# Integrated Hybrid Channel Assignment and Distributed Power Control in Wireless Cellular Networks using Evolution Strategy

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Abstract— The Channel Assignment problem is the problem of determining an optimal allocation of channels to mobile users that minimizes call-blocking and call-dropping probabilities. The Power Control problem is the problem of determining an optimal allocation of power levels to transmitters such that minimizes power consumption. In wireless mobile networks, channels and transmitter powers are limited resources and an efficient use of both these resources can greatly increase the network's capacity. However, very few papers have attempted to concurrently optimize both resource with significant success. We propose a multi-objective evolution strategy that combines the optimizations of Channel Assignment and Power Control. Preliminary results show substantial increase in network's capacity when compared with some current Channel Assignment method.

## I. INTRODUCTION

The cellular principle partitions a geographical area into cells containing each, a base station and a number of mobile terminals. In order to begin communication with a base station, a mobile terminal must obtain a channel from the base station; where a channel consists of a pair of frequencies: one frequency (the down-link) for transmission from the base station to the mobile terminal, and another frequency (the up-link) for the transmission in the reverse direction. A pair of transmitter powers (for the base station and the mobile terminal) must also be assigned in such a way to maintains the signal transmission quality, that is the Carrier-to-Interference Ration (CIR).

### **II. CHANNEL ASSIGNMENT**

The channel assignment problem is the problem of allocating frequencies to mobile terminals and base stations such that the network's capacity, in terms of number of mobile users, is maximal. This is a well-known NP-hard problem [7]. The capacity is maximal when the call-blocking and call-dropping probabilities are minimal. To minimize call-blocking and call-dropping probabilities, a channel assignment scheme must satisfy the interference constraints as well as the demand of channels in the network [10]. These constraints are known as hard constraints. Channel assignment scheme are classified into three categories: fixed channel assignment (FCA), dynamic channel assignment (DCA) and hybrid channel assignment (HCA) schemes. FCA schemes allocate channels permanently to each cells based on

estimated traffic. In DCA schemes, all the channels are available to all the cells. FCA scheme is simpler and outperforms DCA scheme under heavy load conditions, but unlike DCA, FCA does not adapt to changing traffic conditions and user distribution [9]. HCA schemes combine the benefits of both FCA and DCA schemes [8]; here, the total set of channels is partitioned into two subsets: one subset is allocated as in FCA, and the other subset set is allocated as in DCA.

## III. POWER CONTROL

An efficient power control strategy is known to suppress certain interferences, as well as to minimize the total consumption of power. The objective of power control is to assign a power level to each transmitter such that the signal quality, that is the carrier-to-interference ratio (CIR), is maintained and power consumption and interferences are minimized. Thus the problem of channel assignment is highly related to power control. When a call arrives and a channel is assigned to the call without considering power control, the assignment of this channel may cause the CIR of ongoing calls using this channel to drop below the required level, thereby causing forced termination of ongoing calls. In a cellular network, it has been found that users prefer the blocking of a new call to the dropping of an ongoing call.

# **IV. PROBLEM STATEMENT**

Channel assignment schemes help to increase the network's capacity by efficiently distributing the channels across the network, whereas power control strategies focus on every single channel and help to increase the capacity by efficiently adjusting CIR levels of the mobile users that use the same channel. Undoubtedly, optimizing *both* channel assignment and power control *together* can improve network performance and achieve higher capacity. In this paper, we study the problem of jointly optimizing a new hybrid channel assignment (HCA) strategy together with a distributed power control scheme (DPC), in an efficient manner; this is the HCA-DPC scheme. This scheme has not been studied in literature although many HCA and DPC schemes have been discussed separately in literature. Our HCA strategy is similar to the *D*-Ring HCA scheme of [17] with the exception that the DCA part is not based on fixed reuse distance

concept. The reuse distance R is the minimum distance at which two distinct cells i and j can use the same channel, otherwise, there will be *co-channel interference* if the distance between iand j is less than R. We do not need such concept anymore since we will access and use to the CIR values of ongoing calls, and that there will be co-channel interference if the CIR requirements of some ongoing calls are below or above acceptable levels. Our DPC scheme is identical to the one discussed in [1]. We propose an Evolution Strategy (ES) approach, in which we define a multi-objective fitness function that integrates the optimization objectives of HCA and DPC. Other than the fitness function, our ES method is similar in principle to the one used in [17]: we have identical problem representation and identical genetic operators, but with greater ability to escape local optima as well as faster running time.

## V. RELATED STUDIES

Many heuristics have been proposed in the literature to solve FCA, DCA and HCA problems based on fixed reuse distance concept. This includes Neural Networks [5], Simulated Annealing [4], Evolutionary methods [13], [14], [16], [17], and Tabu Search [2]. Very few researchers have studied the problem of the combined optimizations of channel assignment schemes with power control strategies in [6], [11], to name just a few. For instance, a distributed approach to the joint optimization of dynamic channel assignment and power control has been proposed in [6], [11]. Both papers use an interference region, and neighboring cells exchange the channel usage information periodically; a cost function is defined such that channels are selected only when they meet the CIR requirements. None of these approaches are based on computational intelligence methods.

## VI. DISTRIBUTED POWER CONTROL

We consider a cellular radio system with a finite set of B channels and C cells and a set of N transmitter-receiver pairs which share the same channel (i.e. the number of users using the same channel). In wireless cellular network, a channel corresponds to up-link and down-link transmissions between mobiles and base stations. The up-link (mobile-to-base frequency) and the down-link (base-to-mobile frequency) are assumed not to interfere with each other and are allocated in the same manner with the same channel assignment scheme. In this paper, we will only consider the down-link frequency allocation and all relevant propagation effects are modeled by the link gains as in Figure 1. All the results in this paper can be applied to the up-link frequency allocation by changing the notations.

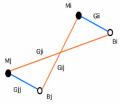


Fig. 1. System Geometry and Link Gains

 $G_{ij}$  denotes the link gain from the base station (the transmitter) in cell j to the mobile (the receiver) using the same channel in cell i. The gain  $G_{ii}$  corresponds to the desired communication link, whereas  $G_{ij}, i \neq j$  corresponds to unwanted co-channel interferences. Let,  $P_j$  be the transmitter power of base station j. The signal power received at receiver i from transmitter j is  $G_{ij}P_j$ . The desired signal at receiver i is equal to  $G_{ii}P_i$ , while the interfering signal power from other transmitters to receiver i is  $\sum_{j\neq i}G_{ij}P_j$ . We use the CIR as measure of the signal quality of mobile i and is denoted by  $\Gamma_i$ :

$$\Gamma_i = \frac{G_{ii}P_i}{\sum_{j\neq i}G_{ij}P_j + \eta_i} \qquad i, j \in \{1, \dots, N\}$$
(1)

where  $\eta_i > 0$  is the thermal noise power at mobile *i*. The CIR is acceptable if  $\Gamma_i$  is above a certain threshold,  $\gamma_0$ , called the minimum protection ratio. This  $\gamma_0$  reflects some minimum quality of service (QoS) that the link must support throughout the transmission in order to operate properly. Hence, for acceptable CIR, have:

$$\frac{G_{ii}P_i}{\sum_{j\neq i}G_{ij}P_j + \eta_i} \ge \gamma_0 \tag{2}$$

In matrix form, the CIR requirements (2) can be written as in [1]:

$$(I - \gamma_0 F)\Pi \ge U \qquad \Pi = (P_1, \dots, P_N)^T > 0$$
 (3)

where  $\Pi$  is the transmitter power vector, I is the  $N \times N$  identity matrix, and U is an element-wise positive vector with elements  $u_i$  defined as:

$$u_i = \frac{\gamma_0 \eta_i}{G_{ii}} \qquad 1 \le i \le N \tag{4}$$

Finally, F is the matrix of cross-link power gains with entries:

$$F_{ij} = \begin{cases} 0 & \text{if } i = j \\ \frac{G_{ij}}{G_{ii}} > 0 & \text{if } i \neq j \end{cases} \qquad i, j \in \{1, \dots, N\}$$
(5)

The objective of power control is to maintain the CIR requirements (2) by adjusting the power vector  $\Pi$  appropriately.

Let  $\rho(F)$  be the maximum modulus eigenvalue of F. It has been shown in literature that if  $\rho(F) < \frac{1}{\gamma_0}$ , then the matrix  $I - \gamma_0 F$  is invertible and positive [12]. In this case the power vector

$$\Pi^* = [I - \gamma_0 F]^{-1} U \tag{6}$$

solves the optimization problem since any  $\Pi$  is such that  $\Pi \ge \Pi^*$ . A good power control strategy is to set the transmitter power vector to  $\Pi^*$  in order to minimize the co-channel interferences and the power consumption [1].

The following distributed power control (DPC) algorithm is proposed in [1]:

$$P_i(k+1) = \frac{\gamma_0}{\Gamma_i(k)} P_i(k) \qquad 1 \le i \le N, k \ge 0$$
(7)

In Equation 7, if  $\rho(F) < \frac{1}{\gamma_0}$  then  $\Pi$  converges to  $\Pi^*$  for  $k \to \infty$ . This gives a simple iterative method for computing the power levels starting from initial power values. Using this equation, each base station *j* increases its transmitter power level independently for each mobile *i* when  $\Gamma_i < \gamma_0$ , and decreases it otherwise in order to minimize power consumption. In our distributed power control scheme, each channel's transmitter and receiver pair measures its co-channel interferences and communicates this information to each other. The transmitter then decides how to adjust its power levels.

# VII. HCA-DPC APPROACH

Each base station j in a cellular network has a computer that store the current state of its cell. The state of the cell includes information about channels, mobiles, and ongoing calls in the cell. Each base station sends its state to all other base stations through a wired network between their computers. Channel assignment is made by the computer of the concerned base station according to the channel usage information stored in the allocation matrix. Let, C be the total number of cells in the network and B the total number of channels in the network. The allocation matrix is the binary matrix  $A_{C\times B}$  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 or released in the network, and each base station receives a copy of the allocation matrix. Also, a network wide distance matrix and link gain matrix holds the distance  $d_{ij}$ 's and the link gains  $G_{ij}$ 's between mobiles and their associated base stations. The total number of channels is divided into two sets: the Fixed Channels set (or FC set: a set of channels permanently allocated to given cells) and the Dynamic Channels set (or DC set: a set of channels available to all cells).

Here, we discuss our HCA-DPC approach. When a new call arrives in a cell and that no channel is available from the FC set to serve the call, we apply Evolution Strategy (ES) on the DC set and obtain a best assignment  $V_k$  of channels. Solution  $V_k$  contains channels to be assigned to all ongoing calls in the cell (ongoing calls maybe re-assigned new channels to minimize blocking or dropping of calls) and the channel to be assigned to the new call. Although  $V_k$  is the best solution returned by ES, the CIR requirements of some channels in  $V_k$  may not be satisfied. Solution  $V_k$  is retained as final solution only if the CIR requirements of *all* its channels are met. Otherwise, the DPC algorithm (Equation (7)) is employed iteratively on  $V_k$  to meet the CIR requirements. If after 10 iterations DPC fails on  $V_k$  then  $V_k$  is rejected, and the second best solution  $V_{k1}$  found by ES is considered as solution. If DPC fails on  $V_{k1}$  then ongoing calls that are being served are not re-assigned new channels and the incoming call is blocked.

We also use DPC to maintain the CIR requirements for all ongoing calls in the *whole* network. Each base station monitors its own ongoing calls. When an ongoing call's CIR remains below the target threshold value  $\gamma_0$  for a predefined amount of

time, the DPC algorithm is requested to adjust its power level. The ongoing call will be dropped after 10 iterations of DPC if its CIR requirement is not met.

The choice of initial power vector  $\Pi_0 = (P_{1_0}, \ldots, P_{N_0})^T$  is not very critical, since many researchers have shown that  $\Pi^*$  is the only positive eigenvector of F and almost any positive start vector will be reasonably close to  $\Pi^*$  [18]. We set the initial value of each  $P_{i_0}$  to 0.2.

## VIII. EVOLUTION STRATEGY FOR HCA-DPC

In this section, we describe a multi-objective  $(\mu, \lambda)$ -ES for determining a (near) optimal assignment of channels that minimizes call-blocking and call-dropping probabilities. Our ES maintains a population of  $\mu$  parent solutions and  $\lambda$  offspring solutions. Each solution is encoded in such a way that appropriate genetic operators can be defined for the evolution of the population. We present the characteristics of our  $(\mu, \lambda)$ -ES in the following sub-sections.

## A. Problem Representation

Let us assume that a new call arrives in cell k, which is already serving  $(d_k - 1)$  calls and  $d_k$  is the number of active channels at cell k after the new call arrives. Our problem is to assign a channel for the new call also with possible re-assignment of channels to the  $(d_k - 1)$  ongoing calls in k, so as to maximize the overall channel usage in the entire network. The CIR requirements and the optimal power issue are dealt by the fitness function and the DPC algorithm respectively. A potential solution,  $V_k$ , is an assignment of channels to all ongoing calls and the new call, at k. We call such a solution a chromosome. We represent  $V_k$  as an integer vector of length  $d_k$ , where each integer is a channel number being assigned to a call in cell k. For example, if k = 1,  $d_k = 4$ , available channel numbers = [1, 2, 3, 4, 5, 6, 7, 8, 9], then a possible solution is  $V_1 = [7, 2, 5, 3]$ .

#### B. Initial Parents and Initial Population

When a call arrives in a cell k at time t, we first search for a channel in the FC set that can serve the call. If no such channel is available from FC then we determine from the DC set the set of eligible channels  $I \subseteq DC$ . Here  $I(k,t) = DC \setminus P(k,t)$ , where P(k, t) is the set of channels of the ongoing calls in k at time t. This information is obtained from the allocation matrix. An initial parent solution (the very first chromosome) is selected from a set G (the initial population) of  $\lambda$  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 k, we preserve in the initial population the  $(d_k - 1)$  channels already allocated to k before arrival of the new call. Thus each solution in G contains a unique integer selected from I(k, t). The remaining  $(d_k - 1)$  integers in all solution vectors are the same and are the channels of the ongoing calls in k, that is P(k, t). For instance, let us consider the following example: a call arrives in cell k at time t, where P(k,t) = [2,5,9] and DC = [1,2,3,4,5,6,7,8,9]. Therefore, I(k,t) = [1,3,4,6,7,8] and  $\lambda = 6$ . Here,  $d_k = 4$  and hence the size of the solution vectors is 4. The 6 solution vectors in Gare thus:  $G_1 = [2, 5, 9, 1]$ ,  $G_2 = [2, 5, 9, 3]$ ,  $G_3 = [2, 5, 9, 4]$ ,  $G_4 = [2, 5, 9, 6]$ ,  $G_5 = [2, 5, 9, 7]$  and  $G_6 = [2, 5, 9, 8]$ . Out of these six candidate solutions, the  $\mu \leq |I(k,t)|$  best solutions are selected as initial parents. Thus, instead of starting from  $\mu$ totally random solutions, we start with solutions containing the  $(d_k - 1)$  channels already allocated to ongoing calls. This way of generating the initial parents will reduce the number of channel re-assignments and thus yields a faster running time. The initial parents are also potentially near optimal solutions since channel assignment for ongoing calls were already optimized previously before the new call arrival in k.

# C. Fitness

In this section, we define a fitness function that expresses both the objectives of HCA and DPC together. With regard to HCA, we are at the moment interested in satisfying only two hard constraints: co-channel interference constraint and traffic demand constraint. Other hard constraints such as co-site interference constraint and adjacent channel interference constraint are left for future research. Beside co-channel and traffic constraints, some conditions may be required to improve the performance of our HCA scheme: they are the packing condition, the resonance condition, and the limiting re-assignment condition [3]. These conditions are called soft constraints. The soft constraints permit to further lower the call blocking or dropping probabilities. When new calls arrive in a cell, the packing condition minimizes the number of *distinct* active channels in the entire network by selecting 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. The limiting re-assignment condition tries to assign, when possible, the same channels assigned to the cell before the new call arrival, thus minimizing the blocking of ongoing calls. The co-channel interference constraint is satisfied by selecting only those channels that meet their CIR requirements. We use DPC to compute the CIR values of given channels to be selected by HCA. With an appropriate fitness function, ES should select only those channels that meet their CIR requirements and such that all the hard and soft constraints are satisfied. Let  $D_k$  be the maximum number of active channels permitted for cell k. Let  $d_k$  be the current number of active channels in k, including channel for new call. Our problem representation already satisfies the traffic demand constraint since  $d_k \leq D_k$ ; a new call will be blocked if  $d_k > D_k$ . Together, the hard and soft constraints can be modeled as an energy function as shown in Equation (8). The minimization of this energy function gives an optimal channel allocation.

$$E(V_{k}) = A_{1} \sum_{j=1}^{d_{k}} cir(V_{k,j})$$
  
-W<sub>1</sub>  $\sum_{j=1}^{d_{k}} \sum_{i=1, i \neq k}^{C} A_{i,V_{k,j}} \frac{1 - interf(i,k)}{dist(i,k)}$   
-W<sub>2</sub>  $\sum_{j=1}^{d_{k}} A_{k,V_{k,j}}$  (8)

k	:	Cell where a new call arrives
$d_k \leq D_k$	:	Number of active channels in $k$
$D_k$	:	Maximum number of active chan-
		nels in k
C	:	Number of cells in network
$V_k$	:	Solution vector for cell k
$E(V_k)$	:	Energy value of $V_k$
$V_{k,j}$	:	$j^{th}$ element of $V_k$
$A_{i,V_{k,j}}$	:	Element at the $i^{th}$ row and $V_{k,i}^{th}$
.,.,,,,		column of matrix A
dist(i,k)	:	normalized distance between cells <i>i</i>
		and k
interf(i,k)	:	Returns 1 if there is co-channel in-
• • • • •		terference between cells $i$ and $k$ , 0
		otherwise
$cir(V_{t-1})$		Returns 0 if $\rho(F) < \frac{1}{2}$ for channel

 $cir(V_{k,j})$  : Returns 0 if  $\rho(F) < \frac{1}{\gamma_0}$  for channel *j*, 1 otherwise

The first term expresses the CIR requirements, as well as the co-channel interference constraint, in terms of the cross-link power gains matrix F: for a channel j, the CIR requirements of all mobiles that use j is satisfied if  $\rho(F) < \frac{1}{\gamma_0}$  (see Section VI). The energy  $E(V_k)$  decreases if channel j is in use in other cells and that  $\rho(F) < \frac{1}{\gamma_0}$  for j. The second term expresses the reaching condition the second term expresses the packing condition: the energy decreases if the  $j^{th}$  element of vector  $V_k$  is in use in some cell *i*, and that cells *i* and *k* are free from co-channel interference (this is determined by computing  $\rho(F)$  for the channel used by k and i). The decrease in energy also depends upon the distance between cells i and k. The third term expresses the limiting re-assignment: it results in a decrease in the energy if the new assignment for the ongoing calls in cell k is same as the previous assignment. The resonance condition is not modeled since our HCA scheme is not based on fixed reuse distance concept. Coefficients  $A_1$ ,  $W_1$  and  $W_2$  are positive constants and their values determine the significance of the different terms. In our experiments, we set  $A_1 = 2.5$ ,  $W_1 = 1.5$  and  $W_2 = 1$ ; these values were determined by trialand-errors. We use this energy function as our fitness function for the ES.

#### D. Mutation

An offspring is generated from a parent by randomly replacing channels of the parent with channels from the set of eligible channels I. The number of swaps S is random and  $1 \le S \le N$ . Parameter  $N = \min(d_k, |I|)$  is the maximum number of swaps. For example, if the eligible channels are I = [1, 4, 6, 8, 9, 10],  $d_k = 4$  and parent P = [7, 2, 5, 3] and S = 2, then N = 4 and one possible offspring is O = [7, 4, 5, 10]. Mutation does not affect  $d_k$  and does not result in multiple copies of channels in O.

## *E.* $(\mu, \lambda)$ -*ES for HCA-DPC*

In this research, we implemented a variant of the  $(\mu, \lambda)$ -ES for solving the HCA-DPC problem. We initially create a random initial population G of  $\lambda$  solutions and a set U of initial parents, as explained in Section VIII-B. We then create subsequent generations. Each generation is obtained by creating  $\lambda$  offsprings as follows: we randomly select a parent from U and mutate it as explained in Section VIII-D, and repeat this process  $\lambda$  times on U to obtain a new G. Finally, the best  $\mu$  solutions in the current G are select as the next parents. We also keep track of the global best solution and preserve it across generations. The inner whileloop optimizes the local best solution in G in order to escape local optima. The global best solution is updated whenever its fitness is worse than that of the local best solution. Our method is elitist since both the local and global best solutions are always passed onto the next generation. The algorithm terminates after 1000 generations and returns the two best solutions so far across all generations.

Algorithm 1 ( $\mu$ ,  $\lambda$ )-ES

```
Given \mu, \lambda, cell k and d_k < D_k
Create initial population \overline{G} = \{G_1, \dots, G_\lambda\} as in Section VIII-B
Create initial parents U = \{U_1, \ldots, U_\mu\} from G as in VIII-B
Evaluate(U)
Global\_best \leftarrow best in U
repeat
   G = \{G_1, \dots, G_\lambda\} \leftarrow Mutate(U)
Evaluate(G)
   Local\_best \gets \mathsf{best} \text{ in } G
   i \leftarrow 0
   while E(Local\_best) > E(Global\_best) and i < 10 do
      C \leftarrow Mutate(Local\_best)
      B \leftarrow Mutate(Global\_best)
      Local\_best \leftarrow best in \{C, B, Local\_best\}
      i \leftarrow i + 1
   end while
   if E(Local\_best) < E(Global\_best) then
      Global\_best \leftarrow Local\_best
   end if
   U = \{U_1, \dots, U_{\mu}\} \leftarrow \text{best in } G \cup \{Local\_best, Global\_best\}
until Stopping Criteria is attained
Return V_k = Global\_best and V_{k1} = Second best
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Although it is not apparent in the  $(\mu, \lambda)$ -ES algorithm, the DPC algorithm is used by the fitness function *E* to meet the CIR requirements of channels in given solutions.

### IX. CELLULAR MODEL ASSUMPTIONS

In this paper, ES is applied to the wireless cellular model used in [17]. The channel assignment assumptions and power control assumptions were proposed in [17]and [1], respectively. The basic characteristics of the model and assumptions are as follows:

1) The topological model is a group of hexagonal cells that form a parallelogram shape with equal number of cells along x-axis and y-axis, as shown in the Figure 2. The network contains 49 cells.

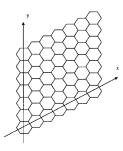


Fig. 2. Wireless Cellular Model

- 2) The total number of channels for the network is 70. A channel serves one call at most. A Fixed Channel set FC is permanently allocated to cells, and a channel permanently allocated to a subset of cells can only serve calls within that subset. A Dynamic Channel set DC is available to all cells. We have  $|FC \cup DC| = 70$ .
- 3) Incoming calls at each cell may be served by any of the channels.
- The selection of a channel is only subject to co-channel interference. Other sources of interference are ignored.
- 5) The basic object of the network model is the link, that is a communication between a base station and a mobile through a channel. By *distributed* power control we refer to per individual link.
- 6) We consider down-link frequencies only.
- 7) Each base station updates its transmitter power levels to meet the desired CIR threshold using Equation (7). The update is based on the interference measured at the mobile's receiver and the base station's transmitter.
- 8) A new call at cell k is blocked if no channel is available to satisfy the co-channel interference, or, if  $d_k > D_k$ . We set  $D_k$  to the total number of channels in the networks. Ongoing calls in the network except in the cell k are dropped if the CIR values remain below  $\gamma_0$  for a certain amount of time.
- 9) Existing calls in a cell involved in a new call arrival may be re-assigned new channels.

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 new call is blocked and not queued. The most fundamental characteristics of this model include: infinite number of users, finite number of channels for the network, no queue for new calls, call arrival follows a Poisson process with mean arrival rate of  $\lambda$  calls /hour, and call duration is exponentially distributed with mean x. Inter-arrival time follows 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 Non uniform traffic distribution is very realistic. We used only non uniform traffic distribution and considered the traffic patterns used in [13] shown in Figures 3 and 4. The entry in a cell represents the mean call arrival rate per hour. With these simulation hypotheses we can compare our results with those obtained in [17].

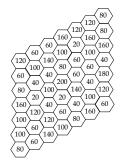


Fig. 3. Non Uniform traffic distribution Pattern 1

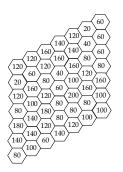


Fig. 4. Non Uniform traffic distribution Pattern 2

#### X. SIMULATIONS AND DISCUSSIONS

In our simulations, we used the following representative ratios of [17]: 21:49 (21 channels in FC set and 49 channels in DC set), 35:35 and 49:21. Results were obtained by increasing the traffic rates by 20%, for all cells in each pattern, with respect to the initial rates on each cell (as in [13]). The performance of the ES for the HCA-DPC problem is derived in terms of blocking probability for new incoming calls and dropping probability for ongoing calls. The blocking probability is the ratio between the number of blocked calls and the total number of call arrivals in the system. The dropping probability is the ratio between the number of dropped calls and the total number of call arrivals in the system. We set  $\gamma_0 = 10$  and  $\eta_i = \frac{1}{10^5}$  for all receivers. The number of iterations of the DPC algorithm, Equation (7), is set to L = 10. We used  $\mu = 1$  and  $\lambda = 10$  in most experiments.

Figures 5, 6, 7 and 8, compare the blocking probabilities of our HCA-DPC with the HCA of [17], for increasing traffic loads on Pattern 1. On call-blocking probabilities, HCA-DPC outperforms HCA on all representative ratios for both patterns. Among all representative ratios, the best performance was obtained with ratio 21:49 and the worst performance given by ratio 49:21 as seen in Figure 8. The call-blocking probabilities increase with the size of the FC set since less channels from the DC set will be available to serve new calls. In particular for heavier traffic loads, our HCA-DPC scheme with larger FC set and smaller DC set will tend to perform as poorly as an FCA scheme. On the other hand, our experiments report faster running times for smaller DC sets. Since most new calls are served from channels in the FC set then less channels from the DC set are eligible for ES to be requested. Results on Pattern 2 for all experiments are not reported here due to lack of space.

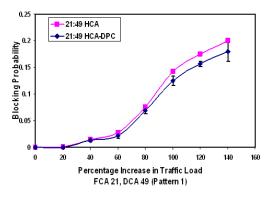


Fig. 5. Blocking probabilities of HCA-DPC vs HCA on Pattern 1 for ratio 21:49

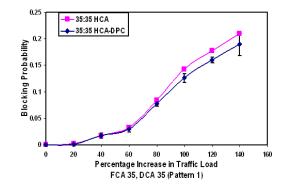


Fig. 6. Blocking probabilities of HCA-DPC vs HCA on Pattern 1 for ratio 35:35

We performed similar experiments for  $1 \le \mu \le 2$  and  $\lambda = 10, 20, 30, 40$ , for both patterns and for all representative ratios, and found that ES was almost insensitive to the different values of  $\mu$  and  $\lambda$ . The difference in call-blocking and call-dropping probabilities were small for any given ratio, and thus we did not report the results here.

Figure 9 shows the call-dropping probabilities of HCA-DPC for increasing loads on Pattern 1 for all ratios. Here, ratio 49:21 yields best performance and ratio 21:49 gives worst performance unlike in Figure 8. As stated in the last paragraph of Section VII, ongoing calls within the whole network are dropped when

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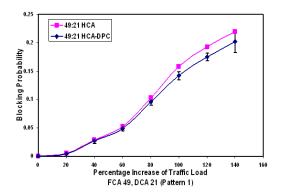


Fig. 7. Blocking probabilities of HCA-DPC vs HCA on Pattern 1 for ratio 49:21

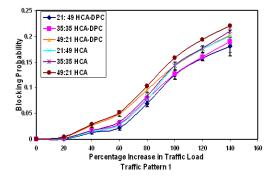


Fig. 8. Blocking probabilities of HCA-DPC vs HCA on Pattern 1 for all ratios

their CIR *remain* below  $\gamma_0$  for a certain amount of time. DPC algorithm will not run long enough to meet their CIR requirements, given that Equation (7) is iterated only L = 10 times at most. When a new call arrives in a given cell, the CIR value of some ongoing calls in other cells may drop below  $\gamma_0$  if those calls use the same channel as the new call. With smaller FC set, most channels will be assigned from the DC set to serve most new calls. In particular, more CIR values will degrade below threshold  $\gamma_0$  for heavier traffic loads.

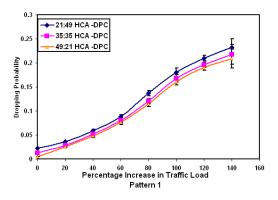


Fig. 9. Dropping probabilities of HCA-DPC on Pattern 1

In Figures 10 and 11 we report call blocking and dropping experiments on different number of iterations of DPC, for ratio 21:49 only. The CIR values can be maintained above  $\gamma_0$  given more time, and thus there is less call-blocking/dropping.

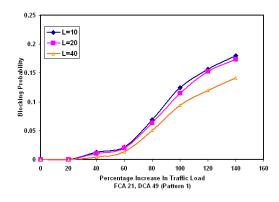


Fig. 10. Blocking probabilities of HCA-DPC on Pattern 1

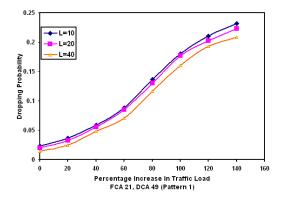


Fig. 11. Dropping probabilities of HCA-DPC on Pattern 1

We determined the number of times channels were assigned from the best solution,  $V_k$ , and the second best solution,  $V_{k1}$ , of ES. Figure 12 shows that for ratio 21:49, at least 93% of the assignments were suggested by  $V_k$  (priority channel list 1) than  $V_{k1}$  (priority channel list 2) for any traffic load. Clearly, ES performs very well and the figure suggests a need to improve ES to further achieve 100% assignments from  $V_k$ .

#### XI. CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

We proposed an evolution strategy that efficiently combines the objectives of both hybrid channel assignment and distributed power control problems in order to increase the capacity of wireless cellular networks. Our HCA-DPC scheme shows significant reductions in call blocking probability when compared to the HCA of [13], [17]. We also obtained interesting preliminary results on call dropping probability. More research is needed to further reduce call-blocking probability and, in particular, to attain a much lower call-dropping probability than call-blocking probability. In order to minimize droppings, we are investigating Proceedings of the 2007 IEEE Symposium on Computational Intelligence in Image and Signal Processing (CIISP 2007)

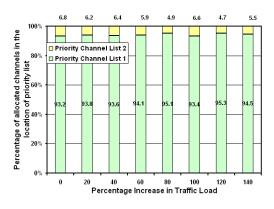


Fig. 12. Assignment  $V_k$  versus Assignment  $V_{k1}$  for Pattern 1

ways to protect and maintain the CIR values of active calls when new calls arrive. We also plan to add interference constraints such as co-site and adjacent-channel interference to reach larger network's capacity.

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