A Note on Using Evolutionary Algorithms for Multiperiod Communication Network Optimisation

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Abstract. This paper addresses the optimisation of telecommunication networks for a multi-period horizon. Four heuristics are presented to cope with the problem to minimise the overall costs for the network over several periods. For the minimisation of cost we use a simple 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 multiperiod problem we have two different choices: Firstly, all periods could be solved synchronously (in parallel). Secondly, the different periods are optimised step by step (serially). With serial optimisation, the algorithm could fail in finding the global minimum, but the computational effort for the parallel optimisation 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 optimisation has to detect a lot of redundant information.

To optimise the overall costs serially we present four different approaches. The first, and most simple, optimises the structure of the network for each period independently of the solutions for other periods. The second approach optimises 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 optimises 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. Lastly we propose an extension of the third approach. In a first step all time periods are optimised sequentially and independently from each other. After the first run over the whole planning horizon we will pick out periods randomly and optimise 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 investigating of the performance shows that we get best results with the third approach.

1 Introduction

This paper addresses the optimization of telecommunication networks for a multiperiod planning horizon. This approach can also be extended to the fields of designing transportation, water, computer or electric power networks. A few years ago the performance of the computers were the most limiting factor for the solvable problems sizes. Nowadays the computational effort is a less restricting limitation, so the use of evolutionary algorithms (EAs) could be a good choice for solving the multiperiod problem.

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

The paper is structured as follows. In the following section we want to give a short literature overview. 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 overview

In this section we want to give a short overview of the research work that was done in the field of multiperiod communication network optimisation.

Most of the research on multi-period network optimisation was done in the operation research field. In the evolutionary computation field a lot of work was done for single-period (Kerhenbaum, 1993; Davis, Orvosh, Cox, & Qiu, 1993; Sinclair, 1995; Elbaum & Sidi, 1996; Ko, Tang, Chan, Man, & Kwong, 1997; Cahn, 1998), but almost no work for multi-period problems. Luss, 1982 is one of the early works in the field of multiperiod planning for networks and gives a systematic overview of the research that was done from 1950 till 1982. Minoux used a dynamic programming approach for solving the problem (Minoux, 1987). For this approach the structure and the routing of the traffic through the network remains constant during the whole design period. Parrish, Cox, Kuehner, & Qiu, 1992 used an approach, where in a first step the costs of each period are optimised 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 modelled as the links of a network[1] and a shortest minimum path through this network was identified. A Lagrangian relaxation was used in Dutta & Lim, 1992. They tried to find lower and upper bounds for the problem and used them as a starting point for a subgradientenmethode. Chang & Gavish, 1993 also used lagrangian relaxation, but combined local and global search. This approach was refined in (Chang & Gavish, 1995) to get better upper and lower bounds. Dutta & Kim, 1996 used a three-step heuristic. First the single periods are optimised separately

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

with a greedy algorithm. In the second step each transition between two periods is optimised. Lastly the routing of the traffic is calculated. A local iterative search algorithm GLIT (Generic Local Improvement Template) is presented in Garcia, Mahey, & 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. Multiperiod 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 Mutiperiod planning

The optimal communication network problem is even in the single-period case hard to solve. We want to describe approaches for solving the multiperiod network optimisation problem with evolutionary algorithms.

3.1 The design problem

For a graph with n nodes there are $0.5 * n(n-1)$ possible links. This results in $2^{0.5*n(n-1)}$ 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 minimise 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 optimisation

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

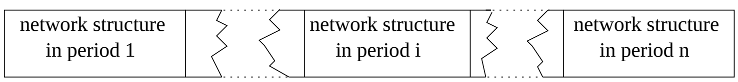

Fig. 1. A schematic representation for the multiperiod problem

For a single-period problem the encoding is obvious. All necessary information about the network must be encoded in a string. If we want to optimise 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. This results even for small problems in long representations. When it comes to optimising the multiperiod 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 fig. 1. However, an encoding like this has some disadvantages:

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

For a n-node network there are $2^{0.5*n(n-1)}$ possible network structures. With k different line capacities the search space grows up to $k^{0.5*n(n-1)}$. Solving this problem for l periods increases the search space to $(k^{0.5*n(n-1)})^l$. Solving a problem of this complexity in reasonable time is even for small network prolems not possible.

Representing the solution space in a string would result in long strings. However, for a good performance of a EA 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 multiperiod problem results for the EA in a tradeoff between getting a stable structure of 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 are not changing over the different periods dramatically. Networks in following periods are similar. This means for the optimisation algorithm that it has to find a lot of redundant information. This leads us to the apporach not to solve the problem parallelly, but in serial[4].

3.3 Serial optimisation

We propose four possible approaches to cope with the multiperiod optimization problem.

One-period scaling optimization With this approach one period is chosen as a starting point for optimisation. This period is optimised independently from 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 avaiable 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.

[2] results in low costs when changing the structure
[3] necessary for a good usage of the lines
[4] Almost all former work described in section 2 used also some kind of serialisation for solving the problem

Discret single period optimization This method optimises the problem for each period separately, without respect 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

One-period backlooking optimization As an extension to the discret single period optimisation this approach takes the modification costs of the network into account. The optimising process starts from the first period and optimises 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.

Iterative optimization As an extension to the one-period backlooking optimisation the optimisation process is not stopped after one cycle, but is continued. After optimising all periods once, periods are picked out randomly and optimised. The GA optimises the overall costs of the multiperiod-problem. They consist of the transistion 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 as the most promising.

4 Experiments

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

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 is increasing in every period with 20%. The costs of the links depend on the length and the capacity and remains 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.

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 cost for installing a link consists of a fixed and length dependent share[5]. Possible line capacities are 64 kBit/s, 512 kBit/s and 2048 kBit/s. The complexity of the problem is low.

Problem 2 In this problem the demand matrix is completely filled[6]. 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 minimisation of cost we use a simple GA (Goldberg, 1989). It is adapted in different ways[7] 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 removing exceeding links in a cycle and adding new links between separated trees[8] randomly.

In all runs we used one-point crossover and a crossover-probability $p_{cross} = 0.75$. The mutation probability[9] 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 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 μ and standard deviation σ of the minimum overall cost of the multiperiod-problem. The overall cost consists of the costs for the network in all three periods and the costs for modifying[10] the network. We show results for the serial and the one period backlooking optimisation for both problems. For both problems the one-period backlooking approach performs better than the serial approach. An application of the one-period scaling up optimisation approach to the first problem and scaling up from the first period showed worse results than for the other approaches.

The computational effort for the scaling up approach was low. It is necessary to optimise 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 with l is the number of periods. For the one-period backlooking approach the effort was similar to the discrete single period approach[11].

[5] Both depend on the capacity of the link
[6] Between every node i and j exists some traffic.
[7] compare subsection 3.3
[8] to get a connected tree
[9] Switching one bit in characteristic vector that represents the tree
[10] adding new links or increasing the capacity of a link
[11] The calculation of the costs, was a little bit more complex, because the transition costs had to be calculated for every evaluation of an individual

	problem 1			problem 2	
	one-period backlooking	discrete single period	scaling up (first period)	discrete single period	one-period backlooking
mean μ	253189.4	262369.2	272617.0	490664.9	518953.4
std. dev. σ	1162.5	4024.6	-	14225.9	13680.4

Table 1. Minimum cost of nework over all three periods for different optimisation approaches.

5 Conclusion

This paper has adressed the optimisation of telecommunications networks for a multiperiod horizon. To optimise the overall costs for all time periods serially we proposed different heuristic approaches. The first, and most simple, optimises 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 optimises the structure of the network for each period independently of the solutions for other periods. The third approach optimises 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 best results with the third approach.

We propose to extend the third approach and to optimise the different time periods iteratively. After the first run over the whole planning horizon we will pick out periods randomly and optimise 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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