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Integrated channel assignment and power control in wireless mobile networks using evolutionary strategy.

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INTEGRATED CHANNEL ASSIGNMENT AND POWER CONTROL IN WIRELESS MOBILE NETWORKS USING EVOLUTIONARY STRATEGY

by

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Abstract

In wireless mobile communication system, radio spectrum is a limited resource. However, efficient use of available channels has been shown to improve the system capacity. The role of a channel assignment scheme is to allocate channels to cells or mobiles in such a way as to minimize call blocking or call dropping probabilities, and also to maximize the quality of service. Channel assignment is known to be an NP-hard optimization problem. In this thesis, we have developed an Evolutionary Strategy (ES) which optimizes the channel assignment. The proposed ES approach uses an efficient problem representation as well as an appropriate fitness function. Our thesis deals with a novel hybrid channel assignment based scheme called D-ring. Our D-ring method yields a faster running time and simpler objective function. We also propose a novel way of generating initial candidate solutions that are near optimal. We have obtained at least better results (as well as faster running time) than a similar approach in literature.

The efficient use of available channels and transmitter power have been shown to improve the system capacity. The role of power control is to assign power level to each transmitter so that the signal quality is maintained and interference is minimized. Existing papers have focused on optimizing the assignment of channels assuming that the allocation of transmitter power is known and fixed (vice-versa). In this thesis, we integrate the problem of channel assignment with power control using the dynamic reuse distance concept. Using an efficient problem representation as well as an appropriate fitness function, we develop an evolutionary strategy which concurrently optimizes channel assignment and power control.

Dedication

This work is dedicated to my husband, Navneet Vidyarthi and my parents.

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First of all, I am deeply indebted to and would like to express my deepest gratitude to my advisor Dr. Alioune Ngom for his patience, supervision, dedication, suggestions and support throughout my graduate studies at Windsor. His overly enthusiasm, deep insight, and mastery of the subject matter have make working on this thesis a wonderful experience. I have had the opportunity to broaden and improve my analytical skills, as well as gain further understanding of how to formulate and solve intricate problems. I owe him lots of gratitude for having me shown this way of research.

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Chapter 1

Mobile Communication

1.1 Overview

Like other technological developments, the development in wireless mobile communication has passed through several stages. The pioneering experiments in land mobile communication dates back to 1920's in Detroit, USA. It was a one-way broadcast made to receivers in mobile police cars. The transmission from vehicles was limited due to the lack of low-power transmitters suitable for use in automobiles. Further progress was made in the 1930s with the development of mobile transmitters and the first two-way mobile radio system in New Jersey, USA. The mobile telephony services were extended to the commercial arena towards the end of the Second World War. In 1946, the first interconnection of mobile users to the public telephone network was done to allow calls from fixed stations to mobile users, when Federal Communication Commission (FCC) granted license to AT & T (American Telephone and Telegraph) Company to operate in St. Louis. The system used a central high-power transmitter to cover a metropolitan area up to 50 miles or more from the transmitter. With this concept it was difficult to reuse the same frequency. The inefficient use of spectrum severely limited the system capacity.

A solution to this problem emerged in the 1970s when researchers at Bell Laboratories in USA developed the concept of the cellular telephone system, which appeared in Bell system proposal during the late 1940's. The cellular concept replaced the use of a large geographical area (where a high-power transmitters is placed at high elevation at the center of the area) with a large geographic area divided into a number of non-overlapping small geographic areas, called cells, equipped with low-power transmitters. A cellular organization allows frequency reuse among geographically-distant cells [MacDonald 65],[Rappaport 96], thus greatly expanding the system capacity. It also allows cells to be sized according to subscribers density and traffic demand of a given area.

1.2 First generation cellular systems

The Nordic countries were the first to introduce cellular services for commercial use with the introduction of the Nordic Mobile Telephone (NMT) in 1981. The system was designed to operate in the 450- and 900-MHz frequency bands. These are noted as NMT 450 and NMT 900. Cellular systems began in the United States in the year 1983 in Chicago with the release of the Advanced Mobile Phone Service (AMPS) operating in 800 MHz, and the other cities followed rapidly. Asia, Latin America, and Oceanic countries later adopted the AMPS standard, and AMPS emerged as the largest potential market in the world for cellular communications. Britain introduced another technology called Total Access Communications System (TACS) in 1985, operating at 900 MHz. Many other countries joined the race, and soon mobile communications services spread across the globe [Smith 01]. Several other technologies were developed but AMPS, NMT and TACS were the most successful technologies [Smith 01]. All these "first-generation" cellular systems were analog systems and provided only the basic speech services.

1.3 Second generation cellular systems

One of the challenges facing analog systems was the inability to handle the growing capacity needs in a cost-efficient manner. Moreover, each system followed different standards, which made it impossible for a person to use the same cellular phone in different countries. As a result, standardization committees for "second-generation" cellular systems worldwide adopted the digital technology, which conformed to at least three standards: one for Europe and international applications known as Global Mobile Systems (GSM); one for North America, IS-54 (North American Digital Cellular); and a third for Japan, Japanese Digital Cellular (JDC) [Feher 95]. The advantages of digital systems over analog systems include ease of signaling, lower levels of interference, integration of transmission and switching, higher capacity potentials, and inclusion of new services (data services, encryption of speech and data and Integrated Services Digital Network) [Feher 95]. Second generation cellular systems are, however, still optimized for voice service and they are not well suited for data communications.

1.4 Third generation cellular systems

Data communication is an important requirement in the current environment of Internet, electronic commerce, and multimedia communications. Not only do subscribers want these services, they want ubiquitous access (i.e. access from everywhere and at all time) to these services too. The third generation systems referred to as Personal Communication Systems (PCS), aim at providing integrated services such as data, voice, image and video to stationary and non-stationary subscribers without temporal and spatial restrictions. The need for "third-generation" mobile communications technology was recognized as far back as the 1980s. The International Telecommunications Union (ITU) was heavily involved and the work within the ITU was originally known as Future Public Land Mobile Telecommunications Systems (FPLMTS). Examples of PCS include Person Handphone System, and Digital Enhanced Cordless Telecommunications (DECT).

1.5 Cellular radio systems

The advent of cellular concept was a breakthrough in the development of mobile communication. The cellular principle divides the covered geographical area into a set of smaller service areas called cells. During the early part of the evolution of the cellular concept, the system designers recognized the concept of all cells with the same shape to be helpful

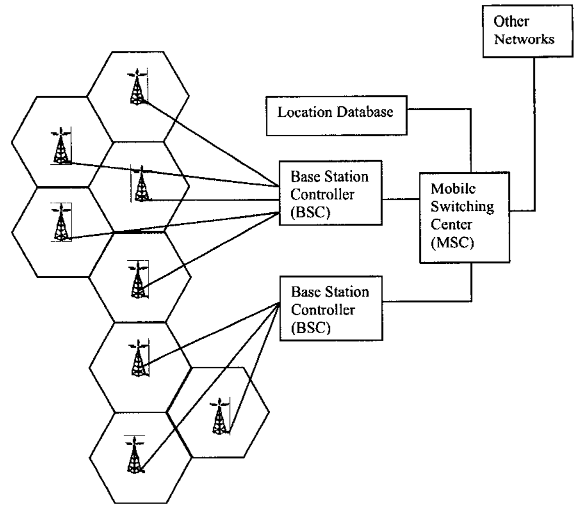

Figure 1.1: Network architecture

in systematizing the design and layout of the cellular system [MacDonald 79]. The 1947 Bell Laboratories paper [MacDonald 79] discussed four possible geometric shapes: the circle, the square, the equilateral triangle, and the regular hexagon. The regular hexagon was found to be the best over the other shapes [MacDonald 79]. In practice, the cell sizes are irregular and depend on the terrain and propagation conditions. Figure 1.1(Modified from [Akyildiz 96], figure 1, pp. 139) shows a typical mobile communication network.

Each cell has a base station and a number of mobile terminals (e.g. mobile phone, palms, laptops, or other mobile devices). The base station is equipped with radio transmission and reception equipments. The mobile terminals within a cell communicate through wireless links with the base station associated with the cell. A number of base stations are connected to the Base Station Controller (BSC) via microwave links or dedicated leased lines. The BSC contains logic for radio resource management of the base stations under its control. It is also responsible for transferring an ongoing call from one base station to another as a mobile user moves from cell to cell. A number of BSC are connected to the Mobile Switching Centers (MSC) also known as Mobile Telephone Switching Office (MTSO). MSC/MTSO is responsible for setting up and tearing down of calls to and from mobile subscribers. The MSC is connected to the backbone wireline network such as the public switched telephone network (PSTN), Integrated Service

Digital Network (ISDN) or any LAN-WAN based network. MSC is also connected to a location database, which keeps information about the location of each mobile terminal. The base station is responsible for the communication between the mobile terminal and the rest of the information network. A base station can communicate with mobiles as long as they are within its operating range. The operating range depends upon the transmission power of the base station. Radio energy dissipates over distance, so the mobile terminals must be within the operating range of the base station.

1.6 Channel allocation

In order to establish a communication with a base station, a mobile terminal must first obtain a channel from the base station. A channel consists of a pair of frequencies: one frequency (the forward link/ downlink) for transmission from the base station to the mobile terminal, and another frequency (the reverse link/ uplink) for the transmission in the reverse direction. An allocated channel is released under two scenarios: the user completes the call or the mobile user moves to another cell before the call is completed. The capacity of a cellular system can be described in terms of the number of available channels, or the number of users the system can support. The total number of channels made available to a system depends on the allocated spectrum and the bandwidth of each channel. The available frequency spectrum is limited and the number of mobile users are increasing day by day, hence the channels must be reused as much as possible to increase the system capacity. The assignment of channels to cells or mobile is one of the fundamental resource management issues in a mobile communication system. The role of a channel assignment scheme is to allocate channels to cells or mobiles in such a way as to minimize the probability that the incoming calls are blocked, the probability that ongoing calls are dropped, and also to minimize the probability that the carrier-to-interference ratio of any call falls below a prespecified value. The channel assignment problem first appeared in [Metzger 70].

1.6.1 Channel assignment schemes

In literature, many channel assignment schemes have been widely investigated with a goal to maximize the frequency reuse. The channel assignment schemes in general can be classified into three strategies: Fixed Channel Assignment (FCA), Dynamic Channel Assignment (DCA), and the Hybrid Channel Assignment (HCA). In FCA, a set of channels are permanently allocated to each cell based on a pre-estimated traffic intensity. In DCA, there is no permanent allocation of channels to cells. Rather, the entire set of available channels is accessible to all the cells, and the channels are assigned on a call-by-call basis in a dynamic manner. Cox et al. [Cox 73] proposed the DCA scheme. One of the objectives in DCA is to develop a channel assignment strategy, which minimizes the total number of blocked calls [Sivarajan 90]. FCA scheme is simple but does not adapt to changing traffic conditions and user distribution. Moreover, the frequency planning becomes more difficult in a microcellular environment as it is based on the accurate knowledge of traffic and interference conditions. These deficiencies are overcome by DCA but FCA out performs most known DCA schemes under heavy load conditions [Lai 96]. To overcome the drawbacks of FCA and DCA, HCA was proposed by Kahwa et al. [Kahwa 78], which combines the features of both FCA and DCA techniques. In HCA one set of channels are allocated as per the FCA scheme, and the another set is allocated as per the DCA scheme. A comprehensive survey of various channel assignment schemes can be found in [Katzela 96].

DCA schemes can be implemented as centralized or distributed. In centralized approach [Lee 87], [El-Dolil 89], [Zhang 89], [Zhang 91], [Mathar 93], [Chuang 93], all requests for channel allocation are forwarded to a central controller that has access to system wide channel usage information. The central controller then assigns the channel by maintaining the required signal quality. In distributed DCA [Cimini 93],[Cimini 92] [Madani 94], [Prakash 95], the decision regarding the channel acquisition and release is taken by the concerned base station based on the information from the surrounding cells. As the decision is not based on the global status of the network, it can achieve suboptimal allocation as compared to the centralized DCA and may cause forced termination of ongoing calls.

1.6.2 Channel assignment constraints

Radio transmission is such that the transmission in a channel causes interferences with other channels. Such interference may degrade the signal quality and the quality of service. The potential sources of radio interference to a call are:

1. Co-channel interference: this radio interference is due to the allocation of the same channel to certain pair of the cells close enough to cause interference,(i.e. pairs of cell within the re-use distance).

2. Adjacent channel interference: this radio interference is due to the allocation of adjacent channels (e.g., f_i and f_{i+1}) to certain pairs of cells simultaneously.

3. Co-site interferences: this radio interference is due the allocation of channels in the same cell that are not separated by some minimum spectral distance.

These constraints are known as electromagnetic compatibility constraints [Ngo 98]. This requires proper channel assignment scheme. The channel assignment problem has been shown to be NP-hard [Hale 80]. The process of channel assignment must satisfy the electromagnetic compatibility constraints and the demand of channels in a cell. These constraints are also known as hard constraints.

Beside, the hard constraints and traffic demand constraints, other conditions may be violated to improve the performance of the dynamic channel allocation technique: They are the packing condition, the resonance condition, and the limitation of reassignment operations [Sandalidis 98a]. These conditions are called soft constraints and were introduced in [Del Re 96]. The soft constraint allows to further lower the call blocking. The packing condition tries to use the minimum number of channels every time a call arrives [Sandalidis 98a]. This condition permits the selection of channels already in use in other cells as long as the co-channel interference constraint is satisfied.

Resonance

With resonance condition, same channels are assigned to cells that belong to the same reuse scheme [Sandalidis 98a]. To understand the significance of resonance condition let us consider the following example: In figure there are seven clusters of cell. The numbers inside the cell indicate the reuse scheme number. Let us assume that a call comes to cell 1 which belongs to reuse scheme 1 (cells:1, 10, 12, and 13). The resonance condition tries to assign channels, which are already in use in the remaining cell of reuse scheme 1. The advantage of this approach is that this will leave channels to be allocated to cells other than this reuse scheme without causing co-channel interference with cells belonging to reuse scheme 1. This reduces the call blocking probability. The objective function should help select a combination of channels that makes maximum use of channels already in use in the reuse scheme to which the cell involved in call arrival belongs.

Limiting rearrangement

Channel reassignment improves the quality of service in terms of lowering call blocking probability. Hence it is an important process in dynamic channel allocation. It is the process of transferring an ongoing call to a new channel without call interruption [Chen 94]. To better understand this process, let us consider a cellular system with nine cells and 10 channels available to the whole system [Sandalidis 98a]. Let us assume that a call arrives in cell no 7 (figure 1.2 shows the channels in use in cell 7).

	channels									
	1	2	3	4	5	6	7	8	9	10
Cell 7	1	0	0	1	0	1	0	1	0	1

Figure 1.2: Channels in use in cell 7

In figure 1.2 the channels that are free to serve an incoming call are: 2,3,5,7 and 9. Considering the co-channel interference scenario let us assume that only channel 4 of this cell can serve a new call. Taking this scenario into account and without considering reassignment the new call will be blocked. With reassignment some ongoing calls in cell

	channels									
	1	2	3	4	5	6	7	8	9	10
Cell 7	0	0	1	1	1	1	0	0	1	1

Figure 1.3: A possible channel assignment after reassignment in cell 7

7 are assigned a new set of channels and the required channel i.e. channel 4 is made available to serve the new call. A possible reassignment might look like the channel assignment shown in figure 1.3:

Hence, the reassignment process greatly affects the call blocking probability. Reassignment in the entire cellular network upon a new call arrival will obviously result in lower call blocking, but it is complex both in terms of time and computation [Sandalidis 98a]. Therefore, the reassignment process is limited to the cell involved in new call arrival. However, excessive reassignment in a cell may lead to increase in blocking probability [Sandalidis 98a]. So a process called limiting rearrangement is considered which tries to assign, where possible, the same channels assigned before, thus limiting the reassignment of channels. Reassignment is done together with the new call. We have considered reassignment only in the cell involved in the new call arrival due to computational reasons as in [Sandalidis 98a].

1.7 Channel reuse

The reuse of channels in cellular system is inevitable and at the same it is directly related to co-channel interference. Co-channel interference is measured by a required Signal to Interference ratio (SIR). Some papers use the term Carrier to Interference Ratio (CIR) instead of SIR. Another measure of co-channel interference is Bit-Error Rate (BER). As a result of co-channel interference, all channels may not be reused in every cell. In an AMPS System, when SIR is equal to 18db, most of the users call the system good or excellent [MacDonald 79]. However, the concept of cellular system enables the discrete channels assigned to a specific cell to be reused in different cells separated by a distance sufficient enough to bring the value of co-channel interference to a tolerable level thereby reusing each channel many times. The minimum distance required between the centers of two cells using the same channel to maintain the desired signal quality is known as the reuse distance (D_s). The distance between any two cells is the minimum number of steps needed to move form the center of one cell to the center of the other. A step is the distance between the centers of two adjacent cells, and is also considered the unit distance (that is it has a value of one). The cells with center-to-center distance less than D_s belong to the same cluster. A group of contiguous cells arranged in cluster makes up the cellular geographic service area with each cell using the entire allocated frequency spectrum. No channels are reused within a cluster. The number of cells per cluster N is a an important parameter because in a practical system it determines the total number of different channel sets that can be formed out of the total allocated spectrum [MacDonald 79].

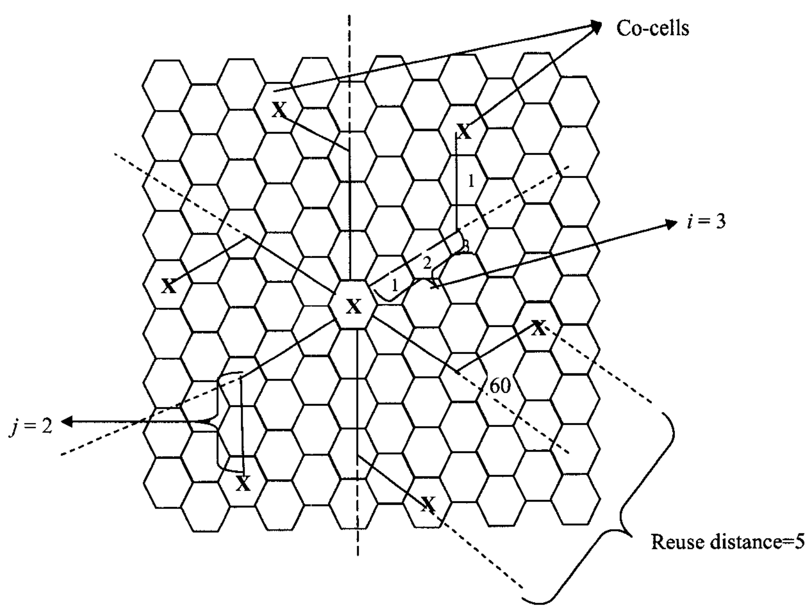

Figure 1.4: Method of locating co-cells in a cellular system

The geometry of hexagonal cells is such that each cell has exactly six equidistant neighbors and the lines joining the centers of any cell and each of its neighbors are separated by multiples of 60 degrees. The nearest co-channel neighbors of a particular

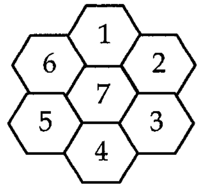

Figure 1.5: Cluster of 7 cells

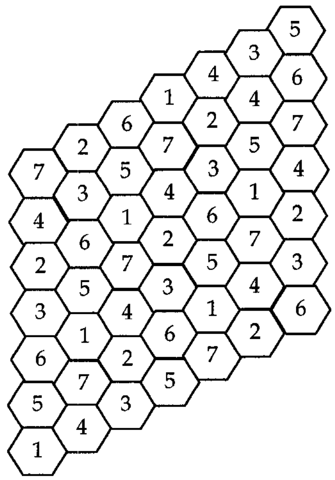

Figure 1.6: Frequency re-use pattern with Ds=3 cell unit

cell, can be found by doing the following: (1) move i cells along any chain of hexagons and then (2) turn 60 degrees counter-clockwise and move j cells, where i and j are non-negative integers [Rappaport 96]. This is illustrated in figure 1.4 for $i = 3$ and $j = 2$. In figure 1.4, cells marked with x are co-channel cells. The value of N is determined by the equation $N = i^2 + j^2 + ij$ [MacDonald 79]. Thus a cluster can only accommodate 1, 3, 4, 7, ... cells. Figure 1.5 (adapted from [Rappaport 96], figure 3.1,pp. 59) shows a cluster of 7 cells with frequency spectrum divided into 7 groups $(1, 2, 3, \ldots 7)$ and figure 1.6 (adapted from [Rappaport 96], figure 3.1,pp. 59) shows the frequency re-use pattern with cluster of 7 cells and cells with same number are co-channel cells. N is related to Ds by the equation $\sqrt{3N} = \frac{Ds}{R}$ [MacDonald, 1979; equation 2, pp. 23] where R is the radius of the cell and the ratio $\frac{Ds}{R}$ is called the co-channel reuse ratio. The smaller value of R provides higher capacity system as it allows more frequency in a given service area but it increases the number of cell boundary crossing. The transmission range of a base station determines the radius R of the cell.

The longer the reuse distance is, the smaller is the co-channel interference level. However, a long reuse distance increases the number of cells per cluster resulting in smaller reuse efficiency. Thus the frequency reuse pattern should be determined taking into consideration both the co-channel interference level and the reuse efficiency.

In traditional, FCA and DCA, the channel assignment is made considering the co-channel interference level determined by a fixed reuse distance determined during network planning. Our proposed D-ring HCA strategy is based on this concept.

1.8 Dynamic channel assignment

The main feature of DCA is that the entire set of available channels is accessible to all the cells, and the channels are assigned on a call-by-call basis in a dynamic manner. This makes the scheme adaptable to the changing traffic conditions. The DCA problem can be simply stated as follows : Let us consider a mobile communication system with C cells and F channels. Let k denote a cell involved in call arrival, $P(k,t)$ denotes the set of channels of the ongoing calls in k at time t, and $Q(k,t)$ denotes the set of channels in the interfering cells of k at time t, i.e. all those cells which are located at a distance less than the reuse distance D. Then the set of eligible channels in k at time t is given by $I(k,t) = F \setminus (P(k,t) \cup Q(k,t))$. The problem of DCA is how to choose channels from the set $I(k,t)$.

1.9 Power control

Power must be allocated to a transmitter to support the communication. Transmitter or receiver power is a scarce resource. Excessive use of power for transmission causes faster drainage of power resulting in short battery life, and also causes interference to other users. In cellular network the signal quality is usually determined by Carrier-to-Interference Ratio (CIR). Here carrier represents the signal power received by a receiver from the transmitter in the cell where it is located, and the interference represents the cumulative effect of signal powers received from transmitters using the same channel in all other cells in the network. The signal quality and the level of interference in the wireless network depends upon the transmitter power. The objective of power control is to assign power level to each transmitter so that the signal quality is maintained and interference is minimized. It consists of techniques and algorithms used to manage and adjust the transmitted power of base stations and mobile terminals. It is required for the forward link (base station to mobiles terminal) as well as for the reverse link (mobile terminal to base station).

Channel assignment allows the efficient use of the available spectrum but the interference limits the spectral efficiency. Power control on the other hand is known to suppress adjacent channel interference, the co-channel interference, and minimizes the consumption of power. Thus the problem of channel assignment is highly related to power control. When a call arrives and a channel is assigned to the call without considering CIR ratio, the assignment of this channel may cause the CIR of ongoing calls using this channel to drop below the required level, thereby causing forced termination of ongoing calls. In cellular networks, it has been found that users tend to prefer the blocking of new calls than the forced termination of ongoing calls.

The power control algorithms proposed in literature can be broadly classified as centralized or decentralized, discrete or continuous. Power control schemes can be centralized with continuous power levels and CIR objectives [Aien 73], [Zander 92a], [Grandhi 93], distributed with continuous power levels and CIR objectives [Zander 92b], [Grandhi 94], [Foschini 93] and distributed with discrete power levels and CIR objectives [Zander 93]. A centralized power control has a central controller that maintains information about all the radio links in the system [Grandhi 93] and it decides control actions for all users. On the other hand, a distributed controller only controls the power of one single transmitter based on local information [Foschini 93]. In power control algorithm with continuous power level, the power levels are assigned from a continuous range whereas in case of discrete power level, the power levels are assigned form a discrete set.

Combination of power control with other resource allocation has been an active area of research. A combination of power control with dynamic channel allocation has been studied in [Ishii 94], a combination with base station assignment has been studied in [Yates 95],[Hanly 95]. In [Papavassiliou 98], the authors have proposed a joint resource allocation algorithm that tries to allocate as many mobile users as possible to every available channel in the system with the simultaneous assignment of base stations and power levels.

1.10 Evolution strategy

In this section we briefly describe an optimization technique called Evolution Strategy (ES). It will be the main optimization tool used in our optimization problem.

Rechenberg [Rechenberg 73] pioneered ES. ES belongs to the class of *evolutionary algorithms.* The term Evolutionary Algorithm (EA) was proposed in 1990 to describe all algorithms based on natural evolution for problem solving. ES was proposed as an optimization method for real-valued vectors. It works on an encoded representation of the solution. The pool of candidate solutions is called *population.* The total number of individuals in a population is called *population size.* Each individual solution is associated with an *objective value.* The objective value is representative of the individual solution's performance in relation to the parameter being optimized. It also reflects an individual solution's performance in relation to other potential solutions in the search space. ES is a random guided hill-climbing technique in which a candidate solution is produced by applying mutations on a given parent solution. The best solution generated in one generation becomes the parent for the next generation. ES is an iterative method so the process of selection and application of mutation is repeated until some terminating criteria is reached. When the termination criterion is reached, the solution to the problem is represented by the best individual so far in all generations. The basic steps of an ES algorithm can be summarized as follows:

1. Generate an initial population of λ individuals
2. Evaluate each individual according to a fitness function.
3. Select μ best individuals called the parent population and discard the rest.

4. Apply reproduction operator i.e mutation to create λ offsprings from μ parents.

5. Go to step 2 unless a desired solution has been found or predetermined number of generations have been produced and evaluated.

The two common variations of ES introduced by Schwefel [Schwefel 81] are the ($\mu+\lambda$)-ES and (μ, λ)-ES. In both approaches μ parents produce λ offsprings. These two approaches differ in the selection of individuals for the next generation. In ($\mu + \lambda$)-ES, μ best individuals from all the ($\mu+\lambda$) individuals are selected to form the next generation, but in (μ, λ)-ES, μ best individuals from the set of λ offspring are selected to form the next generation.

Some of the other most common variants of evolutionary algorithms are: Evolutionary Programming (EP) [Fogel 66], Evolutionary Strategies (ES) [Rechenberg 73], Genetic Algorithms (GA) [Holland 62], [Holland 75], and Genetic Programming (GP) [Koza 92], [Koza 94]. All these approaches differ in three respects: the representation scheme, the reproduction operators, and the selection methods. An introductory survey on GA, EP, and ES can be found in [Fogel 94]. The recent classes of evolutionary algorithms include: Artificial Immune Algorithms [Dasgupta 99] and Artificial life [Langton 86].

1.11 Problem statement

In this thesis, we address the problem of finding an optimal assignment of channels in wireless mobile communication. We propose a new HCA strategy called D-ring HCA strategy using distributed dynamic channel assignment strategy based on fixed reuse distance concept. We also propose a method to integrate the problem of finding an optimal assignment of channels with power control using the dynamic reuse distance concept.

With soft conditions, and hard conditions the dynamic channel allocation problem based on fixed reuse distance concept has been modelled as an energy function in [Del Re 96], [Sandalidis 98a],and [Sandalidis 98b]. The minimization of the energy function gives the optimal channel allocation. Our proposed scheme uses the soft conditions and hard conditions proposed in [Sandalidis 98a].

We have developed an ES method which optimizes the channel assignment. The proposed ES approach uses an efficient problem representation as well as an appropriate fitness function to search for a (near) optimal allocation of channels for a given cell that receives an incoming cell. Our D-ring method yields a faster running time and a simpler objective function. We also propose a novel way of generating the initial population which creates (near) optimal starting solutions.

1.12 Contributions

Our contributions are summarized as follows:

1. Contributions to the application of ES in channel assignment problem domain:
   (a) A original and efficient problem representation for better and faster optimization.
   (b) A novel technique to generate an initial population so as achieve a faster convergence to (near) optimal solutions.
   (c) A simpler and efficient fitness function that allows fast evaluations of solutions.
2. Contribution to channel assignment problem domain:
   (a) A novel channel allocation scheme, called D-ring HCA scheme, which yields a simpler objective function for assignment optimization as well as co-channel free assignments.
3. Contribution to both channel assignment and power control problem domain:
   (a) A method to integrate the problem of channel assignment and power control.
   (b) An ES method for concurrent optimization of HCA and Power control.

1.13 Organization of the document

In chapter 2, first we discuss the use of evolutionary algorithm in wireless mobile communication, and then give a brief survey on existing methods that are relevant to our problem. In chapter 3, we define our D-ring HCA scheme,features of our ES algorithm, and define our method for combining the problem of finding an optimal channel assignment with power control. In chapter 4, we describe the basic assumptions of the cellular model used in the simulation, the various assumptions used in the simulation model, and some of the implementation details, and discuss our results. Chapter 5 concludes the dissertation and discusses future research directions and open problems.

Chapter 2

Literature Review

This chapter discusses the use of Evolutionary Algorithm(EA) in the area of wireless mobile communication and gives a brief survey on the existing methods that are relevant to our problem.

2.1 EA in base station placement

The infrastructure cost and planning complexity of a cellular network is closely related to the number of base-stations required to achieve the desired level of coverage (locations covered by the selected number of base stations) and capacity [Lee 95]. Therefore one of the most challenging design problems in cellular network is deciding on the locations of base stations and the minimum number of base stations required to serve a given area while providing an acceptable quality of service to the mobile users. In the literature many practical approaches have been proposed to solve this problem. This includes the use of GA in [Calegari 97], [Han 01], Simulated Annealing in [Anderson 94], [Hurley 02], and Tabu Search in [Lee 00]. For finding precise base station location, numerous factors such as traffic density, channel condition, interference scenario, the number of base stations, and other network planning parameters [Han 01] must be taken into account. Determining the location of base stations is known to be NP-hard [Calegari 97]. Given a list of potential sites in a service area where base stations may be located, the goal is to use the knowledge of the radio propagation characteristics of the area to select sites in such a way as to minimize their number while maximizing coverage in the area [Krishnamachari 00]. The radio propagation characteristics can be determined using ray-tracing software or by using empirical propagation models for path loss. There exists a trade-off between coverage and the number of base stations. The higher is the number of base stations, the greater is the coverage, but there is also correspondingly greater radio interference and network cost.Some of the papers that describe the application of EA in base station placement problem are briefly described below:

- In [Calegari 97], Genetic algorithm approach has been presented to address this problem. The paper assumes that a list of N possible locations that guarantees 100% radio coverage is known before hand. The candidate solutions are represented using a N bit binary string, with a 1 at each bit position if there is a base station at the location corresponding to that bit, and zero otherwise. The chromosomes are evaluated by the fitness function chosen as shown in equation 2.1 (Equation 2.1 is adapted from [Calegari 97], pp.757).

$$fitness(individual) = \frac{CoverRate^{\alpha}}{NB} \tag{2.1}$$

  Where $CoverRate^{\alpha}$ is the radio coverage (the percentage of locations covered by the selected base stations, and α is a parameter that is tuned to favor coverage with respect to the number of transmitters and is assigned a value of 2 in this paper) and NB is the number of Selected Base stations. This fitness function maximizes the coverage and minimizes the number of transmitters. Selection based on fitness value, one-point crossover and mutation operators (flipping of the value of a randomly chosen bit of the string with a probability of 0.9) are employed.

- Han et al. in [Han 01] have described the base station placement problem using GA with real number representation. Binary string representation considered in [Calegari 97], suffers from representation limit (can represent discrete locations) and hence cannot guarantee optimal solution because the possible base station locations are discrete. The representation chosen in the paper can describe not only the base station location but also their number. In the encoding chosen in the paper for GA, a genome g is vector of the form $g = (c1, ., ck)$ where $ck = (xk, yk)$ is the chromosome for the k^{th} base station position, xk and yk are the x and y coordinates of the k^{th} base station position and the value of k is in the range $1 \leq k \leq K$ where K is the maximum number of base stations. Each genome is evaluated using the following objective function (equation 2.2 is adapted from [Han 01], pp. 2706):

$$f(g) = W_c(\frac{ct}{tot}) + W_e.(\frac{k - n(g)}{k}) \tag{2.2}$$

Where ct is the covered traffic and tof is the total offered traffic. In equation 2.2, the first term is the objective function for coverage and it increases as the covered traffic area increases corresponding to g. The second term is the objective function for economy (cost of the network) and increases as the number of base stations decreases. w_c and w_e are weightage with $(w_c + w_e) = 1$, and the value of w_c and w_e depends upon whether coverage or less number of base stations is preferred. In equation 2.2, K refers to the maximum number of base stations, and $n(g)$ is the number of base stations in the genome g. The paper has defined appropriate crossover and mutation operation for such problem representation.

2.2 EA in network topology

The base station (BS), base station controller (BSC), mobile switching center (MSC), and point of interconnection (POI) to networks like PSTN, ISDN, etc forms the fixed network of the wireless mobile communication network. The important aspect of the overall design of a communication network is the determination of a suitable network topology. This topology must be able to meet the required traffic, reliability etc. at the lowest possible cost. Some of the factors that determine the cost of the topology of the fixed network of the wireless mobile communication include cost of the nodes, the cost of the links, capacity of the links, and constraints such as the maximum number of links allowed per node [Krishnamachari 00]. The key to network design is to formulate the problem in such a way as to minimize this cost of the network topology satisfying the constraints. The problem of designing minimum cost network topologies is closely related to the NP-hard facility location problem [Mirchchandani 98] in Operations Research. The facility location problem aims at placing the facilities on a 2-D plane in such a way that the average distance between them and the existing client locations are minimized [Mirchchandani 98].

In [Shahbaz 95], GA has been used to design the fixed portion of the GSM network and closely related Digital Cellular System 1800 (DCS 1800). The cost function to be minimized is defined as follows (equation 2.3 is adapted from equation 2, [Krishnamachari 00], pp.11):

$$f = \sum_{\forall n} C_n^{NODE} + \sum_{\forall p} C_p^{POI} + \sum_{\forall l \in L^{BS \rightarrow BSC}, L^{BSC \rightarrow MSC}, L^{MSC \rightarrow MSC}} C_l^{LINK} \tag{2.3}$$

subject to the constraints (i) $F_l \leq C_l,, \forall l$ and (ii) $\zeta \leq 0.0001$, where C_n^{NODE} is the cost of all nodes of type n and n is one of the types of BS, BSC, or MSC; where C_p^{POI} is the cost of p^{th} POI and C_l^{LINK} is the cost of the l^{th} link which is one of types $L^{BS \rightarrow BSC}$, $L^{BSC \rightarrow MSC}$, or $L^{MSC \rightarrow MSC}$; F_l and C_l ,represents the flow and capacity of each link respectively; and ζ is the call blocking probability.

Chromosome	Representation
1	x coordinates of BSCs
2	y coordinates of BSCs
3	x coordinates of MSCs
4	y coordinates of MSCs
5	Existence of link between base station and BSCs
6	Existence of link between base BSCs and MSCs
7	Existence of link between base MSCs themselves

Table 2.1: Chromosome representation

The paper represents each candidate solution with a chromosome set consisting of seven chromosomes. The table 2.1 shows the various chromosomes numbered 1 through 7 used in [Shahbaz 95] and their meanings.The paper described 17 problem specific genetic operators applied to find near optimal topologies.

2.3 Channel assignment

The channel assignment problem has been shown to be NP-hard [Hale 80]. In literature, many techniques have been proposed to solve FCA and DCA problem based on fixed reuse distance concept. This include the use of neural networks approach [Duque-Antón 90], [Kunz 91], [Funabiki 92], the use of simulated annealing approach [Duque-Antón 93], [Mathar 93], the use of genetic algorithm approach [Lai 96], [Jaimes-Romero 96], [Smith 98], [Ngo 98], [Chakraborty 99], [Beckmann 99], and the use of graph theoretic approach [Sivarajan 89], [Gamst 82] in FCA. The goal of all these approaches is to provide an optimal assignment of the available radio spectrum.

The neural network approach of Hopfield and Tank [Duque-Antón 90], [Kunz 91] was shown to be an inappropriate technique [Kunz 91a] as it greater tendency to get stuck in local optima.

Some of the disadvantages of graph theoretic [Duque-Antón 93] approach are as follows:

1. Graph theoretic approach is based on hard interference decisions indicating whether the same channel can be simultaneously used in two radio cells. Such a decision is questionable because interference depends upon several uncertain factors such as spatial distribution of traffic.

2. Graph theoretic approach only aims at minimizing the used spectrum. It does not exploit the optimum use of available channels.

Simulated annealing approach [Duque-Antón 93], [Mathar 93], achieves the global optimum asymptotically but its rate of convergence is very slow, and requires a carefully designed cooling schedule [Ngo 98]. Tabu search is good at exploring the search space by avoiding the inefficient paths. This way it requires less computation time as compared to simulated annealing. However, it requires large memory capacity as well as good method for avoiding oscillation of solutions which makes it unsuitable for large scale problems [Stojmenović 02].

2.3.1 EA in fixed channel assignment problem

For every incoming call, a channel is selected with the restraints of electromagnetic constraints (EMC). EMC can be represented by minimum channel separation between any pairs of channels assigned to a pair of cells or cell itself [Thavarajah 99]. If there are F channels to serve C cells in the system, the minimum channel separation is described by a symmetric compatibility matrix $X[C, C]$ and each element of X is a non-negative integer. Each element $X_{ij}(i, j = 1 \ldots C)$ represents the minimum channel separation required between channels assigned to cells i and j.

1. Each diagonal element X_{ii} represents the minimum separation distance required between any two channels at cell i to satisfy co-cell interference constraint and

2. Each non-diagonal element X_{ij} represents the minimum separation distance in channel between any two channels assigned to cells i and j respectively.

For example if $X_{ij} = 0$, then no frequency separation is needed between the channels used in cell i and cell j and the channels used in cell i can be reused in cell j.

If the compatibility matrix is binary, then $X_{ij} = 1$ indicates the same channels cannot be reused by cells i and j, and if it can be reused then $X_{ij} = 0$.

Another basic requirement of channel assignment is the traffic requirement of each cell. A vector T of length C can model the traffic demand of which an element T_i denotes the number of channels used in the i^{th} cell. This vector can be obtained by analyzing the traffic at each cell. In reality, the value of T should be a function of time due to arrival of new calls, termination of ongoing calls, and handovers.

The channel assignment problem is to find the allocation matrix $A[C, F]$ which satisfies all the constraints mentioned above. The allocation matrix $A[C, F]$ is such that the element A_{ij} of A is 1 if channel i is assigned to cell j and a 0 indicates it is not.

In general the cost due to violation of interference constraints can be given as (equation 2.4 is modified from equation 5, [Krishnamachari 00], pp. 13):

$$f' = f_{cosite} + f_{adjacentchannel} + f_{cochannel} \tag{2.4}$$

where

$$f_{cosite} = \sum_{i=1}^{C} \sum_{k=1}^{F} \sum_{l \neq k}^{F} A_{ik} A_{il} \phi(i, l) \tag{2.5}$$

where $\phi(i, l) = 0$ if$|k - l| \geq X_{ij} andi = j$ and 1 otherwise.

$$f_{adjacentchannel} = \sum_{k=1}^{F} \sum_{i=1}^{C} \sum_{j \neq i}^{C} A_{ik} A_{jk} \delta(i, j) \tag{2.6}$$

where $\delta(i, j) = 0$ if $X_{ij} \leq 1$ and 1 otherwise.

$$f_{cochannel} = \sum_{i=1}^{C} \sum_{k=1}^{F} \sum_{j \neq k}^{F} A_{ik} A_{jk} \phi(i, j) \tag{2.7}$$

where $\phi(i, j) = 0$ if $X_{ij} = 0$ and 1 otherwise.

In equation 2.4, f_{cosite} takes care of the co-site interference, $f_{adjacentchannel}$ takes care of the adjacent channel interference, and $f_{cochannel}$ takes care of the co-channel interference. The cost due to the violation of interference $f^{'}$ is minimized if f_{cosite}, $f_{adjacentchannel}$, and $f_{cochannel}$ are minimized. The cost due to the violation of traffic demand requirement i.e. assigning a different rather than required number of channels at each cell can be modeled as an error term $f_{traffic}$ as shown in equation 2.8 (Equation 2.8 is adapted from equation 6, [Krishnamachari 00], pp. 13).

$$f_{traffic} = \sum_{i=1}^{C} (T_i - \sum_{k=1}^{F} A_{ik})^2 \tag{2.8}$$

The cost to be minimized can be expressed as shown in equation 2.9 (equation 2.9 is adapted from equation 7, [Krishnamachari 00], pp. 13).

$$f = f^{'} + f_{traffic} \tag{2.9}$$

In the equation 2.9, f will be minimized if $f^{'}$ and $f_{traffic}$ are minimized. Some of the papers that describe the use of evolutionary algorithms to fixed channel assignment problem discussed in this section are described below:

- In [Lai 96], authors have used GA to find an optimal channel assignment matrix.

The constraints considered in the paper are the interference constraints (co-site and co-channel) and traffic demand. In the encoding chosen in the paper for GA, a chromosome represents a cell in the cellular system and the length of the chromosome is sum of the number of channels required in the cell. Thus, a typical chromosome is a linear arrangement of channels for each cell. Each chromosome is evaluated by an objective function that encompasses traffic demand and interference constraints (co-site and co-channel). The paper uses standard mutation operator and slightly modified partially matched crossover (PMX) proposed in [Goldberg 89].

- Smith in [Smith 98] has also used GA. In the paper, the objective function treats the non-interference constraints (Co-channel, adjacent channel, and Co-site) as soft constraints and traffic demand satisfaction as a hard constraint. With this approach, a solution that minimizes the severity of any interference is always found. This is useful in situations where demand and interference constraints are such that no interference free solutions are available for the network [Smith 98]. Thus the formulation attempts to minimize the severity of any interference. The genetic representation of the solution is binary channel assignment matrix $A[C, F]$. The fitness of the chromosome is measured by (equation 2.10 is adapted form [Smith 98], pp.2014):

$$F(A) = \sum_{j=1}^{C} \sum_{k=1}^{F} A_{jk} \sum_{j=1} C \sum_{l=1}^{F} P_{j,i,(|k-l|)} A_{il} \tag{2.10}$$

subject to demand satisfaction . Here P is a factor that assigns a penalty to each assignment according to the recursive relation: $P_{j,i,m+1} = max(0, P_{j,i,m-1}), P_{j,i,1} = X_{ji}$ and $P_{j,i,1} = 0$ for $m = 1, \ldots M - 1$ and for all $j, i \neq j$. The paper has designed a crossover and mutation operator in such a way that the feasibility of the solution is guaranteed. The paper also provides an insight into the roles of crossover and mutation operator: crossover operator improves co-channel and adjacent channel interference while mutation operator eliminates co-site interference [Smith 98].

- Ngo et al. in [Ngo 98] have used also GA to find an optimal channel assignment matrix. The constraints considered in the paper are interference constraint (Co-channel, adjacent channel, and Co-site constraints), and traffic demand constraint with non-uniform traffic distribution among the cells. In the paper, the authors have described a modified genetic-fix-algorithm that creates and manipulates chromosomes with fixed size (i.e. in binary representation, the number of ones is fixed) and utilizes an encoding scheme called the minimum-separation encoding. In the encoding chosen in the paper for GA, a chromosome is a binary string that represents the channel assignment matrix through concatenation of rows. The chromosome structure incorporates both the traffic demand and co-site constraint. If d_{min} is the minimum number of frequency bands by which channels assigned to x^{th} cell must differ to prevent co-site constraint then the minimum-separation encoding scheme works by eliminating $(d_{min} - 1)$ zeros following each 1 in each row of the channel assignment matrix. This compression reduces the search space. A chromosome is evaluated by an objective function that includes only the co-channel and adjacent channel constraint. The genetic-fix algorithm defines its own mutation and crossover operator in such a way that the fixed number of ones is always preserved.

- Chakraborty et al. in [Chakraborty 99] have used GA to find the minimum required bandwidth that satisfy a given channel demand without violating interference constraints (Co-channel, adjacent channel, and Co-site constraints). In the encoding chosen in the paper for GA, a chromosome is a frequency assignment matrix $A[F, C]$ with elements $A_{ij}(i = 1..M$ and $j = 1 \dots N)$ which is either "0"or "1" or "-1" or "9".

  1. $A_{ij} = 0$: i^{th} channel is not used in the j^{th} cell and the use of i^{th} channel in the j^{th} cell will not result in any interference.
  2. $A_{ij} = 1$: i^{th} channel is used in the j^{th} cell.
  3. $A_{ij} = -1$: i^{th} channel is not used in the j^{th} cell and the i^{th} channel cannot be used in the j^{th} cell.

The paper has considered the value of F to be sufficiently large, so that some channels are left unused even after adequate channels have been allocated to all cells. $A_{ij} = 9$ indicates: i^{th} channel is unused in the j^{th}cell. The fitness of the chromosome is measured by the frequency bandwidth a chromosome uses i.e by its F value. In case of chromosomes with same value of F one with higher number of 0's i.e solution, which allows more channels to be added without violating interference, is considered the fittest. The paper presents an algorithm to generate the initial population, and also defines a genetic mutation operator on those valid chromosomes such that the resulting chromosome is also a valid solution.

2.4 EA in mobility management

In a cellular network, in order to route a call, the mobile terminal need to be correctly located within a fixed time delay. The location management involves two types of activities: paging and location update (LU). Both paging and LU increases network traffic overhead and consume the scarce radio resource. Therefore, during a certain period of time, the total cost of location management involves the sum of two orthogonal cost components: paging cost and LU cost. The two costs are orthogonal because the higher is the frequency of LU, the lesser is the frequency of paging attempts required to locate the mobile terminal [Das 97]. Thus there exists a trade-off between paging cost and LU cost which varies with the size of the location area (LA). If the LA is large, there are fewer inter-LA crossing resulting in a lower LU Cost but the number of base stations needed to be paged increases correspondingly. Therefore one way of reducing LU cost is by effective planning of LA.

LA planning has been considered in [Gamst 91] using graph theoretic approach, in [Markoulidakis 93], [Markoulidakis 94] using two heuristics algorithms, in [Plehn 95] using greedy algorithm, and in [Wang 98] using genetic algorithm. LA planning decomposes a group of cells into LA's in which LU traffic is minimized without violating the paging bound (bandwidth available for paging). In general LU traffic is proportional to the number of mobile terminals crossing the LA border and paging cost is proportional to the number of calls to all mobile terminals in the LA. Some of the papers that describe the use of evolutionary algorithms to mobility management are described below:

- In [Wang 98], GA has been used for the optimal planning of LA to reduce the LU cost. In the paper, it has been assumed that cell planning has already been done, LU and paging traffic have been estimated for each cell, each LA contains disjoint set of cells, and paging bound is fixed for each LA. The LA planning problem has been encoded using binary chromosome using Border-Oriented representation. In border-oriented representation, all borders are numbered sequentially and the corresponding bit in the chromosome is 1 if that particular cell border is to be a border between two adjoining LAs, and 0 otherwise.

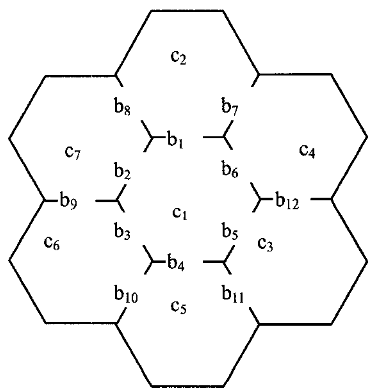

Figure 2.1: Numbering of cells and border

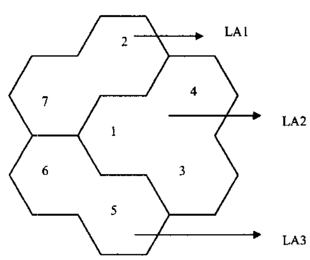

Figure 2.2: An LA planning result

Figure 2.1 (adapted from [Wang 98], figure 2, pp. 989) shows the numbering of borders (b_i) and numbering of cells (c_i) in a system with 7 cells. Figure 2.2 (adapted

1	1	1	1	0	0	1	0	1	0	1	0

Figure 2.3: Border-oriented chromosome structure

from [Wang 98], figure 3, pp. 989) shows an LA planning result of the 7cell system shown in figure 2.1. Figure 2.3 (adapted from [Wang 98], figure 10 (b), pp. 991) shows the border-oriented chromosome structure V of the LA planning shown in figure 2.2. In figure 2.3, $V_i = 1$ if the border b_i exists in the LA planning shown in figure 2.2, otherwise $V_i = 0$. For example, the border b_1 between the cells c_1 and c_2 exits in the LA planning shown in figure 2.2, hence $V_i = 1$.

The chromosomes are evaluated using the following fitness function (equation 2.11 is adapted from [Krishnamachari 00], equation 18, pp. 23):

$$f = \frac{\alpha_1}{2}\sum_{j=1}^{n} v_j w_j + \alpha_2 \sum_{i=1}^{M} max(0, (P_i - B)) \tag{2.11}$$

The first term denotes the LU cost and the second term denotes the cost due to the violation of paging bound. In the equation n is the total number of borders, w_j is the crossing intensity of the $j^t h$ border , v_j is the $j^t h$ bit of the chromosome being evaluated, M is the total number of LA's, P_i is the paging traffic in the i^{th} LA, B is the paging bound which has been considered fixed for each LA, and α_1 and α_2 are constant used to weigh the relative importance of LU cost and paging bound violation. Selection based on fitness value, two-point crossover, and mutation operators (flipping of the value of a randomly chosen bit of the string with a probability of 0.02) are employed. The GA is terminated after 1000 generations.

- One way to reduce the paging cost is to partition the LA into paging zones for each user based on the pre-determined probability of locating the mobile user at different locations within the LA. In reference [Junping 97], authors have used GA in the optimal planning of such paging zones. For each mobile user a multi-layered model is developed based on the mobile-phone usage for different times of activity during a day - home, work, social. LA is decomposed into a set of multiple location layers $\{L_1, L_2, \ldots, L_{ln}\}$ where $1 \leq i \leq ln$ and ln is the number of layers in the multi-layered model, based on the mobility patterns that describe the likelihood of locating the user in a particular cell during a particular time of the day. "For example L_1 refers to the working area, L_2 refers to the home area of a mobile user, L_3 refers to the social activities area and so on" ([Junping 97], pp. 89). Then for each user k the cells in the LA are partitioned into paging zones for each activity layer j such that each zone consists of cells with similar probability of locating the user. When a call is received for a particular user, paging message is first send to the paging zone with highest probability of locating that user at that particular time of day. If the mobile user did not respond to the first paging message, then second paging message is sent to the paging zone with next highest probability, and so on. Thus paging cost is incurred if and only if the paging zone is paged. In the paper, paging cost to locate a mobile user is defines as (equation 2.12 is adapted form [Krishnamachari 00], equation 20, pp. 24):

$$f = N(P_{k,j,l}) + \sum_{l}(1 - \sum_{i=1}^{l-1} prob((P_{k,j,l}).N(P_{k,j,l}).\alpha.\beta \tag{2.12}$$

where $prob(P_{k,j,l})$ is the probability of locating the k^{th} user in the j^{th} activity layer of l^{th} zone, $N(P_{k,j,j})$ is the number of cells in the l^{th} zone, α denote consumption cost in the forward control channel per paging message, and β consumption cost in the fixed link channel consumption in the mobile switching center per paging message. In this scheme each user has unique paging zones. Hence, optimization must be carried out separately for each individual mobile user.

The candidate solutions have been encoded with integer representation. The cells and paging zones in the LA are numbered sequentially. The length of the chromosome equals the number of cells in the LA, gene position correspond to the cell number, and value of a gene at a particular position correspond the paging zone to which the cell number belong. For example, if there are 5 cells (1,2,3,4,5) and 3 paging zones (1,2,3) in a LA, and paging zone 1 contains cell number 1and 2, paging zone 2 contains cell number 4 and 5, and paging zone 3 contains cell number3, then the corresponding chromosome representation is '1322'. The tournament selection mechanism, one-point crossover and mutation operators (flipping of the value of a randomly chosen bit of the string with a certain probability) are employed.

2.5 EA in call admission control

In mobile communication system, it is generally preferred to block a new call then to drop an ongoing call. Hence, allocation of radio resources to every user whenever they are available may not be the optimal strategy in terms of system performance as this may result in an inability to serve a handoff call. Thus one of the important design issues is the finding of a call admission policy that provides optimal system performance. Call Admission Control (CAC) policy determines under what conditions a new call to a mobile in a particular cell should be admitted or blocked.

In reference [Yener 95], authors have considered the evolution of a state-based call admission policies using GA. "A call admission policy is a collection of admit/reject decision corresponding to the services requested at each state of the system" ([Yener 95], pp.2). In each cell, the states refer to the number of occupied channels. The assumptions made by the paper are as follows: a linear cellular system, two types of service request: new call set request and handoff request, three binary decisions: admit a new call, admit a handoff call from the left cell, and admit a handoff call from the right cell. The paper also assumes that all cells can access the F channels available in the system. For a linear cellular system with C cells, the total number of global states for the three decisions is $3(F+1)^C$. The paper has considered a local policy where each cell uses state information from its k left and k right nearest neighbors as well as its own state information. The state space is thus reduced to $3(F+1)^{2k+1}1$. The value of k considered in the paper is 0 and 1. The policy is represented as binary string with a bit 1 for accepting the service and 0 for denying the service. An example with 16 channels and 9 cells need 30 bits for the policy with k =0 and 3000 bits with k =1. The performance of the system is defined as weighted measure of new call and handoff call and is defined as (equation 2.13

is adapted from [Yener 95], equation 1, pp. 2):

$$f = P_n + wP_h \tag{2.13}$$

Where P_n is the new call blocking probability, P_h is the handoff blocking probability and the value of w determines the extent to which dropped calls are considered less desirable than blocked calls. This represents the cost function to be minimized.

2.6 Dynamic channel allocation

In [Jiang 02], the problem of dynamic channel assignment was formulated as a generalization of traditional mutual exclusion problem. They have proposed an algorithm called "Relaxed Mutual Exclusion", which prevents certain pair of cells from simultaneously using the same channel. Singh et al. [Singh 97], Nie et al. [Nie 99] studied the application of reinforcement learning to dynamic channel allocation. They formulated the DCA as a dynamic programming problem. Besides these approaches, a number of DCA algorithms have been proposed [Chen 94], [Chuang 93], [Cox 73], [Del Re 96], [Dimitrijevic 93], [Sivarajan 90], [Sandalidis 98a], [Sandalidis 98b] [Tekinay 91], [Zhang 91], [Zhang 89]. These algorithms can be classified into two classes of DCA schemes based on the type of information used in allocating a channel [Nie 99]: (1) Interference adaptive scheme, and (2) Traffic adaptive scheme. In interference adaptive scheme, the decision regarding the allocation of a channel is based on the measurement of carrier-to-interference ratio. In traffic adaptive scheme, the channel allocation decision is based on the traffic conditions in neighboring cells of a cell involved in call arrival.The interference adaptive scheme has been described in [Furuya 87], [Nettleton 89]. Here the propagation measurement from each base station to mobile and vice-versa are made. A channel l is allocated to a new call if it does not cause any interference to the calls already in progress on l and at the same time does not receive any interference from the existing calls in the system.

2.6.1 Traffic adaptive scheme

The DCA part of D-ring HCA scheme described in this thesis (see section 3.1) is a traffic adaptive scheme. The traffic adaptive schemes can again be classified into various groups. One such category is exhaustive searching DCA [Cox 73], [Del Re 96], [Dimitrijevic 93], [Sivarajan 90], [Sandalidis 98a], [Sandalidis 98b], [Zhang 91], [Zhang 89]. In exhaustive searching each available channel is associated with a cost. The cost of a channel reflects the impact of allocating this channel on the on going calls in the system. When a call arrives, the system tries to allocate the channel with the minimum cost. The proposed D-ring HCA scheme belongs to the class of exhaustive searching DCA scheme.

Here only three types of strategies, namely neural network-based DCA [Del Re 96], genetic algorithm-based DCA [Sandalidis 98b], and evolution strategy-based DCA proposed in [Sandalidis 98a] are briefly described because they are relevant to our approach. Del Re et al. [Del Re 96] have proposed a Hopfield neural network, Sandalidis et al. [Sandalidis 98b] have used a genetic algorithm based approach, Sandalidis et al. [Sandalidis 98a] have discussed an evolutionary strategy based approach to solve the problem of DCA. In each of the above methods, an energy function was formulated for the cell involved in the arrival of a call.

In [Del Re 96], the energy function includes factors such as co-channel interference constraints, traffic requirement, packing condition, limiting rearrangement, and resonance condition. A Hopfield neural network was designed with respect to this energy function. The equilibrium point of the network is found by solving the corresponding energy function iteratively. The stable states (0 or 1) of the neurons gives the desired solution. The performance of the algorithm was measured in terms of probability of blocking of new calls. The neural network approach easily converges to local optima [Ngo 98].

In [Sandalidis 98b], the energy function includes all those terms proposed in [Del Re 96]. A binary chromosome represents a cell from the cellular system where a call is referred. A gene represents a channel (0: the channel is free; 1: the channel is occupied), and the length of the chromosome is always equal to the total number of channels available to the system. The fitness of the chromosome is measured by the energy function. The chromosome with the minimum energy gives the desired solution. The call is blocked if the desired solution causes co-channel interference and does not satisfy the traffic requirement of the cell at that time. Otherwise, the call is successful and the channel usage information of the cell is updated according to the desired solution. The performance of the algorithm was measured in terms of probability of blocking new calls.

In [Sandalidis 98a], the energy function includes all those terms proposed in [Del Re 96] except the traffic requirement term. The traffic requirement is incorporated in the problem representation. Thereby the fitness function is simplified. It uses the same problem representation as in [Sandalidis 98b]. The number of ones in the chromosome is equal to the traffic requirement of the cell at that instant. The energy function determines the fitness of the chromosome. The fittest chromosome is the desired solution. If the desired solution causes interference the call is blocked. Otherwise, the call is successful, and the channel usage information of the cell is updated according to the fittest chromosome. The paper compared its results with those obtained in [Del Re 96] and [Sandalidis 98b]. The performance of the algorithm was found to be better than them.

2.7 Power control

In literature, a number of papers have addressed the problem of power control. Power control schemes based on the CIR measurement have been addressed in [Aien 73], [Fujii 88], [Meyerhoff 74], [Nettleton 83], [Zander 93], [Zander 92b]. In these schemes, the transmitter power is regulated such that the signal quality can maintain a desired CIR target. Aein [Aien 73] addressed the problem of balancing the CIRs on all radio links to reach a common CIR in satellite systems. The existence and uniqueness of a feasible power vector associated with the eigen value of the gain matrix are found to be consequence of the Perron-Frobenius theorem. Aein's balanced power control was further refined by Meyerhoff [Meyerhoff 74]. Meyerhoff proposed an iterative procedure to determine the unique set of carrier power levels and demonstrated that maximizing the common CIR is equivalent to maximizing the minimum CIR over all radio links. Nettleton et al. [Nettleton 83] improved and applied these results to the spread-spectrum system.

Nagatsu[Nagatsu 83] and Fujii et al. [Fujii 88] showed the improvement of system capacity based on CIR based power control schemes by simulation. Zander [Zander 93], [Zander 92b] further refined the concepts of Aein, and Nettleton et al. and focussed on the distributed implementation of these algorithms and the relationship to dynamic channel allocation.

2.7.1 Integrated power control and channel assignment

A distributed approach to the optimization of integrated channel assignment (DCA) and power control has been proposed in [Hać 99] and [Ni 97]. Both papers use an interference region, and neighboring cells exchange the channel usage information periodically. In [Ni 97], every cell maintains a list of the priority of available (free) channels. The priority of a channel is determined by a cost function which is based on the use of the channel in a cell's vicinity. The cost function is such that the farther a given channel is in use from the current cell, the lower will be its cost. The lower the cost, the higher is the priority of the channel. After a channel is selected, the proposed algorithm applies power control to check the CIR value. In [Hać 99], every cell maintains a channel table. The channel table contains channel usage information in a cell's neighborhood and the CIR value for each channel. Each cell also maintains the record of the number of co-channels for each channel. When a call comes to a cell, the proposed algorithm searches for a free channel with desired CIR and highest number of co-channels from the channel table.

Ishii et al. in [Ishii 94] have proposed a dynamic channel allocation algorithm with power control. When a call arrives, the algorithm measures the CIR of all the free channels both at the mobile terminal and the base station. Among the channels with CIR above the required threshold, the one with the minimum CIR at the mobile terminal is allocated to the new call. If no such channel is available, the call is blocked.

Chapter 3

Proposed Methodology

In this thesis, we propose a new HCA strategy called D-ring HCA strategy using distributed dynamic channel assignment strategy based on fixed reuse distance concept. Each base station has a controller (computer). The status of all calls and changes in each cell are being sent to all the other cells using a good wired network between the computers of all cells. Channel assignment is made by the controller of the concerned base station according to the knowledge about the neighbors of a given cell. The thesis investigates an Evolutionary Strategy (ES) based approach using an efficient problem representation and a simplified fitness function as compared to the one proposed by Sandalidis et al. [Sandalidis 98a], and applies it to D-ring HCA scheme. The fitness function takes care of the soft constraints. The hard constraints are taken care of by the problem representation and the proposed new channel allocation scheme. The chosen representation and the mutation operator guarantees the feasibility of the solution.

In this thesis, we also integrate the problem of channel assignment with power control using the dynamic reuse distance concept. We develop an evolutionary strategy which optimizes channel assignment and power control using our new problem representation as well as an appropriate fitness function.

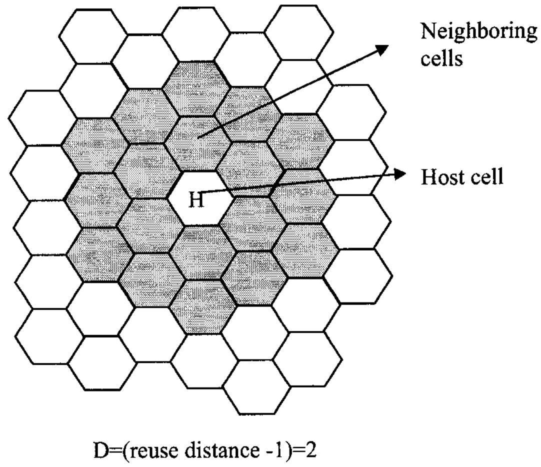

Figure 3.1: Neighbors of a given cell

3.1 D-ring HCA strategy

We propose a new distributed dynamic channel assignment strategy. In this strategy channel assignment is made by the controller of the concerned base station according to the knowledge about the neighbors of a given cell. The neighboring area of a given cell includes all those cells which are located at a distance less than the reuse distance. Conceptually, the neighboring area defines an interference region marked by grey cell belonging to D rings centered in a given cell H as shown in figure 3.1. The channels are allocated to the host cell from a set of channels which excludes all those channels which are not in use in the interference region. As such the selected channels always satisfy the co-channel interference constraint. The channel usage information in the neighbors of a given cell is obtained from the allocation matrix. The allocation matrix, which is a $C \times F$ binary matrix (where C is the total number of cells in the system and F is the total number of channels available to the system). The allocation matrix for each cell is a copy of the system channel pool. Each element a_{ij} in the matrix is one or zero such that

$$a_{ij} = \begin{cases} 1 & \text{if channel j is assigned to cell i} \\ 0 & \text{otherwise} \end{cases}$$

The allocation matrix is updated every time a channel is allocated and released in the network.

3.2 Proposed evolutionary strategy approach

The proposed ES belongs to the class of $(1, \lambda)$-ES. Following sections describe the characteristics of our proposed ES approach: problem representation, generation of initial parent, fitness function and mutation operator to generate offsprings from a given parent, and the algorithm.

3.2.1 Problem representation

Assume a new call arrives in cell k, which is already serving $(d-1)$ calls (d is the traffic demand at cell k after the arrival of the new call). Our problem is to assign a channel for the new call, also with possible reassignment of channels to the $(d-1)$ ongoing calls in k, so as to maximize overall channel usage in the entire network. A potential solution, V_k, is an assignment of channels to all ongoing calls and the new call, at k. We call such solution a chromosome. We will represent V_k as an integer vector of length d, where each integer is a channel number being assigned to a call in cell k. For example: if $k=1$, $d=4$, available channel numbers = [1,2,3,4,5,6,7,8,9], then a possible solution is $V_1 = [7, 2, 5, 3]$. Our representation is more efficient than Sandalidis et al. [Sandalidis 98a]. Sandalidis et al. used a binary representation where the size of a solution vector is independent of the traffic and is equal to the total number of channels in the system pool. The disadvantage of this representation is that although we are interested only on d channels extra memory is consumed in storing the information about other channels. This representation also yields slower evaluation and manipulation of candidate solutions, due to the size of the binary representation. The other advantage of our representation is that the size of the solution vector is short and thus makes it easier and faster to manipulate the vector.

3.2.2 Initial parent

When a call arrives in a cell k at time t, we determine the set of eligible channels I at time t. Here $I(k,t) = F \setminus (P(k,t) \cup Q(k,t))$, where F is the total set of available channels, $P(k,t)$ is the set of channels of the ongoing calls in k at time t, and $Q(k,t)$ is the set of channels in use in the neighboring area of k at time t. This information is obtained from the allocation matrix. The initial parent solution (that is the very first chromosome) is selected from a set G of λ solution vectors where $\lambda = |I(k,t)|$. Each solution vector in G is evaluated according to the fitness function, and the individual with the best fitness is selected as initial parent. Each solution in G contains a unique integer selected from $I(k,t)$. The remaining $(d-1)$ integers in all solution vectors are the same and are the channels of the ongoing calls in the cell i.e. $P(k,t)$. For instance, let us consider the following example: a call arrives in cell 2 at time t, where $P(k,t) = [2,5]$, $F = [1,2,3,4,5,6,7,8,9]$ and $Q(k,t) = [1,3,6,7,8]$. Therefore, $I(k,t) = [4,9]$, and $\lambda = 2$. Here $d = 3$, therefore the size of a solution in G is 3. The two solution vectors in G are thus: $G_1 = [2,5,4]$ and $G_2 = [2,5,9]$. Out of G_1 and G_2, the fittest solution is selected as initial parent. This way of generating initial parent will reduce the number of channel reassignments and therefore yields a faster running time. The initial parent is also a potentially good solution since channels for ongoing calls were already optimized in the previous call arrival in k.

3.2.3 Fitness function

One of the major hard constraints, the co-channel interference is taken care by the D-ring based strategy. This simplifies our fitness function as compared to Sandalidis et al. [Sandalidis 98a] where there is a separate term in the fitness function that represents of co-channel interference. This also leads to a simpler and faster fitness evaluation than in Sandalidis et al. [Sandalidis 98a]. Our problem representation also takes care of traffic demand constraint. The soft constraints can be modelled as an energy function as shown in equation 3.1. The minimization of this function gives an optimal channel allocation [Sandalidis 98a].

$$E = -W_1 \sum_{j=1}^{d_k} \sum_{i=1 i \neq k}^{C} A_{i,V_{k,j}} . \frac{1}{dist(i,k)} + W_2 \sum_{j=1}^{d_k} \sum_{i=1 i \neq k}^{C} A_{i,V_{k,j}} .(1 - res(i,k)) - W_3 \sum_{j=1}^{d_k} A_{k,V_{k,j}} \tag{3.1}$$

k	:	Cell where a call arrives
d_k	:	Number of channels allocated to cell k (traffic demand in cell k)
C	:	Number of cells in the network
V_k	:	Output vector (the solution) for cell k with dimension d_k
$V_{k,j}$	:	j^{th} element of vector V_k
$A_{i,V_{k,j}}$	:	the element located at the i^{th} row and ${V_{k,j}}^{th}$ column of the allocation matrix A
$dist(i,k)$	:	distance (normalized) between cells i and k.
$res(i,k)$	:	Function that returns a value of one if cells i and k belong to the same reuse scheme, otherwise zero.

W_1, W_2, W_3 are positive constants. The first term expresses the packing condition. The energy decreases if the j^{th} element of vector V_k is also in use in cell i, and cells i and k are free from co-channel interference. The decrease in energy depends upon the distance between cells i and k. The second term expresses the resonance condition. The energy increases if the j^{th} element of vector V_k is also in use in cell i, and cells i and k does not belong to the same reuse scheme. The last term expresses the limiting re-assignment. This term results in a decrease in the energy if the new assignment for the ongoing calls in the cell k is same as the previous allocation. The value of the positive constants determines the significance of the different terms. Such energy function represents our fitness function in our proposed ES.

3.2.4 Mutation

An offspring is generated from a parent by randomly swapping values of the parent vector with the corresponding vector of free channels. The number of swaps lies between 1 and

N (inclusively). The parameter N is the maximum number of swaps and takes the value of the length of the parent vector or the numbers of free channels, whichever is less. Given N, we generate a random number S between 1 and N (inclusively). The parameter S represents the actual number of swaps. For example, if the total number of available channels $|F| = 10$, $k = 1$, $d = 4$, and the parent vector $p = [7, 2, 5, 3]$, then the vector of eligible channels $= [1, 4, 6, 8, 9, 10]$. Here $N = 4$, and if number of swaps is $S = 2$, then one possible offspring is $O = [7, \mathbf{4}, 5, \mathbf{10}]$. Since mutation does not affect the length of the parent vector, and does not result in duplicate copy of any position, it always produces feasible solutions.

3.2.5 ES approach

At a given generation, we randomly generate λ offsprings from the actual parent by mutation and select the fittest solution which will form the new parent for the next generation. If the fittest individual's fitness is worst than the former parent's value, the algorithm tries to locally optimize this value. When the local optimization fails to find a better child within a predefined number of generations, a process called destabilization is applied. This process is used to escape from local optimum. During this process one of three possibilities is selected with probability 1/3 and exactly N number of individuals are mutated with the corresponding vector of free channels to form the parent for the next generation. The process terminates when the destabilization process occurs for the fourth consecutive time. The demand of channels in a cell is also known as traffic. The proposed ES is shown in figure 3.2.

When a new call arrives, the cellular system looks for channels which are not in use in the cell and its neighboring area. If no such channel is found the new call is blocked, otherwise the ES algorithm finds a solution vector V_k with a minimum energy. This vector includes channels for all the ongoing calls and the new call. The allocation matrix is updated, and the existing calls are reassigned if any. This completes a call arrival process.

3.2.6 Complexity Analysis

Our algorithm

In each generation, we mutate and evaluate each string:

- Complexity of doing mutation is $O(d_k)$.
- Complexity of evaluating a chromosome according to equation 3.1 is $O(2d_k \cdot C)$.

Since in each generation we have λ strings, therefore complexity of a generation is $O(\lambda \cdot 2d_k \cdot C)$.

Algorithm of Sandalidis et al.

In each generation, each string is mutated and evaluated.

- Complexity of doing mutation is $O(1)$.
- Complexity of evaluating a chromosome according to equation 2 in [Sandalidis 98a] $O(3F \cdot C)$.

Since in each generation there is λ strings, therefore complexity of a generation is $O(\lambda \cdot 3F \cdot C)$.

The parameter F which represents the total number of available channels in the system is much greater than the parameter d_k which represents the traffic demand at a particular time instant. Moreover the time complexity of evaluating a string is less in our proposed algorithm than the one proposed in [Sandalidis 98a]. Therefore it clearly shows that the time complexity of our proposed algorithm is much less than the one proposed in [Sandalidis 98a].

3.3 HCA with power control

Channel allocation allows the efficient use of the available spectrum and hence has been a topic of intense research for many years. But the interference between reused channels limits the spectrum efficiency. Power control on the other hand, can suppress adjacent channel interference, the co-channel interference, and minimize the consumption of power in terminals. Thus, the problem of channel allocation to maximize channel utilization and the problem of power control to maintain desired signal to interference ratio are highly correlated. Co-channel interference is one of the main impairments that limits the spectral efficiency and also degrades the performance of a wireless link. Most of the papers have solved the problem of channel assignment with the assumption that power is pre assigned and fixed. In reality, when a channel l is assigned to a new call, it might deteriorate the quality of ongoing calls of all other users of channel l. This interference is given by carrier-to-interference ratio (CIR). When channel assignment is done without taking into account the CIR ratio, even infeasible channel assignments can be considered as feasible assignment. This is because for some assignments the CIR ratio in a cell may fall below the desired level. Regulating the transmitted power can reduce this interference seen by other users. The transmitted power is increased if the CIR is low and decreased if the CIR is high. This improves the quality of weak links.A substantial increase in the network capacity by combining dynamic channel assignment with power control has been reported in Foschini et al. [Foschini 95].

3.3.1 Problem statement

We consider the channel assignment coupled with power control for the uplink (mobile terminal to base station) only. We consider a cellular system with C cells and F channels. M denotes the number of users communicating in the same channel.

The goal is to determine whether there exists a channel to serve a new call in such a way that each mobile's CIR is acceptable and if it exists find an assignment of channels that minimizes the total transmitted power.

Let P_i denote the transmitter power of mobile i and T_i denote the base station of the cell where mobile i is located. The CIR of mobile i at base station T_i is then given by equation 3.2.

$$T_i = \frac{P_i g_{ii}}{\sum_{k \neq i}^{M} P_k g_{ki} + N_i} \tag{3.2}$$

where g_{ki} is the link gain (actually power loss) from the transmitter of the k^{th} link to the receiver of the i^{th} link, and N_i is the receiver noise at base station T_i . The link gain includes free space loss, multipath fading and other radio wave propagation effects. It depends upon the particular propagation model of the channel [Bambos 00]. The signal quality is acceptable if it is above a certain threshold γ_0

$$T_i \geq \gamma_0, i = 1 \cdots M \tag{3.3}$$

.

In matrix form equations 3.2 and 3.3 can be written as follows [Rashid-Farrokhi 98]:

$$(I - \gamma_0 F)P \geq U \tag{3.4}$$

where $P = (P_1, P_2, \cdots, P_M)$ is the vector of the transmitter power, U is the vector with elements u_i defined as

$$u_i = \frac{\gamma_0 N_i}{g_{ii}} \tag{3.5}$$

where i lies in the range $1 \leq i \leq M$, and I is an $M \times M$ identity matrix, and finally F is a matrix defined as

$$[F]_{ij} = \begin{cases} 0 & \text{if } j = i \\ \frac{g_{ji}}{g_{ii}} > 0 & \text{if } j \neq i \end{cases} \tag{3.6}$$

U is a vector of noise powers rescaled by CIR requirement and link gains, and F is a cross-link power gains [Bambos 00]. The power control problem we solve has the form [Rashid-Farrokhi 98]

$$\begin{cases} min \sum_{i=1} P_i \\ \text{subject to } [I - \gamma_0 F]P \geq U \end{cases} \tag{3.7}$$

The matrix F has a few important properties [Rashid-Farrokhi 98].

One such property is that: The target CIR γ_0 is achievable if the spectral radius of F denoted by $\rho(F)$ is less than $\frac{1}{\gamma_0}$, the power vector $P' = [I - \gamma_0 F]^{-1} U$ solves the optimization problem. Therefore the CIR requirements of all the links are satisfied simultaneously.

The property can be modelled as a function that reprsents the co-channel interference constraint as shown in equation 3.8

$$\sum_{j=1}^{d_k} interf(V_{k,j}) \tag{3.8}$$

where d_k, j and V_k carry the same meaning as described in section 4. The function $interf(V_{k,j})$ returns a value of one if the CIR of channel j drops below the target value γ_0, otherwise zero. This information is obtained from the matrix F as stated in the above property. This function, combined with packing condition and limiting rearrangement can be modelled as an energy function as shown in equation 3.9.

$$fitness \;=\; A_1 \sum_{j=1}^{d_k} interf(V_{k,j}) - W_1 \sum_{j=1}^{d_k} \sum_{i=1 i\neq k}^{C} A_{i,V_{k,j}} \cdot \frac{1}{dist(i,k)} - W_3 \sum_{j=1}^{d_k} A_{k,V_{k,j}} \tag{3.9}$$

A_1 is a positive constant. The energy increases if the CIR of any element of vector V_k is below the required threshold. The minimization of this function gives an optimal allocation of channel. When a new call arrives, the cellular system applies ES algorithm to find a solution vector with minimum energy. The vector includes channels for all the ongoing calls and the new call. If the CIR of any of the allocated channel of the vector is below the desired level, the solution vector is rejected and the new call is blocked. Otherwise, the call is successful. The allocation matrix is updated, and the existing calls are reassigned if any. This completes a call arrival process.

```
Algorithm:
  Generate initial population of λ individuals
  Evaluate individuals according to fitness f
  Select the best individual Best
  Parent = Best
  loop = 0
  Repeat
    loop = loop + 1
    success = false
    Generate λ Neighbors of Parent by mutation
    Evaluate individuals according to fitness f
    Select the best individual Best_child
    If f(Best_child) > f(Best)
      parent = Best_child
      Best = Best_child
      success = true
      no_of_destabilization = 0
    If success = false
      success1 = false
      counter = 0
      Best_child1 = Best_child
    Repeat
      counter = counter + 1
      parent1 = Best_child1
      Generate λ Neighbors of Parent1 by mutation
      Evaluate individuals according to fitness f
      Select the best individual Best_child1
      If f(Best_child1) > f(Best)
        parent = Best_child1
        Best = Best_child1
        success1 = true
        no_of_destabilization = 0
    Until counter = 20 OR success1 = true
    If success1 = false (apply destabilization)
      no_of_destabilization = no_of_destabilization + 1
      If channels_in_use < free_channels
        N = channels_in_use
      else
        N = free_channels
      With 1/3 probability do either one of
        1. Mutate N genes of Best_child1
             parent = Best_child1
        2. Mutate N genes of Best_child
             parent = Best_child
        3. Mutate N genes of parent
             parent = parent
  Until no_of_destabilization = 4
```

Figure 3.2: Proposed ES algorithm.

Chapter 4

Experimental Results and Discussion

The network simulation was implemented in C++ programming language. In literature, several criteria are used to evaluate the performance of a channel allocation scheme: new call blocking probability, bandwidth utilization, message complexity, and channel acquisition delay. Bandwidth utilization refers to the percentage of system bandwidth capacity used for transmitting useful user packets. Message complexity is defined as the number of messages exchanged for each channel acquisition/ release. The channel acquisition delay refers to the average time required for a cell to acquire a channel. In this thesis the performance of the proposed channel assignment algorithm at a particular traffic load was assessed by measuring the new call blocking probability P_n. The parameter P_n is given by

$$P_n = \frac{A}{B} \tag{4.1}$$

Where A=number of new calls blocked in the system and B =number of new call arrivals to that system. The following sections describe the cellular model assumption, traffic model used in the simulation, and discusses the experimental results obtained from the simulations.

4.1 Cellular model assumption

In this thesis, ES is applied to the mobile cellular model proposed in Del Re et al. [Del Re 96]. The basic characteristics of the model are briefly described as follows:

1. The topological model is a group of hexagonal cells that form a parallelogram shape (equal number of cells along x-axis and y-axis) as shown in the figure 4.1(Adapted From [Del Re 96], Fig. 1, pp.26).The wireless network used for simulation consisted of 49 cells.

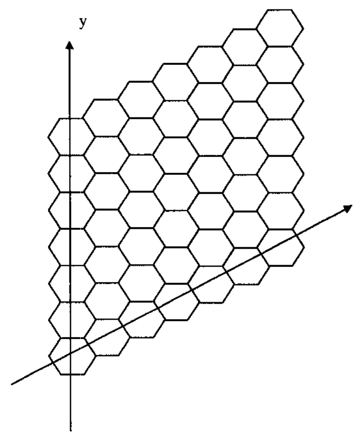

Figure 4.1: Cellular network model.

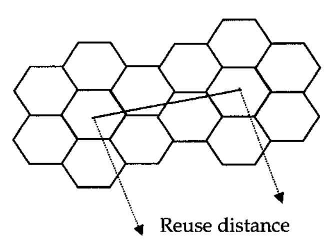

Figure 4.2: Reuse distance used in the model.

2. Cells are grouped in cluster of size 7 cells. The reuse distance is 3 cell units as shown in figure 4.2 (Adapted From [Del Re 96], Fig. 9, pp. 129);

3. A total of 70 channels are available to the whole network. Each channel may serve only one call (i.e. multiplexing techniques are ignored). In FCA, the available

channels are distributed among the cells. In DCA, all channels are put in a central pool. In this strategy channel assignment is made by the controller of the concerned base station according to the knowledge about the neighbors of a given cell.

4. Incoming calls at each cell may be served by any of the system channels.

5. The selection of a channel is only subject to co-channel interference. Other sources of interference are ignored.

6. A call is blocked if the entire set of channels in the network is in use in the cell involved in call arrival and its neighborhood, that is there is no channel that satisfies the co-channel interference.

7. Existing calls in a cell involved in a new call arrival may be rearranged.

With these model assumptions we are able to compare our results with those obtained by [Sandalidis 98a].

4.2 Implementation details

The following sections describe how various parameters used in the simulation are obtained.

4.2.1 Determination of allocation matrix A

The allocation matrix A is dynamic. It is updated every time a call is successful and a call is released. As such allocation matrix A maintains the channel usage information in the network and acts as the central pool of all available channels. At the start of the simulation, A is initialized with zero.

4.2.2 Determination of reuse scheme

Steps:

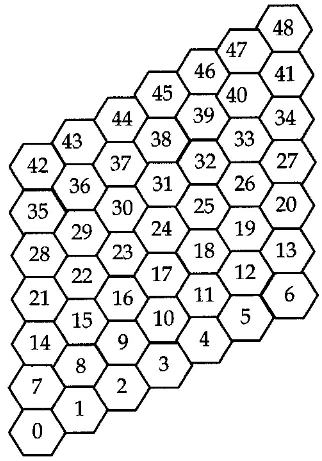

Figure 4.3: Numbering of cell used in the model.

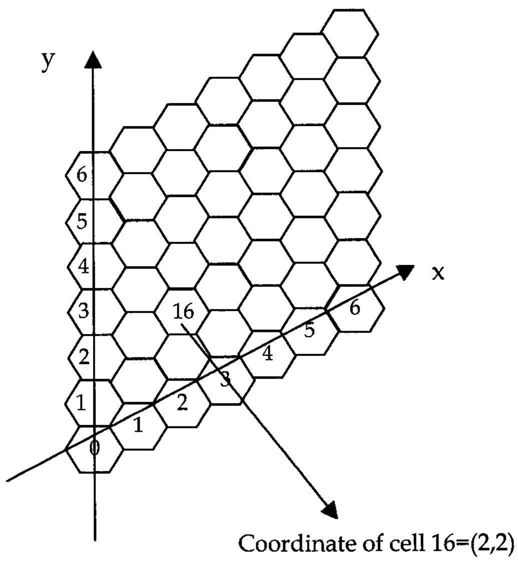

Figure 4.4: Coordinate of a cell.

1. The cells are numbered starting from 0 to $C-1$ (here $C=49$) as shown in figure 4.3.

2. The x and y coordinates of a cell are calculated. For example, the coordinates of cell 16 is (2,2) as shown in 4.4.

3. A reuse distance of 3 cell units with $i=1$ and $j=2$ has been considered to locate the co-channel cells as in [Sandalidis 98a]. These parameters divide the

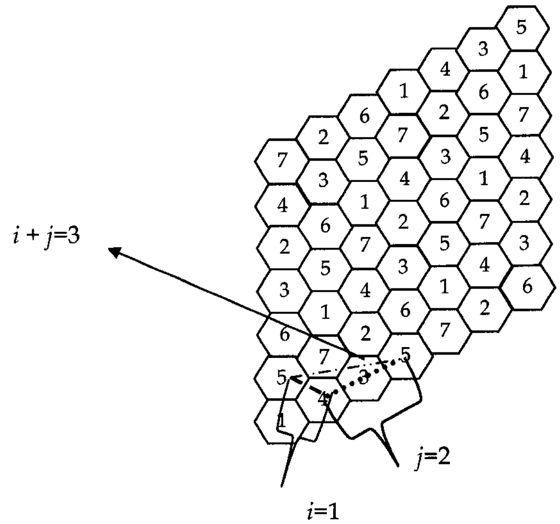

Figure 4.5: Reuse distance calculation with i=1 and j=2.

Y coordinate \ X coordinate	0	1	2	3	4	5	6
0	1	5	6	3	2	4	7
1	4	7	1	5	6	3	2
2	3	2	4	7	1	5	6
3	5	6	3	2	4	7	1
4	7	1	5	6	3	4	4
5	2	4	7	1	5	6	3
6	6	3	2	4	7	1	5

coordinate.eps

Figure 4.6: Co-channel cell matrix.

parallelogram topological model with 49 cells into seven different co-channel cell groups or seven clusters as shown in the figure . Each group has equal number of cells (the same effect can be obtained with $i = 2$, and $j = 1$). From figure 4.3 and figure 3, the co-channel cells of cell 0 are: 11, 15, 26, 30, 41, and 45. These cells belong to co-channel cell group 1. We have defined a matrix called co-channel matrix as shown in figure 4.6 based on figure 4.2. The co-channel matrix is a 5×5 matrix as given below where rows represent the x coordinate of the cells and columns represent the y coordinate of the cells. The element in the i^{th} row and j^{th} column represents the co-channel cell group. Therefore, if the i^{th} row and j^{th} column of the co-channel matrix contains the same number for two given cells, then the two cells belong to the same reuse scheme otherwise not.

4.2.3 Determination of distance between two cells i and K

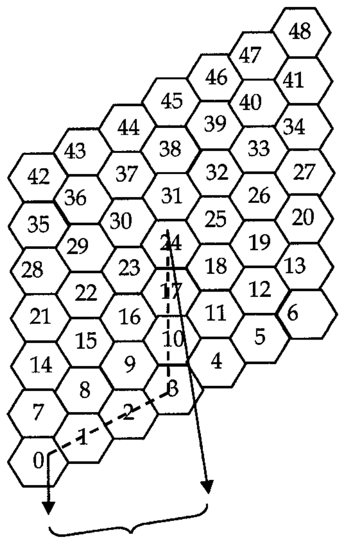

Figure 4.7: Distance between two cells

The distance between two cells is the Manhattan distance. The distance between any two cells is the minimum number of steps needed to move from the center of one cell to the center of the other. A step is the distance between the centers of two adjacent cells, and is also considered the unit distance, that is it has value of 1. For example, if $i = 0$ and $k = 24$. The minimum number of steps required to go from cell i to cell k is 6 as shown in figure 4.7.

4.3 Traffic model

In the model, we assume the traffic model to follow the blocked-calls-cleared queuing discipline. An incoming call is served immediately if a channel is available, otherwise the call is blocked and there is no queuing of blocked calls. The most fundamental characteristics of this model include:

1. Infinite number of users

2. Finite number of available channels
3. Memory-less arrival of requests
4. Call arrival follows a Poisson process with mean arrival rate of λ (calls /hour)
5. Call duration is exponentially distribution with mean x.
6. Inter-arrival time follow a negative exponential distribution with mean x.

The product of the mean arrival rate and the mean call duration gives the traffic load offered to the cellular network. The traffic in the cellular network may either follow uniform or non uniform distribution. In uniform traffic distribution, every cell has the same traffic load. In non uniform traffic distribution, every cell has a different call arrival rate. Non uniform traffic distribution is realistic.

The assumptions and parameters used in the simulation include:

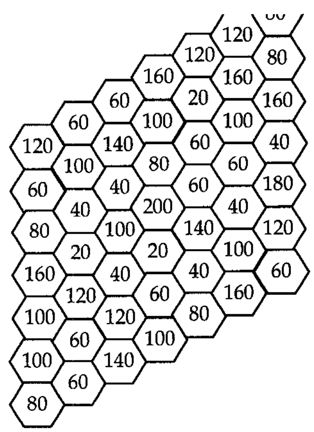

Figure 4.8: Non uniform traffic distribution pattern 1 with initial Poisson arrival rates (Calls/hour).

- For non uniform traffic distribution, we consider the traffic patterns proposed in [Sandalidis 98a] shown in figures 4.8 and 4.9. The figures inside the cell represent the mean call arrival rate per hour.
- call holding time is 180 seconds.

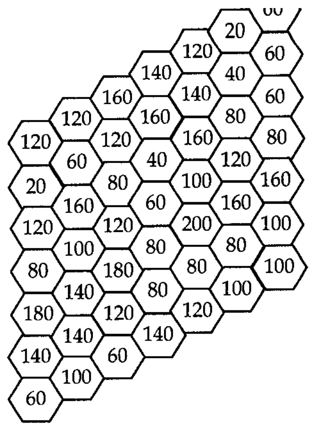

Figure 4.9: Non uniform traffic distribution pattern 2 with initial Poisson arrival rates (Calls/hour).

With these simulation hypothesis we are able to compare our results with those obtained in [Sandalidis 98a].

4.4 Simulation procedure

Let us consider table 4.1 to understand how the simulation works. The column under the heading "*Simulation clock*" shows the time as the simulation progresses, the column under the heading "*Future Event List*"(FEL) shows the list of events to occur in future with the first entry showing the arrival of a call event, and the second entry showing the release of a call event, the column under the heading "*comment*" explains the events in the order that have occurred during that particular time (a*and r* are generated inter arrival call time and call duration time respectively).

At time Clock=0, the first call arrives in the system, and both a call arrival event, and a call release event is entered into FEL. As soon as Clock=0 is completed, the simulation begins. At time 0, the imminent event is (A, 2.03). The clock is advanced to 2.03, and (A, 2.03) is removed from FEL. A call arrival event is executed, and a next call arrival time is entered into FEL. Next the clock is advanced to the next imminent event

Simulation Clock (in seconds)	FEL	Comment
0	$(A, 2.03), (R, 4)$	1. First Arrival Of Call Occurs. 2. (a*=2.03) Schedule the next arrival of call A. 3. (r *=4) Schedule the first release of a call.
0 + 2.03=2.03	$(A, 1.5), (R, 4)$	1. Second arrival Of call occurs. 2.(a*=1.5) Schedule next arrival of call A.
2.03 +1.5=3.53	$(A, 5), (R, 4)$	1. Third arrival of call occurs. 2. (a*=5) Schedule next arrival of call A.
3.53 + 4=7.53	$(A, 5), (R, 6)$	1. First Release of a call occurs. 2. (r*=6) Schedule next release of call R.

Table 4.1: A sample simulation table

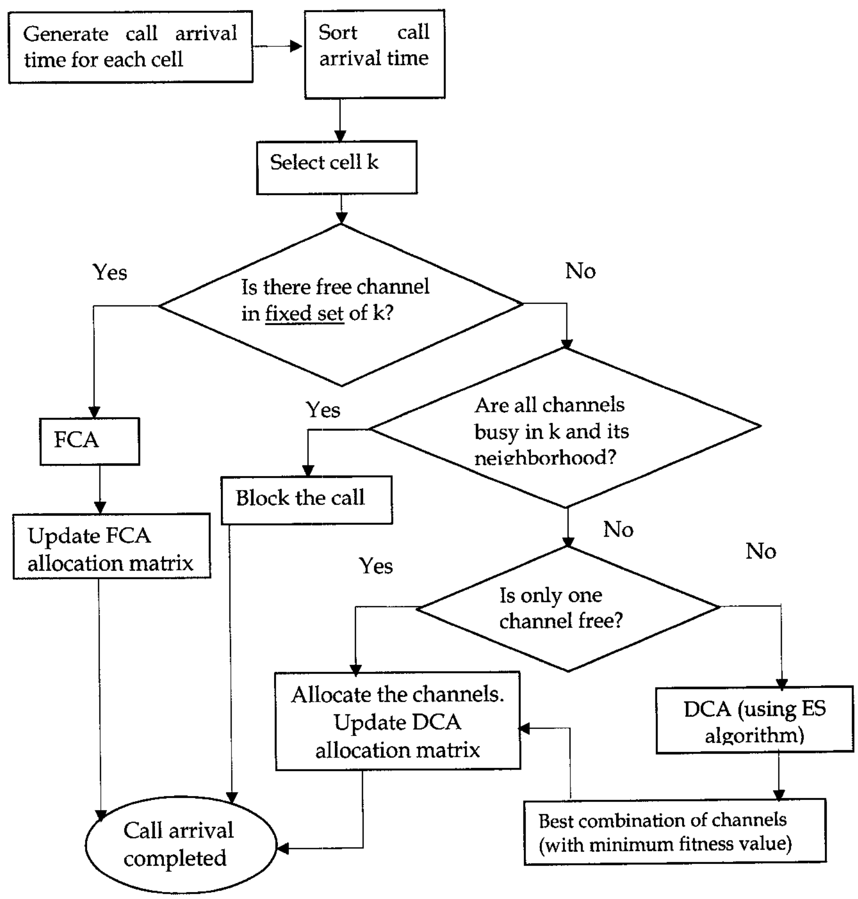

Figure 4.10: Simulation of call arrival event in D-ring HCA Strategy.

time, which is an arrival event and an arrival event is executed, and next arrival event is entered into the FEL. In this way the simulation progresses by executing the imminent

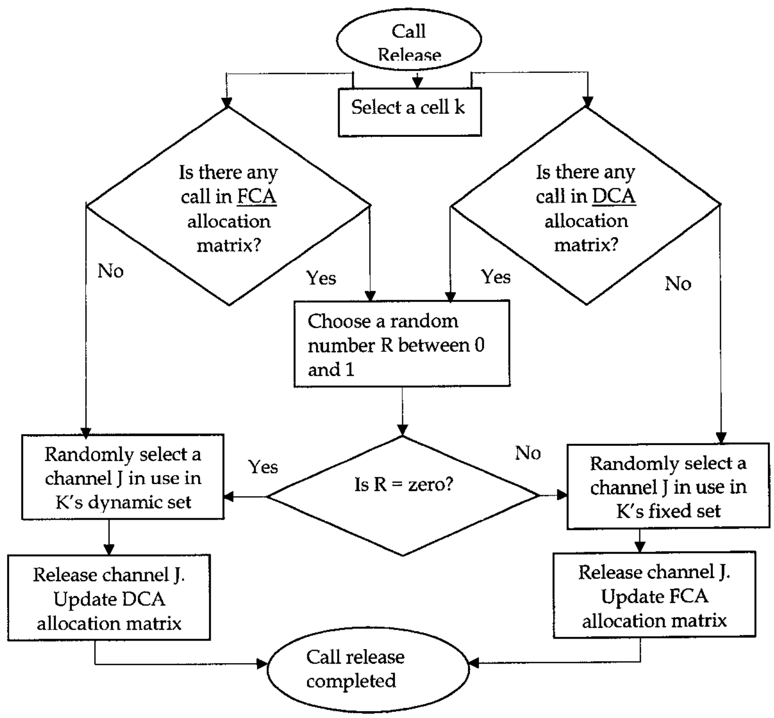

Figure 4.11: Simulation of call release event.

event and advancing the simulation clock accordingly until the simulation clock is less than 3600 seconds. After processing each event, the channel usage information the cell involved in call arrival is updated. To measure the system performance, the number of new call arrivals and new calls blocked in the system is recorded. Figure 4.10 shows the flowchart for the implementation of call arrival event for D-ring HCA strategy, 4.12 shows the flowchart for the implementation of HCA with power control proposed in section 3.3 and figure 4.11 shows the flowchart for the implementation of call release event in both D-ring HCA strategy and HCA with power control.

4.5 Results

In HCA, the total set of available channels is divided into two sets: fixed set and dynamic set. When a call arrives in a randomly selected cell, the cellular system first makes an attempt to serve it from the fixed set of channels. When all the channels in the fixed set are busy, the cellular system applies ES algorithm to find a suitable combination of channels.

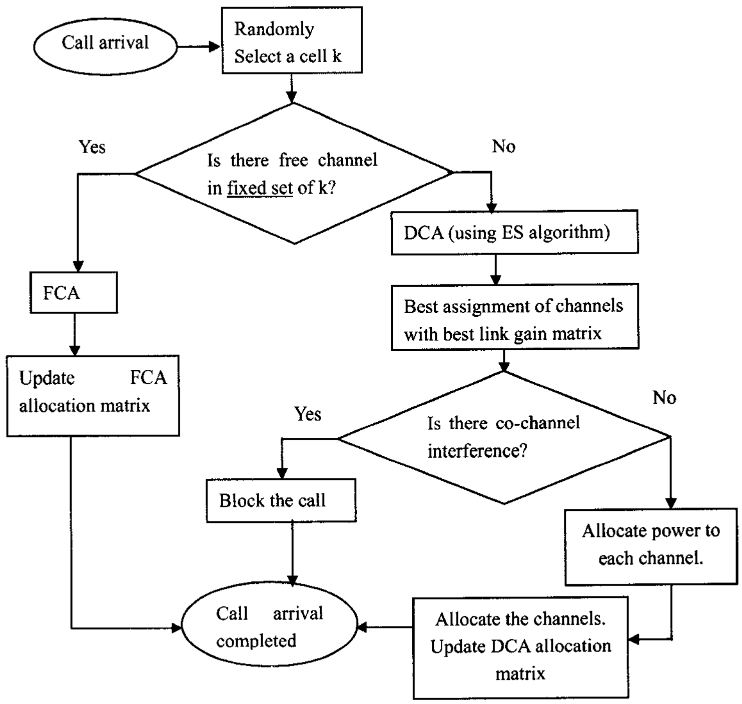

Figure 4.12: Simulation of call release event in integrated power control and HCA.

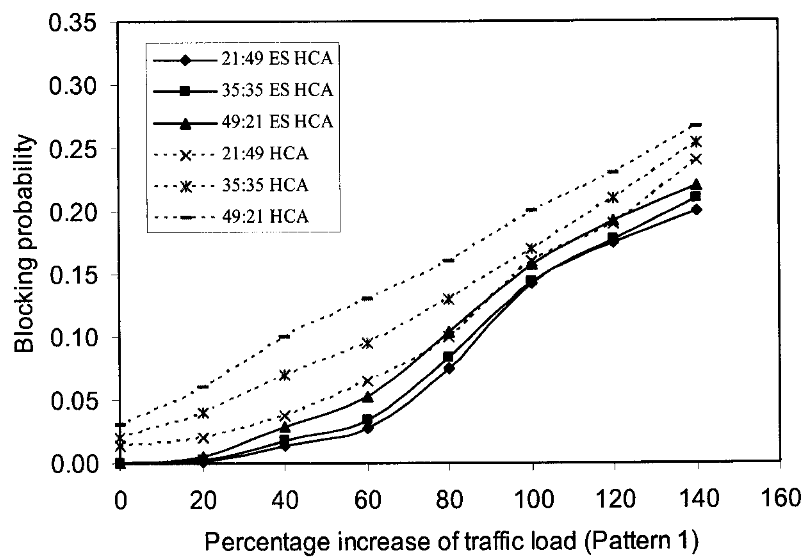

Figure 4.13: Performance of the proposed ES algorithm in terms of blocking probability for the entire cellular network with non uniform traffic distribution according to pattern 1 (Fig. 4.8).

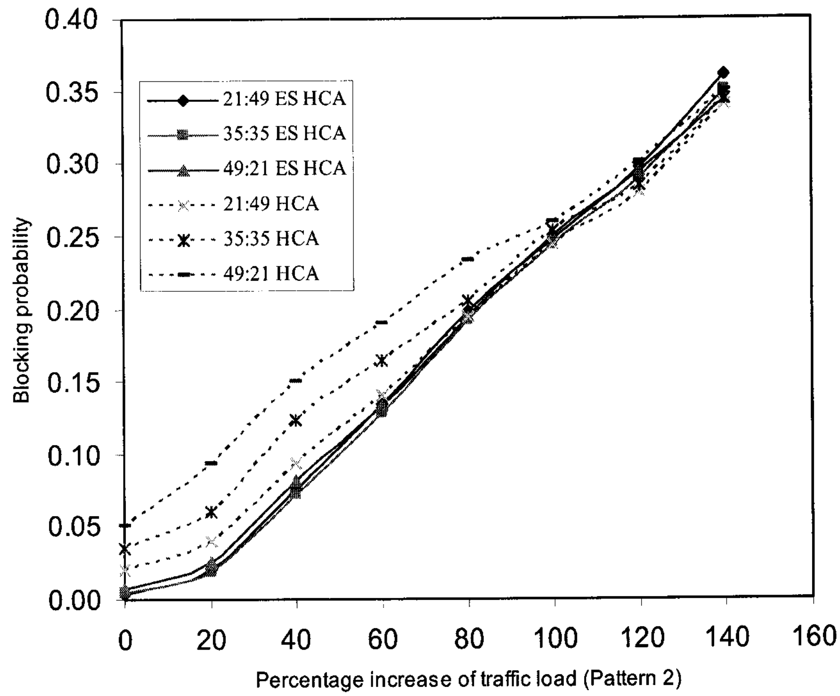

Figure 4.14: Performance of the proposed ES algorithm in terms of blocking probability for the entire cellular network with non uniform traffic distribution according to pattern 2 (Fig. 4.9).

In the simulation, the following representative ratios proposed in [Sandalidis 98a] were used: 21:49 (21 channels in the fixed set and 49 channels in the dynamic set), 35:35, and 49:21. Researchers in mobile communication consider the blocking probability of calls as a proper performance index of channel allocation techniques [Sandalidis 98a]. So, the performance of the proposed ES based algorithm for channel allocation has been derived in terms of the blocking probability for the new incoming calls. The blocking probability is computed for the for the whole network. The values of the positive constraints considered in this paper are as follows: W1=1.5, W2=0.5, and W3=1, same as in Sandalidis et al. [Sandalidis 98a]. The value of λ in the proposed ES is taken to be 40. The simulation results are summarized in figure 4.13 for traffic pattern 1(Fig. 4.8) and in figure 4.14 for traffic pattern 2 (Fig. 4.9).

The simulation results were obtained by increasing the traffic rates for all the cells of both the patterns by a percentage ranging from 0-140 with respect to the initial rates

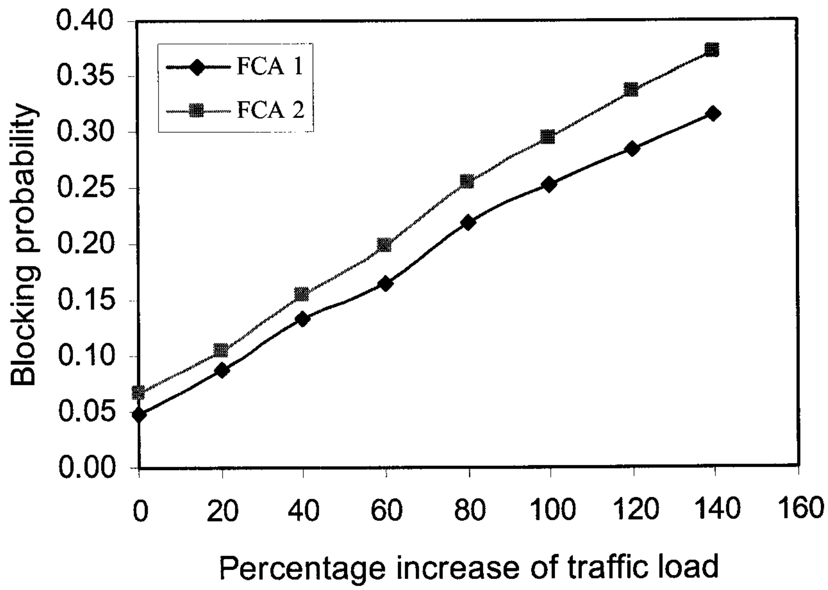

Figure 4.15: Performance of FCA scheme in terms of blocking probability for non uniform traffic distribution according to pattern 1 (Fig. 4.8) and pattern 2 (Fig. 4.9).

of the same cell (as in [Sandalidis 98a]). In these figures the legends with ES HCA show our results and the legends with HCA and dotted line show the results obtained in [Sandalidis 98a]. The results of theoretical FCA for traffic pattern 1 (Fig. 4.8) and traffic pattern 2 (Fig. 4.9) are summarized in Figure 4.15. The results are same as reported in Sandalidis et al. [Sandalidis 98a]. The performance of the proposed algorithm has been compared with the channel allocation schemes proposed in [Sandalidis 98a]. According to our simulations the proposed algorithm produces better results for all the representative ratios for traffic pattern 1 (Fig. 4.8) in comparison with Sandalidis et al. Among all the representative ratios, the best performance was obtained with the 21:49 scheme. However, in terms of running time 49:21 is faster. For traffic pattern 2, our algorithm shows better results for all the representative ratios up to 100 percentage of traffic increase. Beyond 100 percentage the results obtained are as least as good as reported in [Sandalidis 98a]. Tables 4.2–4.4 summarizes the characteristics of the ES based allocation algorithms.

Maximum number of generations	18
Average number of generations	5
Minimum number of generations	4

Table 4.2: Characteristics of 21:49 ES-HCA

Maximum number of generations	19
Average number of generations	5
Minimum number of generations	4

Table 4.3: Characteristics of 35:35 ES-HCA

Maximum number of generations	14
Average number of generations	5
Minimum number of generations	4

Table 4.4: Characteristics of 49:21 ES-HCA

Chapter 5

Conclusion and Future Directions

Channel assignment is an important resource allocation problem in wireless mobile communication. Many heuristics have been proposed in the literature to find an (near) optimal assignment of channels. This thesis has modelled the HCA based on the interference rings and has proposed an ES algorithm to perform channel allocation. ES based algorithm has the advantage of producing reliable solutions in a smaller number of generation as compared to other heuristics such as Genetic algorithm. This is because at each generation only one parent produces all the feasible solutions [Sandalidis 98a]. The greatest advantage of using heuristics is its capability to handle both reassignment of existing calls and allocation of new ones as a unified process [Sandalidis 98a]. Our proposed algorithm uses an integer representation to represent the solution vector. The advantage of our representation over the one used in Sandalidis et al.[Sandalidis 98a] is that it reduces the computation time involved in the calculation of the energy when the demand of channel is less than the total number of available channels. This is generally the case. This is the greatest advantage of our method since time efficiency is an essential factor for the practical utilization of channel assignment techniques. The concept of neighboring area avoids the selection of channels that result in co-channel interference. Therefore, the time required in the determination of co-channel interference is reduced. The chosen representation and the mutation operator also guarantees the feasibility of the solution.

According to our simulations the proposed algorithm produces better results for all the representative ratios for traffic pattern 1 (Fig. 4.8) in comparison with Sandalidis et al. Among all the representative ratios, the best performance was obtained with the 21:49 scheme. However, in terms of running time 49:21 is faster. For traffic pattern 2, our algorithm shows better results for all the representative ratios up to 100 percentage of traffic increase. Beyond 100 percentage the results obtained are as least as good as reported in [Sandalidis 98a]. The real-time simulations carried out in a mobile communication system with 49-cell and 70 channels have demonstrated that our scheme is a good alternative existing schemes.

In this thesis, we have proposed a novel method of combining the problem of channel assignment with power control. The advantage of the proposed method is that it includes reassignment of existing calls. Another advantage is that when a channel is allocated to a new call, power levels of all users using that channel is updated simultaneously. We are currently investigating the performance of the algorithm in terms of call blocking and dropping probability.

Future research directions: The following are some of the interesting open problems related to my research in this area:

- The performance of the proposed algorithm in terms of solution and time can be investigated for different mutation operator, and different ways of generating initial population. In this thesis, we have investigated the mutation operation in which maximum N number of genes are swapped. Some of the other mutation operation may include the swapping of exactly N number of genes, and a mutation operator which involves the generation of neighborhood state of a solution vector as in Tabu Search. The initial population can also be generated randomly.

- The performance of the proposed algorithm can be investigated for different network model and different reuse distance.

- The performance of the algorithm can be investigated without using the neighboring area concept. For this the co-channel interference term in the fitness function of Sandalidis et al. [Sandalidis 98a] have to be introduced in the fitness function. Ni in [Ni 97] has shown that the maximum interference is in the first ring of interfering cells, and it gradually decreases with the increase in the distance between the host cell and the interfering cell. Taking into consideration the findings in [Ni 97], the co-channel interference term can be modified to associate cost with an interfering cell as per its location.

- Our algorithm and problem representation can be investigated for other channel assignment techniques such as DCA and Borrowing Channel Assignment.
- We have considered the theoretical FCA in which the total number of channels available in the fixed set are equally distributed to all the cells in a cluster, and has only optimized the dynamic part of the proposed D-ring HCA strategy.
  - An optimization method can be used to allocate channels from the fixed set to each cell based on the traffic intensity of the cell.
  - The assignment of channels in the fixed set can be done based on the actual CIR in the service area.
- Algorithm proposed in Sandalidis et al. [Sandalidis 1998a] can be investigated with our representation and D-ring scheme.
- The method of combining channel assignment with power control proposed in this thesis can also be implemented in a distributed way.
- We have considered the base station assignment to be known. Optimal assignment of base station along with channel and power can be investigated.

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