A comparison between adaptive algorithms in telecommunications networks planning

Aleksandar Tsenov

Abstract - The main goal of this work is to propose a way to compare two nontraditional algorithms by solving topological problems on telecommunications concentrator networks. The algorithms suggested are the Simulated Annealing Algorithm (SA) and the Genetic Algorithm (GA). The proposed algorithms are used for finding an optimal solution for a small network, the results are being analyzed and some recommendations for the proper use of these algorithms are made.

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, telecommunications 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 [5] 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.

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].

The mathematical model of UCPL is:

\[
\min \sum_{i \in I} \sum_{j \in J} c_{ij} x_{ij} + \sum_{j \in J} f_j y_j \quad (1)
\]

\[
\sum_{j \in J} x_{ij} = 1 \quad (2)
\]

\[
x_{ij} - y_j \leq 0, \quad i \in I, j \in J \quad (3)
\]

\[
x_{ij} \in \{0,1\}, \quad i \in I, j \in J \quad (4)
\]

\[
y_j \in \{0,1\}, \quad j \in J \quad (5)
\]

where:

- \(I\) is the location area;
- \(J\) is set of sub areas for location of the concentrators, whereas \(J \subseteq I\);
$C_{ij}$ 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 $y_{ij}$ 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 $j$;

$y_{ij} = 1$, when concentrator $j$ is located;

$y_{ij} = 0$, when concentrator $j$ is not located;

Equation (1) guarantees 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 of Eq. 3, which becomes:

$$\sum_{j} x_{ij} - y_{ij} < 0 \quad (6)$$

The constraint in Eq. (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 AND GENETIC ALGORITHM

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:

$$P\{\text{accept}\} = \begin{cases} 1, & \text{if } \Delta x \leq 0 \\ \exp(-\Delta x/T), & \text{if } \Delta x > 0 \end{cases} \quad (7)$$

where:

$\Delta x$ is the cost change, and $T$ is a control parameter that is the same temperature. In fact this parameter represents the probability grade for the acceptance of a move that leads to higher cost of the whole solution. In this work this parameter will be named named pseudo-temperature.

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

The Genetic Algorithm (GA) is a heuristic, adaptive approach for deciding topological problems in network 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 GA and additional local search on each population generation during the work of the algorithm. This way the algorithm improves its functionality by applying a set of local search techniques. So the algorithm “teaches” itself and then hands down the learned information to the future populations.

During the work the algorithm produces valid or invalid solutions. An invalid (not fit) solution may occur when: there is an unconnected end-node in the topology or there is an end-node which is connected to more than one supplier sites.

The GA 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.

### IV. THE PROPOSED APPROACH

The main goal of the proposed work is to compare the results of the use of the algorithms while solving one and the same problem. The questions which must be answered are:

- which one algorithm gives better solutions for a given problem;
- how the parameters of the algorithms should be defined;
- how to choose the appropriate algorithm for every single problem;

The proposed approach is being tested over a simple optimization UCPL problem. 25 end-nodes have to be connected to one primary node through concentrators. Many assumptions are made: 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. The cost of every solution is presented in units. All cost parameters are normalized to the cost of one length unit from the line between the network elements. In this experiment the search space has the following dimensions: 200 / 200 length units, the cost of the concentrator is equal 20 units and the end-node costs 0 units.

For the given problem first 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 50 times by using the following parameters: initial pseudo-temperature of the process - 50000 (in all tests); cooling coefficient - 0.9 (in all tests); number of iterations on each pseudo-temperature step - fixed - 200, 1000, 5000 and variable - from 20 to 1000 by step 20; end of work 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 found, are: number of individuals – from 100 to 5000; number of populations – from 100 to 10000; 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 individuals in the populations; random selection.
The algorithm was started 100 times for every combination of parameters values.
In both cases the end-nodes have fixed positions and the position of the primary node is 125/125 (right in the middle of the search space). The positions of the end-nodes are generated randomly.

V. 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 according to the approach described above.

Figure 1 represents the best solutions obtained by the Simulated Annealing algorithm.

The following data represent the process of finding the best solution. The best solution is obtained with 480 iterations on each temperature step and with use of 5 concentrators.

<table>
<thead>
<tr>
<th>Solution</th>
<th>Starting Temp</th>
<th>Cool Ratio</th>
<th>Iterations</th>
<th>Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>500000</td>
<td>0.9</td>
<td>20</td>
<td>1592.85</td>
</tr>
<tr>
<td>2</td>
<td>500000</td>
<td>0.9</td>
<td>40</td>
<td>1599.80</td>
</tr>
<tr>
<td>23</td>
<td>500000</td>
<td>0.9</td>
<td>460</td>
<td>1690.06</td>
</tr>
<tr>
<td>24</td>
<td>500000</td>
<td>0.9</td>
<td>480</td>
<td>1487.04</td>
</tr>
<tr>
<td>25</td>
<td>500000</td>
<td>0.9</td>
<td>500</td>
<td>1637.63</td>
</tr>
<tr>
<td>49</td>
<td>500000</td>
<td>0.9</td>
<td>980</td>
<td>1556.47</td>
</tr>
<tr>
<td>50</td>
<td>500000</td>
<td>0.9</td>
<td>1000</td>
<td>1625.27</td>
</tr>
</tbody>
</table>

The results by the use of other parameters values show higher cost values. The best results are obtained by Starting temperature equal to 500000 for all other combination of parameters. This is the value obtained in earlier author’s work [22] and was proven in [24].

On the Fig. 2 the progress of the cost in the solution 24 with 480 iterations on each temperature step, where the best solution is found, is shown. There are four clear minima in the cost before the absolute minimum is reached. After the 480 iterations the algorithm founds no better solutions.

TABLE I

<table>
<thead>
<tr>
<th>Generation</th>
<th>Lowest Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2344.86</td>
</tr>
<tr>
<td>1</td>
<td>2271.11</td>
</tr>
<tr>
<td>2</td>
<td>2197.11</td>
</tr>
<tr>
<td>3</td>
<td>1971.88</td>
</tr>
<tr>
<td>4</td>
<td>1971.59</td>
</tr>
<tr>
<td>90</td>
<td>1559.30</td>
</tr>
<tr>
<td>91</td>
<td>1559.30</td>
</tr>
<tr>
<td>92</td>
<td>1559.30</td>
</tr>
<tr>
<td>197</td>
<td>1486.93</td>
</tr>
</tbody>
</table>

Fig. 2. The progress of the cost in the best solution obtained with the SA – Algorithm

On the Fig. 3 the best solution with the Genetic Algorithm is shown. There are many differences between the best topologies obtained: The Genetic algorithm uses one more concentrator in comparison to the SA – Algorithm.
The cost of the best solution is **1479.26**. The best result have been found with 1000 individuals, 500 populations, mutation, random selection and full recombination.

Very interesting is the progress of the cost of the solutions with the GA until the optimum is being found.

<table>
<thead>
<tr>
<th>Generation</th>
<th>Lowest Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1486.93</td>
</tr>
<tr>
<td>1</td>
<td>1486.93</td>
</tr>
<tr>
<td>2</td>
<td>1481.23</td>
</tr>
<tr>
<td>3</td>
<td>1481.23</td>
</tr>
<tr>
<td>4</td>
<td>1481.23</td>
</tr>
<tr>
<td>90</td>
<td>1479.26</td>
</tr>
<tr>
<td>91</td>
<td>1479.26</td>
</tr>
<tr>
<td>92</td>
<td>1479.26</td>
</tr>
<tr>
<td>197</td>
<td>1479.26</td>
</tr>
</tbody>
</table>

TABLE II

STATISTICAL DATA FOR GENETIC ALGORITHM

<table>
<thead>
<tr>
<th>Generation</th>
<th>Lowest Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2344.86</td>
</tr>
<tr>
<td>1</td>
<td>2271.11</td>
</tr>
<tr>
<td>2</td>
<td>2197.11</td>
</tr>
<tr>
<td>3</td>
<td>1971.88</td>
</tr>
<tr>
<td>4</td>
<td>1971.59</td>
</tr>
<tr>
<td>90</td>
<td>1559.30</td>
</tr>
<tr>
<td>91</td>
<td>1559.30</td>
</tr>
<tr>
<td>92</td>
<td>1559.30</td>
</tr>
<tr>
<td>197</td>
<td>1486.93</td>
</tr>
</tbody>
</table>

Fig. 3. The best solution obtained with GA
As shown in Table II the optimal solution is being found just before the algorithm stops. That means – the number of the populations is being chosen correctly. Fig. 4. shows he progress of the cost in the best solution obtained with the GA.

![Fig. 4. The progress of the cost in the best solution obtained with the GA.](image)

Very important impact of the solutions has the number of the individuals in the population – in [23] the hypothesis was proven that the number of the individuals must be greater than $N^2$, where $N$ is the number of the end-nodes, but not greater then 2*N. In this case the algorithm has no enough time to manipulate all possible solutions and the best of them may not be found.

As the results show both algorithms have found an almost equal optimal cost for the given problem. That lead to two important conclusions: It is possible to apply such kind of nontraditional algorithms in telecommunications network planning process; The near results show that it may accept the obtained costs as really close enough to the absolute minimum of the cost function for the given problem.

VI. CONCLUSIONS

The proposed work is actually a part 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.

Future works should include solving of Capacitated location Problems and problems that include more constraints such as limited positions for the concentrators, larger number of primary nodes, larger number of end-nodes. The upgrade of the software products include object for solving other types of network topologies – backbones, networks with defined connectivity etc.

REFERENCES