# A Note on Using Genetic and Evolutionary Algorithms for Multi-Period Communication Network Optimization

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# A Note on Using Genetic and Evolutionary Algorithms for Multi-Period Communication Network Optimization


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**Abstract**

This paper addresses the optimization of telecommunication networks for a multi-period horizon. Four heuristics are presented to cope with the problem to minimize the overall costs for the network over several periods. For the minimization of cost we use a simple genetic algorithm (GA). It is adapted in different ways to the special structure of the network problem.

Even in the single-period case, the stated problem is hard to solve. For solving the multi-period problem we have two possible choices: Firstly, all periods could be solved synchronously (in parallel). Secondly, the different periods are optimized step by step (serially). With serial optimization, the algorithm could fail in finding the global minimum, but the computational effort for the parallel optimization is so much higher that it can hardly be used other than in small test problems. In addition to this, the solutions for the periods are very similar, meaning that the parallel optimization has to detect a lot of redundant information.

To optimize the overall costs serially we present four different approaches. The first, and most simple optimizes the structure of the network for each period independently of the solutions for other periods. The second approach optimizes only the structure for the first period, and the structure of the network is not changed for the following periods. Only the capacities of the links are scaled up according to the necessary demands. The third approach optimizes serially the structure of the networks for the different time periods starting from the first. For the fitness of the individuals, the overall cost of the network, including the cost for changing the lines between the periods, is used. Finally we propose an extension of the third approach. In an initial step, all time periods are optimized sequentially and independently from each other. After the first run over the whole planning horizon, we will pick out periods randomly and optimize this period with respect to the previous and next periods. We believe that this extension leads to a more stable and robust solution of the network design problem.

We present some results for the first three approaches for a specific real-world problem. A short investigation of the performance shows that we gain the best results by using the third approach.


## 1 Introduction

This paper addresses the optimization of telecommunication networks for a multi-period planning horizon. This approach can also be extended to the fields of designing transportation, water, computer or electrical power networks. A few years ago the performance of the computers available was the most limiting factor for the solvable problems sizes. Nowadays the computational effort is a less restricting limitation meaning the use of genetic and evolutionary algorithms (GEAs) could be a good choice for solving the multi-period problem.

To optimize the overall costs for all time periods we propose four different heuristic approaches that do not try to solve the overall design problem directly but to serialize the problem.

The paper is structured as follows. In the following section we give a short literature review. In section 3 we describe the problems with a synchronous, parallel solving of the network and propose four serial approaches that try to overcome some of the problems. In section 4 we present results for using some of the approaches for a small real-world application. The paper ends with some concluding remarks.

## 2 Literature review

In this section we give a short review of the research that has been done in the field of multi-period communication network optimization.

Most of the research on multi-period network optimization was done in the operation research field. In the genetic and evolutionary computation field a lot of work has been done for single-period problems (Kerhenbaum, 1993; Davis, Orvosh, Cox, & Qiu, 1993; Sinclair, 1995; Elbaum & Sidi, 1996; Ko, Tang, Chan, Man, & Kwong, 1997; Cahn, 1998; Brittain, 1999), but almost none for multi-period problems. Luss (1982) describes some of the early research in the field of multi-period planning for networks and gives a systematic overview of the research that was done from 1950 till 1982. Minoux (1987) used a dynamic programming approach for solving the problem. For this approach the structure and the routing of the traffic through the network remains constant during the whole design period. Parrish, Cox, Kuehner, and Qiu (1992) used an approach, where in the first step the costs of each period are optimized by a branch and bound approach. A heuristic was used for determining the changes, that are necessary between two periods. To get the overall optimum, the transitions between the periods are modeled as the links of a network[1] and the shortest minimum path through this network was identified. A Lagrangian relaxation was used in Dutta and Lim (1992). They tried to find lower and upper bounds for the problem and used them as a starting point for a subgradient method. Chang and Gavish (1993) also used Lagrangian relaxation, but combined local and global search. This approach was refined in Chang and Gavish (1995) to get better upper and lower bounds. Dutta and Kim (1996) used a three-step heuristic. Firstly, the single periods are optimized separately with a greedy algorithm. In the second step each transition between two periods is optimized. Finally, the routing of the traffic is calculated. A local iterative search algorithm GLIT (Generic Local Improvement Template) is presented in Garcia, Mahey, and LeBlanc (1998). To find promising areas in the search space a genetic algorithm was used. This approach is compared to stochastic descent, simulated annealing and tabu search. Multi-period approaches were not only used for backbone, but also for local-access networks (Balakrishnan, Magnanti, Shulman, & Wong, 1991; Balakrishnan, Magnanti, & Wong, 1995; Bienstock, 1993).

## 3 Multi-period planning

Even in the single-period case, the optimal communication network problem is hard to solve (NP-hard). We want to describe approaches for solving the multi-period network optimization problem

[1]The nodes of the network represent the periods.

using genetic and evolutionary algorithms.

## 3.1 The design problem

For a graph with $n$ nodes there are $n(n-1)/2$ possible links. This results in $2^{n(n-1)/2}$ possible network structures in one period. The location of the nodes is fixed for all periods. The demanded flow between the different locations, the cost structure of the links that can be used for constructing the network, and the routing of the traffic through the network are changing during several periods of the planning horizon. The aim of the design process is to minimize the overall cost for constructing and maintaining the network over $l$ periods. This cost consists of the cost for the network in each period and of the transition costs for upgrading existing lines, or installing new lines.

## 3.2 Parallel optimization

When a genetic algorithm should be used for solving the problem, a representation is necessary for encoding the phenotype of the problem.

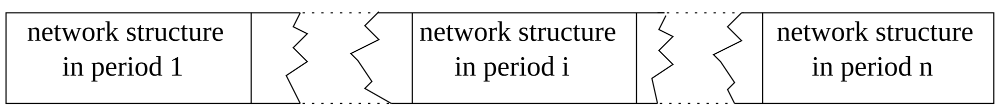


Figure 1: A schematic representation of the multi-period problem with $n$ periods

For a single-period problem the encoding is obvious. All necessary information concerning the network must be encoded in a string. If we want to optimize tree networks, at least the structure of the network must be encoded. Examples for encodings are characteristic vectors, predecessor representations, Pruefer numbers, or the Link and Node biased encoding (Palmer & Kershenbaum, 1994). For meshed networks, additional information about the capacity of the links, and routing of the traffic through the network is necessary. Even for small problems, this results in long representations. When it comes to optimizing the multi-period problem it is necessary to optimize the structure, the capacities of the links, and the routing for each period regarding all other periods. A possible schematic representation of this problem can be formulated as in figure 1. However, an encoding such as this has some disadvantages:

- Computational effort
- Long string length
- Redundancy in good solutions

For a n-node network there are $2^{n(n-1)/2}$ possible network structures. With $k$ different line capacities, the size of the search space reaches $k^{n(n-1)/2}$. Solving this problem for $l$ periods increases the search space to $(k^{n(n-1)/2})^l$. Solving a problem of this complexity in a reasonable length of time is even for small network problems not possible.

Representing the solution space in a string would result in long strings. However, for a good performance of a GEA it is necessary that the building blocks are short and tight together. With such a long string the identification of good building blocks is difficult, and the probability of a failure of the GA high (Rothlauf, Goldberg, & Heinzl, 2000).

Finding the optimal solution for the multi-period problem results for the GEA in a trade off between forming a stable structure for the network[2], and adjusting this structure to the varying demands in the different periods[3]. We could expect that for good solutions the network properties do not change dramatically over the different periods. Networks in following periods are similar. This means that for the optimization algorithm has to find a lot of redundant information. This leads us to an approach where the problem is solved in serial rather than in parallel. Almost all former work described in section 2 also used some kind of serialization for solving the problem.

### 3.3 Serial optimization

We propose four possible approaches to cope with the multi-period optimization problem.

#### 3.3.1 One-period scaling optimization

With this approach one period is chosen as a starting point for optimization. This period is optimized independently of all other periods. The topology that was found for this period is used for all the other periods as well. In each period the flow over the links is determined, and lines with the next higher available capacity that are necessary to fulfill the demand requirements are assigned to each link. In this approach there are no costs for installing new lines.

#### 3.3.2 Discrete single period optimization

This method optimizes the problem for each period separately, without consideration to the other periods. After a solution for each single period is computed the network modification costs are determined. This leads to the overall network costs. Obviously this approach does not take correlations between the periods into account, but adjusts the network structure optimally to every period. If the transition costs are low, this approach could lead to good results.

#### 3.3.3 One-period back-looking optimization

As an extension to the discrete single period optimization this approach takes the modification costs of the network into account. The optimizing process starts from the first period and optimizes the periods serially. The cost function that is used during the GA-run consists of the costs of network transition costs between the current and previous period, and the costs of constructing the current network.

#### 3.3.4 Iterative optimization

As an extension to the one-period back-looking optimization the optimization process is not stopped after one cycle, but is continued. After optimizing all periods once, periods are picked out randomly and optimized. The GA optimizes the overall costs of the multi-period problem. They consist of the transition costs between the networks, and the costs for constructing the network in one period. This approach should work independently of the start solution, and the solution should converge to a good solution iteratively. We believe this approach to be the most promising.

[2] results in low costs when changing the structure

[3] necessary for a good usage of the lines

# 4 Experiments

We want to give a short description of our test problems and the design of the genetic algorithm we used for optimization.

## 4.1 Test problems

Our communication network problems are derived from a real-world 16-node problem from a company with locations all over Germany. The topology of the networks in all three periods $l = 3$ are tree networks. The number and position of the nodes are given and are not changed during the whole planning horizon. The traffic demand between the nodes in the network is given, and increases by 20% between each period. The costs of the links depend on the length and the capacity and remain stable over all three periods. We have additional costs if new links are established, or the capacity of a link is increased between two periods. The cost of the links are based on the structure used by a German telecommunication company.

### 4.1.1 Problem 1

In this 16-node problem 15 branch offices communicate only with one headquarter. For fulfilling the demands between the nodes, different line types with discrete capacities and cost are available. The costs for installing a link consist of a fixed and length dependent share. Both depend on the capacity of the link. Possible line capacities are 64 kBit/s, 512 kBit/s and 2048 kBit/s. The complexity of the problem is low.

### 4.1.2 Problem 2

In this problem the demand matrix is completely filled. Between every node $i$ and $j$ exists some traffic. To make the problem more realistic two additional line types are available. It is possible to use a line of 128 kBit/s and 4096 kBit/s with twice the cost of a 64kBit/s resp. the 2048 kBit/s line. The complexity of the problem is high.

## 4.2 Experimental Design

For the minimization of cost we use a simple GA (Goldberg, 1989). It is adapted in different ways (compare subsection 3.3) to the special structure of the network problem. To represent the network structure, the characteristic vector representation is used. Invalid solutions during the GA-run are repaired by randomly removing exceeding links in a cycle and randomly adding new links between separated trees.

In all runs we used one-point crossover and a crossover-probability $p_{cross} = 0.75$. The mutation probability[4] $p_{mut}$ was set in all runs to 0.001. We choose tournament selection and a tournament size of 4. In all our runs we have a population size of 1000 and stop the GA after 1000 generations. For each problem we performed 50 runs.

## 4.3 Results

We present in table 4.3 the mean $\mu$ and standard deviation $\sigma$ of the minimum overall cost of the multi-period-problem. The overall cost consists of the costs for the network in all three periods and the costs for modifying[5] the network. We show results for the serial and the one period back-

[4] Switching one bit in characteristic vector that represents the tree

[5] adding new links or increasing the capacity of a link

looking optimization for both problems. For both problems the one-period back-looking approach performs better than the discrete single period approach. An application of the one-period scaling up optimization approach to the first problem, and scaling up from the first period, showed worse results than for the other approaches.

| | Problem 1 | | | Problem 2 | |
|---|---|---|---|---|---|
| | one-period back-looking | discrete single period | scaling up (first period) | one-period back-looking | discrete single period |
| mean $\mu$ | 253189.4 | 262369.2 | 272617.0 | 490664.9 | 518953.4 |
| std. dev. $\sigma$ | 1162.5 | 4024.6 | - | 14225.9 | 13680.4 |

Table 1: Minimum cost of network over all three periods for different optimization approaches.

The computational effort for the scaling up approach was low. It is necessary to optimize only one period. The scaling up of the network can be done with almost no computational effort. For the discrete single approach the computational effort is exactly $l$ times higher when $l$ is the number of periods. For the one-period back-looking approach the effort was similar to the discrete single period approach. The calculation of the costs, was slightly more complex, because the transition costs had to be calculated for every evaluation of an individual.

## 5 Conclusion

This paper has addressed the optimization of telecommunications networks for a multi-period horizon. To optimize serially the overall costs for all time periods we proposed different heuristic approaches. The first, and most simple, optimizes only the structure for the first period. The structure of the network is not changed for the following periods. Only the capacities of the links are scaled up according to the necessary demands. The second approach optimizes the structure of the network for each period independently of the solutions for other periods. The third approach optimizes serially the structure of the trees for the different time periods starting from the first. For the fitness of the individuals, the overall cost of the network, including the cost for changing the lines between the periods, is used. We present results for all three approaches and show that we get the best results for a small test problem using the third approach.

We propose to extend the third approach and to optimize the different time periods iteratively. After the first run over the whole planning horizon we will pick out periods randomly and optimize this period with respect to the previous and next periods. We believe that this extension leads to a more stable and robust solution of the network design problem.

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