A Dynamic Sectorization of Microcells for Balanced Traffics in CDMA: Genetic Algorithms Approach*

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Abstract: With the increase of cellular users the traffic hot spots and unbalanced call distributions are common in wireless networks. As a solution to this problem, the CDMA techniques enable a base tranciever station to connect microcells with optical fibers and to control the channels by sectorizing the microcells. To solve the load balancing among microcells we dynamically sectorize the microcells depending on the time-varying traffic.

The microcell sectorization problem is formulated as an integer linear programming which minimizes the blocked and handoff calls in the network. In the proposed sectorization proper, connected, and compact sectors are considered to keep the handoffs as small as possible, while satisfying the channel capacity at each sector. Three genetic algorithms (GAs) are proposed to solve the problem: standard GA, grouping GA and parallel GA.

Computational results show that the proposed GAs are highly effective. All three GAs illustrate outstanding performance for small size problems. The parallel GA which is based on the operators used in grouping GA demonstrates excellent solution quality in a reasonable time.

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1. Introduction

The micro-cellular mobile telecommunication service need to offer good Quality of Services (QoS) and coverage for new and handoff calls at lower cost. As a fast and easy deployment method for the improved service, the microcell-based PCS network has benefits for users as well as providers. The advantage of microcell system includes a significant increase in system capacity with low power at each cell [5]. The microcell system thus reduces cost and enables flexible deployment of cells. However, the micro-cellular network requires a large number of base stations compared to the conventional macro-cellular system. The installation and maintenance of the enormous number of base stations are the most serious problems in the deployment of the micro-cellular network.

One approach to solve this problem is to concentrate radio equipment at the central base station with radio frequency (RF) signals being transmitted to microcells through broadband analog transmission over fiber, coax, or millimeter-wave radio. The use of broadband aspects of fiber optic technology for radio remoting has been studied and tested by Ichikawa et al [6] and Cheong et al [8]. Ichikawa et al [6] propose a microcell radio systems using a centralized control method with a spectrum delivery switch and subcarrier transmission over optical fiber for TDMA and FDMA. A fiber-optic micro-cellular CDMA system is proposed by Cheong et al [8]. The system possibly makes group simulcasting operation via remote antenna control using multi-drop bus type access network, since the hybrid fiber-radio access network is independent of the different channels and gives flexibility in evolution scenarios. Also, the group simulcasting scheme [7, 11] alleviates the degradation of QoS and the congestion of the signaling traffic caused by the frequent handoffs in the micro-cellular CDMA system.

In this paper we examine sectorization of microcells in CDMA system to balance the dynamically changing traffic. The sectorization also reduces handoffs between cells in the same sector by the simulcasting operation based on the bus-type fiber optic network. To balance the traffic it is essential to efficiently manage the channel resource in the system. The proposed channel management in the sectorized micocells is different from the existing channel allocation methods [7, 9, 10]. In previous dynamic channel allocation, fixed basic channels are allocated to each cell and some reserved or borrowed channels are assigned to cells with higher traffic. However, in the proposed method channels are controlled by units called soft and hard capacities and they are assigned to sectors by grouping microcells depending on the time-varying traffic at each cell. Thus the dynamic sectorization that satisfies the soft and hard capacities dramatically reduces call blocking probability and handoff calls.

The remainder of this paper is organized as follows. In Section 2, we discuss fiber-optic micro-cellular systems and dynamic sectorization of microcells. A mathematical model for the microcell sectorization problem is proposed in Section 3. In Section 4, we propose three genetic algorithms (GAs) to solve the problem: standard GA, grouping GA, and parallel GA. The performance of three GAs are compared with the optimal or lower bound solution in Section 5. Finally, we conclude the paper in Section 6.

2. Fiber-optic Micro-cellular CDMA Systems

2.1 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) via bus type optical fiber. 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 and it 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.

In CDMA RF resources are managed by the sets of traffic channel elements. In general three sectors share the resources 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.

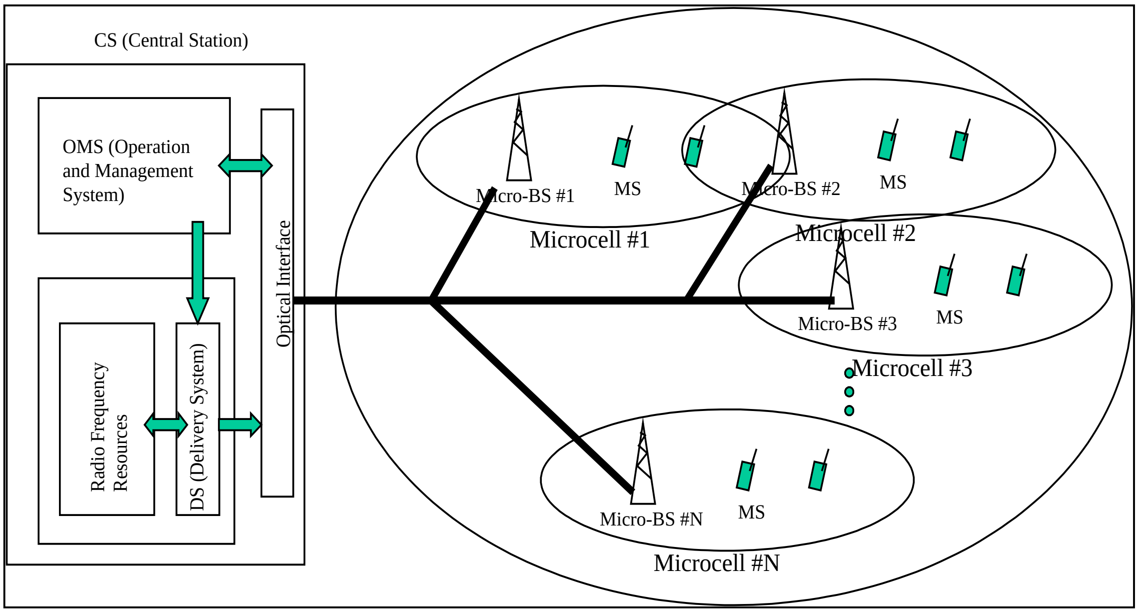


Figure 1. Structure of a Fiber-optic Micro-cellular System

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, and converted to the forward optic signal. The forward optic signal is then transmitted to hybrid fiber-radio access network. At 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, amplified and transmitted into the air.

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.

2.2 Dynamic Sectorization of Microcells

In the fiber-optic microcellular CDMA system introduced in Section 2.1, it is important to sectorize the microcells to cope with dynamically changing traffic and to balance the traffic in each sector. In the microcell system the traffic at each cell is increased or decreased depending on the time periods. Thus it is necessary to dynamically sectorize the cells such that the cells in a sector satisfy the soft capacity (the maximum number of channel elements that a sector can provide) and the sectors in a VBS meet the hard capacity (the total number of channel elements assigned to a VBS).

In this study we are interested in a proper sectorization which satisfies the soft and hard capacities for balanced traffic. Without proper sectorization there may be cases of unbalanced traffic where call blockings are increased in a specific sector even if other sectors have idle channels. Figure 2 shows an example of sectorization where there are nine microcells, three sectors and one VBS. In the example, by assuming 96 channel elements of hard capacity in the

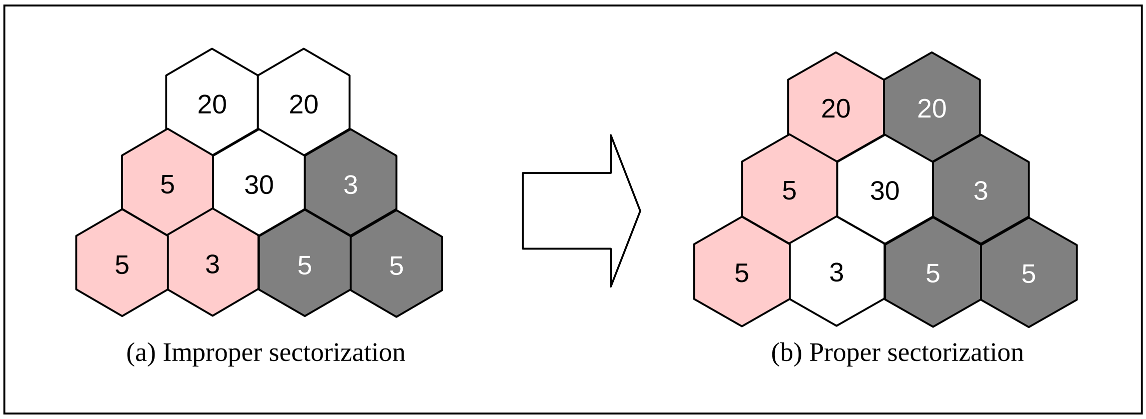
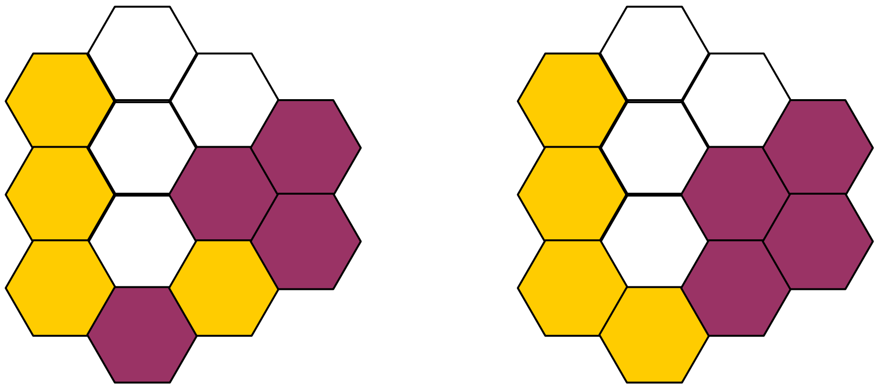


Figure 2. Traffic Distribution and Sectorization

VBS and 40 of soft capacity in each sector, an improper sectorization produces 30 blocked calls, while the other two sectors have idle channels. However, no calls are blocked and the traffic are well balanced in the proper sectorization.

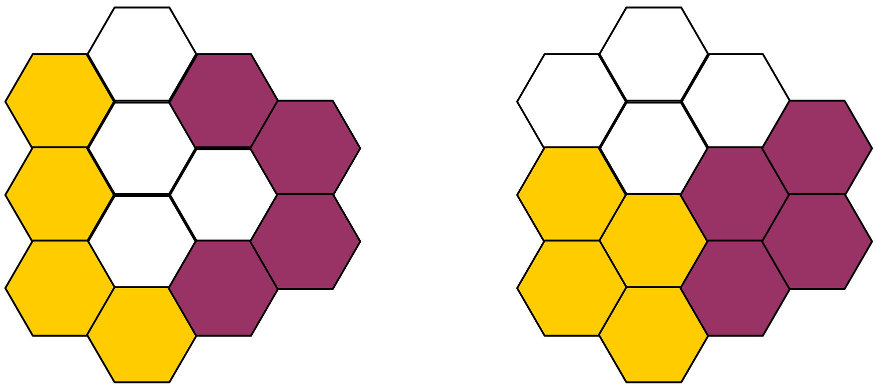
Now, note that all mBSs in a sector broadcast radio signals simultaneously. If these hexagonal mBSs are not connected as in Figure 3 (a), then they may significantly interfere other adjacent simulcasting groups. The disconnected sectorization also generates unnecessary handoffs between sectors. Therefore, cells in a sector need to be *connected.*

Finally, to minimize the handoffs and interference among sectors we consider the *compact* sectorization. Figure 4 (a) shows an example of connected but incompact sectorization in the hexagonal cell environment. A cell surrounded by cells in other sectors may experience higher interference than the cells in compact sectorization. Compact sectorization also reduces handoff



(a) Disconnected sectorization (b) Connected sectorization

Figure 3. Connected / Disconnected Sectorization



(a) Connected but incompact sectorization (b) Connected and compact sectorization

Figure 4. Compact / Incompact Sectorization

calls by decreasing the length of handoff border between two different sectors.

To measure the compactness of sectorization in the hexagonal cell environment we in this study introduce the *compactness index* (CI) which is defined as the ratio of the number of handoff cell sides to the total number of cell sides in a VBS. The CI of the sectorization of Figure 4 (a) is 14/24 and that of (b) is 9/24.

3. Formulation of Microcell Sectorization

In this section we formulate the sectorization problem with mixed integer programming to balance traffic among sectors and to minimize handoffs with connected and compact sectors.

Given the sectorization of cells in time period t, our problem is to obtain new sectorization in period $t+1$ which adaptively balances the change of traffic demands. 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 sectors or cells 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 level the limit in soft capacity is necessary.

3) The cost by soft handoff. When a mobile with an ongoing call moves from one VBS to another VBS, then the mobile needs a soft handoff to different channel elements.

4) The cost by softer handoff. When a mobile with an ongoing call moves from one sector to another in a VBS, then the mobile needs a softer handoff using the same channel element.

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

For the problem formulation we consider a service area with N hexagonal microcells. Each microcell is assumed to have traffic demand TD_i $i=1,\ldots, N$. 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 be the hard capacity of VBS m, $m=1,\ldots, M$ and SEC_m be the set of sectors in the VBS m. Also, let SC_k be the soft capacity of sector k, $k=1,\ldots, K$ and MBS_k be the set of microcells of sector k.

Now to formulate the sectorization we will define variables. Let the binary variable $x_{ik} = 1$, when microcell i belongs to sector k. Let $y_{im} = \sum_{k \in SEC_m} x_{ik}$, then $y_{im} = 1$ when the microcell i belongs to VBS m. Also, let the binary variable $z_{ijm} = 1$, when microcells i and j belong to VBS m. Then the soft handoff cost is computed by using the variable $z_{ij} = 1 - \sum_m z_{ijm}$. Note that soft handoff occurs when two cells i and j belong to different VBS, i.e., $z_{ijm} = 0$. Now by letting the binary variable $w_{ijk} = 1$ when microcells i and j belong to sector k, the softer handoff cost is computed by using two variables $w_{ij} - z_{ij}$ where $w_{ij} = 1 - \sum_k w_{ijk}$. The softer handoff occurs when microcells i and j belong to different sectors in the same VBS.

The cost of forced handoff is computed by employing the current sectorization a_{ik}, which is equal to zero when cell i is in sector k. Since the cost occurs when cell i currently in other sector moves into sector k, the cost becomes $\sum_i \sum_k a_{ik} TD_i x_{ik}$.

The variable hc_m defined as $hc_m = \sum_i TD_i y_{im} - HC_m$ represents the difference between the traffic demand and the hard capacity at VBS m. The variable sc_k defined as $sc_k = \sum_i TD_i x_{ik} - SC_k$ represents the difference between the traffic demand and the soft capacity at sector k. Since the penalty occurs only when the calls are blocked, we apply hc_m^+ and sc_k^+ to the objective function, where $hc_m = hc_m^+ - hc_m^-$ and $sc_k = sc_k^+ - sc_k^-$ and hc_m^+, hc_m^-, sc_k^+ and sc_k^- are nonnegative real variables. Note that when the hard or soft capacity is sufficient to cover the traffic demands, then the dummy variable, hc_m^- or sc_k^- has positive value and hc_m^+ and sc_k^+ becomes zero to minimize the objective function value.

Now, our objective function is to minimize the weighted combination of five cost factors as in (1). They are penalties of blocked calls by hard and soft capacities and handoff calls.

$$c_1 \sum_m hc_m^+ + c_2 \sum_k sc_k^+ + c_3 \sum_i \sum_j h_{ij} z_{ij} + c_4 \sum_i \sum_j h_{ij} (w_{ij} - z_{ij}) + c_5 \sum_i \sum_k a_{ik} TD_i x_{ik} \qquad (1)$$

Now our concern shifts to the constraints required in the formulation. First of all, each microcell has to belong to a sector, that is,

$$\sum_k x_{ik} = 1 \qquad \text{for all i} \qquad (2)$$

The relationship between any two cells in a sector k has to satisfy $w_{ijk} = 1$ if and only if $x_{ik} = x_{jk} = 1$. Thus we have

$$w_{ijk} \le x_{ik},\ w_{ijk} \le x_{jk} \text{ and } w_{ijk} \ge x_{ik} + x_{jk} - 1 \qquad \text{for all } i, j, \text{ and } k \tag{3}$$

The same is true for the relationship between two cells in a VBS m. $z_{ijm} = 1$ if and only if $y_{im} = y_{jm} = 1$ which leads to

$$z_{ijm} \le y_{im},\ z_{ijm} \le y_{jm} \text{ and } z_{ijm} \ge y_{im} + y_{jm} - 1 \qquad \text{for all } i, j, \text{ and } m \tag{4}$$

For connected sectorization, if a sector has more than one microcells, then microcells of the sector has to be connected. For the formulation of connected sectors we employ the cut [16] of MBS_k. If sector k is connected, then any cut that separates cells in MBS_k has at least one common side of the hexagonal cells. Let $S1_k$ be a proper subset of MBS_k, that is, $S1_k \subset MBS_k$, $S1_k \ne \phi$, and $S1_k \ne MBS_k$. Also let $S2_k$ be the opposite set of $S1_k$, that is, $S2_k = MBS_k - S1_k$. Because two subsets are connected, there exists at least one common side of the cells separated by the subsets. Thus we have

$$\sum_{i \in S1_k} \sum_{j \in S2_k} B_{ij} \ge 1 \tag{5}$$

where $B_{ij} = 1$, if two microcells i and j are adjacent.

For compact sectorization, we restrict the length of handoff border with the compactness index CI which is introduced in Section 2.2. In Equation (6) the left term represents the number of handoff cell sides between two different sectors.

$$\sum_{i} \sum_{i<j} w_{ij} B_{ij} \le CI \sum_{i} \sum_{i<j} B_{ij} \tag{6}$$

From the above, the microcell sectorization can be formulated as the following mixed integer linear programming.

Minimize

$$c_1 \sum_m hc_m^+ + c_2 \sum_k sc_k^+ + c_3 \sum_i \sum_j h_{ij} z_{ij} + c_4 \sum_i \sum_j h_{ij} (w_{ij} - z_{ij}) + c_5 \sum_i \sum_k a_{ik} TD_i x_{ik}$$

s.t.

$$\sum_k x_{ik} = 1 \qquad \text{for all } i$$

$$w_{ijk} \le x_{ik},\ w_{ijk} \le x_{jk} \text{ and } w_{ijk} \ge x_{ik} + x_{jk} - 1 \qquad \text{for all } i, j, \text{ and } k$$

$$w_{ij} = 1 - \sum_k w_{ijk} \qquad \text{for all } i \text{ and } j$$

$$y_{im} = \sum_{k \in SEC_m} x_{ik} \qquad \text{for all } m$$

$$z_{ijm} \le y_{im}, \; z_{ijm} \le y_{jm} \text{ and } z_{ijm} \ge y_{im} + y_{jm} - 1 \qquad \text{for all } i, j, \text{ and } m$$

$$z_{ij} = 1 - \sum_{m} z_{ijm} \qquad \text{for all } i \text{ and } j$$

$$\sum_{i \in S1_k} \sum_{j \in S2_k} B_{ij} \ge 1$$

for all $S1_k \subset MBS_k$ where $S1_k \ne \phi$ and $S1_k \ne MBS_k$ and $S2_k = MBS_k - S1_k$

$$\sum_{i} \sum_{i<j} w_{ij} B_{ij} \le CI \sum_{i} \sum_{i<j} B_{ij}$$

$$h_{ij} = p_{ij} TD_i \qquad \text{for all } i \text{ and } j$$

$$hc_m = \sum_{i} TD_i y_{im} - HC_m \qquad \text{for all } m$$

$$hc_m = hc_m^+ - hc_m^- \qquad \text{for all } m$$

$$sc_k = \sum_{i} TD_i x_{ik} - SC_k \qquad \text{for all } k$$

$$sc_k = sc_k^+ - sc_k^- \qquad \text{for all } k$$

$$x_{ik}, w_{ijk}, z_{ijm}, P_k \in \{0,1\} \qquad \text{for all } i, j, k, \text{ and } m$$

$$hc_m^+, hc_m^-, sc_k^+, sc_k^- \ge 0 \qquad \text{for all } k \text{ and } m$$

Note that many grouping problems which are special cases of the sectorization problem are well-known NP-hard problems [15]. This implies that any known exact algorithm will run in time exponential in the size of problem instance. Such an algorithm is thus in most cases unusable for real-world size problem. As an encouraging results on NP-hard problems, we investigate genetic algorithms to solve the sectorization problem and compare the performance with the solutions obtained by the mixed integer programming.

4. 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 exemine 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. The *fitness value* is based on the objective function value of Equation (1) in Section 3. For the fitness value of each individual linear scale by ranking [3] is considered in the three GAs. Linear scaling 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.

4.1 Standard Genetic Algorithm (SGA)

In this algorithm each gene in a chromosome represents the sector to which the corresponding mBS belongs [2]. As operators *uniform crossover* and *bit-flipping mutation* are employed. In the uniform crossover process two chromosomes are randomly chosen with a probability P_c and genes are exchanged with a rate C_R. For the mutation a gene is randomly chosen with a probability P_m and the value of the gene is changed, that is, the mBS changes its sector. For the quality of population, parents are reproduced by the tournament selection and children are generated by the crossover and mutation operation.

4.2 Grouping Genetic Algorithm (GGA)

Grouping GA which is proposed by Falkenauer [1] has several advantages over the straight forward encoding scheme in SGA. First, it reduces the size of search space used by the encoding scheme in SGA. Secondly, the GGA prevents producing a child which has nothing in common to the two identical parents.

The above superiority of GGA over SGA is due to group-oriented operators: group crossover and group mutation. To apply the GGA to our sectorization problem we encode each string into two parts: mBS and sector parts as in Figure 5. The group-oriented operators are applied only to the sector part. Each gene of mBS part represents the sector to which the mBS belongs. The sector part includes sectors that are used for the grouping of the mBSs.

Since the operations are applied to the sector part, the GGA reduces the search space used by the SGA. Note in the SGA that each mBS can be assigned to any sector and this increases the solution space as the number of mBS increases. Grouping operators in GGA also prevents generating a string which is far different from their parents. However in SGA two parents AABCC and BBCAA which are identical in the sense of grouping may produce a child AABAA after recombination at the third crossover site. The child has only two groups instead of three in its parents.

P_1 = A A B B F F B C F D C C E E D C | B A C D E F

P_2 = a a b b d c a b d c c f e e e f | a c d e b f

(a) Parent chromosomes

C_2 = A A b b d c a C d c C C e e e C | a c d e b f A C

(b) Injecting sectors from P_1 to P_2

C_2 = A A b b d c a C d c C C e e e C | d e A C

(c) Updating sector part

C_2 = A A x x d x x C d x C C e e e C | d e A C

(d) Removing mBS part

C_2 = A A E E d A D C d D C C e e e C | d e A C D E

(e) Repairing mBS part by heuristic method

Figure 5. An Example of Group Crossover

An example of the group crossover with 16 mBSs and 6 sectors is shown in Figure 5 and the second child C_2 is produced as follows:

(a) A and C sectors are selected for inheritance from P_1 to C_2.

(b) Inject A and C from P_1 to P_2 in sector and mBS parts and copy P_2 to have C_2.

(c) Remove a, b, c and f from sector part whose genes are replaced by A and C.

(d) Remove genes a, b, c and f from mBS part.

(e) Repair mBS part by adding new sectors D and E, as explained in the repair process at the end of this section.

The group mutation operator is also applied to the sector part. A chromosome is randomly selected for mutation with the probability P_m. The operator randomly eliminates some sectors from the sector part of the chromosome. The mBSs that belong to the sectors are also removed and assigned to other or new sectors by the repair process.

The repair process is a special procedure of GGA to assign sectors to mBSs which are 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, new sectors are added to include the mBSs. If no new sector is available due to the constraint of the hard capacity, then the mBSs are assigned to sectors which minimize the penalty of soft capacity, disconnectedness, or incompactness. Note that the major time-spending procedure in the repair process is to match each unassigned mBS to a proper sector among the K sectors. Since the comparison and selection of proper sector requires $K \log K$ operations, the time complexity is $O(NK \log K)$, where N is the number of mBSs and K is the number of sectors.

Repair Process

Start;

Compute the residual $\boldsymbol{R}=(RS_1, RS_2, ..., RS_K, RH_1, RH_2, ..., RH_T)$;

$RS_k = SC_k - \sum_i TD_i x_{ik}$ and $RH_m = HC_k - \sum_i TD_i y_{im}$;

For $(i=1 ; i \le N ; i{+}{+})${

If ($\sum_k x_{ik} = 0$){

Compute $HP_{ik} = \sum_j p_{ij} x_{jk}$ for all k ;

If (There are sectors such that $RS_k \ge TD_i$ *and* $RH_m \ge TD_i$ *for* $k \in SEC_m$){

Select the sector k^* that has the highest HP_{ik} ;

$x_{ik^*} = 1$;

Update $\boldsymbol{R}$; }

}

}

For $(i=1 ; i \le N ; i{+}{+})${

If ($\sum_k x_{ik} = 0$){

Compute $HP_{ik} = \sum_j p_{ij} x_{jk}$ for all k ;

Select the sector k^* that has the highest HP_{ik} ;

$x_{ik^*} = 1$;

Update $\boldsymbol{R}$; }

}

End;

4.3 Parallel Genetic Algorithm (PGA) with Island Model

In PGA with island model an independent GA is performed at each island and the best string discovered is broadcast to other islands. Grefenstette [12, 13] proposed several parallel implementations of GAs based on different communication methods among islands.

Compared to the traditional GAs, the parallel GA is known to have advantages in overcoming the problem of premature convergence. Extension of distinct species and different search strategy at each island could maintain the diversity of the whole population for a longer period. The PGA that is employed in this paper has five islands and a central evaluator as in Figure 6.

At each island we employ the group crossover and modified mutation operators. The modified mutation is the combination of the bit-flipping mutation in SGA and the group mutation in GGA. It operates not on the sector part but on the mBS part. It randomly selects an mBS to mutate and reassigns a sector by the repair process used in the group mutation.

For the communication among islands the duplicate of the best chromosome of an island is migrated to the adjacent island at the end of a generation. The best chromosome is also reported to the central evaluator. Then the central evaluator evaluates the chromosomes with the objective function (1) presented in Section 3. The role of the central evaluator is to select the best among those reported from islands. If the best is better than that in the memory, then the evaluator broadcasts it to all islands.

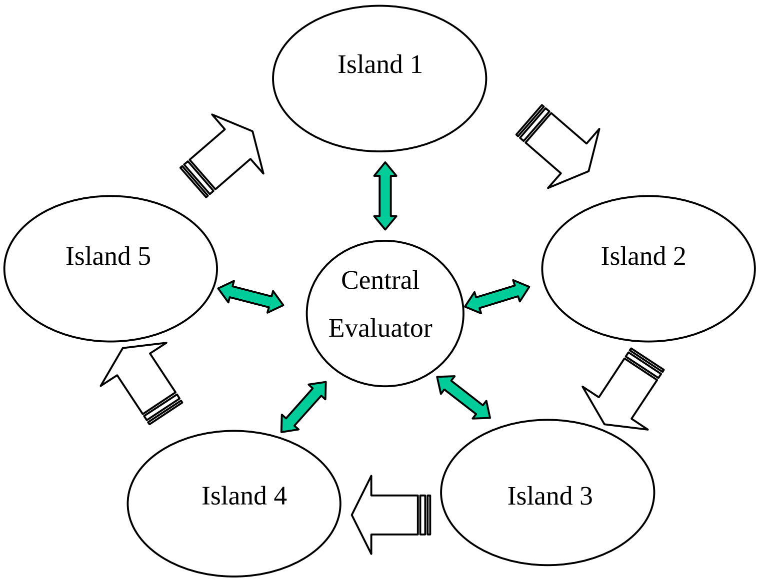
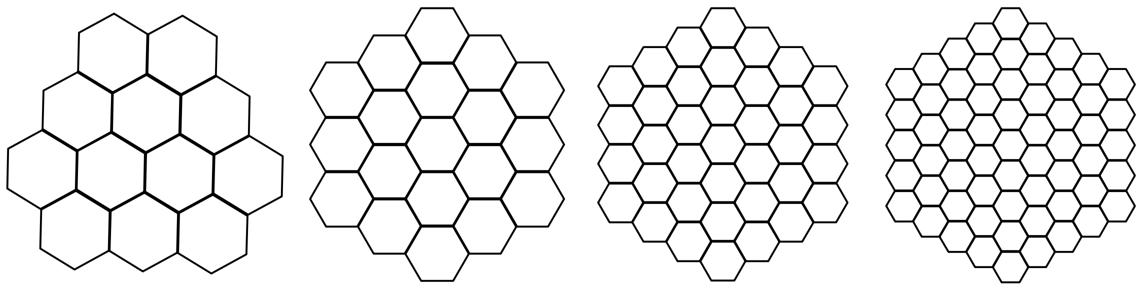


Figure 6. The PGA with Island Model

5. Computational Results

In this section, we test the efficiency of the GAs for the microcell sectorization problem. The algorithms presented 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.

Four test problems are generated as in Table 1 and Figure 7. Traffic is assumed uniformly distributes over microcells. Calls are generated by following Poisson process, where the average call duration time is equal to 2.5 minutes. The number of VBSs and sectors are assumed as in the table. In each problem, the *compact index* is given as in the table to be satisfied by the sectorization. The possible number of sectorizations increases exponentially with the number of microcells. The performance of proposed GAs will be investigated by comparing with the optimal solutions of the formulation in Section 3.



(a) 12-cell (b) 19-cell (c) 37-cell (d) 61-cell

Figure 7. Microcell Structures of Four Examples

The cost coefficients employed for the objective function (1) are $c_1 = 10$, $c_2 = 5$, $c_3 = 2$, and $c_4 = c_5 = 1$. Higher weights are given to c_1 and c_2, because to minimize the blocked calls by hard and soft capacity is the first priority in the sectorization. The weight by the soft handoff c_3 is twiced of that by the softer handoff c_4, since the soft handoff requires two channel elements while the softer handoff requires one. The forced handoff requires one or two channel elements as the softer or soft handoff. However, since the forced handoff only occurs at the beginning of sectorization period, equal weights are given to c_4 and c_5.

5.2. Parameters for GAs

Before investigating the performance of GAs for the sectorization problem, we need to compare the strategies for population selection and crossover methods. We also need to tune the parameters such as crossover probabilities and termination criteria. Experiments are performed by generating ten 37-cell problems with 200 chromosomes in each generation.

Parameters for SGA

In tournament selection two parents are selected and generate two children by crossover and mutation. This process is repeated to generate a new population for the solution convergence [4]. In this study three strategies for the formation of the new population are examined as in Table 2. In "Best N" dominant N-chromosomes are selected for the next generation among N parents and N children. In "Two Children" only the newly born children are included in the population for the next generation. The "Best Two of the Four" selects the dominant two chromosomes among the two parents and two children and the process is repeated until N chromosomes. Table 2 shows that "Best-N" has relatively better performance than two other methods. Uniform crossover is used in all three strategies.

Now, three crossover methods are compared by tuning the P_c. Table 3 shows the performance of one-point crossover with $P_c = 1.0$, two-point crossover with $P_c = 0.9$, and uniform crossover with $P_c = 0.8$ and gene exchange rate 0.4. From Table 3, it is clear that uniform crossover outperforms two other methods in our sectorization problem.

Even if the mutation is an important operator in GA, the mutation probability P_m did not significantly affect our SGA. The mutation probability is set to $P_m = 0.001$ throughput the experiments of SGA.

As a termination criterion in SGA, local trap time (LTT) is considered. The SGA stops when the best solution does not improve during LTT generations. Reasonable local trap times are obtained through computational experiments for the four microcell structures. The local trap times used for the termination of SGA are 10 generations for 12 and 19-cell problems and 40 generations for 37 and 61-cell problems.

Parameters for GGA

The selection method employed in GGA is the same strategy as in SGA. Tournament selection with Best-N chromosomes is performed with 200 individuals in each generation. As explained in Section 4.2, group crossover and group mutation are examined in GGA. Experiment are performed with crossover probabilities 0.8, 0.9, and 1.0. The best result is obtained with $P_c = 0.9$ and gene exchange rate 0.4. Mutation probability is set to 0.001 as in SGA.

The local trap time is also examined for the termination criterion of GGA. Computational results show that 10, 20, 40, and 100 generations for 12-cell, 19-cell, 37-cell, and 61-cell problems respectively are good tradeoff between solution quality and computational time.

Parameters for PGA

For PGA a population of size 200 is divided into five islands as in Figure 6. GGA is performed at each island with the same crossover probability, gene exchange rate and mutation probability. The local trap times for the termination of PGA are obtained as 10 generation for the 12 and 19-cell problems and 30 generations for the 37 and 61-cell problems.

5.2. Performance of the three GAs

Based on the parameters obtained in the preliminary tests 12, 19, 37 and 61-cell problems are solved with the three GAs. To obtain optimal solution or lower bound CPLEX [14] is employed which solves linear optimization problems based on the branch and bound algorithm. The branch and bound solves the sectorization problem by repeatedly including the constraint (6) of the formulation.

Computational results of three GAs and the CPLEX are shown in Tables 4, 5, 6 and 7. The Gap in Tables 4 and 5 represents the relative difference of the solution obtained by GAs from the optimal solution as in the following equation.

$$Gap = \frac{Solution\ Obtained\ by\ GA - Optimal\ Solution}{Optimal\ Solution}$$

In problems with 37 and 61 cells optimal solutions could not be obtained by the CPLEX in a time limit of 3600 CPU seconds. Thus the gap is obtained by the lower bound to the optimal solution and it is represented as Gap* in Table 6 and 7.

From the tables it is clear that SGA provides optimal solutions in 12-cell problems. However, in problems with 37 and 61 cells the performance of SGA is not acceptable.

Both GGA and PGA are proved very powerful for our sectorization problem. PGA presents solutions the gaps of which are less than 5% from the lower bounds even in 61-cell problems. The performance of GGA seams to be dependent on the computational time. The average gap of GGA from the lower bound is increased to 12.65% in 61-cell problems with the same local trap time used in the PGA.

The effect of PGA for the microcell traffic balancing is further investigated. The analysis shows that the call blocking probability is dramatically reduced by the dynamic sectorzation compared to the fixed sectorization. The average reduction effect of the call blocking records 62% in 37-cell and 55% in 61-cell problem. The reduction of handoff calls ranges 13~14% in 37-cell and 7~13% in 61-cell problem compared to the fixed sectorization. For the handoff calls, note that the dynamic sectorization either makes the handoffs unnecessary or generates new handoffs depending on the sectorization of cells.

6. Conclusions

Sectorization of microcells is examined to balance the traffic in the fiber-optic microcellular

CDMA system. Proper sectorization is considered to effectively use the channel elements in each sector that satisfies the soft and hard capacity. Connected and compact sectors are proposed to reduce handoffs and interferences. The microcell sectorization is formulated as an integer linear programming problem which minimizes blocked and handoff calls.

Genetic algorithms are developed to solve the sectorization problem and the solutions are compared with optimal or lower bound solutions. Tournament selection with the "Best N" is adopted in the proposed three GAs. In the Grouping GA, repair process is employed to have feasible solutions after group-oriented crossover and mutation. The process assigns one or more sectors to microcells which are not sectorized due to the group-oriented operators. Parallel GA is also proposed with island model to enhance the performance of standard and grouping GAs. All the operators and the repair process used in the grouping GA are independently applied at each island.

Computational experiments of the three proposed GAs are performed for the microcell sectorization with four different problems. Outstanding performance is illustrated by all the three GAs in small problems. The average gap from the optimal solution is less than 0.2% and 1.5% for 12-cell and 19-cell problems respectively. For large problems optimal solution could not be obtained in appropriate time limit due to the problem complexities. The standard GA failed to search near optimal solutions. The gap is increased with the problem size. The parallel and grouping GAs demonstrate excellent quality in reasonable time. The performance by the parallel GA is very promising and the gap from the lower bound is less than 2.4% in 61-cell problems, which means the real gap from the optimal is clearly less than that.

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Table 1. Specification of Four Test Problems

Problem	# of microcells	# of VBSs	# of sectors	Average traffic/microcell (Erlangs)	Compactness Index
12-cell	12	1	3	9	0.50
19-cell	19	2	6	12	0.65
37-cell	37	3	9	9	0.60
61-cell	61	4	12	7	0.58

Table 2. Comparison of Selection Strategies for New Population

Problem	Best N	Two Children	Best Two of the Four
1	502.111	515.343	523.842
2	768.203	767.615	812.652
3	681.732	727.038	840.616
4	1086.326	1071.018	1119.796
5	513.587	566.694	529.267
6	826.948	994.203	826.948
7	1444.426	1356.372	1444.426
8	367.577	361.158	489.898
9	872.173	1010.103	1045.692
10	823.630	823.630	827.715

Numbers represent the objective function cost in Section 3.

Table 3. Comparison of Crossover Methods

Problem	One-point Crossover	Two-point Crossover	Uniform Crossover
1	587.592	725.861	502.111
2	861.450	851.365	768.203
3	778.148	749.052	681.732
4	1069.675	1050.116	1086.326
5	507.296	484.856	513.587
6	982.043	959.919	826.948
7	1328.447	1072.541	1444.426
8	376.086	374.122	367.577
9	869.766	985.473	872.173
10	725.637	777.198	823.630

Numbers represent the objective function cost in Section 3.

Table 4. Comparison of Three GAs for 12-cell Problems

Problem	CPLEX		SGA			GGA			PGA		
	Optimal	CPU-Time	Solution	CPU-Time	Gap	Solution	CPU-Time	Gap	Solution	CPU-Time	Gap
1	244.490	15.98	244.490	2.00	0.00%	249.147	1.95	1.90%	249.147	2.43	1.90%
2	29.079	4.62	29.079	1.65	0.00%	29.079	1.44	0.00%	29.079	2.12	0.00%
3	287.497	17.63	287.497	2.14	0.00%	287.497	1.62	0.00%	287.497	2.59	0.00%
4	127.702	5.38	127.702	1.83	0.00%	127.702	1.63	0.00%	127.702	2.58	0.00%
5	179.937	5.27	179.937	1.81	0.00%	179.937	1.65	0.00%	179.937	2.58	0.00%
6	29.835	4.56	29.835	1.65	0.00%	29.835	1.44	0.00%	29.835	2.13	0.00%
7	335.673	12.91	335.673	1.83	0.00%	335.673	1.67	0.00%	335.673	2.40	0.00%
8	158.526	5.49	158.526	1.83	0.00%	158.526	1.62	0.00%	158.526	2.38	0.00%
9	248.398	14.39	248.398	2.85	0.00%	248.398	3.62	0.00%	248.398	5.42	0.00%
10	68.872	5.00	68.872	2.51	0.00%	68.872	1.65	0.00%	68.872	2.57	0.00%
		9.12		2.01	0.00%		1.83	0.19%		2.72	0.19%

Table 5. Comparison of Three GAs for 19-cell Problems

Problem	CPLEX		SGA			GGA			PGA		
	Optimal	CPU-Time	Solution	CPU-Time	Gap	Solution	CPU-Time	Gap	Solution	CPU-Time	Gap
1	576.769	828.94	576.769	7.41	0.00%	576.769	11.28	0.00%	576.769	9.54	0.00%
2	363.167	201.41	367.990	11.63	1.33%	363.167	8.49	0.00%	363.167	7.85	0.00%
3	679.120	3600.00	679.442	11.14	0.05%	679.442	17.20	0.05%	679.442	9.66	0.05%
4	456.780	955.82	460.604	8.53	0.84%	456.780	11.28	0.00%	456.780	10.07	0.00%
5	316.051	396.94	316.051	9.98	0.00%	316.051	12.97	0.00%	318.097	10.56	0.65%
6	630.927	2655.32	630.927	10.44	0.00%	630.927	10.88	0.00%	644.328	10.55	2.12%
7	654.360	3600.00	699.790	10.50	6.94%	695.070	16.14	6.22%	693.567	13.42	5.99%
8	361.270	326.86	363.556	8.45	0.63%	361.449	12.91	0.05%	363.556	9.52	0.63%
9	724.467	3600.00	732.998	11.49	1.18%	732.998	11.61	1.18%	732.998	8.47	1.18%
10	971.850	2182.19	971.850	8.47	0.00%	971.850	11.99	0.00%	1007.123	9.64	3.63%
		1834.75		9.80	1.10%		12.47	0.75%		9.93	1.43%

Table 6. Comparison of Three GAs for 37-cell Problems

Problem	CPLEX lower bound	SGA			GGA			PGA		
		Solution	CPU-Time	Gap*	Solution	CPU-Time	Gap*	Solution	CPU-Time	Gap*
1	396.855	502.111	106.84	26.52%	405.271	82.64	2.12%	401.765	101.91	1.24%
2	763.933	768.203	102.02	0.56%	763.933	102.39	0.00%	763.933	270.62	0.00%
3	623.231	681.732	93.73	9.39%	628.601	91.08	0.86%	628.601	115.87	0.86%
4	941.034	1086.326	77.33	15.44%	941.034	131.28	0.00%	973.808	111.18	3.48%
5	468.106	513.587	78.39	9.72%	484.609	88.47	3.53%	504.383	140.38	7.75%
6	821.064	826.948	96.58	0.72%	822.146	92.75	0.13%	826.948	96.49	0.72%
7	1015.255	1444.426	48.29	42.27%	1023.638	138.69	0.83%	1043.027	150.31	2.74%
8	317.401	367.577	92.42	15.81%	325.485	143.87	2.55%	330.184	160.30	4.03%
9	838.291	872.173	104.71	4.04%	838.291	137.20	0.00%	847.401	158.58	1.09%
10	599.228	823.630	90.79	37.45%	605.046	154.20	0.97%	634.008	117.24	5.80%
			89.11	16.19%		116.26	1.10%		142.29	2.77%

Table 7. Comparison of Three GAs for 61-cell Problems

Problem	CPLEX lower bound	SGA			GGA			PGA		
		Solution	CPU-Time	Gap*	Solution	CPU-Time	Gap*	Solution	CPU-Time	Gap*
1	898.635	997.342	217.41	10.98%	914.238	685.51	1.74%	930.583	348.54	3.56%
2	1143.405	1470.982	194.30	28.65%	1168.867	992.07	2.23%	1190.685	942.66	4.14%
3	579.169	964.475	201.31	66.53%	600.623	898.25	3.70%	579.169	604.84	0.00%
4	860.141	918.759	217.38	6.81%	914.196	772.25	6.28%	870.909	440.94	1.25%
5	798.904	871.898	271.80	9.14%	858.931	893.09	7.51%	815.307	357.36	2.05%
6	802.162	1110.336	129.80	38.42%	825.577	1437.95	2.92%	818.834	677.36	2.08%
7	660.817	1031.471	129.62	56.09%	662.811	1596.36	0.30%	687.196	453.13	3.99%
8	518.536	659.610	250.27	27.21%	518.536	500.04	0.00%	524.202	381.26	1.09%
9	784.835	1092.056	129.89	39.14%	840.262	931.10	7.06%	822.580	483.76	4.81%
10	826.035	1006.947	187.97	21.90%	873.041	1001.95	5.69%	833.077	445.39	0.85%
			192.97	30.49%		970.86	3.74%		513.53	2.38%