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## Chapter 2

### Combinatorial Evolutionary Methods in Wireless Mobile Computing

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## 1 Introduction

Like other technological developments, the development in wireless mobile communication has passed through several stages. The pioneering experiments in land mobile communication date back to the 1920s in Detroit, Michigan, USA. In Michigan 1946, the first interconnection of mobile users to the public telephone network was done to allow calls from fixed stations to mobile users. The system used a central high-power transmitter to cover a metropolitan area up to 50 miles or more

from the transmitter. With this concept it was difficult to reuse the same frequency and hence resulted in limited system capacity.

A solution to this problem emerged in the 1970s when researchers at Bell Laboratories in the USA developed the concept of a cellular telephone system, which appeared in a Bell system proposal during the late 1940s. The cellular concept replaced the use of a large geographical area (where a high-power transmitter is placed at a high elevation at the center of the area) with a number of non overlapping smaller geographical areas, called cells, equipped with low-power transmitters. A cellular organization allows frequency reuse among geographically distant cells, thus greatly expanding the system capacity [50, 68]. It also allows cells to be sized according to subscriber density and traffic demand of a given area.

The developments in cellular systems can be divided into three stages: first generation cellular systems, second generation cellular systems, and third generation cellular systems.

### **1.1 First Generation Cellular Systems**

The first generation cellular systems include the introduction of Nordic Mobile Telephone (NMT) in 1981, Advanced Mobile Phone Service (AMPS) in 1983, and Total Access Communications System (TACS) in 1985. Several other technologies were developed but AMPS, NMT, and TACS were the most successful [79]. All these “first-generation” cellular systems were analog systems and provided only basic speech services.

### **1.2 Second Generation Cellular Systems**

One of the challenges faced by analog systems was the inability to handle the growing capacity needs in a cost-efficient manner. Moreover, each system followed different standards, which made it impossible for a person to use the same cellular phone in different countries. As a result, standardization committees for “second-generation” cellular systems worldwide adopted the digital technology, which conformed to at least three standards: one for Europe and international applications known as Global Mobile Systems (GSM); one for North America, IS-54 (North American Digital Cellular); and one for Japan, Japanese Digital Cellular (JDC) [23]. The advantages of digital systems over analog systems include ease of signaling, lower levels of interference, integration of transmission and switching, higher capacity potentials, and inclusion

of new services (data services, encryption of speech and data, and Integrated Services Digital Network) [23]. Second generation cellular systems are, however, still optimized for voice service and they are not well suited for data communications.

### 1.3 Third Generation Cellular Systems

Data communication is an important requirement in the current environment of the internet, electronic commerce, and multimedia communications. The third generation systems referred to as Personal Communication Systems (PCS), aim at providing integrated services such as data, voice, image, and video to stationary and non stationary subscribers without temporal and spatial restrictions. Examples of PCS include Personal Handphone System, and Digital Enhanced Cordless Telecommunications.

The number of subscribers to mobile services is expected to increase in the near future; hence a lot of research has been focused on the efficient use of available resources to maximize the system capacity. Many resource management problems in cellular networks can be modeled as graphs and hence efficient solutions can be found using graph theory techniques. Efficient resource management also involves the use of optimization tools. Traditional methods of search and optimization progress through every point in the entire search space thereby rendering them not only time-consuming but also wasteful of computational resources when implemented in a very complex search space. Therefore, although optimization techniques are in abundance, Evolutionary Algorithms (EA) outperform most of them (in terms of quality of solution) in such problems because of their ability to progress through a population of points without actually going through every point in the entire search space. This chapter provides a comprehensive survey on the application of EA to some of the well-known optimization problems in wireless mobile computing. It also shows how combinatorial approaches such as graph theory methods are used to address the same.

The remainder of this chapter is organized as follows. Section 2 defines some of the fundamental concepts involved in the field of wireless mobile communication; Section 3 gives an overview of two most commonly used EAs. In Sections 4–12, we review some of the papers describing the application of EA and the use of graph theory methods to some of the difficult problems in wireless mobile communication. Conclusions and directions for future work are given in Section 13.

## 2 Cellular Radio Systems

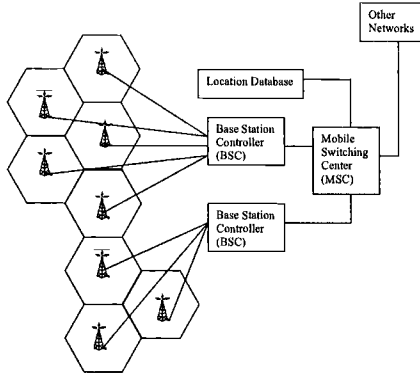


Figure 1: Network architecture.

The advent of the cellular concept was a major breakthrough in the development of wireless mobile communication. The cellular principle divides the covered geographical area into a set of smaller service areas called cells. During the early part of the evolution of the cellular concept, the system designers recognized the concept of all cells having the same shape to be helpful in systematizing the design and layout of the cellular system [49]. The 1947 Bell Laboratories paper [49] discussed four possible geometric shapes: the circle, the square, the equilateral triangle, and the regular hexagon. The regular hexagon was found to be the best over the other shapes [49]. In practice, the cell sizes are irregular and depend on the terrain and propagation conditions. Figure 1 (Modified from [1], figure 1, pp. 139) shows a typical mobile communication network.

Each cell has a base station and a number of mobile terminals (e.g., mobile phone, pagers, laptops, or other mobile devices). The base station is equipped with radio transmission and reception equipment. The mobile terminals within a cell communicate through wireless links with the base station associated with the cell. A number of base stations are connected to the Base Station Controller (BSC) via microwave links or dedicated leased lines. The BSC contains logic for radio resource management of the base stations under its control. It is also responsible for transferring an ongoing call from one base station to another as a mobile user moves from cell to cell. A number of BSCs are connected to

the Mobile Switching Center (MSC) also known as the Mobile Telephone Switching Office (MTSO). The MSC/MTSO is responsible for setting up and tearing down of calls to and from mobile subscribers. The MSC is connected to the backbone wire-line network such as the public switched telephone network (PSTN), Integrated Service Digital Network (ISDN), or any LAN/WAN-based network. MSC is also connected to a location database, which keeps information about the location of each mobile terminal. The base station is responsible for the communication between the mobile terminal and the rest of the information network. A base station can communicate with mobiles as long as they are within its operating range. The operating range depends upon the transmission power of the base station.

## 2.1 Channel Allocation

In order to establish communication with a base station, a mobile terminal must first obtain a channel from the base station. A channel consists of a pair of frequencies: one frequency (the forward link/ downlink) for transmission from the base station to the mobile terminal, and another frequency (the reverse link/ uplink) for the transmission in the reverse direction. An allocated channel is released under two scenarios: the user completes the call or the mobile user moves to another cell before the call is completed. The capacity of a cellular system can be described in terms of the number of available channels, or the number of users the system can support. The total number of channels made available to a system depends on the allocated spectrum and the bandwidth of each channel. The available frequency spectrum is limited and the number of mobile users is increasing day by day, hence the channels must be reused as much as possible to increase the system capacity. The assignment of channels to cells or mobiles is one of the fundamental resource management issues in a mobile communication system. The role of a channel assignment scheme is to allocate channels to cells or mobiles in such a way as to minimize the probability that the incoming calls are blocked, the probability that ongoing calls are dropped, and also to minimize the probability that the carrier-to-interference ratio of any call falls below a prespecified value. The channel assignment problem first appeared in [56].

### **2.1.1 Channel Assignment Schemes**

In literature, many channel assignment schemes have been widely investigated with a goal to maximize the frequency reuse. The channel assignment schemes in general can be classified into three strategies: Fixed Channel Assignment (FCA) [49, 21, 93, 90, 44], Dynamic Channel Assignment (DCA) [12, 93, 18, 78, 11], and Hybrid Channel Assignment (HCA) [41, 93]. In FCA, a set of channels is permanently allocated to each cell based on a pre-estimated traffic intensity. In DCA, there is no permanent allocation of channels to cells. Rather, the entire set of available channels is accessible to all the cells, and the channels are assigned on a call-by-call basis in a dynamic manner. Cox and Reudink [12] proposed the DCA scheme. One of the objectives in DCA is to develop a channel assignment strategy, which minimizes the total number of blocked calls [78]. The FCA scheme is simple but does not adapt to changing traffic conditions and user distribution. Moreover, frequency planning becomes more difficult in a microcellular environment as it is based on accurate knowledge of traffic and interference conditions. These deficiencies are overcome by DCA but FCA outperforms most known DCA schemes under heavy load conditions [44]. To overcome the drawbacks of FCA and DCA, HCA was proposed by Kahwa and Georgans [41], which combines the features of both FCA and DCA techniques. In HCA one set of channels is allocated as per the FCA scheme, and the other set is allocated as per the DCA scheme. A comprehensive survey of various channel assignment schemes can be found in [42].

DCA schemes can be implemented as centralized or distributed. In the centralized approach [46, 20, 93, 92, 54, 9], all requests for channel allocation are forwarded to a central controller that has access to system-wide channel usage information. The central controller then assigns the channel by maintaining the required signal quality. In distributed DCA [10, 11, 51, 67], the decision regarding the channel acquisition and release is taken by the concerned base station based on the information from the surrounding cells. As the decision is not based on the global status of the network, it can achieve suboptimal allocation as compared to the centralized DCA and may cause forced termination of ongoing calls.

### **2.1.2 Channel Assignment Constraints**

Radio transmission is such that the transmission in one channel causes interference with other channels. Such interference may degrade the

signal quality and the quality of service. The potential sources of radio interference to a call are:

1. Co-channel interference: This radio interference is due to the allocation of the same channel to a certain pair of cells close enough to cause interference, (i.e., a pair of cells within the reuse distance).
2. Adjacent channel interference: This radio interference is due to the allocation of adjacent channels (e.g.,  $f_i$  and  $f_{i+1}$ ) to a certain pair of cells simultaneously.
3. Co-site interferences: This radio interference is due to the allocation of channels in the same cell that are not separated by some minimum spectral distance.

These constraints are known as Electromagnetic Compatibility Constraints (EMC) [62]. EMC can be represented by a minimum channel separation between any pair of channels assigned to a pair of cells or the cell itself [86]. If there are  $F$  channels to serve  $C$  cells in the system, the minimum channel separation required for an acceptable level of interference is described by a symmetric compatibility matrix  $X[C, C]$ . Each element  $X_{i,j}(i, j = 1 \dots C)$  represents the minimum separation required between channels assigned to cells  $i$  and  $j$  for an acceptable level of interference.

The reuse of channels in a cellular system is inevitable and at the same time it is directly related to co-channel interference. Co-channel interference is measured by a required Signal to Interference Ratio (SIR). As a result of co-channel interference, all channels may not be reused in every cell. In an AMPS System, when SIR is equal to 18 dB, most of the users call the system good or excellent [49]. However, the concept of a cellular system enables the discrete channels assigned to a specific cell to be reused in different cells separated by a distance sufficient to bring the value of co-channel interference to a tolerable level thereby reusing each channel many times. The minimum distance required between the centers of two cells using the same channel to maintain the desired signal quality is known as the reuse distance ( $D_s$ ). The cells with center-to-center distance less than  $D_s$  belong to the same cluster. No channels are reused within a cluster.

Another basic requirement of channel assignment is the demand of channels in each cell. This channel demand or traffic demand can be modeled by a vector  $\mathbf{T}$  of length  $C$  where an element  $T_i$  denotes the

number of channels used in cell  $i$ . This vector can be obtained by analyzing the traffic at each cell. In reality, the value of  $\mathbf{T}$  should be a function of time due to arrival of new calls, termination of ongoing calls, and handovers.

The process of channel assignment must satisfy the EMC constraints and the demand of channels in a cell. These constraints are also known as hard constraints. This requires a proper channel assignment scheme. The channel assignment problem has been shown to be NP-hard [32].

Besides the hard constraints and traffic demand constraints, other conditions that may be violated to improve the performance of the dynamic channel allocation technique include the packing condition, resonance condition, and limitation of reassignment operations [72]. These conditions are called soft constraints and were introduced in [18]. These constraints allow further lowering of the call blocking.

1. **Packing condition:** The packing condition tries to use the minimum number of channels every time a call arrives [72]. It allows the selection of those channels that are already in use in other cells as long as the co-channel interference constraint is satisfied.
2. **Resonance:** With the resonance condition, the same channels are assigned to cells that belong to the same reuse scheme [72]. This reduces the call blocking probability. The objective function should help select a combination of channels that makes maximum use of channels already in use in the reuse scheme to which the cell involved in call arrival belongs.
3. **Limiting rearrangement:** Channel reassignment improves the quality of service in terms of lowering call blocking probability. Hence it is an important process in dynamic channel allocation. It is the process of transferring an ongoing call to a new channel without call interruption [8]. The reassignment process greatly affects the call blocking probability. Reassignment in the entire cellular network upon a new call arrival will obviously result in lower call blocking, but it is complex both in terms of time and computation [72]. Therefore, the reassignment process is limited to the cell involved in the new call arrival. However, excessive reassignment in a cell may lead to an increase in blocking probability [72]. So a process called limiting rearrangement is considered that tries to assign, where possible, the same channels assigned before, thus limiting the reassignment of channels. Reassignment is done together



with the new call.

## 2.2 Multiple Access Techniques

The radio spectrum is one of the finite resources in the wireless environment. Thus one of the goals in cellular systems design is to be able to handle as many calls as possible in a given bandwidth with some reliability. The Multiple Access Technique (MAT) allows many users to share the common transmission resource, the radio spectrum, without causing interference between users. A good MAT can improve the system capacity. Different types of cellular systems employ various methods of multiple accesses. The traditional analog cellular systems, such as AMPS and TACS standards, use Frequency Division Multiple Access (FDMA). With FDMA, the available spectrum is divided into a number of radio channels of a specified bandwidth, and a selection of these channels is used within a given cell. For example, in AMPS the available spectrum is divided into blocks of 30 kHz [79], and in TACS channels are 25 kHz wide. In this technique only one subscriber at a time is assigned to a channel. The channel cannot be assigned to another user in the same cell during the call.

The second generation digital cellular systems such as IS-54 and GSM use Time Division Multiple Access (TDMA). With TDMA the available radio spectrum is divided into time slots, and only one user is allowed to either transmit or receive at each time slot. Thus, TDMA increases the throughput by sending multiple calls over a single frequency distributed over time. The channel can be assigned to another user in the same cell except that they must transmit at different times.

Due to the increasing demand for mobile communications services, the use of highly efficient multiple access techniques have become imperative. The Code Division Multiple Access (CDMA) is currently considered efficient in achieving high capacity in such systems [65]. So the third generation cellular system uses CDMA. With CDMA, several users can simultaneously access a given frequency allocation thereby increasing the spectral efficiency several times as compared to that achievable by TDMA and FDMA [28]. Beside this, it also supports users with different communication demands, e.g., different data rate requirements. Unique digital codes called pseudo-random code sequences are used to differentiate the subscribers.

## 2.3 Location Management

Wireless networks enable mobile users to communicate regardless of their locations. In contrast to the telephone number in traditional telecommunication systems that specifies the location of the end users, the mobile subscriber (one who subscribes to mobile services) number does not provide the location of the mobile user. Therefore, to handle the mobility of terminals in a wireless network there is a need to address two basic issues: tracking the position of a mobile user (with registrations), and to set up connections or deliver data to mobile users. A location management mechanism is composed of three components: a system database for mapping subscriber numbers to locations, an update operation for informing the system database about the changes in the mobile user's locations known as Location Update (LU), and a search operation for locating the mobile with the help of the system database known as terminal paging. In the current cellular system the coverage area of the system is divided into Location Area (LA) or Registration Area (RA), each consisting of a group of cells that forms a contiguous geographic area. Each LA has its unique identifier (ID). Each LA has a database that keeps a record of the location information of a mobile terminal. For each mobile terminal, the database entry is updated only when the mobile terminal performs a location update. The mobile terminal initiates the location update procedure by sending an update message over the uplink control channel (see Section 2.0). This is followed by some signaling procedures, which update the database. A good survey of different update schemes can be found in [89].

Upon call arrival, the system has to determine in which cell the mobile terminal is currently. Because the system knows the mobile terminal's LA, the search can be confined to the cells within the LA. Thus, a paging operation is triggered to find a target mobile. In paging, polling signals are sent over the downlink control channel to a group of cells where the mobile terminal is likely to be present. All the mobile terminals within the group of cells receive the page message but a response message is sent back over the uplink control channel by only the target mobile terminal. If the response is sent before a predetermined timeout period the paging process is terminated. Otherwise, another group of cells is chosen in the next search iteration. In order to avoid call dropping, the mobile terminal must be located within an allowable time constraint. A comprehensive survey of the various paging schemes proposed in the literature can be found in [89].

### 3 Introduction to Evolutionary Algorithm

During the 1950s and 1960s many scientists were inspired to use the principles of natural evolution based on Darwin's ideas [13] of natural selection as an optimization tool for engineering problems. In 1990, the term Evolutionary Algorithm (EA) was proposed to describe all algorithms based on natural evolution for problem solving.

All EAs work within a similar framework. A representation scheme is chosen to define the set of solutions that represent unique points within the search space. A candidate solution is called a *chromosome*. The pool of candidate solutions is called a *population*. The total number of individuals in a population is called the *population size*. Each individual solution is associated with an *objective value*. The objective value is problem specific and is representative of the individual solution's performance in relation to the parameter being optimized. It also reflects an individual solution's fitness in relation to other potential solutions in the search space.

EA is an iterative process and its goal is to continually improve the fitness of the best solution. It tries to do so by emulating the natural process of biological evolution through the use of natural processes, such as *reproduction*, *recombination*, and *mutation*. Reproduction selects members of a current population to use as parents for the generation of a new population [4]. The mechanisms to determine which and how many parents to select, how many new solutions called offspring to generate, and which individuals will survive into the next generation together represent the selection method. It mimics nature's survival of the fittest mechanism [82]. The selection of parents is based on fitness of each chromosome measured by a fitness evaluating function. The fitness evaluating function is a measure of how good is each member relative to other members of the population [63, 82]. Selection alone cannot create new solutions in the population. Genetically inspired operators, recombination and mutation, generate new solutions in the population. Recombination attempts to create offspring by combining the features of existing parents. The purpose of the mutation operator is to prevent the loss of useful genetic information and hence to maintain diversity within the population [82]. The process of selection and application of reproduction operators is repeated until some terminating criterion is reached. The solution to the problem is represented by the best individual so far in all generations.

The Genetic Algorithm (GA) and Evolutionary Strategy (ES) are

the two most common variants of EAs. An introductory survey on GA and ES can be found in [24].

### 3.1 Genetic Algorithm

Genetic algorithms are stochastic parallel search algorithms based on the principle of evolution and natural selection [34]. They have proven to be robust search algorithms [29]. The implementation of GA in a specific problem starts with six fundamental issues: encoding of solution, creation of initial population, fitness evaluation, selection of progenitors, generation of progeny by genetic operators, and termination criteria. They were pioneered by John Holland [35, 34]. Holland's genetic algorithm is commonly called the Simple Genetic Algorithm (SGA). The general structure of the SGA is as follows [63].

Procedure SGA:

  Begin

    Set control parameters;

    {crossover and mutation probabilities, population size, and chromosome length}

    Initialize population; {at random}

    Evaluate initial population; {fitness of initial individuals}

    Repeat

      Select individuals for next generation; {reproduction}

      Perform crossover and mutation; {obtain new population}

      Evaluate population; {fitness of new individuals}

    Until termination condition is reached;

  End;

Genetic parameters (population size, crossover probability, and mutation probability) should be carefully selected for optimal performance [82]. The choice of these parameters is problem specific and no exact rule exists to determine a suitable combination of these parameters [4]. A joint effect of population size, crossover probability, mutation probability, and number of crossover points in each recombination influences the performance. Goldberg [30] has suggested a population size equal to  $1.65 * 2(0.21 * l)$  where  $l$  is the length of the chromosome for optimal performance. Schaffer et al. [74] have concluded that a small population size 20 to 30, a crossover probability in the range 0.75 to 0.95, and a mutation probability in the range 0.005 to 0.01 perform well.

In recent years, many variations of genetic algorithms have been proposed that bear little resemblance to Holland's original formulation.

Many methods of encoding, crossover, mutation, reproduction, and selection (roulette wheel selection, scaling technique, tournament selection, elitist model, ranking) have been used and have become a subject area of research. Interested readers may refer to [17, 22], and Krishnakumar [43]. The books by Holland [34], Goldberg [29], Davis [15], Michalewicz [57], De Jong [16], and Mitchel [58] provide detailed discussion of genetic algorithms.

### 3.2 Evolution Strategy

Rechenberg [69] pioneered ES. ES was proposed as an optimization method for real-valued vectors. It works on an encoded representation of the solution. ES is a random guided hill-climbing technique in which a candidate solution is produced by applying mutations to a given parent solution. The best solution generated in one generation becomes the parent for the next generation. ES is an iterative method so the process of selection and application of mutation is repeated until some terminating criterion is reached. When the termination criterion is reached, the solution to the problem is represented by the best individual so far in all generations. The basic steps of an ES algorithm can be summarized as follows,

1. Generate an initial population of  $\lambda$  individuals.
2. Evaluate each individual according to a fitness function.
3. Select  $\mu$  best individuals called the parent population and discard the rest.
4. Apply the reproduction operator, i.e., mutation, to create  $\lambda$  offspring from  $\mu$  parents.
5. Go to step 2 unless a desired solution has been found or a predetermined number of generations have been produced and evaluated.

In GA, the fitness of an individual determines its chances of survival into the next generation, whereas in ES only the best individuals survive. The two common variations of ES introduced by Schwefel [75] are the  $(\mu + \lambda)$ -ES and  $(\mu, \lambda)$ -ES. In both approaches  $\mu$  parents produce  $\lambda$  offspring. These two approaches 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  $\lambda$  offspring are selected to form the next generation.

Sections 4–12 discuss the use of the evolutionary algorithm and graph theory methods in the area of wireless mobile communication.

## 4 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 [45]. Therefore one of the most challenging design problems in cellular networks is to decide on the location 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. These include the use of GA [5, 33], simulated annealing [2], [36], and tabu search [47]. For finding precise base station locations, numerous factors such as traffic density, channel condition, interference scenario, the number of base stations, and other network planning parameters [33] must be taken into account. In the base station placement problem, the goal is to select minimum number of base station locations from a list of potential sites while maximizing coverage in the area taking into account the radio propagation characteristics of the area. The radio propagation characteristics can be determined using ray-tracing software or by using empirical propagation models for path loss. There exists a tradeoff 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. Determining the location of base stations is known to be NP-hard [5].

### 4.1 Graph-Theoretical Methods in Base Station Placement

Mathar and Niessen [55] have shown that the base station placement problem in its simplest form is equivalent to minimum dominating set problem in graph theory. Given an undirected graph  $G(V, E)$ , where  $V$  is the set of vertices and  $E$  is the set of edges, a set  $S$  is said to be dominating if for every  $u \in V - S$  there exists a  $v \in S$  such that

$(u, v) \in E$ . The objective is to find a dominating set  $S$  with the minimum cardinality.

## 4.2 EA in Base Station Placement

Some of the papers that describe the application of EA in the base station placement problem are briefly described below.

1. Calégari et al. [5] presented a GA-based approach to address this problem. The paper assumes that a list of  $N$  possible locations that guarantee 100% radio coverage is known beforehand. The candidate solutions are represented using an  $N$  bit binary string. A value of 1 indicates the presence of a base station at the location corresponding to that bit, and zero otherwise. The chromosomes are evaluated by the fitness function shown in equation (1):

$$f = \frac{CoverRate^\alpha}{NB} \quad (1)$$

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) and  $NB$  is the number of selected base stations. This fitness function maximizes the coverage and minimizes the number of transmitters. Selection based on fitness value, one-point crossover, and mutation operators (flipping of the value of a randomly chosen bit of the string with a probability of 0.9) is employed.

Experimental results were carried out on a 70 km  $\times$  70 km digital terrain discretized on a 300  $\times$  300 points grid with  $N = 150$ . The radio coverage of each base station was computed using a radio wave propagation simulation tool. A solution with 52 base stations covering 80.04% was found after 160 generations with a population size of 80 chromosomes. The algorithm was found to be very slow. So in order to speed up the execution, the parallelization of the algorithm with the island concept was investigated. In this concept, the population is partitioned into subpopulations called islands that evolve independently towards the solution. In order to benefit from the information found in an another island, it also supports the migration of individuals from one island to another. The computation time was reduced by running each island of 20

individuals on 4 different processors. They were also able to find a better quality of solution with 41 base stations covering 79.13% of the initial covered surface.

2. Han et al. [33] described the base station placement problem using GA with real number representation. Binary string representation (considered in [5]), suffers from representation limit (can represent discrete locations) and hence cannot guarantee an optimal solution. The real number representation describes both the base station location and its number. The chromosome represents the  $x$  and  $y$  coordinates of a base station. A genome  $g$  is a vector of the form  $g = (c_1, \dots, c_k)$ , where  $c_k = (x_k, y_k)$  is the chromosome for the  $k$ -th base station position, and  $x_k$  and  $y_k$  represent the  $x$  and  $y$  coordinates of the  $k$ -th base station position. The value of  $k$  is in the range  $1 \leq k \leq K$ , where  $K$  is the maximum number of base stations. Each genome is evaluated using equation (2) as follows.

$$f(g) = W_c \left( \frac{ct}{tot} \right) + W_e \left( \frac{K - n(g)}{K} \right) \quad (2)$$

where  $ct$  is the covered traffic and  $tot$  is the total offered traffic. In equation (2), the first term is the objective function for coverage and it increases as the covered traffic area increases corresponding to  $g$ . The second term is the objective function for economy (cost of the network) and increases as the number of base stations decreases.  $W_c$  and  $W_e$  are weight ( $W_c + W_e = 1$ ), and the values depend upon whether coverage or fewer base stations are preferred.  $n(g)$  is the number of base stations in the genome  $g$ .

The paper defined an appropriate crossover and mutation operator. In the crossover operator, a single chromosome is generated from two chromosomes (parents). If the chromosome for the  $k$ -th base station position is defined in both the parents, the corresponding chromosome in the child is the mean of the corresponding coordinates of the parent. Otherwise the child inherits the chromosome from the parent with the defined positions. The selection of individuals for reproduction is done using tournament selection.

Simulation results were carried out on a hexagonal cellular environment with cell radius of 2.5 km and uniform and nonuniform traffic distribution. Under uniform traffic distribution with  $K = 7$  and  $W_c = 1$ , the algorithm after the 700-th generation was able to



find base station locations that provided 97.8% coverage. The algorithm was also tested for economy by varying  $W_e$ . With  $K = 8$  after 700 iterations,  $W_e = 0.3$  provided 81.8% coverage with 6 base stations whereas  $W_e = 0.27$  provided 88.1% coverage with 7 base stations. By varying the weights the user can get the proper number of base stations and coverage. With nonuniform traffic distribution and  $W_c = 0.8$  and  $K = 12$ , a coverage of 99% is achieved after the 1000-th generation.

## 5 Combinatorial Heuristics for Fixed Channel Assignment

The fixed channel assignment problem can be modeled as an undirected graph  $G(V, E)$ , where the set of vertices  $V$  represents the set of radio transmitters or base stations, and the set of edges represents the interference constraints for frequencies assigned to neighboring base stations. Each vertex  $v_i$  is associated with a weight  $w_i$  that represents the demand of channels in the corresponding base stations. Metzger [56] first pointed out that the channel assignment problem is equivalent to the graph coloring problem. A feasible graph coloring solution assigns  $w_i$  different colors to the vertices  $v_i$  in such a way that no two adjacent vertices (i.e., vertices connected by an edge) have the same color. The objective is to minimize the number of colors used. In the channel assignment problem each color corresponds to a channel. Colors are represented by a set of positive integers. The performance of a coloring algorithm is measured in terms of the ratio of the number of colors used to the minimum number of colors required to color  $G$ . This ratio is known as the competitive ratio. Narayanan and Shende [60] proposed an approximation algorithm which is  $4/3$  competitive. The fixed preference allocation algorithm proposed by Janssen et al. [38] is  $3/2$  competitive.

Hale [32] formulated the channel assignment problem as the  $T$ -coloring problem. The  $T$ -coloring problem is a generalization of the graph coloring problem.  $T$ -coloring assigns a nonnegative integer (channel) to each vertex of  $G$  so that the adjacent vertices are assigned channels whose separation is not in a set  $T$  of unallowable separations.

Griggs and Yeh [31] proposed an  $L(2, 1)$ -coloring of a graph for channel assignment. The  $L(2, 1)$ -coloring problem is a generalization of the  $T$ -coloring problem. It assigns a nonnegative integer to each vertex of  $G$  so that the channels assigned to two vertices joined by an edge differ

by at least two and channels differ if the two vertices have a common neighbor.

Roxborough et al. [70] formulated the fixed channel assignment problem with both co-channel and adjacent channel constraints as the  $k$ -band chromatic bandwidth problem and with only the co-channel constraint as the distance  $k$ -chromatic number problem of cellular graphs. The distance  $k$ -chromatic number problem of a graph  $G(V, E)$  with an integer  $k$  is the minimum number of colors required to color the vertices so that no two vertices separated by a distance not exceeding  $k$  have the same color. This is known as proper coloring. In the  $k$ -band chromatic bandwidth problem, a weight  $w(i, j)$  is associated with an edge for all  $i, j \in V$ . The corresponding graph is known as an edge-weighted graph. This weight represents the frequency separation required between the channels used in the corresponding base stations. In the distance  $k$ -chromatic number problem, it has been assumed that the interference does not extend beyond  $k$  number of cells away from the call -originating cell. They have shown that by exploring the regular structure of a cellular network many instances of channel assignment problems can be solved in polynomial time. However, the algorithms presented were not optimal. Sen et al. [76] proposed an optimal algorithm for the distance- $k$  chromatic bandwidth number problem presented in [70], and a near-optimal algorithm for the chromatic bandwidth problem with a performance bound of  $4/3$ .

## 6 EA in Fixed Channel Assignment

1. Smith [80] proposed a GA-based approach to solve the FCA problem. The objective function treats the interference constraints (co-channel, adjacent channel, and co-site) as soft constraints and traffic demand satisfaction as a hard constraint. With this approach, a solution that minimizes the severity of any interference is always found. This helps to find a solution 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 a binary channel assignment matrix  $A[C, F]$  where  $A_{i,k} \in \{0, 1\}$  for  $i = 1 \dots C$ , and  $k = 1 \dots F$ . The fitness of

the chromosome is measured by equation (3):

$$\begin{aligned} \text{Min} \quad & f(A) = \sum_{j=1}^C \sum_{k=1}^F A_{j,k} \sum_{i=1}^C \sum_{l=1}^F P_{j,i,(|k-l|+1)A_{i,l}} \\ \text{s.t.} \quad & \sum_{k=1}^F A_{j,k} = d_j \quad \forall j \end{aligned} \quad (3)$$

where  $d_j$  is the traffic demand of cell  $j$  and  $P$  is a factor that assigns a penalty to each assignment according to the following recursive relation

$$\begin{aligned} P_{j,i,m+1} &= \max(0, P_{j,i,m-1}) \\ P_{j,i,1} &= X_{j,i} \\ P_{j,i,1} &= 0 \end{aligned}$$

for  $m = 1 \dots F - 1$  and for all  $j, i \neq j$ . Here  $X$  is a compatibility matrix of dimension  $C \times C$ . 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 the crossover and mutation operators: the crossover operator improves co-channel and adjacent channel interference and the mutation operator eliminates co-site interference. The algorithm was tested on a problem set given in [81]. It was found that mutation probability of  $p_m = 0.254$  and 500 generations were required to achieve an average interference level of zero with problems of similar complexity but of size  $C = 5$  and  $F = 11$ .

2. Ngo and Li [62] proposed a GA-based approach called the modified genetic-fix algorithm to find an optimal channel assignment matrix in FCA problems. They have considered three interference constraints (co-channel, adjacent channel, and co-site constraints), and the traffic demand constraint with nonuniform traffic distribution among the cells. The proposed algorithm creates and manipulates chromosomes with fixed size (i.e., in binary representation, the number of ones is fixed) and utilizes an encoding scheme called the minimum-separation encoding. A chromosome is a binary string that represents the channel assignment matrix  $A[C, F]$  through concatenation of rows, where  $C$  represents the number of cells and  $F$  represents the number of channels. 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 cell  $i$  must differ to prevent co-site constraint then the minimum-separation encoding scheme works by eliminating  $(d_{\min} - 1)$  zeros following each 1 in each row of the channel assignment matrix. This compression reduces the search space. A chromosome is evaluated by an objective function that includes only the co-channel and adjacent channel constraint. For the co-channel and adjacent channel interference constraint to be satisfied, if channel  $q$  is in cell  $j$  then channel  $p$  cannot be assigned to cell  $i$  if  $|p - q| < X_{i,j}$  ( $p \neq q, i \neq j$ ) where  $X$  is the compatibility matrix of dimension  $C \times C$ . Mathematically, it can be formulated as equation (4):

$$f = \sum_{i=1}^C \sum_{p=1}^F \left( \sum_{j=1, j \neq i, X_{i,j} > 0}^C \sum_{q=p-(X_{i,j}-1), 1 \leq q \leq F}^F A_{j,q} \right) A_{i,p} \quad (4)$$

The chromosome is evaluated by equation (4). The genetic-fix algorithm defines its own mutation and crossover operator in such a way that the fixed number of ones is always preserved. The algorithm was tested on 5 sets of problem with cells ranging from 4 to 25, number of channels ranging from 11 to 309, with 5 different compatibility matrices and 3 different demand vectors. The simulation parameters for GA were set to  $p_c = 0.95$ ,  $p_m = 0.0005$ , population size = 10. The results were compared with the neural network-based approach of [25]. The frequency of convergence of the algorithm for all the problem sets was found to be better than the neural network approach. In the fifth problem, they were able to find better solutions with a shorter channel span than previously reported in the literature.

3. Chakraborty and Chakraborty [6] used GA to find the minimum required bandwidth that satisfies a given channel demand without violating interference constraints (co-channel, adjacent channel, and co-site interference constraints). The chromosome is a frequency assignment matrix  $A[F, C]$  where  $A_{ij}$  ( $i = 1 \dots F$  and  $j = 1 \dots C$ ) is either  $-1$ ,  $0$ ,  $1$ , or  $9$ .

- (a)  $A_{ij} = -1$  indicates that the  $i$ -th channel is not used in the  $j$ -th cell and the  $i$ -th channel cannot be used in the  $j$ -th cell.

- (b)  $A_{ij} = 0$  indicates that the  $i$ -th channel is not used in the  $j$ -th cell and the use of the  $i$ -th channel in the  $j$ -th cell will not result in any interference.
- (c)  $A_{ij} = 1$  indicates that the  $i$ -th channel is used in the  $j$ -th cell.
- (d)  $A_{ij} = 9$  indicates that the  $i$ -th channel is not 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. The fitness of the chromosome is measured by the frequency bandwidth a chromosome uses, i.e., by its  $F$  value. In the case of chromosomes with the same value of  $F$ , the chromosome with the highest number of 0s (a chromosome that 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.

Experiments were carried out for three sets of problems with the number of cells ranging from 21–25, two different sets of compatibility matrices, and three sets of traffic demand vectors. For the network with 25 cells, they were able to obtain the best result reported so far in the literature.

4. Jin et al. [40] considered a cellular network with a fixed number of available frequencies. They formulated a cost model for the FCA problem with available bandwidth as one of the hard constraints. The proposed cost function analyzes each assignment in terms of damage caused to the quality of service by blocked calls and interference between cells. They provided a certain degree of relaxation to the demand constraint and the co-site constraint of EMC. A GA-based approach was proposed to minimize the cost function. The main objective is to find an assignment of channels that minimizes the total amount of blocked calls in the network and the amount of interference experienced by calls. A chromosome represents an allocation matrix  $A[C, F]$ , where  $C$  is the number of cells and  $F$  is the number of available channels. The damage caused by

blocked calls in the network is given by

$$\sum_{i=1}^C \sum_{j=F_i+1}^{n_i} P(Q_i = j)(j - F_i)$$

The term  $\sum_{j=F_i+1}^{n_i} P(Q_i = j)(j - F_i)$  represents the expected amount of blocked calls in cell  $i$ , where  $n_i$  is the amount of mobiles in cell  $i$ ,  $F_i = \sum_{p=1}^F A_{i,p} \geq d_i$  is the number of channels allocated to cell  $i$  ( $d_i$  is the demand of channels in cell  $i$ ), and  $Q_i$  represents the random variable of required channels in cell  $i$ . The damage due to interference between channel  $p$  assigned to cell  $i$  and channel  $q$  assigned to cell  $j$  is in negative proportion to the distance in channels between  $p$  and  $q$ . Hence the damage due to interference is defined by  $f(i, j, p, q)$  where

$$f(i, j, p, q) = \begin{cases} 0 & \text{if } |p - q| \geq X_{i,j} \\ f_{i,p} f_{j,q} \Psi_C(X_{i,j} - |p - q|) & \text{if } |p - q| < X_{i,j} \text{ and } i = j \\ f_{i,p} f_{j,q} \Psi_A(X_{i,j} - |p - q|) & \text{otherwise} \end{cases}$$

where  $\Psi_C(x)$  and  $\Psi_A(x)$  are strictly increasing functions in  $x$ .  $X$  is the compatibility matrix and  $X_{i,j}$  represents the minimum channel separation required between channels assigned to cells  $i$  and  $j$  to avoid interference. The total damage due to blocked calls and interference is given by equation (5).

$$\sum_{i=1}^C \sum_{j=1}^C \sum_{p=1}^F \sum_{q=1}^F f(i, j, p, q) + w \sum_{i=1}^C \sum_{j=F_i+1}^{n_i} P(Q_i = j)(j - F_i) \quad (5)$$

where  $w$  represents the relative weight of damages due to blocked calls to the damages caused by interference.

A heuristic was proposed to generate an initial population with low interference between cells. The paper also defines appropriate an crossover operator. Eight benchmark problems with 21 cells, frequencies ranging from 40 to 64, with three different compatibility matrices, and three sets of communication loads (a: ( $\mu = 5$  to 45,  $\sigma = 1.1$  to 9.11), b: ( $\mu = 8$  to 57,  $\sigma = 1.25$  to 11.62), and c: ( $\mu = 33.9$  to 191.81,  $\sigma = 3.52$  to 21.62)) have been examined. The terminating criterion was either the 1000-th generation or 10

contiguous runs with no improvement. They were able to obtain better solutions with the average number of generations ranging from 52 to 80.

## 7 Combinatorial Methods in Dynamic Channel Assignment

In dynamic channel assignment, the graph to be colored changes over time. Thus, the problem of dynamic channel assignment can be modeled with an ordered sequence of graphs  $G(V, E, w_t), t \geq 1$ , where  $w_t$  is the set of calls to be served by the network at time  $t$  [37]. The algorithm should color graph  $G_t$  before  $G_{t+1}$ . Janssen et al. [37] have presented an algorithm which is  $4/3$  competitive.

## 8 EA in Dynamic Channel Assignment

In the literature, a number of DCA algorithms have been proposed [12, 93, 78, 85, 92, 9, 19, 8, 18, 77, 73, 72, 64, 71, 39]. These algorithms can be classified into two classes of DCA schemes based on the type of information used in allocating a channel [64]: (1) interference adaptive scheme, and (2) traffic adaptive scheme. In the interference adaptive scheme, the decision regarding the allocation of a channel is based on the measurement of the carrier-to-interference ratio. In the traffic adaptive scheme, the channel allocation decision is based on the traffic conditions in neighboring cells of a cell involved in call arrival. The interference adaptive scheme has been described in [26, 61]. Here the propagation measurements from each base station to mobile and vice versa are made. A channel  $l$  is allocated to a new call if it does not cause any interference to the calls already in progress on  $l$  and at the same time does not receive any interference from the existing calls in the system.

### 8.1 Traffic Adaptive Scheme

The traffic adaptive scheme in which an available channel is associated with a cost is called exhaustive searching DCA [12, 93, 78, 92, 19, 18, 73, 72, 71]. The cost of a channel reflects the impact of allocating the channel on the ongoing calls in the system. When a call arrives, the system tries to allocate the channel with the minimum cost. Based on this concept, a GA approach was proposed in Sandalidis et al. [73, 71], and

the application of ES was studied in Sandalidis et al. [72]. Sandalidis et al. [71, 72], modeled the channel assignment constraints (soft constraints, hard constraints, traffic demand) discussed in Section 2.1.2 as an energy function whose minimization gives the optimal allocation. The energy function was formulated for the cell involved in call arrival. They have proposed a binary chromosome to represent a cell involved in call arrival. A gene represents a channel (0: the channel is free; 1: the channel is occupied), and the length of the chromosome is always equal to the total number of channels available to the system. The fitness of the chromosome is measured by an energy function.

1. Sandalidis et al. [71] modeled an energy function that takes care of EMC constraints (co-channel, adjacent channel, and co-site interference), traffic demand, and soft constraints (packing, resonance, and limiting rearrangement discussed in Section 2.1.2) as shown in equation (6).

$$\begin{aligned}
 E = & \frac{W_1}{2} \sum_{j=1}^F \sum_{i=1, i \neq k}^C V_{k,j} \cdot A_{i,j} \cdot interf(i, k) + \frac{W_2}{2} \sum_{j=1}^F V_{k,j} \cdot CSC_{k,j} \\
 & + \frac{W_3}{2} \sum_{j=1}^F V_{k,j} \cdot ADJ_{k,j} - \frac{W_4}{2} \sum_{j=1}^F \sum_{i=1, i \neq k}^C V_{k,j} \cdot A_{i,j} \cdot \frac{(1 - interf(i, k))}{dist(i, k)} \\
 & + \frac{W_5}{2} \sum_{j=1}^F \sum_{i=1, i \neq k}^C V_{k,j} \cdot A_{i,j} \cdot (1 - res(i, k)) \\
 & + \frac{W_6}{2} \left\{ \sum_{j=1}^F V_{k,j} - traf(k) \right\} - \frac{W_7}{2} \sum_{j=1}^F V_{k,j} \cdot A_{i,j}
 \end{aligned} \tag{6}$$



|                |  |
|----------------|--|
| $k$            | : Cell where a call arrives  |
| $F$            | : Number of channels available in the network  |
| $C$            | : Number of cells in the network   |
| $A_{i,j}$      | : Allocation matrix, $A_{i,j} = 1$ if channel $j$ is assigned to cell $i$ , and 0 otherwise  |
| $V_k$          | : Output vector (the solution) for cell $k$ with dimension $F$   |
| $V_{k,j}$      | : $j$ -th element of vector $V_k$ , $V_{k,j} = 1$ if channel $j$ is assigned to cell $k$ , and 0 otherwise                               |
| $interf(i, k)$ | : Function whose value is 1 if there is co-channel interference between cells $i$ and $k$ , otherwise 0                                  |
| $CSC_{i,j}$    | : The $ij$ -th element of matrix $CSC$ , $CSC_{i,j} = 1$ if co-channel interference exists between cells $i$ and $j$ , otherwise 0       |
| $ADJ_{i,j}$    | : The $ij$ -th element of matrix $ADJ$ , $ADJ_{i,j} = 1$ if adjacent channel interference exists between cells $i$ and $j$ , otherwise 0 |
| $dist(i, k)$   | : Distance (normalized) between cells $i$ and $k$  |
| $res(i, k)$    | : Function that returns a value of one if cells $i$ and $k$ belong to the same reuse scheme, otherwise zero                              |
| $traf(k)$      | : The number of channels that cell $k$ must serve, i.e., the traffic demand of cell $k$  |

In equation (6), the first term takes care of co-channel interference, the second term takes care of co-site interference, the third term takes care of adjacent channel interference, the fourth term takes care of packing condition, the fifth term takes care of the resonance condition, the sixth term takes care of traffic demand, and the seventh term takes care of the limiting rearrangement condition.  $W_1, W_2, W_3, W_4, W_5, W_6$ , and  $W_7$  are positive constants that determine the significance of the conditions. In this equation, the rearranging operation is considered only in the cell involved in the new call arrival.

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. Experimental results were carried

out in a parallelogram topological network of 49 hexagonal cells and 70 channels given in [93] under uniform and two nonuniform traffic distribution patterns given in [93]. Roulette wheel selection, two-point crossover, standard mutation operator, population size of 50, crossover probability of 0.75, and mutation probability of 0.05 were used. The GA was terminated after 100 generations. The results were compared with FCA, Borrowing with Channel Ordering (BCO), Borrowing with Directional Channel Locking strategy (BDCL), and Locally Optimized Dynamic Assignment strategy (LODA) schemes proposed in [93] and the Hopfield neural network approach proposed in [18]. The proposed algorithm was compared under three different cases: 1) with co-channel interference constraint only, 2) with co-channel and co-site interference constraints only, and 3) with all the three interference constraints. With uniform traffic distribution the algorithm outperformed all of them in case 1 but showed a poor performance for the other two cases. With nonuniform traffic distribution only case 1 was considered. The performance of the algorithm was better than FCA, BCO, and LODA but poorer than BDCL and the Hopfield neural network approach.

2. Sandalidis et al. [72] proposed an ES-based approach called Combinatorial Evolutionary Strategy DCA (CES DCA) to solve the DCA problem. CES DCA is a  $(1, \lambda)$ -ES. They modeled an energy function as shown in equation (7) that takes care of the packing condition, resonance condition, limiting rearrangement, and co-channel interference.

$$\begin{aligned}
 E = & \frac{W_1}{2} \sum_{j=1}^F \sum_{i=1, i \neq k}^C V_{k,j} \cdot A_{i,j} \cdot \text{interf}(i, k) - \\
 & \frac{W_2}{2} \sum_{j=1}^F \sum_{i=1, i \neq k}^C V_{k,j} \cdot A_{i,j} \cdot \frac{(1 - \text{interf}(i, k))}{\text{dist}(i, k)} + \\
 & \frac{W_3}{2} \sum_{j=1}^F \sum_{i=1, i \neq k}^C V_{k,j} \cdot A_{i,j} \cdot (1 - \text{res}(i, k)) - \\
 & \frac{W_4}{2} \sum_{j=1}^F V_{k,j} \cdot A_{i,j}
 \end{aligned} \tag{7}$$

In equation (7), the first term takes care of co-channel interference,

the second term takes care of the packing condition, the third term takes care of the resonance condition, and the last term takes care of the limiting rearrangement condition. The weights  $W_1$ ,  $W_2$ ,  $W_3$ , and  $W_4$  are positive constants that determine the significance of the conditions, and the other variables carry the same meaning as in Section 8.1.1. The traffic requirement is incorporated into the problem representation. Thereby the fitness function is simplified as compared to [71]. 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 chromosome with the minimum energy gives the desired solution. If the desired solution causes co-channel interference the call is blocked. Otherwise, the call is successful, and the channel usage information of the cell is updated according to the fittest chromosome. The performance of the algorithm was measured in terms of probability of blocking of new calls. Experimental results were carried out in a parallelogram topological network of 49 hexagonal cells and 70 channels given in [93] under uniform and two nonuniform traffic distribution patterns given in [93]. The values of  $W_1$ ,  $W_2$ ,  $W_3$ , and  $W_4$  were set to 10, 3, 1, and 2, respectively. The algorithm was terminated when the destabilization process occurred for the second consecutive time. The population size was set to 50. The performance of the algorithm was compared with FCA, BCO, BDCL, and LODA schemes proposed in [93], the genetic algorithm-based DCA approach (GA DCA) proposed in [73], and the Hopfield neural network approach proposed in [18]. Under uniform traffic distribution, CES DCA outperformed all the algorithms. Under nonuniform traffic distribution CES DCA was compared with FCA, BCO, BDCL, and LODA and it outperformed all of them.

3. Lima et al. [48] proposed two GA-based strategies called GAL and GAS to solve the DCA problem. GAL looks for an idle channel to serve an incoming call, and the assigned channel serves the call until it is terminated, whereas in GAS, an ongoing call can be switched to a different channel. The proposed algorithms take care of co-channel interference based on a fixed reuse distance (three cells) concept. The main objective is to find a channel assignment matrix that minimizes the total amount of blocked calls in the network. A chromosome is represented by a vector  $A_i = 1 \times F$ , where  $F$

is the number of available channels and the  $j$ -th element of  $A_i$  is 1 if channel  $j$  is assigned to cell  $i$ , and 0 otherwise. Assignment of channels to a cell is associated with a cost function defined by equation (8).

$$f = \sum_{i=1}^C \sum_{j=1}^F fit(i, j) \quad (8)$$

where  $C$  represents the number of cells in the system and  $fit(i, j) = n_1(j).r_1 + n_2(j).r_2 + n_3(j).r_3 + n_4(j).r_4$  where  $n_1(j)$  represents the number of compact cells of cell  $i$  using channel  $j$ ,  $n_2(j)$  represents the number of co-channel cells of  $i$  located in the third tier of cells that do not use  $j$ ,  $n_3(j)$  represents the number of other co-channel cells of  $i$  using  $j$ , and  $n_4(j)$  represents the number of channels to be blocked due to assigning  $j$ . Compact cells are the cells located at a minimum average distance between co-channel cells.  $r_1, r_2, r_3, r_4$  are weights that determine the significance of each term with a value of 5, 1,  $-1$ , and  $-15$ , respectively. In GAL only the idle channels undergo mutation. The algorithms are evaluated with a parallelogram topological network of 49 hexagonal cells and 70 channels under uniform and nonuniform traffic distribution [93] and time-varying traffic pattern. GAL and GAS were found to provide lower average call blocking probability as compared to the schemes reported in [93] and [64].

## 9 EA in Hybrid Channel Assignment

1. Sandalidis et al. [72] applied their CES heuristic on the HCA problem. Their method, we call CES HCA, is a  $(1, \lambda)$ -ES. The problem representation and energy function are the same as discussed in section 8.1.2. Experiments were also carried out as discussed in Section 8.1.2. Here three representative ratios were considered: 21:49 (FCA is 21 channels and DCA is 49 channels), 35:35, and 49:21. In all these cases, the algorithm tries to assign a channel from the DCA set only when all the channels in the FCA set are busy. Under uniform traffic distribution, 21:49 CES HCA outperformed FCA and provided better performance than LODA up to 9.5% increase in traffic load, 35:35 CES HCA outperformed FCA and LODA, and 49:21 CES HCA outperformed FCA and LODA and provided almost the same performance as BCO. Under one

nonuniform traffic distribution, 21:49 CES HCA and 35:35 CES HCA outperformed FCA only, and 49:21 CES HCA outperformed FCA and provided almost the same performance as BCO; with another non-uniform traffic distribution, 21:49 CES HCA outperformed FCA and provided almost the same performance as LODA, 35:35 CES HCA outperformed FCA and LODA, and 49:21 CES HCA outperformed FCA and LODA and provided almost the same performance as BCO.

2. Vidyarthi et al. [87] proposed a new HCA strategy, called the  $D$ -ring strategy, using the distributed dynamic channel assignment strategy based on the fixed reuse distance concept. Here,  $D$  is the fixed reuse distance.  $D$  rings of cells around a given cell form the interference region. The channels are allocated to the host cell from a set of channels that excludes all those channels which are in use in the interference region. As such the selected channels always satisfy the co-channel interference constraint. They proposed an ES-based approach for the solution of the HCA using integer vector representation (as chromosome), where each integer at position  $i$  in the vector represents a channel number assigned to a call in the  $i$ -th cell. The disadvantage of the binary string representation considered in [73], [72], and [71] is that although we are interested only in  $d$  channels, extra memory is consumed in storing the information about the other unused channels. Here  $d$  represents the current traffic demand in the cell involved in call arrival. Binary string representation also yields slower evaluation and manipulation of candidate solutions, due to the size of the binary representation. The other advantage of the integer representation is that the size of the solution vector is short and thus it is easier and faster to process.

[87] also proposed a novel way of generating the initial parent and the initial population. Instead of starting from a totally random combination of channel numbers, they start with solution vectors with  $(d - 1)$  channels allocated to the cell by the algorithm in its last call arrival. This way of generating initial parent and initial population will reduce the number of channel reassignments and therefore yields a faster running time. The initial parent is also a potentially good solution because channels for ongoing calls are already optimized.

Compared to Sandalidis et al. [72], the fitness function is simpler. This because one major hard constraint, the co-channel interference, is taken care of by the  $D$ -ring-based strategy. This also leads to a simpler and faster fitness calculation than that of Sandalidis et al. [72]. The problem representation also takes care of the traffic demand constraint as the number of channels in a solution vector equals the demand of channels in the cell. The soft constraints are modeled as an energy function as in [72]. It is shown in equation (9). The minimization of this function gives a near-optimal channel allocation.

$$\begin{aligned}
 E = & -W_1 \sum_{j=1}^{d_k} \sum_{i=1, i \neq k}^C A_{i,V_k,j} \cdot \frac{1}{dist(i,k)} + W_2 \sum_{j=1}^{d_k} \sum_{i=1, i \neq k}^C A_{i,V_k,j} \cdot (1 - res(i,k)) \\
 & - W_3 \sum_{j=1}^{d_k} A_{k,V_k,j}
 \end{aligned} \tag{9}$$

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

$W_1, W_2$ , and  $W_3$  are positive constants. The first term expresses the packing condition. The second term expresses the resonance condition. The last term expresses the limiting reassignment. This term results in a decrease in the energy if the new assignment for the ongoing calls in cell  $k$  is the same as the previous allocation. The value of the positive constants determines the significance of the different terms. The energy function determines the fitness of the chromosome. The fittest chromosome in all the generations is the desired solution. Simulations were carried out as in [72] for nonuniform traffic distribution only. The performance of the algorithm was compared with those obtained in [72]. Under one traffic

distribution, all the representative ratios outperformed their counterpart in [72]. Under another traffic pattern, all the representative ratios outperformed their counterpart in [72] up to 60% increase in traffic load. Beyond 60% their performance was more or less the same.

## 10 Graph Theoretical Methods in Mobility Management

Naor et al. [59] proposed a Cell Identification Code (CIC) for tracking mobile users based on the movement-based location update scheme suggested in [3]. The proposed scheme provides mobile users with location information necessary to reduce the cost of tracking a mobile user. The idea is to identify each cell with a code different from its nearest neighbors in order to facilitate the detection of cell boundary crossing. Thus the movement-based update scheme using CIC is a special case of the graph coloring problem. The objective is to find the minimum number of codes needed to code the vertices such that no two adjacent vertices have the same code. For hexagon-shaped cells only three colors are needed where a color corresponds to a code.

## 11 EA in Mobility Management

In a cellular network, in order to route a call, the mobile terminal needs to be correctly located within a fixed time delay. The location management involves two types of activities: paging and location update (LU). Both paging and LU increase network traffic overhead and consume the scarce radio resource. Therefore, during a certain period of time, the total cost of location management involves the sum of two orthogonal cost components: paging cost and LU cost. The two costs are orthogonal because the higher the frequency of LU is, the lesser is the frequency of paging attempts required to locate the mobile terminal [14]. Thus there exists a tradeoff between paging cost and LU cost that varies with the size of the location area (LA). If the LA is large, there are fewer inter-LA crossings resulting in a lower LU cost but the number of base stations needed to be paged increases correspondingly. Therefore one way of reducing LU cost is by effective planning of LA.

LA planning was considered in [27] using a graph theoretic approach, in [53, 52] using two heuristic algorithms, in [66] using a greedy algo-

rithm, and in [88] using genetic algorithm. LA planning decomposes a group of cells into LAs in which LU traffic is minimized without violating the paging bound (bandwidth available for paging). In general LU traffic is proportional to the number of mobile terminals crossing the LA border and paging cost is proportional to the number of calls to all mobile terminals in the LA. Some of the papers that describe the use of evolutionary algorithms to mobility management are described below.

1. Das and Sen [14] proposed a GA approach for the optimization of the total location management cost. The proposed scheme provides an improvement over the existing zone-based schemes by minimizing the total location management cost for individual users by devising an update strategy for each mobile that considers per-user mobility and call arrival pattern on top of the conventional zone based approach. In the conventional zone-based approach, all mobile users are made to update whenever they cross a LA boundary. Because these LAs are formed based on a common mobility pattern for all the users in the system, this approach leads to a significant number of redundant updates. In the proposed scheme, each user updates only in preselected LAs called his reporting areas. GA has been used to find the optimal update strategy. First, the LAs in the service area are numbered sequentially. Then the update strategy is represented by a binary chromosome  $\{d_n \dots d_2 d_1\}$  where  $i$  is the sequence number of the LA,  $n$  is the total number of LAs in the service area, and  $d_i$  is the decision variable for the user in LA  $i$  such that

$$d_i = \begin{cases} 1 : & \text{if update occurs in LA } i \\ 0 : & \text{otherwise} \end{cases}$$

The total location management cost  $LMC$  has been defined as in equation (10).

$$LMC = \sum_{i=1}^N \pi_i LM_i^{d_i} \quad (10)$$

where  $\pi_i$  is the location probability of the user in the LA  $i$ , and  $LM_i^{d_i}$  is the average location management cost of the user in the LA  $i$ , and is calculated assuming call arrival as a poisson distribution. The chromosome is evaluated using fitness function  $\frac{1}{LMC}$ . Roulette wheel selection mechanism, crossover probability of 0.8, mutation probability of 0.001, and population size of 20 are used.



The algorithm was tested for various values of call arrival rate and ratio of update and paging cost for 10 location areas (with location probabilities  $\pi_0 = \pi_9 = 0.08333$ , and  $\pi_i = 0.1041$  for  $1 \leq i \leq 8$ ). It was observed that for low user residing probability in LAs, low call arrival rate, and high update cost for a user, skipping of updating in several LAs leads to the minimization of the overall location management cost.

2. One way to reduce the paging cost is to partition the LA into paging zones for each user based on the predetermined probability of locating the mobile user at different locations within the LA. Sun and Lee [84] proposed a GA approach for the optimal planning of such paging zones. For each mobile user a multilayered model is developed based on the mobile-phone usage for different times of activity during a day—home, work, social. LA is decomposed into a set of multiple location layers  $\{L_1, L_2, \dots, L_n\}$  where  $1 \leq i \leq n$  and  $n$  is the number of layers in the multilayered model, based on the mobility patterns that describe the likelihood of locating the user in a particular cell during a particular time of the day. For example,  $L_1$  and  $L_2$ , may refer to the home and working area, respectively, of a mobile user. Then for each user  $k$  the cells in the LA are partitioned into paging zones for each activity layer  $j$  such that each zone consists of cells with similar probability of locating  $K$ . When a call is received for a particular user, a paging message is first sent to the paging zone with the highest probability of locating that user at that particular time of the day. If there is no response for the first paging message, then the paging zone with next highest probability is paged, and so on. Thus paging cost is incurred if and only if the paging zone is paged. The paging cost to locate a mobile user has been formulated as defined in equation (11):

$$f = \alpha \cdot \beta \cdot \left[ N(P_{k,j,1}) + \sum_{l=2}^T \left\{ \left( 1 - \sum_{i=1}^{l-1} \text{prob}(P_{k,j,i}) \right) N(P_{k,j,l}) \right\} \right] \quad (11)$$

where  $\text{prob}(P_{k,j,l})$  is the probability of locating the  $k$ -th user in the  $j$ -th activity layer of  $l$ -th zone,  $T$  is the total number of paging zones,  $N(P_{k,j,l})$  is the number of cells in the  $l$ -th zone,  $\alpha$  denotes the consumption cost in the forward control channel per paging

message, and  $\beta$  denotes the consumption cost in the fixed link channel consumption in the mobile switching center per paging message. The objective is to find a paging zone with the lowest cost. In this scheme each user has unique paging zones. Hence, optimization must be carried out separately for each individual mobile user.

The candidate solutions were encoded with integer representation. The cells and paging zones in the LA are numbered sequentially. The length of the chromosome equals the number of cells in the LA, gene position corresponds to the cell number, and the value of a gene at a particular position corresponds to the paging zone to which the cell number belongs. For example, if there are 5 cells (1, 2, 3, 4, 5) and 3 paging zones (1, 2, 3) in an LA, and paging zone 1 contains cell numbers 1 and 2, paging zone 2 contains cell numbers 4 and 5, and paging zone 3 contains cell number 3, then the corresponding chromosome representation is "1322". The tournament selection mechanism and standard crossover and mutation operators were used. Experiments were carried out with different paging zones: system-wide paging zone at different location layers, two-paging zone, three-paging zone, and maximum paging zone (number of paging zone is equal to the number of cells). Paging cost was observed to decrease with the increase in the number of paging zones.

3. Wang et al. [88] proposed a GA approach for the optimal planning of LA to reduce the LU cost. It was assumed that cell planning, LU, and paging traffic for each cell are known beforehand, each LA contains a disjoint set of cells, and the paging bound is fixed for each LA. The LA planning problem was encoded using a binary chromosome with a border-oriented representation. In border-oriented representation, all borders are numbered sequentially and the corresponding bit in the chromosome is 1 if that particular cell border is to be a border between two adjoining LAs, and 0 otherwise.

Figure 2 (adapted from [88], Figure 2, pp. 989) shows the numbering of borders ( $b_i$ ) and numbering of cells ( $c_i$ ) in a system with 7 cells. Figure 3 (adapted from [88], Figure 3, pp. 989) shows an LA planning result of the 7 cell system shown in Figure 2. Figure 4 (adapted from [88], Figure 10 (b), pp. 991) shows the border-oriented chromosome structure  $V$  of the LA planning shown in

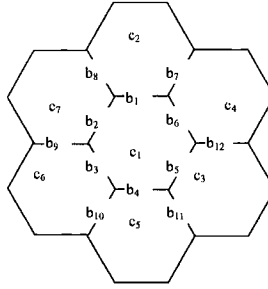


Figure 2: Numbering of cells and border.

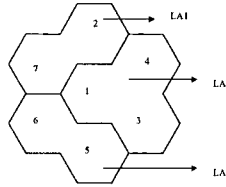


Figure 3: An LA planning result.

|   |   |   |   |   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
|---|---|---|---|---|---|---|---|---|---|---|---|

Figure 4: Border-oriented chromosome structure.

Figure 3. In Figure 4,  $V_i = 1$  if the border  $b_i$  exists in the LA planning shown in Figure 3, otherwise  $V_i = 0$ . For example, the border  $b_1$  between the cells  $c_1$  and  $c_2$  exists in the LA planning shown in Figure 3, hence  $V_i = 1$ .

The chromosomes are evaluated using the fitness function shown in equation (12):

$$f = \frac{\alpha_1}{2} \sum_{j=1}^n v_j w_j + \alpha_2 \sum_{i=1}^m \max \{0, (P_i - B)\} \quad (12)$$

The first term denotes the LU cost and the second term denotes the cost due to the violation of the paging bound. In this equation,  $n$  is the total number of borders,  $w_j$  is the crossing intensity of

border of  $j$ ,  $v_j$  is the  $j$ -th bit of the chromosome being evaluated,  $m$  is the total number of LAs,  $P_i$  is the paging traffic in LA  $i$ ,  $B$  is the paging bound that has been considered fixed for each LA, and  $\alpha_1$  and  $\alpha_2$  are constants used to weigh the relative importance of LU cost and paging bound violation. The objective is to find an LA with minimum cost.

Simulations were carried out with five hexagonal systems with cells ranging from 19–91. The cells were configured as an H-mesh. The cell paging cost and border crossing intensity were generated with normal distribution ( $\mu = 100$ ,  $\sigma^2 = 20$ ). The results were compared with a hill-climbing approach after 100 simulation runs. Selection based on fitness value, standard crossover, and mutation operators were used. Population size, crossover probability, mutation probability, and maximum number of generations were set to 20, 1, 0.02, and 1000, respectively. In all the cases, GA outperformed the hill-climbing approach with a percentage improvement of 10%–29%. Hence the GA approach was concluded to be a robust technique for LA planning.

## 12 EA in Code Division Multiple Access

1. Chan et al. [7] proposed a GA-based approach to solve the resource management problem in direct sequence CDMA systems of a mobile communication network. Transmission power and transmission rate of all connecting users are two important resource management issues. The objective is to minimize the total transmission power and maximize the total transmission rate of all users simultaneously while satisfying the required transmission power, transmission rate, and bit energy-to-noise density ratio of each user. The total cost to be minimized is formulated as shown in equation (13).

$$\begin{aligned}
\text{Min } f = & \alpha \left[ \lambda_p \sum_{i=1}^N p_i + \lambda_r \left( T - \sum_{i=1}^N r_i \right) \right] \\
& + \beta \left( \lambda_x \sum_{i=1}^N x_i \right) \\
\text{s.t. } & P_i^{\min} \leq p_i \leq P_i^{\max} \quad \forall i \\
& R_i^{\min} \leq r_i \leq R_i^{\max} \quad \forall i \\
& \left( \frac{E_b}{N_0} \right)_i \geq \gamma_i \quad \forall i \\
\text{where } & \left( \frac{E_b}{N_0} \right)_i = \frac{\frac{g_{bi} \cdot p_i}{r_i}}{\frac{1}{W} \sum_{j=1, j \neq i}^N g_{bj} \cdot p_j} + \eta \quad \forall i
\end{aligned} \tag{13}$$

- $N$  : Total number of connecting users in the system
- $p_i$  : Transmission power of user  $i$
- $P_i^{\min}$  : Minimum allowed transmission power of user  $i$
- $P_i^{\max}$  : Maximum allowed transmission power of user  $i$
- $r_i$  : Transmission rate of user  $i$
- $R_i^{\min}$  : Minimum allowed transmission rate of user  $i$
- $R_i^{\max}$  : Maximum allowed transmission rate of user  $i$
- $\frac{E_b}{N_0}$  : Received bit energy-to-noise ratio of user  $i$
- $\gamma_i$  : Threshold value of bit energy-to-noise ratio of user  $i$
- $x_i$  :  $x_i = 1$  if user  $i$  violates the QoS requirement and 0 otherwise
- $T$  : A constant larger than the total transmission rate of  $N$  users
- $W$  : Total spread spectrum bandwidth
- $\eta$  : Background noise power
- $g_{bi}$  : Link gain between mobile user  $i$  and base station  $b$

$\lambda_p$  and  $\lambda_r$  represent the fixed cost per unit power in watts and per unit rate in kilo bits per second, respectively.  $\lambda_x$  represents the fixed cost per user who violates her QoS requirement. QoS is a measure of signal quality measured in terms of bit energy-to-noise ratio.  $\alpha$  and  $\beta$  are weights.  $\alpha = 1, \lambda_p = 1, \lambda_r = 1, \lambda_x = 1, \alpha = 1, \beta = 5000, N = 50$ , and  $T = 15000$ . The first term represents the minimization of total transmission power, the second term represents the minimization of total transmission rate, and

the third term takes care of the number of users violating their QoS requirement. The proposed method looks for a solution with the minimum power, maximum rate, and with minimum number of users violating the QoS requirement. Each chromosome is represented by real floating point values. The length of the chromosome is  $2N$ , with two genes per user. One gene represents the transmission power and the other gene represents the transmission rate. The GA is characterized by two-point crossover, roulette wheel selection, population size of 30,  $P_c = 0.8$ , and  $P_m = .01$ . Two approaches have been considered: single objective and multiobjective. The multiobjective approach considers each term of equation (13) as a single function. The GA is terminated after 150 generations in the single objective case, and after 110 in the multiobjective case. The results were compared with simulated annealing, tabu search, and generalized reduced gradient method. GA provided the best results both for single and multiobjective approaches.

## 13 Conclusions and Future Directions

In this chapter, we presented several streams of research on optimization problems in wireless mobile communication that have been conducted by researchers in the past. We also discussed some details on the implementation of the genetic algorithm and evolutionary strategy to these problems. Wireless mobile communications are evolving fast. It is already certain that over the coming years these EAs will play an increasingly important role in solving the optimization problems that come up in various areas of wireless mobile communication. The papers considered in this chapter, have focused on only one problem at a time. But some of the problems in wireless mobile communication are highly correlated. One such example is the problem of minimal assignment of channels while minimizing the allocation of transmitter and/or receiver powers to the mobile terminals. So one can explore the possibility of solving such integrated problems using EAs.

EAs provide near-optimal solutions but solution quality cannot be measured in terms of optimality only. Hence in order to better explore the search space, one of the future research directions could be to use EAs in conjunction with large-scale linear optimization techniques such as Lagrangian relaxation, Benders decomposition, or Dantzig–Wolf decomposition. Although the linear programming relaxation of the prob-

lem would provide a lower bound, efficient heuristic solution procedures based on EAs can be developed to generate feasible solutions to the problem. This would provide us with an indication of how far the obtained solution is from the optimal solution.

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