Strategic Migration Optimization Of Urban Access Networks Using Meta-Heuristics

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***Abstract*—In this paper the concept of network migration and its relation to access networks is introduced. A typical urban migration case (from VDSL to GPON) is studied to provide cost results under given boundary conditions. We investigate the optimization of a migration process over a long period of time using a segmentation of huge urban scenarios into clusters. Although those clusters can be separately migrated and optimized, an evaluation, which cluster shall be optimized in a certain time step is necessary. This strategic optimization can be performed heuristically. The application of those methods to exemplary scenarios is described in the paper. The necessary sequencing of these steps and our achieved results in terms of costs and algorithm performance are explained. The paper provides methods to cope with network changes and increasing demands via usage of planning heuristics.**

I. Introduction

Traffic demand in access networks and traffic aggregation points is expected to increase rapidly in the next years [1]. In contradiction the income of network providers is not proportionally increasing with the consumption of network resources due to shrinking tariffs for end users. These two major problems of telecommunication providers increase the necessity for strategic planning optimization methods to reduce costs significantly. The application of heuristics for the optimization of backbone networks was described in [2], [3], [4], [5], [6].

In this paper we describe a possible workflow to optimize a migration process in an access network within the whole migration period. By network migration we describe the technical process of upgrading and exchanging existing hardware/software (infrastructure) to another network technology, which generates calculable cost savings for its owner. We investigate the shift from classical copper and fiber based Very High Speed Digital Subscriber Line (VDSL) to fiber based Gigabit Passive Optical Network (GPON) technology within a huge urban access network scenario. We will focus on heuristic solutions for this problem, since a calculation using Integer Linear Programming (ILP) was revealed to be too complex. Therefore we investigated several heuristic approaches (*Tabu Search*, *Pre-Calc*, *Genetic Algorithms* and *Deterministic Search*) in terms of performance and algorithmic behavior with the goal to find a method that consumes minimal computation time, but provides better results than a semi-optimal deterministic approach. The migration process is considered as “All-Period”-approach, which includes the optimization over multiple years, in contrast to commonly used “Incremental”-approaches, which cover differences between two migration steps only [7], [8].

The remaining paper is structured as follows. Section II describes the basics of our network migration model. In sec. III our solution heuristics are introduced and applied to the migration case. Our calculation results are shown in sec. IV and a short conclusion is given in sec. V.

II. Network Migration Model

A. Introduction

As start scenario of our migration we use a VDSL network having a fiber connection to the Street Cabinet (SC) and using a copper connection from the SC to the end user. Every user in our test city is connected in this way at the beginning of the migration phase. The target technology is marked as GPON, which was chosen as possible migration case, since equipment of VDSL is partially usable and the technique is providing high data rates, able to cover uprising high network demands. Algorithms and approaches provided in this

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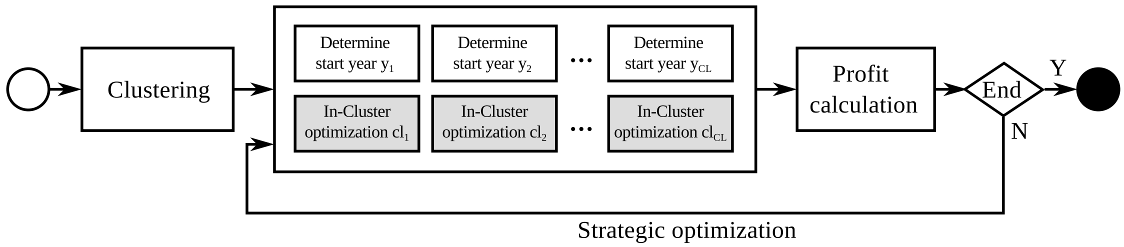

Fig. 1: Applied network migration optimization method

paper can be used also for any generic migration case, if the “In-Cluster”-Migration is implemented accordingly. As “In-Cluster” migration (sec. II-C,[9]) we understand the detailed technological migration process within one cluster of the investigated city. The optimization of that cluster is planned over the complete planning horizon, splitted by the migration start year y_{cl} into pre-migration phase and migration phase. To investigate a separate cluster the initial city has to be segmented into clusters. In this paper we assure that the clustering is done in an earlier phase and is therefore not yet part of the optimization process. Since clustering might be of high importance for the migration result applicable methods from literature are introduced in sec. II-B. As strategic migration (sec. II-D) we understand the question which cluster has to be migrated in which point in time, while considering the constraints of the problem (cost and work time bound). The major steps are visualized in fig. 1.

B. Clustering

The segmentation of the city can be done using precise mathematical methods (e.g. *Linear regression* or *K-Means* [10]). Those methods usually perform well in terms of performance but are assuming equal types of network nodes, which is not the case in our network migration model [8]. Therefore we suggest methods using topological and topographical information, e.g. streets, parks and rivers. This information must be available if a useful clustering shall be made. In Germany for instance an infrastructure map is provided by the “Bundesnetzagentur”. For calculations done in this paper the test city was pre-segmented by a generator providing separate clusters. A disadvantage of this method is that a connection of specific nodes is only possible to clusters they belong to. This can be improved if the clustering process is included in the overall optimization. The advantage of this method is that clusters can be generated to our needs emulating a specific behavior of users within that cluster. This improves the investigation of the migration algorithms.

C. In-Cluster Optimization

“In-Cluster”-optimization is the heuristic migration optimization process of a specific cluster cl, which is connected to the providers’ network. This optimization process delivers a solution $IC_{cl,y_{cl}}$ for a specific start year of the migration y_{cl}, which marks the introduction of optical equipment for end customers. Copper investments are no longer possible after year y_{cl} (while existing infrastructure is still usable). Degrees of freedom for “In-Cluster”-optimization are different possible locations for SCs, placement of new cables and cable ducts, installation of manholes and the connectivity decisions for end users. Users can be connected or disconnected according to the provider needs (a disconnected user does not pay anymore and is expected to move to another provider). Also new customers may appear over the migration period. Fig. 2 shows different options to plan a connection of new customers (yellow) to the network. The new house can be connected directly (green), which marks a nearsighted economic gain, since only new fibers have to be added to the existing cable ducts.

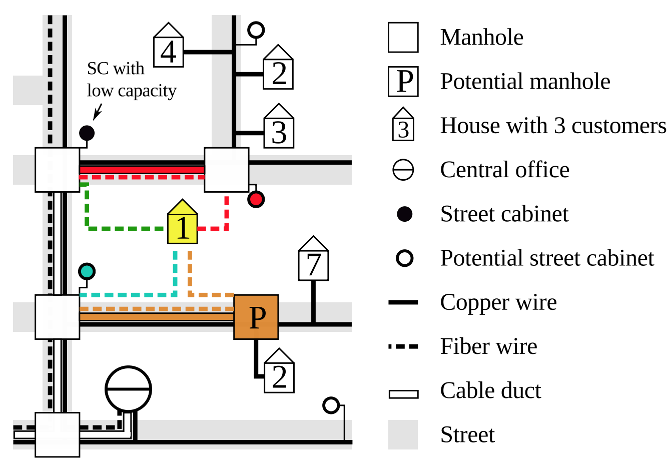

Fig. 2: Different options to connect a new customer (yellow) with “In-Cluster”-migration

Depending on other potential customers it might be more effective to use the red option and to activate a new

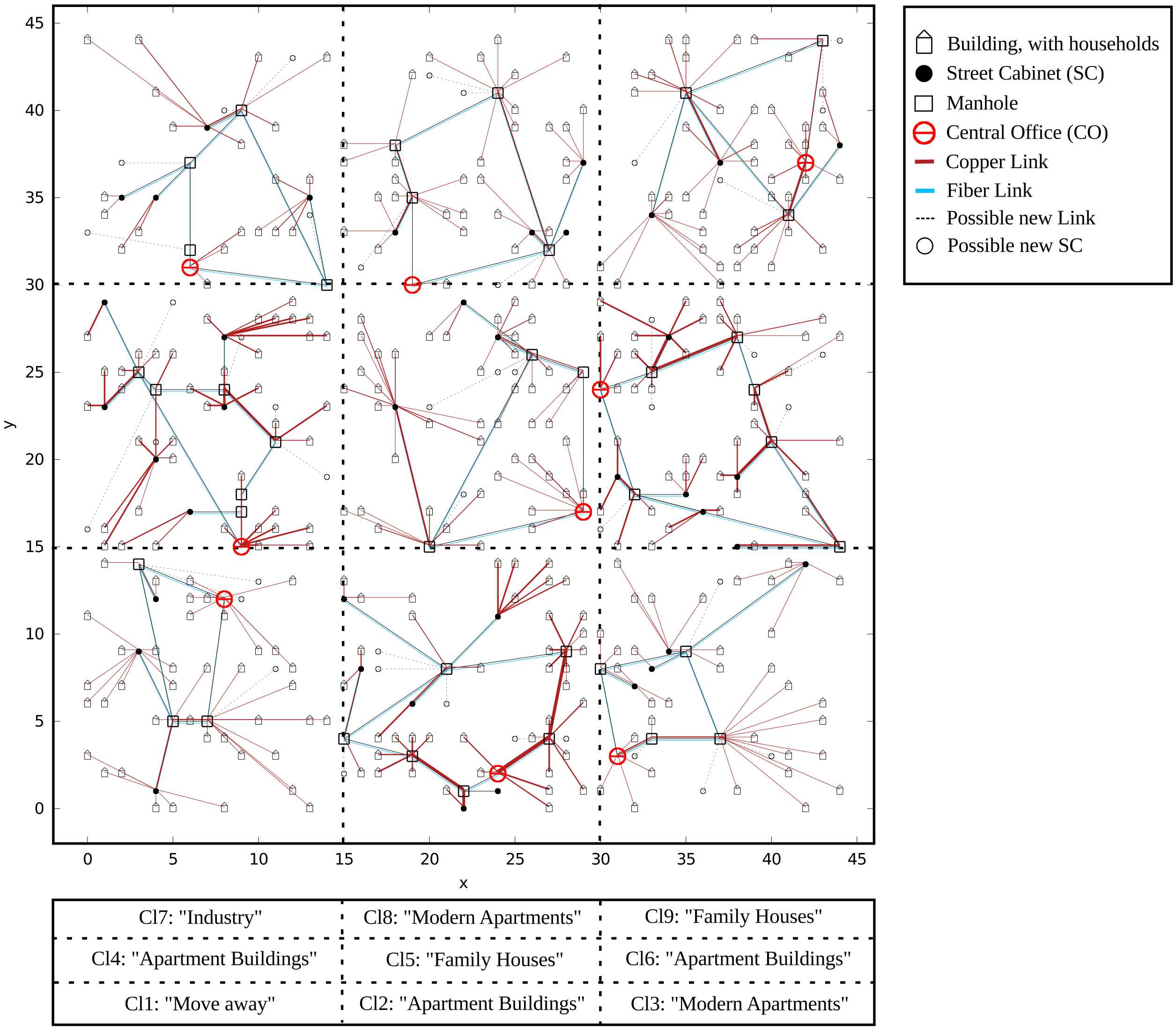

Fig. 3: Applied 9-cluster city scenario including clustering result

SC, install new ducts and a new fiber. Also the placement of new manholes might be an option (brown) that has to be evaluated by an optimization algorithm. Details about “In-Cluster” migration optimization can be found in [9].

D. *Strategic Optimization*

Strategic migration optimization can be understood as long term decision making by the provider to maximize the income of its network and to satisfy the user needs as good as possible. The provider is able to decide, which cluster has to be migrated at which instant of time according to technical limitations and financial constraints. The degree of freedom for strategic optimization is therefore only the value of y_{cl} for each cl. Heuristics applied to generate the results of this paper are described in sec. III.

E. *Scenario*

For our investigations we used a 3-cluster (not visualized in the paper, see [8]), and a 9-cluster Scenario (fig. 3). A cluster type was assigned to each cluster, which was responsible for the “In-Cluster” characteristic (few/many locations for SCs available, singular/multiple households, growth rate). We also use five different forecasts (fig. 5) A,B,C,D and E for connection speeds of end customers for the next years. Model A estimates a possible exponential traffic increase, B a logarithmic, C a linear and D/E a sigmoid behavior (depending on the providers expectations). For a realistic cost modeling a Capital Expenditures (CAPEX) decrease (cost erosion) and an Operational Expenditures (OPEX) increase were implemented. Each cluster contained exactly one Central Office (CO).

III. Heuristic Solution

In order to optimize the strategic migration result, four different heuristic approaches were implemented, *Tabu Search (Random)*, *Pre-Calc*, *Genetic Algorithm* and a *Deterministic* approach. They will be shortly described in the following sections. Details can be found in [8]. *Pre-Calc* and *Deterministic* approach have been chosen as obvious options to improve the strategic optimization process, while *Genetic Algorithms* and *Tabu Search* have been selected from a pool of available backbone improvement heuristics. Other meta-heuristics should be also applied to the problem in following studies to further improve the significance of the results.

A. Cost Model and Objective

Each strategic migration solution S can be rated by a fitness-value P (see eq. 2), which includes the Total Cost of Ownership (TCO) of the network for the complete migration period, as well as earnings generated by customers. The detailed cost model includes CAPEX $C_{CA,cl,y}$, OPEX $C_{OP,cl,y}$ and Implementation Expenditures (IMPEX) $C_{IM,cl,y}$. It can be reviewed in [8]. Basically each device's CAPEX is subject to a yearly cost erosion, while IMPEX and OPEX are modeled as factors basing on the CAPEX of that device. This simple cost model will be enhanced in future improvements. Our objective is to minimize the network's TCO (in Cost Units (CUs), with 1 CU = 1 Euro) and therefore to maximize the profit P (eq. 3). The earnings of a cluster cl (max CL) in year y (max Y) of the network generated by the customers attached to it can be expressed as $E_{cl,y}$. We distinguish between private and business customers in this paper, where a private (copper) customer generates earnings of 35 CU per month, a comparable business customer 63 CU per month.

$$TCO_S = \sum_{y=0}^{Y} \sum_{cl=1}^{CL} (C_{CA,cl,y} + C_{OP,cl,y} + C_{IM,cl,y}) \quad (1)$$

$$P_S = \sum_{y=0}^{Y} \sum_{cl=1}^{CL} E_{cl,y} - TCO_S \quad (2)$$

$$objective: max(P_S) \quad (3)$$

The used cost (and installation time) parameters for the different devices (Optical Network Units (ONUs), Optical Line Terminals (OLTs), Digital Subscriber Line Access Multiplexers (DSLAMs), etc.) are listed in tab. I.

Device	Cost /CU	Work time /h
Splitter	30	1
ONU-Transceiver	50	1
OLT-Transceiver	50	1
ONU	150	1
OLT 4x32	1500	1
OLT 8x32	2000	2
DSL Modem	30	0.5
DSLAM 1152	8000	20
DSLAM 864	5000	16
Duct	6000	100 /km
In-Duct-Fiber	500	40 /km /fiber
Copper	1000	16 /km /wire
Fiber	5000	16 /km /fiber
Cabinet	2000	30

TABLE I: Applied cost and work time parameters

B. Constraints

The main constraints for the problem are the possible maximum budget of the provider per year, the total allowed budget within the migration period and the possible maximum working capacity (manpower) for installation purposes (see [8] for details). The constraints for the strategic migration can be described as follows:

- financial expenses for network development shall not exceed the maximal cost budget per year $B_{C,y}$ defined by the provider (eq. 4)

$$\sum_{cl=1}^{CL} (C_{CA,cl,y} + C_{IM,cl,y}) \leq B_{C,y} \forall y \quad (4)$$

- work time expenses for the installation of network equipment shall not exceed the maximal work time budget per year $B_{W,y}$ defined by the infrastructure, where $t_{W,cl,y}$ is the sum of work time to install new devices (ONUs, splitters, cable ducts, etc.) in cluster cl and year y (high costs and time expenses must be planned for underground construction)

$$\sum_{cl=1}^{CL} t_{W,cl,y} \leq B_{W,y} \forall y \quad (5)$$

Constraints regarding "In-Cluster" migration can be summarized as follows (see [9] for details):

- a network node may support multiple households
- each customer in a household is treated individually but is marked as same network node
- so called empty nodes (holding no customer, SC or CO) provide possible space for new SCs
- cable ducts, copper cables and optical wires can be applied to a link

- all possible links must be defined preliminarily, only those can hold new cables etc.
- direct bury links to customer nodes are allowed when connected to a manhole a SC or a CO (those are associated with very high underground construction expenses)
- electrical distortions on transmission paths are not considered

C. Tabu Search (Random)

As our goal is the ideal selection of migration start years y_{cl} in each cluster cl, as well as a cluster internal optimization, the easiest possible selection method is a random algorithm, determining each $y_{cl} \forall cl$ purely random. Since these generated migration solutions S contain many infeasible solutions $\tilde{S}$ (due to constraint limitations), which involves long calculation times for "In-Cluster"-optimization, we added a tabu list L containing all found pairs of y_{cl}, cl that caused an invalid solution in the past. For generated pairs in S that are not found in L the "In-Cluster"-optimization will be run according to the specified parameters. Either way a pre-calculated "In-Cluster"-solution $IC^{pre}_{cl,y_{cl}}$ is used according to sec. III-D or each cluster solution is newly optimized (delivering $IC^{new}_{cl,y_{cl}}$) and the complete solution S_{new} is checked for validity afterwards. If $y_{cl}, cl \in L$, y_{cl} is chosen again in a random manner. In case that any $IC_{cl,y_{cl}}$ leads to a $\tilde{S}$ the pair y_{cl}, cl is added to L. No solution is possible if for a specific cluster cl no y_{cl} fits to the chosen constraints. This method is limiting the solution space, but is increasing the calculation efficiency in comparison to pure random especially for large problem instances.

D. Pre-Calc

Using the *Pre-Calc* strategy we focus on the reduction of overall calculation time by storing already calculated "In-Cluster"-solutions $IC^{pre}_{cl,y_{cl}}$. For each y_{cl} ($0 \leq y_{cl} \leq Y$, with Y maximum migration period) and cl one possible $IC_{cl,y_{cl}}$ is preliminary calculated and optimized. The resulting set is now used to recombine the "In-Cluster"-solutions to produce strategic solutions S. Those are then checked against the outer constraints of the strategic migration problem (budget and working time). This leads to a very limited solution space and therefore to a limited performance (or cost result) of the migration, but also to a very fast and efficient calculation process.

E. Genetic Algorithm

To avoid the disadvantage of the above algorithms, which strongly limits the solution space, the Genetic Algorithm (GA) meta-heuristic was applied [11], [12], [13]. This method is able to examine the full solution space, but can also search it by a strategy avoiding too many "In-Cluster"-calculations. GAs have been widely applied for many optimization problems, such as time tabling, scheduling and logistics, but also in network migration planning [5]. GAs are based on chromosomes (strategic migration solution S), which are constructed using different genomes ("In-Cluster"-solution $IC_{cl,y_{cl}}$ with migration start year y_{cl} in cluster cl).

We implemented the GA according to fig. 4. A start population M with $\overline{M}$ individuals is randomly generated. Selected from the pool by a roulette wheel method two individuals S_1 and S_2 are used for genetic recombination. Here a one-point-crossover with recombination probability p_R is applied on S_1 and S_2, as well as a randomized mutation with mutation probability p_M afterwards. A mutation is performed as uniformly randomized variation of migration start year y_{cl} of a cluster cl, while each cluster of each individual can be potentially mutated. Then two new solutions are selected from the pool M. If the new generation is complete ($\overline{N} = \overline{M}$), the whole process is repeated for the next generation, until the given number of generations (g_{max}) is reached.

The chromosome with the best fitness value will be selected and validated using the constraints. If the chromosome does not fit into the boundaries, the next best fitness value will be selected, if it is feasible it will be returned as current generation result.

F. Deterministic Algorithm

The genetic algorithm delivers a good migration solution in acceptable time, but it works using random decisions, which might be not useful for some scenarios. Therefore we developed a deterministic approach for the strategic migration (while "In-Cluster"-optimization still works on a random approach). The algorithm tries to use the cheapest solution (greedy) to receive a good suboptimal solution in a short time frame. The method is started using a pool of "In-Cluster"-optimization solutions (pre calculated, see sec. III-D), which will be sorted according to cluster-ID in ascending order and secondly according to TCO in descending order. The best solution of a cluster IC^{best}_{cl} is then checked against the strategic migration constraints. If IC^{best}_{cl} is feasible the cluster

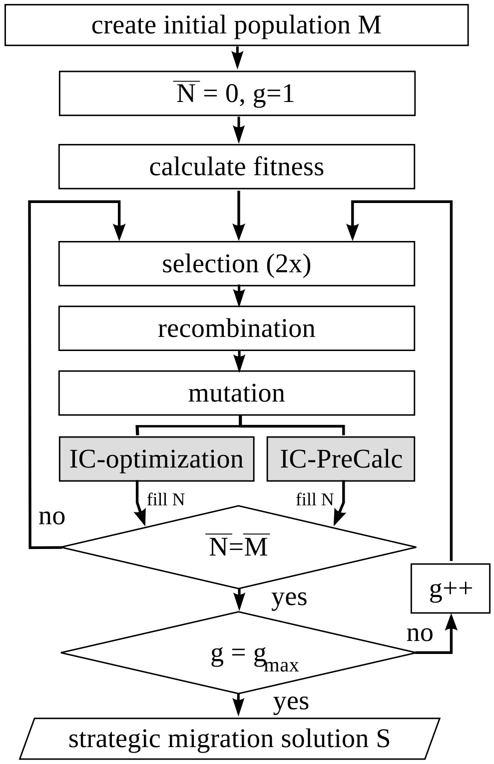

Fig. 4: Applied genetic algorithm

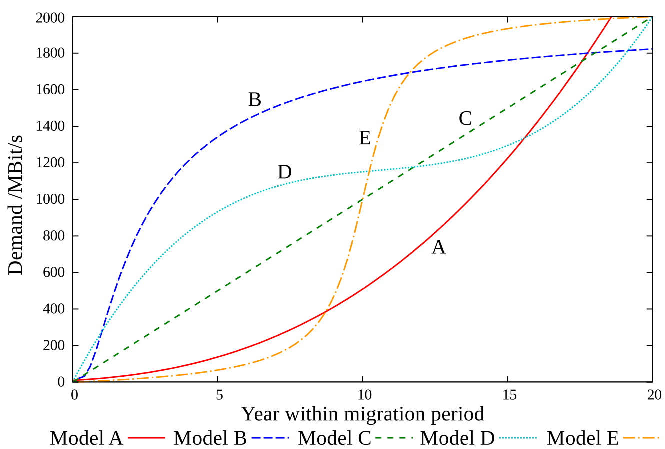

Fig. 5: Forecast models for demands per customer

counter is increased, if not $IC_{cl}^{2nd-best}$ is selected (and so on). In case that all solutions of one cluster disagree with the constraints, no solution could be found and the algorithm terminates. When all clusters are processed the final migration solution S is delivered.

IV. Results

We calculated results for a simple 3-cluster and a 9-cluster (overview netgraph in fig 3) environment, utilizing parameters shown in tab. II. The general planning horizon is 20 years, assuming a preferably clear view on the customer development in the investigated clusters. We discussed different cost and work time limitations producing a large quantity of case studies, while only figures for the bold values are presented in this paper.

Name	Parameter	Value
Planning horizon		20 years
Forecast models		[A,**B**,C,D,E]
Cost erosion		0.05 p.a.
Inflation		0.035 p.a.
Income copper (private)		35 CU
Income fiber (private)		45 CU
Income copper (business)		63 CU
Income fiber (business)		81 CU
IMPEX factor		0.1
OPEX factor		0.3
Cost budget	$B_{C,y}$	[9e5,**1.2e6**,1.5e6,1.8e7,1e7,10e15]
Work time budet	$B_{W,y}$	[**3.2e4**,4e4,6e4,8e4,1e10,10e15]
Max cl migrations per y		[1,2,**3**,5,7,9]
Population size	$\overline{M}$	[5,**10**,20,30,46]
Maximum generations	g_{max}	128
Mutation probability	p_M	[0.01,0.05,**0.1**,0.2,0.5,0.7,1]
Crossover probability	p_R	[0,0.1,0.3,0.5,0.7,**0.9**,1]

TABLE II: Applied heuristic parameters (bold are default values for the results presented in this work)

As expected we can see high computational effort for the random (including tabu search) approach RND (fig. 6), as well as for the GA. This can be explained with a high amount of "In-Cluster" calculations.

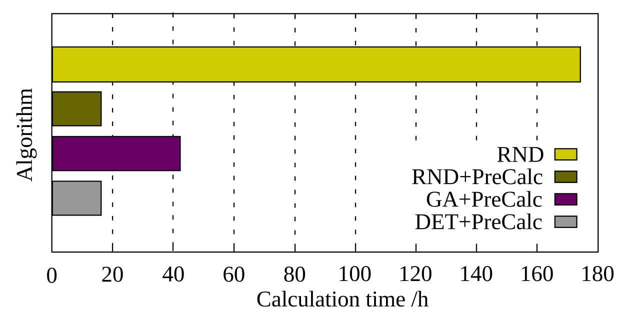

Fig. 6: Calculation time comparison (3-cluster)

In contrary fig. 7 reveals that GA performs a little better than the randomized approaches in terms of profit gain after 32 iterations for all demand curves. The deterministic approach (DET) performs well in terms of computation time and network profit, but it is loosing a great piece of the solution space, which increases the probability to loose good solutions. From our experience (see fig. 8) GA performs better than DET if more calculation time is available and if "In-Cluster"-iterations are increased. The different demand curves also have a strong impact on the migration result (e.g. model E performs best in our case). A negative profit appears because of our constraint that a complete migration for

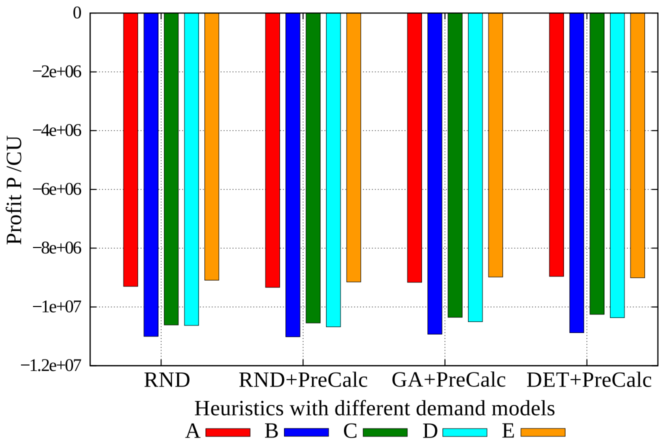

Fig. 7: Algorithm results for different demand forecasts (both 3-cluster scenario, snapshot after 32 iterations)

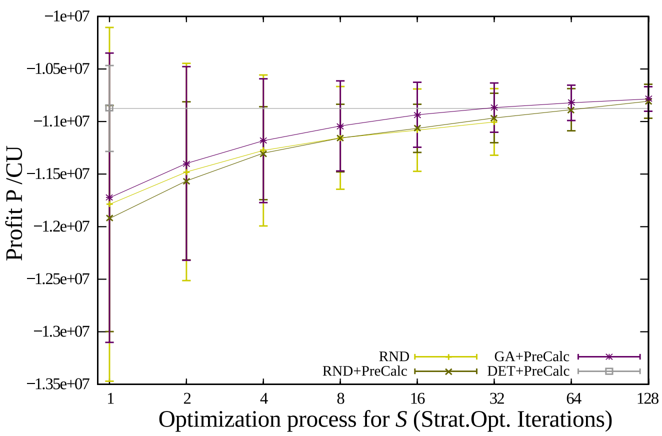

Fig. 8: Algorithm performance (3-cluster Scenario, demand model B)

all clusters has to be performed until the end of the migration period. Also the available DSLAMs are too big for our used test scenario. Demand increase model B delivers the worst results due to high expenses in the beginning, model E performs best because of a well distributed migration of all clusters in the middle of the migration period. Fig. 9 (demand forecast model A) presents the distribution of work time and financial capacities within the migration period for the 9-cluster scenario (best found solution S). We can obtain that the boundaries are exploited mostly in the beginning and in the end of the migration phase. This meets expectations arising from the problem that a migration in the end is favored due to less CAPEX, a satisfaction of user demands in the beginning must be guaranteed, to keep the customers in the network.

Fig. 10 shows a detailed view on the predicted demand situation in cluster 4 of the 9-cluster test network

Fig. 9: Total cost and work time distribution limited by constraints (9-cluster Scenario, demand model A)

of fig. 3. Since demands are constantly rising (black line, demand model A) an upgrade of infrastructure over time is necessary. Therefore the optimization algorithm predicted an early migration start year for that cluster, which leads to an early increase of fiber customers in the cluster. In parallel the amount of copper customers is shrinking due to competitive fiber technology. The rapid demand increase appears due to the structure of the cluster, containing mostly apartment buildings and residential households. The total customer amount (green) may also drop because of customers that have a very high demand for capacity, which is not satisfied. Those customers are assumed to leave the providers network.

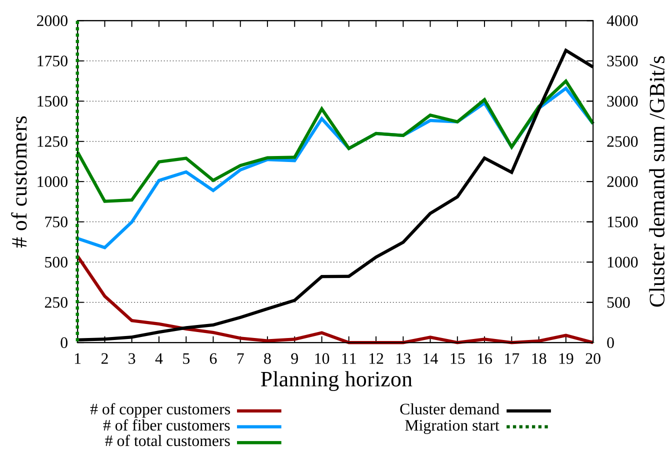

Fig. 10: Number of customers for different technologies and demand increase (cluster 4, demand model A)

In fig. 11 a visual hint for the migration phases of each cluster is given. Dark colors mark a high exploitation of the given constraints, red colors show the financial expenses in the pre-migration phase (before y_{cl}) and blue

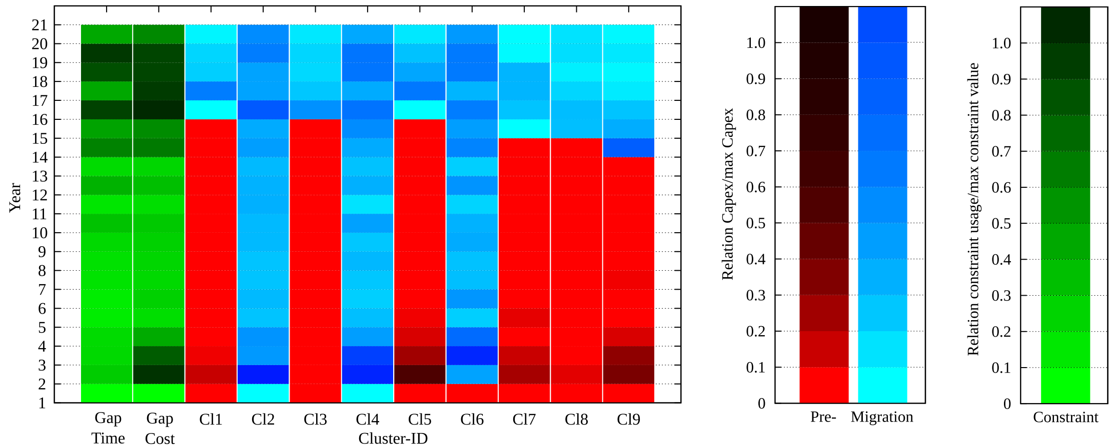

Fig. 11: Migration costs visualized in relation to constraints (9-cluster Scenario, demand model A)

colors expenses after the beginning of the migration. Green colors present how good the strategic constraints are satisfied. We can see that cluster two, four and six have to be migrated early to increase the overall profit of the network for the whole migration period. Also high expenses have to be planned in the pre-migration phase in cluster five, seven and nine.

V. Conclusions

The application of strategic migration optimization methods can save significant costs for network providers. We applied four heuristics to a 3 and a 9-cluster scenario to prove the functionality of the methods and to determine the most efficient algorithm. GA meets our requirements of fast solution improvement and available solution space. The development of the migration toolset allows further investigations of more sophisticated heuristics and the calculation of more realistic scenarios. Also more migration cases can be added and applied to "In-Cluster" improvement. Important is also the improvement of the clustering process and its integration in the optimization.

VI. Ackknowledgement

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