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LOCATION AREA PLANNING USING SIMULATED ANNEALING WITH A NEW SOLUTION REPRESENTATION

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Abstract. *Location area planning problem is to partition the cellular/mobile network into location areas with the objective of minimizing the total cost. This partitioning problem is a difficult combinatorial optimization problem. In this paper, we use the simulated annealing with a new solution representation. In our method, we can automatically generate different number of location areas using Compact Index (CI) to obtain the optimal/best partitions. We compare the results obtained in our method with the earlier results available in literature. We show that our methodology is able to perform better than earlier methods.*

Keywords: Location management, Simulated annealing, Location area planning, Compact index

1. **Introduction.** The substantial growth in micro-cellular communication networks has generated a lot of interest among researchers to provide a good quality of service with minimum cost. Location area management is one of the important areas that has been addressed in literature. One of the strategies for providing a good quality of service at minimum cost is to partition the network into Location Areas (LA). The minimum cost has two components namely location update cost and searching cost. Location update cost is incurred when the user changes itself from one location area to another network. The searching cost incurred when a call arrives, the search is done only in the location area to find the user.

The location area planning problem addressed in this paper can be generally stated as of partitioning a mobile network of n cells into m location areas, without violating the constraints and with the objective of minimizing the total cost. It can be seen that the location area planning problem is a difficult combinatorial optimization problem. There are many similar problems that arise in mobile computing network. Because of this difficult combinatorial complexity, many researchers have used evolutionary methods such as genetic algorithms, ant colony optimization, neural networks, taboo search and other methods for the solution. We will discuss some of the research work from literature that is related to our study.

The problem of assigning cells to switches is formulated as an assignment problem and the solution is given in [1]. In that study [1], the objective is to minimize the sum of handoff traffic cost and cabling cost. This study [1] has generated considerable interest among researchers and this problem was solved by using evolutionary methods [2]. Genetic algorithm, simulated annealing and tabu search techniques were used to obtain solution in [2]. A comparison of tabu search and simulated annealing (with simple homing) for this assignment problem is given in [3] and shown that the performance of tabu search is better than simulated annealing. A double homing approach is presented in [4]. A simulated annealing method by incorporating pricing mechanism is discussed in [5]. For this cell assignment problem, ant colony optimization approach is presented in [6, 7]. In the ant colony approach, the attractiveness of only call volume is used in [6], and a local optimization with a $k - opt$ technique is discussed in [7].

The objective considered in location area planning problem is the sum of handoff traffic cost (location update cost) and the paging cost [8, 9, 10, 11]. This problem is solved using simulated annealing in [8, 10], and a combined genetic-neural algorithm in [11]. An objective function that minimizes the location update cost with a bound on paging cost is considered in [12]. As mentioned in [10, 11], many algorithms have been proposed for the solution of location area planning problem. A number of important research works are given in [10, 11]. Ant colony optimization method has been used in partitioning mobile networks into location areas [13], and reporting cell planning in mobile computing networks [14].

1.1. **Contributions of this study.** In this paper, we consider the location area planning problem with the objective of minimizing the sum of location update cost and paging cost, by using a simulated annealing. Simulated annealing has been used to solve optimization problems [15, 16, 17]. In earlier studies, first, the number of location areas is fixed and then, the cells are assigned to the location areas. In our method, the initial and neighbor solutions are automatically generated with different number of location areas, and the cells are assigned to the corresponding number of location areas. In our study, the initial solutions are first generated using the genetic algorithm method given in [11]. It is known that the initial solution and neighbor solutions are very important for better performance of simulated annealing. For obtaining good initial solution and neighbor solutions in our simulated annealing study, we use the idea of *compact index* given in [18]. The simulated annealing with this good initial solution method was tested on the network examples given in [10, 11]. We are able to obtain better results than the results reported in [10, 11]. Note that, in our method, each test network example was run 50 times using simulated annealing (with good initial solution) and presents the best result obtained in the runs. This is because it is well known that behavior of simulated annealing is stochastic.

In the next section, we describe the location management cost model and other details of our method.

2. **Location Area Planning.** In mobility management systems one of the ways of reducing the total cost is to partition the network into Location Areas (LA). In this process, when a mobile terminal enters a new LA, it updates its location, and as long as it travels within the LA it never updates its location. On the other hand, whenever there is an incoming call, and since the network does not know the exact location of the user in the current LA, it pages the user in all the cells of the last updated LA [11]. In the location area planning problem, the total cost is given as

$$Cost = \beta \times N_{LU} + N_P \tag{1}$$

In the above equation, N_{LU} is the total number of location updates and N_P is the total number of paging operations. β is a constant and it represents the ratio of a location update to a paging in the network. In our simulation, we have used $\beta = 10$. In a given network, the number of location updates is caused because of the user movement and the paging operation is related to incoming calls. We give here the notations used in our study.

- n: total number of cells in the network.
- m: number of location areas.
- w_{cj}: call arrival weight for cell j.
- $h(i,j)$: handoff traffic between cell i and j.
- $s(j)$: number of cells in the location area that has cell j.
- M_k: call handling capacity of location area k.
- N_k: maximum number of cells for location area k.

Here, we present the mathematical formulation of the location area planning problem. For this purpose, we use the following variables.

$$x_{ik} = \begin{cases} 1 & \text{if cell } i \text{ is assigned to Location Area } k \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

$$z_{ijk} = \begin{cases} 1 & \text{if both cells } i \text{ and } j \text{ are assigned to the Location Area } k \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

$$y_{ij} = \begin{cases} 1 & \text{if both cells } i \text{ and } j \text{ are assigned to the same Location Area} \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

$$B_{ij} = \begin{cases} 1 & \text{if cells } i \text{ and } j \text{ are adjacent} \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

With the above variables, the objective function given in Equation (1) is written as

$$Total\ Cost = \beta * \sum_{i=1}^{n} \sum_{j=1}^{n} (1 - y_{ij}) * h(i,j) + \sum_{j=1}^{n} w_{cj} * s(j) \tag{6}$$

$$Total\ Cost = \beta \times Update\ cost + Paging\ cost \tag{7}$$

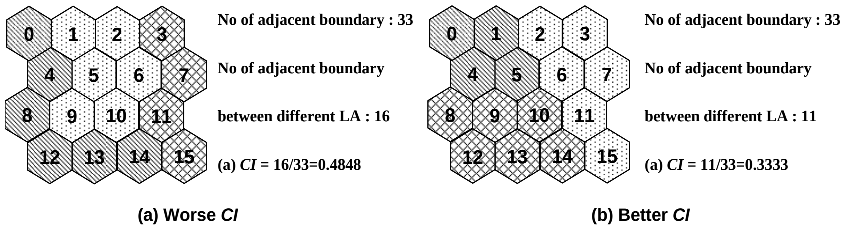

FIGURE 1. Configurations of LA_1 and LA_2

The constraints of the location area planning problem are:

$$\sum_{k=1}^{n} x_{ik} = 1, \quad 1 \le i \le n \tag{8}$$

$$z_{ijk} = x_{ik} * x_{jk} \tag{9}$$

$$y_{ij} = \sum_{k=1}^{m} z_{ijk}, \quad 1 \le i \le n, \quad 1 \le j \le n \tag{10}$$

$$\sum_{j=1}^{n} w_{cj} * x_{jk} \le M_k, \quad 1 \le k \le m \tag{11}$$

$$\sum_{j=1}^{n} x_{jk} \le N_k, \quad 1 \le k \le m \tag{12}$$

The constraint given by Equation (8) ensures that each cell is assigned to only one location area. For a given location area k, M_k is the call handling capacity and N_k is the maximum number of cells that can be assigned.

The Compact Index (CI) used in this paper is defined as

$$CI = \frac{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} (1 - y_{ij}) \times B_{ij}}{\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} B_{ij}} \tag{13}$$

2.1. **Solution representation.** In our approach, the solution (or configuration) is represented as a string of length n, the number of cells in the network. Each cell is assigned another number that represents the location area the cell belongs to. Consider the following 4×4 network.

$$\begin{array}{ccccccccccccccccc} CN & 0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 \\ LA_1 & 1 & 2 & 2 & 3 & 1 & 2 & 2 & 3 & 1 & 2 & 2 & 3 & 1 & 1 & 1 & 3 \\ LA_2 & 1 & 1 & 2 & 2 & 1 & 1 & 2 & 2 & 3 & 3 & 3 & 2 & 3 & 3 & 3 & 2 \end{array} \tag{14}$$

In the above Equation (14), the first row, gives the cell number (CN). The second and third row gives two location area configurations LA_1 and LA_2 respectively. The configurations of LA_1 and LA_2 are shown in Figure 1. The above configurations are with 3 location areas. We can see from this figure that LA_2 is better configuration than LA_1 in terms of Compact Index. In our method, we can randomly generate the configuration with any number of location areas.

We now have two configurations LA_1 and LA_2. The question now is Which configuration (LA_1 or LA_2), we will use in our simulated annealing as a starting solution. In order to get the good starting solution, we use the Compact Index (CI). The compact

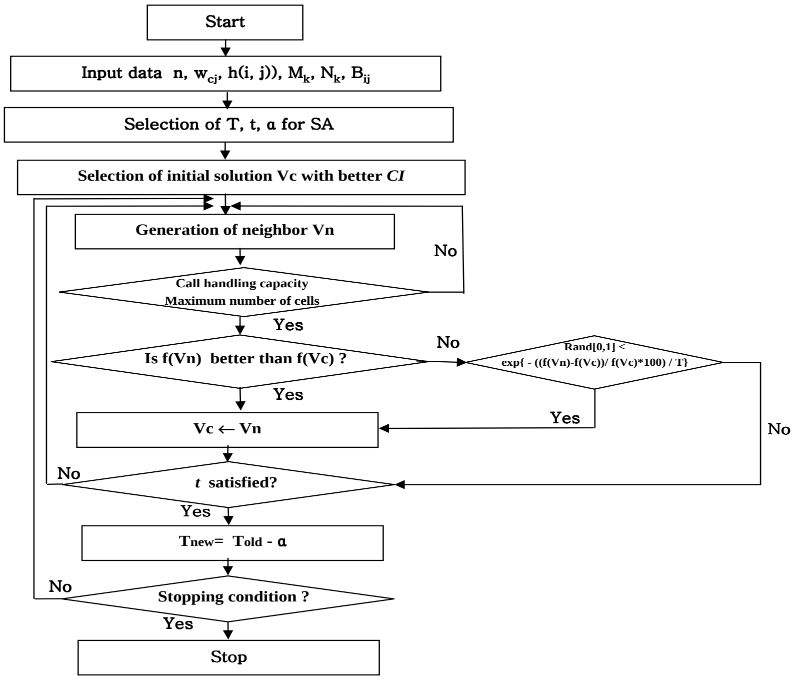

FIGURE 2. Flowchart of SA with compact index

index for LA_1 is $\dfrac{16}{33} = 0.4848$ and compact index for LA_2 is $\dfrac{11}{33} = 0.3333$. We choose the configuration with minimum compact index value. The usage of compact index is used in Simulated Annealing for obtaining the starting solution and also obtaining neighborhood solutions. The flowchart of Simulated Annealing with Compact Index is shown in Figure 2. In Figure 2, T, t, V_c, $f(V_c)$, V_n and $f(V_n)$ are given as:

- T: control parameter that corresponds to temperature in physical annealing.
- t: number of neighbors to search for a fixed T.
- V_c: current solution.
- $f(V_c)$: evaluation value of current solution V_c.
- V_n: new solution.
- $f(V_n)$: evaluation value of new solution V_n.

3. **Simulation Results and Discussions.**

3.1. **Simulation results.** In our simulation, we have used 5×5, 5×7, 7×7, 7×9 and 9×11 networks considered in [10, 11]. In the simulated annealing, the values of parameters used are: T (initial temperature) = 1, t (number of neighborhood search with the same temperature) = 10 and $\alpha = 0.001$ and the simulation was run on Pentium 4, computer (3.4GHz, 2G RAM). In our simulation each of the above network example was run 50 times using simulated annealing (with good initial solution using CI) and present the best result obtained in the runs. This is because it is well known that behavior of simulated annealing is stochastic. The results obtained are given below.

5×5 *network:* We are able to obtain the same configuration obtained in [10, 11]. The number of location areas is 3 and the total cost obtained is 26,990. The compact index for this optimal configuration is 0.2143. The computation time to obtain this best configuration is 1.8 seconds and the solution converges after 800 generations.

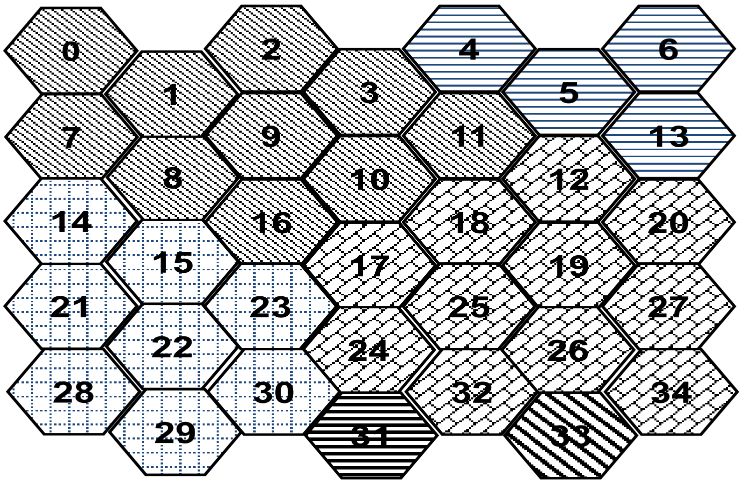

FIGURE 3. Best configuration obtained for 5 × 7 network

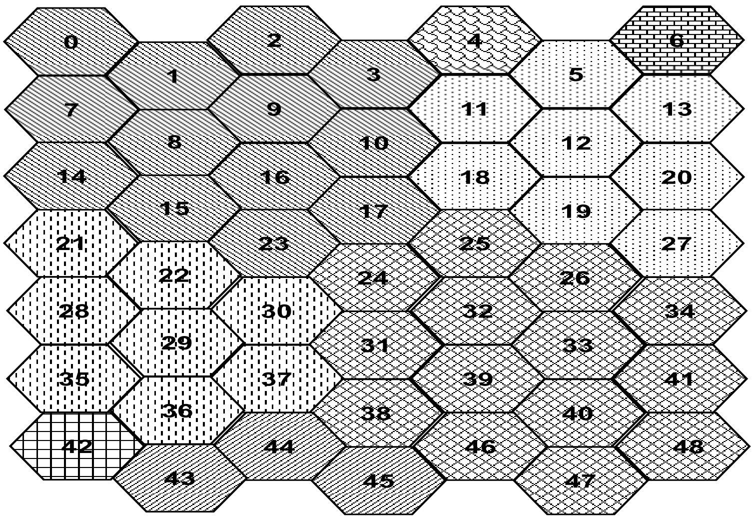

FIGURE 4. Best configuration obtained for 7 × 7 network

5 × 7 *network:* The best configuration obtained for this network is shown in Figure 3. The number of location areas is 6 and the total cost obtained is 39,975 after around 800 generations. The compact index for this best configuration is 0.3049. For the same network results in [10, 11] has 4 location areas and the total cost is 40,085.

7 × 7 *network:* The best configuration obtained for this network is shown in Figure 4. The same configuration is obtained in [11] using GA-HNN3. The number of location areas is 8 and the total cost obtained is 60,606. The computation time to obtain this best configuration is 5 seconds and the solution converges after 800 generations. The compact index for this best configuration is 0.2857.

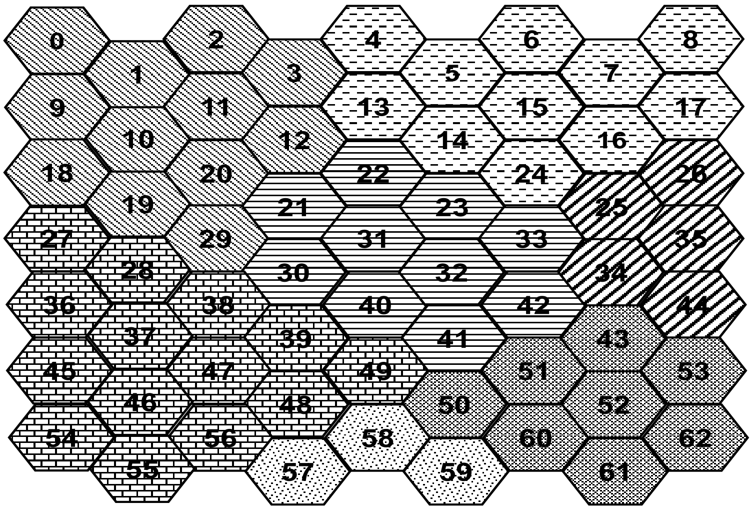

FIGURE 5. Best configuration obtained for 7×9 network

7×9 *network:* The best configuration obtained for this network is shown in Figure 5. The number of location areas is 7 and the total cost obtained is 89,085 after around 800 generations. The compact index for this best configuration is 0.2848. For the same network results in [10, 11] has 7 location areas and the total cost is 90,506.

9×11 *network:* The best configuration obtained for this network is shown in Figure 6. The number of location areas is 11 and the total cost obtained is 169,273. The computation time to obtain this best configuration is 17 seconds and the solution converges after 1000 generations. The compact index for this best configuration is 0.3023. For the same network results obtained in [10] has 10 location areas and the total cost is 172,669. The number generations is around 1500 in [10]. From these networks, we can see that our method performs well.

3.2. **Discussions.** In our approach, we partition the given network into optimal number of location areas using the concept of compact index given in Equation (13). The compact index is defined as the ratio of number of adjacent boundaries between different location areas and the total number of boundaries in the given network. The compact index varies from 0 to 1. The optimality criterion used in our study is minimizing the total cost given by Equation (1). In our approach, the different number of location areas are automatically generated. The three dimensional representation of convergence for the best solution is shown in Figure 7. This figure shows the convergence to the optimal/best solution with different number of location areas. The only additional computation needed in our approach is the selection of initial solution using the of compact index. This additional computation is very small relative to the simulated annealing methodology.

4. **Conclusions.** We have considered the location area planning problem and present simulated annealing method (with compact index) for obtaining the solution. A description of compact index and its use in obtaining the initial solution and generation of neighborhood solution with different number of location areas, in simulated annealing is presented. The test networks considered in earlier studies were used for verification of our approach. A comparison of our approach with earlier methods is presented. It is shown

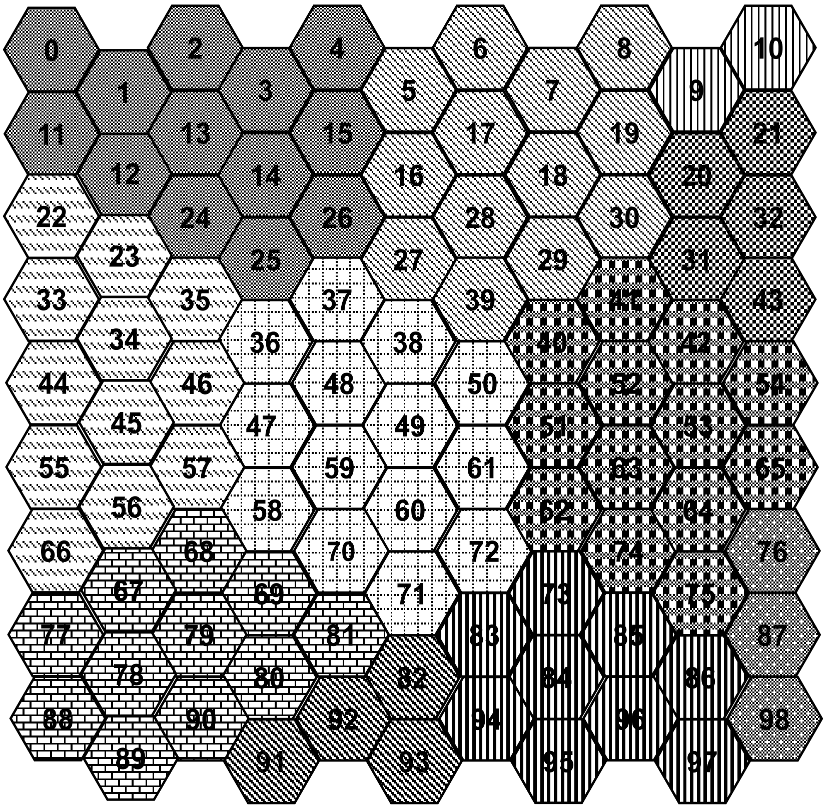

Figure 6. Best configuration obtained for 9×11 network

that our method is able to obtain better location areas for the test networks, than earlier methods, in terms of the cost.

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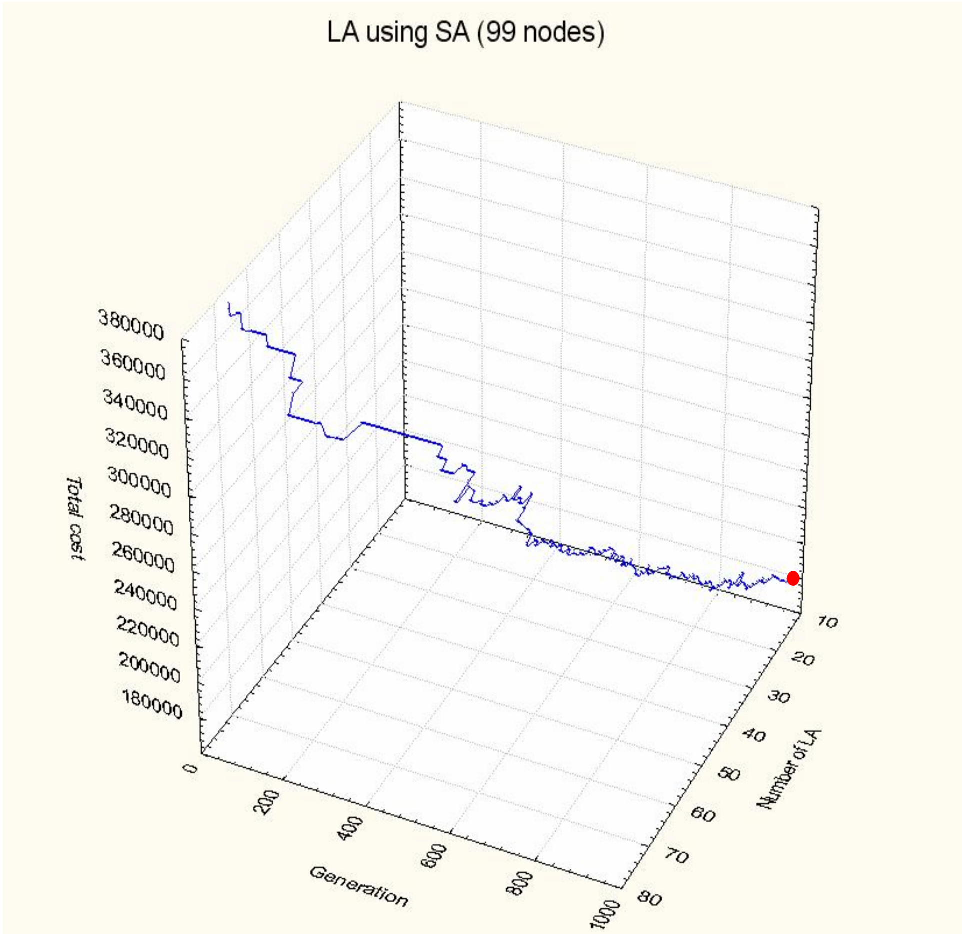

Figure 7. Convergence for the best solution in three dimension

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