A Hybrid Channel Assignment Approach Using an Efficient Evolutionary Strategy in Wireless Mobile Networks

Geetali Vidyarthi, Alioune Ngom, and Ivan Stojmenović

***Abstract*—In wireless mobile communication systems, radio spectrum is a limited resource. However, efficient use of available channels has been shown to improve the system capacity. The role of a channel assignment scheme is to allocate channels to cells or mobiles in such a way as to minimize call blocking or call dropping probabilities, and also to maximize the quality of service. Channel assignment is known to be an NP-hard optimization problem. In this paper, we have developed an evolutionary strategy (ES) which optimizes the channel assignment. The proposed ES approach uses an efficient problem representation as well as an appropriate fitness function. Our paper deals with a novel hybrid channel assignment based scheme called D-ring. Our D-ring method yields a faster running time and simpler objective function. We also propose a novel way of generating the initial population which reduces the number of channels reassignments and therefore yields a faster running time and may generate a possibly better initial parent. We have obtained better results (as well as faster running time) than a similar approach in literature.**

***Index Terms*—Cellular network, channel assignment, evolution strategy (ES), optimization, power control, radio spectrum, wireless mobile communication.**

I. Introduction

THE CELLULAR principle divides the covered geographical area into a set of smaller service areas, called cells. Each cell has a base station and a number of mobile terminals (e.g., mobile phone). The base station is equipped with radio transmission and reception equipment. A group of base stations are connected to the mobile switching center (MSC). The MSC connects the cellular network to other wired or wireless networks. The base station is responsible for the communication between a mobile terminal and the rest of the information network.

II. Channel Assignment

In order to establish the communication with a base station, a mobile terminal must first obtain a channel from the base station. A channel consists of a pair of frequencies: one frequency (the forward link/downlink) for transmission from the base station to the mobile terminal, and another frequency (the reverse link/uplink) for the transmission in the reverse direction. Since the available frequency spectrum is limited the channels must be reused as much as possible in order to increase the system capacity. This requires a proper channel assignment scheme. The role of a channel assignment scheme is to allocate channels to cells or mobiles in such a way as to minimize call blocking or call dropping probabilities, and also to maximize the quality of service (such as minimizing the interference).

The channel assignment problem has been shown to be NP-hard [13]. The process of channel assignment must satisfy the electromagnetic compatibility constraint (co-channel interference, adjacent channel interference, and co-site interference) [19] and the demand of channels in a cell. These constraints are also known as hard constraints.

The channel assignment schemes in general can be classified into three categories: fixed channel assignment (FCA), dynamic channel assignment (DCA), and the hybrid channel assignment (HCA). In FCA, the set of channels are permanently allocated to each cell based on a pre-estimated traffic intensity. In DCA, there is no permanent allocation of channels to cells. Rather, the entire set of available channels is accessible to all the cells, and the channels are assigned on a call-by-call basis. One of the objectives in DCA is to develop a channel assignment strategy, which minimizes the total number of blocked calls [25]. FCA scheme is simple but does not adapt to changing traffic conditions and user distribution. These deficiencies are overcome by DCA but FCA out performs most known schemes in DCA under heavy load conditions [17]. To overcome the drawbacks of FCA and DCA, HCA was proposed by Kahwa *et al*. [15], which combines the features of both FCA and DCA techniques. In HCA one set of channels is allocated as per the FCA scheme, and the another set is allocated as per the DCA scheme.

DCA schemes can be implemented as centralized or distributed. In the centralized approach [7], [10], [18], [29], [30] all requests for channel allocation are forwarded to a central controller that has access to system wide channel usage information. The central controller then assigns the channel by maintaining the required signal quality. In distributed DCA, the decision regarding the channel acquisition and release is taken by the concerned base station based on the information from the surrounding cells. As the decision is not based on the global status of the network, it can achieve suboptimal allocation as

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compared to the centralized DCA and may cause forced termination of ongoing calls.

III. Channel Reuse

The reuse of channels in cellular system is inevitable and at the same it is directly related to co-channel interference. This is a radio interference caused due to the allocation of same channel to certain pairs of cells with geographical separation not enough to avoid deterioration of signal quality. The minimum distance required between the centers of two cells, using the same channel to maintain the desired signal quality, is known as the reuse distance. The longer the reuse distance is, the smaller will be the co-channel interference level. However, a long reuse distance increases the number of cells per cluster resulting in lower reuse efficiency. Thus, the frequency reuse pattern should be determined taking into consideration both the co-channel interference level and the reuse efficiency. In traditional FCA and DCA the channel assignment is made according to the co-channel interference level determined by a fixed reuse distance decided during network planning. Many heuristics have been proposed in the literature to solve FCA and DCA problem based on fixed reuse distance concept. This includes neural networks [12], [16], [27], simulated annealing [9], [18], genetic algorithm [3], [5], [14], [17], [19], [23], [26] evolutionary strategy [22], and the Tabu search [4]. The neural network approach provides sub-optimal solutions because it easily converges to local optima [19]. The simulated annealing approach achieves the global optimum asymptotically but its rate of convergence is slow, and requires a carefully designed cooling schedule [19].

IV. Related Studies

An evolutionary strategy (ES) approach to the optimization of DCA and HCA has been proposed in [22]. Sandalidis *et al.* formulated the channel assignment as combinatorial optimization problem with solutions represented as vectors of binary digits. The size of a solution is always equal to the total number of channels available. In the following sections, we will discuss the ways in which our proposed ES is better than the one proposed in Sandalidis *et al.* [22].

V. Problem Statement

In this paper, we propose a new HCA strategy using distributed dynamic channel assignment strategy based on fixed reuse distance concept. Each base station has a controller (computer). The status of all calls and changes in each cell are being sent to all the other cells using a good wired network between the computers of all cells. Channel assignment is made by the controller of the concerned base station according to the knowledge about the neighbors of a given cell. The paper investigates an ES-based approach with an efficient problem representation and a simplified fitness function as compared to the one proposed by Sandalidis *et al.* [22], and a new channel assignment scheme. The fitness function takes care of the soft constraints. The hard constraints are taken care of by the problem representation and the proposed new channel allocation scheme. The chosen representation and the mutation operator guarantees the feasibility of the solution.

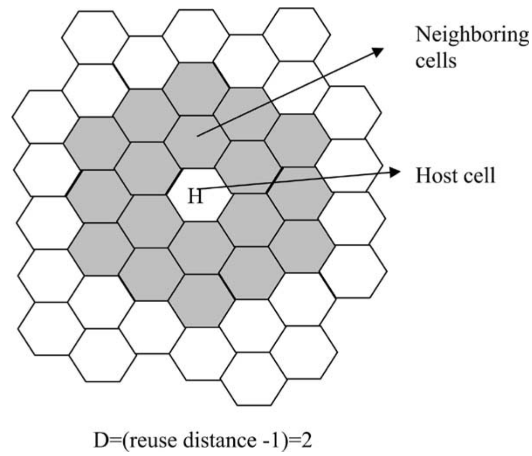

Fig. 1. Neighbors of a given cell.

In Section VI we describe the new model proposed in this paper for hybrid channel assignment. Section VII briefly describes the fundamentals of ES algorithm, gives detail of our proposed ES algorithm including problem representation, generation of initial parent and initial population, fitness function, and examines the application of the proposed ES to HCA, Section VIII describes the basic assumption of the cellular model used in the simulation, Section IX presents the results of simulation, and Section X ovides the discussion of the model and future research directions.

VI. D-Ring HCA Strategy

We propose a new distributed dynamic channel assignment strategy. In this strategy channel assignment is made by the controller of the concerned base station according to the knowledge about the neighbors of a given cell. The neighboring area of a given cell includes all those cells which are located at a distance less than the reuse distance. Conceptually, the neighboring area defines an interference region marked by grey cell belonging to D rings centered in a given cell H as shown in the Fig. 1. The channels are allocated to the host cell from a set of channels which excludes all those channels which are in use in the interference region. As such, the selected channels always satisfy the co-channel interference constraint. The channel usage information in the neighbors of a given cell is obtained from the allocation matrix. The allocation matrix, is a $C \times F$ binary matrix (where C is the total number of cells in the system and F is the total number of channels available to the system). The allocation matrix for each cell is a copy of the system channel pool. Each element a_{ij} in the matrix is one or zero such that

$$a_{ij} = \begin{cases} 1, & \text{if channel } j \text{ is assigned to cell } i \\ 0, & \text{otherwise.} \end{cases}$$

The allocation matrix is updated every time a channel is allocated and released in the network.

VII. Proposed Evolutionary Strategy Approach

Rechenberg [21] pioneered ES. It was proposed as an optimization method for real-valued vectors. It works on an encoded representation of the solutions. Each candidate solution is associated with an *objective value*. The objective value is representative of the candidate solution's performance in relation to the parameter being optimized. It also reflects a candidate solution's performance with respect to other potential solutions in the space. Based on the fitness values, number of individuals are selected and genetic operators (mutation and/or recombination) are applied to generate new individuals in the next generation. The best solutions generated in one generation becomes the parents for the next generation. ES is an iterative method and hence the process of selection and application of genetic operators is repeated until some terminating criteria is reached. Upon reaching the termination criterion, the solution to the problem is represented by the best individual so far in all generations. The basic steps of an ES algorithm can be summarized as follows.

1) Generate an initial population of λ individuals.
2) Evaluate each individual according to a fitness function.
3) Select μ best individuals called the parent population and discard the rest.
4) Apply genetic operator to create λ offsprings from μ parents.
5) Go to step 2 until a desired solution has been found or predetermined number of generations have been produced and evaluated.

An introductory survey on ES can be found in [11]. The two common variations of ES introduced by Schwefel [24] are the $(\mu+\lambda)$-ES and (μ,λ)-ES. In both the approaches parents produce λ offspring. These two approaches differ in the selection of individuals for the next generation. In $(\mu+\lambda)$-ES, μ best individuals from all the $(\mu+\lambda)$ individuals are selected to form the next generation, but in (μ,λ)-ES, μ best individuals from the set of λ offsprings are selected to form the next generation.

A. Problem Representation

Assume a new call arrives in cell k, which is already serving $(d-1)$ calls [$(d-1)$ is the traffic demand at cell k before the arrival of the new call]. Our problem is to assign a channel for the new call, also with possible reassignment of channels to the $(d-1)$ ongoing calls in k, so as to maximize overall channel usage in the entire network. A potential solution, V_k, is an assignment of channels to all ongoing calls and the new call, at k. We call such solution a chromosome. We will represent V_k as an integer vector of length d, where each integer is a channel number being assigned to a call in cell k and d is the new traffic demand at k. For example, if $k=1, d=4$, available channel numbers $=[1,2,3,4,5,6,7,8,9]$, then a possible solution is $V_1=[7,2,5,3]$. Our representation is efficient than Sandalidis *et al.* [22]. Sandalidis *et al.* used a binary representation where the size of a solution vector is independent of the traffic and equals the total number of channels in the system pool. The disadvantage of this representation is that although we are interested only on d channels extra memory is consumed in storing the information about other channels. This representation also yields slower evaluation and manipulation of candidate solutions, due to the size of the binary representation. The other advantage of our representation is that the size of the solution vector is short and thus it is easier and faster to manipulate the vector.

B. Initial Parent and Initial Population

When a call arrives in a cell k at time t, we determine the set of eligible channels I at time t. Here $I(k,t)=F\backslash(P(k,t)\cup Q(k,t))$, where F is the total set of available channels, $P(k,t)$ is the set of channels of the ongoing calls in k at time t, and $Q(k,t)$ is the set of channels in use in the neighboring area of k at time t. This information is obtained from the allocation matrix. The initial parent solution (that is the very first chromosome) is selected from a set G (initial population) of λ solution vectors where $\lambda=|I(k,t)|$. Each solution vector in G is evaluated according to the fitness function, and the individual with the best fitness is selected as initial parent. In order to find an optimal combination of channels for the cell involved in new call arrival, we preserve the $(d-1)$ channels allocated to this cell before the arrival of new call in the initial population. So each solution in G contains a unique integer selected from $I(k,t)$. The remaining $(d-1)$ integers in all solution vectors are the same and are the channels of the ongoing calls in the cell, i.e., $P(k,t)$. For instance, let us consider the following example: a call arrives in cell 2 at time t, where $P(k,t)=[2,5], F=[1,2,3,4,5,6,7,8,9]$ and $Q(k,t)=[1,3,6,7,8]$. Therefore, $I(k,t)=[4,9]$, and $\lambda=2$. Here, $d=3$, therefore the size of a solution in G is 3. The two solution vectors in G are thus: $G_1=[2,5,4]$ and $G_2=[2,5,9]$. Out of G_1 and G_2, the fittest solution is selected as initial parent. So instead of starting from a totally random combination of channel numbers, we start with solution vectors with $(d-1)$ channels allocated to the cell by the algorithm in its last call arrival. This way of generating initial parent and initial population will reduce the number of channel reassignments and therefore yields a faster running time. The initial parent is also a potentially good solution since channels for ongoing calls were already optimized.

C. Fitness

Beside the hard constraint and traffic demand constraint, other conditions may be violated to improve the performance of the dynamic channel allocation technique: They are the packing condition, the resonance condition, and the limitation of reassignment operations [22]. These conditions are called soft constraint and were introduced in [8]. The soft constraint permits to further lower the call blocking probability. The packing condition tries to use the minimum number of channels every time a call arrives [22]. This condition permits the selection of channels already in use in other cells as long as the co-channel interference constraint is satisfied. With resonance condition, same channels are assigned to cells that belong to the same reuse scheme [22]. Channel reassignment improves the quality of service in terms of lowering call blocking probability. Hence, it is an important process in dynamic channel allocation. It is the process of transferring an ongoing call to a new channel without call interruption [6]. Reassignment in the entire cellular network upon a new call arrival will obviously result in lower call blocking, but it is complex both in terms of time and computation [22]. Therefore, the reassignment process is limited to the cell involved in new call arrival. But excessive reassignment in a cell may lead to increase in blocking probability [22]. So a process called limiting rearrangement is considered which tries to assign, where possible, the same channels assigned before, thus limiting the reassignment of channels. One of the major hard constraints, the co-channel interference is taken care by the D-ring based strategy as explained in Section VI. This simplifies our fitness function as compared to Sandalidis *et al.* [22] where there is a separate term in the fitness function to take care of the co-channel interference. This also leads to a simpler and faster fitness calculation than Sandalidis *et al.* [22]. Our problem representation takes care of traffic demand constraint as the number of channels in a solution vector equals the demand of channels in the cell. The soft constraints can be modelled as an energy function as shown in (1). The minimization of this function gives an optimal channel allocation [22]

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

where

k	cell where a call arrives;
d_k	number of channels allocated to cell k (traffic demand in cell k);
C	number of cells in the network;
V_k	output vector (the solution) for cell k with dimension d_k;
$V_{k,j}$	jth element of vector V_k;
$A_{i,V_{k,j}}$	the element located at the ith row and $V_{k,j}$th column of the allocation matrix A;
$\mathrm{dist}(i,k)$	distance (normalized) between cells i and k;
$\mathrm{res}(i,k)$	function that returns a value of one if the cells i and k belong to the same reuse scheme, otherwise zero.

W_1, W_2, and W_3 are positive constants. The first term expresses the packing condition. The energy decreases if the jth element of vector V_k is also in use in cell i, and the cells i and k are free from co-channel interference. The decrease in energy depends upon the distance between the cells i and k. The second term expresses the resonance condition. The energy increases if the jth element of vector V_k is also in use in cell i, and cells i and k does not belong to the same reuse scheme. The last term expresses the limiting re-assignment. This term results in a decrease in the energy if the new assignment for the ongoing calls in the cell k is same as the previous allocation. The value of the positive constants determines the significance of the different terms. We use the energy function as our fitness in the ES.

D. Mutation

An offspring is generated from a parent by randomly swapping values of the parent vector with the corresponding vector of free channels. The number of swaps lies between 1 and N (inclusively). The parameter N is the maximum number of swaps and takes the value of the length of the parent vector or the numbers of free channels whichever is less. Given N, we generate a random number S between 1 and N (inclusively). The parameter S represents the actual number of swaps. For example, if total number of available channels $|F| = 10, k = 1, d = 4$, and the parent vector $p = [7, 2, 5, 3]$, then the vector of eligible channels $= [1, 4, 6, 8, 9, 10]$. Here, $N = 4$, and if number of swaps is $S = 2$, then one possible offspring $O = [7, \mathbf{4}, 5, \mathbf{10}]$. Since mutation does not affect the length of the parent vector, and does not result in duplicate copy of any position, it always produces feasible solutions.

E. ES Approach

The algorithm starts with an initial parent generated as explained in Section VII-B. At every generation, the size of a population is λ. These λ individuals of the new population are randomly generated from the actual parent by the process of mutation as explained in Section VII-D. The fittest individual of the newly generated population called the *Best_child* will form the parent for the next generation provided its fitness is better than the former parent's fitness. In case of a poor *Best_child* the algorithm tries to locally optimize the fitness of the *Best_child*. In this process, we generate a new population from the *Best_child* through the process of mutation and try to find a child better in fitness than the *Best_child* within a predefined number of generations. We call this process local optimization. When the local optimization fails to find a better child within a predefined number of generations, a process called destabilization is applied. This process is used to escape from local optimum. During this process one of three possibilities is selected with probability $1/3$ and exactly N number of individuals are mutated with the corresponding vector of free channels to form the parent for the next generation. The process terminates when the destabilization process occurs for the fourth consecutive time. The demand of channels in a cell is also known as traffic. The proposed ES is shown in Fig. 2. It belongs to the class of $(1, \lambda)$-ES.

When a new call arrives, the cellular system looks for channels which are not in use in the cell and its neighboring area. If no such channel is found the new call is blocked, otherwise the ES algorithm finds a solution vector V_k with a minimum energy. This vector includes channels for all the ongoing calls and the new call. The allocation matrix is updated, and the existing calls are reassigned if any. This completes a call arrival process.

F. Complexity Analysis of Our Algorithm

In our algorithm, in each generation, we mutate and evaluate each string

```
Algorithm:
  Generate initial population of λ individuals
  Evaluate individuals according to fitness f
  Select the best individual Best
  Parent = Best
  loop = 0
  Repeat
    loop = loop + 1
    success = false
    Generate λ Neighbors of Parent by mutation
    Evaluate individuals according to fitness f
    Select the best individual Best_child
    If f(Best_child) > f(Best)
      parent = Best_child
      Best = Best_child
      success = true
      no_of_destabilization = 0
    If success = false
      success1 = false
      counter = 0
      Best_child1 = Best_child
    Repeat
      counter = counter + 1
      parent1 = Best_child1
      Generate λ Neighbors of Parent1 by mutation
      Evaluate individuals according to fitness f
      Select the best individual Best_child1
      If f(Best_child1) > f(Best)
        parent = Best_child1
        Best = Best_child1
        success1 = true
        no_of_destabilization = 0
    Until counter = 20 OR success1 = true
    If success1 = false (apply destabilization)
      no_of_destabilization = no_of_destabilization + 1
      If channels_in_use < free_channels
        N = channels_in_use
      else
        N = free_channels
      With 1/3 probability do either one of
        1. Mutate N genes of Best_child1
             parent = Best_child1
        2. Mutate N genes of Best_child
             parent = Best_child
        3. Mutate N genes of parent
             parent = parent
  Until no_of_destabilization = 4
```

Fig. 2. Proposed ES algorithm.

- complexity of doing mutation is $O(d_k)$;
- complexity of evaluating a chromosome according to (1) is $O(2d_k \cdot C)$.

Since in each generation we have λ strings, therefore complexity of a generation is $O(\lambda \cdot 2d_k \cdot C)$.

In the algorithm proposed by Sandalidis *et al.* [22], in each generation, each string is mutated and evaluated:

- complexity of doing mutation is $O(1)$;
- Complexity of evaluating a chromosome according to [22] $O(3F \cdot C)$.

Since in each generation there is λ strings, therefore complexity of a generation is $O(\lambda \cdot 3F \cdot C)$.

The parameter F which represents the total number of available channels in the system is much greater than the parameter d_k which represents the traffic demand at a particular time instant. Moreover the time complexity of evaluating a string is less

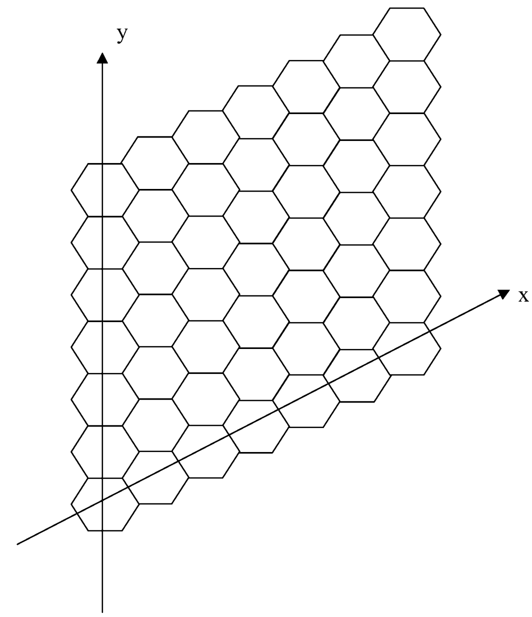

Fig. 3. Cellular network model.

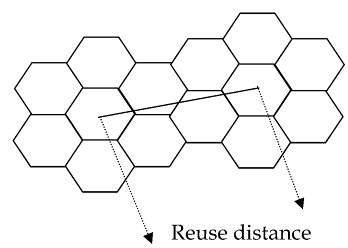

Fig. 4. Reuse distance used in the model.

in our proposed algorithm than the one proposed in [22]. Therefore it clearly shows that the time complexity of our proposed algorithm is much less than the one proposed in [22].

VIII. Cellular Model Assumption

In the paper, ES is applied to the mobile cellular model proposed in Del Re *et al.* [8]. The basic characteristics of the model are briefly described as follows.

1) The topological model is a group of hexagonal cells that form a parallelogram shape (equal number of cells along x-axis and y-axis) as shown in the Fig. 3 (adapted from [8], Fig. 1).
2) Cells are grouped in cluster of size 7 cells. The reuse distance is 3 cell units as shown in Fig. 4. (adapted from [8], Fig. 9]).
3) A total of 70 channels are available to the whole network. Each channel may serve only one call (i.e., multiplexing techniques are ignored). In FCA, the available channels are distributed among the cells. In DCA, all channels are put in central pool. A channel is assigned to an incoming call by a central controller that supervises the whole cellular network.
4) Incoming calls at each cell may be served by any of the system channels.

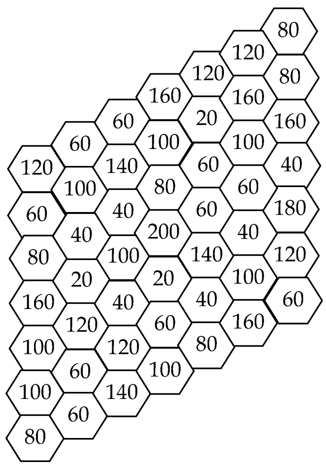

Fig. 5. Nonuniform traffic distribution pattern 1 with initial Poisson arrival rates (calls/h).

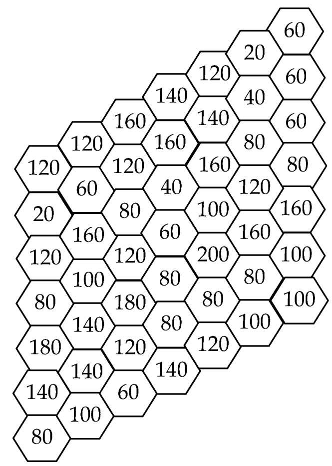

Fig. 6. Nonuniform traffic distribution pattern 2 with initial Poisson arrival rates (Calls/h).

5) The selection of a channel is only subject to co-channel interference. Other sources of interference are ignored.
6) A call is blocked if the entire set of channels in the network is in use in the cell involved in call arrival and its neighborhood, that is there is no channel that satisfies the co-channel interference.
7) Existing calls in a cell involved in a new call arrival may be rearranged.

In the model, we assume the traffic model to follow the blocked-calls-cleared queuing discipline. An incoming call is served immediately if a channel is available, otherwise the call is blocked and there is no queuing of blocked calls. The most fundamental characteristics of this model include: infinite number of users, finite number of available channels, memory-less arrival of requests, call arrival follows a Poisson process with mean arrival rate of λ (calls/h), and call duration is exponentially distribution with mean x. Inter-arrival time follow a negative exponential distribution with mean x. The product of the mean arrival rate and the mean call duration gives the traffic load offered to the cellular network. The traffic in the cellular network may either follow uniform or non uniform distribution. In uniform traffic distribution, every cell has the same traffic load. In non uniform traffic distribution, every cell has a different call arrival rate. The assumption of nonuniform traffic distribution is very realistic. For non uniform traffic distribution, we consider the traffic patterns proposed in [22] shown in Figs. 5 and 6. The number inside the cell represents the mean call arrival rate per hour. With these simulation hypothesis we can compare our results with those obtained in [22].

IX. Simulation

In HCA, the total set of available channels is divided into two sets: fixed set and dynamic set. When a call arrives in a randomly selected cell, the cellular system first makes an attempt to serve it from the fixed set of channels. When all the channels in the fixed set are busy, the cellular system applies ES algorithm to find a suitable combination of channels. In the simulation, the following representative ratios proposed in [22] were used: 21:49 (21 channels in the fixed set and 49 channels in the dynamic set), 35:35, and 49:21. Results were obtained by increasing the traffic rates for all the cells of both the patterns by a percentage with respect to the initial rates of the same cell (as in [22]). The performance of the proposed ES based algorithm for channel allocation has been derived in terms of the blocking probability for the new incoming calls. This blocking probability is the ratio between the new call blocked and the total number of call arrivals in the system. The values of the positive constants considered in this paper are set to $W_1 = 1.5$, $W_2 = 0.5$, and $W_3 = 1$, same as in Sandalidis *et al.* [22]. We tried different values for weights and these weights provide the best result. All the channels in the set I (set of eligible channels) satisfies the hard constraint, so when $|I| = 1$, as there is no scope of optimization the channel is directly allocated to the incoming call. But when $|I| \geq 2$, the proposed ES does optimization. Therefore, the maximum number of initial parents μ that can be selected from I is two. We have tested the performance of the algorithm for $1 \leq \mu \leq 2$ for four different values of λ ($\lambda = 10$, $\lambda = 20$, $\lambda = 30$, and $\lambda = 40$) for traffic pattern 1 with the following representative ratios: 21:49 (21 channels in the fixed set and 49 channels in the dynamic set), 35:35, and 49:21 as shown in Figs. 7–9 respectively. It is evident from these figures that the proposed ES is insensitive to the value of λ and μ so far the blocking probability is concerned. Considering the processing time, μ is set to 1 and λ is set to 10. From Fig. 10, it is evident that inclusion of the destabilization part does not affect the performance of the algorithm in terms of blocking probability, however reduces the computational time. In this figure, ES HCA shows the result with destabilization whereas WD ES HCA shows the result without the destabilization part. The performance of the proposed algorithm has been compared with the channel allocation schemes proposed in [22]. Figs. 11 and 12 compares our results with [22]. In these figures, ES HCA shows our result whereas HCA shows the result obtained in [22]. Fig. 13 shows the results of the simulation for the FCA scheme obtained for the pattern 1 (Fig. 5) and pattern 2 (Fig. 6). The results are same as reported in Sandalidis

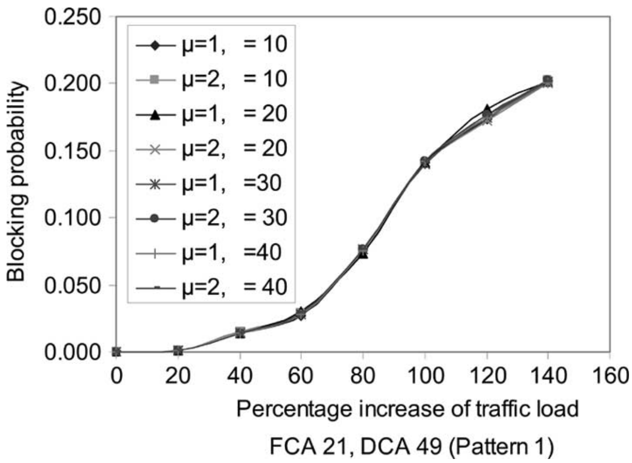

Fig. 7. Performance of the proposed ES algorithm in terms of blocking probability, with different values of μ and λ, for the entire cellular network with nonuniform traffic distribution according to pattern 1 (Fig. 5) for $\mathrm{FCA} = 21$ and $\mathrm{DCA} = 49$.

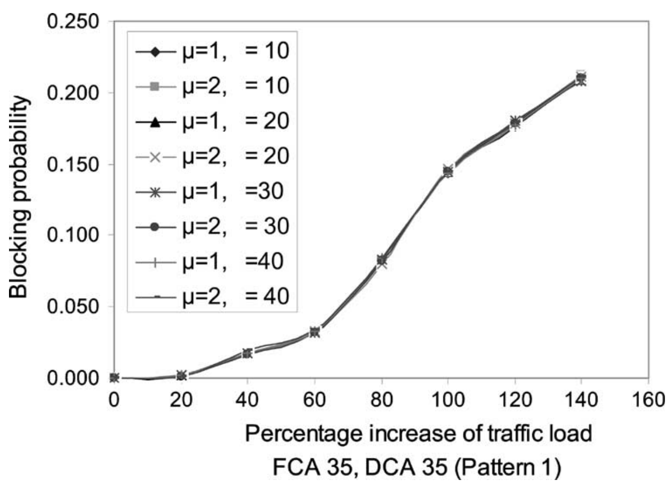

Fig. 8. Performance of the proposed ES algorithm in terms of blocking probability, with different values of μ and λ, for the entire cellular network with nonuniform traffic distribution according to pattern 1 (Fig. 5) for $\mathrm{FCA} = 35$ and $\mathrm{DCA} = 35$.

et al. [22]. According to our simulations, the proposed algorithm produces better results for all the representative ratios for traffic pattern 1 (Fig. 5) in comparison with Sandalidis *et al.* Among all the representative ratios, the best performance was obtained with the 21:49 scheme. However, in terms of running time, 49:21 is more efficient. The convergence of the proposed ES is shown in Table I. The table shows the average and standard deviation of blocking probability for traffic pattern 1 (Fig. 5) for ten runs. For traffic pattern 2, our algorithm out performs [22] for all the representative ratios up to 60% increase in traffic rate. Beyond 60% the results obtained are as good as reported in [22]. Table II summarizes the characteristics of the ES based allocation algorithms.

X. Conclusion and Future Research Directions

The paper has modelled the HCA based on the interference rings and has proposed an ES algorithm to perform channel al-

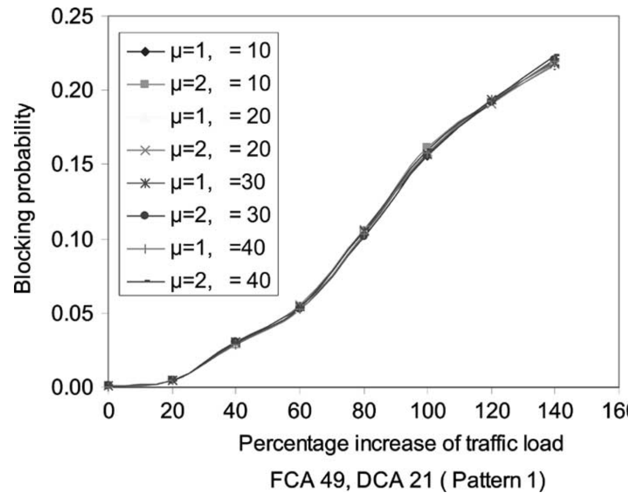

Fig. 9. Performance of the proposed ES algorithm in terms of blocking probability, with different values of μ and λ, for the entire cellular network with nonuniform traffic distribution according to pattern 1 (Fig. 5) for $\mathrm{FCA} = 49$ and $\mathrm{DCA} = 21$.

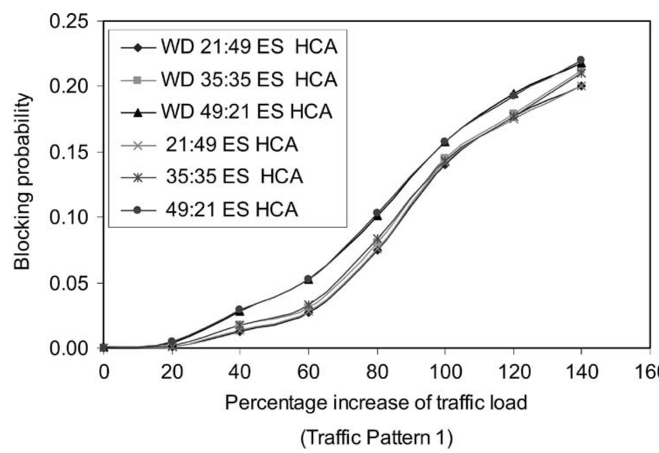

Fig. 10. Comparison of the performance of the proposed ES algorithm in terms of blocking probability with and without destabilization part in the algorithm for the entire cellular network with nonuniform traffic distribution according to pattern 1 (Fig. 5).

location. ES based algorithm has the advantage of producing reliable solutions in a smaller number of generation as compared to other heuristics such as genetic algorithm. This is because at each generation only one parent produces all the feasible solutions [22]. The proposed algorithm uses integers to represent the solution vector. The advantage of the representation proposed in this paper over the one used in Sandalidis *et al.* [22] is that it reduces the computation time involved in the calculation of the energy when the demand of channel is less than the total number of available channels. This is generally the case. The concept of neighboring area avoids the selection of channel that will result in co-channel interference. Therefore, the time required in the determination of co-channel interference is reduced. The chosen representation and the mutation operator guarantees the feasibility of the solution.

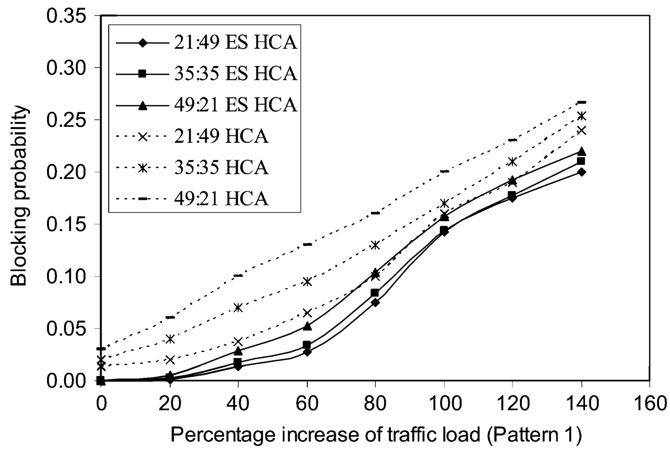

Fig. 11. Performance of the proposed ES algorithm in terms of blocking probability for the entire cellular network with nonuniform traffic distribution according to pattern 1 (Fig. 5).

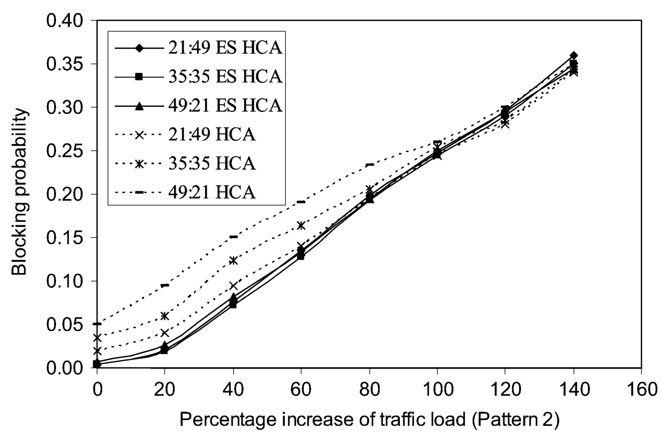

Fig. 12. Performance of the proposed ES algorithm in terms of blocking probability for the entire cellular network with nonuniform traffic distribution according to pattern 2 (Fig. 6).

We are currently investigating the performance of the proposed algorithm in terms of quality of solution and time for different mutation operators, and different ways of generating initial population. Another possible mutation operator involves the generation of neighborhood state of a solution vector as done in Tabu Search method. In our future research work, we will also investigate the use of recombination operator and implement GA for our HCA and thus compare the results.

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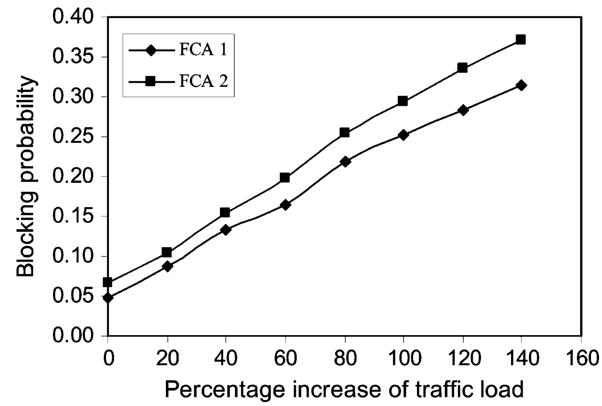

Fig. 13. Performance of FCA scheme in terms of blocking probability for nonuniform traffic distribution according to pattern 1 (Fig. 5) and pattern 2 (Fig. 6).

TABLE I
CONVERGENCE OF THE PROPOSED ES (PATTERN 1)

	% Increase in Traffic load	Blocking Probability	
		Average	SD[1]
FCA 21, DCA 49	0	0.000	0.000
	20	0.001	0.001
	40	0.014	0.001
	60	0.028	0.002
	80	0.075	0.003
	100	0.142	0.002
	120	0.175	0.002
	140	0.231	0.002
FCA 35 , DCA 35	0	0.000	0.000
	20	0.002	0.001
	40	0.017	0.001
	60	0.033	0.001
	80	0.084	0.002
	100	0.145	0.002
	120	0.177	0.003
	140	0.232	0.002
FCA 49, DCA 21	0	0.000	0.000
	20	0.005	0.000
	40	0.030	0.002
	60	0.052	0.001
	80	0.104	0.002
	100	0.159	0.002
	120	0.193	0.001
	140	0.244	0.002

TABLE II
CHARACTERISTICS OF ES-HCA

FCA 21, DCA 49	Max No of generations	18
	Average No of generations	5
	Min No of generations	4
FCA 35, DCA 35	Max No of generations	19
	Average No of generations	5
	Min No of generations	4
FCA 49, DCA 21	Max No of generations	14
	Average number of generations	5
	Min No of generations	4

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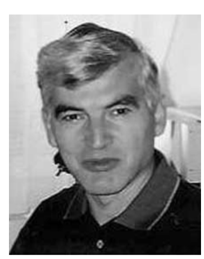

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