Evolutionary Optimization for the Channel Assignment Problem in Wireless Mobile Network

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Abstract— **The channel assignment problem in wireless mobile network is consist of the assignment of appropriate frequency spectrum channels to requested calls while satisfying the electromagnetic compatibility (EMC) constraint. However with the limited capacity of wireless mobile frequency spectrum, an effective channel assignment technique is important for resource management and to reduce the effect of the interference. Most of the existing channel assignment techniques are based on deterministic methods. In this paper, an adaptive channel assignment technique based on genetic algorithm (GA) is introduced. The most significant advantage of GA based optimization in channel assignment problem is its capability to handle both the reassignment of existing calls as well as the allocation of channel to a new call in an adaptive process to maximize the utility of the limited resources. The population size is adapted to the number of eligible channels for a particular cell upon new call arrivals in order to achieve reasonable convergence speed. The MATLAB simulation on a 49-cells network model for both uniform and nonuniform traffic demands showed that the average new incoming call blocking probability for the proposed channel optimization method is lower than the deterministic channel assignment methods.**

Keywords-evolutionary optimization; genetic algorithm; channel assignment problem; wireless mobile network

I. INTRODUCTION

The cellular concept is widespread among the fixed and mobile wireless network service due to the development of radio broadcasting for the mass population. In wireless mobile networks, the cellular principles divide the covered geographical areas into a set of service areas called cells [1]. Each cell consists of a number of mobile station (MS) such as mobile phone, which is connected to a radio base station (RBS). MS requires the allocation of channels from the RBS in order to establish the communication with a base station.

The channel assignment mechanism comprises of efficient channel allocation among the radio cells in a cellular networks while maintaining a desirable level of EMC constraint and traffic demand. In addition, this mechanism plays a major role in minimizing the probabilities of call blocking or call dropping, at the same time maximizing the quality of services.

In general, the channel assignment scheme can be classified into fixed channel assignment (FCA) and dynamic channel assignment (DCA). In FCA, the set of channels are equally allocated to each cell in advance permanently. On the other hand, DCA refers to the set of available channels are assigned dynamically to each cell upon request, instead of utilizing permanent allocation of channels as compared to FCA. The FCA system is simpler but does not adapt to the change of traffic demands. This deficiency is overcome by DCA approach since DCA surpass FCA in terms of its capability in dealing with changing traffic conditions, however it has the drawback of requiring more complex controlling and consuming more computational time under heavy traffic load [1].

Most of the channel allocation methods are based on the deterministic methods. This kind of method requires a set of known input parameters and rules to predict the channel allocation results. However, the channel assignment becomes a complicated process to be solved by the deterministic methods due to its complexity and computational time consuming issues [2].

Techniques such as frequency reuse have been proposed to maximize the channel capacity in cellular network. Frequency reuse concept comprises of using the same frequency channel simultaneously with other cells subject to the base transceiver station (BTS) distance. However this technique would lead to EMC interferences such as co-channel constraint (CCC), adjacent channel constraint (ACC), and co-site channel constraint (CSC). Hence it is very crucial to determine an efficient frequency reuse pattern to minimize the interference. There are numbers of suggested heuristics approaches in the literature to overcome the FCA and DCA problems based on fixed reuse distance concept such as neural networks, simulated annealing, Tabu search (TS) and GA [3].

Coincidence with the evolutionary computation, approaches based on neural networks (NNs) in [4], as well as based on simulated annealing (SA) in [5] have been

investigated. SA is a meta-heuristic method derived from statistical mechanics which perform using the neighborhood principle and measures potential based on cost function. SA achieves the global optimum asymptotically and thus solves the local optimum trap which would happen in NNs, however its drawback is that the rate of convergence is rather slow [6].

A comparison between SA and TS methods indicates that the TS algorithm outperforms SA in terms of its capability of finding the minimum number of frequencies for channel allocation by consuming shorter computational time [7]. In general, TS is also a meta-heuristic technique based on neighborhood principle.

The evolutionary algorithm approaches such as GA outperforms other methods in terms of the ability to explore information over search spaces [8]. This type of algorithm can be used to solve any complicated optimization task, such as optimal-local, multi-constrained and NP-complete problems [9].

GA is originates from the principal of natural selection and survival of the fittest, for finding solutions to highly-nonlinear problems, which are characterized by multimodal solution space [10]. GA has been defined as highly parallel mathematics algorithm by [11] which transforming a set of individuals called population, each with an associated fitness value, into a new generation using operations based on the theories of evolution.

Several GA-based approaches have been used to solve the channel assignment problem. For instance, [12] defined an asexual crossover and a special mutation to solve the channel assignment problem. However such crossover will easily destroy the structure of current solution and thus, causing the algorithm difficult to converge. In [6], the authors suggested a GA approach based on minimum separation encoding scheme, where the number of 1's in each row of the binary assignment matrix corresponds to the number of channels allocated to the corresponding cell. It stated that this algorithm outperforms NN-based approach.

In this paper, a DCA optimization algorithm based on GA will be presented to solve the channel assignment problem. The population size of this algorithm is designed to adapt to the number of eligible channels for a particular cell upon new call request, instead of maintaining a fixed population size throughout the simulation. This would ensure that a reasonable convergence speed can be achieved.

II. OVERVIEW OF CHANNEL ASSIGNMENT PROBLEM

A. Channel Assignment Constraints

Radio transmission with frequency reuse concept in a channel would cause interferences with other channels. Such interference may degrade the quality of the service. Three types of interference are:

1. CCC: Due to the allocation of the same channel to certain pair of the cells within the BTS distance or reuse distance simultaneously.
2. ACC: Due to the allocation of the adjacent channels to certain pairs of cells simultaneously.
3. CSC: Due to the allocation of channels in the same cell are not separated by some minimum spectral distance.

These constraints are included as the EMC constraints. The channel assignment problem is shown to be NP-hard where it assigns the required number of channels to each cell in such a way that the interference is avoided and the frequency spectrum is used efficiently. These EMC constraints are known as hard constraints.

Besides the hard constraints, there are soft constraints to help in reducing the call blocking probabilities. They are the resonance condition, packing condition, and the limitation of reassignment.

The resonance condition allows the same channels to be assigned to cells that belong to the same reuse scheme, so that the use of channels can be maximized within the same reuse scheme. This would reduce the call blocking probabilities in a great extent.

On the other hand, the packing condition is an approach to use the minimum number of channels each time a new call arrives. Hence this condition permits the repeated selection of the channels in use in other cells as long as the CCC interference is maintained.

In DCA, the reassignment process upon a new call arrival will result in lower call blocking, but it is complex in both time and computation effort. Therefore the limitation of reassignment limits this process applied only to the cells which involved in new call arrival. It tries to assign the channels which are assigned before if possible. This could reduce the situation of excessive reassignment in a cell which would lead to increase in call blocking probabilities.

B. Channel Reuse Scheme

The reuse of channels is directly related to CCC interference. The channels to be assigned in different cells need to be separated by a reuse distance sufficient enough to reduce the CCC interference to a tolerable level. Then each channel can be reused many times.

The reuse distance means the minimum distance required between the centers of two cells using the same channel to maintain the desired signal quality. The distance between the centers of two adjacent cells is considered as a unit distance. The cells with center-to-center distance equals to or multiple of the value of reuse distance belong to the same reuse scheme. Within the same reuse scheme, cells may use the same channels.

The number of cells per reuse scheme determines the total number of channel sets that can be formed from the whole frequency spectrum. The longer the reuse distance, means the

smaller is the CCC interference level. However, this results in smaller reuse efficiency. Thus the reuse patterns need to be designed well by taking into consideration both the CCC interference level and the reuse efficiency.

In this proposed approach, a reuse distance of three units has been considered to locate the co-channel cells. This divides the network topology model of 49-cells into seven different co-channel cell groups. The co-channel cell matrix is shown in Table I.

According to Table I, the co-channel cell matrix is a 7×7 matrix with rows represent the *y* coordinate of the cells and columns represent the *x* coordinate of the cells. Each cell in the same reuse scheme can be determined with Manhattan distance, where *i=2*, and *j=1* so that *i+j=3*. This indicates that *y* coordinate moves one unit distance and *x* coordinate moves two units distance to obtain the required three unit of reuse distance. In Table I, the two cells belong to the same reuse scheme if the *i*th row and *j*th column of the co-channel matrix contains the same number for the two cells.

C. Cellular Traffic Model

In the design of this proposed algorithm, the cellular traffic model is simulated based on blocked-calls-cleared principle, means that an incoming call is served at the instance if a channel is available, otherwise the call is dropped with no queuing of blocked calls. There are 70 channels available in this model to be allocated to incoming calls.

The cellular topological model consists of 49 hexagonal cells to form a parallelogram structure, with equal number of cells along both axes, as shown in Fig. 1. The traffic distribution on the cellular network can be either uniform or nonuniform distribution. In uniform cellular traffic distribution, every cell has the same traffic load or demand. On the other hand, in nonuniform cellular traffic distribution, there is different traffic load in each cell. The nonuniform traffic patterns implemented in this model is shown in Table II. Each of the value represents the average call arrival rate per minute for the corresponding cell. The average call holding time is 180 seconds.

III. PROBLEM REPRESENTATION

The channel assignment problem comprises of the assignment of an available channel to a new call with possible reassignment of channel to the ongoing calls in the cell. Assume that a new call arrives in cell *k* with *t*-1 existing calls before the arrival of the new call. Then a potential solution vector, V_k represents the assignment of channels to ongoing calls and the new call at cell *k*. This solution vector of length *t* will be expressed as a chromosome in the genetic algorithm representation, where each gene is a channel number being assigned to a call in cell *k*. The advantage of this representation is that the length of the solution vector is short and hence consumes shorter computational time to manipulate the vector.

IV. GENETIC REPRESENTATION

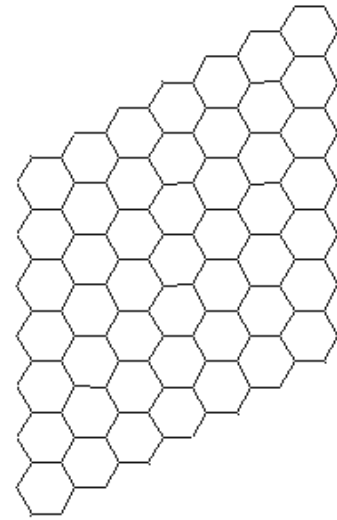Generally, GA provides an efficient approach in searching

Figure 1. 49-cell cellular topological model

for an optimum solution in the channel assignment problem. It is different from deterministic methods since GA uses randomization. Then the generic GA is modified to fit for use with the DCA optimization scheme.

The outline of the generic genetic algorithm is consists of:

1. Generation of initial population: The fundamental of GA to provide a generation of predetermined population size of chromosomes.

2. Selection: During this stage, the evaluation of fitness of chromosome influences the selection chance of the chromosome. The selected fitter chromosome is then used for the reproduction of a new generation of chromosomes.

3. Crossover: Upon selection of parents, both chromosomes perform the process of crossover of their genes to generate the child chromosome, according to a predefined crossover rate.

4. Mutation: An evolutionary process of a chromosome which undergoing random changes of its genes according to a predefined mutation rate.

TABLE I.   CO-CHANNEL CELL MATRIX

y-coordinate	x-coordinate						
	1	*2*	*3*	*4*	*5*	*6*	*7*
1	1	5	6	3	2	4	7
2	4	7	1	5	6	3	2
3	3	2	4	7	1	5	6
4	5	6	3	2	4	7	1
5	7	1	5	6	3	4	4

y-coordinate	x-coordinate						
	1	*2*	*3*	*4*	*5*	*6*	*7*
6	2	4	7	1	5	6	3
7	6	3	2	4	7	1	5

TABLE II.   NONUNIFORM TRAFFIC DISTRIBUTION (SIMULATION CALLS/MINUTE)

y-coordinate	x-coordinate						
	1	*2*	*3*	*4*	*5*	*6*	*7*
1	60	20	15	30	15	60	30
2	60	30	15	30	20	20	60
3	15	30	20	60	60	30	20
4	60	15	20	30	20	30	60
5	20	60	15	60	20	30	20
6	30	20	20	60	30	30	60
7	60	60	15	60	15	20	30

A.   Generation of Initial Population

The algorithm starts by generating an initial population of possible channel allocation solutions. When a new call is arrives in cell k, a set of eligible channels $I(k)$ is determined in order to assign a possible channel to the new call. In this case $I(k) = S - (O(k) \cup U(k))$, where S is the total set of available channels, $O(k)$ is the set of channels allocated to the ongoing calls in cell k, and $U(k)$ is the set of channels used in the neighboring cells which less than the reuse distance with cell k. All the information can be obtained from the channels allocation matrix A. In the initial population P of λ solution vectors where λ is the magnitude of vector $I(k)$, each solution contains a unique integer chosen from $I(k)$. Then the remaining $(t - 1)$ integers in all the solution vectors are the channels allocated to the ongoing calls in cell k.

B.   Evaluation by Fitness Function

After the initial population of individuals is generated, a quality measure is necessary to decide the fitness value of one individual among the whole generation. The quality measure is called as fitness function.

As mentioned before, besides the hard constraints, there are soft constraints such as packing condition, the resonance condition and the limitation of reassignment which further lower the call blocking probabilities and increase the quality of service. These soft constraints are modeled as the fitness function as shown in (1).

$$F = \sum_{j=1}^{t_k} \sum_{i=1 i \neq k}^{C} A_{i,V_{k,j}} . reuse(i,k)$$

$$- \sum_{j=1}^{t_k} \sum_{i=1 i \neq k}^{C} A_{i,V_{k,j}} . \frac{1}{dis(i,k)} - \sum_{j=1}^{t_k} A_{k,V_{k,j}} \quad (1)$$

where

k defines the cell coordinates where a call arrives;

t_k defines the total number of channels allocated to cell k;

C defines the total number of cells in the network model;

V_k defines the solution vector for cell k with dimension t_k;

$V_{k,j}$ defines the j-th element of vector V_k;

$A_{i,V_{k,j}}$ defines the element at i-th row and $V_{k,j}$-th column of the channels allocation matrix A;

$dis(i,k)$ defines the distance between cells i and k;

$reuse(i,k)$ defines a function that returns a value of zero if the cells i and k belong to the same reuse scheme, otherwise return one.

In (1), the first term represents the resonance condition, where the fitness value increases if the j-th element of vector V_k is in use in cell i as well, and cells i and k does not belong to the same reuse scheme. The second term represents the packing condition, where the fitness value decreases if the j-th element of vector V_k is in use in cell i as well, and cells i and k are free from CCC interference. The fitness value decreases with the distance between cells i and k. The last term on the other hand, represents the limiting reassignment condition, where the fitness value decreases if the new allocation for the ongoing calls in cell k is the same as the previous allocation. The minimization of this function value in (1) determines the fittest individual in order to find the optimal channel allocation solution.

C.   Mutation

A fixed mutation rate is selected which indicates the probability for a gene in the chromosome to mutate. A low rate of mutation is sufficient to prevent any gene in the chromosome to remain fixed to a single value in the population. On the other hand, a high rate of mutation will result in random search for optimal solution. Therefore a moderated value needs to be selected to maintain a balance between such extremes.

The parent chromosome is iterated through and randomly determines whether the channel number as the gene will mutate according to the mutation rate. When the channel number is decided to undergo mutation, it will swap the value with the corresponding vector of eligible channels. This process can always produce feasible offspring since it does not affect the length of the parent chromosome and does not produce any duplicate channel number.

D.   Crossover

A crossover rate is selected to indicate the probability for parents' vectors to crossover to produce a better child chromosome which takes the best characteristics from each of the parents. The proposed crossover strategy is one-point crossover to reduce the computational cost. A single crossover point is selected for both parents' vectors. Then the channel

numbers which beyond that crossover point in both vectors are swapped, and results in the child chromosome.

V. SIMULATION RESULTS AND DISCUSSIONS

In the simulation, the performance of the proposed GA based algorithm for the channel assignment is evaluated in terms of the blocking probability for the new incoming calls. The blocking probability is calculated by the ratio of the total number of new call blocked and the total number of call arrived in the cellular network system. An example of a valid assignment of channels which fulfills the constraints and the required number of channels for the network of 49 cells is shown in Fig. 2. This simulation result is optimized by GA and run under nonuniform call traffic distribution as Table II.

The performance of the proposed algorithm is compared with FCA scheme and DCA scheme which based on deterministic method, where the channel allocation results always the same at each simulation, without the optimization by GA. The DCA scheme with deterministic method is based on channel-ordering property, where the first channel in the set of eligible channels is given the highest priority to be assigned to new call request. Fig. 3 shows the call blocking probability result under nonuniform call traffic distribution using Table II as the initial traffic rates. On the other hand, Fig. 4 shows the call blocking probability performance under uniform traffic distribution with average 15 calls per minute as the initial traffic rate. The percentage increase of traffic load implies that the traffic rates for each of the cell increased by a percentage with respect to the initial traffic rates. From these results, DCA scheme based on GA produces the lowest call blocking probability compared to the DCA scheme of deterministic method and the FCA scheme, under both uniform and nonuniform call traffic distribution. The decrease in the call blocking probability is significant to maintain the reliability of the channel allocation scheme.

Specifically, there are several parameters which are important in determining the convergence behavior of the genetic algorithm, such as population size, mutation rate and crossover rate. In this proposed algorithm, the population size is not fixed and is adapted according to the number of eligible channels for a particular cell.

In Fig. 5, the effect of the crossover rate on the convergence speed is demonstrated, with the mutation rate fixed at 0.2. The crossover rate of 0.6-0.8 is suggested in this algorithm in order to maintain a randomized gene exchange between individuals yet promote a reasonable continuity from the previous populations to the current populations, with convergence speed which is comparatively fast.

On the other hand, in Fig. 6, the crossover rate is fixed at 0.8, and the effect of the mutation rate on the convergence speed is investigated.

The mutation probability of 0.2-0.4 is sufficient to avoid local minima when the population of chromosomes evolves from generation to generation, yet with a comparatively fast

convergence speed compared to the simulation results of higher mutation probability. From the results shown in Fig. 5 and Fig. 6, it can be observed that the proposed algorithm is not over sensitive to parameters tuning for moderately selected mutation rate and crossover rate values. The number of generations can be maintained at a desirable level with these moderately selected values. This is an advantage compared to some existing algorithm which is parameter-sensitive, such as simulated annealing.
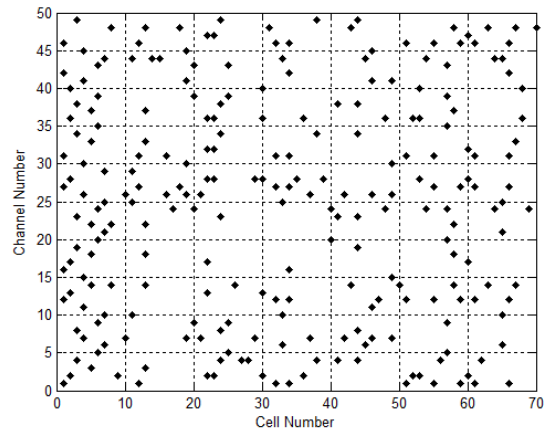

Figure 2. A channel assignment result for the network under nonuniform traffic distribution at iteration=10
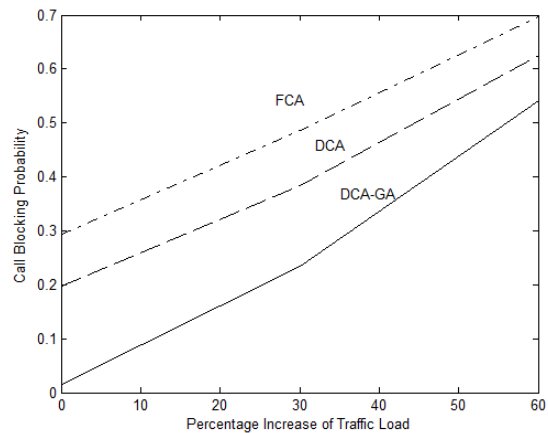

Figure 3. Call blocking probability performance of DCA-GA for the cellular network with nonuniform traffic distribution and comparison with the other channel allocation schemes
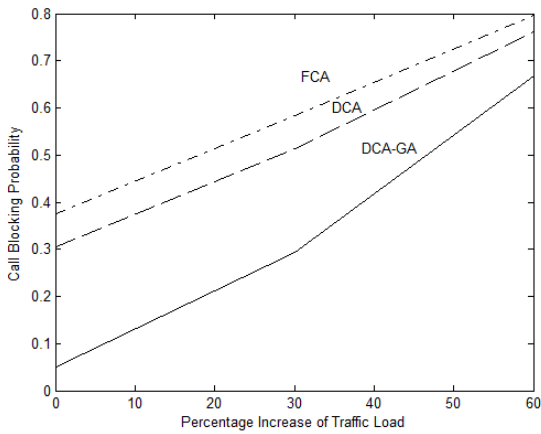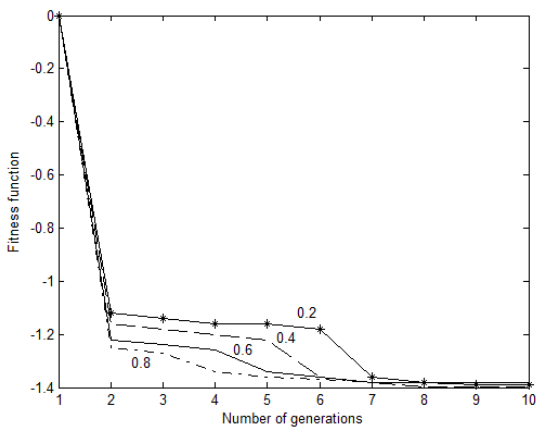
evolutionary process in nature in order to optimize the channel assignment problem. Its characteristics to evolve through generations and to select the fittest optimum chromosomes enable it to be self-optimized from generation to generation.

The concept of channel reuse scheme avoids the allocation of channels which would cause CCC interference. Hence the computation time to determine this type of interference in the process of channel allocation is reduced. Besides that, the combination of the integer genetic representation, the mutation operator and the crossover operator guarantees that the solution found is always feasible.

Figure 4.   Call blocking probability performance of DCA-GA for the cellular network with uniform traffic distribution and comparison with the other channel allocation schemes

The performance of the proposed algorithm has been investigated in terms of the call blocking probability which represents the quality of solutions. In addition, the effect of crossover rate parameter to the convergence speed to find the solution is investigated.

Currently, the simulation is implemented based on sequential fashion, which is not significant in reducing the computational time. In the future research work, it is believed that by implementing the algorithm in parallel fashion, the optimization process will consume shorter computational time.

Figure 5.   Crossover rate and GA convergence

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Figure 6.   Mutation rate and GA convergence

VI.   CONCLUSION

An optimization algorithm based on GA is proposed to solve the NP-complete channel assignment problem in a cellular mobile network. It is capable to mimic the

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