셀룰러 무선망에서 채널할당을 위한 두 가지 최적화 기법

남 인 길[†] · 박 상 호[††]

요 약

본 논문에서는 신경회로망과 유전자 알고리즘을 이용하여 셀룰러 무선채널 할당을 위한 최적화 알고리즘을 제안하였다. 채널할당 과정을 채널할당 문제에 내포된 제한사항들을 나타내는 에너지함수의 최소화 과정으로 규정하였다. 채널간, 인접채널, 사이트간의 세 가지 제한사항이 고려되었다. 최적의 채널할당을 위하여 신경회로망을 이용한 방식에서는 강제적인 채널할당 및 셀 순서 변화 등의 기법이 개발되었고 유전자 알고리즘 방식에서는 자료구조와 적절한 유전연산자를 개발하였다. 실험결과로서, 두 최적화 방법의 채널할당률을 나타내었고 그 결과들을 비교하였다.

Two Optimization Techniques for Channel Assignment in Cellular Radio Network

In-Gil Nam[†] · Sang-Ho Park[††]

ABSTRACT

In this paper, two optimization algorithms based on artificial neural networks and genetic algorithms are proposed for cellular radio channel assignment problems. The channel assignment process is characterized as minimization of the energy function which represents constraints of the channel assignment problems. All three constraints such as the co-channel constraint, the adjacent channel constraint and the co-site channel constraint are considered. In the neural networks approach, certain techniques such as the forced assignment and the changing cell order are developed, and in the genetic algorithms approach, data structure and proper genetic operators are developed to find optimal solutions. As simulation results, the convergence rates of the two approaches are presented and compared.

1. Introduction

The channel assignment problem is concerned with finding an admissible frequency band assignment as small number of channels as possible. Various algorithms [1-7] have been proposed to solve the channel assignment problem. In this paper, two new optimization algorithms based on Hopfield neural network [8, 9] and genetic algorithms [10] for channel assignment in cellular radio networks are presented. The channel assignment problem is formulated as an energy minimization problem. The Hopfield neural network algorithm uses the forced assignment and the changing cell order technique to

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† 정 회 원 : 대구대학교 컴퓨터정보공학부 교수
†† 정 회 원 : 안동대학교 정보통신공학과 교수

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inhibit falling into the local minima which is the disadvantage of neural networks. To escape the local minima, if the number of assigned channels are less than the required channel numbers, one or more channels are assigned such that the total number of assigned channels are the same as the required number of channels in the cell even though energy is increased - the forced assignment. In the previously proposed neural network approaches, heuristics are used to increase the convergence rate [4], and some frequencies are predetermined before channel assignment procedure to accelerate the convergence time [4, 5]. In our algorithm, no heuristics are used and no frequency is fixed before the frequency assignment procedure. An initialization technique which uses the constraints of channel assignment problems and a updating order is developed instead of heuristics and fixed frequency assignment. Updating order is determined by alternating order such that the greatest demand cell as the first, the smallest demand cell as the second, the second greatest cell as the third, the second smallest cell as the fourth channel assignment cell, and so on - the changing cell order technique. In genetic algorithms approach, the fitness function, the structure of strings, and the various genetic operators such as crossover and mutation are developed according to the constrained conditions in the channel assignment problems. Three constrained conditions are considered in this paper as in [11] : co-site constraint (CSC), co-channel constraint (CCC) and adjacent channel constraint (ACC).

2. Channel Assignment Problem

A major problem in the mobile communications is the limitation imposed by the available frequency spectrum. The cellular concept is one way to overcome this limitation of spectrum. Frequency reuse is the essential feature of the cellular concept. Frequency reuse refers to the use of radio channels on the same carrier frequency to cover different areas which are separated from one another by sufficient distances so that there are no interference between the same channels. The channel interference depends on the various parameters such as cell shape, cell size, layout of the cells, applied modulation, etc. We consider three electromagnetic compatability constraints :

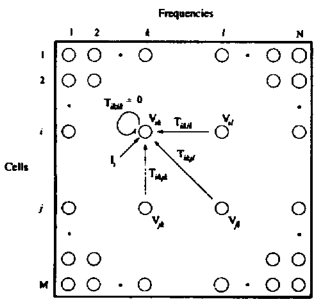
(1) co-channel constraints (CCC) : for each pair of base station it is known whether they may use the same frequencies or not ;

(2) adjacent channel constraints (ACC) : if an ACC is imposed on a system, frequencies adjacent in the frequency domain are not admitted in adjacent cells ;

(3) co-site constraints (CSC) : a minimal distance between frequencies used at the same base station is prescribed.

Given available frequency channels for the system as well as required number of channels for each cell, how should we distribute these frequencies to each cell such that the above constraints are satisfied is the task of channel assignment.

Gamst [11] defined the compatibility matrix $C = (c_{ij})$, which is an $M \times M$ symmetric matrix where M is the number of cells in the mobile networks, and c_{ij} is the minimum frequency separation between frequencies in the cell C_i and C_j. The compatability matrix prescribes the mutual relationship for any pair of frequencies assigned to different radio channels in the system. Each $c_{ii} = k$ represents the minimum separation distance between any two frequencies assigned to cell C_i, which is CSC. CCC is represented by $c_{ij} = 1$, and ACC is represented by $c_{ij} = 2$. The number of channels needed for each cell C_i is presented by the number of required channels (NRC) matrix $R = (r_i)$ where r_i is NRC of the cell C_i and $1 \leq i \leq M$. Let f_{ik} indicate the assigned frequency for the kth call in the cell C_i where $1 \leq i \leq M$ and $1 \leq k \leq r_i$. The condition imposed by the compatibility constraints between f_{ik} and f_{jl} is given by $|f_{ik} - f_{jl}| \geq c_{ij}$ where $1 \leq i, j \leq M$ and $1 \leq k, l \leq r_i$. The channel assignment problem is to find f_{ik} which satisfies the constraint conditions when the number of cells in the mobile networks are given along with the compatibility matrix C and the NRC matrix R.



(Fig. 1) A Hopfield network for the channel assignment problem

3. Neural Network Method

An $M \times N$ two dimensional discrete Hopfield network with fully interconnected neurons is constructed as shown in (Fig. 1), where rows of the array indicate cell numbers and columns of the array represent channel numbers. The number of columns, N, is the lower bound (LB) [12] of the number of channels for a given cellular communication system. The state of each neuron V_{ik} represents an assignment of the channel f_k to the cell C_i : if $V_{ik} = 1$, the channel f_k can be assigned to the cell C_i. In each row, the number of neurons which have the state value of $V_{ik} = 1$ must be equal to r_i since there are r_i requested calls in the cell C_i. The connection between a neuron (i, k) and another neuron (j, l) is denoted by T_{ikjl} which is obtained from the constraints measure between the neurons. The external input to each neuron in the cell C_i is indicated by I_i.

In order to find admissible channel assignment, constraints of the channel assignment problem should be implied in the interconnection weights. Each of the constraints are invoked by inhibitory and excitatory support. No more frequency can be assigned to the cell if the number of assigned channels (NAC) is greater than or equal to r_i. This constraint can be expressed as

$$T^{NC} = -\delta_{ij} \mid 1 - \delta_{kl} \mid \tag{1}$$

where δ is the Kronecker delta function and defined as follows :

$$\delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & otherwise \end{cases} . \tag{2}$$

For the CSC, the assignment of the channel f_k to the cell C_i must be inhibited if the channel f_l is already assigned to the same cell, and $|f_{ik} - f_{il}|$ is less than c_{ii}. This constraint can be expressed by

$$T^{SC} = -\delta_{ij}\, a_{kl}(c_{ii}) \tag{3}$$

where a_{kl} is defined by

$$a_{kl}(x) = \begin{cases} 1 & \text{if } |k - l| < x \\ 0 & otherwise \end{cases} . \tag{4}$$

For the ACC and CCC, the assignment of the channel f_k to the cell C_i must be inhibited if the channel f_l is already assigned to the cell C_j, and the distance of two channels $|f_{ik} - f_{jl}|$ is less than c_{ij}. Hence, this constraint can be defined by

$$T^{CC} = - \mid 1 - \delta_{ij} \mid a_{kl}(c_{ij}). \tag{5}$$

By combining Eqs. (1), (3), and (5), the interconnection weights for channel assignment problem is given by

$$T_{ikjl} = -\delta_{ij} \mid 1 - \delta_{kl} \mid - \delta_{ij} a_{kl}(c_{ii}) - \mid 1 - \delta_{ij} \mid a_{kl}(c_{ij}). \tag{6}$$

The connection weight T_{ikjl} between two nodes V_{ik} and V_{jl} is symmetrical, i.e., $T_{ikjl} = T_{jlik}$, and selffeedback is not allowed, i.e., $T_{ikik} = 0$.

In order to make NAC equal to NRC, excitatory support is provided in the form of external input. When channels are assigned for all neurons except current updating neuron, the input to updating neuron is $-(r_i - 1)$ if assignment is not violated by constraints. Hence, the external input of all neurons for the cell C_i is given by $I_i = (r_i - 1)$. The input to each neuron (i,k), S_{ik}, is given by

$$S_{ik} = \sum_{p=1}^{M} \sum_{q=1}^{N} T_{ikjl} V_{jl} + I_i. \tag{7}$$

If NAC is less than NRC even though the channel assignment for a cell is not violated to three constraints, states of network is hardly changed so that a Hopfield network is stuck at the local minima. In such case, one or more demanded calls may not be assigned forever since the assignment is not violated to the constraints. In order to escape from local minima, we provide excitatory support to the neuron in the form of another external input. In our algorithm, the difference between NRC and NAC is fed to each neuron in order to change the states of neurons by violating constraints if NAC is less than NRC. This excitatory support is given by

$$I^{*}_{ik} = (r_i - \sum_{l=1}^{N} V_{il}). \tag{8}$$

With this excitatory support, the probability of successful assignment can be greatly increased. Total input to each neuron of our modified Hopfield network is given by

$$S_{ik} = \sum_{j=1}^{M} \sum_{l=1}^{N} T_{ikjl} V_{jl} + I_i + I^{*}_{ik}. \tag{9}$$

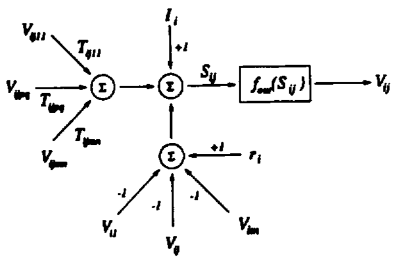
The output of neuron is determined by thresholding the input value which is given by

$$V_{ik} = f_{out}(S_{ik}). \tag{10}$$

where

$$f_{out}(x) = \begin{cases} 1 & \text{if } x \geq T \\ 0 & otherwise \end{cases} \tag{11}$$

and threshold $T = 0$. The schematic diagram of the neuron *(i,k)* of our modified Hopfield network is depicted in (Fig. 2).



(Fig. 2) Schematic diagram of a neuron *(i,k)*

The channel assignment process is characterized as the minimization of the energy function which represents constraints of the channel assignment problem. For the admissible channel assignment, channels should be assigned to all demanded calls in a given system : this is a traffic demand constraint. In order to assign channels to every calls in the cell C_i, NAC of the cell C_i must be the same as NRC of the cell C_i. The energy function for the traffic demand constraint for the cell C_i can be defined as below :

$$E_i^{NC} = (r_i - \sum_{k=1}^{N} V_{ik})^2. \tag{12}$$

By CSC, the channel f_k must not be assigned to the cell C_i if f_l is already assigned in the same cell and $|f_{ik} - f_{il}|$ is less than c_{ii}. The energy function for CSC for the cell C_i is defined as follows :

$$E_i^{SC} = \sum_{k=1}^{N} \sum_{l=1}^{N} V_{ik} V_{il} X_{ikl} \tag{13}$$

where

$$X_{ikl} = \begin{cases} 1 & \text{if } k \neq l \\ & \text{and } l-(c_{ii}-1) \leq k \leq l+(c_{ii}-1). \\ 0 & otherwise \end{cases} \tag{14}$$

By ACC and CCC, the channel f_k must not be assigned to the cell C_i if f_l is already assigned in the cell C_j, and distance of two channels $|f_{ik}-f_{jl}|$ is less than c_{ij}, the minimum channel separation distance between the cell C_i and the cell C_j for ACC and CCC. The energy function for the both of ACC and CCC for the cell C_i can be defined as follows :

$$E_i^{CC} = \sum_{k=1}^{N}\sum_{j=1}^{M}\sum_{l=1}^{N} V_{ik}V_{jl}Y_{ikjl} \tag{15}$$

where

$$Y_{ikjl} = \begin{cases} 1 & \text{if } i \neq j \text{ and } c_{ij} > 0 \\ & \text{and } l-(c_{ij}-1) \le k \le l+(c_{ij}-1). \\ 0 & \textit{otherwise} \end{cases} \tag{16}$$

From Eqs. (12), (13), and (15), the energy function for the cell C_i is given by

$$\begin{aligned} E_i = & \left(r_i - \sum_{j=1}^{N} V_{ij}\right)^2 + \sum_{k=1}^{N}\sum_{l=1}^{N} V_{ik}V_{il}X_{ikl} \\ & + \sum_{k=1}^{N}\sum_{j=1}^{M}\sum_{l=1}^{N} V_{ik}V_{jl}Y_{ikjl}. \end{aligned} \tag{17}$$

Finally the energy function of the neural network for the channel assignment problem is given by

$$\begin{aligned} E = & \sum_{i=1}^{M}\Big(\left(r_i - \sum_{k=1}^{N} V_{ij}\right)^2 + \sum_{k=1}^{N}\sum_{l=1}^{N} V_{ik}V_{il}X_{ikl} \\ & + \sum_{k=1}^{N}\sum_{j=1}^{M}\sum_{l=1}^{N} V_{ik}V_{jl}Y_{ikjl}\Big). \end{aligned} \tag{18}$$

The channel assignment algorithm based on the neural network is summarized in the following steps.

1) The initial state of neurons is set to one or zero according to the initialization method.
2) Repeat the following steps until all neurons are picked.
   a) Pick neuron (i,k) according to the updating method.
   b) Calculate the input to this neuron by Eq. (9).
   c) Decide the new state of this neuron by Eq. (10)
3) Compute the energy E of the current assignment. If $E = 0$, stop and go to step 4),. otherwise repeat the process from step 2)

An initialization technique is developed in order to increase the convergence rate and to decrease iteration number. We grouped channels with B blocks. The minimum number of channels (MNC) is defined as the minimum number of channels needed to assign channels to all the demanded calls. Note that MNC is always less than or equal to LB. The number of channels in a block, W, is defined by

$$W = \begin{cases} c_{ii} & \text{if } LB = MNC \\ \left\lfloor \dfrac{LB-1}{\max(r_i)-1} \right\rfloor & \text{if } LB > MNC \end{cases}. \tag{19}$$

The initialization method is summarized as follows :

1) For the cell C_i with r_i demands, choose a block number b at random and choose randomly a channel number p in the chosen block. Then channel number in the block is $(b-1)\times W+p$ which does not violate with CCC and ACC with previously assigned channels of other cells. Set state of selected neuron (i,k) to '1'.
2) For the remaining calls of the cell, assign a '1' to a neuron (i,l) which has distance of W with previously assigned neuron (i,k) where $l=(k+W) \bmod LB$.

In the Hopfield networks, the updating neurons may be selected randomly or sequentially. In our algorithm, sequential selection is investigated rather than random selection. The procedure of updating neuron is summarized as follows :

1) Decide updating order of cells by alternating order.
2) From the first cell to the last cell in the ordered list, perform cell updating for each cell.
3) If the energy value is zero, stop the iteration or iteration number is same as the predefined maximum number of iteration, stop. otherwise goto step 2).

The cell updating procedure is as follows :

1) Randomly choose one neuron in the current updating cell for the first update.

2) Calculate the input by Eq. (9).
3) Decide the new state of the updating neuron using Eq. (10).
4) Decide the updating direction in the cell such as left or right of the first updating neuron for the rest of neurons.
5) Continue updating for the rest of neurons according to the given direction until all the neurons in the cell are updated.

4. Genetic Algorithm Method

The genetic algorithm is an iterative procedure that maintains a set of candidate solutions called population $P(t)$ for each iteration t. A population consists of a number of possible candidate solutions called strings. At each iteration a new population $P(t+1)$ is created from the previous population $P(t)$ using a set of genetic operators. Conventional genetic algorithms (GA) use fixed-length binary strings and two basic genetic operators. In order to solve problems using GA, a problem is, in general, transformed into an appropriate form for GA. The algorithm proposed in this paper has difference in approaching method such that the representation of strings is modified instead of the problem itself, and appropriate genetic operators are designed. A population can be represented by two-dimensional array of size $P \times Q$. The rows of the array represent strings in a population, and the columns represent channel numbers. There are P strings in a population and each string has number $Q = \sum_{i=1}^{M} r_i$ calls where M is the number of cells in the system and each cell i has r_i calls. The string S_p represents the assignment of channels for the system as potential solution. Each string S_p composed of M cells and each substing S_{pi} for the cell C_i has r_i elements which is the number of requested calls in the cell C_i. The value in the kth feature of S_{pi}, denoted by $S_{pi}(k)$, represents assigned channel number to the kth call in the cell C_i.

The channel assignment problem is formulated as the maximizing a fitness function that is equivalent to the minimization of objective function. We define the objective function for each constraint. Since every feature in a string has been assigned a value, NAC is always equal to NRC. Hence, the traffic demand constraint is not considered in genetic algorithm approach. For CSC, the assigned channel numbers $S_{pi}(k)$ in the substring S_{pi} should apart each other with distance at least c_{ii}. The objective function concerning with CSC, denoted by $E^{SC}_{S_{pi}}$, for each substring S_{pi} in a string S_p is defined by

$$E^{SC}_{S_{pi}} = \sum_{k=1}^{r_i} V_{ik} \tag{20}$$

where V_{ik} represents the state of possible channel assignment with the CSC and r_i is NRC of the cell C_i. If the channel assigned to the kth call in the cell C_i is not violated by CSC, V_{ik} takes value 0 otherwise takes 1 as below :

$$V_{ik} = \begin{cases} 0 & \text{if } |f_{ik} - f_{i(k+1)}| \geq c_{ii} \\ & \text{or } |f_{ik} - f_{i(k-1)}| \geq c_{ii} \\ 1 & \textit{otherwise} \end{cases} \tag{21}$$

where V_{ik} is the channel assigned to the kth call in cell C_i. The objective function $E^{SC}_{S_p}$ for all cells (substrings) in a string S_p is given by

$$E^{SC}_{S_p} = \sum_{i=1}^{M} \sum_{k=1}^{r_i} V_{ik} \tag{22}$$

The objective function $E^{CC}_{S_p}$ for ACC and CCC is defined by

$$E^{CC}_{S_p} = \sum_{i=1}^{M} \sum_{k=1}^{r_i} \sum_{j=1}^{M} \sum_{l=1}^{r_j} V_{ikjl} \tag{23}$$

where i and j are the cell numbers and k and l are call numbers. V_{ikjl} takes value 1 or 0 as below :

$$V_{ikjl} = \begin{cases} 0 & \text{if } |f_{ik} - f_{jl}| \geq c_{ij} \\ 1 & \textit{otherwise} \end{cases} \tag{24}$$

Finally, from Eq. (22) and (23), the objective function for each string is defined by

$$E_{S_p}^{CC} = \sum_{i=1}^{M}\sum_{k=1}^{r_i} V_{ik} + \sum_{i=1}^{M}\sum_{k=1}^{r_i}\sum_{j=1}^{M}\sum_{l=1}^{r_j} V_{ikjl} \qquad (25)$$

By the objective function Eq. (25), the worst assignment gets the highest value. Our aim for this optimization problem is to make strings having objective function value 0 with smaller iteration numbers. Hence, channel assignment problem is formulated as objective function minimization problem. In order to make the channel assignment problem as fitness maximization problem, we defined the fitness function as below :

$$F_{S_p} = \frac{\sigma_p}{\sum_{n=1}^{P}\sigma_p} \qquad (26)$$

where P is the number of strings in a population and

$$\sigma_p = \frac{1}{E_{S_p}} \qquad (27)$$

Genetic algorithms are composed of two operations : reproduction and recombination. Reproduction is a process in which individual strings are selected according to their fitness function values. Strings with a higher fitness value have a higher probability of selection to produce offsprings in the next generation. After selection of good strings, two strings are recombined by some genetic operators such as crossover and mutation, this process is called recombination. The crossover operators proposed in our genetic algorithm are two-point crossover and it can be summarized as bellows :

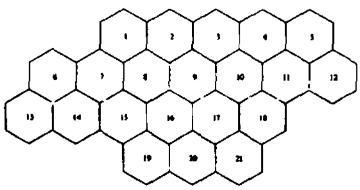
If randomly generated probability of the substring is greater than the probability of crossover, two crossover points are randomly generated and features between two crossover points are swapped each other.

Although reproduction and crossover operations search solution space effectively, if majority of strings search near local minima, most of selected strings are near local minima. In order to provide diversity in searching points, parts of string are modified by mutation operation. In our algorithm, mutation is applied to each substring with mutation probability P_M. Mutation operation developed in this algorithm is summarized as bellows :

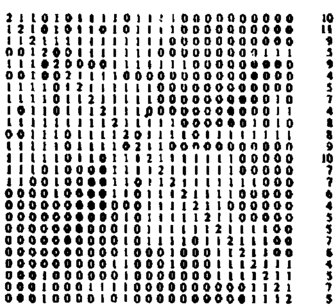
1) For the all assigned channel numbers in the substring, check whether the assignment is violated to all constraints or not.
2) If the assignment for substring is violated with any constraint and randomly generated probability is greater than P_M, mutation operator M1 is applied to substring and then mutation M2 is also applied.
   (1) Mutation operator M1 :
   Assign the randomly selected channel to the 1st call of the ith substring in cell C_i as f_{i1}. For the remaining calls in the same cell, assign channel number $f_{i(p+1)} + \gamma$ to the pth call in cell C_i where $2 \le p \le d_i$ and $\gamma = \lfloor \frac{LB-1}{\max(r_i)-1} \rfloor$.
   (2) Mutation operator M2
   Move the every assigned channel number f_{ik} for the kth call in the ith substring to the $((k+\omega) \bmod r_i)$th call where ω is the randomly chosen integer and $\omega < \gamma$.

5. Simulation Results

A mobile system consisting of 21 or 25 cells is used in our simulations. The 21-cell system is shown in (Fig. 3). Compatibility matrices C and NRC matrices R of 25-cell system and 21-cell system are shown in (Fig. 4) and (Fig. 5), respectively. To investigate the convergence rate and the iteration number, 100 simulation runs were performed with different initial seed number for each run. The convergence rate is the probability of the successful channel assignment. It is the ratio of the number of successful assignment to the total tries. The average iteration number is the average number of iterations when iteration is terminated. If channel assignment is failed, the number of iteration is equal to the maximum number of iteration, 500 for neural network and 100 for genetic algorithm.



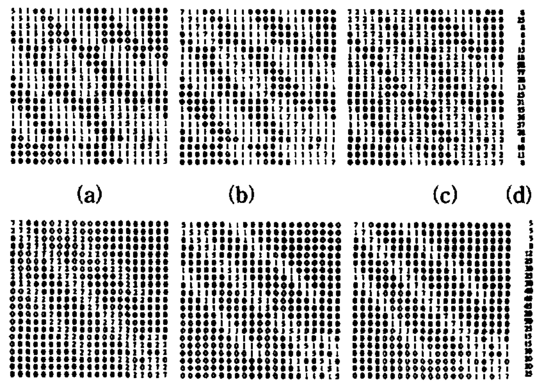
(Fig. 3) The 21-cell system ; The cell number is indicated in each cell



(a) (b)

(Fig. 4) (a) Compatability matrix C1, (b) Demand vector D1

To test our neural network approach, 7 benchmark problems [4] have been examined. <Table 1> shows the specification of the problems, which are also used in [4] and [5]. In <Table 1>, C represents compatibility matrix, ACC implies the presence of ACC on adjacent cells. A '2' or '1' in ACC column represents the presence and absence of ACC respectively. CSC is indicated by the value in column c_{ii}. In the Funabiki's model [4] and Chang's model [5], there are parameters to be determined for the energy function. Funabiki used four heuristics to improve the convergence rate of channel assignment. For the simulation, they [4, 5] also fixed the channel assignment for some cells in order to accelerate the convergence time. In our algorithm, heuristics were not used since there are no parameters to be determined for the energy function and the interconnection weights. In addition, no channel assignment is fixed before the channel assignment procedure. In <Table 2>, the simulation results are compared with the results in [4], and [5].



(a) (b) (c) (d)

(e) (f) (g) (h)

(Fig. 5) Compatability matrices (a) C2, (b) C3, (c) C4, (e) C5, (f) C6, (g) C7, and Demand vectors (d) D2, (h) D3

<Table 1> Problem specifications used in experiments for neural network approach

Problem No.	# of Cells	ACC	C_{ii}	LB	C	D
1	25	1	2	73	C1	D1
2	21	1	5	381	C2	D2
3	21	1	7	533	C3	D2
4	21	2	7	533	C4	D2
5	21	1	5	221	C2	D3
6	21	1	7	309	C3	D3
7	21	2	7	309	C4	D3

To test our genetic algorithm approach, 5 problems have been examined and the results are compared with neural network approach. <Table 3> shows the specification of the problems. The average convergence rates and the average iteration number of neural network approach and genetic algorithm approach are shown in <Table 4>. From the result of problem 10 for genetic algorithm, the average number of generation is zero. It means the admissible channel assignment is done during the generation of the initial population. <Table 5>

shows the cpu times measured in second using Sun Sparcstation 10 for each approach. The parameters used in genetic algorithm are the number of maximum generation, the number of strings in a population, the probability of crossover, and the probability of mutation and the typical values used are 100, 200, 0.9, and 0.03, respectively.

〈Table 2〉 Comparison of simulation results

Problem No.	Funabiki		Choi		Ours	
	iteration	convergence	iteration	convergence	iteration	convergence
1	294.0	9%	73.9	100%	279.9	62%
2	147.8	93%	66.89	100%	67.4	99%
3	117.5	100%	76.59	100%	64.2	100%
4	100.3	100%	70.66	100%	126.8	98%
5	234.8	79%	81.28	100%	62.4	97%
6	85.6	100%	60.57	100%	127.7	99%
7	305.6	24%	105.41	100%	151.9	52%

〈Table 3〉 Problem specifications used in experiments for genetic algorithm approach

Problem No.	# of Cells	ACC	C_{ii}	LB	C	D
2	21	1	5	73	C2	D2
3	21	1	7	381	C3	D2
8	21	2	7	533	C5	D2
9	21	1	5	533	C6	D2
10	21	1	7	221	C7	D2

〈Table 4〉 Comparison of neural network approach and genetic algorithm approach

Problem No.	Neural Network			Genetic Algorithm		
	iteration	convergence	cpu-time	iteration	convergence	cpu-time
2	67.4	99%	313.8	26.29	97%	52.4
3	64.2	100%	595.7	5.46	100%	42.6
8	110.6	98%	586.9	7.35	100%	2108.4
9	29.8	100%	1235.8	0.24	100%	471.7
10	39.2	100%	2189.3	0.00	100%	342.7

6. Conclusion

Two optimization schemes, neural networks and genetic algorithms, are explored to solve channel assignment problems in cellular mobile communications. To avoid falling into the local minima area, the forced assignment technique for the neural networks and the data structure and proper genetic operators are developed. The results observed in this paper show that neural networks and genetic algorithms can be applied to obtain the optimal solutions for the channel assignment in mobile cellular communications. From the simulation results, the convergence rate of two approach is similar although the cpu time of genetic algorithm is, in general, shorter than neural networks. Genetic algorithm, however, needs huge size of memory since genetic algorithms are a kind of multi-point search techniques.

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남 인 길

e-mail : ignam@biho.taegu.ac.kr

1978년 경북대학교 전자공학과(공학사)

1981년 영남대학교 대학원 전자공학과 계산기전공(공학석사)

1992년 경북대학교 대학원 전자공학과 전산공학전공(공학박사)

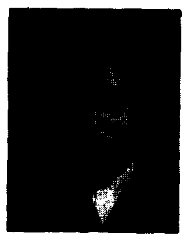
1978년~1980년 대구은행 전산부

1980년~1990년 경북산업대학 전자계산학과 부교수

1990년~현재 대구대학교 컴퓨터정보공학부 교수

1996년~1997년 미국 루이지애나 주립대학 객원교수

관심분야 : 데이터베이스, 이동컴퓨팅



박 상 호

e-mail : spark@anu.andong.ac.kr

1979년 경북대학교 전자공학과(공학사)

1981년 영남대학교 대학원 전자공학과(공학석사)

1989년 Syracuse University(M.S.)

1995년 State University of New York at Buffalo(Ph.D.)

1996년~현재 안동대학교 정보통신공학과 조교수

관심분야 : 멀티미디어통신, 이동통신