# A Dynamic Load Balancing in Wireless CDMA Cellular Networks

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**Abstract**

With the increase of cellular users the traffic hot spots and unbalanced call distributions are common in wireless networks. The CDMA techniques enables a base tranciever station to connect microcells with optical fibers and to control the channels by sectorizing the microcells. Each sector which covers several microcells is assigned a soft channel capacity. To solve the load balancing among microcells we need to sectorize the microcells dynamically depending on the traffic required in each cell.

The load balancing problem is formulated as an integer linear program which minimizes the unserved traffics and handoff calls in the network. Genetic algorithms are developed to solve the problem and computational results are discussed by comparing with other methods.

## 1. Fiber-optic Micro-cellular CDMA Systems

### 1.1 System Structure

In a fiber-optic micro-cellular system as shown in Figure 1 micro-base-stations (mBSs) are connected to a central station (CS). The CS operates and controls the mBSs and connects them to a public switched telephone network or a mobile switching center. In the system mBSs are sectorized such that each mBS in one sector broadcast its radio signal over the mBSs in its sector that is called simulcasting. For the simulcasting operation, the access network between the CS and mBSs should have multi-drop-bus topology. All RF resources are located at the CS and managed by the operation and management system (OMS). All modulator/demodulator sets are installed at the CS and the OMS installed at the CS assigns the resources to sectors according to the traffic demand [4], [6].

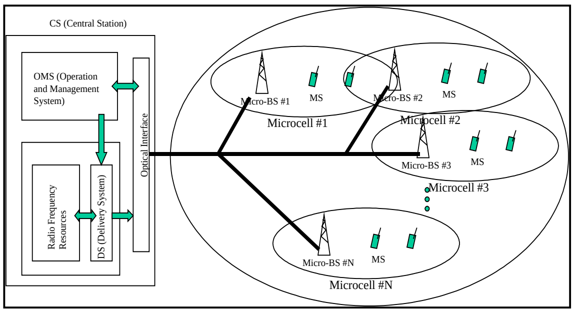



Figure 1. Structure of a Fiber-optic Micro-cellular System

In CDMA RF resources are managed by the sets of traffic channel elements. In general three sectors hold the resources in common for traffic demand. Usually four channel cards, which correspond to 96 channel elements, are assigned to the three sectors. The set of 96 channel elements is called the virtual base station (VBS). Thus one CS usually operates several VBSs.

In forward direction, radio signal corresponding to each sector is converted to different intermediate frequency (IF) signal, combined with forward control channel and reference tone, electronic-to-optic converted to the forward optic signal. The forward optic signal is then transmitted to hybrid fiber-radio access network. In the mBS, the forward optic signal is optic-to-electronic converted, bandpass filtered for screening one IF signal which is assigned to the sector, frequency converted to the original RF band, and amplified and transmitted into the air [5].

In the reverse direction, each radio signal from the primary and diversity receiver antenna is bandpass filtered, frequency converted to different IF band, combined with reverse control channel, and electronic-to-optic converted to the reverse optic signal. The reverse optic signal is then transmitted through the hybrid fiber-radio network to the CS. In the CS, the reverse optic signal is optic-to-electronic converted, bandpass filtered for primary and diversity IF signal which corresponds to each sector, and frequency converted to the original RF band [5].

### 1.2 Dynamic Sectorization of Microcells

In CDMA to meet the traffic demand in a specific service area, it is important to sectorize the microcells

such that they satisfy the capacity of a sector and the capacity of a VBS. The maximum number of channel elements that a sector can provide is called soft capacity while the total number of traffic channel elements assigned to a VBS is called hard capacity.
Note that the traffic at each microcell is increased or decreased from time to time. Thus it is necessary to dynamically sectorize the cells such that the cells in a sector satisfy the soft capacity and the sectors in a VBS meet the hard capacity. Without proper sectorization there may be cases where call blocking occurs in a specific sector even if other sectors have idle channels.

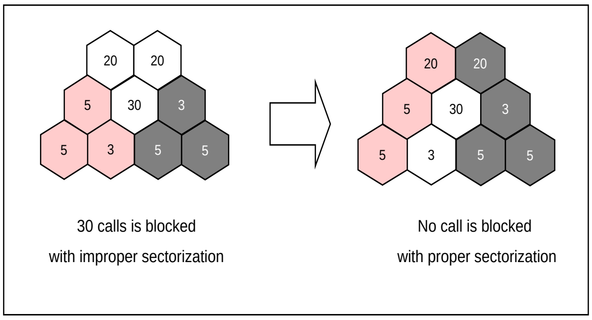
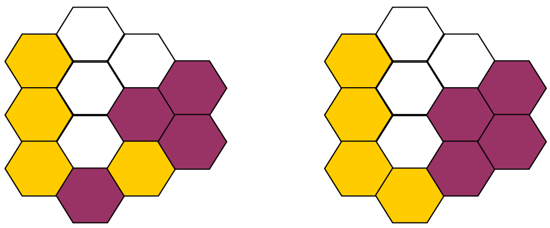


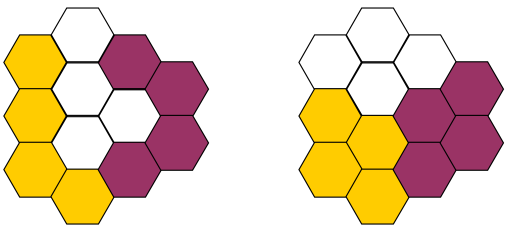

Figure 2. Traffic Distribution and Sectorization

Figure 2 shows an example of sectorization where there are nine microcells, three sectors and one VBS in the system. In the example, by assuming 96 channel elements of hard capacity at the VBS and 40 of soft capacity at each sector, an improper sectorization produces 30 blocked calls, while the other two sectors have idle channels.



(a) Disconnected sectorization (b) Connected sectorization

Figure 3. Connected/Disconnected Sectorization



(a) Incompact sectorization (b) Compact sectorization

Figure 4. Compact/Incompact Sectorization

Now, note that all mBSs in a sector broadcast radio signal simultaneously. If these mBSs are not connected as in Figure 3 (a), then they interfere other simulcasting groups significantly. Therefore, we need to consider the *connectedness of sectors* to solve the grouping of microcells for balanced traffic.
To minimize the interference we also need to consider the *compactness of sectorization*. Figure 4 (a) shows an example of connected but incompact sectorization. A cell surrounded by cells in other sectors may experience higher interference than the cells in compact sectorization. Compact sectorization also reduces handoff calls by decreasing the number of handoff-borders between two different sectors.
To measure the compactness of sectorization we in this study introduce the *compactness index* (CI) which is defined as the ratio of the number of handoff-borders to the total number of borders of a sector. The CI of the sectorization of Figure 4 (a) is 14/24 and that of Figure 4 (b) is 9/24. Note if the required CI is less than 0.5, then the grouping as in Figure 4 (a) will be discarded.

## 2. Formulation of Microcell Sectorization

Suppose that mobile users are distributed over a specific service area composed of $N$ hexagonal microcells. Each microcell has traffic demand $TD_i$ $i=1,..., N$. Let $B_{ij}$ be the adjacency of microcells $i$ and $j$, that is, $B_{ij} = 1$ if microcells $i$ and $j$ are adjacent. Let $p_{ij}$ be the transition probability of mobiles from microcell $i$ to $j$. Then, the handoff calls from microcell $i$ to $j$ becomes $h_{ij} = p_{ij}TD_i$.
Assume that a CS has $M$ VBSs. Let $HC_m$ and $SEC_m$ be the hard capacity and the set of sectors of VBS $m$, $m=1, ..., M$. Also, let $SC_k$ and $MBS_k$ be the soft capacity and the set of microcells of sector $k$.
Given the sectorization of cells in period $t$, our problem is to obtain new sectorization in period $t+1$ which adaptively reflects the changed traffic demand. We consider the following five cost factors in the sectorization problem:

1) The penalty of the blocked calls caused by hard capacity. A VBS has too many cells or sectors that exceeds the hard capacity.
2) The penalty of the blocked calls caused by soft capacity. In CDMA the interference increases as the number of calls in a sector increases. To keep the interference below a certain required level the limit in soft capacity is necessary.
3) The cost of soft handoff. When a mobile with ongoing call moves from one microcell to another each of which belongs to different VBS, then the mobile needs a soft handoff to different channel elements.
4) The cost of softer handoff. When a mobile with ongoing call moves from one cell to another each of which belongs to different sector in a VBS, then

the mobile needs a softer handoff using the same channel element.

5) The cost of forced handoff. When a mBS changes its sector, all ongoing calls in the mBS have to change their pilot PN offsets. In this process each mobile with ongoing call uses two offsets instantaneously.

Thus, our objective function is to minimize the weighted combination of five cost factors. The constraints required in the formulation are

1) Each microcell has to belong to a sector.

2) If a sector has more than one microcells, then microcells of the sector has to be connected.

3) Compact sectorization, such that we restrict the number of handoff-borders has to be less than the compactness index.

## 3. Genetic Algorithms for Microcell Sectorization

Genetic algorithms (GAs) are adaptive procedures that find solutions to problems by an evolutionary process based on natural selection. In practice, genetic algorithms are iterative search algorithms with various applications. They combine survival of the fittest, genetic operations, random but structured searches, and parallel evaluation of solutions in the search space. In general, they use a penalty function to encode problem constraints and allow a search for illegal solutions, e.g., a solution that violates the connectedness or compactness of microcells in our sectorization problem. Allowing a search for illegal solutions may prevent falling down into a local minimum and generate a better solution. In this section, we examine three types of GAs to solve the problem formulated in the previous section: Standard GA, Grouping GA and Parallel GA.

During each *generation* of the three GAs individuals in the current population are rated for their fitness as domain solutions. For the *fitness* value linear scale by ranking [3] is considered to the objective function values of chromosomes. It is known to prevent takeover of the popularities by the superstrings and to accentuate differences among population members. *Tournament selection* [3] is employed in the three algorithms. Two chromosomes are randomly chosen from the previous population and the better is selected for the next population until the number of the selected chromosomes becomes the population size.

### 3.1 Standard Genetic Algorithm (SGA)

In this algorithm each gene in a chromosome represents the sector to which the corresponding mBS belongs [2]. As operators stochastic tournament selection *uniform crossover* and *bit-flipping mutation* are employed. In the mutation a chromosome is randomly chosen with a small probability $P_M$ and the gene of the chromosome is changed, that is, the mBS represented by the gene changes sector.

### 3.2 Grouping Genetic Algorithm (GGA)

Grouping GA which is proposed by Falkenauer [1] has the advantage of reducing redundant chromosomes that are prevalent in SGA representation. It also produces diverse individuals which may not be possible in SGA. In grouping problems SGA usually allows two identical individuals with different encoding. If these two individuals are crossed over the result gives the same solutions as the parents.

The difference of GGA is in grouping-oriented operators: group crossover, group mutation and repair process. A special representation method is applied in GGA for implementation of these operators [1]. In this study we encode the chromosome with two parts: mBS and sector parts. Each gene of mBS part represents a sector to which mBS belongs. The sector part includes sectors that are used for the grouping in the chromosome. Grouping-oriented operators are applied only to the sector part. The mBS part is computed to conform to the results of the sector part.

The group mutation operator is also applied to the sector part. A chromosome is randomly selected for mutation with the mutation probability $P_m$. The operator randomly eliminates some sectors in the sector part of the chromosome. The mBS that belongs to the sectors are also removed and assigned to any other or a new sector by the repair process.

The repair process is a special procedure of GGA. This procedure assigns a sector to each mBS which is not sectorized. If a sector exists which has sufficient soft capacity to include the mBS and the result satisfies the connectedness and compactness, then the mBS is assigned to the sector. Otherwise, a new sector is added to include the mBS. If there is no new sector available due to the constraint of the hard capacity, then the mBS is assigned to a sector which minimizes the penalty of soft capacity, disconnectedness or incompactness.

## 4. Computational Results

In this section, we test the efficiency of the GAs for the microcell sectorization problem. The algorithm described in the previous section was implemented in Visual C++ (Version 6.0), and run on a MMX-200 Intel Pentium based personal computer with 64 Mbytes of memory under Windows 98.

Three test problems are generated as in Table 1. As indicated in the number of permutations of Table 1, the possible number of sectorizations increases exponentially with the number of microcells. The performance of proposed GAs will be partly investigated with the optimal solutions for the formulation.

Table 1. Specification of Three Test Problems

| | | | |
|---|---|---|---|
| Number of microcells | 12 microcells | 19 microcells | 37 microcells |
| Number of VBSs | 1 VBS | 2 VBSs | 3 VBSs |
| Number of sectors | 3 sectors | 6 sectors | 9 sectors |
| Total number of borders | 24 borders | 42 borders | 90 borders |
| Average traffic / microcell | 9 Erlangs | 12 Erlangs | 9 Erlangs |
| Compact Index | 0.50 | 0.65 | 0.60 |
| Number of permutations | $3^{12}$ $\approx 5.31 \times 10^5$ | $6^{19}$ $\approx 6.09 \times 10^{14}$ | $9^{37}$ $\approx 2.03 \times 10^{35}$ |

Both SGA and GGA start with randomly generated 200 strings. To choose proper crossover method the one-point and the uniform corssover are compared with 37-cell sectorization problem. As shown in Table 2 uniform crossover with the bit crossover rate 30% outperforms the one-point method.

For problems with 12-cell, 19-cell and 37-cell, SGA and GGA are examined with possible optimal solutions. From Table 3, 4 and 5, it is clear that both SGA and GGA give near optimal solutions. The gap from the optimal is 6~7 % in the worst case in 19-cell sectorization problem. In all problems GGA seems to outperform SGA, even if the solution quality can not be measured in the 37-cell problems.

Table 2. Comparison of Two Crossover Operators

| Problem | 37-cell Problem | |
|---|---|---|
| | One-point Crossover | Uniform Crossover |
| 1 | 489.290 | 473.120 |
| 2 | 833.893 | 814.935 |
| 3 | 768.220 | 652.993 |
| 4 | 1071.486 | 1076.058 |
| 5 | 517.022 | 492.444 |
| 6 | 1104.329 | 1013.428 |
| 7 | 1444.426 | 1269.974 |
| 8 | 596.607 | 357.621 |
| 9 | 1003.583 | 904.764 |
| 10 | 715.424 | 664.279 |

Table 3. Computational Results for 12-cell Problem

| Prob. | C-PLEX [7] | | SGA | | | GGA | | |
|---|---|---|---|---|---|---|---|---|
| | Sol. | CPU-Time | Sol. | CPU-Time | Gap | Sol. | CPU-Time | Gap |
| 1 | 244.49 | 15.98 | 244.49 | 9.72 | 0.00 % | 244.49 | 7.76 | 0.00 % |
| 2 | 29.08 | 4.62 | 29.08 | 7.36 | 0.00 % | 29.08 | 8.43 | 0.00 % |
| 3 | 287.50 | 17.63 | 287.50 | 7.47 | 0.00 % | 287.50 | 7.54 | 0.00 % |
| 4 | 127.70 | 5.38 | 127.70 | 7.64 | 0.00 % | 127.70 | 7.71 | 0.00 % |
| 5 | 179.94 | 5.27 | 179.94 | 7.58 | 0.00 % | 179.94 | 7.65 | 0.00 % |
| 6 | 29.84 | 4.56 | 29.84 | 7.36 | 0.00 % | 29.84 | 8.43 | 0.00 % |
| 7 | 335.67 | 12.91 | 335.67 | 7.47 | 0.00 % | 335.67 | 7.54 | 0.00 % |
| 8 | 158.53 | 5.49 | 158.53 | 7.47 | 0.00 % | 158.53 | 7.49 | 0.00 % |
| 9 | 248.40 | 14.39 | 248.40 | 7.90 | 0.00 % | 248.40 | 7.47 | 0.00 % |
| 10 | 68.87 | 5.00 | 68.87 | 7.64 | 0.00 % | 68.87 | 7.92 | 0.00 % |
| | | 9.12 | | 7.76 | 0.00 % | | 7.79 | 0.00 % |

Table 4. Computational Results for 19-cell Problem

| Prob. | C-PLEX [7] | | SGA | | | GGA | | |
|---|---|---|---|---|---|---|---|---|
| | Sol. | CPU-Time | Sol. | CPU-Time | Gap | Sol. | CPU-Time | Gap |
| 1 | 576.77 | 828.9 | 576.77 | 18.5 | 0.00 % | 576.77 | 19.2 | 0.00 % |
| 2 | 363.17 | 201.4 | 363.17 | 19.6 | 0.00 % | 363.17 | 18.1 | 0.00 % |
| 3 | 679.12 | 3600.0 | 679.12 | 19.9 | 0.00 % | 679.12 | 54.8 | 0.00 % |
| 4 | 456.78 | 955.8 | 456.78 | 22.1 | 0.00 % | 456.78 | 18.5 | 0.00 % |
| 5 | 316.05 | 396.9 | 320.88 | 25.2 | 1.53 % | 316.05 | 21.7 | 0.00 % |
| 6 | 630.93 | 2655.3 | 630.93 | 18.2 | 0.00 % | 630.93 | 25.3 | 0.00 % |
| 7 | 654.36 | 3600.0 | 697.75 | 31.0 | 6.63 % | 695.07 | 30.4 | 6.22 % |
| 8 | 361.27 | 326.9 | 361.27 | 19.3 | 0.00 % | 361.45 | 20.2 | 0.05 % |
| 9 | 724.47 | 3600.0 | 733.00 | 22.9 | 1.18 % | 733.00 | 21.0 | 1.18 % |
| 10 | 971.85 | 2182.2 | 971.85 | 17.9 | 0.00 % | 973.48 | 19.4 | 0.17 % |
| | | 1834.8 | | 7.76 | 0.93 % | | 24.86 | 0.76 % |

Table 5. Computational Results for 37-cell Problem

| Prob. | SGA | | GGA | |
|---|---|---|---|---|
| | Sol. | CPU-Time | Sol. | CPU-Time |
| 1 | 473.12 | 74.37 | 401.77 | 74.89 |
| 2 | 814.94 | 95.85 | 764.52 | 92.03 |
| 3 | 652.99 | 80.25 | 677.21 | 114.96 |
| 4 | 1076.06 | 79.26 | 986.71 | 91.26 |
| 5 | 492.44 | 76.18 | 469.14 | 112.33 |
| 6 | 1013.43 | 101.50 | 848.92 | 90.70 |
| 7 | 1269.98 | 80.68 | 1077.52 | 122.85 |
| 8 | 357.62 | 79.98 | 324.35 | 143.08 |
| 9 | 904.76 | 76.62 | 866.67 | 133.98 |
| 10 | 664.28 | 83.38 | 650.16 | 129.85 |
| | | 82.81 | | 110.59 |

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