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Satellite Constellation Design and Radio Resource Management Using Genetic Algorithm

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Summary

A novel strategy for automatic satellite constellation design with satellite diversity is proposed. The automatic satellite constellation design means some parameters of satellite constellation design can be determined simultaneously. The total number of satellites, the altitude of satellite, the angle between planes, the angle shift between satellites and the inclination angle are considered for automatic satellite constellation design. Satellite constellation design is modelled using a multiobjective genetic algorithm. This method is applied to LEO, MEO and hybrid constellations. The advantage of this algorithm is automatic satellite constellation design whilst achieving dual satellite diversity statistics.

Furthermore a new strategy of dynamic channel allocation is proposed using a genetic algorithm for use in MSS networks. The main idea behind this algorithm is to use minimum cost as a metric to provide optimum channel solutions for specified interference constraints. The frequency reuse condition for all spotbeams is investigated as a function of time. The update interval time and the sampling time are introduced in order to track time variant coefficients and constraints of the algorithm. The method is demonstrated for S-UMTS based on a MEO satellite constellation. Using this algorithm, it is shown that the proposed model outperforms conventional DCA schemes in terms of capacity of the system and Quality of Service (QoS).

We show in the thesis that the genetic algorithm is a robust method for calculation of dynamic variations in satellite constellation design and provides resource allocation improvements over DCA in MSS system networks.

Key words: satellite constellation design, satellite diversity, genetic algorithm, dynamic channel allocation.

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Contents

Summary	ii
Acknowledgments.....	iii
Contents.....	iv
List of Figures	viii
List of Tables.....	xi
Glossary of Terms	xii
Symbols	xiii
 Chapter 1. Introduction.....	 1
1.1 Background.....	1
1.2 Objectives of Study.....	2
1.3 Outline of Thesis.....	3
1.3 Novel Work in the Thesis	5
 Chapter 2. Fundamentals of Satellite Constellation Design.....	 7
2.1 Introduction.....	7
2.2 Orbital Plane in Space.....	8
2.3 Satellite Coverage Region and Spotbeam Model	11
2.4 Satellite Constellation Constraints.....	16
2.4.1 Elevation Angle and Azimuth.....	16
2.4.2 Inter Satellite Links.....	17

2.4.3 Satellite Diversity	18
2.4.4 Resonant orbits	19
2.4.5 Satellite positioning	21
2.4.6 Earth Radiation Belts	22
2.5 Satellite Constellation Types	24
2.5.1 Polar Orbit Constellations.....	24
2.5.2 Rosette Constellations.....	26
Chapter 3. An Evolutionary Near Resonant Satellite Constellation Design.....	30
3.1 Introduction.....	30
3.2 Basic Concept of Genetic Algorithm.....	31
3.2.1 Evolutionary Computation, Why Genetic Algorithms?.....	31
3.2.2 Genetic Algorithm Elements	33
3.2.2.1 Objective Function.....	33
3.2.2.2 Selection	34
3.2.2.3 Crossover	36
3.2.2.4 Mutation.....	38
3.3 Optimization of Satellite Constellation Design Using GA.	39
3.3.1 GA for Optimisation of Zonal Coverage	39
3.3.2 GA for Discontinuous Global Coverage.....	40
3.4 Genetic Near Resonant Satellite Constellations	41
3.4.1 System Description.....	41
3.4.2 Stochastic Optimisation	42
3.4.2.1 Structure of the Individual	42
3.4.2.2 Objective Function.....	43
3.4.2.3 Selection	44
3.4.2.4 Crossover	45
3.4.2.5 Mutation.....	46
3.5 Experiments and Evaluation	47
3.6 Conclusions.....	52
Chapter 4. Multiobjective Genetic Satellite Constellation Design.....	54
4.1 Introduction.....	54
4.2 Multiobjective Genetic Algorithm.....	55
4.3 System Description.....	57

4.3.1 Dual Satellite Diversity Constraint	57
4.3.2 Orbital Type.....	58
4.4 Multiobjective Genetic Satellite Constellation Design.....	60
4.4.1 Objective Function.....	60
4.4.2 Chromosome Structure	62
4.4.3 Selection	64
4.4.4 Crossover and Mutation.....	64
4.4.5 Fitness Function.....	67
4.5 Experiments and Evaluations.....	69
4.5.1 GSC for MEO Constellation.....	70
4.5.2 GSC for LEO Constellation.....	74
4.6 Conclusions.....	77
Chapter 5. Genetic Hybrid Satellite Constellation Design	79
5.1 Introduction.....	79
5.2 System Model	80
5.3 Genetic process	81
5.3.1 Chromosome Structure	81
5.3.2 Selection	82
5.3.3 Crossover and Mutation.....	83
5.3.4 Fitness Function.....	85
5.4 Experiments and Evaluation	87
5.4.1 Hybrid LEO and MEO Constellations.....	88
5.4.2 Hybrid LEO and GEO Constellations.....	90
5.4.3 Hybrid MEO and GEO Constellations	91
5.5 Conclusions.....	92
Chapter 6. Genetic Dynamic Channel Allocation	94
6.1 Introduction.....	94
6.2 Channel Reuse	96
6.3 Channel Allocation Scheme.....	99
6.3.1 Fixed Channel Allocation (FCA).....	99
6.3.2 Dynamic Channel Allocation (DCA).....	101
6.3.3 Hybrid channel allocation (HCA).....	106
6.3.4 Adaptive dynamic channel allocation	107

6.3.5 Intelligent channel assignment.....	108
6.4 Genetic Dynamic Channel Allocation Algorithm.....	110
6.4.1 Network Model.....	110
6.4.2 Traffic load for Each Spotbeam.....	112
6.4.3 Frequency Reuse Condition.....	116
6.4.4 Genetic Algorithm Process	118
6.4.4.1 Genetic DCA Scenario.....	118
6.4.4.2 Chromosome Structure	121
6.4.4.3 Selection	123
6.4.4.4 Crossover	124
6.4.4.5 Mutation.....	125
6.5 Performance Evaluation.....	126
6.5.1 Assigned channel results.....	126
6.5.2 Blocking Probability.....	127
6.5.3 Dropping Call Probability.....	129
6.5.4 Traffic Carried per Channel.....	131
6.6 Conclusions.....	131
Chapter 7. Conclusions and Future Work.....	133
7.1 Conclusions.....	133
7.2 Future Work.....	136
Papers	138
Bibliography	140
Appendix A. Satellite Location with Respect to Look Angle	147
Appendix B. Spectrum Allocations.....	151
Appendix C. SAINT Traffic Distribution	152
Appendix D Simulation block diagram for satellite constellation design	156

List of Figures

Figure 1.1 Organisation of this thesis.....	3
Figure 2.1. Orbit in space	9
Figure 2.2. Parameters of elliptical orbit.....	10
Figure 2.3. Satellite observed region.....	12
Figure 2.4. Satellite's footprint and spotbeams.....	14
Figure 2.5. Multispotbeams model (a). Spotbeam coverage area, (b) Coverage view	15
Figure 2.6. The azimuth from a point T on the earth	17
Figure 2.7. The angle shift between satellites and between planes scenario.	22
Figure 2.8. Van Allen radiation belt (electrons).....	24
Figure 2.9. Coverage geometry of a polar orbit constellation.....	25
Figure 2.10. Geometry for inclined orbit constellation	28
Figure 3.1. General cycle of GA	32
Figure 3.3 Outline of the genetic algorithm	33
Figure 3.4. Roulette Wheel Selection.....	35
Figure 3.5 Single point crossover operator	36
Figure 3.6 Example of uniform crossover.....	38
Figure 3.7. The genetic near resonant constellation algorithm	42
Figure 3.8 Chromosome structure.....	43
Figure 3.9 The selection process procedure	45
Figure 3.10 The crossover process procedure.....	46
Figure 3.11 The mutation process procedure	46
Figure 3.12 Dual satellite diversity statistics for 14° minimum elevation angle [26].....	50
Figure 3.13 Triple satellite diversity statistics [26].....	51
Figure 3.14. Mean elevation angle statistics [26].....	51
Figure 3.15 Minimum elevation angle statistics	52
Figure 4.1. Satellite diversity	57
Figure 4.2. Satellite constellation's coverage geometry	59
Figure 4.3. GSC chromosome structure	63
Figure 4.4. Multipoint crossover	65
Figure 4.5. Fitness function vs. generation size	68

Figure 4.6 Dual satellite diversity statistics at 13° minimum elevation angle	72
Figure 4.7 Elevation angle statistics for MEO constellation.....	73
Figure 4.8 GA-MEO satellite constellation coverage	73
Figure 4.9. Dual satellite diversity statistics at 14° minimum elevation angle [36].....	75
Figure 4.10. Elevation statistics for LEO constellation	76
Figure 5.1. Satellite diversity for hybrid satellite constellation design	80
Figure 5.2. Hybrid satellite constellation chromosome structure.....	81
Figure 5.3 Multipoint crossover site algorithm	84
Figure 5.4 Genetic hybrid satellite constellation optimisation flow chart	86
Figure 5.5. Dual satellite diversity statistics using GA for single MEO and hybrid LEO/MEO const. at 13° minimum elevation angle	89
Figure 5.6. Dual satellite diversity statistics using GA for single LEO and hybrid LEO/GEO constellation at 14° minimum elevation angle.	91
Figure 6.1. Radio resource management concept.	95
Figure 6.2. Reuse distance.....	97
Figure 6.3. Interference in MSS networks	104
Figure 6.4 Adaptive dynamic channel allocation.....	107
Figure 6.5. Frequency reuse between spotbeams.....	111
Figure 6.6 SAINT traffic distribution	113
Figure 6.7. Local traffic profile (SAINT project)	113
Figure 6.8 Traffic intensity for different spotbeams.	115
Figure 6.9 The example of frequency reuse concept	117
Figure 6.10. The concept of the update and the sampling interval	118
Figure 6.11. Genetic DCA chromosome structure	121
Figure 6.12. Genetic DCA flowchart.	122
Figure 6.13 The variation of the fitness value during the first 550 generations	126
Figure 6.14. Call blocking probability [73].....	128
Figure 6.15 Call blocking probability for different population size [74].....	129
Figure 6.16 Dropping call probability [73]	130
Figure A-1. Satellite location with respect to the angle look.	147
Figure B-1. UMTS/IMT 2000 core bands.....	151
Figure B-2. Advanced MSS bands.....	151
Figure D-1. Block diagram for genetic near resonant constellation design	156

Figure D-2. Block diagram for genetic satellite constellation design	157
Figure D-3. Block diagram for genetic hybrid satellite constellation	157

List of Tables

Table 2.1 The value of the azimuth (ξ) with respect to the relative position of the sub satellite point.....	17
Table 3.1. Selected ranges of the state vector components	47
Table 3.2. Common parameter inputs of the GA	48
Table 3.3. Constellation characteristics for different LEO	49
Table 4.1. GA input parameters	70
Table 4.2. Simulation results for MEO constellation.....	71
Table 4.3. Simulation results for LEO constellation [36]	74
Table 4.4: Effects of different population size for LEO constellation	77
Table 5.1. Hybrid LEO/MEO Constellations	89
Table 5.2. Hybrid LEO and GEO constellations [43]	90
Table 5.3. Hybrid MEO and GEO constellations [43]	92
Table 6.1 Example of assigned channel [73].....	127
Table 6.2. Carried traffic per channel [74]	131

Glossary of Terms

ACeS	Asia Cellular Satellite
ADCA	Adaptive Dynamic Channel Allocation
CIR	Carrier to Interference Ratio
DCA	Dynamic Channel Allocation
DECT	Digital European Cordless Telephone
EFC	Earth Fixed Cell
FCA	Fixed Channel Allocation
FES	Fixed Earth Station
FDMA	Frequency Division Multiple Access
GA	Genetic Algorithm
GEO	Geostationary Orbit
GES	Gateway Earth Station
GOS	Grade of Service
GPS	Global Positioning System
GSC	Gateway Station Control
GW	Gateway
HCA	Hybrid Channel Allocation
ICO	Intermediate Circular Orbit
INSURED	Integrated Satellite UMTS Real Environment Demonstrator
IP	Internet Protocol
ISL	Inter Satellite Link
LB	Lower Bound
LEO	Low Earth Orbit
LES	Land Earth Station
MA	Mean Anomaly
MEO	Medium Earth Orbit
MSS	Mobile Satellite System
MT	Mobile Terminal
QoS	Quality of Service
QPSK	Quadrature Phase Shift Keying
RAAN	Right Ascension of the Ascending Node
SFC	Satellite Fixe
S-UMTS	Satellite UMTS
SAINT	Satellite Integration in the Future Mobile Network
SINUS	Satellite Integration into Networks for UMTS Services
SPCN	Satellite Personal Communication Network
SRA	Staggered Resource Allocation
TDMA	Time Division Multiple Access
UMTS	Universal Mobile Telecommunications Service

Symbols

Chapter 2

i	Inclination angle
Ω	Right ascension of the ascending node (RAAN)
ω	Argument of the perigee
v	True anomaly
E	Eccentric anomaly
a	Semi major axis
e	Eccentricity
N	Total number of satellites
p	Orbital plane
P	Number of planes
s	Number of satellite per plane
α	Earth central angle
θ	Minimum elevation angle
h	Satellite altitude
R_e	Earth's radius
D	Slant path range
N_s	Number of spotbeams
n	Number of tiers
θ_{th}	Beamwidth
f	Carrier frequency
d	Antenna diameter
ξ	Azimuth
T	Satellite period
μ_e	Physical constant related to the Earth and universal gravity
$\dot{\Omega}$	RAAN precession
m	Harmonic factor

Chapter 3

α_x	Crossover probability
α_m	Mutation probability
$f(\cdot)$	Objective function
$g(\cdot)$	Transform function
$F(\cdot)$	Resultant relative fitness
N	Population size
x_i	Phenotypic value of the individual i
N	Number of selection required
L	Chromosome length

k_i	Crossover point
f	Minimization objective function
T	Satellite period to orbit
μ_e	Physical constant related to the Earth and universal gravity
R_e	Earth's radius
$b_{out}(j)$	Output of new bit string (chromosome)
j	Individual index
ρ	Generation index
a	Scaling factor
f_ρ^j	Objective function for individual j and generation index ρ
$P_s(j)$	Probability of selection for mating
M	Population size
Q	Number of individual
$S_{\rho-1}$	Sum of the fitness value

Chapter 4

$f_i(x)$	Maximize/minimize fitness function
ω_i	Weighting factor
δ	Spacing between orbital planes
ω	Phasing angle between satellites
Ω	Right ascension of the ascending node
θ	Elevation angle
α	Angular radius
h	Altitude of satellite
R_e	Earth's radius
θ_s	Angle between planes
ϕ	Angle shift between satellites
J_e	Zonal harmonic as a function of the longitude
$\sim$	
n	Legendre polynomial order
e	Eccentricity of the orbit
$p_{\max}$	Parameter of the satellite constellation for maximum value
$p_{\min}$	Parameter of the satellite constellation for minimum value
$SatDiv$	Satellite diversity availability
C_{tot}	Total chromosome length
N_p	Number of the satellite constellation parameter
CL_p	Chromosome length for each parameter
F_j^l	Quality value of the fitness
Pr_i	Probability of selection for mating of a particular chromosome
$Nvar$	Number of variables of an individual
β	Dynamic parameter in crossover process
LB	Lower bound

UB	Upper bound
r	Random number in interval [0,1]
b	The degree of non uniformity
$c_{\max, \min}$	Vector matrix of bit string in chromosome with the best fitness

Chapter 5

C_{tot}	Total length of the chromosome
p_{j1}	Number of parameters for 1 st layer
p_{j2}	Number of parameters for 2 nd layer
CL_p	Chromosome length for each parameter
(Γ_p^j)	Selected parents
ρ	Generation of individual
$S(.)$	Selection process
j	Individual index
$P_s(j)$	Probability of any individual being selected from the population
$P_{1or2,n}^1$	Group bit string for each parameter of 1 st layer satellite constellation
$P_{1or2,n}^2$	Group bit string for each parameter of 2 nd layer satellite constellation
p_k	A set value of gene's
s_p^{t+1}	Result vector of mutation process
ω	Weighting factor
a	Scaling factor
$E_{\min_k} (.)$	Expectation operators of parameters with minimizing
$E_{\max_k} (.)$	Expectation operators of parameters with maximising
$SatDiv$	Satellite diversity condition
C	Chromosome matrix output of the genes

Chapter 6

N_{ch}	Number of orthogonal channel
N	Number of cells per sector
D	Reuse distance
R_{cell}	Distance between the center of the hexagon and the point joining of two edges
C	Strength of the received carrier power
γ	A constant related to the terrain environment
$\frac{C}{I}$	Carrier to interference ratio
q	Co-channel interference reduction factor
M	Number of system resources
I_{down}	Downlink interference
CH	Group of available channel

ch	The best channel
I_{down_max}	Maximum acceptable downlink interference
I_{up_max}	Maximum acceptable uplink interference
CIR_{down}	Estimated channel to interference ratio (CIR) for downlink
CIR_{down_min}	Minimum acceptable CIR downlink
$C_x(i)$	Suitable cost function
$\Lambda(k)$	Set of available channel
$E_i(t)$	Traffic load in spotbeam i
$E_k(t)$	Traffic load in area k
$Lat(i,j)$	Latitude of cell (i,j)
$Lon(i,j)$	Longitude of cell (i,j)
D_i	Channel requirement for the dynamic channel allocation
e	Random event (a call arrival or departure)
$A(x,e)$	Set action of available current state
t	Update interval time
$\Delta\tau$	Sampling interval time
F	Final fitness function
$I_{ij}(t)$	Co-site interference
$C_{ik}(t)$	Co-channel interference
$C_{j\mu}(t)$	Adjacent co-channel interference
Cl	Chromosome length
S_b	Number of spotbeams
C_{sb}	Number of channel
$P_m(q)$	Probability of any individual
q	Index of individual
Q	Total individual
$S_{\rho-1}$	Sum of the fitness value

Chapter 1. Introduction

1.1 Background

S-UMTS is being developed in Europe as a new generation of mobile satellite communication systems. The research activity on S-UMTS was introduced in the European Union SAINT project and then continued in following projects, SINUS and INSURED. The SAINT project focused on the radio interface and resource management strategy, the potential market and the integration of the satellite into terrestrial network of the 3rd generation of mobile systems. The SINUS project used the results of the SAINT project to develop a S-UMTS test-bed. The SINUS project concentrated on the investigation of the performance of multimedia services for various satellite constellations. The handover experiment between satellite and terrestrial mobile networks that was realized in mobile satellite system (MSS) networks was addressed in the INSURED project. Further research on S-UMTS was supported by the European Space Agency ROBMOD project and focused on the S-UMTS radio interface. Some applications of communication systems such as maritime communication, aeroplane communications via satellite, and mobile IP networks are integrated in the advanced S-UMTS network. For such MSS networks, the dynamic satellite constellation model and the optimisation of the radio resource management are very important.

The main issues for satellite constellation design are minimizing the total number of satellites and minimizing the maximum altitude of the satellites. In addition, other parameters that depend on the nature of the satellite constellation are also important. For example, if the satellite constellation is to be used for the accurate positioning of the mobile terminals, the angle between planes and the angle shift between satellites are very important. Also, the inclination angle parameter is very important for satellite diversity in order to take into account the dual satellite visibility, which can improve even further the accuracy by reducing the geometric dilution of precision. The inclination angle can also be varied to optimise coverage area and diversity over a range of latitudes. In satellite diversity, a user (mobile terminal/MT) communicates with others through a gateway

(GW) via more than one satellite, which changes over time. For example in a shadowing condition, if one of the satellites is shadowed, the other satellite will still be in view for the user to maintain the service. Satellite diversity is used to reduce the link margin requirement, improve the quality of service and combat the shadowing condition.

In MSS networks, efficient resource management is very important to achieve the maximum system capacity. The resource management deals with the allocation of bandwidth, power and carriers with time and space variations. Resource management includes operational frequency planning to handle the mapping of available spectrum resources to network entities (satellite spotbeams and user terminals), assignment of transmission resources to the user and the control of transmitted power. The optimisation of the use of the radio resource allocation is important to ensure the highest level of reliability, availability, and quality of service provided to the users.

1.2 Objectives of Study

The objectives of the study presented in this thesis were the efficient design of the dynamic satellite constellations and efficient radio resource management scheme for S-UMTS. The dynamic satellite constellation design involves various parameters of the satellite constellation being determined simultaneously. A multiobjective genetic algorithm is used in a new approach for the optimisation and the automation of satellite constellation design incorporating satellite diversity. In this study, the total number of satellites, the altitude of satellites, the angle between planes, the angle shift between satellites and the inclination angle are considered to be parameters of the satellite constellation design which can be optimised simultaneously. This new approach to satellite constellation design is called 'genetic satellite constellation' (GSC) design. The implementation of the method is considered for single layer satellite constellation design such as LEO and MEO. The GSC algorithm has been modified and applied to double layer satellite constellation design, as in hybrid satellite constellations, e.g., LEO/MEO, LEO/GEO and MEO/GEO. The performance of the dual satellite diversity statistic and the average elevation angle from this algorithm are also presented in this thesis.

An objective was also to propose a new dynamic channel assignment for MSS networks using the genetic algorithm. In this work, dynamic channel allocation as a means of radio resource management is proposed for the MEO constellation S-UMTS. The main idea behind this algorithm is to use minimum cost as a metric to provide optimum channel solutions for specified interference constraints. The efficiency of bandwidth is the goal of this scheme. The combination of the loading of the traffic variances between spotbeams and the interference adaptation are formulated into the genetic algorithm process. Performance gains in capacity and QoS in the MSS networks were evaluated in this study.

1.3 Outline of Thesis

The organisation of the chapters in this thesis is shown in Fig. 1.1.

Figure 1.1 Organisation of this thesis

The thesis is divided into six technical chapters (Chapter 2 – Chapter 6), which provide the background of the system considered in the study including the fundamentals of satellite constellation design; the proposed genetic algorithm model for near resonant satellite constellation design with satellite diversity; the proposed multiobjective genetic algorithm for automatic satellite constellation design; the modified multiobjective genetic satellite constellation algorithm for hybrid satellite constellation designs and a new proposed model for dynamic channel allocation for MSS networks using the genetic algorithm approach. In all cases we present performance evaluations.

Chapter 2 concentrates on the basic concepts of satellite constellations to make clear the parameters that are needed for satellite constellation design. This chapter also illustrates the types of satellite constellation design and performance characteristics. A spotbeam model that is used in further studies is also presented in this chapter.

Chapter 3 presents the concept of stochastic optimization using genetic algorithms. Implementation of the genetic algorithm for satellite constellation design in previous works is also reviewed in this chapter. A new approach to near resonant satellite constellation design with satellite diversity using the genetic algorithm approach is illustrated in the latter part of this chapter.

Chapter 4 describes a new approach to satellite constellation design with satellite diversity using a multiobjective genetic algorithm and is called the genetic satellite constellation (GSC) design. A multiobjective genetic algorithm is proposed in this work to produce an automatic satellite constellation design. The multiobjective genetic algorithm scheme monitors the number of satellites, the altitude of satellites, the angle between planes, the angle shift between satellites and the inclination angle. Implementations of the GSC scheme for single LEO and single MEO constellations are presented in this chapter. The evaluation of the GSC algorithm is given for dual satellite diversity statistics and average and minimum elevation angle performances.

Chapter 5 illustrates a modified version of the GSC algorithm for hybrid satellite constellation design. This algorithm is called the genetic hybrid satellite constellation design. As examples, the modified GSC is implemented for the hybrid LEO/MEO, LEO/GEO and MEO/GEO constellations. The dual satellite diversity statistical performance is evaluated for the genetic hybrid satellite constellation design.

Chapter 6 describes a new approach to dynamic channel allocation for mobile satellite system (MSS) networks using a new evolutionary algorithm. As background, this

chapter also presents and reviews some channel assignment concepts for cellular and MSS networks. The radio allocation concept for cellular system networks is presented. Some design strategies for channel assignment including fixed channel allocation (FCA), dynamic channel allocation (DCA), hybrid channel allocation and some modified models are also presented in this chapter. The concept of channel allocation for cellular networks is adopted for use in MSS networks. The implementation of the genetic algorithm for dynamic channel allocation in an MSS network environment is described in this chapter. The network model of the mobile satellite system, the traffic distribution scenario and the allocation of the traffic into spotbeams are also described in this chapter. The algorithm used monitors the call arrivals and the interference to optimise the allocation of channels in the radio resource management area. Performance evaluations for the genetic dynamic channel allocation including the number of the channels for each spotbeam, the assigned channels, quality of service (QoS) including call blocking probability and dropping call probability, and the actual carried traffic per channel are also presented in this chapter.

Finally, chapter 8 concludes and suggests future work following on from this thesis and areas that require more attention.

1.3 Novel Work in the Thesis

Chapters 3, 4, 5 and 6 contain the original achievements of this thesis. The novel work of the thesis is as follows:

- Design of a genetic near resonant satellite constellation with satellite diversity to minimize the maximum satellite altitude for LEO constellations.
- Development of software for genetic satellite constellation design to evaluate the satellite diversity statistics and the elevation angle statistics.
- Design of a multiobjective genetic satellite constellation with satellite diversity and its implementation in single LEO and MEO constellations.
- Development of a genetic satellite constellation algorithm for hybrid LEO/MEO, LEO/GEO and MEO/GEO constellations.

- Design of a genetic dynamic channel allocation for MSS networks providing the network model, the traffic load for multispotbeams based on satellite loading and the frequency reuse condition.
- Evaluation of the capacity of the MSS system, its QoS performances and the carried traffic for each satellite of the genetic dynamic channel allocation for MSS networks.

Papers published as a result of work carried out in the thesis are given following the conclusions section of the thesis.

Chapter 2. Fundamentals of Satellite Constellation Design

2.1 Introduction

Originally commercial, satellite communications were used with GEO satellites for fixed communication (INTELSAT), and then extended for mobile communication to ships, aircraft and land vehicles (INMARSAT). The GEO satellites have 0° inclination angles and 0 (zero) eccentricities. GEO's have a circular orbit, which places them in the equatorial plane. The orbit altitude is very high (36,000 km) with high round trip delays, circa 270 ms, high radio signal attenuation and high launch cost. GEO's have also been used for mobile satellite communications with many applications including maritime, aeronautical, land-mobile by INMARSAT and other private operators. Eutelsat, ACeS (Asia Cellular Satellite), Garuda, and Thuraya are all examples of the use of GEO satellite systems for mobile applications.

The first generation of global satellite systems offering personal and mobile satellite communication started with the introduction of low earth orbit (LEO) and medium earth orbit (MEO) constellations. The altitude of LEO satellites is being around 750-2000 km in circular or elliptical orbits. LEO satellites are needed to guarantee the coverage of the whole Earth for a daily service and the round trip time is around 5 – 15 ms. LEO satellites provide advantages in satisfying the link budgets and have lower powers, propagation delay and cell's sizes. Iridium and Globalstar are examples of LEO satellite systems. Iridium was designed with 66 satellites; distributed into 6 planes with 11 satellites for each plane [1]. The first launching of Iridium satellites for a commercial service was in 1996 and a full service commenced in 1998. The Iridium constellation was proposed at near polar inclination ($i=86^\circ$) and has the lowest altitude of all proposed S-PCN constellations at 780 km. The Iridium system provides full duplex voice, data and facsimile services at 2.4 kbit/s. QPSK with FDMA and TDMA multiple access techniques were employed and mobile transmission operates in the 1616-1626.5 MHz band. Due to

financial difficulties Iridium filed for chapter 11 bankruptcy protection in the US in 1999, but in December 2000, Iridium satellite LLC, a new company, took over the system, which is now operational and has 50,000 users (mid 2002). The Globalstar system comprised of 48 satellites distributed into 6 planes with 8 satellites per plane [2]. Globalstar commenced full service in 2000. The Globalstar constellation consists of a Ballard [3] constellation (48, 8, 1/6) at the inclination angle of 52° and 1,414 km altitude. Globalstar does not provide total global coverage but is restricted to 70° latitude, North and South from the Equator.

The ICO constellation [4] was proposed having an altitude of 10,350 km in 1996. ICO (a spin off from INMARSAT) has 10 satellites, distributed into 2 planes with 5 satellites per plane. ICO launched its first satellite in 1998 but has subsequently suspended further deployments. The ICO system was intended to offer global satellite UMTS (S-UMTS) services. The ICO constellation at 10,350 km altitude has satellites in 45° inclination planes. The RAANs are separated by 180° and the planes comprise 5 satellites to give contiguous coverage around the orbit plane. The Globalstar and ICO constellations are used herein as baselines for comparison to a new constellation design approach using the genetic algorithm.

In this chapter, the basic concepts of satellite constellation design for the space segment of mobile satellite systems are discussed. Some constraints of satellite constellation design are specifically examined in order to highlight the problems and the implication to the genetic satellite constellation design. The satellite constellation models are illustrated in the last part of this chapter.

2.2 Orbital Plane in Space

In order to describe satellite position in a three-dimensional space at any given time, six parameters of the satellite constellation are used, and are called the orbital parameters. The configuration of the orbit in space is shown in Fig. 2.1.

- Right Ascension of the Ascending Node (RAAN) is the angle from the Vernal Equinox (x axis) to the ascending node. The ascending node is the point where a

satellite passes from the equatorial plane moving from south to north. The right ascension of the ascending node Ω is in the range 0° and 360° . Similarly a descending node is the point where the satellite crosses the equatorial plane moving in the direction from north to south.

Figure 2.1. Orbit in space

- The inclination angle (i) is the angle between the plane of the orbit and the equatorial plane measured at the ascending node in a counter clockwise direction. The range of the inclination angle is 0° to 180° . When the inclination angle of an orbit is less than 90° , it is called a pro-grade orbit or direct orbit. If the inclination angle is greater than 90° , it is called a retrograde orbit or indirect orbit. When the inclination angle is equal 0° or 180° , it is called an equatorial orbit. If the inclination angle is equal 90° , it is called a polar orbit.
- Argument of the perigee ω is the angle in the orbital plane between the line of nodes and the perigee of the orbit. It is measured counter clockwise from the

ascending node. The line of nodes is the line joining the ascending node and the descending nodes.

- True anomaly (ν) is the angle measured positively in the direction of movement of the satellite from 0° to 360° , between the direction of the perigee and the direction of the satellite. The mean anomaly is the angle from the perigee that the satellite would traverse in the same time t_p , moving at the average orbital angular velocity. Time t_p is the elapsed time since the satellite passed the perigee. The eccentric anomaly (E) is measured at the centre of the ellipse. For the circular orbit, true anomaly and the eccentric anomaly are the same but diverge for elliptical orbits.
- Semi-major axis (a) half is the longest axis within an ellipse and is measured from the halfway point between the two focal points in the ellipse to the perigee point. In other words, the semi major axis describes the size of a conic orbit (ellipse or circle) for satellite communications.
- Eccentricity is a constant ($e = 1 - [r_p / a]$), which describes the shape of the ellipse. A value of the eccentricity between zero and 1 describes an elliptical orbit, whereas an eccentricity of zero describes a circular orbit. If the value of the eccentricity is equal 1, the trajectory of the satellite is a parabola. The eccentricity and the semi major axis in elliptical orbital types are described in Fig. 2.2.

Figure 2.2. Parameters of elliptical orbit

2.3 Satellite Coverage Region and Spotbeam Model

The satellite constellation configuration is defined as the number of orbital planes (p) and the number of satellites per plane (s). The values of p and s should be chosen so as to minimise the total number of satellites ($N = p \times s$) required to provide the specified level of coverage. Other major characteristics of the satellite constellation are: the altitude of satellite; chosen on the basis of both physical and geometric considerations; the inclination angle, which is governed by the global coverage requirement; the level of coverage and the minimum angle of elevation; the eccentricity which determines the orbit's shape; the angle between planes and the angle shift between satellites that are used to determine the satellite positioning accuracy.

Satellite coverage is defined by the minimum elevation angle of the satellite that is measured from the local horizontal to the ground. Beste [5] and Hanson [6] evaluated optimum and partial coverage of satellite constellations. The following sequence of steps were used to find the optimal satellite coverage: minimising the number of satellites to meet the coverage area.

Simple geometry involving spherical and planar trigonometry can provide the required relationship of satellite constellation parameters and is shown in Fig. 2.3. The half of the earth central angle of the satellite's coverage is given by:

$$\alpha/2 = \pi/2 - \theta - \sin^{-1}[R_e \sin(\theta + \pi/2)/(R_e + h)] \quad (2.1)$$

where θ is the minimum elevation angle, h is the satellite altitude, and R_e is the Earth's radius. For a given α and using the cosine rule, the slant path range, D , can be calculated by the following equation:

$$D^2 = (R_e + h)^2 + R_e^2 - 2R_e(R_e + h)\cos(\alpha/2) \quad (2.2)$$

These equations can be converted into latitude and longitude points according to the sub-satellite point and can also be plotted on the Earth map projections by using the same projection as used for the map itself.

The coverage of the satellite is shown in footprint form and every footprint is divided into smaller spotbeams, which are equal to terrestrial cells. The spotbeam concept will be used in satellite diversity and radio resource management system analysis.

The altitude of the satellite and the elevation angle as given above affect the path loss and propagation delay and have been evaluated in [7]. The propagation delay depends on the altitude of the satellite from the Earth's centre and the velocity of light in free space. The total delay experienced by users depends on the relative positions of the user, satellite and ground station [8]. LEO constellations have an advantage of low delay compared to MEO and GEO constellations. The propagation delay for LEO constellation is around 5 to 10 ms from transmitter to receiver and around 30 to 100 ms for MEO constellation. The propagation delay for LEO is of the same order as terrestrial systems and hence can potentially offer similar performance.

Figure 2.3. Satellite observed region

The path loss is an important factor in radio communication systems. The path losses are a function of propagation distance and depend on the carrier wavelength. Reduced path loss provides the possibility to use smaller terminals and for the LEO case, the path loss is lower than for MEO or GEO. The altitude of the satellite is considered as the main parameter of the satellite constellation design along with the total number of satellites. In satellite constellation design, the total number of satellites should be minimized whilst minimizing the launching cost into orbit and minimising the maximum satellite altitude can reduce the propagation delay. The satellite altitude is also dependent on the Earth's radiation belt intensity and this effect will be described in the next sub-section.

The minimum elevation angle is also an important parameter to take account of in the geometry as it is used to evaluate the satellite diversity statistic performance for both FES and mobile terminal. The higher the minimum elevation angle to the mobile terminal the less the effect of shadowing will be on the link [9-10]. For a GEO satellite, higher minimum elevation angles are used to reduce the path length and to provide a shorter transmission delay. The details of the minimum elevation angle will be explained in the next sub-section as it affects the MSS and network characteristics.

The description of the satellite footprint and spotbeams for different satellite altitudes is shown in Fig. 2.4. Multispotbeams are proposed in this study to provide an increased gain to the mobile terminal and so as to re-use frequencies on each satellite thereby increasing the overall capacity of the system. Spotbeams are normally arranged in hexagonal rings as cells in terrestrial networks. The number of spotbeams in an array that consists of n concentric rings (tiers) is given as:

$$N_s = 3n^2 + 3n + 1 \quad (2.3)$$

The strategy to select the number of spotbeams depends on the gain required by the satellite in order to close the link budget to the mobile terminal. The beamwidth (θ) of the satellite antenna is defined as the angle across the spotbeam where the gain is typically within 3 dB of the peak gain. This beamwidth is inversely proportional to the antenna diameter and can be approximated by the following relationship:

$$\theta_{th} \cong \frac{70\lambda}{d} \cong \frac{21.6}{fd} \quad (2.4)$$

where f is the carrier frequency in GHz, d is the diameter of the antenna in m, and θ_{th} is in degrees.

Figure 2.4. Satellite's footprint and spotbeams

The size and shape of all spotbeams on the Earth are assumed the same because with the same size and shape of the spotbeams, the distortion can be corrected by varying the beamwidth of the spotbeams. This is achieved by decreasing the beamwidth of spotbeams in the outer rings of the spotbeam array. This causes a higher gain in the outer spotbeams which can compensate for the additional free space loss in the outer regions. The spotbeam shape is also very important in radio resource management in determining the allocation of traffic channels to spotbeams. The same size and shape of spotbeam is also used to solve the radio resource management problem because this model is simpler to model and is therefore attractive to the system modeler as well as being a good approach to limiting inter-satellite interference. The spotbeam model that is used in this study is shown in Fig. 2.5

Two approaches to spotbeam coverage for Non-GEO satellites are the satellite fixed coverage and the Earth fixed coverage. The satellite fixed coverage simply comprises an array of spotbeams with different beamwidths and gains within the overall satellite footprints, which are fixed with respect to the each satellite. Each satellite's

footprint is then changed to be contiguous so as to provide continuous coverage. Hence the footprints precess with the satellite movement over the Earth's surface. This technique can make use of either phased arrays or fixed parabolic dishes. Earth fixed coverage maintains the position of the satellite footprint coverage constant on the surface of the Earth as the satellite moves. The beams are swept in the opposite direction to the satellite's velocity to maintain pointing on the Earth and one handover between satellites is then needed. For this model, the phased array techniques are mandatory. The main aim of the Earth fixed coverage is to present user terminals with a terrestrial like coverage, where the spotbeams or satellite cells are static with respect to user. Also, the mobility management task is then similar to terrestrial systems. The allocation of radio spectrum to channels for each spotbeam or cell can be done on a geographic basis, as in terrestrial system and inter spotbeam handover is eliminated. The disadvantage of this model is that the satellites must have extra functionality and complexity (so far not implemented) while the inter satellite handover task involves a whole group of users simultaneously as a cell is totally switched between satellites. In this study, the satellite fixed coverage technique is assumed. Furthermore, in this work, we are concerned only with the gain, shape, size and arrangement of the resulting spotbeams.

(a)

(b)

Figure 2.5. Multispotbeams model (a). Spotbeam coverage area, (b) Coverage view

The footprint of each satellite has several spotbeams or cells. In this study, the honeycomb spotbeam arrangement is adopted from previous work in [10] because this spotbeam fills the satellite footprint with a minimum number of circular spotbeams and is similar to the terrestrial cellular structure with circular or regular hexagon constructions.

2.4 Satellite Constellation Constraints

2.4.1 Elevation Angle and Azimuth

The elevation angle is the angle which a satellite makes with the tangent at the specified point on the Earth's surface or the angle above the horizon at which a terminal sees the satellite. Sammut [10] says that for the minimum elevation angle, the origin of the tangent is located at a point in the satellite coverage, which is considered the outermost point at which a user can confidently expect to access the satellite within the limits of the power budget imposed by the system. The elevation angle is very important for MSS network services. As can be seen from the Fig. 2.3, increasing the minimum elevation angle of a satellite can reduce the area of satellite coverage. Besides which, the propagation delay can be reduced together with the reduction of the path attenuation at the edge of the coverage as well as the reduction in the statistical probability of the shadowing and multipath effects if the minimum elevation angle is increased.

The azimuth angle (ξ) of a satellite is the angle which the satellite direction makes with the direction of true North measured in the clockwise direction, as shown in Fig. 2.6. In other words, the azimuth is the angle between North and the path to the satellite in the horizontal plane. Actually, the calculation of the azimuth is more complicated than for the elevation angle due to the relative position of the sub satellite point with respect to the Earth station and the hemisphere. The detailed expression of the elevation angle and the azimuth for Non-GEO and GEO constellations is given in Appendix A. The value of the azimuth with respect to the relative position of the sub satellite point is summarised in Table 2.1

Figure 2.6. The azimuth from a point T on the earth

	Sub-satellite point position (S') relative to the Earth station (ES)	Azimuth (ξ)
Northern Hemisphere	S' Northwest of ES	$360^\circ - \xi$
	S' Southwest of ES	$360^\circ - \xi$
	S' Northeast of ES	ξ
	S' Southeast of ES	ξ
Southern Hemisphere	S' Northwest of ES	$180^\circ + \xi$
	S' Southwest of ES	$180^\circ + \xi$
	S' Northeast of ES	$180^\circ - \xi$
	S' Southeast of ES	$180^\circ - \xi$

Table 2.1 The value of the azimuth (ξ) with respect to the relative position of the sub satellite point.

2.4.2 Inter Satellite Links

Inter satellite links (ISL) can dominate the field of network interconnection in LEO and MEO constellations. They enable high bit rate interconnection between the satellites which enable them to provide the lower delay connections between two distant points on

the Earth's surface. The delay due to the satellite altitude is significant, and the delay problems of the dynamic topology of the ISL sub-network can minimise the overall communication delay [10]. In LEO systems, the inter satellite links are of two types; intra orbit and inter orbit link.

Intra-Orbit links are the links between satellites in the same orbital plane. Here, the satellites fly in a fixed successive arrangement and the antennas can be semi fixed.

Inter-Orbit links are the links between satellites in different orbital planes. Here, the satellite antennas themselves usually need to be steered or phased array can be used to electronically steer the beams. The distance between satellites in different orbits vary within a large range and the Earth may interrupt their mutual line of sight.

Some advantages of Inter Satellite Links are: to create efficient call routing via links between satellites; reduction of the end to end delay particularly in the case of mobile to mobile calls and reduction of the total number of required gateway earth stations and terrestrial infrastructure. With ISL's, the size of the ground segment can be minimized and the footprint of each satellite can be increased.

2.4.3 Satellite Diversity

Satellite diversity is a process by which the user communicates with the Fixed Earth Station (FES) through more than one satellite. Satellite diversity is used to combat shadowing, hence improving the link availability, reducing the link margin requirement and improving the quality of service. Obstacles in the propagation path, such as buildings, trees, etc, cause shadowing of the satellite signal. The occurrence of shadowing depends on the local environment around the mobile terminal. For low satellite elevation angles, the shadowed areas are larger than for high elevations (especially for streets in urban and suburban areas) and the percentage of signal shadowing also depends on the azimuth angle of satellite [11]. If the azimuth distribution of two satellites is large, the probability of a satellite being visible to a mobile terminal is increased. However, a higher system complexity is required in order to track both satellites simultaneously.

Satellite diversity can improve the service availability in terms of the percentage of time that the service is available. The effective performance of using two satellites for radio resource in a diverse combination rather than a single satellite for S-UMTS and S-

PCNs is illustrated in [9]. The radio resource management will be more complex for large azimuth differences and the associated signalling will increase with the number of diversity paths.

The important considerations for exploitation of satellite diversity is the availability of an appropriately positioned Gateway Earth Station (GES) and the mobile user capability to communicate with both satellites. This is mainly due to the links via different satellites having different delays, which would cause disruption to the user unless buffering at each individual GES is used. Such buffering would have to be associated with very high accuracy synchronisation. Furthermore, the links between GES's may rely on the terrestrial network if no ISL is used

Satellite diversity based on soft handover can be divided into two types: switched diversity and continuous diversity. Switched diversity refers to a condition under which the mobile user has more than one satellite visible (at least two satellites will be available to each user) and selects the most appropriate based on a set of criteria. The requirement of switched diversity is that the mobile terminal would need to maintain more than one physical link during the handover process, however the user would only utilise one of these links for communication at any one time. Continuous diversity refers to a condition under which the mobile user communicates through more than one satellite continuously. To maintain continuous diversity, the mobile and the gateway earth station would need to combine more than one physical link and search for upcoming satellites to replace the links that gradually degrade. Continuous diversity is also called combined diversity. The satellites employed in combined diversity schemes should communicate through the same gateway earth station, otherwise the differential propagation delay which is experienced in the separate terrestrial tails may be such that the signals will be impossible to combine once they reach the user terminal.

2.4.4 Resonant orbits

A resonant orbit has the orbit period as an integer division of a sidereal day. In a resonant orbit, its ground track over the Earth repeats on a regular daily basis. The orbit period is synchronized to be an integer division of the Earth's daily rotation. The time it takes the earth to rotate exactly 360° is around 1436 minutes. Through the work of Kepler and

Newton in two body orbit analysis, the period of the orbit (T) depends on the semi major axis of the ellipse swept out by the satellite position vector, assuming constant body mass:

$$T = \frac{2\pi}{\sqrt{\mu_e}} a^{3/2} \quad (2.5)$$

where a is the semi major axis of the ellipse and μ_e is a physical constant related to the Earth and universal gravity ($398600.5 \text{ km}^3/\text{s}^2$). In the constellation design cases considered herein, the circular orbit is used where the orbit eccentricity is 0 (zero) so that the semi major axis becomes the addition of the Earth's radius (R_e) and the orbit altitude (h). Thus in this work the orbits are “near resonant” and do not adhere strictly to the definition of resonance as used in [9].

The highest satellite altitude is usually selected in order to maximize the coverage of each satellite. However, the non-spherical nature of the Earth causes precession of the RAAN, resulting in a non-repetitive ground track. The expression of RAAN precession for circular orbits (eccentricity = 0) is given as:

$$\dot{\Omega} = \frac{d\Omega_e}{dt} = -9.95 \left(\frac{R_e}{R_e + h} \right)^{3.5} \cdot \cos(i) \text{ (°/day)} \quad (2.6)$$

where i is the inclination angle. In one orbit, the change in RAAN is calculated by $\dot{\Omega}/n$, where n is the number of orbits per day.

A satellite with a repetitive ground track will orbit over the exact same points on the Earth and will appear at the same points at the same time every day. This means that networking aspects can be repeated at the same time everyday in a resonant system. A satellite with a repetitive ground track is also called a resonant satellite constellation. The expression for calculating the altitude of a constellation of inclination angle, i , with a repetitive ground track after 12 orbits is given by [9]:

$$\frac{360}{12} = \left(\frac{360}{86160} \left(\frac{h}{331.25} \right)^{1.5} 60 \right) + \left(\frac{9.95 \left(\frac{R}{h} \right)^{-3.5} \cos(i)}{12} \right) \quad (2.7)$$

The Deligo constellation [9] is an example and is designed as a resonant satellite constellation where the sub satellite track is repetitive after the completion of 12 orbits in one sidereal day. The Deligo constellation was designed for LEO with 100% of dual satellite diversity within the range of $\pm 62^\circ$ latitude.

2.4.5 Satellite positioning

Determination of the mobile terminal position can achieve operational efficiency in global wireless networks, as it can reduce the signalling load generated as a normal consequence of service provision. In order to avoid reliance on positioning systems e.g., GPS, the positioning can be determined from the operational constellation itself. For example it can be based on the time delay and Doppler shift between the mobile terminal and the gateway Earth station via a single satellite [14]. Alvarez in [15] and [16] has developed this algorithm for dual and triple satellites with the angle shift between satellites and the angle between planes of the satellite constellation. Thus in the design of an operational constellation we can also incorporate the requirement for determination of positioning as an extra function. The idea of position determination is that there should be enough information available at any place or time to provide a point of intersection between the lines of position generated by measurements. In the network architecture, the network calculates the mobile terminal position through the two-way communication between the terrestrial gateway and the mobile terminal. Further signal processing can be performed on the network side (remote positioning).

As mentioned above, the positioning scenario for a MEO satellite constellation has been introduced with the angle between planes and the angle shift between satellites in [15] and [16]. Fig. 2.7 depicts the model for dual satellite visibility of the different planes and illustrates the angle between planes and the angle shift between satellites. Both of these parameters are used in this study to automatically design the satellite

constellation. In Fig. 2.7, the angle θ is defined as the angle between planes, and the angle shift between satellites (ϕ) is defined as the difference between the angles travelled by the satellites from the line of nodes. The effects of the angle between planes and the angle shift between satellites on satellite constellation design have been evaluated for mobile terminal positioning. The general conclusion is that higher the angle between planes and the smaller the angle shift between satellites the more accurate positioning will be achieved [15].

Figure 2.7. The angle shift between satellites and between planes scenario.

2.4.6 Earth Radiation Belts

The trapped Earth radiation has a strong influence on the choice of satellite orbit altitude. The Van Allen Radiation Belt is sometimes used to define the satellite orbit type. If the

altitude of the satellite is between 600 km and 2,000 km this provides a generally acceptable level of radiation allowing for a reasonable satellite lifetime without significantly increasing satellite cost. In this range, the satellite constellation is designated as LEO. Between 2,000 km and 5,000 km, radiation levels are considered particularly high and to be avoided, as shown in the 1st shaded area between 1.3 and 1.8 Earth Radii from the centre of the earth in Fig. 2.8. Above 5,000 km the levels are again low enough to allow for a lower cost constellation. The region around 10,000 km has been chosen for some MEO constellations. The 2nd radiation belt occurs between 3 and 4 Earth Radii from the Earth's centre translates to altitude of 13,000 km and 25,000 km. For navigation satellites (e.g GPS) constellations, the choice is around 26,000 km altitude due to improve positioning accuracy. At altitudes higher than 30,000 km solar and cosmic radiation becomes predominant.

Within the practical range of satellite altitudes, the radiation due to the Van Allen belts is the main hazard to orbiting spacecraft. This radiation consists of three components, they are proton dose, electron dose and X-ray dose that are produced by the interaction of electrons with any shielding material. The distribution of the electron belts on the equatorial plane is non-uniform. As shown in Fig. 2.8, the distribution of the electron dose is concentrated in a pair of the shaded areas. The lower belt is composed of a rich mixture of protons and electrons. The upper Van Allen Radiation Belt is composed primarily of electrons.

It is very important to note that each of these three components affect different parts of the spacecraft and have different dependence upon the orbit altitude. In satellite constellation design, when fixing the orbit altitude, this will determine the amount of shielding needed to protect the spacecraft electronics and the lifetime of the solar panels. These are important parameters that will affect the system economics. Low altitude satellites fly under the most intense portions of the lower Van Allen Belt. Atomic oxygen in the Earth's upper atmosphere also damages some of the surface components of low altitude satellites. GEO orbit above the most damaging portions of the upper Van Allen Radiation Belt, but they experience more damage from intense solar flares than either low altitude or medium altitude satellites.

Figure 2.8. Van Allen radiation belt (electrons)

2.5 Satellite Constellation Types

2.5.1 Polar Orbit Constellations

Polar orbit constellations have equal numbers of satellites and are distributed symmetrically in each orbital plane. This constellation type is a good candidate for LEO satellite systems. Continuous single satellite coverage of the polar constellation has been introduced by Luder [17]. The satellites in the orbital planes have a common intersection point. Beste [5] introduced the single coverage and triple coverage of the polar constellation by selecting the orbital planes and uniform distribution of satellites over the Earth. Adam and Rider [18] have introduced additional optimization techniques for designing such polar constellations.

The polar orbit constellations can be divided into two groups: arbitrarily phased constellations (i.e. without needing to maintain any inter-satellite phasing angle in the various orbital planes that comprise the constellation) and optimally phased constellations. These groups depend on the type of inter plane satellite phasing. Coverage geometry of a polar orbit constellation is shown in Fig. 2.9.

Figure 2.9. Coverage geometry of a polar orbit constellation

It is important to note that, for the same number of satellites, the optimally phased constellations have better coverage features than the arbitrarily phased constellations. In these constellations, the satellites move in a synchronized manner in the same direction and in such a way that the satellites of two adjacent planes are shifted by one half of the intra orbit spacing (i.e., π/m , where m is the number of satellites in each orbital plane). In the region between the two planes where the satellites are moving in opposite directions the relative geometry is not constant, therefore the angular separation between these two orbital planes must be smaller in order to preserve the Earth coverage features. As shown in Fig. 2.9, for single satellite coverage angle, α , and a number of orbital planes, p , the angular spacing, Δ , can be expressed as:

$$\Delta = \alpha + c, \quad \Delta' = 2c, \quad \text{being} \quad c = \cos^{-1} \left(\frac{\cos \alpha}{\cos(\pi/m)} \right) \quad (2.8)$$

where Δ and Δ' denote the angular spacing between co-rotating and counter rotating orbital planes, respectively.

Using similar satellite coverage geometry to that shown in Fig. 2.9, Adam and Rider [18] have evaluated the total number of satellites for multiple satellite coverage using Lagrange multiplier techniques. For a large number of satellites and for global coverage of the Earth and by making use of the Lagrange multipliers technique, optimally phased polar constellations can be defined by means of the following orbital parameters:

$$P = (2/3)k(\pi/\alpha) \quad (2.9)$$

$$Q = (2/\sqrt{3})j(\pi/\alpha) \quad (2.10)$$

$$N = (4\sqrt{3}/9)n(\pi/\alpha)^2 \quad (2.11)$$

where k and j are the multiple coverage factor for satellites in different planes and in the same plane, respectively, and $n = k \times j$ is the multiple coverage factor of the constellation. An example of the polar orbits is the Iridium system with parameters (6,11,66), where P , Q and N are 6,11 and 66.

2.5.2 Rosette Constellations

The Rosette constellation was introduced by Walker [19], [20] and then extended by Ballard [3] to describe a more complete system. The inclined orbit constellations of the Rosette type have been found to exhibit the best worldwide coverage properties at medium and high altitudes for single and multiple satellite visibility. Circular inclined constellations are proposed with common period orbits and the same inclination angle for all satellites with respect to a reference plane (normally the equatorial plane). The orbits in the Rosette constellation are distributed uniformly in a right ascension angle to an

arbitrary reference plane. The initial phase position of satellites in each orbital plane is proportional to the right ascension of that plane. The geometry of the Rosette constellation adopted by Ballard is shown in Fig. 2.10.

The coverage features are evaluated in terms of the largest possible circle range (or minimum range) from the user anywhere on the earth's surface to the nearest sub-satellite point. This case corresponds to the satellite where the user experiences the minimum elevation angle. The minimum range depends on the minimum elevation angle definition. The minimum elevation angle, $\varepsilon_{\min}$, is calculated by finding the largest circum-circle radius triangles formed by sub-satellite points during a time period over which the satellite geometry repeats. For single satellite visibility, the constellation does not contain other sub-satellite points. The minimum elevation angle can be calculated for a given orbit altitude (h) and the range center angle ϕ as follows:

$$E = \tan^{-1} \left(\frac{\cos \phi - \frac{R_e}{R_e + h}}{\sin \phi} \right) \quad (2.12)$$

where R_e is the Earth's radius.

The Rosette constellation contains N satellites, p planes and s satellites in each plane. The position of the satellite is described by the following parameters: right ascension angle for the j^{th} orbital plane (α_j), the inclination angle (i_j), and the initial phase angle of the j^{th} satellite in its orbital plane at $t = 0$, measured from the point of the right ascension. The orbital parameters for this constellation are as follows:

$$\alpha_i = \frac{2\pi i}{p}, \text{ for } i = 0 \text{ to } N-1 \quad (2.13)$$

$$\beta_i = \beta, \text{ for all } i \quad (2.14)$$

$$m = (0 \text{ to } N-1)/Q \quad (2.15)$$

$$\gamma_i = m \alpha_i \quad (2.16)$$

where m is the harmonic factor, α_i is the right ascension angle for the i^{th} plane, γ_i is the initial phase angle the i^{th} satellite in its orbit plane at $t=0$, measured from the point of right ascension.

Figure 2.10. Geometry for inclined orbit constellation

The Rosette constellation is defined using the (N, p, m) notation. Each value of m defines a different constellation configuration by adjusting the initial satellite phases according to the following relationship:

$$\alpha_i = m\Omega_i \quad (2.17)$$

where the satellites in the same orbital plane have a common value of Ω .

The Rosette constellation design method has been proposed for optimizing constellations of near global coverage when the MEO altitudes are chosen. For LEO

constellations, the Rosette constellation is efficient in that it provides coverage at mid latitudes but not of the polar regions. Examples of the use of Rosette constellations are the LEO Globalstar system (48, 8,1/6) and the proposed MEO, ICO constellation (10,2,2/5). Both of these are designed to maximize the mid latitude range of mobile terminals. An important constellation for dual satellite diversity was proposed by UniS as the Deligo constellation (64, 8,1/8) and was the basis of the subsequent SKYBRIDGE constellation [10].

Chapter 3. An Evolutionary Near Resonant Satellite Constellation Design

3.1 Introduction

The genetic algorithm (GA) is a stochastic global search and optimisation method based on the metaphors of natural biological evolution. The GA concept was introduced in 1970, and the applications of various versions of the GA have rapidly expanded in the past decade. The GA has been used for global optimisation problems, and recently has been used as a robust method to solve many engineering problems.

The GA operates with a population of potential solutions to a problem, applying the principles of survival of the fittest, reproduction, and mutation, to produce a better solution [21]. At each generation, a new set of approximations to the solution is created by the process of selecting individuals according the level of the fitness in the problem domain. All processes of the GA operators are borrowed from the natural genetic process itself. The process leads to the evolution of populations of individuals, which are better suited to their environment than the individuals from which they were created.

Individuals in a population are represented as a bit string in the chromosome structure and children are produced from crossover between two parents. The three basic genetic operators included in the procedure are known as selection, crossover and mutation. All of these operators work on the decision variables. The solution is evaluated, competitively selected and interbred to obtain a higher performance solution.

In this chapter, the basic concept of the genetic algorithm and some existing applications to satellite constellation design are illustrated. Furthermore, genetic satellite constellation (GSC) design for Non-GEO near resonant orbits and inclined circular orbits with dual satellite diversity is also introduced. More explanation on this application is introduced in sub-section 3.3. The performance of a new resonant satellite constellation in

terms of satellite diversity statistics and the minimum elevation angle are also presented in this chapter.

3.2 Basic Concept of Genetic Algorithm

3.2.1 Evolutionary Computation, Why Genetic Algorithms?

The GA is modelled in terms of biological genetic concepts and its evaluation is used to search for the optimal solution of a problem. As a computational representation of natural selection, the GA is adopted by making the analogy to the survival of the fittest individual. This analogy includes representing designs as individuals within a population; performing selection (survival of the fittest) and crossover (mating) of a generation of these designs so as to create children who, in turn, become the population for the next generation. Individuals in a population are represented as a 'bit string' in a chromosome structure and children are produced from crossover processes between two parents. At each generation, a new set of approximations are created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of populations of individuals, which are better suited to their environment than the individuals who created them. All of the operators of the GA work on decision variables. The solution is evaluated, competitively selected and interbred to obtain higher performance solutions.

The simple GA as described by Goldberg in [22], uses the standard GA operators of selecting, crossover (mating) and mutation to optimise a population of individuals according to a static fitness function. In addition, the fitness function is assigned a value to each individual and it is through this that the individual's probability of survival is directly determined. In general we can subdivide the GA cycle process into a four stage cycle as illustrated in Fig. 3.1. These are, the creation of a population of chromosomes, the evaluation of each chromosome, the selection of the fittest chromosomes and the genetic manipulations to produce a new population. The cycle creation, evaluation,

selection and manipulation is repeated until the best solution is found or the process of the GA is stopped if a set condition is satisfied.

Figure 3.1. General cycle of GA

A genetic algorithm process is shown in Fig. 3.2 and a pseudo code outline of the genetic algorithm is shown in Fig. 3.3. The population at time t is represented by the time dependent variable P , with the initial population of random estimates being $P(0)$. Parameters α_x and α_m represent the probabilities associated with the crossover and mutation functions, respectively. Using this outline of the GA process we describe the remainder of the process elements of the GA in the next sections. Some extra functions and operators are added in this study to improve the efficiency of the GA in the specific application.

Figure 3.2 A genetic algorithm process

```

{
  t=0;
  init_population P(t);
  evaluate_fitness P(t);
  while (criterion is not satisfied)
  {
     $\hat{P}$  = select_parents P(t);
    recombine ( $\hat{P}, \alpha_x$ );
    mutate ( $\hat{P}, \alpha_m$ );
    t = t + 1;
    update_population P(t);
  }
  Output best solution;
}

```

Figure 3.3 Outline of the genetic algorithm

3.2.2 Genetic Algorithm Elements

3.2.2.1 Objective Function

The objective function is used to provide a measure of how individuals have performed in the problem domain. For example in the minimization problem, the best individuals should have the lowest numerical value of the associated objective function. The objective function determines the survival of each string in the chromosome structure by providing a measure of its relative fitness. The fitness function that is used to transform the objective function value into a measure of relative fitness can be written as:

$$F(x) = g(f(x)) \quad (3.1)$$

where f is the objective function, g is the transform function that transforms the value of the objective function to a non negative number and F is the resultant relative fitness. This mapping is very important and is always used when the objective function is to be minimised. The lower objective function values correspond to the fitter individuals.

In many cases, the fitness function value corresponds to the number of offspring, which an individual can expect to produce in the next generation. In this case, a proportional fitness assignment is proposed to optimise the solution [22]. Here, the individual fitness of each individual is computed as the individual's raw performance, relative to the whole population. The probability of any individual to be selected from the population can be defined as:

$$P(x_i) = \frac{F(x_i)}{\sum_{i=1}^N F(x_i)} \quad (3.2)$$

where N is the population size and x_i is the phenotypic value of the individual i . This concept may be implemented in several ways that depend on the nature of the application of the GA and will be discussed further in the next section. Equation (3.2) is used to randomly select two individuals for mating to produce two offspring individuals whose fitnesses depend on the parents according to the subsequent process as described in the following sections.

3.2.2.2 Selection

The selection process is very important to accomplish a trade off between two opposing and undesirable tendencies. The selection is composed of the choice of chromosomes and the acceptance condition of these chromosomes to be used in the next population. The use of the population in selection operators is justified to improve a set of individuals in running competition. If only the fittest individuals are chosen every time, it may result in convergence to a local minimum. On the other hand, if the best configurations are not given preference over the weaker ones, there will be no convergence to a solution. Two common selection methods are introduced herein; they are roulette wheel selection and stochastic universal sampling.

A roulette wheel mechanism is commonly used in selection techniques to probabilistically select individuals based on some measure of their performance. A real value interval, Sum , is determined from the sum of the raw fitness values over all the individuals in the current population or the sum of the individuals expected selection

probabilities is as shown in equation (3.2) as $\sum_{i=1}^N F(x_i)$. The individuals are mapped, one to one into contiguous intervals in the range $[0, Sum]$. The size of each individual interval corresponds to the fitness value of the associated individual. Fig.3.4 shows an example process of the roulette wheel. The circumference of the roulette wheel is the sum of all six individuals' fitness values. Individual 6 is the most fit and therefore occupies the largest interval, while individual 1 is the least fit and for this reason occupies the smallest interval within the roulette wheel.

To select an individual, a random number is generated in the interval $[0, Sum]$ and the individual whose segment spans the random number is selected. This process is repeated until the desired number of individuals has been selected. This roulette wheel selection method is known as stochastic sampling with replacement. Any individual whose segment size is greater than zero could entirely fill up the population. An extension of this method is known as stochastic sampling with partial replacement. An individual's segment is selected to prevent dominance of a few individuals. Each time an individual is selected, the size of its segment is reduced by one. If the segment size becomes negative, then it is set to zero.

Figure 3.4. Roulette Wheel Selection

Stochastic universal sampling is based on a variation of the roulette wheel method. Instead of the single pointer used in the roulette wheel method, the stochastic universal

sampling uses N equally spaced pointers, where N is the number of selection required. The population is randomly shuffled and a single random number in the range $ptr = [0, Sum/N]$ is generated. The N individuals are chosen from generating the N pointers spaced by 1 as follows: $[ptr, ptr + 1, \dots, ptr + N - 1]$. Individuals whose positions span the positions of the pointers are selected. As individuals are selected entirely on their position in the population and the spacing between pointers, this method prevents unfit individuals from dominating the selection process. For these reasons, the stochastic universal sampling method is one of the most widely used.

3.2.2.3 Crossover

Crossover is the process of combining the genes of one agent with another to create offspring or new chromosomes in the GA. The process of crossover arguably constitutes the most important step in the context of the genetic algorithm. The variations of crossover are the single point crossover, multipoint crossover, uniform crossover shuffle, reduced surrogate, intermediate crossover, and line crossover.

The simplest form of crossover is the single point crossover. A crossover point is selected at random between 1 and $L - 1$ (where L is the length of the chromosome). This crossover point determines which genetic material each parent will contribute to each of the offspring. The single point crossover operator is illustrated in the following diagram:

Figure 3.5 Single point crossover operator

The mating process may experience no crossover due to the fact that the operator is controlled by the crossover probability factor α_x , decided heuristically by the designer before the GA procedure is begun. Crossover probability, $\alpha_x = 1.0$, will result in a discontinuity from the previous to the present population, as none of the individual members of the population from the previous generation will be retained in the new one. In this respect, it has been suggested that the crossover probability, $\alpha_x < 1.0$, and the optimum value lie in the range 0.5 – 0.6 [21], although with the inclusion of the two fittest individuals, the probability of crossover used in adapted GA can be increased as some continuity is guaranteed. The concept of the single point crossover is applied in this study for the genetic resonant satellite constellation design and the genetic radio resource management algorithms.

The multipoint crossover uses multiple crossover points. Here, m crossover positions, $k_i \in \{1, 2, \dots, L-1\}$, where k_i are the crossover points and L is the length of the chromosome, are chosen at random with no duplicates and sorted into ascending order. Then, the bits between successive crossover points are exchanged between the two parents to produce two new offspring. The section between the first bit string position and the first crossover point is not exchanged between individuals. The concept of the multipoint crossover is used in multiobjective genetic satellite constellation design and the genetic hybrid satellite constellation in chapters 4 and 5. The advantages of the multipoint crossover are that parts of the chromosome representation that contribute most to the performance of a particular individual may not necessarily be contained in adjacent sub-strings, and its disruptive nature which is needed to encourage the exploration of the search space to highly fit individuals, is more robust.

Uniform crossover is used to allow any point to become a potential crossover point. A crossover mask is created at random. This mask has the same length as the parents. The bits of the crossover mask are used to determine which parent contributes its genetic material for each particular bit of the offspring. A uniform crossover example is shown in the following diagram:

Parent 1	= 1 0 1 1 0 0 0 1 1 1
Parent 2	= 0 0 0 1 1 1 1 0 0 0
Mask	= 0 0 1 1 0 0 1 1 0 0
Child 1	= 0 0 1 1 1 1 0 1 0 0
Child 2	= 1 0 0 1 0 0 1 0 1 1

Figure 3.6 Example of uniform crossover

Here, child 1 is produced by taking the bit from Parent 1 if the corresponding mask bit is 1, or the bit from Parent 2 if the corresponding mask bit is 0. Child 2 is created using the inverse of the mask or, equivalently, swapping Parent 1 and Parent 2. Uniform crossover has been claimed to reduce the bias associated with the length of the binary representation used and the particular coding for a given parameter set. When uniform crossover is used with real valued bit strings, it is usually referred to as discrete recombination.

Other types of crossover processes are shuffle crossover, intermediate crossover and line crossover. The shuffle crossover operator randomly rearranges the bits of both parents before a single point crossover is used. Once crossover is complete, the bits of the offspring are un-shuffled. The reduced surrogate operator is used to ensure that the crossover only forms new individuals. The intermediate crossover and the line crossover are used to produce offspring when real value encoding is used. The intermediate crossover and the line crossover produce new genotypes for the offspring that are near to or between the values of the parents' genotypes.

3.2.2.4 Mutation

Mutation is the process in natural evolution where one component of a gene is replaced by another one to form a new gene. This mutation process is completely random with a probability equal to the mutation rate α_m . Mutation is used in GA's for two reasons. The first reason is to ensure that good genetic material can be retrieved if it is lost during the selection or the crossover steps. The second reason that mutation is used is to ensure that the probability of searching a particular string is never zero. A low level of the mutation

serves to prevent any one element in the chromosome from remaining fixed to a single value in the entire population. On the other hand, a high level of the mutation will essentially result in a random search. To maintain a balance between such extremes a value for the mutation probability, α_m , has been suggested within the range 0.01 – 0.025 [22].

There are numerous implementations of the mutation operator. One method is to encourage mutation in individuals that are not as fit as others. This method allows the traits of the fitter individuals to be maintained, while allowing the GA to increase its field of search. The biasing of the mutation towards individuals with lower fitness values to increase the exploration in the search without losing information from the fitter individual has been introduced in [23]. Muhlenbein and Voose [24] have introduced a mutation operator for the real coded GA that uses a non-linear term for the distribution of the range of mutation applied to gene values. Other mutation operations include the trade mutation [25], where the contribution of individual genes in the chromosome are used to direct mutation towards weaker terms, and reorder mutation, which swaps the positions of bits or genes to increase diversity in the decision variable space. In this study, a modified approach to the mutation process is introduced for the multiobjective genetic algorithm when applied for satellite and hybrid constellation design, and will be illustrated in chapters 4 and 5.

3.3 Optimization of Satellite Constellation Design Using GA.

3.3.1 GA for Optimisation of Zonal Coverage

Elliptical and inclined orbits have been considered in determining efficient satellite constellations that cover a zonal region over the Earth [39] using the genetic algorithm. Ely [39] described the constellation design for global coverage using eccentric orbits. The objective of the genetic algorithm in [39] is to minimize the maximum satellite altitude and to minimize the total number of satellites in the constellation for global coverage. The

algorithm is applied to a northern hemisphere coverage problem: CONUS coverage of USA, and an Ellipso coverage problem. The altitude of the satellite as a function of semi major axis and eccentricity, plus the total number of satellites are determined as objective functions of the GA. The original street of coverage concept, developed by Luder and extended by Rider to inclined orbits, is adopted to evaluate zonal coverage using the genetic algorithm. The genetic algorithm used by Ely [39] in his work employs a Roulette Wheel selection and a uniform crossover operator. The GA was successfully applied as an optimisation routine to determine constellations using the elliptic streets of coverage. This also allowed the integer variables of numbers of orbital planes and numbers of satellites per plane to be directly incorporated in the optimisation process, which could not be accomplished with other more traditional calculations based optimisation methods. From Ely's work, it is possible to incorporate eccentricity as an additional factor in producing efficient constellations for regional coverage.

3.3.2 GA for Discontinuous Global Coverage

Discontinuous global coverage is proposed for many satellite applications, such as weather and remote sensing systems. Discontinuous coverage constellations offer impressive savings in complexity for some applications. These constellations are designed by reducing the altitude of optimal continuous coverage constellations arrived at by established techniques (e.g. Walker constellations with street of coverage).

The genetic algorithm approach for discontinuous satellite constellations was introduced in [34] and [40]. Herein [34] and [40], satellite constellation numbers are examined over a range of the altitudes for various discontinuous coverages. The objective function is proposed for the maximum revisit time of the constellation. The maximum revisit time measures the longest time that any point in the region of interest remains uncovered by a satellite. The maximum revisit time function uses a fast, simple propagator, which assumes circular orbits and includes the Earth's rotation and the precession of the right ascension of ascending node.

The genetic algorithm has proven to be adept at fitting coverage holes around fixed grid point locations, where each constellation was evaluated on an array of grid points distributed over a fraction of the Earth's surface. Each grid point is evaluated to

determine if it is in view of at least one satellite over a given length of the orbit propagation. A large fraction of points are randomly generated and changed for every generation. This technique reduces the number of grid points, and therefore the evaluation time and produces more robust constellations in terms of the coverage distributions.

3.4 Genetic Near Resonant Satellite Constellations

3.4.1 System Description

The application of the GA for satellite constellation design in this study is focused on the resonant satellite altitude as described in section 2.4.4. The constellation is assumed to consist of an inclined circular orbit where all satellites have the same inclination angle and altitude. Each orbit contains an equal number of satellites. This constellation is proposed as it offers high diversity global coverage with a trade off between diversity advantage and number of satellites or minimum elevation angle. The contiguous coverage for the same altitude is provided by the dynamic overlap between the satellites in different planes. The satellite constellation is designed for near resonant orbits with repetitive ground tracks and also avoidance of the Van Allen radiation belts.

The design algorithm aims to find the optimum satellite altitude for the near resonant satellite constellation whilst reducing the minimum number of satellites and achieving satellite diversity statistics. The detailed process of the GA for the near resonant altitude is described in the following section. The block diagram of this algorithm is given in Appendix D and is reviewed in Fig. 3.7. The first step is chosen the number of planes and the number of satellites. The altitude of satellite is determined using GA. Then, the RAAN and MA of satellite constellation design are calculated using the above components. By choosing the inclination angle value and the elevation angle, satellite constellation is run on SPOC (Simulation Package for Orbital Constellation) program and it has been developed by Sammut [10] for satellite diversity. The simulation is repeated until the best result of bit string for satellite altitude in chromosome is found.


```

Set the number of planes and the number of satellites;
Identify best individual (element of SatDiv) for resonant altitude;
Apply the genetic resonant altitude;
Set the position of RAAN and MA;
Evaluate its fitness;
  Obtain the set of conflicting bit positions;
  Start with lowest number conflicting bits;
  Repeat {
    Select the inclination allocation;
    Set the elevation angle;
    Test individual's fitness;
    If fitness is improved
      Accept new altitude;
      Evaluate its fitness
    Else
      Increment the number of plane and the number of satellite
  }
while conflicting bit position  $h \leq h_{max}$ ;

```

Figure 3.7. The genetic near resonant constellation algorithm

3.4.2 Stochastic Optimisation

3.4.2.1 Structure of the Individual

Assume the population number for each generation is N . The chromosome structure of the initialisation process is shown in Fig. 3.8. A chromosome represents a bit string of genes and the bits in this chromosome represent the altitude of satellite. An individual includes its parents identification number, a fitness value and the crossover sites.

In this chromosome structure, only one specification of the satellite constellation parameter is included in the genes of the chromosome. This parameter is the altitude of the satellite that is determined from the objective function of the period of the resonant altitude. Other parameters of the satellite constellation design are determined separately in simulation; these are the inclination angle, the number of satellites, the RAAN, the eccentricity and the mean anomaly. The simulation is proposed for simple model of the near resonant constellation and inclined circular orbit.

Figure 3.8 Chromosome structure

3.4.2.2 Objective Function

A measure of the relative fitness of each individual involved in the problem domain is provided by the objective function. The objective of the algorithm is to minimize the maximum altitude of the satellites for different numbers of satellites. The minimization of the maximum altitude of the constellation is derived from a function of the period of the satellite in orbit given in equation 2.5 and can be written as:

$$f = \left(\frac{T^2 \mu_e}{4\pi^2} \right)^{1/3} - R_e \quad (3.3)$$

where T is the period of the satellite to orbit, μ_e is a physical constant related to the Earth and universal gravity ($398,600.5 \text{ km}^3/\text{s}^2$), and R_e is the Earth's radius.

The survival of each gene in the individuals depends on this value. The objective of this algorithm is to minimize the maximum altitude of the satellite for different number of satellites. The output of the bits in the chromosome structure (b) of the process for each individual is defined as:

$$b_{out}(j) = \text{mat}(\{b\}_p^j) \quad (3.4)$$

where p is the generation index, j is the identification of each individual and $\text{mat}(\cdot)$ is the mapping operator of the chromosome.

The fitness value for each individual in each generation of satellite constellation design which provide the dual satellite diversity is given via the following fitness function (also known as “energy”):

$$F_{\rho-1}(j) = \frac{1}{1 + a \cdot f_{\rho-1}^j} \quad (3.5)$$

where $f_{\rho-1}^j$ is the objective function for individual j and generation index ρ , a is the scaling factor which is used to set the maximum possible value of energy for each individual as 1. After creating the objective values for individuals of one generation, these individuals are directed toward the selection, crossover and mutation processes.

3.4.2.3 Selection

The selection process is very important as it gives better survival probability for the fitter individuals compared to their weaker counterparts. If the current generation of individuals is assumed as ρ , the probability of selection for mating $P_s(j)$ for a particular individual is:

$$P_s(j) = \frac{F_{\rho-1}(j)}{\sum_{Q=1}^M F_{\rho-1}(Q)} \quad (3.6)$$

where M is the population size and j is the index of a particular individual and Q is the total individual. The concept of selection is based on a random roulette wheel as explained in subsection 3.3.2.3. The sum of the fitness values of all existing individuals is calculated from 0 to the maximum number of the population, and can be expressed as:

$$S_{\rho-1} = \sum_{j=1}^M F_{\rho-1}(j) \quad (3.7)$$

The algorithm of the selection process with the best individual transfer of the energy value is summarised below in Fig. 3.9:

```

{
   $i = 0$ ;
   $\delta = a * S_{p-1}$  where  $a$  is a random value between 0 and 1
  record the energy value (Fitness);
  while (the energy value <  $\delta$ )
  {
     $i = i + 1$ ;
    The energy value = the energy value + energy $i$ , where energy $i$ 
    is the fitness value of the  $i$  'th individual.
  }
  The best individual is the  $i$  'th individual which is thus selected
}

```

Figure 3.9 The selection process procedure

3.4.2.4 Crossover

Two selected fit individuals from the previous stage go forward to the crossover process. The crossover operator selects the position to cut the chromosomes. The mechanism by which the genetic material between two parents is exchanged via the crossover mark. In this study, the single point crossover operator is used.

The first step of the crossover process is comparison crossover probability with a bias random probability (P_r). If the bias random probability P_r is greater than the crossover probability (P_c), the crossover point is generated randomly. The crossover site position is based on a true or false result of this process. Fig. 3.10 outlines the crossover process:

```

Generate a bias random probability ( $P_r$ ),
If (the result is True)
{
    crossover_site = int(a * L); where a is a random value between 0 and 1
    and int(.) yields the integer part of the input parameter with the
    chromosome length L.
}
else
{
    crossover_site = L.
}

```

Figure 3.10 The crossover process procedure

3.4.2.5 Mutation

The mutation operator directly affects the performance of the genetic engine. The performance can be enhanced by employing a more efficient mutation operator. In this study, a new method to find an optimum order of the altitude of the satellite is proposed, where the bias random probability is generated (biased with the mutation probability, P_m). In the first step, the bias random probability is generated and then compared to the mutation probability. If the bias random probability is smaller than the mutation probability, the mutation process will be true. If this condition is false, the composition of the bit string is retained or there is no mutation process. The procedure for the mutation process is summarised in Fig. 3.11:

```

Generate a biased random probability;
If (the result is True), where biased random probability <  $P_m$ 
{
    Offspring = Parent +  $X * \mu$ , where X is a random value between 0 and 1,
    and  $\mu$  is a small real value.
}
else
{
    No mutation process.
}

```

Figure 3.11 The mutation process procedure

3.5 Experiments and Evaluation

An example of the procedure is given for a LEO constellation with parameters given in Table 3.1. The altitude of the satellites is chosen within a range 700 – 1700 km and is indicated in the bit string of the chromosome structure.

State vectors	Minimum	Maximum
Number of satellites per plane	6	11
Number of planes	6	12
Inclination angle	48.0°	66°

Table 3.1. Selected ranges of the state vector components

The common parameter inputs of the genetic algorithm used in this experiment are shown in Table 3.2. Goldberg [22] suggested a heuristic approach based on the length of the chromosomes to determine the optimum population size. However, this value would increase exponentially with respect to the length of the chromosome. For example, a chromosome with a length of 300 would result in an optimal population size of 1.52×10^{19} . Clearly, a GA with such a population size is not computationally efficient. Consequently, some alternatives based on the spirit of Golberg's argument are proposed for the actual formulation. For example, Hesser *et al.* [28] suggested the amount of variability of the individual chromosomes in the population. Based on their investigations, it was noted that the largest increase in variability occurs within a range of 30 – 110 individuals. A reasonable choice of population should therefore lie in this range. In this experiment, the population size is assumed as 250, because with lower number of population size and the lower individual number will give the small iteration process. Goldberg [22] suggested to get the optimum solution with higher number of population. The maximum of the generation number is chosen as 550. This term is chosen because the genetic algorithm is a stochastic optimization routine which utilizes a random number generation in several of its operators. Different selection of these parameters of the genetic algorithm will produce somewhat different results. The value of the crossover probability and the mutation probability was chosen as 0.6 and 0.02 as suggested in [22].

Parameter input	Value
Population size	250
Generation number	550
Crossover probability	0.6
Mutation probability	0.02
Random number seed	0.0 – 1.0

Table 3.2. Common parameter inputs of the GA

The result of the experiment was a satellite constellation with optimised satellite diversity having an altitude of 1684 km. The total number of satellites was 60 distributed in 6 orbital planes with 10 satellites per plane and with 53.7° inclination angle. Satellite diversity statistics are evaluated for a minimum of elevation angle of 14° and at 45° longitude for all of the plots shown. As stated earlier the choice of different seeds in the GA process leads to a small range of output values. In the plots shown we show the average values.

The propagation delay of this near resonant satellite constellation is 11.23 ms. Delay is very important for transmission from source to destination terminal for some services. If the altitude of the satellites were higher, the delay is also longer. This result is still within the range 5 – 15 ms specified for the LEO system performance [27].

As stated earlier the trapped Earth radiation has great influence on the choice of satellite orbit altitude. The position of the new proposed resonant constellation using the genetic algorithm is ~ 0.264 of Earth's radius. This is still under the lower Van Allen Radiation Belt which is centred at an altitude of ~ 0.6 earth radius (~ 3830 km) and within a LEO satellite defined range. Altitudes between 600 km and 2000 km are acceptable in terms of level of radiation to allow a reasonable satellite lifetime without significantly increasing satellite cost.

The sub satellite track of the genetic near resonant satellite constellation is very close that of a resonant constellation with the repetitive completion after 12 orbits in 1 sidereal day. Using a resonant constellation, the network connectivity and the control between the space segment and the ground segment can be optimised due to the repetitive coverage geometry. Another advantage of the resonant constellation is optimisation of the

mapping between constellation frequency management and traffic demand, hence reducing network control complexity [9]. Constellation characteristics for different LEO constellations are summarised in Table 3.3.

The simulation results for satellite diversity statistics are shown in Fig. 3.12 and Fig. 3.13. The results are compared with Globalstar and Deligo constellations. Fig. 3.12 shows the availability of dual satellite diversity statistics with 14° minimum elevation angle and 45° longitude. Simulations were carried out for different seed numbers (between 0 and 1) and the best results are shown in Fig. 3.12. The results show that the new constellation has a better performance in terms of percentage of availability than the Globalstar, but is not significantly different to Deligo. 100% availability of dual satellite diversity is provided to 66° latitude.

Constellation Parameter	Iridium	Globalstar	Deligo	Genetic Near Resonant
Orbit altitude (km)	780	1424	1626	1684
Number of satellites	66	48	64	60
Number of planes	6	8	8	6
Satellite/plane	11	6	8	10
Inclination angle	86°	52°	54°	53.7°

Table 3.3. Constellation characteristics for different LEO

Figure 3.12 Dual satellite diversity statistics for 14° minimum elevation angle [26]

Fig. 3.13 shows the results of triple satellite diversity statistics for the genetic near resonant and Deligo constellations. For the genetic near resonant constellation, 100% availability of triple satellite diversity can be found between 34° - 54° latitude. These results are again better than the Deligo constellation. At 11° minimum elevation angle, 100% availability of triple satellite diversity was found at latitudes between 32°-58°.

Fig. 3.14 shows the performance of the mean elevation angle for the first highest satellite and the second highest satellite. The experimental results for the genetic near resonant constellation are compared to those of Deligo. All of the experimental results reported in this thesis have been published in [26]. At 16° - 42° latitude, the mean elevation angle for new constellation is higher than Deligo. At higher latitude, the results are almost the same for new constellation and Deligo.

Fig. 3.15 shows the minimum elevation angle statistics for genetic near resonant altitude. The results are compared to those Deligo.

Figure 3.13 Triple satellite diversity statistics [26]

Figure 3.14. Mean elevation angle statistics [26]

Figure 3.15 Minimum elevation angle statistics

3.6 Conclusions

The basic concept of the genetic algorithm and some applications of the genetic algorithm for optimisation of satellite constellation design were reviewed in this chapter. Also, a new approach to the design of near resonant satellite constellations using the genetic algorithm was presented. This new approach to satellite constellation is called the genetic near resonant constellation. Some modifications of the basic genetic algorithm process were included in the design. The genetic satellite constellation was designed for a repetitive ground track and also to avoid the major Van Allen radiation belts. The constellation is assumed to be an inclined circular orbit where all satellites have the same inclination angle and altitude. Each orbit contains an equal number of satellites. This constellation was proposed for LEO systems as they offer high diversity regional coverage with a trade off between diversity and number of satellites or minimum elevation angle. The evaluation of this algorithm was performed for dual satellite

diversity statistics and elevation angle statistics. The results of the genetic near resonant constellation approach gave a new satellite constellation at 1684 km altitude. The total number of satellites was 60 distributed into 6 orbital planes and 10 satellites for each orbital plane with 53.7° inclination angle. This constellation has the following attributes: 100% availability of dual satellite diversity achieved to 68° of latitude and between 34° - 54° of latitude for triple satellite diversity. The satellite altitude remains in the economic LEO system range in terms of radiation effects. The sub-satellite track of the genetic near resonant satellite constellation is repetitive after the completion of almost 12 orbits in 1 (one) sidereal day. The results of the genetic near resonant constellation shows improvements on both Globalstar and on the previously optimised Deligo system and is ideally suited to S-UMTS or S-PCN applications in terms of dual satellite diversity and total number of satellites.

Chapter 4. Multiobjective Genetic Satellite Constellation Design

4.1 Introduction

A proposed model of automatic satellite constellation design using multiobjective genetic algorithms is introduced in this chapter. The automatic satellite constellation means that some parameters of the satellite constellation can be determined simultaneously. In this study, the number of satellites, the altitude of the satellite, the angle between planes, the angle shift between satellites and the inclination angle are parameters of the genetic algorithm. The algorithm is now called genetic satellite constellation (GSC) design. The constellation is assumed to be an inclined circular orbit and is proposed as it offers high diversity global coverage with a trade off between diversity and number of satellites or minimum elevation angle. The satellite constellation is designed for a near resonant orbit with repetitive ground track and also to avoid the major peaks in the Van Allen radiation belts.

The multiobjective genetic algorithm is suited for problems with large numbers of variables [29] - [31]. The multiobjective genetic algorithm problem uses the optimisation of the components of a vector value cost function. The Pareto optimal solution or non-dominated solution is used in such multiobjective genetic algorithms. In the Pareto optimal solution, a set of solutions that are superior to the rest of the solutions in the search space when all objectives are considered but are inferior to other solutions in the space in one or more objectives. The rest of the solutions are known as dominated solutions. Since none of the solutions in the non-dominated set is absolutely better than any other, any one of them is an acceptable solution.

Conventional satellite constellation designs with different orbital types and satellite coverage analysis have been introduced and reviewed in chapter 2. However, in some applications we need to optimise specific characteristics of the satellite constellation. Generally, the satellite constellation design problems are addressed to

minimize the total number of satellites whilst minimizing the maximum satellite's altitude. Previous work in which the genetic algorithm was applied to satellite constellations have merely addressed the general problem of satellite constellation design. Recently, genetic algorithms have been proposed to achieve the optimal discontinuous coverage in satellite constellation geometry analysis [32], [33] and [34]. Multiobjective genetic algorithms for Walker satellite constellations and for zonal coverage area have also been introduced in [39] and [40].

In this study, the automatic design of circular Non-GEO satellite constellations with satellite diversity using genetic algorithms is proposed. The objectives of this algorithm are to minimize the total number of satellites, the maximum satellite altitude, the angle shift between satellites and to maximize the angle between planes and the inclination angle. The simulation is proposed for both LEO and MEO constellations. The performance evaluation of this algorithm is evaluated for dual satellite diversity statistics for both LEO and MEO constellations.

4.2 Multiobjective Genetic Algorithm

A general multiobjective optimisation problem consists of a number of objectives and is associated with a number of inequality and equality constraints. Mathematically, the problem can be written as:

$$\text{Maximize/minimize } f_i(x) = \begin{Bmatrix} f_1(x) \\ f_2(x) \\ \vdots \\ f_n(x) \end{Bmatrix} \quad \text{for } i = 1, 2, \dots, n \quad (4.1)$$

The parameter x is a p dimensional vector having p design or decision variables. Solutions to a multiobjective optimisation problem are expressed mathematically in terms of non-dominated or superior points. They are also known as Pareto optimal solutions. In the Pareto algorithm, non-dominated individuals are all ranked best and the individuals are

consistently assigned better ranks than those which they dominate. In the mathematical sense, a design with a vector of objective v dominates a design with a vector of objective u , as follows:

$$\text{If } \forall_i v_i \leq u_i \text{ and } \exists_i v_i < u_i, \text{ for } i = 1, 2, \dots, n \quad (4.2)$$

In many cases, finding the set of Pareto designs is desirable, because the trade off amongst various objectives can be observed in this set.

In the multiobjective algorithm, the optimisation is approached as a search from point to point and results in one optimal design. One common approach is the weighted objectives approach in which multiple objective functions are combined into one overall objective function F , as follows:

$$F = \sum_{i=1}^n \omega_i f_i(x) \quad (4.3)$$

where $x \in X$, X represents the feasible region, and ω is the weighting factor ($0 \leq \omega_i \leq 1$). All weights are summed up to 1 or $\sum_{i=1}^n \omega_i = 1$. The optimal solution is controlled by the weighting vector. It is clear from the above equation that the preference of an objective can be changed by modifying the corresponding weighting factor. Mathematically, a solution obtained with equal weights for all objectives may offer least objective conflict, but as a real world situation demands a feasible solution, priority must be induced in the formulation. In most cases, each objective is first optimised and all objective function values are computed at each individual optimum solution. Thereafter, depending on the importance of objectives a suitable weight vector is chosen and the single objective function in Equation 4.3 is used to find the desired solution. The various values of the weighting factor and different combinations to each objective function will give different solutions. In this study, the weighting factor is assumed the same for all objective functions as will be illustrated in the next sub-section. In the design of satellite constellations, a parameter set is considered to be the Pareto optimal solution.

4.3 System Description

4.3.1 Dual Satellite Diversity Constraint

Mobile personal satellite systems have a much lower and more critical link margin than terrestrial mobile systems. In addition such systems only operate in environments which offer a lower level of shadowing or blockage and are known as open/highway environments or suburban environments. For example, satellite personal communication networks (S-PCN) are semi line of sight (LOS) systems for which blockage by buildings or major terrain features are major problems for most services. One solution to this problem is to use satellite diversity.

Satellite diversity is a characteristic that can be built into some satellite constellations in order to combat the negative effects of shadowing. Satellite diversity implies that the constellation provides at least two satellites available for communications for all time. Two basic implementations of satellite diversity have been discussed in chapter 2. The dual satellite diversity concept as used in this study is shown in figure 4.1. This diagram illustrates the requirement for a common coverage zone covering both ground station and user terminal in order that the technique of combined diversity can be implemented efficiently.

Figure 4.1. Satellite diversity

Different constellation design methods give different diversity characteristics. A direct trade off exists between satellite diversity statistics and minimum elevation angle for a constant number of satellites and has already been evaluated for the genetic resonant constellation in chapter 3.

4.3.2 Orbital Type

In the design of the multiobjective genetic constellation, the constellation is assumed to be of an inclined circular orbit type for both LEO and MEO constellations. The inclined circular constellations tend to have maximum satellite diversity in the latitude region surrounding the latitude corresponding to the inclination angle. A common orbital period and the same inclination angle (i) for all satellites are applied to different planes (p) of the satellite constellation. Each orbital plane contains an equal number of satellites s which are distributed with interval Δ . The coverage features of this constellation are assumed to be circular. The constellation is designed to give full global coverage with the minimum number of satellites. Such a constellation can be used to offer high diversity global coverage and provide a trade off between diversity and the numbers of satellites or minimum elevation angle as applied in the previous work (chapter 3). The contiguous coverage is provided by the dynamic overlap between satellites in different planes.

The satellite constellation coverage geometry is shown in Fig. 4.2. The spacing between the orbital planes (δ) and the phasing angle between satellites (ω) are the same for all satellites. The right ascension of the ascending nodes is Ω . For a given minimum elevation angle, θ , the angular radius, α , with respect to the Earth's centre between the sub-satellite point and the edge of coverage is given by:

$$\alpha = \cos^{-1} \left(\frac{\cos \theta}{1 + h/R_e} \right) - \theta \quad (4.4)$$

where h is the altitude of the satellite and R_e is the Earth's radius. Clearly, as the satellite's altitude h increases, the radius of the central angle α also increases.

Figure 4.2. Satellite constellation's coverage geometry

Efficient integration of terrestrial and mobile satellite systems requires networking management procedures to minimise the signalling load generated as a normal consequence of system operation. Accurate knowledge of the mobile terminal position is a key factor in achieving this requirement. Although additional networks such as GPS can be used for this purpose, there are some applications in which reliance on additional networks is considered risky. Thus determination of position from the communications constellation itself is an interesting feature. When two or more satellites are simultaneously available, the user's position can be estimated using either absolute range and range rate between a terrestrial gateway and the mobile terminal. The angle between planes and the angle shift between satellites are used as important parameters for such positioning purposes. The angle shift between satellites is defined as the angle travelled by one satellite in its plane measured from the line of nodes until the satellite in the other plane passes through this same reference line. This has been described in [16] and also

reviewed in chapter 2. The effects of the angle between planes and the angle shift between satellites for satellite constellation design has been proposed for mobile terminal positioning. The higher the angle between planes and the smaller the angle shift between satellites, the better accuracy that can be determined for positioning [15] and [16].

4.4 Multiobjective Genetic Satellite Constellation Design

4.4.1 Objective Function

In the current work, the objectives are defined to be hybrid minimising and maximising functions into one overall fitness function. The objectives of this algorithm are: (1) to minimize the total number of satellites in the constellation, and is defined as $s \times p$, where s is the number of satellites in each plane, and p is the number of planes; (2) to minimise the maximum altitude of the satellites; (3) to minimise the angle shift between satellites, (4) to maximize the angle between planes, and (5) to maximise the orbit inclination angle. The objective functions must be defined as outputs of the algorithm. All objective functions are combined into one definitive fitness function. The block diagram of this algorithm is shown in Fig. D-2 (Appendix D).

The minimization of the maximum altitude (h) of the constellation is a function of the period of the satellite orbit and is given in Equation 3.3. Minimising the maximum satellite altitude can reduce the orbital launch cost and can result in reduced propagation delay from ground segment to satellites or from satellites to ground segments.

The concept of the angle between planes and the angle shift between satellites in this study are adopted from [15] – [16], and have been described in chapter 2. In figure 2.7, the angle between planes is defined as the sum of the angle from plane 1 to the line of nodes and the angle from plane 2 to the line of nodes. Mathematically, the angle between planes can be expressed as follows:

$$\theta_s = \theta_{s_1} + \theta_{s_2} \quad (4.5)$$

The angle shift between satellites is defined as the range difference travelled by the satellites from the line of nodes, $(\phi_{s_1} - \phi_{s_2})$. To minimise this angle shift between satellites, the following equation derived from [16] is used:

$$\phi = \phi_{s_1} - \phi_{s_2} \quad (4.6)$$

To maximise the inclination angle for a circular orbit, the function below is derived from [34]:

$$i = \sin^{-1} \left[\frac{2}{3} \left\{ 1 - \left(\left(\tilde{n} \left(\frac{\mu_e}{(R_e + h)^3} \right)^{-1/2} - 1 \right) \frac{2(R_e + h)^6}{3J_e R_e^2} \right) \right\} \right]^{1/2} \quad (4.7)$$

where , J_e is the zonal harmonic as a function of the longitude and $\tilde{n}$ is the Legendre polynomial order for the circular orbit. This formula can be extended for non-circular orbit types. The inclination angle, i , in equation (4.7) can then be re-expressed as:

$$i = \sin^{-1} \left[\frac{2}{3} \left\{ 1 - \left(\left(\tilde{n} \left(\frac{\mu_e}{A^3} \right)^{-1/2} - 1 \right) \frac{2p^2}{3J_e R_e^2} \right) (1 - e^2)^{-1/2} \right\} \right]^{1/2} \quad (4.8)$$

A is defined as $(R_e + h)$ for R_e as the Earth's radius and h is the satellite's altitude. p is defined as:

$$p = (R_e + h)^3 (1 - e^2) \quad (4.9)$$

where e is the eccentricity of the orbit. For the circular orbit, $e = 0$. A careful selection of the orbit inclination angle can reduce the effects of the non-uniform gravitational field on the nominal satellite's orbit and can also improve the accuracy by reducing the geometric dilution of precision for dual satellite diversity. Inclination angles between 45° and 90° are recommended for this purpose [16].

All objective functions are represented in one fitness function and will be described in the next sub-section. In this study, the multiobjective GA approaches include parameters of the satellite constellation, population based non-Pareto approaches and rank schemes based on the definition of Pareto optimality. An initial evaluation is reported in the form of a Pareto best rank for different optimisations of the objective

The multiobjective optimisation is formulated into a problem of searching for a parameter set of satellite constellations in the chromosomes $\{p_{\max_k}, p_{\min_l}\}$ to satisfy the equality of dual satellite diversity. $p_{\max}$ and $p_{\min}$ are parameters of the satellite constellation for maximum and minimum values. The following equality of genes in the genetic satellite constellation design is formulated as:

$$\{p_{\max_k}, p_{\min_l}\}_i \in \text{SatDiv} \quad (4.10)$$

where *SatDiv* is the dual satellite diversity availability, i the generation number, $j=1, \dots, N$ is the identification index for each individual and k or l is the objective for maximum or minimum values. The problem of the multiobjective optimisation is to find a parameter set which yields acceptable constellation parameters for the satellite diversity performance in the regions required.

4.4.2 Chromosome Structure

The chromosome structures in the GA provides the satellite constellation parameters, e.g. the number of satellites, the altitude of satellite's orbit, the angle between planes, the angle shift between satellites and the inclination angle. Using normal GA concepts, the

chromosome is encoded into a binary string of each variable. In simulation, the same length of each chromosome for each variable is applied. The total chromosome length for each variable represents one individual. A population includes N individuals (or chromosomes). According to the GA's generational cycle, a new population is created at each generation out of chromosomes from the previous population. The chromosome structure of the multiobjective satellite constellation design is shown in Fig. 4.3.

The total length of the chromosome is described as follows:

$$C_{tot} = N_p \times CL_p \quad (4.11)$$

where N_p is the number of the satellite constellation parameter and CL_p is the chromosome length for each parameter. The individual (chromosome) is used in further steps of the genetic algorithm, e.g. selection, crossover and mutation.

Figure 4.3. GSC chromosome structure

4.4.3 Selection

The selection is composed of the choice of chromosomes and the acceptance condition of these chromosomes to be used in the next population. The use of the population in selection operators is justified to improve a set of individuals in running competition. The selection mechanism favours the individuals which have increased fitness compared to those which are already in a local optimum. A random selection process is used in this algorithm. A number of solution vectors is chosen from the population with size N in order to be used as parents for the generation of new solutions. The probability of the random vectors, within the limits of a particular chromosome p_i , is directly proportional to the quality value of the fitness F_i^j . The probability of selection for mating of a particular chromosome, Pr_i , is defined as:

$$Pr_i = \frac{F_i^j(p_i)}{\sum_{i=1}^N F_i^j(p_i)} \quad (4.12)$$

Two offspring are produced whose fitnesses depend on the parents according to the crossover and mutation process.

4.4.4 Crossover and Mutation

Crossover is the process of combining the genes of one agent with those of another to create offspring that inherit traits of both parents. The crossover rate is the odds of an agent being selected for the crossover operation. The agents that are not selected will not have their genes changed before proceeding to the mutation phase. Those chosen will be paired with a mate, which is another agent that has also been selected for crossover. From each pair, two offspring will be created that will replace their parents.

The multipoint crossover process is proposed in this algorithm. For multipoint crossover, m crossover positions k_i [1,2,..., Nvar-1], where $i = 1, \dots, m$; Nvar is the number of variables of an individual and is chosen at random with no duplicates and

sorted in ascending order. Then, the variables between successive crossover points are exchanged between the two parents to produce two new offspring. The multipoint crossover process is shown in Fig. 4.4.

Figure 4.4. Multipoint crossover

The crossover of two parents in which each chromosome has the bit string that represents the proposed satellite constellation design parameters is defined as follows:

$$P_{\text{offspring}_1} = \beta \left(\{P_{\text{parent}_2}\}_{l=1}^{\max} \right) + (1 - \beta) \left(\{P_{\text{parent}_1}\}_{l=1}^{\max} \right) \quad (4.13)$$

and

$$P_{\text{offspring}_2} = \beta \left(\{P_{\text{parent}_1}\}_{l=1}^{\max} \right) + (1 - \beta) \left(\{P_{\text{parent}_2}\}_{l=1}^{\max} \right) \quad (4.14)$$

where β is a dynamic parameter taking values in the interval $[0,1]$ and the choice of this value depends on the relative condition of lower bound (LB) and upper bound (UB) between the two different offspring. The value of β is 0 if both the offspring are the same and can be written as:

$$\beta = \begin{cases} [\max(\alpha, \delta), \min(\gamma, \lambda)], \dots, \dots, \text{offspring}_1 \rangle \text{offspring}_2 \\ [0, 0], \dots, \dots, \text{offspring}_1 = \text{offspring}_2 \\ [\max(\gamma, \lambda), \min(\alpha, \delta)], \dots, \dots, \text{offspring}_1 \langle \text{offspring}_2 \end{cases} \quad (4.15)$$

where

$$\alpha = \frac{LB_k^{s_{offspring2}} - offspring_{2k}}{offspring_{1k} - offspring_{2k}}, \quad \delta = \frac{UB_k^{s_{offspring1}} - offspring_{1k}}{offspring_{2k} - offspring_{1k}}$$

$$\gamma = \frac{LB_k^{s_{offspring1}} - offspring_{1k}}{offspring_{2k} - offspring_{1k}}, \quad \lambda = \frac{UB_k^{s_{offspring2}} - offspring_{2k}}{offspring_{1k} - offspring_{2k}}$$

Each chromosome elements for $P_{offspring}$ provide $[p_{offspring_1}, \dots, p_{offspring_m}]$ where m is the length bit in each chromosome. These elements are then used for the mutation process.

To increase the applicability of the above operator (to ensure that β will be non-zero, which actually always nullifies the results of the operator) it is wise to select the applicable gene as a random choice from the intersection of movable genes of both chromosomes. Note that the value of β is determined separately for each single arithmetical crossover and each gene.

Mutation is the process to find a new search chromosome format by changing the value of a randomly chosen position in a substring. A dynamic mutation operator with non-uniform mutation aims to both improve single element tuning and reduce the disadvantage of random mutation. The mutation operator is used to occasionally alter the value of some parameters;

$$P_{offspring}' = P_{offspring} \pm \Delta P_{offspring} \quad (4.16)$$

A non uniform mutation process allows a global exploration of the admissible range [LB, UB] for the parameter during the initial generations and a very local search for the ultimate generations. A non uniform mutation is implemented using the following expression for $\Delta P_{offspring}$:

$$\Delta P_{\text{offspring}} = \begin{cases} \Delta(t, UB - P_{\text{offspring}}) \\ \Delta(t, P_{\text{offspring}} - LB) \end{cases} \quad (4.17)$$

where the value of $\Delta P_{\text{offspring}} = \Delta(t, UB - P_{\text{offspring}})$ if a random digit is 0 and $\Delta P_{\text{offspring}} = \Delta(t, P_{\text{offspring}} - LB)$ if a random digit is 1. The function $\Delta(t, y)$ returns a value in the range $[0, y]$ such that the probability of $\Delta(t, y)$ being close to 0 increases together with the current generation number of t . This property causes the operator to initially search the space uniformly (when t is small), and then locally at a later stage. The following equation is used for this purpose;

$$\Delta(t, y) = y \left(1 - r^{(1 - \frac{1}{T})^b} \right) \quad (4.18)$$

where r is a random number in the interval $[0, 1]$, T is the maximum generation number, and b is a system parameter determining the degree of non uniformity. In this work, the value of b is chosen as 5 as recommended in [46].

4.4.5 Fitness Function

The final fitness function for all objective functions of elements of the dual satellite diversity availability are evaluated for each generation. An interpolation between the best and the worst Pareto rank is evaluated for each fitness value. The same weighting factor for all objective functions is determined to control the optimal solution. The ideal fitness function can be expressed as:

$$F_i^j(p_i) \in \text{SatDiv} = \frac{1}{1 + \frac{\omega \sum_{k=1}^3 f_k(p_{i_min})}{\omega \sum_{k=1}^2 f_k(p_{i_max})}} \times a^{-1} \quad (4.19)$$

where a is the scaling factor and k is the number of the objective function. Different scaling factors are examined to increase the robustness of generation and to map the fitness values in range 0 and 1. All objective functions that are determined as functions of the satellite constellation parameters are elements of satellite diversity. The GA is run simultaneously for all objective functions and the Pareto optimal solution is generated for all objectives. The genetic algorithm process is stopped after the last generation or can be stopped after a specified number of generations. The process is carried out on a group of the fittest individuals that represent all constraint functions of the satellite constellation.

To evaluate the fitness function of the genetic satellite constellation algorithm, Fig. 4.5 shows the normalisation of the fitness value vs. the generation numbers for 350 populations. The optimisation has succeeded in finding a solution with a fitness of 1.

Figure 4.5. Fitness function vs. generation size

The best individual for each generation is chosen according to the fitness value F_i^j . The vector matrix of the bits of the chromosome with the best fitness is evaluated as:

$$c_{\max, \min} = \text{mat} \left[\{ p_{\max_k}, p_{\min_l} \}_{i}^{\max, \text{gen}} \right] \quad (4.20)$$

where $p_{\max_k}$ and $p_{\min_l}$ are the chromosomes for the maximum and minimum of the objective function with the best fitness for the satellite constellation, and $\text{mat}[]$ is the row matrix of the offspring vector. i is the generation number that increases to a maximum value ($\max, \text{gen}$). Finally, the chromosome matrix output of the genes of the satellite constellations can be written as:

$$c = [p_{\max_1}, \dots, p_{\max_k}, p_{\min_1}, \dots, p_{\min_l}] \quad (4.21)$$

The best fitness is chosen by ranking them from 1 to the maximum number of generation when all processes of selection, crossover and mutation are stopped.

4.5 Experiments and Evaluations

Selected range values for the initial input parameters of the GAs are shown in Table 4.1. The simulation is demonstrated for MEO and LEO constellations. The input for simulation for the satellite's altitude is chosen in a range of 9,500 – 13,000 km for MEO constellation and in a range of 700 – 1700 km for LEO constellation. These are assumed to be suitable ranges for satellite altitude for MEO and LEO constellations. The range of inclination angles is chosen between 40° and 65° because this range is close to optimal inclination angles that are reported in previous works [16]. The range of the angle between planes and the angle shift between satellites are chosen between 0° and 90°. In fact if one considered, the impact of the satellite constellation on the mobile terminal positioning, the best value for the angle between planes should be close to 90° and the

angle shift between satellites should be close to 0° . The value of crossover probability and mutation probability is chosen as 0.6 and 0.025 respectively, as suggested in [22] for optimal solution in the GA process.

Population size	350
Maximum of generations	550
Crossover probability	0.6
Mutation probability	0.025
Random seed number	0.2
Range of the angle between planes	$0 - 90^\circ$
Range of the angle shift between satellites	$0 - 90^\circ$
Range of the inclination angle	$40^\circ - 65^\circ$

Table 4.1. GA input parameters

4.5.1 GSC for MEO Constellation

Simulation results show that a MEO constellation with a total number of 8 satellites distributed in 2 planes with 4 satellites per each plane can be found. This total number of satellites is smaller than the number of satellites for the ICO constellation. A comparison of the genetic satellite constellation design results and the ICO constellation is shown in Table 4.2. The inclination angle for the GA constellation is 53° and the altitude of the satellite is 10,948 km. The inclination angle for GAs is higher than ICO's inclination angle. This result is in the range and close to optimum of the inclination angle that is recommended in [16]. An inclination angle of 55° is the optimum inclination angle for avoiding the positioning errors introduced by a satellite drift from its true orbit as a consequence of an asymmetric gravitational field. Inclination angles between 45° and 90° are recommended to take into account that dual satellite visibility can improve even further the accuracy by reducing the geometric dilution of precision. In addition, the inclination angle can be varied in this range to optimise coverage and diversity over a

range of latitudes. The satellite altitude for the GA constellation is higher than ICO's altitude. It is clear that with smaller number of satellites to cover the same coverage area as shown in Fig. 4.2, the altitude of the satellites should be higher. The simulation results indicate that the altitude of the satellite is still within the range recommendation for MEO satellite's orbit altitudes. The angle between planes should be higher and as with previous result in [16], if this angle is close to 90° , the accuracy of positioning performance will be better. The minimization of the angle shift between satellites also gives the accuracy of positioning performance. In this work, the angle between planes and the angle shift between satellites are 85° and 8° .

Constellation parameters	ICO	GA design
Number of satellites	10	8
Number of planes	2	2
Number of satellites per plane	5	4
Orbital altitude (km)	10365	10948
Orbit inclination	45°	53°
Angle between planes	72°	85°
Angle shift between satellites	-	8°
Apogee/perigee	Inclined Circular Orbit	Inclined Circular Orbit

Table 4.2. Simulation results for MEO constellation

The statistical results for dual satellite diversity visibility for ICO and the GA constellation at 13° minimum elevation angle are shown in Fig. 4.6 for longitude of 45° . This value of the elevation angle is chosen because it ensures that unnecessary overlap is reduced in the system without compromising the total coverage in areas where the major traffic arises. Furthermore this approach simplifies the coordination task between network entities directly resulting from the overlap between satellites. The results show that, the percentage of availability of dual satellite diversity of the GA satellite constellation is better than that of the ICO constellation. 100% dual satellite diversity visibility is the optimum for all latitudes, but it is difficult to achieve this in practice. From Fig. 4.6, 100% dual satellite visibility can be achieved at lower latitudes ($0^\circ - 26^\circ$) and at higher latitudes ($86^\circ - 90^\circ$) for the GA constellation. Note, the reduced number of planes and

satellites in the constellation decreases the performance of percentage of the availability of satellite diversity.

In Fig. 4.7, we show the minimum and the average elevation angles for the new GA design approach.

Finally, an illustration of the instantaneous coverage of the GA MEO constellation with 8 satellites and 13° minimum elevation angle is shown in Fig. 4.8.

Figure 4.6 Dual satellite diversity statistics at 13° minimum elevation angle

Figure 4.7 Elevation angle statistics for MEO constellation

Figure 4.8 GA-MEO satellite constellation coverage

4.5.2 GSC for LEO Constellation

The results for a LEO constellation have a total number of 45 satellites distributed into 5 planes with 9 satellites per plane. It should be noted that the total number of satellites is smaller than that of the Globalstar constellation. Inclination angle of 52° is the best fit from the simulation criteria. The inclination angle for the GA constellation and Globalstar are the same. For non-circular orbits, the inclination angle is a significant factor in realizing the satellite altitude. The optimum of the angle shift between satellites and the angle between planes of 10 and 70 degrees respectively are achieved with an orbit altitude of 1656 km. The angle between planes and the angle shift between satellites are still in the range that is recommended for best accuracy of positioning performance. The simulation results for the LEO constellation using GA are summarized in Table 4.3 and compared to those of the Globalstar constellation.

Constellation parameters	Globalstar	GA
Number of satellites	48	45
Number of planes	8	5
Number of satellites per plane	6	9
Orbital altitude (km)	1412	1656
Orbit inclination	52°	52°
Angle between planes	-	70°
Angle shift between satellites	-	10°
Apogee/perigee	Incl. Circ. Orbit	Incl. Circ. Orbit

Table 4.3. Simulation results for LEO constellation [36]

In Fig. 4.9 we show the availability of dual diversity statistics for LEO constellations at longitude 45° . This result is compared to the Globalstar constellation at 14° minimum

Figure 4.9. Dual satellite diversity statistics at 14° minimum elevation angle [36]

elevation angle. This figure shows that the GA constellation is better than Globalstar in terms of dual satellite diversity statistics where 100% of the visibility of dual satellite diversity for GA constellation can be found between 30° - 60° of latitude. The visibility of dual satellite diversity is better until 74° and becomes 0 for the higher latitudes. Except within 9° - 16° of latitude, the dual satellite visibility statistics for the GA constellation is better than those of Globalstar. This is an important improvement in a constellation which relies on dual satellite diversity advantage for its system operations.

The elevation angle statistic for the LEO constellation using the genetic algorithm is shown in Fig. 4.10

Figure 4.10. Elevation statistics for LEO constellation

The selection of the satellite's altitude for the GA satellite constellation is also conditional on the effects of the Van Allen Radiation Belt. The trapped earth radiation has most influence on the choice of satellite orbit altitude. The Van Allen Radiation Belt is used to explain the position of the satellite and its effect as a result of atmosphere radiation. In the Van Allen Radiation Belt, the radius of the LEO constellation using GA is ~ 1.26 earth's radius. This is still beneath the lower belt that is centred at an altitude of ~ 0.6 Earth radius (~ 3830 km). The radius of the MEO constellation using GA is 2.72 Earth's radius in the Van Allen radiation belt. This radius is acceptable because it is still within the acceptable range for MEO orbits within the Van Allen radiation belt.

A different choice of the GA parameter inputs will yield different results. For example, the effect of changing the number of the genetic populations with the same parameter value for others (Table 4.1) gives the different results. An experiment was conducted to evaluate the total number of satellites and the maximum satellite altitude for LEO constellations with results as shown in Table 4.4. For population sizes higher or

equal to 250, the number of satellites and the satellite altitude are constant. This indicates that the optimum result can be achieved with a 250 population size.

Population size	Satellite Number	Altitude (km)
100	64	1534
150	56	1596
200	49	1624
250	45	1656
300	45	1656
350	45	1656
400	45	1656

Table 4.4: Effects of different population size for LEO constellation

4.6 Conclusions

Simulation models of automatic satellite constellation design using a multiobjective genetic algorithm have been presented and evaluated for both LEO and MEO constellations in this chapter. An existing multiobjective genetic algorithm process was used to determine parameters of the satellite constellation simultaneously. A new approach to this constellation design is called the genetic satellite constellation (GSC) design. The multiobjective genetic algorithm scheme monitors the number of satellites, the altitude of satellites, the angle shift between satellites, the angle between planes and the inclination angle. The dual satellite diversity statistics and the average and the minimum elevation angle performances were evaluated for both LEO and MEO constellations. From the experimental results, a new automatic satellite constellation for MEO was produced which has a total number of 8 satellites distributed into 2 planes with 4 satellites per plane, 53° inclination angle and 10948 km satellite altitude. The angle between planes and the angle shift between satellites for this constellation are 85° and 8° ,

respectively. The experimental results for the LEO constellation have a total number of 45 satellites that are distributed in 5 planes with 9 satellites per plane. Inclination angle of 52° is the best fit for the simulation criteria. The angle shift between satellites and the angle between planes of 10 and 70 degrees respectively were achieved with an orbit altitude of 1656 km. The performance in terms of the availability of dual satellite diversity was compared to ICO for MEO and to Globalstar for LEO. The results showed that the availability of dual satellite diversity using the multiobjective genetic algorithm for both LEO and MEO is improved. Using the genetic satellite constellation design, satellite diversity can be optimised whilst at the same time reducing the total number of satellites. The aim of this section has been to show that the multiobjective GA is useful for the optimisation of parameter in constellation design. In the examples used herein we have chosen altitude, number of satellites, the angle between shift satellites, the angle between planes and the inclination with diversity performance as such parameters. It must be realized that for a full systems optimization there could be many other parameters which would include those of the spacecraft itself and launching. The technique would be extended by defining a cost function which weighted all of there parameters and the GA used to optimise this cost function and so produce a more global optimization. Nevertheless the principle has been established using this rather than restricted example set of parameters.

Chapter 5. Genetic Hybrid Satellite Constellation Design

5.1 Introduction

In future, satellite communication networks will need to be designed to have high capacity, high quality and provide highly reliable communication services to all kinds of terminals. This will entail multiple redundant coverage for satellite diversity and relatively high minimum satellite elevation angles. A lower altitude orbit is desirable for communication services to personal and mobile terminals using small antennas and low power transmitters. For lower altitudes the free space loss becomes smaller and larger link margins can be preserved. However in this case, a larger number of satellites are needed. Recently there has been interest in double layer satellite constellations using inter satellite links, such as combinations between LEO and MEO [38]. Potentially, a large number of satellites are needed for such systems. In order to minimize the total number of satellites, the properties of the double layer satellite constellation are of interest. They offer an additional degree of freedom to improve the efficiency of coverage and to separate services between the layers to which they may be more applicable. Particularly effective could be a combination of LEO and MEO, LEO and GEO or combination of MEO and GEO.

In this study, we also thus consider the design of these hybrid satellite constellations. The idea in this approach is that the lower layer satellites, whose number of satellites is large, can be minimized by using connection the user to the upper layer satellite constellation using satellite diversity concept. In this study, the hybrid satellite constellation is also proposed for satellite diversity. The automatic hybrid satellite constellation design is thus considered for application of the genetic algorithm with the outputs of this algorithm being the simultaneous determination of the parameters of each layer of the hybrid constellation. Again we only consider coverage aspects in this work and realize that the networking aspects associated with using satellites in different layers

with their consequent different delays would need to be investigated further a complete application study. The model is modified and extended from the previous work in chapter 4. This new algorithm is called a genetic hybrid satellite constellation design.

5.2 System Model

Herein the genetic satellite constellation design that illustrates the above is developed for such a hybrid constellation. The generalized automatic hybrid satellite constellation is proposed for hybrids between combinations of three layers as shown in Fig. 5.1. The previous model used for the genetic satellite constellation is extended in its chromosome structure to accommodate the extra parameters and operational as normal.

The hybrid satellite constellation is designed to give full global coverage with a minimum number of satellites. This constellation can be used to offer high diversity global coverage with a tradeoff between diversity and satellite numbers or minimum elevation angle. The constellations of the LEO (1st layer) and MEO (2nd layer) orbits are assumed to be inclined circular orbits. The 1st and the 2nd layers of the satellite constellations are designed for a resonant orbit with repetitive ground tracks and also to avoid the Van Allen radiation belts. The circular orbit is proposed for the GEO (3rd layer) which places it in the Equatorial plane.

Figure 5.1. Satellite diversity for hybrid satellite constellation design

5.3 Genetic process

5.3.1 Chromosome Structure

Hybrid chromosomes for parameters of the hybrid satellite constellations are now proposed. The block diagram for this algorithm is shown in Fig. D-3 (Appendix D). The number of satellites, the number of the planes, the altitude of the satellite's orbit, the angle between planes, the angle shift between satellites, and the inclination angle for layers of satellite constellation are represented in the chromosome structure. In simulation, the same length of each chromosome for each variable is applied. The detail of the chromosome structure is shown in Fig. 5.2.

The total length of the chromosome is described as follows:

$$C_{tot} = (p_{j_1} + p_{j_2}) \times CL_p \quad (5.1)$$

where p_{j_1} and p_{j_2} are the number of parameters for both layers of satellites and CL_p is the chromosome length for each parameter. The individual is represented by the total chromosome length and is used in further steps of the genetic algorithm, e.g. selection, crossover and mutation process.

Figure 5.2. Hybrid satellite constellation chromosome structure

5.3.2 Selection

The selection process is most important and contains the essential operators of the generation process in producing the optimal solution. The selection is composed of the choice of chromosomes and the acceptance condition for these chromosomes to be used in the next stage. The use of the population in the selection operators is justified for improving the set of individuals in the running competition. The selected parents (Γ) of generation ρ of individuals from the individuals of the previous generation $\rho - 1$ is calculated using the following equation:

$$(\Gamma_{\rho}^j)_{parent} = S(\Gamma_{\rho-1}), \quad j = 1, 2, \dots, M \quad (5.2)$$

where $S(.)$ is the selection process. Furthermore, to escape from a local optimum, one individual uses only one exploratory path, whereas a population with several paths has a greater chance of continuing its search towards a global optimum. The selection mechanism favours individuals which have improved fitness compared with those which are already in a local optimum. Note however that the selection may prevent the population from escaping from the local optimum. The probability of any individual being selected from the population is defined as:

$$P_s(j) = \frac{(F_j)_{\rho-1}}{(F_{sum})_{\rho-1}} \quad (5.3)$$

where $P_s(j)$ is the probability of the selection of individual j of the previous generation. The individual with the index j is selected, if

$$\sum_{i=1}^j (F_i)_{\rho-1} < (F_{sum})_{\rho-1} \times a \quad (5.4)$$

where a is a real random number between 0 and 1. Two randomly selected parents go forward to crossover and mutation processes.

5.3.3 Crossover and Mutation

The selected individuals are paired up for crossover or recombination subject to their mating distance and crossover probability. Considering that two parents are to be composed to produce two children or offspring, these two randomly selected parents are:

$$(P_1^1, P_2^1) = ((P_{1,1}^1, \dots, P_{1,n}^1), (P_{2,1}^1, \dots, P_{2,n}^1)), \quad (5.5)$$

and

$$(P_1^2, P_2^2) = ((P_{1,1}^2, \dots, P_{1,n}^2), (P_{2,1}^2, \dots, P_{2,n}^2)) \quad (5.6)$$

where $P_{1or2,n}^1$ and $P_{1or2,n}^2$ are the group bit string for each parameter of each layer satellite constellation. The fitness of the two offspring individuals depends on the parents through the crossover and the mutation processes. The best individual is evaluated for each generation. The multipoint crossover process is proposed in this algorithm as illustrated in chapter 4. The offspring is produced from the crossover between two parents with equal probability for all $i = 1, \dots, n$, and can be expressed as:

$$(P_1, P_2) = ((P_{1,1}^{q1}, \dots, P_{1,n}^{qn}), (P_{2,1}^{q1}, \dots, P_{2,n}^{qn})) \quad (5.7)$$

The number of the crossover point is equal to the total number of the parameters of the satellite constellation for both layers that are represented in the chromosome structure. The crossover algorithm presented in chapter 3 and 4 is further developed in the current work for application to hybrid chromosomes. The following algorithm indicates the crossover process for the hybrid genetic algorithm:


```

Generate a bias random probability ( $P_r$ ),
If (the result is True)
{
    crossover_site_1 = int(a *  $L_1$ );
    crossover_site_2 = int(a *  $L_2$ );
    .
    .
    .
    crossover_site_n = int(a *  $L_n$ ); where a is a random value between 0 and 1
    and int(.) yields the integer part of the input parameter with the
    chromosome length L.
}
else
{
    crossover_site_1 =  $L_1$ ;
    crossover_site_2 =  $L_2$ ;
    .
    .
    .
    crossover_site_n =  $L_n$ 
}

```

Figure 5.3 Multipoint crossover site algorithm

A non-uniform mutation process is proposed in this work. For n generation, the lower bound (LB) and upper bound (UB) is implemented for the offspring vector as explained in section 4.4.4. The non-uniform mutation is responsible for the fine tuning capabilities of the system. Moreover, non-uniformity is also applied to a whole solution vector rather than to just a single element, causing the whole vector to be slightly shifted in the space. If the value of a set of the gene's is $\langle p_1, \dots, p_m \rangle$ for all parameters in a hybrid chromosome and the element p_k is selected for this mutation from the set of moveable genes, the result is a vector that can be written as:

$$s_p^{t+1} = \langle p_1, \dots, p_k, \dots, p_m \rangle, \quad \text{with } k \in \{1, \dots, n\} \quad (5.8)$$

p_k' has been determined in sub-section 4.4.4. The new set vector element represents a new bit string in the chromosome. The gene is mutated if the unfair probability is biased with the probability of mutation. This condition has been introduced in subsection 3.3.2.5.

5.3.4 Fitness Function

The final fitness function for all the objective functions are elements of dual satellite diversity visibility and is evaluated for each generation. An interpolation between the best and the worst Pareto rank is evaluated for each fitness value. The same weighting factor (ω) for all objective functions is determined to control the optimal solution. The ideal fitness function can be expressed as:

$$F_j^l = \frac{1}{1 + \frac{\left| \omega \prod_{k=1}^2 E_{\min_k}(s, h, \theta) \right|}{\left| \omega \prod_{k=1}^2 E_{\max_k}(\varphi, i) \right|}} \times a^{-1} \quad (5.9)$$

where j is the generation number, $l = 1, \dots, N$ are the identification index for each individual, k is the number of layer for the hybrid constellation, and a is the scaling factor. Satellite parameters for both LEO and MEO's are represented as s, h, θ, φ and i for the number of satellites, the altitude of the satellite, the angle shift between satellites, the angle between planes and the inclination angle. $E_{\min_k}(\cdot)$ and $E_{\max_k}(\cdot)$ are the expectation operators of parameters with minimizing and maximizing value. A different scaling factor is examined to increase the robustness of generation to map the fitness values in the range 0 and 1. All parameters retain the satellite diversity condition (*SatDiv*).

The process is carried out on a group of the fittest individuals that represent all parameters of the satellite constellation. The chromosome matrix output of the genes of the satellite constellations can be written as:

$$c = [p_1^m, \dots, p_1^n, p_2^m, \dots, p_2^n] \quad \text{for } m=(1, \dots, n) \quad (5.10)$$

where p_{1or2}^m are the parameters of satellite constellations that are proposed in the GA. The genetic algorithm process can be stopped after an optimum number of generations. The best fitness is then chosen by ranking them from 1 to the maximum number of generations and thence stopping the process of selection, crossover and mutation. A ranking selection method is used to emphasize good points. In the current work, the ranking selection of the Pareto optimisation that has been proposed in chapter 4 is extended. The best fitness represents the non-dominated individuals that are assigned as a dummy fitness value. Since individuals in the first Pareto optimal front have the maximum fitness value, they always get more copies than the rest of the population. This is intentional so as to search for non-dominated regions or Pareto optimal fronts. The following flow chart in Fig. 5.4 shows a review of this algorithm.

Figure 5.4 Genetic hybrid satellite constellation optimisation flow chart

Before the selection is performed, the population is ranked on the basis of an individual's non-domination as described in chapter 4. The non-dominated individuals present in the population are first identified from the current population. Then, all these individuals are assumed to constitute the first non-dominated front in the population and assigned a large dummy fitness value. The same fitness value from Equation 5.9 is assigned to give an equal reproductive potential to all these non-dominated individuals. To maintain diversity in the population, these classified individuals are then shared with their dummy fitness values. Sharing methods are discussed elsewhere in [31] and [41]. Sharing is achieved by performing the selection operation using degraded fitness values of the hybrid satellite constellation that are obtained by dividing the original fitness value of an individual by a quantity proportional to the number of individuals around it. This causes multiple optimal points to co-exist in the population. After sharing, these non-dominated individuals are temporarily ignored to process the rest of the population in the same way and to identify individuals for the second non-dominated front. These non-dominated points are then assigned a new dummy fitness value that is retained smaller than the minimum shared dummy fitness of the previous front. This process is continued until the entire population is classified into several fronts.

The population is then reproduced according to the dummy fitness values. Since individuals in the first front have the maximum fitness value, they always get more copies than the rest of the population. This was intended so as to search for non-dominated regions or Pareto optimal fronts.

5.4 Experiments and Evaluation

As an example of the genetic hybrid satellite constellation design, a population size is chosen as 350 with 550 being the maximum number of the generation. The value of crossover probability and mutation probability are chosen as 0.6 and 0.025 as suggested in [22]. The simulation is proposed for the hybrid LEO/MEO, LEO/GEO and MEO/GEO constellations as described in the following sub-sections. The constraint of the satellite's altitude parameter is chosen as 700-1700 km for LEO and 9000-15000 km for MEO. The

plots are again given for a longitude 45° and here the coverage shown is regional (not global).

5.4.1 Hybrid LEO and MEO Constellations

Dual satellite diversity is employed for both LEO and MEO orbits. Simulation results for the satellite parameters are shown in Table 5.1. The hybrid LEO and MEO constellation has 30 satellites for LEO (5 planes $\times$ 6 satellites per plane) and 6 satellites for MEO (2 planes $\times$ 3 satellites per plane). Compared to previous results in [35], the number of satellites is seen to be reduced. Also the maximum satellite altitude for the hybrid constellation for both LEO and MEO are lower than for the single layer of satellite constellation presented in [36]. This will result in lower delay and thus improved QoS for some services. The optimisation of the inclination angle of both LEO and MEO constellations is in range of $50^\circ - 55^\circ$. The orbit inclination in this range can optimise the coverage area and diversity over a predefined range of latitudes. In associated work [16], the inclination angle around 55° has been shown to be optimum in avoiding the positioning errors introduced by a satellite drift from its true orbit as a consequence of an asymmetric gravitational field. The inclination angle around 55° is also closer to the optimum inclination angle for GPS.

The angle between planes and the angle shift between satellites for the hybrid LEO/MEO are close to 90° and 0° respectively. These are also pretty much optimum for use in communications with mobile terminal positioning. Maximizing the angle between planes and minimizing the angle shift between satellites also gives the best accuracy for positioning errors. Simulation results for the angle between planes and the angle shift between satellites results in 76° and 8° for the LEO orbit and 80° and 6° for the MEO orbit. Compared to the results for single LEO and MEO constellations in chapter 4, the angle between planes and the angle shift between satellites for hybrid LEO/MEO are much better.

The most important result in the current work is the achievement of 100% availability of dual satellite diversity statistics down to 13° minimum elevation angle. Compared to the use of GA with a single MEO as shown in Fig.5.5, these results show marked improvement. Thus the results for hybrid LEO and MEO constellations are a good fit to the requirements for satellite constellations for mobile personal

communications which provide fast and accurate user location using the constellation itself.

CONSTELLATION PARAMETERS	LEO (LAYER 1)	MEO (LAYER 2)
Number of satellites	30	6
Number of planes	5	2
Number of satellites per plane	6	3
Orbital altitude (km)	1334	10216
Orbit inclination	52°	51°
Angle between planes	76°	80°
Angle shift between satellites	8°	6°
Orbital type	Inclined circular orbit	Inclined circular orbit
Visibility of dual satellite diversity	100%	

Table 5.1. Hybrid LEO/MEO Constellations

Figure 5.5. Dual satellite diversity statistics using GA for single MEO and hybrid LEO/MEO const. at 13° minimum elevation angle

5.4.2 Hybrid LEO and GEO Constellations

We now apply the design to hybrid LEO and GEO orbits. Especially for the GEO orbit, the number of satellites is chosen as 1 with altitude of 35786 km. In this simulation, GEO is assumed for regional coverage. The inclination and the eccentricity of this orbit are zero (i.e. circular, equatorial orbit). The results show that, the hybrid LEO/GEO constellations have a total number of 28 satellites for LEO that are distributed into 4 planes with 7 satellites per plane; and 1 satellite for GEO in the sequential plane. It should be noted that the total number of satellites is smaller than the hybrid LEO/MEO constellation for LEO orbit. The design results for other parameters are reviewed in Table 3. 100% availability dual satellite diversity statistics for hybrid LEO/GEO constellations can be achieved at 14° minimum elevation angle and is shown in Fig. 5.6. The results are compared to a single LEO constellation that was carried out in chapter 4. The inclination angle for the LEO constellation is 54° and 0° for GEO. For hybrid LEO/GEO constellations, the angle between planes and the angle shift between satellites for LEO orbits are 81° and 6° . It is noticed that marked improvements in the LEO constellation are achieved where the total number of satellites can be drastically reduced whilst the inclination angle, the angle shift between satellites and the angle between planes are very close to optimum performance as recommended in [15] and [16]. Thus, this hybrid satellite constellation can still be used for the accurate positioning of mobile terminals.

CONSTELLATION PARAMETERS	LEO (LAYER 1)	GEO (LAYER 3)
Number of satellites	28	1
Number of planes	4	1
Number of satellites per plane	7	1
Orbital altitude (km)	1432	35786
Orbit inclination	54°	0°
Angle between planes	81°	-
Angle shift between satellites	6°	-
Orbital type	Inclined circular orbit	Circular orbit
Visibility of dual satellite diversity	100%	

Table 5.2. Hybrid LEO and GEO constellations [43]

Figure 5.6. Dual satellite diversity statistics using GA for single LEO and hybrid LEO/GEO constellation at 14° minimum elevation angle.

5.4.3 Hybrid MEO and GEO Constellations

We now look at the hybrid MEO and GEO constellations. The design results are reviewed in Table 5.3. Optimisation results for the inclination angle, the angle between planes and the angle shift between satellites is very close to the ideal condition for accurate satellite positioning previously determined. But the total number of satellites in the MEO constellation is higher than for the hybrid LEO/MEO. Achievement of 100% availability dual satellite diversity statistics is found for 13° minimum elevation angle. The results are compared to a single MEO constellation from the previous work. This result shows marked improvement with the same total number of satellites. The important result in the current work is that the 55° inclination angle for the MEO constellation is the ideal case.

CONSTELLATION PARAMETERS	MEO (LAYER 2)	GEO (LAYER 3)
Number of satellites	8	1
Number of planes	2	1
Number of satellites per plane	4	1
Orbital altitude (km)	10364	35786
Orbit inclination	55°	0°
Angle between planes	86°	-
Angle shift between satellites	4°	-
Orbital type	Inclined circular orbit	Circular orbit
Visibility of dual satellite diversity	100%	

Table 5.3. Hybrid MEO and GEO constellations [43]

5.5 Conclusions

In this chapter, a modified version of the GSC with multiobjective algorithms is proposed for intelligent design of hybrid satellite constellations. As with the GSC, the novelty of the proposed model is the automatic determination of satellite constellation parameters for hybrid LEO/MEO, hybrid LEO/GEO and hybrid MEO/GEO constellations. For LEO and MEO's, the constellation was assumed to be an inclined circular orbit with each orbit containing an equal number of satellites. For GEO, the constellation design was assumed to be a circular orbit. Some extended processes for the non-dominated Pareto optimisation of the multiobjective genetic algorithm was proposed. In simulation, dual satellite diversity was employed for both the lower layer and upper layer orbits. Compared to previous results for single LEO and single MEO constellations, the total number of satellites for the hybrid constellation was seen to be reduced. Also the maximum satellite altitude for the hybrid constellation for both LEO and MEO were lower than for the single layer satellite constellation. The most important result in the genetic hybrid satellite constellation is the achievement of 100% dual satellite diversity statistics down to 14° minimum elevation angle for hybrid LEO/MEO and LEO/GEO, and to 13° minimum elevation angle for hybrid MEO/GEO. Compared to the use of the genetic algorithm with single MEO and LEO constellation in chapter 4, the results for the

hybrid constellation show marked improvement in terms of dual satellite diversity statistics. The important results for the inclination angle, the angle between planes and the angle shift between satellites was that they were found to be ideal results for optimisation of satellite positioning. The ideal objective functions for hybrid satellite constellations were used; however, a practical objective function and different orbital types need to be investigated further in order to confirm the more general applicability of the technique.

Chapter 6. Genetic Dynamic Channel Allocation

6.1 Introduction

Efficient resource management is very important in order to achieve maximum system capacity for cellular and mobile satellite system networks. The efficiency of resource management includes the available spectrum, time, power and space for a transmission signal. The planning of frequencies that handle the mapping of available spectrum resources to the network entities is known as radio resource allocation. The achievement of the highest level of reliability and availability, whilst at the same time guaranteeing QoS are important tasks in managing radio resources. In mobile satellite communication systems, the dynamic characteristics of non-GEO systems provide additional challenges in terms of radio resource management.

The channel allocation problem as part of the radio resource management has become increasingly important in mobile satellite networks as they have evolved. Since the usable frequency spectrum is limited, the optimal assignment problems for channels are important. An illustration of the radio resource management problem in MSS networks with circular spotbeams model is given in Fig. 6.1. It can be seen that it becomes important to use the frequencies within spots as efficiently as possible. Proposals for channel assignment methods have already been developed such as fixed channel assignment (FCA), dynamic channel assignment (DCA) and hybrid channel assignment (HCA) for terrestrial cellular networks and have also applied to mobile satellite networks [49-58].

In mobile satellite system (MSS) networks, multi spot beams are used to increase the frequency reuse efficiency. Moreover, some MSS networks have to take account of satellite movements that are dynamic. The possibility of frequency reuse between spot beams and the traffic load for each spotbeam are continuously changing. The dynamic

channel allocation schemes have been used as an alternative in order to achieve better channel utilization compared to fixed channel allocation.

The concept of channel assignment for MSS networks is adapted from the channel assignment in cellular communication systems. LEO and MEO satellites are used to evaluate the performance of the channel allocation, because these systems have a number of mobility problems that do not exist for GEO systems.

The service area of a mobile satellite system is called the footprint for a single LEO/MEO satellite and is a circular area on the earth's surface, as shown in Fig. 6.1. The footprints consist of smaller cells or spotbeams (ideally in circular) in order to achieve frequency reuse within the footprint itself. Identical frequencies can be reused in different spotbeams if the spotbeams are geographically separated to limit the interference.

In LEO satellite networks, spotbeam handover is most frequently encountered because of the relatively small spotbeam areas and the relatively high speed of the satellites. Frequent spotbeam handovers could cause more handover blocking of calls. Blocking a handover call is generally considered less desirable from a user's point of view than blocking a new call. Priority can be given via different treatment of new calls to decrease the overall handover call blocking. Many solutions have been proposed to achieve this goal for terrestrial wireless networks and also for mobile satellite system networks [52-58]. In this chapter, we review some of the proposed models that have been suggested in the literature.

Figure 6.1. Radio resource management concept.

Additionally in this chapter, a new approach to dynamic channel allocation for mobile satellite system (MSS) networks using a genetic algorithm approach is described. As background, this chapter also presents and reviews some channel assignment concepts for cellular and MSS networks. The radio allocation concept for cellular system networks is presented. Some design strategies for channel assignment including fixed channel allocation (FCA), dynamic channel allocation (DCA), hybrid channel allocation and some modified models are also presented. The concept of channel allocation for cellular networks is then adapted for MSS networks. The implementation of the genetic algorithm for a dynamic channel allocation process in MSS network environments is then described in the following sub-section. The network model of the mobile satellite system, a traffic distribution scenario and the allocation of the traffic into spotbeams are also described in this chapter. The algorithm monitors the call arrivals and the interference to optimise the allocation of channels in the radio resource management scheme. The performance evaluation of the genetic dynamic channel allocation scheme including the number of channels for each spotbeam, the assigned channels, the quality of service (QoS), and the actual satellite carried traffic are also presented.

6.2 Channel Reuse

The cellular network concept for channel reuse is adopted in this study where the service coverage area is divided into cells. Each cell has a set of resources or channels, which can be accessed by the user in the network. In MSS networks, cells are represented as spotbeams that are integrated into the footprint or satellite coverage of the satellite. Usually in cellular networks, the shape of cell is represented by a hexagonal cell structure, however, practically, the shape of cells depends on the local topography. In MSS networks, this concept can be used, but to simplify the analysis, circular shapes of cells (spotbeams) are used.

One of the most basic limitations of mobile communication systems is restricted spectral bandwidth. Fundamental to both cellular and mobile satellite systems is the idea of frequency reuse by which the same frequency or channels can be reused in different geographical locations. The location is referred to as a cell (for cellular communication)

and a spotbeam (for mobile satellite communication). The cell or the spotbeam is allocated a set of channels according to the expected demand in that cell or spotbeam. The entire spectrum is allocated to a cluster of cells or spotbeams arranged in shapes that allow for uniform reuse patterns.

The objective of any mobile system is to increase the capacity of the network and to maximize the efficiency of the system. In order to increase the capacity and the efficiency of the system, the availability of the number of channels needs to be increased by such means as, employing efficient multiple access and modulation techniques for spectrum efficiency and to reuse frequency in different cells or spotbeams. The maximum efficiency is equivalent to maximum utilization of every channel in the system. It is obvious that the shorter the channel reuse distance, the greater the channel reuse over the whole service area [47-48].

Channel reuse is based on the distance between cell centers and called the reuse distance D , as shown in Fig. 6.2. This figure also illustrates the frequency reuse in a 7 cell cluster system. This distance can be related to the number of the orthogonal channel sets N and can be expressed as:

$$N_{ch} = D^2 / 3R_{cell} \quad (6.1)$$

where R_{cell} is the distance between the center of the hexagon and the point joining two edges, or alternatively the radius of a circular cell whose circumference intersects the node on the hexagon's edges.

Figure 6.2. Reuse distance

The geometry of the hexagonal cells restricts the number of cells per sector to N which can be expressed as:

$$N = i^2 + ij + j^2 \quad (6.2)$$

where i and j are integers which relate to the number of cell shifts required before the channel set is reused. The values for N in the above equation can only accommodate 3,4,7,9 and 12 clusters. The important relationship between D and N is the number of channels available in each cell for a limited bandwidth system. Increasing the value of N leads to a greater division of the channel set.

The system capacity can be increased by reducing the number of cells in each sector, as long as more channels are available in the cell. It is clear that by reducing the sector size, the frequency reuse distance can be reduced and the co-channel interference effect can be decreased. In terrestrial mobile radio environments, the strength of the received carrier power at a distance R_{cell} from the transmitter is given by the following expression:

$$C = \frac{1}{R_{cell}^\gamma} \quad (6.3)$$

where γ is a constant related to the terrain environment. For a seven cell re-use configuration, the ratio of the carrier to interference experienced by a mobile from the six cells located at a minimum re-use distance D from the mobile, e.g. on the first tier of the cell cluster re-use pattern, is given by:

$$\frac{C}{I} = \frac{\sum D^\gamma}{R_{cell}^\gamma} = \frac{D^\gamma}{6R_{cell}^\gamma} = \frac{q^\gamma}{6} \quad (6.4)$$

where q is the co-channel interference reduction factor and is given by [49]:

$$q = DR_{cell}^{-1} \quad (6.5)$$

In order to minimize the effect of co-channel interference, power control techniques are employed at the mobile terminal and the base station to ensure that power levels are maintained at the minimum level needed to maintain the target QoS.

6.3 Channel Allocation Scheme

6.3.1 Fixed Channel Allocation (FCA)

In the FCA strategy, a set of nominal channels is permanently allocated to each cell (for cellular networks) or spotbeam (for MSS networks) for its exclusive use. The fixed relationship is assumed between each channel and each cell or spotbeam, in accordance to co-channel reuse constraints.

The full set of available channels in the system is divided into equal groups and a set of channels permanently assigned to each cell. A new call can be served, only if a free channel is available in the set for the cell. If all channels are used, the new call will be blocked and maybe lost even if other channels are available within the frequency reuse area. The total number of available channels in the system is divided into sets, and the minimum number of channel sets required to serve the entire coverage area is related to the reuse distance as shown in equation (6.1).

In the simple FCA strategy, the same number of nominal channels is allocated to each cell. This uniform channel distribution is efficient if the traffic distribution of the system is also uniform. In that case, the overall average blocking probability of the mobile system is the same as the call blocking probability in a cell. In practice, the traffic in the system is not really uniform but has temporal and spatial fluctuations. A uniform allocation of channels to cells may result in high blocking in some cells and also result in a sizeable number of free channels. This could result in poor channel utilization.

In non-uniform channel allocation the number of nominal channels allocated to each cell depends on the expected traffic profile or traffic distribution in that cell. Thus, heavily loaded cells are assigned more channels than those lightly loaded. This is given by the demand vector, where the demand vector indicates the number of channels required in one cell.

Another scheme than can be applied to the FCA model is the channel borrowing scheme. In this scheme, when a cell has used up all of its nominal channels (i.e. channels pre-assigned to the spotbeam or cell), it can satisfy additional demands by borrowing channels from a neighboring cell (as donor) that it has free. This enables the system to adapt to traffic changes. However, a channel can only be borrowed if the borrowed channel does not interfere with those existing in the cell. Other cells (usually neighboring cells) are prohibited from using a channel that is borrowed. This is then known as a locked channel.

Many channel borrowing schemes have been proposed and they differ in the way the free channels are allocated. This scheme can be divided into simple and hybrid types [49]. In a simple borrowing scheme, any channel from the neighboring cells, which is free, can be borrowed. While in a hybrid borrowing scheme, the set of channels assigned to each cell is divided into two subsets. One set is strictly for local use while the other can be borrowed. Borrowing schemes perform better than static FCA under light and moderate traffic while under heavy traffic, static FCA performs better. This is due to channel locking in heavy traffic causing a loss in efficiency [50].

In MSS networks, two approaches to the FCA scheme have been adopted. In the first approach, a set of channels is defined to be assigned to each spotbeam. The first available channel has priority to serve the call arrivals. If no channel is available in that particular spotbeam, the call arrival will be blocked. The number of channels, N , permanently allocated to each cell and the relationship of the number of system resources (the maximum number of available channels) with M is given by Dell [58] as:

$$M = N \times \frac{D^2}{3R_{cell}^2} \quad (6.6)$$

where D and R_{cell} are the reuse distance and the cell radius, respectively.

Another approach is to associate the radio resources with fixed ground areas. Here, the spotbeam antenna is controlled and can be used to fix the footprint coverage for all time. This method will always ensure that the mobile is under the same spotbeam and hence beam to beam handover is not required (Earth fixed cells). The fixed reuse plan is required for either approach so that the permanently assigned channels are based on a worst case interference scenario. In order to take account of the variation of traffic

demand in different geographical locations, some cells may be assigned with more channels than others. The advantage of the FCA approach is the flexibility to adapt to uneven traffic demands by allowing unused traffic channels in one cell to be used in another at any given time. Generally, the FCA is not efficient for MSS network where the resource is limited and the variation of traffic demand is high.

6.3.2 Dynamic Channel Allocation (DCA)

Due to short-term temporal and spatial variations in traffic, the FCA scheme is not able to attain high channel efficiencies. A solution to the issues is proposed via the DCA scheme. In contrast to FCA, in this scheme there is no fixed relationship between channels and spotbeams. All channels are retained in a central pool and are assigned dynamically to satellite spotbeams as new calls arrive in the system. The DCA scheme can be viewed as a single server/single queue system. Whereas the FCA can be viewed as a multi server/multi queue system. DCA gives better utilization of the channels. Ideally, DCA does not require channel pre-assignment as in the FCA.

For the DCA scheme, all channels are kept in a common pool. Any channel can be temporarily allocated to any cell, provided that the constraint on the reuse distance is fulfilled. In satellite systems, a dynamic channel allocation means that all channels of the satellite are variably shared by all spotbeams. The satellite can act as a centralized controller, which holds the pool and assigns the minimum cost channel to an incoming call.

A channel is eligible for use in any spotbeam provided that signal interference constraints are satisfied. Generally, more than one channel might be available in the central pool to be assigned to a spotbeam that requires a channel and a strategy must be applied to select the assigned channel. Katzela and Naghshineh [50] divided the DCA scheme into centralized DCA and distributed DCA depending on the method of control in assigning channels.

In centralized DCA, a centralized controller is used to assign the central pool of channels based on a specified cost function. The cost function will be different for various assigned channels based on constraints such as reuse distance, future blocking probability and the number of times a channel is used.

Common to both DCA methods, we define a particular frequency band as the channel. Time slots can also be used as channels if they are synchronized via a central controller. In time slot reuse partitioning, time is partitioned rather than frequency as in frequency reuse partitioning. The time frame is divided into two portions, defined as dedicated and shared portions. Here a base station requiring a higher QoS is assigned a dedicated timeslot from the dedicated portion whilst those requiring a lower QoS use timeslots from the shared portion. Previous work [52] has suggested a time slot reuse partitioning method to dynamically allocate channels (time slots) using staggered resource allocation (SRA). In the SRA method, each cell is divided into six sub frames. Subscribers in each sector can only transmit in the sub-frames dedicated to that sector. If there is additional data to send, it would be sent in another sub-frame in an order unique to each sector. The sub-frame is thus assigned to each sector in such a manner as to cause minimum interference.

Distributed DCA uses local information about the currently available channels in the cell vicinity or signal strength measurements to allocate a channel, which is less complex than a centralized DCA [53-55]. Since current information such as the signal strength of a channel is used, distributed DCA can adapt to changing traffic conditions. However, without information feedback from non-neighbouring base stations, co-channel interference will occur more frequently, which may lead to deadlock (premature service termination) and instability (interruption on another established link which in turn causes another successive interruption on other links and thus develops a chain reaction). This is especially important in a circuit switched system, where the channel is used for a longer period of time than in a packet switched system.

The subscriber terminals and base stations are required to scan for signal strength in a distributed DCA system. Chuang [55] recommended that in a packet switched system, the base station first scans the channels and selects a number of candidate channels. This selection is passed to the subscriber terminal where it would again scan through them and finally select a channel for transmission. This method of scanning and selecting performs better than if the subscriber terminal or base station alone scans before selecting a channel for transmission.

The main problem in the DCA scheme is how to select the minimum cost according to the interference in the spotbeam. The selected cost function depends on the future call blocking probability in the vicinity of the spotbeam, the usage frequency of the

candidate channel, the reuse distance, channel occupancy distribution under current traffic conditions, radio channel measurements of individual mobile users, or the average blocking probability of the system. In MSS networks, the DCA scheme can be adapted via various strategies, e.g. interference based DCA, CIR based DCA (MaxMin) and CIR based DCA (Max). These concepts have been evaluated in [56-57].

The interference based DCA strategy is based on the DCA scheme already used in DECT (Digital European Cordless Telephone). With this strategy, the basic idea is to maximize the quality of each new link by allocating the channel that minimizes the downlink interference (I_{down}) at the new mobile. A channel is allocated, based on the following equation, where CH is the group of available channels in the spotbeam, and I_{down_max} is the maximum acceptable downlink interference.

$$\min_{\forall(ch \in CH)} \{I_{down}(ch)\} < I_{down_max} \quad (6.7)$$

When the best channel (ch) is found based from the above equation, it can be assigned only if criterion (6.7) is also satisfied;

$$I_{up}(ch) < I_{up_max} \quad (6.8)$$

where I_{up_max} is the maximum acceptable uplink interference.

The CIR based DCA (*MaxMin*) strategy is based on the estimation of CIRs. The basic idea is to allocate the traffic channel that maximizes the minimum CIR on the uplink taking into account the channel interference of all visible mobile terminals or mobile satellites using this traffic channel.

$$\max_{\forall(ch \in CH) \wedge \forall(m \in M_{ch})} \{CIR_{up}(m, ch)\} > CIR_{up_min} \quad (6.9)$$

When the best channel (ch) is found based on (6.8), it can be assigned only if the following criterion (6.10) is also satisfied. CIR_{up_min} is the minimum acceptable CIR_{up} .

$$CIR_{up}(ch) > CIR_{up_min} \quad (6.10)$$

The CIR based DCA (*Max*) strategy is a slight modification of the interference based DCA strategy. The basic idea is to maximize the quality of each new link by allocating the channel that maximizes the estimated CIR_{down} at the new mobile. A channel is allocated based on (6.11), where CIR_{down_min} is the minimum acceptable CIR_{down} . Criterion (6.10) has also to be satisfied.

$$\max_{\forall (ch \in CH)} \{CIR_{down}(ch)\} > CIR_{down_min} \quad (6.11)$$

Fig. 6.3 illustrates a MSS scenario with two satellites, S_m and S_i and two users, m and i , using the same channel ch . Satellites S_m and S_i are connected to mobile terminal m and i , respectively. As the same channel is being used on both down links, the down link signal transmitted by satellite S_i into beam b_i is also received by mobile m . Satellite S_m 's transmission on beam b_m has a similar effect on mobile i . The example of the interferences in MSS networks is also shown in Fig. 6.3

Figure 6.3. Interference in MSS networks

The cost function for the DCA scheme for MSS networks has been evaluated in [58] – [62]. The cost function is used with the assumption that the satellites have on board functionality for the channel allocation and that the optimal channel is derived by an evaluation of the minimum potential blocking scenario resulting from the allocation of channels. In order to allocate the best available channel for cell x for call arrival in that cell, Dell [58-59] has studied a suitable cost function definition $C_x(i)$, such that the best channel j is selected via the following criteria:

$$C_x(j) = \min\{C_x(i)\}, \text{ for } \forall i \in \Lambda(x) \quad (6.12)$$

where $\Lambda(k)$ is the set of available channels at cell x at the instant of the call arrival.

To evaluate the cost function $C_x(i)$ of any channel, a pure DCA concept can be used where a single pool of channels for all mobile terminals can select any traffic channel satisfying the reuse distance constraint. The cost function has been defined by Del Re [59] for the channel i , $C_x(i)$ as follows:

$$C_x(i) = \sum_{k \in I(x)} \{u_k(i)\} \quad (6.13)$$

where

$$u_k(i) = 1 \text{ or } 0 \quad (6.14)$$

The element of $u_k(i)$ is equal 1 if $i \in \Lambda(k)$, and 0 otherwise. Here, $I(x)$ is the set of cells interfering with x and $\Lambda(k)$ is the set of available channels for cell k at the call arrival instant in cell k . The cost function is correlated to the number of interfering cells around cell x for which channel i is available for channel allocation. The minimizing of this cost means that the number of cells in which this channel will be blocked after allocation is also minimized, thereby increasing spectrum utilization.

Another of the DCA schemes for MSS networks allocates a set channel from the FCA scheme ($F_D(x)$) with the minimum reuse distance constraint and then the DCA is used to select the channel that will be used in cell x . If the channel is not available from

the FCA scheme, the process will select another channel in other cells and try again. The cost function for this model is expressed as:

$$C_x(i) \Delta q_x(i) + \sum_{k \in I(x)} \{C_x(k, i)\}, \quad \forall i \in \Lambda(x) \quad (6.15)$$

where the allocation cost contribution for channel $i \in \Lambda(x)$ due to the interfering cell, $C_x(k, i)$ is given by:

$$C_x(k, i) = u_k(i) + 2[1 - q_k(i)], \quad \forall k \in I(x) \quad (6.16)$$

and

$$q_x(i) = 0 \text{ or } 1 \quad (6.17)$$

$q_x(i)$ is equal to 0, if $i \in F_D(x)$, and 1 otherwise. The value of $q_x(i)$ indicates the priority channel allocation to the available channel in $F_D(x)$.

In this study, the dynamic channel allocation concept as illustrated in equation (6.12) - (6.14) is used as a base DCA.

6.3.3 Hybrid channel allocation (HCA)

Hybrid channel assignment schemes are mixtures of FCA and DCA techniques. In HCA, the total number of channels available for the service is divided into fixed and dynamic sets. The fixed set contains a number of nominal channels that are assigned to cells as in the FCA schemes and, in all cases are to be preferred for use in their respective cells. The second set of channels are shared by all users in the system to increase flexibility. When a call requires service from a cell and all of its nominal channels are busy, a channel from the dynamic set is assigned to the call. The channel assignment procedure from the dynamic set can follow any of the DCA strategies described.

The call blocking probability for an HCA scheme is defined as the probability that a call arriving to a cell finds both the fixed and dynamic channels busy. Performance evaluation results of different HCA schemes have been presented in [63] and [10]. The ratio of fixed to dynamic channels is a significant parameter, which defines the performance of the system. It would be interesting to find the optimum ratio in order to achieve better system performance. In general, the ratio of fixed to dynamic channels is a function of the traffic load and would vary over time according to offered load distribution estimations.

6.3.4 Adaptive dynamic channel allocation

The adaptive dynamic channel allocation scheme (ADCA) is based on a dynamic channel allocation scheme. The concept of guard channel is adapted dynamically according to the user location information in the adjacent spotbeams [64]. This technique finds the optimal number of guard channels for future handover. The concept of adaptive dynamic channel allocation is illustrated in Fig. 6.4.

Figure 6.4 Adaptive dynamic channel allocation

When a new call arrives in a spotbeam, the adaptive DCA scheme considers two possible handover events in the spotbeam occurring before the hypothetical handover departure of the new call: (1) handover arrivals from the other spotbeams; and (2) handover departures from the spotbeam in which the new call is being tested for admission. The handover residual time is introduced as the time interval between acceptance and handover departure of a new call. This time interval can be easily computed according to the user location information.

In Fig. 6.4, users A, D, and F are handed over to other spotbeams, and users C and E remain in their spotbeams. Thus, a possible handover arrival to spotbeam #3 during interval residual time would be from the user B. Likewise, a possible user terminal to be handed over from spotbeam #3 would be user F.

In the adaptive DCA scheme, additional assumptions need to be made. Mobile users cross the cellular network with a constant relative velocity orthogonal to the side of the spotbeams. When a handover occurs, the destination spotbeam is the neighboring spotbeam in the direction of the relative satellite user motion. The same channel can be assigned in different spotbeams at the same time provided that these spotbeams are sufficiently separated in space (reuse distance).

6.3.5 Intelligent channel assignment

As mentioned above, the channel allocation problem has become increasingly important in MSS networks. Since the usable frequency spectrum is limited, the optimal assignment problems for the channel are important. Consequently, it becomes important to use the frequency as efficiently as possible. Intelligent channel assignment is one method to optimize channel allocation in either cellular terrestrial networks or MSS networks. Bandwidth allocations for terrestrial and satellite systems in IMT 2000 and UMTS system are described in Appendix B. From Fig. B-1 in Appendix B we can see that two 25 MHz sub-bands are allocated to mobile satellite systems, common to both UMTS and IMT 2000. The band allocated for terrestrial is larger than that for satellite in both IMT 2000 and UMTS. During the World Radio Conference (WRC) 2000, the additional bands 2500-2520/2670-2690 MHz were allocated to the development of the

satellite component of IMT 2000. Frequency bands allocations according to WRC 2000 are shown in Fig. B-2 in Appendix B.

There have been previous proposals for the use of genetic algorithm and neural networks for channel assignment problems [65-71]. They have attempted improved solutions for the frequency assignment problem by formulating new cost functions. Such cost functions take a value of zero if all constraints of the frequency assignment problem are fulfilled by a determined channel assignment. Other schemes propose new methods to minimize the generic nonlinear cost function.

Unfortunately, the minimization of cost function is a difficult problem due to the danger of becoming stuck in a local minima. In cellular networks, the genetic algorithm has been proposed for channel assignment to minimize the interference. The interference types have been identified in a cellular network as co-channel interference and adjacent channel interference. Another approach to optimize channel assignment in cellular networks was proposed by Beckman [69] where the optimization of channel assignment is focused on new calls in the system. Genetic algorithms have been used to search for an optimum call list of channel assignment that do not themselves directly determine an optimal frequency assignment. Genetic algorithms have been used to solve channel assignment problems in cellular networks in [66-67]. A new approach for large populations and evolutionary optimization has also been investigated to improve the quality of the genetic optimization. Simple genetic algorithms for channel assignment in MEO satellite system networks have been proposed in [10]. Intelligent initialization and best individual injection of genetic algorithms were also presented in [10]. In this scheme, the simple genetic algorithm for channel allocation is proposed only for interference adaptation. A cost function of the GA was formulated which evaluates for example the number of interference constraints violated by a given frequency assignment and then tries to minimize this cost function by using a solution representation which automatically avoids any co-site interferences. Unfortunately, interferences between spotbeams (cells) are not automatically avoided by his method, which leads to a poorer performance. Furthermore, even such a process does not lead to an optimal order of the calls and consequently no optimal frequency assignments can generally be found.

6.4 Genetic Dynamic Channel Allocation Algorithm

In this study, we propose a new strategy for dynamic channel allocation using genetic algorithms for multibeam MSS networks. This study focuses on implementing genetic algorithms for combinations of traffic load in each spotbeam using the new call and interference adaptation DCA approach. The update time and the sampling interval time are introduced to retain time variant coefficients and constraints of the algorithm. A genetic algorithm is used to optimize the system design whilst at the same time efficiently solving other system aspects. The main idea of the genetic dynamic channel allocation scheme is to evaluate the cost of using each candidate channel and select the one with the minimum cost provided that certain interference constraints are met.

The objective of this study as a new solution to the dynamic channel allocation is to minimize the 'total bandwidth' in terms of the number of channels to accommodate the traffic load in each spotbeam. Also the optimum use of frequency reuse is satisfied amongst spotbeams. The assigned channels should be able to accommodate the continuously changing traffic load offered in each spotbeam.

The numerical results for channels in a frequency reuse pattern at each update time for each spot beam obtained using the genetic algorithm are presented in this chapter. The QoS performance evaluations of genetic DCA for blocking and dropping call performance are also presented and compared to those obtained using a conventional DCA. Blocking and dropping call probability performance of the genetic DCA are shown to be better than for the conventional DCA. Results obtained so far indicate that the genetic algorithm may be used to better optimise the channel assignment for all MSS networks.

6.4.1 Network Model

MSS networks are proposed for Non-GEO satellite constellations where the number of spotbeams for global coverage is determined for satellite connections to mobile terminals

in the service link. In this study, the frequency channel assignment concept of terrestrial cellular networks is employed for MSS networks. Satellite footprints are divided into spotbeams. The spotbeam is equivalent to a cell in a terrestrial network and the reuse frequency concept is used to link between two spotbeams in the same satellite or to different satellites. The location of the user terminal in the spotbeam is not allowed in the overlap region between two spotbeams. The concept of frequency reuse in MSS networks is shown in Fig. 6.5.

Figure 6.5. Frequency reuse between spotbeams.

As shown in Fig. 6.5, a pair of spotbeams in different satellites cannot share the same frequency when the spotbeams have a common coverage area, but frequency reuse is otherwise allowed. The traffic load for each spotbeam also changes drastically as its coverage moves from an area with light traffic demands to another with heavier demands. A series of frequency channel assignment plans have to be prepared to accommodate traffic requirements under such dynamic environments and constraints.

The frequency reuse between spot beams is determined if the mobile terminal position is not in the overlapped coverage area in one satellite or between two satellites. In Fig 6.5, mobile terminal $f_{i,j}$ can reuse frequencies in spotbeam b or c. The condition for frequency reuse is detected for all spotbeams as a function of time. Update interval time

and sampling time are introduced to detect the condition of the traffic in each spotbeam. The dynamically changing conditions of the channels in spot beams is checked using the update time and depends on the traffic load and the possibility of frequency reuse. The continuously changing traffic load and frequency reuse conditions between update times are evaluated at each sampling time.

The update interval time is used to cope with the dynamically changing conditions of the channel in the spotbeam that also depend on the traffic load and the possibility of frequency reuse. The sampling time is used to reflect the continuously changing traffic load and frequency reuse conditions between update interval times.

6.4.2 Traffic load for Each Spotbeam

In this work, the traffic load is not given directly for each spotbeam, but the traffic load can be forecast for each geographical area. The geographical traffic distribution that is used in this work is adopted from the EU SAINT traffic model [71]. The global traffic distribution is represented in Erlangs for a 36×72 cell grid. Local traffic distribution is determined for each area of 5×5 degrees mesh element on the Earth's surface. This means that the Earth's surface has been divided in to steps of 5° both in latitude and longitude. They are chracterized by the couple index (m,n) where the index m is for the latitude and the index n for the longitude. The detailed distribution of the SAINT traffic model is shown in Appendix C and re-presented as a 3D graph in Fig. 6.6. The SAINT project traffic distribution for S-UMTS worldwide is adopted in this work. The SAINT traffic model is estimated for the total global S-UMTS traffic and its distribution for the year 2010. The traffic model refers to the cellular in-fill users, rural fixed users and international business travellers. This model was used because of its ready availability and the distribution of traffic plays a major role in the determination of the channel allocation efficiency.

Figure 6.6 SAINT traffic distribution

Figure 6.7. Local traffic profile (SAINT project)

The traffic load in spotbeam i can be estimated using the traffic load in area k as follows:

$$E_i(t) = \sum_{area_k \in beam_i} E_k(t) \quad (6.18)$$

where $E_i(t)$ is the traffic load in spot beam i and $E_k(t)$ is the traffic load in terms of Erlangs in area k , which is a function of time. Area k is given for a 5 x 5 degrees mesh element on the Earth's surface in terms of busy hour traffic. The busy hour traffic is determined at each local time by the local traffic profile. A local traffic profile is shown in Fig. 6.7. In this case, we assume the load ratio of the local traffic profile for each spotbeam is the highest between 10.00 and 12.00 hrs and lowest between 23.00 and 6.00 hrs.

An example condition of traffic intensity for different spotbeams as a result of time varying traffic loads for some randomly selected spotbeams is shown in Fig. 6.8. The busy hour traffic is always detected for each local time by the local traffic profile. The local traffic profile is always checked at every update time to evaluate the possibility of reuse frequency in different spotbeams. The condition of the traffic load is different at interval times for each spotbeam. If the traffic load in one spotbeam is low, another spotbeam with high traffic load can use it. Fig. 6.9 shows an example of traffic load and frequency reuse conditions, which are heavily time dependent and the number of channels assigned at update times. Using this concept, the flexible bandwidth in different spotbeams is used as reuse frequency so that the bandwidth can be conserved.

The traffic carried by the satellite spotbeams from the originating traffic distribution in the SAINT project is not so straightforwardly applied as it is for terrestrial models. The principles which determine whether a spotbeam is required to serve a channel originating from a particular grid in the traffic model depends on the connectivity between the spotbeams and area originating the traffic and the suitability of the spotbeam to carry traffic.

Figure 6.8 Traffic intensity for different spotbeams.

The required channel allocations to a cell in the traffic model is to determine the set of spotbeams, which have connectivity with the cell. Each cell is a rectangle, defined by angles of latitude and longitude. The spotbeam coverage areas are represented by the location of their centre, in latitude and longitude. A simple model for assessing the coverage of a cell by a spotbeam is examined as to whether the centre point of the cell is within the coverage area of the beam. A single mathematical comparison must be made to determine connectivity. The centre of each cell (i,j) is a constant for latitude $Lat(i,j)$ and longitude $Lon(i,j)$. Using the index number of the cell, the spotbeam centre can be expressed as [10]:

$$Lat(i,j) = 87.5 - 5i$$

$$Lon(i,j) = 5j - 177.5$$

Using computational methods for the geocentric radius of the spotbeam and the geocentric angle between the center of the spotbeam and the centre of the cell as illustrated in [10], the set of spotbeams having connectivity with the cell (i, j) can be found for all spotbeams in the system. This method is adopted in the current work to determine the distribution of the offered traffic amongst satellites and spotbeams.

The number of channels offered by the cell must be distributed among the spotbeam set and depends on the position of spotbeams within the satellite array and the traffic load carried by the individual satellites. This concept is used to determine the suitability of any spotbeam to carry traffic. The fitness of the traffic is distributed using the roulette wheel procedure. The elevation angle range associated with the beam, the position of the spotbeam with respect to the velocity of the satellite and the current loading of the satellite from which the spotbeam originates are used to determine the fitness of the traffic. The interference scenario, which exists between all spotbeams in the system is determined in a similar way to the connectivity between traffic and spotbeams, by way of a geocentric angle. The separation between spotbeams, which are deemed not to mutually interfere is determined by the reuse geocentric angle and an elevation of angles between all beam centers. This method is similar to the concepts of interference scenarios used in several GA channel allocation proposals.

6.4.3 Frequency Reuse Condition

Using the DCA concept, all channels in spotbeams have the same opportunity to be used. The traffic condition for each spotbeam needs to be evaluated at update interval times. Whence, the number of channels for each spotbeam are detected and the genetic algorithm scheme is applied to the channel allocation process. In this model, the channel assignment for the new call and the interference matrices for spotbeams as a function of time are modelled as final fitness functions of the genetic algorithm. The random events of call arrival or departure and the interference consideration is determined by the channel assignment problem. The new call always continues to detect the condition of the channel that is busy or idle. If the traffic in this channel is over loading, the possibility of guiding another channel to be used is selected using the genetic algorithm.

A set of spotbeams is defined which can reuse the same frequency channel. This concept is the same as that used in terrestrial networks, where a set of cells is defined for frequency reuse purposes. Each set of channels in the spotbeams has the same identification probability as the reuse frequency pattern. In this study, a set of the channels and spotbeams that are used for frequency reuse is defined via a matrix.

Figure 6.9 The example of frequency reuse concept

The number of channels to be assigned changes frequently according to the traffic load variation. The traffic load and the frequency reuse condition in MSS networks are dynamically changing as a function of time. As illustrated in Fig. 6.9, we can see an example of traffic load and frequency reuse conditions. In such dynamic conditions, the reconfiguration of the DCA concept is very suitable for the generation of a pre-planned channel assignment for MSS networks. In this work, the DCA allows a sequence of channel assignments, which are adjusted consistently with the time dependent conditions. The derivation of the number of channels required in one spotbeam at update interval time is shown in the last row of Fig. 6.9 and is derived from the traffic load of spotbeams

and the frequency reuse conditions during the update interval time. The update interval time and the sampling interval time are shown in Fig. 6.10.

Figure 6.10. The concept of the update and the sampling interval

6.4.4 Genetic Algorithm Process

6.4.4.1 Genetic DCA Scenario

The GA concept is applied to allocate the new call at one spotbeam to another one where the traffic intensity is zero or low at that time. The genetic algorithm is applied for each interval time t . A set of spotbeam numbers is denoted by n , which can reuse the same frequency channel. The frequency reuse pattern for each possible frequency assignment is described as a binary vector matrix f .

$$f_{i,j} = 1 \text{ or } 0 \quad \text{for } i \in [1, n] \text{ and } j \in [1, z] \quad (6.19)$$

The spot beam for frequency reuse pattern is shown as follows and implies hard interference requirements.

$$F_{i,k}(t) = \begin{matrix} & \text{Spotbeam Number} \\ \text{Spotbeam Number} & \begin{bmatrix} 1 & 1 & 0 & . & . & . & 1 \\ 2 & 1 & 1 & . & . & . & 0 \\ . & . & . & . & . & . & . \\ i & . & . & . & F_{i,k} & . & . \\ . & . & . & . & . & . & . \\ N & 1 & 1 & 0 & . & . & F_{N,M} \end{bmatrix} \end{matrix}$$

The elements of the matrix are equal to 1 if the j^{th} frequency is assigned to the i^{th} spotbeam and 0 otherwise. Channel allocation is identified in the same manner via a vector matrix at update time t . The channel requirement vector is defined by the Erlang B formula from the traffic load of the spotbeam and is evaluated for every update and sampling interval time. The channel requirement for the dynamic channel allocation problem can be defined as the follows:

$$D_i = \sum_{j=1}^L f_{i,j} = \max_{c \in A(x,e)} [E_{t,\Delta t} \{d_i(x,c,t,\Delta\tau)\}] \quad \text{for } i \in [1,n] \quad (6.20)$$

where x is a configuration, e is the random event (a call arrival or departure), $A(x,e)$ is the set of actions available in the current state (x,e) , $d_i(x,c,t,\Delta\tau)$ is the effective immediate payoff with the discounting, t is the update time until the next event and $\Delta\tau$ is the sampling interval time. The selected cost function in the current work depends on the current traffic condition in the vicinity of the spotbeam. The element i is set as a channel variable for spotbeam x at the call arrival instant in x . The element of matrix D is equal to 1 if the channel can be allocated to the spotbeam and 0 otherwise and is shown in the following matrix:

$$C_{i,k}(t) = \begin{matrix} & \text{Channels} \\ \text{Spotbeam Number} & \begin{bmatrix} 1 & 1 & 0 & . & . & . & 1 \\ 2 & 1 & 1 & . & . & . & 0 \\ . & . & . & . & . & . & . \\ i & . & . & . & C_{i,k} & . & . \\ . & . & . & . & . & . & . \\ N & 1 & 1 & 0 & . & . & C_{N,M} \end{bmatrix} \end{matrix}$$

A few frequencies from neighbouring spotbeams would produce interference to the spotbeam. This means that the frequency assignment in the neighbouring spotbeam has also to be taken into account. Interference is used as the constraint of this algorithm. The interference conditions, such as spotbeam interference, co-spotbeam interference and adjacent co-spotbeam interference are considered as constraints for the dynamic channel allocation strategy. The final cost function of the genetic dynamic channel allocation can be written as:

$$F = \sum_{i=1}^n \sum_{k=1}^{t_i} D_{i,k} + \sum_{i=1}^n \sum_{k=1}^{t_i} \sum_{j=1}^z \sum_{l=1}^{t_j} I_{i,j}(t) C_{i,k}(t) C_{j,l}(t) \quad (6.21)$$

where $I_{ij}(t)$ is the co-site interference, $C_{ik}(t)$ is the co-channel interference and $C_{jl}(t)$ is the adjacent co-channel interference. In genetic algorithms, all interferences should be minimized. Antennas that are located close to each other can cause desensitisation, cross modulation and inter-modulation. These effects cause interference among each other within the same spotbeam since the subscriber antennas are close to each other. This type of interference is called co-site interference. Whenever two spotbeams with the frequency assigned to them transmit at the same time, the receiver will experience co-channel interference. If two adjacent frequency bands are transmitted close together, this will cause the adjacent channel interference. In simulation, the interference level is assumed to be the same (25 dB) for each interference type.

6.4.4.2 Chromosome Structure

The bit strings of the chromosome (individuals) structure in the genetic algorithm are determined as the conditions of these matrices, including call arrival and interference to each spotbeam. One chromosome corresponds to a complete frequency assignment and one gene to one frequency in a spotbeam. The format of the bit string will be changed for every traffic intensity condition at each time interval. The individuals are evaluated and correspond to the channels allocated for the frequency reuse pattern at the update time. The chromosome structure is shown in Fig. 6.11.

Figure 6.11. Genetic DCA chromosome structure

The dynamic length of the chromosome is determined by the total number of spotbeams (S_b) and the number of channels (C_{sb}) for each spotbeam. Mathematically, the chromosome length can be expressed as:

$$Cl = \sum_{i=1}^n Sb_i \quad (6.22)$$

for $i = 1, 2, \dots, n$, spotbeams.

The strategy for the application of the genetic algorithm to the dynamic channel allocation is shown in flowchart form in Fig. 6.12. In order to clearly understand the basic idea of the method that is proposed in this study, it should be stressed that the

optimisation work with the genetic algorithm is done in order to search for an optimal call list and thus to directly find an optimal frequency assignment. This is the major difference between our method and all other previously published applications of genetic algorithms to the channel assignment problem for either cellular systems or MSS networks. The application of a genetic algorithm in general, first requires a so-called initial population, i.e., a chosen number of randomised solution vectors (individuals) corresponding to a randomly generated call list. As already explained in the previous section, the evaluation is performed by the conventional DCA strategy and corresponds to the number of calls within an allocated frequency. This evaluation represents the traffic condition for each spotbeam in interval time t .

Figure 6.12. Genetic DCA flowchart.

The next step of the genetic algorithm is the selection process. This means that a part of the proposed solution vectors (parents) are chosen to be altered in order to generate new, hopefully improved, vectors (children) by the procedures of mutation and crossover that follow. The newly constructed solution vectors are evaluated and added to the next

population. Using the derived fitness for each single solution, the vectors with the lowest quality are omitted from the population. In order to keep the population size (i.e., the number of currently considered vectors) constant, the number of cancelled vectors always equals the number of previously added new solutions. Then the procedure is repeated with this newly generated population, as shown in Fig. 6.12, until we obtain a solution of the desired quality or terminate the search due to having reached a maximum number of iterations. Taking some of their features from the crossover and mutation process also generates new individuals. In this way, supported by the process of selection, the quality of the solution vectors improves in the course of generations (iterations). The following sub-sections explain the process of selection, crossover and mutation in more detail.

6.4.4.3 Selection

The selection composes the choice of chromosomes and their acceptance condition to be used in the next population. Initial population size is generated denoting service allocation for each gene in the chromosome. Population in selection operators is justified in order to improve a set of individuals in running competition. A random selection process is used in this algorithm. The number of solution vectors determined is chosen from the population with size N in order to use as parents for the generation of new solutions. The probability of the random vectors within the limits of a particular chromosome is directly proportional to the quality value of the fitness F . Two offspring chromosomes are produced whose fitness depends on the parents according to the crossover and mutation process. The fitness for each chromosome is calculated according to the fitness function described in Equation (6.21). During the selection process, the value of the genes is changed in order to get improved configurations for the genetic engine fitness value. Assuming that the current generation of individuals is q , the probability of any individual being selected from the population can be defined as:

$$P_m(q) = \frac{F_{\rho-1}(q)}{\sum_{Q=0}^{M-1} F_{\rho-1}(Q)} \quad (6.23)$$

where M is the population size and q is the index of the individual. The selection criteria are based on a random roulette wheel selection as discussed in chapter 3. The sum of the fitness values for all existing individuals is then calculated from:

$$S_{\rho-1} = \sum_{q=0}^{M-1} F_{\rho-1}(q) \quad (6.24)$$

The best pair of genes is carried over to the next population. This random selection strategy also assures that sometimes solutions of lower quality are chosen to produce new vectors. Such a strategy reduces the danger of too rapid a convergence against one single solution, which might otherwise correspond to a local minimum.

6.4.4.4 Crossover

Crossover is the process of combining the genes of one agent with those of another to create offspring that inherit traits of both parents. The crossover rate is the odds of an agent being selected for the crossover operation. The variables between successive crossover points are exchanged between two parents to produce two new offspring. The best individual for each generation is chosen according to the fitness value F . The applicable gene is selected as a random choice from the intersection of movable genes of both chromosomes. The random parameter is chosen in the interval $[0,1]$ that depends on the relative condition of lower and upper bounds between two different offspring. This parameter is determined separately for each single arithmetic crossover for each gene. Then, the chromosome elements are selected for the mutation process. The best chromosome fitness can be written as:

$$chromosome_fitness = \sum_{j=1}^{\max} F_j^l \quad (6.25)$$

where j is the generation number and $l = 1, \dots, N$ is the identification index for each individual.

6.4.4.5 Mutation

Mutation is the process of finding a new search chromosome format by changing the value of a randomly chosen position in a substring. The previous selected solution vector is used to find an optimum channel allocation that depends on the call list and minimizes the total interference. Here, the calls exchange the composition position of the chromosome within the call list. The selection of new calls is used to improve the bit string position within the call list via a random variable. The genetic algorithm process is stopped after the last generation or after a given number of generations. The process is carried out on a group of the fittest individuals to represent the channel allocation. The best fitness is chosen by ranking them from 1 to the maximum number of generation and all processes of selection, crossover and mutation are then stopped.

At the end of each optimisation process, the program reports the individual with the best fitness. Fig. 6.13 shows an example of the progress of the optimisation process carried out in this study. One of the difficulties with the approach described so far is that in any particular run, there is no guarantee that a solution will be found in a reasonable amount of time. This is due to the increasing homogeneity of the population as the search proceeds. It has been observed that repeated applications of the reproduction scheme causes the population members to become very similar to one another, thereby reducing any further improvements. Other researchers have also noticed in experiments with population sizes that population diversity is important if the search is to be sustained [72].

As the homogeneity between the parents increases, the mutation should be increased to levels that would encourage a search for new, yet competitive, genetic material. However, it is suggested that the mutation rate should only be increased if both the selected parents are the same. We notice in this study that no matter how the crossover is performed for such a pair of parents, the resultant assignments will be the same if the effect of mutation is insignificant. Therefore, to encourage greater diversity in the population as well as the propagation of good assignment, the mutation was increased by a factor of two when the genetic materials of both parents were the same. This form of adaptive mutation would not be very disruptive to the existing population since its members are selected with respect to their fitness levels. A new assignment must be competitive before it can become a stable member of the population.

Figure 6.13 The variation of the fitness value during the first 550 generations

6.5 Performance Evaluation

6.5.1 Assigned channel results

As an example of the scheme, a simulation is proposed for S-UMTS based on a MEO satellite constellation. Specifications of non-GEO mobile satellite system networks are chosen with 10 satellites that are distributed into 2 planes and 5 satellites for each plane. The altitude of satellite is 10355 km and the number of spotbeams per satellite is assumed as 121. In this simulation, the traffic load in each spot beam is estimated in Erlangs for each area as a function of time. Update interval time was chosen as 15 minutes with 1

minute as the sampling interval time. The simulation is proposed for 3 hours at peak hour time (between 10.00 and 12 hrs).

In the first experiment of the genetic DCA, the genetic engine starts with an initial population of 250 and then after 550 generations the engine process stops the main operations including selection, mutation and crossover. The mutation probability is chosen to be 0.01 and the crossover probability is 0.6.

SPOT BEAM NUMBER	ASSIGNED CHANNELS
1	11, 36, 54, 61, 79, 90, 102
2	5, 9, 36, 47, 85
3	18, 24, 37, 56, 84, 95, 114, 117
4	3, 18, 49, 77, 105, 107, 129, 147, 165
5	3, 25, 70, 84, 111, 127, 149, 171
6	14, 54, 63, 85, 109, 143, 167, 198
7	6, 18, 27, 56, 93, 106, 127, 154, 170, 184, 195, 197
8	19, 25, 38, 54, 73, 94, 118, 140, 156, 173, 184, 187
9	32, 74, 93, 125, 136, 147, 153, 160, 164, 173, 185, 186, 197
10	6, 14, 23, 27, 47, 62, 73, 77, 105, 116, 127, 135, 147
11	2, 12, 23, 28, 37, 72, 94, 105, 123, 147, 148, 176, 189
12	7, 13, 17, 26, 41, 53, 92, 115, 127, 136, 149, 163, 170, 178
13	12, 17, 19, 37, 42, 69, 89, 116, 123, 141, 170, 194
14	16, 25, 29, 34, 48, 59, 87, 112, 154, 170, 185
15	11, 18, 26, 43, 51, 78, 85, 117, 135, 165
16	10, 19, 25, 27, 39, 57, 83, 97, 118, 173, 184
17	10, 27, 39, 51, 79, 117, 136, 157
18	9, 38, 62, 95, 118, 147
19	7, 18, 63, 85, 120
20	15, 31, 49, 56, 76, 96, 114, 137

Table 6.1 Example of assigned channel [73]

Table 6.1 shows an example result of channel allocations for 20 spotbeams, which emerged from the optimization process. Handover calls are considered to effect the GOS performance in terms of the call blocking and call dropping probability.

6.5.2 Blocking Probability

The experiments to evaluate call blocking probability are subject to two scenarios. In the first scenario, the experiment is performed using parameters given in 6.5.1. The results of call blocking probability performance for the genetic DCA are shown in Fig. 6.14,

where they are compared to the conventional DCA. The mean request call is for 350 calls. From these results, it can be seen that the genetic DCA outperforms conventional DCA. Using the genetic algorithm, channel assignment can be better optimised so that the blocking of new calls can be reduced. With higher mean request calls, the difference in the blocking probability between genetic DCA and the conventional DCA becomes larger. However the blocking probability of genetic DCA tends to decrease more quickly. This condition also indicates that the genetic DCA is preferred for the choice of empty or reduced traffic in a channel for frequency reuse. Genetic DCA can effectively decrease the blocking call rate of new calls.

Figure 6.14. Call blocking probability [73]

In the second scenario, we evaluate the call blocking probability for a mean request of 275 calls and 61 spotbeams per satellite. The maximum number of the generation is chosen to be 500 with 0.01 as the mutation probability and 0.6 as the

crossover probability. In this experiment, the population size of the genetic DCA is chosen as 50 and 150. The performance of the call blocking probability for the genetic and conventional DCA are shown in Fig. 6.15. The results show that the call blocking probability for the genetic DCA model tends to decrease more rapidly as the offered traffic intensity decreases and the population size increases.

Figure 6.15 Call blocking probability for different population size [74]

6.5.3 Dropping Call Probability

This experiment was proposed to evaluate the dropping call probability. The performance of dropping call probability for genetic DCA and conventional DCA are shown in Fig. 6.16. The dropping call probability reflects the limitation of the maximum number of channel measurements that the mobile terminal can make on a satellite link before trying

another satellite. In this simulation, the use of single channel receivers is assumed. This value has to be kept low to prevent long interruptions at handover and therefore the dropping call probability curves reflect the capacity limitation of this single channel receiver scheme. The performance of the genetic DCA is shown for 100 and 250 population sizes, 0.01 mutation probability and 0.6 crossover probability. The results show that, the performance for the genetic DCA is better than for conventional DCA. As illustrated in Fig. 6.16 the genetic DCA scheme substantially improves the dropping call probability performance at the expense of a slight increase in population of the genetic algorithm. It is observed that with an increasing number of population, the dropped call performance can be improved. This is because, as the population is increased, the probability to select the best genes for the lower traffic load channel assignment should increase. This also indicates that the larger population size of the genetic algorithm the more likely it is to select the best genes. The genetic DCA scheme is also more adaptable to changing traffic loads.

Figure 6.16 Dropping call probability [73]

6.5.4 Traffic Carried per Channel

We evaluate the traffic capacity per channel for 61, 36 and 19 spotbeams per satellite respectively. The genetic engine works with a 150 population size and 350 maximum number of generation. The mutation probability is chosen to be 0.01 and the crossover probability is 0.6 as suggested in [22]. The results of the traffic carried per channel for the genetic and the conventional DCA for the whole service area assuming a blocking probability of 3% are summarized in Table 6.3. From these results, it can be seen that the genetic DCA outperforms the conventional DCA. The traffic capacity obtained by using the genetic DCA is 1.23, 1.3 and 1.2 times that for the conventional DCA algorithm for 61, 36 and 19 spotbeams respectively. In addition, the genetic DCA strategy is much more adaptable under conditions of high traffic intensity.

Channel allocation model	61 spotbeams	36 spotbeams	19 spotbeams
DCA	4.86	3.21	2.98
Genetic DCA	5.98	4.18	3.59

Table 6.2. Carried traffic per channel [74]

6.6 Conclusions

This chapter has examined existing and newly proposed models for channel allocation in both satellite and terrestrial cellular networks. Fixed channel allocation (FCA), dynamic channel allocation (DCA) and hybrid channel allocation (HCA) have been used to perform channel allocation. Some existing schemes are also presented in this chapter for comparison purposes. The DCA schemes have been used to address the dynamics in order to achieve a better channel utilization compared to FCA. Also, DCA has been shown to be more flexible than FCA in terms of traffic variations. Genetic algorithms have also

been used to good effect as a robust algorithm to optimise channel planning in cellular networks.

A new algorithm was also proposed and evaluated as a robust method to increase the performance of the dynamic channel allocation in mobile satellite system networks. The main idea behind this algorithm is to use minimum cost as a metric to provide optimum channel solutions for specified interference constraints. In this study, we have considered as an example, MSS spotbeam coverage in which the frequency reuse between two spotbeams is determined if the mobile terminal position is not within overlapped coverage region. A method for distributing the offered traffic amongst satellites and spotbeams, which have instantaneous connectivity with the traffic originating areas has also been described. The combination of traffic load for each spotbeam and interference limited DCA were represented as a chromosome structure within a genetic algorithm. The performance of this algorithm was evaluated in terms of the capacity of the system, the actual traffic for each spotbeam and the quality of service. From the simulation results, it was shown that the traffic capacity obtained using the genetic DCA is improved over the conventional DCA. In addition, the genetic DCA strategy is much more adaptable under conditions of high traffic intensity. Furthermore, the results showed that the quality of service for the genetic DCA model tends to decrease more rapidly as the offered traffic intensity decreases and the population size increases. The new algorithm has been shown to be robust to dynamic variations and can be used to provide resource allocation improvements for DCA in MSS system networks.

Chapter 7. Conclusions and Future Work

7.1 Conclusions

The fundamentals of satellite constellation design were discussed and modeled in chapter 2. Some design techniques used for non-geostationary satellite constellations were studied and presented. Satellite diversity, dynamic coverage characteristics and accurate satellite positioning were associated with particular design approaches. Some constraints of satellite constellation design were studied and presented and then used to develop the automatic satellite constellation design using a genetic algorithm. Polar and inclined circular orbital types were also presented. The polar orbits were proposed for systems, which utilize tracking and inter satellite coordination. The inclined circular orbits were proposed for satellite diversity and for latitudes where traffic originates. The spotbeam model was presented and was implemented for all proposed models of the automatic satellite constellation design and the genetic dynamic channel allocation for MSS networks. For non-GEO systems, the area coverage of the satellite is variable and the coverage shape requires a dynamic process. More simply, the coverage area of each beam is used regularly and provides predictable handover periods between spotbeams. The circular spotbeam model was illustrated and used in the design of satellite constellations and in radio resource management analysis.

The basic concepts of the genetic algorithm together with some extensions were evaluated in chapter 3. Some applications of the genetic algorithm for optimisation of satellite constellation design were also reviewed. In the last section of chapter 3, a new approach to near resonant satellite constellations using the genetic algorithm was presented and is called the 'genetic near resonant constellation'. The genetic satellite constellation is designed for a repetitive ground track and also to avoid the peaks in the Van Allen radiation belts. The constellation is assumed to be an inclined circular orbit where all satellites have the same inclination angle and altitude. Each orbit contains an

equal number of satellites. This constellation was proposed for LEO systems as it offers high diversity global coverage with trade off between diversity and numbers of satellites or minimum elevation angle. The evaluation of this algorithm was performed for dual satellite diversity statistics and elevation angle statistics. The result of the genetic near resonant constellation design shows that a new satellite constellation has a 1684 km satellite altitude. The total number of satellites is 60 distributed into 6 orbital planes and 10 satellites for each orbital plane with 53.7° inclination angle. This constellation has the following advantages: 100% availability of dual satellite diversity can be achieved to 68° of latitude and between 34° - 54° of latitude, triple satellite diversity. The satellite altitude is still within the range of the LEO system and Van Allen radiation belt peaks. The sub-satellite track of the genetic near resonant satellite constellation is nearly repetitive after the completion of around 12 orbits in 1 (one) sidereal day. This constellation is ideally suited to S-UMTS or S-PCN applications.

Automatic satellite constellation design using a multiobjective genetic algorithm was presented and evaluated for LEO and MEO constellations in chapter 4. An existing multiobjective genetic algorithm process was proposed to evaluate several parameters of the constellation simultaneously. A new approach to constellation design was presented and called the genetic satellite constellation (GSC) design. The multiobjective genetic algorithm scheme monitors the number of satellites, the altitude of satellites, the angle shift between satellites, the angle between planes and the inclination angle. The dual satellite diversity statistic and the average and the minimum elevation angle performances were evaluated for both LEO and MEO constellations. Results from the new automatic satellite constellation for MEO's has a total number of 8 satellites that are distributed into 2 planes with 4 satellites per plane, 53° inclination angle and 10948 km satellite altitude. The angle between planes and the angle shift between satellites for this constellation are 85° and 8° , respectively. The experimental results for the LEO constellation have a total number of 45 satellites that are distributed into 5 planes with 9 satellites per plane. A 52° inclination angle is the best fit for the simulation criteria. The angle shift between satellites and the angle between planes of 10 and 70 degrees respectively were achieved with an orbit altitude of 1656 km. The performance of dual satellite diversity availability was compared to the ICO system for MEO and to the Globalstar system for LEO. The results showed that the availability of dual satellite diversity using the multiobjective genetic algorithm for both LEO and MEO is improved using the new design scheme. In

general, using the genetic algorithm, satellite constellation design with satellite diversity can be optimised whilst reducing the total number of satellites in the constellation.

A modified version of the genetic satellite constellation is proposed for hybrid satellite constellations and has been described in chapter 5. As with the GSC, the novelty of the proposed model is the automatic determination of satellite constellation parameters for hybrid LEO/MEO, hybrid LEO/GEO and hybrid MEO/GEO constellations. For LEO and MEO, the characteristics of the satellite constellations are the same as the two previous examples in chapter 3 and 4. For GEO, the constellation design assumed a circular orbit. Some extended process of the non-dominated Pareto optimisation of the multiobjective genetic algorithm was also proposed. In the simulation, dual satellite diversity was employed for both the lower and upper layers of the orbits. Compared to previous results, the number of satellites was seen to be reduced. Also the maximum satellite altitude for the hybrid constellations for both LEO and MEO are lower than for the single layer satellite constellations. The most important result in the genetic hybrid satellite constellation is the achievement of 100% dual satellite diversity statistics down to 14° minimum elevation angle for both hybrid LEO/MEO and LEO/GEO, and to 13° minimum elevation angle for hybrid MEO/GEO. Compared to the use of the genetic algorithm with single MEO and LEO constellations in chapter 4, the results for the hybrid constellation show marked improvements.

A new algorithm was proposed as a robust method to increase the performance of the dynamic channel allocation in mobile satellite system networks in chapter 6. The main idea behind this algorithm is to use minimum cost as a metric to provide optimum channel solutions for specified interference constraints. In this study, we considered an example MSS spotbeam coverage in which the frequency reuse between two spotbeams is determined if the mobile terminal position is not within the overlapped coverage. The combination of traffic load for each spotbeam and interference limited DCA were represented as a chromosome structure within a genetic algorithm. This algorithm was used to evaluate the capacity of the system, the actual traffic for each spotbeam and the quality of service. From simulation results, it was shown that the traffic capacity obtained using the genetic DCA can be increased. In addition, the genetic DCA strategy is much more adaptable under conditions of high traffic intensity. Furthermore, the results showed that the quality of service for the genetic DCA model tends to decrease rapidly as the offered traffic intensity decreases and the population size increases. The new algorithm

has been shown to be robust to dynamic variations and will provide resource allocation improvements in DCA in MSS system networks.

The aim of the work has been to show the potential of the GA in satellite constellation and radio resource management design. Using somewhat simplified examples in both cases it has been demonstrated that the GA approach is valid and can produce optimized designs. It is recognized that for a full practical design more complex 'cost function' which include a larger number of parameters need to be considered to provide a fully optimized solution for a specific application. Nevertheless the principle has been validated and can be built upon in future work.

7.2 Future Work

The genetic satellite constellation design was proposed for inclined circular orbits for Non-GEO constellations and circular orbits for GEO. The following points are suggested for amplification or further work:

- The investigation of the genetic satellite constellation needs to be developed for fully resonant and other orbital types, e.g., elliptical and polar orbits.
- In the current work, satellite location is investigated with respect to the look angles (elevation and azimuth angles) as described in Appendix A. The development of satellite location with respect to the rotating Earth, the celestial sphere and to satellite centred spherical coordinates could be used in future work.
- Also, the genetic satellite constellation design can be developed to involve inter-satellite links, especially for double layer satellite constellation.
- Furthermore, it should be emphasized that the robust and flexible capabilities of the genetic algorithm approach allow the designer to choose complicated design factors (as cost functions) and easily incorporate them into a search for fully optimal satellite constellation designs.

The results of the genetic dynamic channel allocation reported in this study confirm the improved capacity of the system and the quality of service performance under ideal conditions. Future work in this area would be conducted as follows:

- The genetic dynamic channel allocation could emulate aspects of channel assignment within the real mobility management task (inter beam handover) and the channel re-allocation.
- An analytical model of the inter beam handover needs to be established which can be derived from the constellation diversity characteristics, the spotbeam dimensions and the user's location.
- A statistical model of the variation of spotbeam traffic load, which can be derived using typical traffic models could be investigated.
- The performance evaluation of the system for various distributions of the traffic and the DCA in reuse partitioning would benefit from more evaluation.
- Furthermore, theoretical analysis of some characteristics of the DCA model needs to be investigated using the genetic algorithm.
- In addition, the investigation of the position, speed and direction of the mobile user in MSS networks could be derived using the genetic algorithm optimization model.
- The genetic dynamic channel allocation algorithm that has been proposed in this study is implemented for a MEO satellite system with earth fixed cells (EFC), where the antenna beams are steered so as to point toward a given cell on the earth during a given time interval. The application of the genetic dynamic channel allocation to MSS networks with satellite fixed cells (SFC) needs to be investigated in future work. In satellite fixed cells, the footprint is divided into cells, each one corresponding to a specific beam of the satellite antenna radiation pattern. With satellite fixed cell systems, beams maintain a constant geometry with respect to the spacecraft, and the cells on the ground move along with the satellite. Thus the dynamics of the system need to be considered.

Finally, the software of the genetic satellite constellation design and the genetic dynamic channel allocation need to be integrated and developed as an overall tool for complete satellite constellation design.

Papers

Papers published as a result of work in the thesis are listed as follows:

Journal Papers

- [1] **Asvial, M.**, Tafazolli, R., and Evans, B.G., “ Modified GSC for Hybrid Satellite Constellation “, IEE Electronics Letters, Vol. 38 No. 20, 26th September 2002, pp. 1216 – 1217.
- [2] **Asvial, M.**, Tafazolli R., and Evans, B.G., “New Evolutionary Genetic DCA for Resource Management in Mobile Satellite Systems “, IEE Electronics Letters, Vol. 38 No. 20, 26th September 2002, pp. 1213 – 1214.
- [3] **Asvial, M.**, Evans, B.G., and Tafazolli R., “Satellite Constellation Design and Radio Resource Management Using Genetic Algorithm”, submitted to IEE Communication Proceedings.

Conference Papers

- [1] **Asvial, M.**, Sammut, A., Tafazolli, R., and Evans, B.G., “ Optimal Coverage for Non-GEO Satellite Constellation “, the International Astronautical Federation Student Conference, May 10, 2000, London, UK.
- [2] **Asvial, M.**, Sammut, A., Tafazolli, R., and Evans, B.G., “ Asvial Constellation: New S-UMTS Constellation Design with Dual and Triple Satellite Diversity “, the 4th European Mobile and Personal Satellite Communications (EMPS 2000), London, UK, Sept. 2000, pp. 167-172.
- [3] **Asvial, M.**, Tafazolli, R., and Evans, B.G., “ Non-GEO Satellite Constellation Design with Satellite Diversity Using Genetic Algorithm “, the 20th AIAA International Communication Satellite Systems Conference, Montreal, Canada, 12 – 15 May 2002.

- [4] **Asvial, M.**, Tafazolli, R., and Evans, B.G., " Genetic Dynamic Channel Allocation for MSS Networks ", the 5th European Workshop on Mobile/Personal Satellite Communications, Baveno, Italy, 25-26 September 2002, pp. 53-60.
- [5] **Asvial, M.**, Tafazolli, R., and Evans, B.G., " Genetic Hybrid Satellite Constellation Design ", accepted for the 21st AIAA International Communication Satellite Systems Conference, Yokohama, Japan, April 2003.

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Appendix A. Satellite Location with Respect to Look Angle

In this study, the elevation and the azimuth angles are derived from Fig. A-1. The azimuth angle, ξ is the angle measured North Eastward from the geographic North at the Earth station, G , to the sub satellite point. The sub satellite points, S' , is defined as the point where the line joining the centre of the earth, O , and the satellite meets the earth's surface. The elevation angle, θ , is the angle measured upward from this tangential plane at the earth station to the direction of the satellite.

Figure A-1. Satellite location with respect to the angle look.

From Fig. A-1, the following elements are used to derive the elevation and azimuth angles for Non-GEO and GEO satellite locations.

- φ is the central angle or the coverage angle at the centre of the Earth, O , formed by lines OG and OS .

- γ is the tilt angle or the nadir angle at the satellite, formed by the lines GS and OS.
- L_g is the latitude of the earth station.
- l_q is the relative longitude of the earth station.
- L_s is the latitude of satellite. In this coordinate system Northern latitudes and Eastern longitudes are regarded as positive. Furthermore, the latitude of the sub satellite point is the same as the declination angle, δ , of the satellite with respect to the geocentric equatorial coordinate system, that is $L_s = \delta$.
- R_e is the Earth's radius.
- h is the altitude of the satellite.
- R is the slant range of the satellite measured from the earth station.

The angle φ can be calculated by using the cosine law as follows:

$$\cos \varphi = \cos L_g \cos L_s \cos l_q + \sin L_g \sin L_s \quad (\text{A.1})$$

Consider triangle GOS and using the cosine law, the slant range, R , is given by:

$$R = \sqrt{R_e^2 + (R_e + h)^2 - 2R_e(R_e + h)\cos \varphi} \quad (\text{A.2})$$

By using the sine law:

$$\frac{R_e + h}{\sin(90^\circ + \theta)} = \frac{R}{\sin \varphi} \quad (\text{A.3})$$

$$\cos \theta = \frac{\sin \varphi}{\sqrt{1 + \left(\frac{R_e}{R_e + h} \right)^2 - 2 \left(\frac{R_e}{R_e + H} \right) \cos \varphi}} \quad (\text{A.4})$$

Referring to the spherical triangle $\mathbf{GNS}'$, $\angle \mathbf{GNS}' = l_g$ and $\text{arc}(\mathbf{GS}') = \varphi$, using the sine law:

$$\frac{\sin \xi}{\sin(90^\circ - L_s)} = \frac{\sin l_g}{\sin \varphi} \quad (\text{A.5})$$

Since $L_s = \delta$, hence

$$\xi = \sin^{-1} \left[\frac{\cos \delta \sin l_g}{\sin \varphi} \right] \quad (\text{A.6})$$

the actual azimuth angle is shown in Table 2.1.

The condition for a satellite to be visible from an earth station is $\theta \geq 0^\circ$. From Fig. A.1, for this condition to be met:

$$\cos \varphi \leq \frac{R_e}{R_e + h} \quad (\text{A.7})$$

From a geometrical point of view, the minimum condition that the satellite is visible from the earth station is $\theta = 0^\circ$. In practise, the minimum value of θ , termed the minimum elevation angle, $\theta_{\min}$, should be high enough to avoid any propagation factors such as shadowing. It is then possible to express φ in term of $\theta_{\min}$. It can be shown from triangle SGO that:

$$\varphi = \cos^{-1} \left[\frac{R_e \cos \theta_{\min}}{R_e + h} \right] - \theta_{\min} \quad (\text{A.8})$$

Referring to triangle OSG, the tilt angle, γ , measured at the satellite from the sub satellite point to the earth station is given by:

$$\sin \gamma = \frac{R_e}{R} \cos \theta \quad (\text{A.9})$$

For the GEO orbit, since the satellite is placed in the equatorial plane, the satellite's latitude, $L_s = 0^\circ$. The central angle, φ , can be written as:

$$\cos \varphi = \cos L_g \cos l_g \quad (\text{A.10})$$

The elevation angle, θ , can then be expressed as:

$$\cos \theta = \sqrt{\frac{1 - \cos^2 L_g \cos^2 l_g}{1 + \left(\frac{R_e}{R_e + h}\right)^2 - 2\left(\frac{R_e}{R_e + h}\right) \cos L_g \cos l_g}} \quad (\text{A.11})$$

The azimuth angle, ξ , is then re-expressed as:

$$\xi = \sin^{-1} \left[\frac{\sin l_g}{\sqrt{1 - \cos^2 L_g \cos^2 l_g}} \right] \quad (\text{A.12})$$

Appendix B. Spectrum Allocations

The frequency allocation bands for UMTS and IMT 2002 are presented in Fig.B-1 that were identified in World Administrative Radio Conference (WARC) 1992. The bands 1885-2025 MHz and 2110-2200 MHz have been identified for IMT 2000 and considered for UMTS/IMT 2002. Two 25 MHz sub-bands are allocated to mobile satellite systems, common to both UMTS and IMT 2000. In WRC 2000 [75], the additional bands 2500-2520/2670-2690 MHz were allocated to the development of the satellite component of IMT 2000. Frequency bands allocation according to WRC 2000 is shown in Fig. B-2.

Figure B-1. UMTS/IMT 2000 core bands.

Figure B-2. Advanced MSS bands

Appendix C. SAINT Traffic Distribution

The distribution of the traffic grid for S-UMTS in the 36 x 72 grid as presented in the SAINT project is shown in the table below. This traffic is predicted for the S-UMTS system up until the year 2010. The left column represents the grid for latitude and the top row represents the grid for longitude. Here, the longitude is defined into two polarisations. The positive polarization indicates the longitude to west direction from the 0° of longitude and the negative polarization indicates the longitude to east direction from the 0° of longitude (or from GMT position). Also, the latitude is defined into positive and negative polarisation. The positive polarisation indicates the latitude to north direction from the Equatorial and the negative polarisation indicates the latitude to south direction from the Equatorial. Each value in the grid represents the load traffic in Erlangs in the peak hour condition.

Lat\Long	177.5	172.5	167.5	162.5	157.5	152.5	147.5	142.5	137.5	132.5	127.5	122.5	117.5	112.5
87.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0613	0.1172
82.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0232	0.0518	0.1342	0.1756	0.3740	1.0006	1.4036	1.9693	1.5288
77.5	0.0000	0.0000	0.0000	0.5015	1.3203	0.7757	0.5517	0.4672	0.9174	0.8743	1.1601	1.5775	1.2044	0.0488
72.5	0.0000	1.4516	2.3615	2.3669	2.3669	3.1882	3.5187	2.9653	1.0006	2.4236	1.9349	3.0503	1.1687	2.9558
67.5	0.0000	5.8309	5.8309	5.8309	5.8309	5.8309	5.7261	5.8168	5.8309	5.8218	4.4103	2.5048	0.2029	1.1803
62.5	2.3292	4.3714	6.6480	6.8990	6.8990	6.8990	6.8690	6.8990	6.8990	4.8874	0.0000	0.0137	0.4527	6.5983
57.5	0.0000	0.0443	4.1445	7.9157	7.9157	7.9157	7.9157	7.9157	7.9157	7.9124	6.8551	4.7272	1.3046	7.4788
52.5	0.0000	0.0000	0.0957	4.4327	6.2111	6.2111	6.2111	6.2111	6.2111	6.3565	7.2117	7.9394	7.8540	8.8729
47.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2733	6.6621	5.3658
42.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0509	0.0634	0.0000
37.5	0.0000	0.0000	0.0000	0.0000	0.0000	2.0582	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
32.5	0.0000	0.0000	0.0000	0.0000	0.0744	70.1034	132.3330	111.4150	35.0132	0.0000	0.0000	0.0000	0.0000	0.0000
27.5	0.0000	0.0000	0.0000	0.0000	0.0000	8.6350	65.4530	180.5840	174.8550	2.1184	0.0000	16.1924	42.8908	1.7239
22.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	80.5722	198.7460	67.3875	106.3380	20.0526	103.5289	140.2870
17.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	23.4277	68.0242	353.9050	250.2000	0.0000	0.0000
12.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	202.3520	54.3194	31.1780
7.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.9222	47.8349
2.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	2.0441	0.0000	50.2336	65.1820
-2.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	47.1922	70.6503
-7.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	9.2152	68.3641
-12.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	31.6029
-17.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
-22.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
-27.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
-32.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	3.3891
-37.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	17.2294
-42.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	16.4560
-47.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	21.8284
-52.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	2.7420
-57.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
-62.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
-67.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
-72.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
-77.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
-82.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
-87.5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

154

Lat./Long.	-172.5	-177.5
87.5	0.0000	0.0000
82.5	0.0000	0.0000
77.5	0.0000	0.0000
72.5	0.0000	0.0000
67.5	0.0000	0.0000
62.5	0.0000	0.0000
57.5	0.0000	0.0000
52.5	0.0000	0.0000
47.5	0.0000	0.0000
42.5	0.0000	0.0000
37.5	0.0000	0.0000
32.5	0.0000	0.0000
27.5	0.0000	0.0000
22.5	0.0000	0.0000
17.5	0.0000	0.0000
12.5	0.0000	0.0000
7.5	0.0000	0.0000
2.5	0.0000	0.0000
-2.5	0.0000	0.0000
-7.5	0.0000	0.0000
-12.5	0.0000	0.0000
-17.5	0.0000	0.0000
-22.5	0.0000	0.0000
-27.5	0.0000	0.0000
-32.5	0.0000	0.0000
-37.5	0.0000	0.0000
-42.5	0.0000	0.0000
-47.5	0.0000	0.0000
-52.5	0.0000	0.0000
-57.5	0.0000	0.0000
-62.5	0.0000	0.0000
-67.5	0.0000	0.0000
-72.5	0.0000	0.0000
-77.5	0.0000	0.0000
-82.5	0.0000	0.0000
-87.5	0.0000	0.0000

Appendix D Simulation block diagram for satellite constellation design

Block diagram for the genetic near resonant constellation (chapter 3), the genetic satellite constellation (chapter 4) and the genetic hybrid satellite constellation design is shown in Fig. D-1, Fig. D-2 and Fig. D-3. In Fig. D-1, GA is used to optimise the altitude of satellite. In Fig. D-2 and Fig. D-3, the optimisation of some parameters of satellite constellation are proposed using GA. They are the altitude of satellite, the number of satellites, the angle between planes, the angle shift between satellites and the inclination angle. These parameters are represented as the bit strings in the chromosome structure in the GA process.

Figure D-1. Block diagram for the genetic near resonant constellation design

Figure D-2. Block diagram for the genetic satellite constellation design

Figure D-3. Block diagram for the genetic hybrid satellite constellation design

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