Comparison of neural network applications for channel assignment in cellular TDMA networks and dynamically sectored PCS networks

William S. Hortos
Comparison of Neural Network Applications for Channel Assignment in Cellular TDMA Networks and Dynamically Sectored PCS Networks

William S. Hortos
Florida Institute of Technology
Orlando Graduate Center
3165 McCrory Place, Suite 161
Orlando, Florida 32803

ABSTRACT

The use of artificial neural networks (NNs) to address the channel assignment problem (CAP) for cellular time-division multiple access (TDMA) and code-division multiple access (CDMA) networks has previously been investigated by this author and many others. The investigations to date have been based on a hexagonal cell structure established by omnidirectional antennas at the base stations. No account was taken of the use of spatial isolation enabled by directional antennas to reduce interference between mobiles. Any reduction in interference translates into increased capacity and consequently alters the performance of the NNs.

Previous studies have sought to improve the performance of Hopfield-Tank network algorithms and self-organizing feature map (SOFM) algorithms applied primarily to static channel assignment (SCA) for cellular networks that handle uniformly distributed, stationary traffic in each cell for a single type of service. The resulting algorithms minimize energy functions representing interference constraint and ad hoc conditions that promote convergence to optimal solutions. While the structures of the derived neural network algorithms (NNAs) offer the potential advantages of inherent parallelism and adaptability to changing system conditions, this potential has yet to be fulfilled in emerging mobile networks.

The next-generation communication infrastructures must accommodate dynamic operating conditions. Macrocell topologies are being refined to microcells and picocells that can be dynamically sectored by adaptively controlled, directional antennas and programmable transceivers. These networks must support the time-varying demands for personal communication services (PCS) that simultaneously carry voice, data and video and, thus, require new dynamic channel assignment (DCA) algorithms.

This paper examines the impact of dynamic cell sectoring and geometric conditioning on NNAs developed for SCA in omnicell networks with stationary traffic to improve the metrics of convergence rate and call blocking. Genetic algorithms (GAs) are also considered in PCS networks as a means to overcome the known weakness of Hopfield NNAs in determining global minima. The resulting GAs for DCA in PCS networks are compared to improved DCA algorithms based on Hopfield NNs for stationary cellular networks. Algorithm performance is compared on the basis of rate of convergence, blocking probability, analytic complexity, and parametric sensitivity to transient traffic demands and channel interference.

Keywords: Hopfield neural networks, genetic algorithms, cellular radio, personal communication services (PCS), dynamic sectoring.

1. INTRODUCTION

Reliable connectivity of wireless nodes is critical to the throughput and capacity of mobile telecommunication networks. In a personal communication services (PCS) network in order to locate a portable to establish a call, the operator has to assign available channels to radio cells in an spectrally efficient scheme such that the probability of both portable and base station carrier-to-interference ratios exceeding a specified threshold is high. Knowledge of the radio frequency (RF) propagation profile, calculated from the topography and local human infrastructure, is used in conjunction with estimated
spatial densities of caller traffic, to determine interference conditions under which radio cells can simultaneously use the same channel or adjacent channels. Traffic estimates can be used to determine lower bounds to the required number of channels to satisfy network demand.

The channel assignment problem (CAP) is the allocation of the required number of channels to each cell to meet traffic demands subject to interference conditions. Other technical conditions, e.g., on the number of combiners and code spacing, may be considered as well. In its simplest form, when only co-channel interference (CCI) is included, the CAP is known to be equivalent to a graph coloring problem. Since this problem is NP-complete\textsuperscript{1,2}, an exact search for the best solution is impractical due to the exponentially increasing number of computations. While algorithms have been proposed to solve this problem\textsuperscript{1-8}, most are based on a sequential channel assignment according to a heuristic ranking of the local difficulty of the CAP. The sequential nature of these methods is a disadvantage; if several local areas of computational intensity have to be treated in sequence, the connection between them may be too great to allow them to be treated in parallel.

Algorithms for the solution of NP-complete optimization problems, such as, the traveling salesman problem, have been proposed, based on the construction of a neural network (NN)\textsuperscript{9-12}. The use of NNs for a cellular mobile radio system was first presented by Posner\textsuperscript{13}, and by Rauch\textsuperscript{14} for a packet radio network in 1985. Other recent work by Mathar and Mattfeldt\textsuperscript{15} apply simulated annealing methods to the CAP for cellular networks. These applications focus on uniform network structures for TDMA and FDMA access schemes. In 1991 Kunz\textsuperscript{16} proposed the first Hopfield NN model for solving static channel assignment (SCA) in cellular networks using frequency assignment. Kunz did not consider the adjacent channel constraint (ACC) and limited the co-site constraint (CSC) on the minimum separation distance between any two frequencies assigned to a radio cell to 2. The Kunz NNA uses a slow sigmoid function and a decay term in the motion equation in the Hopfield-Tank model, which slows the convergence of the NN under some conditions\textsuperscript{17}. Moreover, the Kunz model requires \textit{ad hoc} modification of the weights in the motion equation for each application, while careful gain control of the sigmoid function has to be provided to obtain valid solutions.

Recently, Del Re, Fantacci and Ronga\textsuperscript{18} have refined the Hopfield NN approach to improve convergence for dynamic channel assignment (DCA) in networks composed of hexagonal cells with stationary traffic. Chan, Palaniswami and Everitt have addressed DCA in similar networks using multilayered feedforward NNs and the Kohonen vector quantizer\textsuperscript{19}. Smith and Palaniswami\textsuperscript{12} have just published a conceptual approach to DCA using a self-organizing NN based on a generalization of Kohonen's SOFM, but do not evaluate its computational limitations in real-time control.

The present work offers Hopfield NN models modified with a reduced number of fixed interference constraints and auxiliary conditions on the coefficients in the energy function to ensure hill-climbing on the hypercube of feasible solutions and avoid spurious states. A non-uniform iteration step size, suggested by S. Abe\textsuperscript{20} for Hopfield NNs, is used to speed convergence of the DCA to more than twice the rates reported by Del Re, \textit{et. al.}. In addition, the effects of dynamically sectored cells on interference thresholds, and, hence, on algorithm performance are considered.

Prior investigations of the NN approach to the CAP have assumed the cellular coverage area is divided into hexagonal cells. Each cell is established by an omnidirectional antenna at the base station in the cell's center. Such cells are termed "omnicells." Each mobile or portable unit requires a channel to communicate with the base station of the cell closest to the unit in propagation distance. The term "channel" refers here to a generic communication resource that can alternately be a frequency in a specified RF band for FDMA, a code for CDMA, or a time slot for TDMA. The same channel can be used simultaneously in different cells provided it is used at a minimum separation distance, d. This minimum distance between cells is a function of the level of CCI required to meet carrier-to-interference specifications for reliable communication.

In addition to omnicell structures, the present work considers networks of sectored cells, enabled by directional antennas at the base stations. This topology has been proposed for next-generation PCS networks. The sectors dynamically partition each base station's coverage area to adapt to the changing spatial traffic distribution and propagation anomalies as well as to mitigate RF interference among the portables.
Channel assignment to network cells can be static (FCA) or dynamic (DCA) \(^{21}\). In FCA a set of channels is permanently assigned to each cell. Thus, a neural approach to FCA need not emphasize rapid convergence over absolute minimization of the energy function. The same set of channels is reused in cells at a distance \(d\) away. FCA also implies that a new call generated in a cell can only be served by an available channel in the set of channels permanently assigned to that cell. If no channel is available, the call is blocked and lost. The number of channels, \(m\), permanently allocated to each cell in an omnicell topology is \(m = M/r\), where \(M\) is the total number of available channels and \(r\) is the reuse factor \(^{22}\). Examples of omnicells and sectored cells are shown in Figure 1.

![Diagram](image)

**Figure 1.** (a) The \(d/R\) relationship and (b) typical hexagonal cell structure superposed with sectored cells

In contrast to FCA, DCA does not permanently assign channels to the cells, but on a call-by-call basis in order to achieve improved network capacity and spectral utilization. DCA is thus well suited to non-uniform and time-varying traffic demands. However, DCA schemes are difficult to realize physically even in networks of modest size, since they require central controller to know the location of all assigned channels with active calls in order to reassign new channels to ongoing calls or allocate free channels to new cells. When a new call arrives or a handoff call requests a new channel in a new cell, the network controller searches through the available communication resources for a channel that satisfies the channel reuse constraints. This search is able to achieve an increase in traffic-carrying capacity, which is critical to PCS systems in areas of dense traffic. The effect of dynamic cell sectoring on the channel reuse factor is discussed in Section 3.

DCA algorithms usually try to pack assigned channels as closely as possible to optimize spectral efficiency. An ideal DCA algorithm should always assign the minimum number of channels to serve as many calls as possible. This may require channel rearrangement on a global basis so that a new call is only blocked if there is no possible reallocation of channels to calls in progress. Genetic algorithms (GAs), known to provide convergence to global minima, are considered in Section 3 for SCA and DCA.

Prevailing NN research of the CAP has viewed network constraints as “hard”, i.e., not to be violated, or “soft”, i.e., selectively satisfied, to minimize the energy function. Constraint thresholds have been assumed fixed \(^{16, 18}\). This view is extended here to networks of sectored cells. Adaptive dynamic cell sectoring allows variable interference thresholds that can improve minimization of the energy function and lead to faster convergence of the resulting DCA algorithms.

2. **ADAPTIVE NEURAL NETWORK MODELS**

2.1 **Hopfield Neural Networks**

Channel assignment algorithms using NNs were first based on the Hopfield model. The general model for each neuron in the network is taken from work by Hopfield and Tank \(^{9}\). The internal state of each neuron \(i\) given by a time-dependent
scalar \( u_i(t) \), the state at equilibrium is assumed to be 0. The output of each neuron \( V_i \) is a fixed function \( f \) of the internal state, that is, \( V_i = f(u_i) \). In general, \( f \), the sigmoid function, may be selected from the set of continuous, bounded, monotonic functions. Selecting \( f \) as the function

\[
f(u) = \frac{1}{2} \left( 1 + \tanh(\alpha u) \right), \quad \alpha \text{ constant.} \tag{1a}
\]

allows interpretation of \( \alpha \) as the temperature or entropy of the system for which the energy is to be minimized. Delays between the internal state and output can be assumed negligible. Generalizing a piecewise-linear approximation to (1a) \(^{18, 23}\), a more robust \( f \) is a saturation function to restrict the internal state between two values, \( \alpha_{\text{min}} \) and \( \alpha_{\text{max}} \) with \( \alpha_{\text{min}} < \alpha_{\text{max}} \):

\[
f(u) = \begin{cases} 
\alpha_{\text{min}} & \text{if } u < \alpha_{\text{min}}, \\
\alpha_{\text{max}} & \text{if } u > \alpha_{\text{max}}, \\
u & \text{otherwise.}
\end{cases} \tag{1b}
\]

The rate of change of the internal state of each neuron is given by the sum of the input from other neurons of the network and from external sources, and of the negative of the internal state, that is, by the differential equation

\[
\frac{du_i(t)}{dt} = \sum_j w_{ij} V_j(t) + I_i(t) - u_i(t). \tag{2}
\]

where \( w_{ij} \) represents the coupling weights between the internal state \( u_i \) and the output \( V_j \), while \( I_i \) is the external input to neuron \( i \). Equation (2) says that \( u_i \) is given as a weighted sum of internal and external inputs, followed by a first-order lowpass filter in the time domain. If we let \( \lambda \) be the time constant, the solution to (2) takes the form

\[
u_i(t) = \int \left( \sum_j w_{ij} V_j(t) + I_i(t) \right) e^{-\lambda(t-t')} dt'. \tag{3}
\]

Equation (2) is simplified by assuming weights \( w_{ij} \) are symmetric, \( w_{ij} = w_{ji} \), and external inputs to the neurons are constant.

Under these assumptions, an energy function \( E \) is defined as

\[
E = -\frac{1}{2}\sum_i \sum_j w_{ij} V_i(t)V_j(t) - \sum_i I_i(t)V_i(t). \tag{4}
\]

Hopfield has shown that for \( \alpha \) sufficiently large, \( E \) approximates a function \( \hat{E} \) that decreases monotonically subject to (2) and is bounded from below \(^{11}\). Therefore, the neural system converges to a stable state in which \( E \) is sufficiently close to a global minimum. The energy function \( E \) represents the distance between the current state of the neural network and the solution state of the network. The function \( E \) is determined by considering all constraints in the given problem. The goal of the neural network model for solving combinatorial optimization problems such as the CAP is to minimize the energy.

The following generic procedure is used to solve the resulting discrete optimization problem:

1. A set of variables taking only the values 0 and 1 are defined. These represent possible solutions to the problem. A variable is assigned to each neuron. Thus, optimization takes place in a hypercube in \( n \)-dimensional space.
2. The optimization criteria are used to construct an energy function \( E \), as in (4).
3. From \( E \) the coupling weights \( w_{ij} \) and the external inputs \( I_i \) are derived.
4. The differential equations (2) describing the internal states of the neurons are solved from an arbitrary initial state. The parameter \( \alpha \) is selected in (1) such that each neuron outputs a 0 or 1 at equilibrium.
5. The result is interpreted in the context of the model.

These steps are applied to the CAP in Section 3.

### 2.2 Genetic Algorithms

GAs are based on an analogy with nature as are neural networks \(^{24}\). The concept of the GA is that the combination of good characteristics or genes from different ancestors can produce offspring with superior fitness to the new environments compared to the fitness of either parent. In this way, species can evolve to become increasingly better suited to their
environments. As global optimization techniques, GAs avoid some of the limitations exhibited by local search methods in difficult search spaces. The conventional approach to DCA using NNs has been to rely on sequential heuristic methods or parallel distributed methods. GAs offer advantages of implicit parallelism coupled with the ability to exploit accumulating information about the search space. In their purest form, GAs are blind search procedures. As such, their convergence can be slow. They use only the genetic coding and associated fitness value of individuals to determine plausible trials in the next generation. GAs belong to the class of stochastic search techniques that operate on a population of individuals to produce better adaptation using a set of genetic operators. They have been shown to do this even with the most basic set of operators.

A GA is an iterative procedure that maintains a set of candidate solutions called a population $P(t)$ for each iteration $t$. At each iteration a new population $P(t+1)$ is created from the previous population $P(t)$ using a set of genetic operators. A population consists of possible candidate solutions called “strings” $s_p$, $1 \leq p \leq P$, where $P$ is the population size. A population can be represented by an array of strings (individuals). For the CAP, the rows of the array represent strings in a population, and the columns represent the channel numbers to be assigned. There are $P$ strings for a population and each string has $T$ calls, the total number of calls in the system, i.e., $T$ is the sum of the number of calls in all cells. A string $s_p$ is composed of $N$ substrings where $N$ is the number of radio cells. Each substring $s_{p,i}$ associated with cell $i$ is composed of $t_i$ calls allocated to that cell. A $P \times T$ two-dimensional array is constructed from a population of strings. Each string represents one particular channel assignment for all cells. The length of each string in the population is the same and will not change during the assignment procedure, unless total traffic demand is time-varying.

The basic genetic operators of selection, crossover, and mutation are the means by which the GA explores the entire search space. The fitness function assigns a value to each individual (string). Through this value the string’s probability of survival is indirectly determined. New strings are produced by randomly selecting any two existing strings as parents usually with a bias toward those strings with a higher fitness, and constructing an offspring from parts of the genetic code of those parents. The genetic operators and objective function of the GA for the CAP are constructed in Section 3.

3. APPLICATIONS TO CELLULAR NETWORKS

3.1 Capacity, Interference, and Sectored Cells

In cellular telephone and PCS networks, CDMA exploits voice activity and spatial isolation to improve system capacity, since its capacity is only interference limited. In both TDMA and FDMA, capacity is also bandwidth limited. Any interference reduction for these multi-access schemes is converted directly into increased capacity. FDMA and TDMA use a frequency reuse pattern to try to increase system capacity. The most widely used is a pattern of seven cells. CDMA, on the other hand, reuses the same frequency for all cells by means of orthogonal codes, which yields a large gain in reuse efficiency. Spatial isolation, based on directional antennas, reduces interference, providing a further increase in capacity.

FDMA and TDMA systems implement frequency reuse to improve spectral efficiency. If two co-channel cells (cells using same channel) can be placed closer, then the same frequency (channel) can be used more frequently in a geographic area. Thus, the number of available frequency channels can support greater traffic, and both system capacity and spectral efficiency are increased. To reduce the minimum separation distance $d$ between two co-channel cells, the power of each cell must be restricted to cover only one of the many local zones in a cell, provided the base station controller has sufficient information to know in which local zone the mobile unit or PCS portable is located. The power transmitted from the cell’s base station to the mobile is then confined to a small area around it. Thus, CCI is reduced and system capacity increases.

In a channel reuse system, such as a cellular telephone or PCS network, the term “radio capacity” is used to measure traffic capacity. The radio capacity $m$ is defined by Lee as

$$m = \frac{M}{r} \quad \text{number of channels/cells (for omnicells)}$$

or

$$m = \frac{M}{r \times S} \quad \text{number of channels/sector (for sectored cells)}$$

(5)

(6)
where $M$ is the total number of (frequency) channels, $r$ is the cell reuse factor, and $S$ is the number of sectors. The reuse factor $r$ can be expressed as

$$r = \frac{(d/R)^2}{3}. \quad (7)$$

d is the co-channel cell separation, that is, the minimum distance, and $R$ is the cell radius as shown in Figure 1(a). The relationship between the carrier-to-interference ratio ($C/I$) and $d/R$ can be expressed as

$$C/I = \frac{(d/R)}{6}. \quad (8)$$

Equation (8) is based on the propagation path loss of 40 dB/decade and omnicells. The radio capacity of omnicell systems, namely, those systems traditionally considered when NN approaches are applied to the CAP, is

$$m = \frac{M}{\sqrt{\frac{2}{3} \left(\frac{C}{I}\right)}} \quad \text{channels/cell.} \quad (9)$$

Any other parameters can be derived from the radio capacity such as Erlangs/cell, Erlangs/km$^2$, cells/km$^2$, etc. The normalized radio capacity is defined as:

$$\tilde{m} = \frac{m}{B_T} \quad \text{channel/cell/spectral band} \quad (10)$$

where $B_T$ is the total spectral bandwidth. When two systems operate in two different spectral bands of length $B_{T_1}$ and $B_{T_2}$, then the radio capacities $m_1$ and $m_2$ are first normalized using (10) as $m_1/B_{T_1}$ and $m_2/B_{T_2}$ before comparing their capacities.

The total number of channels, $M$, is fixed, while $r$ is a variable number that depends on the co-channel separation $d$. However, because of channel reuse, more active traffic channels, i.e., channels with calls in progress, are generated. For example, if one frequency channel is used 50 times, then the number of traffic channels generated is effectively $50M$. Based on an $r = 7$ system, the number of cells needed is $50 \times 7 = 350$ cells. The capacity, $m = M/7$, is measured by the number of frequency channels per cell, which is determined by the cell reuse factor $r$ only, not by the number of total cells in the system. Radio capacity $m$ increases if $r$ is reduced provided that voice quality and data integrity specifications are met.

Power-delivery intelligent cell concepts have been proposed for FDMA and TDMA networks to improve radio capacity by controlling intercell and intracell interference. Two categories of such intelligent cells are considered: zone-divided cells and adaptive antenna arrays. In turn, there are three types of zone-divided cell concepts: sectored cells, intelligent microcells, and reuse of sector beams with directional antennas.

Sectored cells are used to reduce interference. They are typically employed when the natural terrain and/or human infrastructure in the cells vary greatly leading to unevenly distributed interference from other cells. Two common examples of sectored cells are shown in Figure 1(b): a seven-cell/three-sector reuse system ($r = 7$, $S = 3$) and a four-cell/six-sector reuse system ($r = 4$, $S = 6$). Each sector has a separate set of designated channels. The portable moving from one sector or one cell to another sector or cell requires an intracell handoff. The sectored cell approach can alternately be viewed as enlarging the number of network cells or lowering the minimum separation distance.

Based on a cluster of either $r = 7$ cells or $r = 4$ cells, the radio capacities of these two systems are:

$$m_1 = \frac{M}{7 \times 3} = \frac{M}{21} \quad \text{channels/sector} \quad \text{(for a cellular system of } r = 7 \text{ and } S = 3)$$

$$m_2 = \frac{M}{4 \times 6} = \frac{M}{24} \quad \text{channels/sector} \quad \text{(for a cellular system of } r = 7 \text{ and } S = 6)$$

Sectored cells with intracell handoffs do not increase radio capacity, but CCI can be reduced in each case of Figure 1(b):

$$C/I = \frac{R^4}{(d + 0.7R)^4 + d^4} = 285 \quad \text{(24.5 dB)} \quad \text{(for } r = 7, S = 3)$$
\[ \frac{C/I}{d + R} = \frac{R^4}{(d + R)^3} = 395 \text{ (26 dB)} \quad (\text{for } r = 4, S = 6) \]

The computations are again based on the path loss rule of 40 dB/dec. Since only one or two co-channel interfering sectors are affected as shown in Figure 1, the C/I ratio will improve by 7-8 dB over the C/I = 18 dB for an \( r = 7 \) omnicell AMPS system.

**Intelligent microcells** are created when a cell is divided into many subcells or zones as shown in Figure 2. The base station controller must know which subcell the portable is in and deliver the signal to that subcell. When the portable has been assigned a channel for a call, the channel is always associated with that cell and within the cell. The base station controller merely turns on the new subcell while the portable is entering and turns off the old subcell when it leaves. In the process the channel assigned to the portable remains unchanged. In this configuration, one can determine C/I at the portable based on a scenario of having six co-channel interferers at the first tier surrounding the center cell as shown in Figure 3. The desired portable is assumed to be in the subcell of the center cell. There are three interfering subcells, labeled A, and three interfering subcells, labeled B, each in each interfering cell where six interfering mobile units could be located. This is a worst-case scenario as shown in Figure 2. In this case, the voice quality should be maintained at the stated requirement of C/I \( \geq 18 \) dB in each subcell, or the co-channel subcell separation \( d_i \) should be larger than the subcell radius \( R_1 \) by a factor of 4.6, i.e., \( d_i/R_1 = 4.6 \). Based on the six worst interfering subcells, one in each cell, with their minimum \( d_i/R_1 = 4.6 \), the resulting C/I received by the desired portable is approximately

\[
\frac{C/I}{3(4.6R_1)^4} + 3(6R_1)^4} \]

\[ \approx 100 \text{ (20 dB)} \quad \text{(worst case)} \]  
(11)

The average C/I received by the desired portable unit can be calculated by taking the probability of the event that each interfering portable unit is located in one of the three subcells of an interfering cell. Thus,

\[
\frac{C/I}{3(4.6R_1)^4} + 3(6R_1)^4} + (1/3)[2(4.6R_1)^4 + (6R_1)^4] + (1/3)[4(6.5R_1)^4 + 2(8R_1)^4] + (1/3)[6.5R_1)^4 + 2(8R_1)^4]\]

\[ = 193.4 \text{ (22.8 dB)} \quad \text{(average case)} \]  
(12)

From (12) the average C/I nearly equals 23 dB, 5 dB better than the specification for AMPS voice quality. By maintaining the subcell ratio \( d_i/R_1 = 4.6 \) in Figure 3, the co-channel cell separation \( d = 3R \). From (7) the reuse value is then \( r = 3 \).

---

**Figure 2.** Intelligent microcell capacity application.  
**Figure 3.** Six effective interfering cells of center cell.
Reuse of sector beams with directional antennas is another zone-divided-cell concept in which antenna beams are used to restrict the energy to individual mobile or portable units in the cell. In an \( r = 7 \) cellular system, each cell has a set of \( M/r \) channels. At a cell site, if six directional antennas are used to cover 360° in that cell and if the entire set of channels assigned to the cell are divided into two subsets which alternate from sector to sector, then there are three co-channel sectors using each subset in a cell. This configuration, shown in Figure 4, can increase the capacity threefold. If \( S \) sector beams are reused alternately, the capacity is increased by \( S/2 \) times the AMPS omnicell capacity. The reuse of sector beams can be applied to a small-cell system, such as a PCS network, or a large-cell system deployed in a uniform terrain with much less reduction in trunking efficiency.

Adaptive antenna arrays are an alternative to zone-divided-cell methods. With these arrays the antenna pattern can be formed by tracking the portable or mobile unit and nulling the interference. Consequently, if the same frequency channel can be used by \( S \) mobile units in a cell, the radio capacity is increased \( S \)-fold. Furthermore, since an adaptive antenna array is used, the antenna beam is able to follow the mobile unit thereby reducing interference. The reuse factor is lowered from \( r = 7 \) to a smaller value depending on the number \( S \). If \( S \) is large, the \( S \) antenna beams operating at the same frequency to service \( S \) users within a cell can be treated as if they are collectively from an omnidirectional antenna. In this case, \( r = 7 \) remains the same. If \( S \) is restricted to a 120° sector, the the AMPS value \( C/I = 18 \text{ dB} \) can be used to determine the \( d/R \) ratio. Since there are only two interfering cells as shown in Figure 1(b), the \( C/I \) is approximately

\[
C/I = \frac{R^4}{2d^4} = 63 \ (18 \text{ dB}).
\]  

(13)

Solving (13) yields \( d/R = (126)^{1/4} = 3.35 \). The value of \( r \) obtained from (7) is 3.74. Since the adaptive antenna beam follows the portable units, CCI is reduced. Hence, when sectorization is used, a system with reuse factor of \( r = 4 \) is realized.

Adaptive antenna patterns also provide a good method of generating multiple co-channel mobile calls on the reverse links. With identical antenna patterns, the calls are then conducted on the forward links as well. This is due to the reciprocity principle based on Lee’s Model \(^{28}\). The active region around the mobile unit has a radius of approximately 100-200 wavelengths \(^{29}\). The beam angle \( \alpha \) received at the cell site is a function of distance \( R \) as shown in Figure 5:

\[
\alpha = \frac{2 \times 200\lambda}{R}
\]  

(14)

where \( \lambda \) is the wavelength. As radio operation is usually in the UHF band, the beamwidth \( \theta \) is always larger than \( \alpha \). Thus, the isolation between the two co-channel mobile calls will be measured by \( \theta \) not \( \alpha \). Moreover, the definition of the antenna

---

**Figure 4. Reuse of sector beams with directional antennas**

**Figure 5. Intelligent cell with adaptive antenna-array beams.**
beamwidth is not based on the typical 3-dB beamwidth, but on an 18-dB beamwidth. When two co-channel units move closer within one \(\theta\) angle, a handoff is initiated.

3.2 Models of Interference Constraints, Traffic Demands, and Rule-based Conditions

The following conditions summarize the primary interference constraints for most cellular telephone and PCS networks:

1. The co-channel constraint (CCC) is that the same channel cannot be assigned simultaneously to certain pairs of radio cells. The CCC is determined by CCI, which, in turn, can depend on the degree of cell sectorization employed.

2. The adjacent channel constraint (ACC) is that channels adjacent in their domain’s distance metric (frequency, time or code) cannot be assigned to adjacent cells simultaneously. The ACC is related directly to the reuse factor \(r\).

3. The co-site channel constraint (CSC) is that any pair of channels assigned to a radio cell must be at a minimum distance in their domain. This distance may depend on the number of sectors used in the cells.

In a network with \(N\) base stations, each base station establishes a radio cell capable of carrying any of the \(M\) channels available to the entire system. The interference constraints are described by an \(N \times N\) symmetric matrix, called the interference matrix \(C\). Each off-diagonal element \(c_{ij}\) in \(C\) represents the minimum separation channel distance between a channel assigned to cell (or sector) \(i\) and a channel assigned to cell (or sector) \(j\). The CCC is represented by \(c_{ii} = 1\), while the ACC is represented by \(c_{ii} = 2\). Setting \(c_{ij} = 0\) indicates that cells (sectors) \(i\) and \(j\) are allowed to use the same channel. Each diagonal element \(c_{ii}\) in \(C\) represents the minimum separation distance between any two channels assigned to cell (sector) \(i\). This is the CSC and \(c_{ii} \geq 1\) is always satisfied, provided that, in dynamically sectored networks, sectors are considered equivalent to cells. If they are not, one could consider \(c_{ii} = 0\).

The traffic demand for channels in each cell of an \(N\)-cell network is represented by an \(N\)-vector called the traffic demand vector \(T\). Each component \(t_{ji}\) of \(T\) is the number of active channels (new calls and handoffs) to be assigned to cell \(j\). Let \(q_{ki}\) denote the \(k\)th active channel assigned to cell \(i\). Then the interference constraints can expressed as the set of inequalities

\[
|q_{ki} - q_{kj}| \geq c_{ji}, \text{ for } i \neq j, \ 1 \leq i, j \leq N; \ k \neq l, \ 1 \leq k, l \leq t_{ji}, \ 1 \leq t_{ji} \leq t_{ij}.
\]

To model dynamic operating conditions the entries in \(C\) and \(T\) can be considered time-varying, leading to DCA problems with transient traffic demands \(t_{ji}(\tau)\) and interference thresholds \(c_{ji}(\tau)\). As another extension of the model, a \(N\)-vector of cell-sector variables, denoted \(S(T) = [s_i(T), \ 1 \leq i \leq N]\), can be introduced to control the interference constraint thresholds \(c_{ji}(s_i(T))\) as a function of the sectoring at cell \(i\). The sectoring could adaptively respond to time-varying caller demands. In this manner, CCI as discussed above could be controlled to handle transients in the local traffic load.

Since simultaneous use of the same channel in two interfering cells (sectors) is not possible, the interference conditions cannot be violated and may be considered “hard.” Whenever the channel selected by the assignment algorithm does not satisfy these constraints, the corresponding service request or new call is blocked. For this reason, the call blocking probability is a reasonable performance metric for a DCA algorithm.

On the other hand, there are other, primarily rule-based, constraints on network operation that can be violated at the expense of an increase in the energy function to stabilize algorithm performance. These constraints may be considered “soft.” Two proposed soft constraints are the packing constraint and the resonance constraint \(^{18}\). The packing constraint favors assignments that minimize the total number of channels used to satisfy global traffic demand. While this may be important when one system shares the communication resource with another competing network, in general, the number of available channels is fixed and regulated. In this case, global demand could be more efficiently met with methods like cell sectorization. The packing constraint prefers channels already in use in other cells, without violating any hard constraints. If more choices are possible, channels used in the nearest cells are considered. The resonance condition prefers assigning the same channels to cells that belong to the same reuse scheme. The channel assignments are thus obtained by jumping from one cell to another in steps equal to the reuse distance \(r\). These “rule-based” constraints may lead to an optimal assignment in networks with traffic uniformly distributed among the cells. This case does not hold for PCS traffic dynamics in urban areas. However, it has been claimed that, even with non-homogeneous traffic, the two constraints appear to improve convergence \(^{18}\). Another soft constraint limits intracell rearranging by assigning, where possible, the same
channels assigned in the last iteration to each cell. This rule can work in static or slowly varying networks. Unfortunately, none of these rule-based conditions appear to model a suitable response to the known behavior of traffic and interference in dynamic networks. Thus, these conditions are not directly incorporated in this work into the Hopfield NN and GA models.

3.3 Optimization Criteria for Channel Assignment

The CAP is seen to be equivalent to global assignment using the number of available channels to meet the traffic load given by \( T \) while satisfying the constraints determined by \( C \) as well as any auxiliary rule-based conditions. There are variations of the generic optimization problem. If the total number of channels \( M \) is allowed to vary, then one version of the CAP would determine the minimum number of channels required for an interference-free assignment, while completely meeting the traffic demand. If \( M \) is fixed, another version would minimize call blocking, that is, attempt to meet traffic demands, while always satisfying the interference constraints. A third version is based on dynamic sectoring of the cells. For \( M \) again fixed, the number of sectors in each cell is allowed to vary, which is equivalent to letting \( N \) vary, to meet transient traffic demands. This last version also changes the dimensions of the interference matrix \( C \) and possibly the values of the \( c_{ij} \) of the new matrix. An alternative to the third version is to consider both \( M \) and \( N \) fixed and let the dynamic sectoring of the cells change the values of the interference constraints \( c_{ij} \) directly. The last three variations of the CAP are encompassed by the following development.

In actual networks the number of operations required to assign a channel to a newly arriving call is limited. It is assumed that the rearranging operations are local, that is, they must be carried out only in those cells with a new call. Raymond proposed a channel assignment algorithm that reallocates the channels in the entire network at the arrival of every new call. This technique lowers the blocking probability, while it increases implementation complexity. Raymond’s approach highlights a weakness in the original Hopfield NNs for determination of global minima; this is conversely a strength of GAs. Since blocking probability is useful performance metric for DCA algorithms in dynamic networks, global channel assignment is preferred over local assignment here.

3.4 Hopfield Neural Network Representations

A two-dimensional modification of the Hopfield NN model given by (2)-(4) can now be applied to the CAP. A total of \( N M \) processing elements is needed to solve an \( N \)-cell by \( M \)-channel problem. The output of the \( j \)th processing element \( V_{ij} \) indicates if channel \( j \) is assigned to cell (sector) \( i \): \( V_{ij} = 1 \) indicates that channel \( j \) is assigned to cell (sector) \( i \), while \( V_{ij} = 0 \) indicates that it is not assigned to cell (sector) \( i \). In order to meet the traffic demand requirements, a total of \( t_i \) neurons from among \( M \) neurons (channels) for cell \( i \) must have nonzero output, because a total of \( t_i \) calls must be assigned to cell \( i \):

\[
\sum_{j=1}^{M} V_{ij} = t_i
\]

is zero if and only if \( t_i \) neurons for cell \( i \) have nonzero output. For the CSC, if channel \( k \) is within distance \( c_{ik} \) from channel \( j \) and is assigned to cell \( i \), then channel \( j \) must not be assigned to cell \( i \). Thus, the term

\[
\sum_{k=j-1}^{j+1} \sum_{1 \leq k \leq m} V_{ik}
\]

is nonzero if the assignment of channel \( j \) to cell \( i \) violates the co-site constraint.

In the CCC and ACC, if channel \( k \), within the distance \( c_{ik} \) from channel \( j \), is assigned to cell \( t \) for \( c_{ik} > 0 \) and \( t \neq i \), channel \( j \) must not be assigned to cell \( i \), so that the term

\[
\sum_{t=1}^{N} \sum_{k=j-1}^{j+1} \sum_{1 \leq k \leq m} V_{itk}
\]

when \( c_{ik} > 0 \) and \( t \neq i \).
is nonzero if the assignment of channel \( j \) to cell \( i \) violates the co-channel or the adjacent channel constraints.

The general procedure based on the Hopfield NN approach is followed for the CAP. The set of neurons \( V_y \) is initialized at a state within the unit hypercube. Coupling weights and external inputs are established in terms of the entries of the interference matrix \( C \) and traffic demand vector \( T \). In the customary approach the NN is simulated until it attains a steady state or the simulation time elapses, whichever event comes first. The parameter values are chosen so that the final output of each neuron \( V_y \) is either its maximum or minimum value. An output of the neuron \( (i, j) \), \( V_y \), close to the maximum value of 1, is interpreted as a call’s access to channel \( j \) at base station \( i \). While this interpretation allows a "soft decision" on the channel assignment, conditions on the internal dynamics and coefficients of the energy function for the CAP can be provided to ensure convergence to values of 0 or 1 at the vertices of the unit hypercube.

CCI is represented by the action of each neuron \( (i, j) \) to inhibit neurons of the same channel \( j \) and cell \( i' \). Co-site interference is represented by the action of each neuron \( (i, j) \) to inhibit neurons of cell \( i \) and adjacent channels \( j' \) such that \( |j - j'| \leq c_{ij} \), for some integer \( c_{ij} \geq 0 \). The number of channels assigned is controlled by the action of each neuron \( (i, j) \) to inhibit all neurons of the same cell \( i \); each neuron \( (i, j) \) receives an external input in proportion to traffic demand at cell \( i \). The indicator functions for channel interference are:

\[
J_{ij}(x) = \begin{cases} 
1, & \text{if channels } j, j' \text{ interfere by violating } x, \text{i.e., } |j - j'| < x; \\
0, & \text{otherwise.}
\end{cases}
\]  

(15)

In the Hopfield NN formulation of (2)-(4), double-indexed coupling weights \( w_{ij},j' \), corresponding to \( w_{ij} \), are given by

\[
w_{ij,j'} = -A \delta_{ij} - B \delta_{ij} (c_{ij}) - B |1 - \delta_{ij} (c_{ij})|
\]  

(16)

and the external inputs to each neuron \( (i, j) \) are \( I_i = A t_i \) and an optional forced assignment term

\[
\tilde{I}_i = A \sum_{i=1}^{M} V_{ik} - t_i
\]  

(17)

where and \( A \) and \( B \) are nonnegative coefficients on the demand and interference conditions of the CAP, respectively, and

\[
\delta_{ij} = \begin{cases} 
1, & \text{if } i = j \\
0, & \text{otherwise.}
\end{cases}
\]

Thus, the internal state \( u_{ij} \) can be expressed in terms of (16) and (17):

\[
u_{ij} = \sum_{i=1}^{N} \sum_{j=1}^{M} w_{ij,j'} V_{ij'} + I_i - \tilde{I}_i
\]  

(18)

The energy function for the CAP becomes a modified form of that given by Hopfield and Tank 31.

\[
E = \frac{A}{2} \sum_{i=1}^{N} \left( \sum_{j=1}^{M} V_{ij} - t_i \right)^2 + B \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=j-(c_{ij})}^{j+(c_{ij}-1)} V_{ik} V_{ij} + B \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=j-(c_{ij})}^{j+(c_{ij}-1)} V_{ik} V_{ij}
\]

(19)

The energy function \( E \) in (19) has been constructed by considering the constraints in the problem. Note that (19) could be augmented with terms corresponding to the energy associated with violations of the packing, resonance and intracell rearranging conditions, along with the respective coefficient weights \( C, D \) and \( F \) for those terms.

3.5 Convergence Conditions for Hopfield Representations

The energy function in earlier Hopfield NN application was composed of an objective function augmented with terms representing all problem constraints. Since the many terms compete for minimization, this can lead to infeasible solutions. Moreover, the strict descent dynamics of the Hopfield network can lead to convergence to the first local minima found. These problems have limited the use of the Hopfield-Tank models for combinatorial optimization problems. To ensure
feasibility of the final assignment and to escape local minima, the energy function (19) and internal dynamics of the Hopfield NN are modified. With $\alpha_{\text{min}} = 0$ and $\alpha_{\text{min}} = 1$ in (1b), $u_y = V_y$ for $0 < u_y < 1$, and all feasible solutions to the NN given by (2)-(4) and (16)-(19), lie at vertices of the $\mathcal{N}M$-dimensional unit hypercube which also intersects the constraint plane. For the function (19), the first term is considered the objective function, while the other terms with coefficient $B$ measure the deviation of the array of neurons, $V = (V_y)$, from the constraint plane. By normalizing the coefficients, only one parameter needs to be selected. If the parameter is sufficiently large, the constraint terms will be forced to zero and the solution will necessarily lie in the constraint plane.

Following Abe conditions can be imposed on coefficients $A$ and $B$ to ensure that the Hopfield algorithm only leads to feasible channel assignments that are stable points of the system. Abe has shown that the non-vertex points in the unit hypercube are unstable. Thus, they cannot be infeasible solutions, called spurious states. It follows that the only requirement is to suppress spurious states at the vertices, which are adjacent to feasible solutions. If all the feasible solutions are strongly stable, there are no spurious states adjacent to feasible solutions. Consider $V$ to be a vertex of the hypercube and $V(ij)$ an adjacent vertex that differs from $V$ only in its $ij$-th component which is the complement of that component in $V$. Suppose $V$ represents a feasible solution and let $E(V)$ denote its corresponding energy. Then to force $V$ to be a strongly stable point, coefficients $A$ and $B$ must be selected so that $E(V(ij)) > E(V)$ for every pair $i,j$. Beginning with a feasible solution $V$, one or more of its components can be complemented in value, i.e., $0 \rightarrow 1$ or $1 \rightarrow 0$ and the effect on the energy evaluated. In (19) we are interested in the following transitions that increment $E$:

1. Transitions that increase the traffic demand terms in (19), but still satisfy the CSC, ACC, and CCC terms. This corresponds to one or more $1 \rightarrow 0$ transitions in $V$, which imply that $A > 0$.
2. Transitions that increase the energy in (19) of one or more of the CSC, ACC, and CCC terms and leave the traffic demand energy the same. This corresponds to a balanced number of $1 \rightarrow 0$ and $0 \rightarrow 1$ transitions that trigger one or more constraint terms to a positive value. These transitions imply that $B > 0$.
3. Transitions that decrease the traffic demand terms in (19), triggering one or more of the CSC, ACC, and CCC terms. This corresponds to a number of $0 \rightarrow 1$ transitions to meet demand that trigger one or more constraint terms to a positive value, such that the overall value of (19) is increased. Based on the maximum possible decrease in the traffic demand term and the minimum increase in constraint violations, one such condition is

$$B > A \left( \frac{M-2}{2c_{y_{\text{min}}}} \right)$$

where $c_{y_{\text{min}}}$ is the minimum separation distance for all cells $i$ and channels $j$, such that $c_y > 0$. Other conditions on $B$ and $A$ depend on changes to the system parameters.

Another refinement to the Hopfield algorithm has been suggested by Abe to accelerate convergence. This involves use of a deterministic non-linear step size which forces at least one component of the current $V$ to the surface of the unit hypercube at each iteration. Abe has reported that this deterministic step size results in an acceleration the convergence of the Hopfield NNAs two to five times that of same algorithms using a constant step size.

### 3.6 Genetic Algorithm Representations

The GA approach is applied to the CAP by specifying genetic operators and constructing an objective function in terms of the network requirements and constraints. The fitness of a string is its value in the objective function. The selection process must balance two opposing evolutionary forces. If only the fittest strings are selected every iteration, the GA may converge to local minima. However, if the best strings are not preferred over weaker ones, the algorithm may never converge to “fit” solutions. Therefore, the process is based on a biased random selection; strings with higher fitness have a higher probability of being selected to reproduce than their weaker counterparts. The probability of an individual being selected is the ratio of his fitness to the sum total of the fitness of all individuals in the current generation.

The crossover operator promotes structured yet randomized information exchange between strings. Let $\rho_c$ denote the probability associated with crossover. The value $\rho_c = 1.0$ will cause a discontinuity, since no strings from the previous generation will be retained in the next one. Thus, it is recommended that $\rho_c < 1.0$, with values in the range 0.5-0.6. Preliminary simulation results show that with simple crossover a significant number of strings generated have the same
channel assigned to a group of cells that interfere with each other\textsuperscript{24}. One method used to mitigate these problems is a partially matched crossover (PMX) operator that partitions each string into randomly chosen sections\textsuperscript{33}. When the PMX operator encounters a conflict, it will resolve this conflict by using the information from the mapping of channels in crossover segments. Each cell’s assigned channels, represented as a substring, may be restricted so that only non-interfering channels are assigned to that cell. However, while the initial pair of assignments in the parents may not violate this constraint, it may occur that their offspring do. In this instance, the PMX operator resolves such unacceptable assignments by rearranging the conflicting elements in each string.

After selection and crossover, the \textit{mutation operator} may impose on every single gene (assigned channel) an additional random change with a probability equal to the mutation rate $p_m$. The mutation operator protects the algorithm from becoming trapped at local minima. A low mutation rate prevents any one gene in the string from remaining fixed to a single value in the entire population. Conversely, a high level of mutation results essentially in a random search. For balance a value for $p_m$ of 0.01 has been recommended\textsuperscript{25,32}. Several versions of the mutation operator have been proposed for the CAP\textsuperscript{34}. One version assigns the randomly selected channels to the call in each cell according to the CSC and the minimum separation distance with the cell of maximum traffic demand. A second mutation could shift the assigned channels by a random number of channel blocks. In a network with dynamic traffic, the length of the strings is elastic as it depends on time-varying $t_i$ and is a form of mutation. Moreover, the string lengths can also be increased with sectored cells to accommodate the number of active channels, thereby adding variability to each succeeding generation.

The objective function, analogous to the energy function, determines the survival of each string by providing a measure of its relative fitness in satisfying the channel demand in each cell and obeying interference constraints. For each string $s_p$, its fitness value is given by

$$
E = \frac{A}{2} \sum_{i=1}^{N} \sum_{k=1}^{t_i} \sum_{l=1}^{t_k} (1 - \delta_{kl}) \Gamma_{ik} + \frac{B}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{t_i} \sum_{l=1}^{t_j} (1 - \delta_{ij}) \delta_{ijkl}
$$

where

$$
\Gamma_{ik} = \begin{cases} 
0 & \text{if } |q_{ik} - q_{il}| < c_{ik} \\
1 & \text{otherwise};
\end{cases}
$$

$$
\delta_{ijkl} = \begin{cases} 
0 & \text{if } |q_{ik} - q_{jl}| < c_{ij} \\
1 & \text{otherwise};
\end{cases}
$$

$c_{ij}$ is the minimum separation distance between cells $i$ and $j$, $q_{ik}$ is the assigned channel value for the channel $k$ of the cell $i$, and $A$ and $B$ are coefficients that bias their respective terms. Note that $\Gamma_{ik}$ and $\delta_{ijkl}$ provide a measure of the extent to which the CSC and the ACC/CCC conditions are satisfied, respectively.

Whenever the best candidate in the population does not violate any of the requirements and constraints, the search may terminate when there are no significant changes in the difference between $P_{\text{max}}$ and $P_{\text{min}}$ in any two successive generations. Defining the difference at the iteration $n$ by $\Delta'(\mathcal{C}) = P_{\text{max}}^n - P_{\text{min}}^n$ the termination criterion is expressed as

$$
[0.99 \Delta'(\mathcal{C}) \leq \Delta'_{n+1}(\mathcal{C}) \leq 1.01 \Delta'(\mathcal{C})] \quad \text{STOP}
$$

The final channel assignment at the termination of the GA could serve as the initial state for the neurons in a Hopfield NN or SONN algorithm for the CAP, creating a hybrid genetic/Hopfield neural algorithm.

### 4. Simulation Results and Performance Enhancements

The performance of the modified Hopfield NNA and the GA for the CAP was examined, using network requirements that are based on system parameters considered by Kunz\textsuperscript{16}, Lai\textsuperscript{24}, and Funabiki, \textit{et. al.}\textsuperscript{31}. The interference matrices and traffic demand vectors for these problems are shown in Figure 6. The problems represent cellular networks with non-homogeneous traffic. Homogeneous networks are represented by demand vectors with identical components. The effects of time-varying traffic loading are approximated through cyclic rotation of the demand vectors $T$ shown in Figure 6 or the periodic replacement of $T$ with a new vector during the simulation run. Scenarios including the effects of sectored cell
networks were modeled either by changing the reuse factor in the interference matrix or increasing the dimension $N$, treating each cell substring as a set of sector substrings.

Simulations were performed on a personal computer using extensions of the recurrent network models for the Hopfield NNAs and the adaptive learning models for the GAs included in MATLAB’s Neural Network Toolbox. Algorithm performance was measured on the basis of the probability of call blocking and the average number of iterations (ANIs) required for convergence. Since the focus here is DCA under transient demand, convergence is in the sense of (24). It does not imply that the optimal energy or fitness value is reached in all cases, only that the values at some point monotonically decrease to a finite asymptote.

![Figure 6](https://www.spiedigitallibrary.org/conference-proceedings-of-spie)  

Figure 6. Interference matrices and traffic demand vectors used in simulations. Interference matrices (a) $C_2$, (c) $C_3$, (e) $C_4$, and (g) $C_5$. Demand vectors (b) $T_2$, (d) $T_3$, and (g) $T_4$.

### 4.1 Homogeneous Networks and the Modified Hopfield Algorithm

An omniscell network consisting of $N = 21$ radio cells was considered with interference represented by the matrix in Figure 6(c) with $M = 221$ the minimum number of channels. With these specifications, we set $A = 1$ and use relation (20) to determine B in (19) to ensure convergence to stable feasible solutions. The entries in the traffic demand vector $T$ were set initially to $t_i = 4$ for each cell $i$ and later increased to 6, 8, and 16. Each case was repeated for 100 different initial states and the results averaged. The average blocking probabilities for the cases are 0.202, 0.304, 0.138, and 0.26, respectively; corresponding ANIs are 17.4, 24.7, 38.2, and 47.5. The use of directional beams to sector cells into three 120° zones for this network reduced the $c_i$ from 5 to 4 and improved call blocking to approximately 0.153 and ANI of 33.8 when $t_i = 16$.

### 4.2 Non-homogeneous Networks and the Modified Hopfield Algorithm

A typical example of a non-homogeneous network was introduced by Kunz, measuring 24 km by 21 km around Helsinki, Finland. The local terrain and infrastructure were used to establish a non-uniform traffic density. There are 25
base stations, distributed non-uniformly over the area. Based on this data, the field strength distribution was determined and used to compute the traffic assigned to each base station. From this data, the interference matrix and traffic demand vector shown in Figure 6(a) and (b) were generated. Graph-theoretic analysis of the interference determined that at least 73 channels were needed to satisfy the network conditions.

Using the system parameters with $A = 1$ and $B$ determined by (20) for convergence, the stationary case was run. The blocking probability was found to be 0.247, with the ANI equal to 106.7. This is a major improvement over the original convergence in 2450 iterations. Since the blocking probability was unacceptable, the impact of $60^\circ$ sectors in the cells were examined to reduce ACC and CCC in Figure 6(a) with a reuse factor $r = 3$. This resulted in a blocking probability of 0.167 and an ANI of 97.2.

### 4.3 Homogeneous Networks and Genetic Algorithms

A stationary 21-cell network was selected, based on the interference matrix in Figure 6(c). Each cell in this network has three channels available and $t = 1$. These three channels are cyclically arranged, the minimum channel separations for the cells is given by $C$. The GA parameters are $\rho_v = 0.6$, $\rho_w = 0.01$, $\lambda = 1.0$, and $P = 200$. The simulations run until condition (24) was met or 1000 generations elapsed, whichever occurred first.

Improvements can be made to increase the efficiency of the GA. First, the best channel assignment string from the present population, in the sense of (21), is forced to to be a member of the next generation. This step is necessary during the first few generations, since there may not be sufficient copies of the fittest strings to prevent the best ones from elimination from succeeding generations. The infeasible channels are reassigned with feasible ones to achieve the best solution in each generation. However, this new offspring will only survive if there is an improvement in the fitness. Otherwise, no changes will be made and the previous channel assignment holds. The maximum and average values of the fitness (21) were calculated for both with and without the forced reassignment technique. The improved, forcing GA in this case achieved a non-violating solution with a maximum objective value of 59 and an average of 56 in 87 generations, while the non-forcing GA achieved a maximum objective value of 56 and an average of 54 in the same number of iterations. After nearly 1000 generations, the forcing technique only converged to a maximum of 62 and average of 57, while the non-forcing technique attained a maximum of 58 and an average of 56.5. The improved GA for the network was able to locate feasible channel assignments, consisting of a single non-interfering channel for each cell in the 21-cell homogeneous network. The blocking probability was nearly zero for over 100 simulation runs.

### 4.4 Non-homogeneous Networks and the GA Approach

A more realistic test for the GA is the cellular network example from Helsinki, Finland used by Kunz. While the initial population in GAs are usually randomly generated, there is no reason to start with an arbitrary state should a priori information be available to allow construction of an initial population with fit individuals. Thus, instead of a random initial assignment, the GA tries to assign a valid string of channel assignments in all cells. Lai, et al., suggest the approach of assigning feasible channels to as many cells as possible. However, in the event that feasible channels cannot be allocated to some cells, they can be randomly assigned.

The impact of the bias weights, $A$ and $B$, for the CSC and CCC/ACC terms, respectively, on convergence to the final channel assignment was examined. Slightly varying the co-channel bias on the same data set produces the same strings but the order in which these strings are arranged in the population is different. With $B = 1.1$, that is, a 10% greater bias toward the CSC violations, strings can be differentiated that originally were in a group of strings with similar fitness values. Simulations run with $B$ set to 1.1, 1.2 and 1.3 show much faster convergence of the GA than with $B = 1.0$. The values $\rho_v = 0.6$, $\rho_w = 0.01$ were used for this assignment problem in all simulation runs. Changing $B = 1.0$ to $B = 1.1$, for instance, reduces the number of iterations for the 25-cell, 73-channel network from over 2795 to 14. This convergence is better than the modified Hopfield results. To investigate the sensitivity of the GA with $B = 1.1$, the components of vector $T_2$ were cyclically shifted every 100 generations to represent dynamic local traffic at the cells. This revealed the sensitivity of the GA convergence with $B = 1.1$ to local demand shifts. In response to these cyclic demand shifts, the average blocking
probability for this GA varied from 0.01 to 0.343 depending on the size of the demand increment or decrement of the shift. While all cases converged within 200 generations. none converged in less than 14 generations.

5. CONCLUSION

Hopfield NNs and genetic search algorithms have been considered for DCA in TDMA networks with time-varying traffic. Investigations of the limitations of these algorithms in solving the CAP under dynamic conditions have revealed techniques to improve their stability and rate of convergence. The instabilities of the Hopfield-Tank models and difficulty in finding global minima can be corrected by selecting the appropriate activation function and energy function, based on geometric analysis of the set of feasible channel assignments. This analysis leads to changes in the models so that only feasible solutions are strongly stable. Abe's method of deterministic step sizes was applied to accelerate the convergence. Integration step sizes were determined so that at least one component of the array of neurons reaches the surface of the unit hypercube. Simulations of previously examined systems show that the modified Hopfield NN converges much faster than those using heuristic conditions, and faster than more recent Hopfield-based DCA algorithms that use constant step sizes. The convergence results for the improved algorithm to DCA with time-varying traffic are inconclusive. They appear very dependent on the initial conditions selected.

Cell sectoring was shown to decrease the entries of the interference matrix and lead to greater system capacity. This should lead to better performance of the assignment procedure for both the Hopfield and genetic algorithms. Further modeling of the effect of directional antennas and adaptive beamforming in the algorithms is needed. Simulations have shown modest improvement in blocking probabilities in response to transient demands. With dynamic loads, the best solution may contain assignments that violate the interference constraints. Adaptive antennas at the base stations could be cued to add spatially isolation through dynamic sectoring, thereby lowering the interference constraints themselves.

GAs essentially perform an untrained or "blind" search procedure. Thus, in any particular run of the algorithm, there is no guarantee that a solution will be found in a given number of iterations. Although convergence was extremely fast for the Helsinki network by selection of the biases in objective function, there is no method to determine the bias values. The ad hoc bias selection is subject to the same criticism that Kunz and others received for the way they selected coefficients in the Hopfield energy function. This is clearly a problem for DCA. As homogeneity between parents increases, the mutation should be increased to levels that would encourage a search for new, yet competitive, genetic material. Cell sectoring acts like a mutation operator on the strings, changing the values of the constraint thresholds $c_i$. Therefore, to encourage greater diversity in the population as well as the propagation of good assignments, the mutation can be increased by a factor of two (more sectoring within cells) when the genetic material of both parents are the same.

6. ACKNOWLEDGMENTS

This research was performed independently on the basis of the cited references. The author wishes to thank Professor Kaveh Pahlavan and his staff of the CWINS at Worcester Polytechnic Institute for their continuing insights into the behavior and optimization of emerging mobile communication networks.

7. REFERENCES