Genetic Algorithms for Optimal Channel Assignments in Mobile Communications

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ABSTRACT

The demand for mobile communication has been steadily increasing in recent years. With the limited frequency spectrum, the problem of channel assignment becomes increasingly important, i.e., how do we assign the calls to the available channels so that the interference is minimized while the demand is met? This problem is known to belong to a class of very difficult combinatorial optimization problems. In this paper, we apply the formulation of Ngo and Li with genetic algorithms to ten benchmarking problems. Interference-free solutions cannot be found for some of these problems; however, the approach is able to minimize the interference significantly. The results demonstrate the

effectiveness of genetic algorithms in searching for optimal solutions in this complex optimization problem.

Keywords: genetic algorithms, channel assignment, mobile communications, wireless network, optimization.

1 INTRODUCTION

As cellular phones become ubiquitous, there is a continuously growing demand for mobile communication. The rate of increase in the popularity of mobile usage has far outpaced the availability of the usable frequencies which are necessary for the communication between mobile users and the base stations of cellular radio networks. This restriction constitutes an important bottleneck for the capacity of mobile cellular systems. Careful design of a network is necessary to ensure efficient use of the limited frequency resources.

One of the most important issues on the design of a cellular radio network is to determine a spectrum-efficient and conflict-free allocation of channels among the cells while satisfying both the traffic demand and the electromagnetic compatibility (EMC) constraints. This is usually referred to as channel assignment or frequency assignment.

There are three types of constraints corresponding to 3 types of interference [1], namely:

1) Co-channel constraint (CCC)

- where the same channel cannot be assigned to certain pairs of radio cells simultaneously

2) Adjacent channel constraint (ACC)

   - where channels adjacent in the frequency spectrum cannot be assigned to adjacent radio cells simultaneously

3) Co-site constraint (CSC)

   - where channels assigned in the same radio cell must have a minimal separation in frequency between each other.

One of the earlier aims of the channel assignment problem (CAP) is to assign the required number of channels to each region in such a way that interference is precluded and the frequency spectrum is used efficiently. This problem (called CAP1 in [2]) can be shown to be equivalent to a graph coloring problem and is thus NP-hard.

As demand for mobile communications grows further, interference-free channel assignments often do not exist for a given set of available frequencies. Minimizing interference while satisfying demand within a given frequency spectrum is another type of channel assignment problem (called CAP2 in [2]).

Over the recent years, several heuristic approaches have been used to solve various channel assignment problems, including simulated annealing [3], neural networks [4][5][2], and genetic algorithms [6]-[16]. In particular, [8],[13]-[16] used GA for CAP1. [6], [7], and [11] formulated CAP2; however, they were interested only in interference-free situations. [12] gives a unique formulation of CAP2 in terms of GA; however, no simulation results were presented. Ngo and Li [11] developed an effective GA-based approach that obtains interference-free channel assignment by minimizing interference in a mobile network. They demonstrated that their approach efficiently converges to conflict-free solutions in a number of benchmarking problems.

In this paper, we apply Ngo and Li's approach to several benchmarking channel assignment problems where interference-free solutions do not exist. The organization of this paper is as follows. Section 2 states the channel assignment problem (CAP). Section 3 summarizes Ngo and Li's approach to solving CAP with genetic algorithms. Section 4 describes the tests carried out and results obtained, with many choices of parameters. Finally, we conclude the paper in section 5.

2 CHANNEL ASSIGNMENT PROBLEM

The channel assignment problem arises in cellular telephone networks where discrete frequency ranges within the available radio frequency spectrum, called channels, need to be allocated to different geographical regions in order to minimize the total frequency span, subject to demand and interference-free constraints (CAP1), or to minimize the overall interference, subject to demand constraints (CAP2). In this paper, we are interested in CAP2, since it is more relevant in practice compared to CAP1.

There are essentially two kinds of channel allocation schemes - *Fixed Channel Allocation (FCA)* and *Dynamic Channel Allocation (DCA)*. In FCA the channels are permanently allocated to each cell, while in DCA the channels are allocated dynamically upon request. DCA is desirable, but under heavy traffic load conditions FCA outperforms most known DCA schemes. Since heavy traffic conditions are expected in future generations of cellular networks, efficient FCA schemes become more important [11]. The fixed channel assignment problem, or in other words, assigning channels to regions in order to minimize the interference generated has been shown to be a graph coloring problem and is therefore NP-hard.

A cellular network is assumed to consist of N arbitrary cells and the number of channels available is given by M. The channel requirements (expected traffic) for cell j are given by D_j. Assume that the radio frequency (RF) propagation and the spatial density of the expected traffic have already been calculated. The 3 types of constraints can be determined. The electromagnetic compatibility (EMC) constraints, specified by the minimum distance by which two channels must be separated in order that an acceptably strong S/I ratio can be guaranteed within the regions to which the channels have been assigned, can be represented by an $N \times N$ matrix called the compatibility matrix C.

In this matrix C:

- Each diagonal element C_{ii} represents the co-site constraint (CSC), which is the minimum separation distance between any two channels at cell i.

- Each non-diagonal element C_{ij} represents the minimum separation distance in frequency between any two frequencies assigned to cells *i* and *j,* respectively.
- Co-site constraint (CSC) is represented by $C_{ij} = 1$.
- Adjacent channel constraint (ACC) is represented by $C_{ij} = 2$.
- Cells that are free to use the same channels are represented by $C_{ij} = 0$.

For example, suppose the number of cells in the network is N = 4, there are M = 11 channels available and the demand for the channels for each of these cells is given by D = (1,1,1,3). Consider the compatibility matrix suggested by Sivarajan *et al* [1]:

$$\boldsymbol{C} = \begin{pmatrix} 5 & 4 & 0 & 0 \\ 4 & 5 & 0 & 1 \\ 0 & 0 & 5 & 2 \\ 0 & 1 & 2 & 5 \end{pmatrix} \qquad (1)$$

The diagonal terms $C_{ii} = 5$ indicate that any two channels assigned to cell *i* must be at least 5 frequencies apart in order that no co-site interference exists. Channels assigned to cells 1 and 2 must be at least $C_{12} = 4$ frequencies apart. Off diagonal terms of $C_{ij} = 1$ and $C_{ij} = 2$ correspond to co-channel and adjacent channels constraints, respectively.

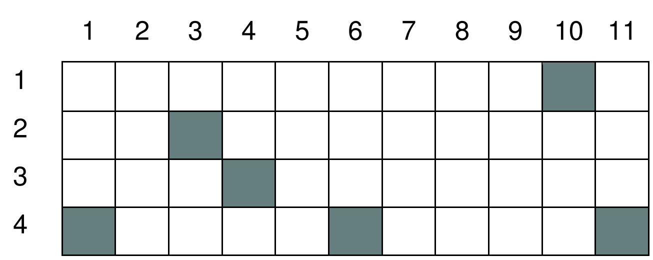

Figure 1. An interference-free assignment for a 4-cell and 11-channel network

The solution space is represented by F as an $N \times M$ binary matrix, where N is the total number of radio cells and M is the total number of available channels. Each element f_{jk} in the matrix is either one or zero such that

$$f_{jk} = \begin{cases} 1 \\ 0 \end{cases} \text{if channel } k \text{ is } \left\{ \begin{matrix} \textit{assigned} \\ \textit{not assigned} \end{matrix} \right\} \text{ to cell } j \qquad (2)$$

This matrix F can be represented by the figure below.

f_{jk}		Channel Number							
		1	2	3	…			m	Row Sum
	1	0	1	0	…	0	1	0	d_1
Cell	2	0	0	1	…	0	0	1	d_2
Number	3	0	0	1	…	1	0	0	d_3
	…								
	n	1	0		…	1	0	1	d_n

Figure 2. Representation of F, an N × M binary matrix.

The cellular network is expected to meet the demand of the traffic and to avoid interference. The first requirement imposes a demand constraint on F. Therefore, for cell i , a total of d_i channels are required . This implies that the total number of ones in row i of F must be d_i . If the assignment to cell i violates the demand constraint, then

$$\left(\sum_{q=1}^{m} f_{jq} - d_i \right) \neq 0 \qquad (3)$$

The second requirement depends on the compatibility matrix C. It is made up of CSC, CCC and ACC. In order to satisfy the CSC, if channel p is within distance C_{ii} from an already assigned channel q in cell i, then channel p must now be assigned to cell i. This can be seen from the equation below.

$$\sum_{\substack{q=p-(c_{ii}-1)\\ q\neq p\\ 1\leq q\leq m}}^{p+(c_{ii}-1)} f_{iq} > 0 \tag{4}$$

To satisfy the requirements for CCC and ACC, if channel p in cell i is within distance C_{ij} from an already assigned channel q in cell j, where $C_{ij} > 0$ and $i \neq j$, then channel p must not be assigned to cell i. This is represented as shown.

$$\sum_{\substack{j=1\\ j\neq i\\ c_{ij}\rangle 0}}^{n} \sum_{\substack{q=p-(c_{ii}-1)\\ q\neq p\\ 1\leq q\leq m}}^{p+(c_{ii}-1)} f_{iq} > 0 \tag{5}$$

Therefore, the cost function can be expressed as

$$C(F) = \sum_{i=1}^{n}\sum_{p=1}^{m}\left(\sum_{\substack{j=1\\ j\neq i\\ c_{ij}\rangle 0}}^{n} \sum_{\substack{q=p-(c_{ii}-1)\\ q\neq p\\ 1\leq q\leq m}}^{p+(c_{ii}-1)} f_{iq}\right) f_{ip} + \alpha \sum_{i=1}^{n}\sum_{p=1}^{m}\left(\sum_{\substack{q=p-(c_{ii}-1)\\ q\neq p\\ 1\leq q\leq m}}^{p+(c_{ii}-1)} f_{iq}\right) f_{ip}$$

$$+ \beta \sum_{i=1}^{n}\left(\sum_{q=1}^{m} f_{jq} - d_i\right) \tag{6}$$

where α and β are weighting factors. Eq.6 comes from a combination of eqs.(3), (4), and (5), since the 3 terms in eq.(6) become positive if any of the constraints represented by eqs.(3), (4), and (5) are not satisfied.

3 SOLVING CHANNEL ASSIGNMENT PROBLEM WITH GENETIC ALGORITHMS

We use a minimum-separation encoding scheme also by *Ngo and Li* [11]. In this scheme, a p-bit binary string represents an individual with q fixed elements and the minimum separation between consecutive elements is represented by d_{min}. The concept of this scheme is to represent the solution in a way such that a one is followed by (d_{min} – 1) zeros encoded as a new "one", denoted as $\tilde{1}$. For example, an individual with p = 10 and q = 3 can be encoded as follows:

$$\frac{Original}{1000100100} \Rightarrow \frac{Encoded}{\tilde{1}\quad 0\quad \tilde{1}\quad \tilde{1}}$$

The length of representation is substantially reduced.

Using the minimum separation scheme, the CSC requirement from the cost function derived earlier can be eliminated and further reduces the search space. Hence, the cost function of the channel assignment problem can be simplified to

$$C(F) = \sum_{i=1}^{n}\sum_{p=1}^{m}\left(\sum_{\substack{j=1\\ j\neq i\\ c_{ij}\rangle 0}}^{n}\ \sum_{\substack{q=p-(c_{ii}-1)\\ q\neq p\\ 1\leq q\leq m}}^{p+(c_{ii}-1)} f_{iq}\right) f_{ip} \tag{7}$$

The cost function can be further simplified by exploiting the symmetry of the compatibility matrix C. Hence, the final cost function is represented by

$$C(F) = \sum_{i=1}^{n-1} \sum_{\substack{j=i+1 \\ c_{ij} \rangle 0}}^{n} \left(\sum_{p=1}^{c_{ij}-1} \sum_{q=1}^{p-1} f_{jq} f_{ip} + \sum_{p=c_{ij}}^{m} \sum_{q=p-c_{ij}+1}^{p-1} f_{jq} f_{ip} + \frac{1}{2} \sum_{p=1}^{m} f_{jq} f_{ip} \right) \qquad (8)$$

In this genetic algorithm approach, the solution space represented by F, a $N \ x \ M$ matrix is treated as a chromosome in the population. This means that if a population is to contain n chromosomes, there will be n F solution matrices in the population, each representing a chromosome. These n F solution matrices are randomly generated and are all possible solutions for the channel assignment problem. The number of chromosomes in a population is stated by the population size, which is a parameter that should be manipulated to obtain an optimized solution [17]. The setting of population size, for any genetic algorithm, is generally quite ad hoc.

Each channel assignment in the network, represented by either a 1 or 0 in the F solution matrix, represents the genes in each chromosome. These genes encode information about which channels have been assigned and vice versa, forming the chromosomes, and thus the F solution matrix. After randomly generating a population of chromosomes, the fitness of each chromosome should be evaluated. Therefore, all F solution arrays in the population are evaluated for their fitness values, by using the final cost function. The lower the cost function value, the fitter the chromosome.

The next step in the genetic algorithm is to generate a new population, using genetic algorithm operators, such as selection, crossover and mutation. The selection process consists of selecting 2 parent chromosomes from a population according to their fitness, i.e., individuals with better fitness have higher chances to be selected. Each F solution array in the population stands a chance to be selected for crossover and mutation, as a parent chromosome.

After selection and encoding, the selected parent chromosomes, or selected F solution arrays (encoded), will undergo crossover, with a probability of crossover, and mutation with a probability of mutation. Crossover probability and mutation probability are parameters that should be manipulated to obtain an optimized solution. The settings of these parameters, like the population size parameter, are on a trial-and-error basis.

Therefore, after crossover and mutation, the new offspring of the parent chromosomes are placed in the new population. For parents whereby no crossover or mutation is performed, they will be placed in the new population too.

The selection, crossover and mutation processes will be repeated until the new population, which has the same size as the old population, is formed. After this procedure, all new rows in the F solution matrix, or chromosomes, will be used for a further run of the entire genetic algorithm until an optimized solution is found.

4 SIMULATION RESULTS

The data sets used to test the performance of the above algorithm originated from various papers. EX1 is the simple example shown in Fig.1 originally used in [1]. EX2 is a slightly larger network similar to EX1 [2] (Table I). The second set of examples (HEX1-HEX4) considered here is based on the 21-cell hexagonal mobile system studied in [18]. The final set of test problems (Kunz1-Kunz4) is generated by Kunz [4] from the topographical data of an actual 24x21 km area around Helsinki, Finland. More details of these data sets can be found in Table I, as well as the original papers [1], [2], [4], [18].

The costs of the solutions obtained using the above GA-based approach are also given in Table I. The results for EX1, EX2, and Kunz4 show that interference-free assignments can be found, as evidenced by a zero objective value, whereas no interference-free assignments were found for other problems.

Problem	Cell No.	Channel No.	Demand Vector	Cost Function
Ex1	4	11	D_1	0
Ex2	5	17	D_2	0
Hex1	21	37	D_3	39
Hex2	21	91	D_4	13.5
Hex3	21	21	D_5	46.5
Hex4	21	56	D_6	14.5
Kunz1	10	30	D_7	13.5
Kunz2	15	44	D_8	24
Kunz3	20	60	D_9	10
Kunz4	25	73	D_{10}	0

Table I. Problem specification and cost function values. The demand matrices D_1, D_2,…, and D_{10} are shown in the captions of Figures 6-15.

4.1 Convergence Behavior of Genetic Algorithm

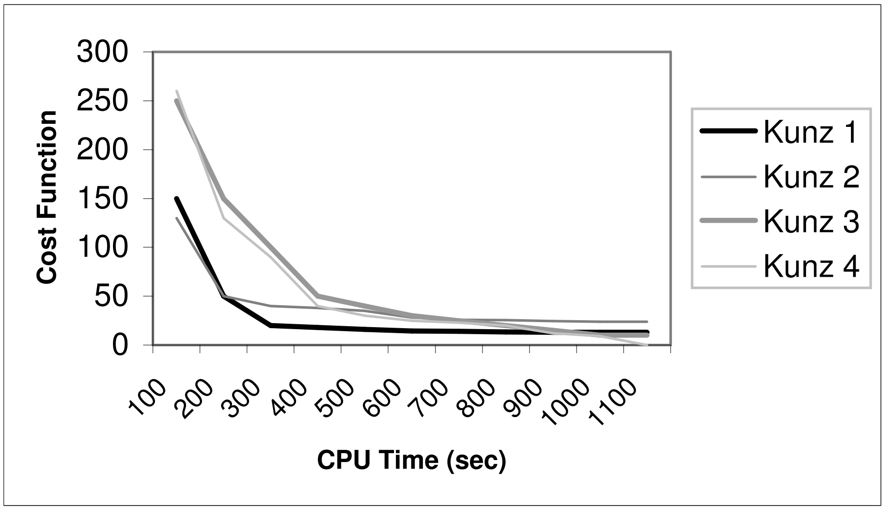

Figure 3. A typical rate of convergence trajectory based on CPU time.

The CPU time taken for each problem is dependent on the size of the problem. A problem with a larger network and more channels tends to take a longer CPU time (Fig.1) or more generations (Figs. 3 and 4) for the minimum cost function to be found.

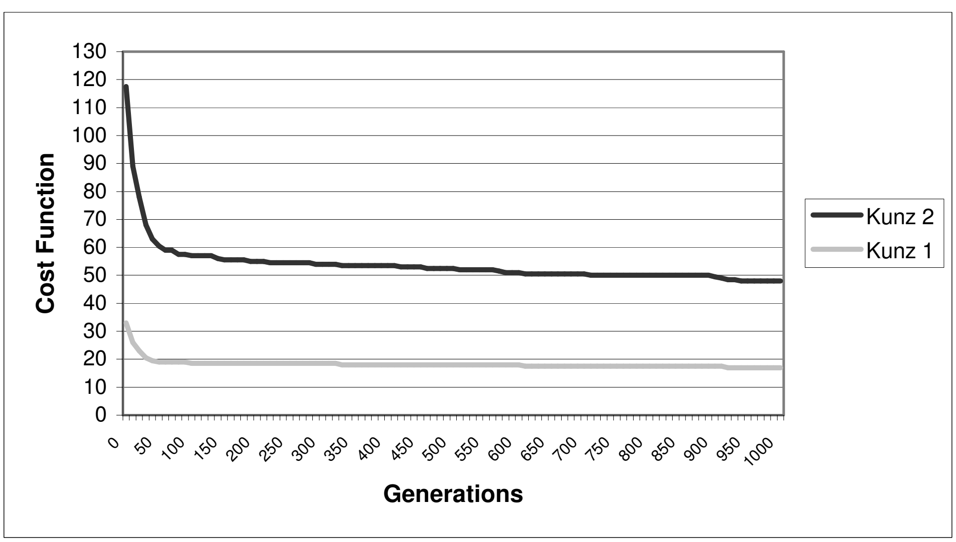

Figure 4. Convergence based on number of generations for Kunz1 and Kunz2 problems.

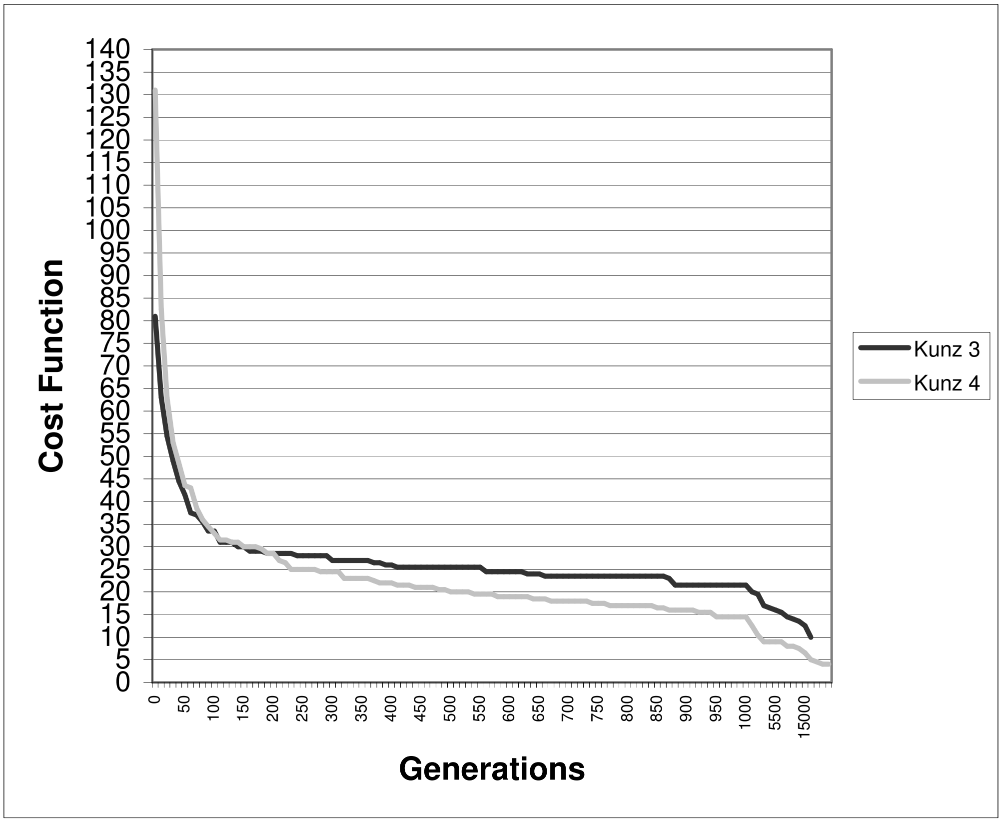

Figure 5. Convergence based on number of generations for Kunz3 and Kunz4 problems.

4.2 <u>Solution Representation for Channel Assignment</u>

We now present the optimal solutions of channel assignment obtained. Each dot in the Figs. 6-15 represents a traffic demand for a particular cell and this demand would be allocated to a channel in a manner such that the interferences are minimized. For example, in problem EX1, there are three demands in cell four, as indicated in Fig.6. These demands are then assigned to channel one, six, and eleven, respectively. We present the detailed assignments for all the test problems, in case the reader wishes to verify or compare with our results.

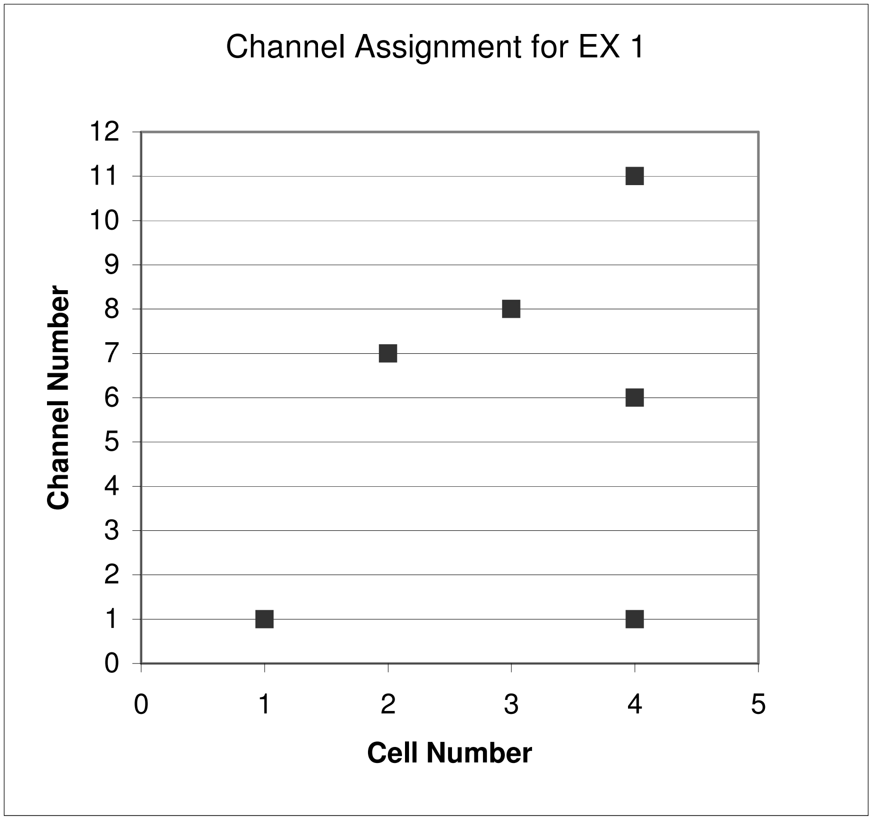

Figure 6. Channel assignment for EX1. Demand matrix D_1= {1,1,1,3}.

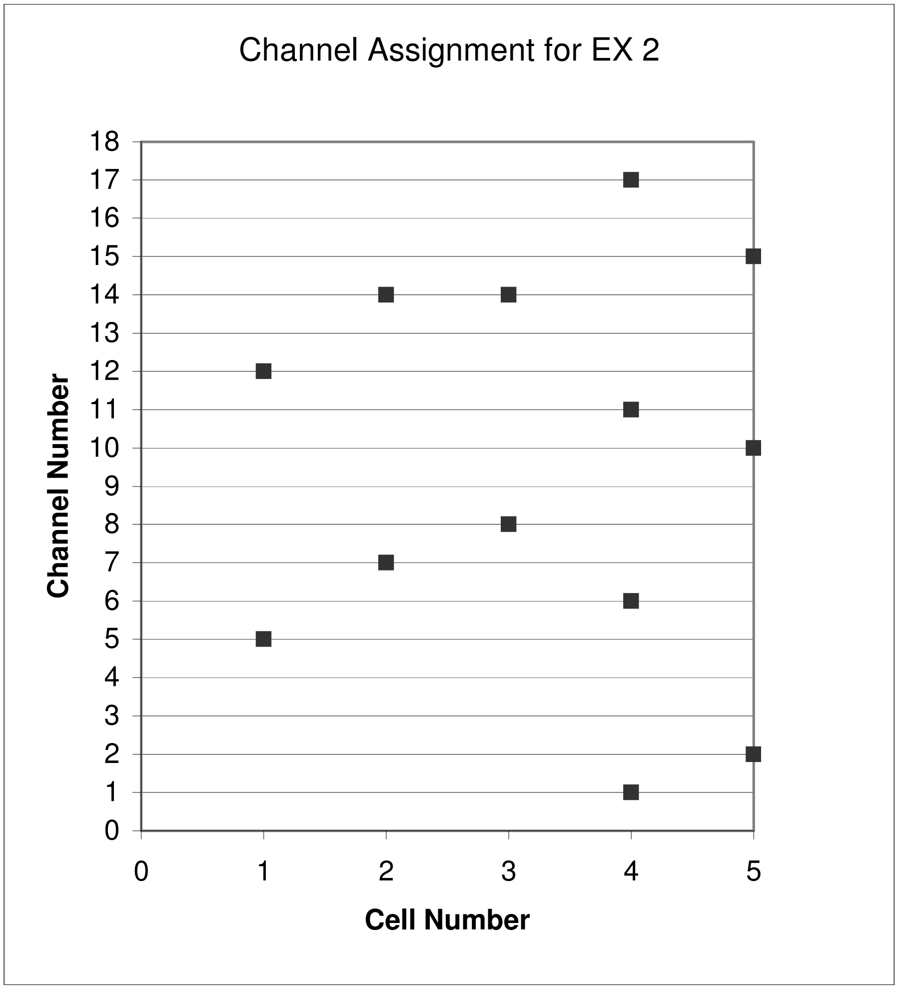

Figure 7. Channel assignment for EX2. Demand matrix D_2= {2,2,2,4,3}.

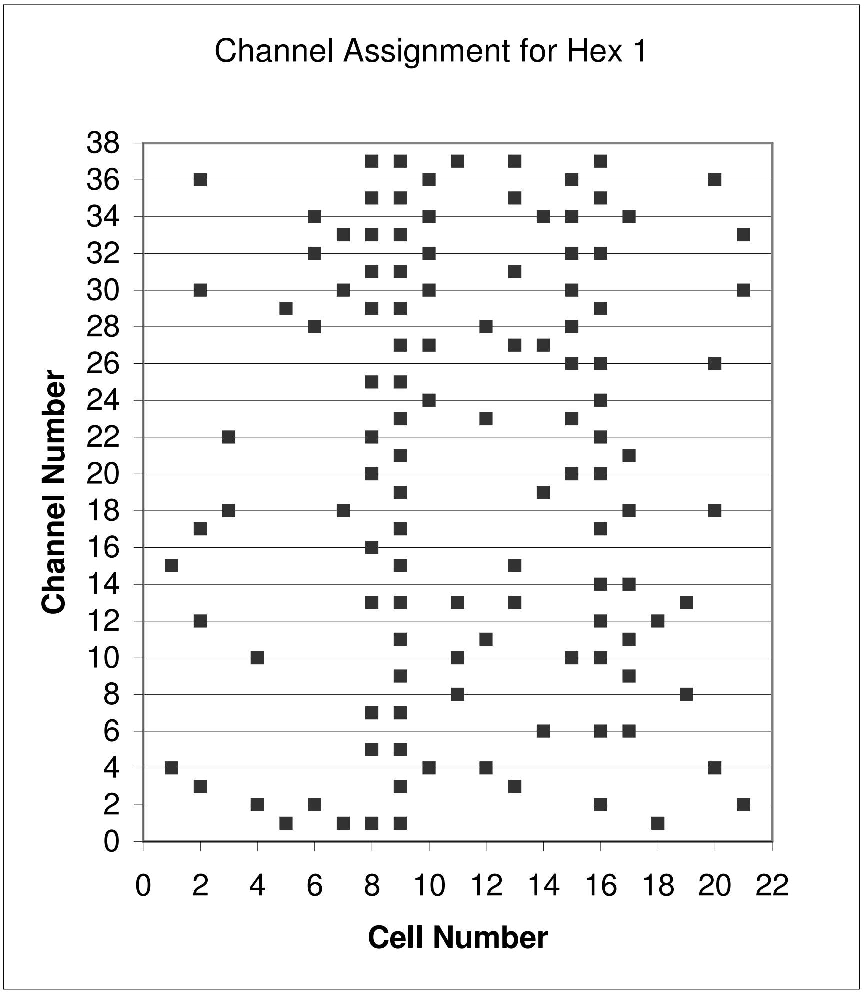

Figure 8. Channel assignment for Hex1. Demand matrix D_3 = {2,6,2,2,2,4,4,13,19,7,4,4,7,4,9,14,7,2,2,4,2}.

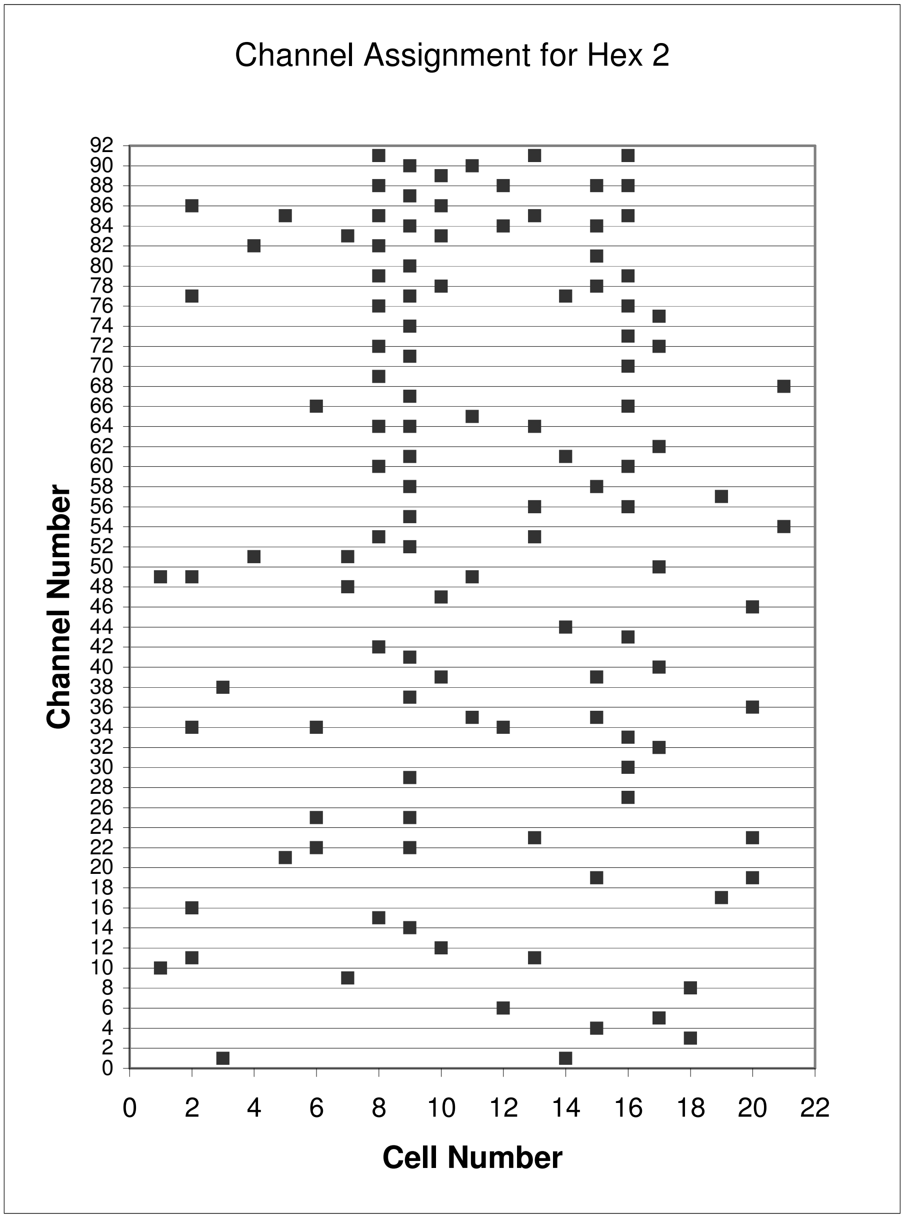

Figure 9. Channel assignment for Hex2. Demand matrix D_4 = {2,6,2,2,2,4,4,13,19,7,4,4,7,4,9,14,7,2,2,4,2}.

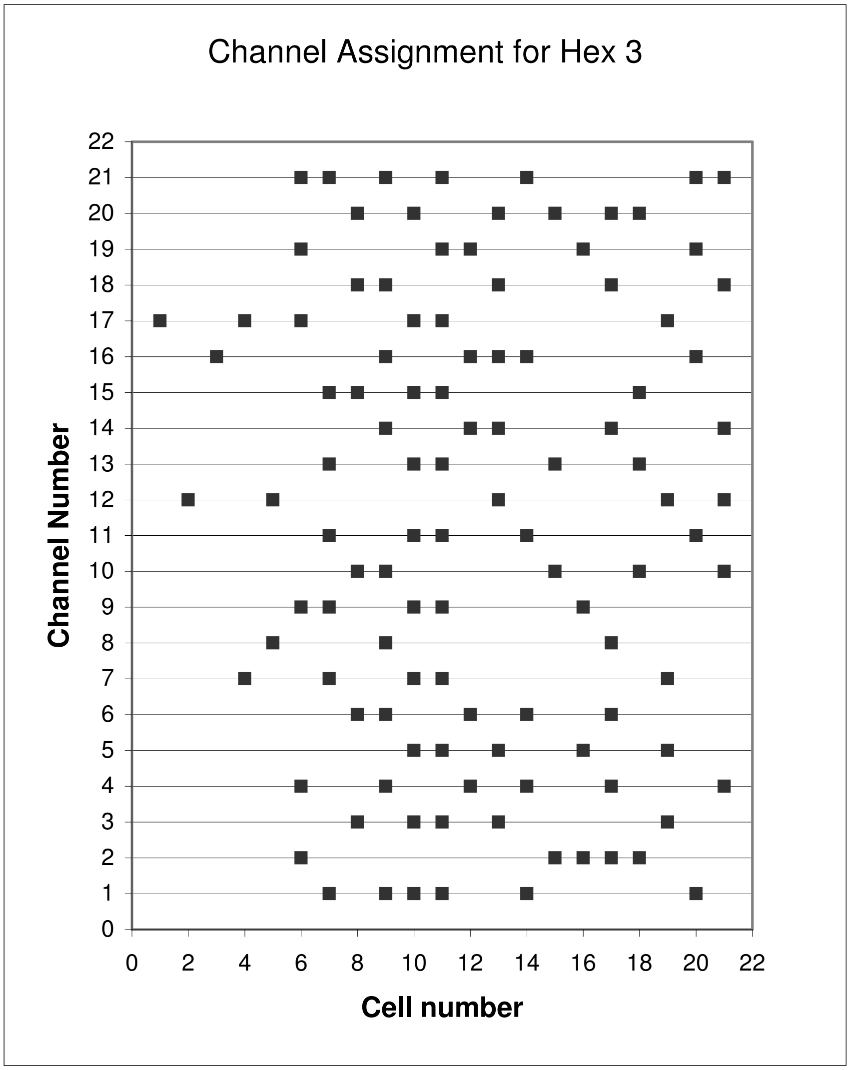

Figure 10. Channel Assignment for Hex3. Demand matrix D_5 = {1,1,1,2,3,6,7,6,10,10,11,5,7,6,4,4,7,5,5,5,6}.

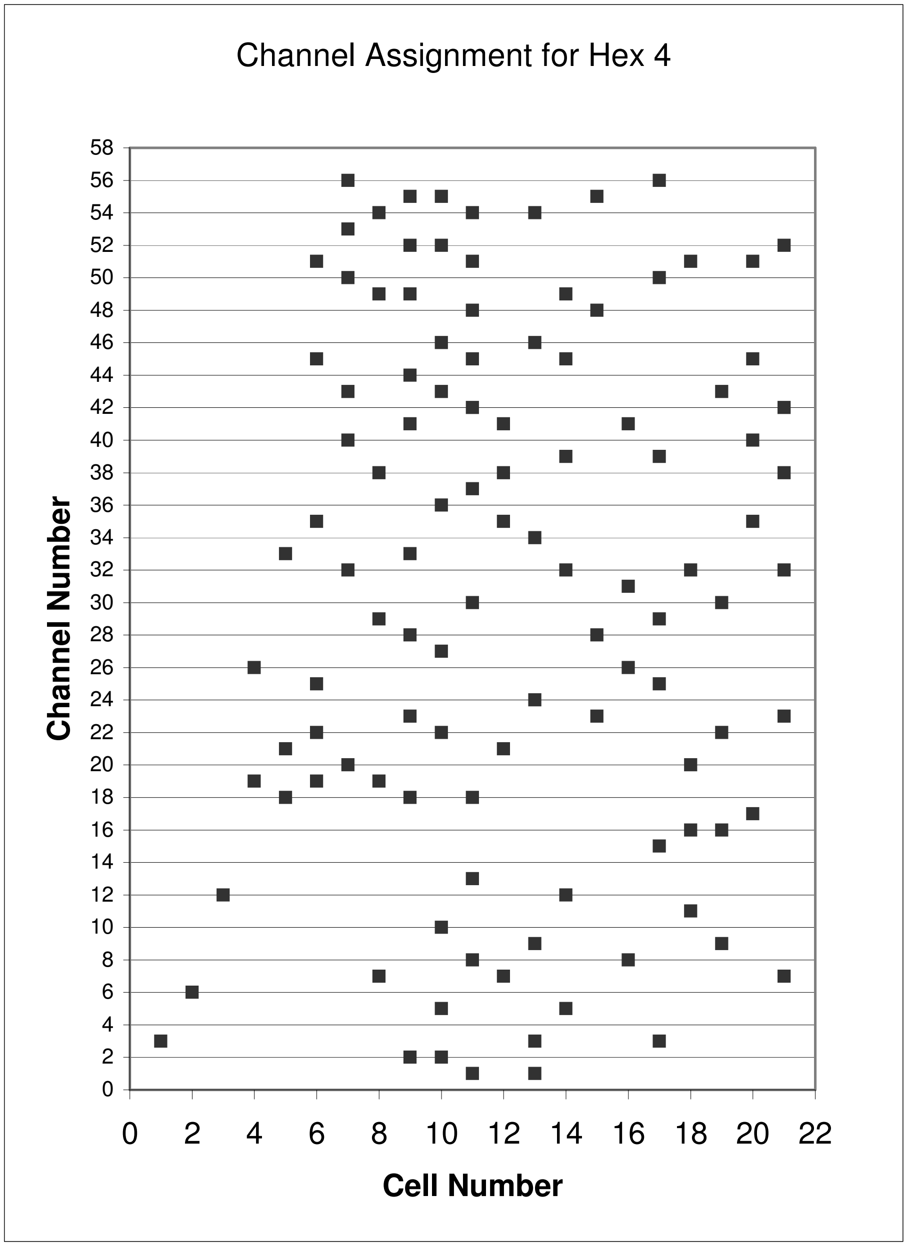

Figure 11. Channel assignment for Hex4. Demand matrix D_6 = {1,1,1,2,3,6,7,6,10,10,11,5,7,6,4,4,7,5,5,5,6}.

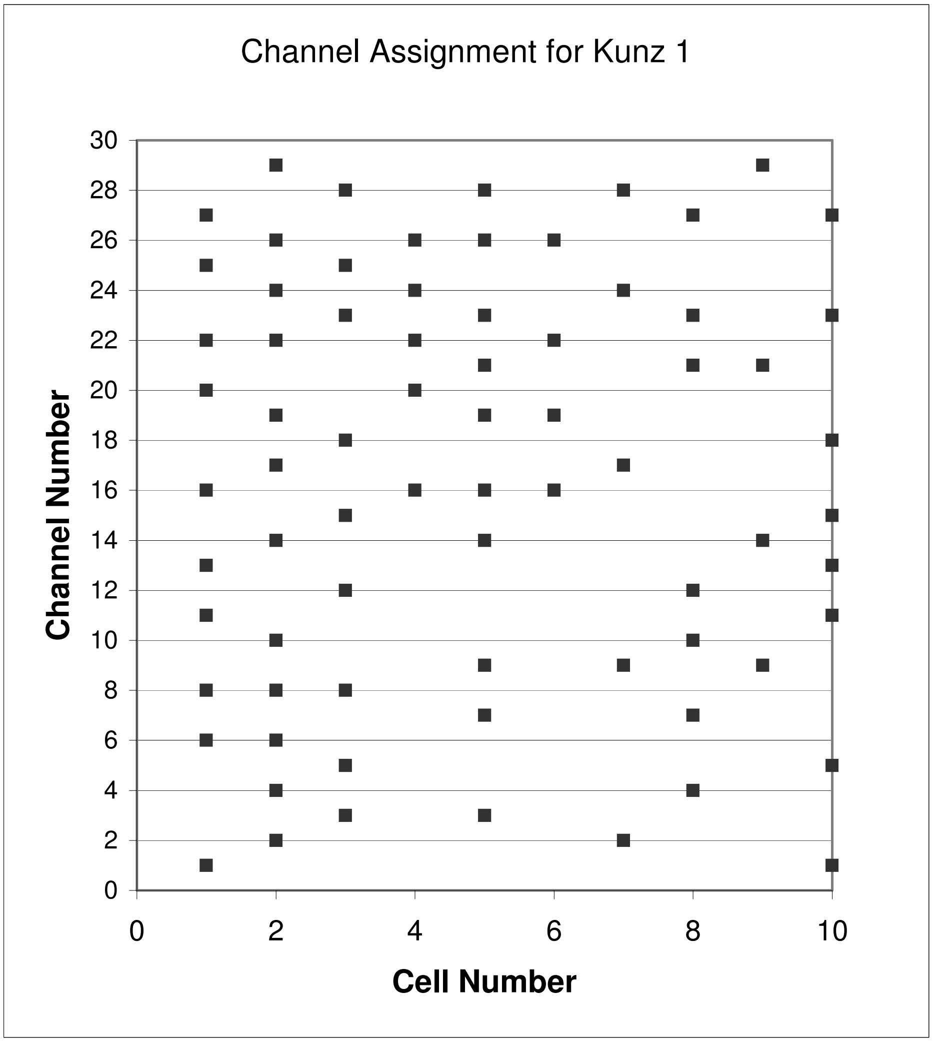

Figure 12. Channel assignment for Kunz1. Demand matrix D_3 = {10,11,9,5,9,4,5,7,4,8}.

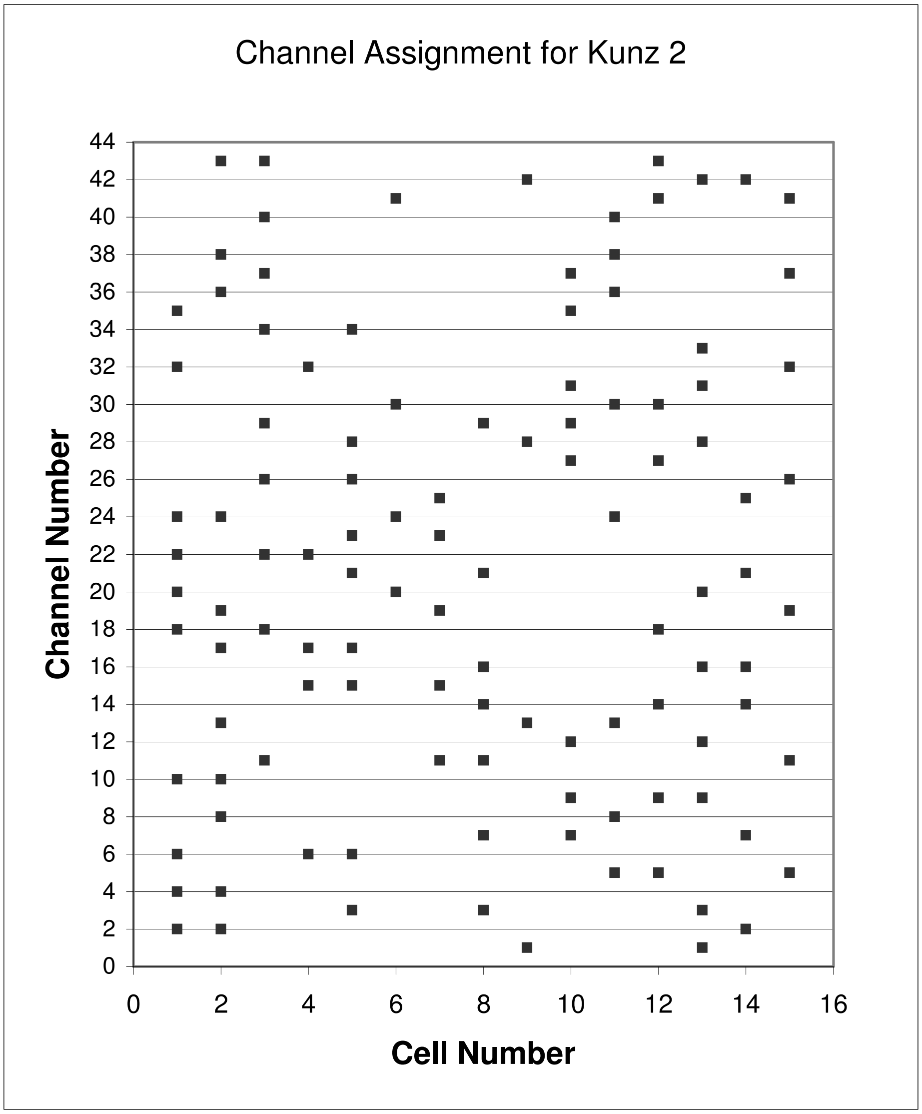

Figure 13. Channel assignment for Kunz2. Demand matrix D_4 = {10,11,9,5,9,4,5,7,4,8,8,9,10,7,7}.

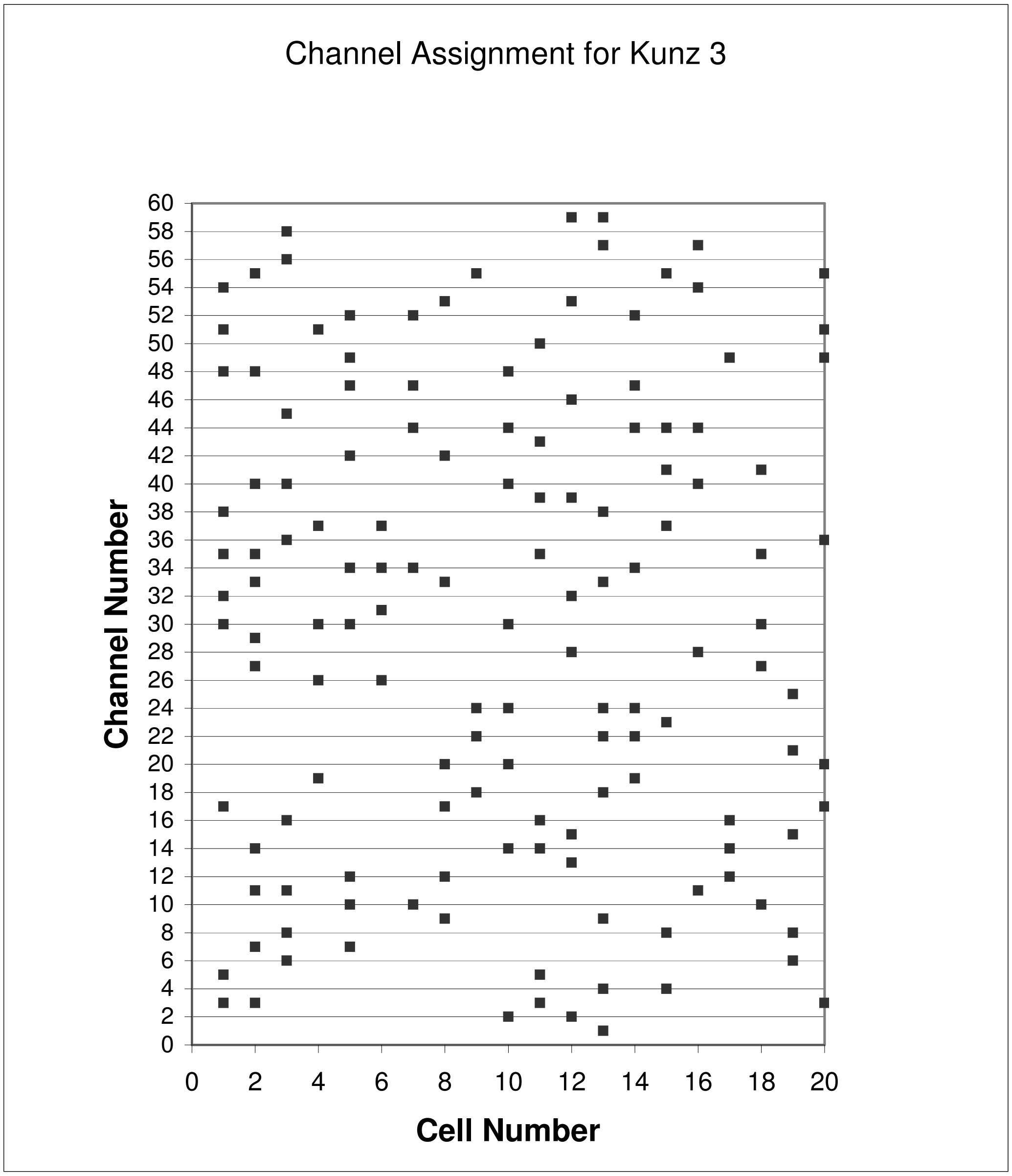

Figure 14. Channel assignment for Kunz3. Demand matrix D_5 = {10,11,9,5,9,4,5,7,4,8,8,9,10,7,7,6,4,5,5,7}

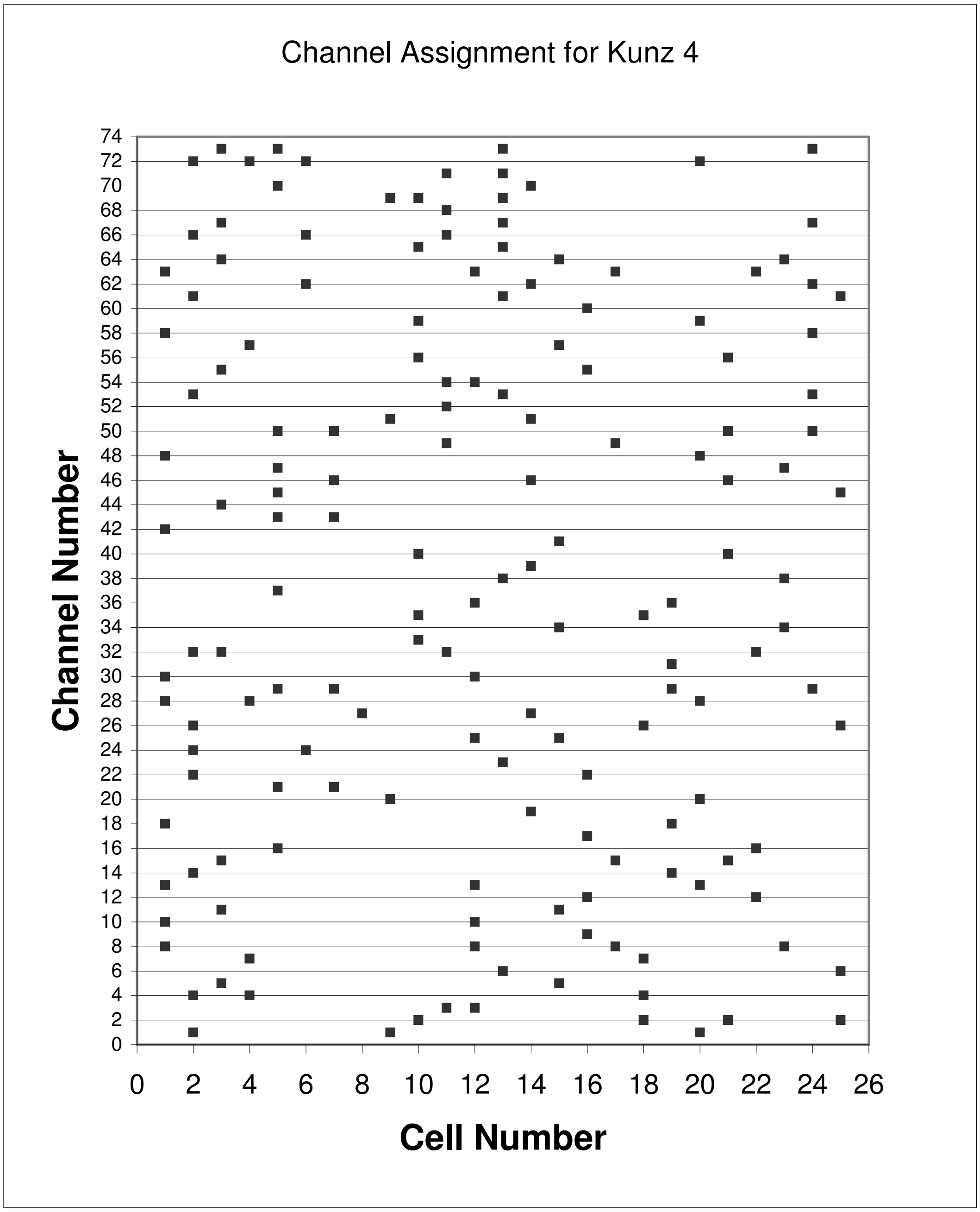

Figure 15. Channel assignment for Kunz4. Demand matrix D_6={10,11,9,5,9,4,5,7,4,8,8,9,10,7,7,6,4,5,5,7,6,4,5,7,5}.

4.3 Crossover Parameter

This section presents the effect of different choices of crossover probabilities. Let us consider population size = 20 and mutation probability = 0.004.

Problem	Probability of Crossover	Cost Function
Hex 1	0.85	35
	0.90	34
	0.95	33
	0.97	33.5
	0.99	34
Hex 2	0.85	14
	0.90	14
	0.95	13.5
	0.97	14.5
	0.99	14.5
Hex 3	0.85	48.5
	0.90	48
	0.95	46.5
	0.97	47
	0.99	47.5
Hex 4	0.85	16
	0.90	15
	0.95	14.5
	0.97	15
	0.99	15.5

Table II. Effect of choices of probability of crossover on the interference results for the Hex problem set.

Problem	Probability of Crossover	Cost Function
Kunz 1	0.85	16
	0.90	14.0
	0.95	13.5
	0.97	14.5
	0.99	15
Kunz 2	0.85	28.5
	0.90	28
	0.95	26
	0.97	28
	0.99	30
Kunz 3	0.85	15
	0.90	13.5
	0.95	13
	0.97	13.5
	0.99	16.5
Kunz 4	0.85	7
	0.90	6
	0.95	3.5
	0.97	5
	0.99	8

Table III. Effect of choices of probability of crossover on the interference results for the Kunz problem set.

Different choices of probability of crossover gave quite different values of the cost function. The results for the Hex and Kunz problem sets are presented in Tables II and III. After many trials on varying the crossover probability, Tables II and III show that a crossover probability of 0.95 tends to give the most satisfactory results (with minimum interference value or cost function) for various problems.

Detailed results of EX1 and EX2 are omitted, since zero-interference can be achieved with a range of parameters tried. This may be because the problem sizes of EX1 and EX2 are small.

4.4 Mutation Parameter

This section presents the effect of different choices of mutation parameters. Let us consider population size = 20 and probability of crossover = 0.95. The simulations were performed by using two different methods of varying the mutation probability. In the first method, an arbitrarily small probability of mutation, e.g., 0.003, is first selected to generate the result. The value is then either increased or decreased to tune into a better solution (with a lower interference value). In the second method, a large probability of mutation, e.g., 0.0900, is initially chosen and gradually decreased until the minimum interference value is found.

From the results obtained for Kunz problem set (Table IV), the second method proved to be more efficient as the cost functions are smaller than the first method with fixed mutation rates. A similar trend of results was found from the simulation of Hex problems.

The results also demonstrated that when the mutation probability is too small, convergence to the minimum interference value is prevented. As the mutation probability is increased, better cost function values can be obtained. However, increasing the mutation probability beyond some critical value introduce too much randomness into the population giving undesirable results with higher interference values (Table IV).

Problem	Probability of Mutation (fix rate)	Cost Function	Probability of Mutation (decreasing rate)	Cost Function
Kunz 1	0.002	17	0.002	13.5
	0.003	16.5	0.003	13.5
	0.004	16	0.004	13
	0.005	17	0.005	13.5
	0.006	18	0.006	14
	0.007	19	0.007	14.5
Kunz 2	0.002	28.5	0.002	28
	0.003	28.5	0.003	24
	0.004	28	0.004	26
	0.005	29	0.005	26
	0.006	29.5	0.006	27
	0.007	29	0.007	28
Kunz 3	0.002	16	0.002	14.5
	0.003	15.5	0.003	14
	0.004	15	0.004	10
	0.005	17	0.005	13
	0.006	16	0.006	14
	0.007	17	0.007	14.5
Kunz 4	0.002	8	0.002	6
	0.003	6.5	0.003	6
	0.004	6	0.004	0
	0.005	5	0.005	3.5
	0.006	7	0.006	4
	0.007	7.5	0.007	5

Table IV. Effects of different choices of probability of mutation on the interference results.

4.5 Population Size

After tuning into a satisfactory crossover and mutation probability, the effect of different choices of population size is considered. The results tend to favor a population of 20 and 30. Greater populations lead to slower convergence and do not provide good solutions. However, too small a population size would lead to unfavorable results as well. For example, from Fig.16 below, a population size 20 proved to be the optimal value for of the Kunz data set. The results are similar for the Hex data set; however, results are independent of the population size for the EX data set.

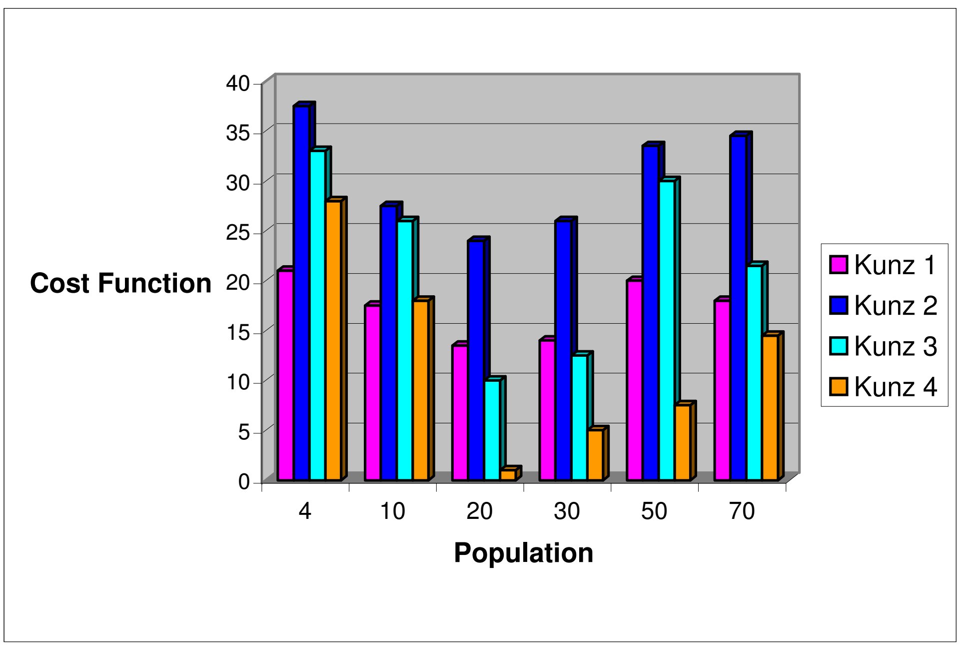

Figure 16. Effect of population size on the cost function.

4.6 Discussion

During the simulation, several parameters, i.e., crossover probability, mutation probability and population size, need to be set. While experimenting on a particular parameter, other parameters were kept constant to allow for comparisons.

The number of generations for different problems needs to be taken into account. For example, for larger problems like Kunz 4, the number of generations needed to obtain a satisfactory result is 100000 as compared to 50000 for Kunz 3.

For any genetic algorithms, the settings of these parameters are generally ad hoc. One general rule was kept throughout the simulation as suggested in [17]. That is to use relatively small population size, high crossover probability, and low mutation probability.

As can be seen from the results presented in this chapter, the algorithm achieved good fitness values for all the benchmark problems.

5 Conclusions

In this paper, we applied Ngo and Li's GA-based approach to CAP2, i.e., channel assignment problems in which the total interference is minimized while traffic demands are satisfied within a given set of available channels. This approach permits the satisfaction of traffic demand requirement and co-site constraint. It is achieved by the use of a minimum-separation encoding scheme, which reduces the required number of bits for representing the solution, and with unique genetic operators that kept the traffic demand in the solution intact. This allowed the search space to be greatly reduced and hence shorten the computation time. The simulations done on benchmark problems showed that this approach could achieve desirable results.

Although we have tested a variety of choices of parameters, such as mutation rate, cross-probability, and population size, more such test with other choices of parameters should be carried out. Implementations of GAs for DCA will also be studied in future work.

REFERENCES

[1] Sivarajan, K. N., McEliece, R. J.: Channel Assignment in Cellular Radio, Proceedings IEEE Vehicular Technology Conference, 1989, 846-850.

[2] Smith, K., Palaniswami, M.: Static and Dynamic Channel Assignment using Neural Networks, IEEE Journal on selected areas in communications, vol. 15, no. 2, 1997, 238-249.

[3] Mathar, R., Mattfeldt, J.: Channel assignment in cellular radio networks, IEEE Trans. Veh. Technol., Vol.42, Feb, 1993, 14-21.

[4] Kunz, D.: Channel assignment for cellular radio using neural networks, IEEE Trans.Veh. Technol., vol. 40, Feb 1991, 188-193.

[5] Funabiki, N., Takefuji, Y.: A neural network parallel algorithm for channel assignment problems in cellular radio networks, IEEE Trans. Veh. Technol., Vol.41, No.4, 1992, 430-437.

[6] Lai W.K., Coghill G.G.: Channel Assignment for a Homogeneous Celular Network with Genetic Algorithms, Conf. Intelligent Information Systems, 1994, 263-267.

[7] Lai W.K., Coghill G.G.: Channel assignment through evolutionary optimization, IEEE Trans. Veh. Technnol., vol. 45, no. 1, 1996, 91-96.

[8] Jaimes-Romero, F.J., Munoz-Rodriguez, D., Tekinay, S.: Channel assignment in cellular systems using genetic algorithms, *IEEE 46th Vehicular Technology Conference*, vol. 2, 1996, 741 -745.

[9] Kim, J.S., Park, S.H., Dowd, P.W., Nasrabadi, N.M.: Channel assignment in cellular radio using genetic algorithm, Wireless Persona Commun, vol.3, no.3, Aug.1996, 273-286.

[10] Cuppini, M.: A genetic algorithm for channel assignment problems, Eur. Trans. Telecomm. Related Technol., vol.45, no.1, 1996, 91-96.

[11] Ngo, C. Y., Li, V.O.K.: Fixed channel assignment in cellular radio networks using a modified genetic algorithm, IEEE Trans. Veh. Technol., Vol.47, No.1, 1998, 163-172.

[12] Smith, K. A.: A genetic algorithm for the channel assignment problem, IEEE Global Technology Conference, vol. 4, 1998, 2013-2017.

[13] Beckmann, D., Killat, U.: A new strategy for the application of genetic algorithms to the channel assignment problem, *IEEE Trans. Veh.Technol., Vol. 48, No. 4, July 1999, 1261-1269.*

[14] Thavarajah, A., Lam, W.H.: Heuristic approach for optimal channel assignment in cellular mobile systems, IEE Proceedings Communications, vol. 146 3, June, 1999, 196 –200.

[15] Chakraborty, G., Chakraborty, B.: A genetic algorithm approach to solve channel assignment problem in cellular radio networks, *Proc. 1999 IEEE Midnight-Sun Workshop on Soft Computing Methods in Industrial Applications*, 1999, 34–39.

[16] Williams, M.: Making the best use of the airways: an important requirement for military communications, *Electronics & Communication Engineering Journal,* vol.12, no.2, April, 2000, 75-83.

[17] Goldberg D. E.: Genetic algorithms in search, optimization, and machine learning. Reading, Mass.: Addison-Wesley, 1989.

[18] A. Gamst, "Some lower bounds for a class of frequency assignment problems", *IEEE Trans. Veh. Tech.,* vol. VT-35, pp. 8-14, Feb., 1986.