An Efficient Evolutionary Algorithm for Channel Resource Management in Cellular Mobile Systems

Harilaos G. Sandalidis, *Student Member, IEEE,* Peter P. Stavroulakis, *Member, IEEE,* and Joe Rodriguez-Tellez

***Abstract*—Modern cellular mobile communications systems are characterized by a high degree of capacity. Consequently, they have to serve the maximum possible number of calls while the number of channels per cell is limited. The objective of channel allocation is to assign a required number of channels to each cell such that both efficient frequency spectrum utilization is provided and interference effects are minimized. Channel assignment is therefore an important operation of resource management and its efficient implementation increases the fidelity, capacity, and quality of service of cellular systems. Most channel allocation strategies are based on deterministic methods, however, which result in implementation complexity that is prohibitive for the traffic demand envisaged for the next generation of mobile systems.**

An efficient heuristic technique capable of handling channel allocation problems is introduced here as an alternative. The method is called a combinatorial evolution strategy (CES) and belongs to the general heuristic optimization techniques known as evolutionary algorithms (EA's). Three alternative allocation schemes operating deterministically, namely the dynamic channel assignment (DCA), the hybrid channel assignment (HCA), and the borrowing channel assignment (BCA), are formulated as combinatorial optimization problems for which CES is applicable. Simulations for representative cellular models show the ability of this heuristic to yield sufficient solutions. These results will encourage the use of this method for the development of a heuristic channel allocation controller capable of coping with the traffic and spectrum management demands for the proper operation of the next generation of cellular systems.

***Index Terms*— Cellular communications, channel assignment schemes, combinatorial evolution strategy (CES), evolutionary algorithms (EA's).**

I. INTRODUCTION

THE appearance of cellular radio and its rapid growth provided an important alternative in the field of wireless mobile communications. The increasing demand of new services in this field, however, is in contrast to the capacity constraints inherent in the current communications systems. Hence, the use of techniques which are capable of ensuring that the spectrum assigned for use in mobile communications will be better utilized is gaining an ever-increasing importance. This makes the task of channel assignment more and more crucial [1].

The channel assignment mechanism involves allocating channels to each radio cell in a cellular radio network efficiently while satisfying the electromagnetic compatibility constraints. Channel assignment is generally classified into fixed and dynamic. In fixed channel assignment (FCA), channels are nominally assigned to cells in advance according to the predetermined estimated traffic intensity. In dynamic channel assignment (DCA), channels are assigned dynamically as calls arrive. The latter method makes cellular systems more efficient particularly if the traffic distribution is unknown or changes with time, but has the disadvantage of requiring more complex control and is generally time consuming [2]. Various extensions or combinations of the above two schemes have been discussed in the literature. The most basic are the hybrid channel assignment (HCA) and the borrowing channel assignment (BCA). In HCA, the set of the channels of the cellular system is divided into two subsets, from which the one uses FCA and the other DCA. In BCA scheme, the channel assignment is initially fixed. If there are incoming calls for a cell whose channels are all occupied, the cell borrows channels from its neighboring cells and thus call blocking is prevented [3], [4].

All the above channel allocation techniques have been based on deterministic methods. That is, they operate on techniques that require a set of known parameters and rules at the outset. Due to the existence of certain hard constraints, however, the channel assignment becomes a difficult process to be solved by deterministic approaches because they are in general complex and time consuming. One of the main conditions that must always be satisfied for the proper operation and reliability of modern cellular systems is the cochannel interference constraint. This constraint prohibits the same channel from being assigned to certain pairs of radio cells that are located within less than a certain distance (reuse distance) [5]. To overcome these problems, heuristics have been suggested in the literature including simulated annealing [6], tabu search [7], neural networks [8], [9] and genetic algorithms [10]–[12] for the FCA problem, and feedforward neural networks [13], Hopfield neural networks [14], [15], and genetic algorithms [16] for the DCA.

This paper investigates an alternative heuristic approach for solving channel assignment problems called a combinatorial evolution strategy (CES). The method belongs to the general category of heuristic optimization methods called evolutionary algorithms (EA's). EA's are search algorithms that are based on the mechanics of natural selection and genetics, as it relates

Manuscript received March 17, 1998; revised June 22, 1998 and September 10, 1998.

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Publisher Item Identifier S 1089-778X(98)09431-4.

to the survival of the fittest individual among a population of alternative ones. Research in EA's follows an exponential growth with applications in numerical function optimization, image processing, system identification, and control, as well as in telecommunications including dynamic routing and switching in communication networks, and resource management [17].

CES was introduced in [18] and [19] as a fast method to solve the quadratic assignment problem and was shown to give better solutions with fast convergence compared to the simple genetic algorithm, which is another representative EA. Quadratic assignment problems are typical combinatorial problems. These are problems that minimize a discrete cost or energy function under the assumptions of a mathematical model. By modeling channel assignment as a discrete problem with the variable of one if a channel is occupied and zero if it is free, channel allocation may mathematically take a combinatorial form.

In our study, three channel allocation schemes (DCA, HCA, and BCA) are formulated as combinatorial problems and thus can be solved by CES. The combinatorial formulation of these proposed schemes allows the simultaneous reassignment of the calls that are being served in the cellular system, which takes places together with the allocation of new calls. This process improves the blocking performance of incoming calls as will be explained later. Section II gives the basic characteristics of EA's and the fundamentals of the CES operation. Section III describes the basic assumptions of a cellular model used for simulations. Section IV examines the application of CES to a DCA model, Section V to a HCA, and Section VI to a BCA. Discussion for the modeling and simulation and directions for further research are provided in Section VII. Simulation results show the capability of CES as an efficient channel assignment technique for cellular networks operating in uniform and nonuniform traffic load conditions.

II. Fundamentals of CES

A. Evolutionary Algorithms

EA's are a class of direct, probabilistic search techniques based on the selection mechanism adopted by natural systems [20]. They operate as general-purpose optimization techniques and have a large repertory of applications to many difficult problems. Genetic algorithms, evolution strategies, and evolutionary programming are some representative EA's. In their very general form, EA's operate as follows: potential solutions called individuals form a population that undergoes a sequence of transformations. These transformations usually operate on a randomly selected portion of a population. The fitter individuals, according to an optimization criterion which is often called a fitness function, are selected according to a selection mechanism, to form the next generation. When a predetermined rule is satisfied after a number of generations, the whole process terminates and the fittest individual at that point is taken to be the solution of the problem [21]. In applying EA's to a specific problem, the designer has to select a representation for potential solutions, an evaluation or

```
Generate λ individuals
Evaluate individuals according to fitness f
Select best individual indiv
indiv1=indiv
counter=0
t=0
Repeat
    t=t+1
    if counter = max-num
            apply destabilization process
            counter=0
    Generate λ individuals from indiv1
    Evaluate individuals
    Select best individual indiv2
    if indiv2 is better than indiv1
            counter=0
            indiv=indiv2
    else counter=counter+1
    indiv1=indiv2
until termination condition
print best individual indiv
```

Fig. 1. CES-structure used for channel allocation.

4	3	6	2	5	1	7

Fig. 2. A typical representation of a solution in CES (#genes = 7). (Reproduced from Nissen [19].)

fitness function that plays the role of the optimization criterion, operators that alter individuals, values for various parameters (population size, probabilities for the application of operators, etc.), and a termination criterion [22].

B. Combinatorial Evolution Strategy

CES is a combinatorial variant of ES's though the mechanisms of coding and mutation appear more comparable with genetic algorithms [23]. ES's were developed in Germany during the 1960's and were initially applied to experimental optimization problems with discrete variables. In ES's, new solutions (offspring), are created from existing solutions (parents), using various operators such as mutation and recombination. Mutation adds vectors of Gaussian random variables with zero mean and specified standard deviation to each individual which also has the form of a vector. Recombination is an operation by which the mixing of different solutions is achieved. The two older representative ES's introduced by Schwefel are the $(\mu + \lambda)$-ES, where μ individuals produce λ offspring and from all the $\mu + \lambda$ solutions the μ best offspring survive to form the next generation, and the (μ, λ)-ES where the μ individuals are selected from the set of λ offspring only [22].

The modified CES heuristic is shown in Fig. 1. The above algorithm, which is explained below and follows the model used by Nissen in [18] and [19], is the result of our effort to adapt this heuristic to our specific problem. Following Nissen, CES is a (1,λ)-ES, [one parent generates λ offspring and individuals are vectors of integers that are generated from parents by randomly swapping values (see Figs. 2–4)]. This process is analogous to the classic mutation operator in ES's.

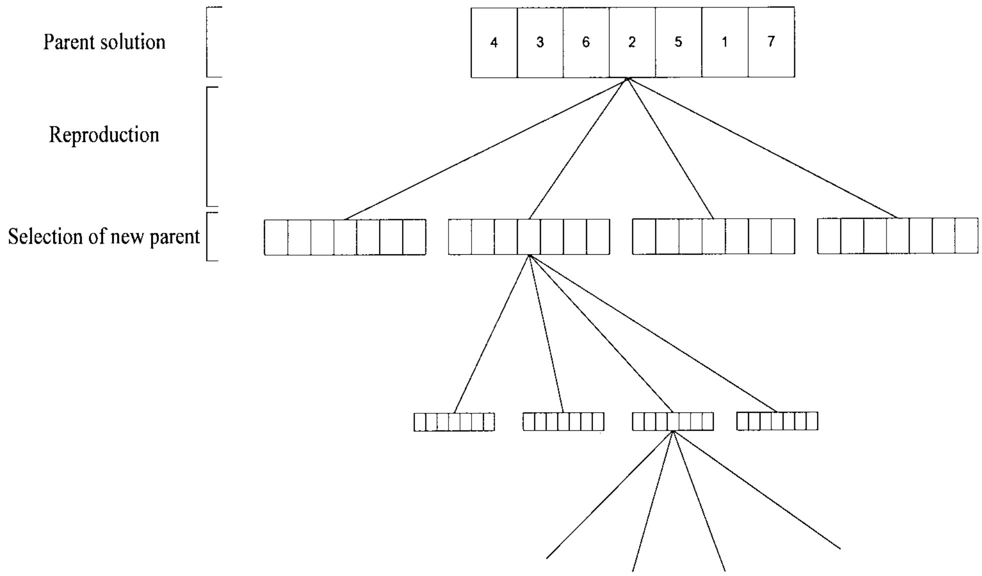

Fig. 3. Basic concept of CES. (Reproduced from Nissen [19].)

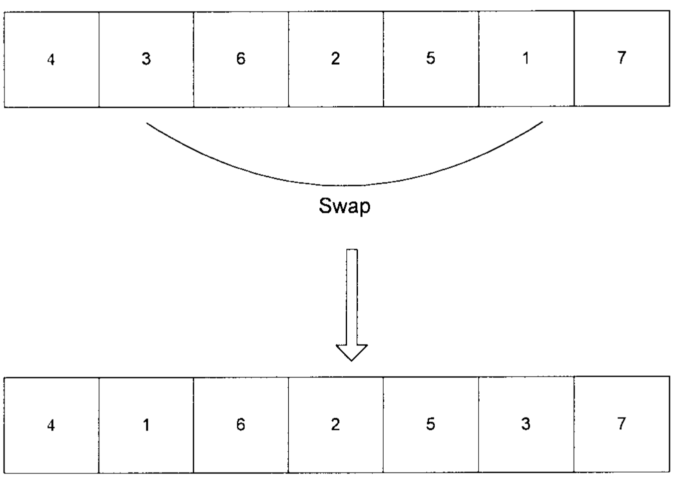

Fig. 4. Swapping operator.

The number of swaps lies anywhere in the interval [0, n] where n is the maximum number of swaps selected arbitrarily. In [19], it is chosen to be either one or two. Recombination of solutions is not considered. In every generation, the fittest child becomes the new parent. If its fitness is not better than the former parent's value, a counter is increased; otherwise it is reset to zero [23]. When the counter obtains a predefined value, a procedure called destabilization is executed. This procedure acts as a controlling mechanism to cope with the problem of premature convergence and thus, avoid the cases of local suboptimal solutions. During this step, the counter is set to zero and a new generation is created with an increased mutation step size (number of swaps). In [19], it is pointed out that at destabilization this number lies in the interval [3, ..., 8]. Thus the individuals produced differ in more than one variable.

In using CES to handle channel allocation problems, the above basic assumptions were followed with the exception that the individuals are composed of bits with values zero and one as explained later.

III. Cellular Model Assumptions

A typical cellular system architecture is shown in Fig. 5 [1]. In this scheme, a service area is divided into many small cells. Cells are defined as individual service areas in which a base station exists. Each station is usually placed in the middle of a cell and has a control unit and one or more antennas. The base station provides the interface between the mobile telephone switch office (MTSO) and the mobile units scattered across a cell. The MTSO is the central coordinating element for all cell sites, controls call processing, handles billing activities, performs channel assignment, and provides the necessary connection with the public switching telephone network (PSTN). When calls arrive in a particular cell they are assigned to channels [3]. A mobile user actually needs two channels: one for the mobile-to-base station link, and another for the base station-to-mobile link. As these two channels are assigned simultaneously, however, in many studies they are taken as a single link. This ideal channel is considered to be a generic communication resource depending on the multiple access technique used by the cellular network and may be a fixed radio frequency for a frequency division multiple access (FDMA), or a particular time slot within a frame for a time division multiple access (TDMA), or a specific code for a code division multiple access (CDMA) [15].

In this study, the proposed heuristic channel assignment strategies (CES-DCA, CES-HCA, and CES-BCA) have been applied to a cellular model that follows the basic characteristics of the one introduced in [24] for the comparison of four algorithmic channel assignment schemes. This model was also used in some other studies as in Del Re *et al.* [15] and Sandalidis *et al.* [16] and forms a good criterion for evaluating the performance of advanced allocation schemes due to its

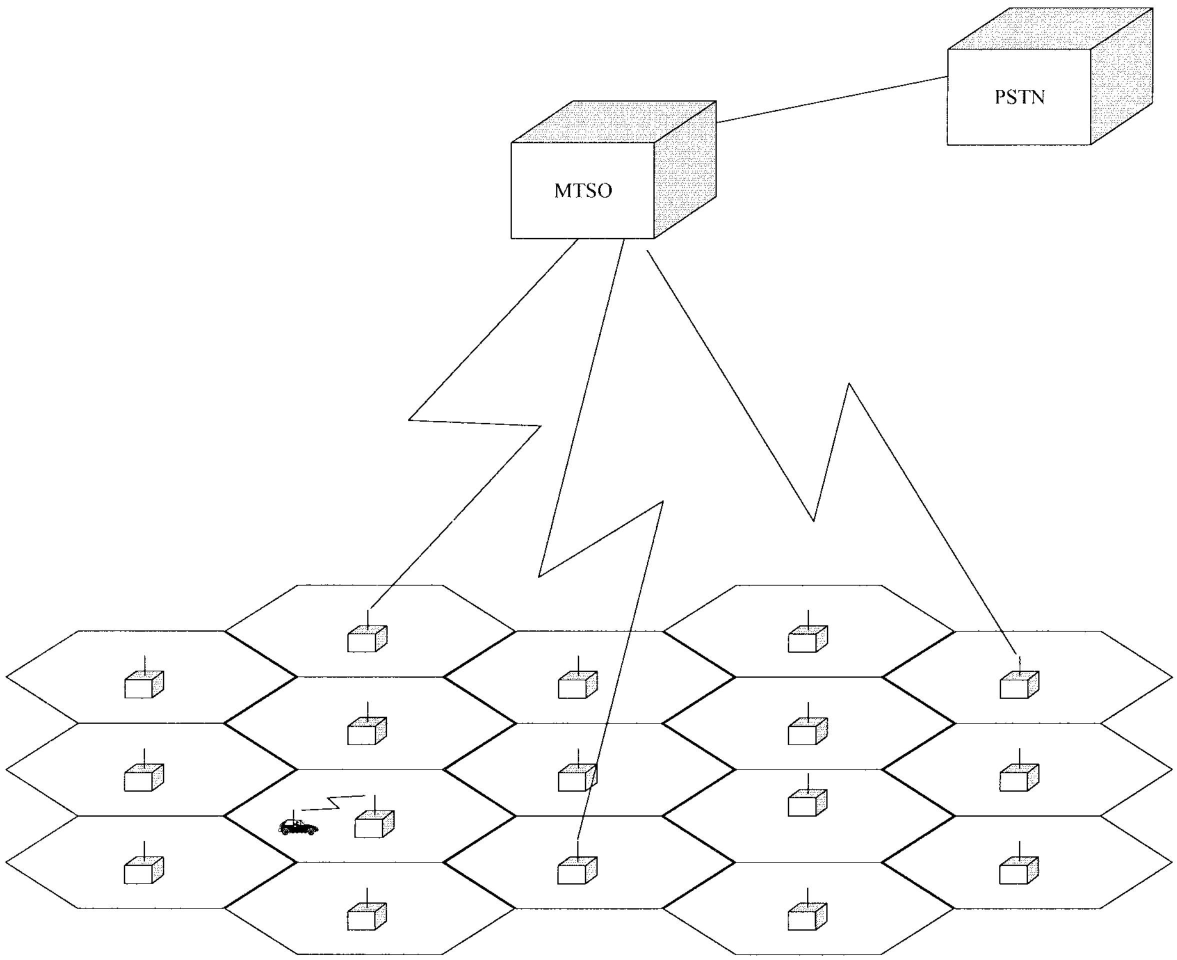

Fig. 5. A typical cellular system architecture.

simplicity without any loss of generality. The characteristics of the mobile system are as follows.

The topological model consists of 49 hexagonal cells that are arranged to form a parallelogram structure (Fig. 6). There are 70 channels available to the system, and each channel may serve only one call. In the case of FCA or BCA, these channels are distributed among the cells and each cell may use a maximum number of channels, which is much less than the number of channels of the system (70). In the DCA case, however, a cell may use any of the 70 channels as these are assigned dynamically. It is understood that if a cell uses all 70 channels at a given time then there will not be any channel available to its neighboring cells due to interference.

Cellular traffic is defined as the aggregate of mobile telephone calls over a group of channels with regard to the duration and the number of calls. Traffic flow or load is defined as the product of the number of calls during a specific period of time, and the average duration is known as call holding time. The number of calls is expressed in terms of the arrival rate (number of calls per unit time), and the average duration is expressed in terms of unit time per call [1]. Hence traffic load is given as the product of the mean arrival rate and the mean call duration and is measured in erlangs. The erlang, as a unit of traffic load, represents a radio channel being occupied continuously for duration of 1 h [25]. In our model, calls arrive

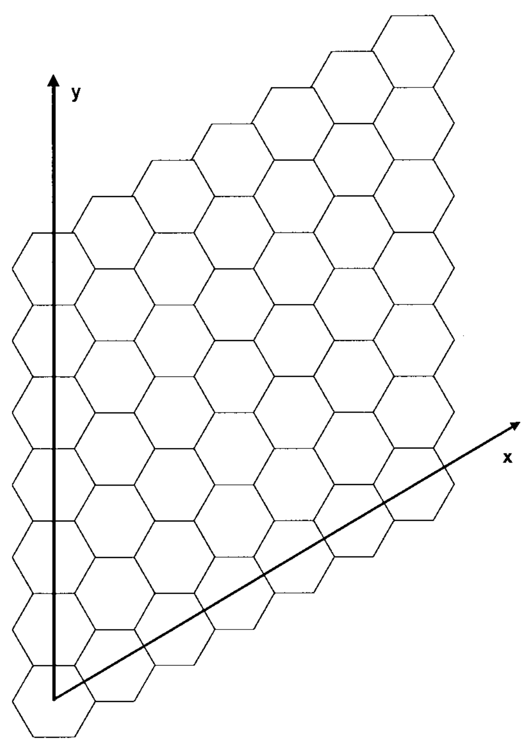

Fig. 6. Cellular topological model used in simulation.

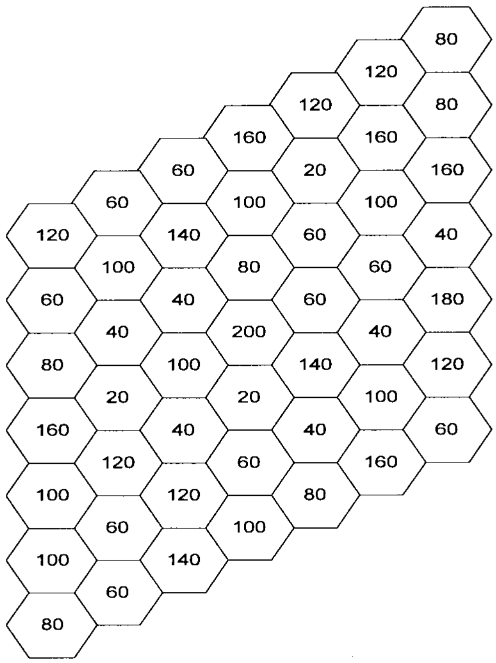

Fig. 7. Cellular nonuniform traffic distribution pattern 1. Numbers in cells express initial Poisson arrival rates (calls/h).

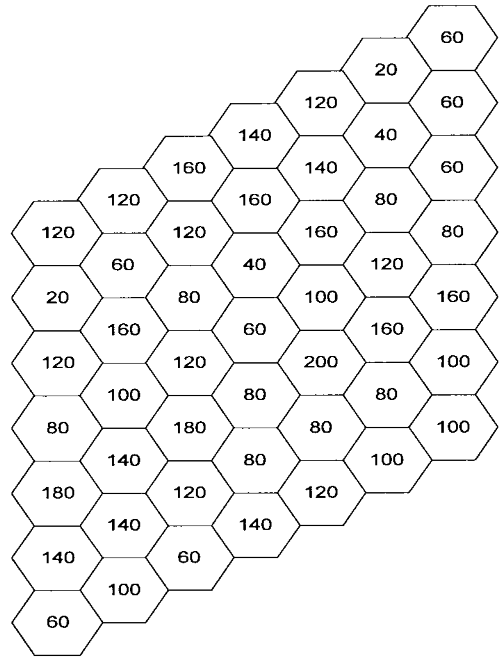

Fig. 8. Cellular nonuniform traffic distribution pattern 2. Numbers in cells express initial Poisson arrival rates (calls/h).

in cells using a Poisson process whereas the call duration is a random variable with exponential distribution of the form

$$f(x) = \begin{cases} b \exp^{-bx}, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (1)$$

where b is the mean duration time of calls [26].

In a cellular system the traffic may be equally distributed among cells (uniform traffic distribution) or not (nonuniform). In the uniform case, every cell has the same traffic load, whereas in the nonuniform case which better models real cellular systems, the load differs in every cell. For the nonuniform case we use the patterns in Figs. 7 and 8. These patterns have also been used in [24]. The numbers in the cells represent initial Poisson arrival rates (calls/h).

Incoming calls at each cell can be served by any of the system channels. In a cellular system, channels used at one cell site may be also used at other cell sites in case of absence of cochannel interference. Cochannel interference is the radio interference between channels using the same frequency. The total suppression of this kind of interference cannot be obtained in cellular systems because they use the frequency reuse concept [27]. Thus to obtain a tolerable value of cochannel interference, the system designer has to maintain a minimum separation distance (frequency reuse concept). Cells may only use the same channels if the distance of their centers is equal or multiple of this minimum distance (reuse distance). If this happens, cells are said to belong to the same reuse scheme. This reuse scheme is obtained by jumping from one cell to another in steps of length equal to the reuse distance [28]. The reuse distance used in this model is assumed to be three cell units [29] (see Fig. 9). For simplicity, other types of interference such as the adjacent channel interference is not taken into account. Their consideration in the model, however, is not a difficult process since they can be included in the energy function as extra terms and it can be shown

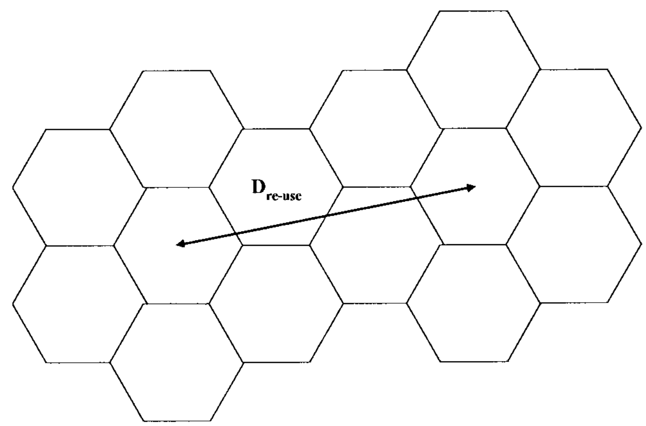

Fig. 9. Reuse distance used in the model. (Reproduced from Hac [29].)

that it results in raising the blocking probability curves of the corresponding channel allocation scheme.

By following the above assumptions, Zhang *et al.* [24] introduced three algorithmic channel schemes: the locally optimized dynamic assignment (LODA), the borrowing with channel ordering (BCO), and the borrowing with directional channel locking (BDCL). LODA is a DCA scheme that tries to optimize system performance by means of minimizing a cost criterion. In this scheme, channels are assigned so that the estimated blocking probability is minimized for future calls. BCO and BDCL are advanced channel-borrowing-based DCA strategies that lead to a more improved performance. A Hopfield neural network and a genetic-based DCA scheme provided in [15] and [16] are also considered. The performance of the channel allocation schemes has been derived in terms of the blocking probability for the incoming calls. The blocking probability is computed for the nine central cells. Simulation

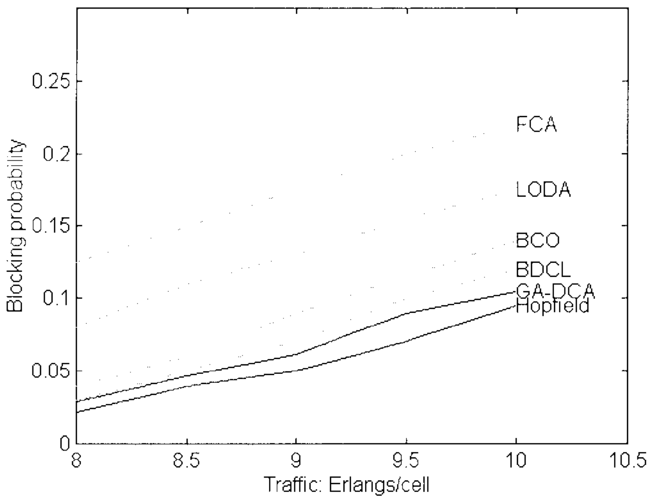

Fig. 10. Steady-state blocking probability performance of various competitive channel assignment schemes for the entire cellular network with uniform traffic distribution among cells.

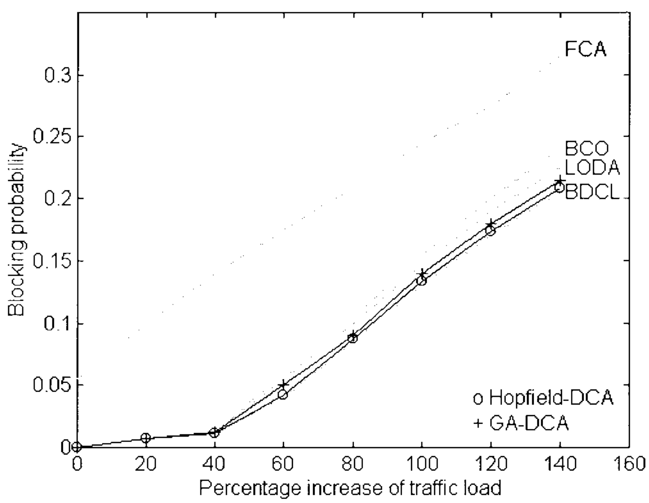

Fig. 11. Steady-state blocking probability performance of various competitive channel assignment schemes for the entire cellular network with nonuniform traffic distribution according to pattern 1 (Fig. 7). A percentage increase of traffic load implies that the traffic rates for all cells of pattern 1 are increased by a percentage with respect to the initial rates of the same cells.

results were obtained and are shown in Figs. 10–12 for the cases of uniform and nonuniform traffic load conditions. For nonuniform traffic cases, [15], [16], and [24] provide the performance of their proposed channel allocation techniques in relation with the percentage increase of the initial traffic Poisson arrival rates for each cell that are given in patterns 1 and 2 of Fig. 7 and 8, respectively.[1] Curves for theoretical FCA with erlang-B distribution are also provided for comparison.

To simulate the performance of CES-DCA, CES-BCA, and CES-HCA, the simulation has been implemented in MATLAB environment using a Pentium PC (100 MHz). For comparison

[1] Looking for example at Fig. 11, 20% load percentage increase implies that the traffic rates for all cells of pattern 1 in Fig. 7 are increased by 20% with respect to the initial rates for a given time duration. (For instance, an initial traffic rate 120 calls/h in a cell becomes now $120 + 120{*}20\% = 144$ calls/h.)

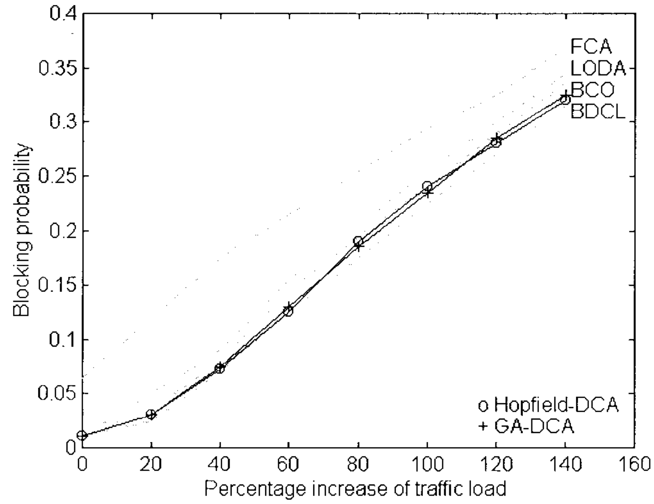

Fig. 12. Steady-state blocking probability performance of various competitive channel assignment schemes for the entire cellular network with nonuniform traffic distribution according to pattern 2 (Fig. 8). A percentage increase of traffic load implies that the traffic rates for all cells of pattern 2 are increased by a percentage with respect to the initial rates of the same cells.

with the available results in the literature based on the blocking probability, we had to derive results based on the same parameters. The term blocking probability is the ratio of the nonaccepted (blocked) calls to the total number of calls that arrive in the cellular system. After considering a large number of calls, this ratio, for a given traffic load,[2] converges to a limit. Hence the curves of the CES-based channel assignment techniques that are presented later show this steady-state blocking probability of the cellular system. According to our simulations, we have noticed that after 1000 incoming calls in the CES-DCA and CES-HCA and 800 calls in CES-BCA, for a given traffic load, in the cases of uniform and nonuniform traffic distributions, this ratio does not change significantly. Nevertheless, the curves in the schemes that are presented later are obtained after generating 1200 calls for a specific traffic load.

IV. CES-DCA Model

Dynamic channel assignment schemes provide many advantages, as explained before, compared to fixed channel methods and for that reason various deterministic DCA schemes have been proposed. The implementation complexity of the common deterministic DCA approaches together with the time requirement for their on-line operation, however, are two basic serious problems that led to the possible use of heuristics. In this section, CES is applied to a centralized DCA. A centralized DCA involves a single controller selecting a channel for each cell and normally results in a more efficient allocation than distributed DCA schemes which involve a number of controllers scattered across the network [30].

The general model described previously is used where the channel selection is subject to cochannel constraint. In

[2] In the case of uniform traffic distribution, the traffic load varies between 8–10 erlangs/cell (8, 8.5, 9, 9.5, 10) and in the case of nonuniform it is found according to the patterns of Figs. 7 and 8 (0, 20, 40, 60, 80. 100, 120, 140, and 160% increase of traffic load).

our formulation, when a call arrives to a particular cell, the calls that are being served by some channels (busy) are reassigned together with the assignment of the new call. Channel reassignment is an important operation in dynamic assignment schemes and improves the grade of service even more. By the reassignment we denote the process by which a call is transferred to a new channel without call interruption [31].

To better understand the meaning of reassignment, assume that we have a cellular system with nine cells and ten channels available to the whole system. Assume that a new call arrives at the seventh cell and that the state of this cell regarding the available channels is given by the following vector: (1 0 0 1 0 1 0 1 0 1). This means that the first, fourth, sixth, eighth, and tenth channels in that cell are busy. Hence the second, third, fifth, seventh, and ninth channels are free and may serve new calls. Now assume that the only proper channel, to not cause interference, is the fourth channel. If no reassignment occurs, the incoming call will obviously be blocked. If we reassign the calls that are being served to other channels, however, then there is a way the call in the fourth channel to be transferred to another channel without blockage. Hence, the fourth channel becomes free and may be now assigned to the new call. A possible vector after reassignment will now contains six busy channels and may be of the following form: (0 0 1 1 1 1 0 0 1 1) (the fourth channel is now dedicated to the incoming call). Hence, the process of reassignment of the calls that are being served, affects to a large extent the blocking probability of the incoming calls.

Reassignment of the calls that are being served takes place simultaneously with the assignment of the new call to new channels. The outcome of this process is to find proper combinations of channels every time a call arrives in order not to cause interference. The process of reassignment is difficult to be accomplished by algorithmic allocation methods due to the increased complexity. A proper use of CES may generate adequate solutions and cope with this problem. Rearranging channels in the whole cellular structure when a call arrives in a particular cell could obviously result in a lower blocking probability [31], but it is too time consuming to be practical. Therefore, only rearrangement in the cell involved in a new call arrival is considered [15].

The cochannel interference is a hard constraint. Other conditions that may improve the performance of the allocation technique and are considered as soft conditions are the packing, the resonance, and the limitation of rearranging operation. These conditions were introduced in [15] and are also used here. With the packing condition, the minimum number of channels is tried to be used every time a call arrives. This condition allows the use of channels that are already used in other cells without violating the cochannel constraint. If more choices are possible then channels used in adjacent cells are considered. The resonance condition assigns the same channels to cells that belong to the same reuse scheme. Finally, with the last condition, we try to restrict rearranging into acceptable levels by reassigning the same channels because excessive rearrangement may lead to undesirable results as far as the blocking probability is concerned.

The above four conditions may be expressed mathematically and formulated to constitute the following quadratic energy function:

$$E = \frac{A}{2} \cdot \sum_{j=1}^{CH} \sum_{\substack{i=1 \\ i \neq k}}^{CE} V_{k,j} \cdot A_{i,j} \cdot \mathrm{interf}(i,k) - \frac{B}{2} \cdot \sum_{j=1}^{CH} \sum_{\substack{i=1 \\ i \neq k}}^{CE} V_{k,j} \cdot A_{i,,j} \cdot \frac{(1-\mathrm{interf}(i,k))}{\mathrm{dist}(i,k)} + \frac{C}{2} \cdot \sum_{j=1}^{CH} \sum_{\substack{i=1 \\ i \neq k}}^{CE} V_{k,j} \cdot A_{i,j} \cdot (1-\mathrm{res}(i,k)) - \frac{D}{2} \cdot \sum_{j=1}^{CH} V_{k,j} \cdot A_{k,j} \tag{2}$$

whose minimization leads to an optimum solution. With the above formulation, DCA becomes a combinatorial optimization problem. In the above formula the following parameters are used.

CE	The number of cells (49).
CH	The number of channels allocated to a cell (70).
k	Cell where a call arrives.
$\boldsymbol{V}_k$	Output vector for cell k, with dimension CH (problem variable). $V_{k,j} = 1$ if channel j is assigned to cell k, otherwise $V_{k,j} = 0$.
$A_{i,j}$	The ijth element of the allocation table $\boldsymbol{A}$, which is one if channel j is assigned to cell i and zero otherwise $(i = 1, \ldots, CE, j = 1, \ldots, CH)$.
interf(i, k)	Function whose value is one if there is cochannel interference between cells i and k, otherwise zero.
dist(i, k)	The distance between cells i and k, normalized to the distance between the centers of two adjacent cells.
res(i, k)	Function whose value is one if cells i and k belong to the same reuse scheme, otherwise zero.

Equation (2) follows, in principle, the context of the formulation described in [15]. The first term expresses the hard condition. The energy function increases in case a channel j which is assigned in cell i is selected by cell k that interferes with i. The packing condition is expressed by the second term. The energy decreases if channel j assigned to cell i is also selected by cell k and $\mathrm{interf}(i, k) = 0$. Energy reduction depends on the distance between i and k. The third term corresponds to the resonance condition as it can be easily verified whereas the fourth term decreases the value of the energy function if the actual assignment is equal to the previous one.

A, B, C, and D are positive constants that may be varied by the designer and determine the significance of the respective terms. In our case $A = 10$, $B = 3$, $C = 1$, and $D = 2$. When a call arrives, the CES-DCA algorithm finds a vector $\boldsymbol{V}_k$ that minimizes the energy function. This vector contains suggested channels to be used by the existing calls that are being served (reassignment) and the new call (new allocation). If any of the busy channels of vector $\boldsymbol{V}_k$ lead to possible cochannel

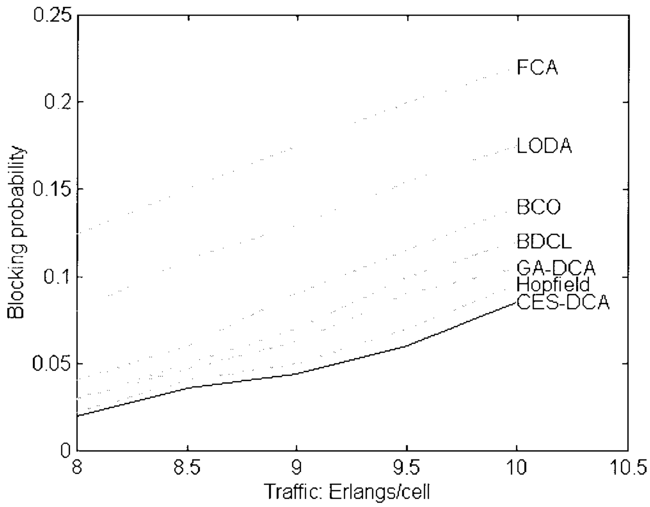

Fig. 13. Steady-state blocking probability performance of CES-DCA for the entire cellular network with uniform traffic distribution among cells and comparison with other channel allocation schemes.

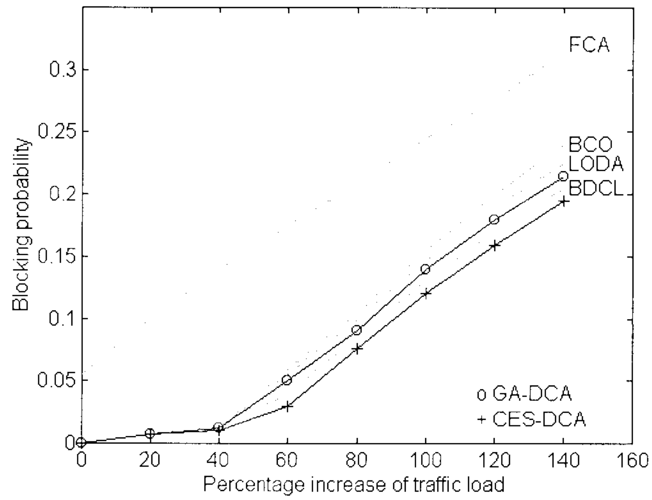

Fig. 14. Steady-state blocking probability performance of CES-DCA for the entire cellular network with nonuniform traffic distribution according to pattern 1 (Fig. 7) and comparison with other channel allocation schemes. A percentage increase of traffic load implies that the traffic rates for all cells of pattern 1 are increased by a percentage with respect to the initial rates of the same cells.

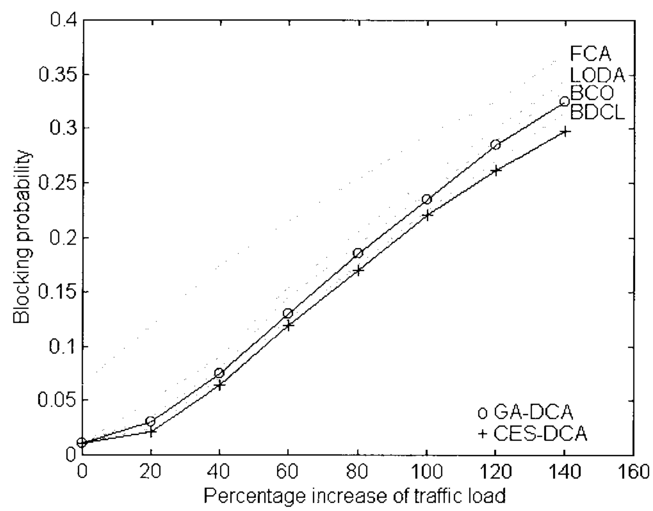

Fig. 15. Steady-state blocking probability performance of CES-DCA for the entire cellular network with nonuniform traffic distribution according to pattern 2 (Fig. 8) and comparison with other channel allocation schemes. A percentage increase of traffic load implies that the traffic rates for all cells of pattern 2 are increased by a percentage with respect to the initial rates of the same cells.

interference, $\boldsymbol{V}_k$ is rejected, the calls that are being served are not reassigned and the incoming call is blocked.

The specific form of CES shown in Fig. 1 was used. Individuals are considered to be vectors of binary digits. These vectors represent a cell where calls are referred to. The bit values represent channels. If a bit is one the channel in this cell is occupied and if zero the channel is free. The number of bits in a vector is equal to the total number of channels. The optimization criterion (fitness function) is the energy function described above. Swapping is chosen to affect primarily busy channels, as it is not useful in free ones. The number of active "genes" in an individual, which also represents the number of busy channels, is initialized to be equal to the requested number of channels of cell k. Since swapping does not affect this number, CES always produces a vector with the adequate number of active channels in cell and hence the population does not contain infeasible solutions. The population contains possible combinations of channels to be used for allocation in the cell where a call arrives. Population size is fixed to 50 individuals. The process stops when the destabilization process occurs for second time. It must be noted that the maximum number of the counter is set to ten. By increasing it, it is possible to achieve better results but this is less important compared to the increased call service time that is also introduced.

The curves for CES-DCA, similar to the channel assignment curves used also by other authors, are shown in Figs. 13–15. For the model used, CES-DCA produces the lowest blocking probability compared to the other schemes. A reader may perhaps observe that the differences in blocking probability performance are small but we must point out that in a study of channel assignment even a small decrease in blocking probability is important for the reliability of a cellular system. Comparing CES-DCA with GA-DCA [16], CES-DCA gives superior performance, is faster as the search is set to terminate when destabilization occurs for the second time, in contrast to the GA approach where the search is terminated after a prespecified number of generations, and moreover the population does not contain infeasible solutions as in the GA-DCA due to the effect of genetic crossover primarily and genetic mutation secondly [32]. A proper comparison of CES including the number of energy function evaluations is not available since from all of the channel assignment schemes studied only the Hopfield-DCA and the GA-DCA work as function evaluation minimizers. The cost function for these two schemes differs from ours, however, as it contains an extra term which controls the avoidance of infeasible solutions that these two heuristics, in contrast to CES, may generate. More details about the CES-DCA scheme are given in [33].

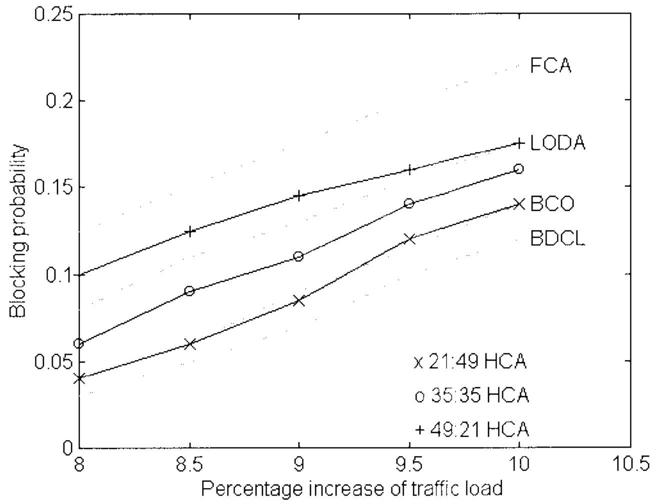

Fig. 16. Steady-state blocking probability performance of CES-HCA for the entire cellular network with uniform traffic distribution among cells and comparison with other channel allocation schemes.

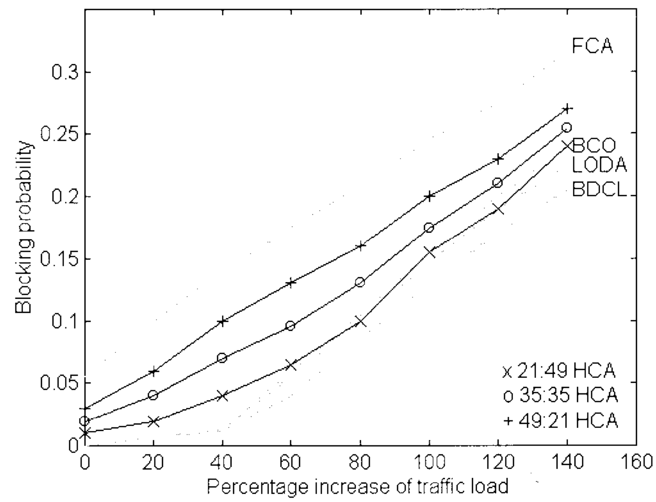

Fig. 17. Steady-state locking probability performance of CES-HCA for the entire cellular network with nonuniform traffic distribution according to pattern 1 (Fig. 7) and comparison with other channel allocation schemes. A percentage increase of traffic load implies that the traffic rates for all cells of pattern 1 are increased by a percentage with respect to the initial rates of the same cells.

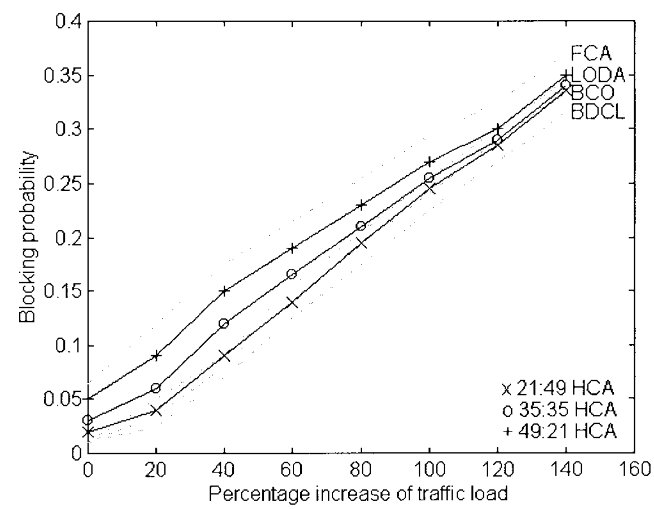

Fig. 18. Steady-state blocking probability performance of CES-HCA for the entire cellular network with nonuniform traffic distribution according to pattern 2 (Fig. 8) and comparison with other channel allocation schemes. A percentage increase of traffic load implies that the traffic rates for all cells of pattern 2 are increased by a percentage with respect to the initial rates of the same cells.

V. CES-HCA MODEL

As previously mentioned, the FCA is a simple channel assignment technique in the sense that it requires a moderate amount of base-station equipment but it cannot attain a high efficiency of total channel usage over the whole service area if the traffic varies dynamically from cell to cell. On the other hand, the DCA exploits the limited frequency spectrum more efficiently but requires more elaborate control for channel assignment operations, which becomes evident in practical cellular networks [34]. HCA was proposed in [35] to combine the advantages of FCA and DCA. In this scheme, channels are divided into two subsets, A and B. The channel set A contains channels that are used in the system employing the FCA scheme whereas the set B contains those channels that can be used in any cell in the system employing the DCA technique. The ratio A : B is set *a priori* by the cellular network designer.

Here, the model assumptions mentioned previously were followed and the following representative ratios were used: 35 : 35, 49 : 21, and 21 : 49. In all cases, whenever a call arrives to a random cell, the cellular system tries to serve it randomly from a set of fixed allocated channels. If no channel from set A is available then the DCA process using CES, which determines a suitable channel from set B, takes place. The same characteristics for CES presented in previous are also valid. Simulation results are shown in Figs. 16–18 [36].

According to our simulations the 21 : 49 scheme produces better results in comparison with 35 : 35 and 49 : 21, respectively. Keeping in mind, however, that the selection of fixed channels to serve calls is a predetermined process, rather than the dynamic one that uses the CES-method for allocation, the 49 : 21 scheme is obviously more time efficient. Hence, for a specific cellular network the proper HCA-scheme may be used according to designer's primary interests in blocking probability or time performance.

VI. CES-BCA MODEL

BCA was developed to increase the performance of FCA. In the simple BCA, a channel set is nominally assigned to each cell. When all fixed channels become busy, the cell borrows channels from adjacent cells under the condition of no interference. Otherwise, the call is blocked. When a channel is borrowed, several other cells are prohibited from using that channel. However the process of finding the proper channel to be borrowed, is usually performed randomly [3], [34].

The effectiveness of the simple BCA is enhanced by the proper use of the CES technique. The proposed heuristic BCA is studied using the general cellular model of Section III and its basic features are as follows [37].

At first, channels are nominally allocated to each cell using the basic principles of fixed channel assignment. By taking into account that the channel reuse distance is three cell units, each cell may use ten nominal channels from the total 70, and of course the same channels may be used again in cells that belong to the same reuse scheme.

When a call arrives to a random cell, the cellular system tries to serve it with a nominally allocated channel which is chosen randomly. In case that all nominal channels are busy then a neighboring cell is chosen. This cell is chosen to be the one with the smallest number of busy channels. After finding the proper neighboring cell, the borrowing channel process starts. When a channel is borrowed by a cell (say k) from a cell (say μ), there is an increased possibility the same channel will be used by cells that belong to the reuse scheme of μ and interfere with cell k. Hence, a proper channel must be borrowed. In many cases, the optimum channel that avoids the occurrence of interference may be busy. For this purpose rearrangement of channels is taken into account. The choice of channels from the cell μ can be made according to an energy function that has the following form:

$$\frac{A}{2}\sum_{\substack{i=1\\ i\neq\mu\\ i\neq k}}^{CE}\sum_{j=1}^{CH} V_{\mu j}\cdot \mathrm{res}(\mu, i)\cdot \mathrm{interf}(i, k)\cdot A_{ij} - \frac{B}{2}\sum_{j=1}^{CH} V_{\mu j}\cdot A_{\mu j} \tag{3}$$

where

- CE: the number of cells (49) in the model;
- CH: the number of channels (10) allocated to a cell;
- k: cell involved in a new arrival of a call;
- μ: cell that is selected to lend channels;
- $A_{i,j}$, V_{μ}, $\mathrm{interf}(i, k)$, $\mathrm{res}(i, \mu)$: the same quantities used also in formula (2).

A and B are constant parameters that bias the respective terms. The first term increases the energy function if:

a) channel j from cell μ is selected to be assigned in k;
b) cell k is subject to cochannel interference with cell $i\,(\mathrm{interf}(i, k) = 1)$;
c) cell i belongs to the reuse scheme of cell μ;
d) cell i uses channel j.

The second term simply lowers the value of the energy function limiting the rearranging process effect.

The output of the optimization process is a vector $\boldsymbol{V}_{\mu}$ of channels. Channels are reassigned, and one of them that does not lead to interference is borrowed by cell k from μ. If such channel does not exist then the call is blocked. The following parameter set was chosen $A = 7$, $B = 2$.

As in the previous heuristic allocation schemes, individuals are considered to be vectors of binary digits that correspond to the cell that has to lend channels. The number of bits in a vector is equal to the number CH of channels used in a cell. The number of active genes is initialized to be equal with the requested number of channels of cell μ. As the number of channels that a cell serves $(CH = 10)$ is now sufficiently smaller than the corresponding number in previous heuristic allocation techniques (CES-DCA, CES-HCA), smaller values for the parameters of CES are required. Hence, the population number is fixed to ten, the maximum number of the counter

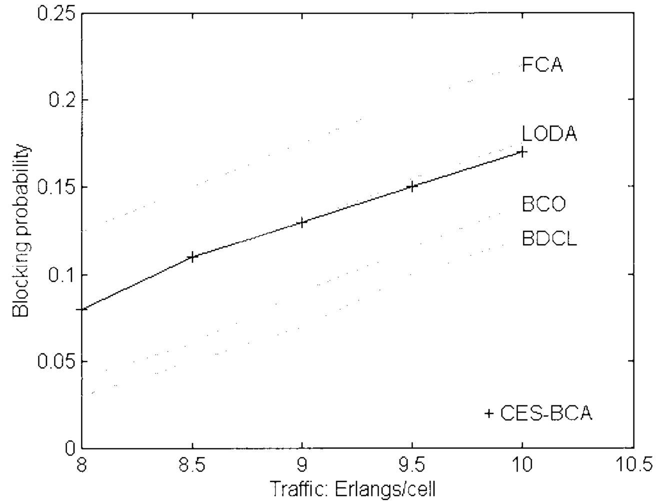

Fig. 19. Steady-state blocking probability performance of CES-BCA for the entire cellular network with uniform traffic distribution among cells and comparison with other channel allocation schemes.

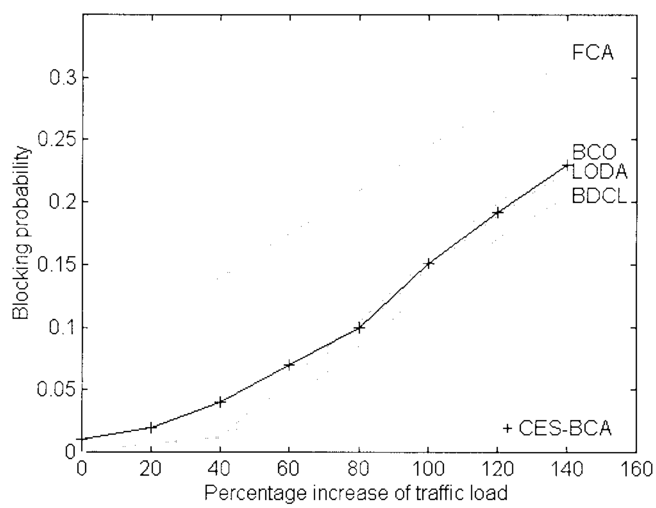

Fig. 20. Steady-state blocking probability performance of CES-BCA for the entire cellular network with nonuniform traffic distribution according to pattern 1 (Fig. 7) and comparison with other channel allocation schemes. A percentage increase of traffic load implies that the traffic rates for all cells of pattern 1 are increased by a percentage with respect to the initial rates of the same cells.

is set to seven, and the process stops when destabilization process occurs for second time.

Simulation results are shown in Figs. 19–21. The blocking probability performance of CES-BCA, though a static approach, is comparable to that of advanced algorithmic schemes.

VII. Discussion and Directions for Further Research

Channel assignment is an interesting topic of research. Many studies published in the literature suggest new allocation schemes or improvements of some well-established methods such as FCA or DCA in respect of blocking probability mainly. Research in this area has shown that the blocking probability

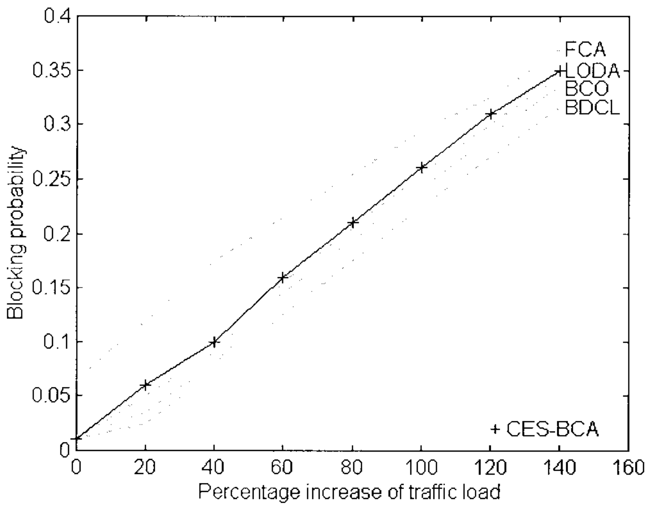

Fig. 21. Steady-state blocking probability performance of CES-BCA for the entire cellular network with nonuniform traffic distribution according to pattern 2 (Fig. 8) and comparison with other channel allocation schemes. A percentage increase of traffic load implies that the traffic rates for all cells of pattern 2 are increased by a percentage with respect to the initial rates of the same cells.

of an incoming call of a general allocation scheme in a cellular system is improved if we simultaneously consider the concept of reassignment of existing calls that are being served in the system. Rearranging existing calls as soon as a call arrives is a time consuming process for an allocation scheme implemented deterministically [30]. Heuristic methods solve this problem sufficiently by viewing it as a combinatorial one. We have seen in the case of DCA, every time a call arrives CES-DCA produces a vector containing channels for servicing the existing and the incoming calls, whereas in the BCA approach, the optimum channel to be borrowed is found after rearrangement of channels in the selected lending cell. The greatest advantage for using heuristics is that they handle reallocation of existing calls and allocation of new ones as a unified process.

Because of the different mechanisms used by resource management methods to perform channel allocations (some consider only allocation of incoming calls, others view them as optimization problems, etc.), researchers in mobile areas view allocation techniques as “black boxes.” Therefore, they are primarily interested in the outcome of the process and the proper performance index for this is the blocking probability of calls.

Our study modeled three channel allocation schemes, namely the DCA, HCA, and BCA, as combinatorial problems and used a powerful heuristic to perform channel resource management. In contrast to other heuristics, CES has the advantage of producing reliable results by exploring the search space provided by a particularly small number of generations efficiently. This is because only one parent in each generation produces a significant number of feasible offspring (50 offspring in each generation for DCA and HCA and ten for BCA). Hence with a small number of generations, it is more likely to find an acceptable solution in comparison with other heuristics and especially other EA’s such as GA’s where acceptable solutions are obtained after a great number of generations (e.g., 100 or 200). For this reason it is a good alternative method that may be used for on-line problems such as DCA.

TABLE I
CHARACTERISTICS FOR CES-DCA PER EACH DYNAMIC ALLOCATION

Population size	50
Number of genes per individual	70
Destabilization counter	10
Worst number of generations	69
Best number of generations	21
Average number of generations	45
Average number of fitness evaluations	2250

According to our simulations to a commonly accepted ideal cellular model, CES-DCA shows to have the best performance in comparison with some other allocation schemes such as LODA and BDCL. Moreover, CES-DCA assigns channels dynamically and therefore is a full on-line process. In our model, vectors (individuals) of 70 channels (genes) are generated. Partial dynamic schemes such as HCA or static such as BCA even though they provide worse performance, as far as blocking probability is concerned, they can serve calls more rapidly. This is due to the nature of their allocation mechanisms. Therefore, heuristic implementations such as CES-HCA and CES-BCA are also proposed. In the partial dynamic allocation of the 21 : 49, 35 : 35, and 49 : 21 CES-HCA schemes, vectors of 49, 35, and 21 channels are generated, whereas in BCA, we have vectors of ten channels. Hence, the complexity of an allocation process is decreased dramatically compared to vectors of 70 channels in CES-DCA. For these reasons CES-BCA and CES-HCA are sufficient candidates for the present cellular networks, whereas CES-DCA may be used in small or future cellular systems where the use of fast controllers would compensate the loss in time performance. Tables I–V summarize the characteristics and provide some statistics for comparison of the CES-based allocation schemes.

As the use of heuristic methods in telecommunications and particularly in resource management has been growing rapidly over recent years, there is much more work to be done as these methods are applied in the area of channel resource management. Further research should have the following indicative directions.

- The appropriate modeling of resource management problems and their investigation through heuristic methods is an area of open research. Thus it will be interesting to formulate well-known centralized or decentralized allocation schemes for macrocellular systems such as LODA or BDCL as combinatorial problems and investigate their performance using heuristic techniques.

TABLE II
CHARACTERISTICS FOR 21:49 CES-HCA PER EACH DYNAMIC ALLOCATION

Population size	50
Number of genes per individual	49
Destabilization counter	10
Worst number of generations	51
Best number of generations	21
Average number of generations	33
Average number of fitness evaluations	1650

TABLE III
CHARACTERISTICS FOR 35:35 CES-HCA PER EACH DYNAMIC ALLOCATION

Population size	50
Number of genes per individual	35
Destabilization counter	10
Worst number of generations	46
Best number of generations	21
Average number of generations	27
Average number of fitness evaluations	1350

TABLE IV
CHARACTERISTICS FOR 49:21 CES-HCA PER EACH DYNAMIC ALLOCATION

Population size	50
Number of genes per individual	21
Destabilization counter	10
Worst number of generations	39
Best number of generations	21
Average number of generations	23
Average number of fitness evaluations	1150

TABLE V
CHARACTERISTICS FOR CES-BCA PER EACH BORROWING ALLOCATION

Population size	10
Number of genes per individual	10
Destabilization counter	7
Worst number of generations	22
Best number of generations	15
Average number of generations	17
Average number of fitness evaluations	170

- The use of advanced heuristic techniques is worth investigating. The CES is found to be a suitable technique but the field of EA's is growing day by day. Recent research has shown that the combination of EA's with other general-purpose heuristics such as neural networks is leading to more advanced optimization strategies and a possible application of such an approach to channel assignment is a worthwhile topic.
- The application of CES to models where traffic load conditions are changed dynamically is important to examine the robustness of the method.
- The implementation of a CES operating in a parallel machine which would minimize call service time sufficiently or otherwise would maximize the effectiveness of the particular channel assignment algorithm is also very challenging.
- The hardware implementation of a CES-based controller and its use in practical cellular environments including urban, suburban, and rural territories with real conditions could lead to a set of new products in cellular systems.

VIII. CONCLUSIONS

The use of the CES as a global heuristic approach for solving combinatorial problems was introduced in [18] and [19] and was verified through its adaptation in solving three classic representative channel allocation strategies: the DCA, the HCA, and the BCA. By viewing the above schemes as combinatorial problems, their complexity is simplified and the allocation process becomes an optimization task for which the CES is able to give adequate solutions which can easily be implemented. Curves for the CES-DCA, the CES-HCA, and the CES-BCA have been generated and compared with representative channel allocation techniques in terms of blocking probability for uniform and nonuniform traffic distribution environments. The CES-DCA was found to be the most effective channel allocation scheme. Since the CES-HCA and the CES-BCA are also comparable to advanced dynamic allocation strategies such as LODA, however, they may also be used as effective channel allocation schemes because their partial static channel assignments lead to more time efficient operation than CES-DCA.

ACKNOWLEDGMENT

The authors would like to thank D. B. Fogel and the anonymous referees for the valuable comments, which improved readability of the manuscript.

REFERENCES

[1] A. Mehrotra, *Cellular Radio. Analog and Digital Systems.* Norwood, MA: Artech House, 1994.
[2] W. C. Jakes, *Microwave Mobile Communication.* New York: Wiley, 1974.
[3] W. C. Y. Lee, *Mobile Cellular Telecommunications Systems.* New York: McGraw-Hill, 1989.
[4] K. Okada and F. Kubota, "On dynamic channel assignment in cellular mobile radio systems," in *Proc. IEEE Int. Symp. CAS,* 1991, pp. 938–941.
[5] R. C. V Macario, *Cellular Radio: Principles and Design,* 2nd ed. New York: Macmillan, 1997.
[6] M. Duque-Anton, D. Kunz, and B. Ruber, "Channel assignment for cellular radio using simulated annealing," *IEEE Trans. Veh. Technol.,* vol. 42, pp. 14–21, Feb. 1993.
[7] D. J. Castelino, S. Hurley, and N. M. Stephens, "A tabu search algorithm for frequency assignment," *Ann. Oper. Res.,* vol. 63, pp. 301–319, 1996.
[8] D. Kunz, "Channel assignment for cellular radio using neural networks," *IEEE Trans. Veh. Technol.,* vol. 40, pp. 188–193, Feb. 1991.
[9] N. Funabiki and Y. Takefuji, "A neural network parallel algorithm for channel assignment problems in cellular radio networks," *IEEE Trans. Veh. Technol.,* vol. 41, pp. 430–437, Nov. 1992.
[10] M. Cuppini, "A genetic algorithm for channel assignment problems," *European Trans. Telecom. Rel. Techn.,* vol. 5, pp. 285–294, 1994.
[11] K. Lai and G. G. Coghill, "Channel assignment through evolutionary optimization," *IEEE Trans. Veh. Technol.,* vol. 45, pp. 91–96, Feb. 1996.
[12] R. Dorne and J. K. Hao, "Constraint handling in evolutionary search: A case study of the frequency assignment," in *Proc. Problem Solving from Nature—PPSN IV,* H. M Voigt, W. Ebeling, I. Rechenberg, and H.-P. Schwefel, Eds. Berlin, Germany: Springer, 1996, pp. 801–810.
[13] P. T. H. Chan, M. Palaniswami, and D. Everitt, "Neural network-based dynamic channel assignment for cellular mobile communication systems," *IEEE Trans. Veh. Technol.,* vol. 43, pp. 279–288, May 1994.
[14] K. Nakano, M. Yokono, M. Sengoku, Y. Yamaguchi, S. Shinoda, S. Motooka, and T. Abe, "An application of dynamic channel assignment to a part of a service area of a cellular mobile communication system," *IEICE Trans. Fundamentals,* vol. 75, pp. 369–379, Mar. 1992.
[15] E. Del Re, R. Fantacci, and L. Ronga, "A dynamic channel allocation technique based on Hopfield neural networks," *IEEE Trans. Veh. Technol.,* vol. 45, pp. 26–32, Feb. 1996.
[16] H. G. Sandalidis, P. P. Stavroulakis, and J. Rodriguez-Tellez, "Implementation of genetic algorithms to a channel assignment problem in cellular communications," in *Proc. 6th Int. Conf. Advances in Communications and Control (COMCON 6),* June 1997, pp. 453–460.
[17] P. Mars, J. R. Chen, and R. Nambiar, in *Learning Algorithms: Theory and Applications in Signal Processing, Control, and Communications.* Boca Raton, FL: CRC, 1996.
[18] V. A. Nissen, "A new efficient evolutionary algorithm for the quadratic assignment problem," in *Operations Research Proc. Papers 21st Annual Meeting of DGOR in Co-operation with OGOR,* 1993, pp. 259–267.
[19] ——, "Solving the quadratic assignment problem with clues from nature," *IEEE Trans. Neural Networks,* vol. 5, pp. 66–72, 1994.
[20] T. Bäck, *Evolutionary Algorithms in Theory and Practice.* Oxford, U.K.: Oxford Univ. Press, 1996.
[21] T. Bäck, U. Hammel, and H. P. Schwefel, "Evolutionary computation: Comments on the history and current state," *IEEE Trans. Evol. Comput.,* vol. 1, pp. 3–17, Apr. 1997.
[22] Z. Michalewicz, *Genetic Algorithms + Data Structures = Evolution Programs,* 3rd ed. New York: Springer-Verlag, 1996.
[23] Y.-Z. Lu, *Industrial Intelligent Control, Fundamentals and Applications.* New York: Wiley, 1996.
[24] M. Zhang and T.-P. Yum, "Comparisons of channel assignment strategies in cellular mobile telephone systems," *IEEE Trans. Veh. Technol.,* vol. 38, pp. 211–215, Nov. 1989.
[25] J. Bellamy, *Digital Telephony.* New York: Wiley, 1991.
[26] M. C. Jeruchim, P. Balaban, and K. S. Shanmugan, *Simulation of Communication Systems.* New York: Plenum, 1992.
[27] A. Mehrotra, *Cellular Radio Performance Engineering.* Norwood, MA: Artech House, 1994.
[28] W. C. Y. Lee, *Mobile Communications Design Fundamentals.* Wiley, 1993.
[29] A. Hac, "Cellular network model with hand off delays," in *Proc. IEEE Int. Conf. Communications ICC,* 1995, pp. 1834–1838.
[30] G. Stuber, *Principles of Mobile Communication.* Norwell, MA: Kluwer, 1996.
[31] P.-A. Raymond, "Performance analysis of cellular networks," *IEEE Trans. Commun.,* vol. 39, pp. 1787–1793, Dec. 1991.
[32] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning.* Reading, MA: Addison-Wesley, 1989.
[33] H. G. Sandalidis, P. P. Stavroulakis, and J. Rodriguez-Tellez, "Combinatorial evolution strategy-based implementation of dynamic channel assignment in cellular communications," in *Proc. 6th IEE Int. Conf. Telecommunications,* 1998, pp. 170–174.
[34] D. E. Everitt, "Traffic engineering of the radio interface for cellular mobile networks," *Proc. IEEE,* vol. 82, pp. 1371–1382, Sept. 1994.
[35] T. J. Kahwa and N. D. Georganas, "A hybrid channel assignment scheme in large-scale, cellular-structured mobile communication systems," *IEEE Trans. Commun.,* vol. COM-26, pp. 432–438, Feb. 1978.
[36] H. G. Sandalidis, P. P. Stavroulakis, and J. Rodriguez-Tellez, "Simulation and performance of a heuristic channel assignment model in cellular system," in *Proc. ICT'98 Int. Conf. Telecommunications,* 1998, pp. 247–251.
[37] ——, "Borrowing channel assignment strategy using computational intelligence methods," in *Proc. 48th Annu. Vehicular Conference, IEEE VTC'98,* 1998, pp. 1685–1689.

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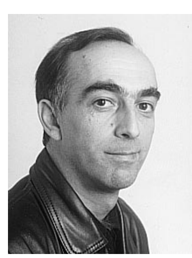
Dr. Stavroulakis is the Founder of the Telecommunication Systems Institute of Crete.



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