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DCA Using Genetic Algorithm in Mobile Cellular System

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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 paper exploits the potential of the Genetic Algorithm to solve the cellular resource allocation problem. It is an optimization problem and the genetic algorithm is efficiently applied to handle this. As the number of channel is usually limited and therefore should be reused. So this paper investigates on DCA. The performance of the system is evaluated in 64 hexagonal cell arrangement having 20 channels. Numerical results show that the average call blocking probability of the system is lower than the fixed channel assignment.

Keywords : Mobile communications, cellular system, channel assignment, genetic algorithms.

I. INTRODUCTION

Many heuristic algorithms exist for the task allocation problem, but most are limited to specific cases [10]. The use of evolutionary algorithms in scheduling, that apply evolutionary strategies from nature, allows for the fast exploration of the search space of possible schedules. This allows for good solutions to be found quickly and for the scheduler to be applied to more general problems. The genetic algorithm (GA) [6] evolutionary strategy has been shown to consistently generate more efficient solutions than other evolutionary strategies when applied to scheduling in heterogeneous distributed systems [2].

The new generations of wireless access system will be able to offer wideband services, as multimedia. The demand increase in bandwidth and the increasing number of users requesting simultaneous access to the transmission medium require a great effort to improve the performance of wireless communication systems. Due to the limited broadband spectrum available in cellular networks, to ensure an appropriate performance efficient channel allocation strategies are essential Channel allocation can be viewed as a large-scale dynamic optimisation problem with multiple goals and constraints in a stochastic environment. Approaches based on reinforcement learning [1], [2], evolutionary algorithm [3], heuristic oriented search [4] and neural networks, have been successfully employed in solving channel allocation problems. These approaches offer advantages over the ones which do not consider environment dynamics, mainly because the intelligence strategies can be adapted in accordance with the information obtained in the environment behaviour.

A general genetic algorithm consists of an initial population followed by selection, crossover and mutation operations [14]. The CSVR uses the genetic algorithm process shown in Fig. 1 to find the best channel ordered list for each AP.

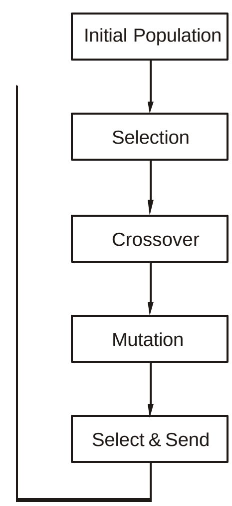

Fig. 1. Genetic Algorithm performed by CSVR.

II. BASIC CONCEPTS OF CHANNEL ASSIGNMENT

Channel assignment schemes can be classified based on the manner in which the co-channels are separated. Katzela and Naghshineh [13] divided the schemesinto fixed channel (FCA), dynamic channel assignment (DCA) and hybrid channel assignment HCA). In the FCA scheme, a set among the total number of channels is permanently indicated to a cell for its exclusive use. The same set can be again indicated to other cells,inaccordance with the co-channel reuse distance. This uniform channel distribution is efficient if the traffic distribution is also uniform. In the DCA scheme, any channel can be used in all the cells. However, a channel is assigned to a cell only under request. To prevent co-channel interference, it is necessary to know he channel status of all cells.

The implicit parallelism, simplicity and robustness of the Gas are the basis of the DCA GA based strategies proposed in this paper. Such proposed strategie attempt to allocate channels to cells in such a way that the average blocking probability is minimized in the whole system. In the GAL strategy, the assigned channels remain in operation while their call lasts, and the GA looks for idle channels to allocate new call requests. In the GAS strategy, the calls can be switched to different channels during the call holding time.

The Genetic algorithm concept can be explained as basic principles of Genetic Algorithm (GA) were first proposed by Holland [4]. It is inspired by the mechanism of natural selection where stronger individuals would likely be the winners in a competing environment.

Here, GA uses a direct analogy of such natural evolution. It presumes that a potential solution of a problem is an individual and can be represented by a set of parameters. These parameters, regarded as the genes of a chromosome, can be structured by a string of values in binary form. A positive value, known as fitness value, is used to reflect the degree of “goodness” of the chromosome, which is generally correlated with the objective function of the problem. In this way the work is further proceeded with the strategy of genetic algo in the allocation of channel applied in mobile cellular system.

III. PROPOSED MODELS

The objective of the proposed algorithms is to seek for a channel assignment policy exhibiting the lowest blocking rate for new calls. The proposed algorithms are applied to a mobile communication system in which the geographic area is subdivided in to hexagonal cells as shown in Fig. 2 and each cell is served by only one radio-base station.

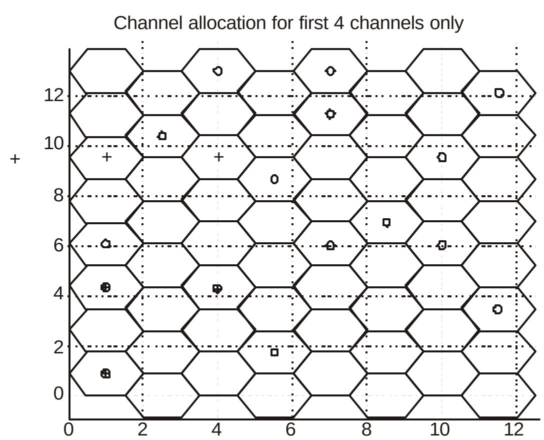

Fig. 2. Hexagonal shapped cells.

A traffic model that considers the whole phenomena present in a mobile system is very hard to obtain. Some phenomena as the call-dropping rate are irregular and not statically significant [14]. Therefore, to simplify the model, a mobile user will be located in one of the cell during the call duration time, and the minimum acceptable value for carrier-to-interference ratio (C/I) will be assumed as 18 dB. This C/I value implies D = 4.41R [1], where R is a minimum reuse distance equal to is the cell radius. Therefore, if a channel has been assigned to cell *i* , it cannot be reused in the two tiers adjacent to cell *i*. The topology considered is illustrated in Fig. 3.

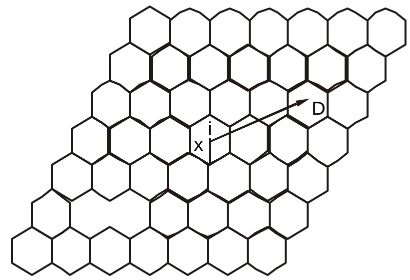

Fig. 3. Cell *i* and the corresponding interference cells.

The assumptions used in the algorithms include [1]:

1. New call arrival follow a Poisson distribution with either uniform or nonuniform mean interarrival times amont the cells. The mean arrival rate, *l* ranges from 20 to 200 calls/h in each cell;

2. The call holding time follows an exponential distribution with mean call-duration 1 μ. In this paper, 1 μ = 180 *s* for all calls;

3. The offered traffic ρ_i in cell *i* is given by $\mu_i = \lambda_{i\mu}$;

4. There are M = 20 available channels in each one of the 64-cell system.

5. Blocked new and handover calls are drop and cleared (Erlang-B).

A. Representation and Operators

Let there be N cells and M channels in the system. A cell can use any available channel if such a choice satisfies the minimum reuse distance. The evaluation of the assignments demands prior knowledge of the cells centre positions and the channel status of all cells.

In the proposed models, each gene represents a channel state and the channels of a cell form a chromosome. The set of all cells composes an individual representing an assignment policy. Hence, each individual is denoted by a vector of dimension $V = N \times M$, as shown in Table 1.

Table 1: Policy System Representation.

C_{11}	C_{12}	. . .	. . .	C_{21}	C_{22}	. . .	C_{2M}	. . .	C_{N1}	C_{N2}	. . .	C_{NM}

where c_{ij} = 1, if channel *j* is in use in cell *i* 0, otherwise

The proposed models seek for a policy, that is, a set of states of all the cells optimising the system use. The proposed GA models use the standard genetic operators (selection, crossover, and mutation) together with random-immigrant mechanism [7], adaptive parameters [8], truncation selection scheme [9], greedy policy [11] and three-point crossover strategy [10].

The number of control parameters in a GA, including mutation, crossover, and selection rates, must be determined. The most important parameter is the amount of variability in the individual chromosomes in the population [5], as the highest increase in the variability occurs in the range from 30 to 110 individuals [3]. In this paper, a population size of 75 individuals provided the best balance between performance and convergence time.

For the parents selection, the truncation selection mechanism chooses the 10% best individuals of the population, which mate randomly, two by two, to produce an offspring. The greedy policy selects the best individual of the population with reinsertion rate of 0.10, applied to the crossover operator. The next population is completed through the inclusion of random immigrants, which uses a rate equal to 0.20. This value guarantees the increase of the population diversity.

To keep the population diversity, the mutation, crossover and reproduction rates were adapted in accordance with the parents diversity. When the parents diversity approximates to one, mutation rate is reduced and the crossover and reproduction rate are increased. Such dynamics preserves the information and increases the exploitation of the fitted individuals. When the parents diversity is low, the increase of the mutation rate and the simultaneous decrease of the other two rates have to occur, expanding the exploration of the solution space.

The other important component of the proposed model is the formation of the initial population, which is composed of three mechanisms : the first one generates individuals randomly; the second reinserts the k-most fitted individuals of the last generation in the current one and the third includes the best-fitted individuals of the previous populations.

B. Fitness Function

The fitness function estimates the adequacy of each individual to the environment with respect to the objective function. The procedure for fitness calculation considers different variables involved in channels assignment for new call attempts, aiming to accomplish the highest number of request calls, in an optimised form,considering the current state of the system. For the system investigated, the fitness function of a cell i is calculated by the weighted sum

$$fit(i, k) = n_1(k)r_1 + n_2(k)r_2 + n_3(k)r_3 + n_4(k)r_4 \quad \text{... (1)}$$

where $n_1(k)$ is the number of compact cells refering to cell i, in which channel k is in use; Compact cells are those cells with minimum average distance between co-channel cells. In the case of a regular hexagonal layout (Fig. 1), compact cells are located in the third tier with three cells apart from the considered cell; $n_2(k)$ is the number of co-channel cells, located in the third tier, that do not use channel k; $n_3(k)$ is the number of other co-channel cells currently using channel k; $n_4(k)$ is the number of channels to be blocked if channel k is assigned; r_1, r_2, r_3, and r_4 are coefficients associated with $n_1(k)$, $n_2(k)$, $n_3(k)$, and $n_4(k)$, respectively.

The fitness function (1) is an extension of the one proposed by Nye and Haykin [1], considering the additional parameter $n_4(k)$. The total fitness function is calculated as follows :

$$fit_{tot} = \sum_{i=1}^{N}\sum_{k=1}^{M} fit(i,k) \quad \text{... (2)}$$

The fitness function (1) estimates the cost due to the assignment of each channel k for each cell i, *i.e.*, (1) represents the cost associated with choosing channel k to comply with the currently call attempt in cell i. Considering cell i as a reference, the idea is to associate low rewards with distant co-channel cells and high rewards with co-channel cells located at the minimum compact distance. The coefficients were ordered as $r_1 > r_2 > r_3 > r_4$, where $r_1 = +5$, $r_2 = +1$, $r_3 = -1$ and $r_4 = -15$. Thus, the fitness function aims to penalise the assignment options proportionally to its number of blocked channels.

IV. RESULTS

The performance of the genetic algorithm is evaluated using 64 hexagonal cells working under uniform and non-uniform traffic distribution. The testing period for all the algorithms lasts ten simulated hours.

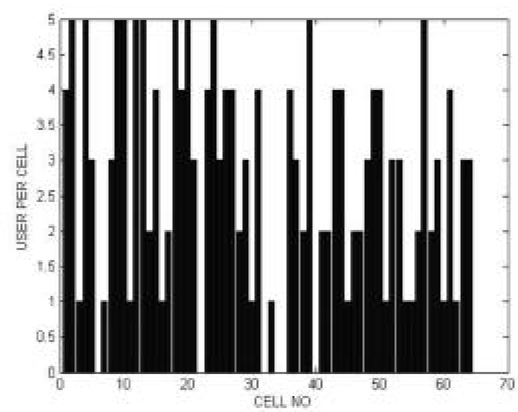

Fig. 4. User per cell depending upon load at each cell.

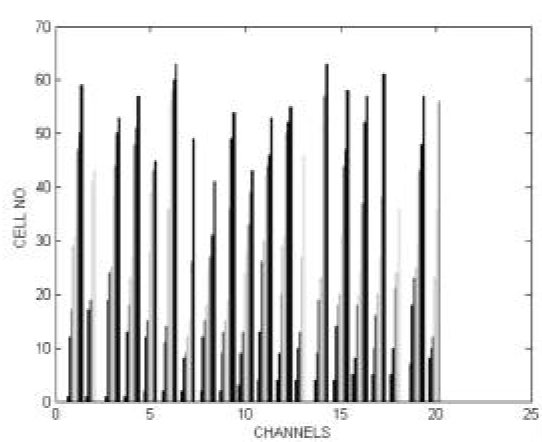

Fig. 5. User per cell depending upon load at each cell.

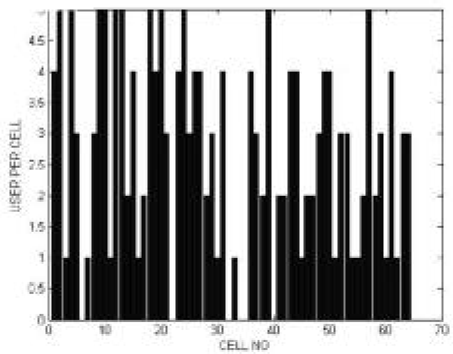

Fig. 6. Total channel allotted to each cell.

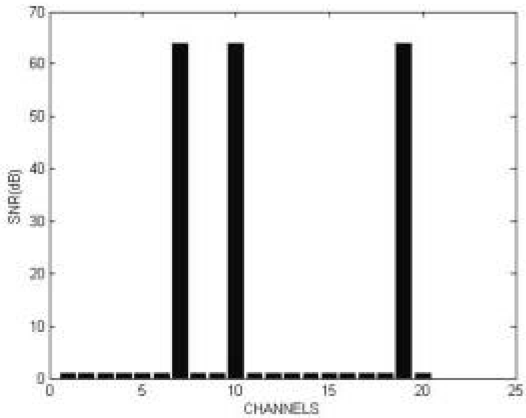

Fig. 7. Distance between cells.

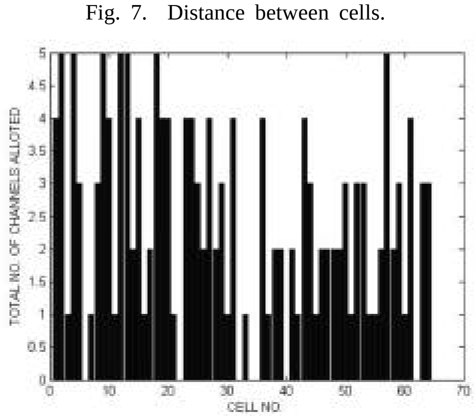

Fig. 8. SNR for each channel.

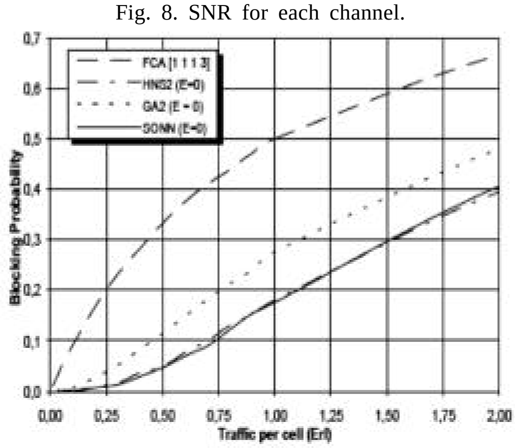

Fig. 9. Blocking Probability comparison between FCA and DCA.

V. CONCLUSIONS

This paper based on GA were proposed to solve the dynamic channel allocation problem in mobile communication systems. Numerical results show that the average call blocking probability is reduced as reported in the literature [1], [2], [12]. The use of GA in channel assignment can improve the system performance and open new perspectives for the application of these algorithms. The results presented suggest that the call blocking probability and SNR is reduced. A possible future study could consider the propagation and mobility issues as call dropping rate, outage, roaming and handover.

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