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**INTEGRATED HYBRID CHANNEL ASSIGNMENT  
AND DISTRIBUTED POWER CONTROL IN  
WIRELESS MOBILE  
NETWORKS USING EVOLUTION STRATEGY**

**By  
TAHIRA FARID**

**A Thesis Submitted to the Faculty of Graduate Studies and Research  
through School of Computer Science  
in Partial Fulfillment of the Requirements for the Degree of  
Master of Science at the University of Windsor**

**Windsor, Ontario, Canada**

**2006**

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# Abstract

The primary goal of a cellular radio system is to provide communication services to a large number of mobile users. However, the increasing demand of new services in this field is in contrast to the limited resources such as radio spectrum and transmitter power available in the current communication systems. As the number of mobile users grows rapidly, available channels and transmitter power must be used efficiently to improve the system capacity. The role of Channel Assignment is to allocate channels to cells or mobiles in such a way as to minimize call blocking or call dropping probabilities, as well as to maximize the quality of service. On the other hand, 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 and vice versa.

In this thesis, we develop an efficient evolution strategy to address the problem of integrating Channel Assignment and Power Control. The proposed approach uses an efficient problem representation, defines an appropriate fitness function and mutation operators to optimize both Channel Assignment and Power Control. Our experiments and discussions show better system capacity, decrease in the blocking probability while maintaining the desired carrier-to-interference (CIR) ratio compared to the experiments done in literature employing only Channel Assignment.

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# Chapter 1

## Introduction

### 1.1 Mobile Communication

Mobile communication is the fastest growing field in the telecommunication industry. 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 when personnel of the Detroit police department's radio bureau began experimenting on a band near 2 MHz for vehicular mobile service. In 1928 the department commenced regular one-way radio communication with its patrol cars. Further progress was made in 1933 when one police department in New Jersey initiated regular two way communications with its patrol cars, a major advance over previous one-way systems. This two way radio became standard throughout the country as the very high frequency system placed transmitters in patrol cars to enable patrolmen to communicate with headquarters and other cars instead of just receiving calls.

The mobile telephony services were extended to the commercial arena towards the end of the Second World War. By late 1940s, Bell Systems embarked on a program of supplying "public correspondence systems" (communication among a variety of users provided by a common carrier. Federal Communi-

cation Commission (FCC) classified these services as Domestic Public Land Mobile Radio Service (DPLMRS). In 1946, the first interconnection of mobile users to the public telephone network was made to allow calls from fixed stations to mobile users, when 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 became difficult to reuse the same frequency. The inefficient use of spectrum severely limited the system capacity. By 1969, ITMS (Improved Mobile Telephone Service) became the first standard automatic 450 MHz frequency range service which allowed assignment of free channels automatically and the system was full duplex and customers could do their own dialing. In spite of the fact that mobile service was, indeed, a scarce luxury, by late 1970's, the demand for service was rising rapidly [38].

A solution to this problem emerged in 1974 when researchers at Bell Laboratories in USA developed the concept of wireless cellular telephone system and eventually the authorization was granted to Illinois Bell in 1978. 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. This cellular organization allowed frequency reuse among geographically distant cells, thus greatly expanding the system capacity [47], [56]. It also allowed cells to be sized according to subscribers' density and traffic demand of a given area.

## 1.2 Evolution of Cellular Systems

The Nordic Mobile Telephone System (NMT) was the first to introduce cellular services for commercial use in Sweden in 1981 using frequencies in the

450 to 900 MHz band. In 1983, cellular systems began in the United States in Chicago with the release of the Advanced Mobile Phone Service (AMPS) operating in 800 MHz, and other cities followed rapidly. Asia, Latin America and Oceanic Countries later adopted to the AMPS standard and AMPS emerged as the largest potential market for cellular communications. Britain introduced another technology called Total Access Communications Systems (TACS) in 1985, operating at 900 MHz. Many other technologies were developed, however, AMPS, NMT and TACS were the most successful technologies [67]. These are all part of the "First Generation" cellular systems and were analog systems providing only basic speech services.

Despite of the popularity of the analog systems, they were unable to handle the growing capacity needs in a cost efficient manner. Each system followed different standard making 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 three standards; one for Europe and international applications known as Global Mobile Systems (GSM), one for North America known as IS-54 or TDMA (North American Digital Cellular), and a one for Japan known as Japanese Digital Cellular (JDC). The advantages of digital systems over analog system included ease of signaling, lower levels of interference, integration of transmission and switching, higher capacity potentials, and new services like data services, encryption of speech and data and Integrated Services Digital Network [71]. Second generation cellular systems are, however, still optimized for voice services and are not well suited for data communications.

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 times) to these services. The "Third Generation"

cellular 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) [71].

### 1.3 Cellular Radio Systems

The beginning of cellular concept gave a major breakthrough in the development of mobile communication systems. Though most people say "cell phone", this term is actually short for "cellular phone", which is named after the wireless technology that they work on. The cellular principle divides a covered geographical area into a set of smaller service areas, called cells. Four possible geometric shapes were proposed for the design and layout of the cellular system: the circle, the square, the equilateral triangle, and the regular hexagon. Among the four, the regular hexagon was found to be the best over the other shapes [46]. In practice, the cell sizes are irregular and depend on the terrain and propagation condition. Figure 1.1 shows typical cellular system architecture.

Each cell has a base station and a number of mobile terminals i.e. mobile phones, palms, laptops, or other mobile devices. The base station is equipped with radio transmission and reception equipments. The mobile terminals communicate through wireless links with the base station associated with the cell. The base station provides the interface between the mobile telephone switch office (MTSO) and the mobile units scattered across a cell. The MTSO is the



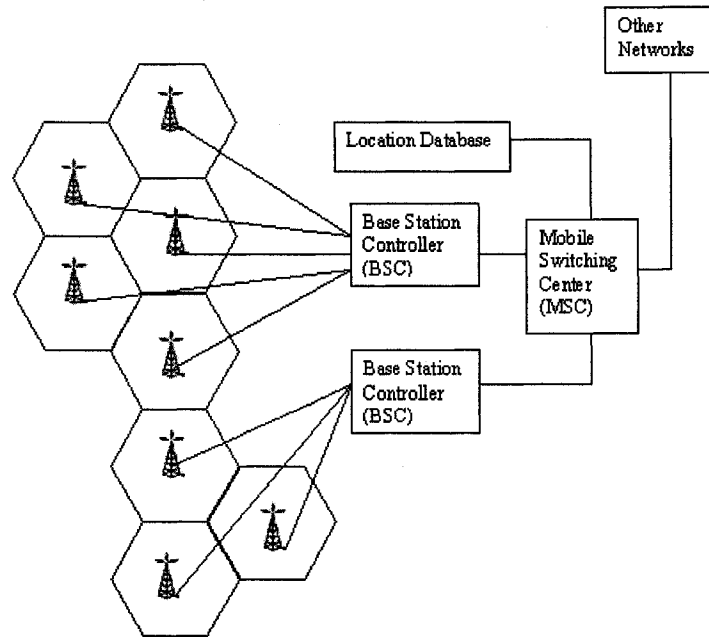


Figure 1.1: Cellular Network Architecture

central coordinating element for all cell sites, controls call processing, handles billing activities, performs channel assignment, and provides the necessary connection with the public switching telephone network (PSTN) [61]. 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 mobile terminals as long as they are within its operating range and the operating range depends on 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.

## 1.4 Channel Assignment

To establish communication with a base station, a mobile terminal must obtain a channel from the base station. A channel comprises of two frequencies; one frequency (the forward link or downlink) for transmission from the base station to the mobile terminal, the other frequency (the reverse link or uplink) for transmission from the mobile terminal to the base station. As these two channels are assigned simultaneously, however, in many studies they are considered as one single link. This ideal link is considered to be a generic communication resource depending on the multiple access technique used by the cellular network and may be a fixed radio frequency for a frequency division multiple access (FDMA), or a particular time slot within a frame for a time division multiple access (TDMA), or a specific code for a code division multiple access (CDMA) [58].

The capacity of a cellular system can be described in terms of the available channels or the 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 since the number of mobile users is increasing everyday, the channels must be reused as much as possible to increase the system capacity. This requires proper channel assignment scheme. The role of a channel assignment scheme is to allocate channels to cells or mobiles in a way as to minimize the call blocking or call dropping probabilities, and also to maximize the quality of service.

### 1.4.1 Channel Assignment Schemes

Many channel assignment schemes have been studied extensively to maximize the frequency reuse. Channel assignment is generally classified into two categories: Fixed Channel Assignment (FCA) and Dynamic Channel Assignment (DCA). 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 as 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 [15]. DCA method makes cellular systems more efficient in real-life scenarios where the traffic distribution is unknown or changes with time, but has the disadvantage of requiring more complex control and is generally time consuming [61].

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 outperforms most known DCA schemes under heavy load conditions [Lai 96 from GT]. Various extensions or combinations of FCA and DCA schemes have been discussed in the literature. The most basic are the Hybrid Channel Assignment (HCA)[73] and the Borrowing Channel Assignment (BCA) [11]. HCA combines the feature of both FCA and DCA and one set of channels are allocated as per the FCA scheme and another set is allocated as per the DCA scheme. In BCA, the channel assignment is initially fixed. If a cell has all the channels occupied, for incoming calls the cell borrows channels from its neighboring cells and thus call blocking prevented [61]. A comprehensive survey on channel assignment schemes can be found in [39].

#### **1.4.2 Channel Assignment Constrains**

In the process of channel assignment, radio transmission in a channel may cause interferences in other channels. Such interferences degrade the signal quality and the quality of service. Some of the potential sources of radio interference to a call are Co-channel Interference (caused by allocation of the same channel to certain pair of the cells close enough to cause interference), Adjacent Channel Interference (caused by allocation of adjacent channels to certain

pairs of cells simultaneously) and Co-site Interference (caused by allocation of channels in the same cell that are not separated by some minimum spectral distance). These constraints are known as hard constraints or electromagnetic compatibility constraints [50]. To overcome the hard constraints like cochannel interference constraint, heuristics have been proposed in studies for FCA and DCA including simulated annealing [20], tabu search [9], neural networks [41], [25] and genetic algorithms [16], [43], [18] and Evolutionary Strategy [61]. The process of Channel Assignment must satisfy the hard constraints and the demand of the channels in a cell. Beside these constraints there are some other conditions that may improve the performance of the channel allocation technique. These conditions are called soft constraints and are the packing condition, the resonance condition and the limitation of reassignment operations [58].

With the packing condition, the minimum number of channels is used every time a call arrives. This condition allows the use of channels that are already in use in other cells without violating the cochannel interference constraint.

The resonance condition allocates the same channels to cells that belong to the same reuse scheme. Reuse scheme allows 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 reused distance.

Finally, limiting reassignment tries to assign, where possible, the same channels assigned before, thus limiting the reassignment of channels. This is due to the fact that excessive rearrangement may lead to undesirable results in terms of blocking probability [61].

### 1.4.3 Dynamic Channel Assignment

The traditional channel allocation method, the Fixed Channel Allocation (FCA) is not very efficient for utilization of available spectrum, and impractical in microcell communication systems as large number of cells, irregularities in propagation and traffic distribution make pre-allocation of channels almost impossible. Dynamic Channel Allocation (DCA) had long been pursued as the answer for coping with time and spatial variations of traffic demand in communication networks.

In DCA, 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. DCA can be depicted 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  $t$ . then the set of eligible channels in  $k$  at time  $t$  is given by  $I(k, t) = F - P(k, t)$ . The problem of DCA is to choose channels from the set  $I(k, t)$  as carefully as not to select any interfering channels in the eligible channel poll.

## 1.5 Power Control

Power must be given to a transmitter to support 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 the Signal-to-Interference Ratio (SIR) or the Carrier-to-Interference Ratio (CIR). CIR is defined as the ratio between the desired averaged received signal power from the transmitter of the cell where it is located and the overall averaged received signal power from transmitters using the same channel including the background noise [60]. The signal quality and

the level of interference in the network depend upon the transmitter power. Power control is a resource management process that is used to adjust transmission power in each base-mobile link such that the interference in other receiver locations is minimized, the signal quality is maintained.

Power control can suppress the adjacent channel interference, the cochannel interference, and minimize power consumption to extend terminal battery life. Undoubtedly power control can raise the network capacity. It consists of techniques and algorithms used to manage and adjust the transmitter power of base stations and mobile terminals. This is required for the forward link as well as the reverse link.

### 1.5.1 Related Studies

In the design of large high capacity cellular radio systems, cochannel interference caused by frequency reuse is the single most limiting factor on the system capacity. Many transmitter power control schemes have been proposed to control this interference for a given channel allocation. Most of the early work in power control schemes has focused on algorithms that aim at keeping the received power of the desired signal at some constant level. This has the favorable effect that the requirements on the receiver dynamic range are smaller, which results in better adjacent channel protection [79]. Results indicate an increase of capacity by roughly a factor of two compared to systems with fixed transmitter power. However, detailed investigations show that the constant-received power control has only limited ability to reduce cochannel interference.

In [1], Aein took an analytical approach towards frequency reuse interference in satellite systems and introduced the concept of CIR balancing. The balancing concept was successfully used in [3] in the context of cellular radio in general and spread-spectrum systems in particular which was further investigated to construct power control procedures to minimize the interference

probability in [77] and [78]. These power control procedures along with some other centralized approaches, however, depend on full knowledge of the gain in all propagation paths, both intended base-mobile paths and unwanted, interference paths. Therefore, these optimum algorithms serves mainly as a tool to derive upper bounds on the performance of interference control schemes, rather than being suited for actual implementation [79].

Many distributed power control approaches have been proposed and investigated which are suitable for practical implementation and require far less measurements and allow distributed operations. In [2], author proposed a simple proportional control algorithm which increases the transmitter power when the CIR level is too low and decreases the power when the CIR level is more than adequate. 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 [49], [73], [36], a combination with base station assignment has been studied in [34], [75]. In [55], 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 simultaneous assignment of base stations and power levels.

The power control algorithms proposed in literature can be broadly classified as centralized or decentralized (distributed). Centralized power control schemes have been proposed in [1],[28], [77], [78] while many decentralized power control schemes have been proposed and can be found in [23], [29], [74], [79]. A centralized power control has a central controller that maintains information about all the radio links in the system and it decides control actions for all users. A detailed study on the power control problem can be found in [60]. On the other hand, a distributed controller only controls the power of one single transmitter based on local information. In this thesis, we propose a distributed power control strategy coupled with hybrid channel assignment to result in a stable, distributed algorithm.

Different approaches towards the optimization of integrated channel assignment (DCA) and power control have been proposed in [14], [24], [31], [45], [49], [63]. In this thesis, we propose a distributed power control strategy coupled with hybrid channel assignment to optimize channel allocation in such a way that the CIR requirements are met to maintain desired signal quality and minimum power is consumed.

## 1.6 Fundamentals of Evolution Strategy

In this section, we briefly describe a heuristic approach called Evolution Strategy (ES) which is the main optimization tool used in our optimization problem. Rechenberg [59] pioneered ES. This method belongs to the general category of heuristic optimization methods called Evolutionary Algorithms (EA). EA was proposed in 1990 to describe a class of direct, probabilistic search techniques based on the selection mechanism adopted by natural systems [5]. Genetic Algorithms (GA), Genetic Programming (GP), Evolution Strategy (ES) and Evolutionary Programming (EP) are some of the representatives of EA. A survey on GA, EP, and ES can be found in [22].

ES was initially applied on optimization problems with discrete variables. In ES, the pool of candidate solution is known as the population and the total number of individuals in a population is known as the population size. Each individual solution is associated with an objective value. The objective value represents 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. In ES, a candidate solution (offspring) is produced from a given existing solution (parent) by applying various reproduction operators like mutation and recombination. Mutation adds vectors of Gaussian random variables with zero mean and specified standard deviation to each individual which also has the form of a vector



[61]. With recombination operator, mixing of different solutions is achieved. The best solution generated in one generation becomes the parent for the next generation. It is an iterative method, therefore, the process of selection and application of reproduction is repeated until a terminating criterion is met. At the end, the solution of the problem is represented by the best individual so far in all generations. Following the basic steps involved in an ES algorithm:

1. Generate  $\lambda$  individual as the initial population
2. Evaluate individuals according to fitness  $f$
3. Select  $\mu$  best individuals as the parent population and discard the rest
4. Apply reproduction operator i.e. mutation to create  $\lambda$  offspring from  $\mu$  parents
5. Continue from Step 2 until the termination criteria is met or the pre-determined number of generations have been produced and evaluated.

Schwefel [68] introduced two common variations of ES;  $(\mu + \lambda)$ -ES and  $(\mu, \lambda)$ -ES. Both the approaches use  $\mu$  parents to produce  $\lambda$  offsprings. However, they differ in the selection of individuals for the next generation. In  $(\mu + \lambda)$ -ES,  $\mu$  best individuals from all the  $(\mu + \lambda)$  individuals are selected to form the next generation, but in  $(\mu, \lambda)$ -ES,  $\mu$  best individuals from the set of  $\lambda$  are selected to form the next generation. In this thesis, we take the model used by Nissen in [51], and [52] to adapt to the ES heuristics to our specific problem. Following Nissen, ES is a  $(1, \lambda)$ -ES, where one parent generates  $\lambda$  offsprings and individuals are vectors of integers that are generated from parents by randomly swapping values. Figure 1.2 depicts a typical representation of a solution in ES and Figure 1.3 and 1.4 depicts the concept of ES and the swapping operator. We also employ  $(\mu + \lambda)$ -ES with  $\mu = 1$  and compare both  $(1, \lambda)$ -ES and  $(1 + \lambda)$ -ES.  $(\mu + \lambda)$ -ES has been adopted from [54].

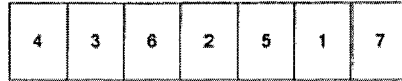


Figure 1.2: A Typical Representation of a Solution in ES genes=7 Reproduced from [61]

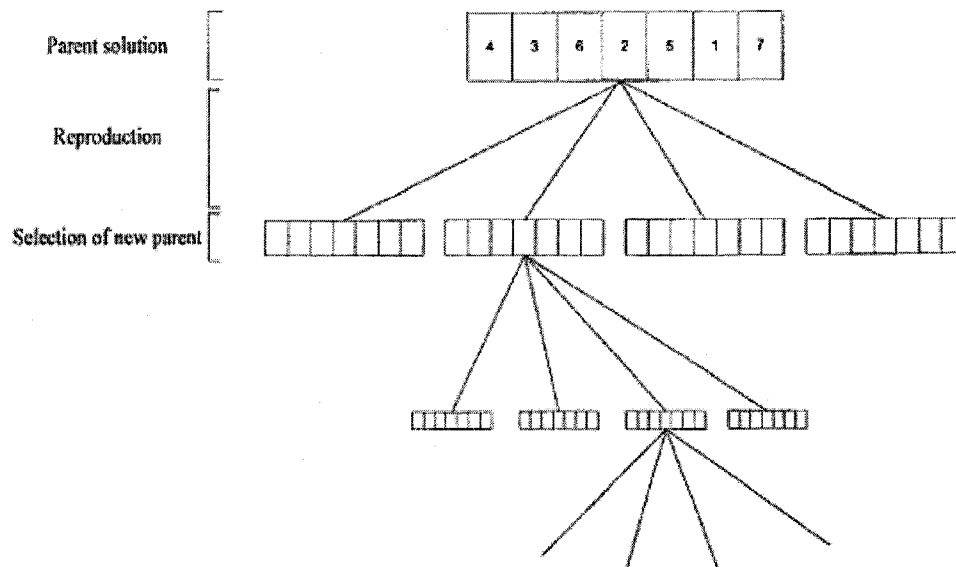


Figure 1.3: Basic Concept of ES Reproduced from [61]

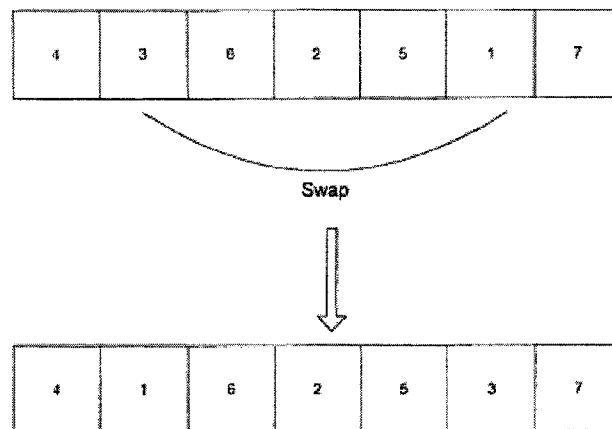


Figure 1.4: Swapping Operator Reproduced from [61]

## 1.7 Problem Statement

In this thesis, we integrated hybrid channel assignment and distributed power control (HCA-DPC) using Evolution Strategy to address the problem of finding an optimal assignment of channels given the transmitter power and co-channel interference is minimized. The HCA strategy used is adopted from [73]. We have modified the energy function employed in [73] for ES to include the CIR requirements. The minimization of the energy function gives the optimal channel allocation with the best link gain matrix to meet the CIR requirements and to optimize power.

Our proposed scheme uses the hard and soft conditions in [73]. Our ES method optimizes the channel assignment as well as the power consumption and minimizes interference. An efficient problem representation and an appropriate fitness function is used to search for a (near) optimal allocation of channels with efficient CIR objectives for a given cell that receives an incoming call. The performance of our method yields better results than that of [73].

## 1.8 Contributions

Our contributions are as follows:

1. An original, novel and efficient Evolution Strategy approach integrating Hybrid Channel Assignment (HCA) with Distributed Power Control (DPC) for better and robust optimization.
2. An objective function using channel allocation and power control scheme for channel allocation optimization with cochannel free assignment.
3. An efficient way to incorporate power control into channel assignment in way to that selection of channels always meet the CIR requirements and optimal power is achieved.
4. ES to integrate both channel and power resource management which yields less call blocking probability.

5. A novel way to handle the dropping of ongoing calls using the distributed power control algorithm.
6. Employ both  $(\mu, \lambda)$ -ES and  $(\mu + \lambda)$ -ES algorithm and compare their performances to our specific problem.

## 1.9 Organization of the Report

Chapter 2 introduces the contribution of evolutionary algorithms in wireless mobile communication area and gives a brief survey on the existing methods that are relevant to our problem. In Chapter 3 we describe the HCA scheme, the ES algorithm, the DPC scheme and our method of combining the problem of finding an optimal channel assignment with power control. Chapter 4 deals with basic assumptions of the cellular model used in the simulation, implementation details and results. Finally Chapter 5 concludes the dissertation and discusses future research directions and open problems.

## Chapter 2

# Literature Review and Survey

This chapter details the contribution of Evolutionary Algorithm in the field of Wireless Mobile Communication, compares different approaches as well as also surveys the existing methods that are used for both channel and power resource management schemes 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 [71]. Therefore, one of the most challenging design problems in cellular network is deciding on the locations of the 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 [8], [32], Simulated Annealing in [4], [35] and Tabu Search in [44].

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 must be taken into account [32]. De-

terminating the location of base stations is known to be NP-hard. Given a list of potential sites in a service area where base station 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 [71]. 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 [8], 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.

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

Where  $CoverRate^\alpha$  is the radio coverage (the percentage of locations covered by the selected base stations, and  $\alpha$  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. Finally,  $NB$  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.

## 2.2 EA in Call Admission Control

In mobile communication system, it is generally preferred to block a new call than 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 [76], authors have considered the evolution of a state-based call admission policies using GA. According to them, a call admission policy is a collection of admit/reject decisions corresponding to the services requested at each state of the system. 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 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 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  $3(F+1)^{2k+1}$ . The value of  $k$  is either 0 or 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 [76].

$$f = P_n + wP_h \quad (2.2)$$

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.

## 2.3 Channel Assignment

The channel assignment problem has been shown to be NP-hard [33]. 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 [19], [25], [41], the use of simulated annealing [20], the use of genetic algorithm [7], [10], [?], [43], [50], [66], and the use of graph theoretic approach [27], [64] 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 [19], [41] was shown to be an inappropriate technique as it had greater tendency to get stuck in local optima [42]. Some of the disadvantages of graph theoretic approach [20] are the following:

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

Simulated annealing approach [20], [48], achieves the global optimum asymptotically but its rate of convergence is very slow and requires a carefully designed cooling schedule [50]. Tabu search is good at exploring the search space by avoiding the inefficient paths. This way it requires less computational time as compared to simulated annealing. However, it requires large memory ca-



capacity as well as good method for avoiding oscillation of solutions which makes it unsuitable for large scale problems [71].

### 2.3.1 EA in Fixed Channel Assignment

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 [70]. 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  $X_{ij}(i, j = 1 \cdots C)$  represents the minimum channel separation required between channels assigned to cells  $i$  and  $j$ .

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

In general the cost due to violation of interference constraints can be given in Equation 2.3 [40].

$$f' = f_{cosite} + f_{adjacentchannel} + f_{cochannel} \quad (2.3)$$

where,

$$f_{cosite} = \sum_{i=1}^C \sum_{k=1}^F \sum_{l \neq k}^F A_{ik} A_{il} \phi(i, l) \quad (2.4)$$

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

$$f_{adjacentchannel} = \sum_{k=1}^F \sum_{i=1}^C \sum_{j \neq i}^C A_{ik} A_{jk} \delta(i, j) \quad (2.5)$$

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

$$f_{cochannel} = \sum_{i=1}^C \sum_{k=1}^F \sum_{j \neq k}^F A_{ik} A_{jk} \phi(i, j) \quad (2.6)$$

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

In Equation 2.3,  $f_{cosite}$  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 requirements i.e. assigning a different rather than required number of channels at each cell can be modeled as an error term  $f_{traffic}$  as [40]:

$$f_{traffic} = \sum_{i=1} (T_i - \sum_{k=1} A_{ik})^2 \quad (2.7)$$

The cost to be minimized can be expressed as shown in Equation 2.8 [40].

$$f = f' + f_{traffic} \quad (2.8)$$

In Equation 2.8,  $f$  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 is described below:

- In [43], 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 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. The paper uses standard mutation operator and slightly modified partially matched crossover (PMX).

- In [66], GA is used as well. The objective function treats the non-interference constraints (co-channel, co-site and adjacent channel) 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. 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 2.9 [66].

$$F(A) = \sum_{j=1}^C \sum_{k=1}^F A_{jk} \sum_{j=1}^C \sum_{l=1}^F P_{j,i,(|k-l|)} A_{il} \quad (2.9)$$

subject to demand satisfaction.

Here  $P$  is a factor that assigns a penalty to each assignment according to the recursive relations:  $P_{j,i,m+1} = \max(0, P_{j,i,m-1})$ ,  $P_{j,i,1} = X_{ji}$  and  $P_{j,i,1} = 0$ , for  $m = 1, \dots, m-1$ . 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.

- Paper [50], has also used GA to find an optimal channel assignment matrix. The constraints considered in the paper are interference constraint (co-channel, adjacent channel and co-site), and traffic demand constraints 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 utilize an encoding scheme called the minimum-separation encoding. In the encoding chosen 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 constraints. The genetic-fix algorithm defines its own mutation and crossover operator in such a way that the fixed number of ones is always preserved.

- In [10], authors have used GA to find the minimum required bandwidth that satisfy a given channel demand without violating interference constraints. In the encoding chosen for GA, a chromosome is a frequency assignment matrix  $A[F, C]$  with elements  $A_{ij}$  ( $i = 1 \dots M$  and  $j = 1 \dots N$ ) which is either 0 or 1

or -1 or 9.

$A_{ij} = 0$  :  $i^{th}$  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.

$A_{ij} = 1$  :  $i^{th}$  channel is used in the  $j^{th}$  cell.

$A_{ij} = -1$  :  $i^{th}$  channel is not used in the  $j^{th}$  cell and the  $i^{th}$  channel cannot be used in the  $j^{th}$  cell.

The paper 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 that the  $i^{th}$  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.

### 2.3.2 Dynamic Channel Allocation

In [37], the problem of dynamic channel assignment was formulated as a generalization of traditional mutual exclusion problem. They have proposed an algorithm called "Relaxed Mutual Exclusive" algorithm which prevents certain pair of cells from simultaneously using the same channel. In [69], authors have 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 [12], [13], [15], [58], [17], [64], [61], [62], [80], [81]. These algorithms can be classified into two classes of DCA schemes based on the type of information used in allocating a channel [71].

1. In the interference adaptive scheme, the decision regarding the allocation

of a channel is based on the measurement of carrier-to-interference ratio. In [26] and [53], the propagation measurement is made from each base station to mobile and vice-versa. 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. In traffic adaptive scheme, the channel allocation decision is based on the traffic conditions in neighboring cells of a cell involved in a call arrival.

Various traffic adaptive schemes have been proposed. The traffic adaptive schemes can be classified into various groups. One such category is exhaustive searching DCA [15],[17], [58], [62], [65], [80], [81]. Exhaustive searching D-ring HCA has also been proposed in [73]. In exhaustive searching each 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. Our proposed HCA strategy employs an exhaustive searching DCA while it adheres to interference adaptive scheme as it allocates a channel also based on the carrier-to-interference ratio.

### 2.3.3 EA in Dynamic Channel Allocation

Neural network based DCA [58], genetic algorithm based DCA [62], evolutionary strategy based DCA [61] and evolutionary strategy based HCA [73] have been proposed which are described below as they are relevant to our approach. All the approaches use an energy function for the cell involved in the arrival of a call.

- In [58], the energy function includes factors such as co-channel interference, 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, i.e. 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 [50].

- In [62], the energy function includes all those terms proposed in [58]. A binary chromosome represents a cell from the cellular system where a call is referred. A gene represents a channel where a free channel is assigned a 0 while an occupied channel is assigned a 1. 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 of new calls.

- In [61], the energy function includes all those terms proposed in [58] except the traffic requirement term. The traffic requirement is incorporated in the problem representation, therefore, the fitness function is simplified. It uses the same problem representation as in [62]. 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 update according to the fittest chromosome. The proposed algorithm performed better than those proposed in [58] and [62].

- In [73], authors proposed a new HCA strategy called D-ring strategy using distributed dynamic channel assignment based on fixed reuse distance concept. The fixed reuse distance is labeled as  $D$  which states that  $D$  rings of cell around a given cell would form the interference region. Channels are

allocated to a host cell from the channels which are not in the D ring zone of the host, therefore, cochannel interference is always satisfied. The length of the chromosome is equal to  $d$  where  $d$  represents the current traffic demand in the cell involved in a call arrival. The size of solution vector is smaller than [61] and yields a faster running time. Also, it takes care of the traffic demand constraint as the number of channels in the solution vector equals the demand of channels in the cell.

The fitness function is simplified as compared to [61], as one of the major hard constraints, the co-channel interference is taken care by the D-ring strategy. The soft constraints like packing condition, resonance and limiting reassignment are taken care by the energy function which provides simpler and faster calculation than [61]. The minimization of the energy function gives a near optimal channel allocation. Our proposed dynamic channel allocation methodology is based on this HCA strategy where we use dynamic reuse distance concept rather than D-ring strategy for the cochannel interference constraint and integrate this approach with an efficient power control scheme.

## 2.4 Power Control Schemes

Various power control algorithms have been proposed in the literature [6], [23], [29], [30], [57], [74], [78], [79]. All the power control approach presented can be described as centralized or distributed power control. One major constraint discussed in most of the papers is the cochannel interference that every user generates for all other users when sharing the same channel. Some techniques proposed sectorization and beamforming using smart antenna arrays to suppress interference, while some other techniques proposed adaptively controlling the power levels of all the users in the network. The idea is to keep the power level for every user at its minimum required level according to the current



channel condition. This would eliminate unnecessary interference to other users and would also minimize the power consumption for the user.

Aein [1] 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 consequences of the Perron-Frobenius theorem. Aein's work was refined further and an iterative procedure was proposed 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. In [3], authors improved and applied these results to the spread-spectrum system. Zander [77], [78] refined the concepts of [1] and [3] and focussed on the distributed implementation of these algorithms and their relationship to dynamic channel allocation.

Below the methods proposed in [6] and [57] are discussed briefly which are relevant to our problem.

- In [57], the interference reduction capability of antenna arrays and the power control algorithms have been considered as means to increase the capacity of the wireless communication networks. The beamformer with omnidirectional antennas is used as well as power control algorithms to maximize the CIR and noise ratio. An iterative algorithm is proposed to jointly update the transmitter powers and the beamformer weights so that it converges to the jointly optimal beamforming and transmission power vector.

A set of  $M$  transmitter-receiver pairs which share the same channel is considered. The CIR at the  $i^{th}$  receiver is given by Equation 2.10 [57].

$$\Gamma_i = \frac{G_{ii}P_i}{\sum_{j \neq i} G_{ji}P_j} \quad (2.10)$$

The link gain between transmitter  $i$  and receiver  $j$  is denoted by  $G_{ij}$ , and the  $i^{th}$  transmitter power by  $P_i$ . For an isotropic antenna with unity gain in all

directions, the signal power received at receiver  $i$  from transmitter  $j$  is  $G_{ji}P_j$ . The acceptable link quality is determined by  $\Gamma_i \geq \gamma_0$ , where  $\gamma_0$  is a certain threshold, the minimum protection ratio.

A decentralized power control is achieved by the following Equation 2.11 [57].

$$P_i^{n+1} = \frac{\gamma_0}{G_{ii}} \left( \sum_{j \neq i} G_{ji} P_j^n + N_i \right) = \frac{\gamma_0}{G_{ii}} I_i \quad (2.11)$$

Where  $P_i^n$  is the  $i^{th}$  mobile power at the  $n^{th}$  iteration step.  $I_i$  is the interference at the  $i^{th}$  receiver as well as the link gain between each receiver and its transmitter. That is, there is no need to know all the existing path gains and transmitter powers to update the powers. At each iteration, transmitters update their powers from the interference measured at the receivers and the link gain between each transmitter and its own receiver. Starting from an arbitrary power vector, this iteration converges to the optimal solution.

- In [6], distributed power-control algorithm with active link protection has been studied to maintain the quality of service of operational (active) links above given thresholds at all times (link quality protection). Based on the concept of active link protection, this approach supports the implementation of admission control. The two main ideas of this approach are 1. the gradual power up of new links entering the channel and 2. the introduction of a performance protection margin cushioning the links already in it. The CIR is defined same as in [57]. The CIR requirements is defined by

$$R_i \geq \gamma_i, i \in \{1, 2, 3, \dots, N\}$$

Transforming the CIR requirements into matrix form, the paper approached the problem from eigen-value solution. The paper showed that the distributed power control (DCP) algorithm would converge to the optimal power vector in order to minimize the power spent. The DPC algorithm is coupled with active link protection which updates transmitter powers in steps (time slots). The pa-

per proposed formulas to keep the active links remain active at all times using a protection margin and the new links to power up gradually to induce a limited degradation on active ones. The paper also proposed an approach called Time-out-Based Voluntary Drop-Out (VDO) to depict the drop-out horizon of new links attempting to gain admission in the network. The simulation studies showed that the serious of algorithms achieved superior performance lowering the average admission delay.

## 2.5 Integrated Channel Assignment and Power Control

While dynamic channel assignment achieve higher levels of capacity by dynamically distributing the traffic accorss the channels, power control techniques focus on every channel and try to mitigate the cochannel inteference by dynamically adjusting the power levels of the cochannel users at their minimum required level. This is the main idea behind the research motivation on integrated distributed dynamic channel and power allocation. Undoubtedly, dynamic channel allocation and power control together can improve performance and achieve higher capacity. Many integrated dynamic channel and power allocation (DCPA) algorithms have been proposed based on different power control algorithms [14], [45], [49], [72], [24].

In [14], a pilot based minimum interference DCA scheme is integrated with a fast fixed-step power control algorithm, while fast fading and user mobility effects are not considered. In [45], three different types of minimum interference DCA algorithms are integrated with a slow integrator power control algorithm. Pedestrian mobility along with a low power update rate is considered, and it is assumed that the fast fading effects are averaged out. In [72], a simulation study was performed to investigate the joint effects of some simple signal-to-interference-plus-noise ratio (SIR) based and signal-level-based power control

algorithms along with a minimum interference reassignment scheme. Fast fading effects are also neglected and low power update rates are assumed. Other approaches differ in results for neglecting effects such as dynamics of user arrival or departures, user mobility and base station handoffs.

### 2.5.1 DCA with Power Control

In [49] and [31], a distributed approach to the optimization of integrated channel assignment (DCA) and power control has been proposed. Both the papers use an interference region and neighboring cells exchange the channel usage information periodically. In [49], every cell maintains a list of the priority of available (free) channels. The priority of 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 farther a given channel is from the current cell, the lower the cost. The lower the cost the higher is the priority of a channel. After a channel is selected, the proposed algorithm applies power control to check the CIR value. In [31], 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 cochannels for each channel. When a call comes to cell, the proposed algorithm searches for a free channel with desired CIR and highest number of cochannels from the channel table. As compared to these two approaches, our approach uses an energy function as part of the ES algorithm and the CIR requirements is embedded in the ES algorithm to take care of cochannel interference, therefore, there is no need for defining any interference region separately.

In order to incorporate channel-gain variations due to user mobility and fading, in [63], authors proposed a DCA scheme based on a novel predictive power control algorithm and showed that how simple Kalman filters (using a set of available measurements, corrupted with Gaussian noise, a Kalman filter recursively obtains the minimum mean squared error estimates of a set

of variables that are varying according to a given dynamic model) may be designed and implemented in order to obtain the predicted measurements of both the channel gains and the interference powers. They also presented that the predictive power control algorithm satisfies the sufficient conditions for global stability of the network.

Below are some of the details of the system mode, integrated DCA and predictive power control measure used in [63].

- The authors considered cochannel interference among the users and focused on uplink channel, i.e. the channel from mobiles to base stations. A fixed-power pilot (control) channel on the downlink is assumed which facilitates DCA and can be used by the mobiles for initial base station assignments and base station handoffs. Only SIR is considered as the measure for QoS in the system. The received SIR on an assigned uplink channel for user  $i$  is shown as Equation 2.5.1 [63].

$$r_i = \frac{g_{ii}p_i}{\sum_{j=1, j \neq i}^M g_{ij}p_j + \eta_i} \quad (2.12)$$

Where,  $p_i$  is the transmitter power for user  $i$ ,  $g_{ii}$  is the channel gain (or attenuation) from user  $i$  to its intended base station,  $g_{ij}$  is the channel gain from user  $j$  to the intended base station of user  $i$ , and  $\eta_i$  is the receiver noise intensity at the intended base station of user  $i$ . Also,  $M$  is the total number of users sharing the channel. The optimal power level for the new user can be shown in Equation 2.5.1 [63].

$$P_n = \frac{I_{no}}{g_{nn}} \frac{\gamma_n}{1 - \frac{\gamma_n}{\gamma_{max}}} \quad (2.13)$$

Where,  $\gamma_n$  is the SIR threshold that the new user wants to achieve,  $\gamma_{max}$  is the maximum achievable SIR for the new user and  $I_{no}$  is the local mean interference-plus-noise level at the intended base station of the new user before it is admitted to the network. In order to model the interference plus noise similar to channel gains, a white noise driven first-order Markov variations is

used. From [63] that is

$$\bar{I}_i(n) = \bar{I}_i^0 + \delta\bar{I}_i(n) \quad (2.14)$$

$$\delta\bar{I}_i(n) = a\delta\bar{I}_i(n-1) + w_I(n-1) \quad (2.15)$$

Where  $w_I$  is a zero mean white Gaussian noise sequence,  $\bar{I}_i^0$  is a constant bias which accounts for the antenna gains and the distance loss in the filter. Simple Kalman filters presented in the paper obtains predicted estimates of the local mean channel gains and the local mean interference-plus-noise levels. These predicted estimates are then incorporated in a integrator algorithm to update the power levels of all the users in the network.

## Chapter 3

# Proposed Methodology

In this thesis, we propose a Hybrid Channel Assignment (HCA) strategy integrated with Distributed Power Control (DPC) based on Evolution Strategy approach. We consider a cellular system with the area under coverage divided into cells and each cell has its own base station. All users communicate with their assigned base stations through a single hop.

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 and power control is made by the controller of the concerned bases station according to the knowledge of other given cells. The thesis investigates an Evolutionary Strategy (ES) based approach using an efficient problem representation and defines an appropriate fitness function and mutation operators. The HCA with ES has been adopted from [73].

The system can be an FDMA/TDMA system where for the hard constraint, we only consider the cochannel interference among the users, and no adjacent or co-cite channel interference are assumed. We assume that each user will experience interference only from the users sharing the exactly same channel or link. The soft constraints considered are limiting reassignment and packing condition which are taken care by the fitness function. In [73], the fitness

function incorporates resonance as another soft condition to take care of the reuse distance concept. Our approach employs dynamic reuse distance concept through the use of CIR, therefore, there is no need to check for resonance condition in our energy function. The co-channel interference constraint is also taken care by the fitness function. The traffic requirement constrain is incorporated in the problem representation. The chosen representation and the mutation operator guarantees the feasibility of the solution.

Both Channel Assignment and Power control are integrated using  $(\mu, \lambda)$ -ES and  $(\mu + \lambda)$ -ES. The HCA part provides the optimal allocation of channels with best link gain matrix. The goal is to determine if there exists a channel to serve a new call in such a way that each mobile's CIR is acceptable. Finding such assignment of channels that minimized the total transmitted power by achieving an optimal power vector is the task of the Distributed Power Control (DPC) scheme. The DPC scheme employs a distributed CIR balancing Eigenvalue solution to to achieve the optimal power vector (adopted from [6] and [57]. By *distributed* we refer to per individual link (since the basic object of the network model is the link) in the system model.

### 3.1 HCA Strategy

We adopt to the HCA strategy proposed in [73]. In [73], a D-ring strategy is proposed (Figure 3.1) in the problem representation, where 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 cells belonging to D rings centered in a given cell H as shown in Figure 3.1. In our approach, we incorporate the CIR requirements in the energy function to take care of the cochannel interference constrain, therefore, there is no need for a fixed D-ring reuse distance concept as in [73] since our energy function of ES dynamically uses the reuse distance



concept.

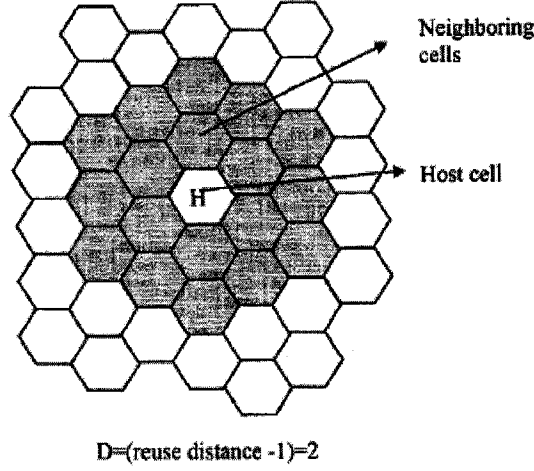


Figure 3.1: Neighbors of a Given Cell [73]

The total number of available channels are divided into two sets, Fixed and Dynamic. When a new call arrives, if there is no channel available in the Fixed Channel Pool, channels are used from the Dynamic Channel pool. The channel assignment is made by the central controller of the concerned base station as such that the selected channels always satisfy the soft and the hard constraints by employing dynamic reuse distance concept. The channel usage information in the neighbors of a given cell is obtained from the allocation matrix. Let,  $C$  be the total number of cells in the system and  $F$  be the total number of channels available to the system. Then the allocation matrix is a  $C \times F$  binary matrix. 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

$$a_{ij} = \begin{cases} 1 & \text{if channel } j \text{ is assigned to cell } i; \\ 0 & \text{otherwise.} \end{cases} \quad (3.1)$$

The allocation matrix is updated every time a channel is allocated and released

in the network. Also, system wide distance matrix and link gain matrix hold the distance and the link gains between mobile terminals and base stations.

## 3.2 Power Control

We integrate both channel assignment and power control (called the HCA-DPC algorithm) using Evolution Strategy. The problem of channel allocation is to maximize channel utilization and the problem of power control is to maintain desired signal to interference ratio which are highly related. Cochannel 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 or fixed and vice versa. In reality, when a channel  $l$  is assigned to a new call, it might deteriorate the quality of ongoing calls of all the other users of channel  $l$  because of interference created among each other. One of the widely studied approach to deal with such interference is the Carrier-to-interference ratio (CIR). When a channel assignment is done without taking into consideration the CIR ratio, for some assignments, the CIR ratio for a user in a cell may fall below the desired level for sharing the same link with other users. Regulating the transmitter power can reduce this interference seen by other users and also minimize the consumption of power. A substantial increase in the network capacity by combining dynamic channel assignment with power control has been reported in [14], [24], [45], [49], [63] and [72].

### 3.2.1 Problem Statement

We consider a cellular radio system with a finite set of  $F$  channels and  $C$  cells and a set of  $N$  transmitter-receiver pairs which share the same channel (i.e. the number of users communication in the same channel). The shared channel can be a frequency band in frequency-division multiple access (FDMA), a time

slot in time-division multiple access (TDMA) or even CDMA spreading codes. In FDMA system, the channels are non-overlapping frequency bands and in spread-spectrum system, the whole spectrum can be viewed as a single channel and interference basically reflects cross-correlation effects between codes in CDMA transmission [6].

In the cellular communication network paradigm, links or channels correspond to up-stream and down-stream transmissions between mobiles and base stations. Since uplink (mobile-to-base) and downlink (base-to-mobile) channels are assumed not to interfere with each other, and in principle, there is no big difference between downlink and uplink channel allocation, we only consider the downlink (base to mobile) situation and all relevant propagation effects are modeled by the link gains as in Figure 3.2. All the results in this thesis can be applied to uplink by changing the notations.

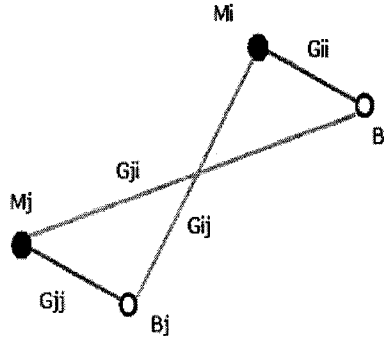


Figure 3.2: System Geometry and Link Gains

$G_{ij}$  denotes the link gain or path gains from the base station (transmitter) in cell  $j$  to the mobile (receiver) using the same channel in cell  $i$ . The gain  $G_{ii}$  corresponds to the desired communication link, whereas the  $G_{ij}, i \neq j$  corresponds to unwanted interference link (radio wave propagation effects). Let,  $P_j$  be the transmitter power of base  $j$ . The signal power received at receiver  $i$  from transmitter  $j$  is  $G_{ij}P_j$ . The desired signal at receiver  $i$  is equal to  $G_{ii}P_i$ , while the interfering signal power from other transmitters to receiver  $i$  is  $\sum_{j \neq i} G_{ij}P_j$ .

We assume that the transmission or signal quality to be dependent only on the carrier-to-interference ratio (CIR),  $\Gamma$ , experienced by the receiver. The CIR of mobile or receiver  $i$  can now be expressed as:

$$\Gamma_i = \frac{G_{ii}P_i}{\sum_{j \neq i} G_{ij}P_j + \eta_i}, \quad i, j \in \{1, 2, \dots, N\} \quad (3.2)$$

Where,  $\eta_i > 0$  is the thermal noise power at its receiver node.

The quality of the link from transmitter  $j$  to receiver  $i$  depends solely on  $\Gamma_i$ . The quality is acceptable if  $\Gamma_i$  is above a certain threshold  $\gamma_0$ , the minimum protection ratio. This minimum protection ratio reflects some minimum QoS that the link must support throughout the transmission in order to operate properly. The  $\gamma_0$  is determined based on the signaling scheme and the link quality requirements (target bit error rate). Hence, for acceptable link quality,

$$\frac{G_{ii}P_i}{\sum_{j \neq i} G_{ij}P_j + \eta_i} \geq \gamma_0 \quad (3.3)$$

In matrix form, the CIR requirements 3.2, 3.3 can be written as [6]:

$$(I - \gamma_0 F)P \geq U \quad \text{and} \quad P > 0 \quad (3.4)$$

Where,  $P = (P_1, P_2, \dots, P_i, \dots, P_N)^T$  is the column vector of transmitter powers,  $I$  is an  $N \times N$  identity matrix, and  $U$  is an element-wise positive vector with elements  $u_i$  defined as:

$$u_i = \frac{\gamma_0 \eta_i}{G_{ii}}, \quad 1 \leq i \leq N. \quad (3.5)$$

$U$  is the vector of noise powers rescaled by CIR requirements and link gains

[6]. Finally,  $F$  is the matrix of cross-link power gains with entries:

$$F_{ij} = \begin{cases} 0 & \text{if } i = j; \\ \frac{G_{ij}}{G_{ii}} > 0 & \text{if } i \neq j. \end{cases} \quad (3.6)$$

Where,  $i, j \in \{1, 2, 3, \dots, N\}$ .

The objective of the power control scheme is to maintain the link quality by keep the CIR above  $\gamma_0$ , therefore, adjust the power vector  $P$  such that Equation 3.4 is satisfied.

The matrix  $F$  has non-negative elements, therefore, it is reasonable to assume that it is irreducible (From standard matrix theory, if a non-negative matrix  $A$  is irreducible iff for any vector  $x > 0$ ,  $Ax > 0$  holds true). Now, given that  $F$  is irreducible, according to Perron-Frobenius theorem ([6], [57]) the maximum value of  $\gamma_0$ , for which there exists a positive power vector  $P$  such that Equation 3.4 is satisfied is  $1/\rho(F)$ . Here,  $\rho(F)$  is the maximum modulus eigenvalue of  $F$ . Also, according to this theorem, the power vector  $P$  that satisfies Equation 3.4 is the eigenvector corresponding to  $1/\rho F$  and is positive.

It has been shown in literature that if the maximum modulus eigenvalue of  $F$  is less than  $1/\gamma_0$ , the matrix  $I - \gamma_0 F$  is invertible and positive. In this case the power vector

$$P^* = [I - \gamma_0 F]^{-1} U \quad (3.7)$$

solves the optimization problem in the sense that any other  $P$  satisfying Equation 3.4 would require as much power from every transmitter i.e.  $P \geq P^*$ . Hence, if it is possible to satisfy the CIR requirements for all links simultaneously, a good power control strategy is to set the transmitter powers to  $P^*$  in order to minimize the power spent [6].

### 3.2.2 Distributed Power Control (DPC)

Many centralized power control algorithm to solve Equation 3.7 have been proposed in literature. They require all link gains in the network and noise levels at receivers. A distributed power control (DPC) algorithm is proposed in [23] which is the following:

$$P(k+1) = \Gamma P(k) + U, \quad k = 1, 2, 3, \dots \quad (3.8)$$

This equation converges to  $P^*$  if  $\rho F < 1$ . The first term refers to the cross-link interference and the second term refers to noise both rescaled by  $G_{ii}$ . The disadvantage of this approach is that it is necessary to make separate local measurements of cochannel interference  $\sum_{i \neq j} G_{ij} P_j$ , noise power  $\eta_i$  and propagation gain  $G_{ii}$ .

We adopt to the DPC algorithm proposed in [6] which is a simplified version of Equation 3.8.

$$P_i(k+1) = \frac{\gamma_0}{\Gamma_i(k)} P_i(k) \quad \text{for every link } i \in \{1, 2, 3, \dots, N\} \quad (3.9)$$

Following Equation 3.9, each link independently increases its power when its current CIR is below the threshold  $\gamma_0$  and decreases it otherwise in order to meet the required CIR threshold. It may be noted that since all the links do the same, the objective is achievable only at the limit  $k \rightarrow \infty$  (if feasible). In our *distributed* power control scheme, each channel's transmitter and receiver pair measures the interference and communicates this information to each other. The transmitter then decides how to adjust its power.

### 3.3 Proposed Evolution Strategy Approach

The proposed ES belongs to the class of  $(\mu, \gamma)$ -ES and  $(\mu, \gamma)$ -ES with  $\mu = 1$ . This section describes the characteristics of our proposed ES approach: problem representation, generation of initial population, fitness function and mutation operator to generate offspring from a given parent and also describes  $(\mu, \gamma)$ -ES and  $(\mu, \gamma)$ -ES algorithm.

#### 3.3.1 Problem Representation

Let us assume that a new call arrives in cell  $k$ , which is already serving  $(d - 1)$  calls and  $d$  is the traffic demand at cell  $k$  after the new call arrives (this takes care of the traffic requirement constraint). 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 the overall channel usage in the entire network. The CIR requirements and the optimal power issue are dealt by the fitness function and the DPC algorithm respectively. A potential solution,  $V_k$ , is an assignment of channels to all ongoing calls and the new call, at  $k$ . We call such a solution a chromosome. We 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  $V_1 = [7, 2, 5, 3]$ . This representation (adopted from [73]) is more efficient than [61] as they 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 the representation used in [61] is that although we are interested in only  $d$  channels, extra memory is consumed in storing the information about other channels. This also yields slower evaluation and manipulation of candidate solutions due to the size of the binary representation. The advantage of our representation is that the size of the solution vector is short and it is easier and faster to manipulate the vector.

Also, our algorithm performs faster than that of [73] as we have removed the destabilization part used in [73]. It has been shown in [73] that the inclusion of destabilization does not affect the performance of the ES algorithm in terms of blocking probability, however, certainly reduces the computational time.

### 3.3.2 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  $I(k, t) = F \setminus P(k, t)$ , where,  $F$  is the total set of available channels and  $P(k, t)$  is the set of channels of the ongoing calls in  $k$  at time  $t$ . This information is obtained from the allocation matrix. The initial parent solution (the very best chromosome) is selected from a set  $G$  of  $\lambda$  solution vectors where  $\lambda = |I(k, t)|$ . Each solution vector in  $G$  is evaluation 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 example, a call arrives in cell 2 at time  $t$ , where  $P(k, t) = [2, 5, 9]$ ,  $F = [1, 2, 3, 4, 5, 6, 7, 8, 9]$ . Therefore,  $I(k, t) = [1, 3, 4, 6, 7, 8]$  and  $\lambda = 6$ . Here,  $d = 4$ , therefore, the size of the solution vector is 4. The 6 solution vectors in  $G$  are thus:  $G_1 = [2, 5, 9, 1]$ ,  $G_2 = [2, 5, 9, 3]$ ,  $G_3 = [2, 5, 9, 4]$ ,  $G_4 = [2, 5, 9, 6]$ ,  $G_5 = [2, 5, 9, 7]$  and  $G_6 = [2, 5, 9, 8]$ . Out of the six, 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 were already optimized in the previous call arrival in  $k$ .



### 3.3.3 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 number of free channels, whichever is smaller. Given  $N$ , we generate a random number  $S$  between 1 and  $N$ . 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 the number of swaps,  $S = 2$ , then one possible offspring is  $O = [7, 4, 5, 10]$ . 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.

### 3.3.4 Fitness Function

The CIR requirements of using any channel is taken taken by our fitness function. Our fitness function integrates power control with channel assignment as opposed to the one proposed in [73], thus providing a more robust fitness function. Our problem representation takes care of the traffic demand constraint. The soft constraints (limiting reassignment and packing condition) and the CIR requirements can be modeled as an energy function as shown in Equation 3.10. The minimization of this function gives an optimal channel allocation.

$$fitness = A_1 \sum_{j=1}^{d_k} cir(V_{k,j}) - W_1 \sum_{j=1}^{d_k} \sum_{i=1, i \neq k}^C A_{i,V_{k,j}} \frac{1 - interf(i, k)}{dist(i, k)} - W_2 \sum_{j=1}^{d_k} A_{k,V_{k,j}} \quad (3.10)$$

$k$	:	Cell where a call arrives
$d_k$	:	Number of channels allocated to cell $k$ (traffic demand in cell $k$ )
$C$	:	Total number of cells in the system
$V_k$	:	Solution Vector 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 cell $i$ and $k$
$interf(i, k)$	:	Function returns 1 if there is interference between cells $i$ and $k$ , 0 otherwise
$cir(V_{k,j})$	:	Function returns value of 0 if $\rho(F)$ of channel $j < \frac{1}{\gamma_0}$ , and 1 otherwise

The first term expresses the CIR requirements in terms of matrix  $F$ . The energy decreases if channel  $j$  is in use in other cells and the  $\rho(F)$  of  $F$  for the cells is less than  $\frac{1}{\gamma_0}$ . The function  $interv(V_{k,j})$  returns 1 if  $\rho(F)$  of any  $j$  falls below  $\frac{1}{\gamma_0}$ , 0 otherwise. The second term expresses the packing condition. The energy decreases if the if the  $j^{th}$  element of vector  $V_k$  is also in use in cell  $i$  and cells  $i$  and  $k$  are free from cochannel interference. The decrease in energy depends upon the distance between cells  $i$  and  $k$  and  $interf(i, k) = 0$  if  $\rho(F)$  of  $F$  for the cells  $i$  and  $k$  is less than  $\frac{1}{\gamma_0}$ . The third term expresses the limiting reassignment. 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.

$A_1$ ,  $W_1$  and  $W_2$  are positive constants that may vary by the designer and determine the significance of the respective terms. In our case  $A_1 = 2.5$ ,  $W_1 = 1.5$  and  $W_2 = 1$ . Such energy function represents our fitness function in our proposed ES.

### 3.4 HCA with DPC

When a new call arrives, the cellular system tries to assign the new call from the fixed channel pool. If there is a fixed channel available, the channel is assigned to the new call. Otherwise, it applies the ES algorithm to find a solution vector with minimum energy from the dynamic channel pool.

The vector includes all the suggested channels for ongoing calls and the new call. Our solution vector is carefully designed so that the best assignment of channels meet the  $\rho(F) < \frac{1}{\gamma_0}$  criteria and imply that power eventually converge to the optimal while fulfilling the CIR requirements.

If the CIR of any of the busy allocated channel of the vector is below the desired level, it employs the distributed power control algorithm in Equation 3.9 to adjust the power levels (increase or decrease) of each channel iteratively to meet the CIR requirements. The Equation 3.9 gives a step size for each channel towards meeting optimal power. We choose the number of iterations for power level adjustments as 10 here. If after 10 iterations, all the channels do not meet the CIR requirements, then  $V_k$  is rejected and a second best solution from our ES is taken as  $V_{k1}$  and checked for CIR requirement in the same way as mentioned above. If any of the busy channels of the new vector  $V_{k1}$  falls below the threshold,  $V_k$  is rejected, the calls that are being served are not reassigned and the incoming call is blocked. Unlike the proposed ES in [73], where the solution vector  $V_k$  is assigned to calls without considering the link quality, our solution makes sure the link quality is maintained. Also, in our solution free channel pool  $I$  is larger than that of [73], and less number of calls are blocked (if first  $V_k$  fails, it adopts to the second best  $V_{k1}$ ) from ES, thus thus increasing the system capacity.

We set the initial power value as  $P(0) = 0.2$ . The initial power issue will be discussed in details in the next chapter.

If a call is in service, we also adopt the step size equation 3.9 to maintain

its quality. Each base monitors its own served calls at some amount of time interval (assuming base stations are synchronized). When a call's CIR remains below the target value for a predefined time, the power control procedure is requested. However, if the number of iterations of power level adjustments are larger than the allowed value, but the CIR is still below the threshold, the call is dropped.

The next section illustrates our ES approach. Starting from a random initial population  $P$  of  $\mu$  candidate solutions, we create a set  $M$  of  $\lambda$  mutants by the process of mutation. The next  $\mu$  parents are selected from the best in  $P \cup M$  and  $M$  for our  $(\mu + \lambda)$ -ES and  $(\mu, \lambda)$ -ES respectively. We also keep track of the fittest solution *Global\_best* ( $V_k$ ) and the second fittest solution *Global\_best2* ( $V_{k1}$ ) and preserve them across generations. The inner while-loop tries to locally optimize the actual best solution in  $P \cup M$  and  $M$  depending on the ES used in order to escape from a local optimum trap. The *Global\_best* solution is update only when its fitness is worse than the fitness of the local best solution found in the current population  $P \cup M$  and  $M$  respectively. We have omitted the destabilization part used in the ES algorithm in [73] since it was shown that excluding the destabilization does not affect the performance of the algorithm, however, reduces the computational time. In our algorithm, the total number of generations created is 1000 and the total number of local optimizations in each generation is 10. At the end of the algorithm, the fittest individual  $V_k$  along with the second fittest individual  $V_{k1}$  from the best given generation is returned by the algorithm.  $V_{k1}$  is chosen from the second best generation if the second generation's fittest individual outperforms the best generation's second fittest individual. The suggested solution vector is used for optimizing channels in a way that would maximize the channel allocation, meet the desired CIR threshold and the transmitter powers would eventually converge to the optimal.

The ES algorithm is given in the next section.

### 3.5 ES algorithm

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**Algorithm 1**  $(\mu, \lambda)$ -ES

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Given traffic demand  $d_k$  of cell  $k$   
Generate set  $G$  of  $\lambda$  individuals  
Generate an initial random population  $P = \{P_1, P_2, \dots, P_\mu\}$  from  $G$   
Evaluate( $P$ )  
 $Global\_best \leftarrow$  best in  $P$   
**repeat**  
     $M = \{M_1, M_2, \dots, M_\lambda\} \leftarrow Mutate(Global\_best)$   
    Evaluate( $M$ )  
     $Local\_best \leftarrow$  best in  $M$   
     $i \leftarrow 0$   
    **while**  $f(Local\_best) \leq f(Global\_best)$  and  $i \leq 10$  **do**  
         $C \leftarrow Mutate(Local\_best)$   
         $B \leftarrow Mutate(Global\_best)$   
         $Local\_best \leftarrow$  best in  $\{C, B, Local\_best\}$   
         $i \leftarrow i + 1$   
    **end while**  
    **if**  $f(Local\_best) > f(Global\_best)$  **then**  
         $Global\_best \leftarrow Local\_best$   
    **end if**  
     $P = \{P_1, P_2, \dots, P_\mu\} \leftarrow$  best in  $M \cup \{Local\_best, Global\_best\}$   
**until** Stopping Criteria  
Return  $Global\_best, V_k$ 

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**Algorithm 2**  $(\mu + \lambda)$ -ES

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Given traffic demand  $d_k$  of cell  $k$   
Generate set  $G$  of  $\lambda$  individuals  
Generate an initial random population  $P = \{P_1, P_2, \dots, P_\mu\}$  from  $G$   
Evaluate( $P$ )  
 $Global\_best \leftarrow$  best in  $P$   
**repeat**  
     $M = \{M_1, M_2, \dots, M_\lambda\} \leftarrow$  Mutate( $P$ )  
    Evaluate( $P \cup M$ )  
     $Local\_best \leftarrow$  best in  $P \cup M$   
     $i \leftarrow 0$   
    **while**  $f(Local\_best) \leq f(Global\_best)$  and  $i \leq 10$  **do**  
         $C \leftarrow$  Mutate( $Local\_best$ )  
         $B \leftarrow$  Mutate( $Global\_best$ )  
         $Local\_best \leftarrow$  best in  $\{C, B, Local\_best\}$   
         $i \leftarrow i + 1$   
    **end while**  
    **if**  $f(Local\_best) > f(Global\_best)$  **then**  
         $Global\_best \leftarrow Local\_best$   
    **end if**  
     $P = \{P_1, P_2, \dots, P_\mu\} \leftarrow$  best in  $P \cup M \cup \{Local\_best, Global\_best\}$   
**until** Stopping Criteria  
Return  $Global\_best, V_k$ 

---

## Chapter 4

# Experiments and Discussion

The network simulation was implemented in Java programming language using Eclipse IDE. In the literature, several criteria are used to evaluate the performance of a channel allocation scheme: new call blocking probability, call dropping 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  $P_n$ , and the ongoing call dropping probability  $P_m$ . The parameter  $P_n$  is given by

$$P_n = \frac{\text{number of new calls blocked in the system}}{\text{number of new call arrivals to that system}} \quad (4.1)$$

The parameter  $P_m$  is given by

$$P_m = \frac{\text{number of ongoing calls dropped from the system}}{\text{number of calls admitted to that system}} \quad (4.2)$$

Blocking probability is the ratio between the new calls blocked and the

total number of call arrivals in the system and dropping probability is the ratio between the ongoing calls dropped and the total number of calls admitted in the 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 Network Model Assumption

In this thesis, ES is applied to the mobile cellular model proposed in [58] and also used in [73]. The power control model assumptions were proposed in [6]. The basic characteristics of the model and some facts are 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 ([73]). The wireless network used for simulation consists of 49 cells.

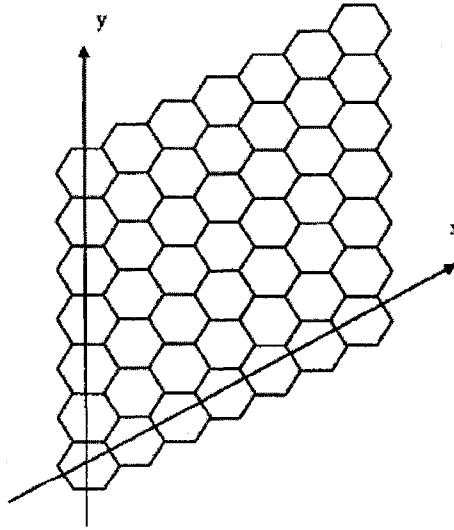


Figure 4.1: Cellular Model Assumption

2. 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 central pool. A channel is assigned to an incoming call by a central controller that supervises the whole cellular network.

3. Incoming calls at each cell may be served by any of the system channels.
4. The selection of a channel is subject to meeting the CIR requirements based on cochannel interference. Other sources of interference are ignored.
5. The basic object of the network model is the link, hence, by "distributed" power control we refer to per individual link.
6. Each base station's transmitters update their power to meet the desired CIR threshold using the step up power Equation 3.9. At each iteration, transmitters update their powers based on the interference measured at the receivers and the current transmitter power.
7. When a call arrives in a cell, first the fixed channel pool for that particular cell is checked. If there are channels available, the channel is assigned to the call with appropriate transmission power. Otherwise, ES is applied in the entire cell to find suitable channels for existing calls (reassignment) and for the new call (new allocation). If for any busy channel, CIR goes below the desired threshold, step size equation 3.9 is used for power adjustments to achieve the desired threshold. The number of iterations for equation 3.9 is set to 10 in our model. A new call is blocked only if after attempting two suggested solutions, the CIR of any busy channel is still below the desired level.
8. Existing calls in a cell involved in a new call arrival may be rearranged.

9. If a call is in service, step size equation 3.9 is used to maintain its quality. Each base monitors its own served calls at some amount of time interval (assuming base stations are synchronized). When a call's CIR falls below the target value for a predefined time, the power control procedure is requested. However, if the number of iterations of power level adjustments are larger than the allowed value, but the CIR is still below the threshold, the call is dropped from the system.

With these model assumptions, we are able to compare our results with those obtained by [73].

## 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 the cross-link gain Matrix $F$

We assume that the link gains due to user mobility stay constant for the duration of the convergence of the algorithm. Therefore, it is implicitly assumed that the fading rate of the channel is much slower than the power update date.

We assume that all link gains are affected by shadow fading. The average signal power is assumed to decrease with the fourth power of the distance. The interference or attenuation factors  $G_{ij}$  are given by:

$$G_{ij} = \frac{1}{d_{ij}^4}$$

Where,  $d_{ij}$  is the distance between the  $i^{th}$  mobile and the  $j^{th}$  base station. The cross-link power gain matrix  $F_{ij}$  contains entries 0 if  $j = i$  and  $\frac{g_{ji}}{g_{ii}} > 0$  if  $j \neq i$ . The Distance matrix  $D$  contains entries  $d_{ij}$ .

#### 4.2.3 Determination of distance between two cells $i$ and $K$

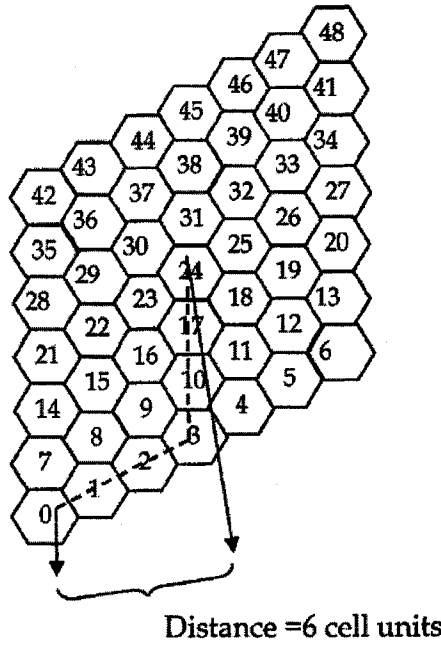


Figure 4.2: Distance between two cells

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  $k = 12$ . The minimum number of steps required to go from cell  $i$  to cell  $k$  is 4 as shown in figure 4.2.

### 4.3 Traffic Model

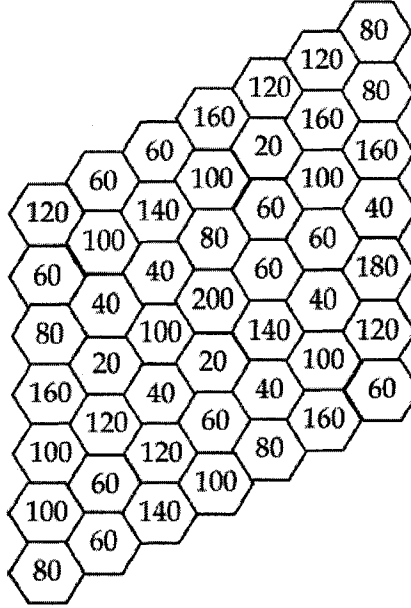


Figure 4.3: Non Uniform traffic distribution pattern 1 with initial Poisson arrival rates (Calls/hour)

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: infinite number of users, finite number of available channels, memory-less arrival of requests, call arrival follows a Poisson process with mean arrival rate of  $\lambda$  (calls /hour), and call duration is exponentially distribution with mean  $x$ . 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.

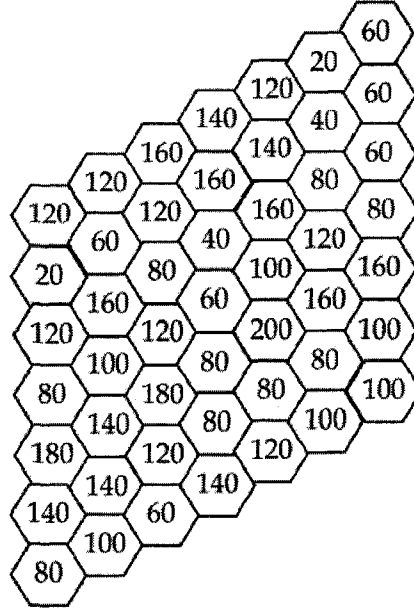


Figure 4.4: Non Uniform traffic distribution pattern 2 with initial Poisson arrival rates (Calls/hour)

The assumptions and parameters used in simulation include:

- For non uniform traffic distribution, we consider the traffic patterns proposed in [73] shown in Figures 4.3 and 4.4. The figures inside the cell represent the mean call arrival rate per hour.
- call holding time is 180 seconds.

With these simulation hypothesis we were able to compare our results with those obtained in [73].

## 4.4 Initial Power Issue (Link Admission)

The choice of initial vector  $P_0$  is not very critical, since many researchers have shown that  $P^*$  is the only positive eigenvector of  $F$  and almost any positive start vector will be reasonably close to  $P^*$  [79]. In our case we set the value for  $P_0$  as 0.2. One important issue discussed in [6] is that when a new link

suddenly powers up to  $P_0$  it may strongly interfere with already active links to cause their CIR go below  $\gamma_0$  temporarily. The problem here is the sudden and uncoordinated appearance of the new user which is unknown to the existing ones. To avoid this scenario, in our case, the active links keep updating their power. Further improvements in this area for power protection between new links and already active ones is a subject of our future research.

## 4.5 Simulation

In HCA, the total set of available channels are divided into two sets, fixed and dynamic. A call arrives in a randomly selected cell and the cellular system makes a attempt to serve it from the fixed channel set. When all channels in the fixed set are busy, ES is applied to find a suitable combination of channels and power control procedure is called to maintain the CIR requirements by adjusting the power levels of the transmitters. In the simulation, the following representative ratios were used (also used in [73]):

- 21 : 49 (21 channels from fixed set and 49 channels from dynamic set)
- 35 : 35 (35 channels from fixed set and 35 channels from dynamic set)
- 49 : 21 (49 channels from fixed set and 21 channels from dynamic set)

Results were obtained by increasing the traffic rates for all the cells by 20% with respect to the initial rates of the same cell. The performance of the proposed ES based Channel assignment and distributed power control algorithm has been derived in terms of blocking probability for new incoming calls and dropping probability of ongoing calls. We also evaluated the speed of call setup where we simulated how many allocated channels (allocated new calls) are from the first suggested solution vector and from the second solution vector. We call the solution vectors as priority channel list 1 and 2. The values of positive constants considered are  $A_1 = 2.5$ ,  $W_1 = 1.5$ , and  $W_2 = 5$ . The

initial transmitter power is set to  $P(0) = 0.2$ , the desired CIR threshold is  $\gamma_0 = 10$  and noise power  $\eta_i = \frac{1}{10^5}$  for all receivers. We tried different values for weights and these weights provided the best result. In our simulation, in case  $|I| = 1$ , the initial population contains only one parent and this parent is directly chosen as the initial parent. When  $|I| \geq 2$ , the maximum number of initial parents  $\mu$  that can be selected from  $I$  is two. Considering the processing time,  $\mu$  is set to 1,  $\lambda$  is set to 10 and  $L$  (no of power adjustments) is set to 10. We have compared our results (graphs are based on average of 10 runs with Standard Deviations) with that of [73] in terms of call blocking probability for both Pattern 1 and 2 which are given in Figures 4.5, 4.6, 4.7, 4.8 and 4.9. Our results show better performance with increasing traffic load for new call blocking probability compared to [73] for pattern 1 with 21:49, 35:35 and 49:21 and for pattern 2 with 21:49, 35:35 and 49:21. Results show better performance for all the representation ratios for traffic pattern 1.

Figure 4.10, 4.11 and 4.12 show the performance of our algorithm using different  $\mu$  and  $\lambda$  values for traffic pattern 1 for the representative ratios 21:49, 35:35 and 49:21. From the results, it is evident that the ES is insensitive to the values of  $\mu$  and  $\lambda$ .

Figure 4.13 shows the call dropping probability for our  $(\mu, \lambda)$ -ES for traffic pattern 1 with the representative ratios 21:49, 35:35 and 49:21. Figure 4.14 and 4.15 show the blocking and dropping probability using different values of  $L$  (10,20,40) for traffic pattern 1 for FCA 21 and DCA 49.

Figure 4.16 shows the performance of our  $(\mu, \lambda)$ -ES and  $(\mu + \lambda)$ -ES in terms of call blocking probability for representative ratio 21:49 with nonuniform traffic distribution according to pattern 1.  $(\mu + \lambda)$ -ES performs slightly better than  $(\mu, \lambda)$ -ES in our simulation.

Figure 4.17 shows the speed of call setup. We simulated how many allocated channels are from suggest channel vector  $V_k$  (Priority Channel List 1) and from the second suggest channel vector  $V_{k1}$  (Priority Channel List 2). The figure

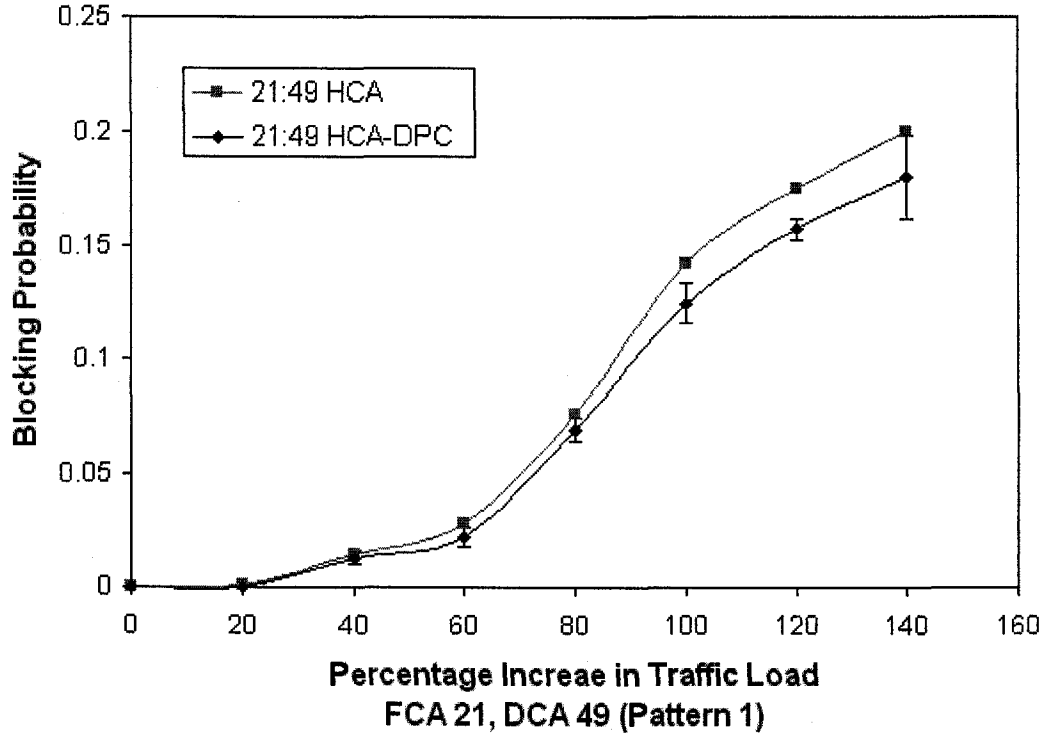


Figure 4.5: Performance of proposed  $(\mu, \lambda)$ -ES (HCA-DPC) in terms of blocking probability compared to the HCA proposed in [73] with FCA 21 and DCA 49,  $\mu = 1$ ,  $\lambda = 10$ ,  $L = 10$  (Pattern 1)

shows the percentage of the allocated channels in the location of the priority channel list with different traffic loads. We can see that more than 94% of the allocated channels are from  $V_k$ . That means more than 94% of allocated channels have undergone the set-up probing with the first solution vector after those channels are found to satisfy the CIR requirement.

Figure 4.18, 4.19 and 4.20 are the flow charts for the implementation of the call arrival, call release and call maintenance (power update to maintain CIR requirement of active channels) events for our proposed scheme.



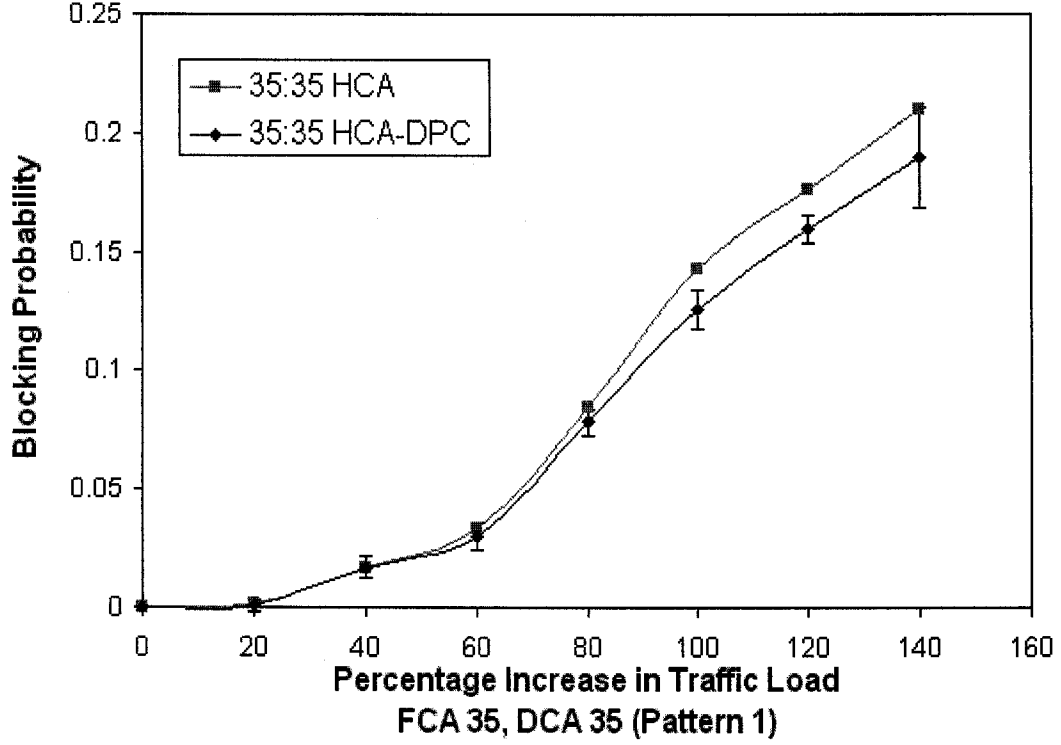


Figure 4.6: Performance of proposed  $(\mu, \lambda)$ -ES (HCA-DPC) in terms of blocking probability compared to the HCA proposed in [73] with FCA 35 and DCA 35,  $\mu = 1$ ,  $\lambda = 10$ ,  $L = 10$  (Pattern 1)

Table 4.1: Characteristics of 21:49 HCA-DPC

Maximum number of generations	20
Average number of generations	11
Minimum number of generations	7

Table 4.2: Characteristics of 35:35 HCA-DPC

Maximum number of generations	17
Average number of generations	10
Minimum number of generations	5

Tables 4.1 to 4.4 summarizes the characteristics of the ES based channel assignment and distributed power control algorithm.

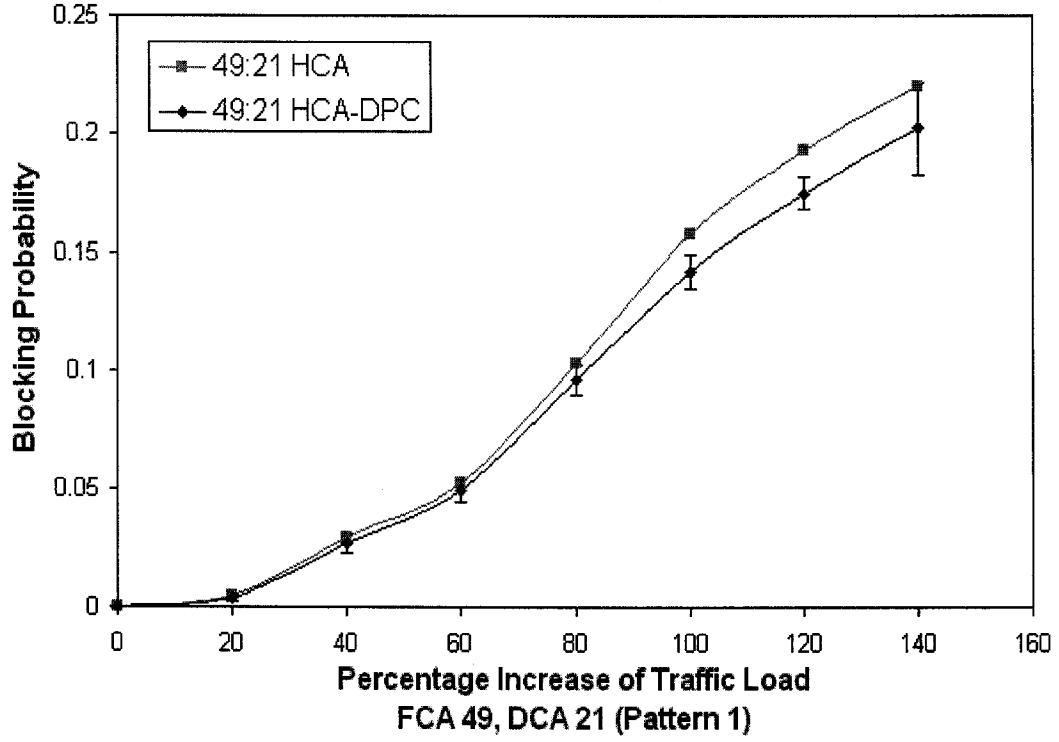


Figure 4.7: Performance of proposed  $(\mu, \lambda)$ -ES (HCA-DPC) in terms of blocking probability compared to the HCA proposed in [73] with FCA 49 and DCA 21,  $\mu = 1$ ,  $\lambda = 10$ ,  $L = 10$  (Pattern 1)

Table 4.3: Characteristics of 49:21 HCA-DPC

Maximum number of generations	16
Average number of generations	11
Minimum number of generations	6

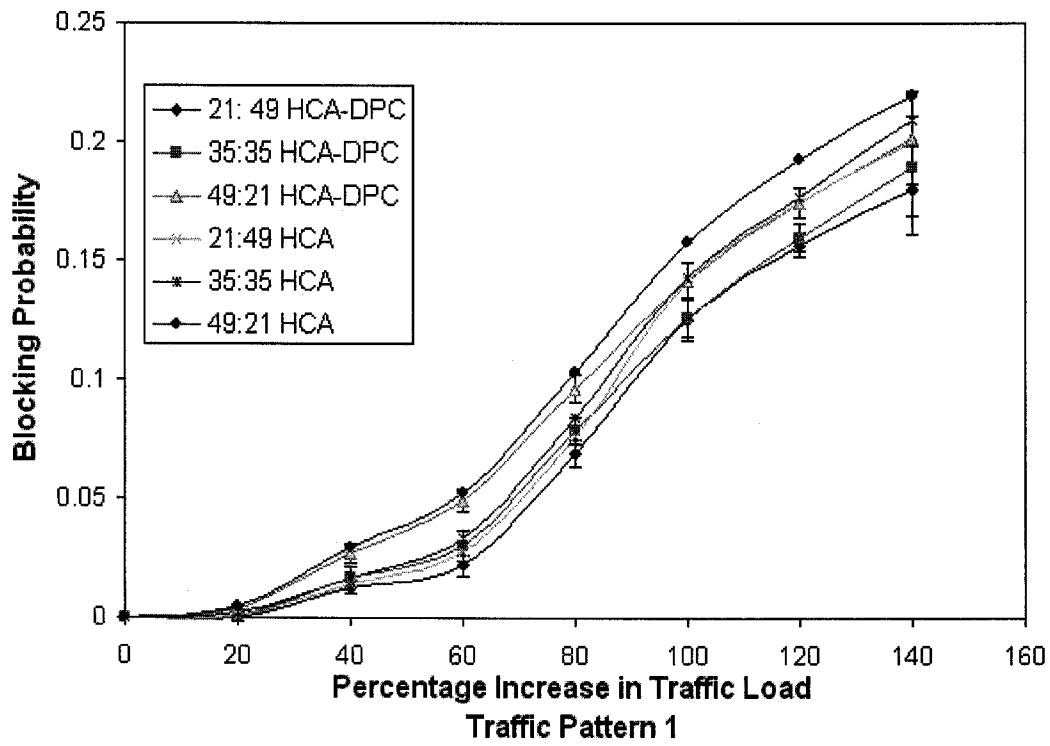


Figure 4.8: Performance of proposed  $(\mu, \lambda)$ -ES (HCA-DPC) in terms of blocking probability compared to the HCA proposed in [73] for the entire cellular network with non-uniform traffic distribution according to pattern 1

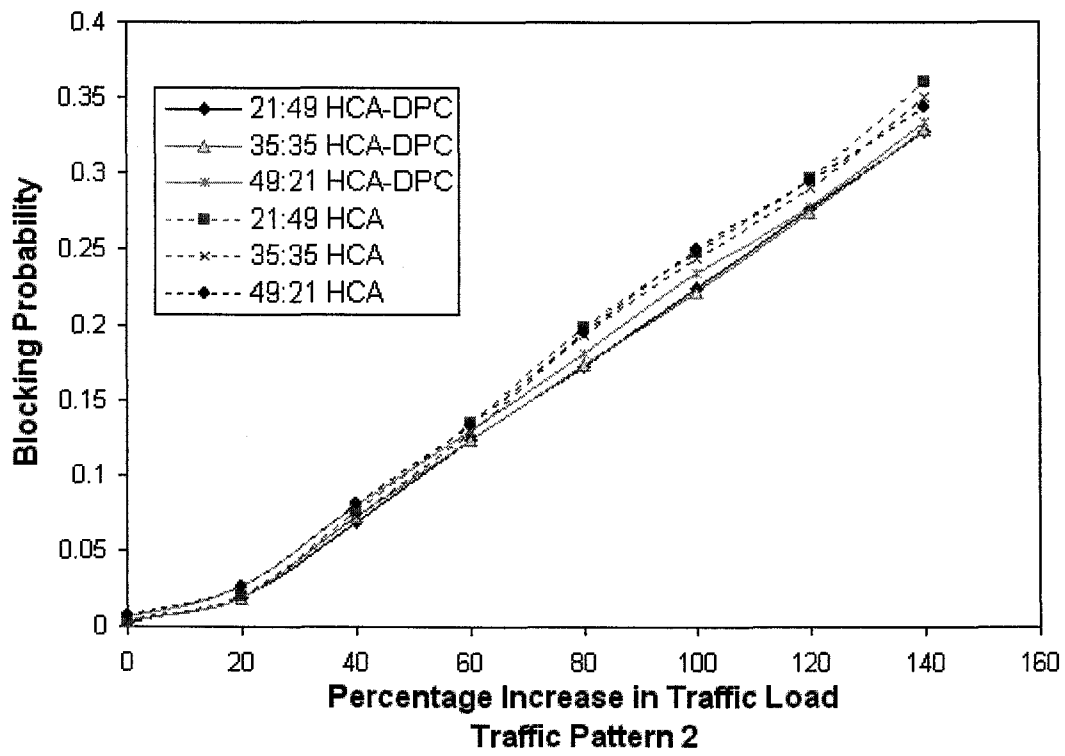


Figure 4.9: Performance of proposed  $(\mu, \lambda)$ -ES (HCA-DPC) in terms of blocking probability compared to the HCA proposed in [73] for the entire cellular network with non-uniform traffic distribution according to pattern 2

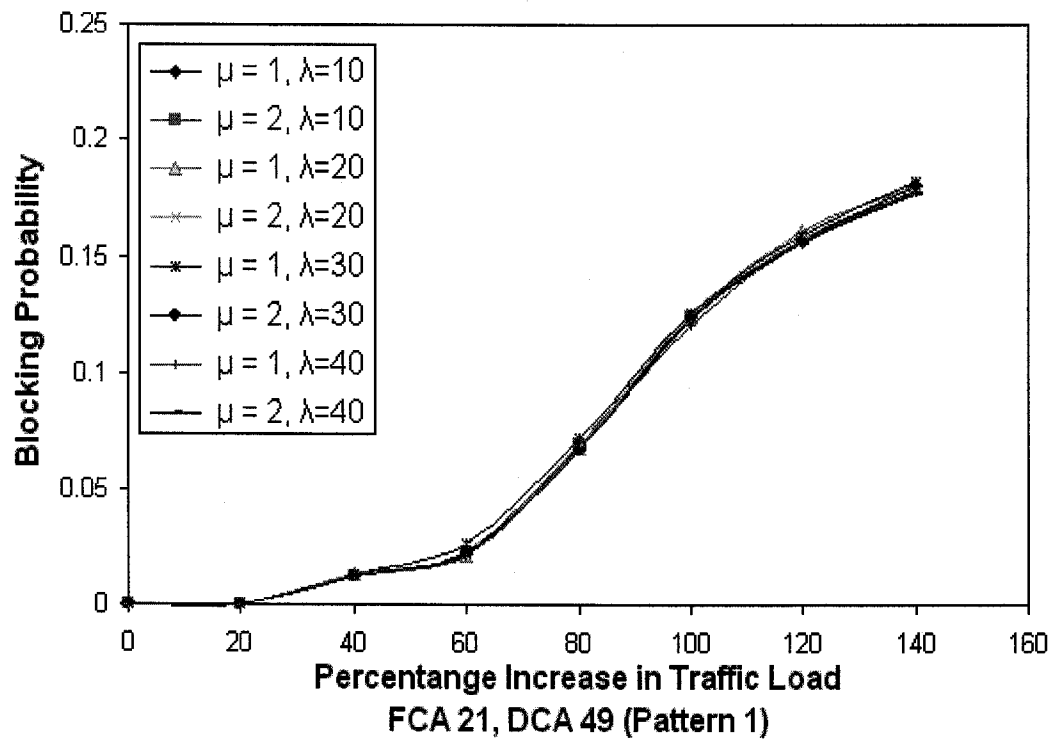


Figure 4.10: Performance of proposed  $(\mu, \lambda)$ -ES (HCA-DPC) in terms of blocking probability for different values of  $\mu$  and  $\lambda$  with nonuniform traffic distribution according to Pattern 1 for FCA 21 and DCA 49

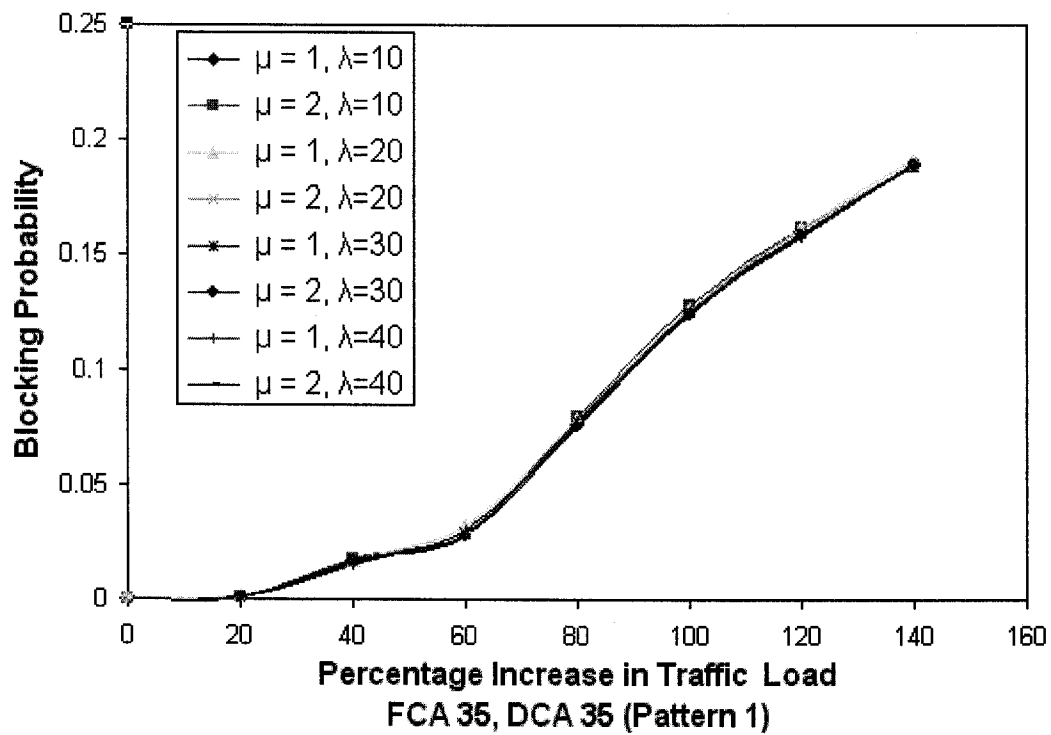


Figure 4.11: Performance of proposed  $(\mu, \lambda)$ -ES (HCA-DPC) in terms of blocking probability for different values of  $\mu$  and  $\lambda$  with nonuniform traffic distribution according to Pattern 1 for FCA 35 and DCA 35

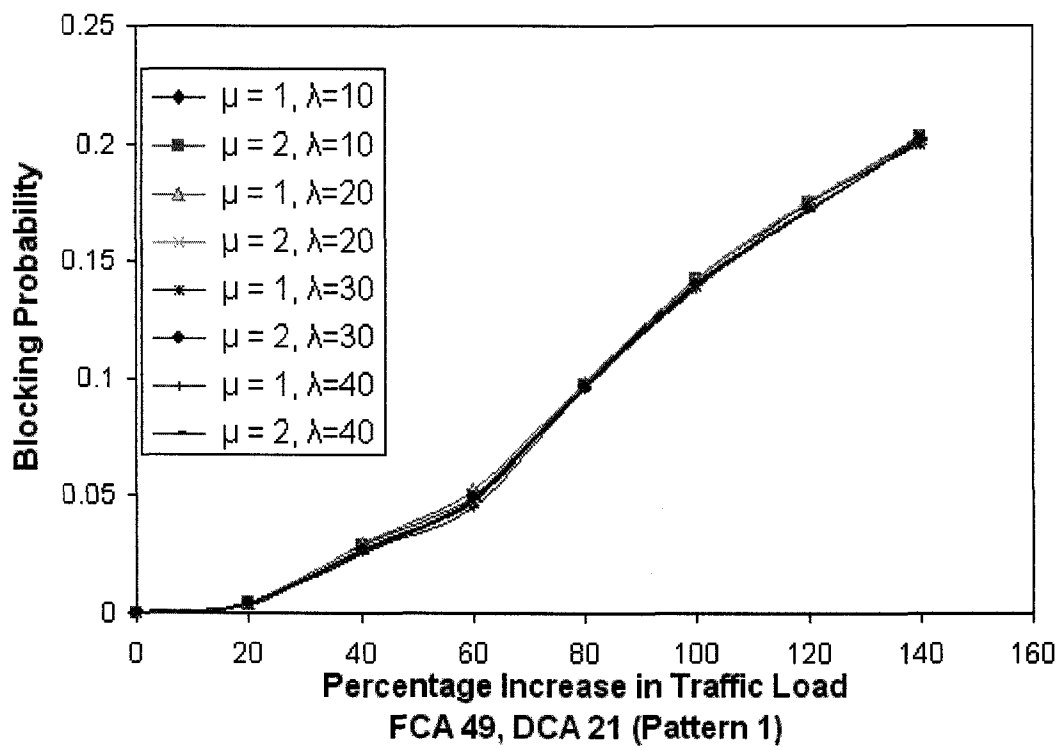


Figure 4.12: Performance of proposed  $(\mu, \lambda)$ -ES (HCA-DPC) in terms of blocking probability for different values of  $\mu$  and  $\lambda$  with nonuniform traffic distribution according to Pattern 1 for FCA 49 and DCA 21

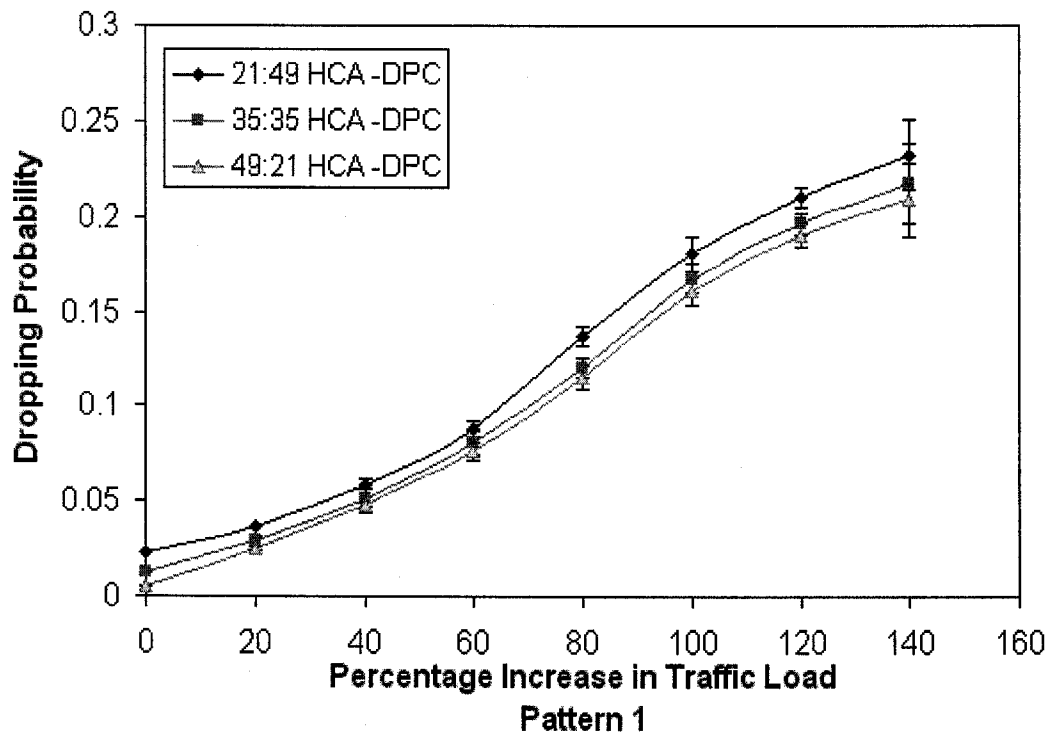


Figure 4.13: Performance of proposed  $(\mu, \lambda)$ -ES (HCA-DPC) in terms of dropping probability for the entire network with nonuniform traffic distribution according to Pattern 1



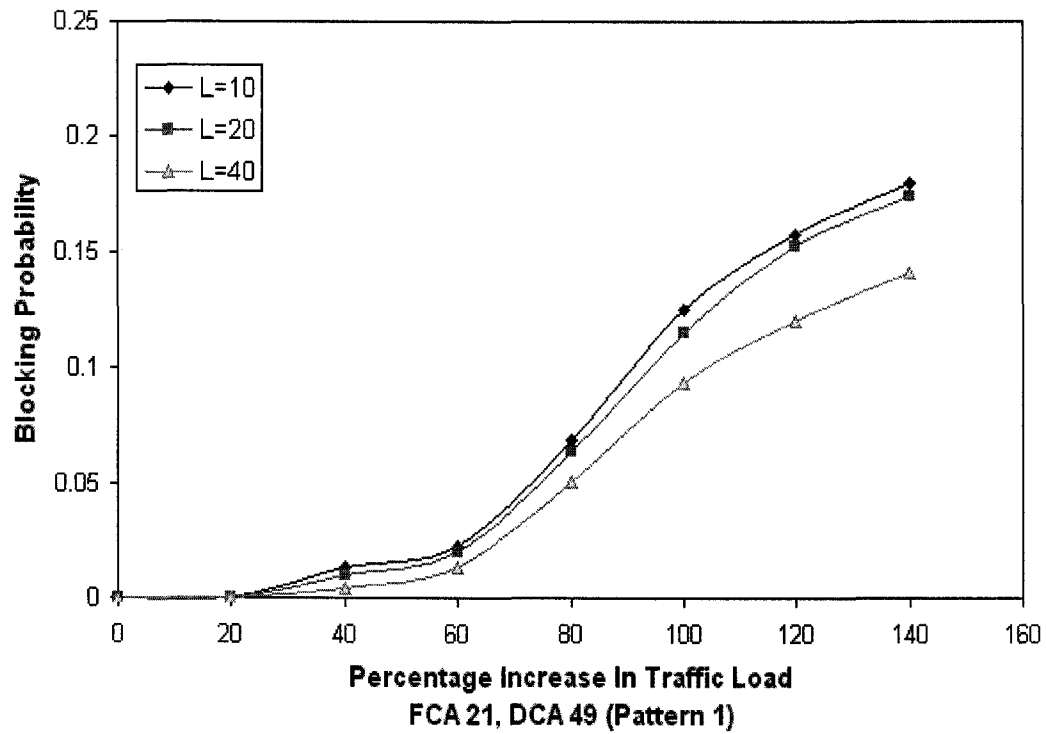


Figure 4.14: Performance of proposed  $(\mu, \lambda)$ -ES (HCA-DPC) in terms of blocking probability using different values of  $L$  with nonuniform traffic distribution according to Pattern 1 for FCA 21 and DCA 49

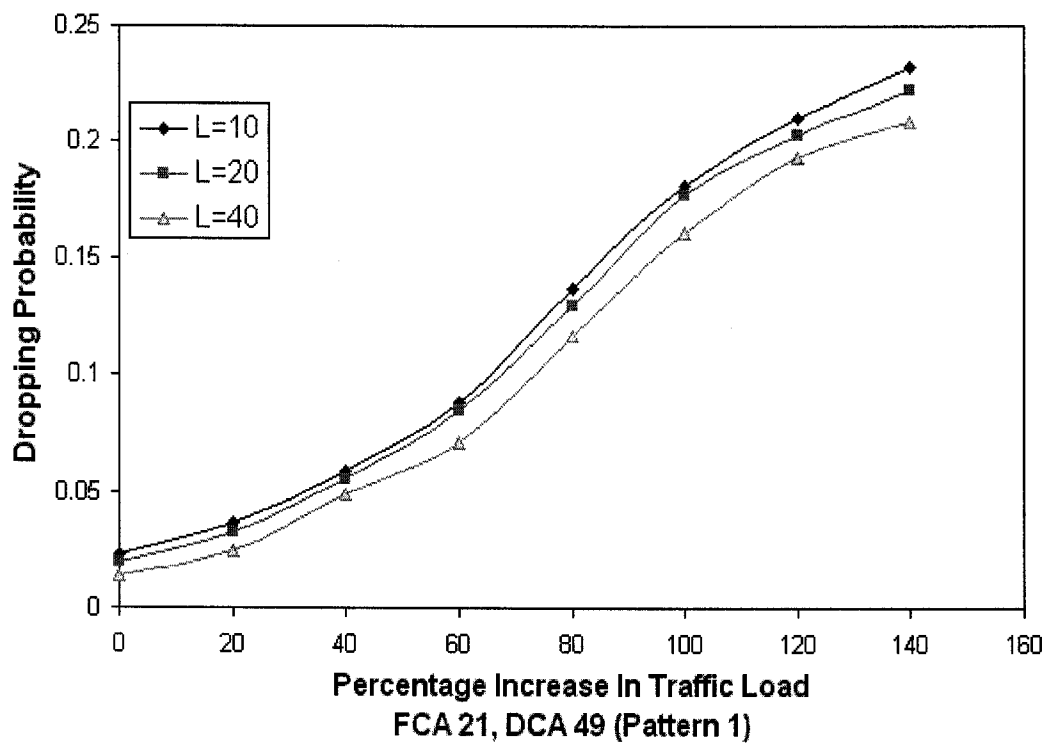


Figure 4.15: Performance of proposed  $(\mu, \lambda)$ -ES (HCA-DPC) in terms of blocking probability using different values of  $L$  with nonuniform traffic distribution according to Pattern 1 for FCA 21 and DCA 49

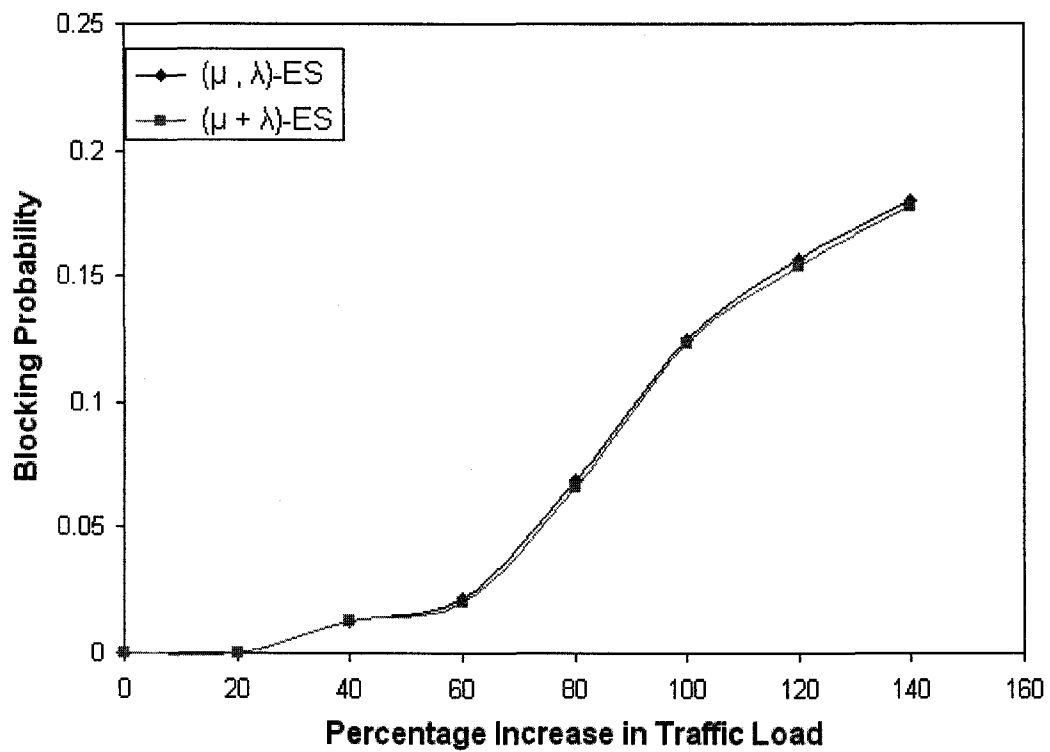


Figure 4.16: Performance of proposed  $(\mu, \lambda)$ -ES (HCA-DPC) and  $(\mu, \lambda)$ -ES (HCA-DPC) in terms of call blocking probability with nonuniform traffic distribution according to Pattern 1 for FCA 21 and DCA 49

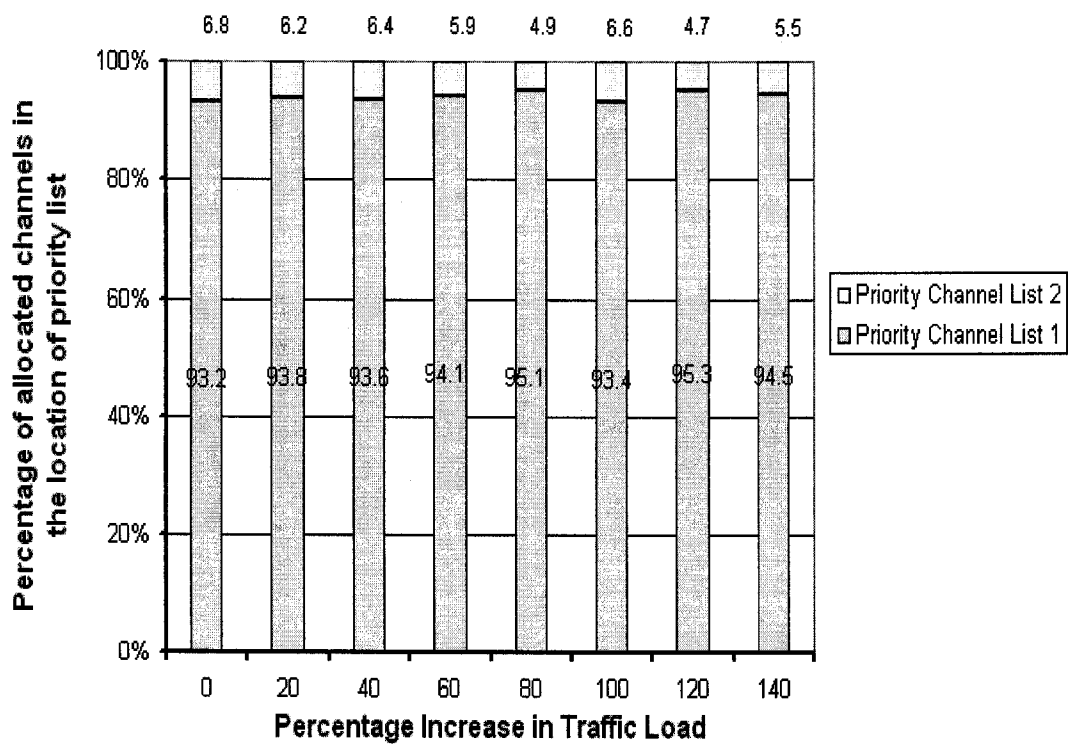


Figure 4.17: Performance of proposed  $(\mu, \lambda)$ -ES (HCA-DPC) and  $(\mu, \lambda)$ -ES (HCA-DPC) in terms of call blocking probability with nonuniform traffic distribution according to Pattern 1 for FCA 21 and DCA 49

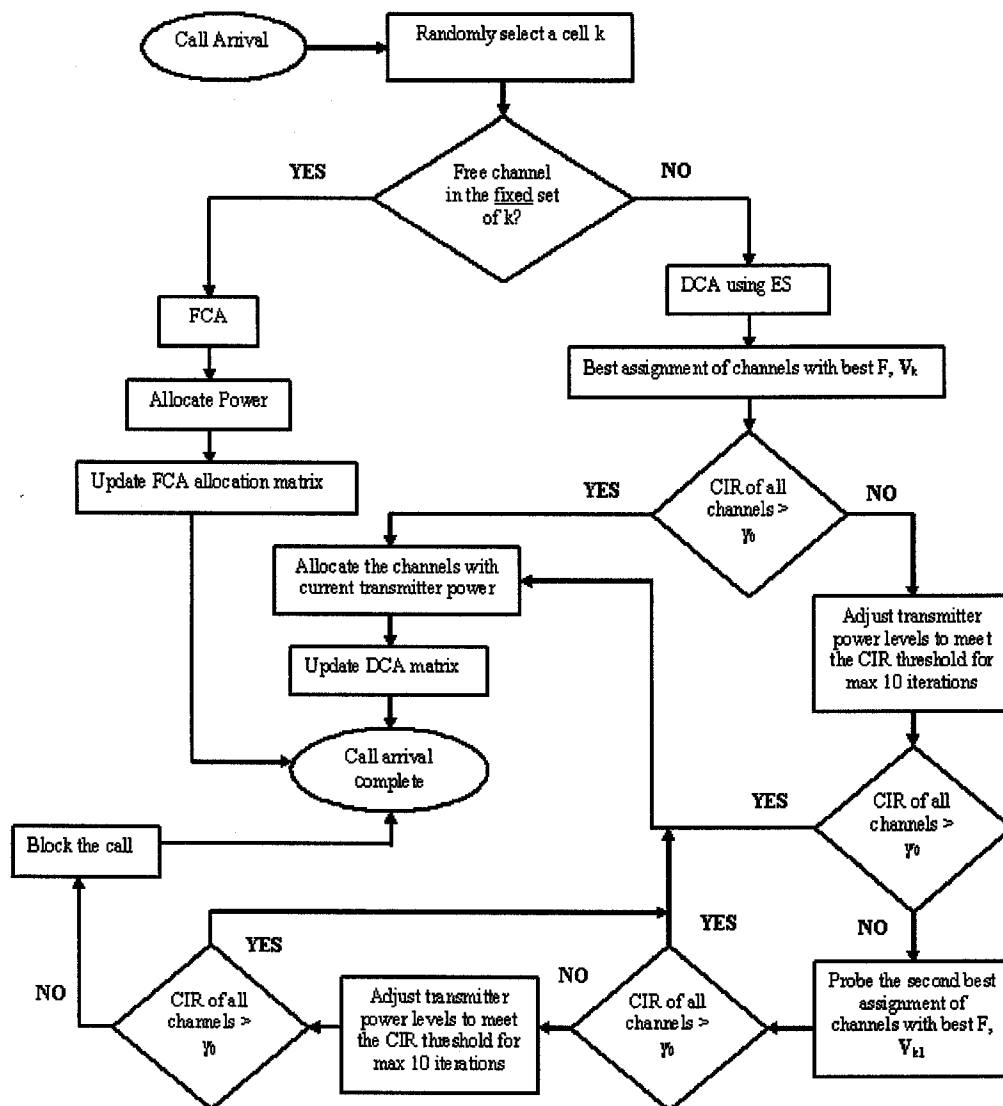


Figure 4.18: Simulation of Call Arrival Event

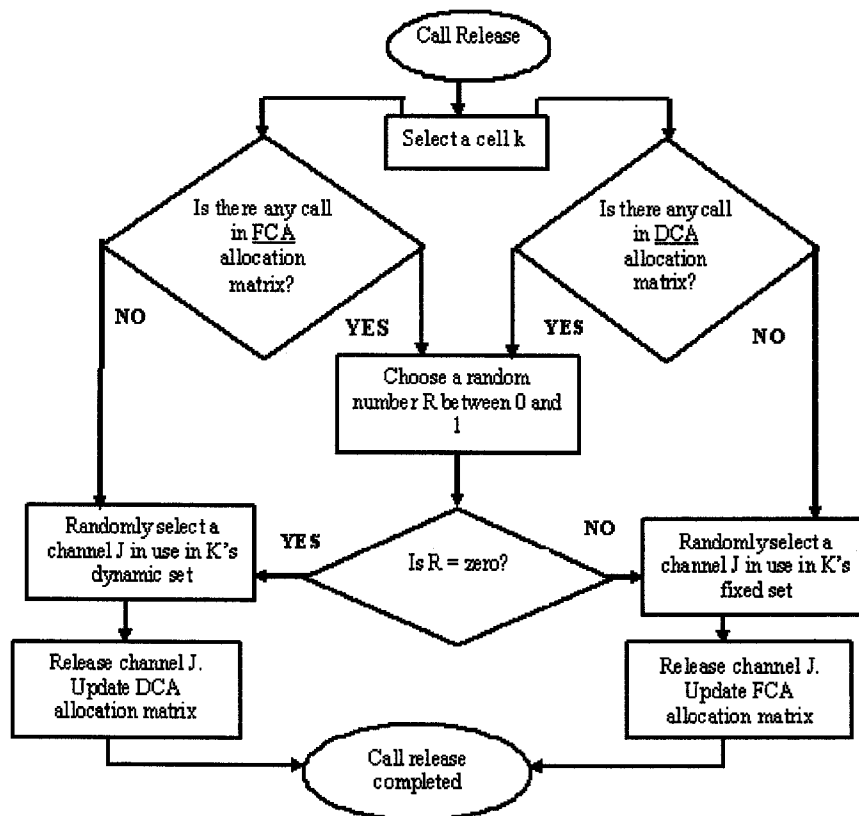


Figure 4.19: Simulation of Call Release Event

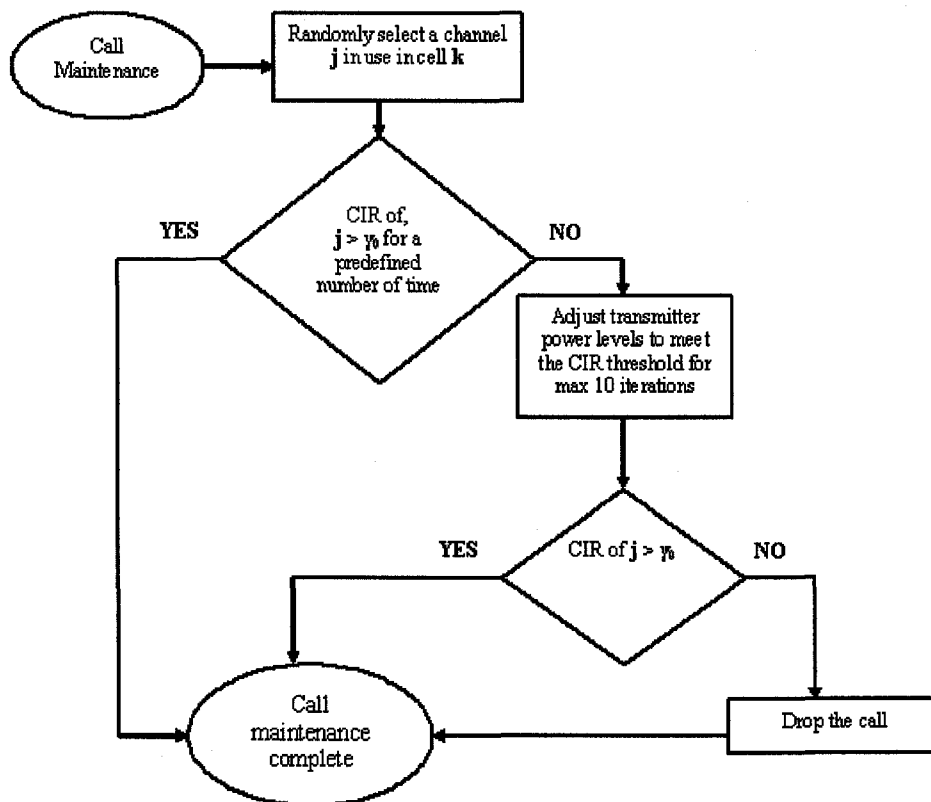


Figure 4.20: Simulation of Call Maintenance Event

## Chapter 5

# Conclusion and Future Direction

Dynamic Channel assignment is an important resource allocation problem in wireless mobile communication. It can maximize the assignment of channels but assigning a channel to a new call might result in call drop of on-going calls or call-block of new calls. The power control can suppress the adjacent channel interference (for non-orthogonal channels), the cochannel interference (for orthogonal channels), and minimize power consumption to extend terminal battery life. Undoubtedly, the power control can raise the network capacity and the channel assignment is highly correlative with power control.

We proposed an HCA strategy combined with distributed power control DPC using Evolution Strategy which showed significant improvement in call blocking probability in compared to [73], provided desired signal quality and minimized the power consumption. We used ES based algorithm to perform channel allocation which 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 [61].

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 [61]. The proposed algorithm uses an integer representation to represent the solution vector. The chosen representation and the mutation operator guarantees the feasibility of the solution. Our proposed algorithm also uses an efficient step size equation towards the optimal power utilization and maintaining the desired signal level. Our threshold based implicit admission control scheme only admits a new call if it can achieve the desired CIR threshold. Even though our real time simulations of the mobile communication system performed better the computation time was a bit slower than [73].

Further research need to be done on the proposed scheme to consider user mobility, provide some protection margin cushioning the already active links. Some predictive power control approach can also be considered to provide predictive measurements of both channel gains and interference levels to to be used to update the power levels. Finally, an admission control mechanism can be considered to adjust the tradeoff between blocking new calls and dropping active calls.

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