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# Simulated Annealing and Genetic Algorithm in Telecommunications Network Planning

Aleksandar Tsenov

***Abstract*****—**The main goal of this work is to propose a way for combined use of two nontraditional algorithms by solving topological problems on telecommunications concentrator networks. The algorithms suggested are the Simulated Annealing algorithm and the Genetic Algorithm. The Algorithm of Simulated Annealing unifies the well known local search algorithms. In addition - Simulated Annealing allows acceptation of moves in the search space witch lead to decisions with higher cost in order to attempt to overcome any local minima obtained. The Genetic Algorithm is a heuristic approach witch is being used in wide areas of optimization works. In the last years this approach is also widely implemented in Telecommunications Networks Planning. In order to solve less or more complex planning problem it is important to find the most appropriate parameters for initializing the function of the algorithm.

***Keywords*****—**Concentrator network, genetic algorithm, simulated annealing, UCPL.

## I. Introduction

THE problem of developing an optimally design of a network in order to meet a given set of specifications (such as prescribed traffic requirements, achieving a desired level of reliability, respecting a given maximum transit time), while minimizing total cost, arises in a wide variety of contexts: computer networks, telecommunication networks, transportation networks, distribution systems [5], [6], [11], [12].

Network design algorithms draw an increasing amount of attention nowadays. Considering the complexity, high cost factor and fast deployment times of communications systems (such as IP and ATM backbones, optical networks, numerous types of access structures etc.), network operators can benefit a lot from the use of network design tools [15], [16].

These tools can help speeding up and 'automating' the design process, ensuring superior quality (i.e. lower cost and/or better Quality of Service) and more justifiable solutions. Network design tools typically incorporate a wide range of functionality, such a geographical database handling, traffic estimation, link dimensioning, cost calculation, equipment configuration databases etc.

The real benefit of using these tools, however, comes from the possibility of using the network - algorithmic optimization approaches. In this way, there arises a possibility for finding solutions of better quality in much shorter time, as compared to the manual network design.

The planning of telecommunications networks can be defined as follows: it must be realized the functionality of the lower 4 levels of the OSI (Open System Interconnection) reference model by fulfilling the necessary and preliminary specified technological requirements.

It must be realized: the physical connectivity between the networks and between the subscribers and the network; the procedures for reliable transfer of information and signalization; the establishment, the control and the release of the connections in the network; the logical connection and the transfer of separate information blocks.

According to some works there are 4 stages in the network planning process: building the topological structure; synthesis of the network; traffic load assignment; realization.

The four stages define an iterative process which has to find an optimal solution for a predefined cost function according to the geographical network plan.

The cost function may be defined in conformity with several network characteristics - realizations cost, life cycle cost, connection lengths, reliability.

## II. Location–Allocation Problems

The general problem involves the allocation of customers to a number of (supplier) sites. They can be broadly divided into two types: site generation problems and site selection problems. Site generation problems require that the optimization chooses a location for the sites from a continuous space. For site selection problems, the sites are chosen from a finite set of candidate locations. It is the second of these groups of problems that is concentrated on here [2], [14].

The objective function for a solution to a location-allocation problem may be defined in many ways but is usually the total cost, distance or time for supplying all the customers, or some combination of these three. Although for some applications such as the placement of a fire station, it may be minimization of the maximum distance between location and customer.

An example problem is illustrated in Fig. 1 [20], where there are four possible sites and ten customers to be supplied. An example solution to the problem is illustrated; sites A, C and D have been chosen to supply the ten customers.

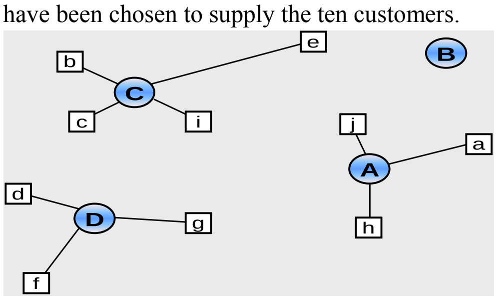


Fig. 1 Example location-allocation problem; there are four possible sites (A-D) to which the 10 customers (a-j) must be allo-cated. A line

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Aleksandar Tsenov is with Telecom Department at Technical University of Sofia, Kliment Ohridsky Blvd 8, Sofia, Bulgaria (e-mail: akz@tusofia.bg).

connecting a site and a customer shows that this site supplies the customer

The following section describes some representations of location–allocation problems, oriented to application of nontraditional algorithms for optimizing these types of problems.

### *A. Representations*

There are many possible representations available but it is important to develop the one that is both suited to the problem and that works efficiently with a crossover operator.

Preferably, the representation and operators can be used unchanged for harder problems. For example, it is desirable that a general-purpose representation and optimizer be found that can be used on a multi-period access network-planning problem. That is, the aim is to produce a general algorithm that covers this class of problems.

### *B. Simple Strategy*

A simple representation for a location-allocation problem is a bit string of length equal to the number of candidate sites. If a bit is equal to one then the corresponding location is present

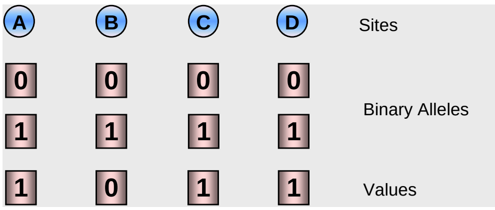


Fig. 2 Simple representation for a location-allocation problem. For each site is represented whether that site is in the solution using binary valued alleles. Each customer is then assigned to the site, which can supply it most cheaply. The values in the final line show how the example in Figure 1 would be represented, that is a solution where sites A, C and D are present

in the solution, if zero it is not. The customers can then simply be assigned to the nearest (or lowest cost connection) site.

Fig. 2 illustrates this representation and shows the possible allele values and the allele values necessary to represent the solution shown in Fig. 1.

This approach is used for the warehouse location problem and for optimizing the topology of concentrator networks. This representation is not being discussed further due to its inflexibility for representing harder capacity constrained and dynamic problems.

### *C. Customer Specifies Location*

A more general representation for the problem is one where for each customer there is a set of alleles which represent all the possible sites that can supply the customer, the actual allele chosen represents the site which supplies the customer. This representation is used for a concentrator-location problem. It is good as there is no redundancy. A diagram illustrating this representation is shown in Fig. 3.

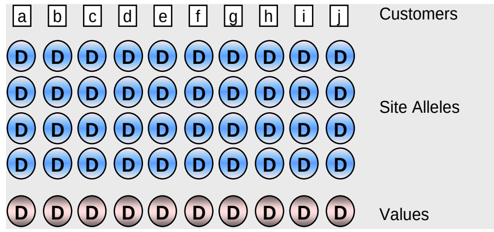


Fig. 3 A representation where each customer has a set of alleles that represent which sites could supply the customer. The values in the final line show how the example in Fig. 1 would be represented

### *D. Location-Allocation Problems in Network Planing*

On the first stage of the planning process the telecommunication equipment must be located and the customers must be allocated.

The one possible way to find an optimal decision for this problem is to use cheaper communication equipment. In most cases this equipment consists of simple multiplexers concentrators.

There are many known concentrator location problems. One of them is the UCPL (Uncapacitated Plant Location) problem [9].

### *E. UCPL*

The mathematical model of UCPL is:

$$\min \sum_{i \in I} \sum_{j \in J} c_{ij} x_{ij} + \sum_{j \in J} f_j y_j \qquad (1)$$

$$\sum_{j \in J} x_{ij} = 1 \qquad (2)$$

$$x_{ij} - y_j \le 0, \qquad i \in I,\ j \in J \qquad (3)$$

$$x_{ij} \in \{0,1\}, \qquad i \in I,\ j \in J \qquad (4)$$

$$y_j \in \{0,1\}, \qquad j \in J \qquad (5)$$

where:

*I* is the location area;

*J* is set of sub areas for location of the concentrators, whereas $J \in I$;

$C_{ij}$ is the cost function – it represents the cost for connecting the end node *i* to the concentrator *j*;

$f_j$ is the cost for connecting the concentrator *j* to a node from the higher network level.

For the parameters $x_{ij}$ and $y_j$ may define:

$x_{ij}$ = 1, when end node *i* is connected to concentrator *j*;

$x_{ij}$ = 0, when end node *i* is not connected to concentrator *j*;

$y_j$ = 1, when concentrator *j* is located;

$y_j$ = 1, when concentrator *j* is not located;

Equation (1) guaranties the connectivity of one end node to one and only one concentrator. Equation (2) defines the connection of end node *I* to concentrator *j* only when the concentrator *j* exists.

The CPL (Capacitated Plant Location) model differs to the UCPL by the constraint (3), which becomes:

$$\sum_{j \in J} x_{ij} - y_j < 0 \qquad (6)$$

The constraint (6) shows that the terminal $i$ is connected to the concentrator $j$, only when $j$ exists and when $j$ consists of free capacity.

## III. Simulated Annealing

The algorithm of the Simulated Annealing (SA) is an approach that integrates most of the local search algorithms. These algorithms accept the next step only when it reduces the cost. So they reach a local minimum and stop searching [1], [7], [8], [19], [22], [24].

An essential feature of simulated annealing is that it can climb out from a local minimum, since it can accept worse neighbors at the next step. Such an acceptance happens with a probability that is smaller if the neighbor quality is worse.

The probability of the acceptance can be presented as follows:

$$P\{\text{accept}\} = \left\{ \begin{array}{l} 1, \text{ if } \Delta \le 0 \\ \exp(-\Delta/T), \text{ if } \Delta > 0 \end{array} \right\} \tag{7}$$

where:

$\Delta$ is the cost change, and $T$ is a control parameter that is called temperature.

There are four problems by the initializing of the algorithm – defining the initial temperature, defining the cooling schedule, defining the number of iterations on each temperature step and stop criterion.

## IV. Genetic Algorithm

The considered network topologies are generated and optimized by using Genetic Algorithms (GA). GA is a heuristic, adaptive approach for deciding topological problems in net-work planning. GA is developed by John Holland and is based on the principles of the nature selection – surviving of fit individuals and loosing of non fit individuals [3], [9], [10].

For the purpose of this work a Memetic Algorithm was implemented. Memetic algorithm is type of jointly implementation of simple Genetic Algorithm and additional local search on each population generation during the work of the algorithm.

During the work the algorithm produces valid or invalid solutions. An invalid (not fit) solution is when:

- there is an unconnected end-node in the topology;

- there is an end-node which is connected to more than one supplier sites.

### *A. Initial Population*

The genetic algorithm begins by creating a random initial population. There is very important to obtain the optimal number of individuals in the initial population in order to:

- give the algorithm enough genetic material for creating “fit” offspring;

- reduce the working time by finding the optimal solution of any problem.

The number of the individuals depends in most cases of the representation of the problem and of the number of the genes in the chromosome.

### *B. Number of Populations*

The number of populations in the algorithm is also important for finding the best solution of a definite problem. This number must be large enough to obtain the optimal solution, and at the same time it must be not too large, because of the computing time and the production of too many unused solutions. The number of population depends of the complexity of the problem.

### *C. Selection*

The selection method determines how individuals are chosen for mating. If you use a selection method that picks only the best individual, then the population will quickly converge to that individual. So the selector should be biased toward better individuals, but should also pick some that aren't quite as good (but hopefully have some good genetic material in them).

In selection the individuals producing offspring are chosen. The first step is fitness assignment. Each individual in the selection pool receives a reproduction probability depending on the own objective value and the objective value of all other individuals in the selection pool. This fitness is used for the actual selection step afterwards.

The most popular selection schemes are: rank - based assignment; roulette wheel selection; tournament selection; stochastic remainder sampler; stochastic uniform sampler.

Some of the more common methods include roulette wheel selection (the likelihood of picking an individual is proportional to the individual's score), tournament selection (a number of individuals are picked using roulette wheel selection, then the best of these are chosen for mating), and rank selection (pick the best individual every time). Threshold se-lection can also be effective.

### *D. Replacement*

Replacement schemes are used by genetic algorithms with overlapping populations to determine how the new individuals will be assimilated into the population.

The most popular replacement schemes are: replace worst; replace best; replace parent; replace random; replace most similar (crowding).

*Replace worst* and *replace most similar* are the only really useful replacement schemes. Sometimes *replace parent* can be effective, but usually when the parents are similar to the offspring and this is just *replace most similar*.

## V. The Proposed Approach

Many works from the past years present the authors attempt to solve location-allocation problems using one of both algorithms.

The main goal of the proposed work is to find the way for combined use of the algorithms. The questions which must be answered are:

- which one algorithm may give better solution for a given problem;

- how the parameters of the algorithms should be defined;

- is there a consequence of use, which one algorithm must be performed first;

The proposed approach is being tested over a simple optimization UCPL problem. 50 end-nodes have to be connected to one primary node through concentrators. There are no constraints for placing the concentrators and for their capacity. The cost function is defined as the lowest price of the topology by given prices for concentrator, end-node and 1 meter line between the end-nodes and the concentrators and between the concentrators and the primary node.

### A. *First Step*

For a given problem the Simulated Annealing is performed. The obtained solution includes the position of the concentrators and the proposed connections to the end-nodes.

The algorithm of the Simulated Annealing was applied 20 times by using the following parameters:

- initial temperature of the process - 5000 (in all tests);
- cooling coefficient - 0,9 (in all tests);
- number of iterations on each temperature step -
  a) fixed - 200, 1000, 5000;
  b) variable - from 20 to 200 by step 20;
- end criterion - 200 iterations without improvement of the cost.

The parameters applied where obtained during previous works [22], [24].

The same problem is being solved by the use of GA - there are no constraints for placing the concentrators.

The algorithm finds the positions of the concentrators without any constraints [4], [13], [21], [23]. The parameters of the algorithm, where the best solution was fund, are:

- number of individuals in one population - 500;
- number of populations - 300;
- use of mutation with probability = 1/N (where *N* is the number of the end-nodes);
- crossover probability = 0,7;
- use of local search;
- replacement of all solutions in the populations;
- random selection (Monte Carlo - algorithm).

### B. *Second Step*

The obtained concentrator positions are used as fixed site positions in the Genetic Algorithm. Then the Genetic Algorithm tries to optimize the solution by changing connections, removing concentrators and so on.

The GA is applied by the use of the parameter values defined above. The only difference is that the algorithm uses the obtained concentrator positions and don’t changes them during the operation.

The algorithm may only decide - to use or not to use any concentrator in the current solution.

The algorithm is started 100 times for both cases:

1. concentrators placed by SA on the first step;
2. concentrators placed by GA on the first step.

## VI. Experimental Results

The experiments where fulfilled with the use of two software products both developed by the author.

The first one is named SATelNetOptimisation and is used for finding optimal topological solutions applying the Simulated Annealing algorithm. The graphical user interface provides many opportunities for the users:

- definition of the search space;
- set up the parameters of the algorithm;
- real-time display of the optimization process;
- solution explorer;
- cost estimation;
- save functions.

The second product is named PonOpt because of it first propose - optimization of Passive Optical Networks. The product was upgraded in order to solve more complex problems - optimization of concentrator networks. It provides:

- loading initial data from a text file;
- graphical presentation of the search space;
- costing the network components;
- set-up the algorithm parameters;
- presentation of best solutions on each generation;
- presentation of the ever best solution;
- cost estimation;
- save functions.

The following pictures shows the solutions found by the algorithms on the first step of the method described above.

The first four figures represent the best solutions obtained by the Simulated Annealing algorithm.

On the Fig. 4 the best solution is shown in case of 200 iterations on each temperature step. Fig. 5 and Fig. 6 show the best solutions for 1000 and 5000 iterations on each temperature step respectively.

Fig. 7 differs from the other figures - it presents 10 solutions - one for each number of iterations. When selecting the appropriate row the graphical presentation of the topology is also presented.

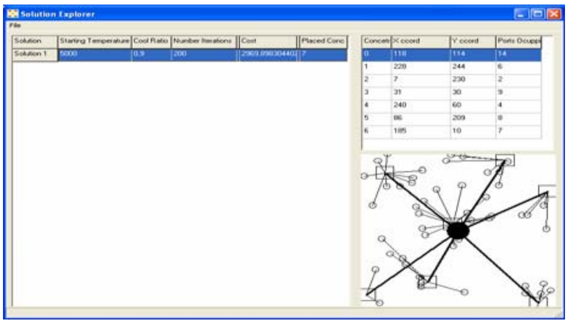


Fig. 4 Simulated Annealing solution for 200 iterations on each temperature step. This solution uses 7 concentrators

The picture on Fig. 4 shows the working area of the Solution explorer. It becomes clear that the solution with 200 iterations on each temperature step consists of 7 concentrators. All cost parameters are normalized to the cost of one length unit from the line between the concentrator and the end-node. One length unit corresponds to the distance between two points in the search space. In this experiment the cost of the concentrator is equal 20 units and the end-node costs 1 unit. The cost value in this case is **2838.55** units.

In the solutions, shown on Fig. 5 and Fig. 6, the algorithm uses 6 concentrators, but the large amount of iterations leads to achieving of great number of almost equal solutions without improvement of the cost. The costs of the obtained solutions are: **2910.46** units (for 1000 iterations) and **2758.90** units (for 5000 iterations) respectively.

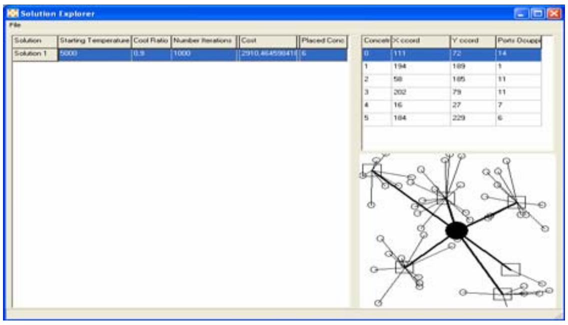


Fig. 5 Simulated Annealing solution for 1000 iterations on each temperature step

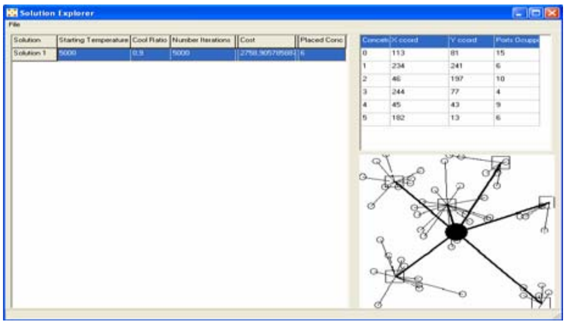


Fig. 6 Simulated Annealing solution for 5000 iterations on each temperature step

The large number of iterations on the higher temperature allows the algorithm to accept moves with high probability that don't lead to better solutions. That is the reason for the high cost in the first three cases.

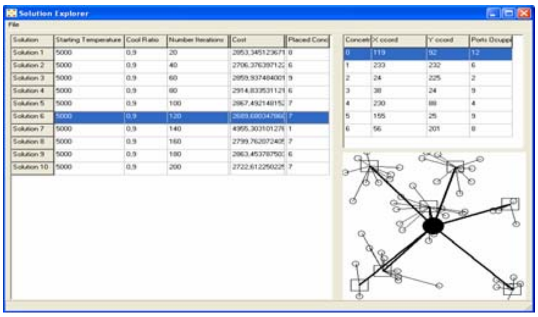


Fig. 7 Simulated Annealing solution for variable number of iterations (from 20 to 200 by step 20) on each temperature step

Fig. 7 shows an attempt with variable number of iterations from 20 to 200 by step 20. So 10 solutions are achieved and one from them is the best ever solution with the algorithm of SA. This is the solution shown on the sixth row in the table and the cost is 2689.68 units. Such type of experiment allows the obtaining of the optimal number of iterations on each temperature step - in this case 120 iterations.

The next Fig. 8 shows the solution obtained with the Genetic Algorithm by the circumstances of the first step of the experiments method - the concentrator positions are chosen free over the whole search space. That means - this is one competitive solution (with no constraints) to the best solution obtained by the Simulated Annealing.

The solution differs considerable from the best solution by the SA - algorithm. There are 15 concentrators used, but the length of the lines is smaller. The cost in this case is **2557.22** units.

This result should lead to the conclusion that the Genetic Algorithm works better than the SA - algorithm. This is not completely thru because of the type of the problem - in this case the GA searches the positions of the concentrators among practically unlimited number of candidate sites.

More interesting should be the case when the GA has to choose from a limited number of candidate sites - in the real world there exist definite structure of the physical network, including ducts, distribution points and it is more important to optimize the existing network instead to plan it from the beginning.

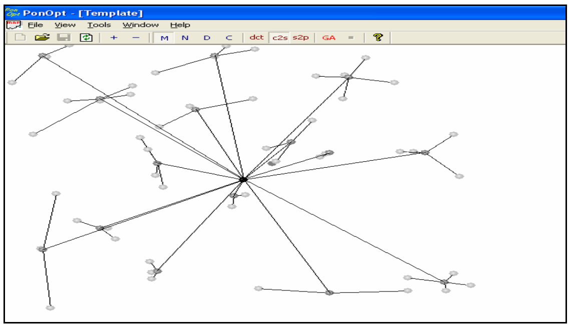


Fig. 8 Genetic Algorithm solution by the circumstances of step one from the experiments method

That is the reason why the second step of the experiment is being proposed. On this step the best solutions (with SA and GA respectively) are further manipulated with Genetic Algorithm. In this case there is a constraint in the algorithm - the concentrators may be placed on the sites, obtained on the first step by the algorithms.

The two following Figures show the final solutions in both cases: Fig. 9 - GA-optimization after the unconstrained GA on the first step is performed; and Fig. 10 - GA optimization of the best SA solution.

There is a common characteristic in both final solutions - the algorithm did not use all possible sites for placing the concentrators. This reduces the overall cost of the solutions and the costs of the final topologies are: **2221.33** units in the first case (Fig. 9) and **2536.16** in the second (Fig.10).

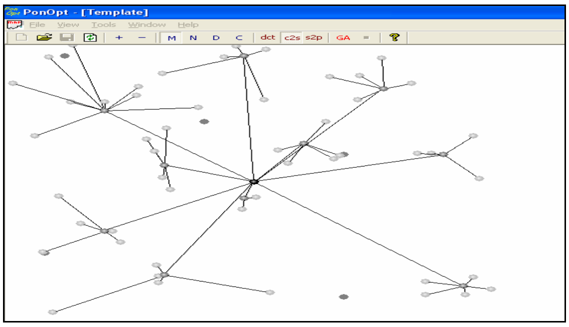

Fig. 9 Solution with Genetic Algorithm, applied over the solution obtained with GA and shown on Fig. 8

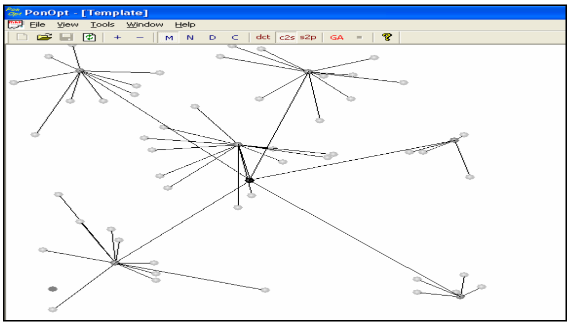

Fig. 10 Solution with Genetic Algorithm, applied over the solution with SA shown on Fig. 7

The additional Genetic Algorithm finds better solutions because of the good start conditions: at the first step a large amount of the bad solutions are being throw off and the algorithm operates over potential good solutions in order to find the best of them.

## VII. CONCLUSIONS

The proposed work is actually a generalization of the attempts of the author to define an appropriate approach for implementing of non traditional algorithms in the telecommunications networks planning.

The results show that such an approach may lead to good results. In the future a deeper research over the impact of the parameterization of the algorithms is to be performed. Different problems require different parameters in order to achieve the optimal solution.

The software products are also upgraded in order to solve capacitated location problems and topological problems not only in the access area, but also in the backbones, where the cost function may present connectivity, traffic load, multiplexed channels etc.

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