Radio Resource Management based on Genetic Algorithms for OFDMA Networks

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—献给我最亲爱的爸爸妈妈

Dedicated to my family

Abstract

OFDMA will be the multiple access scheme for next generation networks, including LTE and LTE-A. These networks will provide higher data rates than now, up to several hundred Mbps.

These new networks, using a higher carrier frequency and offering flexible bandwidth for different application types, require advanced techniques for radio resource management.

One approach that has been suggested to improve the radio resource management is to use smart and semi-smart antennas, so that the coverage of a certain cell can be divided into several adjustable sectors by using different antenna patterns. However, for a multi-cell environment, there is a need to prevent there being a gap between adjacent cells as the antenna patterns change. In this work, Genetic Algorithms are used to optimize the antenna patterns to get better coverage together with better cell throughput, at the same time making sure there are no gaps.

This thesis not only considers the overall problem, but also investigates the suitability of the Genetic Algorithm itself, with it being optimized to improve the performance of the radio resource management in LTE networks. The influence of selection rate and mutation rate on GA is investigated and tested by simulation.

These Genetic Algorithms are used in a model of multi-cell LTE networks to optimise subchannel allocation combined with dynamic sectorisation. Different types of scenarios are considered and the Genetic Algorithm is used to solve the problem of combining subchannel allocation with dynamic sectorisation to give the best overall performance of the LTE network.

Acknowledgement

I would like to give my gratitude to all the people who have helped me during my PhD life.

First I would give my big thank to my supervisor, Laurie Cuthbert. Without him, there would never be this thesis. During my 3-year PhD life, he has always been supportive, helpful and passionate. He really gave lots of guidance and support for both my study and life. His enthusiasm, selflessness, absorption will always be a good example for me. His wisdom, humour and kindness would be the valuable wealth which I will treasure all my life.

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Finally, my love and thanks to my parents, the two most important people in my life, who have always been supporting and encouraging me.

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List of Abbreviations

3GPP	3rd Generation Partnership Project
64-QAM	64-level Quadrature Amplitude Modulation
AGA	self-Adaptation Genetic Algorithm
BS	Base Station
COST	Cooperative for Scientific and Technical
CS	Circuit Switch
DFT	Discrete Fourier Transform
DSGA	Genetic Algorithm with Dual Species
DSSS	Direct-Sequence Spread Spectrum
DVB	Digital Video Broadcasting
EDGE	Enhanced Data Rate for GSM Evolution
eNB	evolved NodeB
EPC	Evolved Packet Core
ETSI	European Telecommunications Standards Institute
E-UTRAN	Evolved Universal Terrestrial Radio Access Network
EV-DO	Evolution-Data Only
FDM	Frequency-Division Multiplexing
FDMA	Frequency Division Multiple Access
FRF	Frequency Reuse Factor
GA	Genetic Algorithm
GGSN	GPRS Gateway Support Node
GPRS	General Packet Radio Service
GSM	Global System for Mobile Communications
GW	Gateway
HSCSD	High Speed Circuit Switch Data
HSDPA	High Speed Downlink Packet Access
HSPA	High Speed Packet Access
HSUPA	High Speed Uplink Packet Access
ISI	Inter symbol interference
IDFT	Inverse Discrete Fourier Transform

ICI	Inter-Cell Interference
ITU	International Telecommunication Union
J-TACS	Japanese Total Access Communication System
LTE	Long Term Evolution
MAC	Media Access Control
Max C/I	Maximum carrier/interference ratio
MGA	Modified Genetic Algorithm
MIMO	multiple-input and multiple-output
MME	Mobility Management Entity
MSM	Mating selection mechanism
NAS	Non-access stratum
NMT	Nordic Mobile Telephone
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency Division Multiplexing Access
OGM	Offspring generation mechanism
OSM	Offspring selection mechanism
PAPR	Peak-to-Average Power Ratio
PDCP	Packet Data Convergence Protocol
PDSN	Packet Data Serving Node
PF	Proportional Fairness
PS	Packet Switch
QoS	Quality of Service
RLC	Radio Link Control
RRC	Radio Resource Control
RRM	Radio Resource Management
SAE	System Architecture Evolution
SC-FDMA	Single Carrier Frequency Division Multiple Access
SGSN	Serving GPRS Supporting Node
SINR	Signal to Interference plus Noise Ratio
TACS	Total Access Communication System
TDMA	Time Division Multiple Access
TSP	Travelling Salesman Problem

UMB	Ultra Mobile Broadband
WiMAX	World Interoperability for Microwave Access

List of Symbols

NP	Number of policies in one generation of GA
f_0	Subcarrier spacing of OFDM symbols
$s_0, s_1, \ldots, s_{M-1},$	M modulated source symbols of OFDM system
$S_0, S_1, \ldots, S_{M-1},$	M samples of DFT of s_m
$X_0, X_1, \ldots, X_{M-1},$	M frequency domain smple after subcarrier mapping
$x_0, x_1, \ldots, x_{M-1},$	transmitted time domain channel symbols after IDFT of X_m
β	distribution parameter
N_c	number of cell centre users
Ne	number of cell edge users
$P_1 = (p_1^1, p_1^2, \ldots, p_1^n)$	one parent of GA
$O_1 = (o_1^1, o_1^2, \ldots, o_1^n)$	one offspring of GA
γ	Arithmetic crossover adjustment parameter
n	tournament scale of tournament selection
L_p	pathloss
L_{rts}	multi-screen loss
d	distance between the mobile user and eNB
h_{Roof}	average height of building
h_{Mobile}	height of the mobile devices
w	Street width
b	distance of adjacent buildings
$L_{\varnothing}$	loss due to incident angle of the street
L_{BS2B}	loss due to the difference between BS height and the height of buildings
$\varnothing$	incident angle relative to the street
KR	Racian factor
$\underset{g_1}{\rightarrow}, \underset{g_2}{\rightarrow}, \cdots \underset{g_n}{\rightarrow}$	Gain in n directions of an antenna
$Served_{ir}(n,i)$	Number of users served by patten n of sector r, eNodeB i
$fi\ (n,i)$	fitness condition of the n^{th} individual of GA
$G_{i,j,k}$	channel gain from eNodeB i to user k on channel j

$P_{i,j,k}$	transmission power from the i^{th} eNodeB on channel j for user k
$N_{i,j,k}$	AWGN of user k located in i^{th} base station on the j^{th} channel
$SINR_{i,j,k}$	SINR of user k served by eNodeB i on channel j
$C_{i,j,k}$	Capacity of user k served by eNodeB i on channel j
I	total number of BSs or eNBs
J	total number of subchannels
K	total number of users per cell
R	total number of sectors per cell
$f_1(x), f_2(x),\ldots, f_m(x)$	m objective functions of GA
$R_k(t)$	the instantaneous achievable rate at TTI t
$T_k(t)$	tiltered average throughput
α	Balance parameter of multi-objective fitness function of GA
$theta_1, theta_2,\ldots, theta_R$	angle vector of R antennas used in one cell
$Ave_i(n,i)$	average throughput of Cell i, policy n
$Fair_i(n,i)$	user unfairness of the n^{th} policy of cell i

Chapter 1 Introduction

1.1 Motivation

With the successful deployment and application of 3G communication networks, higher data rates are being demanded by end users. Orthogonal frequency division multiplexing (OFDM) is a promising technique to provide high data rate transmission for future networks. It can split high bit-rate data stream across a set of overlapping orthogonal subcarriers thus improve the spectrum efficiency. The bandwidth of each subcarrier is narrower than the propagation channel, so OFDM can eliminate frequency-selective fading.

OFDM access (OFDMA), based on OFDM, is now emerging as an important multiple-access scheme for wireless broadband networks such as World Interoperability for Microwave Access (WiMAX), IEEE 802.20 mobile Wireless MAN, 3rd Generation Partnership Project (3GPP) Long Term Evolution (LTE) and 3GPP2 Ultra Mobile Broadband (UMB).

Among the advanced standards based on OFDM, LTE has been the focus of both the technological and academic field recently. Research has varied from physical layer technology such as dynamic modulation method to radio resource allocation methods such as subcarrier and subchannel allocation and frequency reuse schemes.

One approach to improve the radio resource efficiency of future wireless communication systems based on OFDMA is the topic of this thesis.

1.2 Research Scope

The research of the thesis basically focuses on the improvement of coverage and capacity combined with radio resource allocation schemes including dynamic sectorisation, subchannel allocation and power control. Also, the thesis considers the suitability of the algorithm itself.

Specific aspects included are:

i. The inclusion of advanced physical layer techniques, here the use of smart antennas to take full advantage of antenna directivity and reduce inter-cell interference (ICI) and improve system throughput [30].
ii. New joint radio resource management (RRM) schemes, combining semi-smart antenna, sectorisation schemes and frequency reuse schemes.

During the deployment of these novel techniques in a multi-cell environment, problems may arise such as: "holes" in the coverage because of gaps between different antenna patterns; limitation of radio resource such as subcarriers and subchannels; and heavy and unbalanced user distributions. All of these make RRM a challenging topic for OFDMA based wireless networks. Optimisation of coverage, subchannel allocation, systematic throughput, power consumption and user fairness need to be considered during the RRM design.

In this work, a multi-cell environment deployed with semi-smart antennas is considered. With the use of semi-smart antennas, coverage of a certain cell can be divided into several adjustable sectors by different antenna patterns so distributing resources to where they are needed. However, for a multi-cell environment, there could be gaps between adjacent cells with different antenna patterns. An efficient scheme for the change of antenna patterns of multi-cell environment is needed.

For the frequency reuse issue, different kinds of schemes have been introduced to mitigate ICI and to increase the system throughput; however, introducing frequency reuse schemes can limit the radio resource per unit area, leading to drawbacks in a heavily-loaded scenario. In contrast the dynamic sectorisation combined with subchannel allocation scheme considered in this work can provide efficient load balancing; user fairness can also be considered during the design.

Algorithm optimisation is also investigated and optimized in the work to solve the combined problem more efficiently.

1.3 Research Contributions

The work reported in this thesis is novel and the main contributions of this thesis consist of the following:

1. Coverage improvement based on Genetic Algorithms (GA)

The thesis proposes a dynamic sectorisation method based on using a GA to solve the coverage problem. The multiple patterns of semi-smart antennas serving the coverage area are randomly generated. These random antenna patterns are then optimized by a GA to solve the coverage problem. After the classical procedures such as selection, crossover, mutation by GA, an optimal combination of antenna patterns is obtained for a certain user distribution condition.

2. Capacity improvement based on Genetic Algorithms (GA)

By using a GA to change the sectorisation of the cells, the transmission power of the base stations (BS) is also adjusted so that the inter-cell interference is minimized and system throughput is enhanced. System throughput is optimized by the GA.

3. Combined optimisation of coverage and capacity

By successfully using a GA in OFDMA based cellular networks, coverage and capacity can be improved efficiently. A multi-objective fitness function of the GA is designed to give a trade-off between the coverage and capacity for a multi-cell scenario. Improvement of both the capacity and coverage is achieved by the combined design. Results of points 1-3 are evaluated and discussed in detail in Chapter 5.

4. GA optimisation

There are several random processes in GA itself such as crossover, selection, mutation, together with several different adjustable variables such as selection rate, mutation rate; this means that the GA is full of uncertainness. To better use GAs in the design of OFDMA based cellular networks, the suitability of a GA is researched and optimized. Different methods and variables in GA procedures are set up and compared and the most suitable and stable GA parameter setup is achieved. Detailed GA optimisation results can be found in Chapter 6.

5. Joint radio resource management algorithm

This proposed algorithm improves the system performance in the following aspects: (i) load balance (ii) system throughput and (iii) user fairness. The previously designed and optimized GA is used in a multi-cell environment to optimize the radio resource allocation. Different kinds of scenarios are simulated to test the performance of the algorithm. This part of work can be seen as benchmark of RRM for OFDMA based cellular networks. Joint radio resource management algorithms can be found in Chapter 7 and Chapter 8.

1.4 Author's Publications[1]

[1] Dapeng Zhang, Laurie Cuthbert. "Architecture of QoS guaranteed joint design of node-disjoint multipath routing and subcarrier allocation in OFDMA mesh networks," IEEE MESH 2009, Athens/Glyfada, Greece,Jun., 2009.

[2] Dapeng Zhang, Laurie Cuthbert, " Dynamic Subcarrier and Power Allocation in LTE Networks," Wicom 2009, Beijing, China, Sep., 2009.

[3] Xu Yang, Yapeng Wang, Dapeng Zhang, Laurie Cuthbert, "Resource Allocation in LTE OFDMA Systems Using Genetic Algorithm and Semi-Smart Antennas," WCNC

1 These only include relevant publications

2010, Sydney, Australia, Apr., 2010.

[4] Dapeng Zhang, Laurie Cuthbert, "Dynamic Sectorisation Based on Genetic Algorithms for OFDMA Networks," ICCTA 2011, Beijing, China, Oct., 2011.

1.5 Thesis organization

The remainder of the thesis is organised as below.

Chapter 2 describes the background information of OFDMA based wireless networks and RRM methods. This chapter starts with the development of wireless communication networks, followed by recent standards and architecture of OFDMA-based networks. After that, development and the state-of-art technologies of LTE is studied as an example of OFDMA based networks. RRM schemes such as frequency reuse schemes and smart antennas are investigated in the last part of this chapter.

Chapter 3 considers fundamental concepts of genetic algorithms. Following a consideration of the theory of and mechanisms in GAs, the chapter considers how GAs can be implemented in a simulation.

Chapter 4 investigates the simulation of LTE OFDMA systems. The whole multi-cell system is divided into several sub modules and the sub modules are studied and designed.

Chapter 5 focuses on dynamic sectorisation based on GA. Four main functions of GA are investigated for application in the simulator: encoding, selection, crossover and mutation. Parameters are set up, coverage and throughput issues are optimized by the GA and the design of the fitness function is investigated to give optimal overall system performance.

Chapter 6 researches the optimisation of GA. As there are several random procedures and functions in GA, the performance of optimisation results may vary a lot. This chapter investigates the robustness and stability of GAs and the influence of parameter adjustment on the performance of GA in giving the optimal solution for the RRM in LTE networks.

Chapter 7 evaluates and tests the scheduling combine resource management algorithm. The optimized GA investigated in Chapter 6 is used to give optimal solution of RRM in OFDMA based networks, considering system throughput, coverage, warp around and scheduling.

Chapter 8 introduces a new system architecture, where smart antennas only change their angle of the coverage within the cell, avoiding getting gaps between antenna patterns. System throughput, load balance, user fairness and subchannel allocation are considered and testified through simulation.

Chapter 9 concludes the work of this thesis, discussing some open issues and future trends of RRM in OFDMA based networks.

Chapter 2 Background

2.1 Current evolution in wireless communication systems

In the evolving history of wireless communications, performance and efficiency in highly mobile environment has always been the main target for system design.

With the progress from both industrial and academic research, the 3G mobile systems are now widely deployed all over the world giving a 2Mbps peak data rate. All these three 3G standards are based on direct-sequence spread spectrum (DSSS) [31]; however, a common scheme for future wireless networks will be OFDM and OFDMA [32] in order to provide an even higher data rate, meeting the ever-growing demand of end users. LTE will be the natural successor to 3G [33][103][104].

Future wireless communication systems are expected to provide higher data rates supporting multiple types of services. In LTE, traditional circuit-switched (CS) and packet-switched (PS) networks will merge into an all-IP network that can support different kinds of Quality of Service (QoS) [1][105]. The aim of 3GPP LTE is to develop a framework of high data rate, low-latency, and optimized radio access technology to support varied bandwidths from 1.25MHz to 20MHz to meet the flexible mobile services supporting different kinds of mobile devices. LTE is proposed to provide a maximum data rate of 300Mbits/s with a bandwidth of 20MHz. Also, it can support user mobility of 350km/h with a latency of 10 milliseconds and coverage of 30km. Furthermore, an LTE system can accommodate 200 users per cell.

The expected trend for future communication systems is shown in Figure 2.1. The top arrow shows the timeline of 3GPP [3], the main standard development group for mobile communication systems. This includes LTE that aims at improving the spectrum efficiency, network capacity, user throughput and latency. LTE will be based on OFDM and OFDMA, the dominating technology for the next generation wireless communication systems.

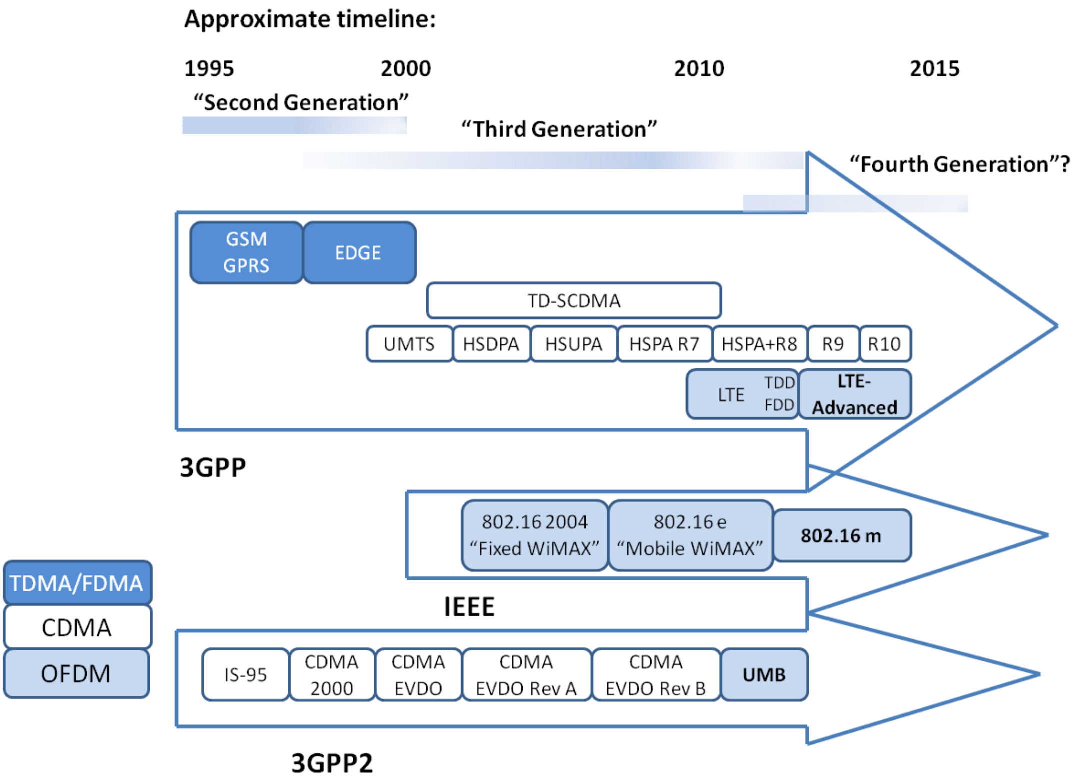

Figure 2.1 Continuous timeline of future communication systems[2]

The 3GPP evolution is based on backward compatibility. In the original Release 99 edition [4], all the features need to support the original implementation were defined by the International Telecommunication Union (ITU). High Speed Downlink Packet Access (HSDPA) and High Speed Uplink Packet Access (HSUPA) were introduced in Release 5 and Release 6 respectively by 3GPP. After that, High Speed Packet Access (HSPA) is a further enhancement that was announced in Release 7. The concept of HSPA+ was introduced in Release 8, which is also backward compatible. In Release 9, emphasis is put on MIMO enhancements, SON and femtocells, and Release 10 focuses on LTE-A. The continuous release process is shown in Figure 2.2 [4]. The commercial deployment of 3GPP is shown in Figure 2.3 [4].

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2 Figure 1.1 from reference [3]

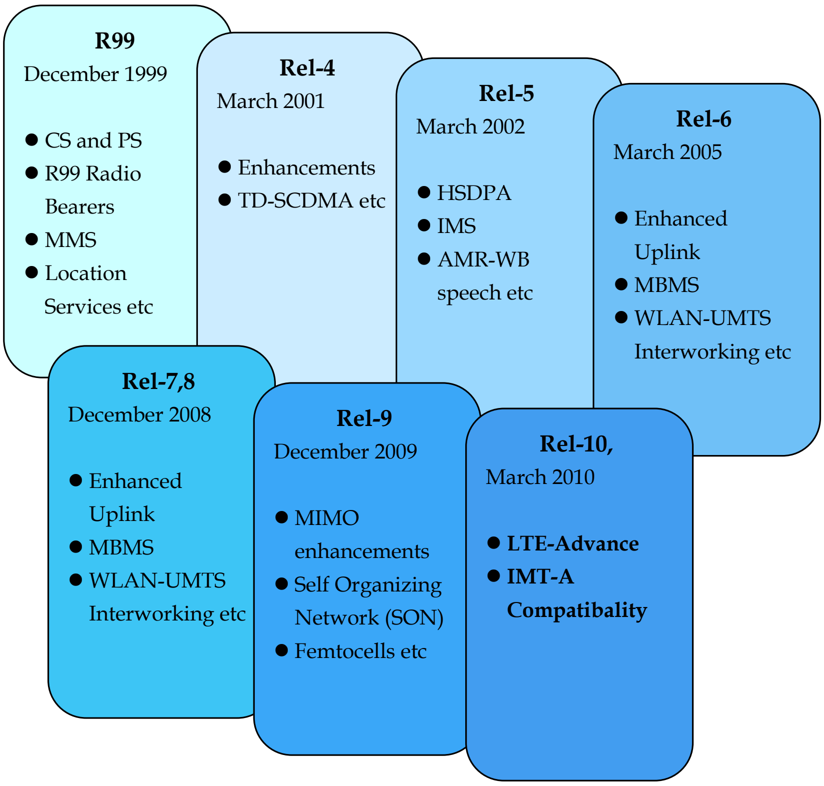

Figure 2.2 Continuous release of 3GPP[3]

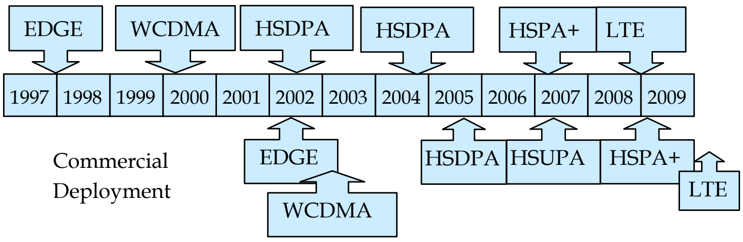

Figure 2.3 Commercial deployment of 3GPP[4]

The trend in typical data rates is shown in Figure 2.4. WCDMA can provide a service based on a data rate up to 2 Mbps, HSDPA gives 7.2-14.4 Mbps, HSPA evolution 21-42 Mbps and LTE will offer a data rate of 150 Mbps and even 300 Mbps with LTE 4×4 (LTE with 4 input 4 output multiple-input and multiple-output (MIMO)) [28]

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[3] Based on Figure 1.3 from reference [4]

[4] Figure 1.3 from reference [28]

[106][107].

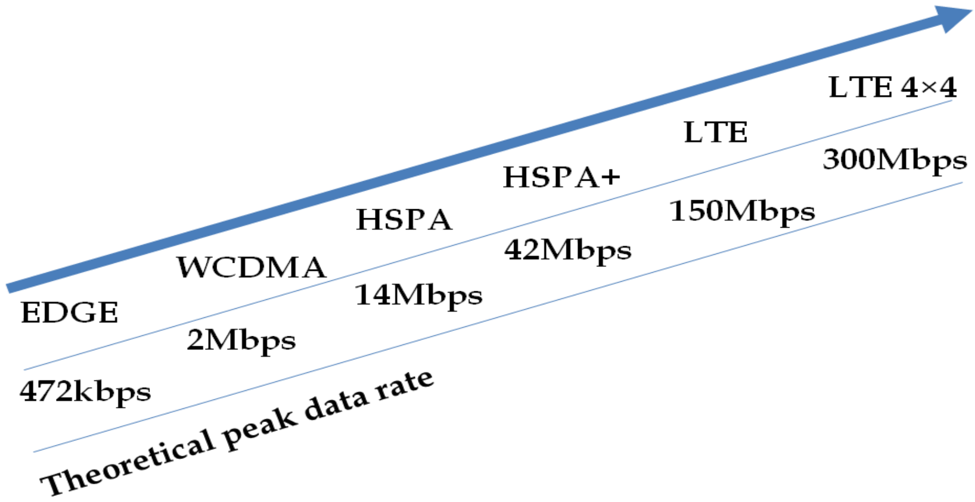

Figure 2.4 Typical peak data rate[5]

The second track in the evolution scenario is from the IEEE 802 LAN/MAN standard committee. The 802.16 standard, also known as WiMAX, is being continuously promoted by the WiMAX Forum. In the first 802.16-2004 edition, only fixed users are supported, while in the later 802.16e version, known as "Mobile WiMAX", mobile users are supported. Also, the new 802.16m standard will consider the future enhancement of the communication system.

The third track of the promotion is 3GPP2. The 3GPP2 track is mainly based on IS-95, which is the American standard, CDMA2000 that is mainly used in the USA, Japan and Korea. This track is toward the so-called Evolution-Data Only (EV-DO) systems .The latest evolution of 3GPP2 is known as Ultra-Mobile Broadband (UMB) based on OFDM technology.

All of the evolution tracks are targeted at providing more flexible, packet-oriented, system supporting multi services. The aims for LTE are listed below [2].

- All IP-based architecture.

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[5] Figure 1.11 from reference [28]

- Reduce delay, both for the connection establishment and transmission.
- Increase data rate for users.
- Simplify network architecture.
- Increase cell-edge data rate.
- Reasonable power consumption for mobile terminals.
- Capability of roaming to the existing 2G and 3G communication networks.

2.2 OFDMA Networks

OFDM has been one of the key technologies in the development of wireless networks. OFDM uses orthogonal multi subcarriers to carry multiple substreams in parallel, so it offers advantages over conventional FDM as explained below. The main mobile evolution approaches (WiMAX, LTE, LTE-A and UMB) to 4G networks also use OFDM as the multiplexing method.

OFDM, transmitting overlapping orthogonal subcarriers, has the following advantages:

- It is robust against Inter symbol interference (ISI) and multipath fading.
- It can adjust modulation and coding for each subcarrier.
- It uses simple equalizers.
- It has low-complexity modulation through using DSP technology.
- It is more spectrum efficient than conventional FDM.

OFDMA is the access method based on OFDM, with which different groups of subcarriers (in frequency) can be assigned to different users [31]. OFDMA, as based on OFDM, has the following advantages in addition to the 5 advantages for OFDM:

- It can take advantage of frequency diversity through distributed subcarriers.
- It can take advantage of multiuser diversity through contiguous subcarriers.

A typical OFDM subcarrier spectrum distribution is shown in Figure 2.5 [4]. Here

Δf stands for the subcarrier spacing while Tu stands for per-subcarrier modulation symbol time.

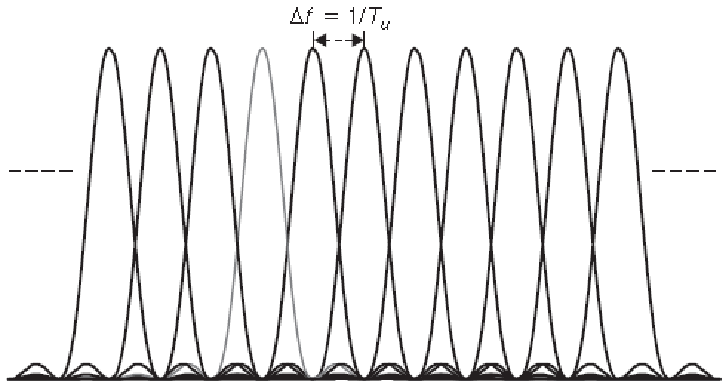

Figure 2.5 OFDM subcarrier spectrum[6]

A typical OFDM signal $x\ (t)$ is expressed as Equation(2.1)

$$x(t) = \sum_{k=0}^{N_c-1} x_k(t) = \sum_{k=0}^{N_c-1} a_k\ (m) e^{-j2\pi k \Delta f t} \tag{2.1}$$

Here $x_k\ (t)$ is the k^{th} modulated subcarrier with frequency of $f_k = k \cdot \Delta f$, $a_k(m)$ is the modulation symbol applied to the k^{th} subcarrier during the m^{th} OFDM symbol interval. N_c is the number of OFDM subcarriers.

The OFDM modulation and demodulation are shown in Figure 2.6 and Figure 2.7 respectively [4].

[6] Figure 4.2 from reference [4]

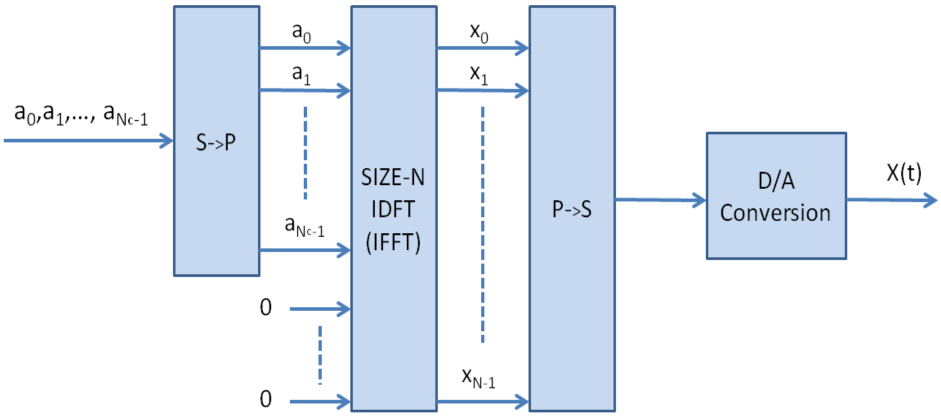

Figure 2.6 OFDM modulation for LTE systems[7]

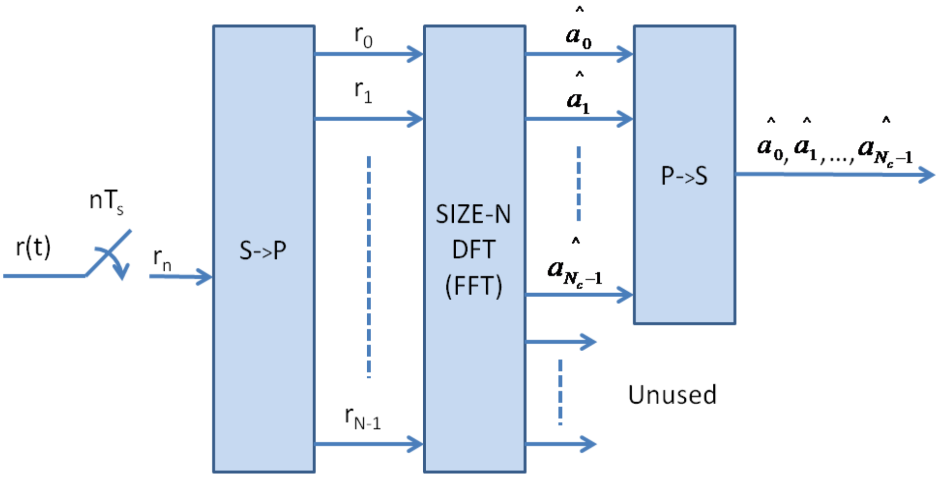

Figure 2.7 OFDM demodulation diagram for LTE systems[8]

By the use of IFFT, OFDM modulation can be simplified in LTE systems. A typical 3GPP LTE system uses a basic subcarrier spacing equal to 15*kHz*. Also, the number of subcarriers depends on the transmission bandwidth. A typical figure is 600 users operating on 10*MHz*. In this situation, N is chosen to be 1024 while $f_s = N \cdot \Delta f =$ 15.36 MHz.

Similar to OFDM modulation, in the demodulation module, sampling with sampling rate of $f_s=1/T_s$ is done and then followed by a size N FFT.

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[7] Figure 4.6 from reference [4]

[8] Figure 4.7 from reference [4]

Typical downlink data rate by OFDM is shown in Table 2.1 [6].

Table 2.1 Typical downlink OFDM parameters[9]

Transmission BW(MHz)		1.25	2.5	5	10	15	20
Sub-frame duration		0.5ms					
Subcarrier spacing		15 kHz					
Sampling frequency MHz		1.92 (1/2×3.84)	3.84	7.68 (2×3.84)	15.36 (4×3.84)	23.04 (6×3.84)	30.72 (8×3.84)
FFT size		128	256	512	1024	1536	2048
Number of occupied subcarriers		76	151	301	601	901	1201
Number of OFDM symbols per sub frame(Short/Long CP)		7/6					
CP length(μs/samples)	Short	(4.69/9)×6	(4.69/18) ×6	(4.69/36) ×6	(4.69/72) ×6	(4.69/108) ×6	(4.69/144) ×6
	Long	(16.67/32)	(16.67/64)	(16.67/128)	(16.67/256)	(16.67/384)	(16.67/512)

2.3 Basic Technologies in LTE

LTE, as one typical network based on OFDMA, has attracted focus from both the academic and industrial fields. To realize LTE systems, several key technologies will be used. Among them, the main technologies are multicarrier technologies including OFDM, as described later, Single Carrier Frequency Division Multiple Access (SC-FDMA) and multiple antenna technologies.

LTE uses OFDMA for the downlink and SC-FDMA for the uplink.

2.3.1. SC-FDMA technology

SC-FDMA, because of its resistance to frequency-selective fading, is introduced into LTE system as the uplink transmission technology. It overcomes the disadvantage of OFDMA of high Peak-to–Average Power Ratio (PAPR) [5], because, with SC-FDMA, power amplifiers at mobile terminals can be simpler and more power-efficient than OFDMA. However, because of the high signalling rate, the frequency domain

[9] Table 1 from reference [28]

equalizer of SC-FDMA link is much more complicated than that of OFDMA. Based on the reason explained above, SC-FDMA is chosen as the uplink access technology for LTE. With most of the benefits of OFDMA, SC-FDMA can reduce power consumption and enhance coverage [108].

As SC-FDMA is used only for the uplink for LTE, complicated equalizers are required only at the base stations but not at the mobile terminals. Figure 2.8 shows the block diagram for SC-FDMA [28].

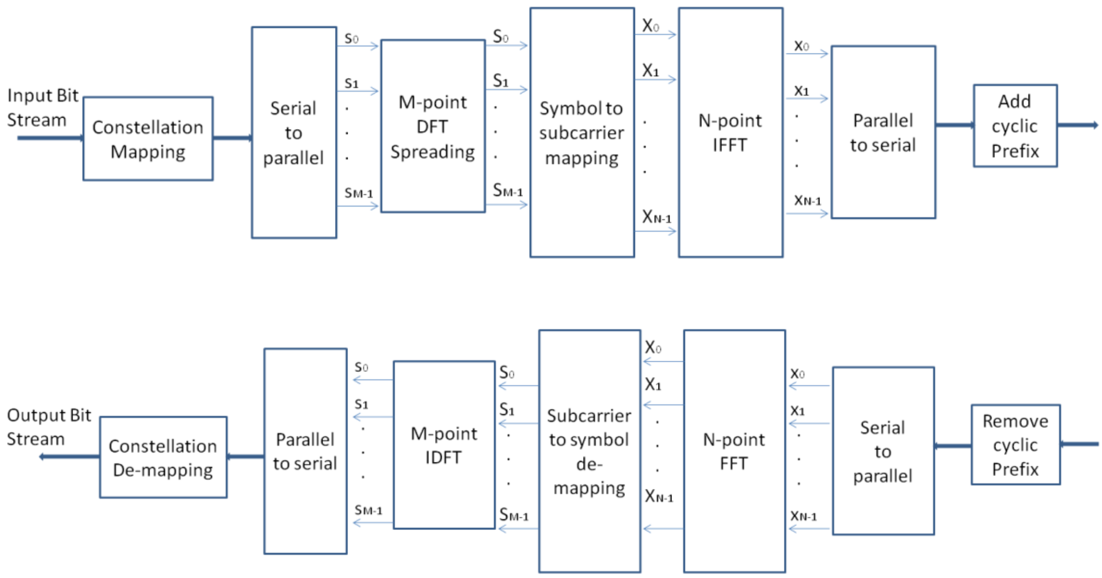

Figure 2.8 Block diagram for SC-FDMA[10]

For practical systems, a dynamic mapping method is used to choose the modulation method: from BPSK in weak channels up to 64-level Quadrature Amplitude Modulation (64-QAM) in strong channels. Here the *M*-point Discrete Fourier Transform (DFT) generates *M* frequency domain symbols that modulate *M* out of *N* orthogonal subcarriers spread over a bandwidth of

$$w_{channel} = N \cdot f_0 \; [Hz] \tag{2.2}$$

Here f_0 is the subcarrier spacing. The channel transmission rate can be expressed as

10 Figure 4.13 from reference [28]

Equation (2.3). Here R_{source} stands for the input bit stream rate.

$$R_{channel} = \frac{N}{M} \cdot R_{source} \ [symbols/second] \tag{2.3}$$

Let Q denote the bandwidth spreading factor

$$Q = \frac{R_{channel}}{R_{source}} = \frac{N}{M} \tag{2.4}$$

In Figure 2.8, $s_0, s_1, s_2, \ldots, s_{M-1}$ denote modulated source symbols. $S_0, S_1, S_2, \ldots, S_{M-1}$ denote M samples of the DFT of s_m. $X_0, X_1, X_2, \ldots, X_{M-1}$ represent the frequency domain samples after subcarrier mapping and $x_0, x_1, x_2, \ldots, x_{M-1}$ represent the transmitted time domain channel symbols obtained from the inverse DFT of X_m.

In summary, SC-FDMA is used to optimize the range and power consumption in the uplink of LTE and OFDMA is used in the downlink to minimize receiver complexity.

The typical parameters provided by SC-FDMA are shown in Table 2.2 [6].

Table 2.2 Typical parameters for Uplink by SC-FDMA technology[11]

Transmission BW (MHz)		1.25	2.5	5	10	15	20
Timeslot duration		0.675 ms					
Sub-carrier spacing		15 kHz					
Sampling frequency (MHz)		1.92 (1/2×3.84)	3.84	7.68 (2× 3.84)	15.36 (4× 3.84)	23.04 (6× 3.84)	30.72 (8× 3.84)
FFT size		128	256	512	1024	1536	2048
Number of occupied sub-carriers		76	151	301	601	901	1201
Number of OFDM symbols per Timeslot (Short/Long CP)		9/8					
CP length (μs/samples)	Short	7.29/14	7.29/28	7.29/56	7.29/112	7.29/168	7.29/224
	Long	16.67/32	16.67/64	16.67/128	16.67/256	16.67/384	16.67/512
Timeslot Interval (samples)	Short	18	36	72	144	216	288
	Long	16	32	64	128	192	256

2.3.2. Multiple Antenna Technology

One of the primary technologies in LTE is multiple antenna technology to realise pre-coding diversity and spatial diversity. By the use of multiple antennas, better system performance of LTE can be realized - such as system capacity, coverage and higher data rates.

The multiple antenna technology can benefit LTE systems in the following ways.

1. Provide additional diversity

The well-known diversity gain can be realized by spatial reuse, when large inter-antenna distance is provided or by polarization diversity, when different antenna polarization directions are used.

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[11] Table 2 from reference [6]

2. Provide coverage solution

By using multiple antenna technology, the shape of the antenna beam can be adjusted; for example, the antenna gain in a certain direction can be maximized. A typical multiple antenna technology is shown in Figure 2.9 [28]. Figure 2.9 illustrates multiple antennas both at the transmitter and the receiver. It is a 2×2 antenna configuration, with 2 antennas at the transmitter and 2 for the receiver.

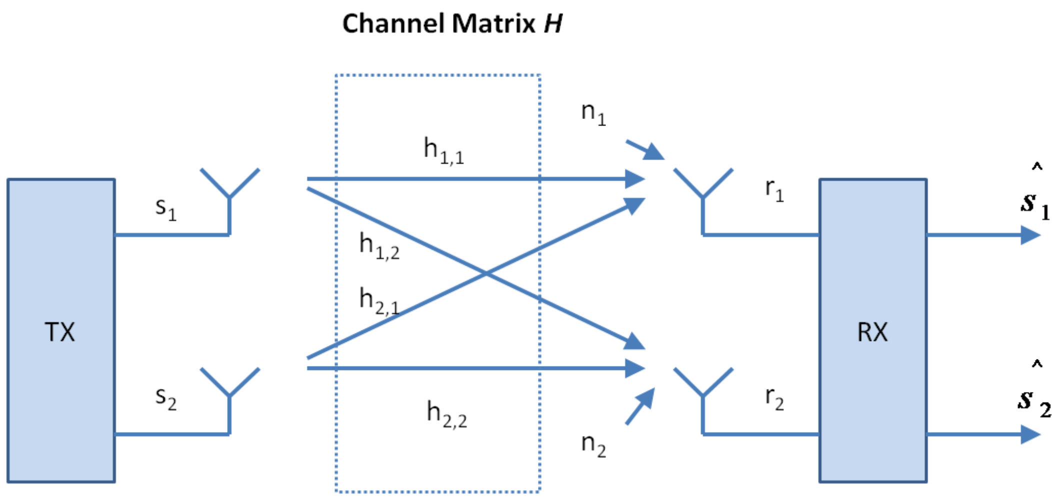

Figure 2.9 Typical 2×2 multiple antenna in LTE[12]

2.4 LTE architecture

The basic LTE architecture is shown in Figure 2.10 [3].

The LTE consists of the Evolved Universal Terrestrial Radio Access Network (E-UTRAN) and Evolved Packet Core (EPC) network. The non-radio aspects of the LTE are considered under the term System Architecture Evolution (SAE). The core network of LTE (EPC) consists of the Mobility Management Entity (MME) and the SAE gateway. eNB stands for evolved NodeB (eNodeB), which is the base station in LTE systems. In such an architecture, eNBs can communicate with each other

[12] Figure 4.20 from reference [28]

through the X2 interface while the communication between the E-UTRAN and the EPC can be realized through the S1 interface.

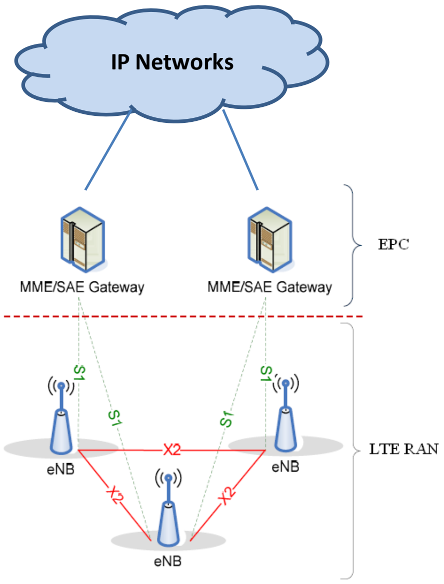

Figure 2.10 Basic LTE architecture[13]

The LTE architecture with current wireless technology is shown in Figure 2.11 [7]. LTE will use a flat architecture with fewer architectural layers [7] which can reduce latencies and improve system performance. eNBs will connect to the gateway then to the IP networks.

[13] Figure 2.3 from reference [3]

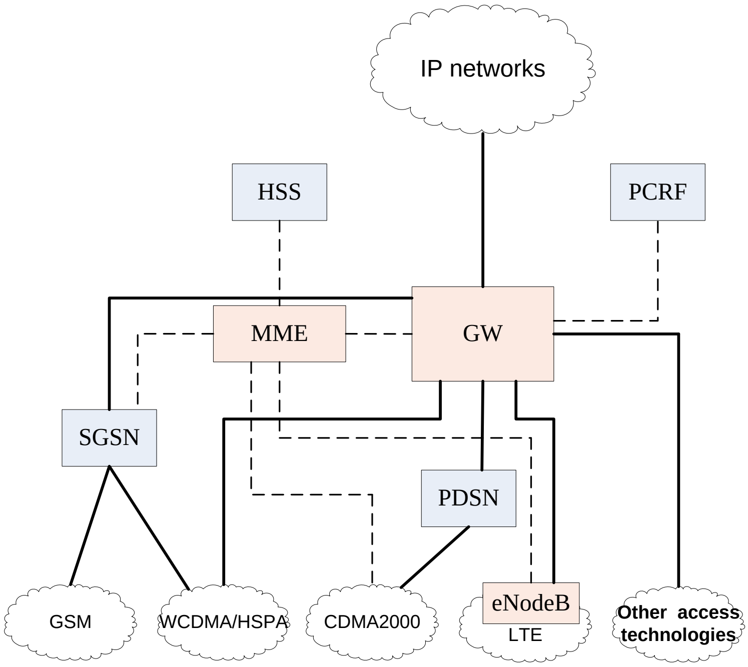

Figure 2.11 LTE architecture with current wireless technology[14]

Such a systematic architecture shows good compatibility for all access technologies. The dashed lines stand for the control interface, while the solid lines stand for user data interface. The gateway (GW) can serve as a packet data network or a serving gateway. The Mobility Management Entity (MME), which controls signalling, is isolated from the GW for simplicity in the GW structure and flexible deployment of the network.

GSM and WCDMA can access to the evolved core network through the Serving GPRS Supporting Node SGSN. In such a situation, the gateway serves as a GPRS Gateway Support Node (GGSN) for GSM and WCDMA HSPA users. CDMA2000 users can connect to the GW through Packet Data Serving Node (PDSN).

LTE base stations will communicate with the core network through the RAN-CN interface. To provide high speed service, all the base stations will connect to their neighbouring base stations.

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14 Figure 2 from reference [7]

The radio interface protocol is shown in Figure 2.12 [7]. The radio interface protocol has the same structure as HSPA.

- PDCP (Packet Data Convergence Protocol) deals with the compression of the header and security issues.
- RLC (Radio Link Control) deals with data transmission without loss.
- MAC (Media Access Control) protocol deals with bidirectional scheduling.
- RRC (Radio Resource Control) deals with the setup procedure of header, mobility management in active mode, and the systematic information broadcasting.
- NAS (Non-accesrs stratum) protocol handles mobility management of idle mode and the setup of services.

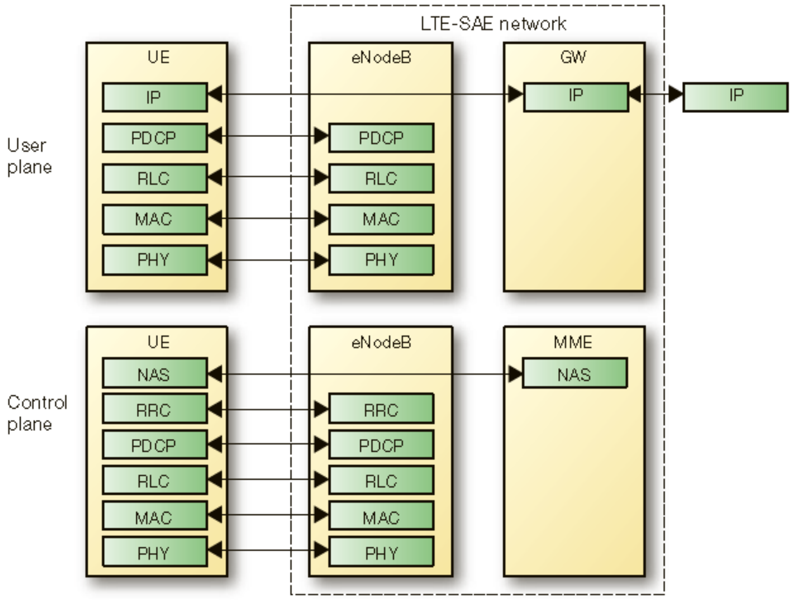

Figure 2.12 Radio interface protocol of LTE[15]

[15] Figure 3 from reference [7]

2.5 Radio resource allocation for OFDMA networks

A lot of research has been done about frequency reuse based on different algorithms and also on smart antennas to improve the throughput of LTE. To improve the overall performance of OFDMA networks, advanced design techniques are used as shown in Figure 2.13.

Cell splitting is used when the demand for capacity is more than the cell can offer. In order to give better service of the cell, a micro/macro cell combination can be deployed where users with higher speeds can be served by macro cell and users with lower mobility are served by micro cells. By the use of sectorisation, one cell can be divided into multiple cells to increase the cell throughput. Sectorisation is always investigated together with frequency reuse and advanced antennas. Picocells and femtocells are used to further increase the indoor coverage.

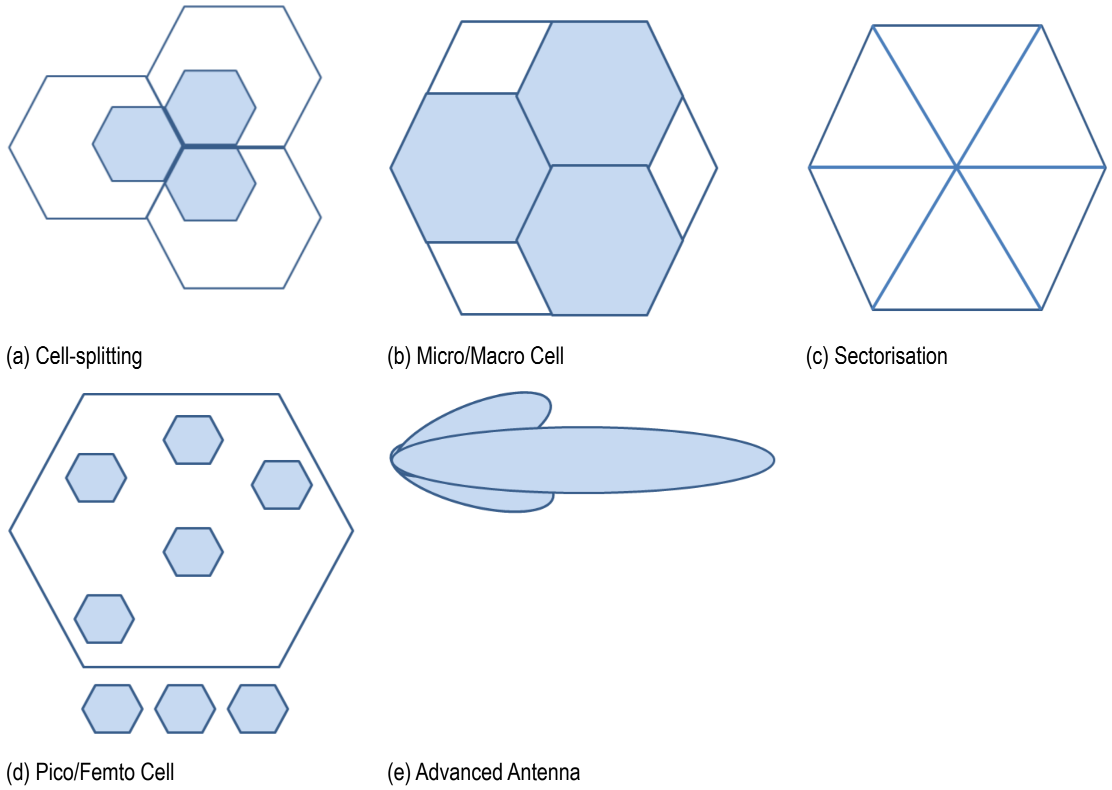

Figure 2.13 Advanced radio resource management methods[16]

Work in this thesis is based on sectorisation and advanced antennas, together with subcarrier and subchannel allocation schemes.

2.5.1 Sectorisation of Cellular Networks

An improved sectorisation scheme has been proposed by Li-Chun Wang and Kin K. Leung [41]. They introduced a Narrow Beam Quad-Cell, in which each cell is divided into 4 sectors each covered by their own antenna as shown in Figure 2.14. In Figure 2.14, the left figure shows the radiation pattern of the antenna used in the paper. The right figure shows sectorisation by the use of a Narrow Beam Quad-Cell. The proposed scheme works well with GSM networks and enhances system throughput.

[16] Figure2.4 from reference [41]

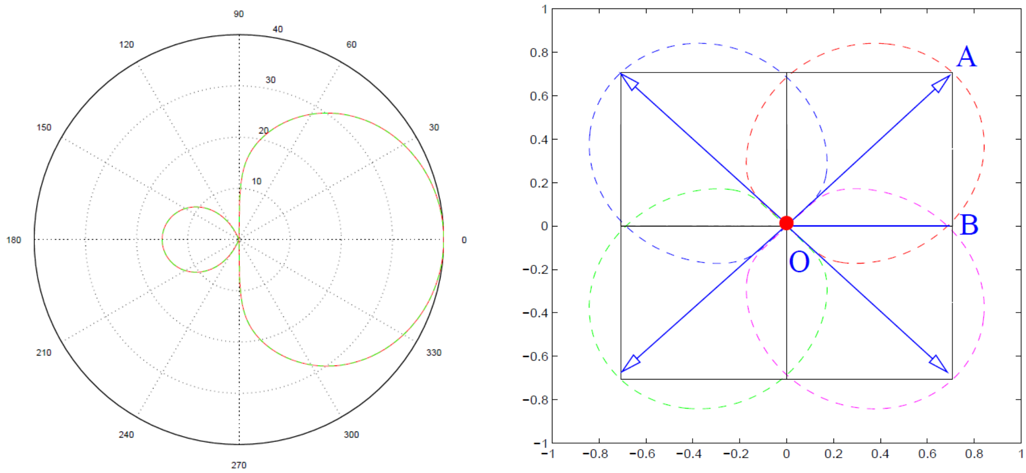

Figure 2.14 Illustration of Narrow Beam Quad-Cell[17]

Changyoon Oh and Alyin Yener, et.al have proposed a graph theory based sectorisation algorithm for CDMA systems with a joint power control and sectorisation based on graph theory that maximises SIR and improves system throughput [38][39][40].

Chae Y. Lee and Hyon G. Kang, et.al proposed a dynamic sectorisation scheme based on Genetic Algorithms for CDMA networks [42]. Handoffs and interference are reduced by their scheme.

This literature shows that sectorisation works well with both GSM and CDMA based networks, but the feasibility of OFDMA networks still needs proving. Work in [42] is based on GA, while working with CDMA – but in CDMA the network architecture is totally different form LTE as described previously. Also, sectorisation in that work is based on the grouping of microcells and channel borrowing; sectorisation in this thesis will be based as described in Section 2.5.

2.5.2 Frequency reuse

Sectorisation is sometimes investigated together with frequency reuse schemes,

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17 Figure1 and Figure 6 from reference [41]

another intensively researched topic for cellular networks. The main idea of frequency reuse is to constrain the mutual interference among neighbouring cells to improve system throughput [44][45][46][109][110].

In classical cellular networks, the radio resource management is adopted to avoid ICI from neighbouring cells. For classical radio management, as the Frequency Reuse Factor (FRF) can limit the availability of the frequency spectrum and the capacity of the system, the FRF is usually chosen to be as near 1 as possible so that such schemes suffer from severe ICI because of their low FRF. For radio resource management in LTE, the FRF and resource allocation should be more flexible to meet different needs as the services provided by LTE will be more flexible. Thus different sectorisation methods with different frequency reuse schemes are investigated.

In Ericsson's scheme [8], only part of the radio channel is available at the cell edge which is orthogonal in adjacent cell edges while the whole radio channel is available at the cell centre where the transmission power is limited to reduce interference by not letting significant signal propagate to the next cell. As shown in Figure 2.15, different colours stand for different segments of subcarriers.

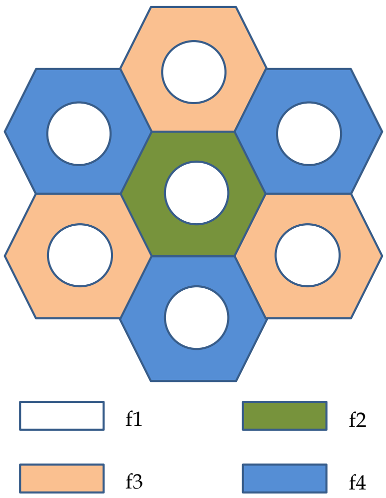

Figure 2.15 Ericsson's subcarrier allocation scheme[18]

[18] Figure 1 from reference [8]

In Haipeng LEI's scheme [8], the radio channel is divided into two groups: the super group and the regular group. The super group will be used for the cell centre and the subcarriers of the regular group will be divided into three segments. Each of the sets will be allocated to one of the sectors of the cell. Also, the number of subchannels of a certain sector can be adjusted. The scheme is shown in Figure 2.16 [8].

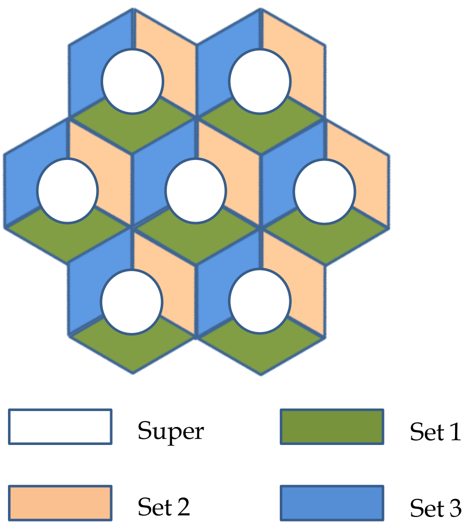

Figure 2.16 Multi-cell two-group subcarrier allocation[19]

In Ki's proposal [9], an incremental frequency reuse scheme for an OFDMA cellular system is designed. The whole frequency spectrum is divided into two parts, the basic part and the incremental part. The basic part consists of several segments of orthogonal subcarriers. During the resource allocation procedure, the basic segments of subcarriers will be allocated first. The users served by the basic segments will have no ICI. After that, if there are still un-served users, incremental segments of subcarriers that overlap in spectrum are allocated among cells to provide service to the un-served users. The incremental subcarriers will be randomly selected to balance the ICI among the cells. The incremental frequency reuse scheme is shown in Figure 2.17 [9].

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[19] Figure 2 from reference [8]

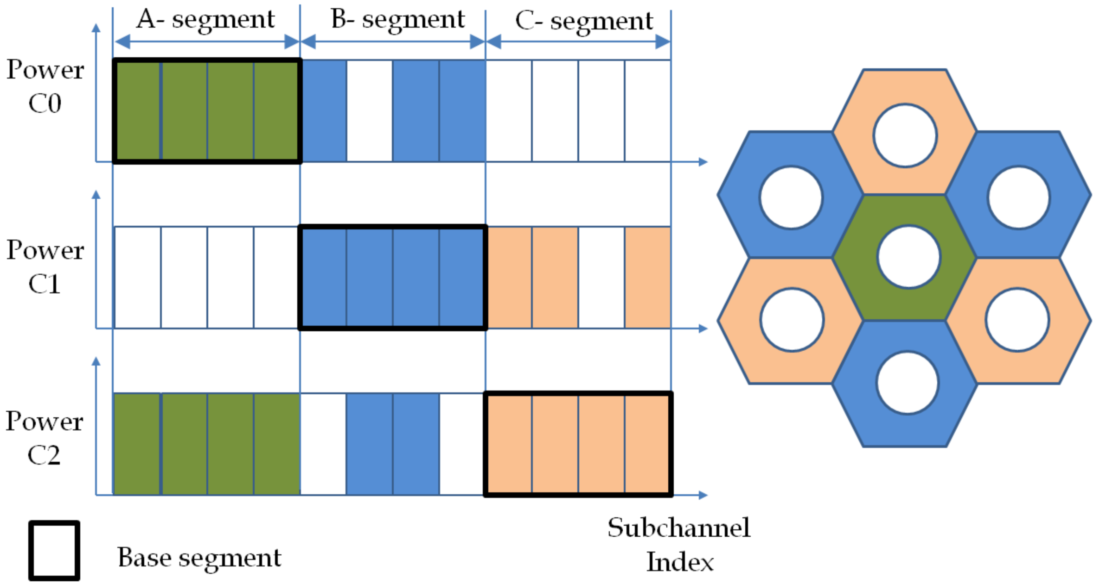

Figure 2.17 Incremental frequency reuse scheme for OFDMA[20]

An efficient frequency reuse scheme by cell sectorisation is introduced by Arsh Boustani [43]. In his work, a multi-cell OFDMA based wireless network is investigated and simulated, where each of the cells is divided into 8 sectors, with 1/16 of the total available subcarriers as shown in Figure 2.18. Comparison shows that their proposal outperforms the conventional FRF Systems. However, by sectorisation of 8 and usable subcarriers of 1/16 the total number, the available wireless radio resource for each sector may be limited heavily; as a result, it might not work with heavily loaded scenarios. Also, a subcarrier allocation scheme is not considered in their work as subcarriers are randomly allocated.

[20] Figure2 from reference [9]

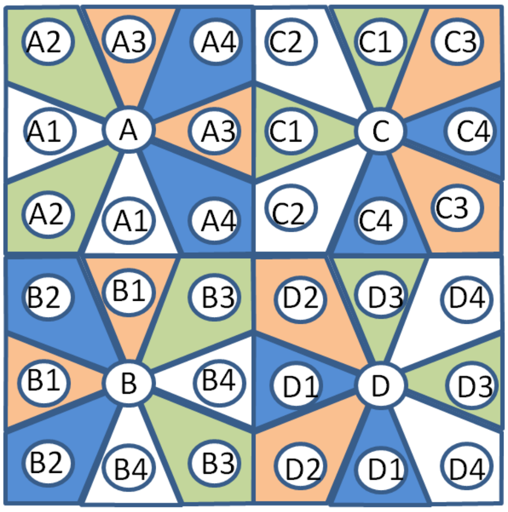

Figure 2.18 An Efficient Frequency Reuse Scheme[21]

In the author's proposal [11] shown in Figure 2.19, radio resource allocation is combined with energy saving.

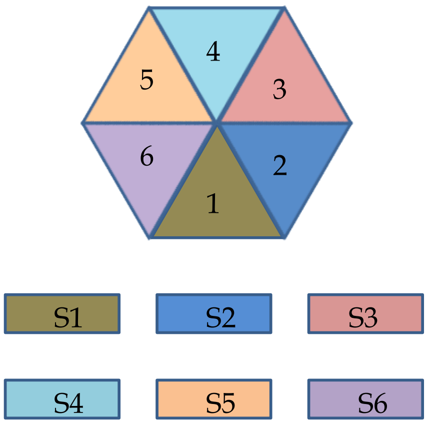

Figure 2.19 Subcarrier allocation of six segments

In this proposal, one cell is divided into six similar parts, each of them called a segment, labelled as 1-6 in Figure 2.19. An equal quantity of subcarriers will be allocated to segments 1-6, known as S1-S6. There are N subcarriers in one cell so that S1-S6 each contains $N/6$ subcarriers. There are K users and the power of subcarrier n

[21] Based on Figure3 from reference [43]

allocated to user k is defined as *pk,n*.

Each segment can be divided into two parts, the central part and the edge part. The area of the central part can be dynamically adjusted by the user distribution condition of different segments. A parameter β is defined to describe the distribution. The number of users in the central part is defined as N_c and the number of users of the cell edge area is defined as N_e, Thus β can be defined as in Equation (2.5).

$$\beta = \frac{N_c}{N_c + N_e} \tag{2.5}$$

Here, the central part can be adjusted according to different β and different distribution conditions of a certain segment. The central part adjustment is shown in Figure 2.20. Relevant results can be found in [11].

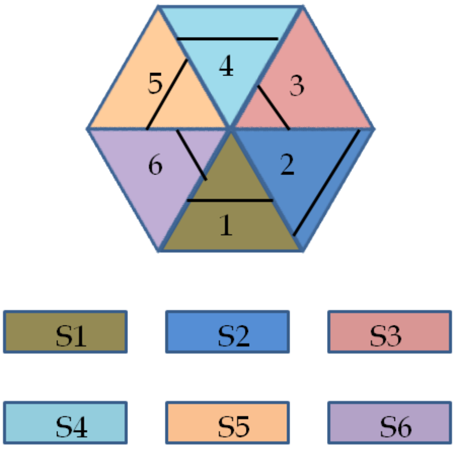

Figure 2.20 Central part allocation of different segments[22]

Also, other similar dynamic frequency reuse and radio resource management methods can be found in [12][13][14][15][16][17].

[22] Figure 5 from reference [11]

2.5.3 Smart Antenna technology

Smart antennas are widely discussed and introduced in [3][4][5]. A smart antenna usually contains an antenna array and the digital signal processing unit to adaptively transmit and process the signal. This is usually referred as a fully-adaptive antenna.

Using a smart antenna can improve the system capacity by reducing the interference and increasing the spectrum efficiency tremendously; however, the digital processing can make the structure of smart antenna complicated and the cost expensive.

Semi-smart antenna, in contrast, are much simplified in structure while keeping some extend of the "intelligence" of smart antenna. No complicated digital signal processing unit is needed by semi-smart antennas, which have been used to solve the load balancing issue and the pattern control for 3G WCDMA networks [18][19][20]. It can also be used to solve the cell coverage and radio resource management issues in LTE. The suitability of Semi-smart antenna in solving RRM issues for OFDMA based networks needs investigation and discussion, which is one main task for this thesis.

2.6 Summary

Background information and related works have been introduced in this chapter including basic concepts for OFDM and OFDMA. LTE, the next generation wireless communication system that uses OFDMA has been introduced, together with other relevant technologies such as SC-FDMA and multiple antenna technology. Finally, related works on radio resource allocation in LTE are discussed including frequency reuse schemes and sectorisation. RRM for OFDMA based networks with the deployment of multiple antenna techniques will be investigated in Chapter 5, Chapter 7 and Chapter 8.

Chapter 3 Genetic Algorithms

3.1 Introduction

Genetic algorithms (GAs) emerge from the idea of "Survival of the fittest" introduced by Darwin [29] and the idea of "Genetic theory" introduced by Mendel [71]. GA as a heuristic machine learning algorithm was first introduced in the 1960s by Holland [72]. In a GA, the offspring will be evaluated by a certain algorithm and the fitter individuals (according to that algorithm) have priority to generate offspring.

Nowadays GAs are widely used in areas such as Mathematics [93], Economy [94], Aeronautics [95], Signal Processing [95], Biology [96], Automation [97][98][99], Neural networks and Microwave techniques [100].

The techniques to implement a GA have been optimized a lot during its deployment into different academic and industrial fields. Guo has proposed and compared three kinds of enhanced GA in [47]; Zhi-Qiang Chen has proposed an efficient real-coded Genetic Algorithm based on the similarity between the individuals for the crossover and mutation operator [48].

GA has also been combined with other heuristic algorithms to give optimisation results to certain problems. For example, GA has been combined with ant colonies to give better optimisation for control problems [49]. In Yan Tai-shan's work, a combined work of GA and Neural Network is proposed and simulated. The combined algorithm can give better speed and precision of convergence [50].

3.2 Concepts of GA

As the basic idea of GA comes from biology, it contains "biological" terms and procedures and the main ones are listed below.

Chromosome. Living organisms consist of cells containing chromosomes, which are in the charge of the phenotype of different organisms. In GA, a solution of a certain problem can be seen as a chromosome.

Gene. A chromosome consists of genes.

Locus. Each gene has its own position in the chromosome, called locus.

Search space. When looking for a solution for a certain problem, the set of all the feasible solutions for the problem is called the search space.

Encoding. The mapping procedure from a practical problem to a mathematical problem is called encoding.

Population. When solving a certain problem using GA, the solution starts with a set of solutions (chromosomes), called population.

Individual. Each solution of a certain population is called an individual.

Offspring. To get a better solution of the problem, individuals are taken from the population to generate the new population. Individuals or chromosomes of the new population are called offspring of the previous population.

Population scale. The number of individuals *NP* of one population is the population scale.

Decoding. The mapping from the mathematical problem to the practical problem is called decoding, which can be seen as the reverse procedure of encoding.

3.3 Key functions of GA

The basic idea of GA is searching the optimal solution for a certain problem starting from a group of potential solutions (population) of the problem, using the three main procedures: selection, crossover, and mutation. The GA can get better and better individuals from generation to generation. In each of the generations, the fitness of each individual will be evaluated and individuals more fitted to the solution can be selected to generate offspring. Crossover and mutation procedures will be done based on basic genetic ideas. The most important procedures of GA are the encoding method, selection, crossover and mutation.

3.3.1. Encoding

In a GA, encoding is of great importance as the performance of chromosomes is realized by the encoding procedure. The encoding procedure may influence the whole performance of the GA and it is relevant to the design of all the other procedures of GA. The encoding should obey the following rules.

*Completeness***.** All the points of the problem space can be mapped to the space (search space) after encoding.

*Robustness***.** All the points after encoding can find a relevant point before encoding of the problem space.

*Non-redundancy***.** Each point after encoding can find one and only one relevant point before encoding of the problem space.

There are different kinds of encoding methods such as binary string encoding, real encoding and tree encoding [75]. The most used encoding method is binary string as that approach was used in early applications and has remained popular. Different kinds of encoding are introduced as below.

*Binary string encoding***.** In binary string encoding, each chromosome is represented by a string of 0s and 1s. One example of binary string encoding is shown in Figure 3.1.

Figure 3.1 Example of binary string encoding

Real Encoding. In real encoding, each chromosome consists of a string of a real number. An example of real encoding is shown in Figure 3.2.

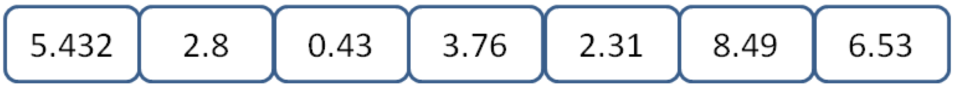

Figure 3.2 Example of real encoding

Tree encoding. In tree encoding, the chromosomes consist of some objects from programming language such as commands and functions. Tree encoding is usually used for programming. One example of tree encoding is shown in Figure 3.3

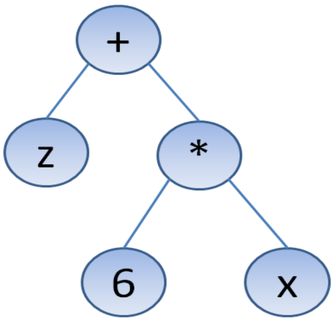

Figure 3.3 Example of tree encoding

3.3.2. Cross over

In the cross over procedure, two parent individuals will be selected from the population to exchange part of their chromosomes to generate offspring. Three main mechanisms control the procedure of cross over.

Mating selection mechanism (MSM). MSM decides how to choose father and mother from the whole population to generate offspring.

Offspring generation mechanism (OGM). OGM decides the generation of offspring with parents selected by MSM. Methods such as how to cross over the chromosomes of the parents and how many offspring will be generated by a pair of parents are decided by OGM.

Offspring selection mechanism (OSM). OSM decides which offspring go to the next generation among all the offspring generated.

One example of cross over is shown in Figure 3.4. Two parents have chromosomes as P1: 010111001, P2: 110010110, when choosing the cross over point as 6, genes from no. 6 onwards exchange, producing two offspring O1: 010110110 and O2: 110011001.

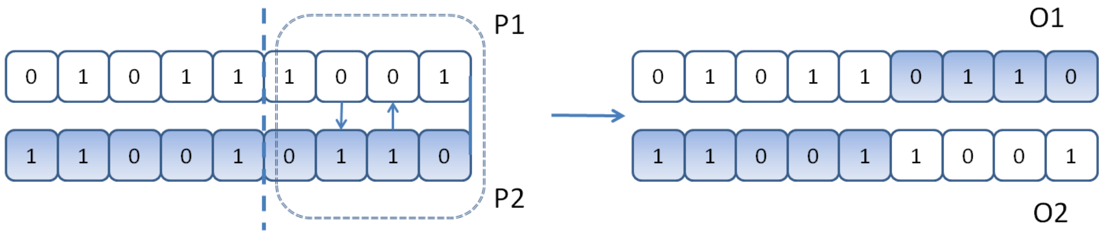

Figure 3.4 Example of cross over

The main types of cross over methods are (i) one point cross over (ii) two point crossover (iii) uniform cross over (iv) arithmetic cross over and (v) heuristic cross over. Here it is assumed that the two parent chromosomes are P_1 and P_2, where $P_1 = (p_1^1, p_1^2, \dots, p_1^n)$ and $P_2 = (p_2^1, p_2^2, \dots, p_2^n)$. O_1 and O_2 represent the chromosomes of the two offspring. Different cross over methods are introduced below.

One-point cross over. In one point cross over, a target gene $i \in \{1,2, \dots, n-1\}$ will be chosen as the cross over point. Genes before i will be kept and genes of the parents after the point will exchange to generate new offspring. The two offspring O_1 and O_2 are shown in Equation (3.1). An example of one-point cross over is shown in Figure 3.4.

$$O_1 = (p_1^1, p_1^2, \dots, p_1^i, p_2^{i+1}, p_2^{i+2}, \dots, p_2^n)$$
$$O_2 = (p_2^1, p_2^2, \dots, p_2^i, p_1^{i+1}, p_1^{i+2}, \dots, p_1^n) \tag{3.1}$$

Two-point cross over. Two cross over points $i, j \in \{1,2, \dots, n-1\}$, where $i<j$, are selected and genes between the two points are exchanged between the two parents to generate offspring. The two offspring O1 and O2 are shown in Equation (3.2). One example of two-point cross over is shown in Figure 3.5.

$$O_1 = (p_1^1, p_1^2, \dots, p_1^i, p_2^{i+1}, p_2^{i+2}, \dots, p_2^j, p_1^{j+1}, p_1^{j+2}, \dots, p_1^n)$$
$$O_2 = (p_2^1, p_2^2, \dots, p_2^i, p_1^{i+1}, p_1^{i+2}, \dots, p_2^j, p_2^{j+1}, p_2^{j+2}, \dots, p_2^n) \tag{3.2}$$

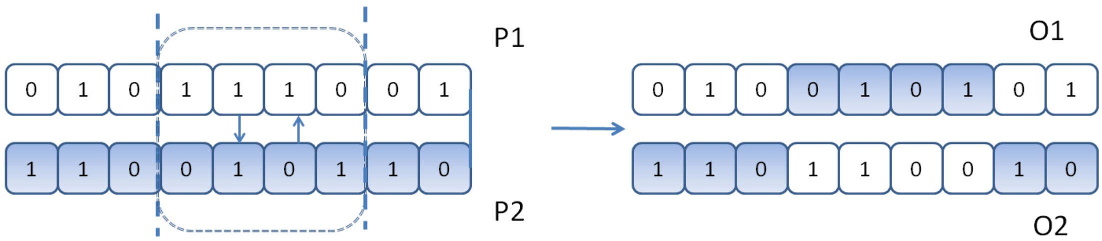

Figure 3.5 Two point cross over

Uniform cross over. In uniform cross over, the cross over operator that decides which genes of a certain parent go to the offspring is determined by a certain probability, known as the mix ratio. The ratio is approximately 0.5 in uniform cross over, which means randomly selected half of the genes will come from one parent and the other half come from the other parent. By using uniform cross over, cross over can be done in gene level instead in segment level, which will bring more flexibility to the offspring. The two offspring generated by uniform cross over is $\mathrm{O_m} = (o_m^1, o_m^2, \dots, o_m^n)$, where m=1,2.

$$o_m^i = \begin{cases} p_1^i & m = 0 \\ p_2^i & m = 1 \end{cases} \tag{3.3}$$

One example of uniform cross over is shown in Figure 3.6.

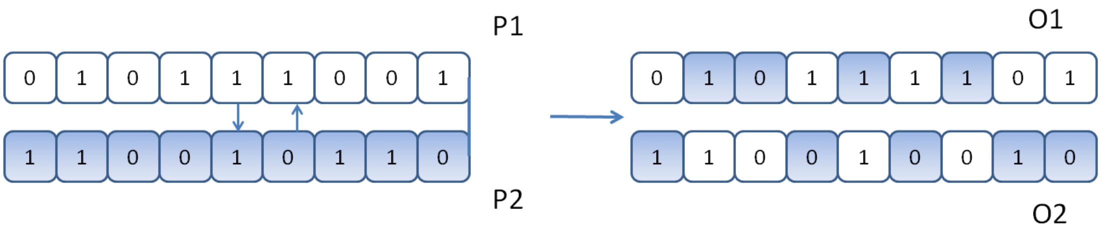

Figure 3.6 Uniform cross over

*Arithmetic cross over***.** In Arithmetic cross over, two parents generate offspring by a parameter $\gamma\epsilon[0,1]$. The two offspring generated is described in Equation (3.4).

$$O_m = (o_m^1, o_m^2, \dots, o_m^n) \quad m = 1,2 \tag{3.4}$$

Where $\mathrm{o}_1^{\mathrm{i}} = \gamma * p_1^i + (1-\gamma) * p_2^i$, $\mathrm{o}_2^{\mathrm{i}} = \gamma * p_2^i + (1-\gamma) * p_1^i$.

By doing so, a certain percentage of the genotype from one parent based on γ will carry on to the offspring while a 1-γ percentage of genotype will come from the other parent as shown in Figure 3.7.

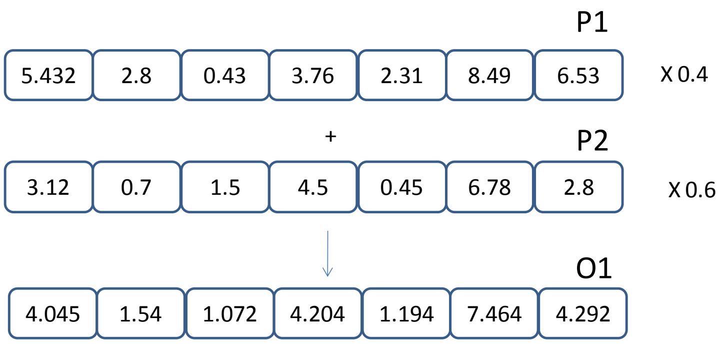

Figure 3.7 Arithmetic cross over

3.3.3. Selection

Selection is an important procedure of GA. In selection, a decision is made which individuals should carry on to the next generation based on their fitness. Individuals with better fitness have a larger probability to carry on to the next generation compared with those with worse fitness. Let f_i stand for the fitness of the i^{th}

chromosome, then the whole fitness of the population is $\sum f_i$. Then the probability of the ith individual to generate offspring is $\frac{f_i}{\sum f_i}$.

There are several common used selection methods such as roulette wheel selection, stochastic selection, tournament selection, truncation selection as described below.

Roulette wheel selection. Roulette wheel is a simple selection method in which the probability of a certain individual can be selected is based on its fitness. Individuals with better fitness have higher probability to be selected. It does not mean the most fitted individuals will carry on to the next generation. Table 3.1 illustrates an example of roulette wheel selection. Fitness, selection probability and accumulative probability of each individual are listed in Table 3.1. When using roulette wheel selection method, a real number between 0 and 1 will be randomly generated and the number will be used as a pointer to choose the individuals.

An example of roulette wheel selection is shown in Figure 3.8, where 6 pointers are given with the value of: 0.35, 0.13, 0.62, 0.49, 0.90 and 0.27. In this case, finally selected individuals are number 1-5, and 7.

Table 3.1 Fitness and selection probability of individuals

Individual	1	2	3	4	5	6	7	8	9	10	11
Fitness	4.0	3.4	3.2	3.0	2.2	2.0	1.8	1.0	0.8	0.6	0.2
Selection Probability	0.18	0.15	0.14	0.13	0.1	0.09	0.08	0.05	0.04	0.03	0.01
Cumulative Probability	0.18	0.33	0.47	0.6	0.7	0.79	0.87	0.92	0.96	0.99	1.00

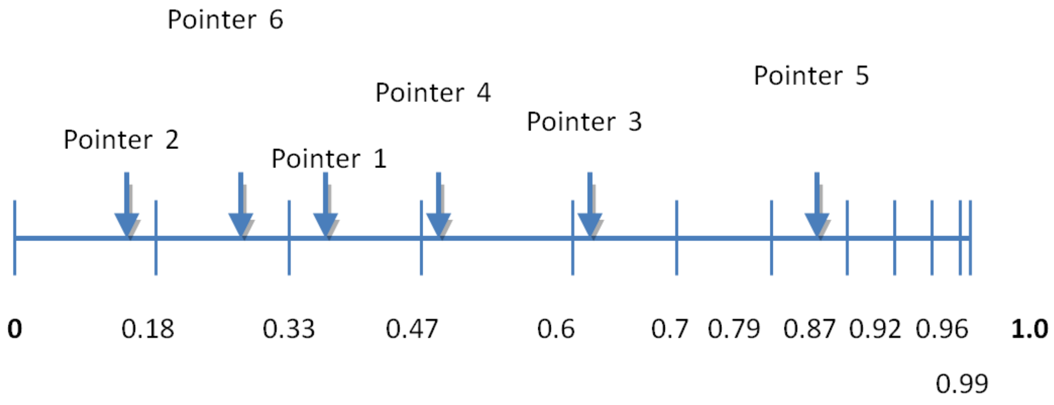

Figure 3.8 Example of roulette wheel selection

Stochastic selection. Stochastic selection is similar to roulette wheel selection; the difference is that in stochastic selection, selection will be made by pointers of the same distance. As shown in Figure 3.9, when selecting n individuals, the space between two pointers will be $1/n$, while the first pointer is generated randomly between 0 and $1/n$.

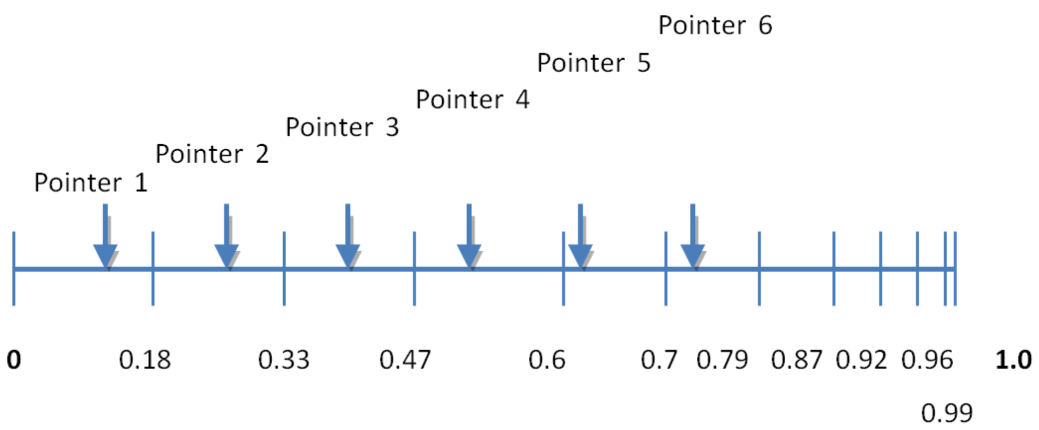

Figure 3.9 Example of stochastic selection

Tournament selection. In tournament selection, several individuals are selected randomly from the population and the most fitted individual can carry on to the next generation. Tournament has more randomness in the selection procedure but can guarantee that individuals with better fitness have higher probability to be chosen. How many individuals are selected in one match, known as, the tournament scale, *n*, is usually set to 2. Tournament selection follows the following steps.

- First, *n* individuals are selected from one population according to the tournament scale. After comparison, the individual with the best fitness can carry on to the next generation.
- Second, the first step is done *NP* times, thus *NP* individuals may carry on to the next generation, where *NP* is the number of individual of the population.

Truncation selection. In truncation selection, all the individuals are queued by fitness and only the individuals with top fitness can carry on to the next generation. The percentage of selected individual can be set up manually.

3.3.4. Mutation

One or more genes of a chromosome is altered in the mutation procedure, aiming at bring new possibilities to the population. The new genes generated by the mutation procedure can prevent the GA stagnating to a local optimum. The mutation probability can be set up manually.

Inversion mutation. In inversion mutation, some bits are selected and the values are inverted. Inversion mutation is used combined with binary string encoding. One example of inversion mutation is shown in Figure 3.10.

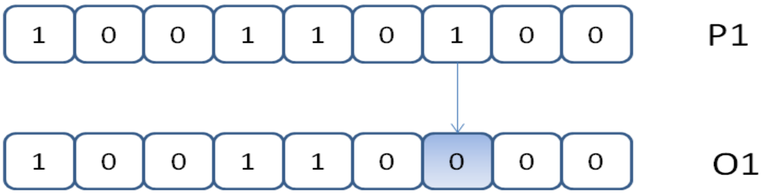

Figure 3.10 Inversion mutation

Order changing mutation. In order changing mutation, some bits are selected and the values are exchanged. One example of order changing mutation is shown in Figure 3.11.

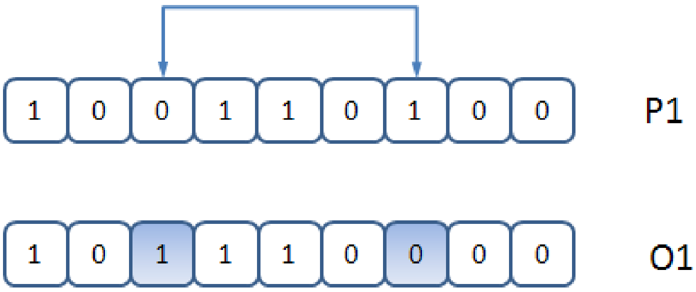

Figure 3.11 Order changing mutation

Uniform mutation. In uniform mutation, a chosen bit is replaced by a randomly generated value between the upper and lower bound defined manually.

3.4 Procedure of GA

A GA will follow a certain procedure to give optimal or sub-optimal solution for a certain problem.

First, some kind of encoding method is selected based on the problem. A certain amount of chromosomes are generated randomly as the first population. After encoding, a fitness function is designed to evaluate the individuals. Three key functions will be carried out (cross over, selection and mutation) to get the second generation. GA operates from generation to generation and finally can get the target solution of the problem. The flow chart is shown in Figure 3.12.

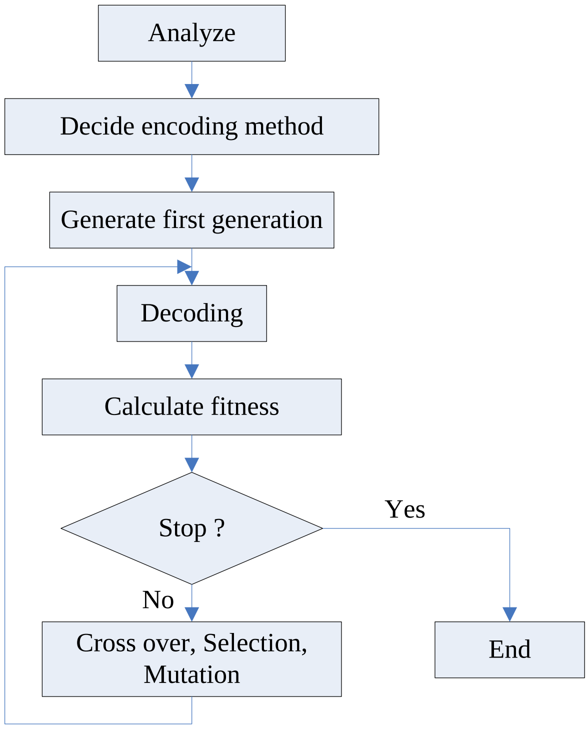

Figure 3.12 Flow chart of GA

3.5 GA and communication networks

GAs have been used in various fields such as function optimisation, automation, data mining, image processing, and of course, wireless communications.

In the wireless communication field, GA is deployed to solve various problems such as routing, resource allocation, etc.

A novel dynamic ant genetic algorithm is reported in Xue-Mei Sun's work [51] to give QoS routing for wireless mesh networks. Y. B. Reddy has proposed a GA based approach for resource allocation in Multi-user OFDM systems [52]. In that work, a GA is used to solve the bit and power allocation problem for multi-user OFDM systems. Also, GA has been used to give solution for dynamic sectorisation for OFDM systems as referred to in [52].

Y.B. Reddy's work might at first be thought to be the nearest to this work, but it is designed to minimize the total transmission power, so that a single objective genetic algorithm is developed to give optimisation of the transmission power; however, the work in this thesis considers coverage, capacity, subchannel and subcarrier allocation, together with user fairness. Also, dynamic sectorisation and multiple antenna techniques are taken into account. With sufficient two-dimensional radio resources from OFDMA and all of these objectives, optimisation based on GA is really a challenging topic.

3.6 Summary

This chapter introduces the concepts of GA, including gene, locus, search space, encoding, population, individual, offspring, population scale and decoding. Basic thought, policy and applicable fields of GA are introduced. Also, the key functions including encoding, cross over, selection, mutation are described and studied in detail. Different kinds of methods for the key functions are studied. The policy of the GA functions are investigated and discussed in detail. Based on the description of key functions, the procedure of the GA is described and researched and an example of a flow chart is given in the end of this chapter. Finally, some implementations of GA in wireless communication networks are mentioned.

Chapter 4 Simulator for LTE OFDMA systems

4.1 System configuration

A systematic simulation was set-up for LTE OFDMA system. The simulator models a multi-cell scenario consisting of 7 cells based on related work discussed in [10],[11] and [13]. The whole system is divided into the modules listed below and the whole flow chart is shown in Figure 4.1.

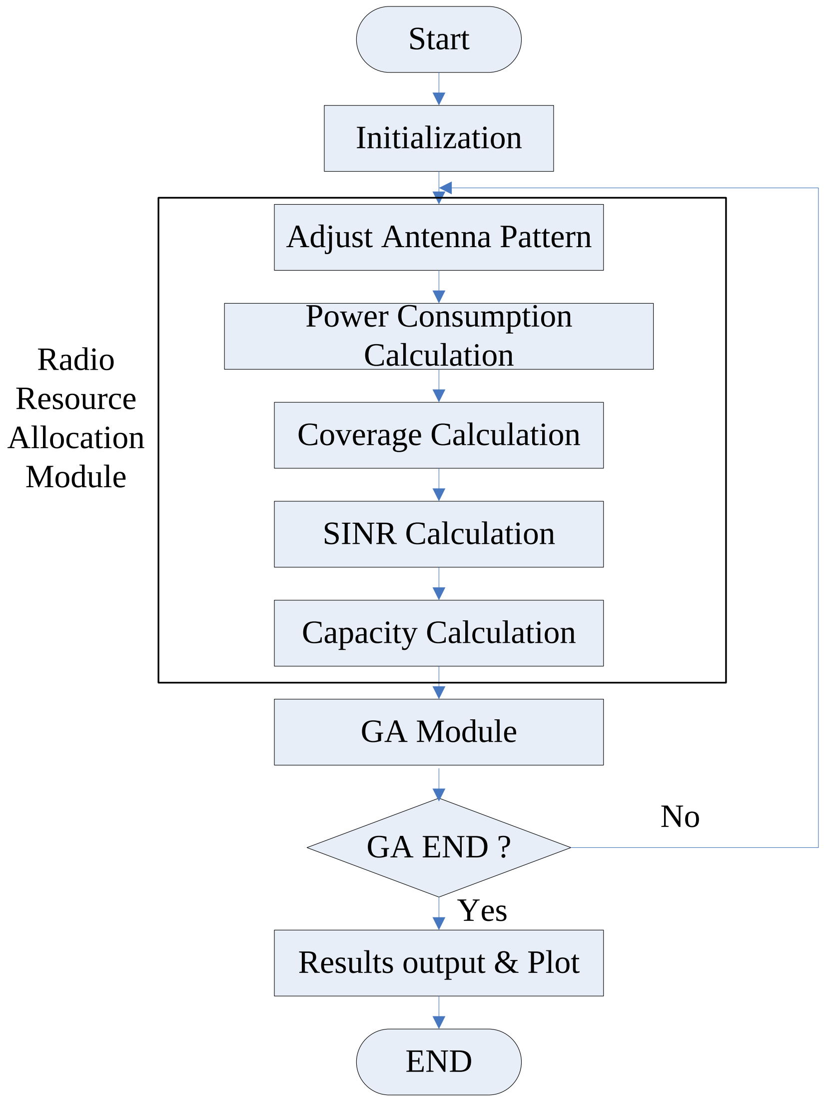

Figure 4.1 Simulator flow chart

Modules: All the coding for the modules listed below was written by the author.

Initialization module: In the initialization module, the multi-cell module is set up and base stations and users of all the 7 cells are distributed into the cells. User and base station initialization are based on parameters listed in Chapter 4, Chapter 6, Chapter 7 and Chapter 8 respectively. Different types of user initialization can be found in Chapter 8.

Antenna pattern adjustment module: In the antenna pattern adjustment module, the antenna pattern and transmission power of each sector of the 7 cells is adjusted. Different antenna pattern adjustments will lead to different coverage of the multi-cell model and different power consumption. Two different types of antenna adjustment modules are used as described in Chapter 5 and Chapter 8 respectively.

Power consumption module: In this module, the power consumption of each sector of the 7 cells is calculated. The detailed power consumption calculation is described in Section 4.3.3.

Coverage Calculation module: In this module, the coverage information of all the sectors of different cells is calculated and recorded for the use of GA algorithm.

Signal to Interference plus Noise Ratio **(SINR) calculation module**: In this module, the SINR of all the users distributed into the multi-cell module is calculated based on the transmission power, channel gain and interference from the adjacent cells. SINR calculation is based on Equation 5.2.

Capacity calculation module: In this module, the capacity of each user is calculated based on the transmission power and SINR results from the SINR calculation module.

GA module: In this module, the whole procedure of the GA algorithm is realized and selection is done based on multi-objective fitness function. Different GA modules are described in Chapter 5, Chapter 7 and Chapter 8 respectively.

4.2 Simulation parameters

A systematic simulator for LTE network is set up using the MATLAB R2010a ® platform. The simulation is based on a multi-cell model of 7 cells as shown in Figure 4.2. The simulations of Chapter 5 and Chapter 6 are based on the parameters in Table 4.1, as introduced in [4] [76] [77] , but the simulation parameters used for Chapter 7 and Chapter 8 are a little bit different as explained in those two chapters.

Table 4.1 simulation parameters for multi-cell LTE model

Parameters	Values
Cellular layout	hexagonal, BS in the centre
Number of Cells	7
Radius of Cell	1000m
Inter-cell distance	866m
Bandwidth	20MHz
Subcarrier frequency	15kHz
Allocable subcarrier number	200
Total transmission power of BS	20W
Users per Cell	80
User distribution	Uniform
Path loss exponent	4(LOS)

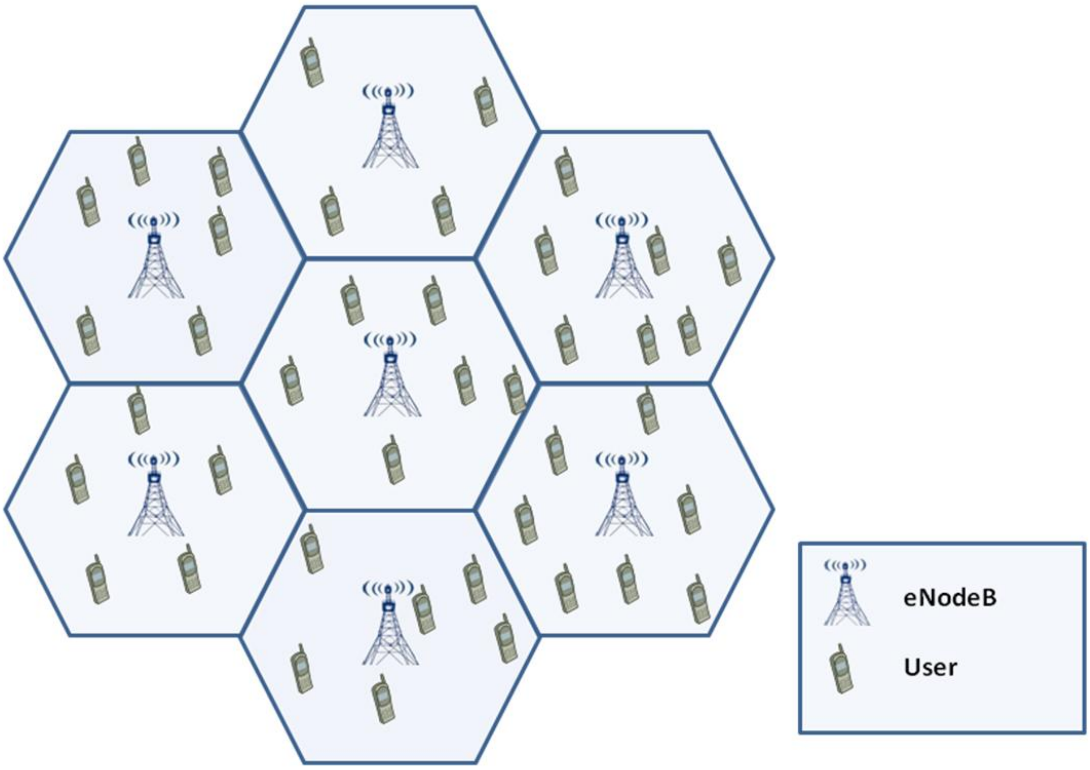

Figure 4.2 Multi-cell systematic model

The parameters used for GA algorithm are shown in Table 4.2. The population size can vary from several tens to 100s [80] or even 1000s. A commonly used population size is around 50 [49] [78] [79]. As the encoding objective of this thesis is the antenna gain vector or angle vector, the chromosome length is quite short so one point cross over is selected as the crossover method for the work of Chapter 5 and Chapter 6. The crossover point is controlled between 1/4 and 2/3 of the chromosome to make sure the offspring can carry on both parents' genotype. The selection part contains the parents' selection and the offspring selection. Normally the harsh offspring selection scheme works well with a weak parent selection scheme as described in section 6.4, so that the random parent selection scheme and truncation offspring selection scheme is selected. The influence of selection rate is also studied in section 6.4, while here the selection rate is chosen to be 0.4 as commonly used from the literature [79]. The influence of mutation rate on the algorithm is investigated in section 6.5; here the mutation rate is chosen as 0.01 as typically used from others' works [81] [82].

Table 4.2 GA Parameters

Population size	50
Cross over method	One point cross over
Generation	70-150
Cross over probability	25%-66.7%
Crossover parents Selection method	Random Selection
Offspring Selection method	Truncation selection
Selection rate	0.4
Mutation method	Inversion mutation
Mutation Rate	0.01

4.3 Module description

In this part, the function of the whole simulation system is divided into small modules and the functions of the different modules are described.

4.3.1 Initialization module

Function description: In this module, all the initialization functions are done including the set-up of the multi-cell model, initialization of user locations, initialization of the coverage of each cell, etc. The flow chart of initialization module is shown in Figure 4.3

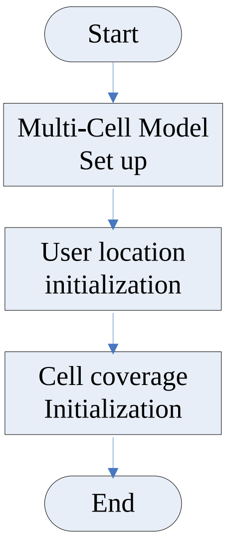

Figure 4.3 Flow chart of Initialization module

4.3.2 Antenna pattern adjustment module

Function description: In this module, antenna patterns of different sectors of different cells are adjusted to solve the coverage and capacity issue. The conception of the sector is introduced below.

Each cell is divided into 3 sectors and each sector contains a 4-element array antenna for pattern forming. By adjusting the excitation of amplitude and phase of the excitation of each identical antenna element, different overall antenna patterns can be realized. The 4-element array antenna has been proposed for OFDMA based systems to enhance the systematic throughput, as described in the literature: [83][84].

Modelling a cell for this work as the sum of the real antenna patters is a complex process so the approach adopted here is to follow that of authors in previous work for WCDMA [18][19], whereby the optimisation is performed on a discrete model and then if necessary the real antenna patterns can be fitted to that discrete model.

Figure 4.4 shows how the discrete model is set up with the circular radiation pattern being considered as a set of *slices* – the length of that slice depending on the amplitude of the radiation. The terminology used here follows, but is slightly different from that of Yao [20], because the term *sector* has a specific meaning here in terms of the number of sectors per cell, rather than part of the discrete model. The circular frontier (outer reach) of each cell is defined by the maximum outreach of its radiation patterns. The whole cell is divided into 3 sectors and in each sector there are four 30° slices. Note that the number of slices is not directly related to the number of antenna elements – more antenna elements give more degrees of freedom to fit the discrete model. In previous work, smaller slices have been used – for example Lin Du [19], used 5-degree. Each slice consists of segments and it is the excitation of these segments that defines the modelled radiation pattern.

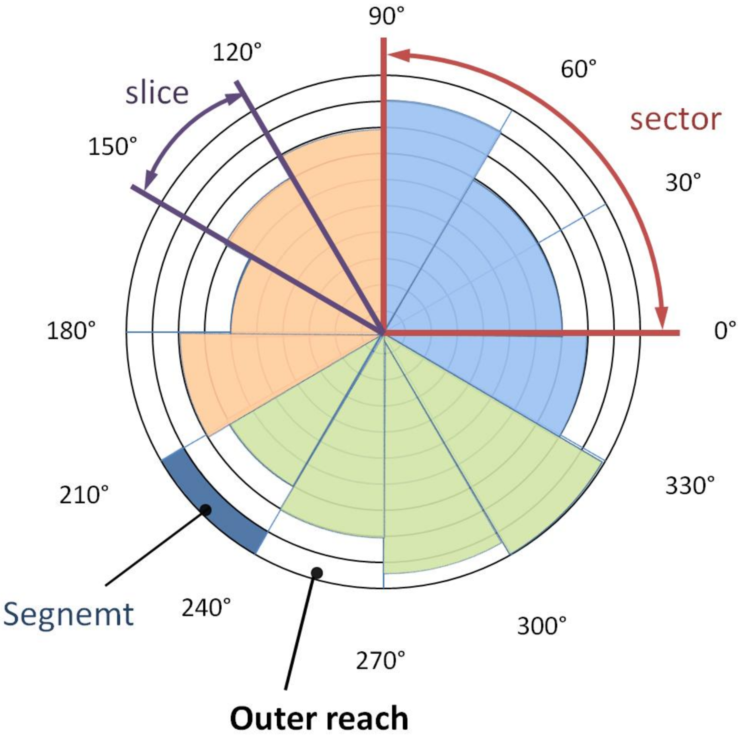

Figure 4.4 Pattern forming by adjustment of the antenna elements

4.3.3 Channel module

In wireless communication systems, the channel model selected plays an important role since it can significantly influence systematic performance. In this section, the pathloss model and fast fading model are considered and they are implemented in the channel module for the OFDMA simulator.

Pathloss model

The pathloss models commonly used for wireless communication systems are the Hata Okumura model [85], the COST-231 model [86] and the IMT-2000 model [87]. The COST-231 model is widely used in Europe for GSM 1800-MHz system. The COST-231 is one of the models anticipated to be used for LTE channel prediction [53].

The COST-231 model covers frequencies from 800MHz to 2 GHz, and the distance from the end users to base stations can vary from 20m to 5km. The pathloss is given by:

$$L_P = 32.4 + 20\,log(d/km) + 20\,log(f_c/MHz) + L_{rts} + L_m \tag{4.1}$$

where L_{rts} stands for rooftop to street diffraction and scatter factor, while L_m denotes the multi-screen loss and d stands for the distance between the mobile users and eNB. f_c denotes the carrier frequency in MHz. Formulas for these two factors are given by:

$$L_{rts} = 10\,log(f_c) + 20\,log\left(\frac{\Delta h_{Mobile}}{m}\right) + L_{\emptyset} - 10\,log\left(\frac{w}{m}\right) - 16.9 \tag{4.2}$$

$$L_m = L_{BS2B} + K_a + K_d\,log\left(\frac{d}{km}\right) + K_f log\left(\frac{f_c}{MHz}\right) - 9log\,(\frac{b}{m}) \tag{4.3}$$

Where h_{Roof} denotes the average height of buildings, h_{Mobile} stands for the height of the mobile devices. w stands for street width, b is the distance of adjacent buildings, $L_{\emptyset}$ is the loss due to incident angle of the street, and L_{BS2B} gives the loss due to the different between BS height and the height of buildings. All the parameters are given as below:

$$L_{\emptyset} = \begin{cases} -10 + 0.354\emptyset, & 0 \le \emptyset \le 35° \\ 2.5 + 0.075(\emptyset - 35), & 35° \le \emptyset \le 55° \\ 4 - 0.114(\emptyset - 55), & 55° \le \emptyset \le 90° \end{cases} \tag{4.4}$$

$$L_{BS2B} = \begin{cases} -18\,log\left(1 + \frac{\Delta h_{Base}}{m}\right), & h_{Base} \ge h_{Roof} \\ 0, & h_{Base} < h_{Roof} \end{cases} \tag{4.5}$$

$$K_a = \begin{cases} 54, & h_{Base} > h_{Roof} \\ 54 - 0.8\frac{\Delta h_{Base}}{m}, & d \ge 500m, h_{Base} \le h_{Roof} \\ 54 - 0.8\frac{\Delta h_{Base}}{m}\frac{d/km}{0.5}, & d < 500m, h_{Base} \le h_{Roof} \end{cases} \tag{4.6}$$

$$K_d = \begin{cases} 18, & h_{Base} < h_{Roof} \\ 18 - \frac{15(\Delta h_{Base})}{h_{roof}}, & h_{Base} \ge h_{Roof} \end{cases} \tag{4.7}$$

$$K_f = \begin{cases} 4 + 0.7\left(\frac{f_c/MHz}{925} - 1\right), & midsize\ city/suburban \\ 4 + 1.5\left(\frac{f_c/MHz}{925} - 1\right), & metro\ area \end{cases} \tag{4.8}$$

Here Ø is the incident angle relative to the street. The relationship of the parameters is shown in Figure 4.5.

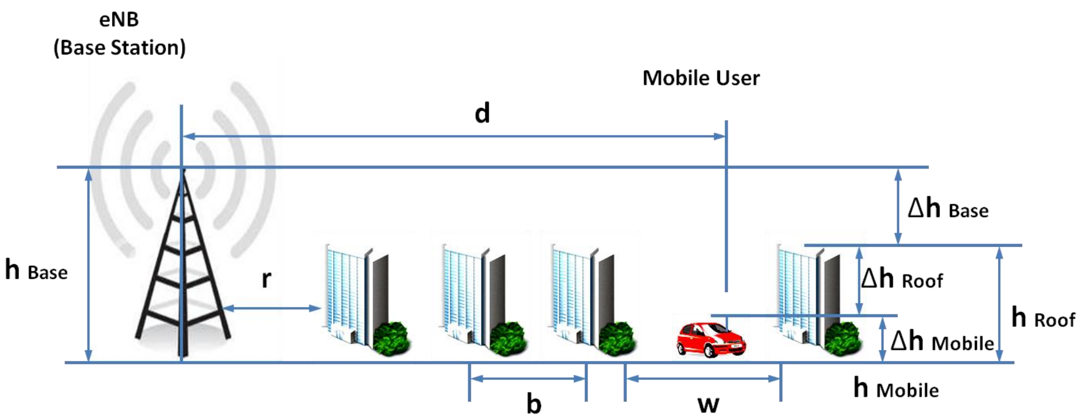

Figure 4.5 Typical propagation situation and definition of parameters[23]

Considering the parameters for the COST formulas, the pathloss model for LTE is described as below [53]:

$$L_p = 35.3 + 37.6 * log\,(d/m) \tag{4.9}$$

Fast fading model

OFDM resists the multi-path effect produced by fast fading; however, this work considers the joint design of radio resource allocation combing the subchannel allocation together with the sectorisation, so that a fast fading model is needed for the simulator.

When considering the fast fading model, a line of sight environment is considered. The fast fading will obey a Rician distribution [54]. The Rician factor is defined by 3GPP in literature [88] as KR = 13-0.03*d (dB), where d is the distance between the user and eNodeB.

4.3.4 Radio resource allocation module

In this module, radio resource allocation is done step by step. First, power consumption of each sector of each cell is calculated according to the output of the

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[23] Figure 4.4.1 from reference [86]

antenna adjustment module. After that, the SINR is calculated according to the channel model, the transmission power of the BS and interference from the adjacent BSs. The capacity of each user and the whole system is calculated based on the power and SINR. The flow chart of radio resource allocation module is shown in Figure 4.6.

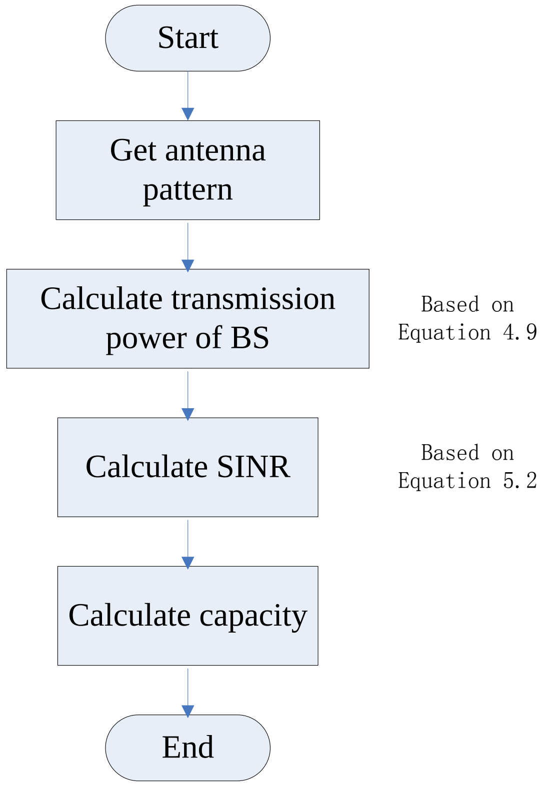


Figure 4.6 Flow chart of radio resource allocation module

4.3.5 Genetic Algorithm module

This module implements the GA as described in Chapter 3. The GA module consists of encoding function, selection function, cross over function and the mutation function, which will be described in detail in Chapter 5. Detailed GA function design and relevant parameters of GA are listed in Chapter 5, Chapter 6, Chapter 7 and Chapter 8.

4.4 Summary

In this chapter, the simulator used in this thesis for the LTE OFDMA system is described and the whole system is divided into several sub-modules including initialization module, antenna pattern adjustment module, coverage calculation module, channel model, SINR calculation module, capacity calculation module and GA module. Each module is investigated and introduced in detail. Simulation work of Chapter 5, Chapter 6 will be based on the architecture described in this Chapter. Work of Chapter 7 and 8 added new modules such as wrap around module and scheduling module which will be described in those two Chapters.

Chapter 5 Genetic Algorithms for optimising antenna patterns

5.1 Introduction

In LTE systems, the cell edge users will suffer more interference from adjacent cells; as a result, the QoS of cell edge users may not be guaranteed or the interference may be so severe that they may not even be served.

Dynamic sectorisation has been investigated to solve the coverage problem and the throughput issue of 3G cellular network [19][20]. In this chapter, dynamic sectorisation based on GA is investigated to solve the coverage and throughput issue by optimising semi-smart antenna patterns.

5.2 Coverage issue based on GA

As discussed in Chapter 2, dynamic sectorisation can be realized by the use of semi-smart antennas [18][19][20] for WCDMA cellular networks. In this part, a GA based coverage solution is investigated for OFDMA networks.

5.2.1 Encoding for GA

There are several encoding methods for GA. The binary string encoding is the basic encoding method and the most close to simulating the encoding procedure of the natural chromosome. Also, real encoding GA has been widely used recently [23][24]. For this research, the binary string encoding is chosen as the encoding method as it can be easily used to provide a distributed solution for GA. The object parameter for encoding is the gain of antennas in various directions. The gain value is shown as $gain = \left[\underset{g_1}{\rightarrow}, \underset{g_2}{\rightarrow}, \cdots \underset{g_n}{\rightarrow}\right]$. Here $\underset{g_1}{\rightarrow}, \underset{g_2}{\rightarrow}, \cdots \underset{g_n}{\rightarrow}$ stands for the gain in the n directions of a certain antenna. When considering different antennas of a cell, the g is described as $GAIN = [gain_1, gain_2, gain_3, \dots gain_m]$, i.e. the gain vector of the m antennas used in one cell. When this idea is extended to a multi-cell model, there is a gain vector of cells $G = [GAIN_1, GAIN_2, GAIN_3, \dots GAIN_r]$. Here $GAIN_1, GAIN_2, GAIN_3, \dots GAIN_r$ stands for the gain vector of the r cells.

5.2.2 Selection of GA

For the selection part, a distributed fitness function is used to select the best fit offspring of the GA with a certain selection rate described in Equation (5.1)

$$f_i(n,i) = \sum_{r=1}^{R} Served_{ir}(n,i) \tag{5.1}$$

Here $f_i\ (n,i)$ shows the fitness condition of the n^{th} individual of the GA and R stands for the number of sectors in each cell. Parameter i represents the sequence number of the cell and r stands for the sequence number of the sector. $Served_{ir}(n,i)$ calculates the total number of users covered by a certain antenna pattern of one cell. By this distributed selection procedure, a certain amount of individuals will be selected according to the selection rate and the fitness condition of it. Selection rate in this chapter is chosen as 0.4 as explained in Chapter 4 and the influence of selection rate on the GA is researched in Chapter 6.

5.2.3 Crossover procedure of GA

There are several methods for crossover in GA such as Simple Crossover, Two-point crossover, Uniform crossover, Arithmetical crossover [25]. In the simulator described in this thesis, the refined simple crossover is used. As the chromosome of genome is short, randomly selected one point crossover is used for the crossover procedure. The probability of crossover of one pair of genome is chosen from 25%~67%. Each pair of parents will generate only one child. This follows the OGM described in Section 3.3.2, which is commonly used for GA simulations [57][58][59].

5.2.4 Mutation Procedure of GA

Several papers deal with the influence on the probability of mutation on GA [26][27]. Mutation provides the incidental change on chromosome of genomes to bring new probability for the whole population. In this research, a mutation rate of 0.01 is chosen for simulation as explained in Chapter 4. The influence of mutation rate on the GA is investigated in Chapter 6.

5.3 Capacity issue based on GA

5.3.1 System model

In LTE systems, by the use of OFDM, the ICI impact of each subcarrier is reduced so that the fading on each sub channel can be seen as flat fading. With the assumption that all the users are fixed, the Doppler effect and inter channel interference (ICI) can be ignored, the SINR of sub channel j transmitted by BS i can be described as below [101][102].

$$SINR_{i,j,k} = \frac{G_{i,j,k}P_{i,j,k}}{N_{i,j,k} + \sum_{i' \neq i} G_{i',j,k}P_{i',j,k}} \tag{5.2}$$

In Equation (5.2), $G_{i,j,k}$ represents the channel gain from base station i to user k on channel j; $P_{i,j,k}$ denotes the transmission power from the i^{th} base station on channel j for user k. Here i represents the cell being considered and i' is an interfering cell. $\sum_{i' \neq i} G_{i',j,k}P_{i',j,k}$ is the total interference from adjacent base stations of user k on channel j. $N_{i,j,k}$ denotes the AWGN of user k located in i^{th} base station on the j^{th} channel.

5.3.2 System capacity

By the use of Equation (5.2), the SINR for a certain subcarrier can be calculated. If the number of subcarriers is large enough and considering that the fading of different subcarriers are independent, the equation can be seen as a Gaussian process.

According to Shannon's channel capacity theory, the capacity of a certain channel can be described below by Equation (5.3)

$$C_{i,j,k} = \frac{1}{2} log\left(1 + SINR_{i,j,k}\right) \tag{5.3}$$

If it is assumed that the BS has a maximum amount of transmission power P, it can be shown in Equation (5.4).

$$P_{i,j} \leq P \;\; \forall i, j \tag{5.4}$$

By Equation (5.3) and (5.4) that the capacity issue is to maximize the system capacity. In the multi-cell LTE OFDM system, no centralized management of central station is given, so all the BSs has the same priority. Thus the problem tends to be maximize the total capacity of the whole network shown in Equation (5.5).

$$\begin{gathered} max \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \frac{1}{2} log\left(1 + SINR_{i,j,k}\right) \\ P_{i,j,k} \leq P \;\; \forall\, i, j, k \end{gathered} \tag{5.5}$$

Here I stands for the total number of base stations, J stands for the total number of channels and K is the total number of users.

5.3.3 Fitness function design

The GA algorithm design for the capacity issue is almost the same as for the coverage issue. The encoding, crossover and mutation are similar as described in Section 5.2. However, the fitness function design is different.

To solve the capacity problem, as investigated in Secrtion 5.3.1 and Section 5.3.2, the aim is to maximize the capacity of the whole network. Considering the R sectors in each of the cell, the fitness function for the capacity issue is listed as Equation (5.6).

$$f_i(n, i) = \sum_{j=i}^{J} \sum_{k=1}^{K} \sum_{r=1}^{R} \quad C_{i,j,k}(n, i) \tag{5.6}$$

Here f_i *(n)* shows the fitness condition of the n^{th} individual of the GA, R stands for the number of sectors in each cell; i stands for the sequence number of the cell and j

stands for the sequence number of sector while k stands for the sequence number of the users. By this distributed selection procedure, a certain amount of individuals will be selected according to the selection rate and the fitness condition.

5.4 Combination design of coverage and capacity

During the deployment of the novel OFDMA based multi-cell networks, problems may arise such as gap between different antenna patterns or limitation of available subchannels – all of which makes radio resource management a challenging topic for OFDMA based networks. Optimisation of coverage, throughput, subchannel allocation and power consumption are all objectives needing optimisation in the network. In this part the multi-objective optimisation is considered.

In general, many problems emerging from engineering and science are multi-objective problems [55][111]. In general, the multi-objective optimisation problems contain a number of goals and constraints: as each goal is always conflicted, it is difficult to solve these multi-objective optimisation problems. In practical projects, it is generally required to provide a lot of reasonable solutions to provide choice to the decision makers. From this point of view, it is necessary to design a convenient and robust algorithm for the multi-objective problems [56].

As the sub-objectives of a multi-objective optimisation problem often conflict with each other, the performance improvement of one sub-objective may lead to performance degradation of another sub-objective, so that there usually does not exist an absolute optimal solution to the sub-objectives. In such a situation, it is important to coordinate and compromise with the sub-objectives. The concept of a Pareto optimal solution [57][58] is introduced to the multi-objective function, in which lots of Pareto optimal solutions are given, so that the key point to solve the multi-objective problems is to find a set of Pareto optimal solutions.

An example of multi-objective optimisation problem is shown in Equation (5.7)

$$f(x) = (f_1(x), f_2(x), \dots, f_m(x)) \tag{5.7}$$

where $x \in R^n$, $x = (x_1, x_2, \dots, x_n)$, $x_i \in [a_i,\ b_i]$, is the decision vector, while $f(x) \in R^m$ is the objective vector.

Solutions for the coverage and capacity issue are described in Section 5.6.1 and 5.6.2 respectively; however when considering the real situation, it is necessary to consider both the coverage and capacity. In this part the combination design of the coverage and capacity issues is investigated. As an absolute optimisation of all the $f(x) \in R^m$ usually does not exist, a solution is considered as a Pareto optimal solution as described below.

- Definition 1 (Pareto dominance [59]): A given objective vector $u = (u_1, u_2, \dots, u_m)$ is said to dominate $v = (v_1, v_2, \dots, v_m)$ $(u \geq v)$ if and only if u is partially less than v, as shown in Equation (5.8) and (5.9).

$$\forall i \in \{1, \dots, m\}, u_i \leq v_i \tag{5.8}$$
$$\exists i \in \{1, \dots, m\}, u_i < v_i \tag{5.9}$$

- Definition 2 (Pareto optimality): A solution $x_u \in [a,\ b]$ is said to be Pareto-optimal if and only if there is no $x_v \in [a,\ b]$ for which $v = f(x_v)$ dominates $u = f(x_u)$.

GA models are described as in Equation (5.1) and (5.2). When considering the combined design, the main issue is to design the fitness function. Different from the fitness functions used in 5.1 and 5.2, a multi-objective fitness function is designed for the combined design as shown in Equation (5.10).

$$f_i(n,i) = \sum_{j=i}^{J} \sum_{k=1}^{K} \sum_{r=1}^{R} C_{i,j,k}(n,i) + \alpha \times \sum_{r=1}^{R} Served_{ir}(n,i) \tag{5.10}$$

By using Equation (5.10), the GA is able to select individuals with good character of capacity and coverage. This algorithm will make balance between capacity and coverage by adjusting parameter α. Here as the results of capacity and coverage are of different magnitude, a balance has to be made between the two issues to realize the design of a multi-objective fitness function. The rage of α is investigated and test in Chapter 7.

5.5 Initialization

Before any simulation can take place, initial patterns have to be generated. In this work, the initial antenna patterns of the 7 cells are randomly generated. One of the simulated results of the initialization of the system is shown in Figure 5.1.

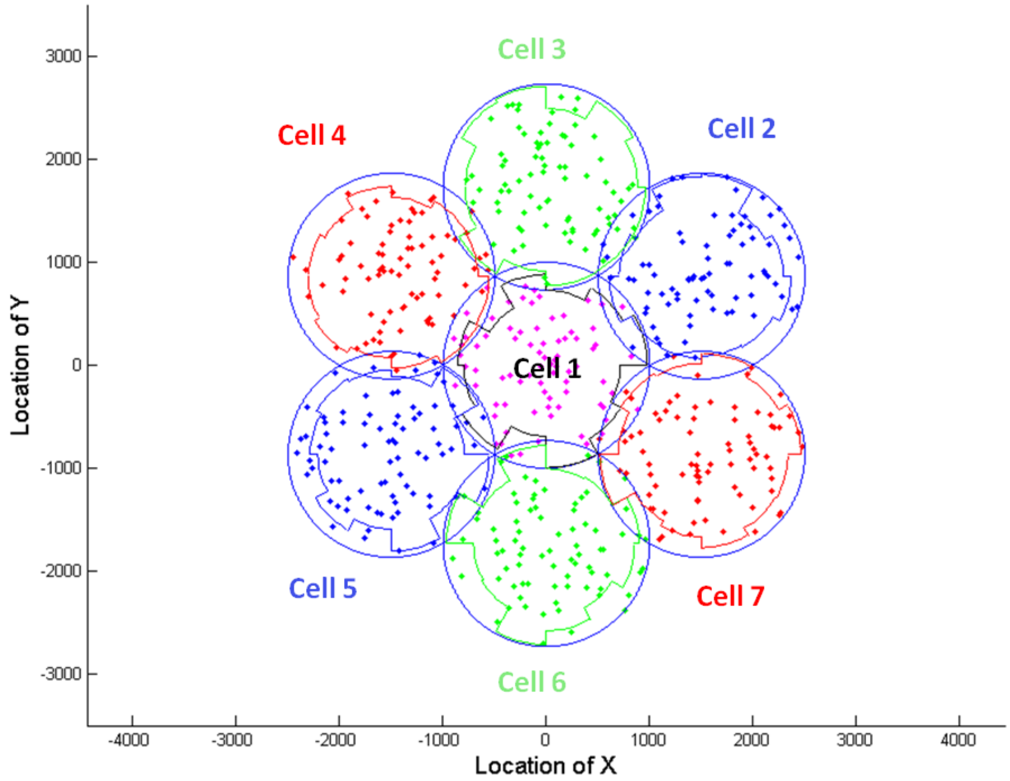


Figure 5.1 Initialization of 7-cell LTE model

Here, in the figure, the blue circle describes the range of the 7 cells and the coloured outline represents the initial pattern for that cell. Users are shown as dots, the colour showing which cell they would be in if the cell radius was the full range.

Figure 5.2 describes the service information of 7 cells with the colour for each user changed according the judgment of the coverage conditions of all the 7 cells. The colour of the dot indicates which cell it is served by – users coloured black are not served at all because they are in "gaps" of coverage.

The fitness of a certain pattern depends on how well it serves all users.

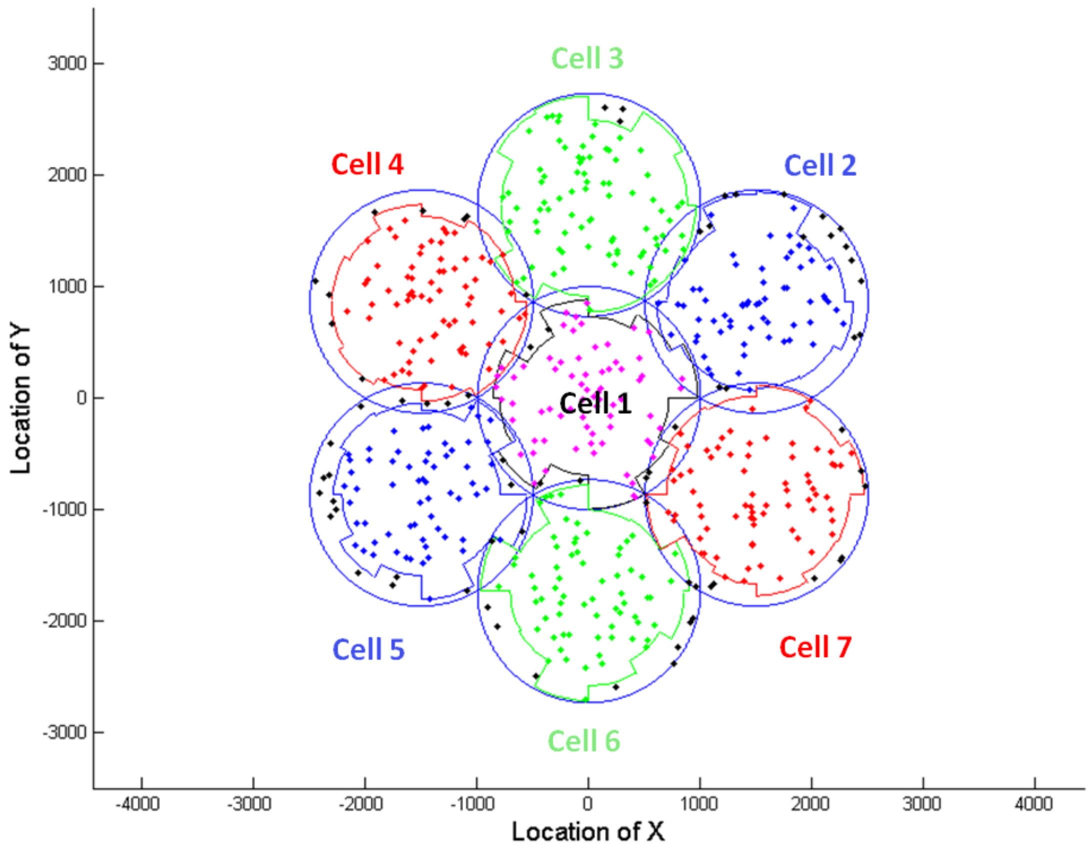


Figure 5.2 Served conditions of 7-cells

Each user has specific information defining their attachment to the network: (i) location, (ii) attached cell, (iii) slice and (iv) segment. The network will also know the overall load and proportion of served users. This can be determined by cell and by slice as illustrated in Figure 5.3.

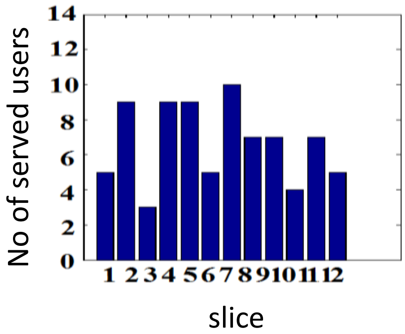


Figure 5.3 Example distribution of users served

5.6 Simulation results

5.6.1 Coverage

As explained previously, the whole simulation of GA consists of encoding, selection, crossover, and mutation procedures. The parameters for the GA are shown in Table 4.2.

In the simulation, for simplicity, a population size of 50 is chosen; 70 generations of the multi-objective GA are simulated for the combination of capacity and coverage. A crossover rate of 0.4 and a mutation rate of 0.01 are chosen. It is assumed that the radius of a particular slice can be adjusted from 600m to 1100m.

Figure 5.4 shows the first offspring of crossover with and Figure 5.5 that of the best individual of that generation.

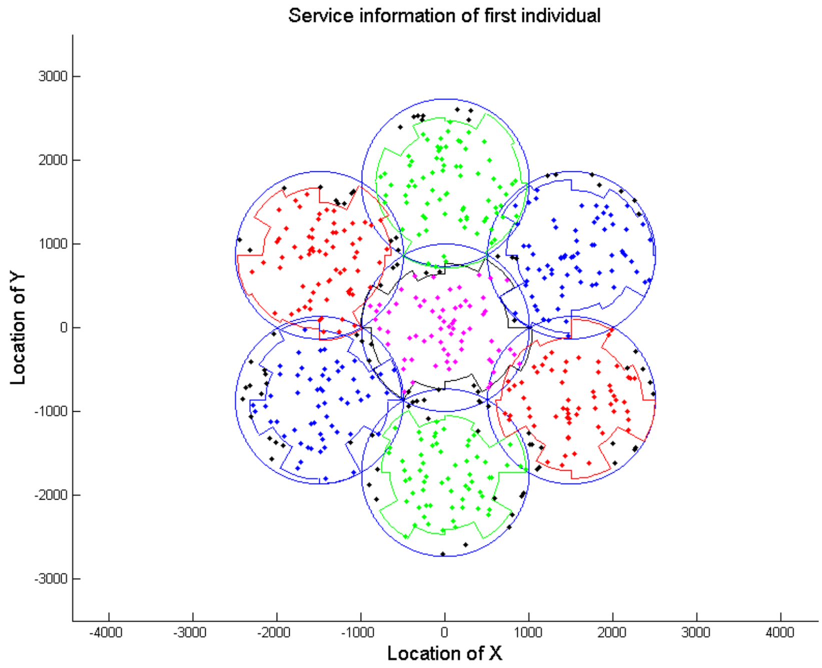


Figure 5.4 Service information by the first pattern generated by GA

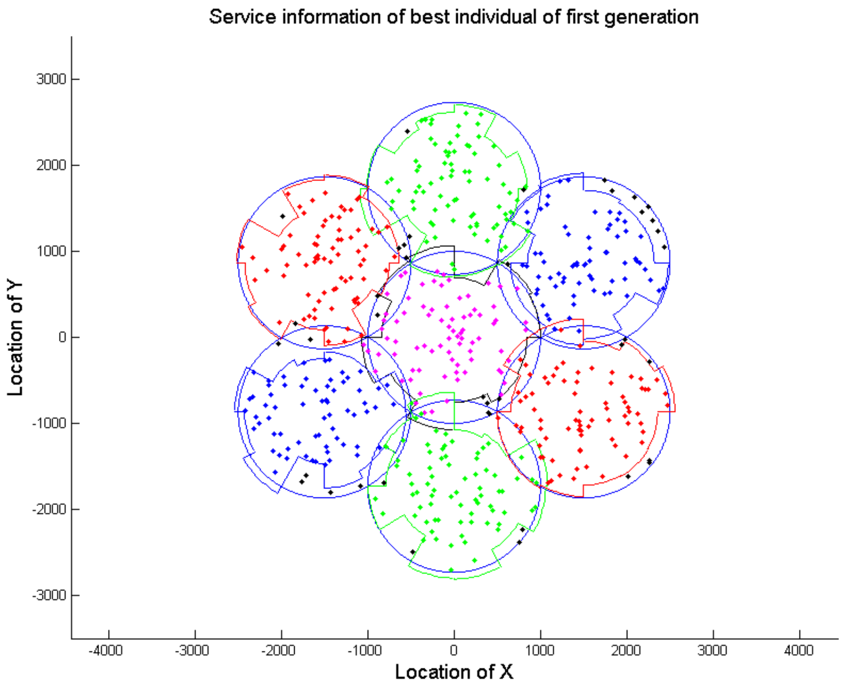


Figure 5.5 Service information of most fit offspring of the first generation

The antenna pattern of the best individual different generations is shown in Figure 5.6. From the figure it can be seen that with the growth of generation, the black dots standing for users that are not served become fewer which means gaps between antenna patterns are decreasing.

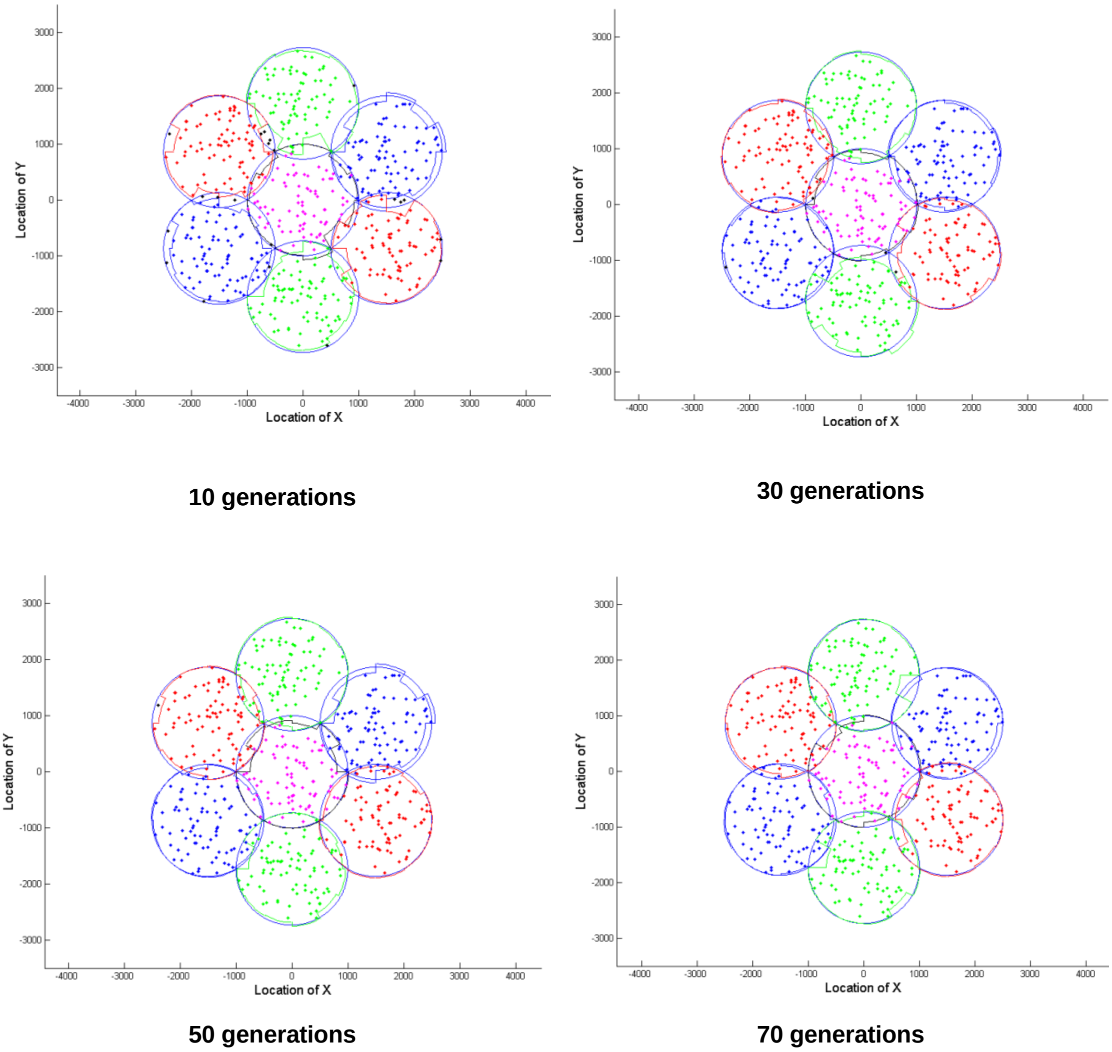
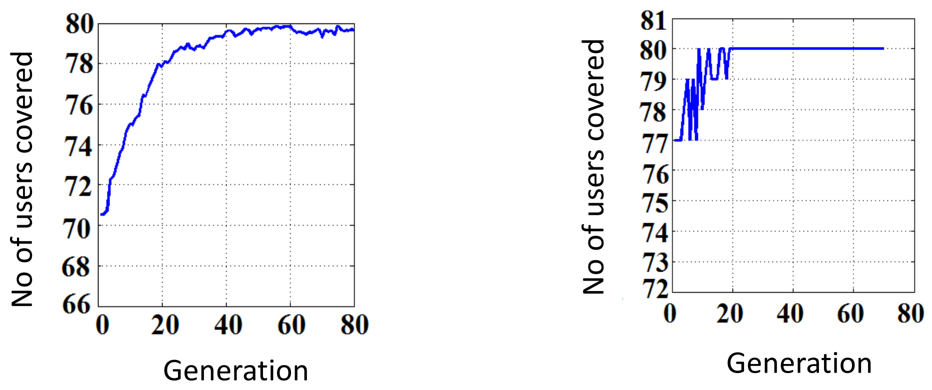


Figure 5.6 Antenna patterns after different generations

However, while looking at antenna patterns shows how they are changing, it does not provide any information on the capacity of the network or of the number of users being served.

The 7-cell model being used for the simulation model does not have wrap-round but this purpose that does not matter since the interest is on the centre cell and how it interacts with the surrounding cells to maximise coverage and capacity. So, in this section, to show the way in which the GA is working, only the centre cell (cell 1) will be considered.



(a) Average over all offspring **(b) Best offspring in each generation**

Figure 5.7 Coverage within cell 1 by generation

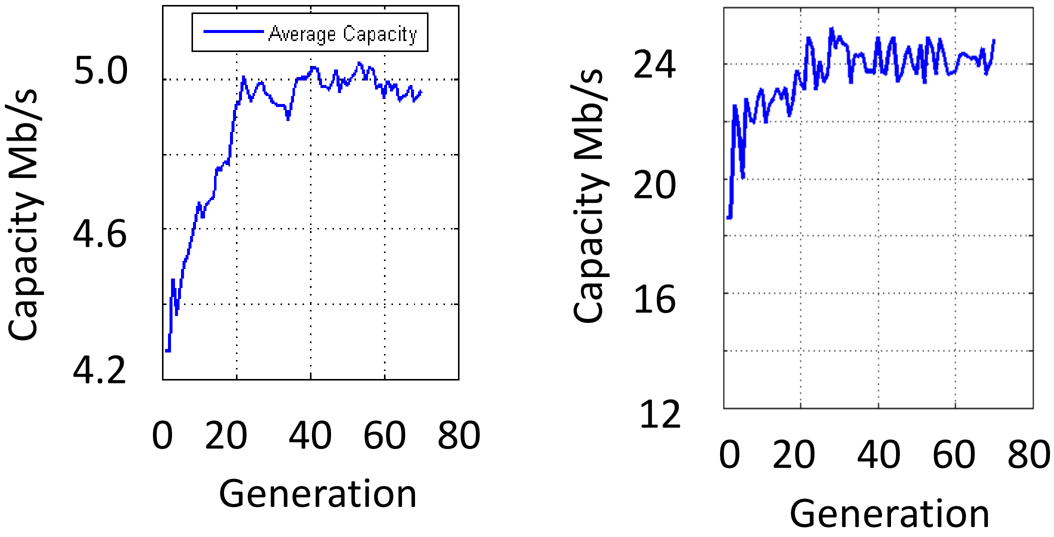
Figure 5.7(a) shows the average coverage for cell 1 of all the individuals by generation: it can be seen that the average coverage grows with heredity from generation to generation and tends to a maximum around the 50^{th} generation with following generations fluctuating around 78. However, the average coverage never reaches the total number of 80 as during each generation there is random cross over and mutation that may generate degraded individuals.

The coverage from the best offspring is shown as a function of generation in Figure 5.7(b). Here, the individual with the best coverage is selected and plotted: this time the best coverage individual meets the maximum number of coverage of 80 users and the phenotype keeps that value afterwards.

5.6.2 Capacity

The GA parameters used for simulation are the same as introduced earlier.

Figure 5.8 (a) shows the average capacity of each individual within cell 1 as a function of generations; Figure 5.8 (b) shows the capacity resulting from the best individual. Clearly the best offspring leads to much greater capacity – 23Mbps instead of the 4.6 Mbps average,



(a) Average over all offspring **(b) Best offspring in each generation**

Figure 5.8 Capacity within cell 1 by generation

5.7 Summary

This chapter introduced the GA algorithm as a tool for optimising smart antenna patterns considering both the issues of coverage and capacity. Simulations show that the results converge at around 50 generation for both the optimisation of coverage and of capacity – and that the results of the best offspring are very good indeed.

Chapter 6 GA algorithm optimisation

6.1 Introduction

As explained in Chapter 3, a GA is a kind of artificial intelligence machine-learning algorithm focusing on giving optimal or sub-optimal solutions to a certain problem. The GA itself can be divided into several procedures and each of the procedure consists of many functions or methods so that how to set up all the functions and choose all the parameters to get better performance of GA is of great importance. Also, as described in Chapter 3, a GA consists of several procedures such as selection and mutation, so that the robustness of the GA algorithm should be taken into account. This chapter mainly focuses on the optimisation of the GA algorithm and robustness design of the GA.

6.2 GA optimisation

GA optimisation has attracted a lot of research interest in recent years. Lots of new mechanisms, parameter control methods and combination with other evolutionary algorithms have been investigated intensively.

Li Juanhuan, et al have proposed a genetic algorithm with dual species (DSGA) [60]. In their work, by using two different isolated species of individuals, different parameter setups are used. One of the subpopulations emphasizes local exploitation ability while the other subpopulation focuses on global exploration ability. The results show outperformance over standard GA.

A two-stage genetic algorithm has been investigated by Yongming Wang et al [61]. In their work, the GA is divided into two stages: (i) a group of candidate parameters is setup and compared to find the fittest control parameters during a fraction of the time (ii) the fittest control parameters produce an efficient solution that can lead to the optimum solution faster and avoid the solution becoming trapped in local optima.

S. Ghoshray and K.K. Yen have introduced a Modified Genetic Algorithm (MGA), a refined genetic algorithm that efficiently combines simple genetic algorithms with simulated annealing. The results show that the MGA they proposed can provide more efficient search heuristics for solving various optimisation problems. Also, their results are more precise compared with classical GA [62].

A kind of adaptive immune genetic algorithm has proposed by Weijian Ren, Qiong Wang, Wei Lv, et.al [63]. In their work, the immune genetic algorithm, which is a combination of a genetic algorithm and biological immune thinking, is investigated. Their algorithm is used to solve the Travelling Salesman Problem (TSP) and simulation results show better adaptability with increasing size.

All the above research contributes to a new function design or combination of GA with other heuristic algorithms. However, in some sense, developing efficient techniques that identify which algorithm or which control parameter of the same algorithm performs well under which specific conditions is at least as important as developing new algorithms [61].

Work in this chapter mainly focuses on the robust and optimized parameter setup of the GA designed for OFDMA network resource allocation.

6.3 Robustness design of GA

The robustness of GA is investigated and verified through simulation in this part of the thesis. The robustness of GA is whether the randomness of GA may influence the performance of GA in giving optimal solution to the radio resource management of OFDMA based wireless network systems. Actually, the stability of the GA is one of the main problems when facing actual use [66]. To verify the effect of the evolution route of the GA, the same first generation individuals are used for each comparison in the simulation.

6.3.1 Robustness of coverage

6.3.1.1 Robustness based on average capacity

Distributed average coverage of the system based on 5 runs is shown in Figure 6.1. As can be seen from the figure, the results of 5 runs group together and there is not much difference in the results. All of the 5 runs get to the maximum coverage at about 30 or 40 generations, and fluctuate around the maximum value afterward. Converge in the work of this thesis is defined as the state where the result remains within 5% of the maximum (or minimum for the user unfairness measure). No obvious degradation can be found from the figure.

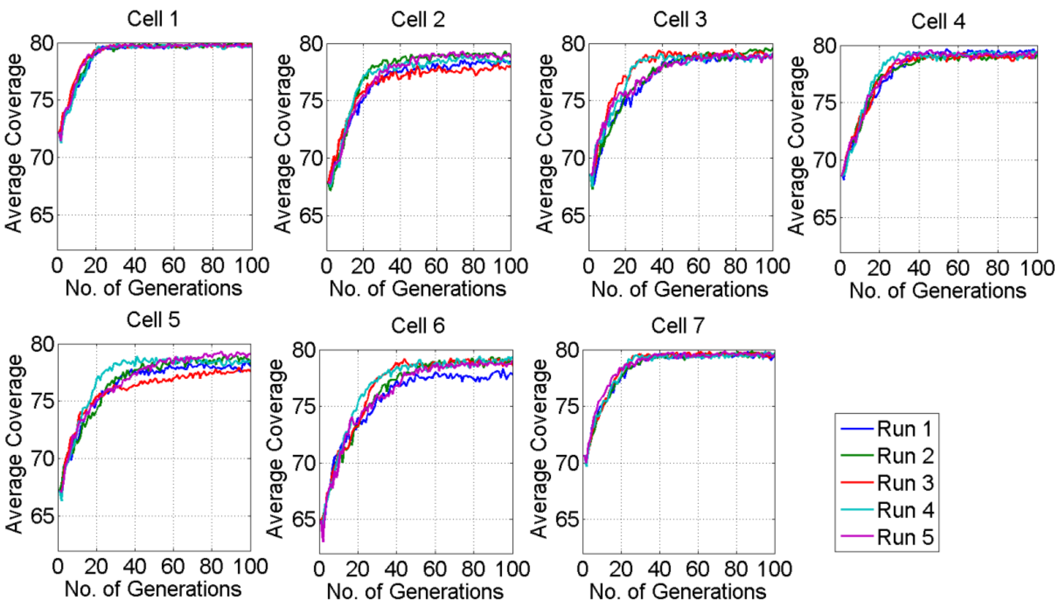


Figure 6.1 5 runs of average coverage-7 cells

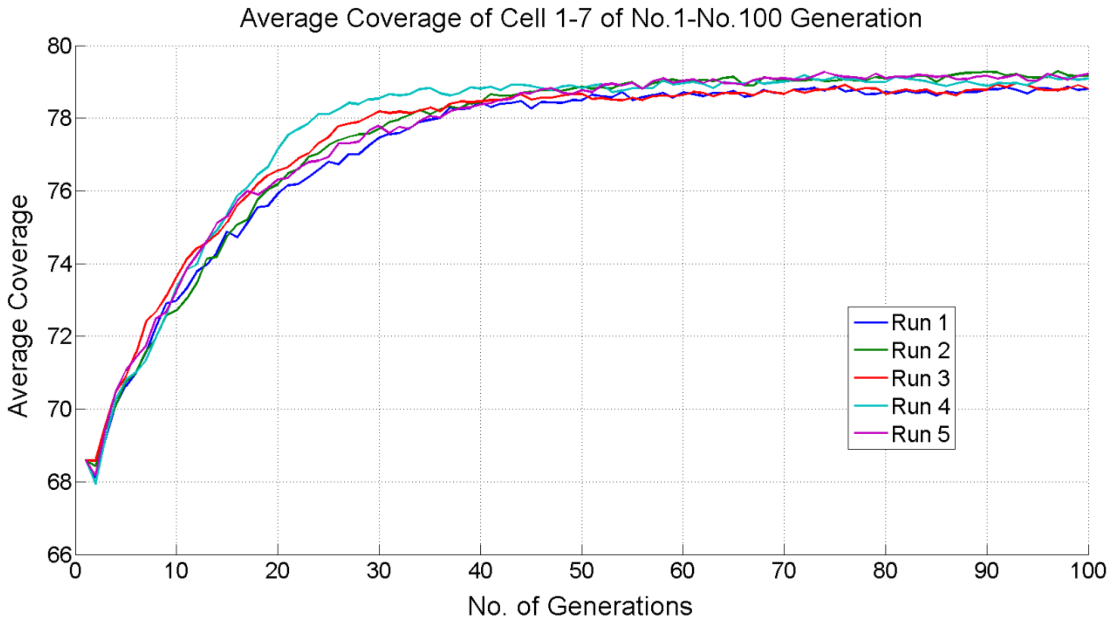


Figure 6.2 5 runs of overall average coverage

Figure 6.2 shows the overall average coverage, that is, the average value of all of the 7 cells with the coverage of all the individuals. The results accord with each other quite well. The simulation results meet the maximum value gradually at around 30th generation and no degradation is witnessed.

Table 6.1 Mean standard deviation of the GA

9	Cell1	Cell2	Cell3	Cell4	Cell5	Cell6	Cell7	Average
1	0	0	0	0	0	0	0	0
2	0.006158	0.007804	0.006116	0.005459	0.007562	0.012764	0.001673	0.003385
3	0.005985	0.007855	0.008584	0.006077	0.007882	0.006633	0.003483	0.002289
4	0.00266	0.006667	0.011421	0.004076	0.003977	0.004137	0.002671	0.002308
5	0.00219	0.005488	0.011382	0.003973	0.004874	0.002224	0.004156	0.002047
6	0.003946	0.005143	0.00928	0.007791	0.005145	0.00335	0.006186	0.003396
7	0.006441	0.011179	0.010479	0.00437	0.008914	0.009017	0.004454	0.00516
8	0.005571	0.006317	0.010749	0.006634	0.008854	0.007037	0.007273	0.003939
9	0.006379	0.008213	0.006589	0.0057	0.002969	0.009298	0.005943	0.002795
10	0.004307	0.003352	0.008894	0.006685	0.007742	0.006471	0.006005	0.004294
11	0.006807	0.008364	0.013438	0.006065	0.010803	0.002865	0.004414	0.005368
12	0.0068	0.003922	0.012417	0.003153	0.009397	0.007538	0.005004	0.004519
13	0.006994	0.00454	0.010692	0.004512	0.007286	0.006009	0.006432	0.00372
14	0.006871	0.004327	0.012109	0.007163	0.007785	0.009302	0.004534	0.004852
15	0.00505	0.006949	0.011097	0.006207	0.006059	0.008847	0.004868	0.003087
16	0.005424	0.008249	0.012287	0.009056	0.006067	0.011125	0.007041	0.005732

17	0.002964	0.010084	0.012906	0.006203	0.007341	0.013885	0.003333	0.005453
18	0.002744	0.007572	0.009433	0.008306	0.00824	0.00835	0.004643	0.004157
19	0.001495	0.009656	0.010612	0.007196	0.01033	0.008115	0.005502	0.004798
20	0.001921	0.010077	0.011245	0.007073	0.011834	0.010459	0.004181	0.005424
21	0.002011	0.010976	0.009254	0.004521	0.011705	0.010315	0.003926	0.006255
22	0.0018	0.007886	0.010522	0.007116	0.009365	0.011879	0.005019	0.006523
23	0.001345	0.010847	0.016207	0.00625	0.009547	0.009376	0.002152	0.006318
24	0.000886	0.008623	0.014574	0.007066	0.009997	0.012507	0.00404	0.006833
25	0.000663	0.008732	0.012955	0.00589	0.009359	0.010605	0.003803	0.006005
26	0.00112	0.006074	0.014213	0.007811	0.009328	0.012166	0.00418	0.00651
27	0.00115	0.007626	0.01214	0.004821	0.01037	0.013988	0.0053	0.006265
28	0.000975	0.00821	0.014807	0.004213	0.008666	0.012387	0.003761	0.006073
29	0.00258	0.007466	0.011829	0.004948	0.011054	0.011253	0.004474	0.005588
30	0.000914	0.005265	0.012861	0.005821	0.009778	0.009091	0.004429	0.004908
31	0.001856	0.00843	0.012865	0.004961	0.009529	0.011782	0.001655	0.00518
32	0.001156	0.007261	0.012135	0.004779	0.009033	0.011113	0.001397	0.004624
33	0.000512	0.006189	0.010252	0.00415	0.010178	0.010965	0.002005	0.004411
34	0.000903	0.006098	0.009654	0.00464	0.010423	0.012227	0.002588	0.00413
35	0.001484	0.003834	0.007381	0.005071	0.010494	0.011617	0.001534	0.003956
36	0.000947	0.005255	0.007667	0.002676	0.010163	0.012368	0.002144	0.003155
37	0.00106	0.005312	0.00863	0.004548	0.009438	0.008043	0.001757	0.001898
38	0.00155	0.00371	0.008765	0.004496	0.008769	0.011035	0.001785	0.002174
39	0.000996	0.007293	0.010157	0.002703	0.009147	0.00954	0.000878	0.002609
40	0.001164	0.006427	0.006579	0.004359	0.007238	0.009825	0.001084	0.002022
41	0.000647	0.007143	0.005175	0.002088	0.010708	0.009499	0.001279	0.002489
42	0.000861	0.006784	0.003404	0.002202	0.008709	0.009751	0.001233	0.001615
43	0.001083	0.006719	0.005928	0.002453	0.006967	0.009005	0.00197	0.002174
44	0.000809	0.004834	0.005802	0.002856	0.008818	0.008927	0.00171	0.001805
45	0.001198	0.007853	0.0051	0.002533	0.008644	0.009536	0.002845	0.002706
46	0.001194	0.00764	0.003085	0.00287	0.008109	0.005963	0.002004	0.001911
47	0.001309	0.006991	0.003999	0.002569	0.008442	0.005549	0.002427	0.001929
48	0.001149	0.006729	0.002582	0.001571	0.006479	0.006057	0.00169	0.001906
49	0.000586	0.004455	0.004296	0.003998	0.009099	0.007267	0.002538	0.001797
50	0.001325	0.004702	0.005253	0.001854	0.006627	0.003368	0.001645	0.001719
51	0.001214	0.008843	0.003301	0.002773	0.00788	0.005897	0.00184	0.001656
52	0.001244	0.00691	0.002813	0.001468	0.008506	0.006908	0.001365	0.002017
53	0.001089	0.006908	0.003621	0.00356	0.009225	0.006204	0.00275	0.002031
54	0.000849	0.007082	0.002704	0.004354	0.008494	0.004574	0.002067	0.001937
55	0.001529	0.007004	0.002463	0.003004	0.008885	0.006384	0.002529	0.002575
56	0.000293	0.005313	0.00171	0.002712	0.008211	0.004092	0.001708	0.001757
57	0.001485	0.006828	0.002412	0.001633	0.009079	0.004721	0.000561	0.002104
58	0.00086	0.006616	0.002801	0.002663	0.008588	0.005651	0.000905	0.002455
59	0.000984	0.006981	0.00182	0.001727	0.00831	0.00645	0.001565	0.00257
60	0.000293	0.006194	0.001327	0.003647	0.007008	0.004118	0.001325	0.002029
61	0.00117	0.005568	0.003241	0.000972	0.007705	0.004363	0.002004	0.002176
62	0.000666	0.005883	0.002069	0.001148	0.007017	0.006759	0.00241	0.002138

63	0.000996	0.008235	0.002799	0.001716	0.007584	0.004904	0.001892	0.002239
64	0.000846	0.00577	0.003681	0.001399	0.007973	0.004988	0.001236	0.002162
65	0.000762	0.006761	0.00293	0.00236	0.006746	0.005367	0.001095	0.002046
66	0.001568	0.00766	0.003109	0.003334	0.007476	0.005388	0.002223	0.001811
67	0.001641	0.008297	0.001908	0.003505	0.008604	0.006002	0.002074	0.002367
68	0.001847	0.007497	0.002029	0.002791	0.007003	0.005981	0.001019	0.002027
69	0.000487	0.007814	0.002461	0.002781	0.005958	0.00716	0.001075	0.002146
70	0.000751	0.006214	0.003012	0.003039	0.008453	0.006604	0.001026	0.002351
71	0.000558	0.006437	0.002478	0.002485	0.006634	0.006194	0.001859	0.001738
72	0.000401	0.007371	0.001979	0.003451	0.006247	0.006552	0.00113	0.002258
73	0.000768	0.007704	0.001081	0.002078	0.005537	0.005444	0.00113	0.001881
74	0.001045	0.007199	0.003673	0.00392	0.008059	0.008754	0.00254	0.002367
75	0.001397	0.005549	0.001701	0.002414	0.006003	0.006911	0.001207	0.001759
76	0.000535	0.006033	0.003186	0.001592	0.006789	0.006275	0.001191	0.001836
77	0.001181	0.006402	0.00353	0.003305	0.007852	0.006662	0.001006	0.001913
78	0.000601	0.006513	0.003568	0.002474	0.006473	0.005858	0.001717	0.001963
79	0.000673	0.005656	0.002246	0.00227	0.006497	0.007685	0.001011	0.002559
80	0.001459	0.006293	0.001946	0.002914	0.00628	0.007031	0.000987	0.002299
81	0.000375	0.009176	0.002757	0.00177	0.006941	0.009047	0.001904	0.002721
82	0.000906	0.007868	0.001933	0.001399	0.006255	0.007071	0.00094	0.002041
83	0.001773	0.006395	0.001961	0.001959	0.007447	0.010232	0.001656	0.00266
84	0.000517	0.005438	0.002237	0.002528	0.007291	0.0067	0.001617	0.002395
85	0.001373	0.006302	0.00297	0.001921	0.008322	0.007312	0.001617	0.002498
86	0.00191	0.005405	0.002575	0.002339	0.007232	0.006835	0.002136	0.002523
87	0.001061	0.005826	0.003162	0.003117	0.00775	0.007553	0.000537	0.002767
88	0.001052	0.006013	0.004453	0.003318	0.005832	0.008024	0.00234	0.002509
89	0.001092	0.007129	0.002928	0.00213	0.006271	0.006475	0.001964	0.002598
90	0.000369	0.006721	0.003067	0.003476	0.007336	0.005816	0.001248	0.002565
91	0.000559	0.005366	0.003946	0.002041	0.007055	0.005306	0.001251	0.002028
92	0.000702	0.004167	0.001668	0.002275	0.006954	0.004717	0.001866	0.001734
93	0.000634	0.00257	0.003845	0.002231	0.007711	0.005714	0.000907	0.002102
94	0.001599	0.004931	0.005119	0.002414	0.006558	0.007648	0.002477	0.001956
95	0.001296	0.00331	0.002169	0.001943	0.007751	0.003631	0.002045	0.001601
96	0.000849	0.004961	0.003701	0.003668	0.006522	0.006136	0.001129	0.002337
97	0.000931	0.00689	0.002778	0.002559	0.006498	0.007867	0.002298	0.002646
98	0.001177	0.004203	0.002902	0.003864	0.00526	0.007247	0.002629	0.001746
99	0.001311	0.005726	0.00346	0.002254	0.005819	0.005599	0.001239	0.001898
100	0.001094	0.004119	0.002881	0.001404	0.006464	0.006808	0.001306	0.002219
Max.	0.006994	0.011179	0.016207	0.009056	0.011834	0.013988	0.007273	0.006833
Min.	0.000293	0.00257	0.001081	0.000972	0.002969	0.002224	0.000537	0.001601

The mean standard deviation of the 5 runs of GA is illustrated in Table 6.1. As the same first generations are used for all the simulation, the standard deviations of the first generation are all 0, which is not taken into account. The figures with blue background show the maximum among generations while figures with green background show the minimum value. From Table 6.1 it can be seen that the standard deviation varied from 0.0005 to 0.016, which is not much difference. That means taking the average coverage into account, the robustness of the algorithm is quite good. Also, the largest value of the standard deviation of the 5 runs takes place from the 13th to 27th generation, before the GA has stabilized and approached the optimum.

6.3.1.2 Robustness based on best coverage

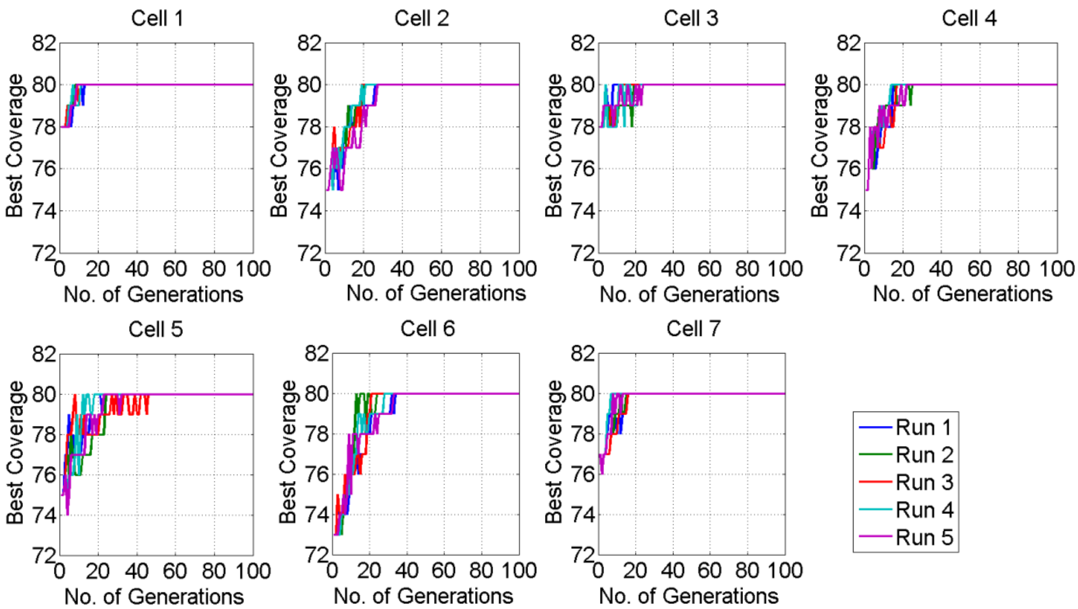


Figure 6.3 5 runs of best coverage-7 cells

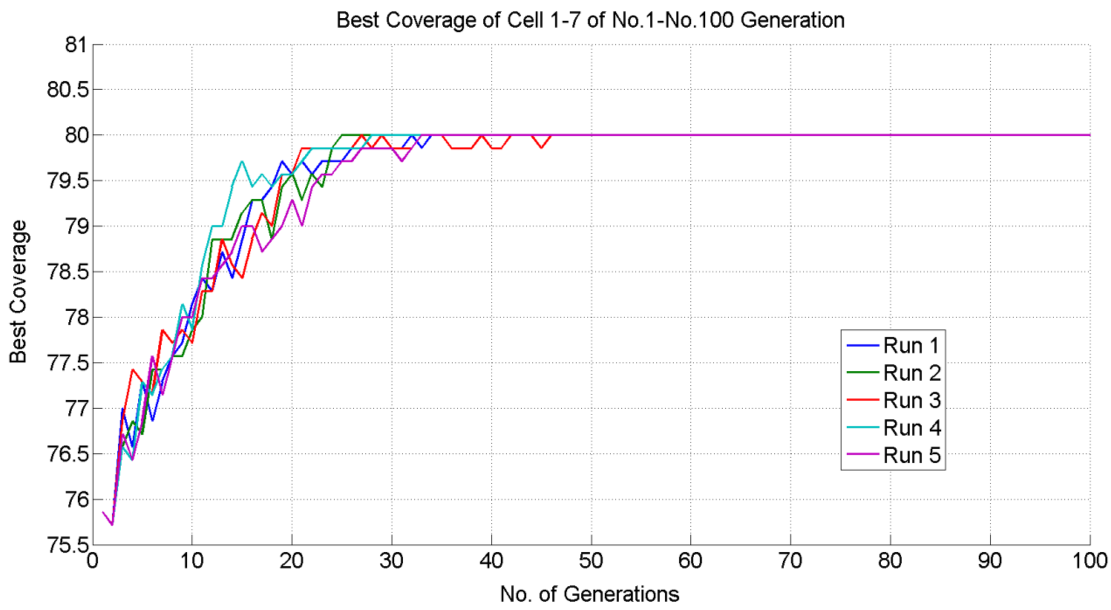


Figure 6.4 5 runs of overall best coverage

The simulation results of 5 runs with best coverage, that is, the results of the individual with maximum number of users served of a certain generation, is shown in Figure 6.3. From the figure it can be seen that that results of 5 runs group together and have very good consistency. All the results meet the maximum number of coverage at around 30th generation and give good performance till the end of simulation.

Figure 6.4 shows the overall best coverage of 5 runs. From the figure it can be seen that the results of 5 runs accord with each other well and all the 5 runs of best coverage gradually increase with the increase of generation and they meet the maximum value at around 35th – 45th generation. There is no obvious degradation in the algorithm.

6.3.2 Robustness of capacity issue

6.3.2.1 Robustness based on average capacity

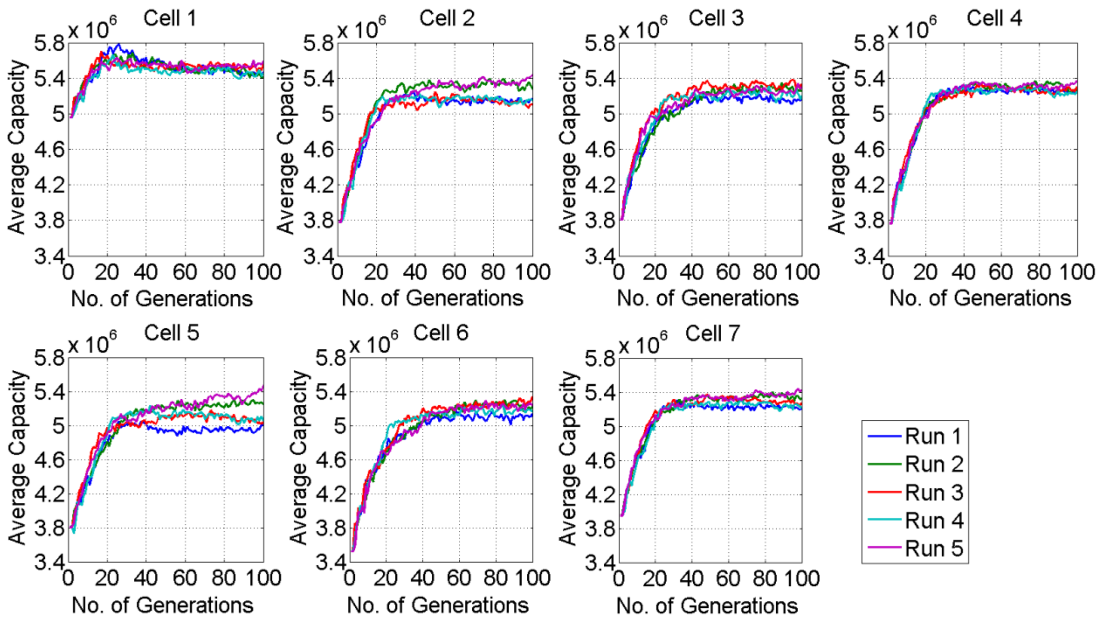


Figure 6.5 5 runs of average capacity-7 cells

Figure 6.5 illustrates the average capacity of 7 cells respectively. As can be found from the figure, all the 5 runs results are very similar and gradually grow with the evolution of generation, meeting the maximum capacity at around 30th to 40th generation, the results fluctuating around the maximum capacity afterwards.

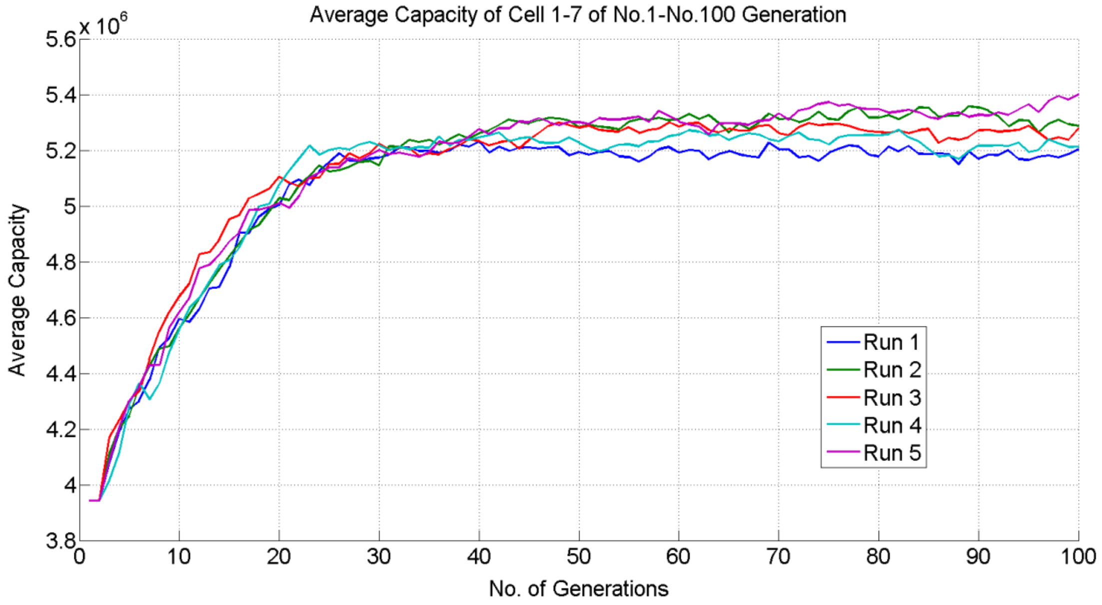


Figure 6.6 5 runs of overall average capacity

The 5 runs of overall average capacity are shown in Figure 6.6. All the 5 runs results follow the same trend and all the results gradually increase with the increase of generations. The results meet the maximum capacity at around 35th generation and fluctuate around the maximum value afterwards.

6.3.2.2 Robustness based on best capacity

Figure 6.7 shows a similar set of results for the best capacity. All the 5 curves group together and they gradually improve with the number of generations. After meeting the maximum value of best capacity at around 30th -40th generation, the results fluctuate around the optimal value. No obvious degradation is witnessed in the simulation.

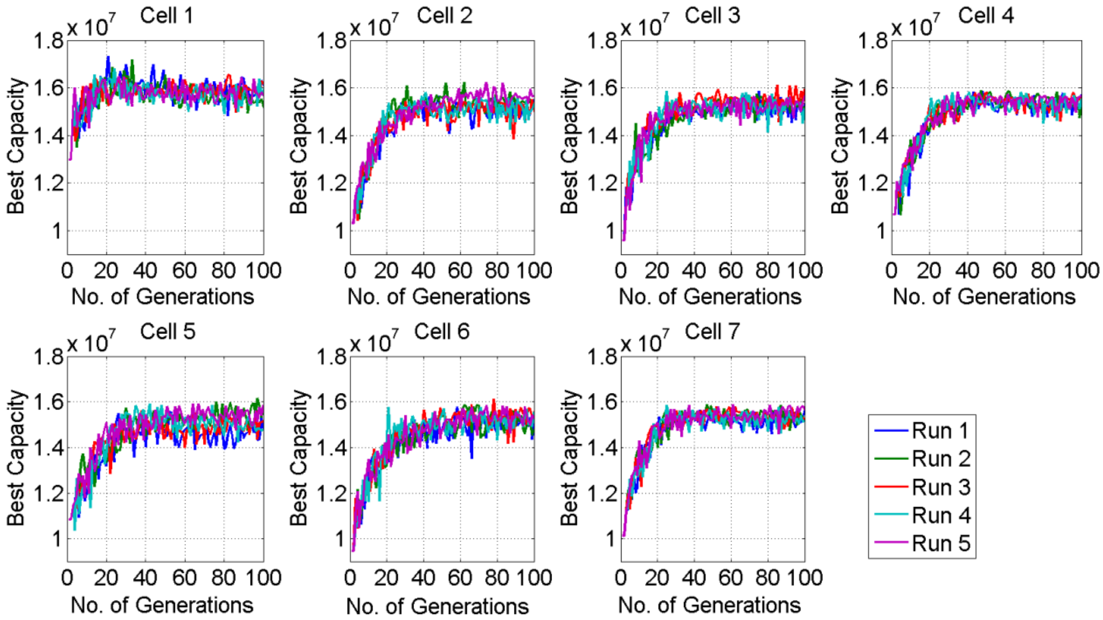


Figure 6.7 5 runs of best capacity - 7 cells

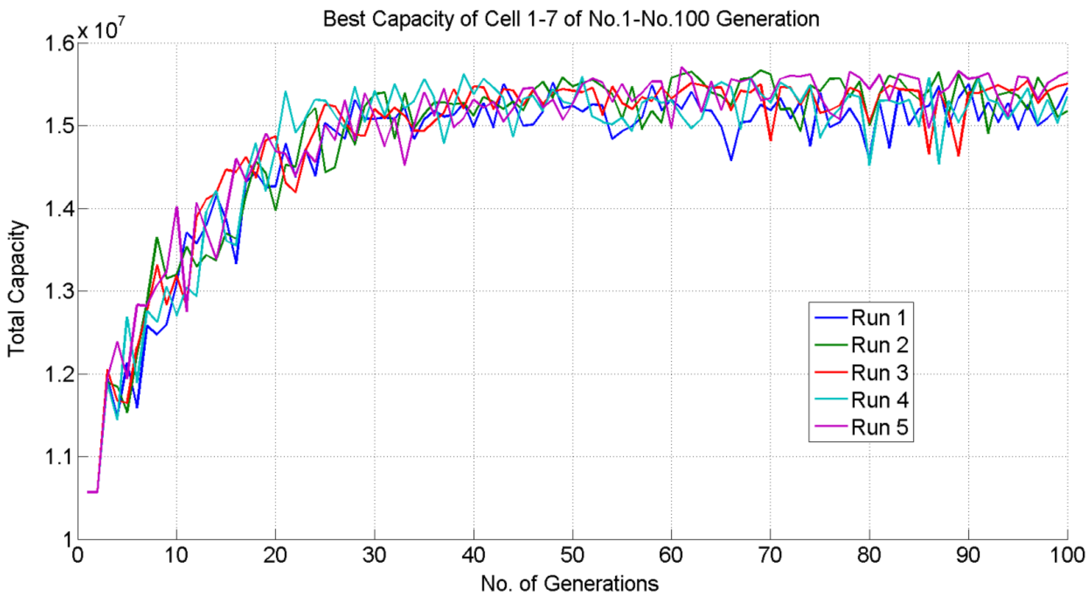


Figure 6.8 5 runs of overall best capacity

Figure 6.8 shows the results for the overall best capacity. The results fluctuate more than the overall average capacity; however, the individual results are similar to each other. All the simulation results meet the maximum value at around the 30th generation and fluctuate around the maximum value afterwards.

From the above results and analysis based on coverage and capacity of GA optimisation, the GA designed in this thesis is robust and steady.

6.4 Influence of selection rate on GA

When designing a GA, the procedures and functions may influence the performance of the GA as there are lots of probabilities of combinations with each setp of GA design. Also, when all the functions are set to a certain method or function, different parameters can again influence the performance of GA. Selection rate is one important parameter in GA design as it can control the constitution of the offspring. In this part, the influence of selection rate on GA is studied and simulation results are given to assess it.

A higher selection rate tends to select more individuals from the population with good genes so that the good genes and performance may be passed onto the next generation: thus it can converge to the optimal solution of a certain problem efficiently. A lower selection rate tends to select fewer individuals from the "good" population, but it may create more possibilities from the new individuals arising from the cross over procedure.

The selection procedure consists of two aspects:

(i) how the parent individuals are selected;

(ii) which offspring should survive to the next generation.

It is clear that the more "elitist" a selection algorithm is, the more a GA behaves like a local search procedure, (i.e. a hill-climber, a "greedy" algorithm) and is less likely to converge to a global optimum [64]. Because of this, in most cases, a strong selection method, (e.g. truncation survival) is combined with a weak parent selection method, (such as uniform parent selection) – this is the approach adopted in this work.

In this part, the selection rate is varied from 0.2 to 0.8 with a step size of 0.2. Different results are compared and analyzed.

6.4.1 Selection rate design based on coverage issue

The average coverage of GA based on different selection rate varied from 0.2 to 0.8 is shown in Figure 6.9. From Figure 6.9 it can be seem that results with selection rate 0.4, 0.6, and 0.8 give almost the same performance; however, the result with selection rate of 0.2 has a low convergence rate. Results with selection rate 0.4, 0.6, and 0.8 meet the maximum value of average coverage at around the 30^{th} to 40^{th} generation while the result with selection rate 0.2 converges to the maximum value at around 60^{th} generation.

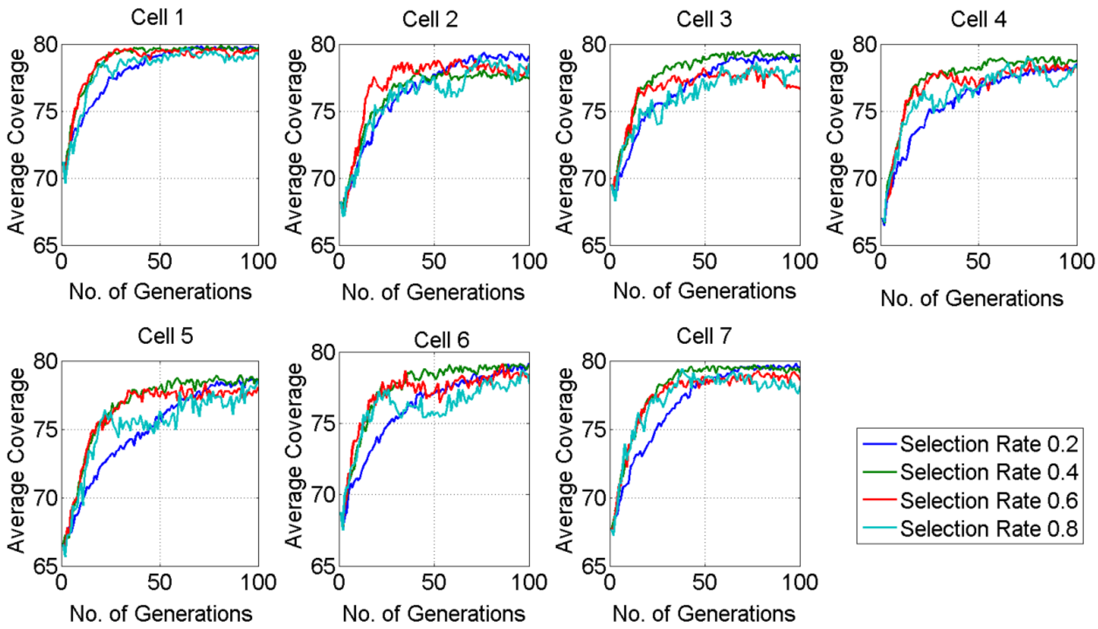


Figure 6.9 Average coverage based on selection rate 0.2-0.8

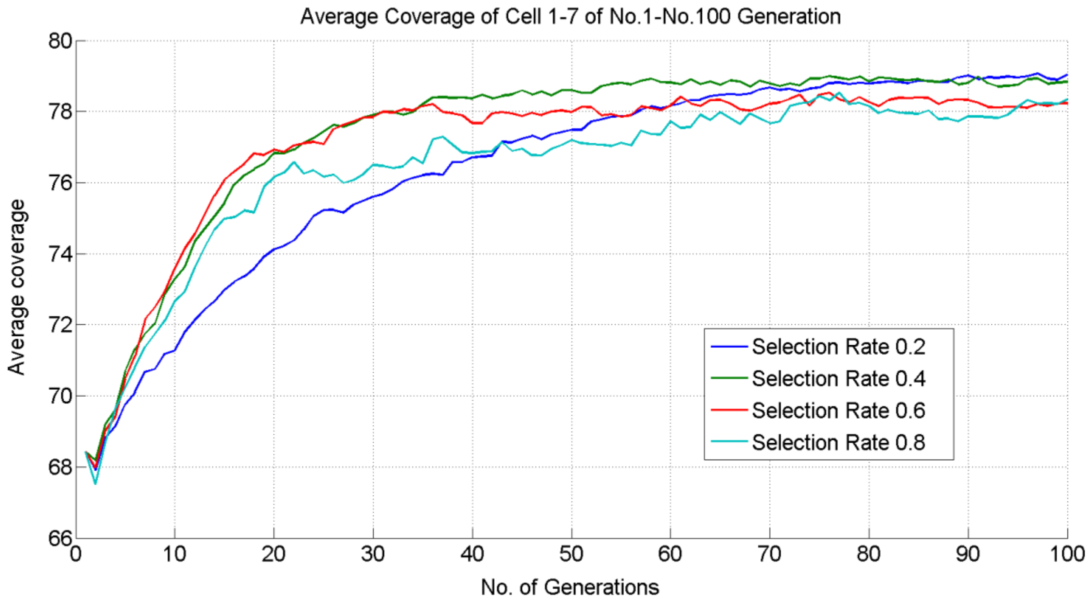


Figure 6.10 Overall average coverage based on selection rate 0.2-0.8

Figure 6.10 shows the overall average coverage results with different selection rates. It gives the similar performance to those in Figure 6.9 and the result with selection rate 0.2 has a slower convergence.

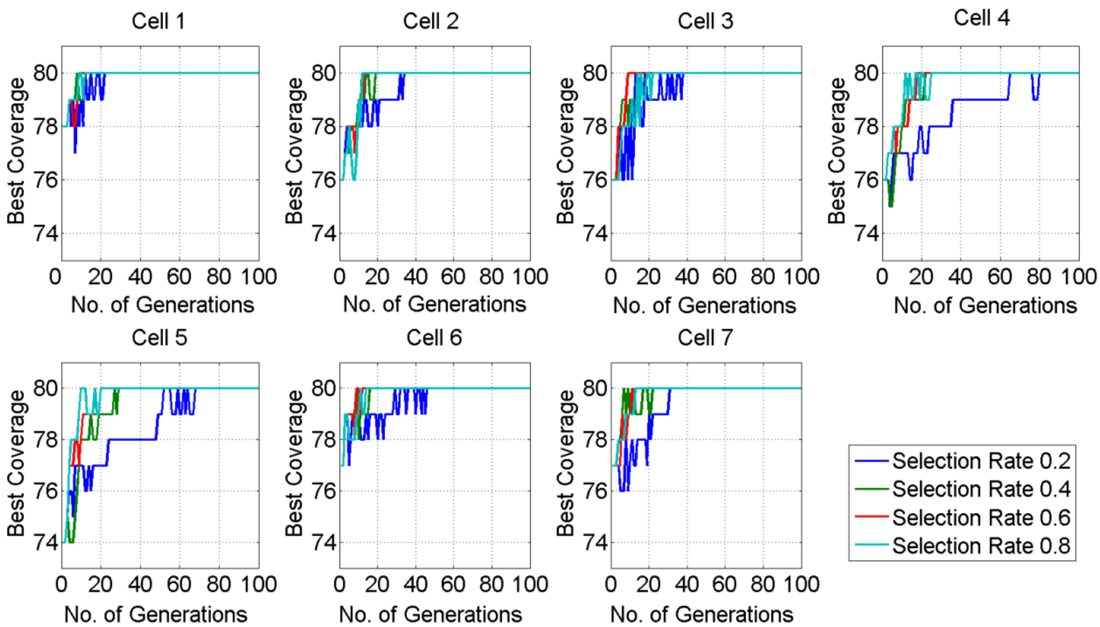


Figure 6.11 Best coverage based on selection rate 0.2-0.8

The best coverage based on selection rate varying between 0.2-0.8 is shown in Figure

6.11. From the figure it can be seen that results with cross over rate of 0.4, 0.6 and 0.8 give almost the same performance while selection rate 0.2 again gives the slowest convergence rate, with cell 4 having a particularly bad performance.

Figure 6.12 shows the overall best coverage with the different selection rate. From the figure it can again be found that selection rates 0.6 and 0.8 give a fast convergence rate as they converge to the maximum value between the 20th and 25th generations. However, selection rate 0.4 converges to the maximum value around 30th generation which is still reasonable.

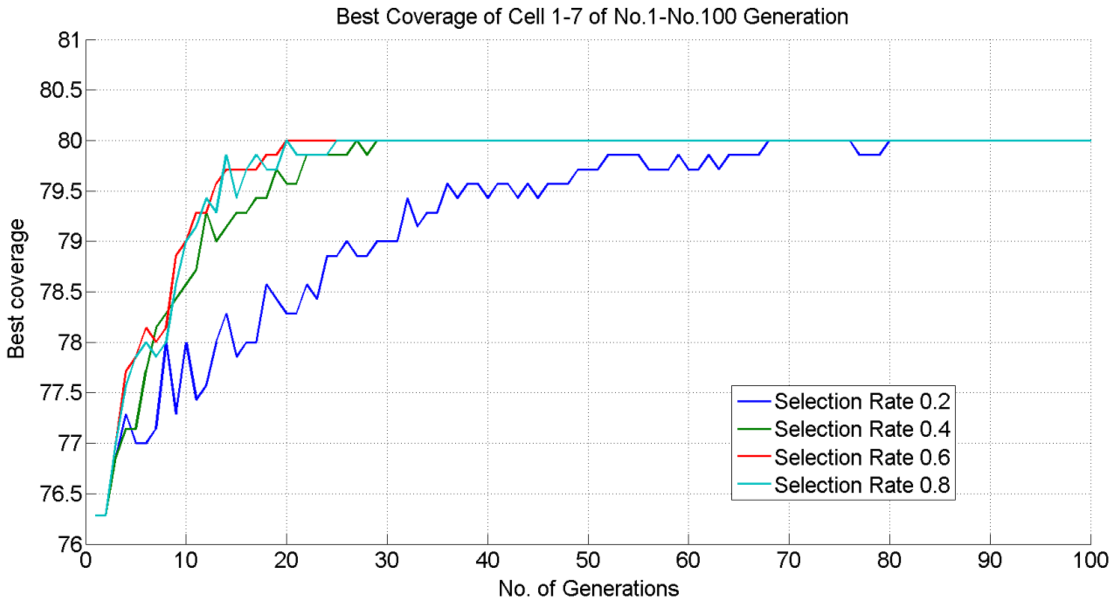


Figure 6.12 Overall best coverage based on selection rate 0.2-0.8

The average capacity results using the same selection results are shown in Figure 6.13, from which it can be seen that the overall situation is the same.

6.4.2 Selection rate design based on capacity issue

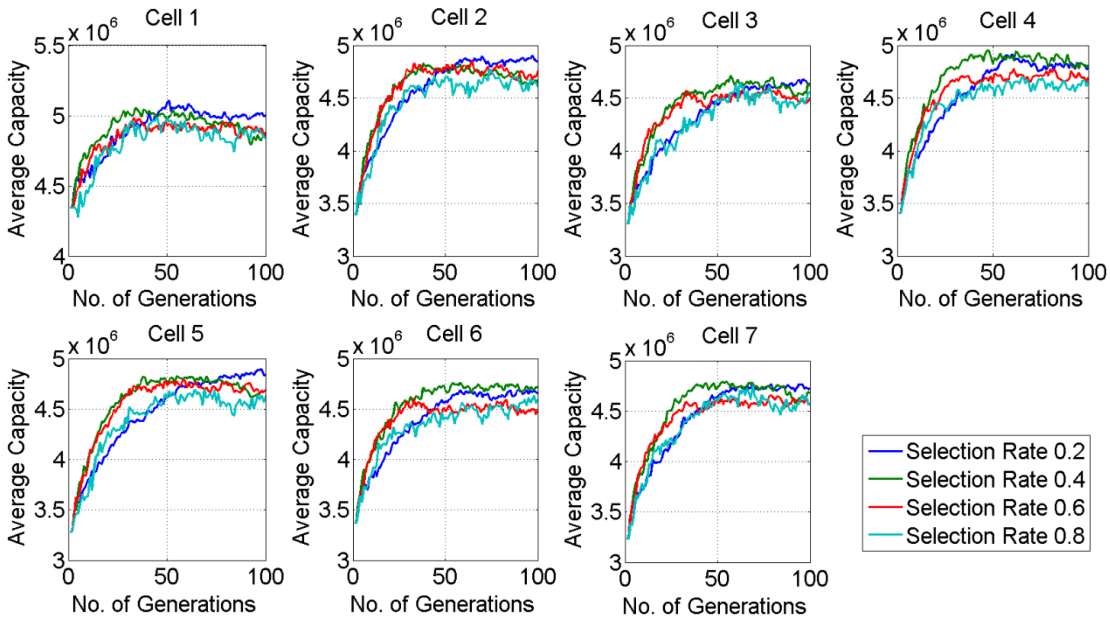


Figure 6.13 Average capacity based on selection rate 0.2-0.8

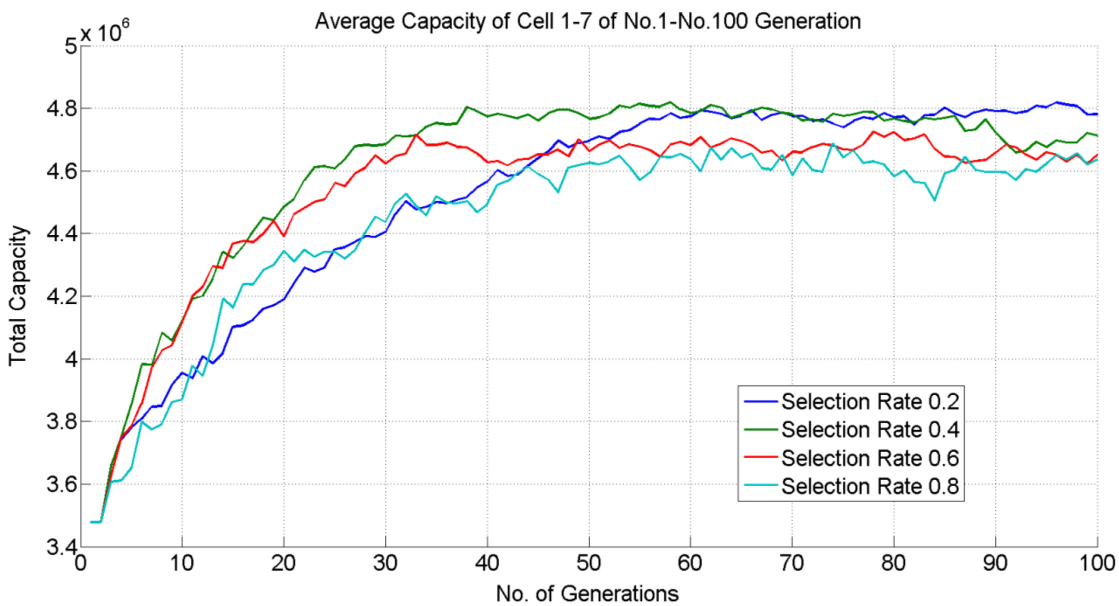


Figure 6.14 Overall average capacity based on selection rate 0.2-0.8

In Figure 6.14, the overall average capacity shows similar tendencies, but in this case the selection rate of 0.4 is clearly the best in terms of convergence and overall capacity. Interestingly, despite its slower convergence, a selection rate of 0.2 eventually gives the best capacity because it introduces more "fresh" individuals so is less likely to be stuck in a local optimum.

Results for best capacity are shown in Figure 6.15 and Figure 6.16; these show that selection rate 0.8 is the worst.

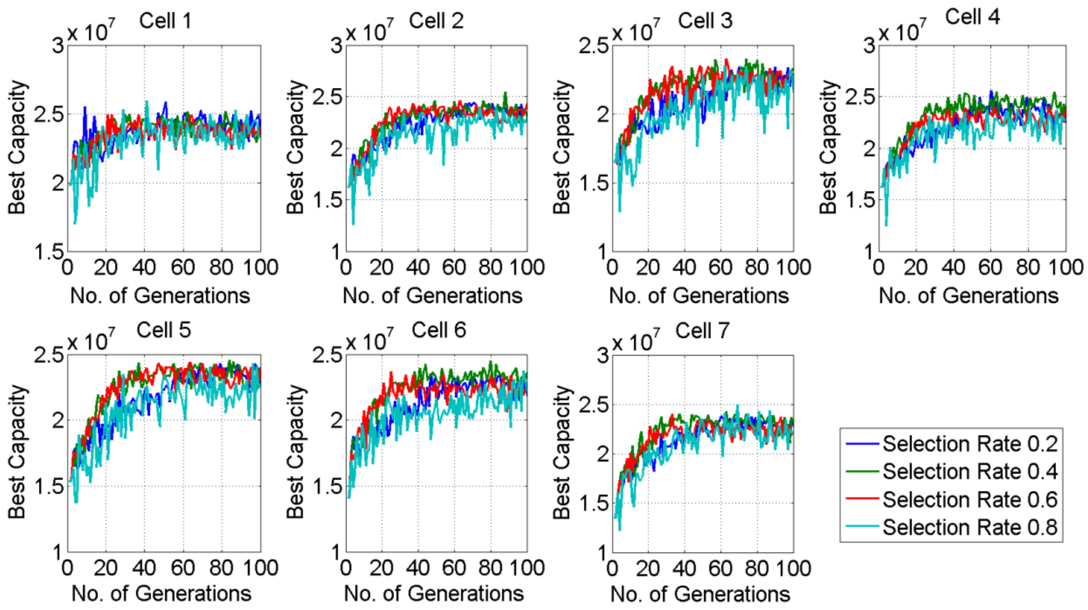


Figure 6.15 Best capacity based on selection rate 0.2-0.8

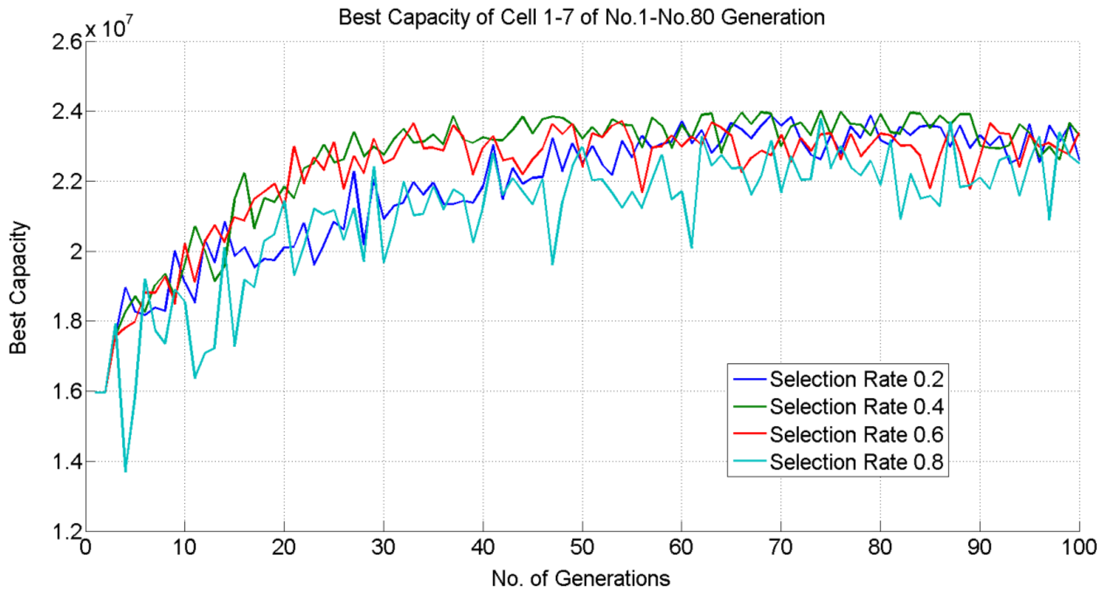


Figure 6.16 Best overall capacity based on selection rate 0.2-0.8

Considering all these results that address both the coverage issue and capacity issue, the selection rate should be chosen as 0.4 or 0.6.

6.5 Influence of mutation rate on GA

Mutation randomly changes one or more genes of a chromosome – i.e. randomly flips one or more bits in an individual and mutates the bits to create a new offspring. Offspring created by mutation may have some new characteristics that not found in the parent [65]. The mutation rate is probably the most sensitive parameter in GA as it introduces new chromosomes that can help avoid local optima. A lot of work in the literature aims at designing new mutation functions.

Baojun Huang has proposed a self-organizing GA based on mutation with cycle probabilities. In that work [65], a new mutation operator is designed where the mutation rate can be kept low for a long time so that the crossover operator plays a leading role in the GA, allowing the algorithm to fully search the domain. However, for some short periods, the mutation rate is raised to a high value to bring the algorithm out of any local optimum. Simulation shows improvement over the self-adaptation genetic algorithm (AGA).

In Yong Zhou's work [66], a GA with dynamic mutation is investigated: the dynamic mutation operator effectively overcomes premature convergence to a local minimum and improves the convergence speed by 60%~ 130% compared with a conventional genetic algorithm.

Kremena Royachka has proposed a high-performance optimisation of GA in [67] with a GA that has "random walk selection" and "adaptive threshold mutation". Adaptive threshold mutation makes use of position dependent information so that it focuses mutation on those locations that contribute most to the overall penalty of the current chromosome. The results show that the adaptive threshold mutation is "contradictory", which is, it works well for some problems while extremely bad for the others. This shows that sensitivity to the mutation policy is something that does need to be taken into account.

This part of the thesis considers the influence of mutation rate on GA. In order to guarantee the stability of the GA, the mutation rate is usually set to a small number and here it is varied from 0.01 to 0.09.

In a similar way to the selection rate, the effect of mutation rate value is considered for coverage and capacity, looking at average and best conditions. Here the results are presented first and then the conclusions drawn on the best value to use.

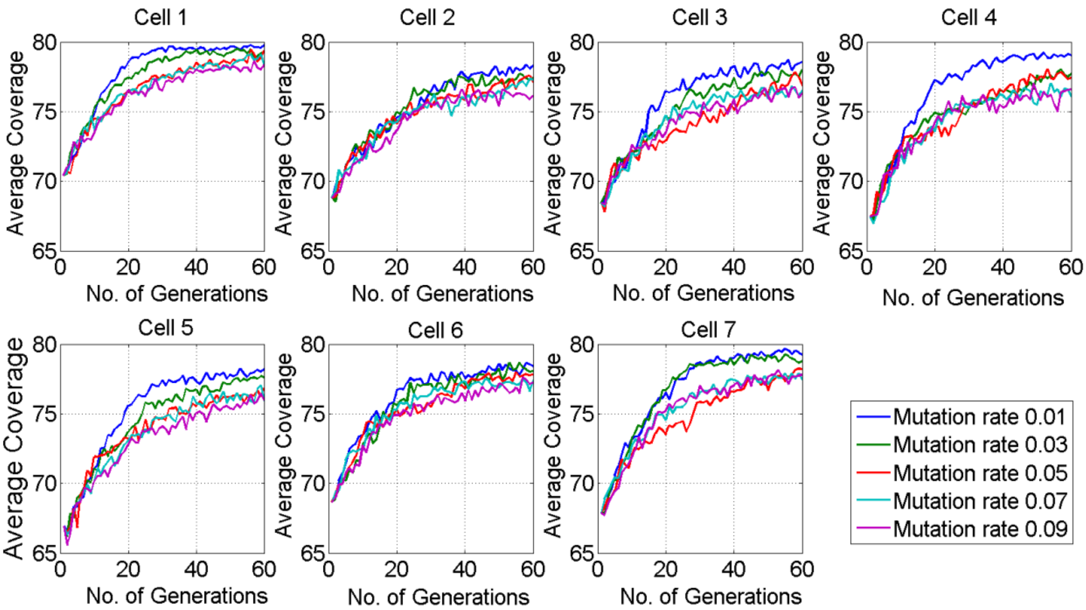


Figure 6.17 Average coverage based on mutation rate 0.01-0.09

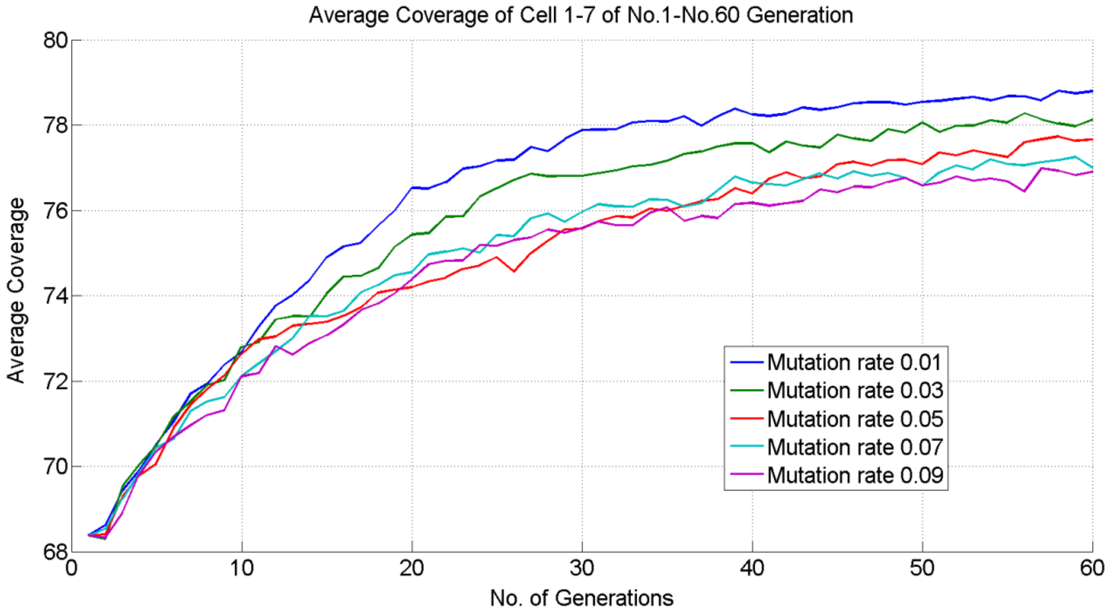


Figure 6.18 Overall average coverage based on mutation rate 0.01-0.09

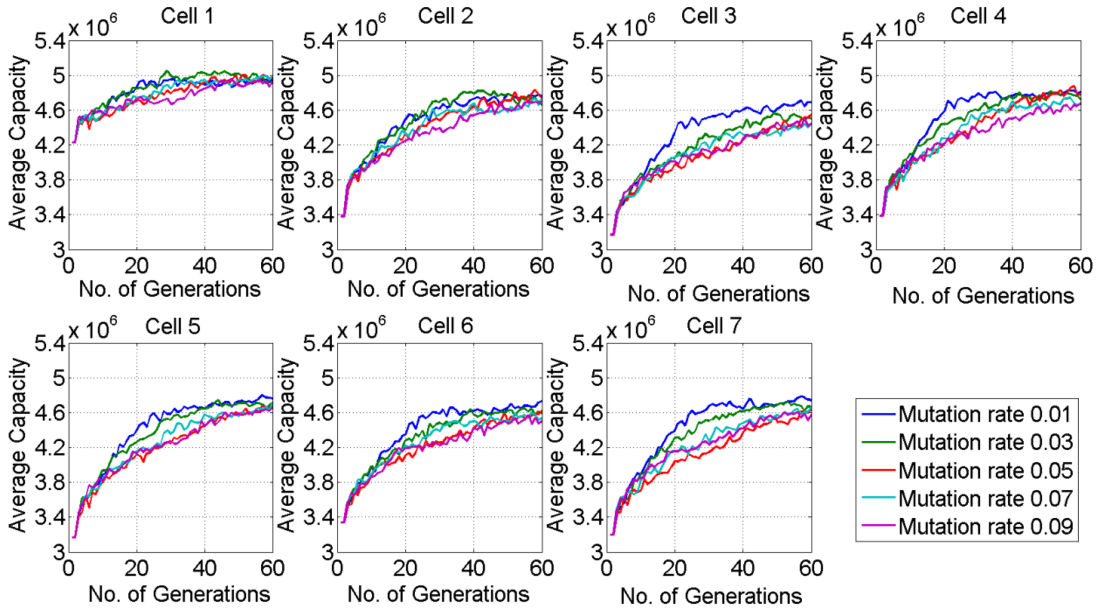


Figure 6.19 Average capacity based on mutation rate 0.01-0.09

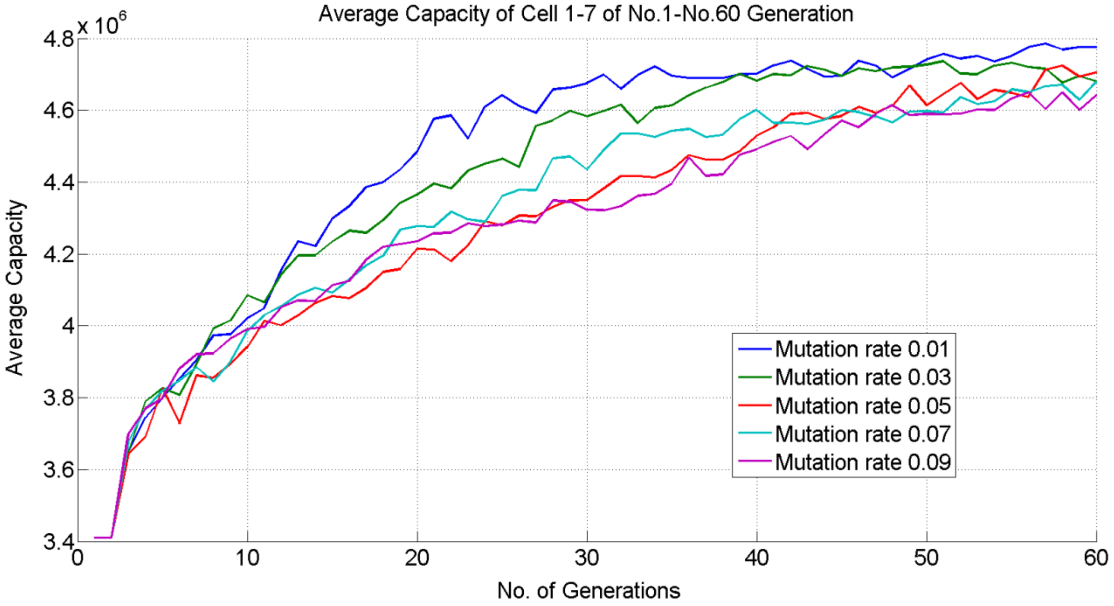


Figure 6.20 Overall average capacity based on mutation rate 0.01-0.09

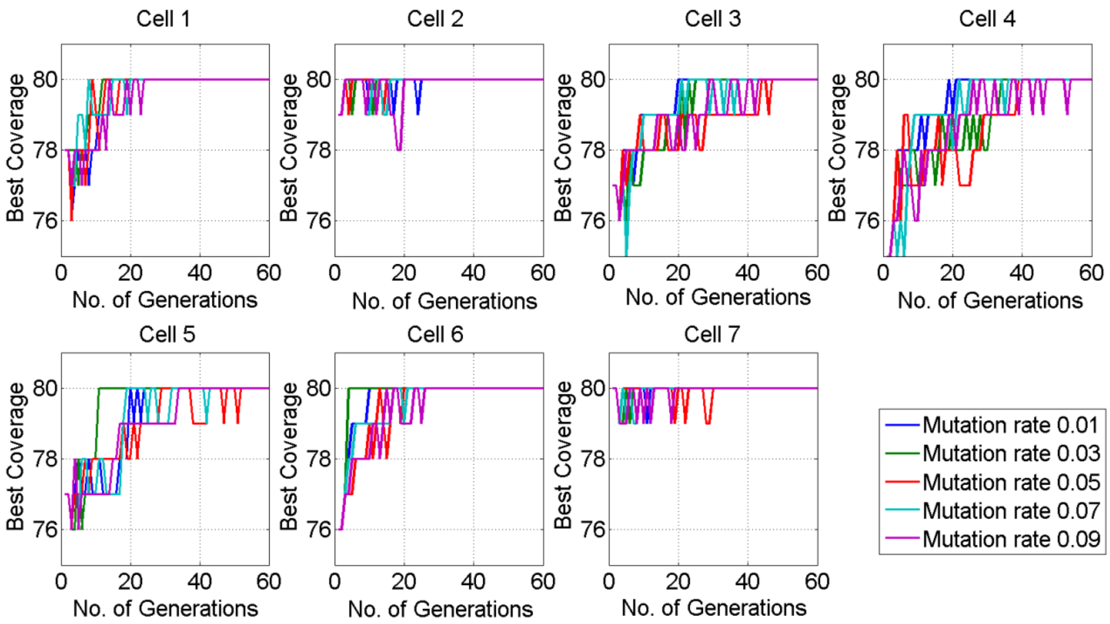


Figure 6.21 Best coverage based on mutation rate 0.01-0.09

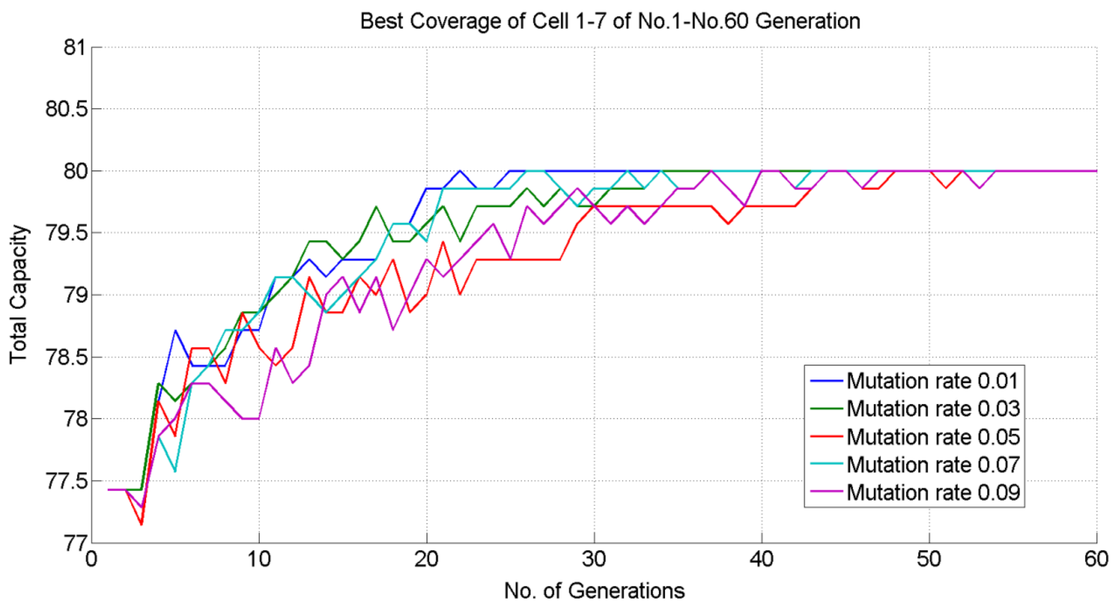


Figure 6.22 Overall best coverage based on mutation rate 0.01-0.09

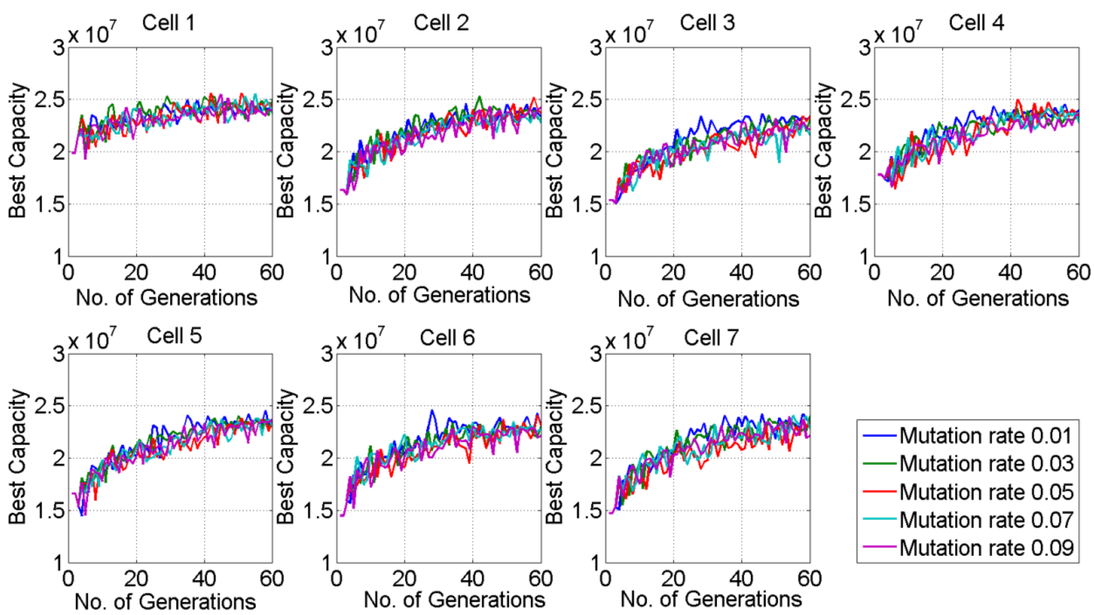


Figure 6.23 Best capacity based on mutation rate 0.01-0.09

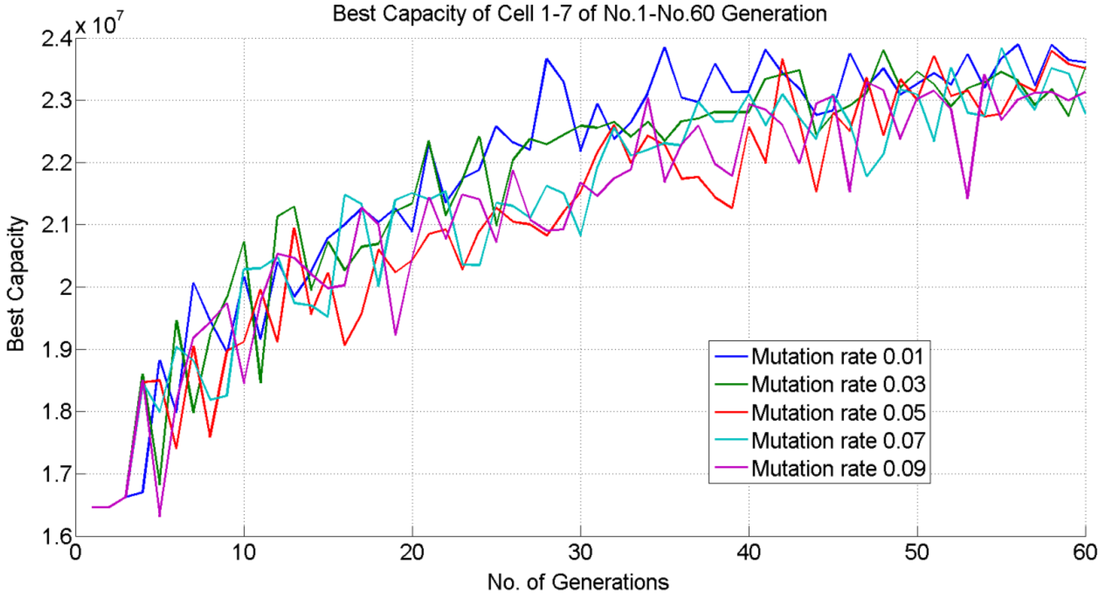


Figure 6.24 Overall best capacity based on mutation rate 0.01-0.09

The average coverage and the overall average coverage results (Figures 6.19 and 6.20) show that a mutation rate 0.01 gives the best convergence speed, followed by mutation rate 0.03 and 0.07, however, mutationrate with 0.05 and 0.09 gives the slowest convergencce rate. This is the same with the best coverage and overall results of the best coverage in Figures 6.21 and 6.22.

Figures 6.23 and Figure 6.24 show the capacity of the best fitted individual of each generation. From Figure 6.23 it can be seen that the capacity fluctuates a lot, but in Figure 6.24 the mutation rate 0.01 gives best overall capacity, slightly better than the others.

A mutation rate of 0.01 therefore gives the best performance overall.

6.6 Summary

In this chapter, the sensitivity of the GA algorithm has been investigated through simulation. Also, the optimisation of the GA is investigated to better optimise the semi-smart antennas to solve the coverage and capacity issues for OFDMA based networks. Through simulation and comparison, summary can be drawn as below:

i) The robustness of the GA algorithm was investigated and verified through simulation of 5 runs with the same first generation population. The GA gives good robustness in finding the optimal solution of radio resource management issue given the randomness of crossover, selection and mutation procedure. The results of GA coincide with each other well.

ii) The influence of crossover rate on the algorithm was investigated. When considering the combination of coverage issue and capacity issue, a selection rate in the range 0.4 to 0.6 is the best choice from a serious of selection rate 0.2, 0.4, 0.6, and 0.8.

iii) Mutation rate tests show that a mutation rate of 0.01 among 0.01, 0.03, 0.05, 0.07 and 0.09 can give better results, leading to a better performance of the GA.

Results show that GA designed in this thesis is robust. Selection rate for work of this thesis should be chosen as 0.4 or 0.6 and mutation rate should be set up as 0.01.

Chapter 7 Scheduling Combined Radio Resource Allocation Design

7.1 Introduction

In Chapter 5, the GA is investigated to optimise antenna patterns thus enhancing system throughput and solving the “antenna gap” problem and the sensitivity of parameters was researched and tested through simulation in Chapter 6 to give better performance of the GA.

In this chapter, scheduling will be introduced into the systematic model of the simulator and wrap around will be added into the simulator to reduce the cell-edge effect. Also, the balance policy between the different objectives of GA is considered.

7.2 7-cell wrap around model

No wrap around model is used so far in the 7-cell simulator in this thesis, which means that only the central cell users suffer from the interference of the surrounding 6 cells - the surrounding 6 cells suffer less interference than the central cell.

Wrap around is considered and added into the simulator for the work in this chapter. By adding wrap around into the simulator, more accurate interference of the outer-cells can be calculated and the simulator can be extended to a network consisting of several copies of the original network [89][90]. The wrap around model used in this work is shown in Figure 7.1.

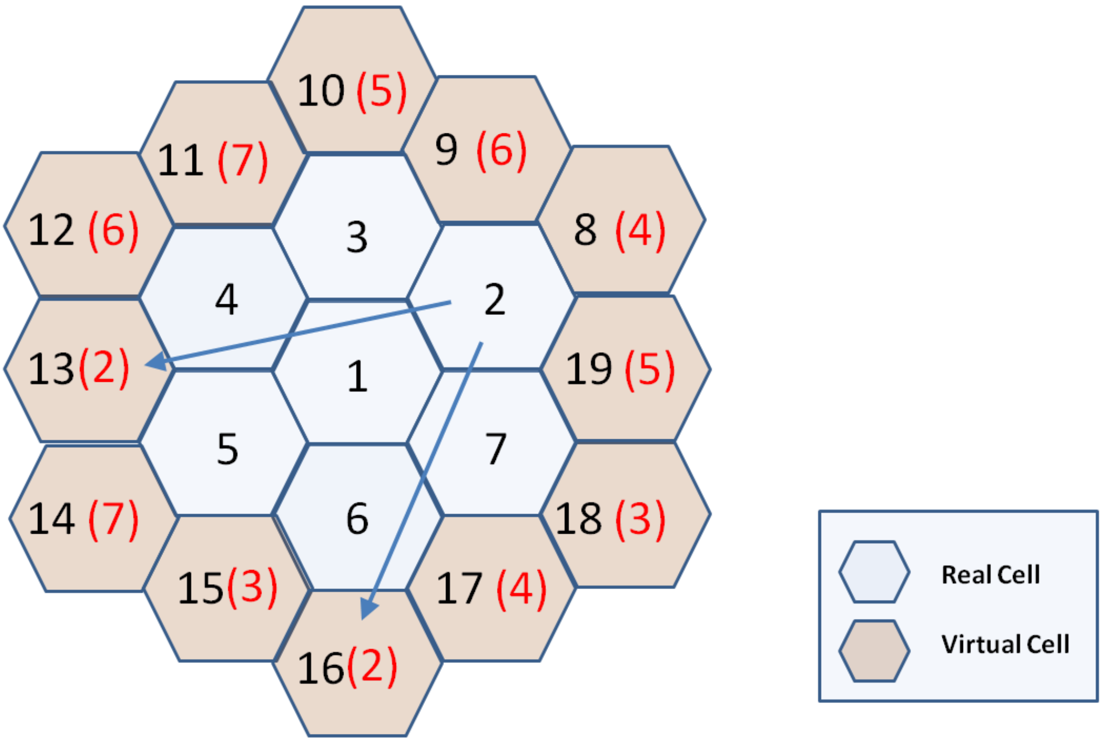


Figure 7.1 7-cell wrap around model

As shown in Figure 7.1, a 7-cell wrap around model is used. In the figure, cells coloured in blue stand for the real 7 cells, which are the targets. Cells coloured in pink are virtual cells, which are wrapped around the 7 cells. Numbers in black are the index number of the 7 cells while numbers in red are the index number of the real cell corresponding to the virtual cell. For example, 16 is the index number of a virtual cell, while the corresponding real cell is cell 2. The virtual cells thus have the same antenna configuration, traffic, fading, etc except the location. By using such a wrap around model, the interference can be more accurate, as each of the real cells will suffer from 6 1st-tier interference from adjacent cells.

Taking cell 2 as an example, users in cell 2 will suffer interference and antenna cover from cell 1, cell 3, cell 8 (corresponding real cell 4), cell 19 (corresponding real cell 5), cell 9 (corresponding cell 6), and cell 7. This wrap around model, when simulating the radio resource management of the real cells, will take the real cell and the surrounding 6 cells into account. The interference from the 2nd tier cells are not considered in simulation of this chapter as that interference suffers more path loss.

7.3 Scheduling

In the previous chapters, a GA is used to give optimisation of antenna patterns to enhance system throughput and give better coverage among the cells. When considering complex channel conditions, radio resource allocation problem is a main concern. Furthermore, when there are too many users in some areas, the scheduling method should be taken into account. In this chapter, scheduling is considered together with radio resource allocation issue using the GA optimized antenna patterns.

The three main scheduling methods are Round Robin, Max C/I and Proportional Fairness (PF)[31][91]. In the Round Robin scheduling strategy, the users take turns in using the radio resources. It can be seen as a kind of fair scheduling strategy as it allocates the same amount of radio resources to users on a certain communication link. However, by using the Round Robin method, some radio resources will be allocated to users with bad channel condition, which leads to lower overall system throughput. Max C/I, on the other hand, takes the instantaneous channel conditions into account when doing radio resource allocation. Users with the best channel condition are often referred to as Max C/I (or maximum carrier/interference ratio). Max C/I scheduling method tends to give best system throughput. However, the Max C/I scheduling will starve users with bad channel conditions thus some users might be never served. Max C/I scheduling can be described by equation (7.1) [92].

$$\arg\max_{k} R_k \tag{7.1}$$

where R_k is the instantaneous data rate for user k.

A more realistic scheduling strategy should consider both the instantaneous channel condition and the user fairness. Proportional Fairness scheduling takes both channel condition and user rates into consideration and is described as below. During the t^{th} TTI, transmission opportunity is given to user k^* based on the maximum $R_k(t)/T_k(t)$, where $R_k(t)$ is the instantaneous achievable rate at TTI t, and $T_k(t)$ is the average throughput over a past time-window t_c for user k and t_c is a tuning parameter that determines the trade-off between fairness and throughput. The average throughput is updated after each scheduling time as follows:

$$T_k(t+1) = \begin{cases} \left(1 - \frac{1}{t_c}\right) T_k(t) + \frac{1}{t_c} R_k(t), & k = k^* \\ \left(1 - \frac{1}{t_c}\right) T_k(t), & k \neq k^* \end{cases} \tag{7.2}$$

For OFDMA system, user k will be given PRB n according to following equation:

$$\arg\max_k \frac{R_{k,n}(t)}{T_k(t)} \tag{7.3}$$

7.4 System parameters

The systematic architecture of the modified simulator is shown in Figure 7.2. The wrap around model is added to the initialization model, and the PF scheduling model is added before the GA model. In such architecture, the GA will work between the generations to give optimisation to the antenna patterns while the PF scheduling works between the TTIs to allocate the subchannels. The scheduling will work every TTI while the GA will work every generation, which is equivalent to 10 TTIs.

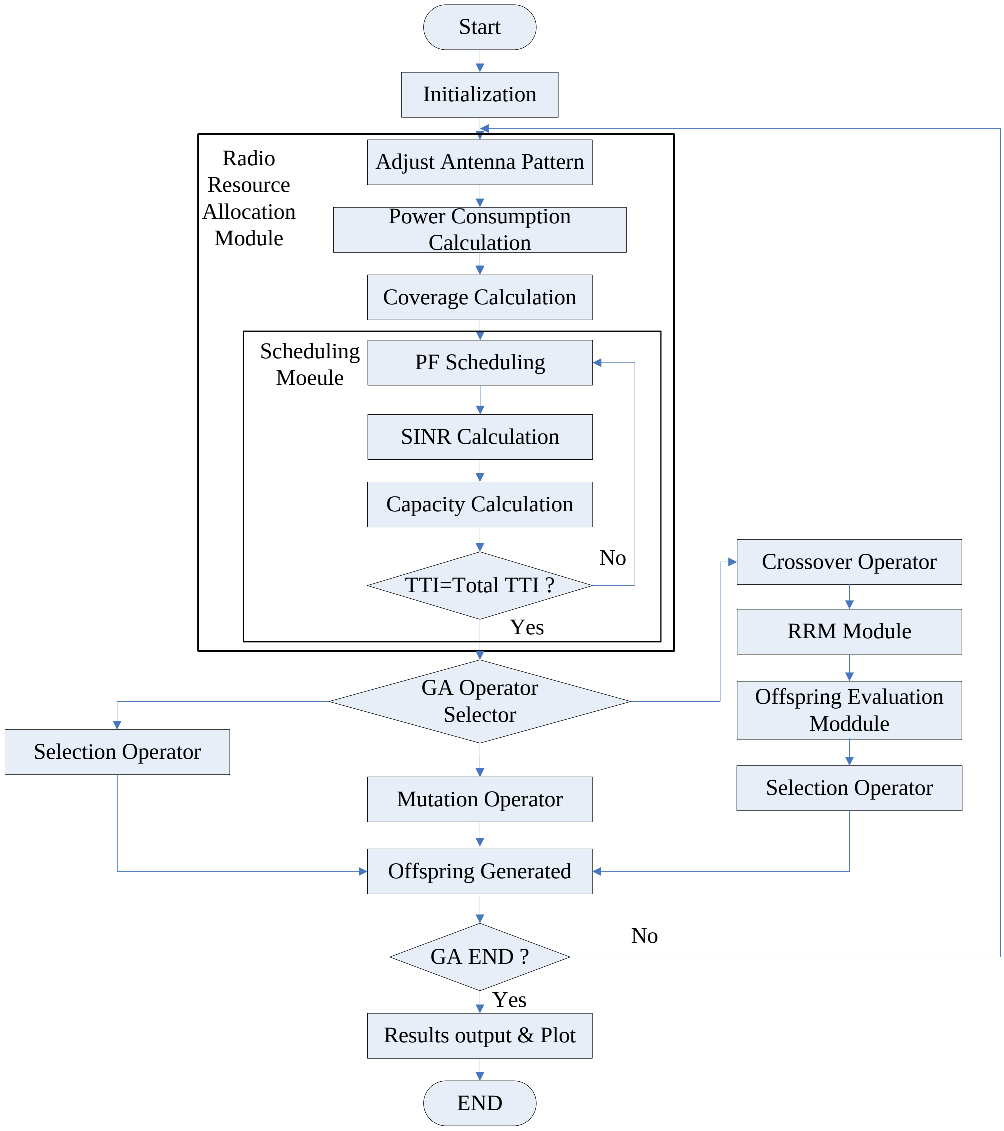


Figure 7.2 System architecture

In this chapter, the system parameters are as shown in Table 7.1 using the same cell architecture as described in Chapter 4.3.2 with a 7 cell wrap around model as described in section 7.2, with a cell radius of 288m and inter-cell distance of 500m. The eNodeBs have a 20MHz bandwidth with a subcarrier frequency space of 15KHz. The GA parameters are listed in Table 7.2. Different parameters compared with basic parameters as described in Chapter 4 are highlighted in Table 7.1 and Table 7.2.

Real encoding GA is used for simulation in this chapter. GA parameters are chosen based on the optimisation results from Chapter 6, with a cross over rate of 0.4 and mutation rate of 0.01. The population size is kept at 50 as used in Chapter 5 and Chapter 6 while the number of generations is varied from 50 to 200 for comparison. Furthermore, the parameter α is varied from 0 to 40×10^5, to test the balance policy of the multiple objectives.

Table 7.1 System parameters

Parameters	Values
Cellular layout	hexagonal, BS in the centre***, with wrap around***
Number of Cells	7
Radius of Cell	***288m***
Inter-cell distance	***500m***
Bandwidth	20MHz
Subcarrier frequency space	15kHz
Allocable subchannel number	***25***
Total transmission power of BS	20W
Users per Cell	80
User distribution	uniform
Distance attenuation	***L=35.3+37.6*log(d) d= distance in meter***
Scheduling method	***PF***
TotalTTI	***10***

Table 7.2 GA Parameters

Population size	50
Cross over method	***Arithmetic crossover***
Generation	***50-200***
Cross over probability	25%-66.7%
Crossover parents Selection method	Random Selection
Selection method	Truncation selection
Selection rate	0.4
Mutation method	***Uniform mutation***
Mutation Rate	0.01
Parameter α	***$0\text{-}40 \times 10^5 \times TotalTTI$***

7.5 Simulation results and analysis

For each policy of a certain generation, 10 TTI of simulation is run, 50 to 200 generations of simulation are done.

Figure 7.3 shows the capacity comparison after optimisation versus without optimisation. For the simulation, parameter α of the objective function is chosen as 0 to test the capacity value and it can be seen that the capacity results with algorithm optimisation have a 4.6 % of enhancement over no algorithm optimisation. Also, the capacity is around 1.3×10^8 bps, so that the parameter α in the objective function should be around several $10^5 \times$TotalTTI according to Equation (5.10).

Figure 7.4 shows the comparison of coverage of optimised results and without optimisation; this shows that the coverage is not ideal, as not all the users can be covered, which means there are gaps between antenna patterns. Although the capacity enhancement is obvious, the coverage is not ideal. This means that the two objectives, the coverage and system capacity, conflict. How to best balance the two objectives is a matter of optimising the balance parameter α. Based on the calculation in the previous parts, α should be around several $10^5 \times$TotalTTI, so here a range from 0 to $40 \times 10^5 \times$TotalTTI was used. From the earlier work, 50 generations should be enough for the simulation, but to check, some simulations were carried out with up to 200 generations.

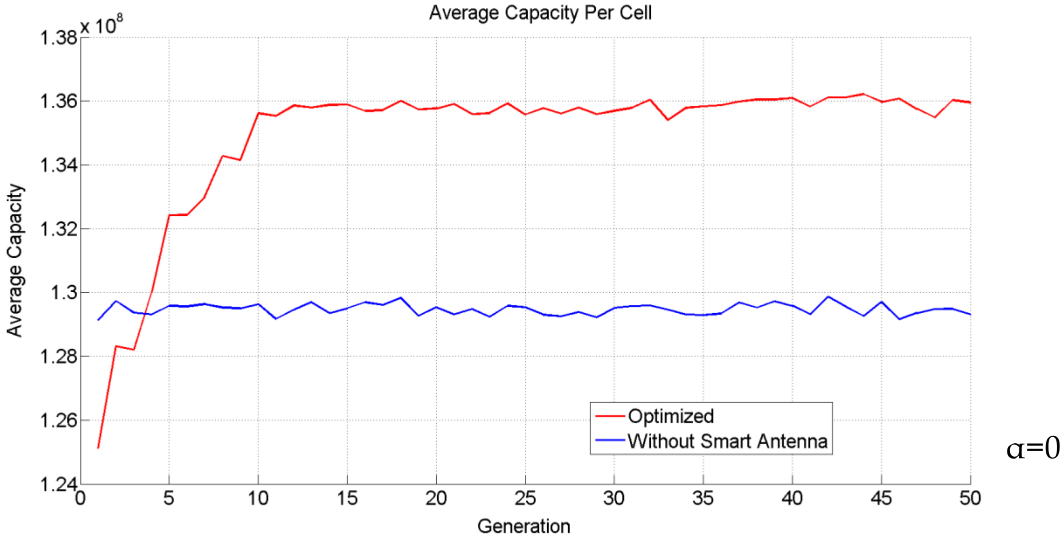


Figure 7.3 Capacity comparison (bps)

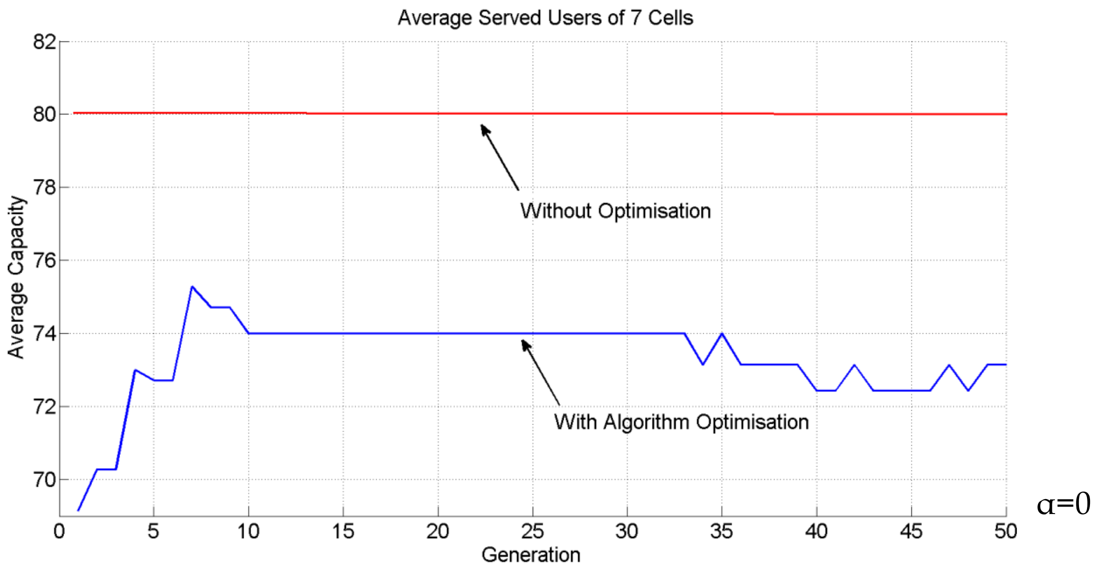


Figure 7.4 Coverage comparison

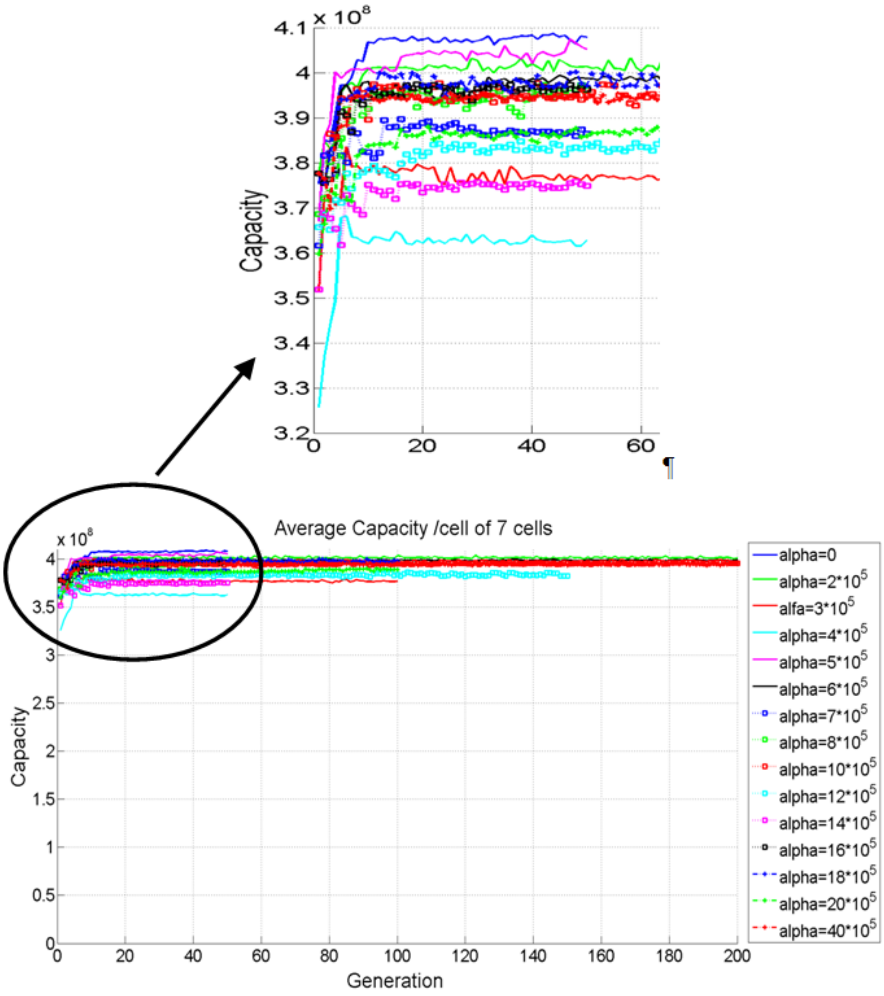


Figure 7.5 Capacity comparison with different α

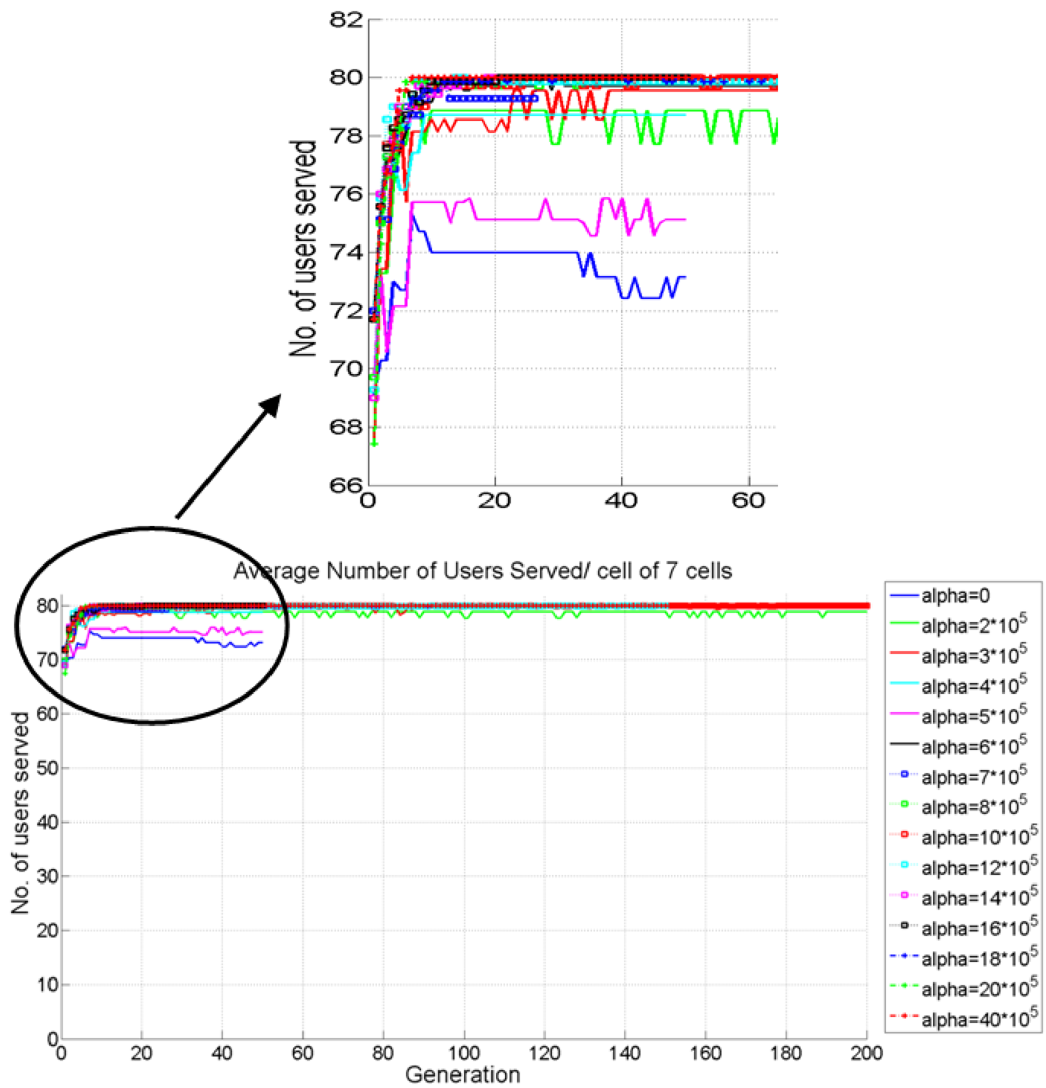


Figure 7.6 Coverage comparison with different α

Figure 7.5 shows the capacity comparison with different values of α. From the figure a small value of α often corresponds to large capacity results, as less emphasis is being put on the coverage. As a result, some users far away from the eNodeBs will be ignored and will never be covered by the antenna patterns, which means gaps between antenna patterns forming. Figure 7.6 shows the coverage and the effect of gaps between the antenna patterns.

Comparing the two figures it can be seen that α equals to $6\times10^5\times$TotalTTI, can be seen as good compromise between the capacity and coverage issues.

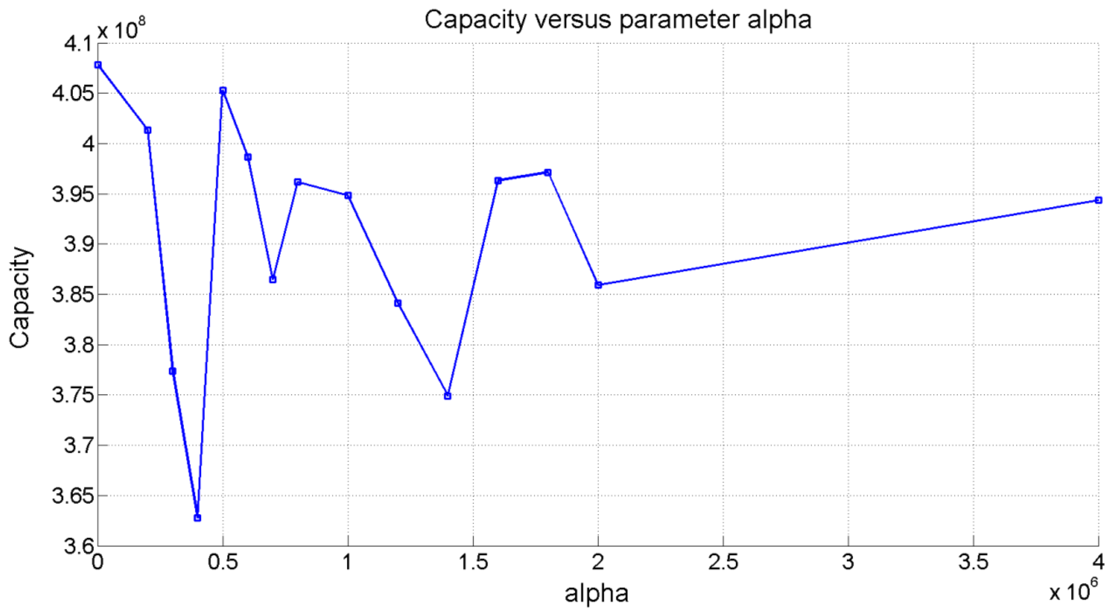


Figure 7.7 Capacity result comparison: Capacity versus alpha

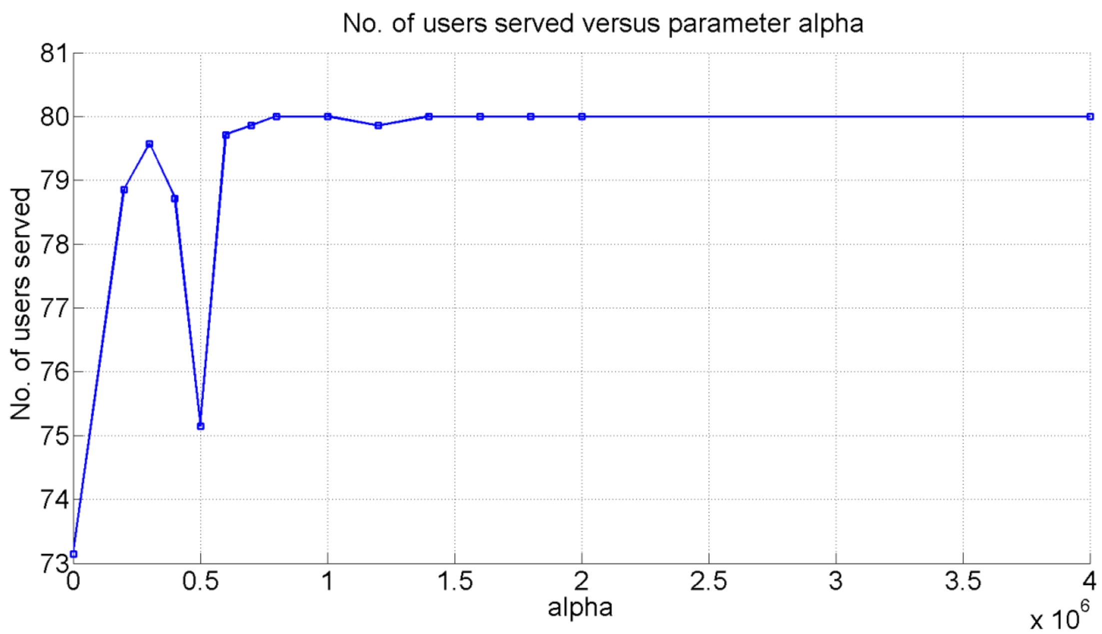


Figure 7.8 No. of users comparison: No. of users versus alpha

The relationship between capacity, number of users served and parameter alpha are shown in Figure 7.7 and Figure 7.8 respectively. The two figures do not show a linear relationship, so that although using a pricing factor can improve the multi-objective fitness function it is hard to fine tune the value to an optimum.

7.6 Summary

In this chapter, the wrap around model is added into the previous simulator to solve the cell edge effect together with PF scheduling to balance the system throughput and user fairness. The balance parameter α is testified through simulation and the policy of having a multi-objective function of the selection procedure of GA is investigated. First α is set to 0 to test the magnitude of the capacity, through which the range of α can be decided. After that, different values of α are set up and tested through simulation. Results show that the two objectives, system throughput and cell coverage do conflict so that a certain α value should be selected as a balance. Results also show that α with small magnitude cannot get satisfying coverage results; while α with large magnitude cannot give a linear relationship between the coverage and capacity.

Furthermore, this choice is likely to vary with different user distributions and so is something that needs to be investigated in a lot more scenarios to assess its sensitivity. To avoid this, the next chapter presents a different, novel, approach that guarantees there will be no “holes” in coverage.

Chapter 8 Changing coverage angle

In the previous chapters, the GA was investigated and testified through simulation to apply semi-smart antennas to the radio resource management problem for OFDMA based networks. Results show improvement of both system throughput and coverage, but since these two aspects conflict, a balance parameter has to be used. The problem with a balance parameter is how best to choose it in such a way that it fits a wide range of scenarios.

In this chapter, a different 6-sector system architecture is deployed, where the smart antennas only change their angle of coverage *within the cell* – this avoids getting the gaps in coverage that were a problem earlier. This saves the need for a balance parameter.

To test this approach, different user scenarios are considered.

In this chapter, the GA designed in Chapter 7 will be used with the parameters from Chapter 6. Also, the effect of fast fading on the system performance is taken into consideration. System performance, throughput and user fairness are evaluated through simulation.

8.1 System model

In this chapter, a 7-cell LTE system architecture is used as shown in Figure 4.2, however; the system layout is different and the specific system parameters are shown in Table 8.1. Different parameters compared with the basic parameters listed in Chapter 4 are highlighted. Each cell consists of one BS, that is located in the centre of the cell and a directional antenna is used allowing each cell to be divided into 6 sectors, with each of the sectors covering an area of 30-60°, as used for GSM [68] and as proposed for LTE networks [69].

Adjusting the sectorisation of the multi-cell LTE system is difficult as both the covering area and the position of the sectors are dynamic. Considering this problem, each sector of the 6-sector model of each cell is divided into 2 virtual sectors. Firstly, taking the 0°, 60°, 120°, 180°, 240° and 300° point lines as the central line of each of the sector, each sector is made up of 2 virtual mini-sectors, with the two virtual mini-sectors being adjusted symmetrically. After testifying the symmetric sectorisation method, asymmetric virtual sector adjustment is controlled by GA to give the sectorisation full freedom.

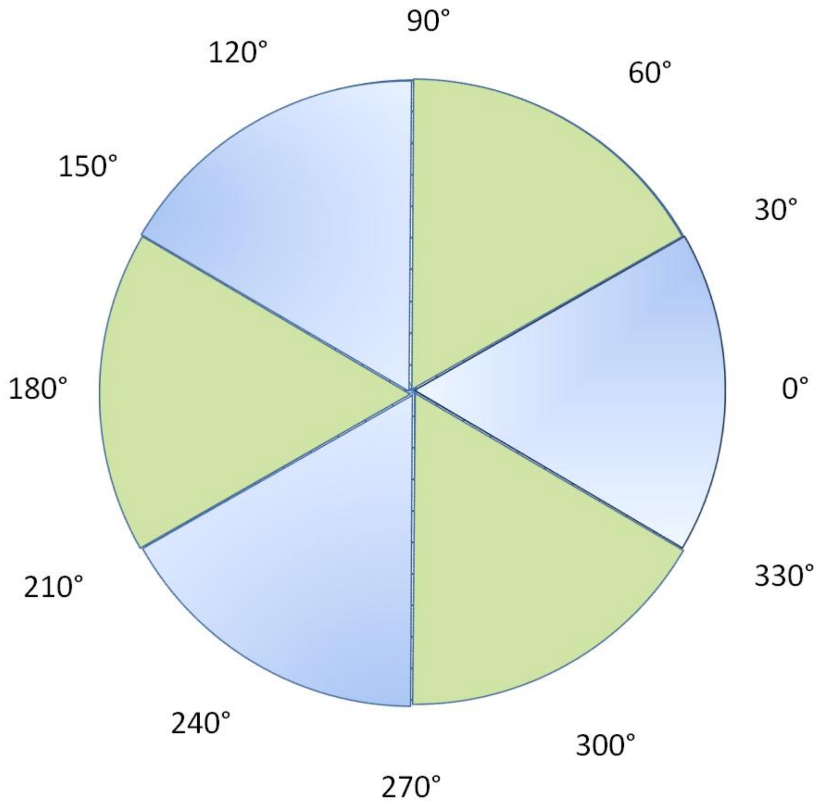


Figure 8.1 Sectorisation model

Table 8.1 System parameters

Parameters	Values
Cellular layout	hexagonal, BS in the centre ***with warp around***
Number of Cells	7
Radius of Cell	***288m***
Inter-cell distance	***500m***
Bandwidth	20MHz
Subcarrier frequency	15kHz
Allocable subchannel number	***25***
Total transmission power of BS	20W
Users per Cell	***150-180***
User distribution	***Uniform and hotspot***
Distance attenuation	***L=35.3+37.6*log(d) d= distance in meter***
Scheduling method	***PF***
Total TTI	***10***

Encoding method is real encoding in this Chapter, the same as Chapter 7. Arithmetic crossover method and uniform mutation method are selected as they work well with real coding [66]. The population size, selection rate and mutation rate stay as 50, 0.4, and 0.01 as optimized in Chapter 6.

Detailed GA parameters used in this chapter are shown in Table 8.2. Different parameters setup compared with basic parameters listed in Chapter 4 are highlighted.

Table 8.2 GA Parameters

Population size	50
Cross over method	***Arithmetic crossover***
Generation	***50***
Cross over probability	25%-66.7%
Crossover parents Selection method	Random Selection
Selection method	Truncation selection
Selection rate	0.4
Mutation method	***Uniform mutation***
Mutation Rate	0.01

8.1.1 Real Encoding

Real encoding is explained in section 3.3.1. The object parameter for encoding is the angle of the antenna in a certain cell. When considering different antennas of a cell, $THETA$ is described as equation (8.1).

$$THETA = [theta_1, theta_2, theta_3, \dots theta_R] \tag{8.1}$$

Here $theta_1$, $theta_2$, $theta_3, \dots$ $theta_R$ stand for the angle vector of R antennas used in one cell. When deployed into a multi-cell model, this becomes $\Theta = [THETA_1, THETA_2, THETA_3, \dots THETA_I]$. Here $THETA_i$, stands for the gain vector of the i^{th} cell.

8.1.2 Selection

As the aim is to enhance the systematic capacity, for the coverage issue is solved by sectorisation within the cells. Considering the scheduling with different TTIs, the fitness function for the selection procedure of the GA is defined as:

$$f_i(n,i) = \frac{\sum_{r=1}^{R} \sum_{k=1}^{K} \sum_{t=1}^{T} C_{i,j,k,t(n,i)}}{\sum_{r=1}^{R} K_r \times T} \tag{8.2}$$

Here f_i (n,i) shows the fitness condition of the n^{th} policy of cell i and R stands for the number of sectors in each cell. Variable i represents the sequence number of the cell and j is the sequence number of the sector. Parameter k stands for the sequence number of user. T denotes the number of TTIs being simulated in each policy and K_r is the number of users in the r^{th} sector.

By using Equation (8.2), policies with better system throughput can be selected to carry on to the next generation.

8.1.3 Crossover

Arithmetic crossover is selected as the crossover method for working with real encoding and Equation (3.4) is used for arithmetic crossover. Every time when a new offspring is needed, one "father" and one "mother" are randomly selected from the generation and crossover is done the Equation (3.4), using γ varied from 0.25 to 0.67.

8.1.4 Mutation

Uniform mutation is selected as the mutation method in this thesis as its randomness can maintain the variety of the group and robustness [70]. By using uniform mutation, a new policy can be randomly generated between the upper and lower bounds defined manually.

8.1.5 User fairness

User fairness calculation is based on the capacity of each user. Although PF is used to balance the channel condition and user fairness during scheduling within each TTI, fairness is still needed when evaluating a certain policy of a generation. User fairness is based on following equations.

$$Ave_i(n,i) = \frac{\sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{t=1}^{T} C_{i,j,r,k,t(n,i)}}{\sum_{r=1}^{R} K_r \times T} \tag{8.3}$$

Where $Ave_i(n,i)$ shows the average throughput of Cell i, policy n.

$$Fair_i(n,i) = \sqrt{\frac{\sum_{r=1}^{R}\sum_{k=1}^{K_r}[C_{i,j,r,k,t}(n,i) - Ave_i(n,i)]^2}{\sum_{r=1}^{R} K_r}} \tag{8.4}$$

$Fair_i(n,i)$ stands for user unfairness of the n^{th} policy of cell i and R stands for the number of sectors in each cell. Variable i represents the sequence number of the cell and j is the sequence number of the sector. K_r is the number of users in the r^{th} sector. From Equation (8.4) it can see that smaller values of $Fair_i(n,i)$ lead to better fairness and there is less difference between the users.

Based on all the operators and function designed above, the flow chart of the simulator is described in Figure 8.2.

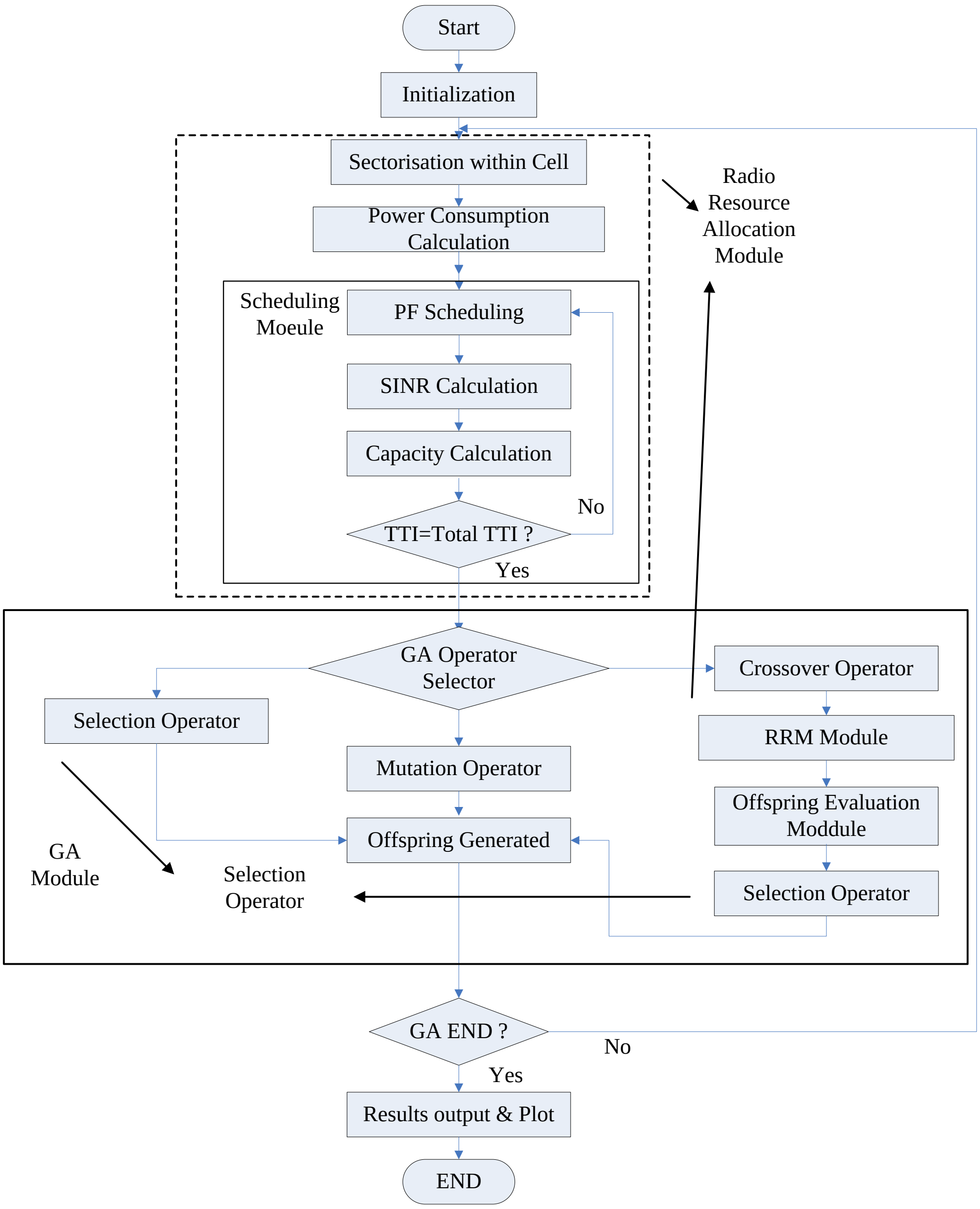


Figure 8.2 Flow chart of simulator

8.2 Simulation results and analysis

Different scenarios have been set up to test the algorithm. Different numbers of users with different distributions and different types of hotspot scenarios are tested through simulation. For each policy belonging to a certain generation, the simulation runs for 10 TTIs to average out the channel conditions on the GA.

8.2.1 Uniform distribution

In this part, the scenario is set up as uniform distribution, all the users are randomly distributed across the 7 cells. Different numbers of users are distributed in the cells among different round of simulations and the number of users varied from 60 to 240 to test the scheme.

Figure 8.3 shows the initialization condition with all sectors having the same angle.

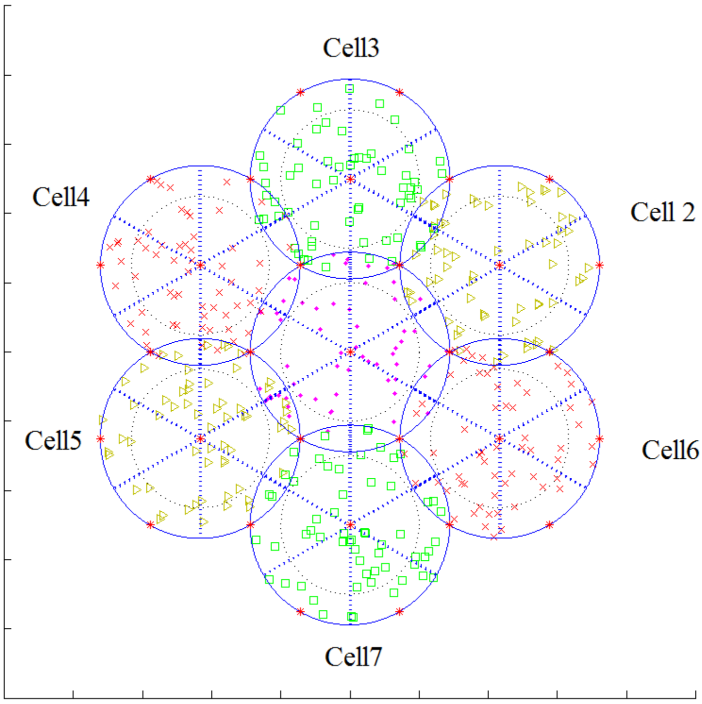
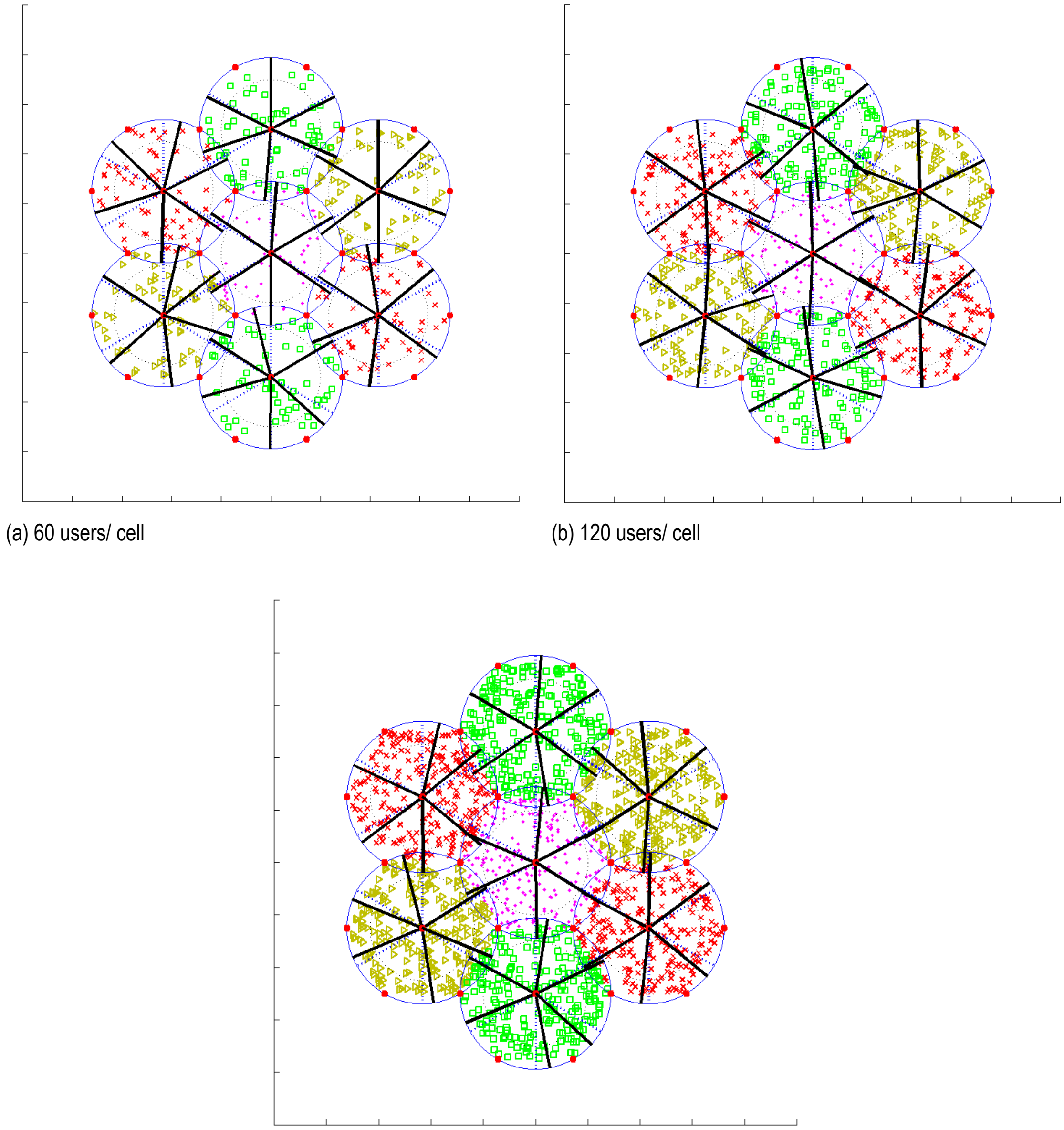


Figure 8.3 Initialization with equal sectorisation

Sectorisation results are shown in Figure 8.4 with 60, 120 and 240 random distributed users respectively. Figure 8.4(a) shows the same scenario as Figure 8.3 but after running the GA; the solid lines show the edge of each of the sector after optimising the antenna patterns and these can be compared with the original dashed lines. As the users are randomly distributed in the 7 cells, the algorithm cannot give much change to the sectorisation for all the 3 scenarios.



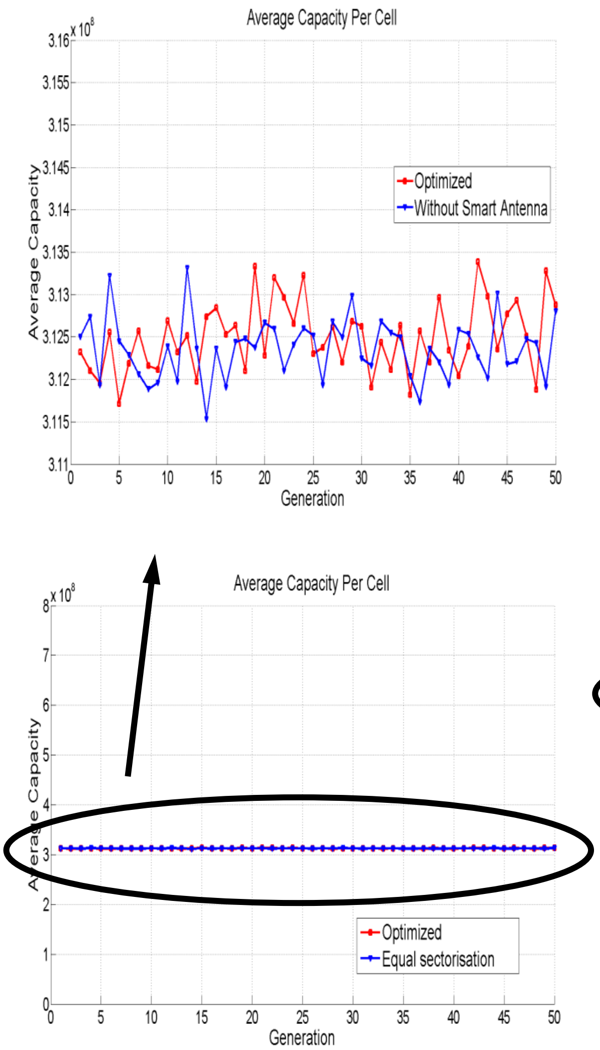
(a) 60 users/ cell (b) 120 users/ cell

(c) 240 users/ cell

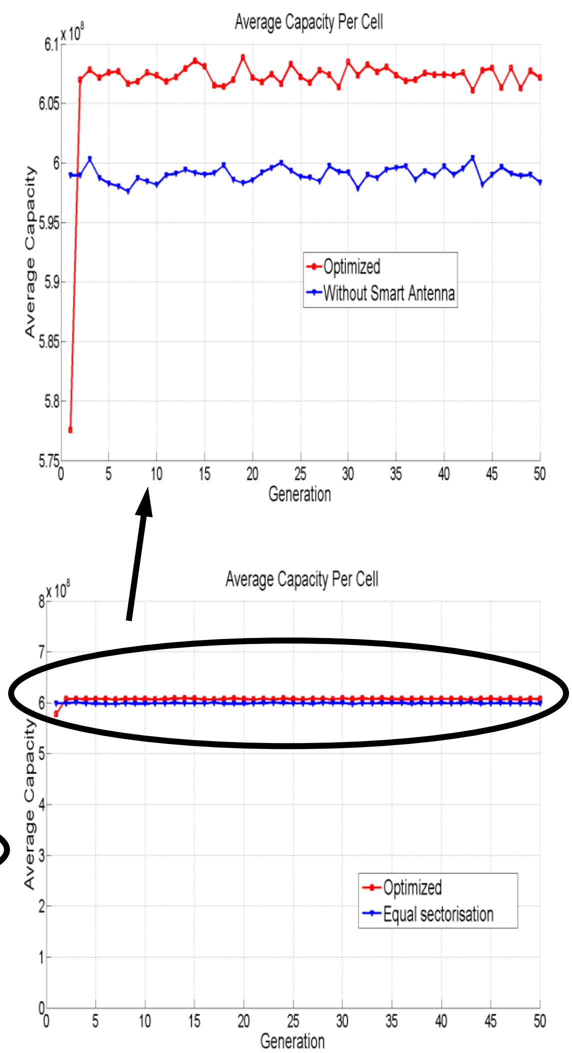
Figure 8.4 Sectorisation results of 50th Generation

Capacity results of 60, 120 and 240 users with the best fitness are shown in Figure 8.5. From Figure 8.5 (a) it can be seen that the algorithm does not give any significant enhancement of system throughput, as there are too few users in the cell, but it does give very small enhancement (1.5% and 2.4% from Figure 8.5 (b) and 8.5 (c) respectively) as the number of users is increased. That is mainly because the algorithm can make use of multiuser diversity with the growing number of users.

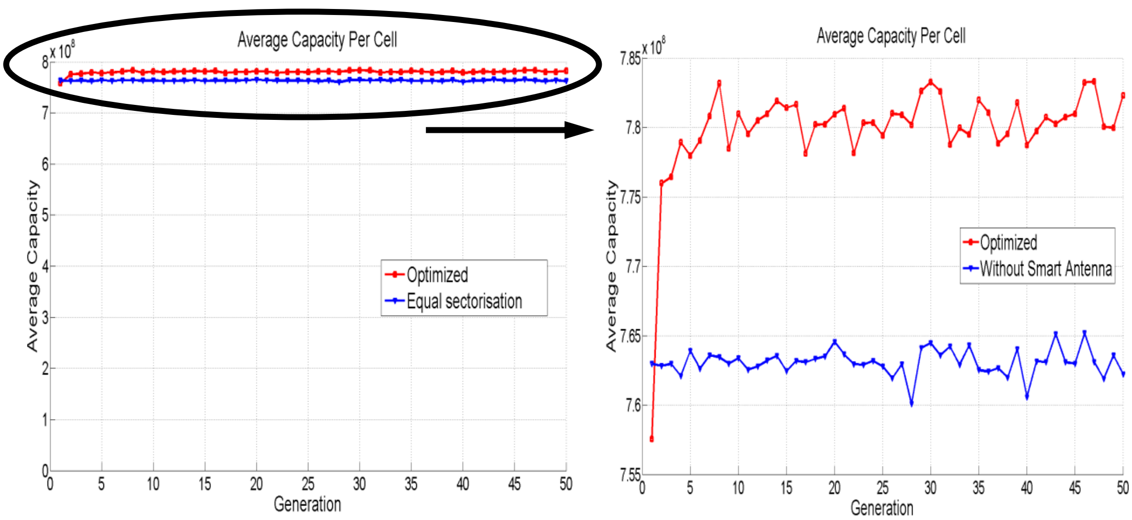
Note though, there are no gaps in coverage.



(a) 60 users/ cell



(b) 120 users/ cell

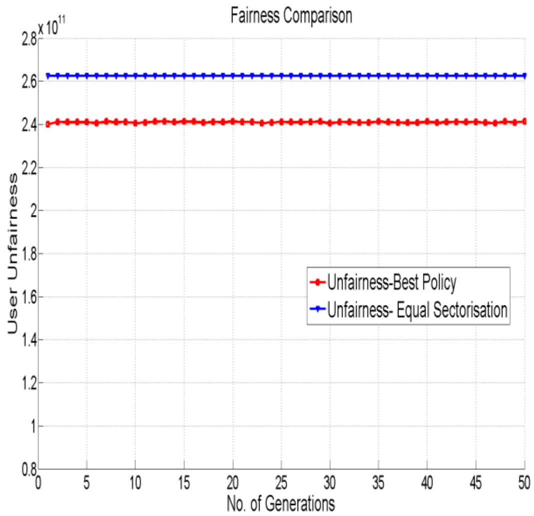


(c)240 users/ cell

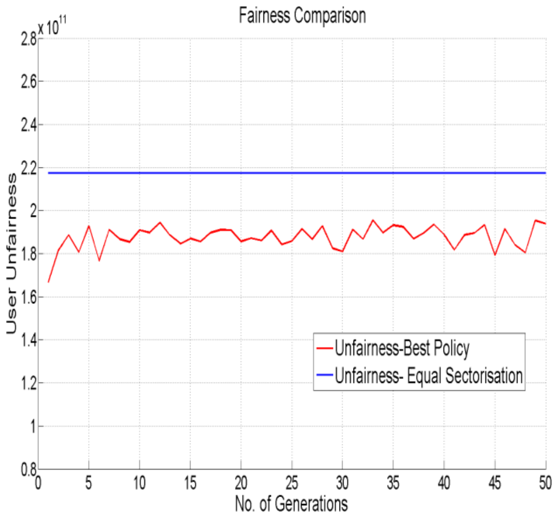
Figure 8.5 Capacity comparison

Unfairness comparison of optimised results and equal sectorisation is shown in Figure Figure 8.6, *remembering that smaller unfairness values represent better fairness*. The fairness with the algorithm optimisation is better than with equal sectorisation and is more pronounced as the number of users increases. The enhancement of fairness with user numbers of 60, 120 and 240 are 8.0%, 10.9% and 53.9% respectively.

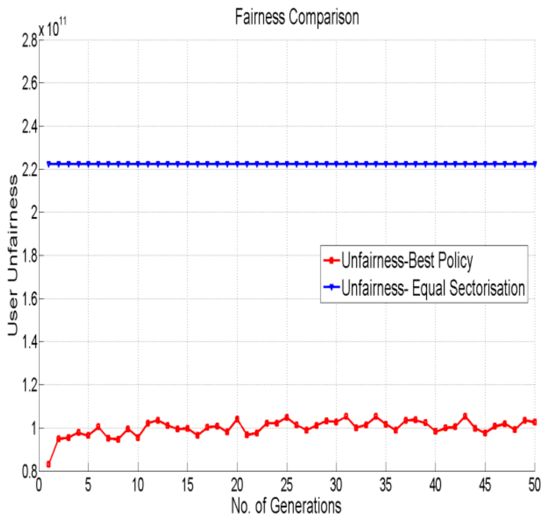
It is clear from these results that while there is little capacity improvement with uniform user distribution, the algorithm is worth using because of its improvement in fairness.



(a) 60 users/ cell



(b) 120 users/ cell



(d) 240 users/ cell

Figure 8.6 Unfairness comparison

8.2.2 Hotspot distribution

In this section, hotspot scenarios are considered. Each cell is heavily loaded with an unbalanced user distribution with the number of users varying from 60-240, with 30 uniformly distributed users (being between 12.5% and 50% of the total users), with the other 50% - 87.5% being located in 3 hot spots in each cell as shown in Figure 8.7. This means some of the radio resources are not used efficiently.

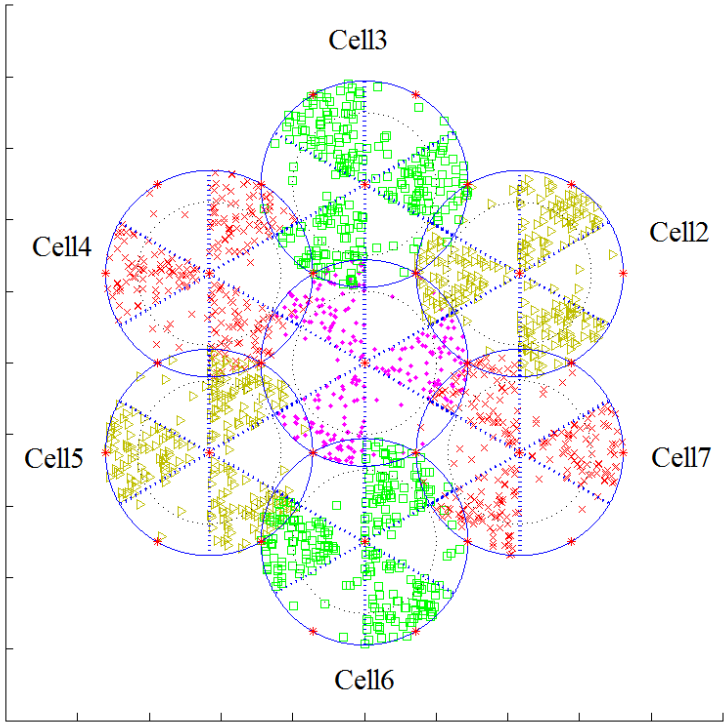
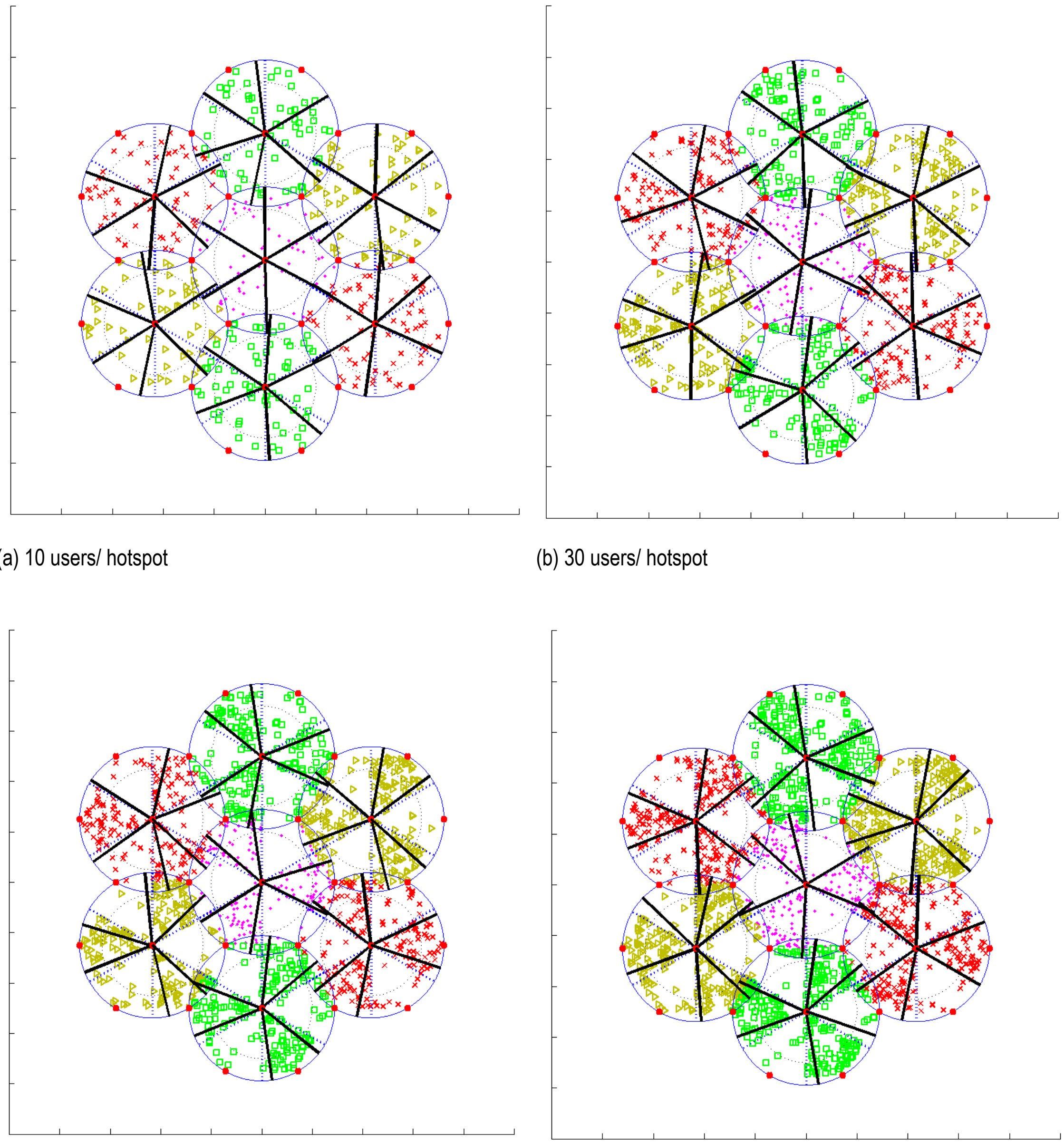


Figure 8.7 Layout of hotspot scenario



(a) 10 users/ hotspot

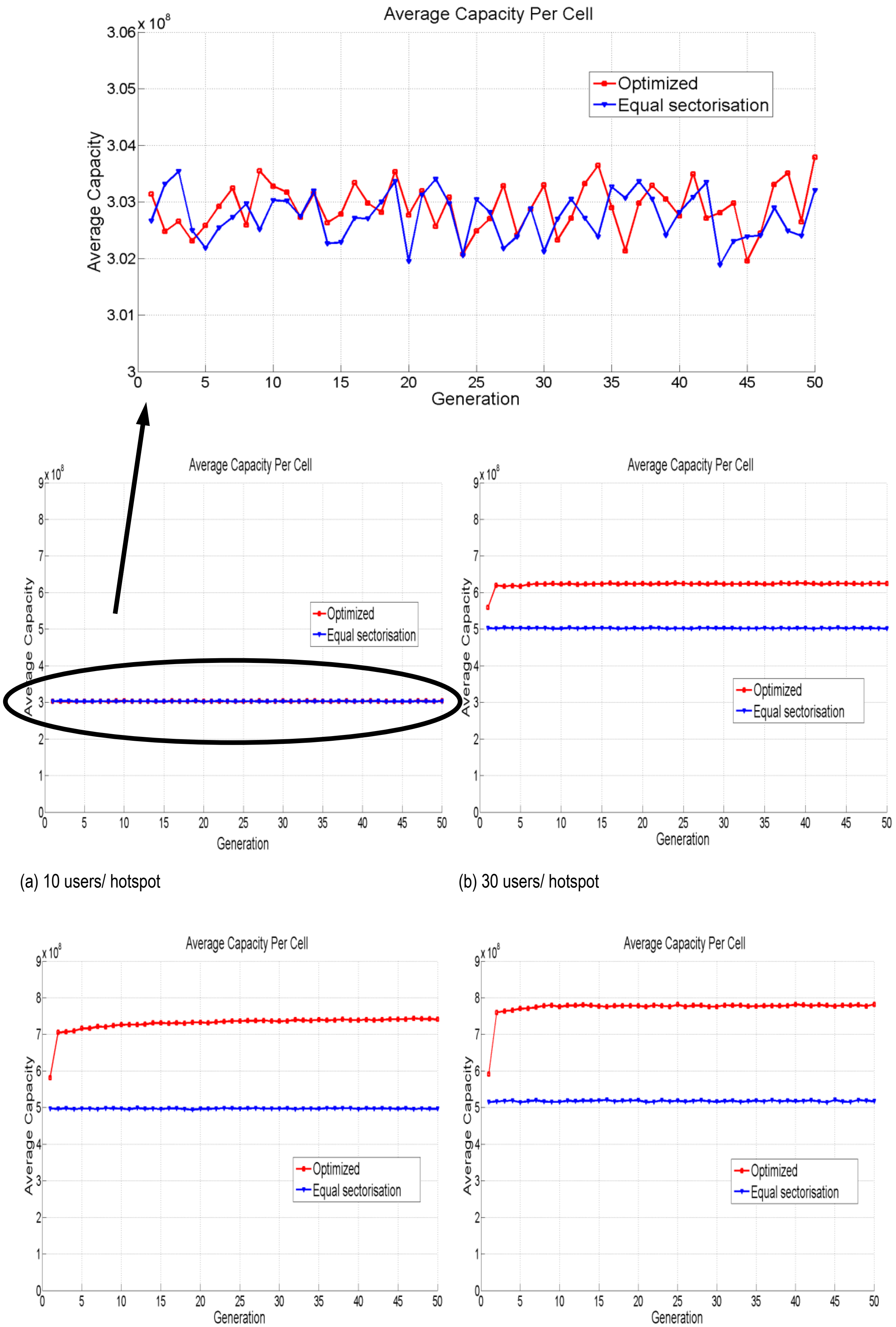
(b) 30 users/ hotspot

(c) 50 users/ hotspot

(d) 70 users/ hotspot

Figure 8.8 Sectorisation result of 50th Generation

Comparison of sectorisation with GA optimisation and equal sectorisation are shown in Figure 8.8, with 30, 90, 150 and 210 hotspot users respectively. From the figure it can be seen the change in sectorisation becomes more pronounced as the number of users increases and the system tries to balance the load.



(a) 10 users/ hotspot

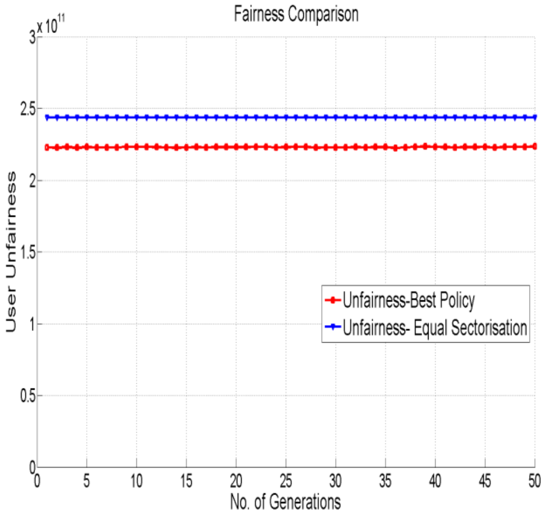
(b) 30 users/ hotspot

(c) 50 users/ hotspot

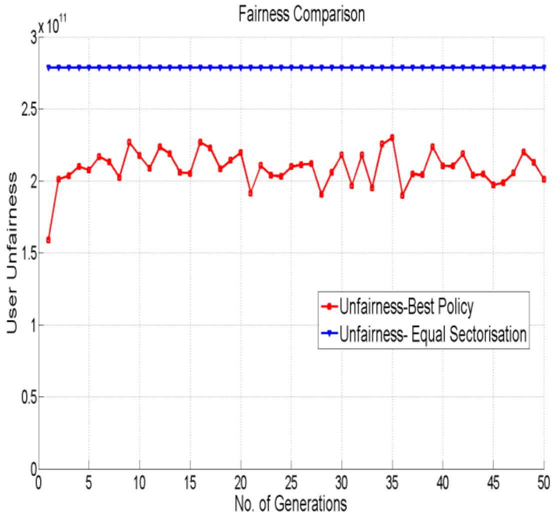
(d) 70 users/ hotspot

Figure 8.9 Capacity comparison of hotspot scenario

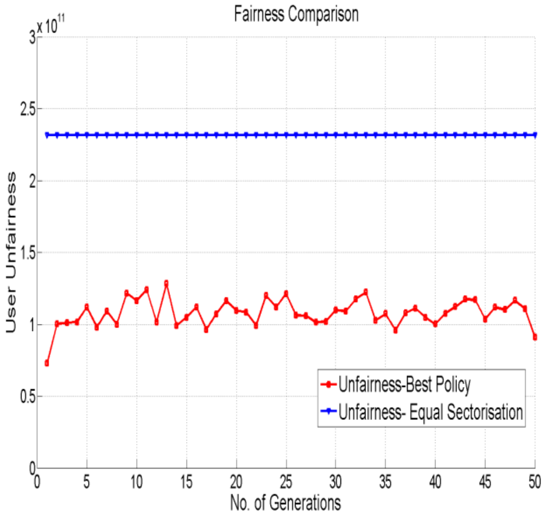
Figure 8.9 shows the throughput in terms of the individual with best fitness of each generation compared with that from equal sectorisation. Results in Figure 8.9 is based on Equation (8.4). The system throughput with the GA is about 25%, 49% and 51% greater than that without for 30, 50, and 70 users per hotspot scenarios respectively. This result is reached at about the 10th to 15th generation – this is very fast convergence. With 10 users/hotspot the load is so small that there is no increase in capacity with optimisation.



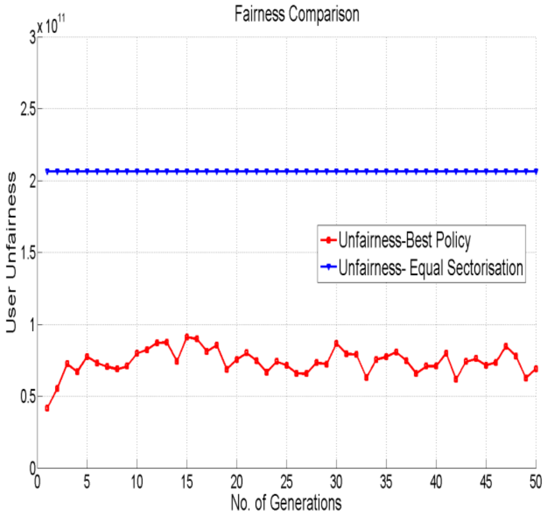
(a) 10 users/ hotspot



(b) 30 users/ hotspot



(c) 50 users/ hotspot



(d) 70 users/ hotspot

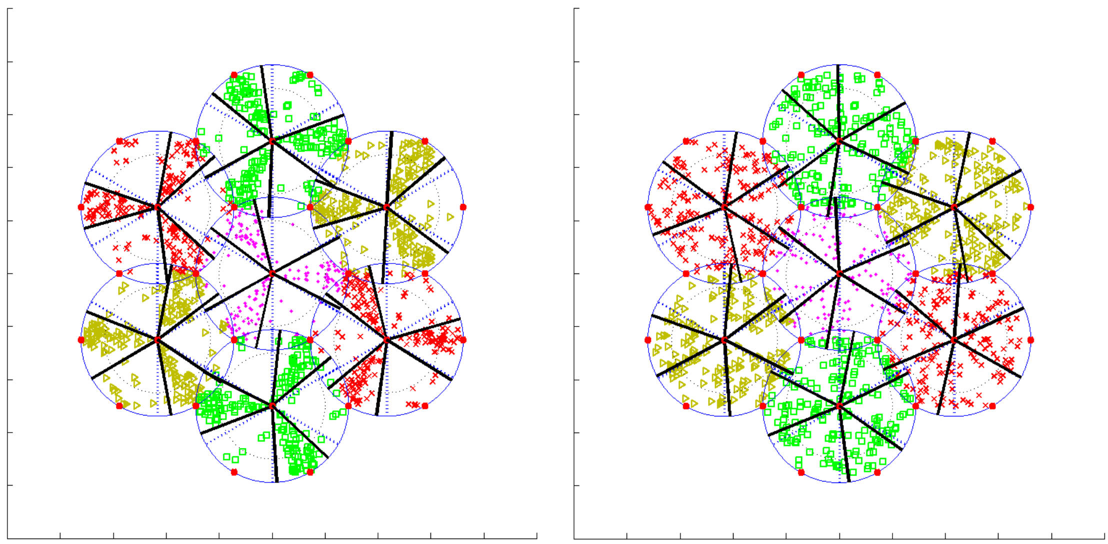
Figure 8.10 Fairness comparison of hotspot scenario

Figure 8.10 shows the fairness in terms of the best capacity of the individuals of each generation compared with that from equal sectorisation - the user fairness has a significant improvement of 8%, 28%, 52% and 67% respectively.

From the above comparison, the algorithm works well with an unbalanced user distribution for heavily loaded OFDMA networks.

8.2.3 Hotspot variation distribution

In this section, the performance of the joint design scheme is researched through simulation based on different types of hotspots. In each round of the simulation, each cell consists of 3 hotspots, with 50 hotspot users in each, and 30 uniformly distributed users in each cell. The hotspots are fan-shaped with an angle varying from 30 degree to 110 degree. As the covering area of the sectors varies from 30 to 90 degree areas, hotspots with less than 30 degree angle are not considered. Also, with 120 degree in each of 3 hotspots, the user distribution becomes uniform, so that scenario of hotspots with 120 degree angle is also not considered.



(a) hot spot angle 30°　　　　(b) hot spot angle 90°

Figure 8.11 Examples of hotspot user distribution

Figure 8.11 shows examples of hotspot distribution with different angles. A 30 degree hotspot makes it too centralized so that although the sectors shrink to the extreme, no ideal load balance can be realized. On the other hand, the 90 degree hotspots tend to uniform distribution and load balance can be easily realized; however, there is not much difference between the optimized sectorisation and the equal sectorisation.

Instead of showing the comparison of different rounds of simulations, a comparison of system capacity among different rounds' of simulation is shown in Figure 8.12, but it is easier to see the effects by plotting against hotspot angle as in Figure 8.13, which shows that a hotspot with 60° gives the best system enhancement of around 50% when the scenario is extreme, with half the sectors heavily loaded and half the sectors lightly loaded. The system capacity enhancement decreases either side of that value.

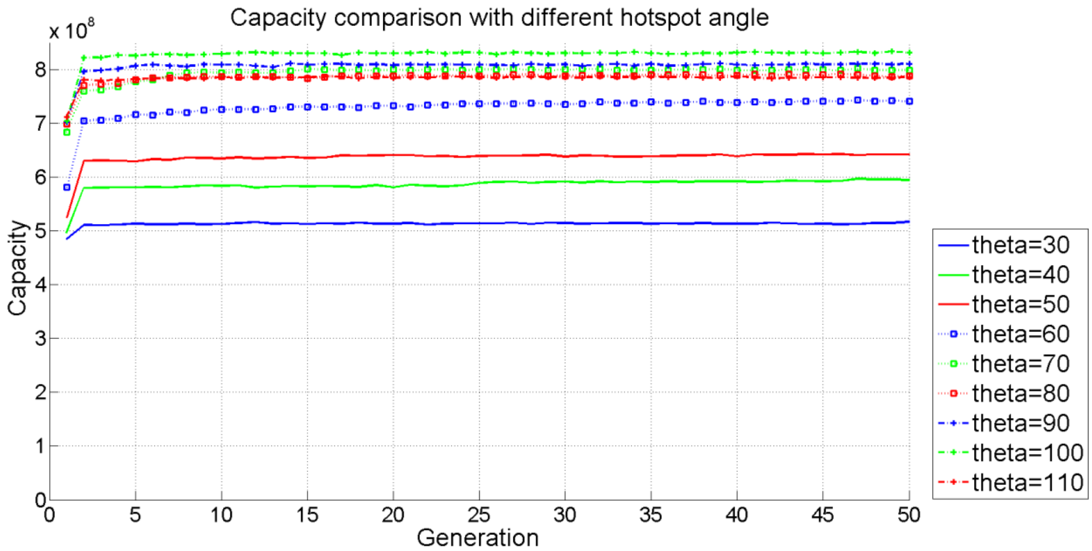


Figure 8.12 Capacity comparison with different types of hotspot

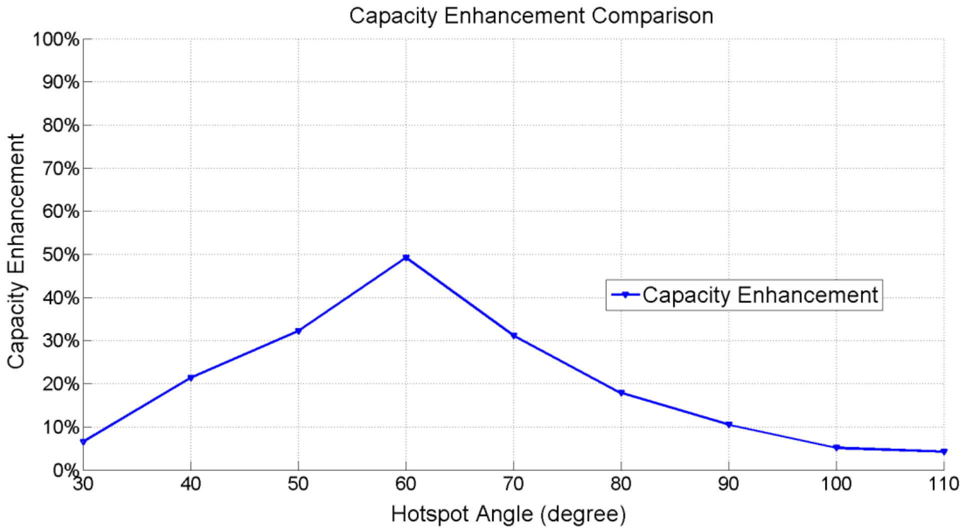


Figure 8.13 Capacity enhancement with different hotspot angle

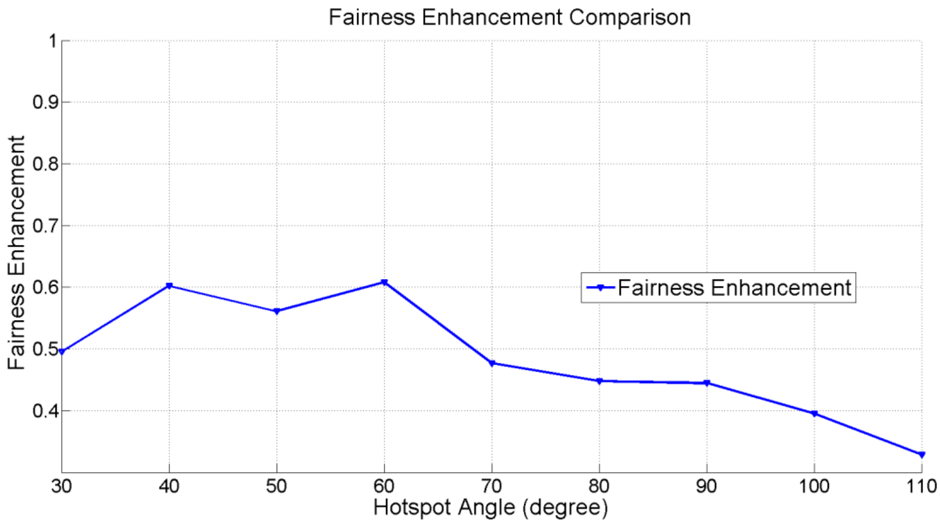


Figure 8.14 User fairness enhancement with different hotspot angle

Figure 8.14 shows the user fairness enhancement and again the best improvement is at around 60 degree.

8.3 Summary

In this chapter, a real encoding GA based joint radio resource allocation scheme is implemented to optimise a 6-sector cell architecture that avoids gaps by only changing the effective angle of the sector and not the radius. This also avoids the need for co-operation between cells.

Working together with the PF scheduling method, both system throughput and user fairness are considered in this chapter. Different kinds of scenarios are considered and compared.

With uniform user distribution, system capacity enhancement grows with the number of users per cell, when multiuser diversity can be gained. However, the improvement in system capacity with uniform user distribution is modest. User fairness has an obvious enhancement varied from 8.0% to 53.9%.

With uniform hotspot user distribution, system throughput has an enhancement within 25% and 51% and a user fairness improvement between 8% to 67%.

With hotspot variation user distribution, throughput has an enhancement of 8% to 50% and user fairness has an improvement of 20% to 60%.

The convergence speed of the algorithm designed in this Chapter is around 10 to 15 generations, which is a very fast convergence speed.

Chapter 9 Conclusions and Future work

In this thesis, the radio resource allocation problem for OFDMA based networks is investigated by using genetic algorithms to adjust the semi-smart antenna and directional antenna patterns to optimise throughput and fairness. The robustness and performance of the algorithm has been investigated through simulation

A novel joint radio resource allocation scheme based on sectorisation combined with scheduling has also been researched to overcome some of the deficiencies of the basic genetic algorithm approach and its performance investigated using different user distributions.

9.1 Conclusions

Novel conclusions arising from investigation and simulation of this thesis are:

- Using a GA algorithm to control the radiation pattern of semi-smart antennas can enhance the capacity of OFDMA based networks. However, using a GA with binary string encoding to control the antenna pattern formation can lead to gaps between the adjacent cells occurring, although cell coverage and system throughput can be enhanced; an approach to overcome this problem of gaps being formed is considered in Chapter 8.
- The GA designed in this thesis can converge around the 30th to 40th generation, which is a reasonable convergence speed for a GA. This can be seen as a benchmark in the future GA optimisation for OFDMA based networks.
- GA optimisation has also been investigated. The choice of a range of parameters has been investigated and the results show good stability for the GA designed in this thesis. The influence of selection rate and mutation rate have also been investigated. Results show that a selection rate of 0.4 or 0.6 and mutation rate 0.01 can give the best result, considering stability and convergence speed.

- When considering the multi-objective problem of capacity and coverage enhancement, it is difficult to balance system capacity and cell coverage during the adjustment of the sector radius. It is hard to fine tune the balance between the two conflicting objectives for different user distribution scenarios.
- A novel joint radio resource management algorithm is designed to improve the systematic performance of load balancing, system throughput and user fairness. By using the GA to change the angle of every sector, keeping the radius constant, the problem of holes in coverage is avoided and the approach is very effective in terms of improving system capacity and user fairness for most scenarios, especially for hotspots. The results give an improvement of around 50% in capacity and around up to 60% in user fairness. The joint algorithm shows good stability with different user distribution scenarios. Convergence speed of this GA based scheme is from 10 to 15 generations, which is a very fast convergence.

9.2 Future work

This thesis focuses on RRM in OFDMA based networks, taking LTE as an example. GA is chosen as the specific optimisation algorithm for the RRM problem. Simulator and results in this thesis can be viewed as a benchmark for RRM problem solving for OFDMA networks. Suggestions for future work can be summarized as follows:

- Overlay antenna system design. Work of this thesis focuses on system capacity and user fairness enhancement by employing semi-smart antennas controlled by a GA. Future work could consider a GA-based overlay antenna system design, as introduced in Section 2.5. In the overlay scenario, an omni-direction antenna can be used to serve the cell-centre users while the cell-edge users can be served by semi-smart antennas adjusted by GA. How this mitigates interference is worth investigating for this topic.
- User mobility combined design: the work in this thesis did not consider mobility as all users were stationary. The effect of different user mobility models could be

a topic of research in the future as mobility is an important aspect of the real environment.

- User distribution: different numbers and types of hotspot scenarios and how they can affect the algorithm performance can also be taken into account.
- GA optimisation: another topic should be the optimisation of the GA. As a GA is a kind of complicated machine learning algorithm, study on GA optimisation has never stopped. Work in this thesis is based on the parameter optimisation of the GA but designing new functions to give the GA better performance would be another future research trend.

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