Registration Area Planning for PCS Networks Using Genetic Algorithms

Tsan-Pin Wang, Shu-Yuen Hwang, and Chien-Chao Tseng

***Abstract*— In a personal communication services (PCS's) network, the signaling traffic required to support user mobility is extremely high due to the huge numbers of users and the small sizes of cells. The requirement to minimize this traffic increases the importance of registration area (RA) planning in the PCS network design. In the literature, several heuristic algorithms have been proposed for RA planning, however, they may get trapped into local minimums and may lack robustness. In this paper, we reformulate the problem of RA planning as a cost-optimization problem and propose genetic algorithms for RA planning in PCS networks. Simulation results show that genetic algorithms are robust for RA planning.**

***Index Terms*— Personal communication services, registration area planning.**

I. Introduction

A PERSONAL communication services (PCS's) network [2], [3] is a digital communication system that enables subscribers to initiate or receive calls at any time from any location. To do this, the system must support the mobility of users and be able to find users as they move from cell to cell (*roaming*). Thus, a called portable must be located before a connection can be established [4], [5]. There are two alternatives to this task: paging and registration. Paging is impractical since a PCS network may cover an extremely large area. In the registration scheme [6], the system area is divided into several RA's (or location areas in cellular networks). In general, an RA consists of an aggregation of cells forming a contiguous geographical region.

When a portable enters a cell which belongs to a different RA, a *location update* (LU) procedure that informs the network about the portable's new location is performed. When a portable is called, first the RA being traversed by it is determined and then a paging procedure is applied within that RA to identify the specific base station servicing its connection. During the paging process, every base station in the RA broadcasts a specific message to inform the portable this connection request. Both LU and paging generate network traffic overhead in PCS networks and consume the scarce radio resource. Moreover, LU also increases the load of distributed location databases and thus increases the implementation complexity of the databases [7], [8].

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Due to the huge numbers of users and the small sizes of cells in PCS networks, the signaling required to support user mobility, e.g., paging and location updating, is significant. RA planning has therefore been playing an increasingly important role in improving the PCS network performance. In general, RA dimensioning [9], [10] is based on the tradeoff between the amount of signaling caused by paging and location updating. As the sizes of the RA's increase (decrease), the paging cost increases (decreases) and the LU cost decreases (increases). An RA planning algorithm during the design of a PCS network should be able to minimize the overall network location updating and paging cost.

In the literature, there has been little research on RA planning for PCS networks [9]–[12]. RA planning decomposes a group of cells into RA's in which LU traffic is minimized without violating the paging bound. It can be mapped into a graph-partition problem, which is a well-known NP-complete problem [13]. Consequently, an exact search for optimal solutions is impractical due to exponential growth in execution time. Previous researchers have used graph models to represent RA planning and utilized greedy approaches to solutions. Gamst [9] proposed a graph theoretical model and presented a greedy method for RA planning. Markoulidakis *et al.* [10], [11] proposed two heuristic algorithms to obtain better results by adjusting the border weights in future mobile telecommunication networks. Plehn [12] proposed a weighted greedy algorithm that consists of two phases—the merge and exchange phases. According to their experience, the algorithm performed superior to previously used methods. Although heuristics has been proposed to obtain better results, RA planning was generally based on the hill-climbing algorithm.

However, *hill-climbing* [14] approaches may get trapped into local minimums and lack robustness. In addition, the graph theoretical models have the following drawbacks.

1) A tradeoff between LU traffic and preset configurations (*soft preset*) is impossible. A preset is a given in an RA configuration that might have been planned in a previous state of expansion of the network or might have been fixed by the planning engineer. In practice, presets are generally required in PCS network design due to the existing network configuration. The advantage of presets is that they provide a network designer a way to state his/her preference during the planning stage to reduce the cost of network installation. In this paper, we consider two types of presets: *soft* and *hard presets*. A soft preset is a preset configuration that can be violated. For example, some neighboring cells may be preset to

belong to a certain RA only when this preset does not significantly increase network cost. A *hard preset*, on the other hand, is inviolable.

2) They cannot support soft constraints. A soft constraint allows some violation, for example, the paging bound can be broken if it greatly reduces LU traffic.

The graph theoretical approach aims only to minimize network cost. It does not quite hit the actual problem. Moreover, some paging bandwidth may be locally reserved for network growth, e.g., cell splitting in heavy-load areas.

To overcome these drawbacks, formulating RA planning as a cost-optimization problem is obviously superior to conventional graph theoretical models. Genetic algorithms [15], [16] have been considered as robust stochastic search algorithms for various optimization problems. In this paper, we propose genetic algorithms for RA planning in PCS networks.

The organization of this paper is shown as follows. In Section II, we formally define the RA planning problem. In Section III, we present a brief introduction to genetic algorithms and propose a genetic approach for RA planning. In Section IV, we provide details on customizing RA planning. The simulation results are presented in Section V. Finally, a conclusion is given in Section VI.

II. RA Planning

Proper design of RA's is based on a tradeoff between paging traffic and LU traffic. Generally, paging traffic is less critical than LU traffic [9] since LU affects not only the radio resource, but the load of distributed location databases as well, so the optimization goal is to minimize LU cost without violating the paging bound of each RA. In this paper, a general definition of RA planning will be examined. Our RA planning objective is to minimize LU traffic on the network subject to the constraints such as the paging bound of each RA, preset configurations, and other specific constraints.

In general, paging traffic is proportional to the number of calls to all portables in the RA while LU traffic is proportional to the number of portables crossing RA borders. Prior to the RA planning procedure, PCS network designers must collect these data as input parameters. Although obtaining these data may present considerable difficulty in practice, it can be accomplished in the following ways. Markoulidakis and Sykas [17] proposed a model to estimate location update and handover rate for mobile communication, and practical PCS networks such as the global system for mobile communications (GSM) may provide data that enable an approximation of this information. Without loss of generality, we may assume then that these data are already available. The basic assumptions used in this paper are shown as follows.

1) Cell planning has been done. In each cell, LU and paging traffic have been estimated.
2) Each RA contains a disjoint set of cells—RA overlapping is not allowed in this paper.
3) The bandwidth available for paging in each RA, i.e., the paging bound, is limited.

Based on these assumptions, we first describe the graph models and relevant algorithms and then derive a general model for optimization. In graph models, a PCS network configuration is defined by a weighted (undirected) graph $G = (V, E, f, g)$, where V is the set of vertices, E is the set of edges, f is a function whose domain is V, and g is a function whose domain is E. Each vertex represents a cell, and each edge denotes a border between cells. The function f assigns weights called paging cost to the vertices in V, and the function g assigns weights called LU cost to the edges in E.

```
Procedure hill-climbing
{C is the set of all borders.}
{S is the solution set.}
  begin
    S = C;
    do
      x = select the border with maximum cost from C;
      S = S - {x};
      C = C - {x};
      if S violates the paging bound then
        S = S ∪ {x};
    while (C is not empty);
      report S;
  end
```

Fig. 1. A hill-climbing algorithm for RA planning.

In this model, the hill-climbing algorithm shown in Fig. 1 is performed to explore the solution. Edges in graph G are removed only when the removal would not violate the paging bound for any RA. Hill-climbing algorithms ensure the correctness of solutions by preventing searches that lead to illegal nodes, however, they do not ensure optimal or even near-optimal solutions. Moreover, supporting soft presets and constraints is nontrivial in this model.

In this paper, we formulate RA planning as a cost-optimization problem in which solutions are described by a cost function and techniques for minimizing (or maximizing) the cost function. We also remove constraints by means of a weighted penalty function that assigns weights according to constraint importance. Thus, RA planning is reduced to the cost-optimization problem.

Consequently, let X denote the set of objectives and Y represent the set of constraints, where the goal of RA planning is to minimize a cost function $F(X, Y)$, which is defined as follows:

$$F(X,Y) = \sum_{X_i \text{ in } X} w_i f(X_i) + \sum_{Y_j \text{ in } Y} u_j g(Y_j) \qquad (1)$$

where w_i and u_j are weights for the objective i and constraint j, respectively. The objective function f is a function that maps from objectives to costs and contributes to the RA planning goal. The penalty function g is a function that maps from constraints to costs and punishes violation of constraints such as paging bounds, soft presets, and others. The objective and penalty functions are calculated using the configuration graph making this model a general form of RA planning. For special cases, let X contain only the total LU cost and Y contain only the paging bound constraint, where our goal is to minimize the LU cost without violating the paging bound constraint as previous work.

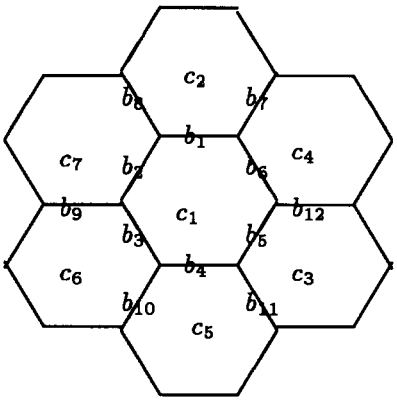


Fig. 2. An example of the H-mesh configuration with dimension 2.

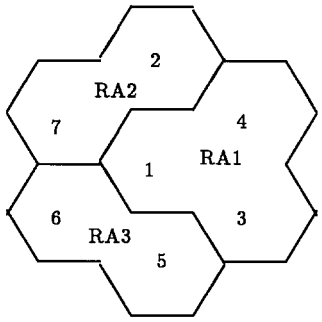


Fig. 3. An RA planning result for Fig. 2.

We use a simple example of the H-mesh configuration [18] with dimension 2 to illustrate RA planning as shown in Fig. 2. In this example, c_i denotes the paging cost of the ith cell and b_i denotes the LU cost of the ith border. Assume that the paging bound for each RA is 30 for all i and $c_i = 10$ and $i = 5,\ 6,\ 8,\ 10,\ 12$, and $b_i = 100$, otherwise, $b_i = 50$. Fig. 3 shows the optimal result for this example: $RA1$ consists of cells 1, 3, and 4, $RA2$ consists of cells 2 and 7, and $RA3$ consists of cells 5 and 6.

III. Genetic Approach to RA Planning

Genetic algorithms have been applied to various optimization problems. In general, they use a penalty function to encode constraints and allow a search for illegal nodes, e.g., a node may violate the paging bound. Allowing a search for illegal nodes may prevent falling down into a local minimum and generate a better solution. It is well suited to the cost-optimization model we propose for RA planning. In this section, we first review the fundamentals of genetic algorithms and then describe the representation and fitness function for RA planning.

A. Fundamentals of Genetic Algorithms

In principle, genetic algorithms [15], [16] 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 nodes in the search space.

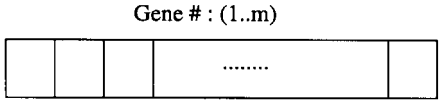


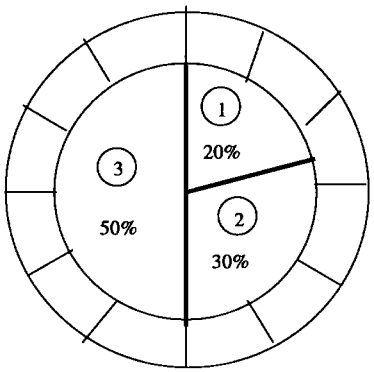
Fig. 4. A chromosome.

In general, genetic algorithms maintain a population of individual candidate solutions to specific domain challenges. An individual can be represented by a string (*chromosome*) as shown in Fig. 4. During each iteration, or called generation, the individuals in the current population are rated for their fitness as domain solutions. The fitness function evaluates the "goodness" of each individual. As a result of this evaluation, a new population of candidate solutions is generated using specific genetic operators. Generally, genetic algorithms make use of three primary operators called *selection, crossover, and mutation*, which are described below.

1) *Selection (or Reproduction)*: Individuals in the population can be heuristically or randomly initialized. The population of the next generation reproduces using a probabilistic selection process. Practically, reproduction allocates offspring strings using a roulette wheel [15] with slots sized according to fitness as shown in Fig. 5. In this example, the fitness of chromosomes 1, 2, and 3 are 20, 30, and 50, respectively, and the percentage of chromosomes 1, 2, and 3 are 20% (20/20 + 30 + 50), 30% (30/20 + 30 + 50), and 50% (50/20 + 30 + 50) in the offsprings, respectively. Thus, individuals with higher fitness have more chances to reproduce. In order to guarantee the convergence [19] of genetic algorithms, the best individuals from the previous population along with a fixed percentage, called the clonation percentage, is retained in the new one. This also assures a more efficient search of the solution space.
2) *Crossover*: After reproduction, crossover proceeds with a probability p_c. This operator takes two randomly chosen parent individuals as input and combines them to generate two children. This combination is performed by choosing two crossing points in the strings of the parents and then exchanging the allelic values between these two points as shown in Fig. 6. The crossover operator provides a powerful exploration capacity by exchanging the information from two parents.
3) *Mutation*: The crossover operator may lead to falling into a local minimum of the fitness function because generated children tend to be very similar to their parents. In order to reduce this phenomenon, mutation operates with a probability p_m and creates new individuals by modifying one or more of the gene values of an existing individual, as shown in Fig. 7. It provides a random search in the problem space and prevents complete loss of genetic features through selection and elimination. Thus, the mutation operator reduces the probability of falling into a local minimum of the fitness function.

No.	Chromosome	Fitness	% of Total
1	0101	20	20%
2	1001	30	30%
3	1101	50	50%

(a)



(b)

Fig. 5. Simple selection allocates offspring chromosomes using a roulette wheel with slots sized according to fitness.

Before Crossover
0 0 | 0 0 0 | 0
1 1 | 1 1 1 | 1
After Crossover
0 0 | 1 1 1 | 0
1 1 | 0 0 0 | 1

Fig. 6. Two-point crossover (| denotes a crossing point).

Before Mutation 0 0 | 0 | 0 0 0
Mutation Point ↓
After Mutation 0 0 | 1 | 0 0 0

Fig. 7. Mutation.

Following reproduction, crossover, and mutation, the new population is ready for testing. Genetic algorithms decode new strings, calculate fitness, and then generate a new population. Fig. 8 depicts the outline of a genetic algorithm. The recombination process invokes a set of genetic operators, such as crossover and mutation.

The construction of a genetic algorithm for any problem can be separated into the following tasks.

1) Choose the representation of the genetic chromosome.
2) Design a set of genetic operators.
3) Define the fitness function.
4) Determine the probabilities controlling the genetic operators.

Each of the tasks above may greatly affect the quality of obtained solutions as well as the performance of the genetic algorithm. In the following sections, we examine how each of them applies to the problem of RA planning.

B. Representation

In our study, two representation schemes were used to encode the RA planning problem—cell- and border-oriented.

1) *Cell-Oriented Representation*: Cells are labeled from one to the total number of the cells and RA's are labeled from one to the total number of RA's. The cell representation of chromosome structure is shown in Fig. 9(a), where the ith cell belongs to the v_ith RA. For example, the chromosome of the example shown in Fig. 3 is shown in Fig. 9(b).

```
Procedure genetic algorithm
{Pop is the population set}
{gen is the generation number}
  begin
    preprocess;
    gen = 0;
    initialize Pop(gen);
    while (not termination condition) do
      begin
        evaluate Pop(gen);
        select Pop(gen);
        recombine Pop(gen);
        gen := gen + 1;
      end
    postprocess;
  end
```

Fig. 8. A genetic algorithm.

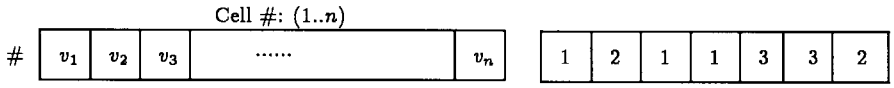
2) *Border-Oriented Representation*: Borders are labeled from one to the total number of borders. The border representation of chromosome structure is shown in Fig. 10(a), where $v_i = 1$, and is the border i (b_i), which exists in RA planning, otherwise, $v_i = 0$. For example, the chromosome of the example shown in Fig. 3 is shown in Fig. 10(b).

Choosing cell- and border-oriented representation is a trade-off. Cell-oriented representation is excellent for evaluating paging cost, but poor at evaluating LU cost. On the other hand, border-oriented representation is superior to cell-oriented representation at evaluating LU cost, but inferior at evaluating paging cost. Without loss of generality, we concentrate mainly on border-oriented representation hereafter.

C. Genetic Operators

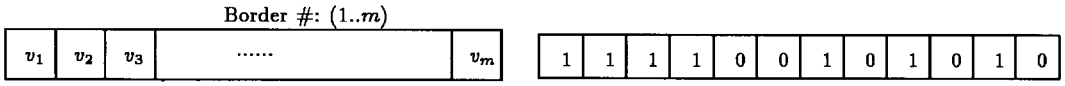
There is no special genetic operator designed for RA planning. Three general operators discussed in previous sections are used to explore the state space.

1) The selection operator produces individuals with higher potential to be optimal solutions.
2) The crossover operator explores the solution space by exchanging the information from two parents.
3) The mutation operator provides opportunities for long jumps from local minima.



(a) (b)

Fig. 9. Cell chromosome structure of the RA planning.



(a) (b)

Fig. 10. Border chromosome structure of the RA planning.

D. Fitness Function

Generally, genetic algorithms use penalty functions to punish violations of constraints. The penalty function of paging bound for RA planning is shown below

$$C_{\text{paging}} = \sum_{i=1}^{m} \max(0, (\text{PAGE}(i) - \text{BOUND})) \tag{2}$$

where m denotes the total number of RA's, PAGE(i) denotes the paging traffic of the ith RA, and BOUND represents the paging bound. This penalty function punishes the violation of the paging bound for each RA.

Thus, the cost function is equal to the total cost generated by LU traffic plus the paging penalty as shown in the following:

$$\text{Cost} = \frac{A}{2} \sum_{i=1}^{m} LU(i) + B \times C_{\text{paging}} \tag{3}$$

where m denotes the total number of $RA's$, $LU(i)$ denotes the LU traffic of the ith RA, and parameters A and B are used to balance the relative importance of the penalty function and the objective function.

In border-oriented representation, let n_b be the total number of borders, w_i represent the crossing intensity of the ith border, and v_i be the value of the ith chromosome (either zero or one). For the sake of convenient computation, the cost function for border-oriented representation could be rewritten as follows:

$$\text{Cost} = \frac{A}{2} \sum_{i=1}^{n_b} v_i w_i + B \times C_{\text{paging}}. \tag{4}$$

Since the selection operator will try to maximize the fitness function, we need to convert the cost function into maximization form. This can be done by defining the fitness function as follows:

$$\text{Fitness} = C_{\max} - \text{Cost} \tag{5}$$

where $C_{\max}$ denotes the maximum value *observed so far* of the cost function in the population. Let cost be the value of the cost function for the chromosome, and $C_{\max}$ can be calculated by the following iterative equation:

$$C_{\max} = \max(C_{\max}, \text{cost}) \tag{6}$$

where $C_{\max}$ is initialized to zero.

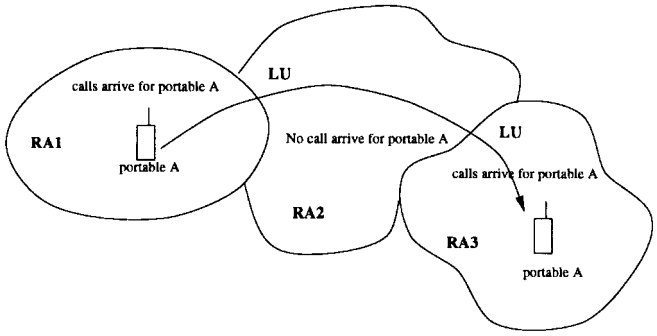


Fig. 11. Example of useless location updating.

E. Initial Population

Individuals in the population can be initialized randomly or heuristically. We use the result of hill climbing as one individual and randomly generate other individuals to construct the initial population. Moreover, the preset of the cell configuration (either soft or hard presets) also provides the information of constructing the initial population.

IV. Customizing RA Planning

In this section, we discuss some details of applying genetic algorithms to RA planning.

A. Useless Location Updating

Useless location updating [10] refers to the case of subsequent LU's without using the updated information as shown in Fig. 11. In this example, the LU in RA2 is a useless location updating since no calls arrive for portable A during the time period that the portable A was in RA2. As we mentioned in Section I, the reason for updating location information is to make the network be able to locate a portable whenever this portable is called. Thus, useless location updating indicates the waste of signaling and database access. It is not necessary for a portable to perform LU's much more frequently than the portable receives calls. To improve the network performance, we should minimize the probability of useless location updating.

The probability of useless location updating P_{ulp} can be defined as the probability of two subsequent LU's caused by the same portable traversing an RA without the arrival of any

incoming calls as follows[1]:

$$P_{\text{ulp}} = P[t_m < t_c] = \int_{t_c=0}^{\infty} \int_{t_m=0}^{t_c} f_m(t_m) f_c(t_c)\, dt_m\, dt_c \tag{7}$$

where the notation used is listed as follows:

- t_m time interval between the previous phone call to a portable and the time when the portable moves out of the RA;
- t_c independent and identically distributed random variable which represents the time interval between two consecutive calls directed from an RA to a portable;
- $f_c(t)$ density function for the random variable t_c;
- $f_m(t)$ density function for the random variable t_m.

The following equation is then added to the cost function and affects the fitness function:

$$C_{\text{ulp}} = C \times P_{\text{ulp}} \tag{8}$$

where C is the parameter for adjusting the weight of the useless location updating. The fitness function handles the fitness of genetics such that C_{ulp} reduces the impact of useless location updating.

B. Presets and Constraints

A preset or constraint can be defined by a string $v = \langle v_1 \cdots v_i \cdots v_n \rangle$, where n is the number of cells: $v_i = 1$ if the ith border is necessary to exist, $v_i = 0$ if the ith border is necessary to remove, otherwise, $v_i = *$, which ignores the ith border. For example, we preset assignment of cells 1 and 2 to the same RA, i.e., border 1 is not necessary to exist in the example shown in Fig. 2. The preset string v is equal to $\langle 0 * \cdots * \rangle$.

The penalty function of the preset V_{preset} can be defined as the following:

$$V_{\text{preset}} = \sum_{i=1}^{n} f(b_i, v_i) \tag{9}$$

where

$$f(b_i, v_i) = \begin{cases} 0, & \text{if } b_i = v_i \text{ or } v_i = * \\ 1, & \text{otherwise.} \end{cases}$$

In a similar manner, we can compute the penalty of constraint V_c. The following equations are added to the cost function to deal with soft (hard) presets and constraints:

$$C_{\text{preset}} = D \times V_{\text{preset}} \tag{10}$$

$$C_c = E \times V_c. \tag{11}$$

However, large parameters may outweigh the importance, on the other hand, small parameters may lead to generation of illegal solutions. Finding appropriate parameters is not a trivial job. A postprocessing stage is necessary to filter out illegal solutions in dealing with *hard* presets or constraints.

[1] Assume t_m and t_c are *i.i.d.* with exponential distributions, so this equation can be greatly simplified [7].

C. Improving Algorithm Performance

Although genetic algorithms work well for RA planning, we propose some techniques to improve algorithm performance and run-time efficiency.

1) Probability of Mutation: In the beginning of the algorithm, we may initialize a large mutation probability value to search a larger state space. However, this might not obtain better results as the algorithm near convergence. We resolve this problem by decreasing the probability of mutation by half after a predefined number of generations, for example, 100 generations.

2) Heuristics: It is easy to encode search heuristics in genetic algorithms using the mutation operator. In this paper, we propose two heuristics to improve the performance of genetic algorithms.

1) *Large-Weight Preference*: We prefer to remove borders with large weights, e.g., the probability of mutation from one to zero of large weights is also large as shown in the following:

$$P_m(i) = \frac{w_i}{\sum_j w_j}. \tag{12}$$

On the other hand, we also prefer to add borders with lower weights in a similar manner.

2) *Relatively Large-Weight Preference*: We prefer to remove borders with large weights relative to their neighbors. The weights are adjusted relative to the minimum weight in the same RA, called *relative weights*. These relative weights (r) are then used to calculate the probability of mutation as follows:

$$r_i = \frac{w_i}{m_i} \tag{13}$$

$$P_m(i) = \frac{r_i}{\sum_j r_j} \tag{14}$$

where m_i represents the minimum weight of borders including the border i, which constitutes a single RA. Note that these heuristics implies extra processing[2] that is proportional to the number of borders and the number of chromosomes in the generation because we need to know the RA which each border belongs to. To avoid this overhead, the authors suggest that these heuristics should not be frequently applied.

V. Simulation Results

We simulated a hexagonal system in which the cells are configured as an *H mesh* [18]. The paging cost for each cell and the crossing intensity for each border were generated from a normal random number with mean 100 and variance 20. The paging bound per RA was 800 in our simulations. The parameters used by the genetic algorithm throughout the simulations are listed below.

1) Population size $= 20$.

[2] This overhead should not be the disadvantage of our approach since heuristic approaches of graph theoretical models require the same processing.

TABLE I
COMPARISON OF HILL CLIMBING AND GENETIC ALGORITHM IN TERMS OF THE LU COST

H-Mesh	# 0f cells	Hill-Climbing		Genetic Algorithm		Improvement($\frac{HC-GA}{GA}$)
		Mean	Variance	Mean	Variance	
n = 3	19	1391	33163	1141	6166	22%
n = 4	37	3870	122408	2991	24847	29%
n = 5	61	6681	115601	5846	91531	14%
n = 6	91	11070	148928	10068	215639	10%

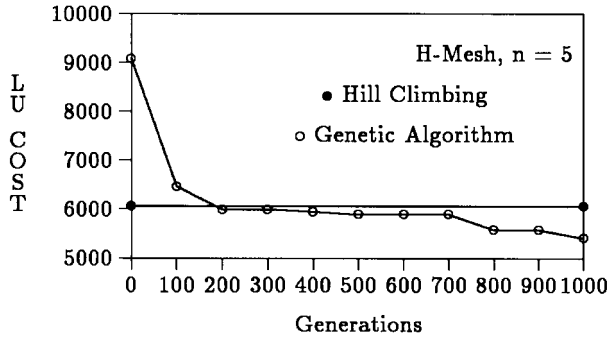


Fig. 12. A tradeoff between LU cost and execution time in a single run.

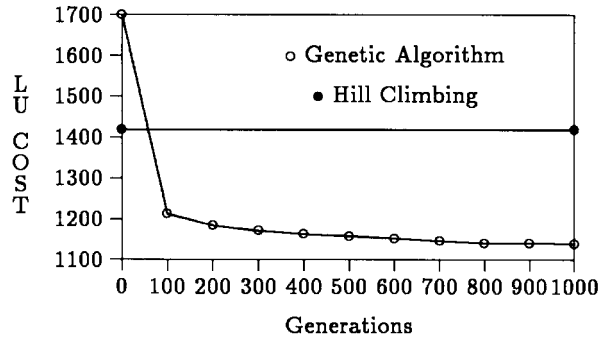


Fig. 13. H mesh $n = 3$. Results of RA planning over 100 runs.

2) Clonation percentage $= 0.3$.
3) Crossover probability $p_c = 1.0$.
4) Mutation probability $p_m = 0.02$.
5) Maximum number of generations $= 1000$.

The simulation was performed on a Sun Sparc10 workstation. After 100 simulation runs, the mean and variance of the results in terms of the LU cost were collected. These results were compared to those of hill climbing as shown in Table I and found to be superior after 1000 generations.

Fig. 12 shows the behavior of the genetic algorithm and a tradeoff between solution quality and run-time efficiency. In the first 200 generations, the LU cost rapidly decreases. The genetic algorithm may get trapped in a local minimum from the 200th to 700th generation. After the 700th generation, the algorithm jumps from the local minimum and the LU cost continues decreasing. Generally, as the execution time increases, the LU cost decreases. That is, the longer the time of execution, the better the result we obtained.

Figs. 13–16 show the mean results of RA planning in 100 simulation runs. Genetic algorithms with a random initial population prove to be superior to hill climbing in 100 generations (except in the case of Fig. 16). As the number of cells increases, it takes a longer execution time to obtain better results.

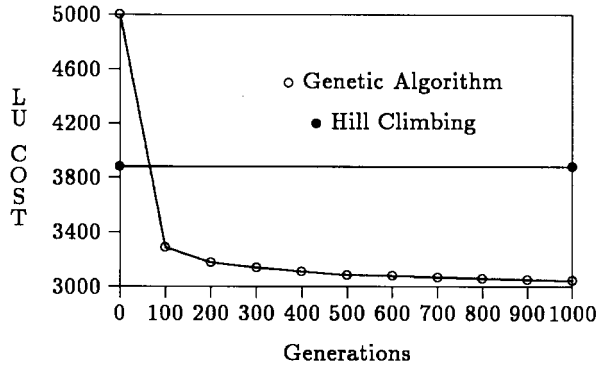


Fig. 14. H mesh $n = 4$. Results of RA planning over 100 runs.

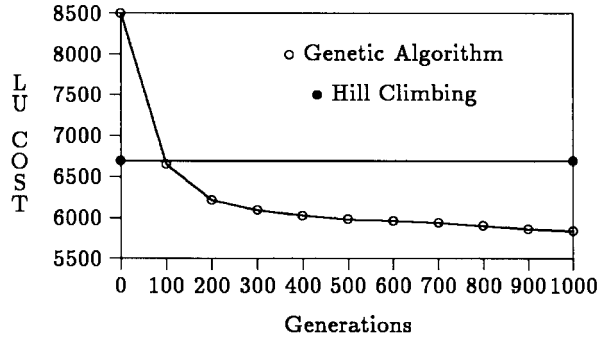


Fig. 15. H mesh $n = 5$. Results of RA planning over 100 runs.

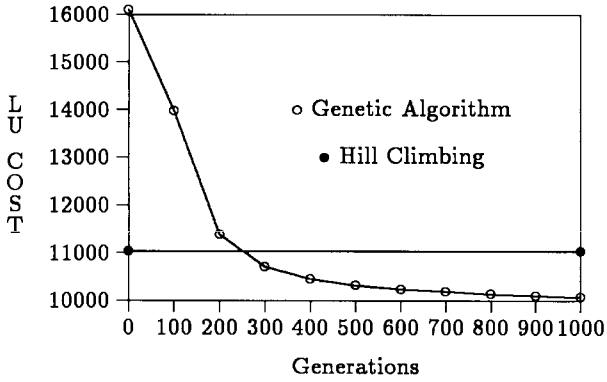


Fig. 16. H mesh $n = 6$. Results of RA planning over 100 runs.

VI. Conclusions

In this paper, we reformulated RA planning as a cost-optimization problem and proposed a stochastic search method based on a genetic approach. Simulation results showed that genetic algorithms are robust for RA planning.

In our model, search nodes are represented as strings determining which borders exist between cells. Three general genetic operators—selection, crossover, and mutation—were employed. Additionally, defining the fitness function required neither *a priori* knowledge nor information on the possible form of the solution. The only task was to penalize the individual strings that might violate specific constraints. Control parameters for genetic algorithms can be determined either by a sophisticated technique [20] or by experience. Experiential parameters may not be optimal, but at least feasible for the RA planning.

In summary, the advantages and limitations of using genetic algorithms for the problem of RA planning are listed as follows.

1) *Simplicity*: Defining representation, operators, and fitness function requires neither *a priori* knowledge nor information on the possible form of the solution.
2) *Flexibility*: Genetic algorithms are flexible for supporting soft presets and soft constraints.
3) *Convergence*: Genetic algorithms are guaranteed to converge [19]. Illegal solutions can be filtered out in the postprocessing stage. By adjusting parameters of the penalty function, we will always be able to obtain a legal solution. Furthermore, the longer the time of execution, the better the result obtained.
4) *Robustness*: As a reviewer pointed out, heuristic approaches will be much more efficient compared to the traditional genetic algorithms in extreme cases where the number of illegal solutions is a remarkable percentage of the total possible solutions. This drawback can be alleviated by using heuristics to avoid random search in the space of illegal solutions. Our approach has encoded some heuristics and by no means excludes heuristics proposed in other papers: it is robust for a diversity of cases. In general cases, it performs much better than heuristic approaches. On the other hand, our approach would be little less efficient compared to heuristic approaches in some special cases, but it has the potential to obtain better solutions. Unfortunately, heuristics imply extra processing which will be applied in the population of the generation. The limitation of our approach is that network designers should be able to estimate the cost of applying heuristics and decide the frequency of applying these heuristics.
5) *Parallelism*: Parallelism is inherent in genetic algorithms.

The time complexity of hill climbing, genetic algorithms, and exhaustive searches is $O(m)$, $O(m \times n \times n_p)$, and $O(2^m)$, respectively, where m denotes the total number of the borders, n is the maximum number of generations, and n_p is the population of the generation. Practically, the population of the generation is a small constant, e.g., $n_p = 20$ in our simulations. Thus, the time complexity of genetic algorithms is equal to $O(m \times n)$. Considering the tradeoff between run-time efficiency and solution quality, genetic algorithms appear to be a quite valuable approach to RA planning in designing PCS networks.

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