Dynamic Load Balancing using an Ant Colony Approach in Micro-cellular Mobile Communications Systems

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Abstract
This chapter uses an ant colony meta-heuristic to optimally load balance code division multiple access micro-cellular mobile communication systems. Load balancing is achieved by assigning each micro-cell to a sector. The cost function considers handoff cost and blocked calls cost, while the sectorization must meet a minimum level of compactness. The problem is formulated as a routing problem where the route of a single ant creates a sector of micro-cells. There is an ant for each sector in the system, multiple ants comprise a colony and multiple colonies operate to find the sectorization with the lowest cost. It is shown that the method is effective and highly reliable, and is computationally practical even for large problems.

1 Introduction

In the last 15 years there has been substantial growth in micro-cellular mobile communication systems. It is imperative to provide a high level of service at minimum cost. With the substantial increase in cellular users, traffic hot spots and unbalanced call distributions are common in wireless networks. This decreases the quality of service and increases call blocking and dropping. One of main design problems that addresses micro-cellular systems is location area management. This location area management problem can be generally stated as: For a given a network of n cells, the objective is to partition the network into m location areas, without violating transmission constraints, and with minimum cost. This chapter addresses the problem of providing good quality of service at a reasonable level of cost for code division multiple access (CDMA) micro-cellular systems. To provide the best service for a given number of base stations and channels, the call load must be dynamically balanced considering the costs of call handoffs and call blockage. This is a location management optimization problem that can be accomplished through sectorization of the micro-cells. Figure.1 shows an example grouping which has one virtual base station (VBS) and three sectors. The maximum number of channel elements assigned to a VBS is termed hard capacity (HC). The maximum number of channel elements that a sector can accommodate is termed soft capacity (SC). HC is assumed to be 96 and SC is assumed to be 40 in this example. In Figure.1 (a) the total call demand is equal to HC (96) but, the total call demand in one sector is greater than 40 resulting in 30 blocked calls in that sector. Figure.1 (b) has no blocked calls with the same HC and SC. Blocked calls are one consideration, while handoff calls are another. A disconnected grouping of micro-cells generates unnecessary handoffs between sectors as shown in Figure. 2 (a). Therefore, the cells in a sector need to be connected compactly, as shown in Figure. 2 (b).

To minimize handoffs and interference among sectors, a measure of sector compactness, as Lee *et al.* [14] proposed, can be used. The following is a mathematical equation of the compactness index (CI):

$$CI = \frac{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} x_{ij} \times B_{ij}}{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} B_{ij}} \tag{1}$$

There are n cells. B_{ij} is 1 if cells i and j are adjacent, otherwise 0. If the sectors of cells i and j are the same, then $x_{ij} = 0$, otherwise 1. The CI's for Figures.2 (c) and (d) are 14/24=0.583 and 9/24=0.375, respectively. If 0.5 is chosen as the maximum CI, then Figure.2 (c) is infeasible.

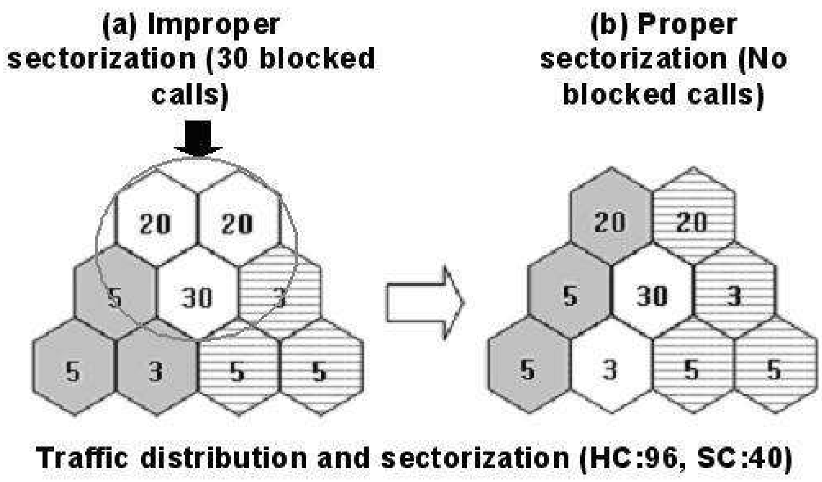


Fig. 1. Improper and proper groupings of micro-cells

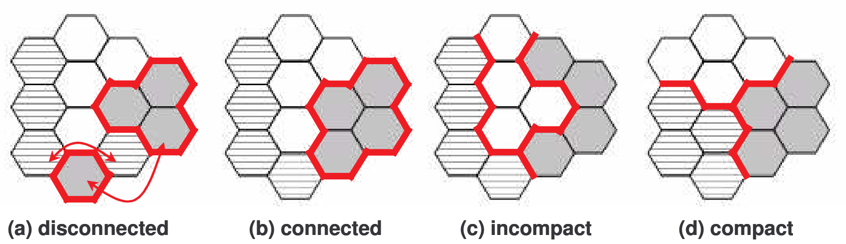


Fig. 2. Examples of micro-cell groupings

The grouping problem of cells is an NP-hard problem [11]. For load balancing of CDMA wireless systems previous research has explored the use of optimization heuristics. Kim and Kim [13] proposed a simulated annealing approach to minimize the cost of handoffs in the fixed part of a personal communication system network. Demirkol *et al.* [4] used SA to minimize handoff traffic costs and paging costs in cellular networks. Chan *et al.* [2] presented a genetic algorithm (GA) to reduce the cost of handoffs as much as possible while service performance is guaranteed. Lee *et al.* [14]

used a GA to group cells to eliminate large handoff traffic and inefficient resource use. In their proposed sectorization, properly connected and compact sectors are considered to keep the handoffs as few as possible while satisfying the channel capacity in each sector. Brown and Vroblefski [1] altered the GA approach of [14] with less disruptive crossover and mutation operators, that is, operators that better maintain the structure of previous solutions in newly created solutions. They report improved results over the Lee *et al.* GA. The same authors used a grouping GA on a related problem to minimize location update cost subject to a paging boundary constraint [22]. Using the same fundamental problem formulation of [1] and [14], we propose a new heuristic based on an ant colony system for dynamic load balancing of CDMA wireless systems.

2 Ant Approach for Dynamic Load Balancing

The ant colony approach is one of the adaptive meta-heuristic optimization methods inspired by nature which include simulated annealing, GA and tabu search. The ant colony paradigm is distinctly different from other meta-heuristic methods in that it *construct* an entire new solution set (colony) in each generation, while others focus on *improving* the set of solutions or a single solution from previous iterations. The ant optimization paradigm was inspired by the behavior of real ants. Ethnologists have studied how blind animals, such as ants, could establish shortest paths from their nest to food sources. The medium that is used to communicate information among individual ants regarding paths is pheromone. A moving ant lays some pheromone on the ground, thus marking the path. The pheromone, while gradually dissipating over time, is reinforced as other ants use the same trail. Therefore, efficient trails increase their pheromone level over time while poor ones reduce to nil. Inspired by the behavior of real ants, Marco Dorigo introduced the ant colony optimization approach in his Ph.D. thesis in 1992 [5] and expanded it in his further work, as summarized in [6, 7, 8, 9]. The characteristics of ant colony optimization include:

1. a method to construct solutions that balances pheromone trails (characteristics of past solutions) with a problem-specific heuristic (normally, a simple greedy rule)

2. a method tod both reinforce and evaporate pheromone.

Because of the ant paradigm's natural affinity for routing, there have been a number of ant algorithm approaches to telecommunications in previous research. Chu, *et al.* [3], Liu, *et al.* [15], Sim and Sun [19], Gunes, *et al.* [12] and Subing and Zemin [20] all used an ant algorithm for routing in telecommunications. Shyu, *et al.* [17, 18] proposed an algorithm based upon the ant colony optimization approach to solve the cell assignment problem. Subrata and Zomaya [21] used an ant colony algorithm for solving location management problems in wireless telecommunications. Montemanni, *et al.* [16] used an ant colony approach to assign frequencies in a radio network. More recently, Fournier and Pierre [10] used an ant colony with a local optimization to minimize handoff traffic costs and cabling costs in mobile networks.
Dynamic load balancing can be affected by grouping micro-cells properly and grouping can be developed through a routing mechanism. Therefore, we use ants and their routes to choose the optimum grouping of micro-cells into sectors for a given CDMA wireless system state.

2.1 Overview of the algorithm

In our approach each ant colony (AC) consists of ants numbering the same as the number of sectors, and there are multiple colonies of ants (C colonies) operating simultaneously. That is, each ant colony produces one dynamic load balancing (sectoring) solution and the number of solutions per iteration is the number of colonies. Consider an example of accomplishing sectorization. There is one VBS and three sectors. In step 1, the ant system generates three ants, one for each of the three sectors. In step 2, a cell in each sector is chosen for the ant to begin in. In step 3, an ant chooses a cell to move to - moves are permitted to any adjacent cell that has not already been assigned to a sector. Step 4 continues the route formation of each ant, which results in sectorization of all micro-cells.
The flowchart in Figures 3 and 4 gives the details of the algorithm. The variable *optimal* describes the best solution found so far (over all colonies and all iterations). The current available capacity of each VBS and each sector are calculated to determine which ant

to move first for sectorization. The cell chosen for an ant to move to is based on the amount of handoff traffic (described in section 2.4). When all cells are sectorized, CI is calculated using equation (1). If CI is less than the specified level, the solution is feasible. Otherwise, it is infeasible (not compact enough) and discarded. After all feasible solutions are evaluated the minimum cost solution of an iteration is assigned to the variable *best*.

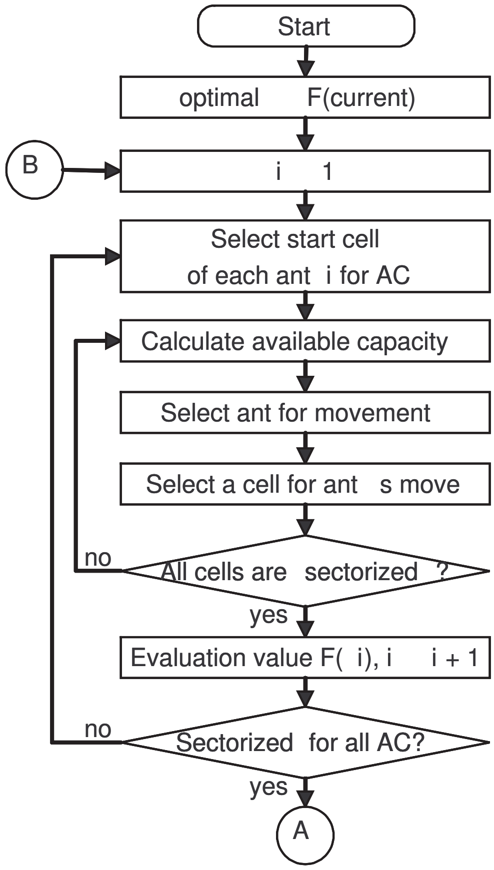


Fig. 3. Ant colony algorithm for dynamic load balancing

After all cells are sectorized by the ants in all colonies, the pheromone levels of each cell's possible assignment to each sector are updated using equation (2). In this equation, $\tau_{ik}(t)$ is the

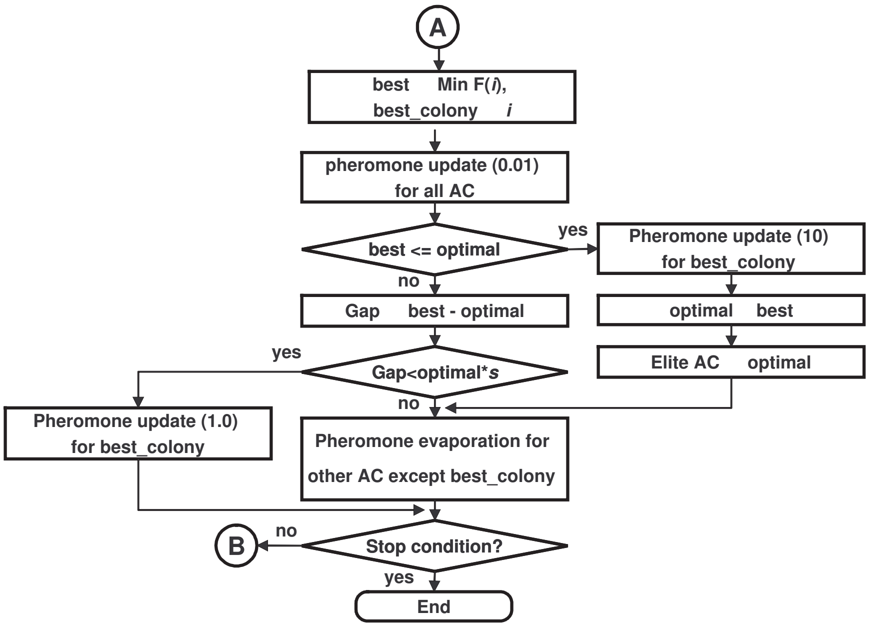


Fig. 4. Ant colony algorithm for dynamic load balancing Contd.

intensity of pheromone of cell i for assignment to sector k at time t. $\Delta\tau_{ik}$ is an amount of pheromone added to cell i for assignment to sector k (we use a straightforward constant for this amount = 0.01). $\Delta\tau^*_{ik}$is an elitist mechanism so that superior solutions deposit extra pheromone. If the best solution of the colonies 1 to C is also better than current value of the variable *optimal*, we add a relatively large amount of pheromone = 10.0. If the best solution of the colonies 1 to C is worse than current value of the variable *optimal* but the difference (GAP) between the values of the variables *best* and *optimal* is less than the value of *optimal**0.05, that is, the objective function of the best solution in the colony is within 5% of the best solution yet found, we add an amount of pheromone = 1.0. ρ is a coefficient such that $(1-\rho) \times \tau_{ik}(t)$ represents the evaporation amount of pheromone between times t and $t+1$. We use $\rho = 0.5$.

$$\tau_{ik}(t+1) \ = \ \rho \times \tau_{ik} \ + \ \sum_{j=1}^{C} \Delta\tau_{ikj} \ + \ \Delta\tau^*_{ik} \tag{2}$$

From equation (2), it can be seen that the amount of pheromone change is elitist. That is, the pheromone deposited for the best ever solution is three orders of magnitude greater than an ordinary deposit of pheromone and the amount deposited for the best solution in the C colonies (if it meets the GAP criterion) is two orders of magnitude greater than usual. This elitism helps the ant system converge relatively quickly.

2.2 Evaluation

The total cost is composed of the cost of blocked calls, the cost of soft and softer handoffs, and the cost of forced handoffs. Blocked calls are caused by exceeding HC or SC. When a mobile station with an ongoing call moves from one VBS to another, then a soft handoff occurs. When a mobile station with an ongoing call moves from one sector to another within a VBS, then a softer handoff occurs. When a cell changes its sector, all ongoing calls in the cell have to change sectors and a forced handoff occurs.

The cost of a micro-cellular system as proposed by Lee *et al.* [14] is used in this chapter and calculated based on the new grouping in time period $t+1$ given the grouping of cells in time period t. There are M virtual base stations ($BS_m, \quad m = 1, , M$); there is call demand of TD_i in each of the N cells, there is handoff traffic of h_{ij} from cell i to cell j, and there are K groupings (sectors) of micro-cells (SEC_k).

The objective cost function [14] is

$$\begin{aligned} Min \;\; F \;&=\; c_1 \sum_m Max \left\{ \sum_{i \in BS_m} TD_i - HC_m, 0 \right\} \\ &+\; c_2 \sum_k Max \left\{ \sum_{i \in SEC_k} TD_i - SC_k, 0 \right\} \\ &+\; c_3 \sum_i \sum_j h_{ij} z_{ij} \;+\; c_4 \sum_i \sum_j h_{ij}(w_{ij} - z_{ij}) \\ &+\; c_5 \sum_i g_i TD_i \end{aligned} \tag{3}$$

The first term is a summation over the M virtual base stations of the blocked calls due to hard capacity. The second term is a summation over the K sectors of the blocked calls due to soft capacity. The third term is the soft handoff traffic between adjacent cells with different VBS's. The fourth term is the softer handoff traffic between adjacent cells in different sectors within a VBS. The fifth term is the amount of forced handoff after sectorization (reconfiguration). z_{ij}, w_{ij}, and g_i are binary variables. $z_{ij}$is 1 if cells i and j are in different VBS's. w_{ij} is 1 if cells i and j are in different sectors. g_i is 1 if cell i changes sectors from the existing sectorization to the newly proposed one. c_1, c_2, c_3, c_4, and c_5 are weighting factors. The values of c_1, c_2, c_3, c_4, and c_5 are 10, 5, 2, 1, and 1 for examples in this chapter, as proposed by Lee *et al.* [14]. Larger weights are given to c_1 and c_2 because minimizing the blocked calls caused by hard and soft capacity is the first priority of sectorization.

2.3 Determination of starting cell for each ant

The following is the probability that cell i in sector k is selected for start.

$$p(i,k) \;=\; \frac{TD_i}{\sum_{j \in SEC_k} TD_j}, \quad i \in SEC_k \tag{4}$$

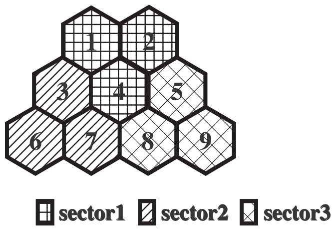
Greater probability is given to cells that have large call demands to reduce forced handoff costs. We have one VBS and three sectors in the example shown in Figure.5. Cell 4 in sector 1 has the highest probability (0.428) of starting. Cells 3 and 6 in sector 2 have the same highest probability (0.385) in sector 2. Cells 8 and 9 in sector 3 have the same highest probability (0.385) in sector 3.

2.4 Movement of each ant

The current available capacity of each VBS and each sector must be calculated. These are used to define ant movement. Capacities are calculated using following equations.

$$C\_BS_m \;= Max \left\{ HC_m - \sum_{i \in BS_m} TD_i,\; L_{BS} \right\} \quad for\ all\ m \tag{5}$$

$$C\_SEC_k \;= Max \left\{ SC_k - \sum_{i \in SEC_k} TD_i,\; L_{SEC} \right\} \quad for\ all\ k \tag{6}$$



Cell	1	2	3	4	5	6	7	8	9
TD	20	20	5	30	3	5	3	5	5

p(1,1) = 20/70 = 0.286
p(2,1) = 20/70 = 0.286
p(4,1) = 30/70 = 0.428

p(3,2) = 5/13 = 0.385
p(6,2) = 5/13 = 0.385
p(7,2) = 3/13 = 0.230

p(5,2) = 3/13 = 0.230
p(8,2) = 5/13 = 0.385
p(9,2) = 5/13 = 0.385

Fig. 5. Selection of starting cell for each ant

Figures 6 and 7 are examples where HC=96, SC=40, lower bound of VBS (L_{BS})=3, and lower bound of sector (L_{SEC})=2. The available capacity for VBS's and sectors (C_BS_m and C_SEC_k) are calculated using equations (5) and (6). We use the lower bounds of VBS and sectors (L_{BS} and L_{SEC}) to find the lowest total cost for sectorization. When searching for the optimal solution, we must consider that there are handoff costs and blocked calls. In other words, we might be able to save greater handoff costs even though we have some blocked calls in a VBS or sector. If cells 3, 4, and 8 are selected for sector 1 as shown in Figure (7, sector 1 has no chance to be selected by an ant for sectorization because there is no current available capacity in sector 1 of VBS 1. To allow blocked calls in sector 1, a chance (2/72=2.8%) is given to sector 1 using the lower bound of sector 1. The value of the lower bound is given by the user based on expected blocked calls in the system. If we have a large lower bound, there is a high possibility of blocked calls.

If there is more than one VBS, a VBS for beginning movement must be chosen first. $P_{BS}(m)$ is the probability that VBS BS_m is selected to be moved from by an ant. After choosing VBS m', one of sectors in VBS m' must be chosen. $P_{SEC}(k, m')$ is the probability that sector k in VBS m' is selected to be moved from by an ant. $P_{BS}(m)$ and $P_{SEC}(k, m')$ are calculated by the following.

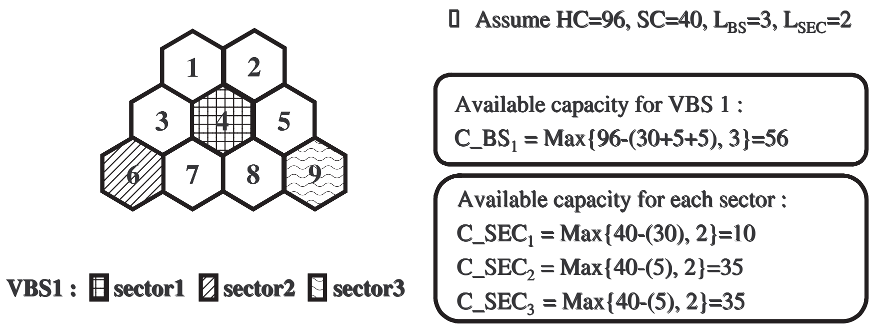


Fig. 6. Calculation of available capacity for VBS and sectors

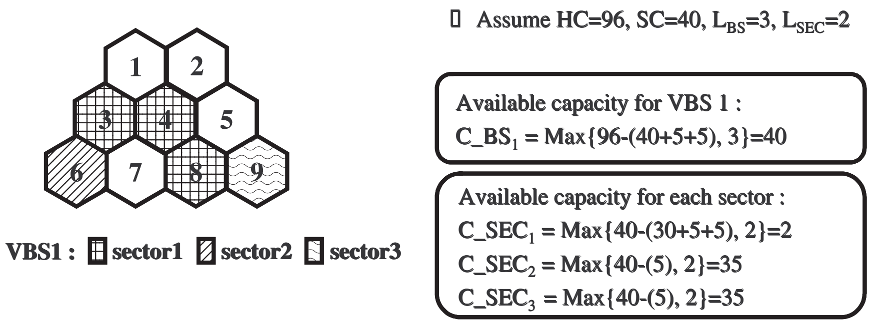


Fig. 7. Calculation of available capacity for VBS and sectors using lower bounds

$$P_{BS}(m) = \frac{C\_BS_m}{\sum_{u=1}^{M} C\_BS_u} \qquad for\ all\ m \tag{7}$$

$$P_{SEC}(k,m') = \frac{C\_SEC_k}{\sum_{l \in m'} C\_SEC_l} \quad for\ \ all\ \ k \in BS_{m'} \tag{8}$$

Which cell to be moved to by an ant is selected based on the amount of handoff traffic. $H_k(i)$ is the probability that cell i in N_k, is selected to move to first by an ant based on amount of handoff traffic, h_{ij}. N_k is the set of cells which are not yet chosen for sector k and are adjacent to the cells of SEC_k.

$$H_k(i) = \frac{\sum_j (h_{ij} + h_{ji})}{\sum_i \sum_j (h_{ij} + h_{ji})}, \quad for\ \ all\ i \in N_k,\ \ and\ \ j \in SEC_k \tag{9}$$

$phero(i,k)$ is the intensity of pheromone for cell i being assigned to sector k at time t which is $\tau_{ik}(t)$. This is indicative of the suitability of cell i for sector k. We set 0.001 for initial values of $phero(i,k)$ because the denominator of equation (10) cannot equal 0. $phero(i,k)$ is updated using equation (2) from section 2.1. $phero_k(i)$ is a probability of suitability of cell i for sector k.

$$phero_k(i) = \frac{phero(i,k)}{\sum_{k=1}^{K} phero(i,k)} \quad for \;\; all \;\; i \in N_k \tag{10}$$

Cell i is a cell adjacent to sector k. This cell has not been assigned to any sector yet. The probability that cell i will be assigned to sector k is

$$p_k(i) = \frac{\alpha H_k(i) \; + \; \beta phero_k(i)}{\sum_{l \in N_k}(\alpha H_k(l) \; + \; \beta phero_k(l))} \quad for \;\; all \;\; i \in N_k \tag{11}$$

This probability considers both handoff traffic (termed the local heuristic in the ant colony literature) and pheromone. α and β are typical ant colony weighting factors where α weighs the local heuristic and β weighs the pheromone. For this chapter, $\alpha = 1$ and $\beta = 1$, giving equal weight to the local heuristic and the pheromone.

3 Experiments and Analysis

We consider three benchmarking problems from [14] (Table.1). We have recoded the GA proposed by Lee *et al.* [14] to compare the performance of our ant approach and the GA for these problems. 100 replications were performed of each algorithm for each problem. We use 10 ant colonies at each iteration, where each ant colony finds one solution. So, we have 10 different solutions at each iteration. We found the optimal solutions of the 12 and 19 cells problems using ILOG 5.1 to validate the performance of the heuristics. We terminate the ant system and the GA in these first two problems when an optimal solution is found and in the last problem (37 cells) by a CPU time of each replication of 3600 seconds. We define the convergence rate as how many times an optimal (or best found for the last problem) solution is obtained over 100 replications.

Table 1. Description of three benchmarking examples from Lee *et al.* [14]

	12 cells	19 cells	37 cells
Number of cells	12	19	37
number of VBSs	1	2	3
Number of sectors	3	6	9

For the 12 cell problem the objective function values of the old and the new groupings at times t and $t+1$ are 255.604 and 217.842 as shown in Figure.8. We have three ants in each colony because there are three sectors in one VBS. For the traffic distribution, we use an Erlang distribution with average traffic of 9. We set minimum CI to 0.5. We find an optimal solution with evaluation value of 217.842 using ILOG 5.1 with execution time = 4.42712 CPU seconds. The convergence rate of the ant approach to this optimal solution is 100% with 0.00711 CPU seconds per iteration while the convergence rate of GA is 98% with 0.02082 CPU seconds per iteration.

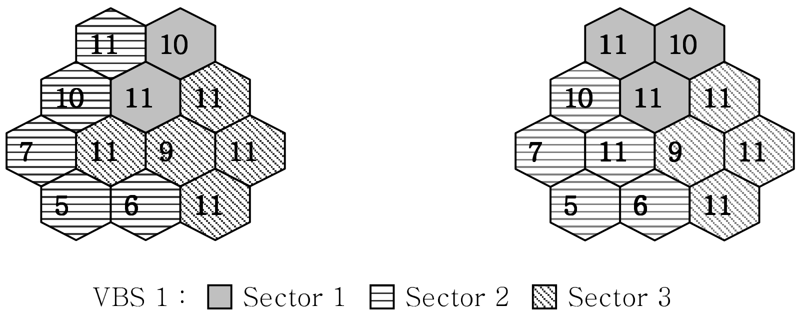


Fig. 8. Comparison of groupings of 12 cells at time t and $t+1$

For the 19 cell problem the evaluation values of the old and the new groupings at times t and $t+1$ are 601.388 and 284.597 as shown in Figure 9 using an Erlang distribution with average traffic=12. We have six ants in each colony because there are six sectors. We set minimum CI =0.65. We find the optimal solution using ILOG

5.1 with an execution time 995.82 CPU seconds. The convergence rate of the ant approach to this optimal solution is 100% with 0.06419 CPU seconds while the convergence rate of GA is 99% with 0.78378 CPU seconds.

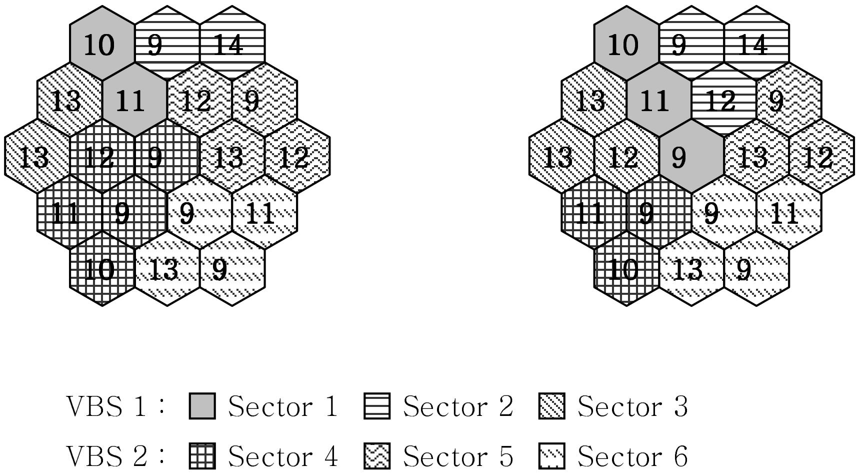


Fig. 9. Comparison of groupings of 19 cells at time t and $t+1$

For the large 37 cell problem, the evaluation values of the old and the new groupings at times t and $t+1$ are 1091.18 and 726.288 as shown in Figure 10 using an Erlang distribution with average traffic 9. We have nine ants in each ant colony because there are nine sectors. We set minimum CI =0.65.
Because this problem is too large to find the optimal solution exactly, we compare the performance of the ant approach and the GA using convergence rate within limited CPU time. The convergence rates of 100 replications of the ant approach are 73, 77, 86, and 88% for computation times of 5, 10, 20, and 30 CPU seconds as shown in Table.2. Convergence rates of the GA are 7, 12, 18, and 18% for the same computation time. Not only does the ant approach far exceed the convergence rate to the best solution but the solutions

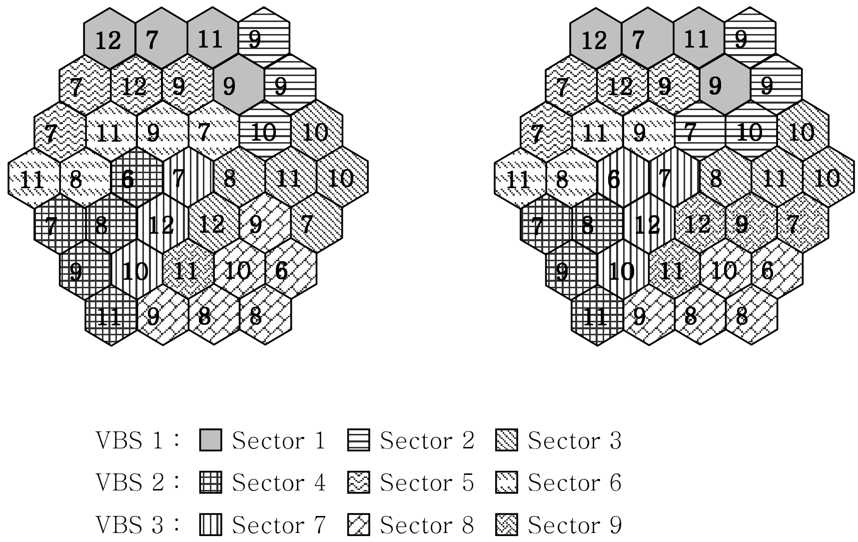


Fig. 10. Comparison of groupings of 37 cells at time t and $t + 1$

found by the ant approach that are not the best are much closer to the best than those found by the GA (Figures11,12,13,14).

Table 2. Results of the ant colony approach and GA [14] for the 37 cell problem over 100 replications

Algorithm	Execution time	Objective minimum	maximum	average	convergence rate
	5.0 Sec	766.288	773.661	766.9409	73/100
Ant System	10.0 Sec	766.288	773.661	766.9057	77/100
	20.0 Sec	766.288	768.354	766.5772	86/100
	30.0 Sec	766.288	768.354	766.5359	88/100
	5.0 Sec	766.288	888.258	798.7183	7/100
GA[14]	10.0 Sec	766.288	904.401	795.9874	12/100
	20.0 Sec	766.288	874.574	785.0495	18/100
	30.0 Sec	766.288	875.031	780.5263	18/100

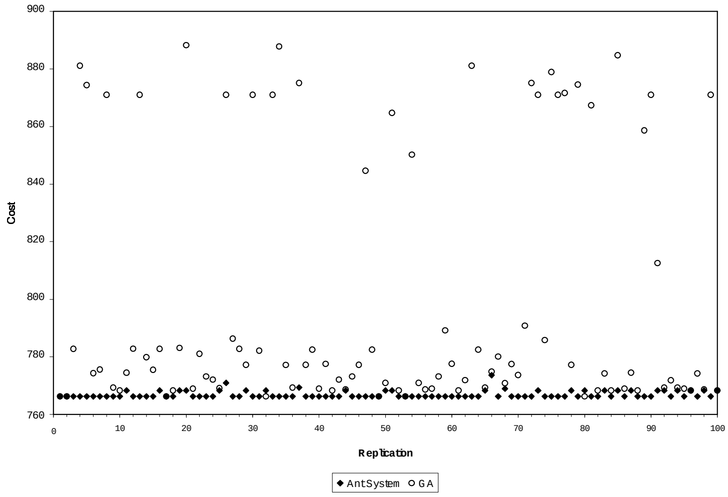


Fig. 11. Comparison of results using GA [13] and the ant colony for 37 cell problem over 100 replications (a) 5 seconds

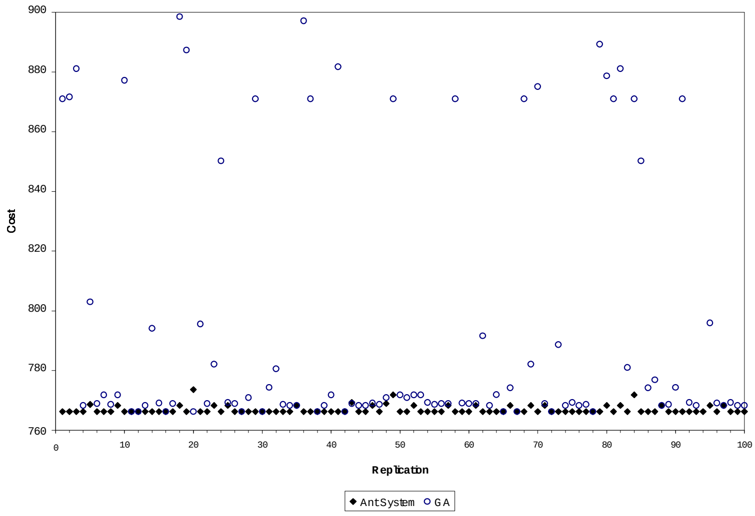


Fig. 12. Comparison of results using GA [13] and the ant colony for 37 cell problem over 100 replications (b) 10 seconds

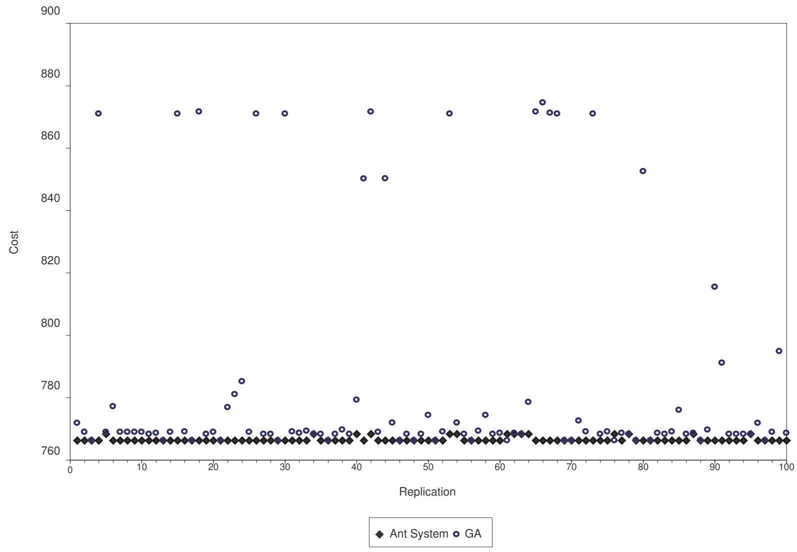


Fig. 13. Comparison of results using GA [13] and the ant colony for 37 cell problem over 100 replications (c) 20 seconds

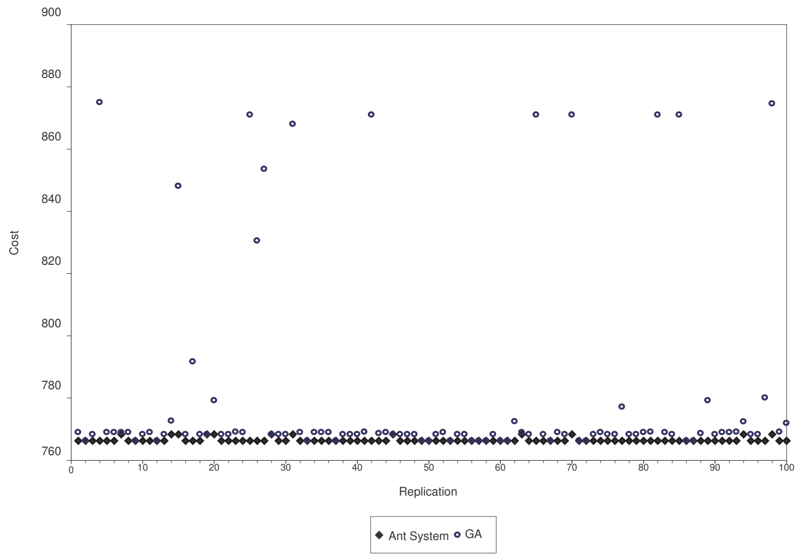


Fig. 14. Comparison of results using GA [13] and the ant colony for 37 cell problem over 100 replications (d) 30 seconds

4 Conclusions

We have used the routing capability of the ant system paradigm to good effect in the problem of dynamic routing of micro-cellular systems. Our approach is computationally quick and reliable in terms of how close to optimal a given replication is likely to be. Using three test problems from the literature, we produced decidedly better results than the earlier published genetic algorithm approach and achieved optimal on the problems whose size allowed enumeration. There are some parameters to set for the ant system, but we chose straightforward ones and the method does not seem sensitive to their exact settings. The probabilities used for placement and movement of the ants were intuitively devised considering call traffic and available capacities.

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