3: OFDM system model

Data to be transmitted is first arranged in parallel for each subchannel and modulated independently. The complex numbers (X_k) which represent the signal constellation of each subchannel are transformed into the time domain by performing an Inverse Fast Fourier Transform (IFFT). Assuming that we have N subchannels, the output of the IFFT which consists of N samples x_n is

$$x_n = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X_k e^{j2\pi\frac{kn}{N}} \tag{2.20}$$

In order to ensure that the received time-domain OFDM symbol is demodulated from the channel's steady-state response, each time-domain OFDM symbol is extended by the so-called cyclic extension or guard interval of N_g samples duration, as shown in Fig.2.4. If the cyclic prefix is longer than the impulse response of the channel, the inter-OFDM symbol interference due to the channel memory is completely eliminated.

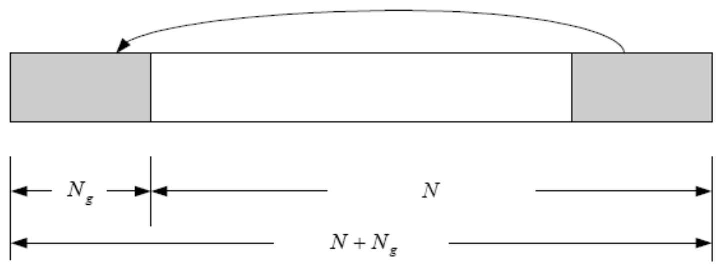


Figure 2.4: The cyclic prefix of an OFDM symbol

After removing the cyclic prefix at the receiver, we retrieve the complex number X_k by FFT. As we have inserted a cyclic prefix, the received signal is the result of a circular convolution between x_n and the channel response h. The result of the FFT on the received signal is then merely a product of X_k and H_k. Where, H_k is the frequency response of the channel on k^{th} subchannel. By including the channel noise, we have

$$\hat{X}_k = H_k X_k + \eta_k \tag{2.21}$$

where η_k is the additive white noise in the frequency domain. In addition, the frequency response of the channel at time t can be calculated as:

$$H(f,t) = \int_{-\infty}^{\infty} h(t,\tau) e^{-j2\pi ft} d\tau = \sum_l \alpha_l(t) e^{-j2\pi f \tau_l(t)} \tag{2.22}$$

and H_k is obtained by substituting f with the frequency of the k^{th} subchannel.

2.3. Orthogonal Frequency Division Multiple Access

Despite the advantages of OFDM in mitigating the channels' impairments as mentioned before, it suffers from disadvantages like under-utilization of transmitter power and network subchannels. Particularly, when an OFDM transmitter accesses the channel in a time division manner (e.g., TDMA) the transmitter is forced to transmit on all available subchannels N, although it may require a less number of subchannels to satisfy its transmission rate requirement. Thus, the transmitter power requirement increases with the number of subchannels. This disadvantage motivates the development of a physical layer technology where transmitters are multiplexed in time and frequency, i.e., OFDMA. In this technology, the subscribers are exclusively assigned only a subset of the network available subchannels in each time slot [LL05], [APC05]. OFDMA typically uses FFT size much higher than OFDM, and divides the available subchannels into logical groups called subchannel. Unlike OFDM that transmits the same amount of energy in each subchannel, OFDMA may transmit different amounts of energy in each subchannel. The number of time slots as well as the subchannels can be dynamically assigned to each subscriber. Such a dynamic assignment is referred to as dynamic subchannel assignment and introduces multiuser diversity. The multiuser diversity gain arises from the fact that the utilization of given resources varies from one subscriber to another. In the dynamic subchannel assignment case, channel information is used to assign the subchannels best suited for each user. This is advantageous in the sense that users at different locations have different channel conditions, and most likely different optimal subchannels. The benefit is that high throughput rate can be obtained, the disadvantages are that; channel information is needed, subchannels must be reassigned whenever conditions change, leading to additional signaling overhead whenever subchannels are reassigned.

OFDMA can support a number of identical down-streams, or different user data rates, (e.g. assigning a different number of subchannels to each user). Based on the subchannel conditions, different baseband modulation schemes can be used for the individual users/subchannels, e.g. Quadrature Phase shift Keying (QPSK), 16-QAM and 64-QAM and so on. This has been investigated in number of researches [AK94, WS95, GC97, CG01, GC98, QC99, VG03] and is referred to as adaptive subchannel, bit, and power allocation or QoS allocation.

2.4. Multiple Input Multiple Output Antenna System

2.4.1. MIMO Structure

MIMO/multiantenna systems are one of the most popular areas that have drawn enormous attention in recent years [ML02, RC98a, WSG94, MM80, Fos96, FG98]. Multi-antenna is one of the key technologies for mitigating the negative effects of the wireless channel, providing better link quality and/or higher data rate without consuming extra bandwidth or transmitting power. The usage of multiple antennas at either receiver, transmitter or at both locations provides different benefits, namely array gain, interference reduction, diversity gain and/or multiplexing gain. MIMO is a smart antenna technology that uses AAs for the transmitter and receiver. MIMO systems use multiple inputs and multiple outputs for each channel. In such systems, the use of multiple antennas at both the transmitter and receiver helps to exploit the spatial dimension freedom and combat the harmful effects in mobile radio communication and therefore improve the system performance. Besides the performance enhancement, deploying multiple antennas can bring a huge increase in the system capacity, which is one of the most critical issues for current wireless communication services.

Diversity is one of the most effective techniques to combat fading in wireless communications. The main idea behind diversity is to send multiple copies of the transmitted signal via multiple (presumably independent) channels to the receiver. When the channels have low, or ideally zero, cross-correlation, the probability that all of them fall into deep fading simultaneously is very low [HT01]. That means if one radio path undergoes a deep fade at a particular point in time and/or frequency and/or space, another uncorrelated path may have a strong signal at that point. By having more than one path to select from, both the instantaneous and average SNR at the receiver can be greatly improved. Parallel to diversity techniques, a recently new approach in multi antenna transmission systems is spatial multiplexing. With respect to diversity technique, spatial multiplexing aims at increasing data rate of the system. Spatial multiplexing techniques require that multiple antennas be present at both transmitter and receiver. Such antenna arrangement is often referred to as MIMO.

MIMO increases channel capacity by transmitting multiple data streams over one frequency. With Spatial Multiplexing, the spatial data throughput of the channel is increased. Alternatively, MIMO system can provide Spatial Diversity, which improves signal quality by transmitting redundancy, e.g., using Alamouti Space-Time code [PNG03]. Spatial multiplexing is suitable for near-field communication and spatial diversity for far-field communication. With higher spectral efficiency and reduced fading, a MIMO system is able to increase link range and data throughput of the communication without additional power and bandwidth.

The block diagram of a MIMO system is shown in Fig.2.5. At the transmitter side, the input data stream is demultiplexed into j parallel substreams.

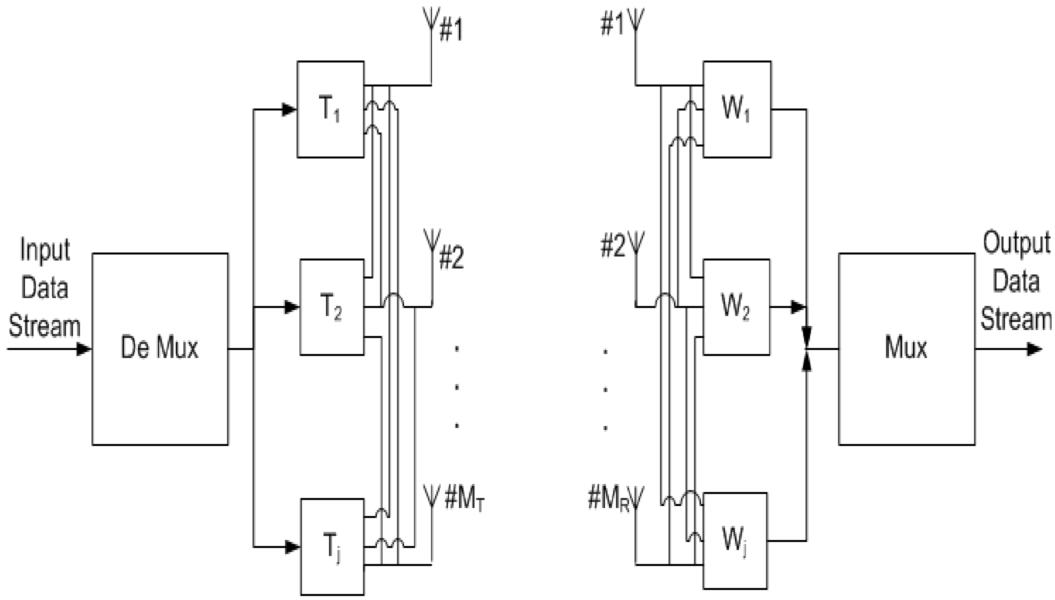


Figure 2.5: Block diagram of MIMO systems

Each substream is transmitted over all transmit antennas in the same frequency band with different transmit antenna weights (T_1, T_2, …,T_j). At the receiver, the multiple antennas, using suitable corresponding weights (W_1, W_2, …,W_j), can separate the substreams and give an estimation of the original data stream.

Let **H** denote the channel matrix, with the (M_R, M_T)-th element being the channel coefficient between the M_T transmit antenna and the M_R receive antenna. Typically, the channel matrix is related to the channel fading, angles of arrival and departure, and the AA response. That is,

$$\mathbf{H} = \sum_{q=1}^{Q} \beta_q \boldsymbol{\alpha}^{Rx}\left(\theta_q^{Rx}\right) \boldsymbol{\alpha}^{Tx}\left(\theta_q^{Tx}\right)^T \tag{2.23}$$

where Q is the total number of paths in space (i.e., from different angles of arrival), and β_q is the corresponding fading coefficient. Likewise, $\boldsymbol{\alpha}^{Rx}\left(\theta_q^{Rx}\right)$ and $\boldsymbol{\alpha}^{Tx}\left(\theta_q^{Tx}\right)^T$ are the array responses for arrival angle θ_q^{Rx} and departure angle θ_q^{Tx} , respectively.

Let x_j denote a data symbol of the j^{th} substream and P_j denote the amount of transmit power allocated to x_j. Then, the data received by the M_R receive antennas are given by

$$\mathbf{r} = \left[r_1, r_2, \ldots\ldots, r_{M_R}\right]^T \tag{2.24}$$

$$= \mathbf{H}\sum_{j=1}^{J}\mathbf{t}_j\sqrt{P_j x_j} + \mathbf{n}$$

where **n** is the noise vector with i.i.d, complex Gaussian entries each having variance σ^2. After receive weight combining, we get

$$y_j = \mathbf{w}_j^H \mathbf{r}$$

$$= \mathbf{w}_j^H \mathbf{H}\sum_{j=1}^{J}\mathbf{t}_j\sqrt{P_j x_j} + \mathbf{w}_j^H \mathbf{n} \qquad (2.25)$$

2.4.2. MIMO Multiplexing using Singular Value Decomposition

SVD of the channel characteristic matrix is used in precoding, equalization and beamforming for MIMO and OFDM communication systems (e.g., Institute of Electrical and Electronics Engineers (IEEE) 802.11n). Pre-coding schemes of MIMO and OFDM systems require complex SVD.

Precoding consists of all spatial processing that occurs at the transmitter to maximize the signal power at the receiver input. The system requires the knowledge of the CSI at the transmitter. SVD-based pre-coding techniques make use of the fact that a column of **V** is an eigenvector of $\mathbf{H}^{\boldsymbol{H}}\mathbf{H}$, which corresponds to an Eigenmode of the communication channel. (For instance, singular value s_i defines the quality of the i^{th} Eigenmode).

It was proved in [RC98a] that SVD based STVC allows the collection of the signal power in space and is a theoretical means to achieve high capacity for MIMO systems. By SVD, the $M_T \times M_R$ channel matrix can be decomposed into

$$\mathbf{H} = \mathbf{U}\mathbf{S}\mathbf{V}^H = \sum_{j=1}^{rank(\mathbf{H})} \mathbf{u}_j s_j \mathbf{v}_j^H \qquad (2.26)$$

where

$$\mathbf{U} = \left[\mathbf{u}_1, \mathbf{u}_2, \ldots\ldots, \mathbf{u}_{M_R}\right]$$

denotes the left singular vectors and

$$\mathbf{V} = \left[\mathbf{v}_1, \mathbf{v}_2, \ldots\ldots, \mathbf{v}_{M_T}\right]$$

represents the right singular vectors. $s_1, s_2, \ldots, s_{rank(\mathbf{H})}$ are singular values, and are arranged in descending order, without loss of generality. It was pointed out in [RC98a] that by configuring the transmit antenna weights using right singular vectors **v** and receive antenna weights using left singular vectors **u**, up to *rank*(**H**) parallel channels are constructed. By doing so, the received vectors in equation.2.25 can be written as

$$y_j = \mathbf{u}_j^H \mathbf{H} \sum_{j=1}^{J} \mathbf{v}_j \sqrt{p_j x_j} + \mathbf{u}_j^H \mathbf{n}$$
$$= s_j \sqrt{p_j x_j} + \mathbf{u}_j^H \mathbf{n} \qquad (2.27)$$

given that $J \leq rank(\mathbf{H})$.

2.4.3. SVD-Based SDMA

The use of multiple antennas also enables SDMA, which allows intra-cell bandwidth reuse by multiplexing spatially separable users [MM80]. If the transmitters have knowledge of the channel, SVD in conjunction with multiuser detection (MUD) is a straightforward method to configure the transceivers [KC00a, KC00b, WMCL00].

It was pointed out in [KC00a] that most of the signal power is collected by the maximum singular value, especially in an outdoor environment. Therefore, data are transmitted on the maximum singular mode in our work by configuring the antenna weights using the largest singular vectors for each user. The block diagram of MIMO SDMA is presented in Fig.2.6.

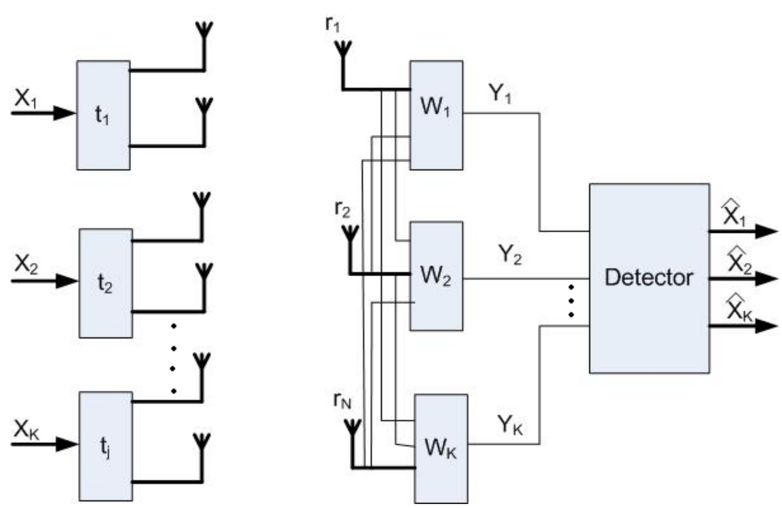


Figure 2.6: Block diagram of MIMO SDMA systems

Define x_k to be the data to be transmitted by user k and P_k to be the corresponding transmit power. Let $\mathbf{H}_k$ denote the channel matrix between user k and the BS and $\mathbf{u}_k$, s_k, and $\mathbf{v}_k$ be the corresponding singular vectors and singular value relevant to the maximum singular mode, respectively. The signals received by the M_R receive antennas are given by

$$\begin{aligned}\mathbf{r} &= \left[r_1, r_2, \ldots, r_{M_R}\right]^T \\ &= \sum_{k=1}^{K} \mathbf{H}_k \mathbf{v}_k \sqrt{p_j x_j} + \mathbf{n} \\ &= \mathbf{US}\sqrt{\mathbf{P}\mathbf{x}} + \mathbf{n}\end{aligned} \tag{2.28}$$

where

$$\mathbf{U} = \left[\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_k\right]$$

$$\mathbf{x} = \left[x_1, x_2, \ldots, x_k\right]^T$$

$$\mathbf{S} = diag\left(s_1, s_2, \ldots, s_K\right)$$

$$\sqrt{\mathbf{P}} = diag(\sqrt{p_1}, \sqrt{p_2}, \ldots, \sqrt{p_K})$$

The output of the receive weight combining then becomes

$$\begin{aligned}\mathbf{y}^{MF} &= \mathbf{U}^H \mathbf{r} \\ &= \mathbf{U}^H \mathbf{US}\sqrt{\mathbf{P}}\mathbf{x} + \mathbf{U}^{\mathbf{H}}\mathbf{n} \\ &= \Re\mathbf{S}\sqrt{\mathbf{P}}\mathbf{x} + \mathbf{U}^H\mathbf{n}\end{aligned} \tag{2.29}$$

where $\Re = \mathbf{U}^H\mathbf{U}$ is the correlation matrix with the $(k, k')^{\text{th}}$ entry being the correlation between the two users' singular vectors, i.e.,

$$\rho_{k,k'} \equiv \mathbf{u}_k^H \mathbf{u}_{k'}\,. \tag{2.30}$$

For such a simple receiver, which is referred to as the matched filter (MF) receiver, $\mathbf{y}^{MF}$ includes the desired signal, Multiple Access Interference (MAI) from co-channel users, as well as additive noise. It is well known that such a receiver has many problems, especially, when MAI increases. As a result, a MUD needs to be applied to jointly estimate the transmitted signal for all users and suppress the MAI.

The optimal ML MUD tries to jointly minimize the bit error probability. By finding the most probable transmitted data symbol for all users, the detector separates the signals from simultaneous users in an optimal way, in the sense of the *aposteriori* probability. It is easily derived that the ML metric for a combination of transmitted symbols $\mathbf{x} = \left[x_1, x_2, ..., x_k\right]$ is given by

$$\psi(\mathbf{x}) = \left\| \mathbf{r} - \sum_{k=1}^{K} \mathbf{H}_k \mathbf{v}_k \sqrt{p_k x_k} \right\|^2 \tag{2.31}$$

where $\|\bullet\|$ denotes the Frobenius norm. The optimal solution can be obtained as

$$\hat{\mathbf{x}} = \arg_{\mathbf{x}} \min\left[\psi(\mathbf{x})\right] \tag{2.32}$$

The ZF receiver is one of the most popular linear receivers. It applies the inverse of the correlation matrix to the output of the MF receiver to decouple the data. The decision statistics become

$$\begin{aligned} \mathbf{y}^{ZF} &= \Re^{-1}\mathbf{y}^{MF} \\ &= \left[s_1\sqrt{p_1}x_1, s_2\sqrt{p_2}x_2, ..., s_k\sqrt{p_k}x_k \right]^T + \mathbf{n}' \end{aligned} \tag{2.33}$$

where $\mathbf{n}$' is a $K \times 1$ noise vector which is equal to $(\mathbf{U}^H\mathbf{U})^{-1}\mathbf{U}^H\mathbf{n}$. The covariance matrix of the noise vector is

$$\boldsymbol{\eta} = \sigma^2 (\Re)^{-1} \tag{2.34}$$

Subsequent to the ZF filter, y^{ZF} is fed into a slicer, which determines the nearest constellation points and generates a hard decision, $\hat{\mathbf{x}}$.

The ZF detector completely cancels the MAI at the cost of enhancing the noise term. Furthermore, the performance will be severely degraded when the correlation matrix, $\Re$, becomes near singular [KC00a].

The MMSE receiver is another linear MUD type. Such a receiver takes into account both the MAI and the noise term. The designing criteria of the MMSE receiver is to minimize the mean square error

$$MSE = E\left[\|\tilde{\mathbf{x}} - \mathbf{x}\|^2 \right]$$

It can be shown that the mapping is given by

$$\mathbf{y}^{MMSE} = \left(\Re + \sigma^2 (\mathbf{S}\sqrt{\mathbf{P}})^{-2} \right)^{-1} \mathbf{y}^{MF} \tag{2.35}$$

Parallel interference cancellation (PIC) is one of the most widely used nonlinear decision feedback detectors. Generally the researchers adopt a multistage detection approach as is the case in PIC. The ZF filter is employed as the initial stage to get a tentative decision $\hat{\mathbf{x}}$. And, then proceed by regenerating the interference to the k^{th} user and then subtract it from the received signal to obtain more reliable bit decisions. These steps are performed for all users in a multistage fashion. Considering the d^{th} stage, we have the decision statistic

$$y_k^{PIC}(d) = \mathbf{u}_k^H \left(\mathbf{r} - \sum_{\substack{k'=1 \\ k' \neq k}}^{K} \mathbf{u}_{k'} s_{k'} \sqrt{p_{k'}} \hat{x}_{k'}^{(d-1)} \right) \tag{2.36}$$

where $\hat{x}_{k'}^{(d-1)}$ is the tentative estimated decision of user k of the $(d\text{-}1)^{\text{th}}$ stage, which is obtained from $y_k^{PIC}(d)$.

2.5. Adaptive Modulation

The basic idea of adaptive modulation is to take advantage of the variation of the fading channel. Instead of maintaining a fixed transmit rate at a given time, adaptive modulation adjust the transmit rate and power according to the channel situation. The water pouring principle [Bla87] gives a theoretical explanation of this idea. The water pouring criterion states that under a certain power constraint, the overall information rate of an arbitrary channel is maximized by transmitting more power where the attenuation and noise are smaller. In other words, a higher transmission rate should be used when the channel is under a good condition and vice versa. Many algorithms have been proposed to use adaptive modulation in the time domain to exploit the time-variant channel capacity [AK94, WS95, GC97, CG01, GC98, QC99, VG03]. They gave impressive result in increasing the transmission rate or improving the system performance.

The notion of adaptive modulation in the context of OFDM was proposed as early as 1989 by Kalet [Kal89], which was further developed by Chow et al [CCB95] and was refined for duplex wireless links, for example in [KH00a]. The basic idea of such algorithms is to apply high modulation levels on the subchannels with favorable channel conditions to improve the spectral efficiency, while transmitting few bits on the subchannels in deep fades to avoid bit errors.

In order to allocate appropriate modulation modes to the subchannels, three allocation criterions were investigated in the literature. They are the fixed-threshold controlled algorithm, upper bound BER algorithm, and fixed-throughput adaptation algorithm [KH00b]. In these criterions, transmission modes are adapted in order to maximize the data rate given a fixed long-term or instantaneous BER, or to minimize the bit errors given a fixed data rate.

Adaptive transmission is only applicable to duplex communication systems, since the transmission parameter adaptation relies on some form of channel estimation and signaling. In order to efficiently react to the changes in channel quality, the following steps have to be taken [KH00a]:

- Channel quality estimation;
- Choice of appropriate parameters for the next transmission; and
- Signaling or blind detection of the employed parameters.

2.6. Conclusion

In this chapter, we attempted to understand and characterize the challenging and multifaceted broadband wireless channel.

- In order to calculate the average value of the channel power one can use a model based on the distance between the transmitter and the receiver, the carrier frequency, and the pathloss exponent.
- The large-scale changes from the average channel power are characterized as *lognormal shadowing*.
- The small-scale changes in the channel power are known as fading. Autocorrelation function provides an insight about the behavior of Broadband wireless channels.
- A number of diversity-achieving techniques are available for both narrowband and broadband fading.
- OFDM can be used as modulation technique in order to overcome the effects of ISI inherent in broad band channels.

- Although it is possible to use any multiple-access techniques—FDMA, TDMA, Code Division Multiple Access (CDMA), Carrier Sense Multiple Access (CSMA) — along with OFDM. But the OFDMA which is basically FDMA-TDMA hybrid provides best results.
- OFDMA is capable of providing high capacity and flexible accommodation of many users through multiuser diversity and adaptive modulation.
- Spatial diversity can provide significant reduction in BER without needing power to be increased by considerable amount.
- Further reduction in BER can be achieved through, diversity gains provided by the use of multiple receive antennas, multiple transmit antennas, or a combination of both.

Chapter 3
Evolutionary Algorithms

3.1. Introduction

Optimization, stated simply, is the process of finding the minimum or maximum of some mathematical function. An optimization problem involving a single variable can usually be easily solved. Taking the derivative of an analytical function, setting it equal to zero and solving, results in the critical points of that function, including the optimal minimum and maximum values. Functions of two or more variables can be solved in a similar method. However, functions of multiple variables can prove very difficult to solve. When many hundreds or thousands of variables exist in a problem, classical optimization methods are simply not powerful enough and new approaches are required.

Functions may also have multiple local maximum or minimum points. Some common optimization techniques such as hill-climbing [Dav91], have difficulty locating multiple maxima or minima. For example, consider a function with three maxima of equal value. In trying to locate the peaks of the function, standard hill-climbing techniques would start at some initial location and climb to the top of one of the peaks.

This single peak would be declared as the maximum. Searching with this approach provides no information about the other peaks of equal value, nor does it prove anything about the global maximum. The global maxima could be located somewhere else entirely in the design space and the same problem exists when locating the minima. The choice of where to start the search has a large impact on the final answer when using gradient search methods.

It is possible to write optimization algorithms that perform global, rather than local searches. One example of a global optimization algorithm is the EA [Gol89, Hol75]. Work by Mitchell and Holland [MH93] has shown that EAs can outperform hill-climbing techniques.

This section looks at modern techniques that fall within the area of computational intelligence (sometimes called soft computing). Computational Intelligence is an umbrella term that groups together many different types of computer based methodologies and algorithms.

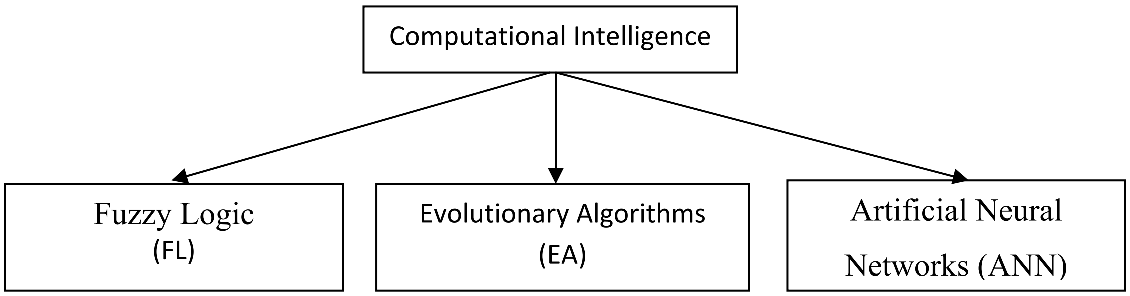


Figure 3.1: Computational Intelligence Techniques.

Fig.3.1 shows three common areas within Computational Intelligence. These three main areas are fuzzy logic, EAs and ANNs. Fuzzy logic and ANNs are mapping (classifier) methods, rather than optimization tools, but they have been applied in the field of array pattern optimization. Fuzzy logic [Zad65] is a method for processing uncertain or noisy input data into crisp decisions or control signals for a system. While it is a powerful technique in its own right, it has limited applicability in MIMO-OFDM optimization where the input parameters (such as excitation sets) are more certain. It is not uncommon for the actual design of fuzzy systems to require optimization before good results are obtained [Soe03, Ala95].

ANNs [BJ90, Lip87, Koh88] or simply Neural Networks refer to a group of algorithms that typically operate on a large number of simple interconnected components (or neurons). This networking enables the entire algorithm to perform much more powerful computations by combining the limited processing power of the separate components. It is basically an information-processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing neurons working in unison to solve specific problems. ANN learns by examples in a way similar to human learning system. ANNs are configured for a specific application, such as pattern recognition or data classification through a learning process. ANNs are very popular in the research community and their main strength lies in their ability to identify patterns or trends in data.

ANNs have been used in some wireless application like antenna performance optimization although a literature search only uncovered a small number of examples. Aboul-Dahab et al [DHK98] used an ANN in the receive chain of a linear array antenna to weight a received pattern to reduce sidelobe levels. The results were very impressive - low sidelobe patterns were produced with up to -80dB sidelobes. A similar technique proposed by Reza and Chrostodulou [RC98b] trained an ANN, that took a radiation pattern as an input and as an output, produced a design for a linear array and a set of weights to achieve the pattern.

Wireless Sensor Network (WSN) have a fuzzy nature and different parameters are involved in it's behavior, ANNs through dimensionality reduction, obtained simply from the outputs of the neural-networks clustering algorithms, leads to lower communication costs and energy savings[KTD05]. Moreover due to centralized nature of WSNs in which all data from the sensor nodes often have to be sent to a (usually external) BS, Neural Networks capability in prediction of sensor readings at BS, can highly decrease unneeded communications and save considerable energy.

From the above examples, it is clear that ANNs have application in wireless communication area and that they can be formulated to model non-linear problems. Unfortunately, ANNs themselves are not optimizers. One disadvantage of ANNs is the fact that individual relations between the input and the output variables are not developed by engineering judgment. Consequently, the ANN tends to be a ‘black box’ system or input/output table without analytical basis. As such ANNs does not prove understandable insight on how a problem is solved. Also the computation time to develop and train a neural network can be demanding, particularly for problems with large number of parameters.

The other important subset of computational intelligence is the area of EAs. EA is actually an umbrella term used to describe a number of computer based problem solving approaches. EAs are stochastic optimization techniques based on the principles of natural evolution. EAs, as we know them now, began their existence during the late 1960s and early 1970s (some earlier references to the topic exist though; see [Fog98]). In these years and almost simultaneously scientists from different places in the world began the task of putting Nature at work in algorithmic, and more precisely in search or problem solving duties.

EAs use computational models based on some sort of the known mechanisms of evolution as key elements in their design and implementation. The use of EAs for optimization tasks has become very popular in the last few years, spanning virtually every application domain.

A variety of EAs are in existence. The most popular of them are Genetic Algorithms, Evolutionary Programming (EP), Differential Evolution (DE), Evolution Strategies (ES), Genetic Programming (GP), Population Based Incremental Learning (PBIL), Particle Swarm Optimization and Ant Colony Optimization (ACO). The basic concept of all the above listed EAs is to simulate the evolution of individual structures via processes of selection, reproduction and mutation. The processes depend on the perceived performance of the individual structures as defined by an environment.

To be precise, EAs maintain a population of structures, which evolve according to predefined rules of selection and 'genetic operators'. Examples of genetic operators include 'crossover' and 'mutation'. The algorithm manipulates a collection *P* of individuals (the *population*), each of which comprises one or more chromosomes. These chromosomes allow each individual represent a potential solution for the problem under consideration. Initially, the population is generated at random or by means of some heuristic seeding procedure. Each individual in *P* receives a *fitness* value: a measure of how good the solution it represents for the problem being considered. Subsequently, this value is used within the algorithm for guiding the search. Reproduction focuses attention on high fitness individuals, thus exploiting the available fitness information. Recombination and mutation perturb those individuals, providing general heuristics for exploration of the search space. More precisely, the process comprises three major stages: *selection* (promising solutions are picked from the population by using a selection function), *reproduction* (new solutions are created by modifying selected solutions using some reproductive operators), and *replacement*. If imperfect reproduction is added the population can begin to explore the search space and will move to individuals that have an increased selection probability and that inherit this property to their descendants.

These population dynamics follow the basic rule of the Darwinistic evolution theory, which can be described in short as the “survival of the fittest” [Dar59]. The common EA variants are shown below in Fig.3.2.

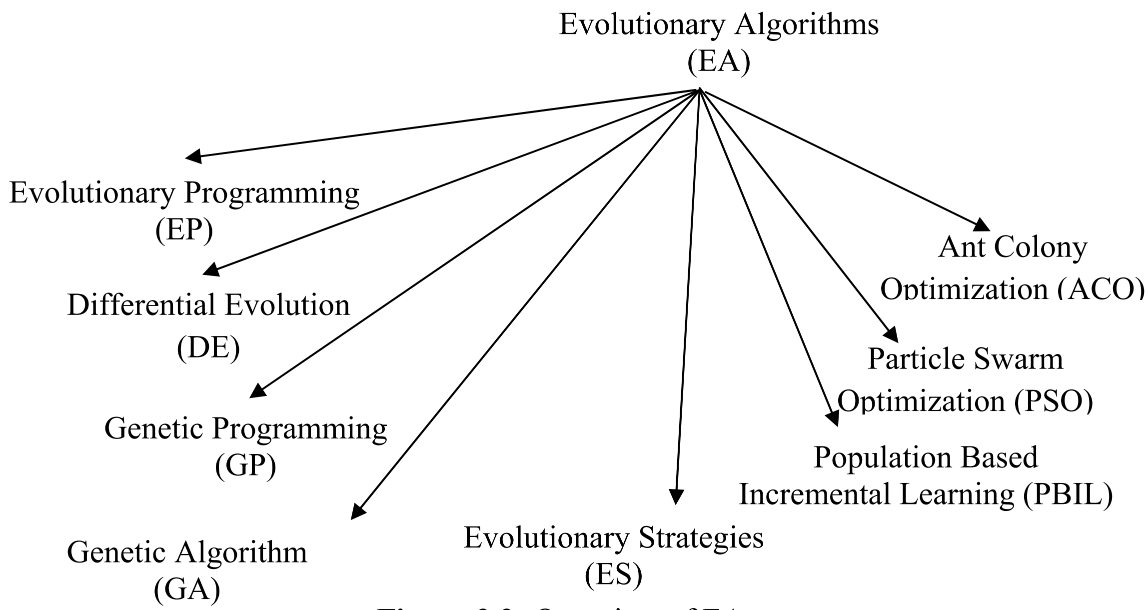


Figure 3.2: Overview of EAs

3.1.1. Genetic Algorithm

The GAs are possibly the most widespread variant of EAs. GA is a replica of machine learning which derives its behavior from a metaphor of some of the mechanisms of evolution in nature [Gol89, Hol75]. GA exhibit the clearest mapping from the natural process of evolution onto a computer system, because they stress on the coding of attributes into a set of genes.

The algorithm creates a population of individuals represented by chromosomes. The chromosome is a string of variables that is analogous to the chromosomes present in nature. The individuals in the population then go through a process of simulated evolution modeled on the Darwinian theory of natural selection.

The main feature of GAs is the use of a recombination (or *crossover*) operator as the primary search tool. The rationale is the assumption that different parts of the optimal solution can be independently discovered, and be later combined to create better solutions. Additionally, mutation is also used, but it was usually considered a secondary background operator whose purpose is merely `keeping the pot boiling' by introducing new information in the population (this classical interpretation is no longer considered valid though).

GAs are used in a number of different application areas. One example is in multidimensional optimization problems in which the chromosome can be used to encode the values for the different parameters being optimized.

In practice the genetic model of computation can be implemented by having arrays of bits or real valued numbers to represent the chromosomes. During the evolutionary model, the genetic operators of crossover and mutation modify the chromosomes.

One iteration of this algorithm is referred to as a generation. The first generation of this process operates on a population of randomly generated individuals. From there on, the genetic operations, in concert with the fitness measure that defines the measure of success of each individual, operate to improve the population.

A selection mechanism is used to choose individual members from the current generation as parent solutions for the subsequent generation. Solutions with the highest fitness tend to be selected more often and hence pass on their genetic information to their offspring. This exchange strengthens the population over time until it converges on a solution.

3.1.2. Evolutionary Programming

The term EP was originally conceived by Lawrence J. Fogel in the 1960s [FOW66]. Although the general idea of using a computer to simulate evolution appeared in primitive forms throughout the 1950s [Fog98]. EP focuses on the adaption of individuals rather than in the evolution of their genetic information. This implies a much more abstract view of the evolutionary process, in which the behavior of individuals is directly modified (as opposed to manipulating its genes).

It is basically a stochastic optimization strategy similar to GAs, but instead places emphasis on the behavioral linkage between parents and their offspring, rather than seeking to emulate specific genetic operators as observed in nature. Traditionally, EP uses asexual reproduction (also known as mutation), i.e. introducing slight changes in an existing solution-and selection techniques based on direct competition among individuals.

Evolutionary programming is similar to evolutionary strategies, although the two approaches were developed independently.

In all Evolutionary Programming methods, each member of the current population is used to generate an offspring, therefore the selection mechanism used to choose parent solutions in the GA is not used. Each offspring is placed into a new population. When all offspring have been generated, the current population is merged with the new population of offspring, and a separate selection procedure is used to generate a current population for the next generation.

In EP and GAs, there is an underlying assumption that a fitness landscape can be characterized in terms of variables, and that there is an optimum solution (or multiple such optima) in terms of those variables. For example, if one was trying to find the shortest path in a Travelling Salesman Problem, each solution would be a path. The length of the path could be expressed as a number, which would serve as the solution's fitness. The fitness landscape for this problem could be characterized as a hyper-surface proportional to the path lengths in a space of possible paths. The goal would be to find the globally shortest path in that space, or more practically, to find very short tours very quickly.

The basic EP method involves 3 steps:

(Repeat the steps until a threshold for iteration is exceeded or an adequate solution is obtained):

(1) Randomly choose an initial population of solutions. The number of solutions in initial population greatly affects the speed of optimization, but no definite answers are available as to how many solutions are appropriate.

(2) Each solution is replicated into a new population. Each of these offspring solutions are mutated in accordance of distribution of mutation types. Mutation types may range from minor to extreme with a continuum of mutation types in between. The severity of mutation is judged on the basis of the functional change imposed by it on the parents in the population.

(3) Suitability of each offspring solution is assessed by computing its fitness. Typically, a stochastic tournament is used to determine N solutions to be retained in the next population of solutions. Although the retention of offspring’s for the population is sporadically deterministic. There is no requirement to keep the

population size constant, nor it is required that only a single offspring be generated from each parent.

It should be pointed out that EP typically does not use crossover as a genetic operator. Although mutation is used but it simply changes the aspects of the solution according to a predefined statistical distribution. This distribution weights minor variations in the behavior of the offspring as highly probable and substantial variations as increasingly unlikely. Further, the severity of mutations is often reduced as the global optimum is approached (similar to the reduction in temperature of simulated annealing).

3.1.3. Differential Evolution

The main idea behind DE [SP95] is a scheme for generating trial parameter vectors. The basic strategy is that the weighted difference between two randomly selected solutions from the population is used as the source of a random variation for a new trial solution. DE has been shown to outperform variants of EAs on certain test cases.

3.1.4. Genetic Programming

GP provides a method for automatically creating a working computer program from a high-level problem statement of the problem [Koz89, Koz90]. Essentially, GP could be viewed as an evolution program in which the structures evolved represent computer programs. Such programs are typically encoded by trees. The final goal of GP is the automatic design of a program for solving a certain task, formulated as a collection of (input, output) examples.

GP achieves this goal of automatic programming (also sometimes called program synthesis or program induction) by genetically breeding a population of computer programs using the principles of Darwinian natural selection and biologically inspired operations. The operations include reproduction, crossover, mutation, and architecture-altering operations patterned after gene duplication and gene deletion in nature. GP can search the space of possible computer programs for an individual computer program that is highly successful in solving (or approximately solving) the problem at hand.

GP is the extension of the genetic model of learning into the space of programs. That is, the objects that constitute the population are not fixed-length character strings that encode possible solutions to the problem under consideration. The population actually is made up of programs that, when executed, are the candidate solutions to the problem. These programs are expressed in GP as parse trees, rather than as lines of code. Using parse trees has advantages since it prevents syntax errors, which could lead to invalid individuals, and the hierarchy in a parse tree resolves any issues regarding function precedence. Thus, for example, the simple program " $a + b*c$ " would be represented as shown in Fig.3.3: or to be precise, as suitable data structures linked together to achieve this effect.

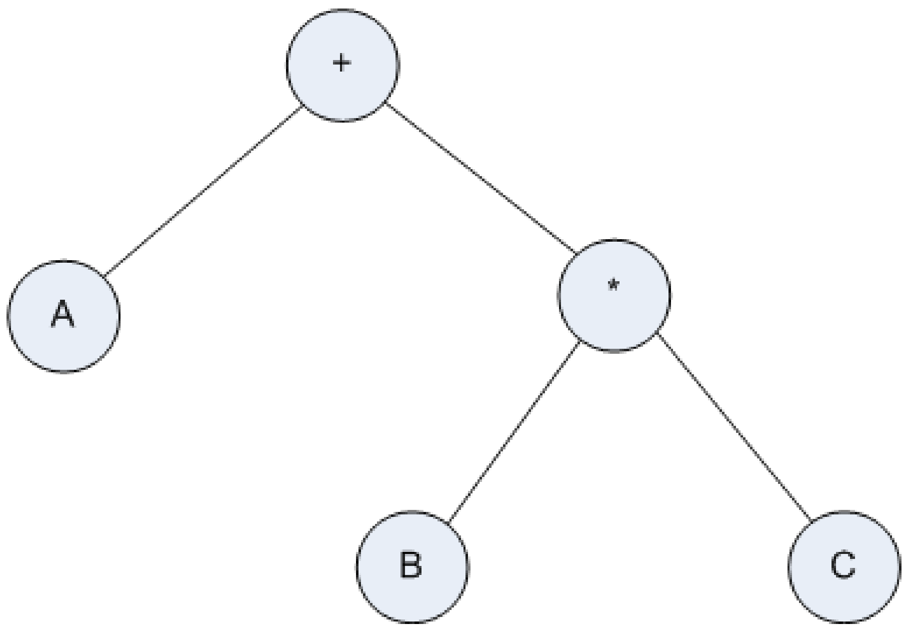


Figure 3.3: Tree Structure of GP

The programs in the population are composed of elements from two sets known as the function set and the terminal set. These sets typically contain fixed symbols selected to be appropriate to the solution of problems in the domain of interest.

In GP the crossover operation is implemented by taking randomly selected subtrees in the individuals (selected according to their fitness) and exchanging them. GP usually does not use mutation operators.

Although GP was initially based on the evolution of parse trees the current scope of GP is much broader. In [BNKF98] Banzhaf et al. described several GP systems using either trees, graphs or linear data structures for program evolution and in [Lan98] Langdon discusses the evolution of data structures.

3.1.5. Evolutionary Strategies

GAs and EP are not the only type of evolutionary computing methods. Modeling biological evolution on a computer began in the 1960s. ES were introduced in the 1960s by Rechenberg [Rech65] and further developed by Schwefel [Sch95]. His first versions of the algorithms used real-valued parameters and began with a parent and a mutated version of a parent. Whichever had the highest cost was discarded. The winner produced a mutated version and the process repeated. Populations and crossover were not incorporated until later years. A general version of the algorithm, known as the ($\mu + \lambda$) evolution strategy, was developed by Back [Bac97] in 1997. In this strategy, μ parents produce λ offspring. In succeeding generations only the best μ of the λ offspring and μ parents are allowed to survive until the next generation. The first attempts at using ES to solve discrete optimization were also made by Schwefel [BS02].

ES are in many ways very similar to EP and to GAs. As their name implies, ES also simulate natural evolution. The differences between EPs and ES arise primarily because the original applications for which the algorithms were developed are different. Similarly, while GAs were applied to solve discrete or integer optimization problems, ES were applied first to continuous parameter optimization problems associated with laboratory experiments.

In a GA, mutation is usually a secondary operator, fixed in value and applied with low probability, while crossover is the primary search operator. In ES each variable has an adaptive mutation rate that is usually normally distributed with a zero mean. Therefore when trying to optimize five values, a further five mutation rate variables are required. Such a mutation mechanism enables the ES to evolve its own mutation strategy parameters in accordance with the problem under consideration as the search progresses through generations, a process termed self-adaptation by Schwefel [Sch87]. Like EP, considerable effort has focused on adaptive mutation as the algorithm progresses. Unlike EP, however, recombination has an important role in ES, especially in adapting mutation.

A variety of recombination operators have been used in ES. Some of them are similar to GA crossover operator, which combine components from two randomly selected parents. Some of the other recombination operators allow components to be taken directly from any of the solutions in the parent population without any change in them.

Recombination is applied not only to the control variables but also the strategy parameters. Indeed, in some ES implementations different recombination operators are applied to different components of the solution representation.

3.1.6. Population Based Incremental Learning

Population-based incremental learning (PBIL) algorithms were first proposed by Baluja [Bal94] as an abstraction of GAs, which explicitly maintain the statistics contained in a GA's population. As a class of EAs, PBILs have proved to be very successful on numerous stationary benchmark and real-world problems. The PBIL algorithm is a combination of evolutionary optimization and competitive learning. PBIL is basically a guided search algorithm that obtains its directional information from the previous best solutions. Typically a binary string is used to encode the optimization variables and a real-valued second string, known as the prototype vector is generated of the same length as the binary string. The standard PBIL starts from a probability vector that has a value of 0.5 for each bit location. This probability vector is called the *central probability vector* since it falls in the central point of the search space. Sampling this initial probability vector creates random solutions because the probability of generating a

1 or 0 on each locus is equal. As the search progresses, each element of the probability vector is updated by small increments so as to favor the generation of either a one or a zero for the corresponding bit in a trial solution vector. The initial value of 0.5 provides zero bias. To avoid the chances of being trapped in local minima the probability vector is allowed to mutate by a small amount at each generation of the algorithm. A number of empirically derived tuning parameters are required in order to promote good performance. For example, the number of trial vectors that are generated and evaluated before updating the probability vector must be chosen (typically 100).

A term known as the learning rate determines the probability vector update increment (typically 0.1). Smaller values result in wider searches, but slower convergence.

Similarly a negative learning rate can be used to distance the probability vector from the worst performing solutions (typically 0.075). The probability and amount of mutation must also be set for the probability vector. The search progress stops when some termination condition is satisfied, e.g., the maximum allowable number of iterations is reached or the probability vector is converged to either 0.0 or 1.0 for each bit position. It is possible to implement a PBIL algorithm using only twenty lines of code (excluding the objective function evaluation) [Hug98].

3.1.7. Particle Swarm Optimization

PSO algorithm was introduced by Russel Eberhart (an Electrical Engineer) and James Kennedy (a Social Psychologist) in 1995 [KE95]. PSO belongs to the categories of Swarm Intelligence techniques and EAs for optimization. It was inspired by the social behavior of birds, which was studied by Craig Reynolds (a biologist) in late 80s and early 90s. He derived a formula for representation of the flocking behavior of birds. The formula was later used in computer simulations of virtual birds, known as Boids. Ebenhart and Kennedy recognised the suitability of this technique for optimization and came up with the Particle Swarm Optimiser.

The representation of the optimization problem is similar to the encoding methods used in GAs. The main difference is in the search mechanism. In PSO, the variables are called dimensions that create a multi-dimensional hyperspace. "Particles" fly in this hyperspace and try to find the global minima/maxima, their movement being governed by a simple mathematical equation. PSO has no evolution operators such as crossover and mutation. Each particle has a position and velocity associated with it and hence requires the same storage as ES.

PSO has been successfully applied in many areas: function optimization [FY01], ANN training [KM02] and fuzzy system design [EAT02].

3.1.8. Ant Algorithms

Ant algorithms (or Ant Systems) are a novel technique first developed by Dorigo et al. in 1991 [DMC91]. The Ant System is a population-based approach. In this respect it is similar to GAs although there is not a population of solutions being maintained.

Rather, there is a population of ants, with each ant finding a solution and then communicating with the other ants in the hope it will help them find even better solutions.

Ants can find the shortest path to food by laying a pheromone (chemical) trail as they walk. This pheromone is detected by other ants which in turn follow the trail. If one imagines an ant's nest and a source of food some distance from the nest, the ant has many routes it can follow to get from the nest to the food source. Ants that happen to pick the shorter path will create a strong trail of pheromone faster than the ones choosing a longer path. Since stronger pheromone attracts ants better, more and more ants choose the shorter path until eventually all ants have found the shortest path. If a single ant takes a long route to the food source, its pheromone trail will be weaker than if it were to take a short route, as pheromone intensity reduces with time (evaporates). If more ants are introduced, over time, the shorter route will be followed more often than the weaker route as the pheromone builds up on it. Over time, the route will become the major path to the food. The first ACO algorithms were designed to solve the traveling sales person problem [PFTV92], because this problem closely resembles finding the shortest path to a food source [DM97]. Initial attempts at an ACO algorithm were not very satisfying until the ACO algorithm was coupled with a local optimizer. One problem is premature convergence to a less than optimal solution because too much virtual pheromone was laid quickly. To avoid this stagnation, pheromone evaporation is implemented. In other words, the pheromone associated with a solution disappears after a period of time.

Some of the finer details of the algorithm are left out here for brevity, but there are many sources of literature available on the internet at the time of writing [DS04b, Cha07].

3.2. Evolutionary Algorithm

This section and the remainder of this chapter contains an introduction to the basic EAs and outlines the procedures for solving problems using the simple GA.

EAs are becoming very popular with the electromagnetic community. The reason for the sudden popularity of EAs is simple - the gradient optimization methods that were most popular in engineering disciplines have not performed consistently across the variety of electromagnetic design problems. The global search conducted by EAs is proving much more capable in this field of design.

EAs are designed to search a much wider area of the design space, and could potentially provide a set of optimal solutions to a given problem. The EA approach was selected for this research because many different solutions can be expected to be found for resource allocation in MIMO OFDMA systems, and it is important for the designer to explore as much of the potential decision space as possible, before selecting a single design or control solution. Often with complicated designs, an ExS of the entire design space is not feasible due to the high computational burden. EAs can help find good solutions in a much shorter time.

The purpose of an EA is to search a problem's decision space in order to find its optimal solutions in objective space, as shown in Fig.3.4.

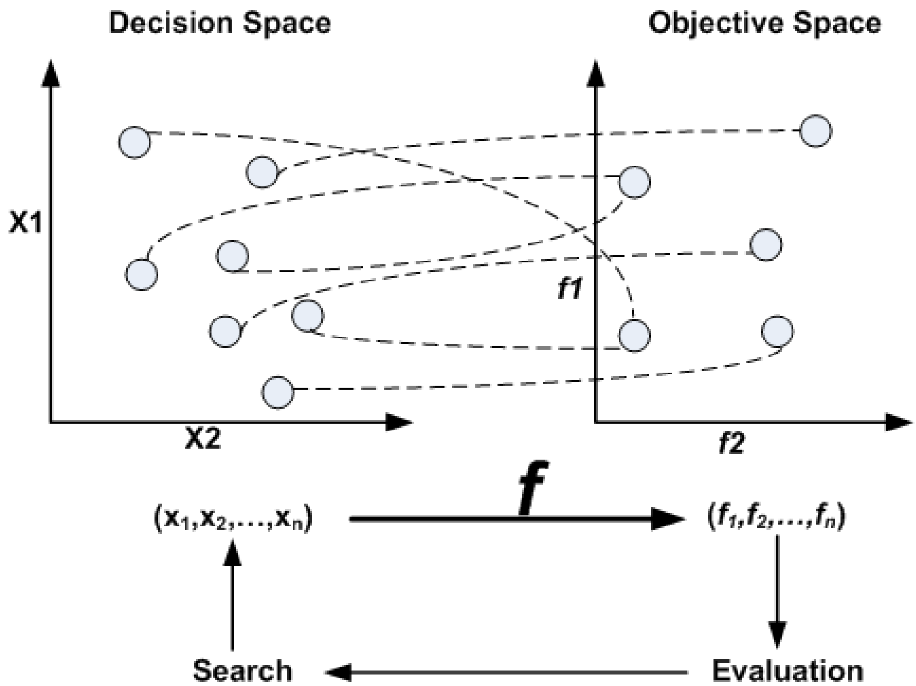


Figure 3.4: Decision and Objective Space

The EA is a stochastic global search method that mimics Charles Darwin's evolutionary theories of natural selection (survival of the fittest) [Dar59]. EAs operate on a population of potential solutions, applying the principle of survival of the fittest to produce increasingly better approximations to a solution. In theory, it is possible for them to find true globally optimum solutions provided they exist within the decision search space and if certain optional genetic operators are included for example "Mutation".

At this point it is worth summarizing some of the analogous terms, see Table 3.1.

In each generation (iteration), a new set of individuals (chromosome) is created by the process of selecting individuals (solutions) in accordance to their level of fitness (success) in the problem domain and 'breeding' them together using operators similar to natural genetics. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals that they were created from, in other words, better solutions to a problem.

Table 3.1: Evolutionary/Genetic Analogies.

Optimization Term	**Evolutionary/Genetic Analogy**
Variable	Gene
String or vector of variables	Chromosome
Set of variables that represent a single solution.	Individual (defined by one or more chromosomes)
Set of solutions	Population
Iteration	Generation
Success or performance	Fitness

3.2.1. Encoding

In GAs, each possible solution of the optimization problem under consideration should be encoded as a finite-length string over some alphabet. The coding techniques used can be classified into the following two categories: a binary coding and a permutation coding. The binary representation is mostly preferred for the coding of the solutions. For example, a problem with two variables, x_1 and x_2, may be mapped onto the chromosome structure as:

$$\left\{ \underbrace{1,\ 0,\ 1,\ 1,\ 1,}_{x_1}\ \underbrace{0,\ 1,\ 1,\ 1,\ 0,\ 1,\ 0,\ 0}_{x_2} \right\}$$

In the above example, a binary chromosome has been used, where x_1 contains 5 bits and x_2 uses 8 bits. The number of bits used affects the level of accuracy or the range of individual decision values that are required. A consequence of increasing the number of bits used to represent a parameter is the expansion of the decision search space size. In such a case EA is required to search a much larger solution space, thus slowing down convergence rate. The increased chromosome length forces a problem specific trade-off between the probability of finding a globally optimal solution and the overall algorithm run time.

The EA search process is capable of operating on a coded decision variables rather than the decision variables itself. This encoding is the main strength of an EA - the genotype need not to contain numerical optimization values directly and can instead contain complex encoding of systems, processes or methods, the result of which represent a solution to a problem.

The second coding scheme, the permutation coding, is used for sequencing problems such as scheduling problems and traveling salesman problems. This type of encoding is useful when individual fitness depends on positions of genes in the chromosome. For such type of problems, permutation strings of a set of integers are more natural representation than binary strings. Fig.3.5 shows examples of strings generated by the binary coding and by the permutation coding. The string generated by the binary coding consists of binary “0s” and “1s”.

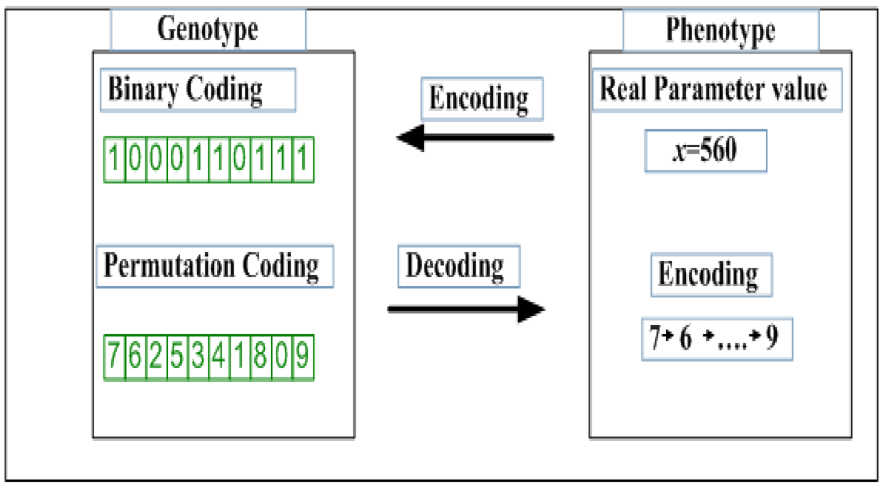


Figure 3.5: Genotype and phenotype.

The binary string after being treated by GAs is often decoded to the parameter value in integer, real number, and so on. The permutation string on the other hand consists of numerals “1” to “*n*”. Each numeral in the string corresponds to a job in scheduling problems or to a city in traveling salesman problems, while *n* is the total number of jobs or cities. Then jobs are processed according to their order in the permutation when scheduling problems are considered, or cities are visited according to their order in the permutation in traveling salesman problems.

As shown in Fig.3.5, strings which consist of binary or numeral elements are called genotype, and solutions which are decoded from strings are called phenotype. GAs acts over the strings in genotype domain and return the solution strings which are then decoded to phenotype domain. That is, the users of GAs get final solutions of their optimization problems after the strings obtained by GAs are decoded into the solutions in the phenotype domain.

3.2.2. Initial Population

The GA starts with a group of chromosomes known as the population. Once the chromosome encoding is defined, the next stage is to generate a set of random chromosomes. Each chromosomes worth is assessed by the cost function. So at this point, the chromosomes are passed to the cost function for evaluation.

The size of the initial population is a user defined parameter and should be decided upon with reference to the number of variables to be optimized and the total number of solutions in the decision space. If the initial population is too small it may not reach to efficient solution. On the other hand if the population is too large the algorithm might not converge or may take long time to find a solution. The chromosomes in later generations will largely be formed using the genes contained in the initial population and so the diversity of the initial 'building blocks' can influence the exploration of the search space [GSL01].

Population sizes of 30, 60 or 100 are common, but some researchers use population sizes of several hundred or more. The final choice is often decided by time taken to evaluate a single solution. In real time applications like resource allocation in MIMO-OFDM systems where the wireless channels changes within very short duration, the time taken by algorithm to converge becomes a very important criterion. This becomes even more crucial when the channel is assumed to be constant during the period of allocation.

There exist some variants of EAs known as Micro-GAs that use a very small population size of around 10 individuals in order to speed up convergence and are suitable to operate in real-time applications [Kri89].

3.2.3. Objective Functions and Fitness Assessment

Once the chromosome(s) belonging to each individual in the population have been decoded into the phenotypic domain, it is possible to assess the performance, or fitness, of each of them.

This assessment is done through a fitness function which characterizes an individual's performance in the problem domain under consideration. In the natural world, the performance would be an individual's ability to survive in its present environment. Depending on its environment, there can be several traits which an individual is desired to possess. This is easily realized using the following example of herbivores:

Example 3.1 (Herbivores): *In nature, an herbivore needs to be able to find food at the same time should be able to either avoid or defend itself against hungry carnivores. Only the ability to find food is not sufficient, as the appearance of a carnivore could be fatal to the herbivore. Similarly, the ability to defend itself from being killed by a carnivore is also not sufficient without the ability to find food; in such a case herbivore would starve to death. If no carnivores had been present in the environment, it would suffice for the herbivores to be able to find food in order to ensure its survival.*

The example clearly illustrates how the desired traits of the individuals depend primarily on its environment. Those who are fitter for survival in an environment will have a higher probability of continued survival. Based on this fitness, the individuals are selected for inclusion in the next generation.

EAs rely on many evaluations of the fitness function to guide their search and so it is important that the functions are as efficient as possible. To illustrate the point, consider an EA with a initial population size of 40, and is allowed to evolve for 50 generations. If there is no other stopping criterion used, there will be 2000 fitness function evaluations. Suppose the EA takes 1 second to evaluate the fitness of a solution, then all the evaluations would require more than half an hour to get over.

GAs actually searches for a string (chromosome) representing one of the possible solutions, with a better fitness value in the genotype domain. For example, in case of function optimization problems, the objective function value $f(\boldsymbol{x})$ is calculated by substituting the solution $\boldsymbol{x}$ decoded from the corresponding binary string obtained by GAs. When the function value $f(\boldsymbol{x})$ is better, the string in the genotype domain which corresponds to the solution $\boldsymbol{x}$ is assigned better fitness value. For example, in a maximization problem, a fitter individual will have a higher fitness value than a weaker solution.

Since the EAs are guided by a single fitness value so the objectives in case of more than one objective, have to be combined in some way. The combination is achieved by using a fitness function that is simply some function of the objective values. Common fitness functions include sum of objectives (equation.3.1) or weighted sums (equation.3.2).

$$F = f_1 + f_2 + f_3 .... + f_n \tag{3.1}$$

$$F = w_1 f_1 + w_2 f_2 + w_3 f_3 .... + w_n f_n \tag{3.2}$$

There can be many possible variants of fitness functions and some degree of experimentation is required to determine the one which is most suitable for a particular problem type. The assignment of fitness values establishes the basis for selection of pairs of chromosomes that will undergo crossover during reproduction. In order to keep the analogy with the process of natural selection, the fitter solutions must be selected for reproduction more often than the weaker solutions.

3.3. Selection Operator

This operator selects individuals in the current generation to be used for constructing the next generation. This operator in GAs is analogous to the process of natural selection in biology. Fitter individuals are more capable of survival and breeding. In GAs, selection allows the search to move towards better solutions as long as the fitness is measured in terms of the objective function of the problem at hand. Therefore, the first step in selection is evaluation of fitness.

The evaluation of the fitness is performed in such a way that it can be decided to which extent different individuals should survive. In this "survival of the fittest" approach some individuals with very good fitness would in general be preferred to individuals with low fitness. At the same time low fitness individuals could be lucky to survive. The set of selected individuals is usually referred to as the mating pool. In general, the purpose of the selection operation is to emphasize fit individuals in the population by giving them more chance to breed than less fit individuals.

In case, when a few individuals with low fitness survive, they allow for a continued exploration of the search space for more fruitful regions. An example of this kind of selection can be seen from Darwin's finch:

Example 3.2 (Darwin's finch) *Droughts that affect plants producing small seeds will tend to favor those finches with large beaks. Since the finches with smaller beaks finds it more difficult to handle large seeds. However, even though the smaller beaked finches are less fit than the finches with large beaks, some of them manage to survive. In such a case, the finches with small beaks that survive the drought can replenish their numbers when the drought has ended. In case a drought then affects the plants producing large seeds, the finches with smaller beaks will be better fit for this environment than finches with larger beaks. Thus, had the lesser fit finches not survived the drought, and then the droughts could most likely have eradicated both the small and large beaked finches.*

The example above describes the effect of changes in the environment on the different populations. For a fixed environment also, the same considerations is equally valid. In such a case, one area of the environment may not be suitable for some individuals, but the other parts of the environment may be better suitable for the same individuals. In the above example, this would correspond to a migration of the affected finches to another area not affected by droughts.

Selection on its own will not allow the full potential of evolution to occur. If only selection took place, the result would be that the best individual of the initial population, which may be far from optimal, would quickly dominate the entire population. As such, selection corresponds to an exploitation of the existing individuals. However, in order to evolve there is a need for discovery or exploration as well. The exploration will allow for new individuals with different features to emerge, which may or may not prove better than those already present in the population. This makes it a necessity to perform some alterations on the population in order to explore for new and better features for the individuals.

Selection preserves characteristics of fit individuals to be used to construct new offspring, and also removes bad individuals so that the overall population fitness improves over successive generations. The following subsections describe the most common selection schemes used in GAs, with a brief analysis of the selection pressure imposed by the selection scheme.

3.3.1. Elitist Selection

Elitism basically refers to carrying over good performing chromosomes from the old generation to new generation without change. This prevents the possibility of losing good chromosomes from one generation to the next.

Elitism is a general concept and there exists a number of ways to employ elitism in GAs [Deb01]. One of the ways to realize elitism is to favor the top individuals and to ignore the weaker ones. According to this selection scheme, individuals in the population are sorted according to their fitness values. The best *n* individuals are included in the selection process and the remaining are discarded. The selection among the best *n* individuals is realized just in the way as it is done in uniform selection. That is, each individual that belongs to top *n* has a probability of (1/*n*) of getting selected. The pseudo-code given in Fig.3.6 illustrates the mechanism:

```
ElitistSelection (Population p, Integer n) : returns an Individual
        begin
                sort population p according to fitness values
                of individuals in descending order;
                assign Integer i a random number from the range [0, n-1];
                return the i^th individual of population p;
        end;
```

Figure 3.6: Elitist Selection Algorithm

This selection method is widely used for its contributions in the speed of convergence, because of obvious reasons. However, it should be used carefully, in order not to encounter premature convergence. Using elitism has also been shown to guarantee a global convergence under some assumptions since the best chromosome in the population is monotonically improved. The assumption is that any chromosome must be reachable from any other chromosome by means of mutation and recombination.

3.3.2. Roulette Wheel Selection

The simplest selection scheme is roulette-wheel selection, also called stochastic sampling with replacement [Bac97]. Because of its simplicity, roulette wheel selection scheme is often used as a selection operator. Let N_{pop} be the number of strings in each population in GAs, that is, N_{pop} is the population size. We denote N_{pop} strings in the current generation by $\psi = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_{N\text{pop}}\}$. Each solution $\boldsymbol{x}_i$ is selected as a parent string according to the selection probability $P_s(\mathbf{x}_i)$. In the roulette wheel selection scheme, the selection probability $P_s(\mathbf{x}_i)$ is defined as follows:

$$P_s(x_i) = \frac{f(x_i)}{\sum_{j=1}^{N_{pop}} f(x_j)}, \ for \ \ i = 1, 2, ..., N_{pop} \tag{3.3}$$

where $f(\cdot)$ is the fitness value of the solution $\boldsymbol{x}$.

The individuals are mapped to contiguous segments of a line, such that each individual's segment is equal in size to its fitness. A random number is generated and the individual whose segment spans the random number is selected. The process is repeated until the desired number of individuals is obtained (called mating population). This technique is analogous to a roulette wheel with each slice proportional in size to the fitness. Obviously, this selection mechanism cannot be used directly with a GA where negative fitness values are allowed. In order to employ roulette wheel selection in such situation, a transformation over the fitness values can be applied. Fig.3.7 shows an example of the proportional representation for a selection pool of ten individuals. Pseudo code for Roulette wheel algorithm is given in Fig.3.8.

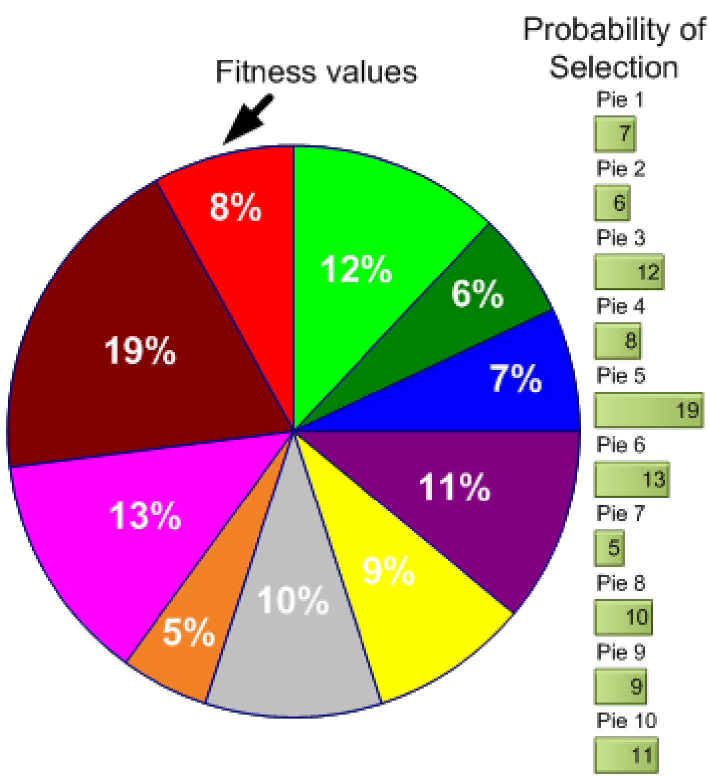


Figure 3.7: Roulette Wheel Selection

```
RouletteWheel (Population p) : returns an Individual
    Begin
    // first of all, calculate the sum of fitness values of all
    // individuals, if it is not known beforehand
        initialize Real fitnessSum as 0.0;
        for all Individual ind of population p, increase
        fitness Sum with the fitness value of ind;
        // randomly assign a value to determine
        // how much the wheel will turn
        assign Real threshold a random turn amount by
        fitnessSum * (a random real number from range
        [0.0, 1.0]);
        // find the partition where the ball on the wheel
        will stop
        initialize Real cumulative as 0.0;
        for each Individual ind of population p do
    begin
        increase cumulative by the fitness value of ind;
        if cumulative >= threshold then
        return ind;
        else
        continue with other individuals in p;
    end;
    end;
```

Figure 3.8: Roulette Wheel Selection Algorithm

The basic advantage of roulette wheel selection is that it does not discard any of the individuals in the population and provides a chance to all of them to get selected. Thus, it preserves the diversity in the population. That is, the individuals with not so high fitness also get a chance to transfer their genetic content to next generations. Some of these individuals may be hiding very valuable alleles. If it was not so, none of the gamblers would put their money into danger by selecting a slice on the wheel other than the widest one.

3.3.3. Tournament Selection

Tournament selection runs a "tournament" among *n* randomly chosen individuals in the population. The individuals are then ranked and one individual is selected based on a given probability distribution. That is, with probability p_1 choose the best individual in the tournament, with probability p_2 choose the second best, and so on. The parameter *n* represents the tournament size.

A variant of this method, referred to as deterministic tournament selection, always selects the best individual in any tournament.

Tournament Selection (**Population** *p*, **Integer** *tournament Size*) :
returns an **Individual**

begin

// select an individual randomly as the current winner

assign **Integer** *i* a random number in the range [0, (size of *p*) - 1];

initially set **Individual** *winner* as the i_{th} individual of population *p*;

// at each remaining tournament step, select an individual

// randomly. If it is better, update the the winner

initialize **Integer** *tournamentStep* as 1;

while *tournament Step* < *tournamentSize* **do**

begin

assign **Integer** *i* a random number in the range [0, (size of *p*) - 1];

if fitness value of the i_{th} individual of population *p* is better than fitness of the current *winner* **then** change *winner* as the *i*th individual of *p*;

increment *tournamentStep* by 1;

end;

return *winner*;

end;

Figure 3.9: Tournament Selection Algorithm

The pseudo-code given in Fig.3.9 illustrates this selection technique. In the pseudo-code given in Fig.3.9, an individual can be compared with itself, although this may sound weird in a real tournament. However, among all randomness in GA processes, this situation can simply be ignored.

Fig.3.10 shows an illustration of binary tournament selection. Two individuals are chosen randomly from the population to become competitors in a tournament selection. When maximizing, the individual with the higher fitness value becomes the contest winner and is selected as a parent. The procedure is repeated if two parents are required to form offspring solutions (the number of parents required is dependent on the exact formulation of the EA - an offspring solution could be produced by just one parent).

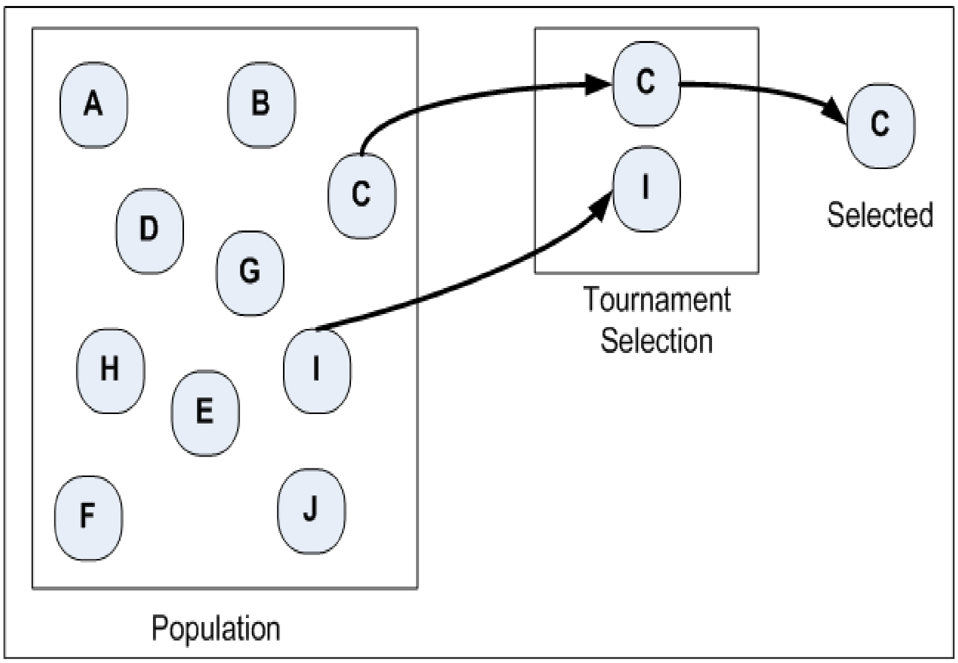


Figure 3.10: Binary Tournament Selection

3.4. Genetic Operators

Once two individuals have been selected as parents, a number of genetic operators are applied to their chromosomes to form new offspring.

The basic genetic operator is known as crossover or recombination. Like its counterpart in nature, crossover produces new individuals that have some parts of both parents' genetic material. Recombination through crossover can be severely disruptive to the candidate solutions and for that reason many researchers avoid the use of crossover altogether for some problems.

In nature, the features of an individual are contained in the genome. Since the genes interact with each other to create the different features, the genes themselves can be considered as Building Blocks [Gol02]. These building blocks can be recombined to form new and perhaps better features. Based on the fact that superior individuals must have had features that were superior, the building blocks of those individuals, must have been better than average.

Recombining these better than average building blocks should thus on average yield increasingly better features in the resulting individuals. This can also be realized from the following example:

Example 3.3 (Recombination) *In a group of herbivores, the individuals with the features such as primitive sight and/or smell would be better fit for finding food and avoiding predators than those without such abilities. If one of these herbivores with only primitive sight were to mate with an herbivore with a primitive sense of smell, they could give birth to an offspring with both those features which would make it more fit than either of the parents.*

3.4.1. Single/Multi-point Crossover

A basic type of crossover is known as 'single-point' crossover. A single-point crossover forces a break in the chromosomes of the parents so that each child obtains genetic information from each parent. In order to keep the population size constant, two children are produced from two parents.

The break is made randomly and one child gets the binary code of one parent to the left of the break, while the binary code to the right of the break comes from the other parent. The other child gets the opposite. Each child inherits certain traits from both parents in this manner. The procedure is best explained diagrammatically as in Fig.3.11.

In the chromosome shown, each gene has two possible values, 0 and 1, the set of valid values for each gene is known as the alleles. There are other types of crossover – multipoint crossover allows multiple breaks in the chromosome instead of a single break and uniform crossover gives a 50% chance of each allele coming from either parent. The disruptive nature of multi-point crossover appears to encourage the exploration of the search space, rather than favoring the convergence to highly fit individuals early in the search, thus making the search more robust [SJ91a].

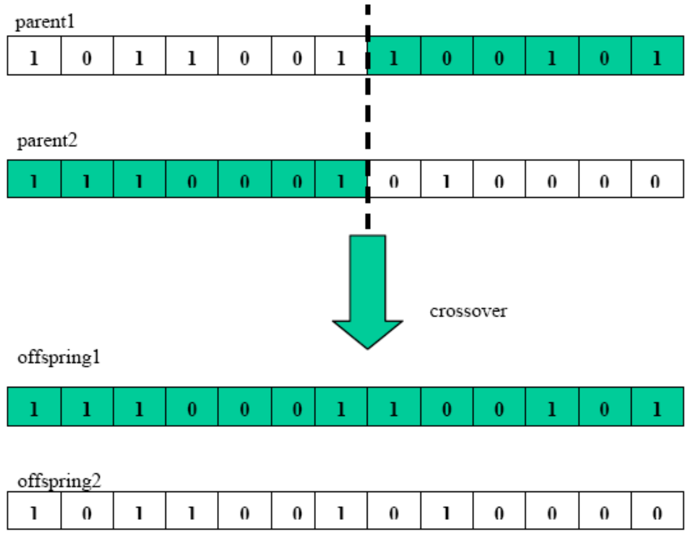


Figure 3.11: Single point crossover

Both single and multi-point schemes are equally applicable to both real valued and binary chromosomes. Many studies have demonstrated that single point crossover, although simple, does not perform well as the first and last genes can never be passed together to a child solution [Neu97].

3.4.2. Uniform Crossover

Another obvious alternative, which removes any bias, is to make the crossover process completely random—the so-called uniform crossover. Uniform crossover [Sys89] is a simple recombination scheme that makes every bit or value a potential crossover point. A binary string with the same length as the chromosome structures is created at random and the parity of the bits in the string indicates which parent will supply the offspring with which bits. Consider the following two parents P1 and P2, binary string S, and resulting offspring C1 and C2:

P1	=	1	1	0	0	1	1	0	1	0	1
P2	=	1	0	1	0	1	0	1	0	1	0
S	=	1	0	0	1	1	1	0	0	1	1
C1	=	1	1	0	0	1	1	0	1	1	0
C2	=	1	0	1	0	1	1	1	0	0	1

DeJong and Spears [SJ91b] produced a theoretical analysis that was able to characterize the amount of disruption introduced by a given crossover operator exactly. In particular, the amount of disruption in uniform crossover can be tuned by choosing different values of probability *p,* for the swapping of bits. This extra parameter can be used to control the amount of disruption during recombination without introducing a bias towards the length of the representation used. When uniform crossover is used with real-valued genes, it is usually referred to as discrete recombination.

Recombination is, however, not the only alteration that needs to be performed on the individuals.

This would only lead to an exploitation of building blocks already present in the initial population and not allow for new discoveries to take place. The issue can be solved by introducing mutations.

3.4.3. Mutation

After selection and crossover, mutations are also permitted in order to explore regions of the design space that may have already become extinct or have never been explored.

In GAs, mutation is randomly applied with low probability, typically in the range 0.001 and 0.05, and modifies elements in the chromosomes. Binary mutation is quite simple; it is done by flipping a bit from 0 to 1, or the other way around, according to a specific probability.

Mutation is often seen as a mechanism for ensuring the probability of searching any given string will never be zero. It also acts as a safety net to recover good genetic material that may be lost through the action of selection and crossover [Gol89]. Each new child solution is a candidate for mutation.

Example 3.4 (Mutation) *For an animal living in a dry environment, such as a desert, a mutation that will allow an individual to conserve water better or more efficiently would help in aiding the chances of survival. Counter to that is the case where a mutation could require the individual to use more water or at a faster rate, which would render the individual more vulnerable to the scarce presence of water in the dry environment.*

A creep mutation as shown in Fig.3.12, randomly selects a single bit to be changed (child 1) and a jump mutation swaps two random bits within the child's binary string (child 2).

Mutation is to be used cautiously as it can prevent population convergence if it is applied too often. It is important to mention that low mutation rate results in less exploration, while high mutation rate could be disruptive. With real-valued encoding, a mathematical operation is performed on values within the chromosome. The operation may be a simple multiplication or division and again, there are many different schemes available. For example one scheme may take a single value and change it to the maximum (or minimum) possible according to the range bounds for the variable. Others are subtler and may apply only a small change to the variable value.

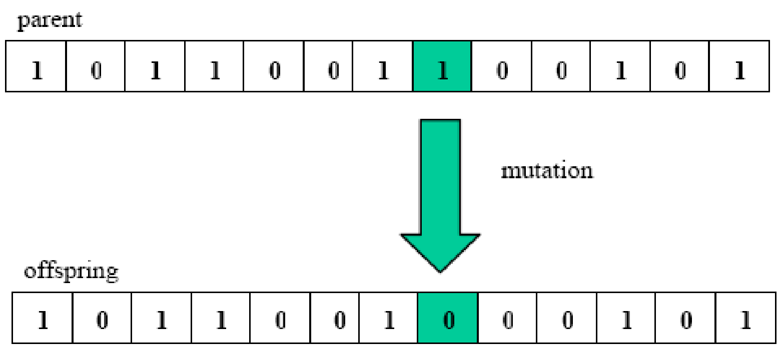


Figure 3.12: Illustration of mutation operation

Wright [Wri91] demonstrated how real-coded GAs may take advantage of higher mutation rates than binary-coded GAs, increasing the level of possible exploration of the search space without adversely affecting the convergence characteristics. Similarly, Tate and Smith [TS93] argued that for any genotypic coding containing alphabets more complex than binary, high mutation rates can be both desirable and necessary. They gave examples of how high mutation rates and non-binary coding yielded significantly better solutions than the normal, more conservative approach to mutation.

The exact mathematical operation (or inversion of bits) used is best chosen with regard to the type of chromosome encoding scheme used and the size of the search space.

It is often suggested that mutation has a somewhat secondary function, that of helping to preserve a reasonable level of population diversity-an insurance policy which enables the process to escape from sub-optimal regions of the solution space, but not all authors agree. Proponents of EP, for example, consider crossover to be irrelevant, and mutation plays the major role.

The advantage and the drawback of mutations is the unpredictability. Even though mutations can create new or improve on existing good features, they can also result in destruction of useful features or create unwanted features.

3.5. Reinsertion and Elitism

It is common to see fixed population sizes in EAs as they are easy to implement. Typically, the original population is completely replaced by the new offspring solutions and the EA is described as being steady-state [Sys91].

If fewer individuals are produced by recombination than the size of the original population, then the fractional difference between the new and old population sizes is termed a generation gap [JS93]. If one or more of the highest fitness individuals are deterministically allowed to propagate through successive generations, the GA is said to use an elitist strategy.

Elitist strategies compare the fitness values of a new generation with those of the previous generation. If the highest solution from the previous generation is higher than the best solution from the new generation, an individual from the new generation is removed and the previous best is inserted to replace it. This ensures the survival of the fittest rule applies between generations as well as within them. Haupt [HMM93] ensured elitism to occur by keeping the top 50% of each population during each generation, but this approach does not make an efficient search as their will be fewer new chromosomes contributing to the search in each generation.

Elitism is a useful function, particularly when search spaces are large and good solutions prove difficult to find and maintain in the population.

3.5.1. Termination

There are no set rules for termination of an EA. Termination criteria may be set at some given number of generations, or after some measure of convergence has been reached. Eventually, the population will tend to converge to a common point. The choice depends on the problem at hand. The basic termination criterion is when a user-specified computational budget is consumed. This budget can be measured in terms of the number of iterations or CPU time. This criterion of termination does not guarantee that a global optimum is found; it only returns the best solution found for the given budget.

An illustration of this convergence can be seen in human biological evolution. The Europeans and Africans each progressed down separate paths. The Europeans developed pale skin, while the Africans developed dark skin. These isolated populations are said to have converged because each individual, within the separated populations, holds a common trait. Technically, while Europeans lost the dark pigments from their skin, Africans maintained it – it helps to prevent sunburn and also reduces production of vitamin D.

The GA, as an optimization tool, can also arrive at this kind of convergence in design within its encoded design parameters. In practice, a standard GA should be run several times to account for this convergence and the inherent random processes. The initial creation of individuals, selection of parents, crossover reproduction, and child mutations are all based on random number draws. Different results can be expected between one initial randomization seed and another. On the other hand, these differences are not guaranteed and different seeds could end with the same results. It is good practice to record the seeds used to initialize random number generators so that the results found are repeatable.

It is common to simply stop a GA once a certain number of generations have been completed. Stopping the GA raises the question "Has the GA found the best possible solution to my problem?" and unfortunately, the only way to answer the question is to perform an ExS. A good practice to follow when deciding upon termination of the algorithm is to ask the question "Has the GA found a good solution?"

3.6. GA Flow Chart

The diagram shown in Fig.3.13 presents the steps involved in a basic GA. When applying a GA to a new problem, it is necessary to fine-tune some of the important settings in order to improve the overall performance. The number of individuals in a population is one such parameter. Too few individuals will restrict the search while too many will slow it down. The population size is usually balanced against acceptable run times. The other settings that influence performance are the probabilities of occurrence of the genetic operators (crossover and mutation).

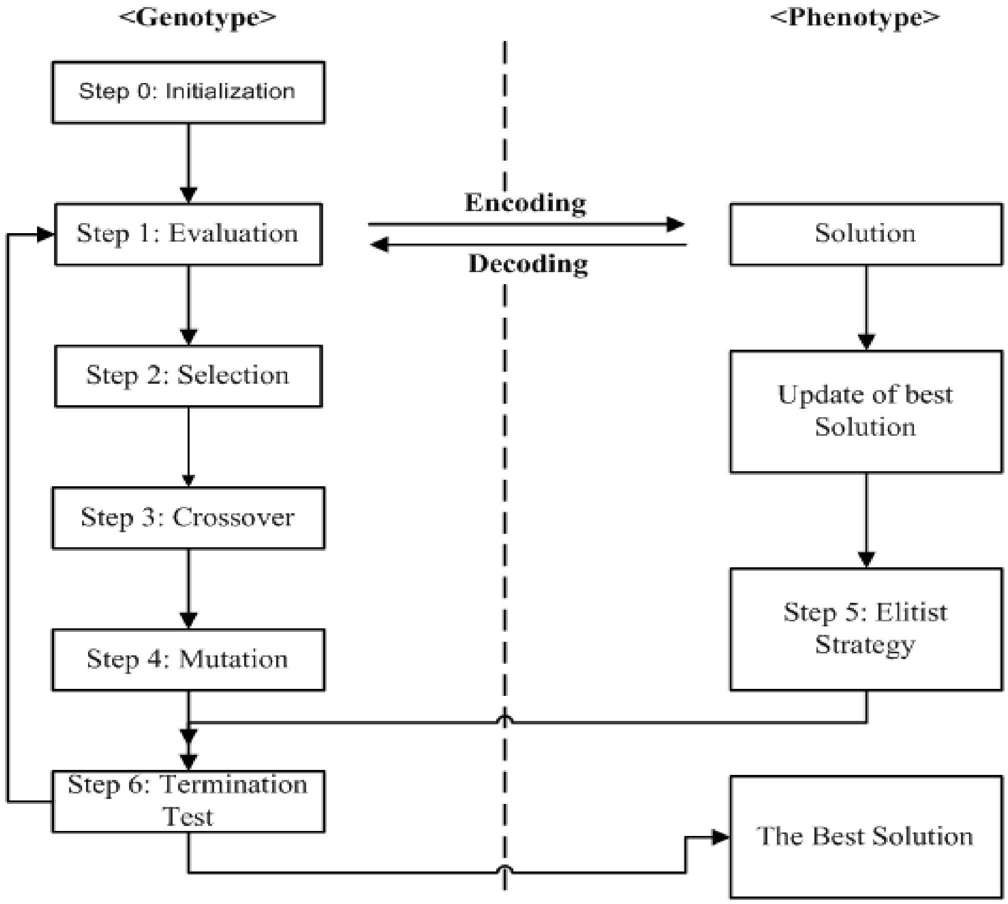


Figure 3.13: GA Flow Chart

Crossover and mutation occur with distinct probabilities defined at the start of the algorithm. Probability of crossover is usually kept at higher side as crossover is the main mechanism for exploration, set typically at 60 to 80%. Without crossover, the offspring created will be exact copies of their parents.

On the other hand probability of mutation is kept much lower as it can disrupt convergence. Typical values of probability of mutation are 1% to 5%. It should be noted that 100% mutation level will turn the algorithm into a random search.

3.7. Multi-Objective Genetic Algorithm

In this section, we consider an extension of GAs from single-objective optimization problems to the case of multi-objective optimization problems. Since Schaffer's work

[Sch85], extensions of GAs to multi-objective optimization were proposed in several manners (e.g., see Fonseca & Fleming [FF93, FF95], Horn et al.[HNG94], Kita et al.[KYMN96], Kursawe [Kur91], Murata & Ishibuchi [MI95], and Tamaki et al. [TMA$^+$94], TMA95]). The Italian economist Vilfredo Pareto in 1896 first stated the concept of 'Pareto optimality', which constitutes the origin of research in multiobjective optimization [Par96]. According to this concept, the solution to a multiobjective optimization problem is normally not a single value, but instead a set of values called the Pareto set. Many real-world problems involve simultaneous optimization of several incommensurable and often contradicting objectives. Examples of conflicting objectives may include maximizing speed and safety in a car, or keeping costs low and quality high in manufacturing. The problem considered in Chapter-6 is also a multiobjective variant of resource allocation problem in MIMO-OFDM systems. The two contradicting objectives here are rate maximization and power minimization. Application of a single objective GA that combines objectives in a single fitness function can only be expected to converge to a single solution.

When there is only one fitness function, it is possible to use the relations <, > and = to distinguish if one fitness value is better than another or if they are equal. As such, it is possible for the single fitness case to perform this comparison for all combinations of fitness values and based on this it can be determined which solution is better than others. However, as soon as each solution is assigned more than one fitness value, it is no longer possible to use these simple one dimensional relations and it is thus necessary to introduce a new way of determining which fitness value is better than another. This is where dominance comes into the picture.

In most of the cases, there is no single optimal solution to a problem, but instead a set of alternative solutions. These solutions are optimal in the wider sense such that no other possible solution in the search space is superior to them, considering all objectives. One can find some solutions which are good for one objective, but bad for another. This forces the designer to make a tradeoff from between the objectives. The set of all the possible optimal solutions is often called as a trade-off surface, or more precisely, a Pareto optimal set.

The basic scheme of GAs for single-objective optimization problems remains the same even for multi-objective optimization problems. That is, the coding method used for multi-objective optimization problems is exactly the same as described for single objective problems in Subsection 3.2. Genetic operators such as the crossover and the mutation also remain same as in Subsections 3.4. Only, the genetic operators such as evaluation, selection, and elitist strategy are required to be modified for multi-objective optimization problems. Before we describe modified genetic operators for multi-objective optimization problems, we first explain the background of multi-objective optimization problems followed by description of a MOGA.

3.8. Background of multi-objective genetic algorithms

The basic idea of MOGAs is to find set of all non-dominated solutions of an optimization problem with multiple objectives. Let us consider the following multi-objective optimization problem with *n* objectives:

$$\text{Maximize } f_1(\mathbf{x}), f_2(\mathbf{x}),..., f_n(\mathbf{x}) \tag{3.4}$$

where $\boldsymbol{x}$ is a vector to be determined, and $f_1(\cdot)$, $f_2(\cdot)$, ..., $f_n(\cdot)$ are *n* objective functions to be maximized. A particular solution which is not dominated by any other feasible solutions of the multi-objective optimization problem is known as a non-dominated solution.

Solution **x** is said dominated by the solution **y** if they satisfy following in-equalities

$$\forall i : f_i(x) \leq f_i(y) \text{ and } \exists\, j : f_j(x) < f_j(y). \tag{3.5}$$

Fig.3.14 depicts examples of non-dominated solutions. In Fig.3.14 open circles represent a set of dominated solutions while filled circles represent a set of non-dominated solutions, in a two-dimensional objective space, respectively. The two-dimensional objective space of Fig.3.14 corresponds to the following two-objective optimization problem:

$$\text{Maximize } f_1(x) \text{ and } f_2(x). \tag{3.6}$$

It can be observed from Fig.3.14 that, multi-objective optimization problems usually have more than one number of non-dominated solutions.

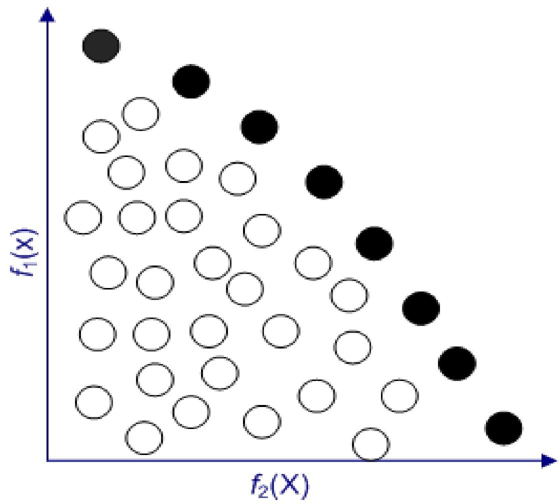


Figure 3.14: Non-dominated solutions (filled circles) and dominated solutions (open circles).

The purpose of any MOGAs is not to determine a single optimal solution but to find all the non-dominated solutions of the problem under consideration (equation.3.4). Since it is not possible to choose a single optimal solution for a multi-objective optimization problem without iterative interaction with the decision maker, generally the set of non-dominated solutions is shown to the decision maker. Then depending on the requirements the decision maker can chose one of the non-dominated solutions. Since Schaffer's work [Sch85], extensions of GAs to multi-objective optimization problems have been proposed in several manners. Fonseca & Fleming [FF95] have published an excellent survey of GAs for multi-objective optimization. Almost all the multiobjective optimization approaches which have been proposed till date can be categorized into two broad classes: a "population-based non Pareto approach" or a "Pareto-based approach" on the basis of their selection schemes [FF95].

An early GA application on multiobjective optimization by Schaffer [Sch85] opened a new avenue of research in this field. The algorithm, called vector evaluated genetic algorithm (VEGA), performs the selection operation based on the objective switching rule (population-based non Pareto approach), i.e., selection is done for each objective separately, filling equally portions of mating pool. Afterwards, the matting pool is shuffled, and crossover and mutation are performed as usual.

Fonseca and Fleming [FF95] proposed a Pareto-based ranking procedure (MOGA), where the rank of an individual is equal to the number of solutions found in the population where its corresponding decision vector is dominated. The fitness assignment is determined by interpolating the fitness value of the best individual (nondominated) and the worst one (most dominated).

Kursawe [Kur91] has also proposed a "population-based approach" where he suggested an idea to choose one of the *n* objectives according to the user-definable probability assigned to each objective.

Thus GAs have *n* search directions in Schaffer [Sch85] and Kursawe [Kur91]. We show the search directions of these approaches in Fig.3.15 for the case of the two-objective optimization problem in equation.3.6. It is clear from Fig.3.15 that, these approaches can easily find the solutions A and D, but it is not easy to find the solutions B and C.

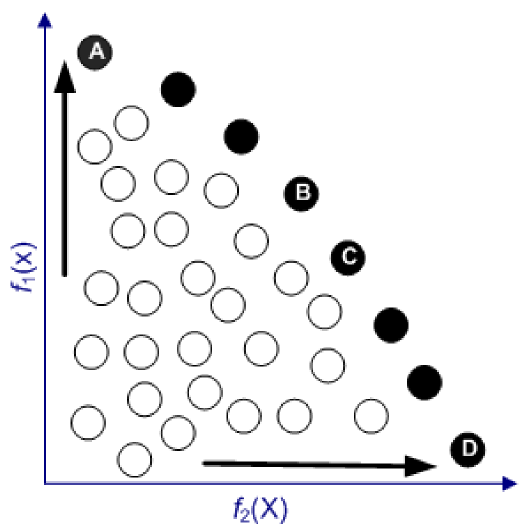


Figure 3.15: The search directions in Schaffer's approach and Kursawe's approach.

In order to make a GA to find all the possible non dominated solutions, it is required to keep a variety of individuals (i.e., solutions) in each generation.

The Niched Pareto genetic algorithm (NPGA) proposed by Horn, Nafpliotis, and Goldberg uses the concept of Pareto dominance and tournament selection in solving multi objective problems [HNG94]. In this method, a comparison set of T_{dom} individuals is randomly picked from the current population before the selection procedure. In addition, we choose two candidates from the current population that will compete to survive to the selection operation. For selecting the winner, these two candidates are compared with those T_{dom} of the comparison set using a non domination criterion given by the inequalities in equation.3.5 (when all objectives are to be maximized). If one candidate is dominated by the comparison set but the other is not dominated, the latter is selected for the crossover operation. If neither or both are dominated by the comparison set, a fitness sharing technique is adopted (for details, see [HNG94]).

3.8.1. Evaluation

The values of n objective functions are required to be evaluated, in order to find solutions of an n-objective optimization problem using GA. Using these values of n objective functions, the fitness value of each chromosome string is assigned. Here, GA is used to search a string with a higher fitness values in the genotype domain in way similar to single-objective optimization problems. A way to transform the values of objective functions to the fitness value of each string in the genotype domain is to combine the n objective functions into a scalar function as follows:

$$f(\mathbf{x})=w_1f_1(\mathbf{x})+w_2f_2(\mathbf{x})+\ ...\ +w_nf_n(\mathbf{x}) \qquad (3.7)$$

where $f(\mathbf{x})$ is the fitness function of $\mathbf{x}$, and $w_1,...,w_n$ are non-negative weights for the n objectives. These weights satisfy the following relations:

$$w_i \geq 0 \text{ for } i = 1,2,...,n \qquad (3.8)$$

$$w_1+w_2+\ldots+w_n=1 \qquad (3.9)$$

If we use constant weight values for the problem in equation.3.6 with two-objective functions, the direction in which GAs will search for solutions is fixed (Fig.3.16).

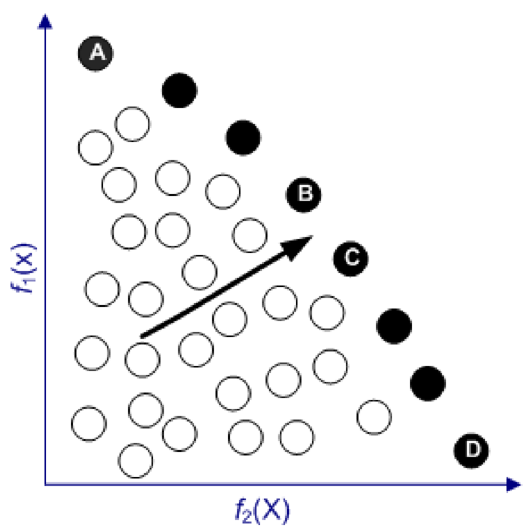


Figure 3.16: The search direction determined by the constant weight vector (w_1,w_2)= (0.5, 0.5).

From the above discussions, we can see that neither the constant weight value approach nor the choice of combining the objectives in to one objective is appropriate for finding all possible non-dominated solutions of the multi-objective optimization problem in equation.3.4. This is because a GA is required to search in various search directions in order to find a variety of non-dominated solutions. In order to realize various search directions, one can use randomly assigned weight values. The weight values can be assigned using following fuction:

$$w_i = random_i / (random_1 + \dots + random_n), \; i = 1, 2, \dots, n \tag{3.10}$$

where $random_1$, $random_2$, ..., $random_n$ are non-negative random real numbers (or non-negative random integers). The fitness function with various weights is utilized in the selection operator.

3.8.2. Selection

In order to select a pair of parent strings from current population **Ψ** for mating to generate an offspring, the n weight values (w_1, w_2, ...,w_n) are randomly generated using equation.3.10. Then the fitness value corresponding to each solution **x** in the current population **Ψ** is calculated as the weighted sum of the n objectives using equation.3.7. The selection probability $P_s(\mathbf{x}_i)$ of each string **x,** based on the linear scaling is defined by the roulette wheel selection as follows:

$$P_s(x_i) = \frac{f(\mathbf{x}_i) - f_{\min}(\boldsymbol{\psi})}{\sum_{j=1}^{N_{pop}} f(\mathbf{x}_i) - f_{\min}(\boldsymbol{\psi})}, \quad \text{for } i = 1,\ 2,\ \dots, N_{pop} \tag{3.11}$$

where $f_{\min}(\mathbf{\Psi})$ is the minimum fitness value (i.e., the worst fitness value) in the current population **Ψ** . According to this selection probability, a pair of parent strings is selected from the current population **Ψ**.

An offspring (i.e., a child string) is generated by crossing over of the selected pair of parent strings. Then a mutation operator is applied to this child string. For another pair of selected parent strings, separate n random weight values (w_1, w_2, ...,w_n) are used. That is, a different weight vector is used for each selection. Thus the selection in MOGA will have different search directions as shown in Fig.3.17.

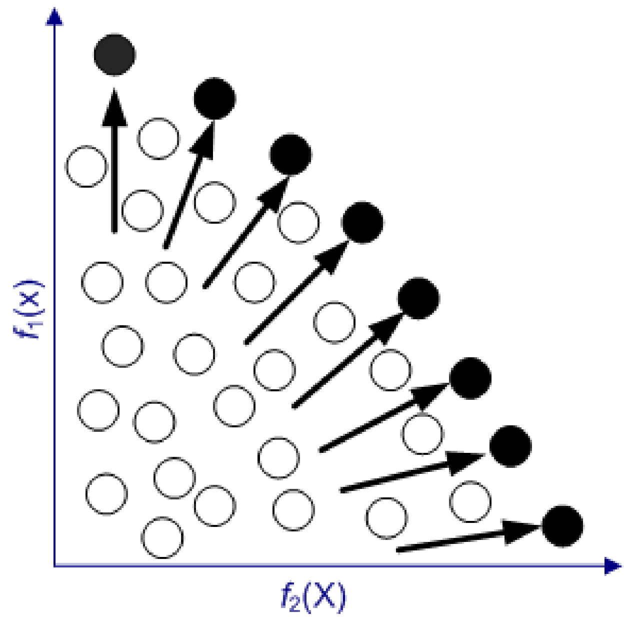


Figure 3.17: Various search directions of the MOGA.

3.8.3. Elitist strategy

During each execution of GAs for multi-objective optimization, two sets of solutions are usually stored: a current population and a tentative set of non-dominated solutions. After evaluating all the strings in the current population, the tentative set of non-dominated solutions is updated by the current population. That is, if any string in the current generated population is not dominated by any other strings in both the currently stored population and the tentative set of non-dominated solutions, then this string is added to the tentative set. This step is followed by elimination of all the solutions dominated by the newly added solution from the tentative set. In this manner, the tentative set of non-dominated solutions is updated in every generation of GAs for multi-objective optimization problems. From the tentative set of non-dominated solutions, a few solutions are randomly selected and added to the current population. The randomly selected non-dominated solutions may be viewed as a kind of elite solutions because they are added to the current population with no genetic operations applied on them. Update procedure of the current population and the tentative set of non-dominated solutions is illustrated in Fig.3.18.

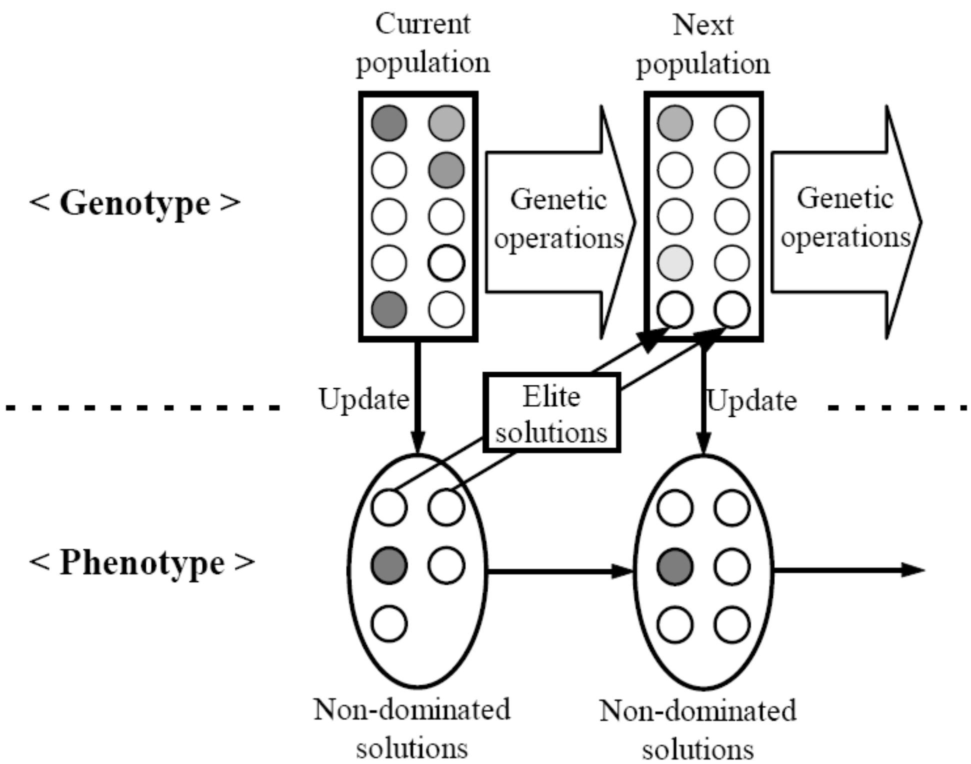


Figure 3.18: Update of the two sets of strings stored in the MOGA [MI95]

3.9. MOGA Flow Chart

In the previous section we considered some modified genetic operations such as evaluation, selection, and elitist strategy in order to construct a GA for multi-objective optimization problems. We can now construct MOGA by employing those operations for multi-objective optimization. The outline of the MOGA (Fig.3.19) can be written as follows:

Step 0 (Initialization): Randomly generate an initial population of N_{pop} strings where N_{pop} is the population size.

Step 1 (Evaluation): Decode strings to solutions in the phenotype world. Next calculate the values of the n objectives for each solution. Then update the tentative set of non-dominated solutions.

Step 2 (Selection): Repeat the following procedure to select parent strings to generate N_{pop} strings.

(i) Randomly specify the weight values w_1, w_2, ...,w_n in the fitness function equation.3.7 by equation.3.10.

(ii) According to the selection probability in equation.3.11, select a pair of parent strings.

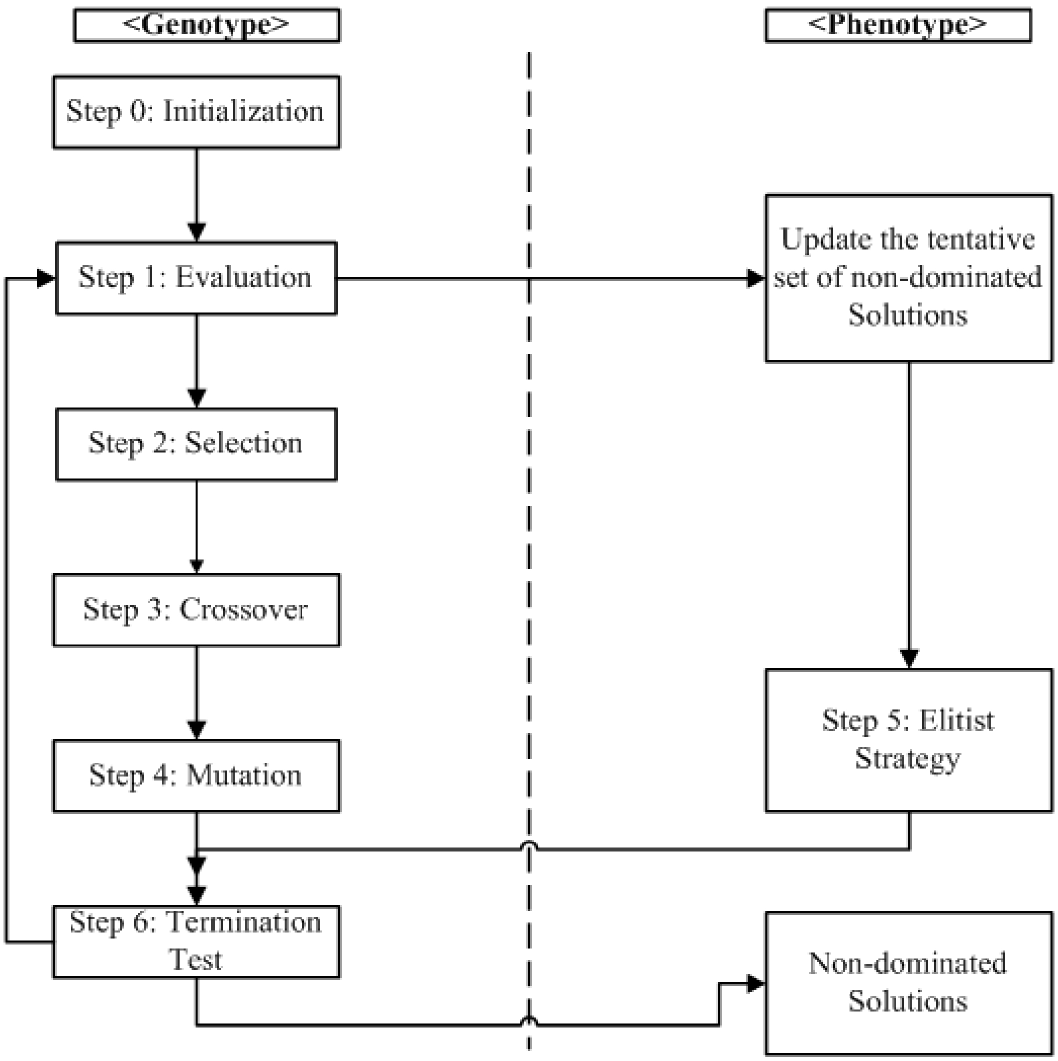


Figure 3.19: Outline of the MOGA.[Deb01]

Step 3 (Crossover): Apply a crossover operator to each of the selected pairs in Step 2, with crossover probability P_c.

Step 4 (Mutation): Apply a mutation operator to each of the generated strings with mutation probability P_m .

Step 5 (Elitist strategy): Randomly remove N_{elite} solutions from the generated N_{pop} solutions, and add N_{elite} solutions that are randomly selected from the tentative set of non-dominated solutions.

Step 6 (Termination test): If a pre-specified stopping condition is satisfied, stop this algorithm. Otherwise, return to Step 1.

3.10. Conclusion

Optimization tools must be flexible, robust and acceptably efficient in order to tackle real world problems. In this chapter the basics of EAs as optimization tool were discussed. Potential of EAs and there comparisons with other optimization techniques for solving real world problems was discussed in detail. It was shown through examples that EAs can be adapted to perform numerical optimization tasks in situations where conventional approaches have proven inadequate. Specifically GAs were shown to be flexible with many different representations and operator sets developed, and to be sufficiently robust and reliable to allow their use in real world applications.

Since the problem at hand is a multiobjective problem with the two contradictory objectives. It was discussed how the usual practice of treating multi-objective optimization problems by scalarizing them into a single objective is not always suitable for real world problems. It was also discussed in detail that a multiple objective problem will not result in a single optimal solution but a number of Pareto-optimal solutions. In this chapter, we compared the methodology adapted in MOGA in comparison to single objective GA.

With this foundation, it is thus possible for the reader to get a better understanding of why EA is such a promising tool when it comes to solving real world engineering problems.

Chapter-4

Resource Allocation in OFDMA Systems using PSO

4.1. Introduction

OFDM is a promising modulation technique which mitigates the effect of frequency selective fading, inherent in high data rate environments. OFDM is essentially a type of multicarrier modulation scheme based on the idea of dividing a given high-bit-rate data stream into several parallel lower bit-rate streams, and modulating each stream on separate carriers-often called subchannels or tones. Multicarrier modulation schemes eliminate or minimize ISI by making the symbol time large enough so that the channel-induced delays would be an insignificant fraction of the symbol duration. Therefore, in high-data-rate systems in which the symbol duration is small, being inversely proportional to the data rate, splitting the data stream into many parallel streams would increase the symbol duration of each stream such that the delay spread is only a small fraction of the symbol duration.

OFDM is used in WLANs, and can support high data rate transmission. It can also be used for multiple accesses [TV05, Law99]. Multiuser OFDM also known as OFDMA adds multiple access to OFDM by allowing a number of users to share an OFDM symbol. OFDMA can take advantage of channel diversity among users in different locations by adaptively assigning subchannels depending on channel characteristics. This approach allows efficient use of all the subchannels.

Resource allocation in OFDMA [WCLM99, WSEA04, KPL06, JL03, SRDS08, GAS07, Red07, TZWZ07, SAE05, SAE03, HA10, HA11, Isl11] includes subchannel allocation, power allocation, and bit loading. The development of efficient resource management techniques for such a setup has drawn enormous attention in recent years. Solutions to the resource allocation problem in OFDMA have been broadly divided into two categories: Margin Adaptive (MA) and Rate Adaptive (RA) [SAE03]. Resource allocation was tackled in [WCLM99] using the MA scheme, wherein an iterative subchannel and power allocation algorithm was proposed to minimize the total transmit power, given a set of fixed user data rates and the BER requirements. In [JL03] the rate adaptive method was used, wherein the objective was to maximize the total data rates over all users subject to power and BER constraints. It was shown in [JL03] that in order to maximize the total capacity, each subchannel should be assigned to the user with best gain on it. However, no consideration was given to the fairness of allocation among the users, which could leave some users with low channel gains, without any channel being allocated to them. In [WSEA04, SAE05, SAE03], proportional fairness was incorporated by imposing a set of nonlinear constraints into the optimization problem. GAs, which are a class of EAs, were used in [SRDS08, GAS07, Red07, TZWZ07] for resource allocation. In this chapter the use of the PSO technique, which is a bio-inspired EA, has been proposed for subchannel allocation followed by WFA [PF05] for power allocation among the users.

4.2. OFDMA Model

We considered an OFDMA system with K users and N subchannels, shown in Fig.4.1. Serial data from all the users was fed into the resource allocation block at the transmitter, which then allocated bits from different users to different subchannels. It was assumed that each subchannel would have a bandwidth that is much smaller than the coherence bandwidth of the channel and that the instantaneous channel gains on all the subchannels of all the users would be known to the transmitter. Using this channel information, the transmitter would apply the subchannel, bit, and power allocation algorithm to assign different subchannels to different users and the number of bits/OFDM symbol to be transmitted on each subchannel. Depending on the number of bits assigned to a subchannel, the adaptive modulator would use a corresponding modulation scheme, and the transmit power level would be adjusted according to the subchannel, bit, and power allocation algorithm. The principle behind adaptive modulation is simple: transmit at as high a data rate as possible when the channel is good, and at a lower rate when the channel is poor, thus limiting the number of dropped packets. Each user's data would be distributed across the set of subchannels assigned to the user. The assumption was that each subchannel would be uniquely assigned to a single user and two or more users would never share the same subchannel.

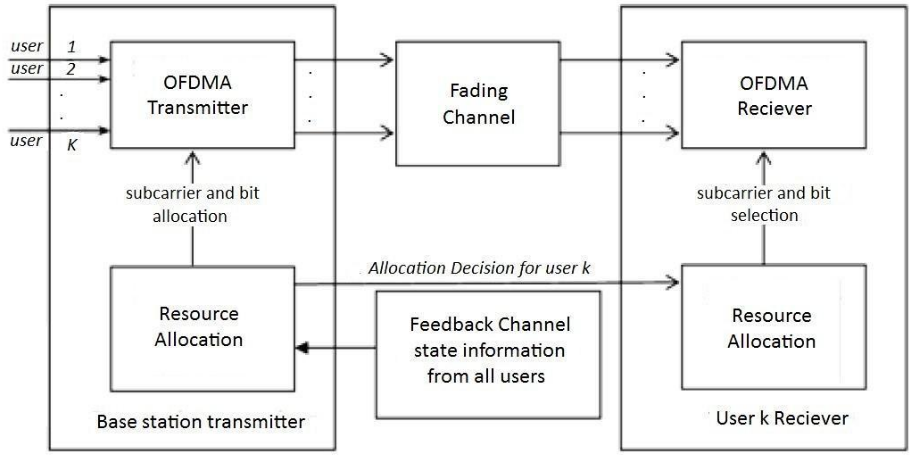


Figure 4.1: OFDMA system Model

The optimization problem was formulated on the same lines as in [SAE03]. The subchannels and power would be allocated in such a way that the total error free capacity would be maximized while satisfying the total power constraint (P_{tot}).

The optimization problem could hence be postulated as follows:

$$\max_{\rho_{k,n},p_{k,n}} \sum_{k=1}^{K}\sum_{n=1}^{N}\frac{\rho_{k,n}}{N}\log_2\left[1+\frac{p_{k,n}h_{k,n}^2}{N_o\frac{B}{N}}\right] \tag{4.1}$$

Subject to the constraints:

$$C_1: \quad \sum_{k=1}^{K}\sum_{n=1}^{N} p_{k,n} \le P_{tot}$$

$$C_2: \quad p_{k,n} \ge 0 \quad \forall\ k,n$$

$$C_3: \quad \rho_{k,n} \in \{\ 0,1\ \}\ \forall\ k,n$$

$$C_4: \quad \sum_{k=1}^{K}\rho_{k,n} = 1\ \ \forall\ n$$

$$C_5: \quad R_1 : R_2 : R_3 .... : R_k = \Phi_1 : \Phi_2 : \Phi_3 : ...... : \Phi_1, \forall i, j \in \{1,....,K\}; i \ne j$$

In equation.4.1 N_o is the power spectral density of AWGN, B is the total available bandwidth and $h_{k,n}$ is the channel gain for user k in subchannel n. In C_1, P_{tot} is the total available power and $p_{k,n}$ is the power allocated for user k in the subchannel n. According to C_3, $\rho_{k,n}$ can only be either 1 or 0, indicating whether subchannel n is allocated to the user k or not. C_4 restricts allocation of one subchannel to one user only. C_5 is the proportional rate constraint where $\Phi_1 : \Phi_2 : \Phi_3 : \ldots\ldots\ldots : \Phi_k$ are normalized proportionality constants and $\sum_{k=1}^{K} \Phi_{k,n} = 1$. We relaxed this fairness criteria with more emphasis on the fact that all users should get at least one channel, so that $\sum_{n=1}^{N} \rho_{\mathrm{k,n}} \geq 1, \forall k$ .The capacity for user k, denoted as R_k, is defined as

$$R_k = \sum_{n=1}^{N} \frac{\rho_{k,n}}{N} \log_2 \left[1 + \frac{p_{k,n} h_{k,n}^2}{\mathrm{N_o} \dfrac{B}{N}} \right] \tag{4.2}$$

Note here that the rates defined in equation.4.1 and equation.4.2 are rates per Hertz of bandwidth, i.e. they have units of bits/sec/Hz.

4.3. Related Work

The resource allocation problem in equation.4.1 is an NP-hard combinatorial optimization problem with non-linear constraints. Hence, it is highly improbable that the problem could be solved optimally using polynomial time algorithms. An optimal solution would require joint allocation of power and subchannels to the users. There are few instances where subchannel and power were jointly allocated using MOGAs like NSGA-II [SRDS08]. Because of high computational complexity involved, such multi-objective algorithms may not be suitable for real time applications. Furthermore, the BS would have to rapidly compute the optimal subchannel and power allocation if the wireless channel changes quickly. Hence suboptimal algorithms with lower complexity would be preferred for cost-effective implementations. Separating the subchannel and power allocation is a way to reduce the complexity since the number of variables in the objective function is almost reduced by half.

In this chapter we propose the use of PSO algorithm, which belongs to the class of heuristic search algorithms. To justify the use of PSO as compared to GAs for the resource allocation problem under consideration, we shall briefly introduce and compare them on the basis of their working principle.

PSO is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by the social behavior of bird flocking or fish schooling [KE95]. The primary motivation of GAs has been the principles of evolution and genetics. PSO shares many similarities with evolutionary computation techniques such as GAs. The system is initialized with a population of random solutions and searches for optima by updating generations using a combination of deterministic and probabilistic rules. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. PSO has been successfully used to solve highly non-linear mixed integer optimization problems in various domains of engineering. In [AK12] and [RNS09], two swarm intelligence based algorithms, a modified version of the Artificial Bee Colony algorithm and Gravitation Search Algorithm (GSA), were introduced respectively. In GSA the members of the population interact with each other based on the Newtonian gravity and the laws of motion. The algorithm in [AK12] was used efficiently for solving real-parameter optimization problems. The authors in [SLGZ10] proposed a novel variant of PSO called cellular particle swarm optimization, and explored how particle swarm works in the view of cellular automata. Extensive use of ACO, another bio-inspired algorithm, has been done at the network layer of communication systems for solving routing problems. However implementation of such algorithms has not been done extensively in the physical layer. MOGA was used in [SRDS08] to solve the resource allocation problem. However its high computational cost has been its major drawback. It was statistically proven in [HCWV05], that PSO is computationally more efficient than GA for similar results. This is primarily because PSO has fewer parameters to adjust. In PSO, the population size, the inertial weight and the acceleration constants summarize the parameters to be selected and tuned, whereas in GA the population size, the selection, crossover and mutation strategies, as well as the crossover and mutation rates influence the results. In [CMM+10] it was shown that PSO outperforms GA in a practical engineering application pertaining to trajectory tracking controller.

Wireless channels are highly dynamic, thus resulting in the channel characteristics changing in short intervals of time. Thus the channel gains of users for various subchannels change frequently. This demands a new allocation pattern of subchannels in order to maximize the sum capacity. Thus quick allocation of the subchannels is a highly desired characteristic of the allocation algorithm. Being computationally less expensive than GA, PSO is better placed to quickly arrive at an optimal allocation. PSO has been used earlier in [AZC+11] for adaptive equalization of channels and in [KS10] for interference reduction through beam-forming and power control in wireless communication systems.

The PSO algorithm was used to solve the Resource allocation problem in [GAS07] through MA allocation. However, fairness among the users was not considered. In the case of large path loss differences among users, 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. Because of this, the users with lower average channel gains may not be able to transmit any data due to non allocation of subchannels to them. In this chapter, the use of PSO for RA resource allocation has been proposed. The proportional fairness among the users is also enforced by ensuring that at least one subchannel is made available to each user.

As compared to other optimization techniques, the Swarm intelligence based systems are very flexible and robust with respect to environmental constraints and disturbances which make them very attractive for technical realizations [RW03]. Moreover, swarm intelligence inherits some important advantages such as:

- *Scalability:* The number of individuals can be adapted to the network size.
- *Fault tolerance:* Since the behavior of a swarm is not controlled by a centralized entity, the loss of a few individuals does not cause catastrophic failure.
- *Adaptation:* The swarm can react to environmental changes due to the fact that each individual has the ability to adapt. This leads to a high value of flexibility.
- *Speed:* Changes in the network can be spread very quickly among network users.
- *Modularity:* Individuals act independently of other network layers.

- *Autonomy:* Little or no human control is required. This decentralized or agent-based aspect leads to a much greater speed of convergence.
- *Parallelism:* Operations of individuals are executed in a parallel manner.

4.4. Resource allocation in OFDMA system using PSO

PSO is a bio-inspired algorithm which derives its core motivation from the concept of Swarm intelligence. In nature we find many insects which live in colonies and carry out complex social activities in an efficient and highly optimized pattern. This bio-intelligence is referred to as Swarm intelligence, which forms the core of PSO. These algorithms are particularly used when the solution space to be scanned is huge and the time constraint to arrive at near optimal solution is rigid. Linear search of the entire solution space would not be computationally feasible because of the time constraint. Hence these algorithms are particularly efficient when the parameters in problem are highly dynamic. Swarm intelligence techniques have already effectively been used in other fields of engineering [TY09]. Comparing to other algorithms, PSO has higher global-optimization capability, depends on less parameters and is computationally efficient in solving large scale mathematical optimization problems. PSO also has faster astringency in most optimization problems [KE01]. In the PSO algorithm a set of virtual particles are initialized to a set of solutions in the hyperspace. The hyper space is a geometrical visualization of the solution space with various variable parameters corresponding to the various dimensions. The movement of these particles in the hyperspace leads to their convergence to the most optimal position. The maximum capacity is achieved when each channel is assigned to the user having maximum gain for that channel but the fact that channel gains, especially in wireless applications, are highly dynamic with respect to user as well as time, makes rapid optimum allocation infeasible when using the traditional methods. The PSO algorithm does not search the solution space linearly [GAS07]. Therefore the possibility of finding an optimum solution before exhausting all possibilities is high. Assuming that the order of iterative optimization for E elements in the average case consists of two parts $O(E)*O(\xi(E))$, the complexity order using PSO [GAS07] will reduce to $O(\mathrm{Log}E)*O(\xi(E))$, where the $O(\mathrm{Log}E)$ corresponds to number of iterations required to reach optimal solution and the $O(\xi(E))$ corresponds the complexity of the optimization logic applied. Our customized PSO aided algorithm arrives at a near optimum solution with acceptable computational complexity.

The algorithm is initialized with a population of N_p particles which are capable of spanning the hyperspace. Each particle is defined by a position vector and velocity vector in the hyperspace and also carries with it the memory of its best position so far (local best) and also the best position taken by the entire population so far (global best). Each position is a possible input to the fitness function. Consequently, a position yielding a higher fitness value is deemed better than one giving a lower value. The guiding equations of the algorithm attempt to converge the particles towards the global maximum and one shift of each member of the population is considered as one iteration.

The PSO algorithm in [Yhe08] was customized to make it feasible for application in the OFDMA system model. It assumes a continuous hyperspace with all positions of the particle being acceptable. However in our customized algorithm the position vector of each particle represents an allocation of subchannels. For example, a position vector [a b c d] would mean that the first channel is allocated to the user 'a' and the second channel to user 'b' and so on. All such position vectors represent feasible solution points in hyperspace of N dimensions and are discrete in nature. So in each generation, the particle would be moved to the discrete position nearest to itself in the hyperspace after updating the position vector. Also the criteria of fairness would ensure that in each solution at least one subchannel is granted to each user. The velocity of the particles represented the speed with which the particles converged (referred to as swarming) to the global optimum point (allocation). This has a direct bearing on the computational complexity of the algorithm.

Notations used are as follows:

D: The total number of dimensions. Each particle is defined by a position and velocity vector consisting of the values in all dimensions. Since each position vector is a possible subchannel allocation the number of dimensions is equal to the number of subchannels. So $D = N$ (total number of subchannels).

N_p: The number of particles (population). It is also referred to as the number of bees.

T: The number of generations (iterations).

$r_{p,i,j}$ and $r_{g,i,j}$: The random number uniformly distributed in [0, 1] used for the j^{th} dimension of i^{th} particle $i=1,2,....N_p$; $j=1,2,......D$.

c_p, c_g: The cognition learning factor and the social learning factor.

w: The inertia weight function. Takes value between 0.1 and 0.9.

$x_{t,i,j}$: The j^{th} dimension of the position of particle i, at iteration t where t=1,2,……T; $i=1,2,....N_p$ and $j=1,2,......D$.

$\mathbf{X}_{t,i}$: $\mathbf{X}_{t,i} = (x_{t,i,1}, ... x_{t,i,D})$ is the position vector of particle i at iteration t. Each position vector has the values of all dimensions of that particle, where t=1,2,…T, i=1,2,....N_p and j=1,2,……D. Each position vector represents a possible allocation of subchannels.

$v_{t,i,j}$: the j^{th} dimension of the velocity vector of particle i at iteration t, where t=1,2,……T ; i=1,2,….N_p and j=1,2,……D.

$\mathbf{V}_{t,i}$: $\mathbf{V}_{t,i} = (v_{t,i,1}, ... v_{t,i,D})$ is the velocity vector of particle i at iteration t, which also has D dimensions, where $t=1,2,......T$; $i=1,2,....N_p$ and $j=1,2,......D$.

$\mathbf{P}_{t,i}$: $\mathbf{P}_{t,i} = (p_{t,i,1}, ... p_{t,i,D})$ is the best position of particle i so far until iteration t, called the $\mathbf{P}_{best}$ for that particle, i.e. it gives highest value of fitness function among all positions taken so far where $t=1,2,......T$; $i=1,2,....N_p$ and $j=1,2,......D$.

$\mathbf{G}_t$: $\mathbf{G}_t = (g_{t,1},.....g_{t,D})$ the best solution among $\mathbf{P}_{t,1}$, $\mathbf{P}_{t,2}$, …. $\mathbf{P}_{t,N_p}$ at iteration T. It is called $\mathbf{G}_{best}$. Hence $\mathbf{G}_{best}$ is position vector that gives highest value of fitness function attained so far in all particles and in all iterations up to current iteration (iteration t) where $t=1,2,......T$.

$F(\bullet)$: The fitness function value of •. The • is a position vector of the particle whose fitness function is to be calculated. Fitness function is sum rate of OFDMA system.

U(•), L(•): A vector (of length D) specifying upper and lower bounds for all dimensions of •. Here • stands for position vector or velocity vector. In case of the position vector, the lower and upper bounds of the dimensions are equal to 1 and the number of users (K) respectively.

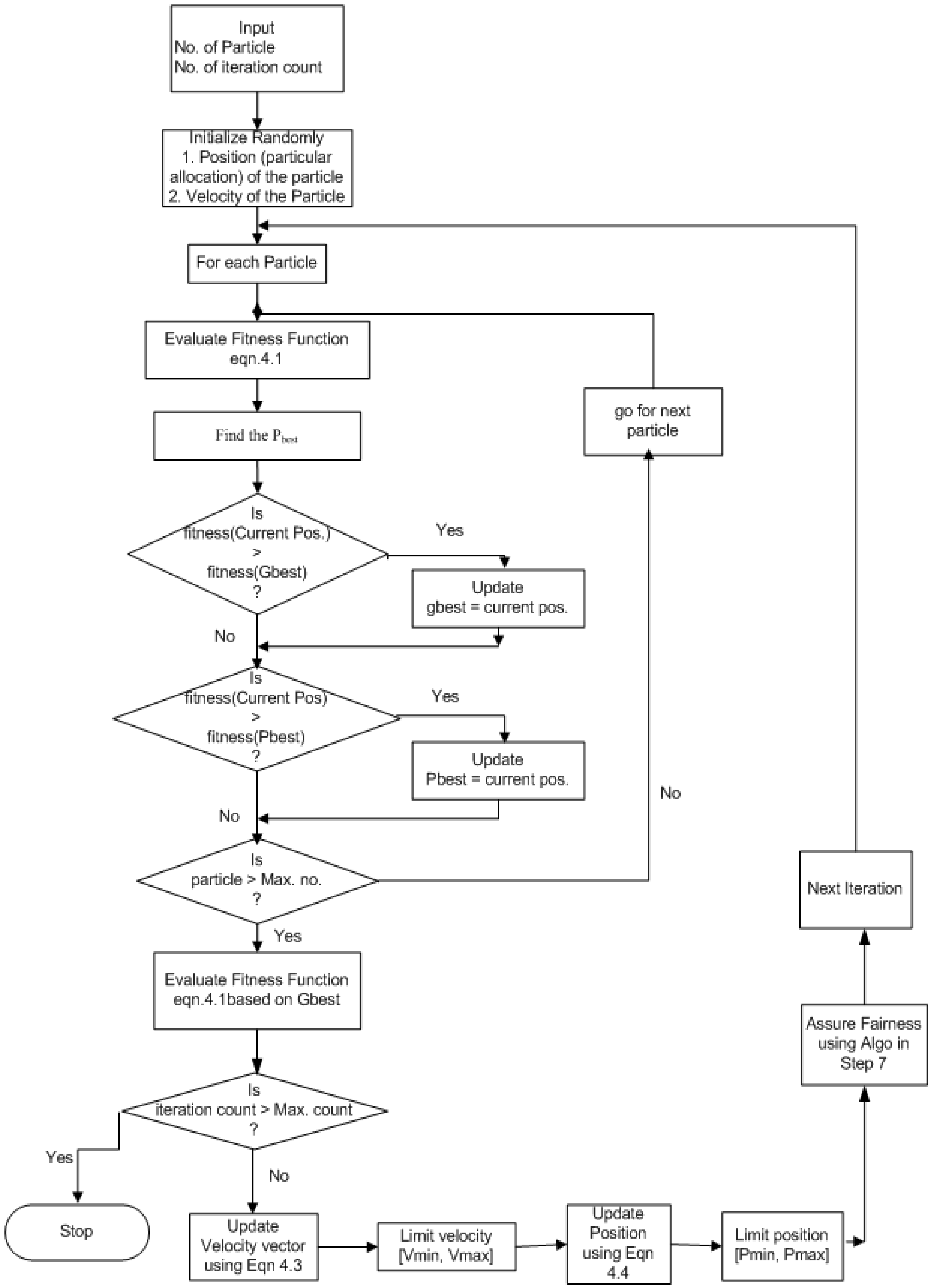


Figure 4.2: PSO Algorithm Flow chart

The steps in the algorithm are as follows:

STEP 1: Initialize parameters and population with random positions and velocities such that each position gives a particular allocation of all the subchannels.

STEP 2: Evaluate the fitness value (the desired objective function giving sum rate of OFDMA system) for each particle.

STEP 3: Find the P_{best}: If the fitness value (sum rate) of particle *i* is better than its best fitness value (P_{best}) in history, then set the P_{best} to the current fitness value. Repeat this step for all particles.

STEP 4: Find the G_{best}: If any P_{best} is updated and is better than the current G_{best} then update G_{best}.

STEP 5: Calculation of velocity vector: Calculate velocity vector for each particle according to following equation:

$$v_{t,i,j} = wv_{t-1,i,j} + c_p r_{p,i,j}(p_{t-1,i,j} - x_{t-1,i,j}) + c_g r_{g,i,j}(g_{t-1,j} - x_{t-1,i,j}) \tag{4.3}$$

Adjust the velocity vector to meet its range if necessary using L(V) and U(V).

STEP 6: Calculation of position vector: Using the corresponding velocity vector move each particle to the next position according to the following equation.

$$x_{t,i,j} = x_{t-1,i,j} + v_{t,i,j} \tag{4.4}$$

Adjust the position vector to meet their range if necessary using L(X) and U(X). Move the particle in the *N* dimensional hyperspace to a discrete position nearest to itself. On ensuring that the position of each particle of population is discrete, go to step 7.

STEP 7: After step 6, certain particles may represent solutions which are feasible but still unacceptable due to the fairness criteria. The fairness criteria was relaxed with more emphasis on the fact that all users should get at least one channel. Hence to ensure fairness in the algorithm the following steps were taken for each particle of current generation:

a) Define following sets for each particle using its position vector :

   A: {i | i is the user having no subchannel allocated to it}

   B: {j | j is the user having more than one subchannel allocated to it}

   C_k :{ s | s is the subchannel allocated to user *k*}

b) While A $\neq \mathbf{\Theta}$ (null set)

i) Find k satisfying $R_k / \Phi_k \ge R_j / \Phi_j \quad \forall j \in B$

ii) For the found k, find n satisfying $\left|h_{k,n}\right| \le \left|h_{k,s}\right| \quad \forall s \in C_k$

iii) For the found n, find m satisfying $\left|h_{m,n}\right| \ge \left|h_{i,n}\right| \quad \forall \mathrm{i} \in A$

iv) For the found k, n and m, $C_k = C_k - \{n\}$, $C_m = C_m + \{n\}$ and $A = A - \{m\}$ update set B

v) Update the position vector by setting $\mathbf{x}_{t,u,n} = m$, where u is the particle for which the steps are being currently implemented (u=1, 2, 3……N_p)

Carrying out the above steps for all particles ensured that they moved in the hyperspace to points which are both feasible and acceptable locations.

STEP 8: Stopping criterion: If the maximum number of iterations is reached, then stop; otherwise go back to STEP 2.

4.5. Results

Assumptions and Constants:

For various constants required in the calculation, their accepted values [SAE03] were used:

N (Number of subchannels)	64
N_o(Power Spectral Density of Noise)	1.1565×10^{-8} W/Hz;
B(Bandwidth)	1 MHz;
P_{tot}(Total Power)	1W

Channel gains of the users on the subchannels have a Rayleigh distribution [SAE03]. This channel gain matrix is generated once and kept constant throughout the simulations.

PSO Parameter Tuning

The main parameters of the canonical PSO model are w, c_p, c_g, maximum velocity $V_{\max}$ and the population size (swarm size) S. The fine tuning of these parameters determine how it optimizes the search-space. For instance, one can apply a general setting that gives reasonable results on most problems, but seldom is very optimal. Since the same parameter settings not at all guarantee success in different problems, we must have knowledge of the effects of the different settings, so that we can pick suitable parameters for any problem.

For instance, the inertia weight w controls the momentum of the particle: if $w << 1$, only little momentum is preserved from the previous time-step; thus quick changes of direction are possible with this setting. The concept of velocity is completely lost if $w = 0$, and the particle then moves in each step without knowledge of the past velocity. On the other hand, if w is high (>1) we observe the same effect as when c_p and c_g are low: Particles can hardly change their direction and turn around, which of course implies a larger area of exploration as well as a reluctance against convergence towards optimum. Usually c_p equals to c_g and ranges from [0, 4].

The maximum velocity V_{max} determines the maximum change one particle can undergo in its positional coordinates in each iteration. Usually we set the full search range of the particle's position as the V_{max}. However, with the use of w in the velocity update formula (as in equation.4.3), tuning V_{max} to some extent has become unnecessary; at least convergence can be assured [CK02] without proper tuning of V_{max}.

It is quite a common practice in the PSO literature to limit the number of particles in the range 10‑60. Van den Bergh and Engelbrecht [BE01] have shown that though there is a slight improvement of the optimal value with increasing swarm size, a larger swarm increases the number of function evaluations to converge to an error limit. Eberhart and Shi [ES00] illustrated that the population size has hardly any effect on the performance of the PSO method. This fact was verified through simulation and the detailed analysis is presented in section 4.5.4.

Considering the above facts, we applied parameter tuning only for w, c_p and c_g. Following ranges, based on literature survey were used for these parameters:

_w three levels: (0.2, 0.4 and 0.6)

_$c_p = c_g$ three levels: (1, 2 and 3)

Based on the range of parameters selected, PSO algorithm effectively has two parameters, and each parameter has three levels; hence, we have 09 different conditions.

In order to have more comprehensive analysis, each of these 09 conditions for PSO, were simulated 10 times each, for all cases of the problem set under consideration.

Each set of simulations was allowed to run for 100 iterations. The simulation results showed that the PSO algorithm performs better in terms of convergence and capacity for $c_p = c_g = 2$ and $w = 0.2$. Moreover, there was very slight improvement in capacity after 40 iterations, when these parameters were used for simulation. Hence these parameters were used for the rest of the simulations.

4.5.1. Sum Capacity vs. Number of Users

Table 4.1 and Fig.4.3 show the variation of average sum capacity with the number of users, for a fixed number of subchannels (N=64). The Population (set of possible subchannel allocations) size was also fixed to 12 bees and maximum number of iterations was restricted to 40. The algorithm was executed 100 times for each set of users and then the average of sum capacity was calculated. It is evident from Fig.4.3 that the use of PSO for subchannel allocation for OFDMA systems has consistently higher sum capacity than the method in [SAE03]. The average capacity gain of about 20% was obtained over method in [SAE03].

Table 4.1: Variation of sum capacity with number of users

Users(K)	Sum capacity (bits/s/Hz)			
	PSO (32)	PSO (64)	[SAE03](64)	PSO (128)
2	4.62	4.59	4.42	4.57
4	4.69	4.68	4.50	4.65
6	4.77	4.75	4.57	4.72
8	4.87	4.82	4.96	4.79
10	4.89	4.87	4.62	4.85
12	4.93	4.92	4.64	4.89
14	4.99	4.98	4.65	4.94
16	5.07	5.00	4.66	4.99

Moreover, as the number of users increases, the sum capacity also increases; this is because of added multiuser diversity gain. Multiuser diversity is obtained by opportunistic user scheduling at either the transmitter or the receiver. The effect of multiuser diversity is predominant in systems with large number of users, as with the increasing number of users in the system, the probability that a given subchannel is in a deep fade for all users' decreases.

On the other hand, keeping all other parameters fixed when we increased the number of subchannels to 128 the sum capacity decreased slightly as compared to the sum capacity with 64 subchannels. Similarly, when the number of subchannels were reduced to 32 the sum capacity obtained was slightly better than that with 64 subchannels. Since a the subchannel bandwidth of each subchannel is equal to the total bandwidth divided by the number of subchannels, the bandwidth of each subchannel is reduced and increased with increase in the number of subchannels and reduction in the number of subchannels respectively. Moreover, since the total bandwidth and power were kept constant, each subchannel was then left with either less power and less bandwidth or more power and more bandwidth respectively. This was verified (Table 4.1, Fig.4.3) with the slight decrease/increase in sum capacity with increase/decrease in the number of subchannels.

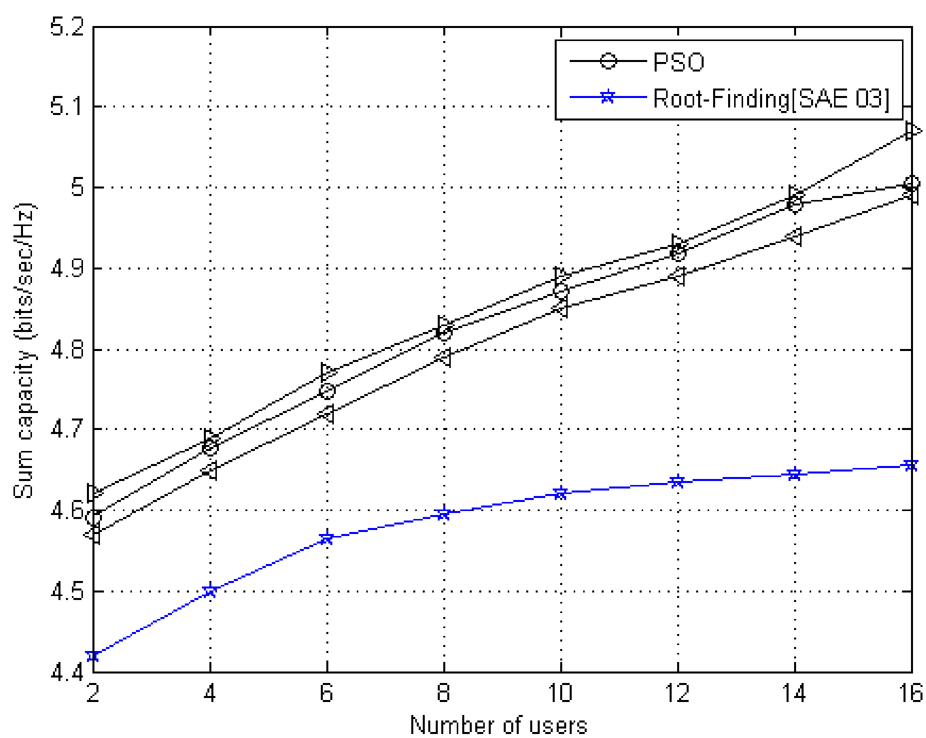


Figure 4.3: Sum capacity versus Number of users

The complexity analysis PSO aided subchannel allocation and its comparison with the method in [SAE03] is presented in following sub section.

4.5.2. Complexity Analysis

In order to analyze the computational complexity of the algorithm, recall that K refers to the total number of users in the system. N on the other hand refers to the number of subchannels, which is a power of 2 and much larger than K.

The subchannel allocation method proposed in [SAE03] is basically a three step process. Step 1 of the algorithm calculates number of subchannels to be allocated to each user while taking care of proportional fairness. This step requires 1 division and K multiplications, and thus has a complexity of $O(K)$.

The actual subchannel assignment is done in step 2, which involves sorting the subchannel gains $H_{k,n}$ for each user k, therefore requiring $O(K\,N \log_2 N)$ operations. The user with best gain on a particular subchannel is then allocated that subchannel. It then searches for the best user k among K users for the remaining N - K unallocated subchannels, thus requiring another $O((N - K)K)$ operations. In Step 3, it allocates the remaining N^* subchannels to the best user, and thus requires $O(K)$ operations. These operations pertain to the subchannel allocation, and the asymptotic complexity is $O(KN\log_2 N)$.

Calculating the number of subchannels to be allocated to each user before actual allocation on the basis of SNR introduces extra overhead. In step 2 sorting of subchannels on the basis of gains is another overhead. In the proposed PSO aided subchannel allocation, these overheads are removed by relaxing the proportionality constraint such that each user should get at-least one subchannel while searching and allocation of subchannels is performed simultaneously.

In each iteration the fitness function is evaluated for each particle with a complexity of $O(N)$. The double summation, over all subchannels and users, involved in the sum capacity calculation using equation.4.1 reduces to a single summation, over all subchannels only. This is due to two reasons: Firstly, due to the constraints (C_3 & C_4) that each subchannel should be assigned to a unique user and is not shared among users. Secondly, the user to which that subchannel is assigned is known to us from the particle position for each iteration. This reduces the overhead of having to sort through the gains of different users on a particular subchannel as required in [SAE03].Then the fitness value of particle i is compared with its previous best fitness value (P_{best}) in history, with a complexity of O(1). This step is repeated for each particle, if we represent number of particles by M, this step requires M comparisons. Hence the complexity of this step is O(M). If the value of P_{best} is updated in previous step and is found to be better than the current G_{best} then G_{best} is updated. In worst case scenario when all P_{best} were updated, it will again require M comparisons with complexity of O(M). Similarly the updating velocity vector and position vector for each particle will have maximum complexity of O(M).

In the light of the above discussion, it is clear that the main complexity lies in calculation of fitness function for each particle in each iteration. If we represent maximum number of iterations by I, the complexity of our algorithm will be O(NMI). It is quite a common practice in the PSO literature to limit the number of particles to the range 10–60 [KE01].Though there is a slight improvement in the optimal value with increasing swarm size, a larger swarm increases the number of function evaluations to converge to an error limit. Hence for a fixed population size and number of iterations the complexity of our algorithm can be written as O(N).

Moreover, for actual scenarios where the number of subchannels and users will be very large the complexity O(NMI) will be much less than O($KN\log_2 N$) in [SAE03]. Furthermore it is evident from Fig.4.4 and Fig.4.5 that PSO attains much higher sum capacity as compared to method in [SAE03] for a population size and number of iterations as low as 2 and 10 respectively. So the assumption of neglecting population size M and number of iteration I in complexity calculation for actual scenarios is justified.

Thus the PSO aided subchannel allocation outperformed the results in [SAE03] by obtaining better sum capacity without being computationally expensive.

In order to show that the algorithm was robust we studied the effect of variations of number of iterations and population size on sum capacity. The following sections discuss the results we obtained for these simulations.

4.5.3. Sum capacity obtained vs. Number of iterations

In order to study the effect of number of iterations on sum capacity, we fixed the number of users to 16 and population size to 12 bees. As it is evident from Fig.4.4 the sum capacity initially increased with the number of iterations and then gradually saturated for the higher values. This showed that, initially the particles were consistently moving to new positions giving higher values of fitness function and then slowly converged to a near optimal point.

It is also evident from Fig.4.4 that proposed method provided significant gain in sum capacity over method in [SAE03] for number of iterations as low as 10. Moreover after few more iterations the sum capacity saturated to near optimal value, which reaffirms the fact that PSO aided subchannel allocation, is capable of providing higher sum capacities for significantly less number of iterations.

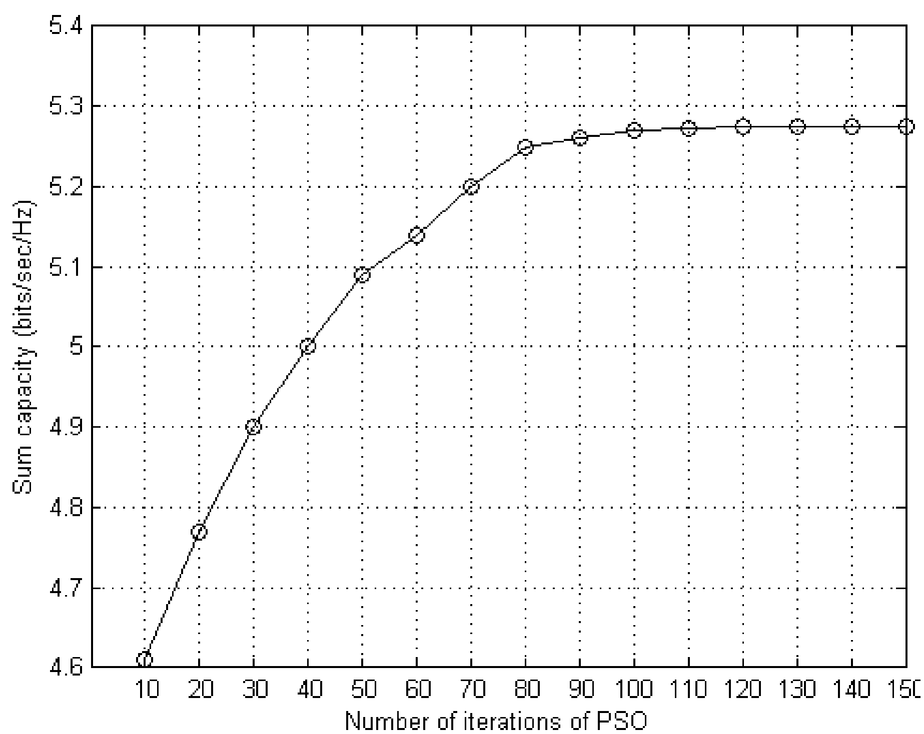


Figure 4.4: Sum capacity versus number of Iterations

4.5.4. Sum Capacity vs. Population size

In order to study the effect of population size (number of bees) on sum capacity, we fixed the number of users to 16 and maximum number of iterations to 40. As it is evident from Fig.4.5 the sum capacity initially increased with the number of bees and then rapidly saturated to near optimum value. It is also evident from Fig.4.5 that even for very low value of number of bees the proposed method provided significant capacity gain over method in [SAE03]. The sum capacity obtained saturates to near optimum value for a population size of as low as 16.

This reaffirms the fact that PSO aided subchannel allocation in OFDMA systems is capable of providing significant capacity gains even with very low population size and number of iterations, without being computationally expensive.

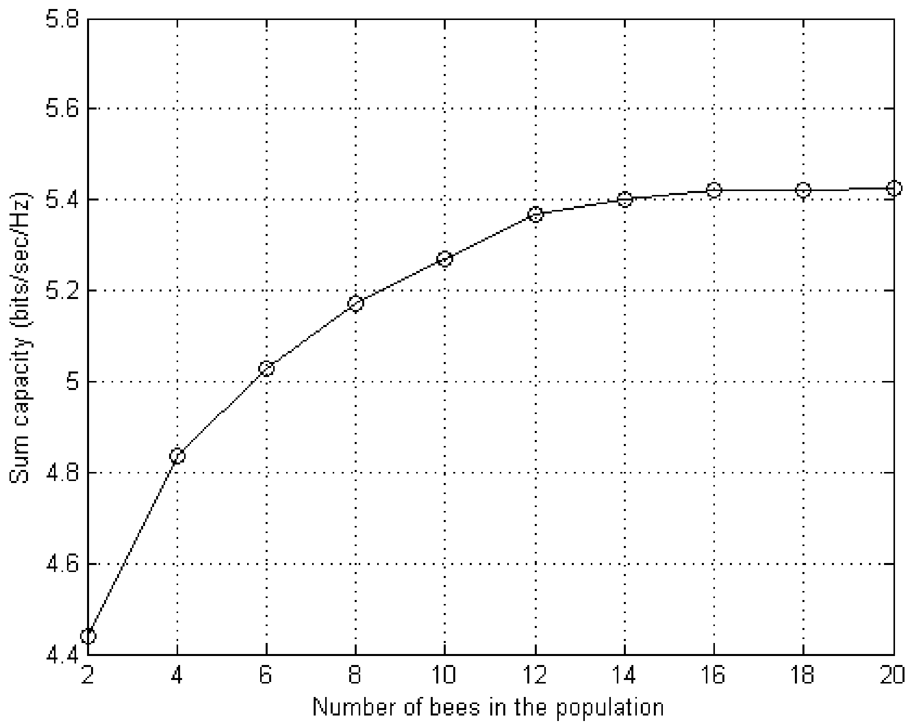


Figure 4.5: Sum capacity versus population size (Bees)

4.6. Conclusion

In this chapter, we have proposed the use of PSO, a stochastic optimization technique, for subchannel allocation in downlink of OFDMA systems followed by power allocation using WFA. The results produced by the simulations indicate that the algorithm performs better in terms of sum capacities as compared to [SAE03]. The sum capacity increases with the increase number of users. The sum capacity also increases initially with the increase in number of iterations and population size but rapidly saturates to a near optimal value.

This result suggests that PSO aided subchannel allocation can provide significant gain in capacity even with very small population size and number of iterations. Moreover in PSO aided subchannel allocation the search and subchannel allocation is performed simultaneously as compared to traditional methods where the subchannels are first sorted in accordance of their gains and then allocation is performed. This significantly reduces the complexity of PSO aided allocation.

The complexity of our algorithm was assessed to be O(N) as compared to O($KN\log_2 N$) for that of method in [SAE03]. Hence it may be concluded that the proposed algorithm is order of magnitude faster as compared to the method in [SAE03]. This fact makes PSO aided subchannel allocation a suitable choice for practical wireless systems like WiMAX (802.16e) where the convergence rate plays a very important role as the wireless channel changes rapidly. The fact that the channel is assumed to be constant during allocation makes convergence rate a very important parameter for wireless systems.

Chapter-5

Resource Allocation in OFDMA Systems using Novel Genetic Algorithm

5.1. Introduction

The advent of new generation of communication technologies has ushered in an era of high data rates and better reliability. Spatial Multiplexing offers high channel capacities or transmission rate for the same bandwidth with no additional power requirements by employing multiple antennas at the transmitter and receiver. However, high data transmission is limited by ISI. OFDM uses the spectrum efficiently by spacing the channels closer together as well as it has the ability of reducing ISI. The combination of these two technologies has been researched for the most promising candidate technique for the next generation wireless systems.

Users of multiuser OFDM system observe multipath fading but have independent fading parameters due to their different locations. The probability that a subchannel has been in deep fade for one user may also be in deep fade for other users is quite low. Hence, in multiuser system the channel diversity increases as the number of user increases. Therefore, in multiuser OFDM environment, the system needs to allocate bits as well as subchannels adaptively to the users. There are two classes of resource allocation schemes; fixed and adaptive resource allocation. Fixed allocations use TDMA or FDMA to allocate each user an independent time slot of subchannel. But fixed schemes do not consider the current channel condition for each user, in order to enhance the system performance.

Adaptively assigning resources to each user based on the channel condition can improve system performance when compared to fixed scheme, this is called multiuser diversity.

Adaptive subchannel and modulation for multiuser OFDM systems with SISO has been extensively studied [Law99, RABT02, WCLM99, JL03].

Adaptive subchannel allocation algorithm for MU MIMO OFDM has been at the centre of current research [CLC10, PB10, ASC11, CLL11]. This is due to the large system capacity that is produced by using adaptive algorithms for resource allocation in such systems. Subchannel allocation algorithms that maximize the capacity of each user have been studied in [Red07, TZWZ07, KPL06, SA11b].

As discussed in Chapter-4, there are two broad classifications for resource allocation problem for multiuser OFDM systems: MA and RA [KPL06, STTA12, SA11a]. In MA approach the emphasis is on minimizing the total transmit power subject to the constraints of data rate and BER. Authors, in [WCLM99] proposed a MA scheme, wherein an iterative subchannel and power allocation algorithm was proposed. RA approach, on the other hand tries to maximize the total throughput of the system while taking in to consideration the constraints of power budget and/or BER. Authors in [JL03], proposed a RA method to maximize the total data rates over all users subject to power and BER constraints. It was shown in [JL03] that in order to maximize the total capacity each subchannel should be assigned to the user with best gain on that subchannel.

The MA Optimization technique has been dealt with efficiently in [Red07, TZWZ07]. GA has been used here for resource allocation and has been shown to provide better results than normal iterative algorithms. In [KPL06], it was shown that RA optimization can be solved sub-optimally by separating Subchannel and Bit Loading Allocation. The RA optimization problem is a mixed binary integer programming problem. In [WSEA04], the proportional rate constraint is added to the existing RA optimization problem. However, the introduction of this constraint makes the optimization problem non-linear thus increasing the difficulty in finding the optimal solution because the feasible set is not convex.

Rate maximization and satisfying total power constraints are two seemingly conflicting objectives [SRDS08] with a lot of trade-offs. To simplify the problem, both of them are dealt with separately. In this chapter, we propose the use of a modified GA to allocate subchannels in a downlink OFDMA system, with the aim to maximize total capacity. The same algorithm is then extended and applied to downlink MIMO OFDMA system for obtaining subchannel allocation. The proposed GA is used to generate the subchannel allocation assuming equal power to all users. After the subchannel allocation, the bit loading can be performed using equation.5.12 (section 5.3).

5.2. System Model and Problem Formulation

A MIMO OFDMA system model is shown in Fig.5.1. Subchannel information is sent back to the BS from all users through an individual feedback channel. The BS of a downlink MIMO OFDMA system applies the combined subchannel and power allocation algorithm to assign subchannels to different users. It also provides the number of bits/OFDM symbol from each user to be transmitted on each subchannel. Depending on the number of bits assigned and the corresponding modulation scheme, the power allocated to each subchannel is determined. This subchannel and bit allocation information is then transmitted to the receiver along with each OFDM symbol. Separate control channels are used for transmitting this information. Therefore each user needs to decode the bits on its respective assigned subchannel. The BS is updated every time the subchannel information changes.

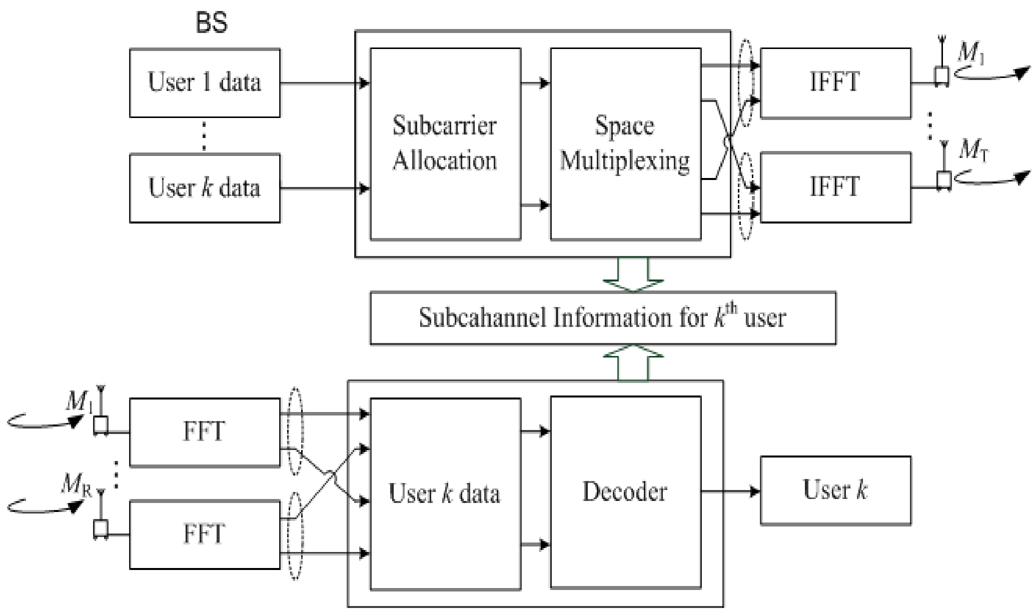


Figure 5.1: MIMO OFDMA system block diagram

We consider a system having K users and N subchannels, with maximum power constraint of P_{tot}. It is assumed that the BS has perfect information about CSI through feedback channels. Furthermore it is assumed that no two users can share same subchannel.

In order to support the assumption of perfect CSI at the transmitter, the wireless channel is considered to be slowly time-varying, frequency-selective Rayleigh faded with a total bandwidth of B. Each user is assumed to experience independent fading and the channel gain of k^{th} user in n^{th} subchannel is denoted by $g_{k,n}$, with AWGN $\sigma^2 = N_o\ B/N$ where N_o is the noise power spectral density. SNR for corresponding subchannel is thus denoted as $h_{k,n}=g_{k,n}/\ \sigma^2$ and the k^{th} user's received SNR on n^{th} subchannel is $\gamma_{k,n}=p_{k,n}\ h_{k,n}$, here $p_{k,n}$ is power allocated to k^{th} user on n^{th} sub carrier.

In practical modulation schemes, the transmit power $p_{k,n}$ and hence the SNR have to be adjusted according to the required BER. In [WCLM99], the required receive power for supporting $r_{k,n}$ bits per symbol in the case of M level QAM with square signal constellations at a given BER p_e, is given by:

$$f_k(r_{k,n}) = \frac{N_0}{3}\left[Q^{-1}\left(\frac{p_e}{4}\right)\right]^2 (2^{r_{k,n}} - 1) \tag{5.1}$$

However, as in [WSEA04], to formulate the resource allocation problem, the approximate expression is used for BER. The BER of a square MQAM with Gray bit mapping in AWGN as a function of received SNR $\gamma_{k,n}$ and number of bits $r_{k,n}$ has been approximated tightly to within 1 dB for $r_{k,n} \geq 4$ and BER $\leq 10^{-3}$ as:

$$BER_{\mathrm{MQAM}}\left(\gamma_{k,n}\right) \approx 0.2\exp\left[\frac{-1.6\gamma_{k,n}}{2^{r_{k,n}} - 1}\right] \tag{5.2}$$

Solving for $r_{k,n}$, we have

$$r_{k,n} = \log_2\left(1 + \frac{\gamma_{k,n}}{\Gamma}\right) = \log_2(1 + p_{k,n}H_{k,n}) \tag{5.3}$$

Where $\Gamma \approx -\ln(5BER)/1.6$ is a constant SNR gap, and $H_{k,n} \approx h_{k,n} / \Gamma$ is the effective sub channel SNR.

The objective function of resource allocation problem in multiuser OFDM systems with proportional rate constraint is formulated as [WSEA04]:

$$\max_{c_{k,n}p_{k,n}} \sum_{k=1}^{K}\sum_{n=1}^{N} \frac{c_{k,n}}{N} \log_2\left(1 + \frac{p_{k,n}H_{k,n}}{\mathrm{N_o}B/N}\right) \tag{5.4}$$

Subject to constraints:

$$C_1 : c_{k,n} \in \{0,1\} \forall k,n$$

$$C_2 : p_{k,n} \geq 0 \forall k,n$$

$$C_3 : \sum_{k=1}^{K} c_{k,n} = 1 \forall n$$

$$C_4 : \sum_{k=1}^{K}\sum_{n=1}^{N} c_{k,n}p_{k,n} \leq \mathrm{P_{tot}}$$

$$C_5 : R_i : R_j = \Phi_i : \Phi_j \forall i,j \in \{1,....K\}, i \neq j$$

Where $c_{k,n}$ is the subchannel allocation indicator such that $c_{k,n}$= 1 if and only if subchannel n is assigned to user k, and P_{tot} is the transmit power constraint. In C_5

$$R_k = \frac{B}{N}\sum_{k=1}^{K} c_{k,n} r_{k,n} \tag{5.5}$$

is the total data rate for user k and $\Phi_1 : \Phi_2 : \ldots : \Phi_K$ are the normalized proportionality constants where $\sum_{k=1}^{K} \Phi_k = 1$.

Note that constraints C_1 and C_2 ensure the correct values for the subchannel allocation indicator and the power respectively. C_3 imposes the restriction that each subchannel can only be assigned to one user, and C_4 and C_5 are the power and proportional rate constraints respectively.

The optimization problem in equation.5.4 is generally very hard to solve. It involves both continuous variables $p_{k,n}$ and binary variables $c_{k,n}$. Such an optimization problem is called a mixed binary integer programming problem. Furthermore, the nonlinear constraints in equation.5.4 increase the difficulty in finding the optimal solution because the feasible set is not convex.

Extending the above problem formulation for OFDMA [WSEA04] to MIMO OFDMA systems, with the same assumption of each subchannel can be used only by one user at each time. Then each subchannel has a narrowband channel with M_T and M_R antennas at the transmitter and the receiver respectively, which can be modeled by an $M_T \times M_R$ channel matrix:

$$\mathbf{H}_{k,n} = \begin{pmatrix} h_{11} & \cdots & h_{1M_T} \\ \vdots & \ddots & \vdots \\ h_{M_R 1} & \cdots & h_{M_R M_T} \end{pmatrix} \tag{5.6}$$

If we can extract some suitable parameters from $\mathbf{H}_{k,n}$, then we can use same algorithm to solve the problem for both OFDMA and MIMO OFDMA.

For the MIMO OFDMA system, the optimization problem can be formulated as:

$$\max_{c_{k,n} p_{k,n}} \sum_{k=1}^{K}\sum_{n=1}^{N} \frac{c_{k,n}}{N} \log_2 \left[\det(\mathbf{I}_{N_R} + \frac{p_{k,n}\mathbf{H}_{k,n}\mathbf{H}_{k,n}^H}{\mathrm{N_o} B/N}) \right]$$

$$= \max_{c_{k,n} p_{k,n}} \sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{i=1}^{M} \frac{c_{k,n}}{N} \log_2 \left[1 + \frac{p_{k,n}\lambda_{k,n,i}}{\mathrm{N_o} B/N} \right] \tag{5.7}$$

Where $M = \min(M_R, M_T)$, $\boldsymbol{\lambda}_{k,n,i}$ is the i^{th} Eigen-value of matrix $\mathbf{H}_{k,n}\mathbf{H}_{k,n}^H$ .According to Jensen in-equation:

$$\sum_{i=1}^{M} \log_2 \left[1 + \frac{p_{k,n}}{\mathrm{N_o} B / N} \lambda_{k,n,i} \right]$$

$$\leq M \log_2 \left[1 + \frac{p_{k,n}}{\mathrm{N_o} B / N} \frac{1}{M} \sum_{i=1}^{M} \lambda_{k,n,i} \right]$$

$$= M \log_2 \left[1 + \frac{p_{k,n}}{\mathrm{N_o} B / N} \frac{1}{M} tr(\mathbf{H}_{k,n} \mathbf{H}_{k,n}^H) \right] \quad = M \log_2 \left[1 + \frac{p_{k,n}}{\mathrm{N_o} B / N} \frac{1}{M} \left\| \mathbf{H}_{k,n} \right\|_F^2 \right] \tag{5.8}$$

We can see that the Frobenius-norm of $\mathbf{H}_{k,n}$ can represent the channel condition of user k in subchannel n. If the SNR is high enough, the left side of in equation.5.8 can be rewritten as:

$$\sum_{i=1}^{M} \log_2 \left[1 + \frac{p_{k,n} \lambda_{k,n,i}}{\mathrm{N_0} B / N} \right]$$

$$\approx \log_2 \left[\prod_{i=1}^{M} \frac{p_{k,n} \lambda_{k,n,i}}{\mathrm{N_0} B / N} \right]$$

$$= \log_2 \left[\left(\frac{p_{k,n}}{\mathrm{N_0} B / N} \right)^M \det(\mathbf{H}_{k,n} \mathbf{H}_{k,n}^H) \right] \tag{5.9}$$

So in high SNR case, the determinant of $\mathbf{H}_{k,n}\mathbf{H}_{k,n}^H$ is also a suitable parameter.

In a system with K users and N subchannels, there are K^N possible subchannel allocations, since it is assumed that no subchannel can be used by more than one user. For a certain subchannel allocation, an optimal power distribution can be used to maximize the sum capacity, while maintaining proportional fairness. The maximum capacity over all K^N subchannel allocation schemes is the global maximum and the corresponding subchannel allocation and power distribution is the optimal resource allocation scheme. However, it is prohibitive to find the global optimizer in terms of computational complexity. A suboptimal solution using GA is proposed in this chapter to reduce the complexity significantly while still delivering performance close to the global optimum.

5.3. Proposed Solution

Assuming low SNR and $N_1{:}N_2{:}\ldots{:}N_k=\Phi_1{:}\Phi_2{:}\ldots{:}\Phi_k$ in the sub channel allocation algorithm. The second assumption above holds true and is a valid assumption as used in [WSEA04]. The proposed steps (Fig.5.2) are as follows:

Step 1: Input number of generations (G), Channel gain matrix ($\mathbf{H}$), Total Power (P_{tot}), Bandwidth (B), number of channels (N), number of users (K), and Proportional fairness ratio $\Phi_1 : \Phi_2 : \ldots : \Phi_k$.

Step 2: Create initial population of chromosomes (possible subchannel allocation) and calculate their capacities using either

$$\max_{c_{k,n} p_{k,n}} \sum_{k=1}^{K} \sum_{n=1}^{N} \frac{c_{k,n}}{N} \log_2 \left(1 + \frac{p_{k,n} H_{k,n}}{\mathrm{N_o} B / N} \right) \text{(for SISO)}$$

or

$$\sum_{k=1}^{K} \sum_{n=1}^{N} \frac{c_{k,n}}{N} M \log_2 \left[1 + \frac{p_{k,n}}{\mathrm{N_o} B / N} \frac{1}{M} tr(\mathbf{H}_{k,n} \mathbf{H}_{k,n}^{H}) \right] \text{(for MIMO)} \tag{5.10}$$

Step 3: Sort all chromosomes in the increasing order of their capacities.

Step 4: Generate probability levels for each chromosome based on their total capacities that is, the chromosome with highest capacity has highest probability of selection for crossover.

Step 5: Select two chromosomes from the entire population based on their fitness values (sum capacity).

Step 6: Select two points randomly on the parent chromosome for crossover (Two point crossover).

Step 7: Generate two child chromosomes (new subchannel allocation) by swapping parent chromosomes from starting to first random point and from second random point to end of chromosome.

Step 8: Replace the two chromosomes of lowest capacities with the two new child chromosomes.

Step 9: Select a chromosome from the entire population for mutation.

Step 10: Flip the channels allocated to users in the selected chromosome.

Step 11: If user has more channels than he should, corresponding channel (based on channel gain) is allocated to the user with less number of channels.

Step 12: If any user has less number of channels, unallocated channel with highest channel gain is allocated to that user.

Step 13: Calculate capacities for each chromosome using equation.5.10.

Step 14: Decrement G.

Step 15: If G = 0 select the chromosome with highest capacity, otherwise go back to **Step 4.**

Power Allocation

With subchannel allocation having been carried out, i.e. $\{\boldsymbol{\eta}_k\}_{k=1}^{K}$ ($\boldsymbol{\eta}$ represents set of all subchannels) have been determined, a power fine-tuning can be carried out in order to further improve the system capacity. For SISO case, the optimal power allocation with known subchannel allocation is provided in [WSEA04]. It is important to note that the system capacity is not sensitive to the power allocation [JL03, BC07, KHK05] at high SNR condition due to the logarithmic calculation in the objective function (equation.5.4). Thus, we used equal power allocation for faster results.

Similarly for MIMO with subchannel allocation known, the optimization problem in equation.5.7 reduces equivalent to maximizing the following cost function by using Lagrangian relaxation:

$$
\begin{aligned}
L = &\sum_{k=1}^{K}\sum_{n=1}^{N}\left[\sum_{i=1}^{M}\log_2\left(1+\frac{p_{k,n}\lambda_{k,n,i}}{\mathrm{N_o}B/N}\right)\right]+\chi_1\left(\sum_{k=1}^{K}\sum_{n=1}^{N}p_{k,n}-P_{tot}\right) \\
&+\sum_{k=2}^{K}\chi_k\left[\sum_{n=1}^{N}\sum_{i=1}^{M}\log_2\left(1+\frac{p_{1,n}\lambda_{k,n,i}}{\mathrm{N_o}B/N}\right)\right]-\frac{\Phi_l}{\Phi_K}\sum_{n=1}^{N}\sum_{i=1}^{M}\log_2(1+\frac{p_{k,n}\lambda_{k,n,i}}{\mathrm{N_o}B/N})
\end{aligned}
\tag{5.11}
$$

where χ_1 and χ_k are Lagrangian multipliers. Differentiating L with respect to $p_{k,n}$,and setting each derivative to 0, we can obtain the optimal power distribution for a single user:

$$
\sum_{\mathrm{i=1}}^{\mathrm{M}}\frac{\lambda_{\mathrm{k,n,i}}}{1+\frac{p_{k,n}\lambda_{k,n,i}}{\mathrm{N_o}B/N}}=\sum_{\mathrm{i=1}}^{\mathrm{M}}\frac{\lambda_{\mathrm{k,m,i}}}{1+\frac{p_{k,m}\lambda_{k,m,i}}{\mathrm{N_o}B/N}}
\tag{5.12}
$$

for $n,m\in\boldsymbol{\eta}_k$ and k=1,2,…,K.

Note that the function f(x)=x/(1+px) is monotonically increasing and tends to $1/p$ i.e. $\lim_{\mathrm{x}\to+\infty}\left[\mathrm{x}/(1+p\mathrm{x})\right]=1/p$. Thus, an approximation to equation.5.12 can be obtained under high SNR as: $\mathrm{M}/P_{k,n}=\mathrm{M}/P_{k,m}$.

That is equivalent to $P_{k,n}$ = $P_{k,m}$ for $n,m\in\boldsymbol{\eta}_k$, $\mathrm{n}\neq\mathrm{m}$ and k=1,2,…,K. Due to no subchannel sharing among users, it can be concluded that power could be approximately distributed across all subchannels of each user in an equal manner. Obviously, this equal power allocation is not optimized to improve fairness. However, it achieved near optimal proportional fairness for our problem when combined with the proposed subchannel allocation.

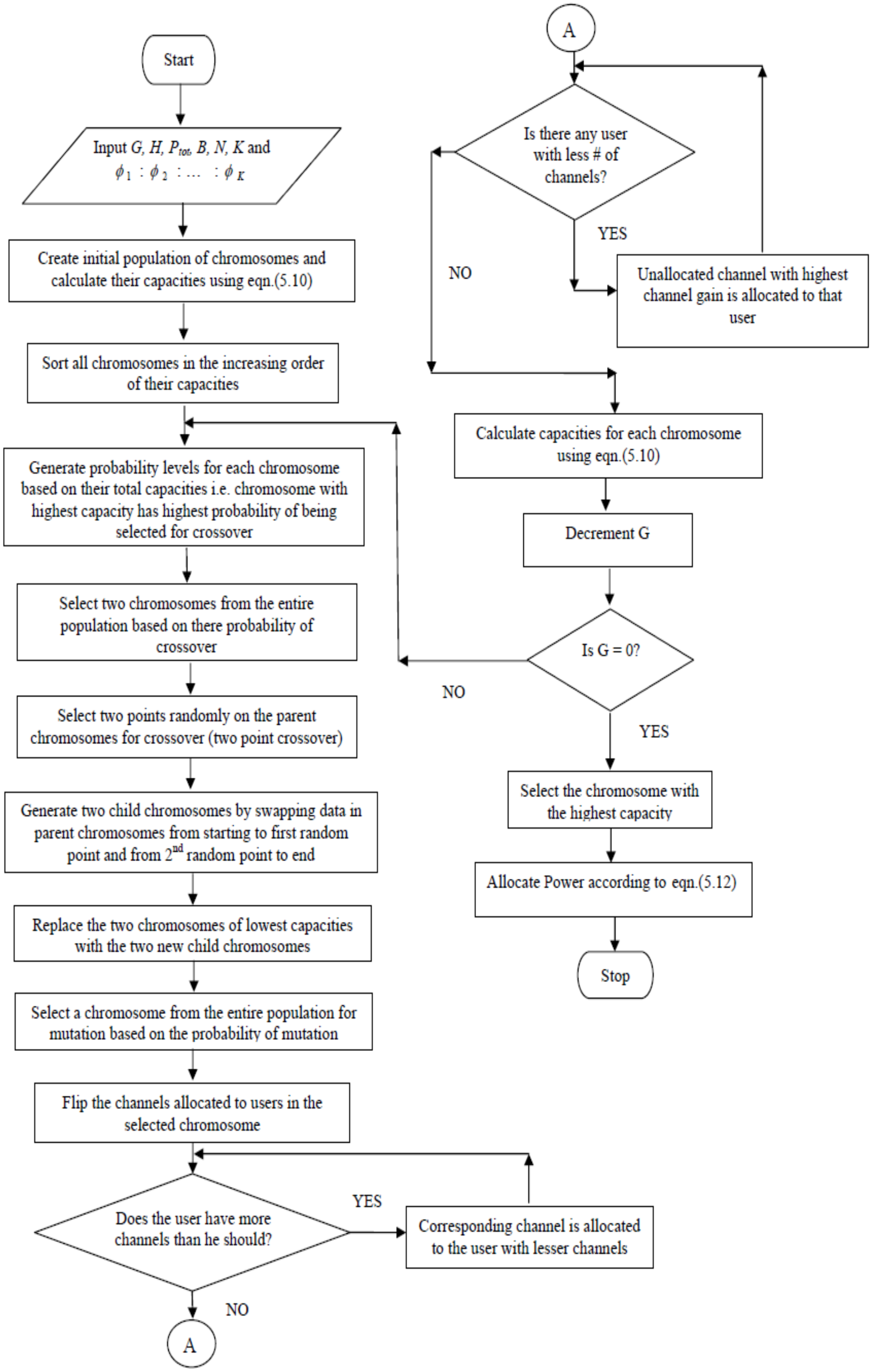


Figure 5.2: Flow chart representation of proposed steps

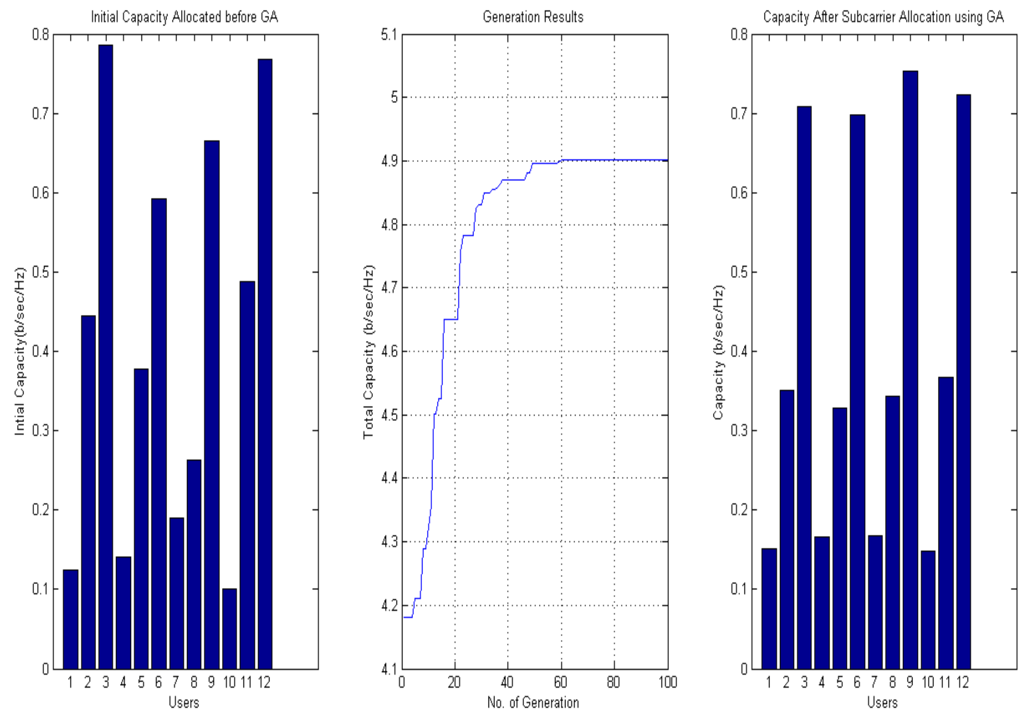
5.4. Simulation Results

The frequency selective multipath channel had been modeled as consisting of six independent Rayleigh multipaths, with an exponentially decaying profile. A maximum delay spread of 5μs and maximum Doppler of 30 Hz has been assumed. The channel information is sampled every 0.5 ms to update the subchannel and power allocation. The total power was assumed to be 1 W, the total bandwidth as 1 MHz, and total subchannels as 64. The average subchannel SNR is 38 dB, and BER $\leq 10^{-3}$, giving an SNR gap $\Gamma = -\ln(5 \times 10^{-3})/1.6 = 3.3$. This constant is used in the calculation of the rate $r_{k,n}$ of user k in subchannel n given in equation.5.10.

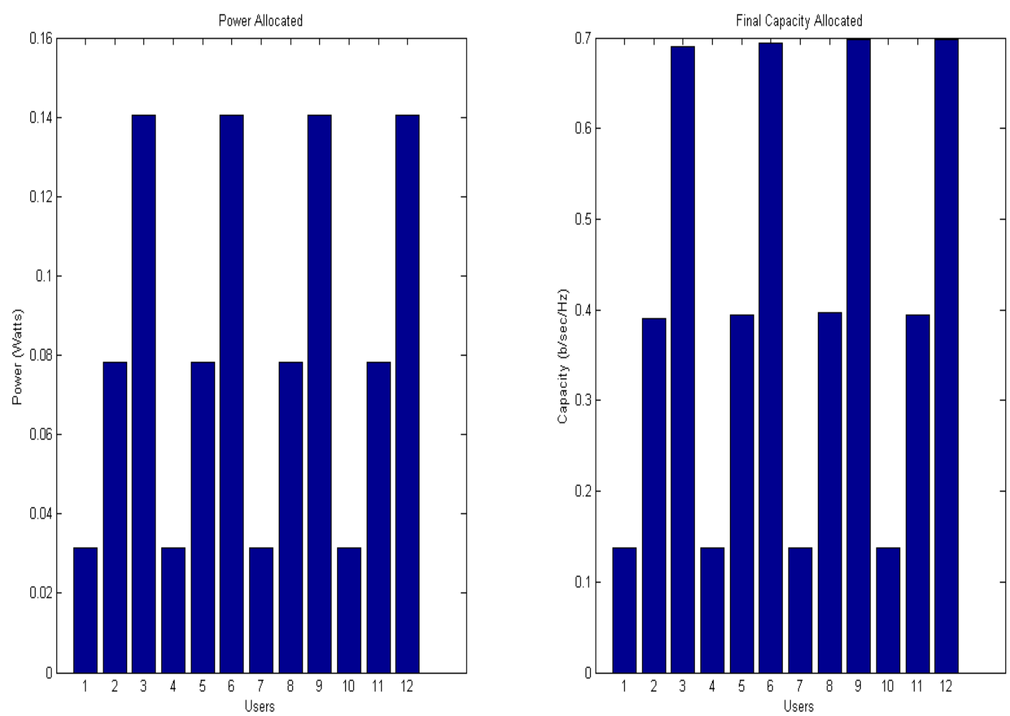
For selecting the probabilities of crossover and mutation, we considered three set of each of these parameters. The set of values of probability of crossover and mutation considered were 0.7, 0.8, 0.9 and 0.01, 0.02, 0.03 respectively. Each of these 09 possible combinations was simulated for each problem set. In each of these simulations the population size and number of iterations were fixed to 100 each. The best results were obtained for probability of crossover as 0.9 and that of mutation as 0.03. Hence these values were used for all simulations later.

The performance of proposed algorithm is presented in two parts. In the first part, we present the explanation of the simulation results obtained for different set of users. In the second part we compare the results obtained by proposed method with that of [WSEA04].

In the first part of simulation, the proportional rate constraint $\Phi_1:\Phi_2:\ldots:\Phi_k$=1:2:4..:1:2:4 was strictly enforced. The number of users considered was 12, 16, 20 and 24. The simulation results obtained using GA for subchannel allocation and allocating power using optimal power allocation in [WSEA04]/eqn5.12 for SISO/MIMO are shown in Fig.5.3-5.5/Fig.5.6-5.8 respectively. The algorithm was executed 100 times for each set of number of users. The best, average and worst results were selected manually on the basis of final proportionality obtained. In each figure the three graphs in part (a), from left to right depicts the initial capacity of each user before applying GA, the capacities obtained in each generation of GA and the final capacity of each user after the sub channel allocation using GA. While part (b), from left to right shows power allocated using optimal power allocation and final capacity allocated after power and subchannel allocation.

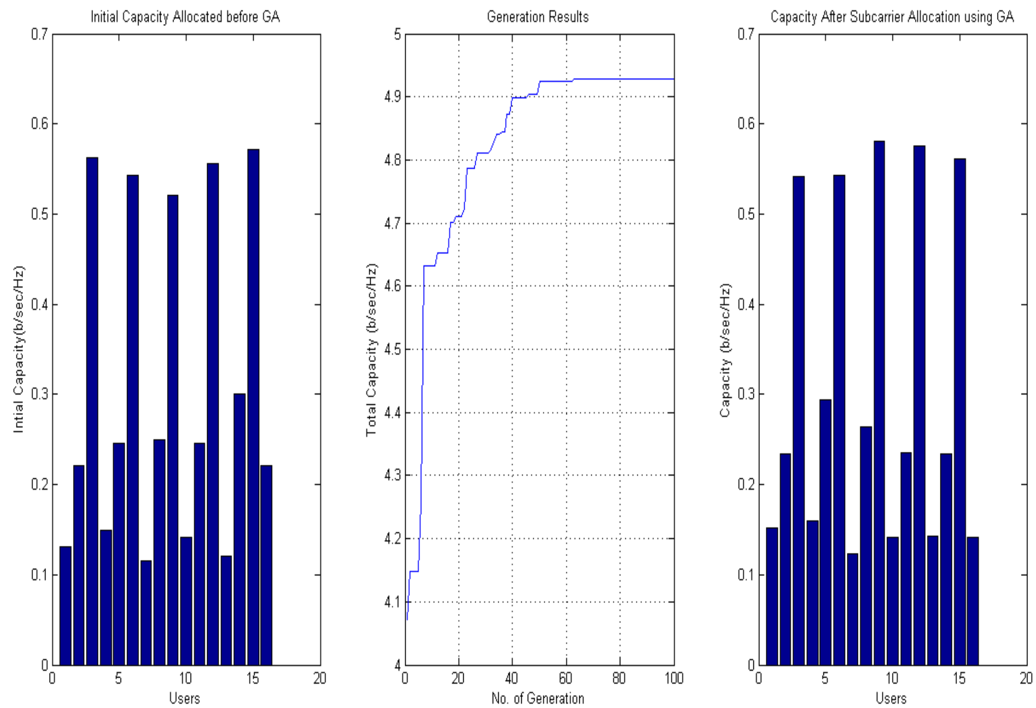


(a)

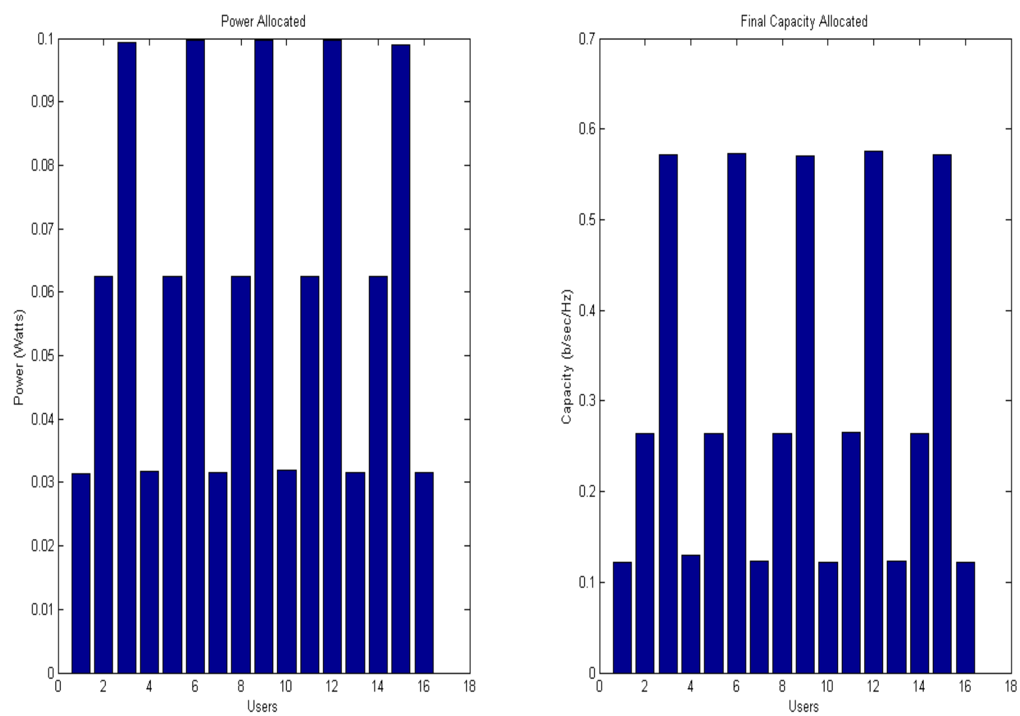


(b)

Figure 5.3.(a,b): Best Case simulation results, SISO system with 12 users (a) Capacity after Subchannel allocation using GA (b) Capacity after Subchannel allocation using GA and Power allocation using Optimal Power allocation.

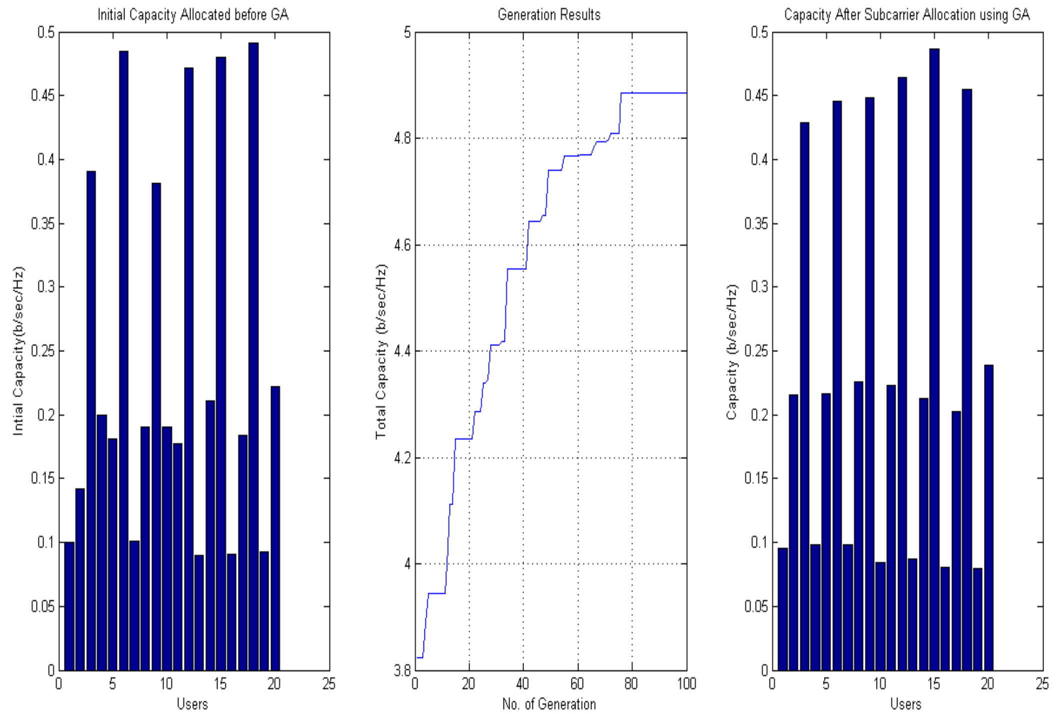


(c)

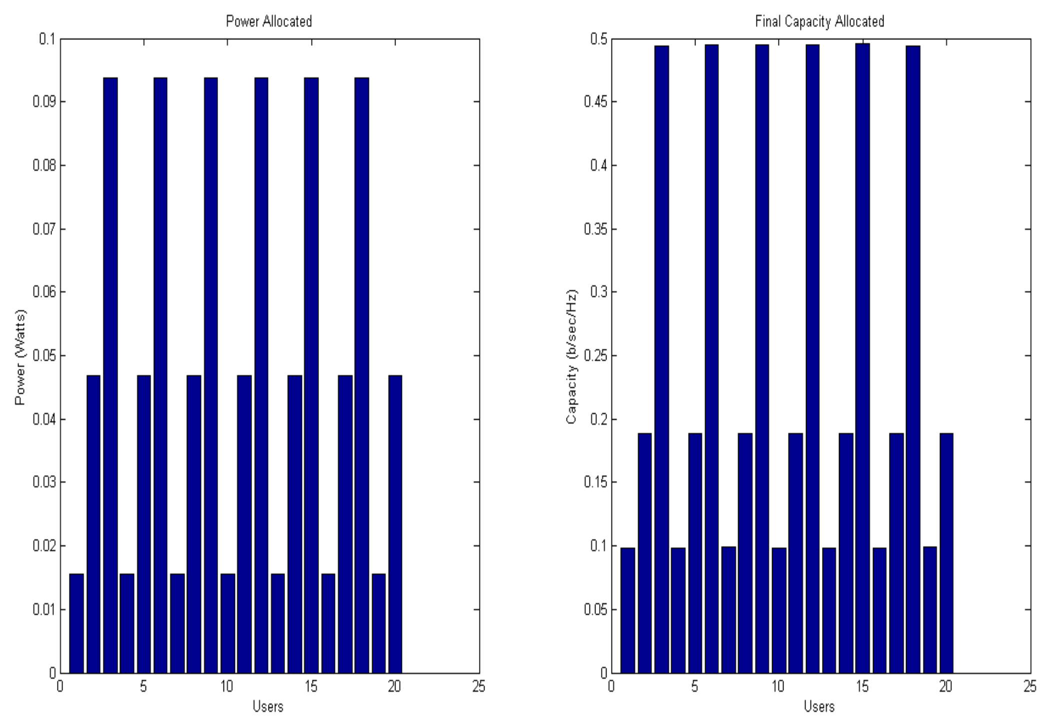


(d)

Figure 5.3.(c,d): Best Case simulation results for SISO system with 16 users (c) Capacity after Subchannel allocation using GA (d) Capacity after Subchannel allocation using GA and Power allocation using Optimal Power allocation.

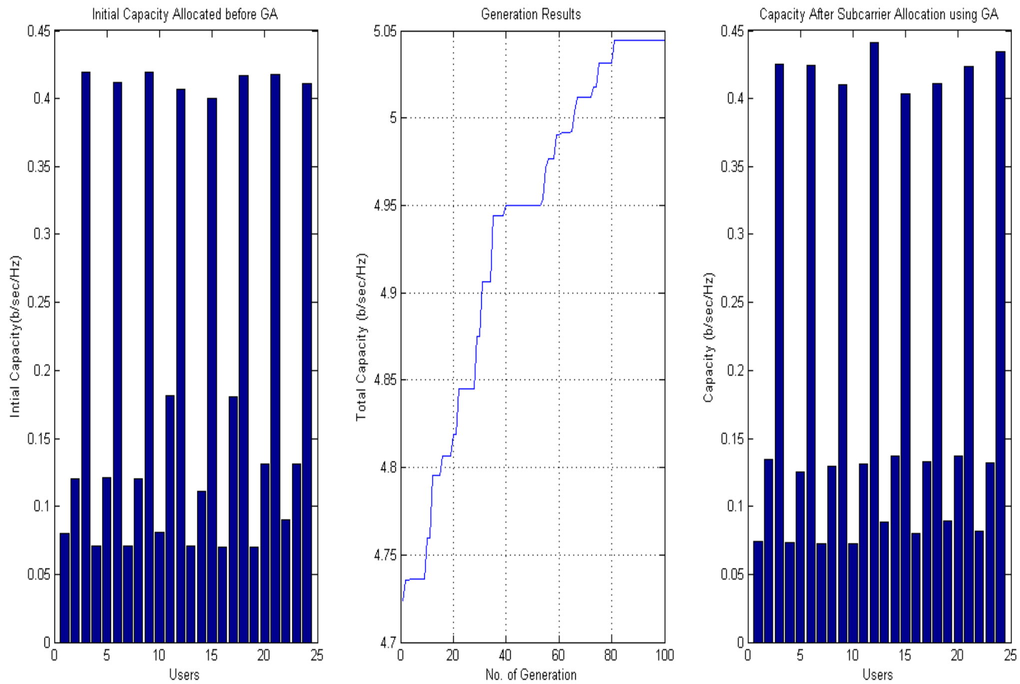


(e)

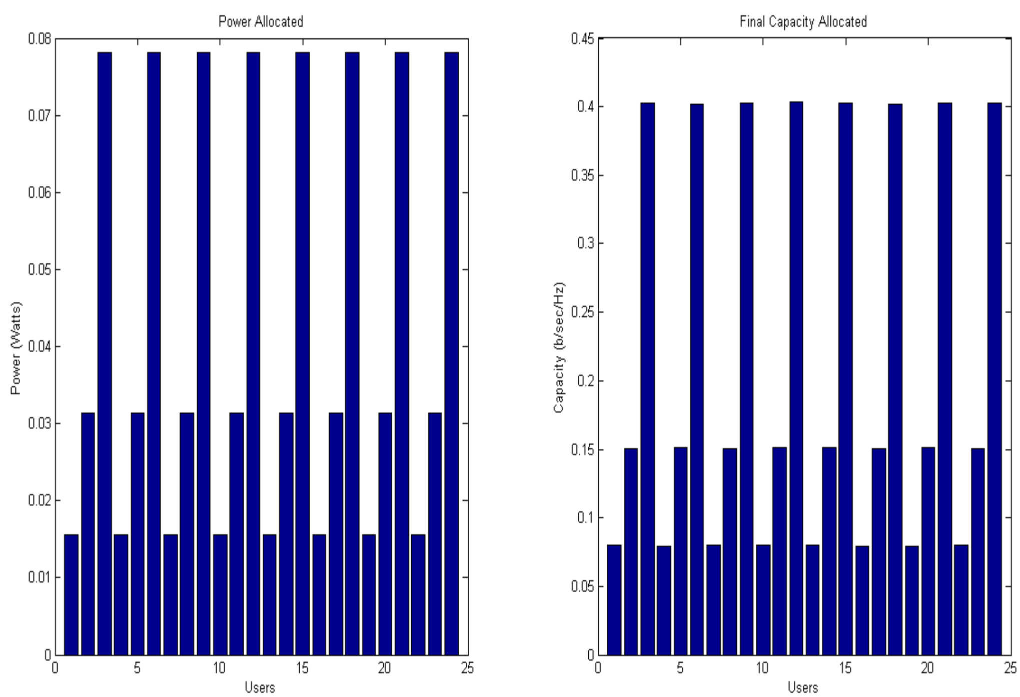


(f)

Figure 5.3.(e,f): Best Case simulation results SISO system with 20 users (e) Capacity after Subchannel allocation using GA (f) Capacity after Subchannel allocation using GA and Power allocation using Optimal Power allocation.

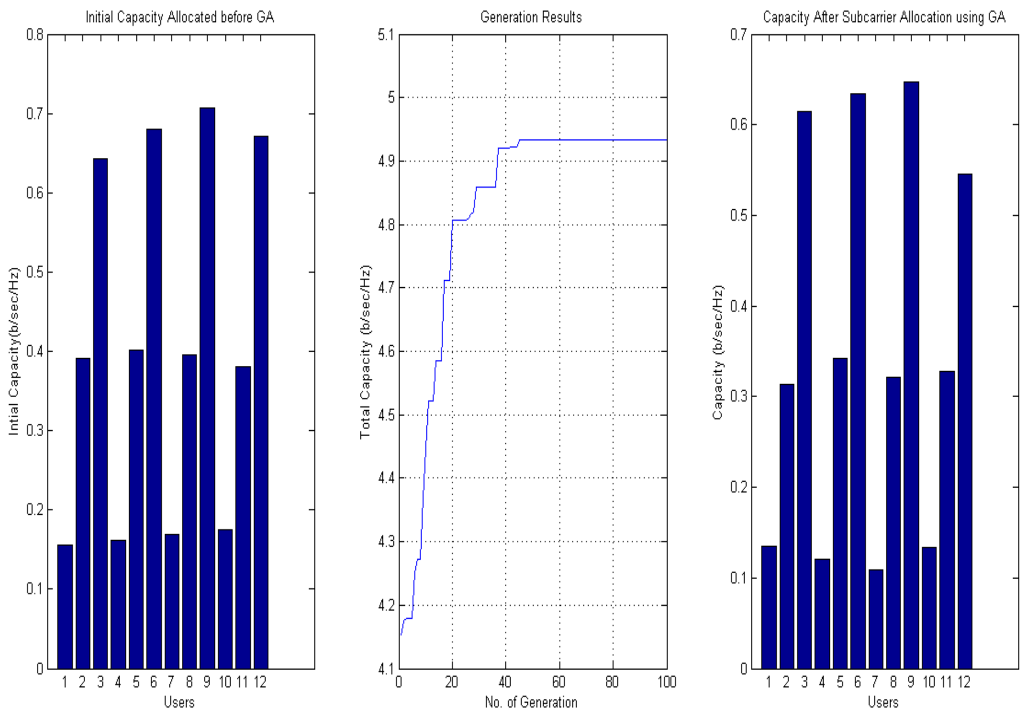


(g)

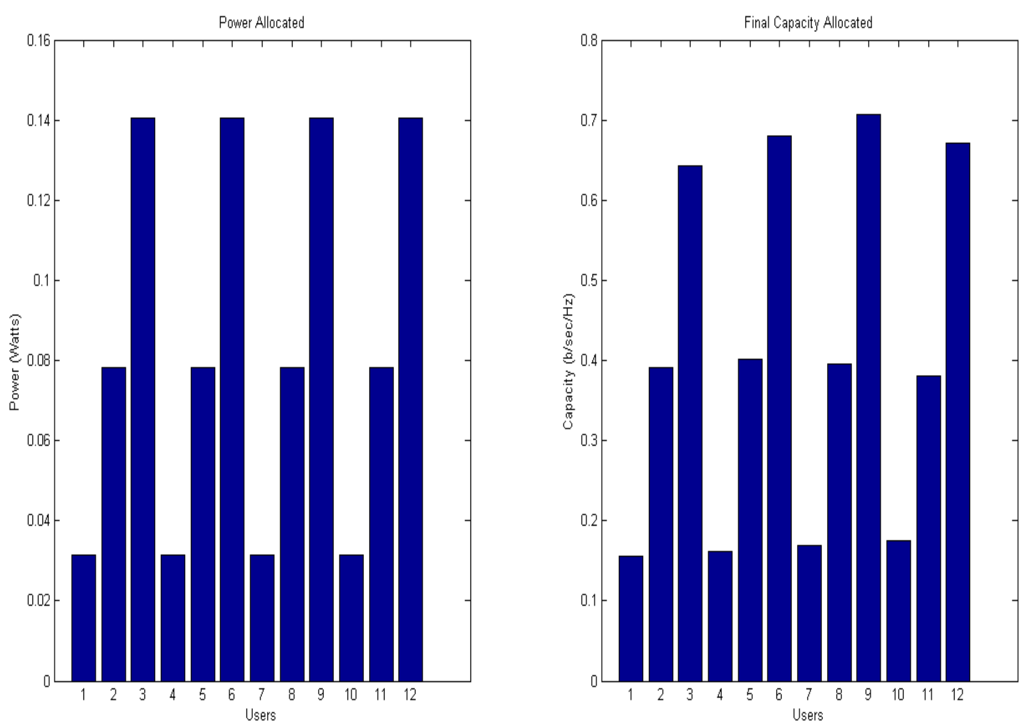


(h)

Figure 5.3.(g,h): Best Case simulation results SISO system with 24 users (g) Capacity after Subchannel allocation using GA (h) Capacity after Subchannel allocation using GA and Power allocation using Optimal Power allocation.

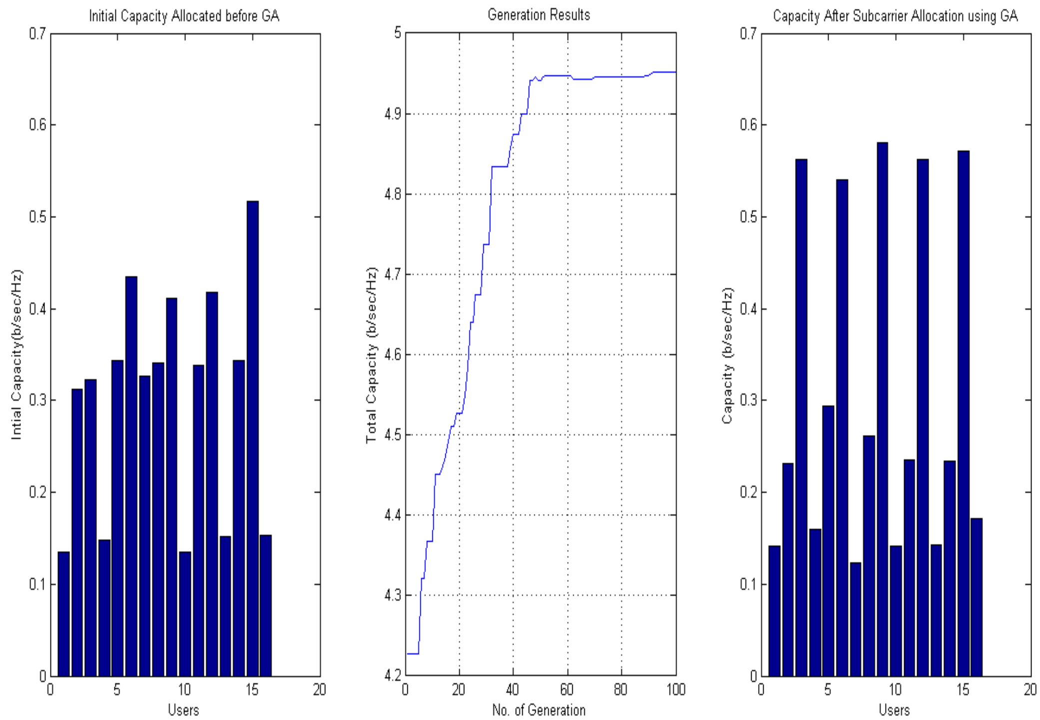


(a)



(b)

Figure 5.4.(a,b): Average Case simulation results for SISO system with 12 users (a) Capacity after Subchannel allocation using GA (b) Capacity after Subchannel allocation using GA and Power allocation using Optimal Power allocation.



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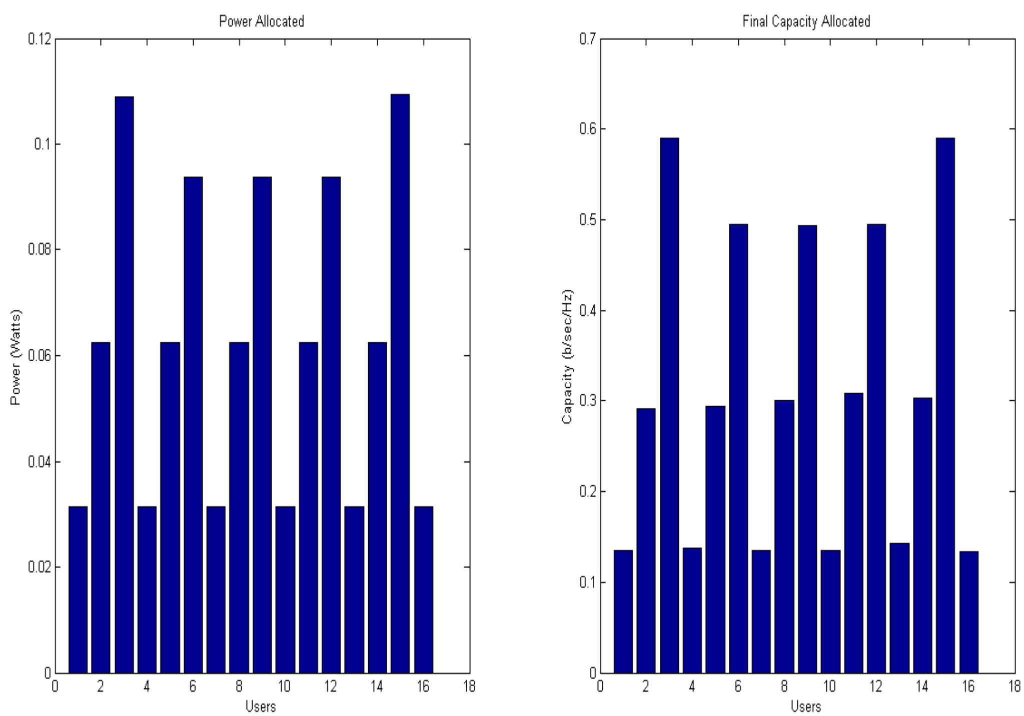
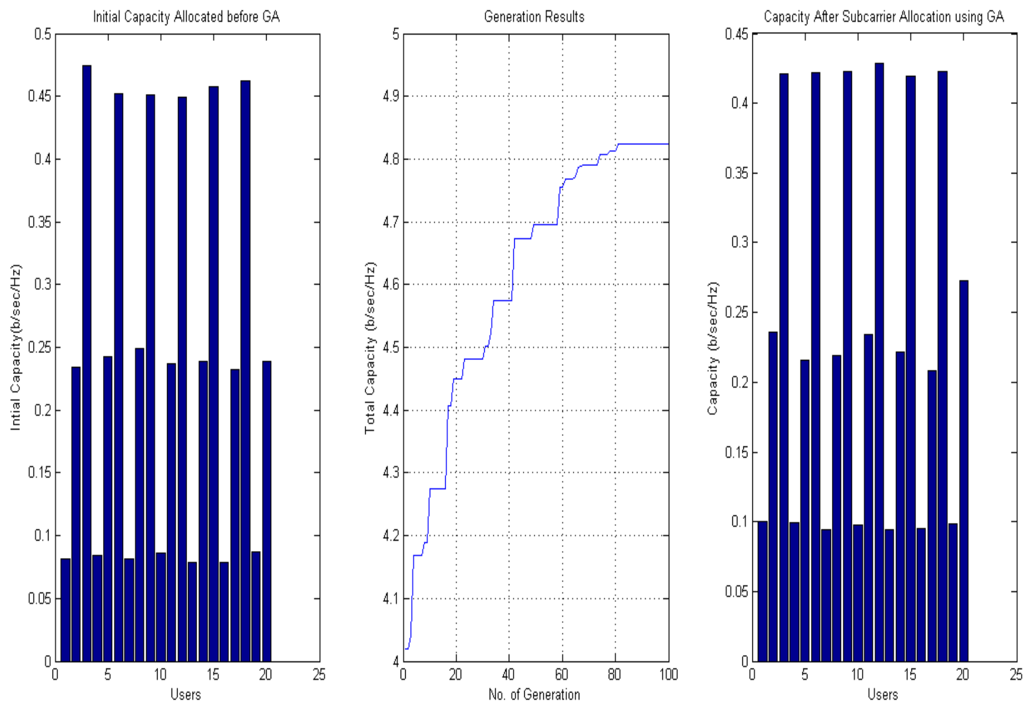


(d)

Figure 5.4.(c,d): Average Case simulation results for SISO system 16 users (c) Capacity after Subchannel allocation using GA (d) Capacity after Subchannel allocation using GA and Power allocation using Optimal Power allocation.



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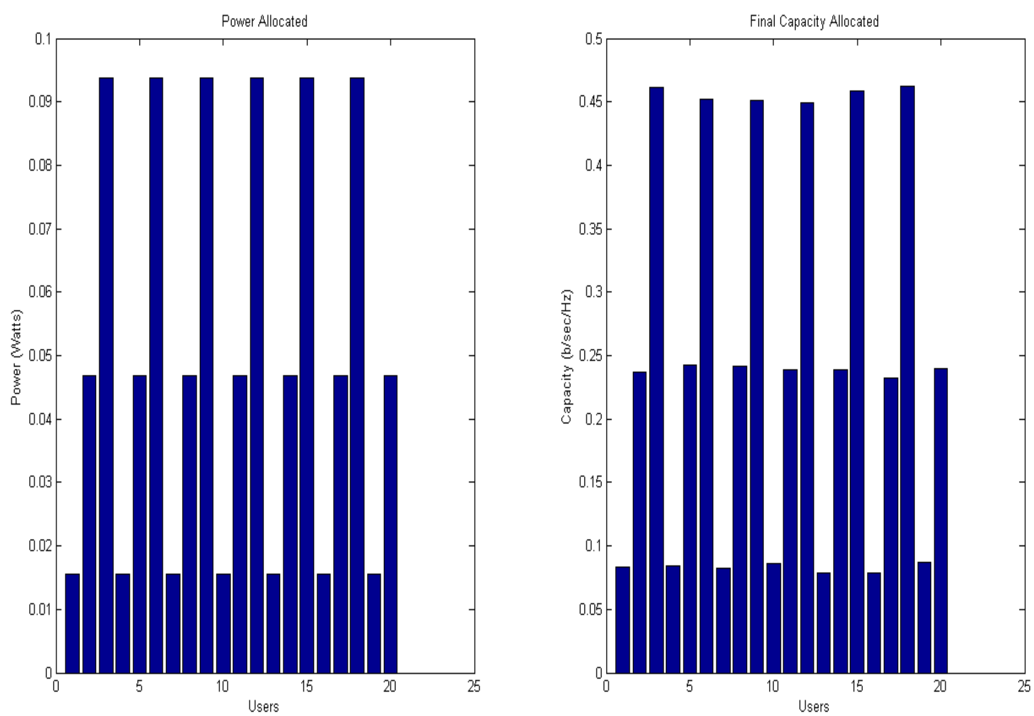
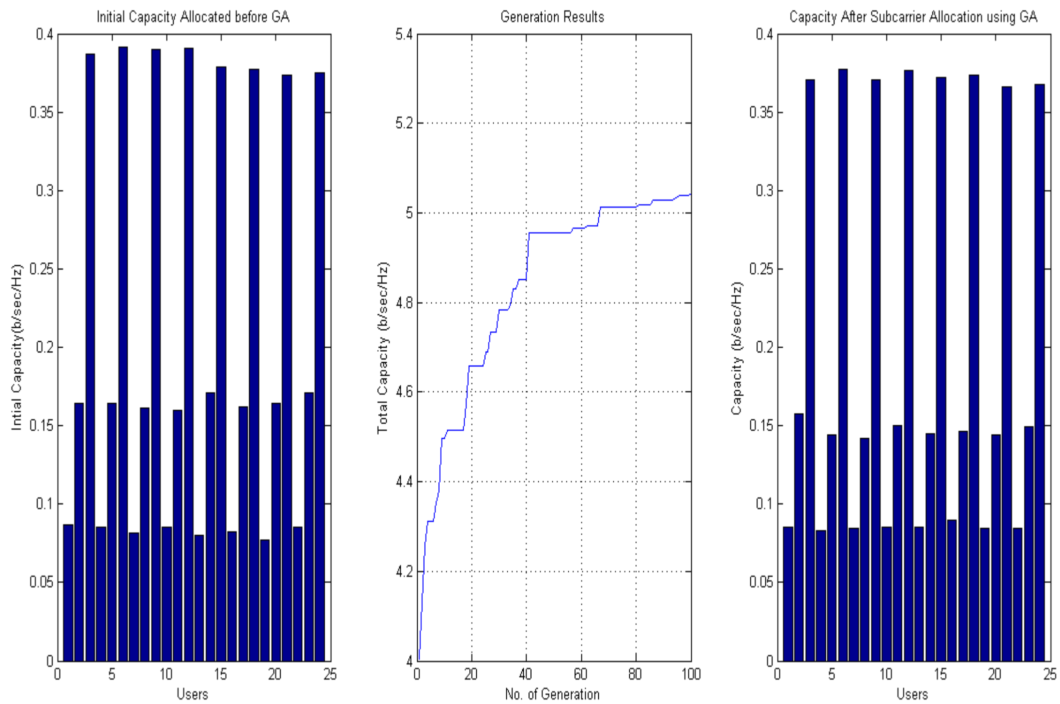


(f)

Figure 5.4.(e,f): Average Case simulation results for SISO system 20 users (e) Capacity after Subchannel allocation using GA (f) Capacity after Subchannel allocation using GA and Power allocation using Optimal Power allocation.



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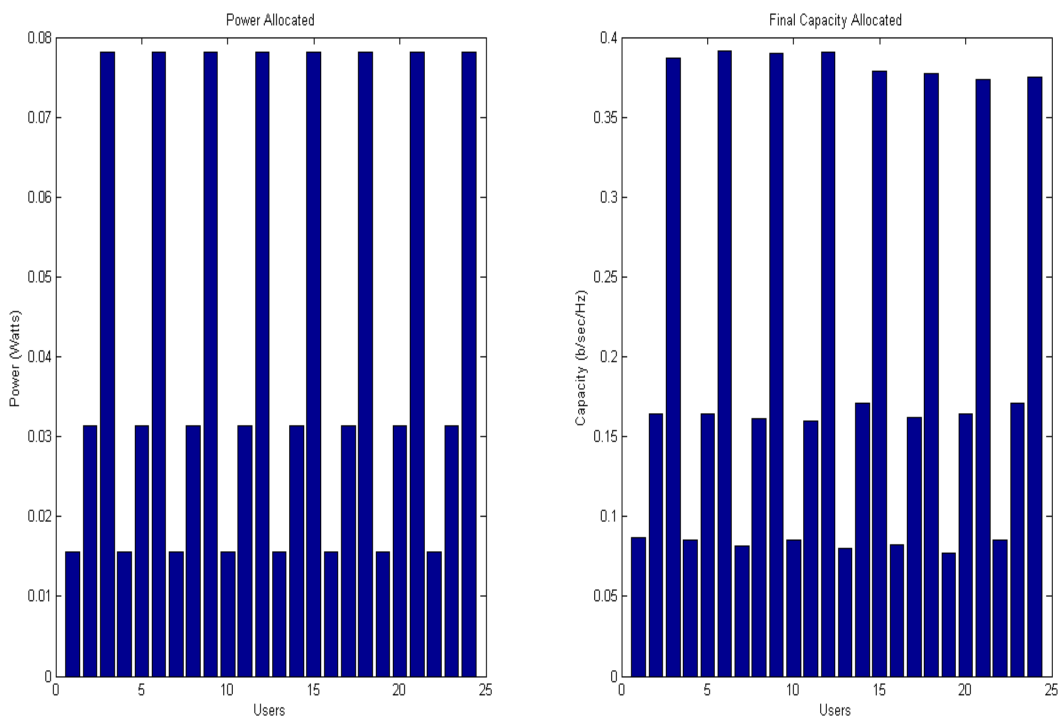
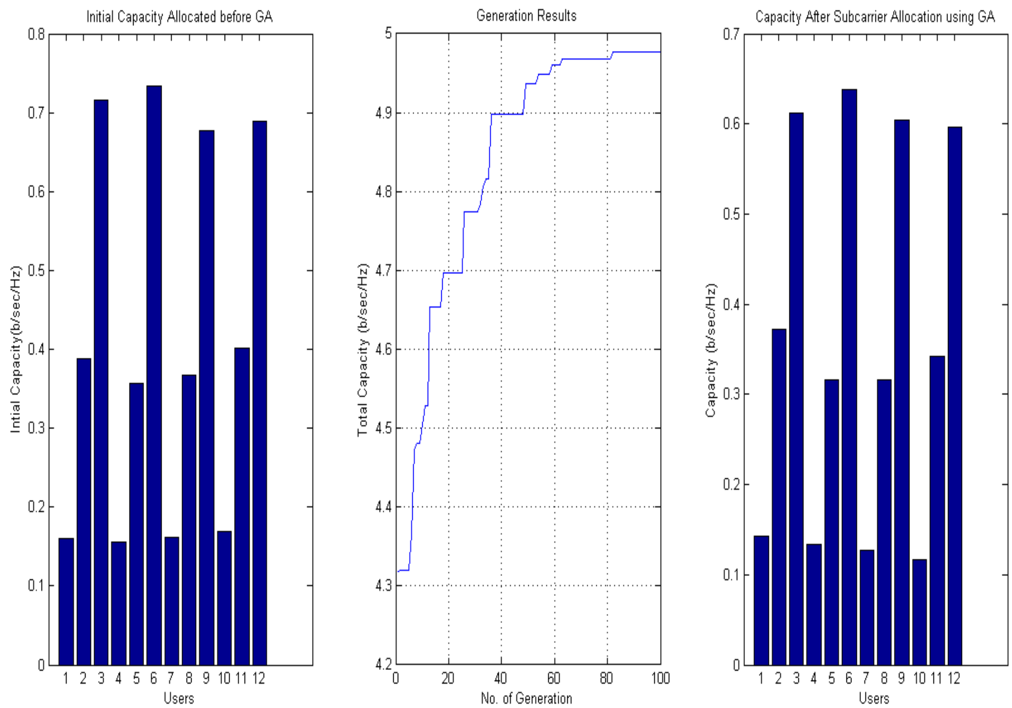
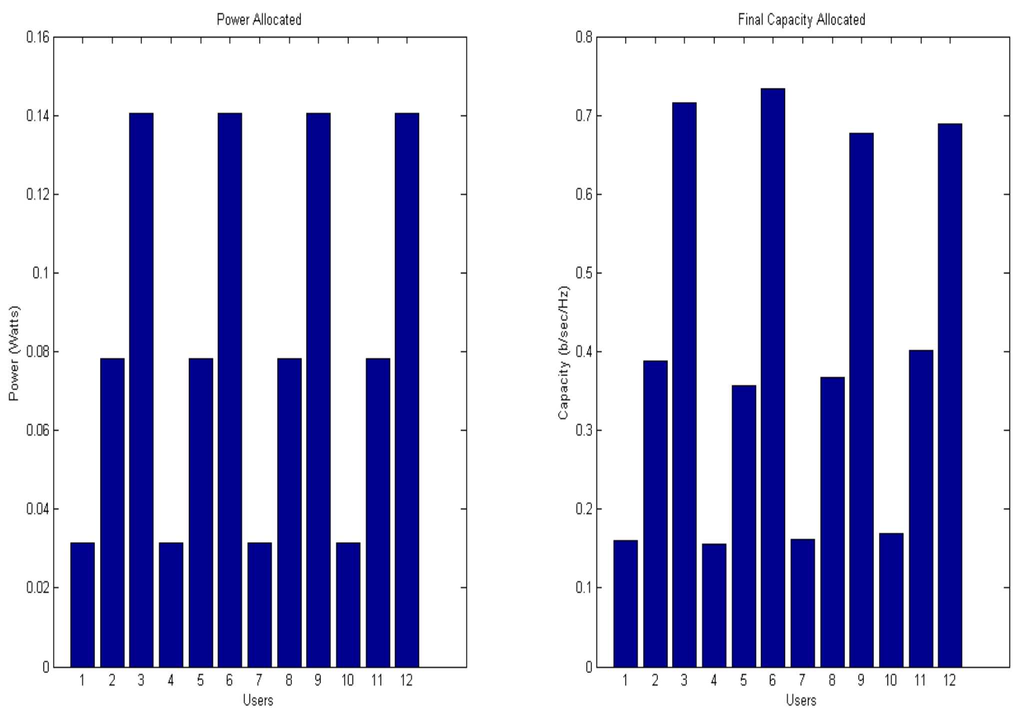


(h)

Figure 5.4.(g,h): Average Case simulation results for SISO system 24 users (g) Capacity after Subchannel allocation using GA (h) Capacity after Subchannel allocation using GA and Power allocation using Optimal Power allocation.

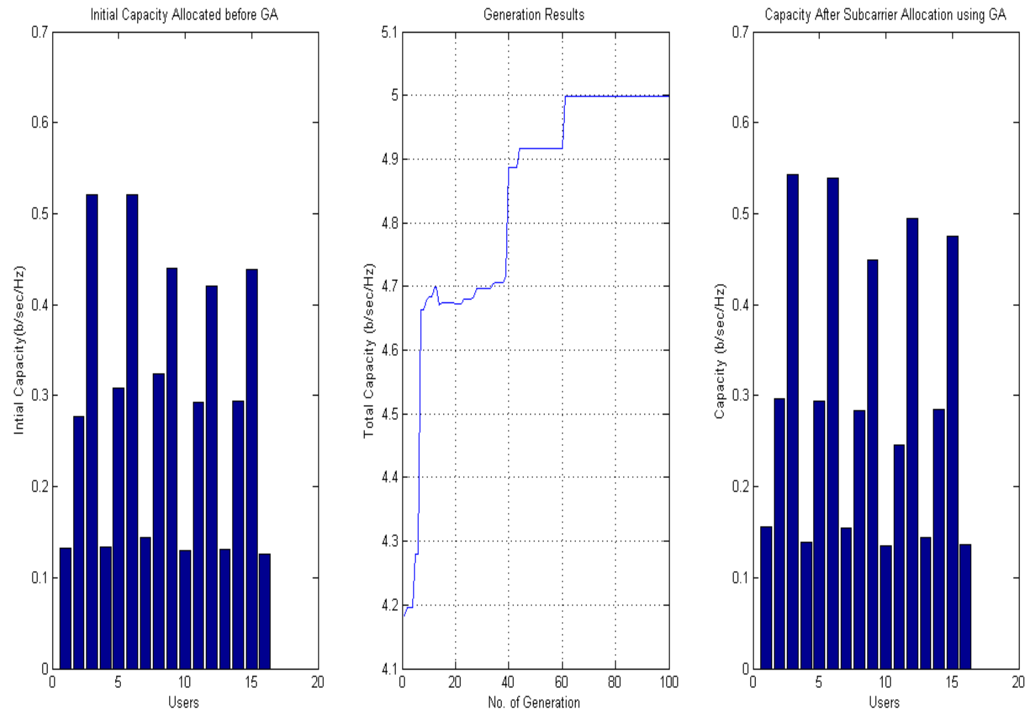


(a)



(b)

Figure 5.5.(a,b): Worst Case Simulation results for SISO system with 12 users (a) Capacity after Subchannel allocation using GA (b) Capacity after Subchannel allocation using GA and Power allocation using Optimal Power allocation.



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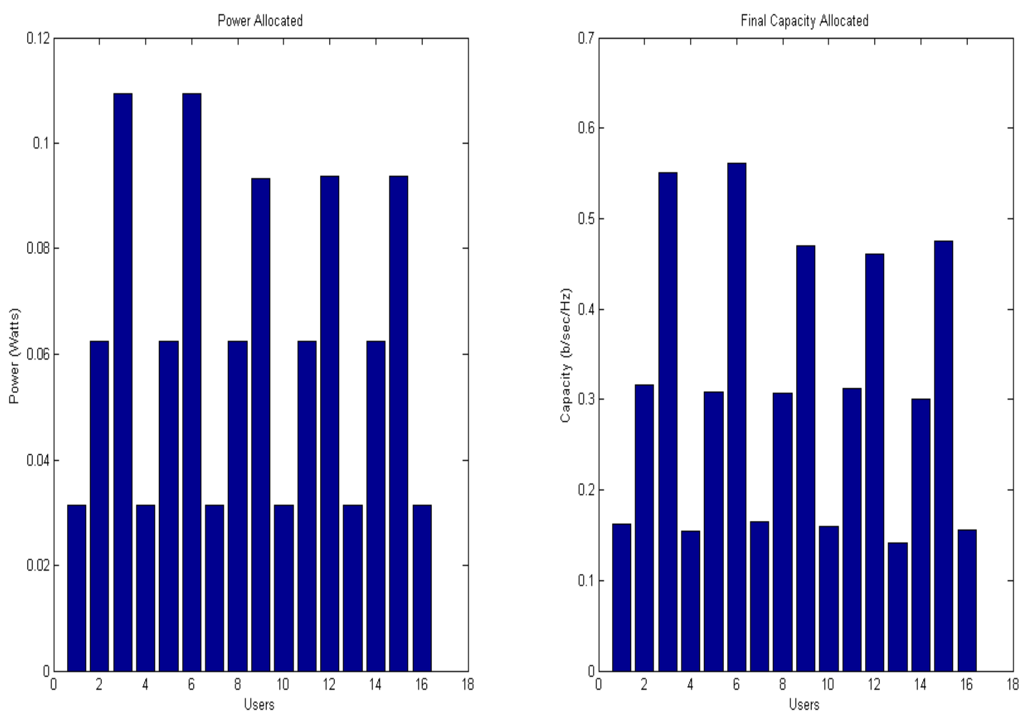
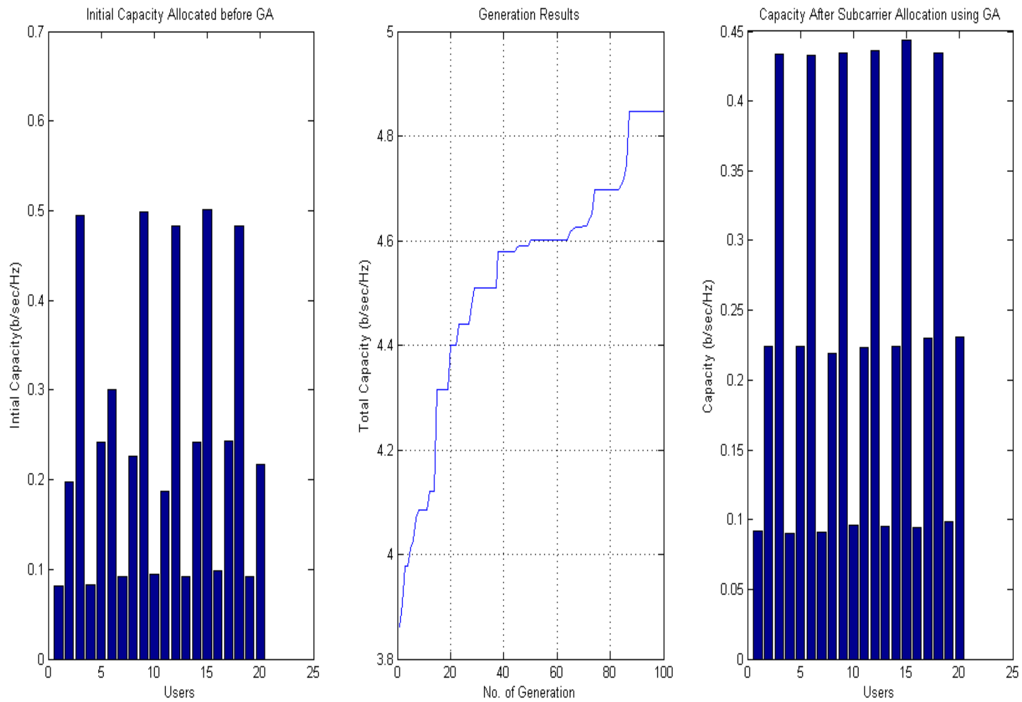


(d)

Figure 5.5.(c,d): Worst Case Simulation results for SISO system with 16 users (c) Capacity after Subchannel allocation using GA (d) Capacity after Subchannel allocation using GA and Power allocation using Optimal Power allocation.



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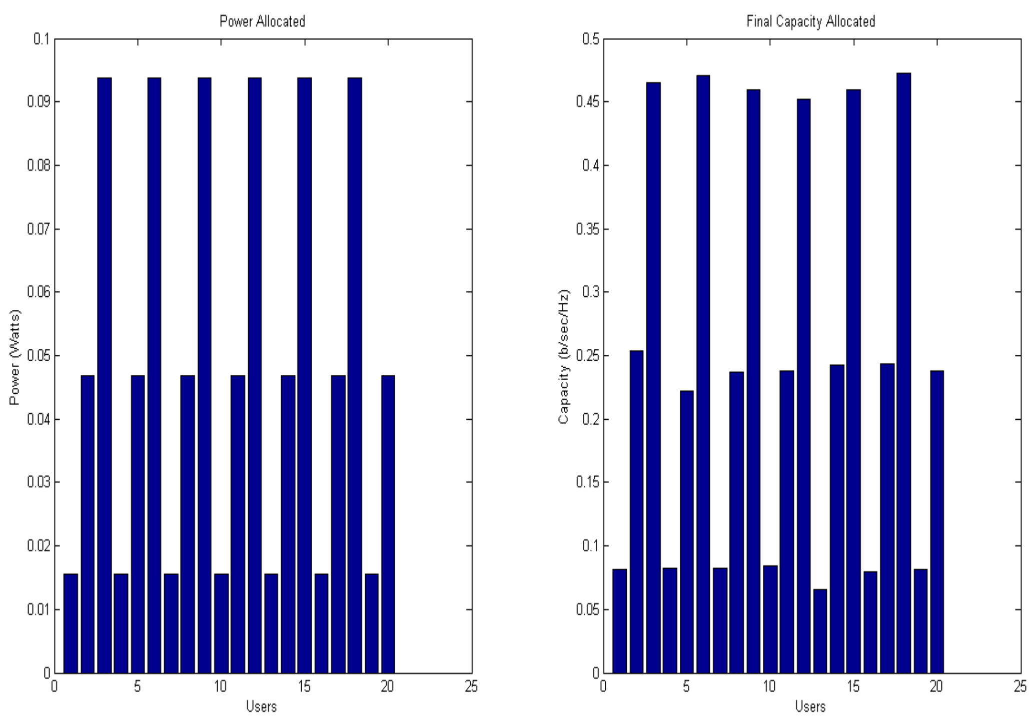
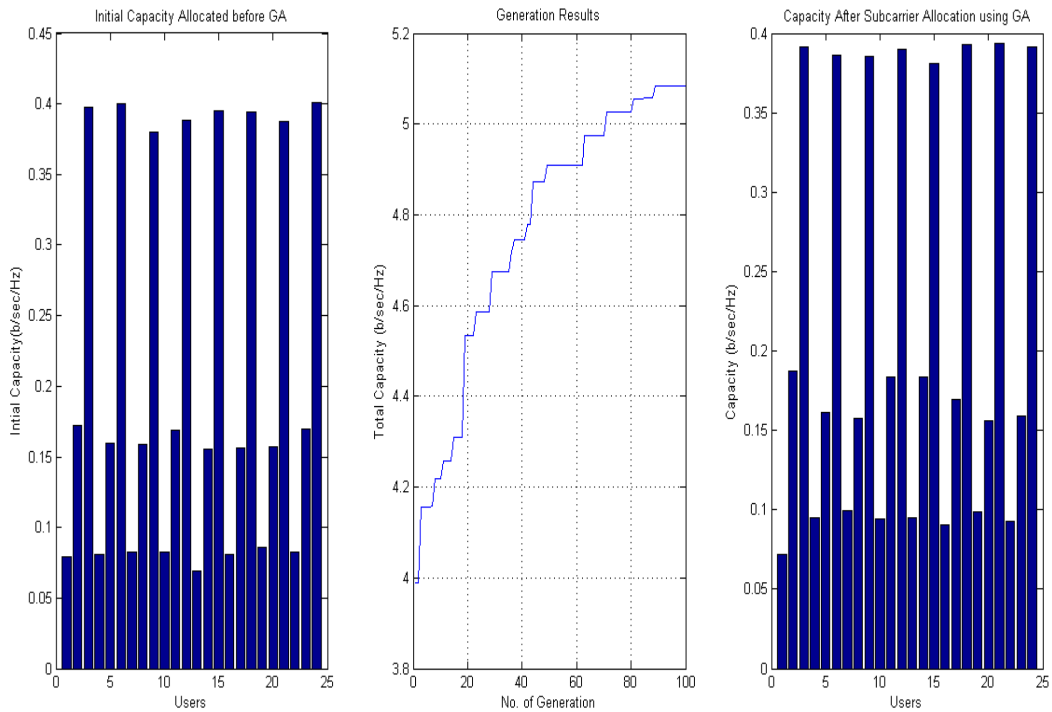


(f)

Figure 5.5.(e,f): Worst Case Simulation results for SISO system with 20 users (e) Capacity after Subchannel allocation using GA (f) Capacity after Subchannel allocation using GA and Power allocation using Optimal Power allocation.



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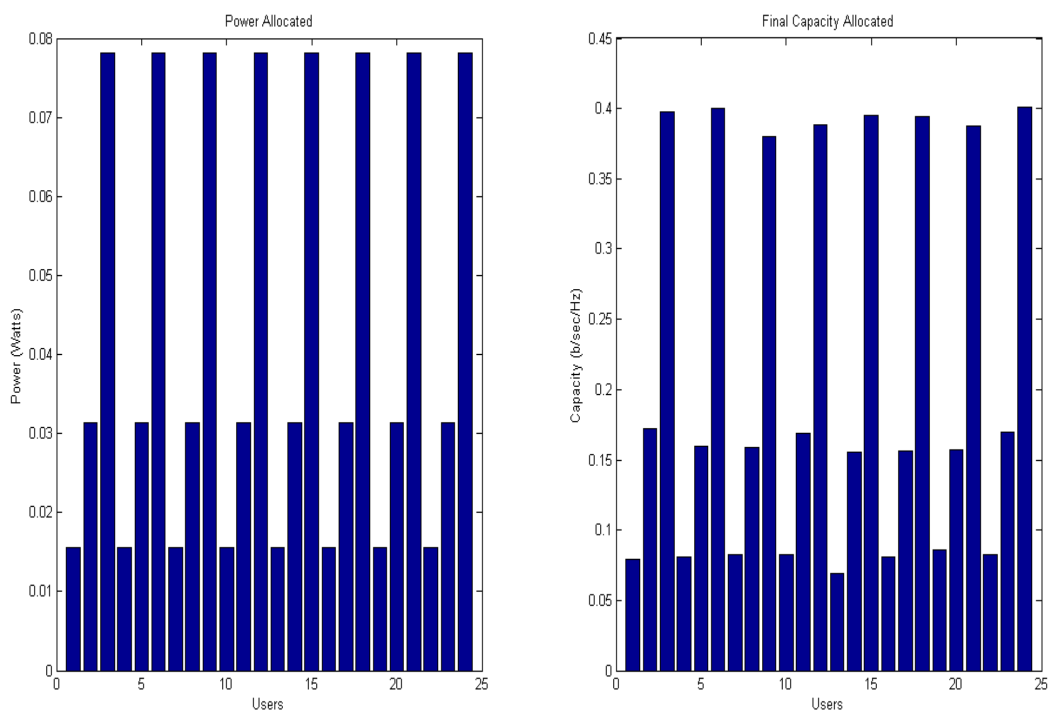
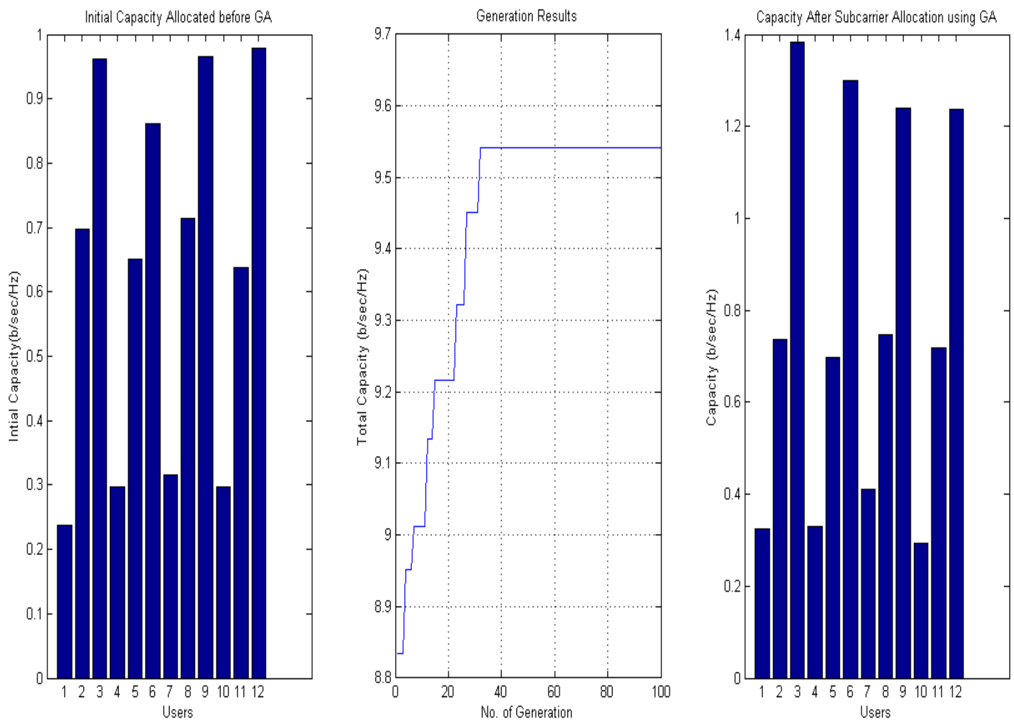
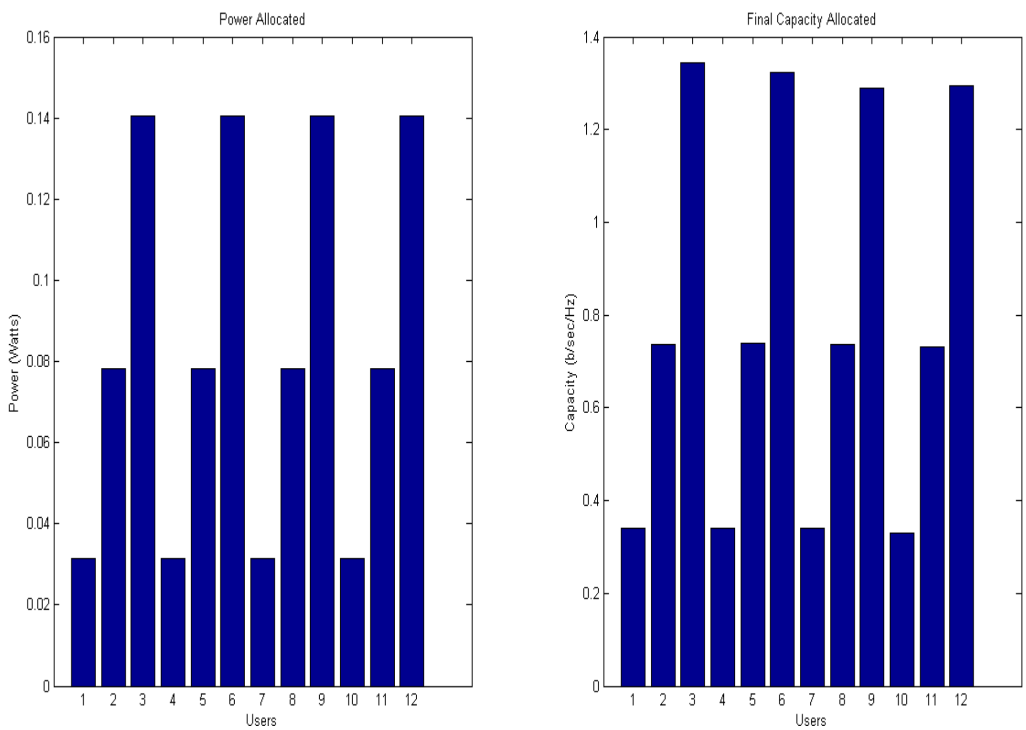


(h)

Figure 5.5.(g,h): Worst Case Simulation results for SISO system with 24 users (g) Capacity after Subchannel allocation using GA (h) Capacity after Subchannel allocation using GA and Power allocation using Optimal Power allocation.

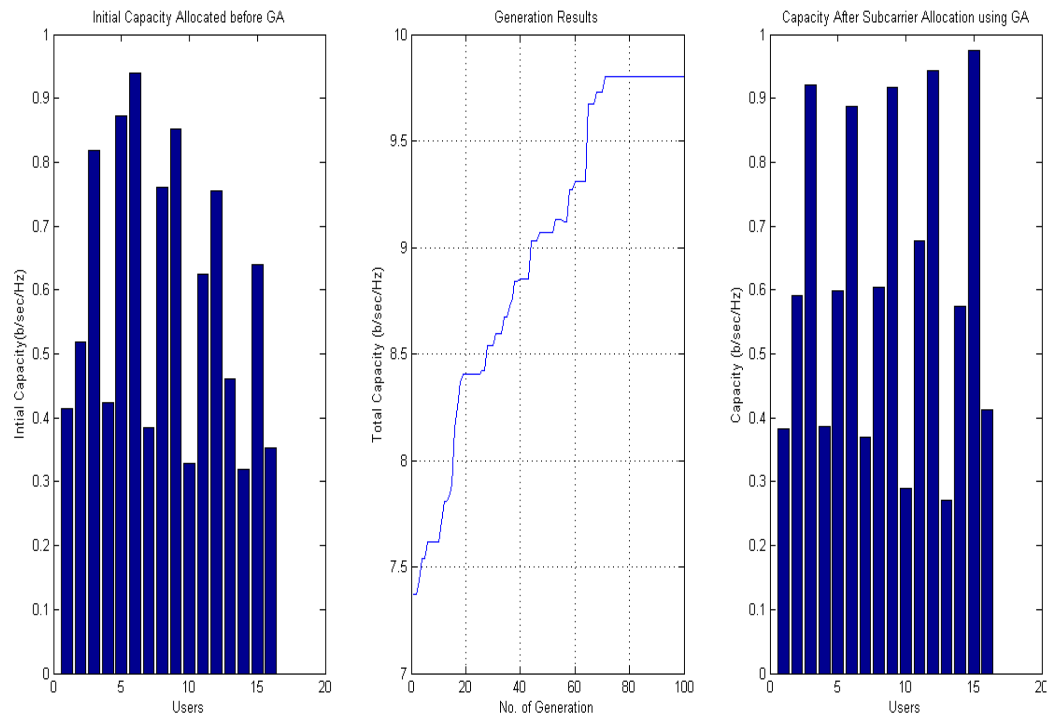


(a)



(b)

Figure 5.6.(a,b): Best Case Simulation results for MIMO system with 12 users (a) Capacity after Subchannel allocation using GA (b) Capacity after Subchannel allocation using GA and Power allocation using equation.5.12



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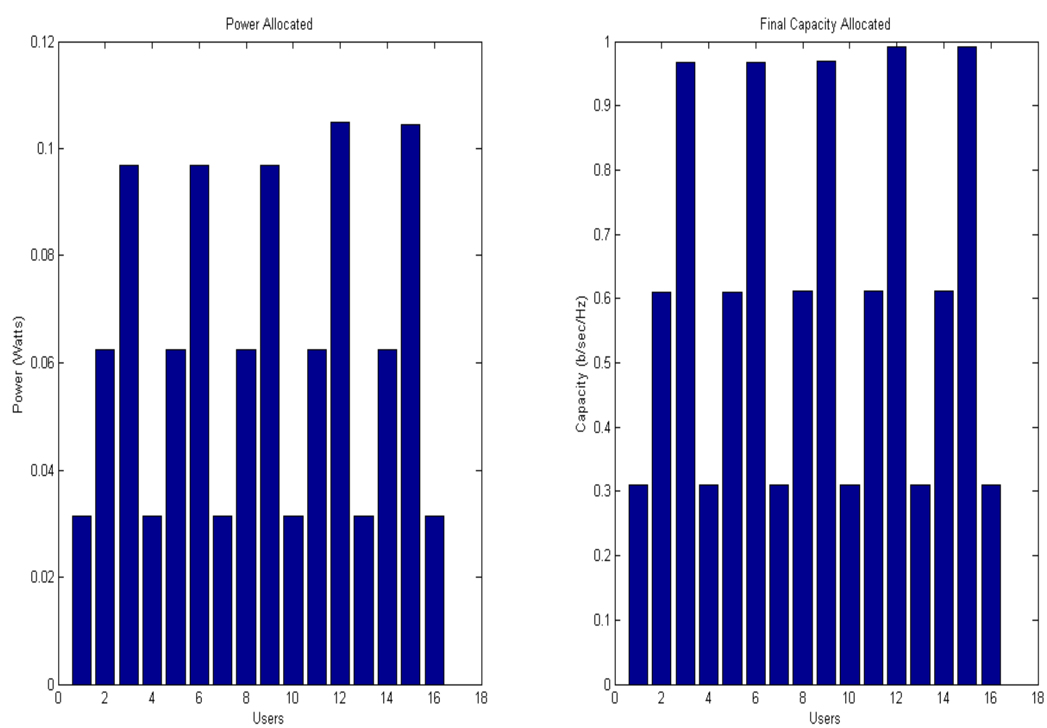
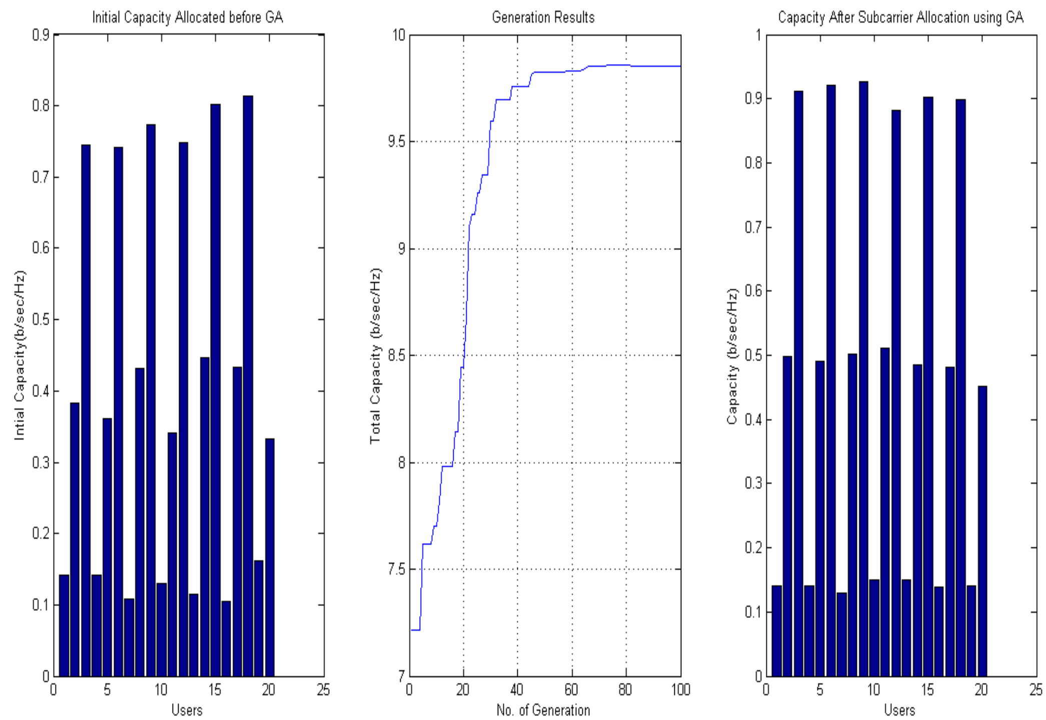


(d)

Figure 5.6.(c,d): Best Case Simulation results for MIMO system with 16 users (c) Capacity after Subchannel allocation using GA (d) Capacity after Subchannel allocation using GA and Power allocation using equation.5.12



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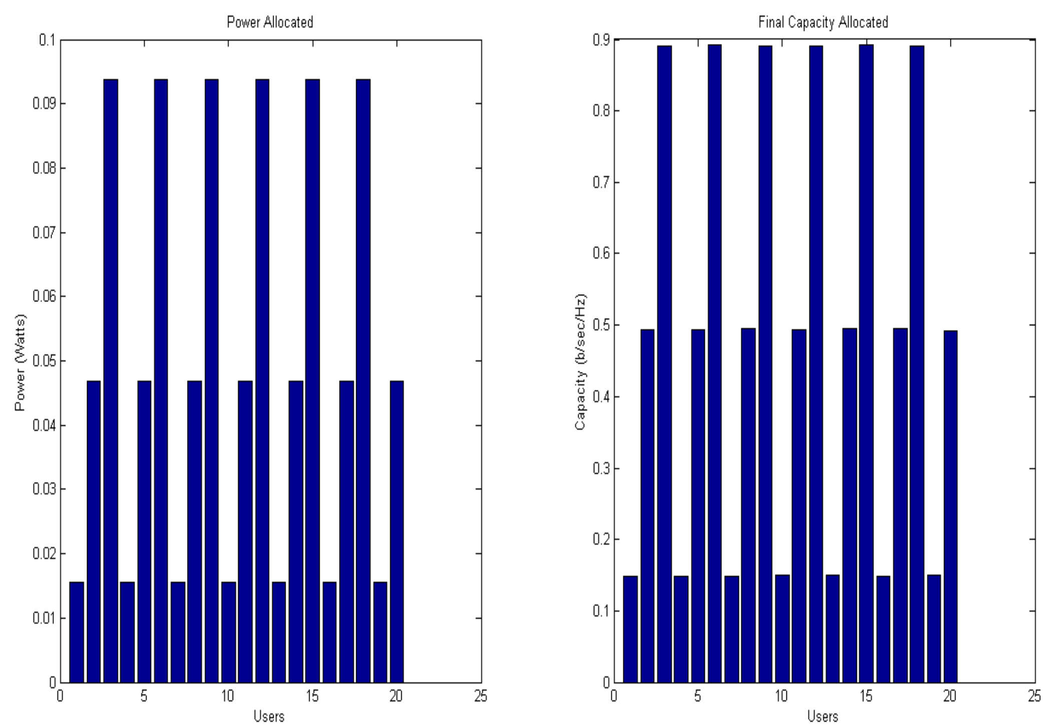
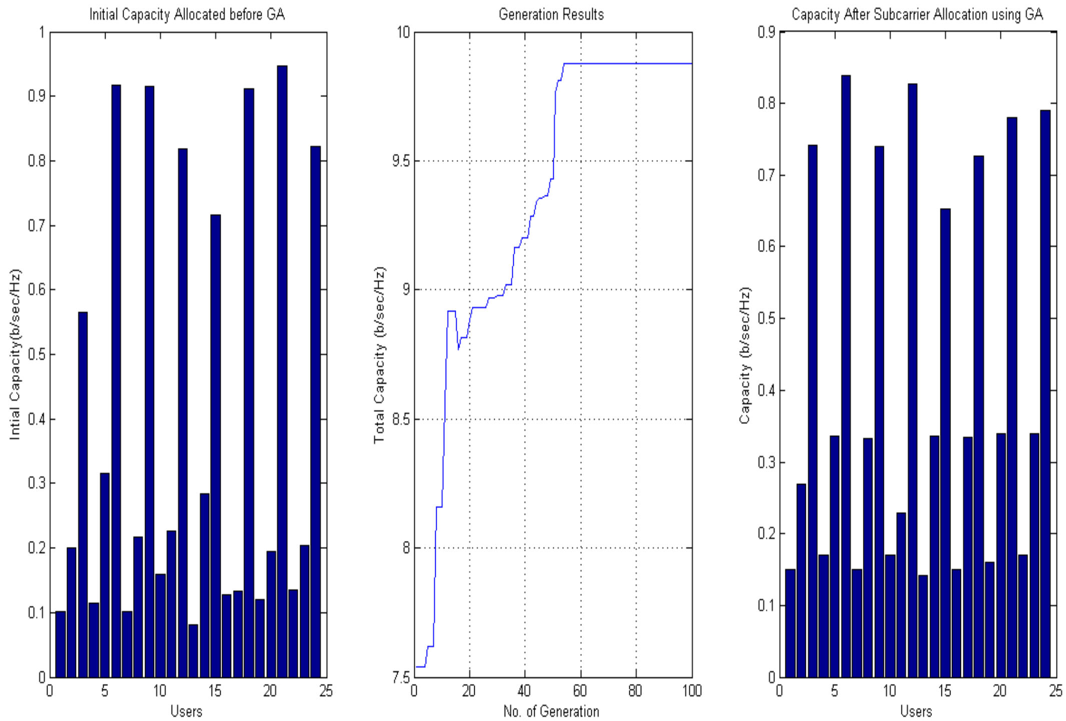


(f)

Figure 5.6.(e,f): Best Case Simulation results for MIMO system with 20 users (e) Capacity after Subchannel allocation using GA (f) Capacity after Subchannel allocation using GA and Power allocation using equation.5.12



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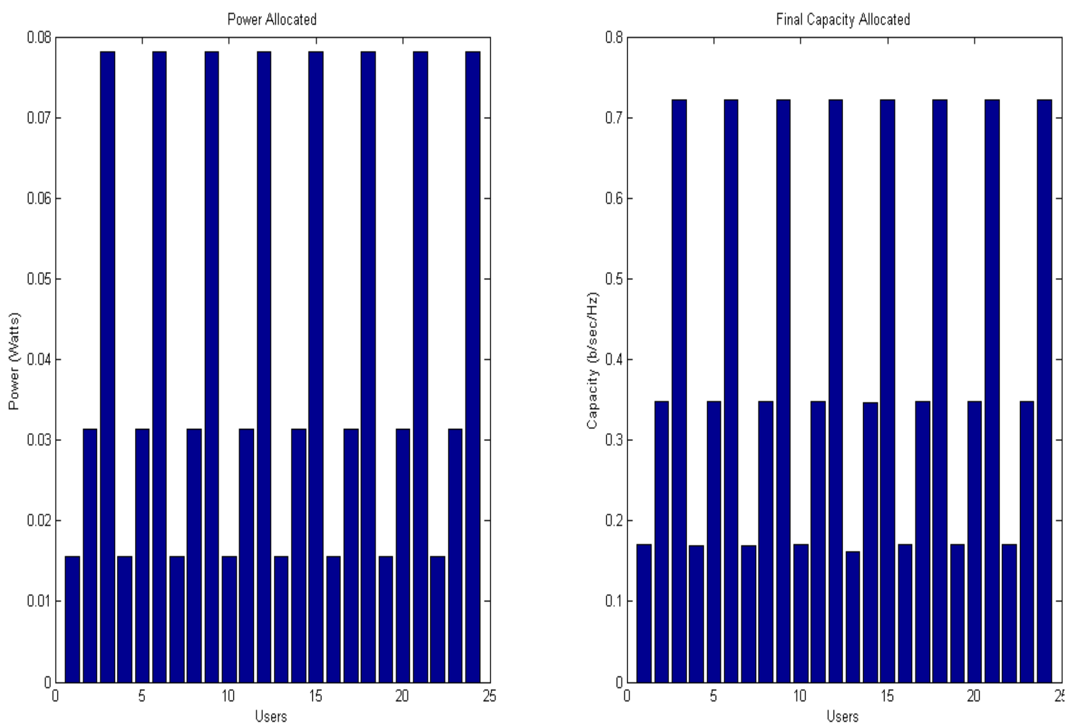

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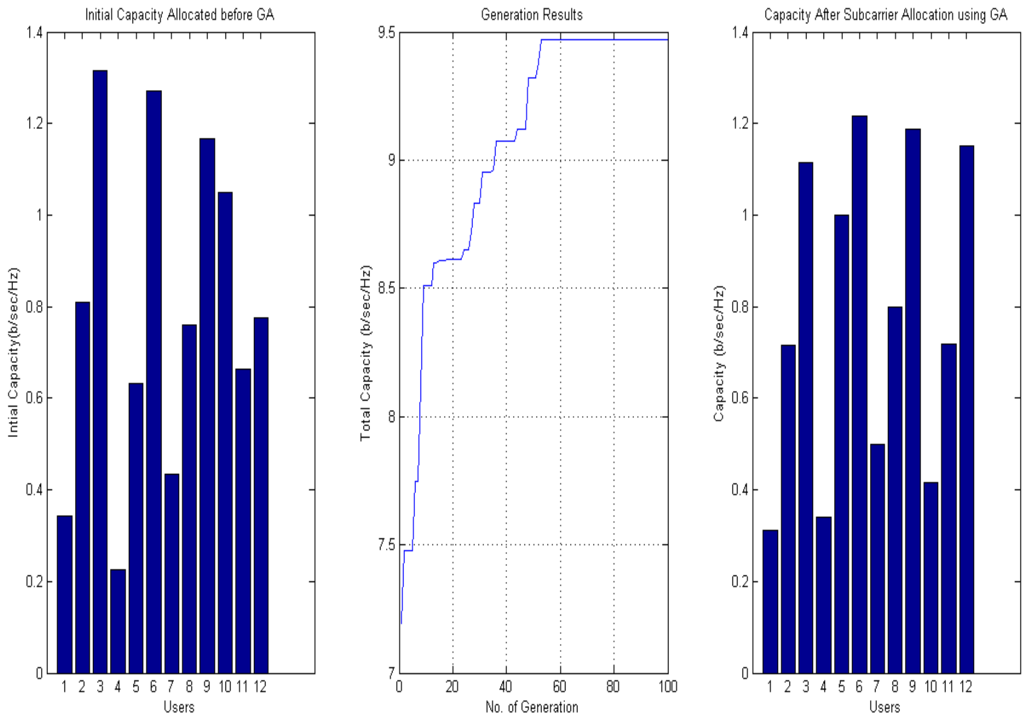
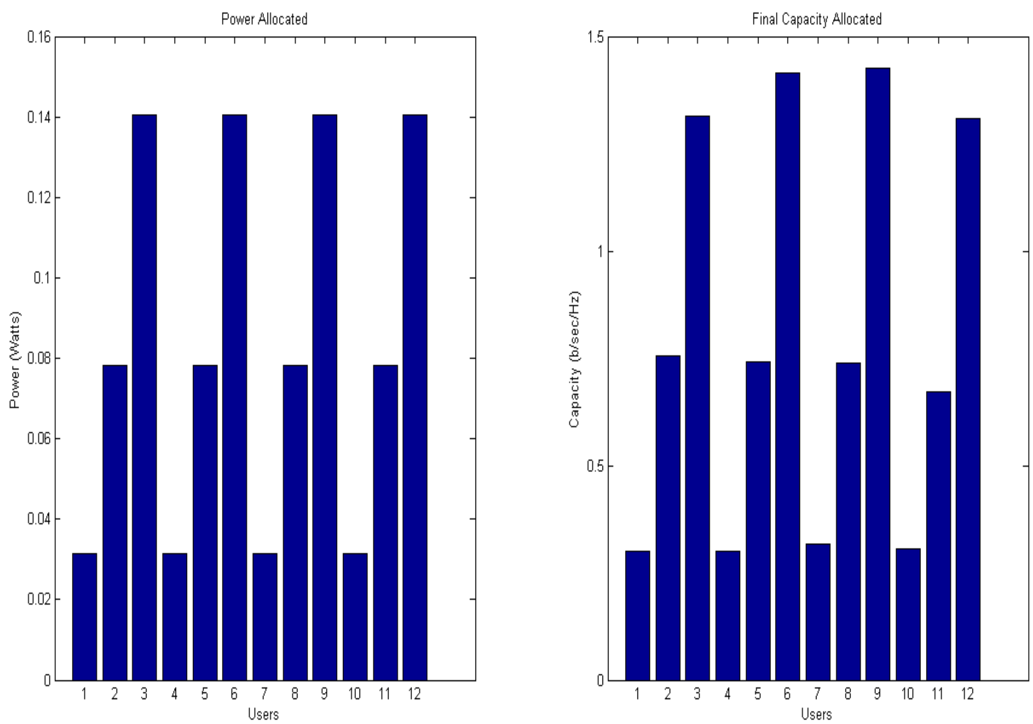
Figure 5.6.(g,h): Best Case Simulation results for MIMO system with 24 users (g) Capacity after Subchannel allocation using GA (h) Capacity after Subchannel allocation using GA and Power allocation using equation.5.12

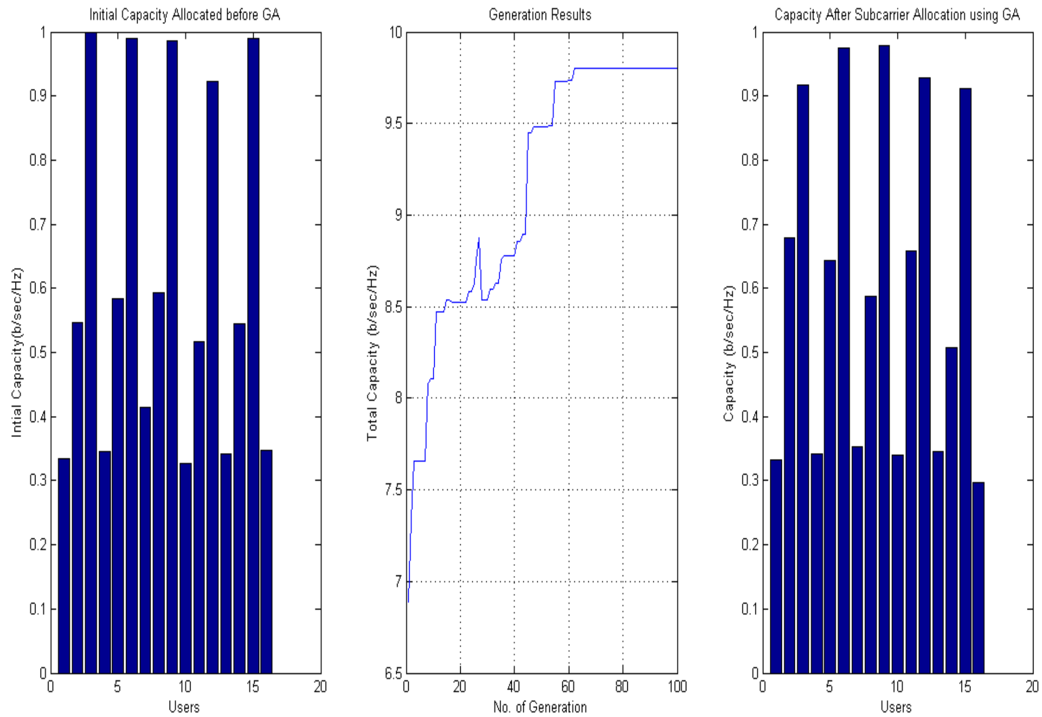


(a)



(b)

Figure 5.7.(a,b): Average Case Simulation results for MIMO system with 12 users (a) Capacity after Subchannel allocation using GA (b) Capacity after Subchannel allocation using GA and Power allocation using equation.5.12



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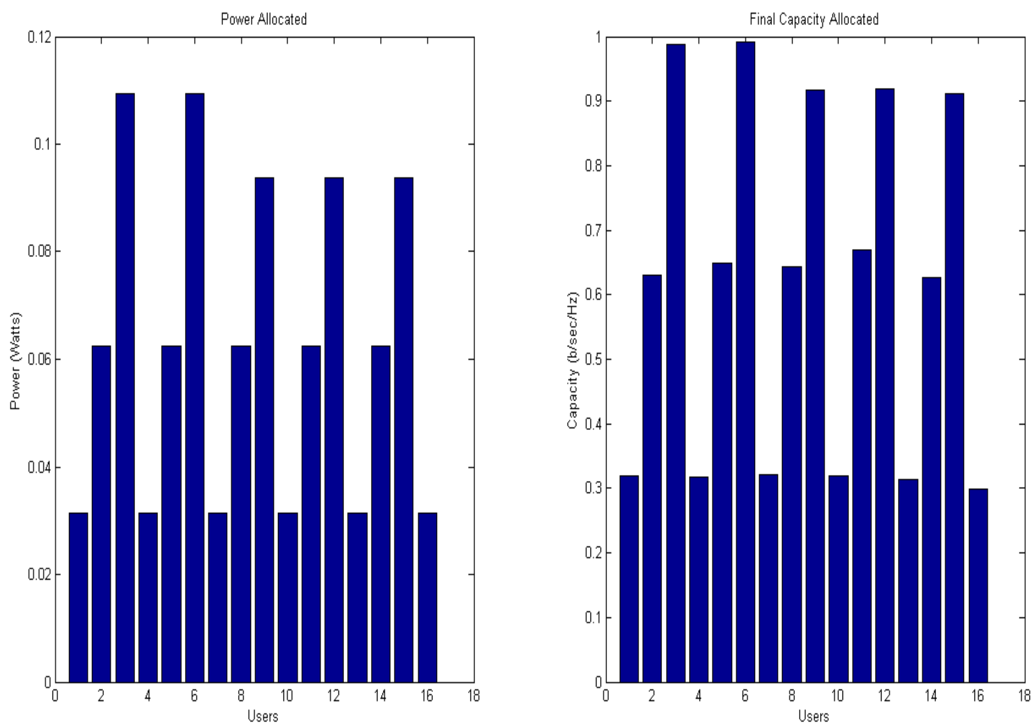

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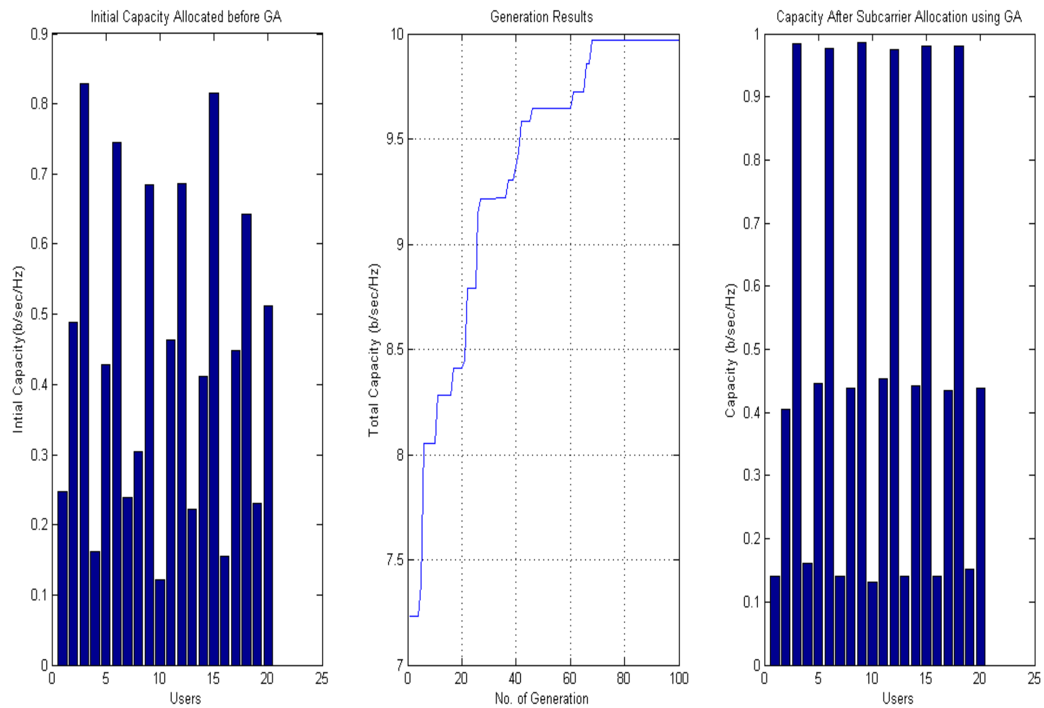
Figure 5.7.(c,d): Average Case Simulation results for MIMO system with 16 users (c) Capacity after Subchannel allocation using GA (d) Capacity after Subchannel allocation using GA and Power allocation using equation.5.12



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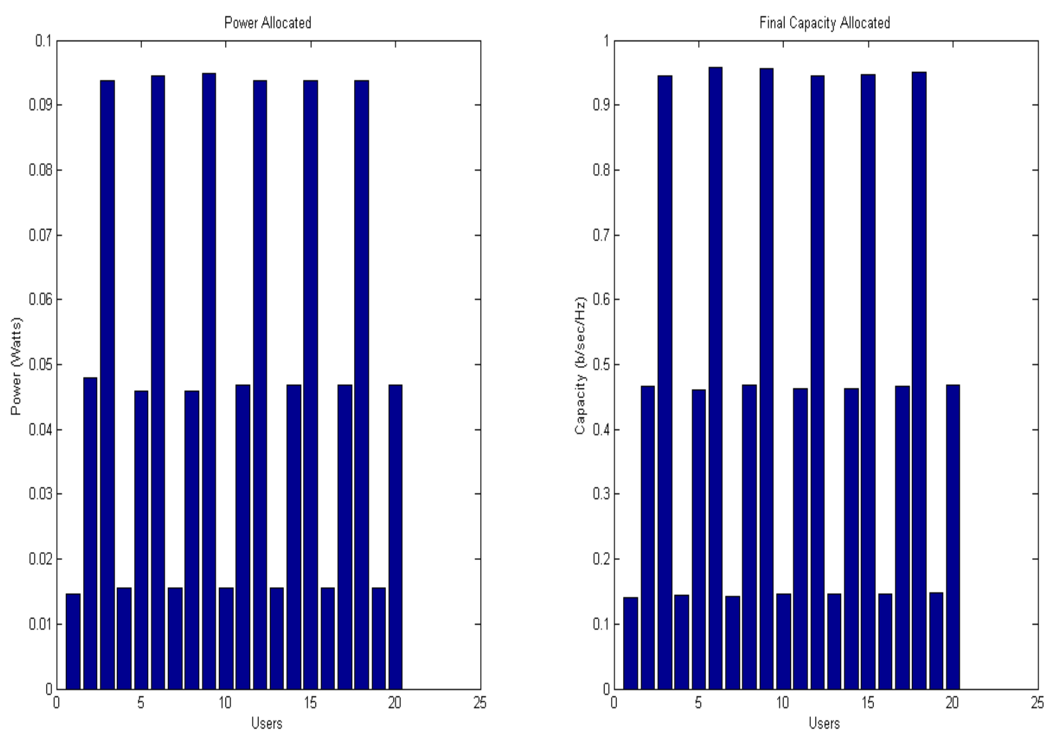

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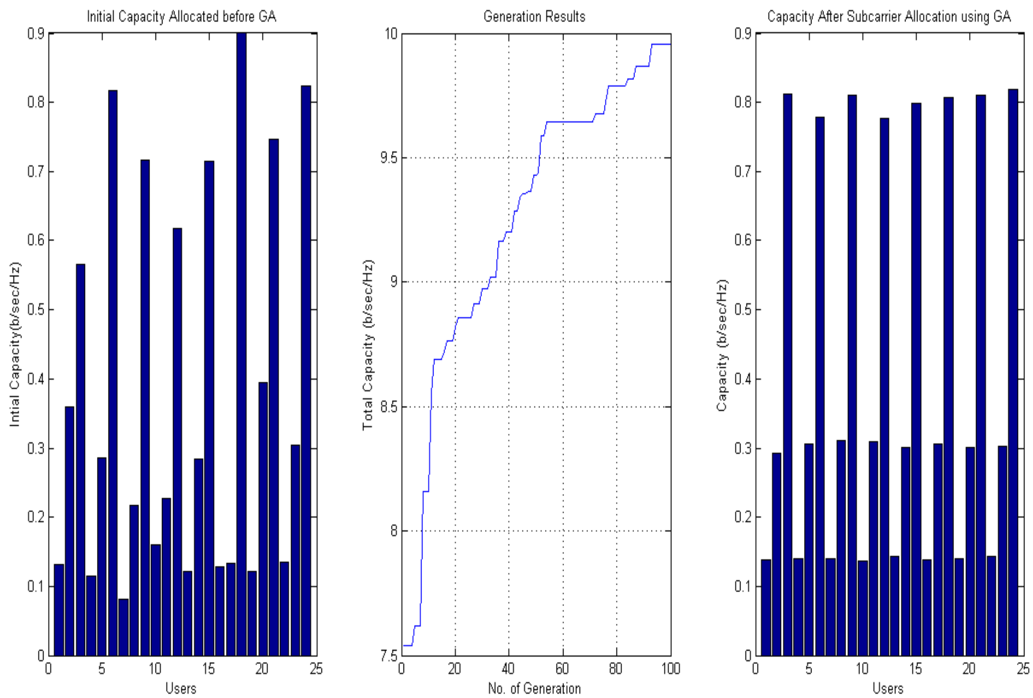
Figure 5.7.(e,f): Average Case Simulation results for MIMO system with 20 users (e) Capacity after Subchannel allocation using GA (f) Capacity after Subchannel allocation using GA and Power allocation using equation.5.12



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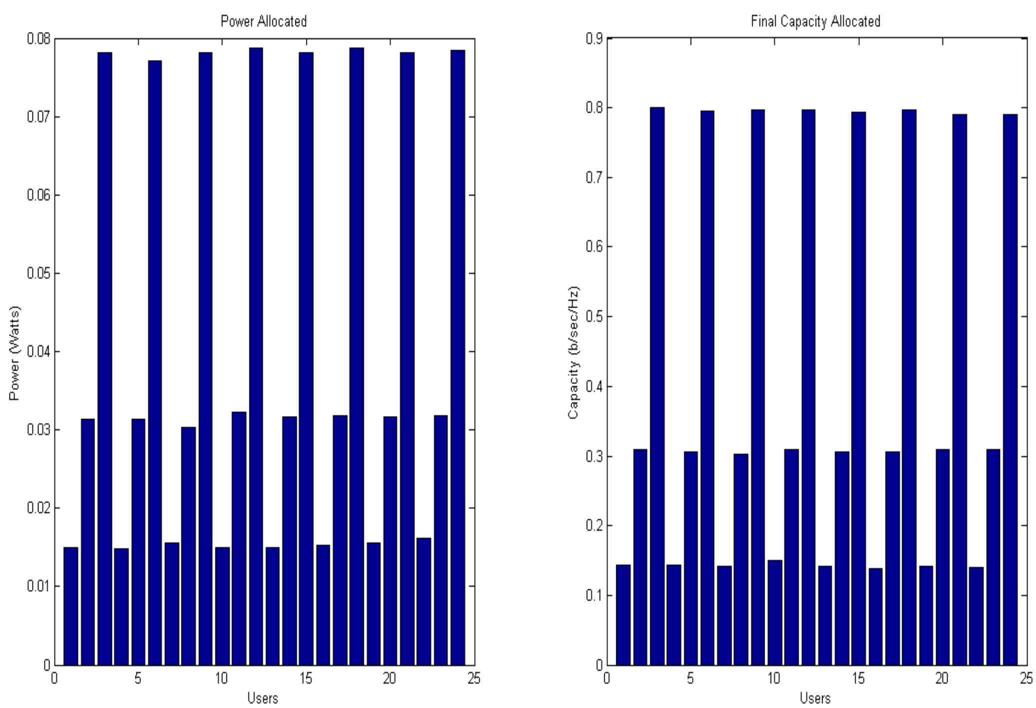
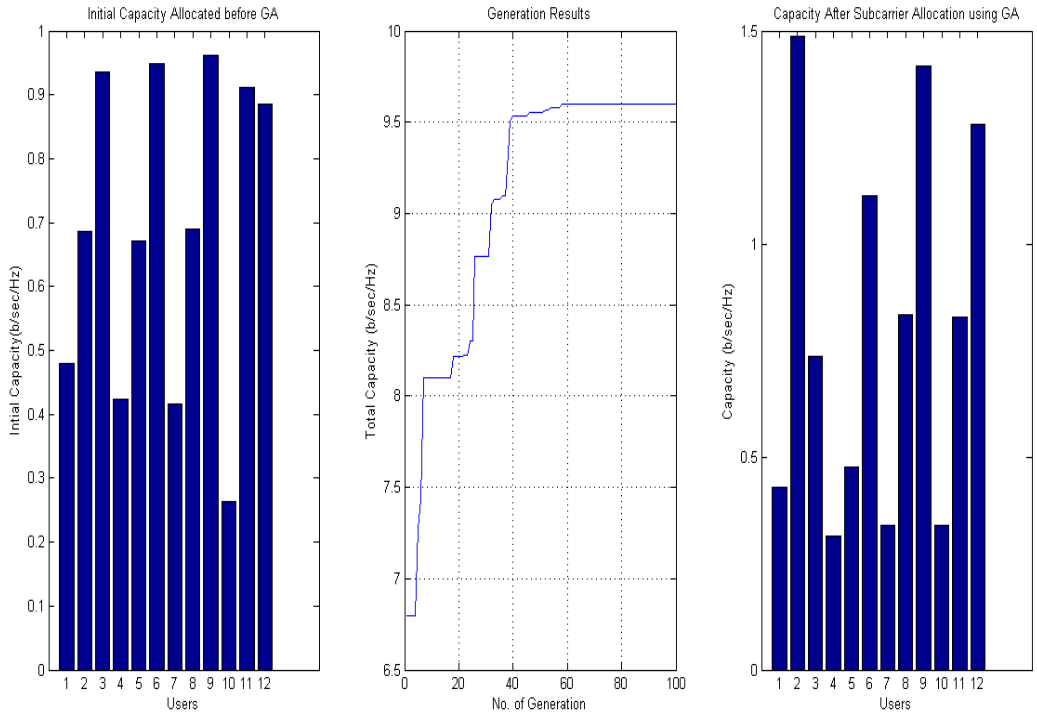
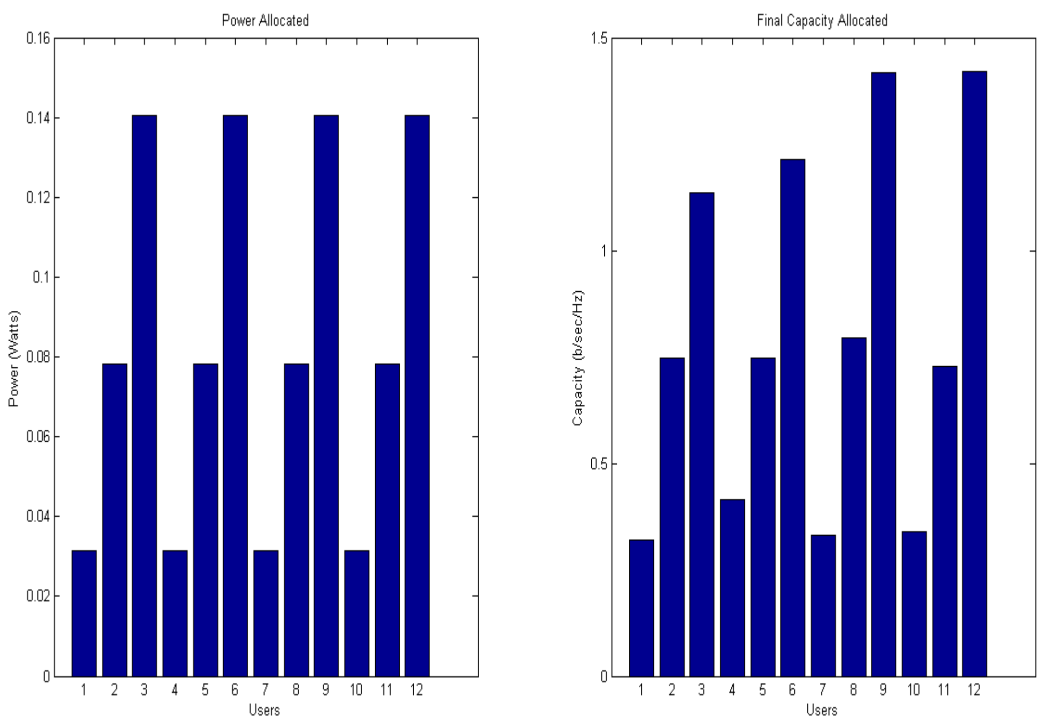


(h)

Figure 5.7.(g,h): Average Case Simulation results for MIMO system with 24 users (g) Capacity after Subchannel allocation using GA (h) Capacity after Subchannel allocation using GA and Power allocation using equation.5.12

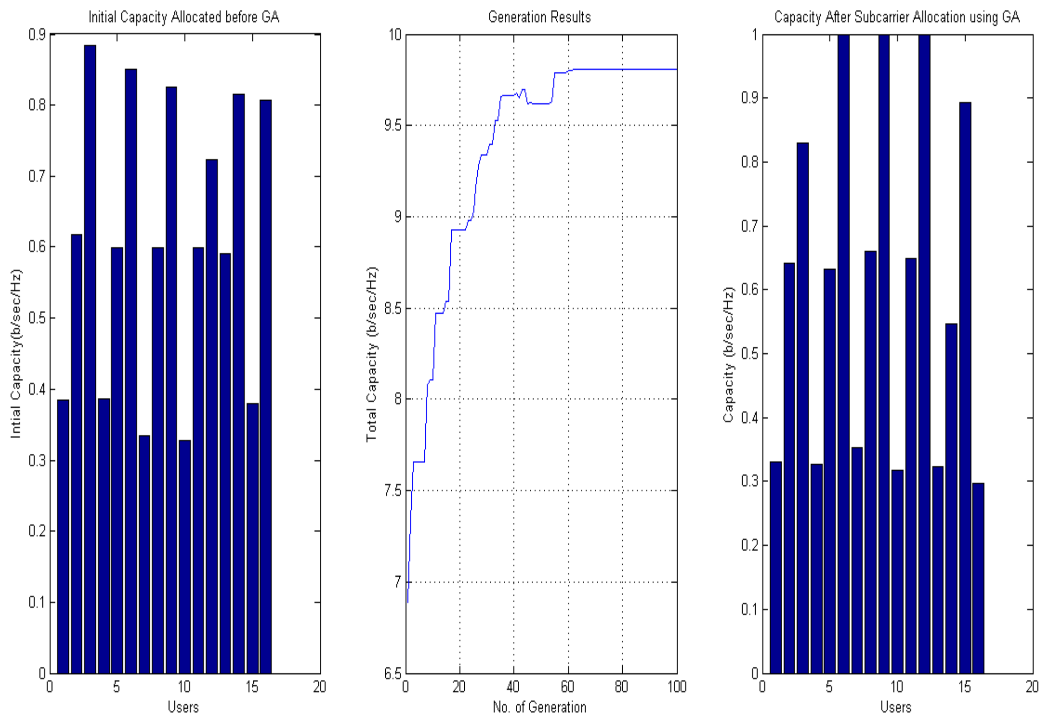


(a)



(b)

Figure 5.8.(a,b): Worst Case Simulation results for MIMO system with 12 users (a) Capacity after Subchannel allocation using GA (b) Capacity after Subchannel allocation using GA and Power allocation using equation.5.12



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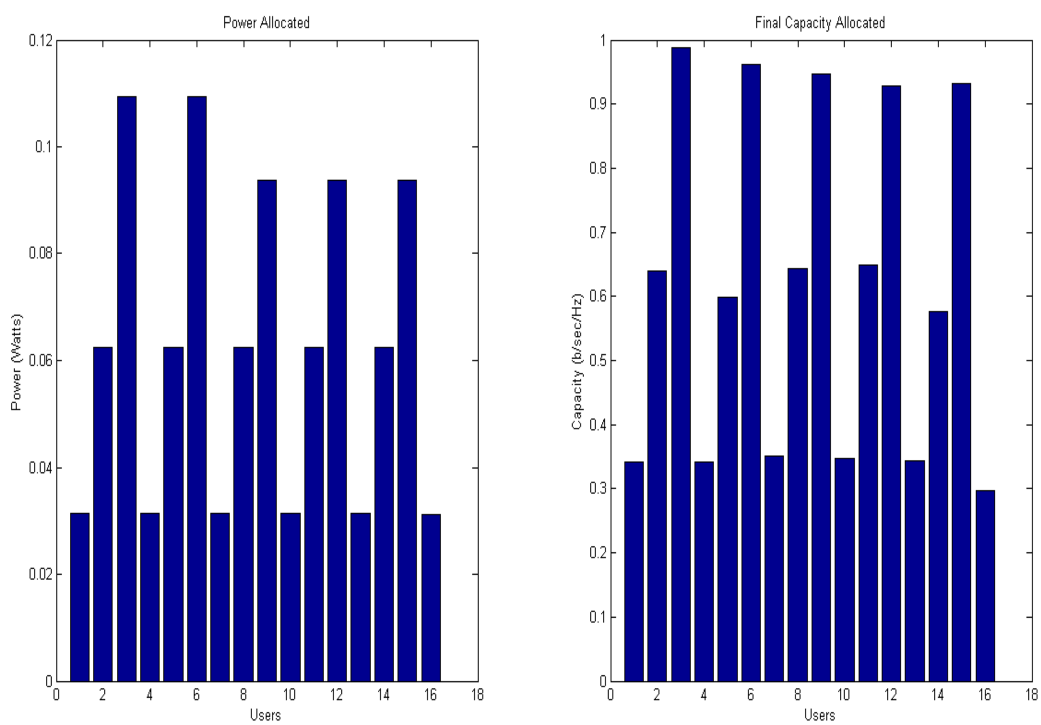
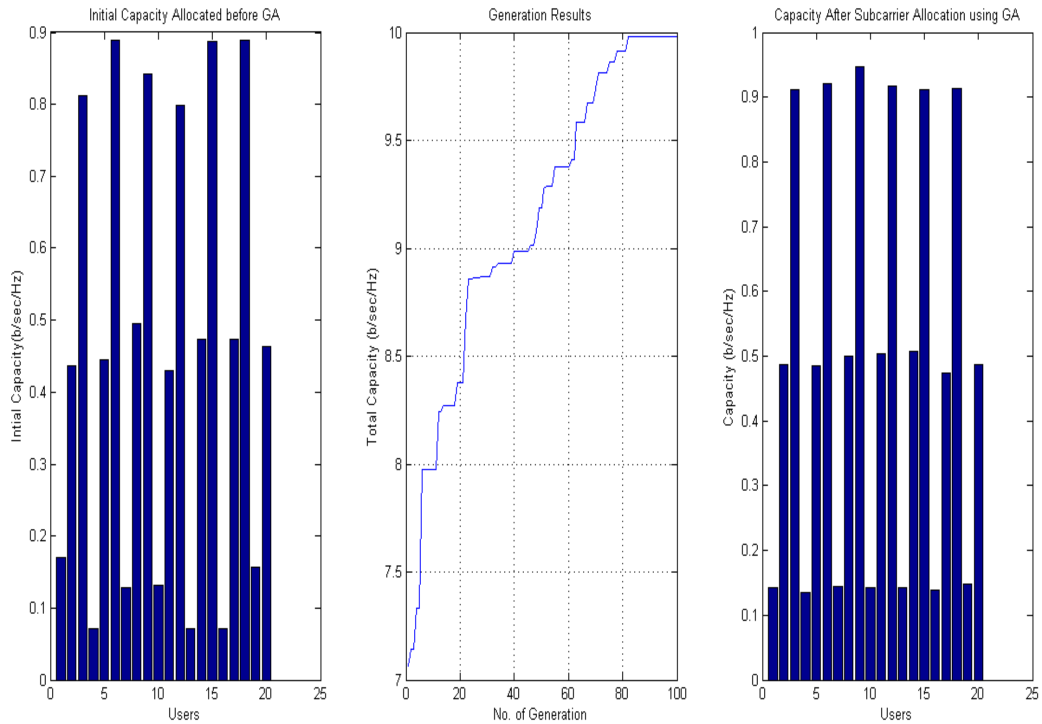


(d)

Figure 5.8.(c,d): Worst Case Simulation results for MIMO system with 16 users (c) Capacity after Subchannel allocation using GA (d) Capacity after Subchannel allocation using GA and Power allocation using equation.5.12



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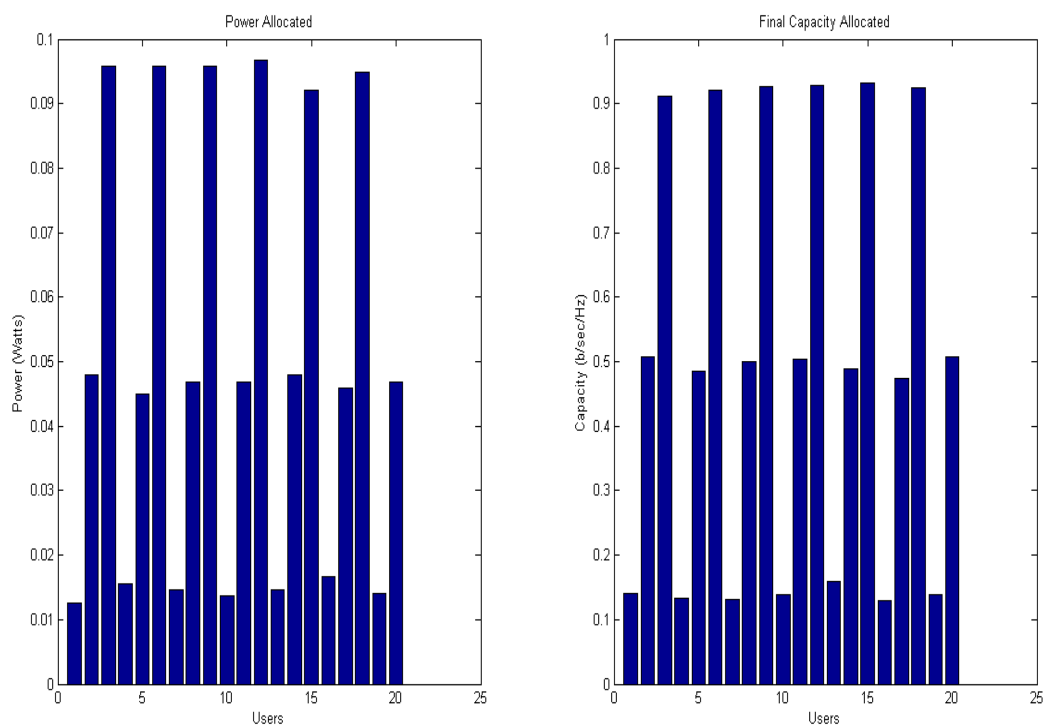
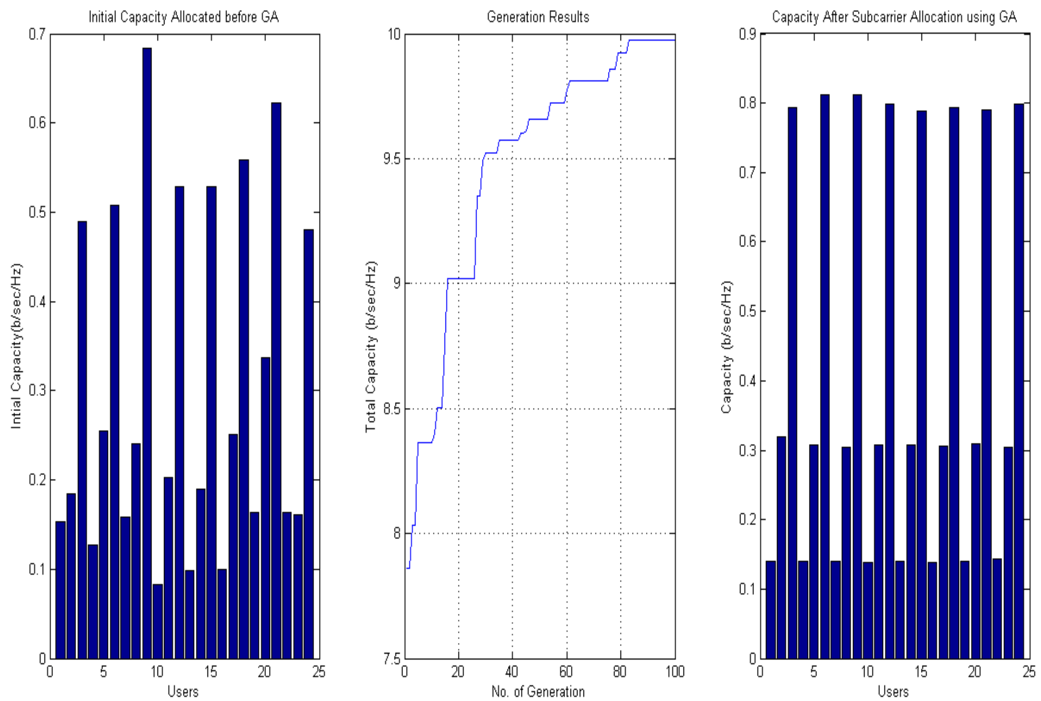


(f)

Figure 5.8.(e,f): Worst Case Simulation results for MIMO system with 20 users (e) Capacity after Subchannel allocation using GA (f) Capacity after Subchannel allocation using GA and Power allocation using equation.5.12



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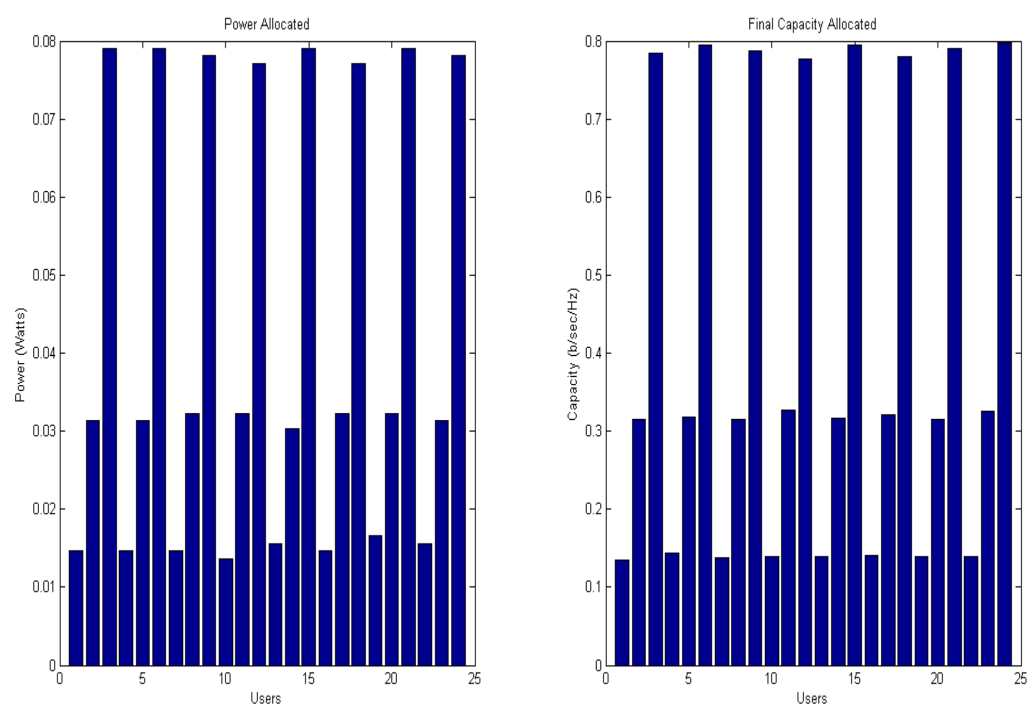


(h)

Figure 5.8.(g,h): Worst Case Simulation results for MIMO system with 24 users (g) Capacity after Subchannel allocation using GA (h) Capacity after Subchannel allocation using GA and Power allocation using equation.5.12

It can be observed from the comparison of right most and left most graphs in part (a) that the capacities obtained after subchannel allocation using GA sticks closely to the proportional rate constraint for all the cases. It can also be observed that the sum capacity increases with the number of generation of the GA, which is in consistence with the expected performance of GA.

The optimal power allocation also closely follows the rate constraints and hence the final capacities for all set of users are also in proportion. A comparison of simulation results for 12 and 16 users with that of 20 and 24 users reveals the fact that the sum capacities sticks closely to the proportionality constraints with the increase in number of users.

The strict adherence to proportionality constraints with increase in number of users can also be attributed to the expected performance of GA, the GA tends to perform better as the search space becomes complex.

These results reaffirm the fact that, the proportional rate constraints can be strictly enforced in resource allocation algorithms using GAs. The cost of strictly enforcing proportionality is slight reduction in capacity.

In the second part, we compared the results obtained by proposed method with those obtained by the method used in [WSEA04]. For this comparison, in place of using exact expression for power allocation in optimal power allocation[WSEA04]/equation.5.12, we used the equal power allocation approximation discussed in section 5.3.

Table 5.1 and Fig.5.9 shows the comparison of total capacity obtained by the proposed method with the capacity obtained by method in [WSEA04].We also compared the total capacity which can be obtained by method in [WSEA04], when used for MIMO OFDMA. The number of users was varied from 2-16 in increments of 2. A total of 1000 different channel realizations and 100 time samples for each realization were used for each of the number of users.

The total capacity obtained by the proposed method is consistently higher than that obtained by [WSEA04]. It can be observed that proposed algorithms provided an approximate capacity gain of 21% for SISO case and about 70% for MIMO case, over the method in [WSEA04]. Also the total capacity increases with the number of users which is the effect of diversity gain. The capacity obtained for MIMO is almost 2 times the capacity obtained in [WSEA04], this is in consistence with the fact that with the fact that MIMO systems have additional spatial multiplexing gain of order of $\min(M_T, M_R)$.

Table 5.1: Total capacity versus number of users

S.No	Users (K)	Sum Capacity (SISO) Bits/Sec/Hz				Sum Capacity (MIMO) Bits/Sec/Hz			
		[WSEA04]	Proposed			[WSEA04]	Proposed		
			Best	Avg.	Worst		Best	Avg.	Worst
1	2	4.52	4.74	4.78	4.80	8.52	8.85	8.92	8.98
2	4	4.57	4.79	4.81	4.83	8.57	9.09	9.11	9.18
3	6	4.62	4.83	4.84	4.86	8.62	9.25	9.27	9.28
4	8	4.65	4.86	4.88	4.89	8.65	9.38	9.41	9.42
5	10	4.665	4.885	4.89	4.895	8.70	9.45	9.46	9.48
6	12	4.70	4.90	4.913	4.92	8.75	9.54	9.55	9.56
7	14	4.71	4.915	4.915	4.915	8.80	9.67	9.73	9.75
8	16	4.72	4.92	4.928	4.931	8.90	9.80	9.84	9.87

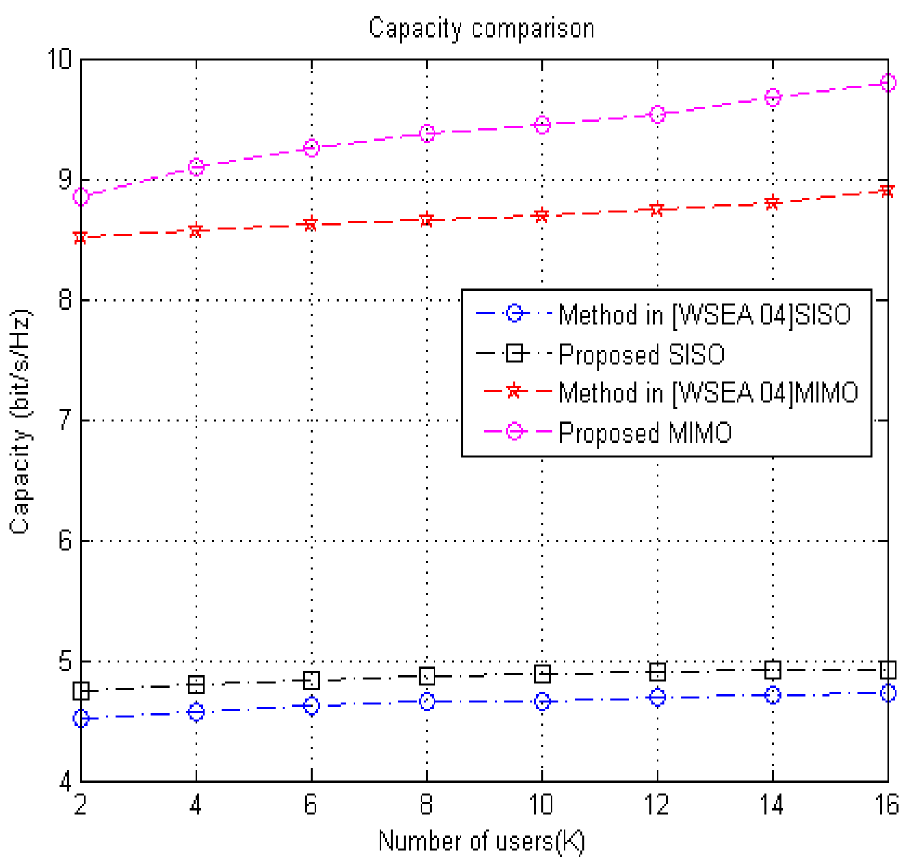


Figure 5.9: Total capacity versus number of users.

In order to analyze the computational complexity of the algorithm, recall that K refers to the total number of users in the system. N on the other hand refers to the number of subchannels, which is a power of 2 and much larger than K.

The subchannel allocation method proposed in [WSEA04] is basically a three step process. Step 1 of the algorithm calculates number of subchannels to be allocated to each user while taking care of proportional fairness. This step requires 1 division and K multiplications, and thus has a complexity of $O(K)$.

The actual subchannel assignment is done in step 2, which involves sorting the subchannel gains $H_{k,n}$ for each user k, therefore requiring $O(KN\log_2 N)$ operations. The user with best gain on a particular subchannel is then allocated that subchannel. It then searches for the best user k among K users for the remaining N-K unallocated subchannels, thus requiring another $O((N-K)K)$ operations. In Step 3, it allocates the remaining N^* subchannels to the best user, and thus requires $O(K)$ operations. These operations pertain to the subchannel allocation, and the asymptotic complexity is $O(KN\log_2 N)$.

Calculating the number of subchannels to be allocated to each user before actual allocation on the basis of SNR introduces extra overhead. In step 2 sorting of subchannels on the basis of gains is another overhead. In the proposed GA aided subchannel allocation, these overheads are removed by relaxing the proportionality constraint such that each user should get at-least one subchannel while searching and allocation of subchannels is performed simultaneously.

In each generation the fitness function is evaluated for each individual with a complexity of $O(N)$. The double summation, over all subchannels and users, involved in the sum capacity calculation using equation.5.10 reduces to a single summation, over all subchannels only. This is due to two reasons: Firstly, due to the constraints (C_3 & C_4) that each subchannel should be assigned to a unique user and is not shared among users. Secondly, the user to which that subchannel is assigned is known to us from the fitness function for each iteration. This reduces the overhead of having to sort through the gains of different users on a particular subchannel as required in [WSEA04].On the basis of fitness value two individual with lowest fitness values are replace by two child individuals with best fitness. Step 2 of proposed algorithm does not require sorting the individuals on the basis SNR but on the basis of their fitness function. This step is part of GA itself and hence reduces the overhead of having sorted individuals on the basis of their SNRs. Rest of the procedure remains same for both the algorithms.

In the light of the above discussion, it is clear that the main complexity lies in calculation of fitness function for each individual in each generation (G). The asymptotic complexity of our algorithm will be O(NG).Since number of generation is a user defined parameter, it can be set to small value to reduce the complexity. Defining the initial population randomly may require more number of generations for GA to converge. If, based on previous results the initial population is defined close to the expected results, the number of generations can be reduced significantly. This reduction in number of generations will result in less complexity of the algorithm.

5.5. Conclusion

In this chapter, we proposed a novel GA for solving rate adaptive resource allocation problem with proportional rate constraints for downlink OFDMA systems. In Section 5.4, we proposed a low complexity subchannel allocation scheme using GA to maximize the total throughput while maintaining rate proportionality among the users. Steps 11 and 12 in proposed algorithm, add deterministic component to otherwise probabilistic GA, and enhance the overall performance of the algorithm.

The simulation results show that the proposed method strictly sticks to the proportional rate constraints. It was also shown that relaxing proportionality constraints achieves higher data rates and reduces the computational complexity of the algorithm.

The proposed algorithm achieves 20 to 70 % higher data rates, and is computationally less expensive as compared to previous algorithms in this area.

Chapter 6

Multi-Objective Resource Allocation using NSGA –II for OFDMA Systems

6.1. Introduction

This chapter investigates the problem of joint subchannel and bit allocation in downlink of OFDMA [Law99, RABT02, WCLM99, JL03, Red07, SA09, STTA12, SWA10, TZWZ07, KPL06, WSEA04, SRDS08, SAE03, RC00, SAE05] and MIMO OFDMA [SA11a, XHZL05, HYY06, GLX^{+}09, CLC10, PB10, ASC11, CLL11] systems. Using SVD, the MIMO fading channel of each subchannel is transformed into an equivalent bank of parallel SISO subchannels. To achieve the capacity bound, one must solve a multiuser subchannel allocation and the optimal bit allocation jointly. To alleviate the computational complexity of joint subchannel and bit allocation, several suboptimal solutions have been proposed [Law99, RABT02, WCLM99, JL03, Red07, TZWZ07, KPL06, WSEA04, SRDS08, SAE03, RC00, SAE05, XHZL05, HYY06, GLX^{+}09]. These suboptimal solutions handle subchannel and bits individually. We propose the use of NSGA – II [SRDS08, DPAM02, SD95] which is a MOGA, for joint allocation of bits and subchannels, in the downlink of OFDMA system. NSGA – II is intended for optimization problems involving multiple conflicting objectives. Here the two conflicting objectives are Rate Maximization and Transmit Power Minimization. The simulation results indicate remarkable improvement in terms of convergence over previous approaches involving EAs [GLX^{+}09, TZWZ08]. At the same time capacity achieved by the proposed algorithm is found to be comparable with that of previous algorithms.

6.2. System Model

The system under consideration is a OFDMA/MIMO OFDMA system in downlink where the perfect CSI is assumed at both the receiver and transmitter. We assume that one subchannel can be used only by one user at each time. Then each subchannel has a narrowband channel with M antennas at both the transmitter and the receiver, which can be modeled by an M x M channel matrix $\mathbf{H}=[h_{i,j}]$, where $h_{i,j}$ is the channel gain at the receive antenna i from transmit antenna j. The SVD of $\mathbf{H}$ can be written as:

$$\mathbf{H} = \mathbf{U}\mathbf{\Lambda}^{1/2}\mathbf{V}^{\dagger} \tag{6.1}$$

Where $\mathbf{U}$ and $\mathbf{V}$ are unitary matrices, $\mathbf{V}^{\dagger}$ denotes the transpose conjugate of $\mathbf{V}$, and $\mathbf{\Lambda}$ is a diagonal matrix. The elements of $\mathbf{\Lambda} = diag([\lambda_1,\ldots,\lambda_m])$ are real and ordered so that $\lambda_1 \geq \ldots \geq \lambda_m \geq 0$. Following the SVD analysis, the channel matrix H is decomposed into a number of independent orthogonal modes of excitation, which are referred to as eigen-modes of the Channel [XHZL05]. The parallel decomposition of the channel is obtained by defining a transformation on the channel input and output $\boldsymbol{x}$ and $\boldsymbol{y}$ through *transmit precoding* and *receiver shaping* respectively. In transmit precoding the input to the antennas $\boldsymbol{x}$ is generated through a linear transformation on input vector $\tilde{\boldsymbol{x}}$ as $\mathbf{x} = \mathbf{V}\tilde{\mathbf{x}}$. Receiver shaping performs a similar operation at the receiver by multiplying the channel output $\mathbf{y}$ with $\mathbf{U}^{\dagger}$

$$\boldsymbol{y}_m = \sqrt{\boldsymbol{\lambda}_m}\,\boldsymbol{x}_m + \tilde{\boldsymbol{n}}_m, \qquad \text{for } m = 1,\ldots,M. \tag{6.2}$$

Here $\tilde{\boldsymbol{n}} = \mathbf{U}^{\dagger}\boldsymbol{n}$, and $\boldsymbol{n}$ refers to AWGN.

In the transmitter, the serial data from the users are fed into the subchannel and bit allocation block which allocates bits from different users to different subchannels. We assume that each subchannel has a bandwidth that is much smaller than the coherence bandwidth of the channel and that the instantaneous channel gains on all the subchannels of all the users are known to the transmitter. Using the channel information, the transmitter applies the combined subchannel, bit, and power allocation algorithm to assign different subchannels to different users and the number of bits/OFDM symbol to be transmitted on each subchannel. Depending on the number of bits assigned to a subchannel, the adaptive modulator will use a corresponding modulation scheme, and the transmit power level will be adjusted according to the combined subchannel, bit, and power allocation algorithm.

The bit allocation information is used to configure the demodulators while the subchannel allocation information is used to extract the demodulated bits from the subchannels assigned to the k^{th} user.

In the frequency selective fading, different subchannels may have different MIMO channels. The MIMO channel matrix $\mathbf{H}_{k,n}$ for the k^{th} user and the n^{th} subchannel is decomposed into M parallel SISO channels, where channel gains are given by $\sqrt{\lambda_{k,n,m}}$'s ($\lambda_{k,n,1} \geq \ldots \geq \lambda_{k,n,m} \geq 0$) . We assume that the single-sided noise power spectral density is N_o for all the users. Furthermore, let $f_k(c)$ be the rate-power function which depends on the QoS requirements and modulation scheme of the k^{th} user. In order to maintain the required QoS, the transmit power for the k^{th} user and the m^{th} eigen-mode of the n_{th} subchannel must be equal to:

$$P_{k,n,m} = \frac{f_k(c_{k,n,m})}{\lambda_{k,n,m}} \tag{6.3}$$

Where $c_{k,n,m}$ is the bits allocated for unit channel gain. The overall transmit power is given by

$$Ptotal = \sum_{k=1}^{K}\sum_{n=1}^{N}\rho_{k,n}\sum_{m=1}^{M}\frac{f_k(c_{k,n,m})}{\lambda_{k,n,m}} \tag{6.4}$$

Where the subchannel allocation indicator $\rho_{k,n}$ is defined as

$$\rho_{k,n} = \begin{cases} 1, & \text{if the n-th subchannel is allocated to k-th user} \\ 0, & \text{otherwise} \end{cases}$$

For square M-QAM, $f_k(c)$ can be expressed as:

$$f_k(c) = \frac{\mathrm{N}_0}{3}\left[Q^{-1}\left(\frac{p_e(k)}{4}\right)\right]^2 (2^c - 1) \tag{6.5}$$

Where $p_e(k)$ is the minimum BER requirement for the k^{th} user, $\mathrm{N}_0/2$ is the variance of the AWGN, and $Q(x)$ is the Q-function

6.3. Problem Formulation

Problem for resource allocation in ODFMA systems is formulated [SRDS08] with the goal to maximize the minimum data rate among all the users subject to the constraint that the total power cannot exceed a given value. Here we modify the power objective slightly and assume that the total available transmission power is limited to a certain range with a typical value PT .We then have a second objective to bring the total power as close to PT as possible.

The new multi-objective optimization problem is

$$\max_{c_{k,n},\rho_{k,n}} \min_k R_k = \max_{c_{k,n},\rho_{k,n}} \min_k \sum_{n=1}^{N} c_{k,n}\rho_{k,n}$$

$$\min_{c_{k,n},\rho_{k,n}} \left| PT - \sum_{k=1}^{K}\sum_{n=1}^{N} \rho_{k,n} \frac{f_k(c_{k,n})}{\alpha_{k,n}^2} \right|$$

where $\alpha_{k,n}$ is the channel gain of user k^{th} subchannel n.

Subject to constraints:

$$C_1 : \sum_{k=1}^{K} R_k \leq ND_{\max}$$

$$C_2 : \sum_{k=1}^{K} \rho_{k,n} = 1, and\, \rho_{k,n} = \{0,1\}$$

The above resource allocation problem for OFDMA systems can be extended to MIMO OFDM systems as follows:

$$\max_{c_{k,n,m},\rho_{k,n}} \min_k R_k = \max_{c_{k,n,m},\rho_{k,n}} \min_k \sum_{n=1}^{N}\sum_{m=1}^{M} c_{k,n,m}\rho_{k,n} \tag{6.6 a}$$

$$\min_{c_{k,n,m},\rho_{k,n}} \left| PT - \sum_{k=1}^{K}\sum_{n=1}^{N} \rho_{k,n} \sum_{m=1}^{M} \frac{f_k(c_{k,n,m})}{\lambda_{k,n,m}} \right| \tag{6.6 b}$$

Subject to constraints:

$$C_1 : \sum_{k=1}^{K} R_k \leq NMD_{\max}$$

$$C_2 : \sum_{k=1}^{K} \rho_{k,n} = 1, and\, \rho_{k,n} = \{0,1\}$$

where R_k**,** denotes the transmit bits per OFDM symbol for the k^{th} user, D is a set of available bits in the adaptive modulation, and $D_{\max}$ denotes the maximum value in the set D. Constraint C_2 takes care of the fact that one subchannel is assigned to one user only.

6.4. Allocation Using NSGA-II

GAs [Gol89, Deb01, Red07, GLX[+]09, TZWZ08, DPAM02, Cha95, Cox05, SD95] are a class of EAs. They provide novel approaches to problem solving technique inspired by biological evolution. GAs enable efficient search in the solution space of any function so as to get a solution set that optimizes the function. This efficiency with GAs is due to operators analogous to the ones found in natural evolution of species (to evolve better species): Selection, Crossover, and Mutation. Every solution in the population is evaluated by a “fitness function” and assigned a “fitness” value which indicates how favorable the various traits of that solution are, and how much the solution optimizes the fitness function. This fitness value decides the participation of a solution in evolving an optimum solution. Through crossover, fragments of the two different solutions are mixed to give rise to new offspring with combined traits of both parent solutions. Through mutation, a wider set of the actual solution space is explored (more than what is available in the initial population). Every intermediate solution set (population of chromosomes), called a generation, goes through fitness evaluation, crossover and mutation to evolve fit solutions.

The basic GA works to optimize a single objective function. However, many optimizations and resource allocations involve tradeoffs between various objectives and parameters and therefore are multi-objective [Deb01, SRDS08, DPAM02, SD95]. For two conflicting objectives, each objective corresponds to a different optimal solution. Thus in multi-objective problems, there is no single optimum solution, but many acceptable solutions. The emphasis then shifts to finding a solution that – handling minimum conflicts – delivers a satisfactory solution for all objectives. A higher level qualitative choice can be made for one possible solution among the set of optimum solutions.

NSGA–II

NSGA uses an effective non-domination sorting algorithm to optimize multiple objective functions [SD95]. NSGA-II improves the computational complexity of NSGA and also incorporates elitism [TZWZ08]. NSGA solves multi-objective problems by using the concept of domination. In NSGA-II the initial population is sorted into fronts [SD95]; where the individuals in the first front are not dominated by any other individuals in the current population, the individuals in the second front are dominated only by the individuals in the first front and so on. An individual solution is said to dominate another if its fitness values with respect to every objective fitness function is superior to the corresponding values for the other individual. The individuals in the r^{th} front are assigned a rank of r. In addition, crowding distance, a parameter that measures how close an individual is to its neighbors, is also calculated for each individual. A larger average crowding distance indicates a greater diversity in the population.

In [Red07] the MA optimization problem was addressed using GA, where each individual chromosome was coded as an array of elements that represented subchannels. Here we extend the analogy to simultaneously allocate subchannels and bits, while taking constraint (C_1 and C_2) into consideration. Each individual chromosome is coded as an array of N(SC-1,….,SC-N) elements, where N is the number of subchannels (SC). Each of these N elements is binary coded with ($\log_2 K+\log_2 D$) bits, where the first ($\log_2 K$) bits of the n^{th} element represent the user to which the n^{th} subchannel is assigned, and the next ($\log_2 D$) bits represent the number of bits allocated to the n^{th} subchannel. The size of each individual chromosome is given by $N\times(\log_2 K+\log_2 D)$. Keeping the value of $D \leq D_{max}$ satisfies constraint (C_1) and since each subchannel is assigned to exactly one user, constraint (C_2) is satisfied. The last row of Fig.6.1 depicts how the chromosome would be considered for crossover and mutation.

<table>
<tr><th colspan="2">SC-1</th><th colspan="2">SC-2</th><th>………</th><th colspan="2">SC-N</th></tr>
<tr><td>K1
001</td><td>C1
10</td><td>K2
011</td><td>C2
01</td><td>………</td><td>K2
101</td><td>C2
11</td></tr>
<tr><td colspan="7">00110 01101………………….10111</td></tr>
</table>

Figure 6.1: Schematic representation of chromosome

The standard NSGA-II algorithm is as follows (Fig.6.2):

[**Start**] Generate a random population of N chromosomes (suitable solutions for the problem).

[**Fitness**] Evaluate the multiobjective fitness of each chromosome x in the population.

[**Rank**] Rank population by following steps:

- [**Domination Rank**] Rank population by using *Non-dominated sorting algorithm* described in subsection 6.4.3**.**
- [**Crowding Distance**] Calculate the crowding distance by using *crowding distance calculation* algorithm described in subsection 6.4.3.

[**New population**] Create a new population by repeating the following steps until the new population is complete.

- [**Selection**] Select two parent chromosomes from a population based on the crowding selection operator which is described in subsection 6.4.4.
- [**Crossover**] With a crossover probability cross over the parents to form new offspring (children). If no crossover was performed, offspring is the exact copy of parents. The single point binary crossover operator is explained in section 6.4.5.
- [**Mutation**] With a mutation probability mutate new offspring at each locus (position in chromosome). Bit wise mutation operator is explained in section 6.4.5.
- [**Accepting**] Place new offspring in the new population.

[**Replace**] Use new generated population for a further run of the algorithm.

[**Test**] If the end condition is satisfied (e.g. reaches a constant number of generations in this paper), stop, and return the best solution in current population.

[**Loop**] Go to [**Fitness**].

The following sub-sections provide detailed description of the steps [Deb01, DPAM02, SD95] involved in multi-objective resource allocation in MIMO OFDMA system using NSGA-II algorithm:

6.4.1. Population Initialization

The number of individuals in the population, P and the number of generations, G are fixed beforehand and can be changed for different runs of the algorithm. The 2-D population consists of binary numbers (bits). The Population size (for some K, D, N and P) is $P \times (N \times (\log_2 K + \log_2 D))$. Each individual is created by generating a random string of 0's and 1's.

6.4.2. Evaluate Objective functions

The fitness values of the objective functions equation.6.6.(a) and equation.6.6.(b) are calculated for each individual. The chromosome represents the subchannel number and the number of bits allocated to that individual. The value of gain corresponding to that subchannel and power required corresponding to the number of bits allocated is substituted in equation.6.6.(a) and equation.6.6.(b) respectively to calculate the fitness of each individual.

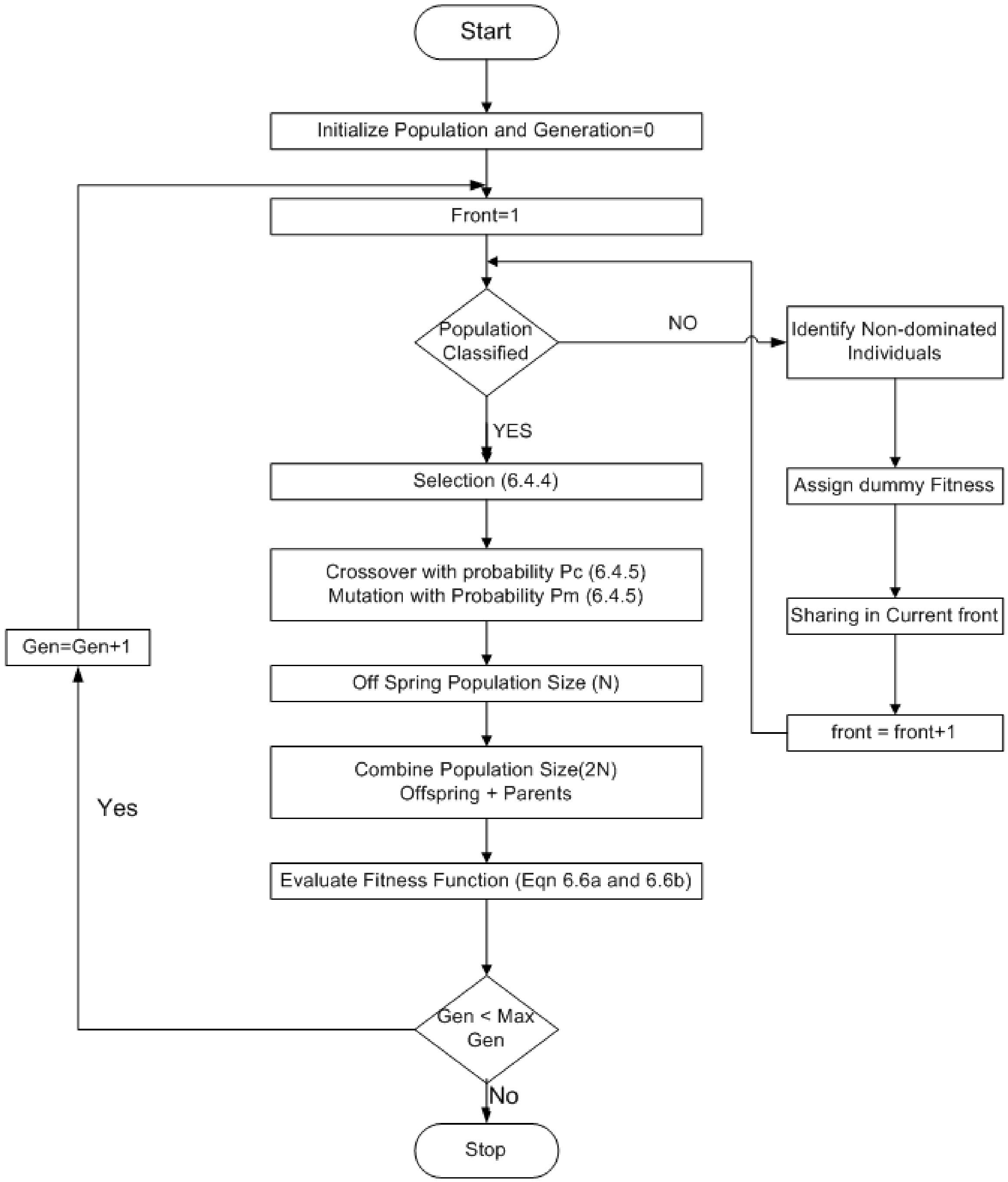


Figure 6.2: Flow Chart NSGA-II Algorithm

6.4.3. Non-Dominated Sorting

The population is now sorted into fronts based on non-domination and each individual is assigned a rank. Once the non-dominated sort is complete the crowding distance is assigned. Since the individuals are selected based on rank and crowding distance all the individuals in the population are assigned a crowding distance value.

The fast non-dominated sorting algorithm and crowding distance calculation [SD95] is described below:

Non-dominated sorting algorithm:

- For each individual p in main population P do the following:
  - Initialize $S_p = \Theta$(null set). This set would contain all the individuals that are being dominated by p.
  - Initialize $n_p = 0$. This would be the number of individuals that dominate p.
  - For each individual q in P
    - If p dominates q then
      - add q to the set Sp i.e. $S_p = S_p \cup \{q\}$
    - Else if q dominates p then
      - increment the domination counter for p i.e. $n_p = n_p + 1$
  - If $n_p = 0$ i.e. no individuals dominate p then p belongs to the first front. Set rank of individual p to one i.e $p_{rank} = 1$. Update the first front set by adding p to front one i.e $F_1 = F_1 \cup \{p\}$.
- This is carried out for all the individuals in main population P.
- Initialize the front counter to one i.e. $i = 1$.
- Following is carried out while the i_{th} front is nonempty i.e. $F_i \neq \Theta$(null set);
  - $Q = \Theta$(null set); The set for storing the individuals for $(i + 1)_{th}$ front.
  - For each individual p in front F_i
    - for each individual q in S_p (S_p is the set of individuals dominated by p)
      - $n_q = n_q - 1$, decrement the domination count for individual q.
      - If $n_q = 0$ then none of the individuals in the subsequent fronts would dominate q. Hence set $q_{rank} = i + 1$. Update the set Q with individual q i.e. $Q = Q \cup \{q\}$.

- Increment the front counter by one i.e. $i=i+1$.
- Now the set Q is the next front and hence $F_i = Q$.

This algorithm is better than the original NSGA since it utilize the information about the set that an individual dominates (S_p) and number of individuals that dominate the individual (n_p).

Crowding Distance calculation:

Crowding distance is assigned front wise and comparing the crowding distance between two individuals in different front is meaningless. The crowding distance is calculated as below:

- For each front F_i, l is the number of solutions in a non dominated set I.
    - Initialize the distance to be zero for all the individuals i.e. $F_i(d_j) = 0$,where j corresponds to the j_{th} individual in front F_{i}.
    - For each objective function m
        - Sort the individuals in front F_i based on objective m i.e. $I = sort(F_i, m)$.
        - Assign infinite distance to boundary solutions (solutions with smallest and largest function values) for each individual in F_i i.e. $I(d_1) = \infty$ and $I(d_l) = \infty$.so that the boundary points are always selected for all other points.
        - For $j = 2$ to $(l\text{-}1)$
            - $I(d_j) = I(d_j) + \dfrac{I(j+1).m - I(j-1).m}{f_m^{\max} - f_m^{\min}}$
            - $I(j).m$ is the value of the m_{th} objective function of the j_{th} individual in I.
            - $f_m^{\max}$ and $f_m^{\min}$ are the maximum and minimum values of the m_{th} objective function.

The basic idea behind the crowing distance is finding the Euclidian distance between each individual in a front based on their m objectives in the m dimensional hyper space. The individuals in the boundary are always selected since they have infinite distance assignment.

6.4.4. Tournament selection

Once the individuals are sorted based on non-domination and with crowding distance assigned, the selection is carried out using a crowded- comparison-operator ($\prec_n$).The crowded-comparison operator guides the selection process at the various stages of the algorithm towards a uniformly spread-out Pareto optimal front.

Assume that every individual i in the population has two attributes:

- Non-domination rank p_{rank} (individuals in front F_i will have their rank as $p_{rank} = i$).
- Crowding distance $F_i(d_j)$

We now define a partial order $\prec_n$ as:

- $p \prec_n q$
- if $p_{rank} < q_{rank}$
- or if p and q belong to the same front F_i then $F_i(d_p) > F_i(d_q)$ i.e. the crowing distance should be more.

That is, between two solutions with differing non-domination ranks, we prefer the solution with the lower (better) rank. Otherwise, if both solutions belong to the same front, then we prefer the solution that is located in a lesser crowded region. The individuals are selected by using a binary tournament selection with crowded-comparison-operator to fill the mating pool, which is taken to be of size P.

6.4.5. Crossover and Mutation

As proposed by Deb [SD95] real-coded GA's use *Simulated Binary Crossover (SBX)* operator for crossover and *polynomial mutation*. Since our chromosome was binary coded, we used single point binary crossover with bit wise mutation. Single point binary crossover and bit wise mutation are explained in following paragraphs:

Single point Binary Crossover:

Crossover is the mechanism by which design characteristics between any paired individuals are exchanged to form two new (child) individuals. It is analogous to reproduction and biological crossover, upon which GAs are based.

In single point crossover a point on both parents' organism strings is selected. All data beyond that point in either organism string is swapped between the two parent organisms. For example consider two parents as shown below, in single point crossover bits after the crossover point (shown by |) are swapped between two parents to get offspring chromosomes.

Parent1: 011101|0101 Parent 2: 100111|0111

Offspring 1: 011101|0111 Offspring 2: 100111|0101

Bit wise Mutation:

In GAs, mutation is a genetic operator used to maintain genetic diversity from one generation of a population of chromosomes to the next. It is analogous to biological mutation. The classic example of a mutation operator involves a probability that an arbitrary bit in a genetic sequence will be changed from its original state. A common method of implementing the mutation operator involves generating a random variable for each bit in a sequence. This random variable tells whether or not a particular bit will be modified. The probability of mutation is given by P_m which is usually at-least 100 times less than P_c. The purpose of mutation in GAs is to allow the algorithm to avoid local minima/maxima by preventing the population of chromosomes from becoming too similar to each other, thus slowing or even stopping evolution. This reasoning also explains the fact that most GA systems avoid only taking the fittest of the population in generating the next but rather a random (or semi-random) selection with a weighting toward those that are fitter.

For example a parent 011101**0**101with the bit to be mutated represented in bold, after mutation will give an offspring 011101**1**101.That is the bit 0 in the parent is replaced by bit 1 in the offspring.

6.4.6. Generation of new population

An intermediate population consisting of the parents and offspring of the current population is created and is sorted using non-domination. The new population is filled up by taking the best individuals from the combined population based on rank and crowding distance. Steps 6.4.4, 6.4.5 and 6.4.6 are repeated for G number of generations.

In [TZWZ08] elitism was assured by using Largest Weighted Delay First, LWDF. Here since all the best individuals from the current and previous populations are added to the new population, elitism is guaranteed. The best individual chromosome from the final population gives the desired allocation of subchannels and bits per subchannel.

6.5. Simulation and Results

Assumptions and Constants

For various constants required in the calculation, their accepted [SAE03, RC00] values were used, as given below :

BER	10^{-3}
N_0(Power Spectral Density of Noise)	-80dBW
D_{max}	8 (Low SNR) and 16 (High SNR)
B (Bandwidth)	1 MHz

The wireless channel [RC00] was modeled as a frequency-selective channel consisting of six independent Rayleigh multipaths. Each multipath component was modeled by Clarke's flat fading model. The downlink OFDM/MIMO channel between any couple of transmitting and receiving antennas is assumed to have power delay profile which is exponentially decaying with e^{-2l}, where l is the multipath index. Hence, the relative power of the six multipath components are [0, −8.69, −17.37, −25.06, −34.74, −43.43] dB. Channel gains generated using above described model were then kept constant throughout the simulations.

Total Power (PT) was varied from -30 dB to +30dB, assuming the reference power level for dB calculations as 1W. Different permutations of probability of crossover (P_c) and that of mutation (P_m) were considered, for different runs of algorithm. For every run of the algorithm we also considered different permutations of the number of users K, for fixed number of subchannels N(64). For MIMO case the equal number of antenna at transmitter (M_T) and receiver (M_R) were assumed i.e. M=min(M_T,M_R)=2.

NSGA-II Parameters tuning

The effectiveness of any algorithms depends on the choice of its parameters. Selection of best parameters is required in order to avoid premature convergence, to ensure diversity in the search space, to intensify the search around best solution regions, etc. Inappropriate choice of parameters may lead to premature convergence or stagnation.

In this subsection we present an empirical testing approach to find the best tuning parameters of NSGA-II algorithm for the problem under consideration.

In order to keep the number of combinations tractable, Population Size was fixed a priori to 50. We have applied parameters tuning only for the crossover probability (P_c) and mutation probability (P_m) and number of generations. We considered the following ranges for these parameters:

_ Number of Generations: three levels (50, 80 and 100).

_ P_c for both NSGA-II and SPEA-2: three levels (0.7, 0.8 and 0.9).

_ P_m for both NSGA-II and SPEA-2: three levels (0.01, 0.02 and 0.03).

Due to this fact, NSGA-II algorithm has three parameters, and each parameter has three levels; hence, we have 27 different conditions.

In order to have more comprehensive analysis, each of these 27 conditions for NSGA-II, were simulated 10 times each, for two extreme cases of the problem set.

The channel gain matrix once generated was kept constant during the tuning process. The number of subchannels was fixed to 64, bandwidth to 1MHz and BER to 10^{-3}. For the number of users, D_{max} and power, there two extreme levels were used. That is number of users considered was 2 and 16, D_{max} was taken as 8 (Low SNR) and 16 (High SNR) while the power considered was -30 and +30 dB.

NSGA-II worked well for all the parameters considered but the performance, in terms of CPU time and capacity was found to be slightly better for the following set of values:

Set 1: $P_c = 0.9$, $P_m = 0.03$; Set 2: $P_c = 0.8$ $P_m = 0.02$, for all number of generation and all set of problem specific values. Thus these values were used for all problem sets considered in this chapter.

Convergence Analysis

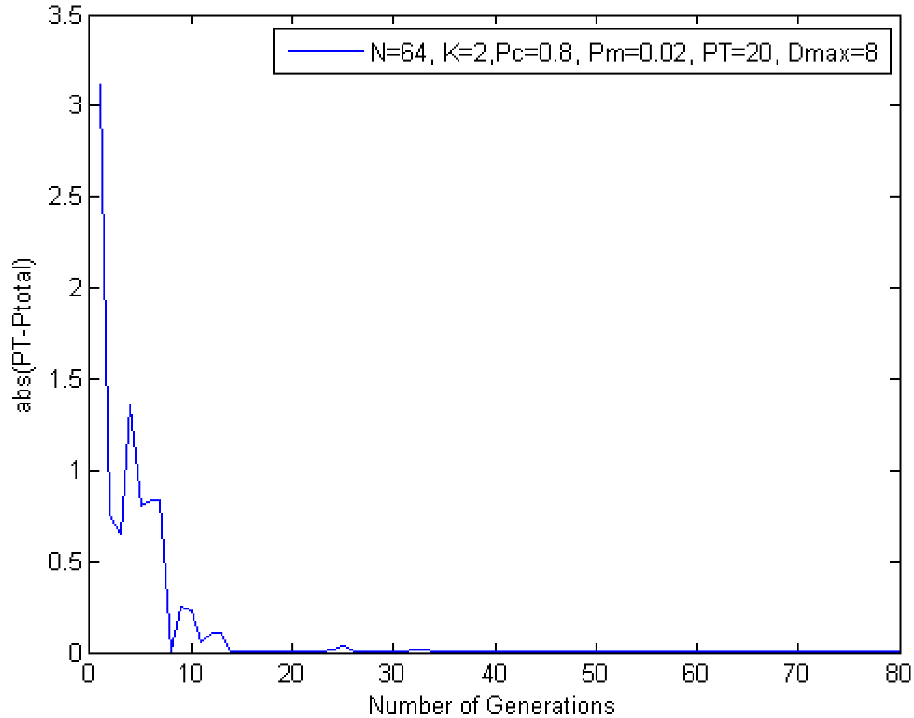
The results (Table 6.1-6.2 and Fig.6.3-6.8) obtained for the various simulations reaffirmed that applying multi-objective optimization to resource allocation problems in OFDMA/MIMO OFDMA gives more efficient solutions in terms of convergence. By convergence here, we mean that the difference of transmitted power and typical total power goes to zero and the minimum user data rate attains a constant value. Figs.6.3, 6.4 and 6.5 depict the results obtained by best, average and worst chromosome respectively, for SISO case. While, Figs.6.6, 6.7 and 6.8 show the results obtained by best, average and worst chromosome respectively, for MIMO case. The worst, average and best values were manually selected out of 100 simulation runs performed for each set of data inputs in table 6.1 and 6.2. The number of generations required, even by the worst chromosome generated by applying NSGA-II, for convergence were substantially less than that by algorithms in [Red07, SWA10]. Even though we jointly optimize allocation of subchannels and power as compared to only power optimization in [Red07], our algorithm, in worst case took 40 (Fig.6.5(a)) for SISO and 49 (Fig.6.8(a)) generations for MIMO to converge as compared to 60 required in [Red07]. Furthermore, the NSGA-II required less number of generations to converge as compared to its multi-objective counterpart PAES [SWA10].The ACO based solution in [AC10] required around 52 generations for convergence.

Table 6.1: Maximum number of generations required for convergence for different set of experiments (SISO)

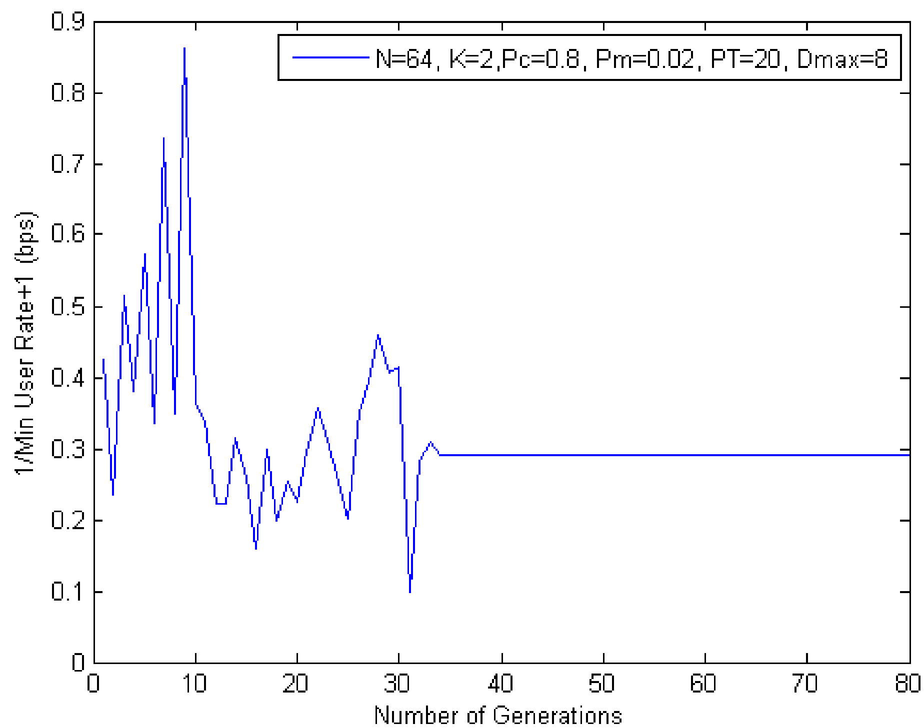
S. No.	User (K)	Sub-carries (N)	Population	Max. Generation	P_c	P_m	D_{max}	*PT* (dB)	Max. Generation for Convergence		
									Best	Avg	Worst
1	2	64	50	80	0.8	0.02	8	20	34	36	40
2.	4	64	30	100	0.8	0.02	16	-30	22	24	30
3.	8	64	50	50	0.9	0.03	8	-10	26	26	31
4.	16	64	30	50	0.9	0.03	8	0	26	31	34

Table 6.2: Maximum number of generations required for convergence for different set of experiments (MIMO)

S. No.	User (K)	Sub-carries (N)	Population	Max. Generation	P_c	P_m	D_{max}	*PT* (dB)	Max. Generation for Convergence		
									Best	Avg	Worst
1	2	64	50	80	0.8	0.02	8	20	41	44	49
2.	4	64	30	100	0.8	0.02	16	-30	21	31	32
3.	8	64	50	50	0.9	0.03	8	-10	28	28	27
4.	16	64	30	50	0.9	0.03	8	0	22	26	26

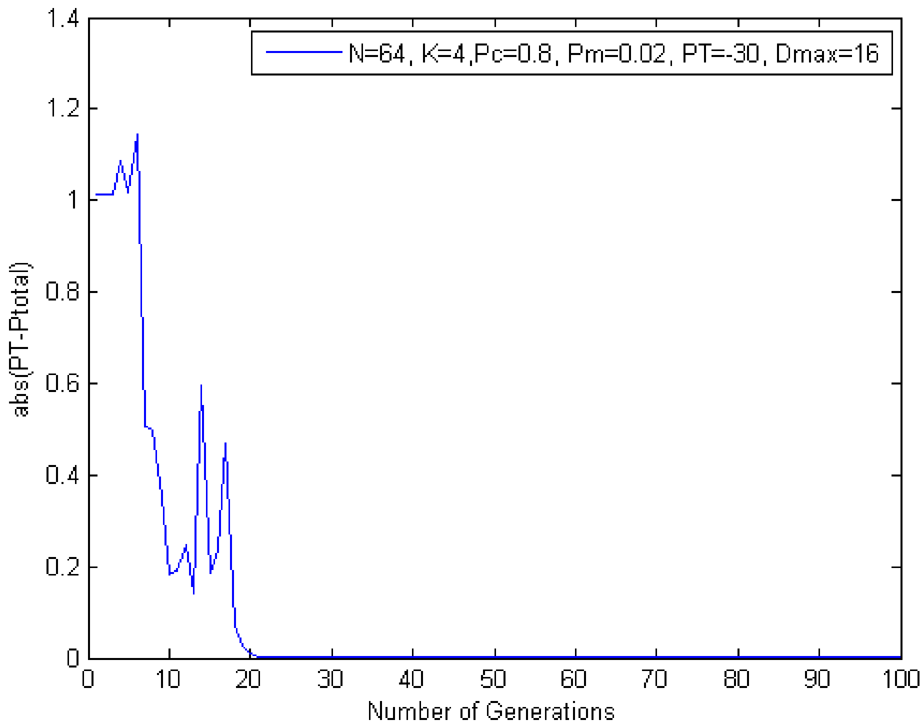


(a)

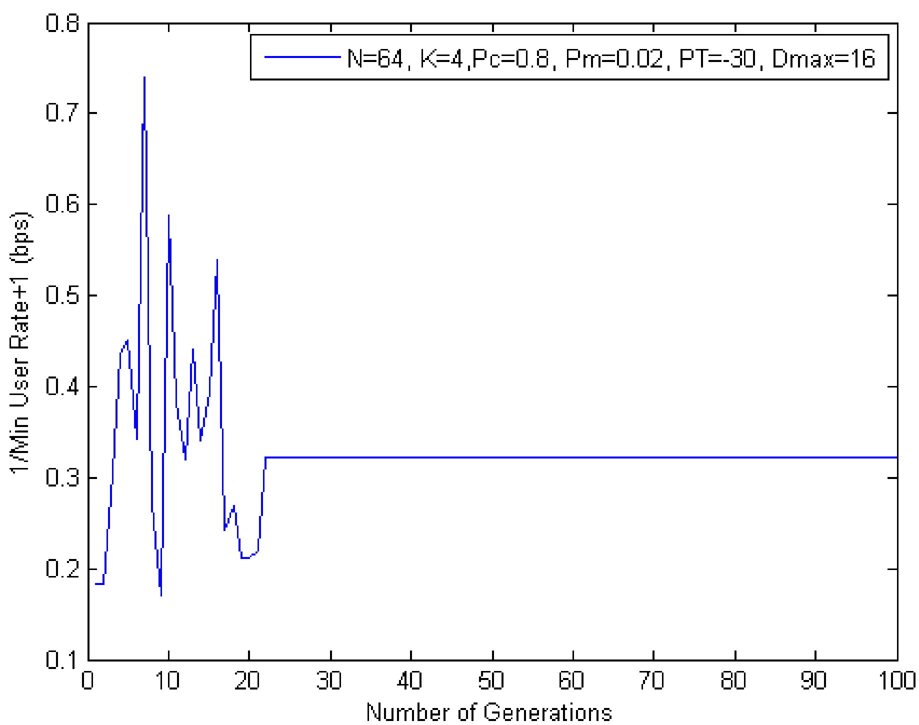


(b)

Figure 6.3.(a-b): Simulation results for permutations of conditions in Table.6.1 (Row-1, Best Case)

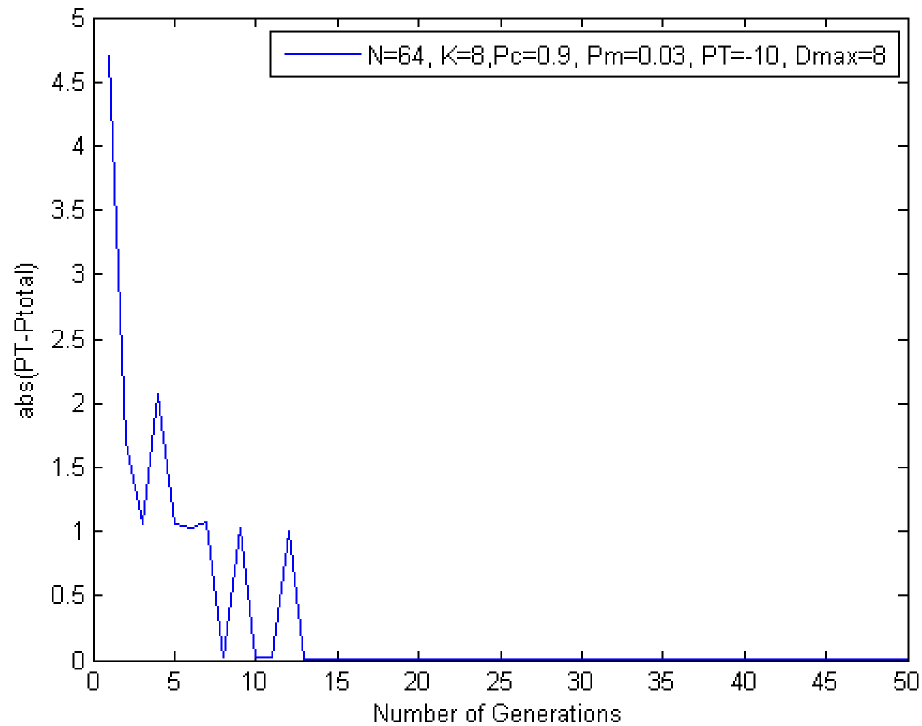


(c)

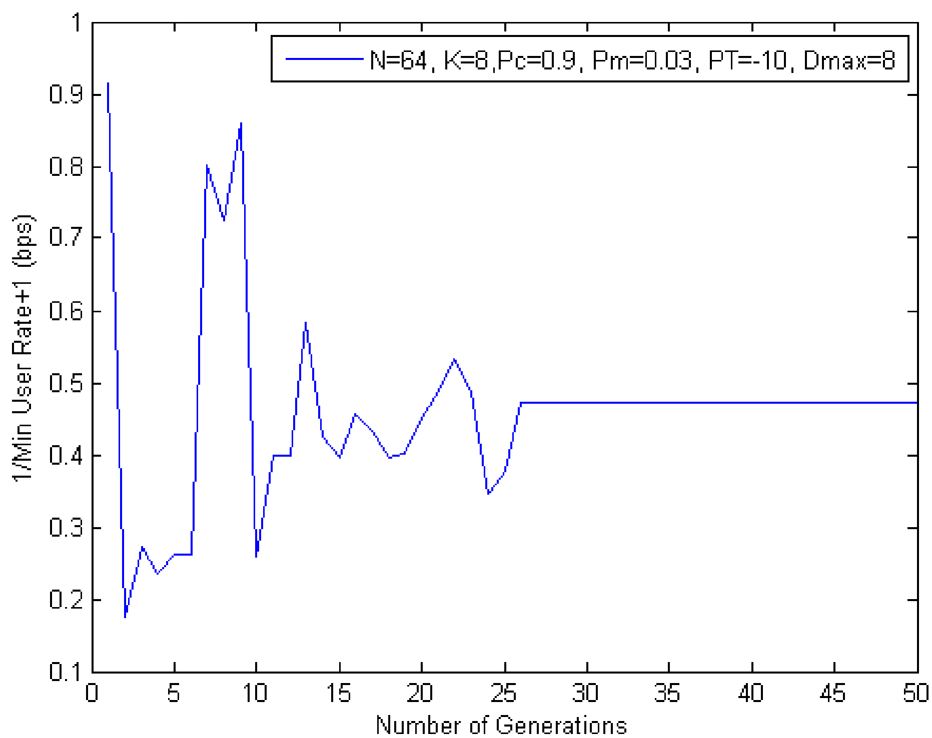


(d)

Figure 6.3.(c-d): Simulation results for permutations of conditions in Table.6.1 (Row-2, Best Case)

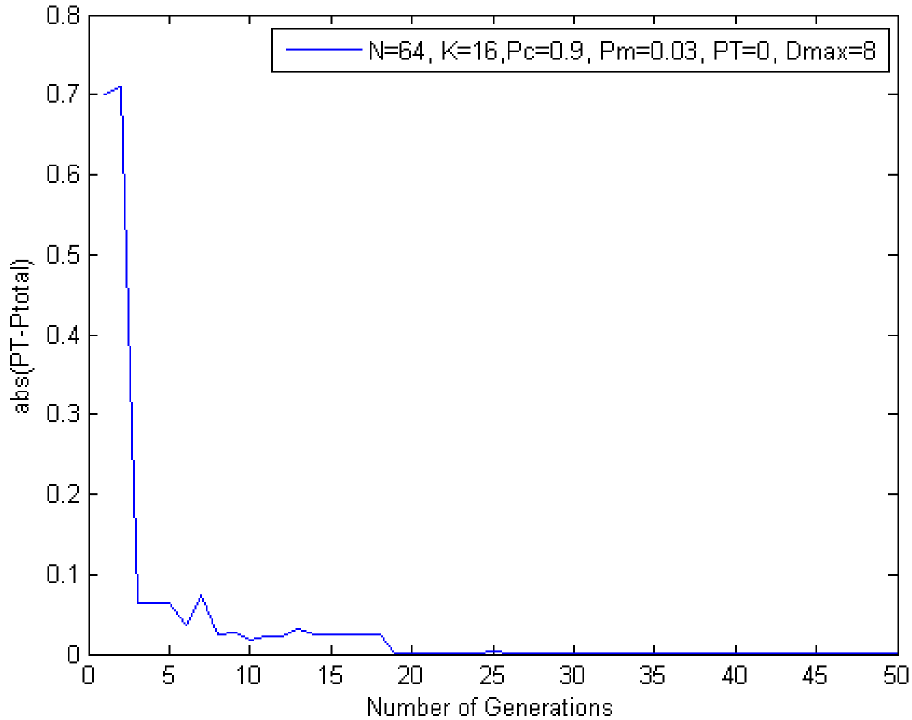


(e)

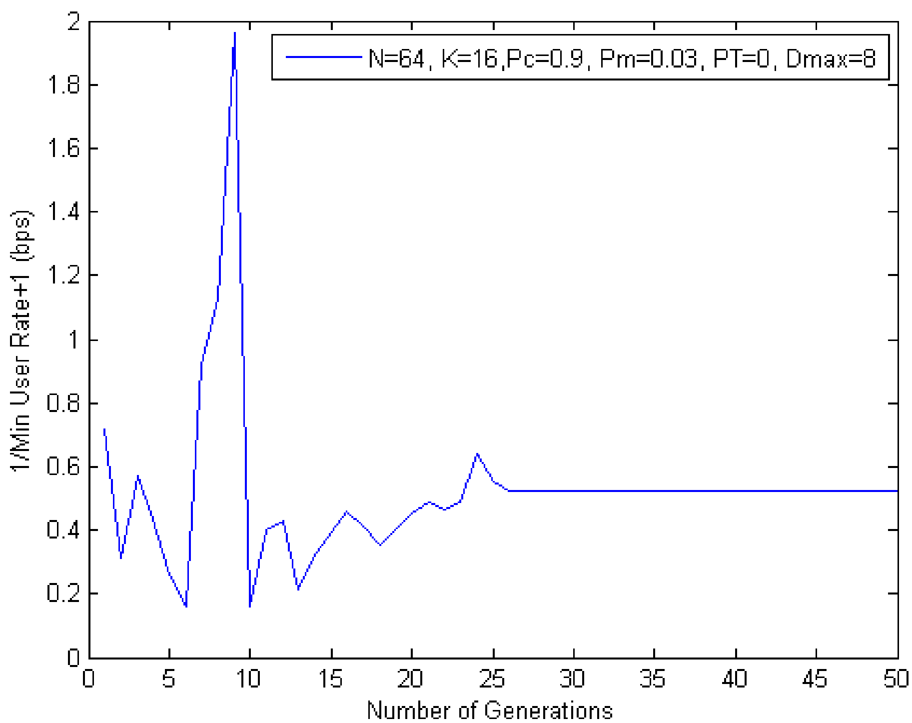


(f)

Figure 6.3.(e-f): Simulation results for permutations of conditions in Table.6.1 (Row-3, Best Case)

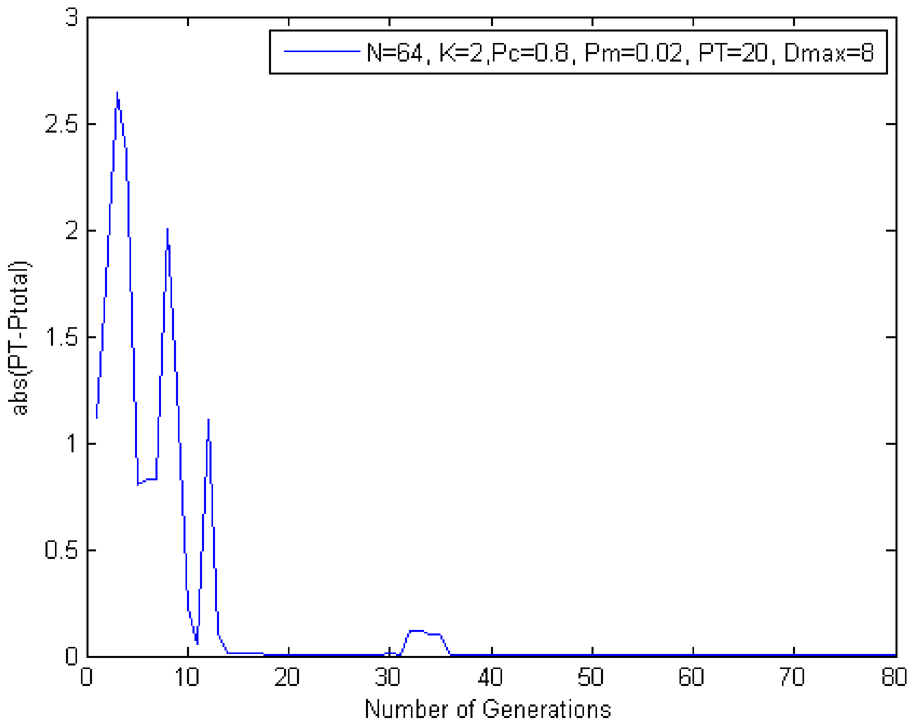


(g)

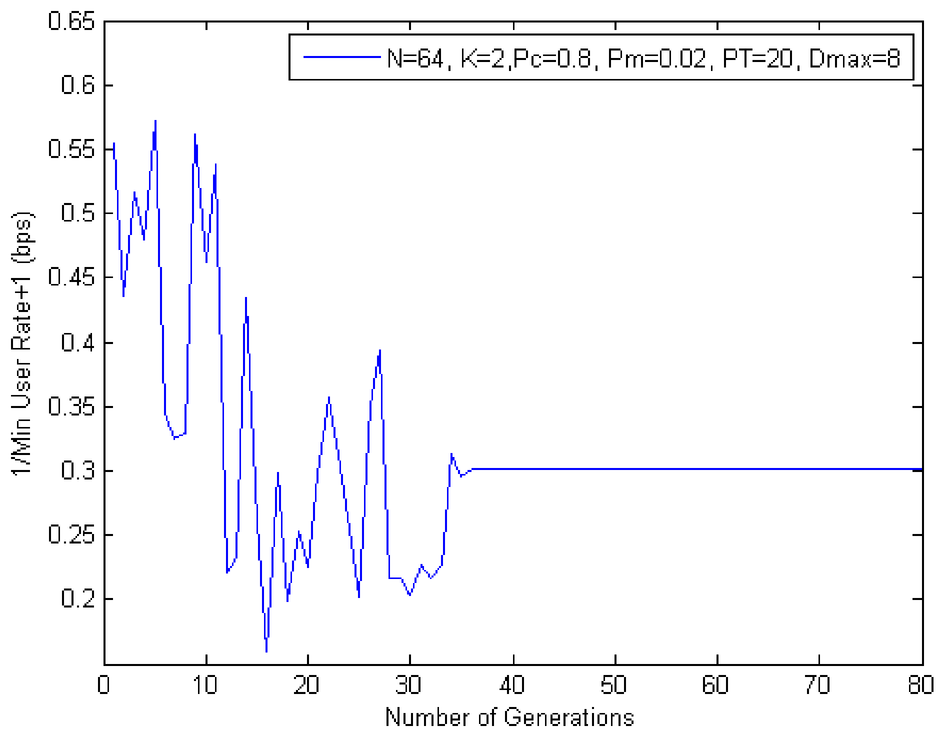


(h)

Figure 6.3.(g-h): Simulation results for permutations of conditions in Table.6.1 (Row-4, Best Case)

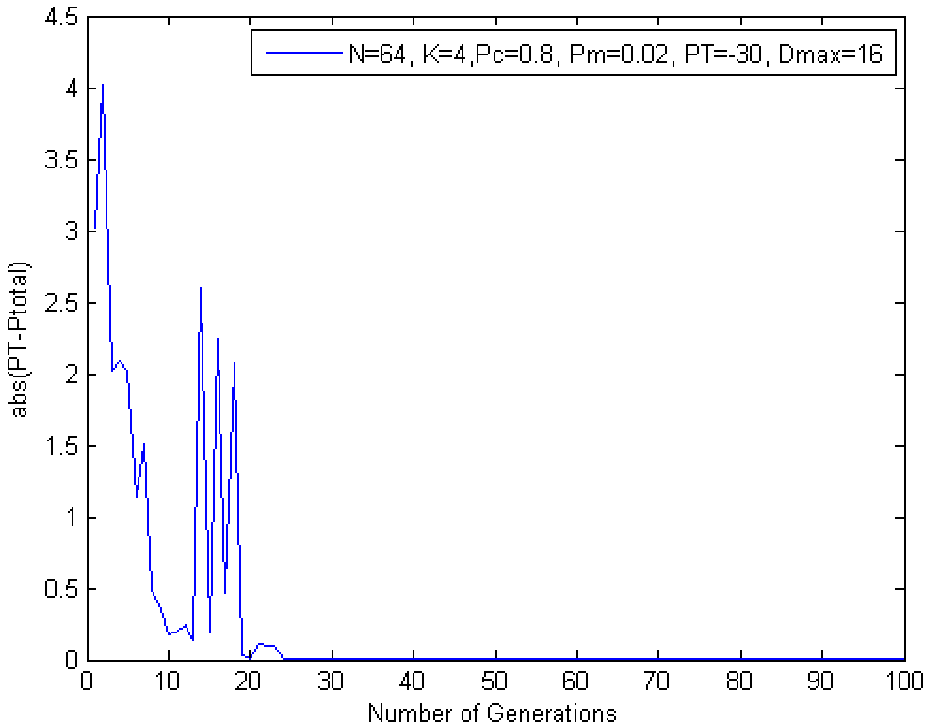


(a)

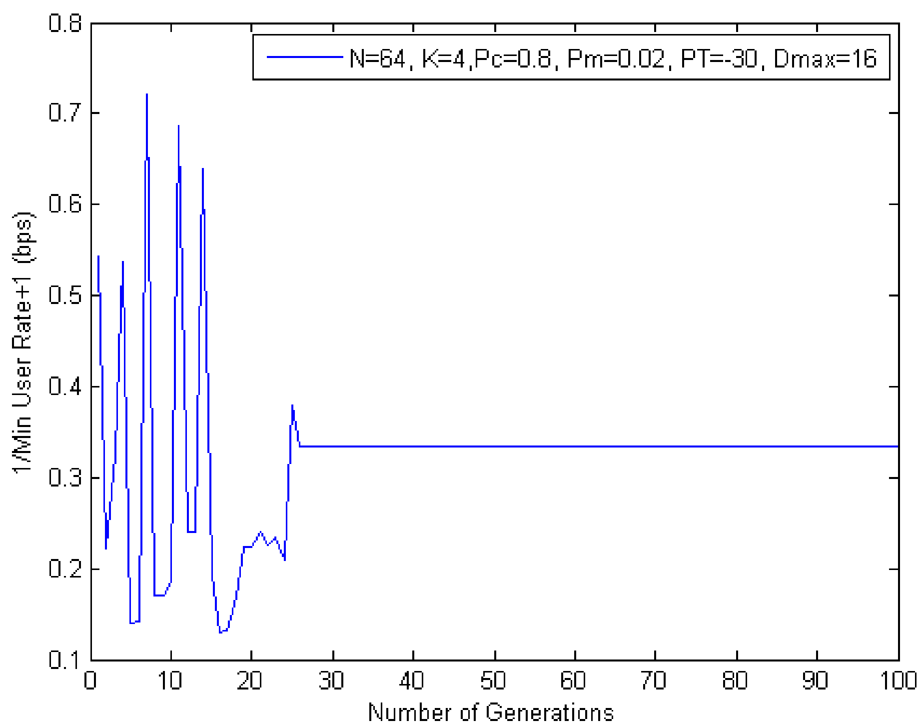


(b)

Figure 6.4.(a-b): Simulation results for permutations of conditions in Table.6.1 (Row-1, Average Case)

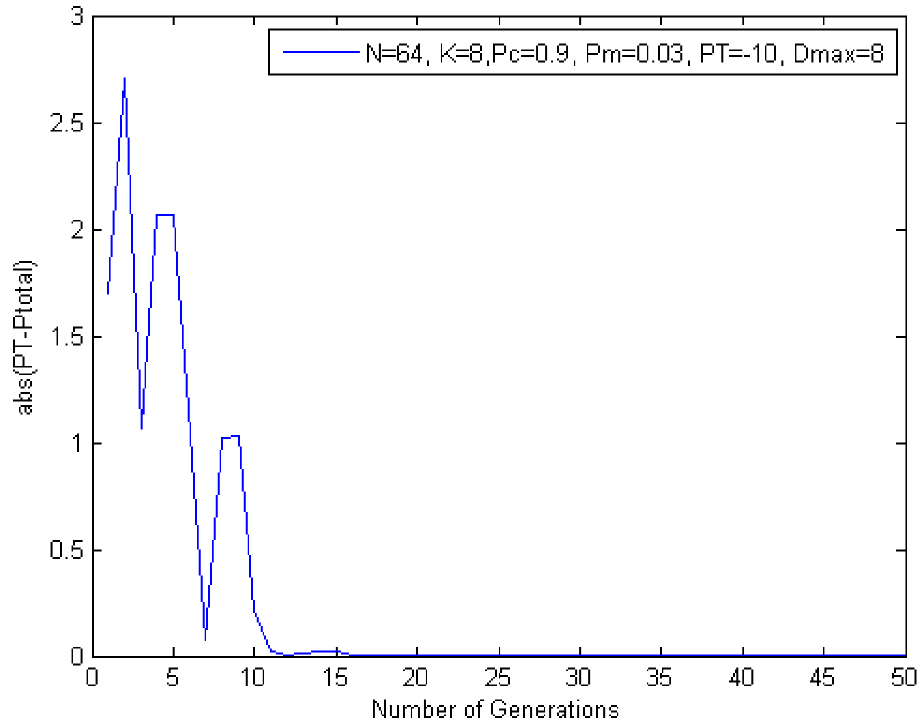


(c)

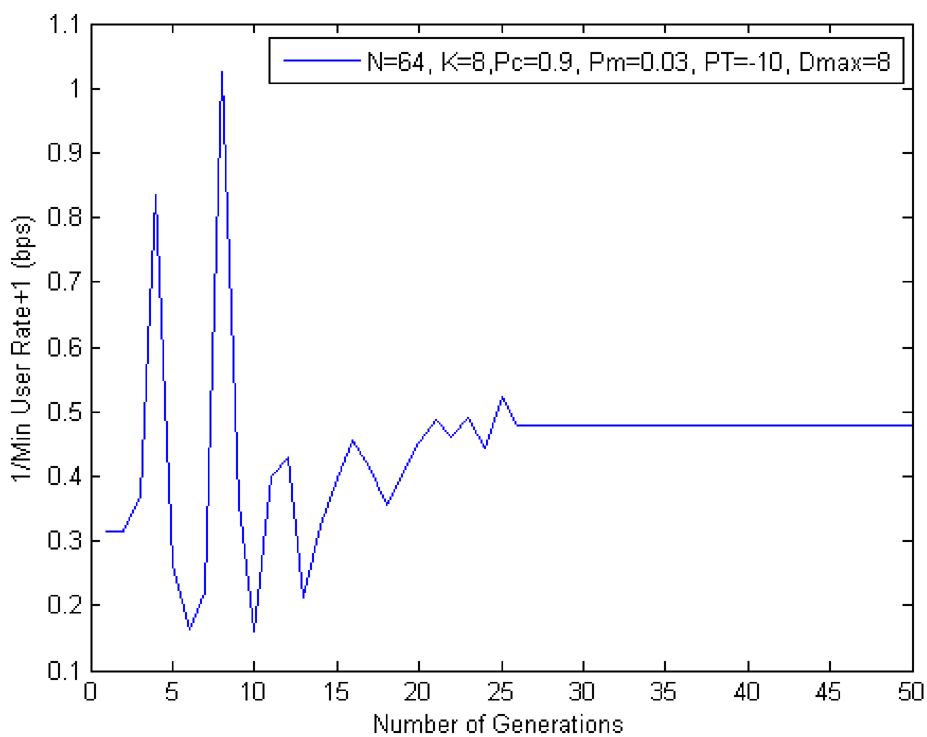


(d)

Figure 6.4.(c-d): Simulation results for permutations of conditions in Table.6.1 (Row-2, Average Case)

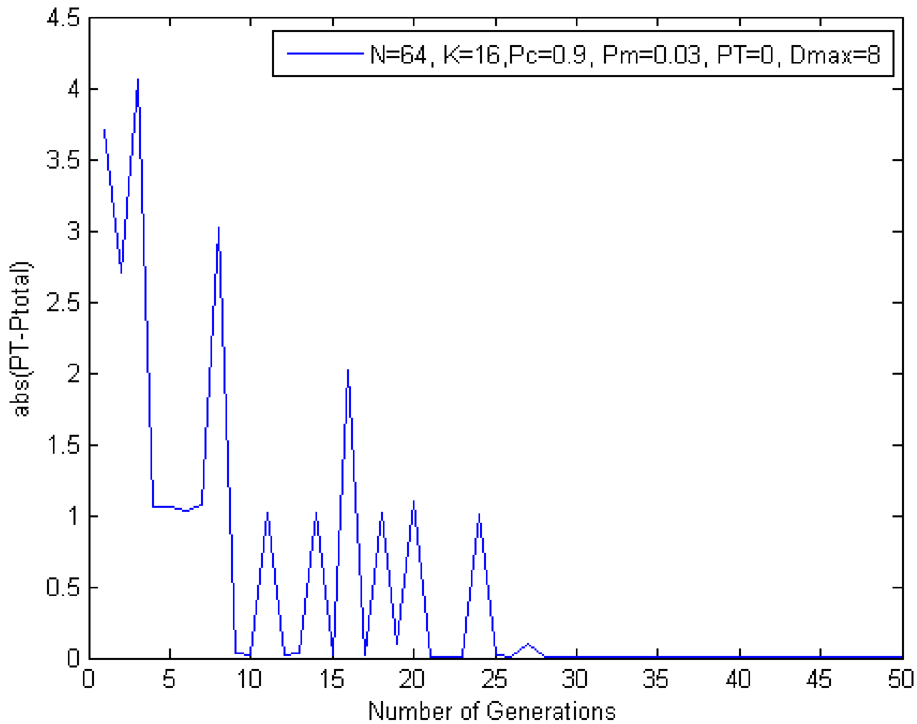


(e)

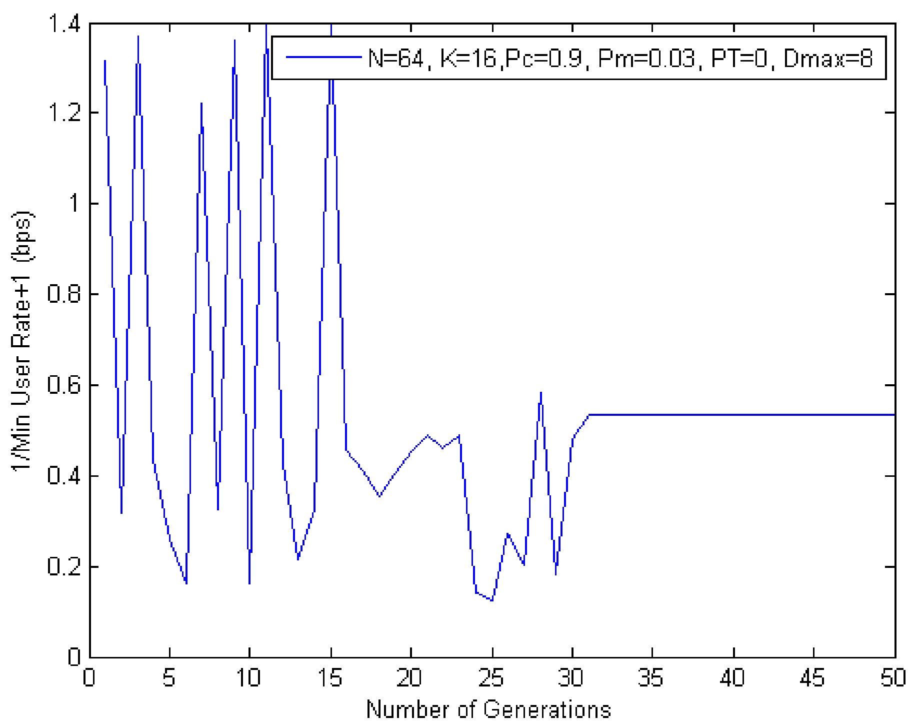


(f)

Figure 6.4.(e-f): Simulation results for permutations of conditions in Table.6.1 (Row-3, Average Case)

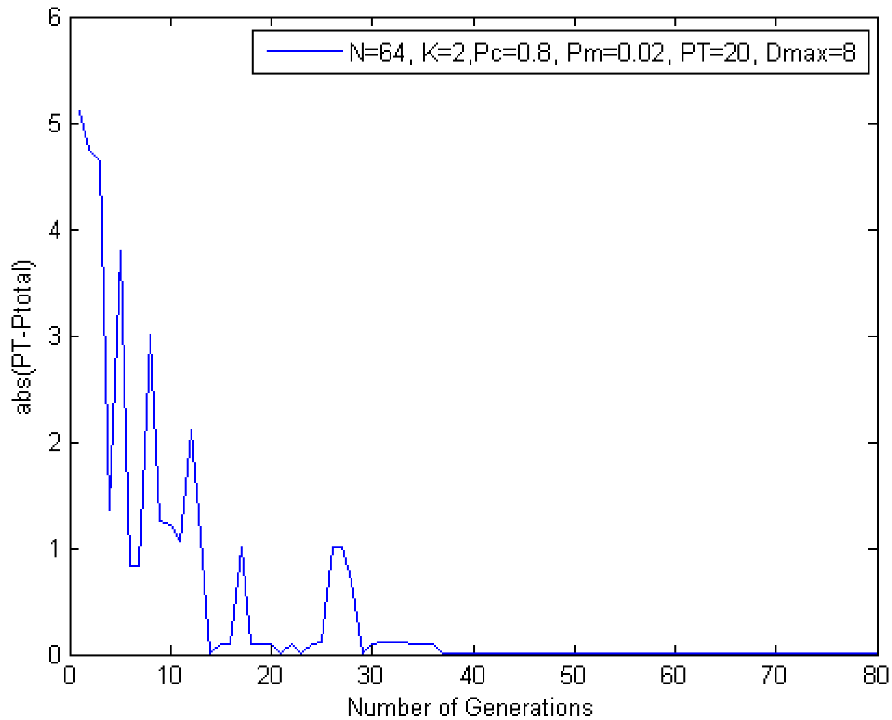


(g)

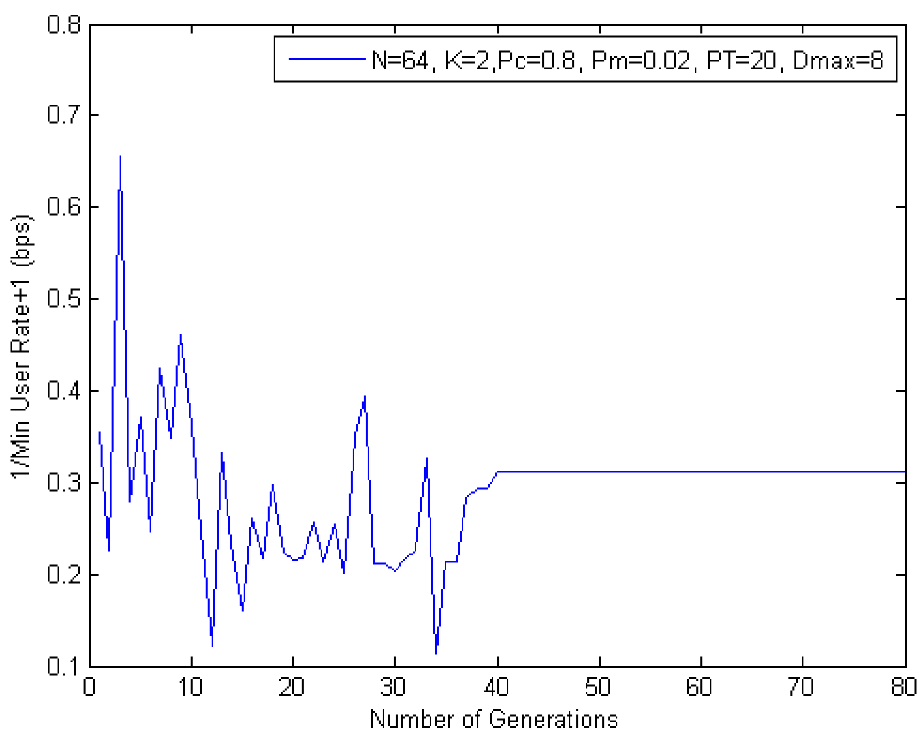


(h)

Figure 6.4.(g-h): Simulation results for permutations of conditions in Table.6.1 (Row-4, Average Case)

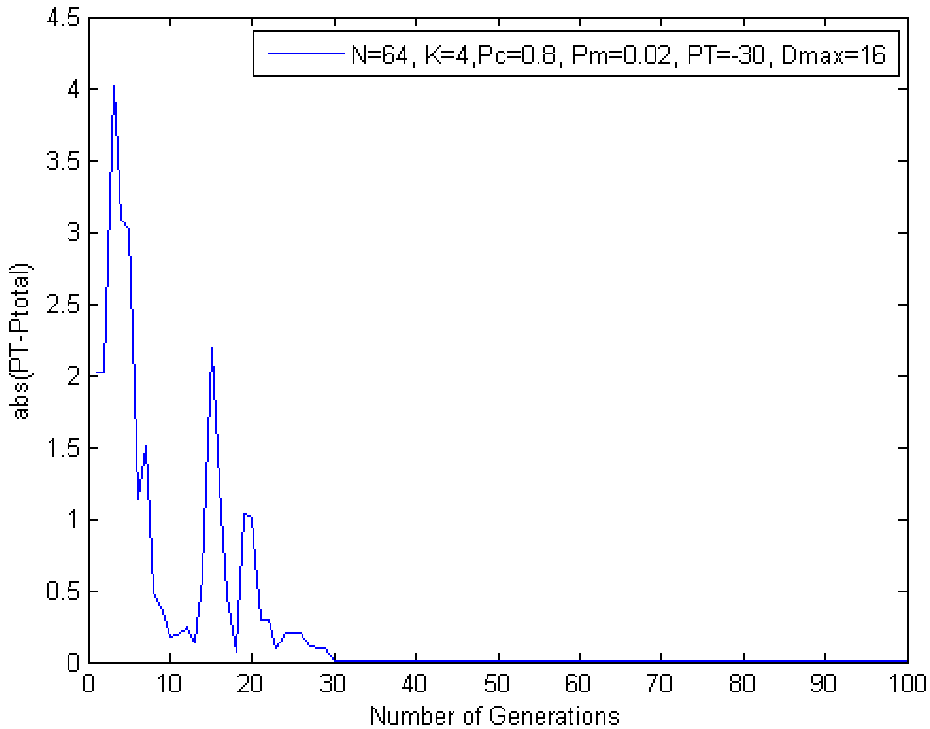


(a)

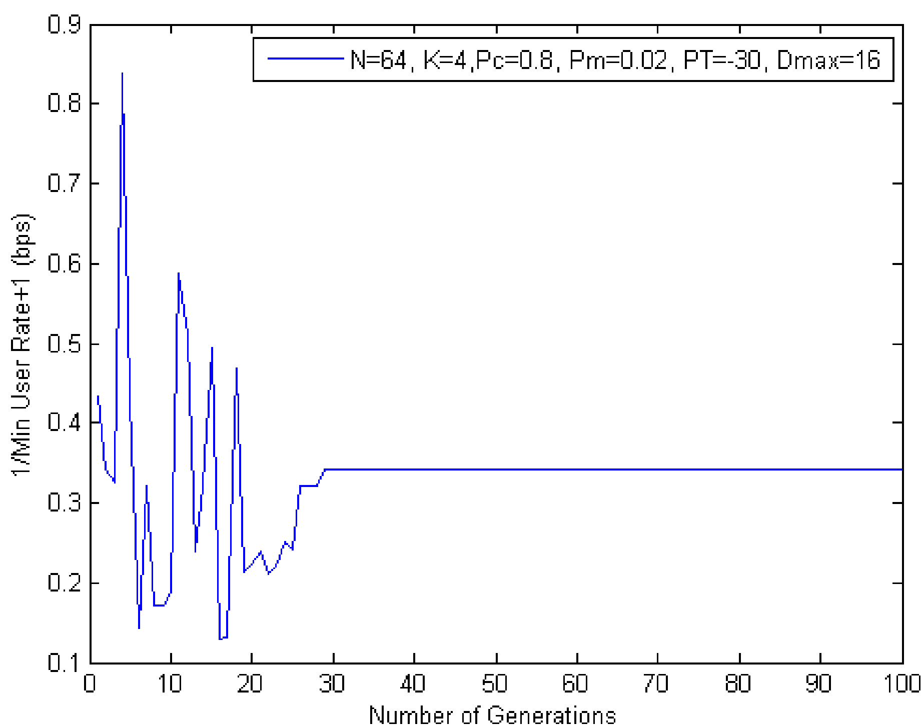


(b)

Figure 6.5.(a-b): Simulation results for permutations of conditions in Table.6.1 (Row-1, Worst Case)

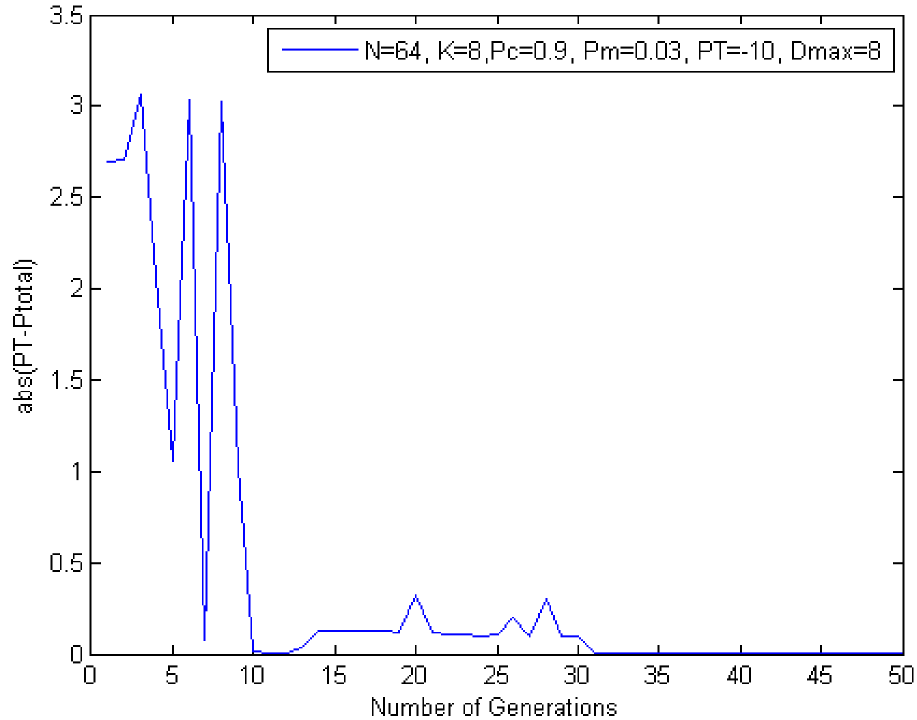


(c)

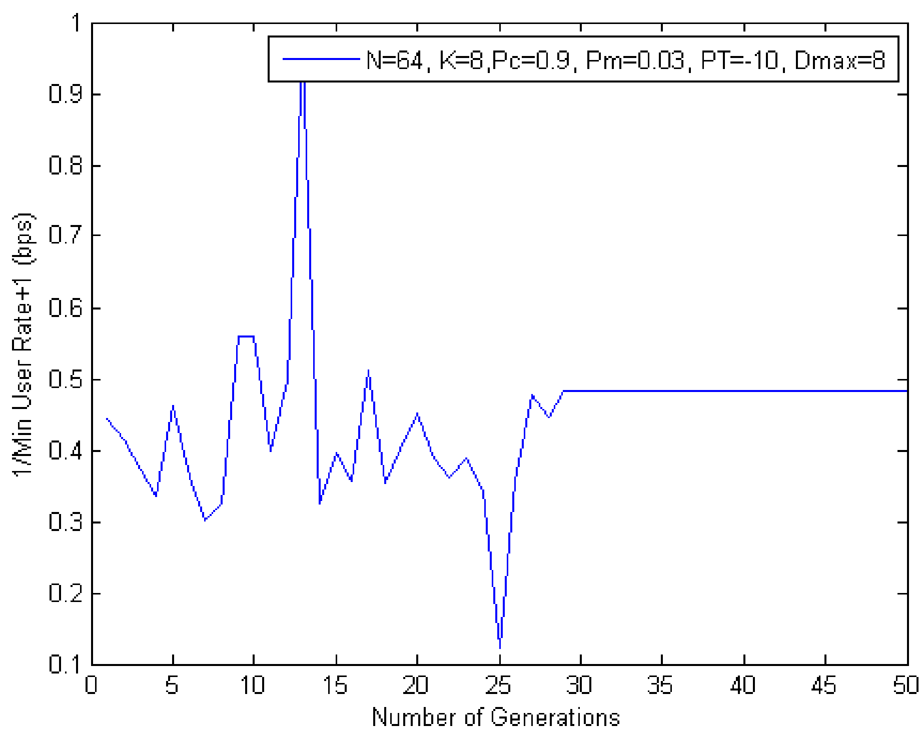


(d)

Figure 6.5.(c-d): Simulation results for permutations of conditions in Table.6.1 (Row-2, Worst Case)

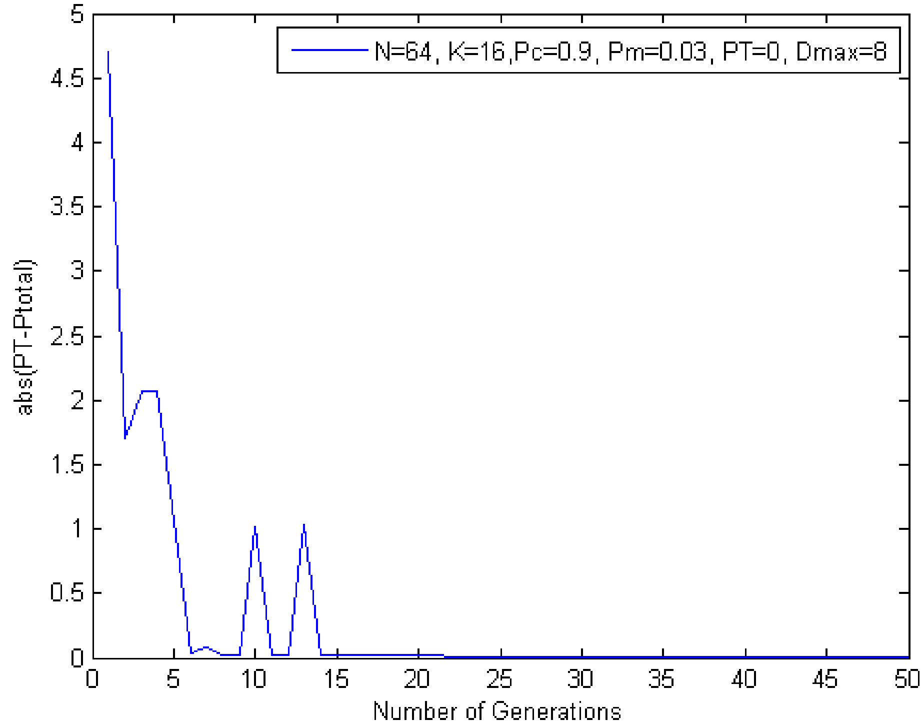


(e)

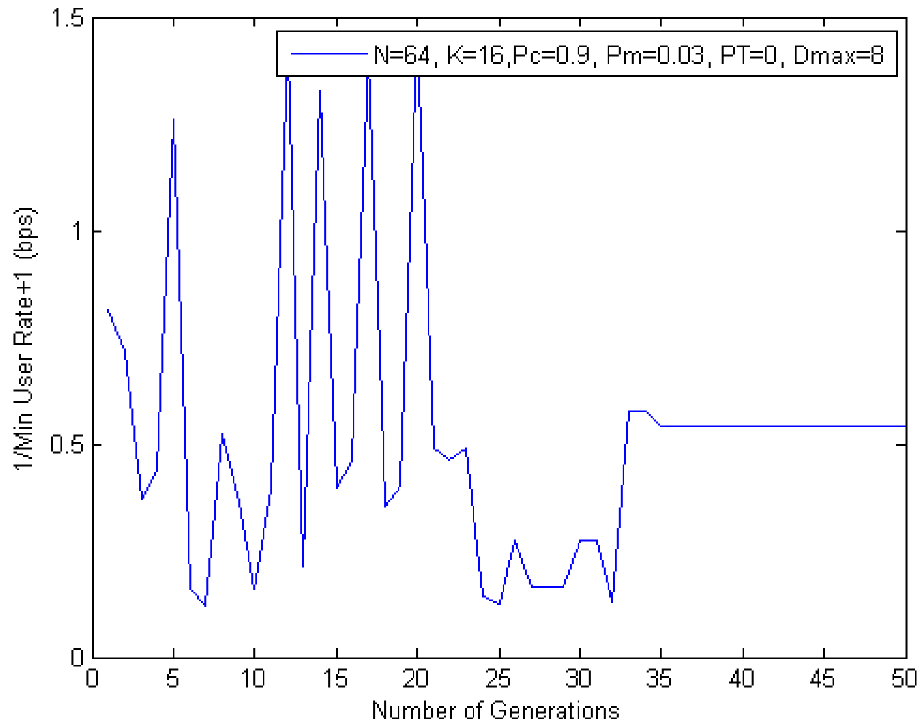


(f)

Figure 6.5.(e-f): Simulation results for permutations of conditions in Table.6.1 (Row-3, Worst Case)

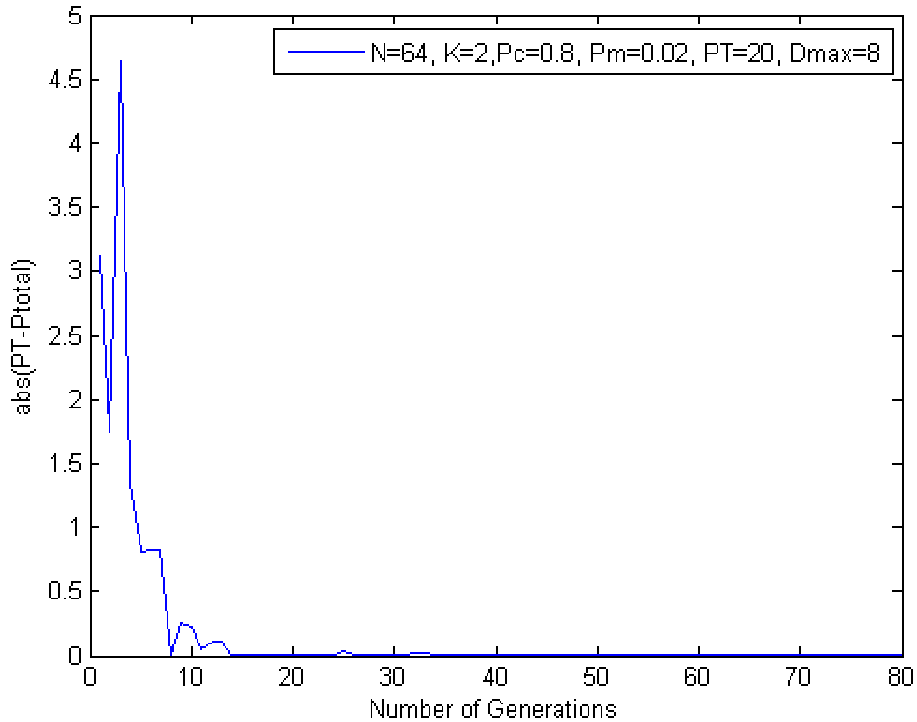


(g)

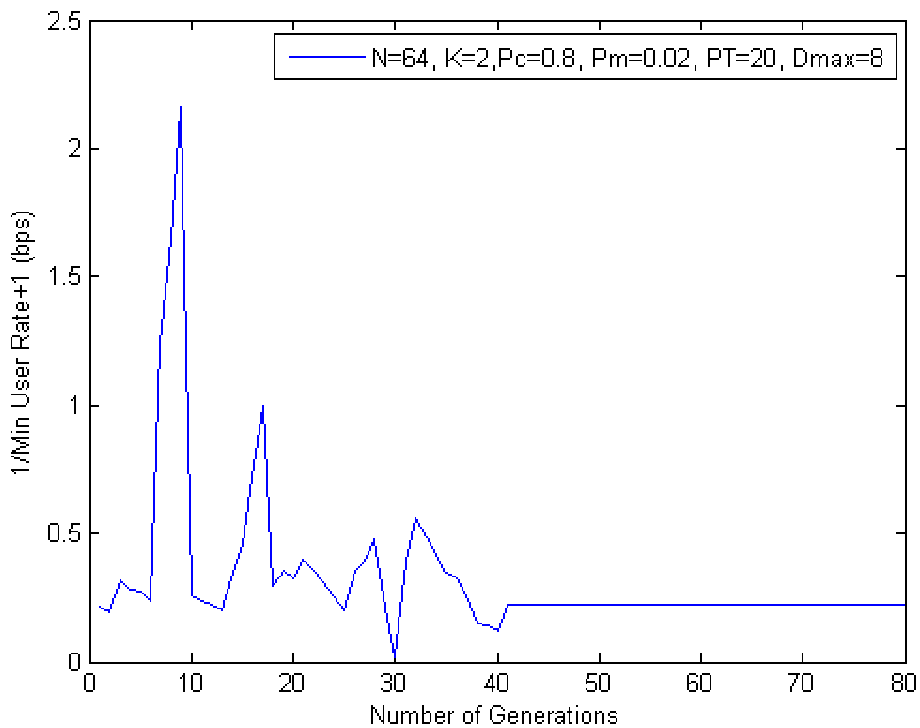


(h)

Figure 6.5.(g-h): Simulation results for permutations of conditions in Table.6.1 (Row-4, Worst Case)

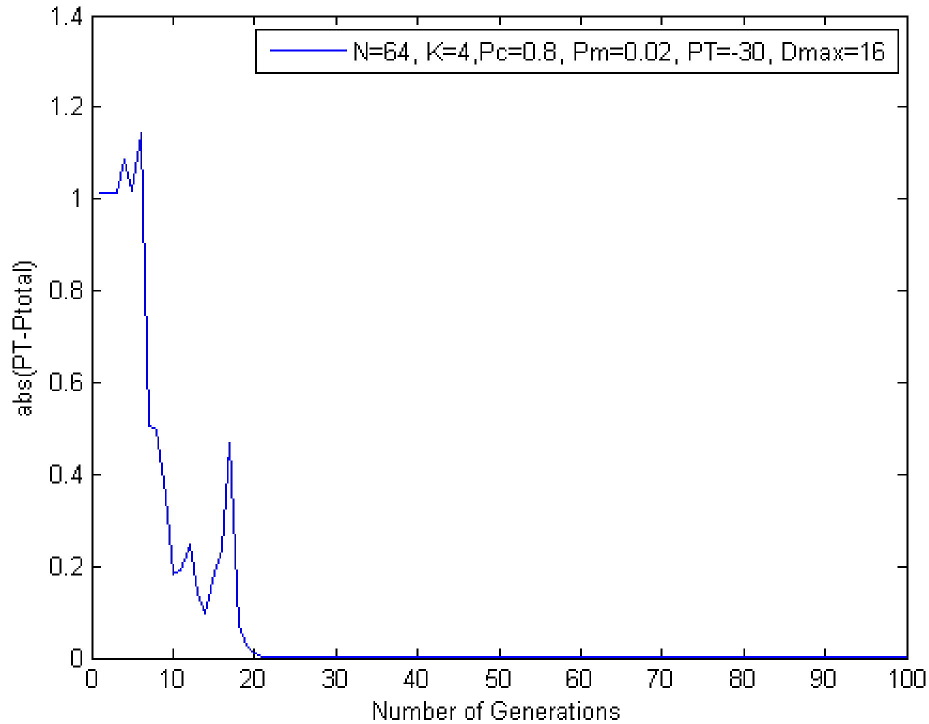


(a)

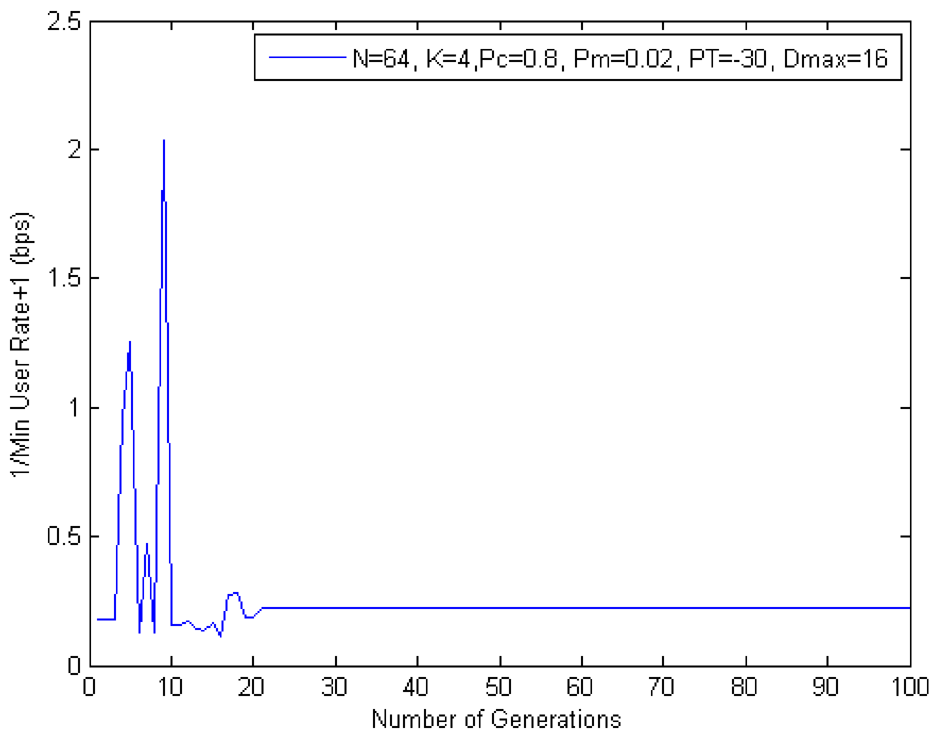


(b)

Figure 6.6.(a-b): Simulation results for permutations of conditions in Table.6.2 (Row-1, Best Case)

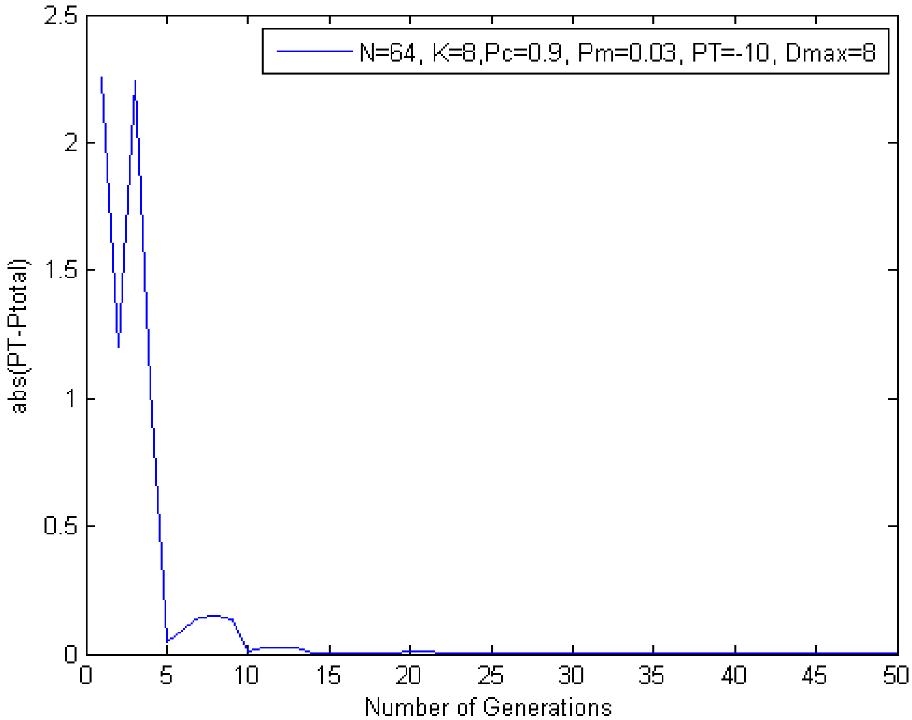


(c)

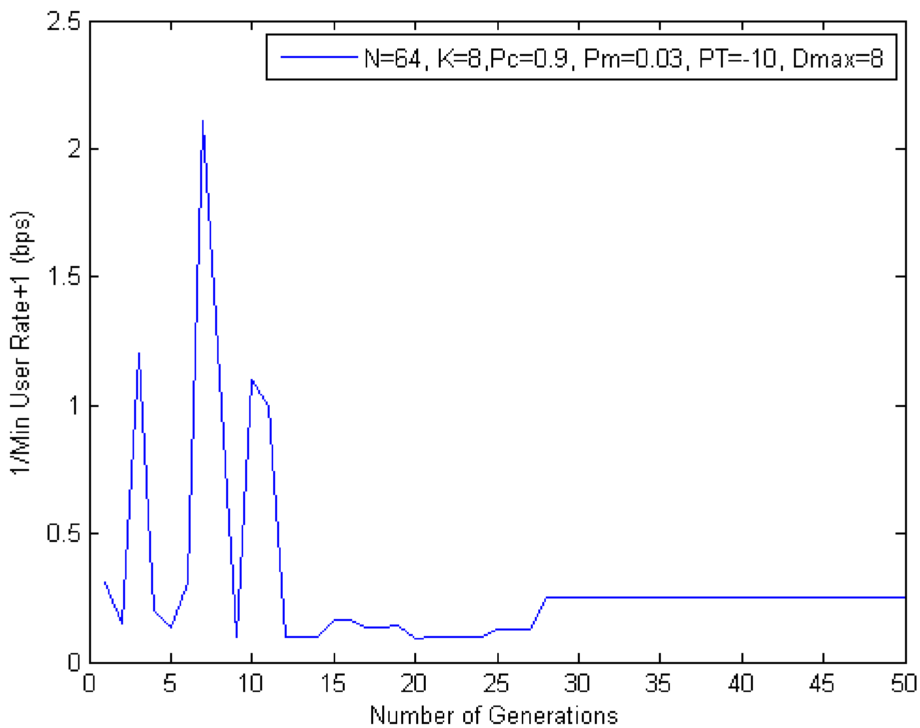


(d)

Figure 6.6.(c-d): Simulation results for permutations of conditions in Table.6.2 (Row-2, Best Case)

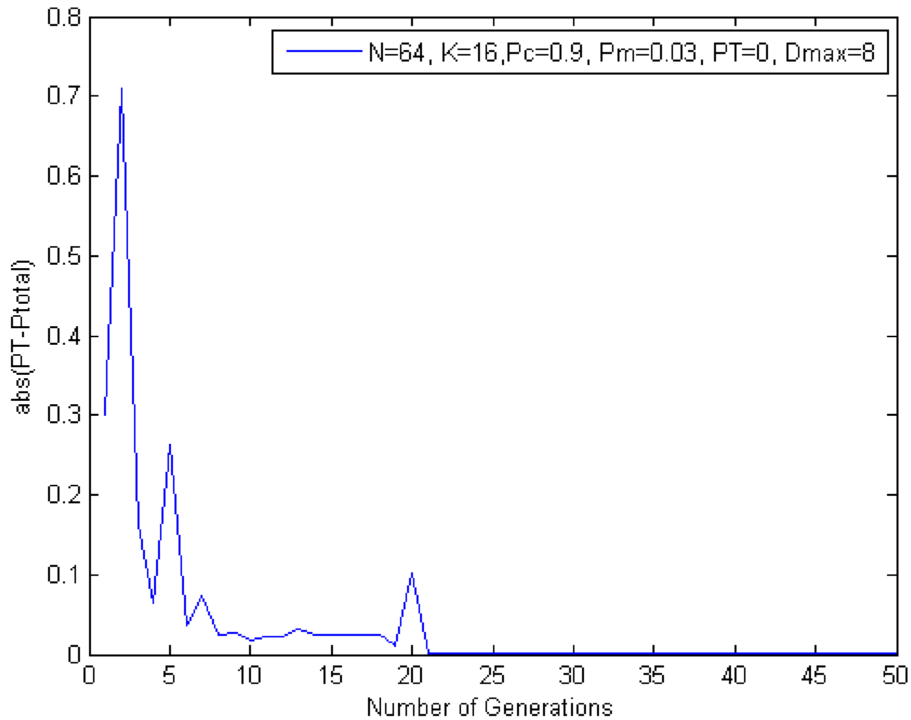


(e)

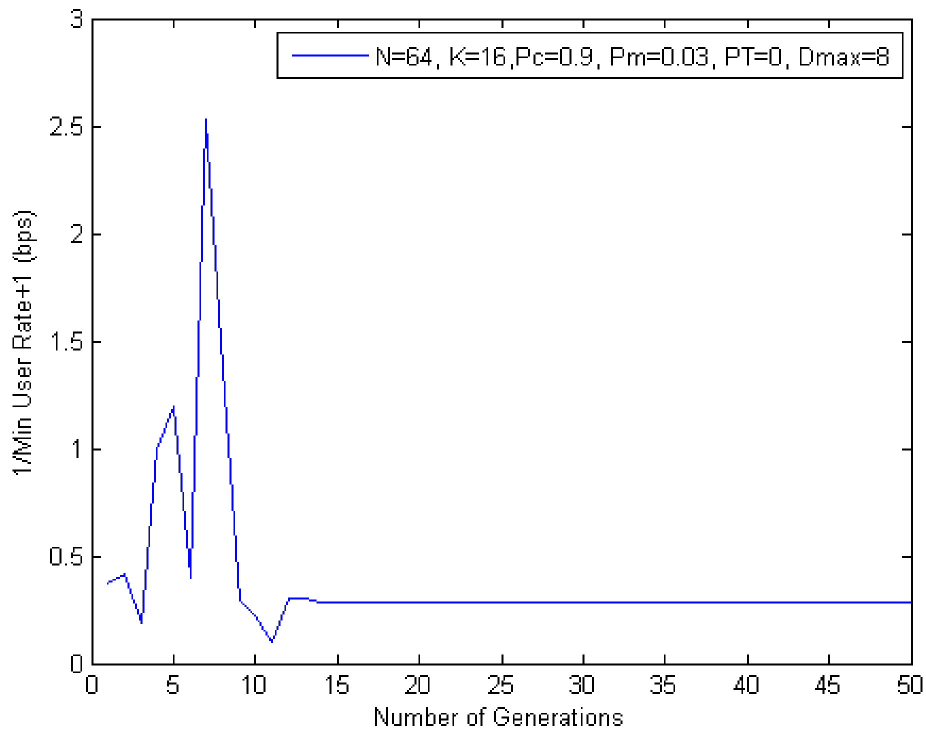


(f)

Figure 6.6.(e-f): Simulation results for permutations of conditions in Table.6.2 (Row-3, Best Case)

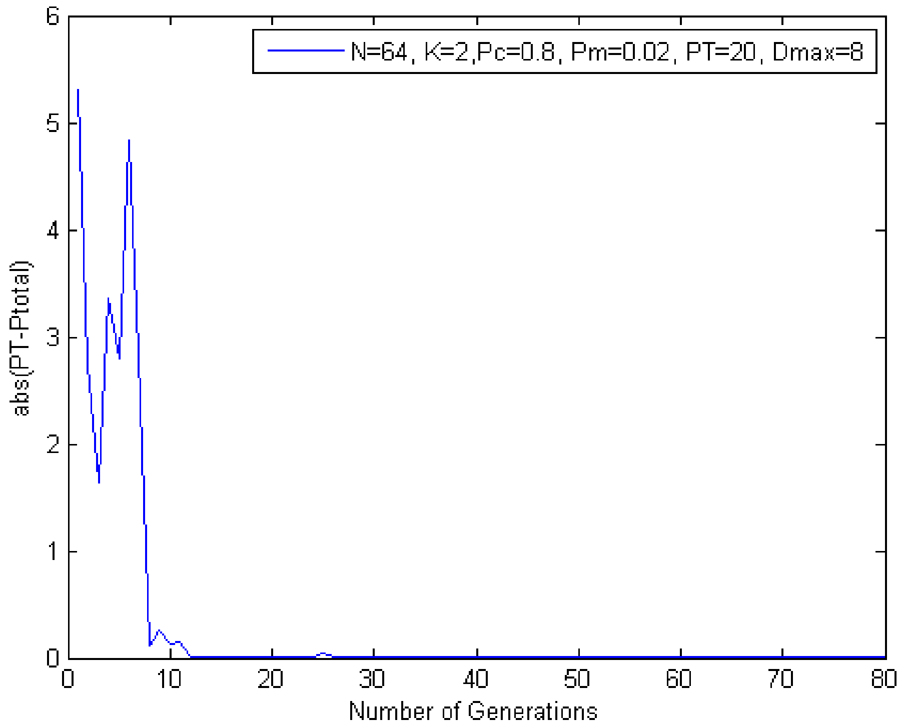


(g)

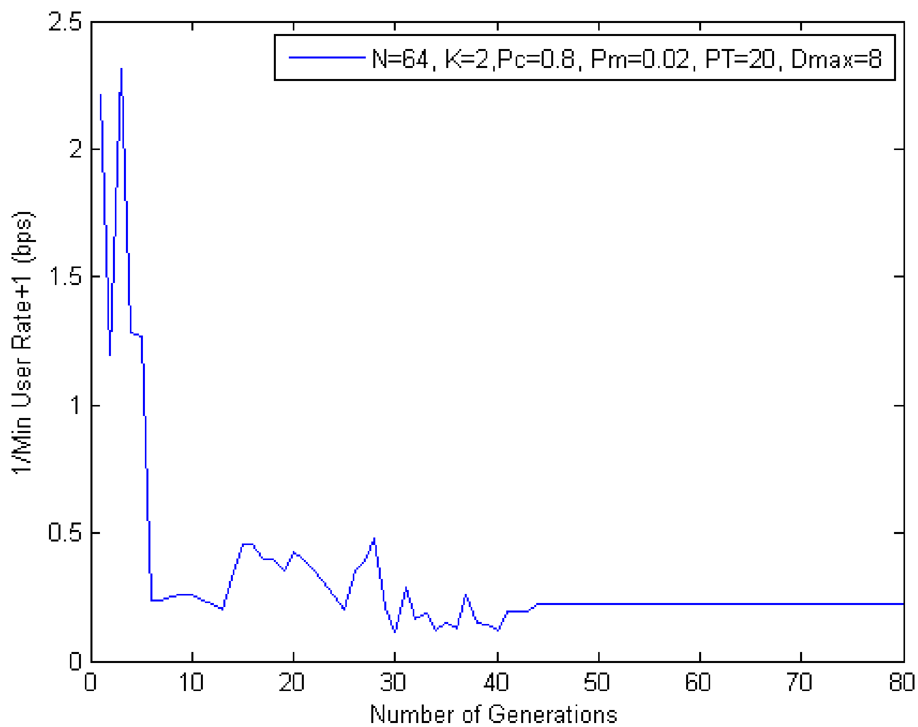


(h)

Figure 6.6.(g-h): Simulation results for permutations of conditions in Table.6.2 (Row-4, Best Case)

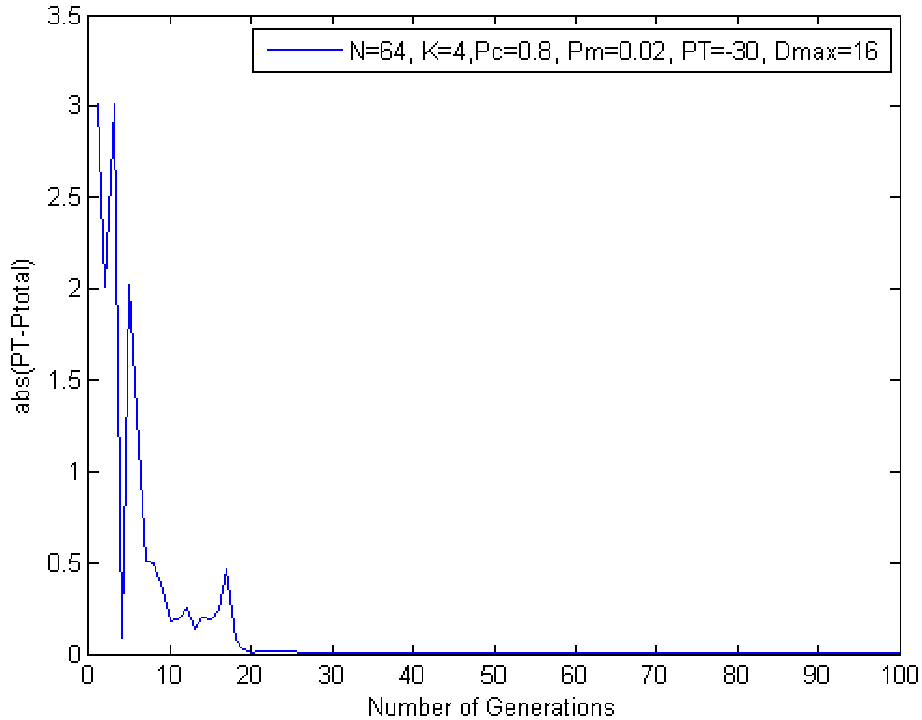


(a)

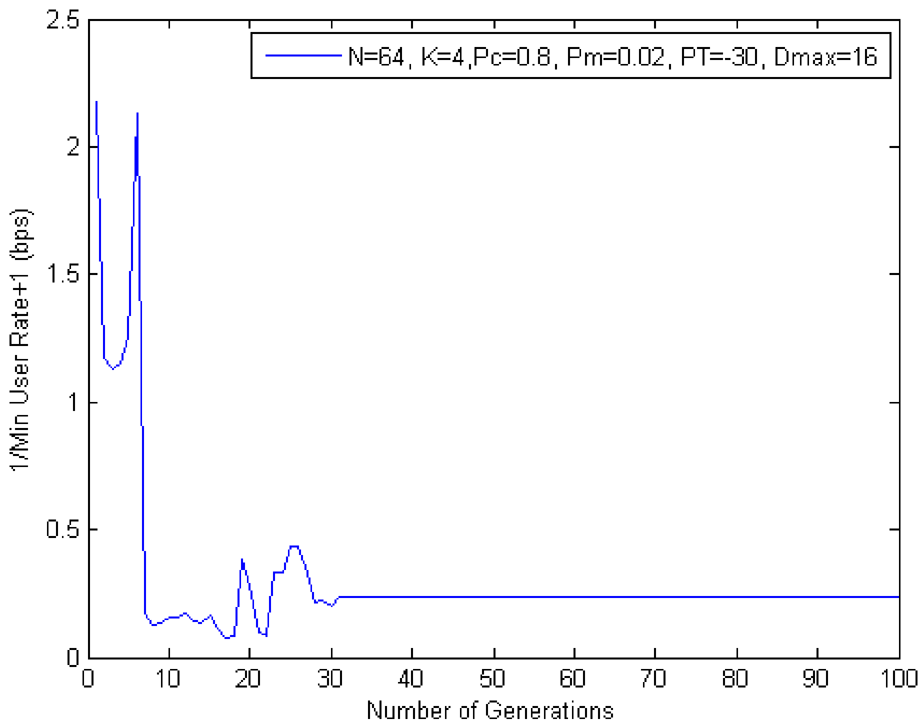


(b)

Figure 6.7.(a-b): Simulation results for permutations of conditions in Table.6.2 (Row-1, Average Case)

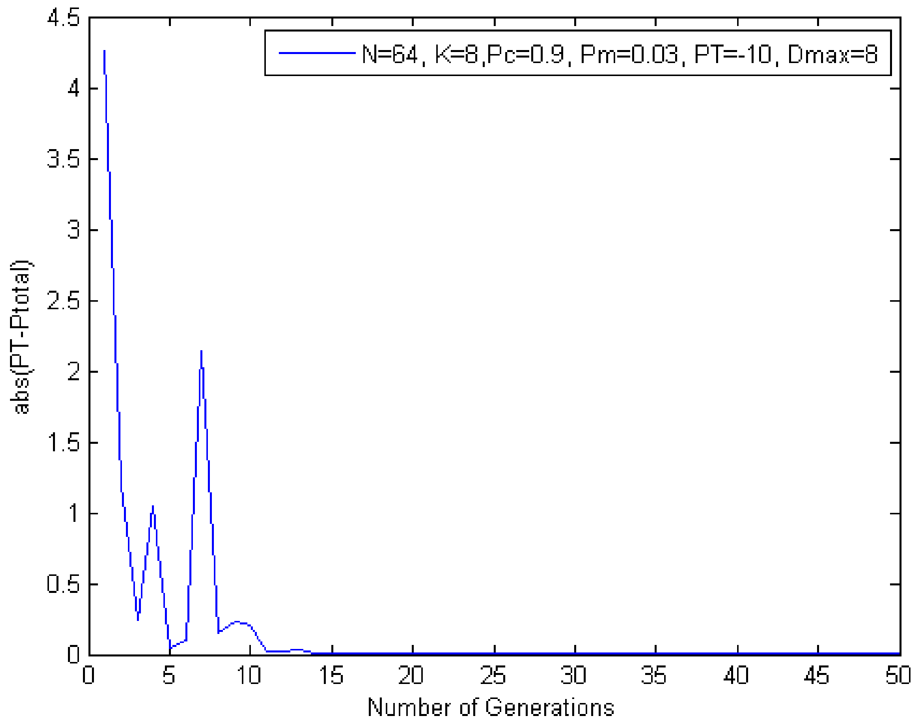


(c)

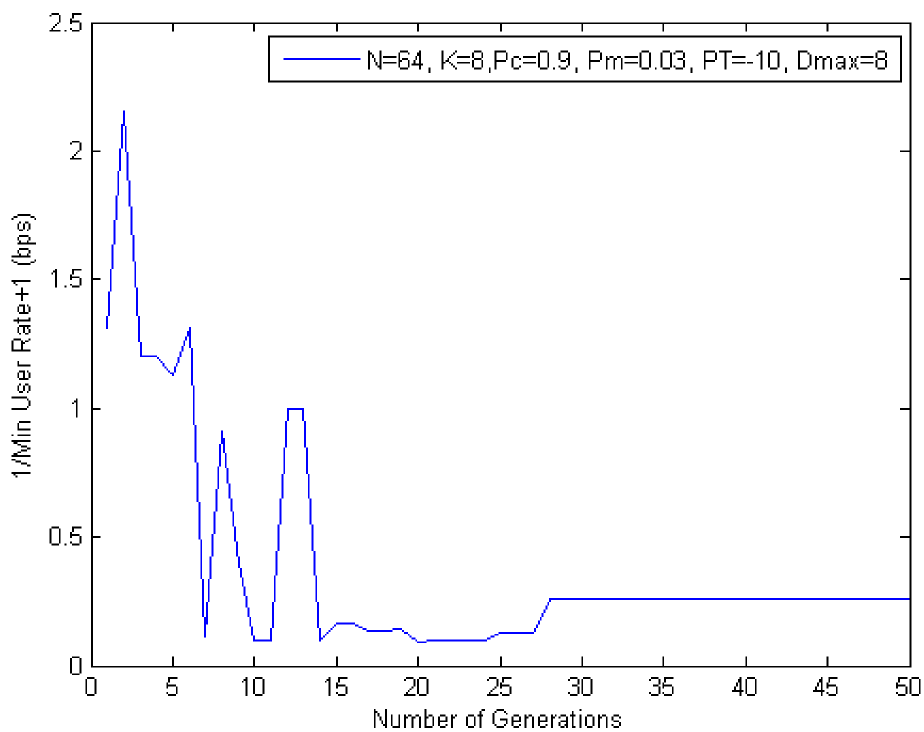


(d)

Figure 6.7.(c-d): Simulation results for permutations of conditions in Table.6.2 (Row-2, Average Case)

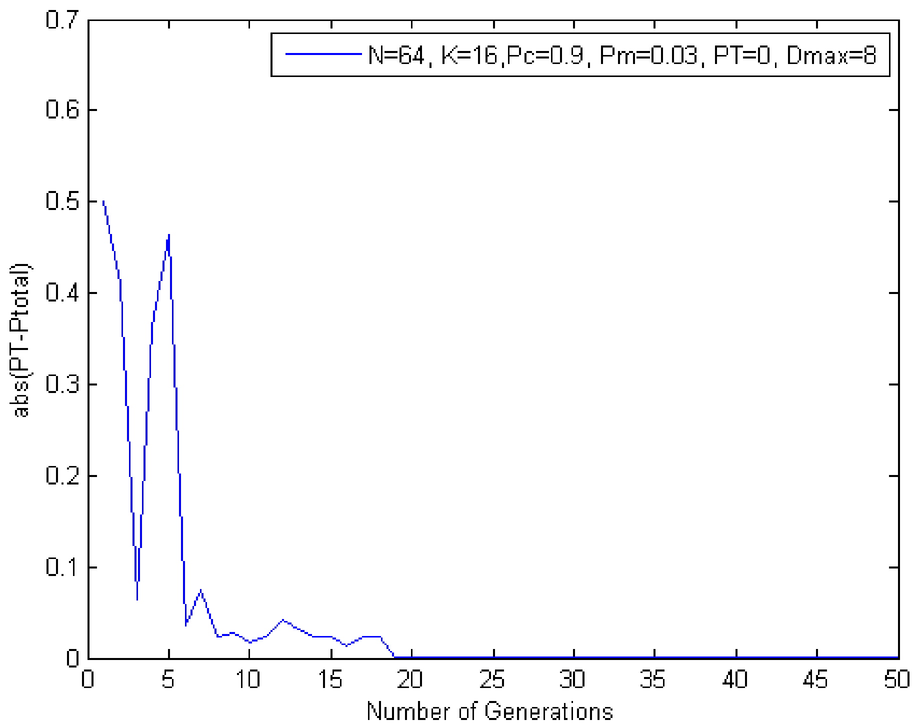


(e)

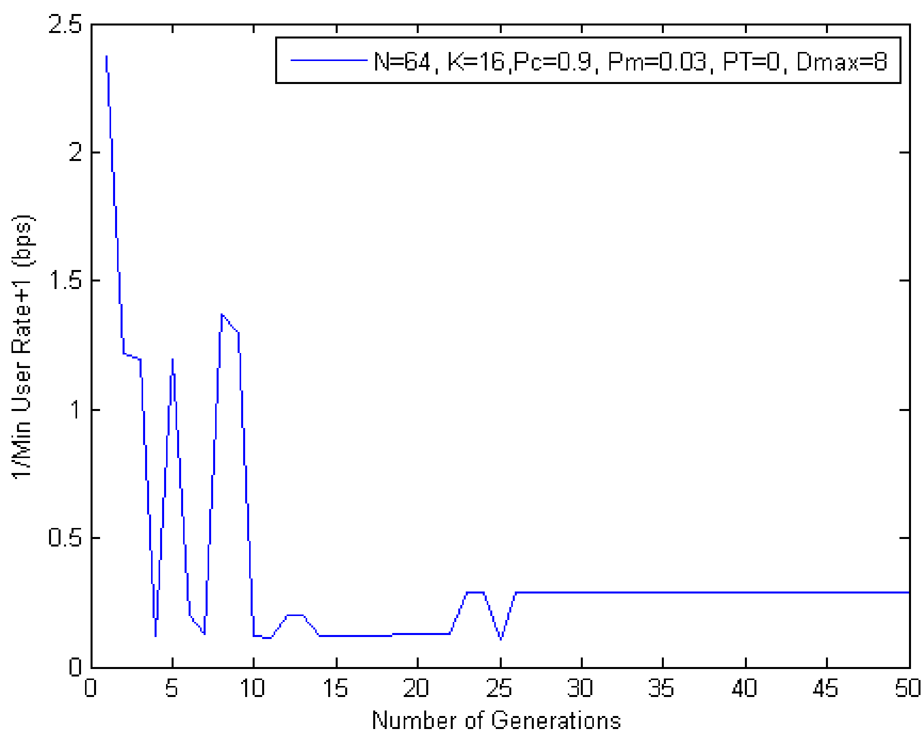


(f)

Figure 6.7.(e-f): Simulation results for permutations of conditions in Table.6.2 (Row-3, Average Case)

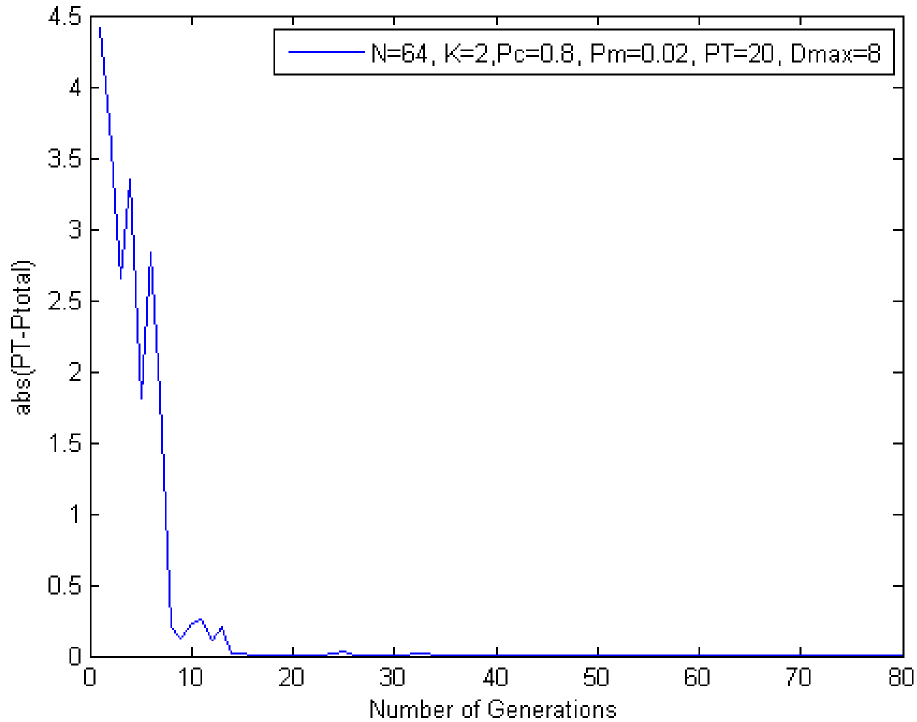


(g)

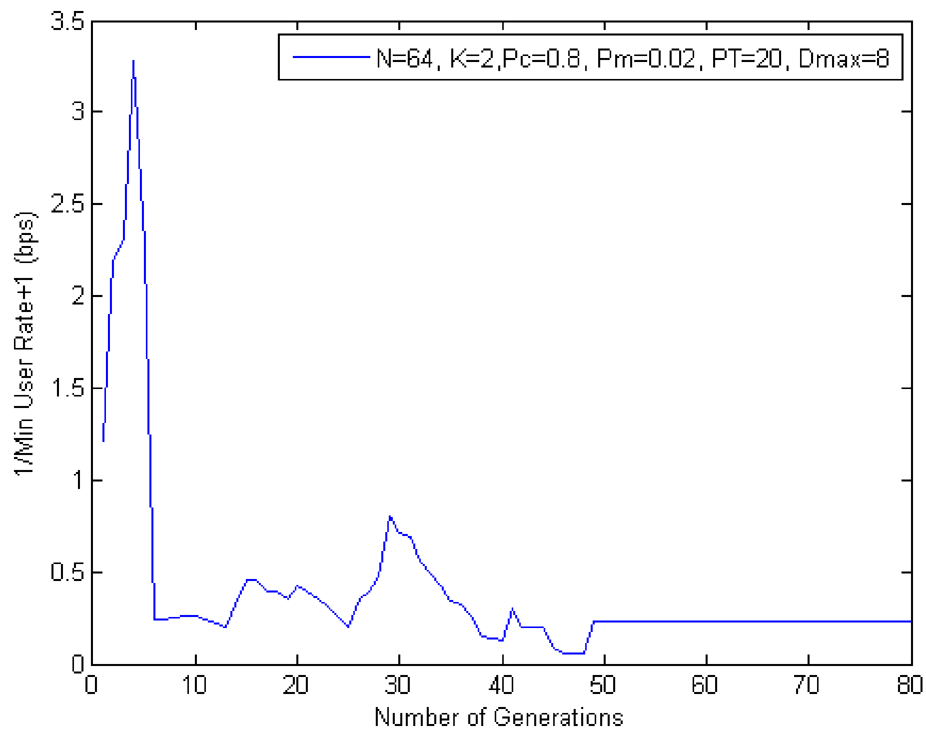


(h)

Figure 6.7.(g-h): Simulation results for permutations of conditions in Table.6.2 (Row-4, Average Case)

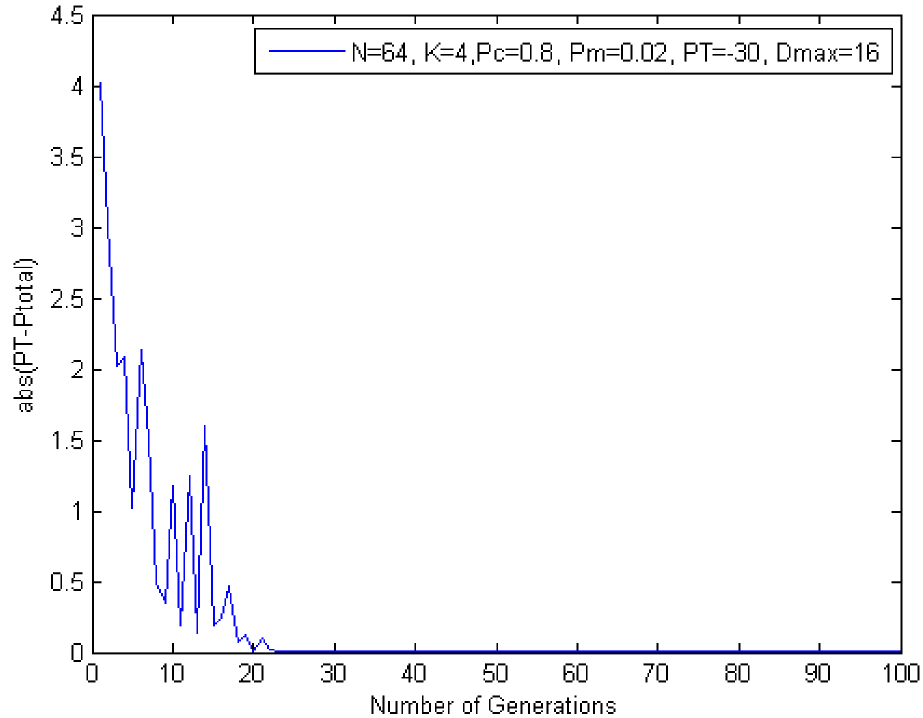


(a)

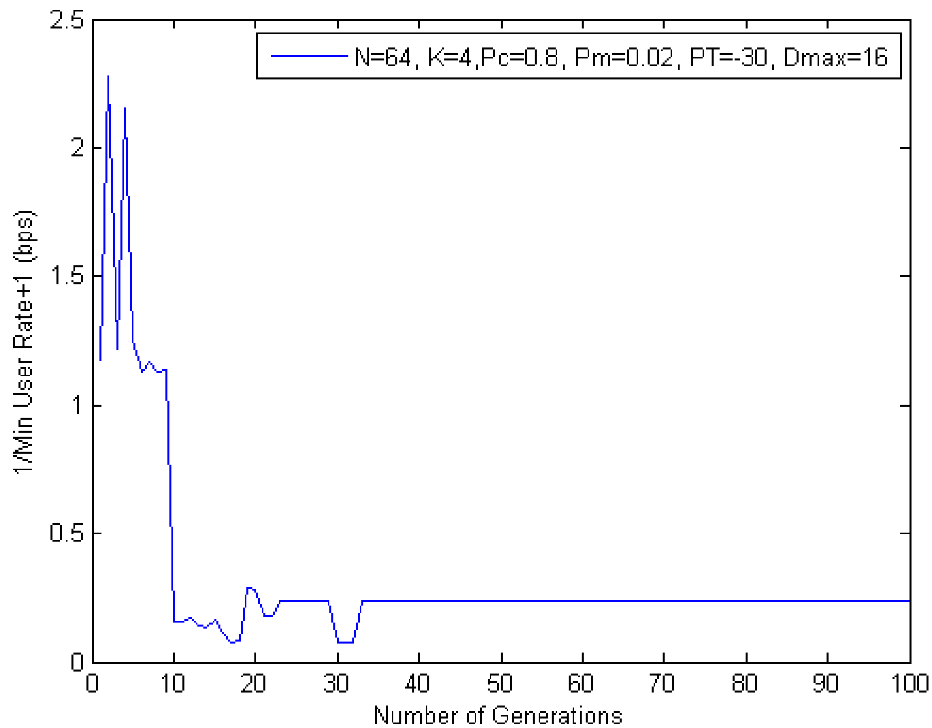


(b)

Figure 6.8. (a-b): Simulation results for permutations of conditions in Table.6.2 (Row-1, Worst Case)

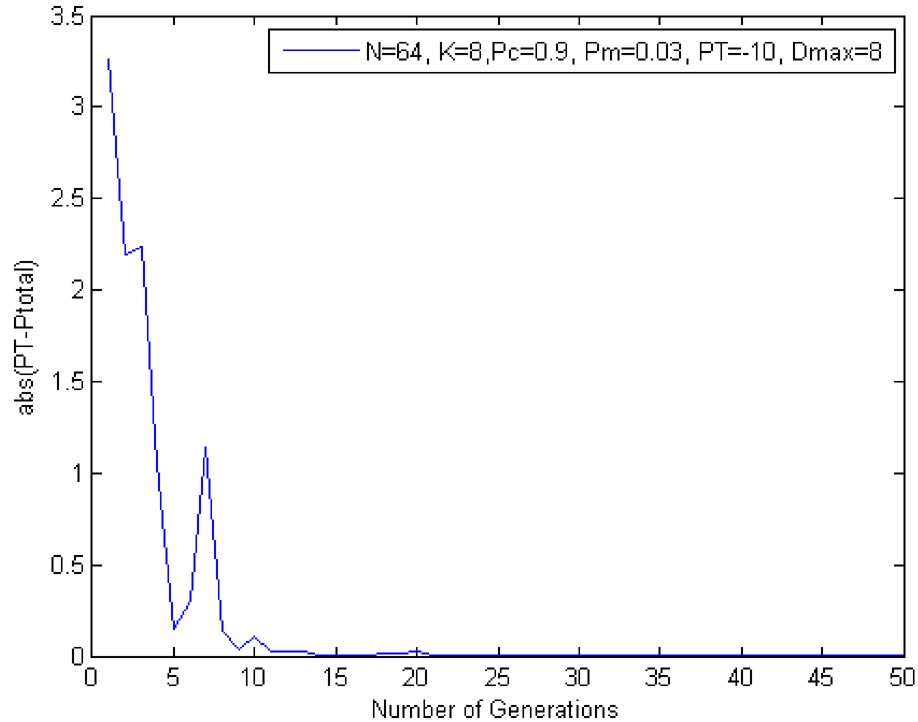


(c)

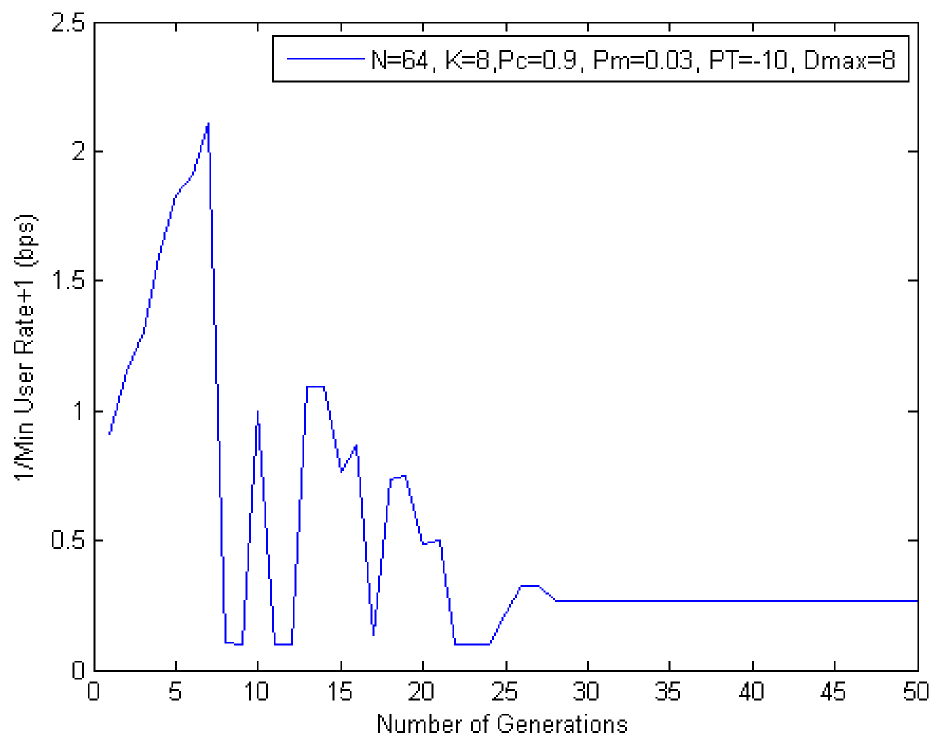


(d)

Figure 6.8. (c-d): Simulation results for permutations of conditions in Table.6.2 (Row-2, Worst Case)

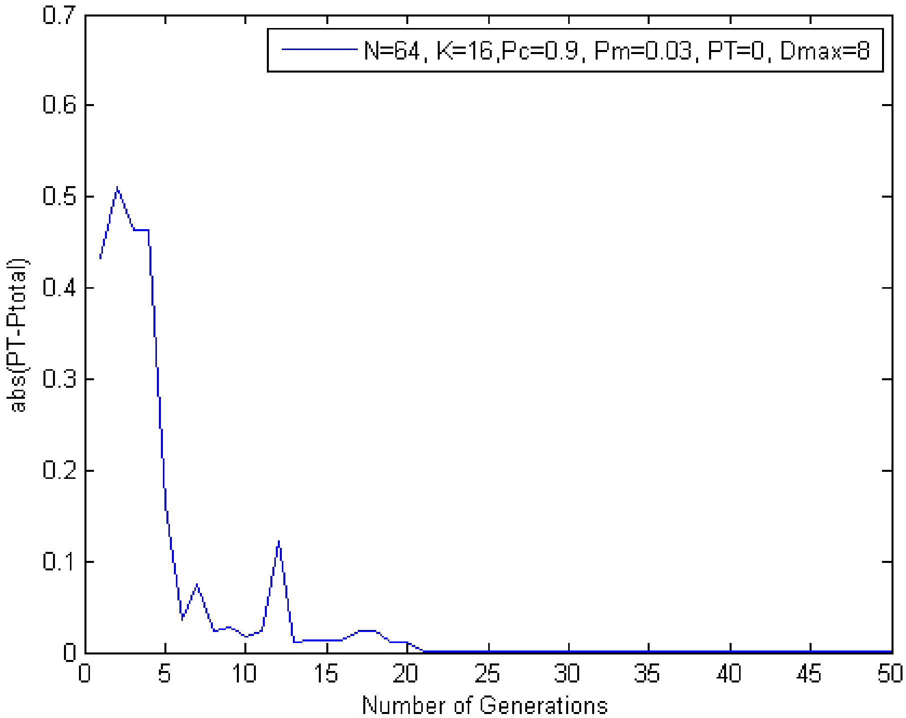


(e)

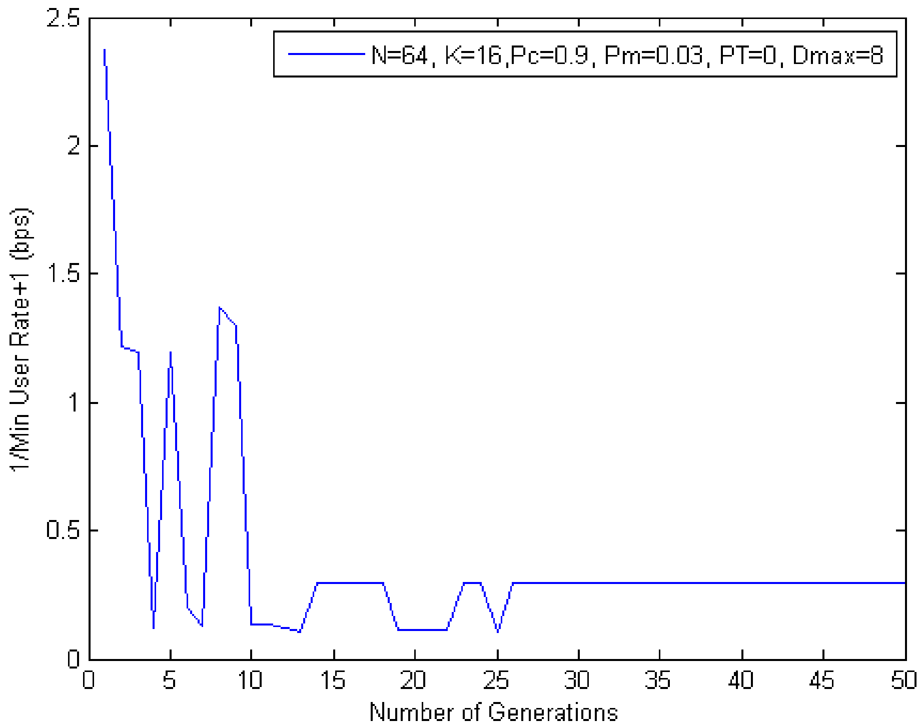


(f)

Figure 6.8. (e-f): Simulation results for permutations of conditions in Table.6.2 (Row-3, Worst Case)

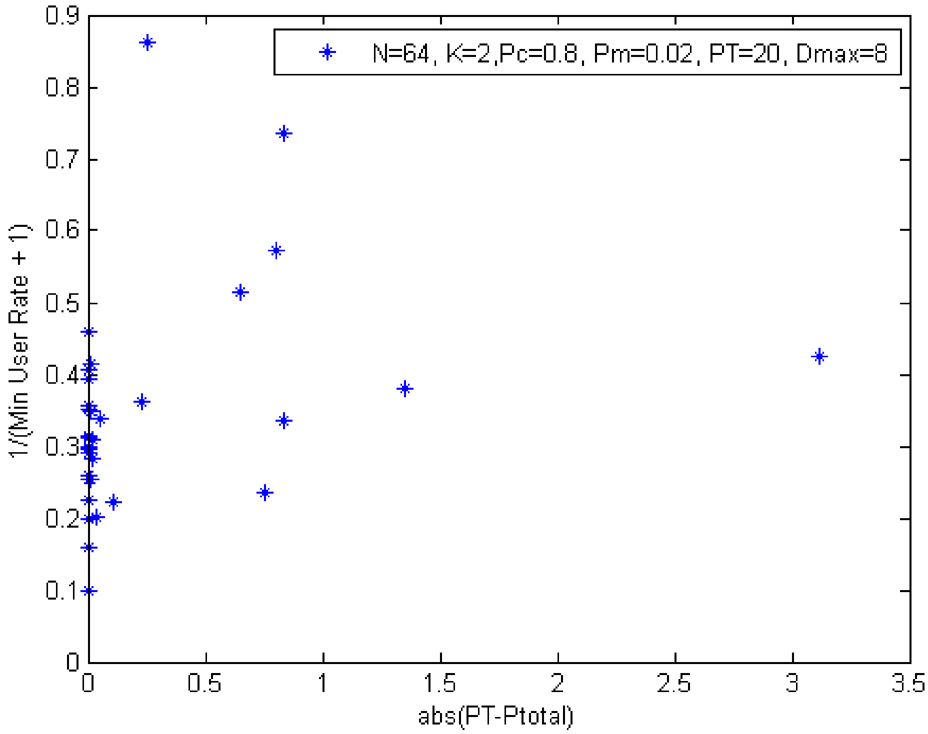


(g)



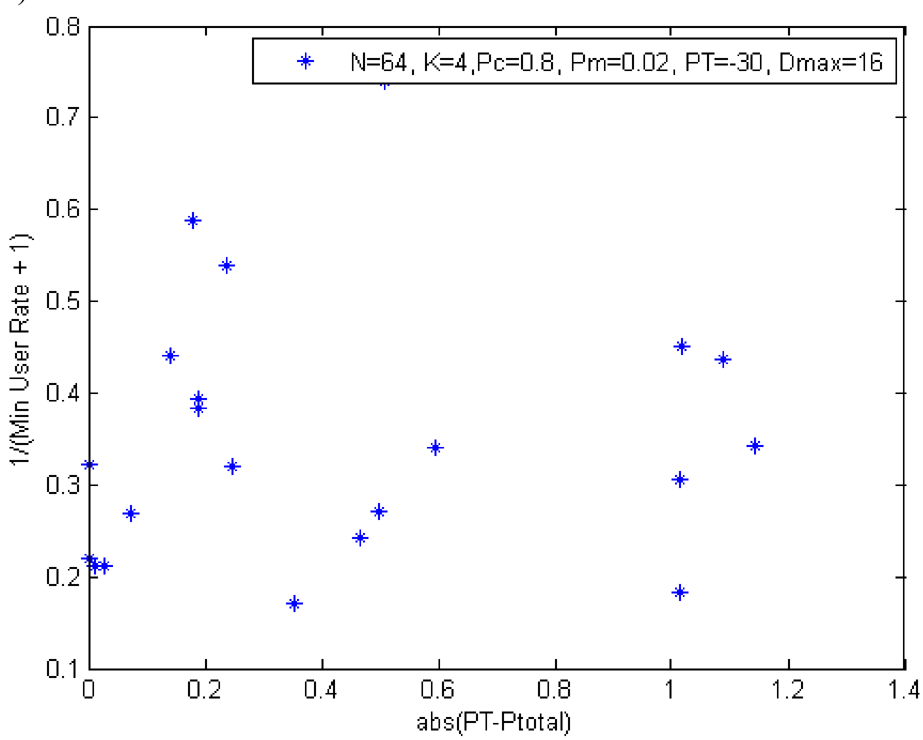
(h)

Figure 6.8. (g-h): Simulation results for permutations of conditions in Table.6.2 (Row-4, Worst Case)



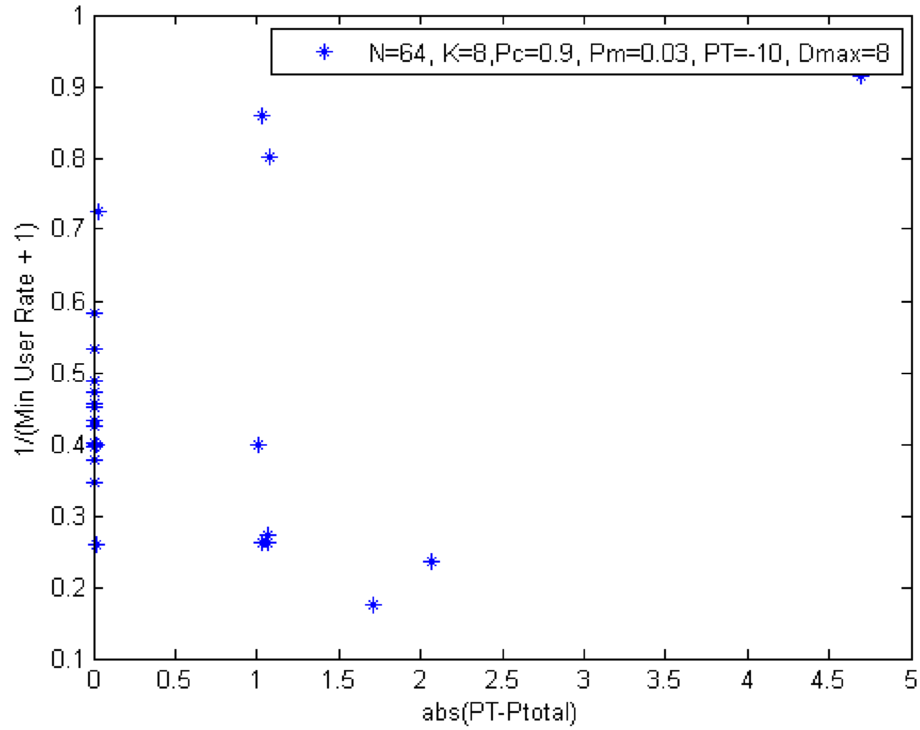
(a)

Figure 6.9.(a): Pareto fronts obtained for permutations of conditions in Table.6.1(Row-1, Best Case)



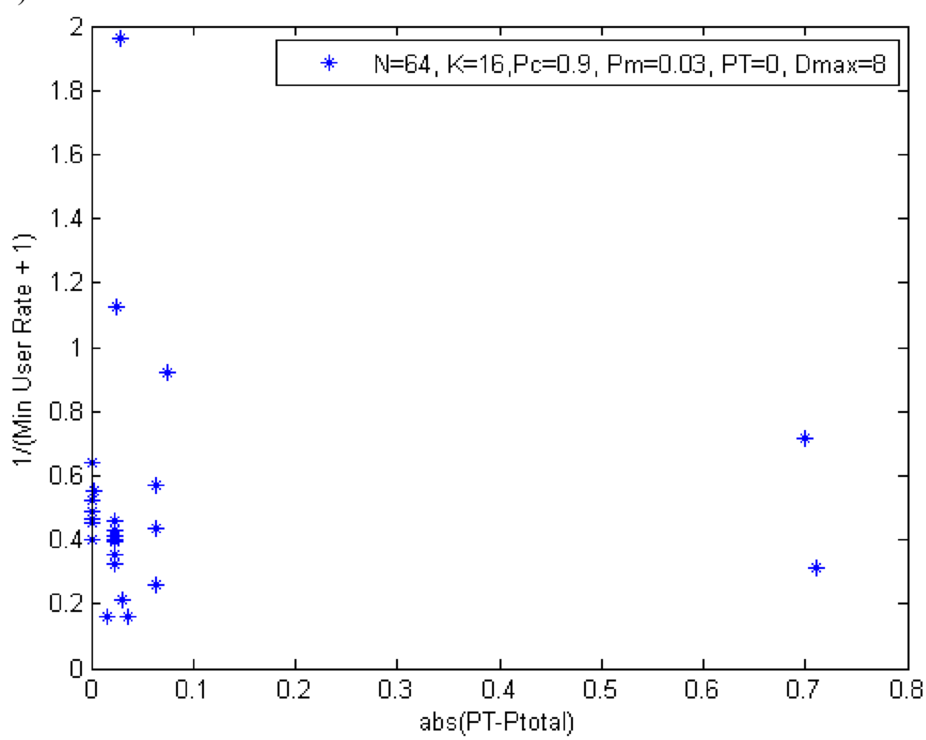
(b)

Figure 6.9.(b): Pareto fronts obtained for permutations of conditions in Table.6.1(Row-2, Best Case)



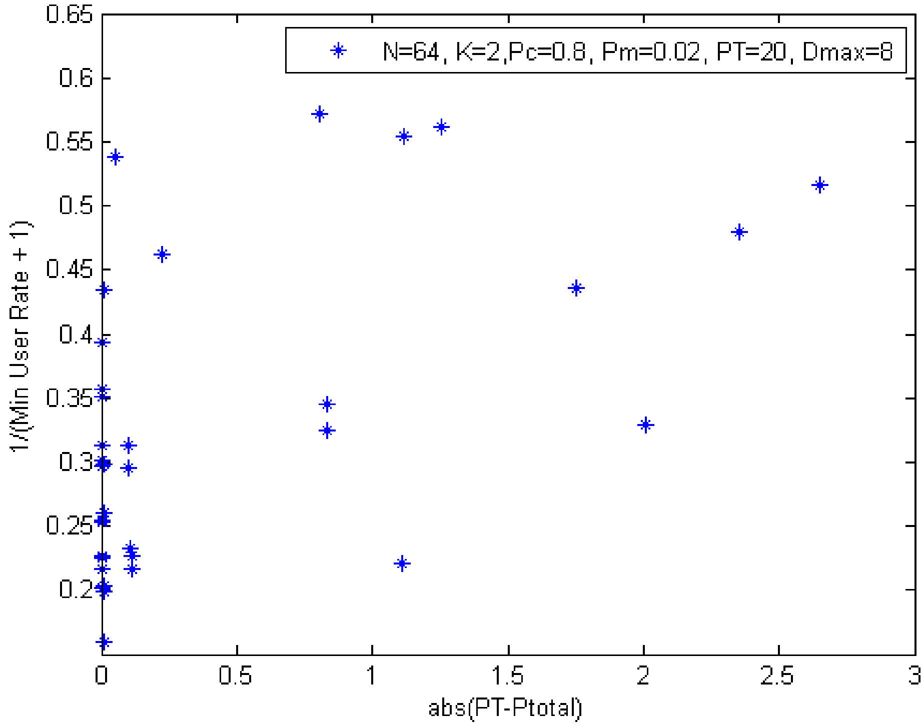
(c)

Figure 6.9.(c): Pareto fronts obtained for permutations of conditions in Table.6.1(Row-3, Best Case)



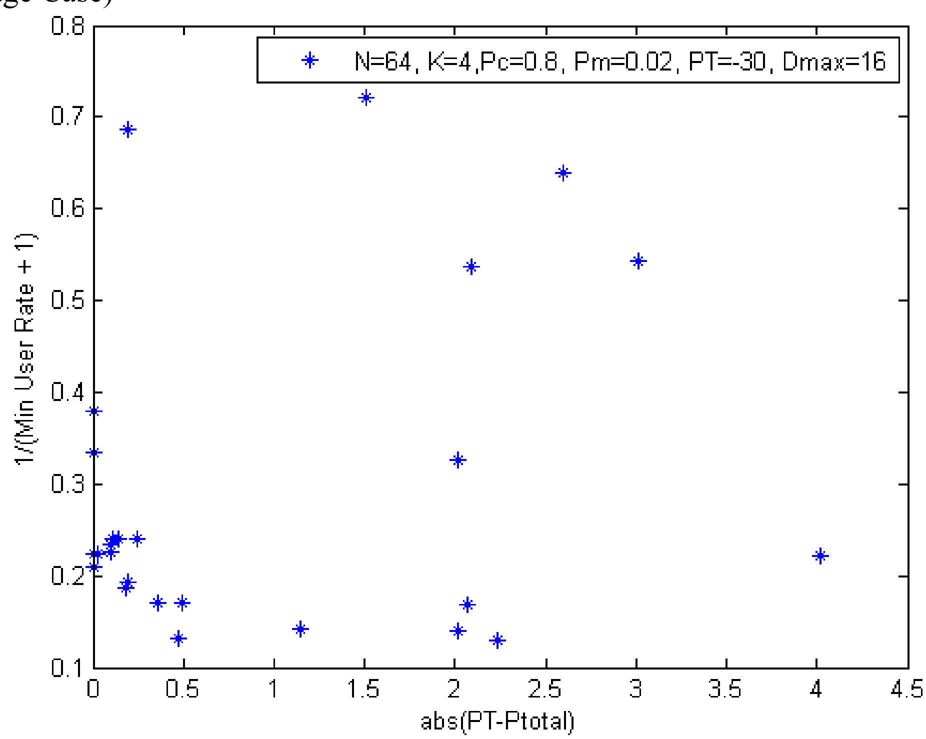
(d)

Figure 6.9.(d): Pareto fronts obtained for permutations of conditions in Table.6.1(Row-4, Best Case)



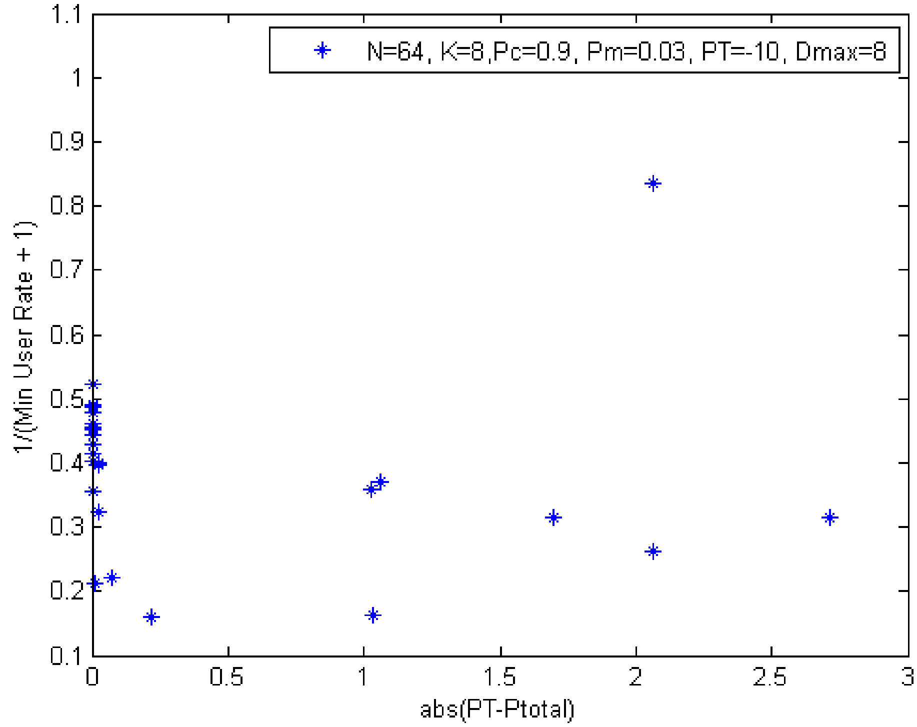
(a)

Figure 6.10.(a): Pareto fronts obtained for permutations of conditions in Table.6.1(Row-1, Average Case)



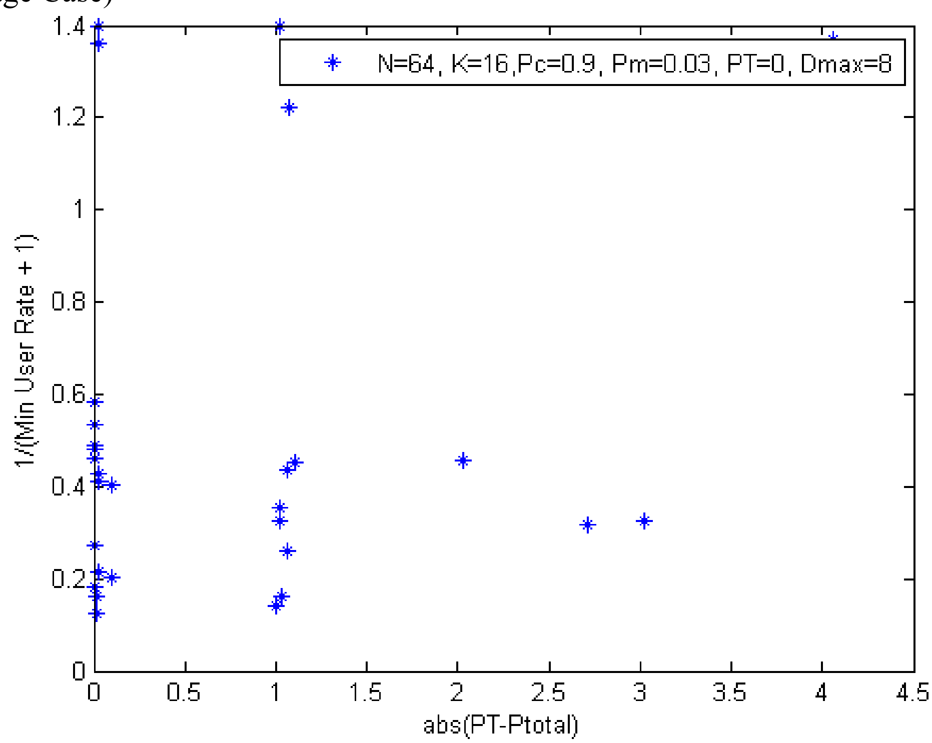
(b)

Figure 6.10.(b): Pareto fronts obtained for permutations of conditions in Table.6.1 (Row-2, Average Case)



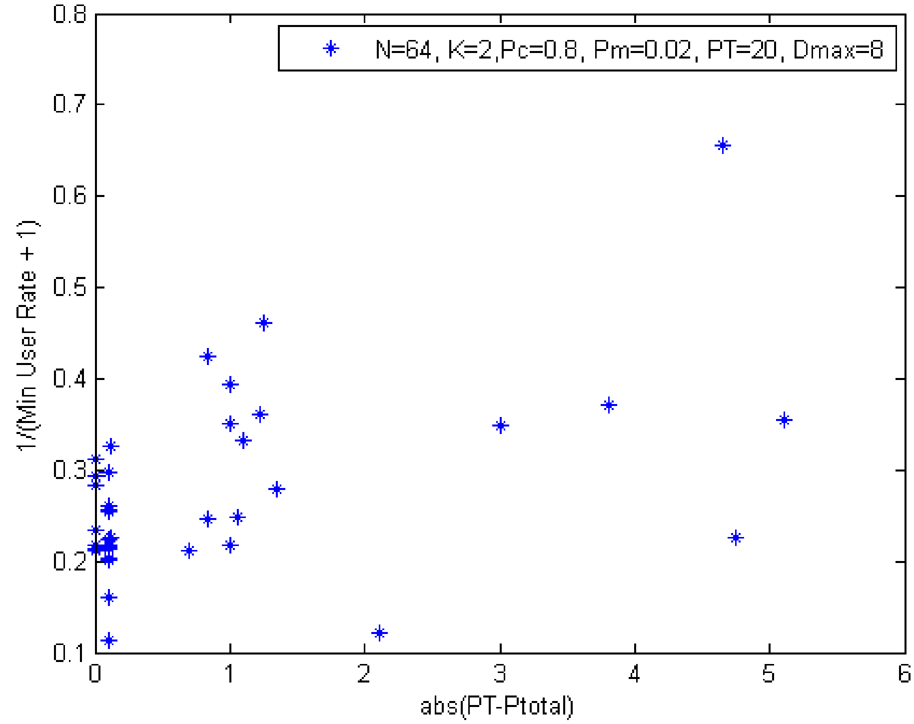
(c)

Figure 6.10.(c): Pareto fronts obtained for permutations of conditions in Table.6.1(Row-3, Average Case)



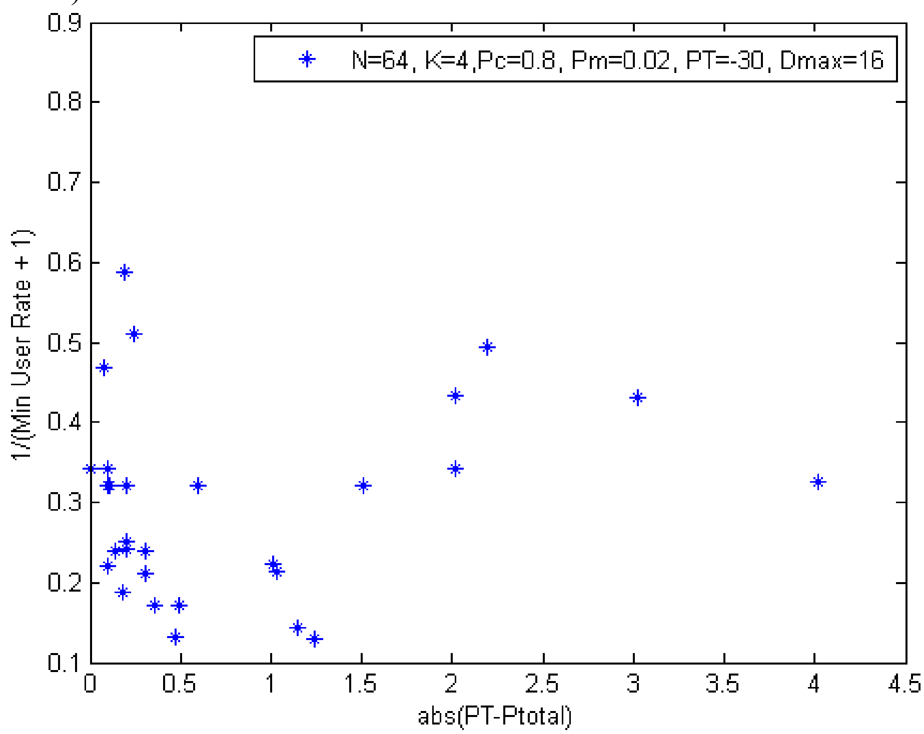
(d)

Figure 6.10.(d): Pareto fronts obtained for permutations of conditions in Table.6.1(Row-4, Average Case)



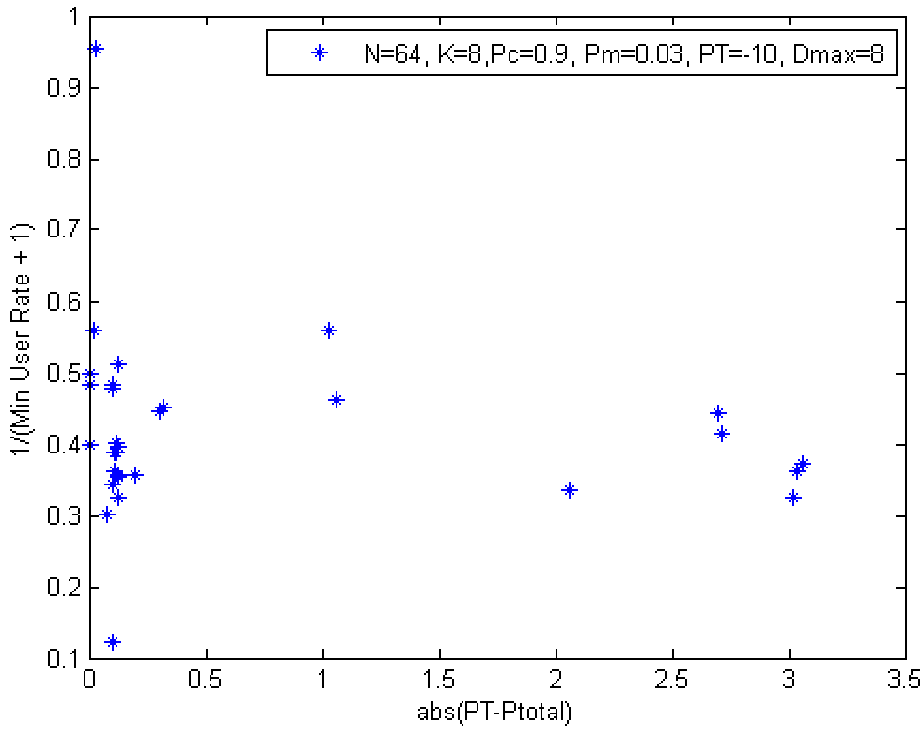
(a)

Figure 6.11.(a): Pareto fronts obtained for permutations of conditions in Table.6.1(Row-1, Worst Case)



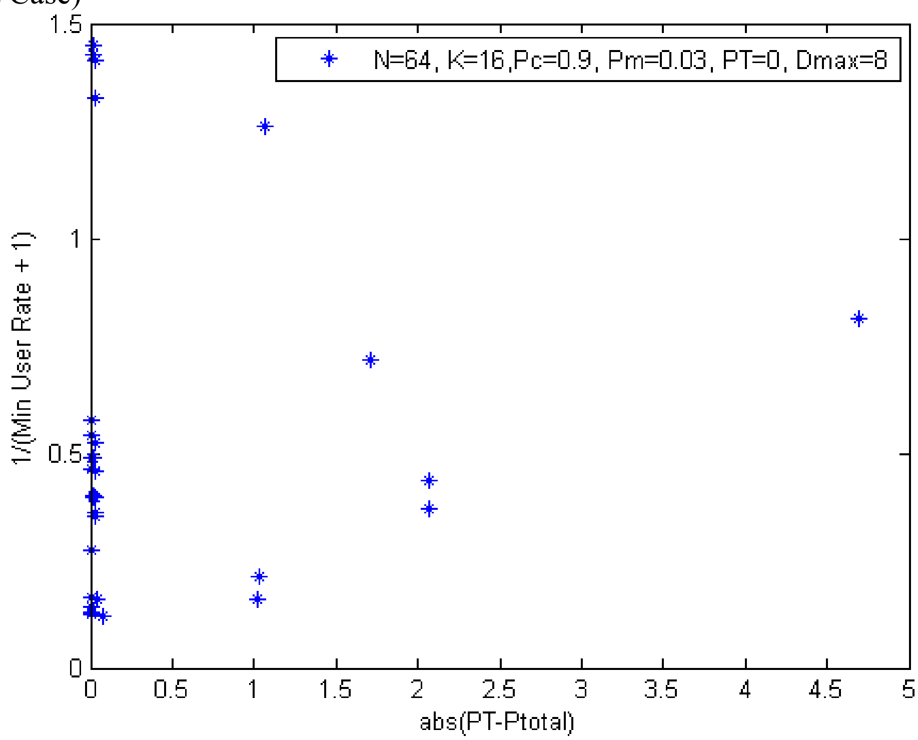
(b)

Figure 6.11.(b): Pareto fronts obtained for permutations of conditions in Table.6.1(Row-2, Worst Case)



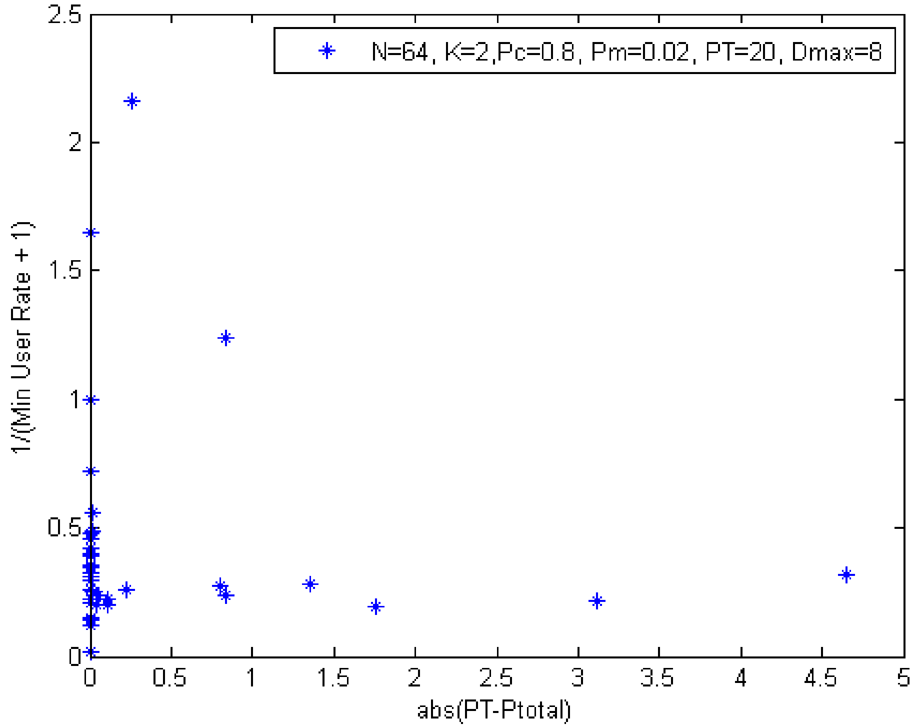
(c)

Figure 6.11.(c): Pareto fronts obtained for permutations of conditions in Table.6.1(Row-3, Worst Case)



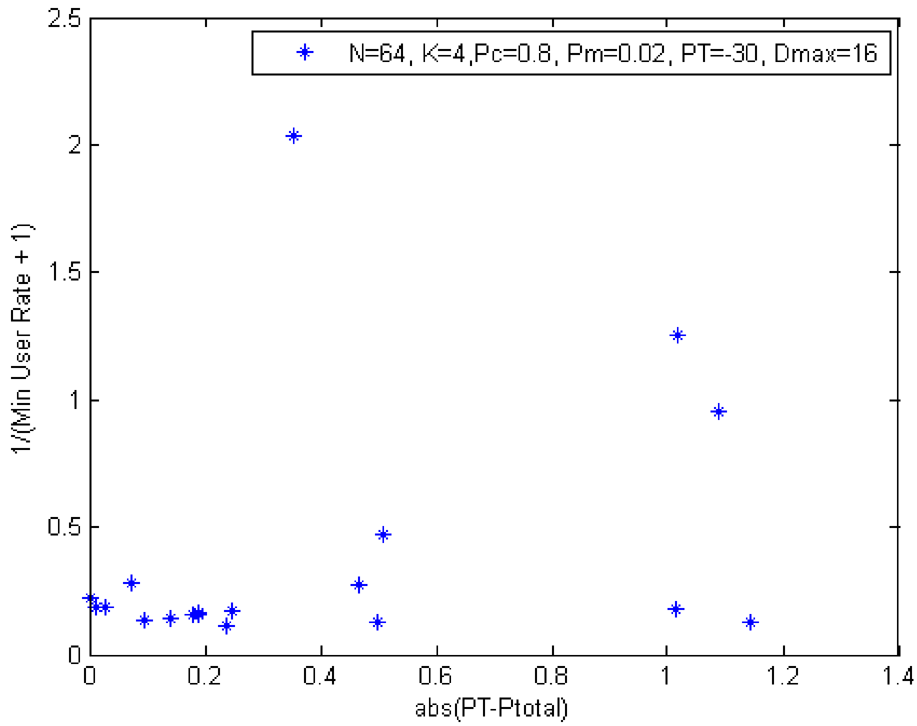
(d)

Figure 6.11.(d): Pareto fronts obtained for permutations of conditions in Table.6.1(Row-4, Worst Case)



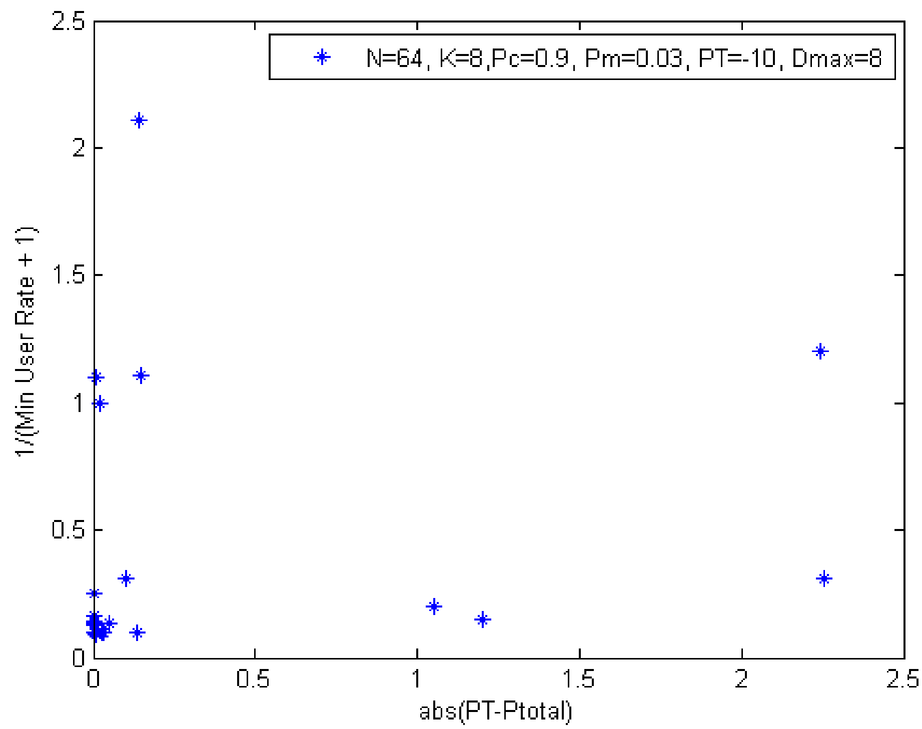
(a)

Figure 6.12.(a): Pareto fronts obtained for permutations of conditions in Table.6.2(Row-1, Best Case)



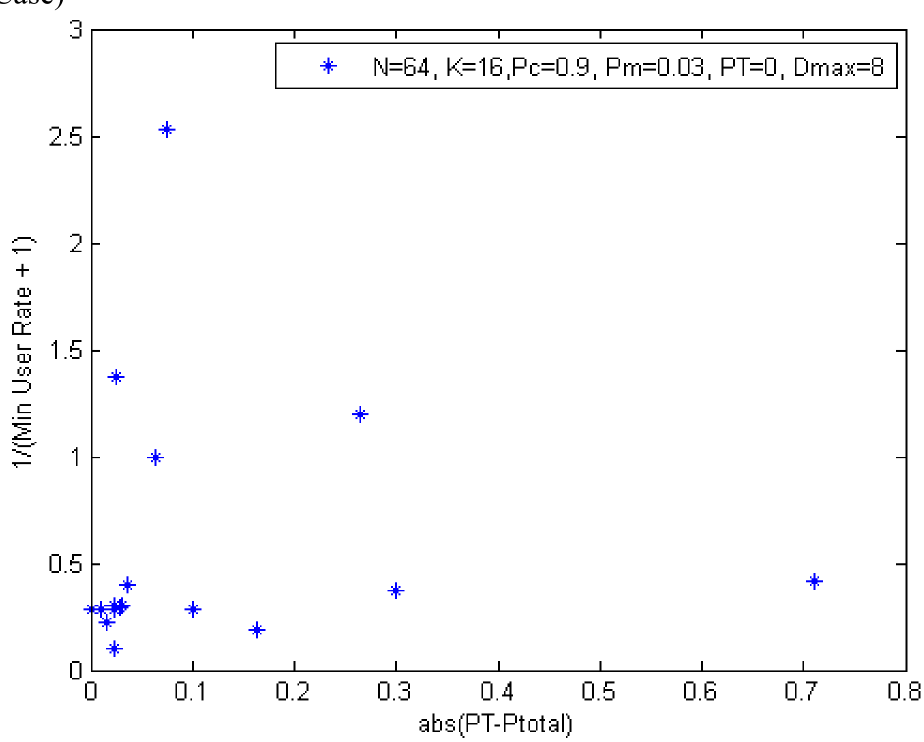
(b)

Figure 6.12.(b): Pareto fronts obtained for permutations of conditions in Table.6.2(Row-2, Best Case)



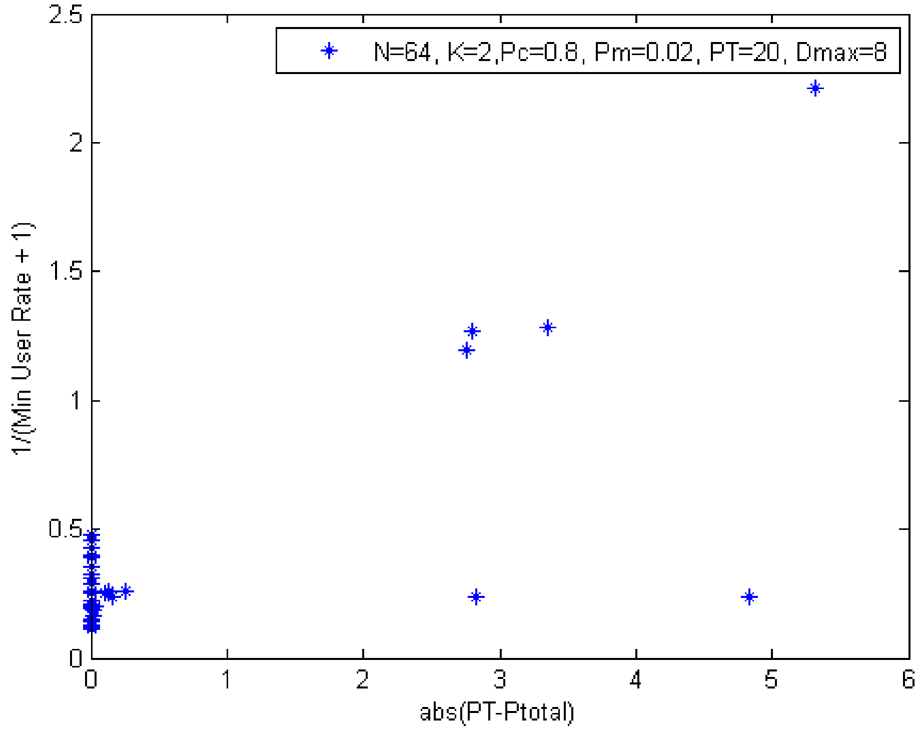
(c)

Figure 6.12.(c): Pareto fronts obtained for permutations of conditions in Table.6.2(Row-3, Best Case)



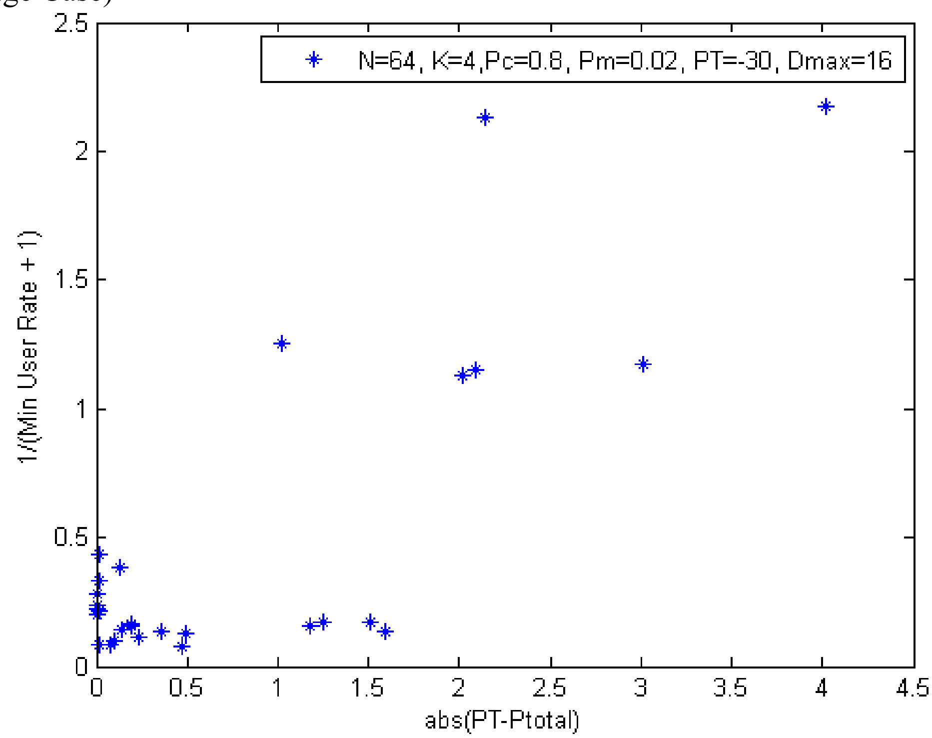
(d)

Figure 6.12.(d): Pareto fronts obtained for permutations of conditions in Table.6.2(Row-4, Best Case)



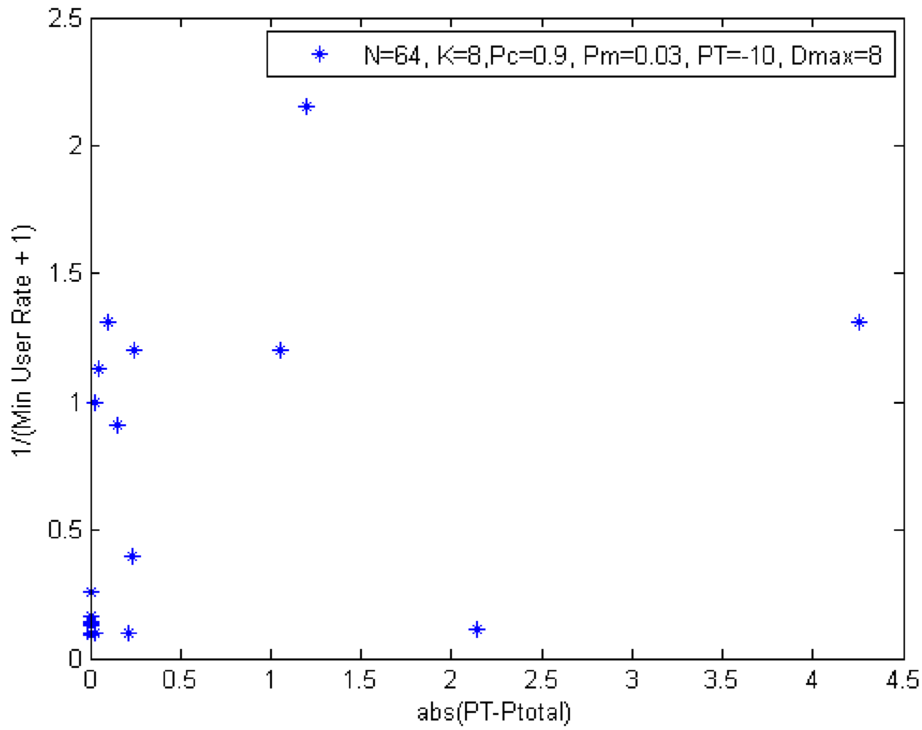
(a)

Figure 6.13.(a): Pareto fronts obtained for permutations of conditions in Table.6.2(Row-1, Average Case)



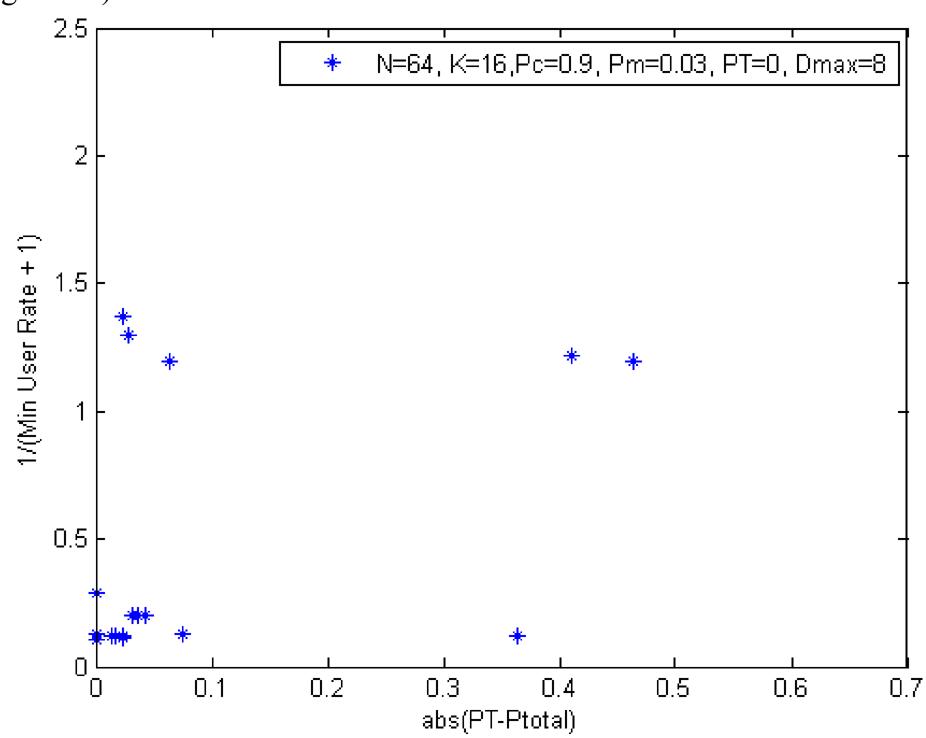
(b)

Figure 6.13.(b): Pareto fronts obtained for permutations of conditions in Table.6.2(Row-2, Average Case)



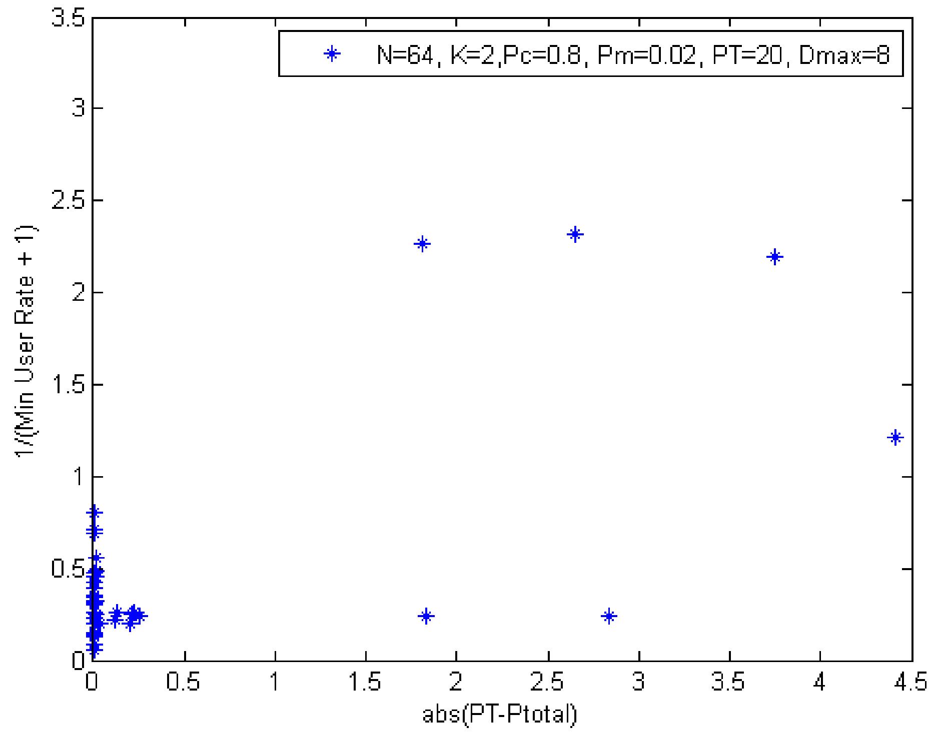
(c)

Figure 6.13.(c): Pareto fronts obtained for permutations of conditions in Table.6.2(Row-3, Average Case)



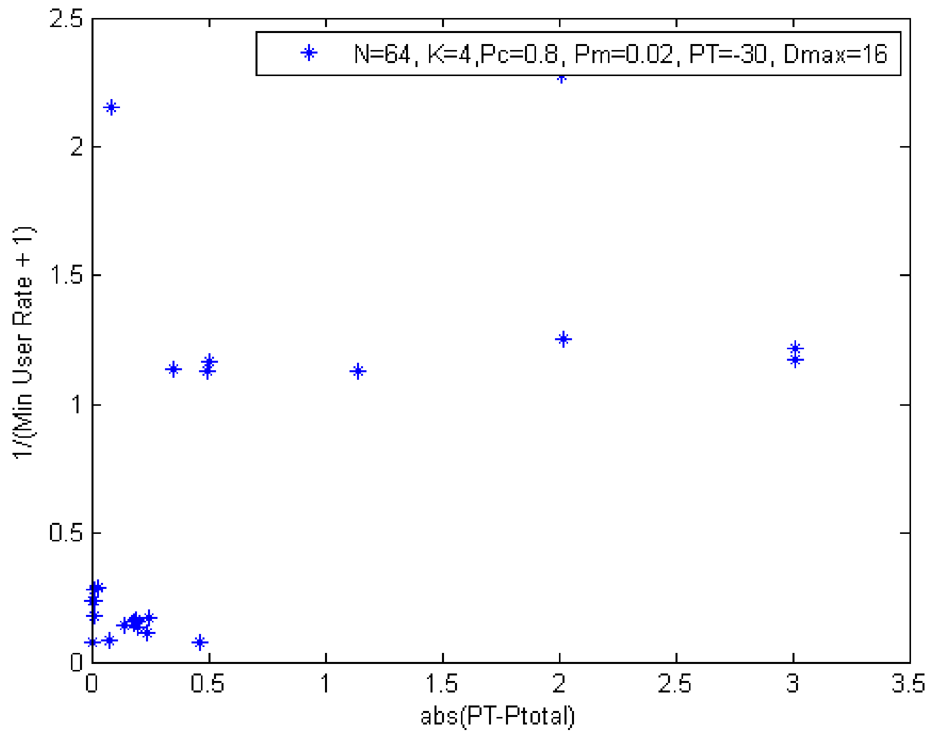
(d)

Figure 6.13.(d): Pareto fronts obtained for permutations of conditions in Table.6.2(Row-4, Average Case)



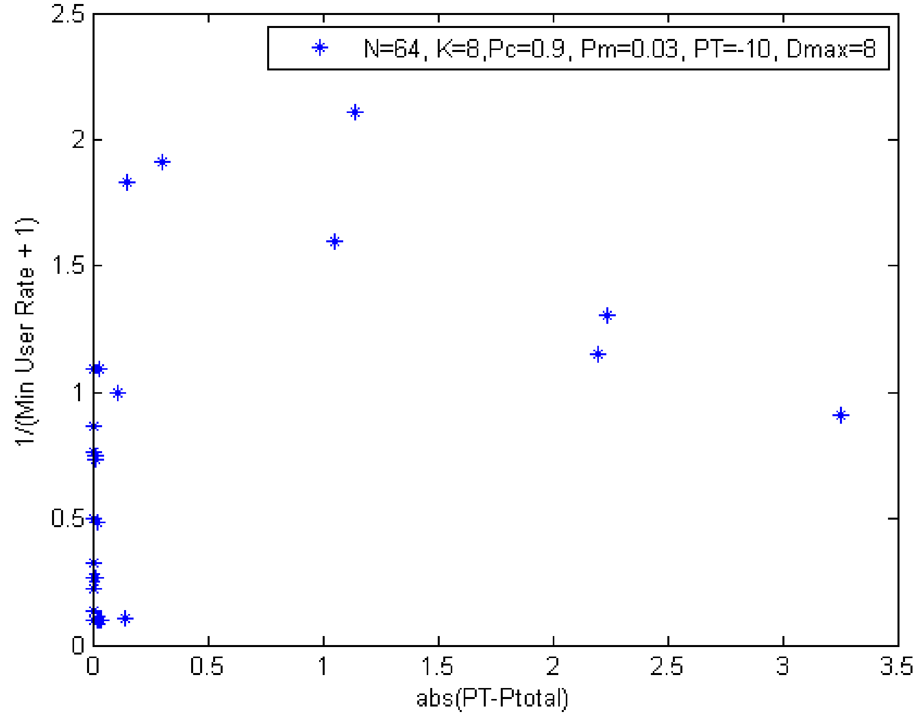
(a)

Figure 6.14.(a): Pareto fronts obtained for permutations of conditions in Table.6.2(Row-1, Worst Case)



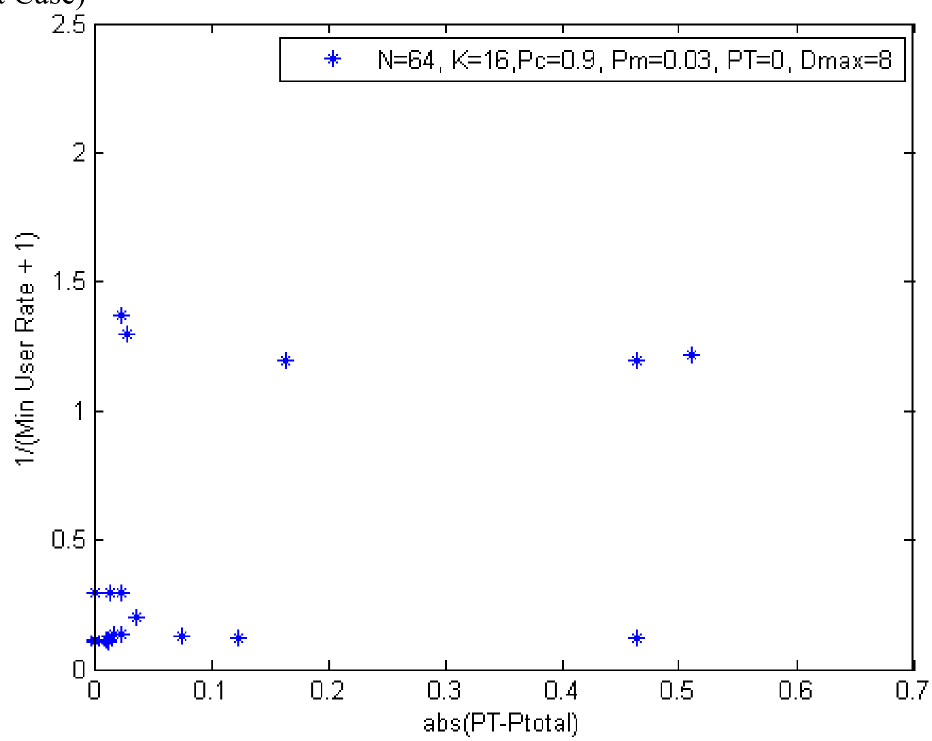
(b)

Figure 6.14.(b): Pareto fronts obtained for permutations of conditions in Table.6.2(Row-2, Worst Case)



(c)

Figure 6.14.(c): Pareto fronts obtained for permutations of conditions in Table.6.2(Row-3, Worst Case)



(d)

Figure 6.14.(d): Pareto fronts obtained for permutations of conditions in Table.6.2(Row-4, Worst Case)

In the light of above discussion it can be concluded that the NSGA-II based solution is of the order of magnitude faster as compared to [AC10, Red07, SWA10], which is an important result as our assumption of perfect CSI is time dependent.

The faster convergence rate of the algorithms makes it suitable for practical wireless applications. Since the channel gains are assumed to be constant during the period of allocation and considering the fact that wireless channels tends to change quickly, a faster allocation algorithm is preferred. The faster convergence rate of the algorithms is because of relaxation in the power constraint. The algorithm can be made to work even faster if we can predict the expected power required to be transmitted in each allocation.

Finally, in order to have a conceptual illustration of the non-dominated Pareto sets (fronts), Fig.6.9.(a-d) – Fig.6.11.(a-d) depicts the Pareto fronts obtained corresponding to best, average and worst chromosome respectively, for SISO case. While, Fig.6.12.(a-d)-Fig.6.14.(a-d) shows the Pareto fronts obtained corresponding to best, average and worst chromosome respectively, for MIMO case.

From Figs.6.9-6.14 it is clear that most of the solutions obtained by the algorithm minimized the difference of Total power and power utilized to zero. The solution, with zero difference of two powers and final constant rate was selected as the best solution.

Analysis of Results obtained for SISO System

In this subsection we present analysis and comparison of various results obtained for SISO Systems.

Sum Capacity versus Number of users

The wireless channel is modeled as before, and the total transmit power available at the base station is 1 W. The power spectral density of additive white Gaussian noise is -80 dBW/Hz, and the total bandwidth is 1 MHz, which is divided into 64 subchannels. The maximum path loss difference is 40 dB, and the user locations are assumed to be uniformly distributed.

Table 6.3 show the variation of sum capacity obtained with the number of users, for a fixed number of subchannels (N=64). We considered many combinations of NSGA-II parameters as shown in Table 6.3. Table 6.3 also depicts the results obtained for average and worst chromosome generated by NSGA-II algorithm in each case. The comparison of results for worst chromosome with that of best chromosome highlights the fact that the performance of NSGA-II for the worst case and best case are more or less same. In worst case the capacity obtained was slightly lower than the best and average case but it was still higher than that obtained by methods in [SAE03, WSEA04, GLX+09]. Fig. 6.15 shows the comparison of worst case capacity obtained by NSGA-II with the capacity obtained by methods in [SAE03, WSEA04, GLX+09].

Table 6.3: Simulation results for various permutations of Population (Pop), Generations (Gen), Probability of Crossover (P_c) and Probability of Mutation (P_m) for fixed number of subchannels (64) , Maximum number of Bits (D_{max}=8) and SNR (30 dB) and maximum power of 1W.

S. No.	**Users (K)**	**Sub carries (N)**	**Sum Rate (Bits/sec/Hz)**					
			Pop =30,Gen=50		**Pop =50,Gen=80**		**Pop =80,Gen=100**	
			P_C=0.9, P_m=0.03	**P_C=0.8, P_m=0.02**	**P_C=0.9, P_m=0.03**	**P_C=0.8, P_m=0.02**	**P_C=0.9, P_m=0.03**	**P_C=0.8, P_m=0.02**
Best Case								
1	16	64	5.15	5.18	5.21	5.19	5.26	5.24
2.	8	64	5.10	4.97	5.15	5.12	5.19	5.16
3.	4	64	4.99	5.03	5.09	5.05	5.14	5.17
4.	2	64	4.78	4.69	4.76	4.79	4.91	4.94
Average Case								
1	16	64	4.94	4.96	5.01	5.09	5.13	5.17
2.	8	64	4.88	4.91	4.97	4.94	5.01	5.04
3.	4	64	4.73	4.71	4.79	4.83	4.88	4.86
4.	2	64	4.69	4.64	4.71	4.70	4.74	4.82
Worst Case								
1	16	64	4.83	4.80	4.84	4.87	4.92	4.95
2.	8	64	4.84	4.73	4.82	4.85	4.87	5.88
3.	4	64	4.64	4.69	4.73	4.78	4.77	4.81
4.	2	64	4.60	4.58	4.65	4.63	4.68	4.72

The sum capacity increases with the increase in number of users which can be attributed to the effect of multiuser diversity. The sum capacity also increased with the increase in number of generations and population which is in consistence with the behavior of GAs.

It is also possible to extract the random parameters generated by NSGA-II in any case and fix them for all set of simulations. All GAs are stochastic in nature, that is, they makes random choices of their internal parameters. That is why we get slightly different results each time we run the GA. The GA uses the default MATLAB pseudorandom number stream. Each time GA calls the stream, its state changes. So that the next time GA calls the stream, it returns a different random number. This is why the output of GA differs each time we run it. If we need to reproduce our results exactly, we can call GA with an output argument that contains the current state of the default stream, and then reset the state to this value before running GA again.

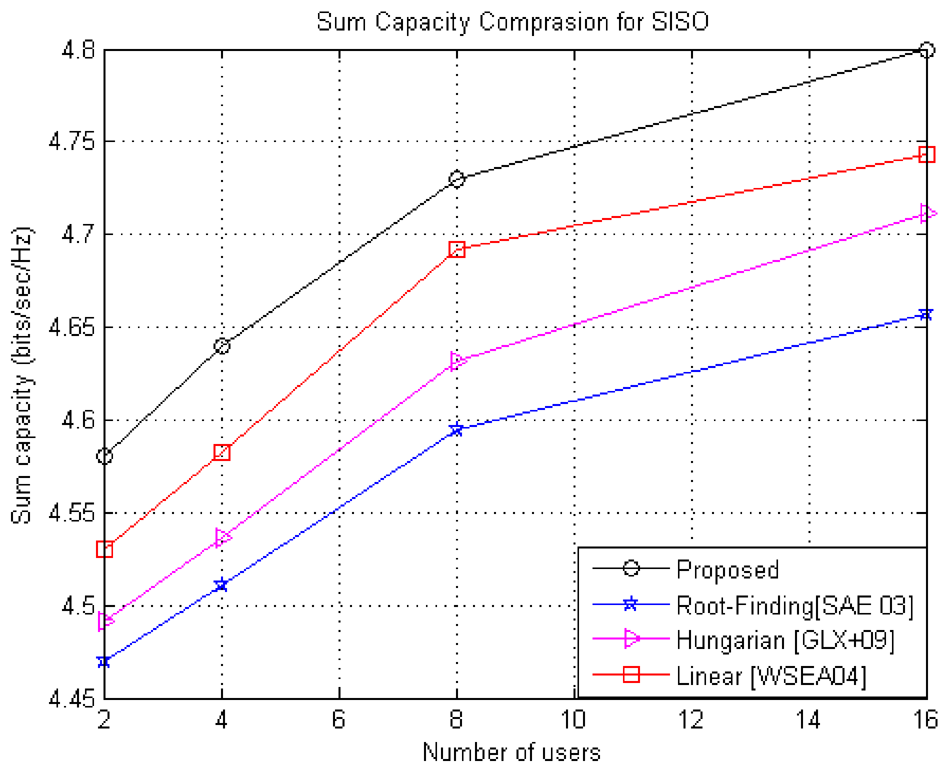


Figure 6.15: Sum Capacity versus Number of Users (SISO)

Minimum user capacity versus number of users

In this subsection, we compare the minimum user capacity achieved by the proposed algorithm with the method used in [SAE05] and [RC00]. The same simulation parameters were used as in the previous subsection.

Fig.6.16 shows the comparisons of minimum user data rate obtained versus number of users for the SISO system. From Fig.6.16, it is evident that adaptive resource allocation achieves significant capacity gain over non-adaptive TDMA. Also the adaptive scheme with optimal power allocation proposed by Shen et al. [SAE05] achieves even higher capacity than the scheme with equal power distribution [RC00]. Proposed algorithm outperforms both [SAE05] and [RC00] by consistently achieving higher minimum user data rates for all sets of users. Moreover since the algorithm maximizes the minimum user data rates fairness among the users is innately guaranteed.

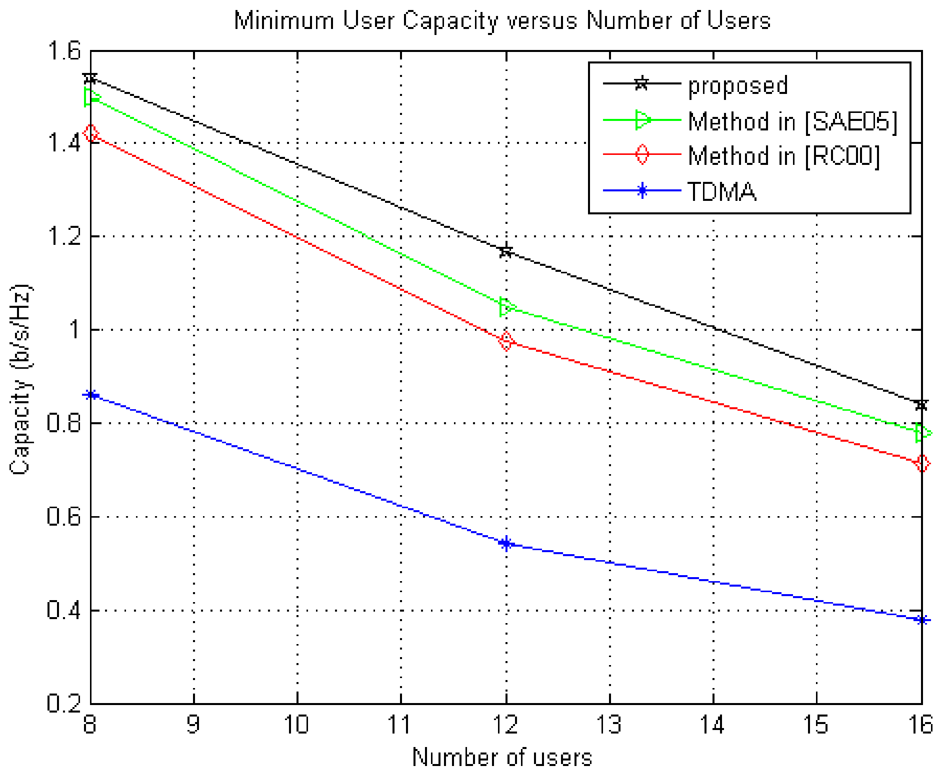


Figure 6.16: Minimum User Capacity versus Number of Users

Capacity gain versus number of users

Fig.6.17 shows the comparison of capacity gain over TDMA obtained by the proposed algorithm with that of methods in [SAE05] and [RC00].

From Fig.6.17 it can be observed that, the capacity gain over TDMA increases as the number of users increase; this is because of added multiuser diversity gain. Multiuser diversity is obtained by opportunistic user scheduling at either the transmitter or the receiver. The effect of multiuser diversity is predominant in systems with large number of users, as with the increasing number of users in the system, the probability that a given subchannels is in a deep fade for all users' decreases.

In a system with 16 users and 64 subchannels, the proposed scheme achieves 31.6% and 49% higher capacity than the scheme with optimal power distribution [SAE05] and equal power distribution [RC00] respectively, when compared to fixed TDMA.

The main advantage of using NSGA-II algorithm provides better sum capacity together with joint allocation of subchannels and power. NSGA-II provides optimal solution to the problem of joint allocation of the subchannels and power to the users without being awfully complex. As in NSGA-II aided subchannels and bit (which in turn provides power allocation using equation.(6.5)), the search and allocation of the best subchannels and the number of bits on each subchannels is performed simultaneously.

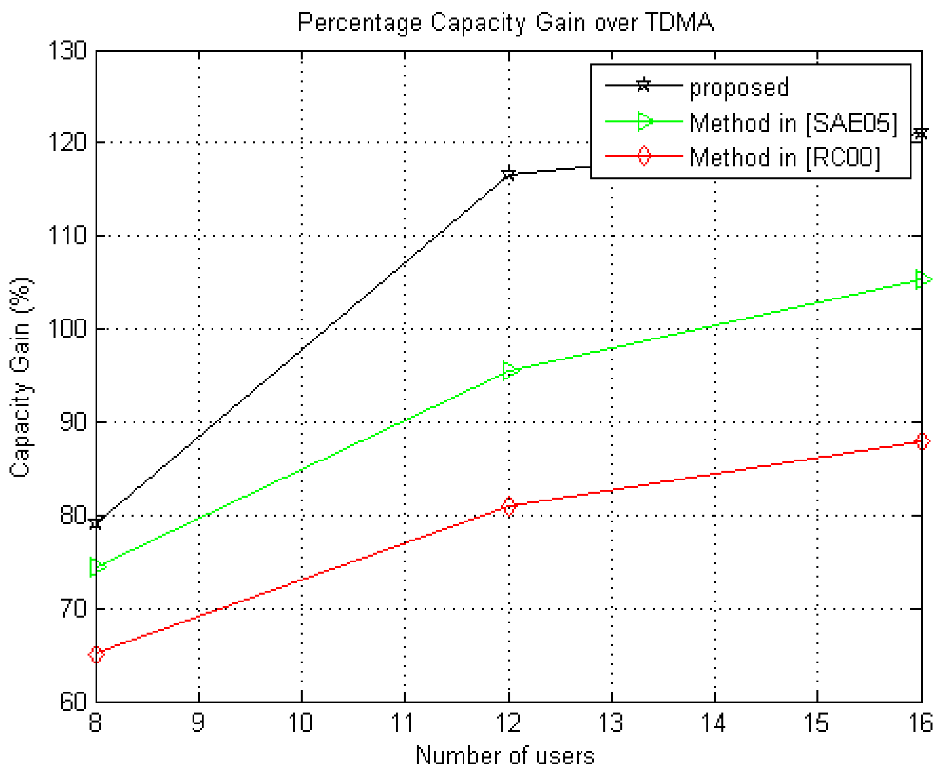


Figure 6.17: Percentage Capacity Gain over TDMA

Analysis of Results obtained for MIMO System

In this subsection we present analysis and comparison of various results obtained for MIMO Systems. We assumed two antennas each at transmitter and receiver side. The wireless channel is modeled as before, and the total transmit power available at the base station is 1 W. The power spectral density of additive white Gaussian noise is -80 dBW/Hz, and the total bandwidth is 1 MHz, which is divided into 64 subchannels.

Sum Capacity versus Number of users

Fig.6.18.(a) and (b) depicts the sum capacity obtained by NSGA-II for fixed SNR of 4.6 dB and 24.6 dB respectively. It can be observed from Fig.6.18 that the sum capacity obtained using NSGA-II is significantly higher as compared to methods in [RC00, GLX$^+$09]. For the low SNR case NSGA-II provided an approximate capacity gain of 70% and 90% over the algorithms used in [RC00] and [GLX$^+$09] respectively. Similarly for high SNR case approximate capacity gain of about 28% and 48% was obtained. These capacity gains obtained prove the suitability of our algorithm for wide range of SNRs.

Table 6.4: Simulation results for various permutations of Population (Pop), Generations (Gen), Probability of Crossover (P_c) and Probability of Mutation (P_m) for fixed number of subchannels (64) , Maximum number of Bits (D_{max}=16) and SNR (30 dB) and maximum power of 1W.

S. No.	**Users (K)**	**Sub carries (N)**	**Sum Rate (Bits/sec/Hz)**					
			Pop =30,Gen=50		**Pop =50,Gen=80**		**Pop =80,Gen=100**	
			P_C=0.9, P_m=0.03	**P_C=0.8, P_m=0.02**	**P_C=0.9, P_m=0.03**	**P_C=0.8, P_m=0.02**	**P_C=0.9, P_m=0.03**	**P_C=0.8, P_m=0.02**
Best Case								
1	16	64	21.32	21.27	22.14	22.26	24.37	24.73
2.	8	64	20.07	20.31	21.63	21.48	23.41	23.79
3.	4	64	19.68	19.84	21.12	20.92	23.17	22.92
4.	2	64	18.94	19.03	20.48	20.53	22.11	22.43
Average Case								
1	16	64	21.08	21.03	21.91	21.97	23.91	24.21
2.	8	64	19.85	19.94	21.21	20.92	23.04	23.16
3.	4	64	19.14	19.32	20.81	20.22	22.86	22.32
4.	2	64	18.42	18.73	19.97	20.23	21.86	21.98
Worst Case								
1	16	64	20.87	20.73	21.82	21.77	23.87	23.93
2.	8	64	19.72	19.81	21.05	20.75	22.93	22.97
3.	4	64	19.02	19.18	20.72	20.07	22.73	22.12
4.	2	64	18.27	18.62	19.83	20.15	21.77	21.81

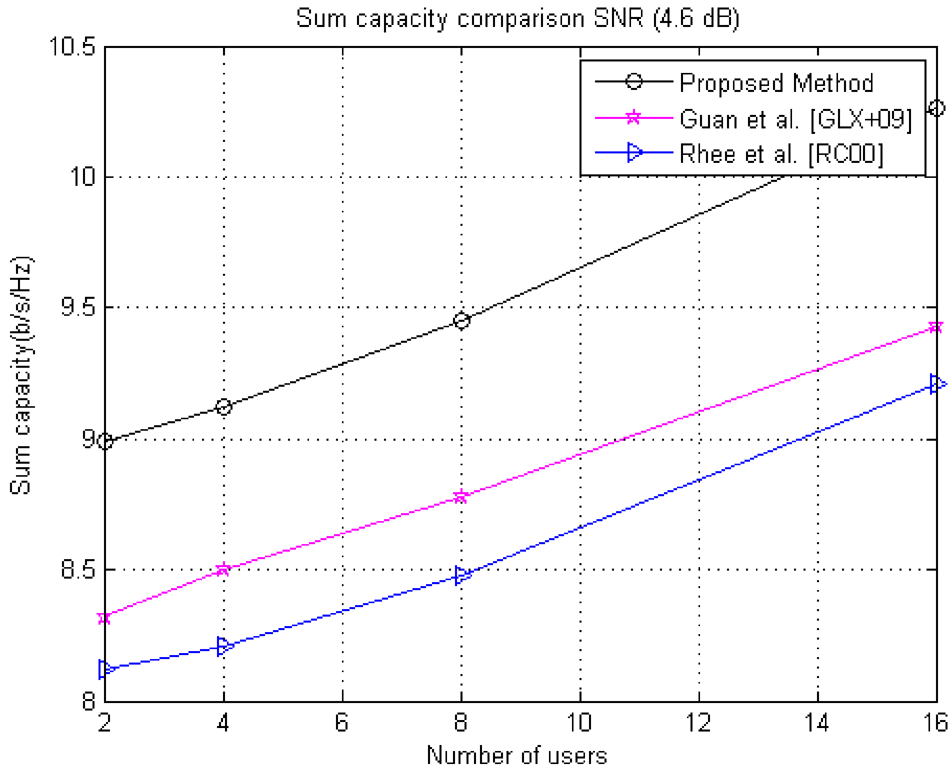


Figure 6.18 (a): Sum Capacity versus Number of Users for SNR=4.6dB (MIMO)

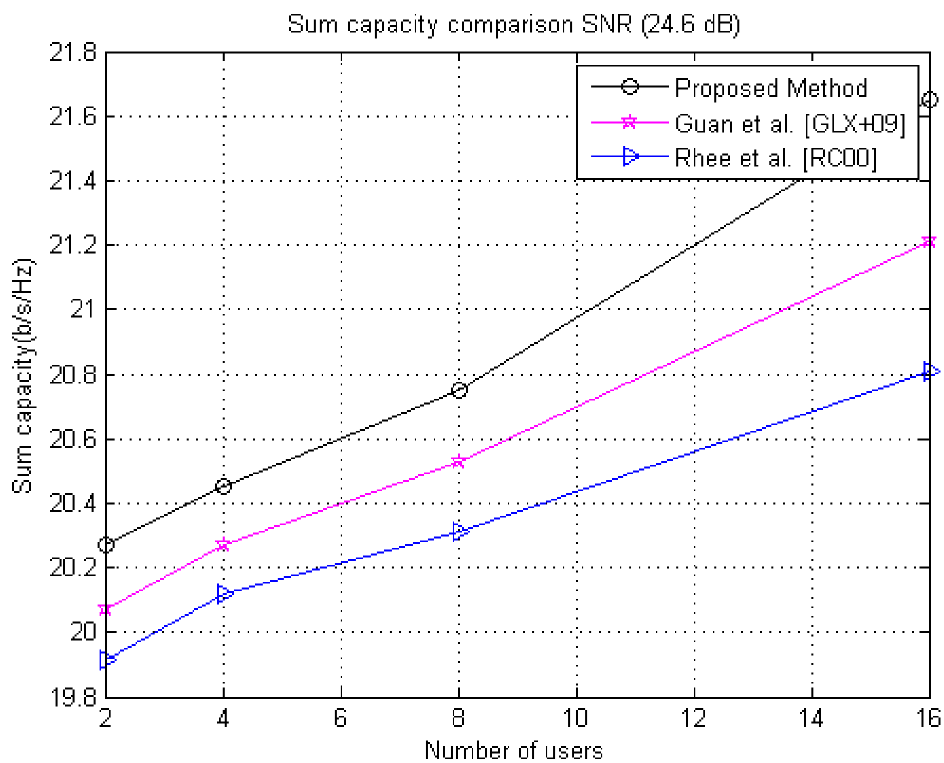


Figure 6.18 (b): Sum Capacity versus Number of Users for SNR=24.6dB (MIMO)

It is also evident from Fig.6.18. (a) and (b) that the sum capacity increases with number of users for fixed SNR which is effect of multiuser diversity gain. In wireless communications, diversity gain is the increase in SNR ratio due to some diversity scheme, or how much the transmission power can be reduced when a diversity scheme is introduced, without a performance loss. With the increase in number of antenna used at the transmitter and receiver this gain can be further increased at the cost of additional complexity

Sum Capacity versus SNR

The plots in Fig.6.19 of sum capacity versus SNR reaffirm the fact the proposed algorithm provides consistently higher capacities for wide range of SNRs. In the light of above discussion it can be concluded the proposed solution is valid for wide range of wireless environments.

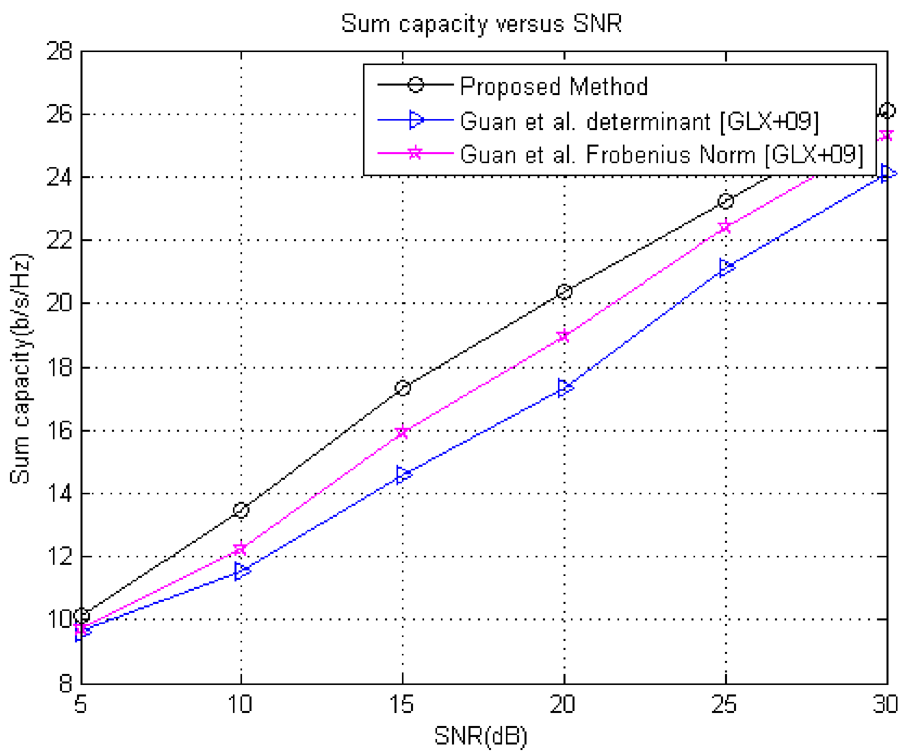


Figure 6.19: Sum Capacity versus SNR for MIMO system

Furthermore, the results obtained were consistent and with-in the bounds with the expected results for $K < N$. We also observed that if we could estimate the maximum typical Total Power ($< PT$) that would be utilized, based on the channel conditions and the data rate requirements, and if we set our constraint near to this value, the algorithm converges much faster than without this. It was also found that as the population size increased, there was a marked improvement in the performance of the GA, as is evident from Table 6.4 and the algorithm produced better results. This is in consistence with the expected performance of efficient GAs.

In the case of K=N, the randomly generated initial population causes the algorithm to be stuck at the local minimum and tends to make R_{MIN}=0. It can thus be inferred that the algorithm works best only for K<N.

Complexity Analysis

In [DPAM02], the complexity for various stages of the NSGA-II has been found out. The complexity of the fitness function is combined at each stage of the algorithm to calculate the overall complexity as listed in Table 6.5. Evaluating fitness function using equation.6.6.(a) and equation.6.6.(b) involves three loops to be executed for each individual. The loops involve summation over all the antennas (M), summation over all the users (K) and over all the subchannels (N). These calculation are repeated for each individual (P), hence involves a complexity of O($PKNM$).

Complexity of non dominated sorting part can be calculated realizing that the body of the first inner loop (for each $p \in F_i$) is executed exactly P times as each individual can be the member of at most one front and the second inner loop (for each $q \in s_p$) can be executed at maximum (P-1) times for each individual [each individual dominates (P-1) individuals at maximum and each domination check requires at most J comparisons] results in the overall computations O(JP^2).

The complexity of this crowding distance calculation part is governed by the sorting algorithm. Since J independent sorting of at most P solutions (when all population members are in one front *I)* are involved, the above algorithm has computational O($J \log_2 P$)complexity.

Finally the tournament selection algorithm requires to select two individuals randomly from the entire population, results in complexity of O(P).

Certain operations like generation of random numbers, comparisons, accessing elements of array vectors and mathematical operations have been assumed to take constant time.

These operations occur for every generation. Hence the total Complexity can be calculated as:

$$\begin{aligned} &G \times [O(PKNM) + O(JP^2) + O(J \log_2 P) + O(P)] \\ &\cong O((PG)(KNM + JP)) \end{aligned} \tag{6.7}$$

Where G = Number of Generations, P = Population Size, K = Number of Users, N = Number of Subchannels, J = Number of Objectives = 2, M=Number of Antennas

Table 6.5: Complexities of various operations in the algorithm (MIMO)

Operation	**Complexity**
Evaluating fitness function for each individual	O($PKNM$)
Non-Dominated Sorting	O(JP^2)
Crowding Distance Calculation	O($J \log_2 P$)
Tournament Selection	O(P)

For some constant N and M, the complexity of the algorithms is $O(GP^2)$ which is better than that suggested in [TZWZ08].

6.6. Conclusions

In this chapter, the use of NSGA-II has been proposed for simultaneous bit-loading and subchannel allocation in MIMO OFDMA. The solution generated by the algorithm is found to be suitable for different sets of users and subchannels taking multiple conflicting objectives into account. The simulation results indicate that the optimized Sum Rates obtained by proposed method are significantly higher than those obtained by [RC00, GLX+09]. Since the algorithm is used to maximize the minimum users capacity it guarantees fairness among the users. It is also shown that complexity of this algorithm is significantly lower than previous works in this area, which implies that the addition of another objective does not add complexity or computational overhead to the algorithm. Faster convergence of the algorithm to desired results confirms the conclusion of it being low complex. We have also proposed a method for faster convergence by reformulating the constraint of total power.

In [SD95] it was shown that using diversity to adapt Genetic Operator values gives better results. NSGA-II calculates crowding distance as a measure of diversity, and this calculation is a part of the algorithm and not an overhead operation. Therefore, the adaptability of operators based on diversity can be easily implemented using the crowding distance. This can be a possible extension of proposed algorithm in the future. Also modification of objective function to add some sort of proportional fairness among the users in place of max-min can be implemented to add to the sum capacity of the system.

Chapter 7
Conclusions

7.1. Introduction

The increasing demand for wireless multimedia services requires reliable and high-rate data communications over a wireless channel. As the data rate requirements increase channel-aware adaptive resource allocation is becoming more critical to system performance.

Enabled by multicarrier modulation and multi-antenna technologies, multiple parallel channels can be created in either the frequency or spatial domain. Compared to single channel systems, resource allocation in multiuser multichannel systems is more challenging because of the additional degree of freedom for resources. In this thesis, we study the performance of adaptive resource allocation in multiuser multichannel wireless communication systems. Adaptive resource allocation can usually be formulated as an optimization problem. The optimal solution is typically very difficult to obtain due to the large number of variables. Further, the wireless channel is time-varying, so adaptive resource allocation should be performed to match the channel variations.

GAs are a class of evolutionary algorithms. They provide novel approaches to problem solving technique inspired by biological evolution. GAs enable efficient search in the solution space of any function so as to get a solution set that optimizes the function. This efficiency with GAs is due to operators analogous to the one's found in natural evolution of species (to evolve better species): Selection, Crossover, and Mutation.

This thesis presents resource allocation algorithms for both multiuser OFDM systems and multiuser MIMO OFDM systems.

7.2. Summary of Contributions

The first contribution of this thesis is a low complexity subchannel allocation algorithms using PSO. In Chapter-4 we proposed the use of PSO, a stochastic optimization technique, for subchannel allocation in downlink of OFDMA systems followed by power allocation using WFA [Bla87]. The results obtained by the simulations indicate that the algorithm provides average capacity gain of about 20% over the method used in [SAE03]. It was also proved that, PSO aided subchannel allocation can provide significant capacity gain even with very small population size and number of iterations. Moreover in PSO aided subchannel allocation the search and subchannel allocation is performed simultaneously as compared to traditional methods where the subchannels are first sorted in accordance of their gains and then allocation is performed. This significantly reduces the complexity of PSO aided allocation. Calculating the number of subchannels to be allocated to each user before actual allocation on the basis of SNR introduces extra overhead. Moreover, sorting of subchannels on the basis of gains is another overhead. In the proposed PSO aided subchannel allocation, these overheads are removed by relaxing the proportionality constraint such that each user should get at-least one subchannel while searching and allocation of subchannels is performed simultaneously. The complexity of our algorithm was assessed to be $O(N)$ as compared to $O(KN\log_2 N)$ for that of method in [SAE03]. Hence it may be concluded that the proposed algorithm is order of magnitude faster as compared to the method in [SAE03]. This fact makes PSO aided subchannel allocation a suitable choice for practical wireless systems like WiMAX (802.16e) where the convergence rate plays a very important role as the wireless channel changes rapidly. The fact that the channel is assumed to be constant during allocation makes convergence rate a very important parameter for wireless systems.

The second contribution of this thesis is a novel GA for resource allocation in multiuser OFDM systems, in which the tradeoff between total throughput and user fairness can be easily evaluated. In downlink multiuser OFDM systems, data streams from multiple users are multiplexed into each OFDM symbol. Hence, the basestation can serve multiple users simultaneously. While the channel conditions of different users are largely independent due to users' different locations, multiuser OFDM can exploit the multiuser diversity to improve the system performance. Previous works either maximize the total system throughput without consideration of user data fairness or provide maximum fairness among users with the sacrifice of system throughput. In this thesis, we propose to maximize the total throughput while maintaining user data rates proportional. With the proportional rate constraints, the data rate fairness among users can be flexibly controlled by a set of parameters. Further, the total system throughput is also adjustable by varying the proportional fairness parameters.

The formulated optimization problem for adaptive resource allocation in multiuser OFDM systems includes both continuous and binary variables and, hence, is difficult to solve. To lower the computational complexity, we propose a suboptimal algorithm that separates the subchannel and power allocation among users.

The GA is used allocate subchannels among the users to maximize the total throughput while maintaining rate proportionality among the users. Steps 11 and 12 in proposed algorithm, add deterministic component to otherwise probabilistic GA, and enhance the overall performance of the algorithm.

By separating the subchannel and power allocation, the number of variables each step has to optimized is almost reduced by half. First, the subchannels are allocated among users assuming equal power is distributed in each subchannel. Second, transmit power is optimally allocated among users and within each individual user according to the subchannel allocation scheme. In general, the optimal power allocation is the solution to a set of nonlinear equations, which can be found iteratively with the Newton-Raphson method.

Further, with the proposed resource allocation algorithm, the sum capacity is distributed more fairly and flexibly among users than the sum capacity maximization algorithm. Since the proposed adaptive resource allocation applies to each channel realization, proportional data rates can be assured among users for any time scale of interest. Further, the proposed optimization framework allows different users request variable priorities of their services with different prices, which is suitable for systems with heterogeneous user services.

Finally we extended the above problem to MIMO OFDMA system. The problem of resource allocation in MIMO OFDMA systems is more challenging as compared to SISO. Since each subchannel now has a narrowband channel with M_T and M_R antennas at the transmitter and the receiver respectively, which can be modeled as an M_T x M_R channel matrix, $\mathbf{H}_{k,n}$.

If we can extract some suitable parameters from $\mathbf{H}_{k,n}$, then we can use same algorithm to solve the problem for both OFDMA and MIMO OFDMA. We investigated two scenarios: High SNR case and Low SNR Case.

The determinant of $\mathbf{H}_{k,n}\mathbf{H}_{k,n}^{H}$ and Frobenius-norm of $\mathbf{H}_{k,n}$ can represent the channel condition of user k in subchannel n, in high SNR and low SNR respectively. The simulation results for low SNR case show that the proposed method strictly sticks to the proportional rate constraints. It was also shown that relaxing proportionality constraints achieves higher data rates and reduces the computational complexity of the algorithm.

The proposed algorithm achieves higher data rates, and is computationally less expensive as compared to previous algorithms in this area.

The third contribution is a combined solution to both subchannel allocation and bit loading in the downlink of OFDMA and MIMO OFDMA system, using a MOGA i.e. NSGA-II.

In order to achieve the capacity bound, one must solve a multiuser subchannel allocation and the optimal bit allocation jointly. To alleviate the computational complexity of joint subchannel and bit allocation, several suboptimal solutions have been proposed. These suboptimal solutions handle subchannel and bits individually. Our solution to the problem in Chapter-4 is one of the suboptimal solutions. In Chapter-4 only subchannel allocation was considered as an objective for GA and bit loading was done using Water-filling Algorithm.

Rate maximization and minimizing transmit power are two seemingly conflicting objectives. To solve such an RA optimization, we may combine them into a single objective. But the solutions will not be optimal considering all possible trade-offs. If they are considered as two separate objectives, then the solutions will cater to most of the trade-offs. We use NSGA-II to optimize RA considering two such objectives: Rate maximization and Minimizing Total Transmit power. We relaxed the power constraint such that the total power was limited to a small range with a specified typical value. We use NSGA-II as it combines the problem solving capability of GA without being constrained to use a single objective

In Chapter-5 we propose the use of NSGA–II, for joint allocation of bits and subchannels, in the downlink of OFDMA and MIMO OFDMA system. Using SVD, the MIMO fading channel of each subchannel is transformed into an equivalent bank of parallel SISO subchannels**.** Each user's signal is pre-multiplied by a precoding matrix before transmission. The precoding matrix of each user lies in the null space of all other users' channels, hence inter-user interference is completely eliminated if the channel state information of all users is available at the basestation. The effective channel for every user, therefore, is a point-to-point MIMO channel, rendering a simpler receiver structure.

The resource allocation in multiuser MIMO systems aims to distribute the transmit power optimally such that a certain objective function, e.g. the sum capacity studied in this thesis, is optimized. Although it has been shown, that DPC is optimal for the sum capacity of downlink multiuser MIMO systems, cost-effective coding schemes that approach the DPC sum capacity, however, are still unavailable.

In this thesis, we formulate an optimization problem for resource allocation with both transmitter precoding and receiver post-processing to maximize the total system throughput. While the optimal post-processing matrices at the receivers are difficult to obtain, we restrict ourselves to a set of selection matrices. The selection matrices allow each user to select a subset of receive antennas to use. Although for a particular user, his/her throughput may be reduced by using fewer receive antennas, the system throughput can increase because additional spatial dimension is saved for other users. Further, since the precoding and post processing matrices are designed at the basestation, the post-processing matrices should be conveyed to their own users, which increase system overhead. Due to the simple structure of the selection matrices, less system overhead is required for the selection matrices than the optimal post-processing matrices.

The simulation results indicate remarkable improvement in terms of convergence over previous approaches involving EAs. At the same time capacity achieved by the proposed algorithm is found to be comparable with that of previous algorithms.

7.3. Comparison of proposed Algorithms

In this section we present the comparisons of resource allocation algorithms presented in this thesis. The comparison is presented in tabular form as follows:

Table7.1: Comparison of Proposed Algorithms

Algorithm/Criteria	**PSO**	**Novel GA**	**NSGA-II**
Number of Objectives	Single	Single	Two
Objective Function	Rate Maximization	Rate Maximization	Minimum User Rate Maximization and power Minimization
Sum Capacity	Best & flexible	Good & flexible	Low & inflexible
Fairness	Poor	Good & flexible	Best
Complexity	Lowest	Low	High
Subchannel Sharing	No	No	No
Constraint on number of users	Nil	Nil	Can be in power of 2 only

Chapter 8
Future Research

In this section, we propose several future research topics for multicarrier and/or multi-antenna wireless systems, potentially for other researchers interested in this area.

- ***Semi-Adaptive Resource Allocation for Multiuser OFDM Systems***

For multiuser OFDM systems discussed in this thesis, it was assumed that adaptive resource allocation is performed as soon as the user channels are changed. The system overhead for conveying the channel state information from the users to the basestation and the resource allocation schemes from the basestation to the users has not been incorporated into the problem formulation. While this system overhead is negligible for slow varying channels, it may be large for systems with fast channel variations. One possible solution to reduce the system overhead is a semi-adaptive resource allocation, where the subchannel allocation among users is performed once and remains fixed throughout the whole transmission period, hence the subchannel allocation scheme only needs to be conveyed to users once. The subchannel allocation can be performed based on, e.g., the average channel condition of all users and/or the data rates, bit error rates, and service priorities required by different users. The subchannel allocation shall be carried out when one user's service is fulfilled or new service requests are admitted. Power allocation among the subchannels assigned to each user can still be adapted to the channel variations. Further, since the subchannel allocation is fixed, the resource allocation algorithm is much easier to realize in practical systems.

- ***Implementing Adaptive Resource Allocation with Proportional Data Rate Constraints in Multiuser OFDM systems***

Several aspects on the proposed proportional data rate resource allocation algorithm need to be investigated before practical implementation. For example, the set of system parameters $\{\Phi\}_{k=1}^{K}$ should be determined based on users' target applications. A simple example is to let users choose their Φ_k from a set pre-determined discrete value to represent their service priorities.

The basestation, after receiving users' requests, can grant a subset of users for transmission based on the available resources. Other methods to determine the proportional data rate constraints need further study. Another implementation issue is on the solution to a system of non-linear equations, which is required for the optimal power distribution among users. In practical systems, the channel-to-noise ratio of different users can vary significantly, largely due to the different user locations and path loss, which could make the system of non-linear equations ill-conditioned. Hence efficient and accurate implementation of the proposed algorithm is very important to obtain the optimal power allocation. Grouping users with similar channel-to-noise ratios and performing the proposed algorithm to each user group is a possible solution to make the system of non-linear equations less ill-conditioned, as the channel-to-noise ratio in each user group is about the same value. Another method to lower the computational complexity is to allocate the subchannels such that the system of non-linear equations is reduced to the linear case.

- ***Maximizing Ergodic Sum Capacity with Ergodic Proportional Rate Constraints in Multiuser OFDM Systems***

The adaptive resource allocation in multiuser OFDM systems proposed in this thesis was a static algorithm, i.e. for each channel realization, the algorithm should be carried out and the proportional rate constraints are strictly applied for each channel realization. Although the proposed algorithm guarantees proportional rates in any time scale, the ergodic sum capacity is not necessarily optimized. A future research is to optimize the ergodic sum capacity while maintaining users' ergodic rates proportional. Thus, multiuser diversity can be even further exploited to improve the ergodic sum capacity.

- ***Impact of Imperfect Channel State Information for Adaptive Resource Allocation***

Users' channel state information (CSI) is required at the basestation for adaptive resource allocation in both multiuser OFDM and multiuser MIMO systems. In this thesis, it was assumed that channel station information is perfectly known at the basestation through a separate feedback channel. The CSI is usually estimated at the receivers and, hence, prone to estimation errors. Moreover, feedback delays may cause outdated CSI used by the adaptive resource allocation algorithm. The impact of imperfect CSI to the system performance with adaptive resource allocation needs further study. Channel prediction and limited feedback techniques can be combined with adaptive resource allocation to combat the effects of feedback delay and reduce the amount of feedback information.

- ***Fixed-Point Implementation of Adaptive Resource Allocation Algorithms***

Since adaptive resource allocation should be performed frequently to match the wireless channel variations, low complexity algorithms are desirable for practical implementations. However, even the low complexity algorithms require a certain amount of computational efforts. For example, the optimal power allocation for multiuser OFDM systems proposed in the thesis requires solving a set of nonlinear equations iteratively and Singular Value Decomposition is necessary for multiuser MIMO systems to find the spatial eigenmodes of different users. Currently these algorithms are implemented with floating-point arithmetic. Future research shall map the proposed low complexity algorithms into fixed-point implementations and lower the memory footprint.

- ***Adaptive resource allocation for delay-sensitive applications in wireless packet networks***

This algorithm proposed in Chapter 6 is suitable for data services that are delay-insensitive but not tolerable of errors. In future communications systems, real-time services such as teleconferencing, video, wireless multimedia, etc. will become more and more popular. These applications impose a maximum allowable delay on each packet. When designing the resource allocation algorithms for such delay-sensitive applications, we should not only consider each user’s channel conditions and the reservation of the service share as the algorithm in Chapter 6 does, but also consider the waiting time and the maximum tolerable delay of the packets. This will add more constraints and considerations on the resource allocation algorithms. It is thus of interest to investigate the feasibility and realization of the resource management on delay-sensitive services.

- ***Joint MAC-PHY design for rate adaptive PHY layer transmission***

In the algorithm proposed in Chapter 6, system service rate is fixed if there are enough packets to be transmitted. Resource allocation for wireless networks would be much more complicated if rate adaptation, such as adaptive coded modulation, is involved. In this case, the service rate for multiple users on different subchannels will vary significantly from one to another, which introduces difficulties in resource management and performance analysis. Nonetheless, it is widely accepted that rate adaptation is able to greatly improve the system spectral/power efficiency. Therefore, it is worthwhile to study a practical resource allocation algorithm for wireless networks when rate adaptation is included.

- ***Practical intelligent resource management implementation for wireless packet networks***

In the proposed algorithms, the optimization procedure in every frame is independent of each other. In real systems, the channel conditions and queueing states are correlated in consecutive frames. In order to reduce the computational complexity, it is of interest to develop a reduced-complexity algorithm in which the resource allocation scheme in one frame is obtained by updating the allocations in the previous frames. By doing so, the high computational complexity is relieved since we do not have to implement a complete optimization procedure for each frame.

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LIST OF PUBLICATIONS

Peer Reviewed Conference:

1. **Nitin Sharma**, Rao. A, Dewan. A, Safdari, M **“**Rate adaptive resource allocation for multiuser OFDM using NSGA – II” *Proc. IEEE Conference on Wireless Communication and Sensor Networks (WCSN-2008), IIITA & DAVV, Indore,Dec. 2008.*

Peer Reviewed Journals:

1. **Nitin Sharma**, Dr K R Anupama, “A novel Genetic Algorithm for Adaptive Resource Allocation in Multiuser OFDM Systems with Proportional Rate Constraint” International Journal of Recent Trends in Engineering, Academy Publishers, Vol 2, No. 5, November 2009, PP-135-139.
2. **Nitin Sharma,** Sidharth Wagh, Dr K R Anupama, “Multi-Objective Resource Allocation In Multiuser OFDM Using PAES”. International Journal of Recent Trends in Engineering and Technology, ACEEE, USA,Vol 3, No. 3, 2010, PP-121-125
3. **Nitin Sharma**, Dr K R Anupama, “On the use of NSGA-II for multi-objective resource allocation in MIMO-OFDMA systems” Wireless Netw (2011) 17: PP-1191–1201**. (Impact factor 1.088).**
4. **Nitin Sharma**, Dr K R Anupama**, “**A novel Genetic Algorithm for Adaptive Resource Allocation in MIMO-OFDM Systems with Proportional Rate Constraint**”.** Wireless Personal Communications Volume 61, Number 1, PP-113-128, 2011, DOI: 10.1007/s11277-010-0013-9. (**Impact factor 0.503**).
5. **Nitin Sharma**, Anand K tarcar, Varghese Antony Thomas, Dr K R Anupama**,** "On the use of Particle Swarm Optimization for Adaptive Resource Allocation in OFDMA Systems with Proportional Rate Constraints". Information Sciences Volume 182, Issue 1, 1 January 2012, PP- 115-124. (**Impact factor 3.291**)

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