Using a Genetic Algorithm as a Decision Support Tool for the Deployment of Fiber Optic Networks

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***Abstract*—Fiber optics is a relatively new technology, which many telecom operators have been considering using. However, telecom operators are skeptical in using it, because of its high cost. In order to evaluate the viability of such a costly investment, techno-economic models are employed. These models evaluate the investment from both technical (e.g., optimal network design) and economical (e.g., profitability) perspectives. However, an area that has not received much attention is the deployment plans of a given fiber optic investment. Existing works usually compare manually predefined deployment plans that are considered profitable, and then apply techno-economic analysis. While this indeed offers valuable information, it does not guarantee that the examined plans are the optimal ones. This should be considered as a major disadvantage, because there could be other deployment plans that could offer significantly higher profit. This paper offers the first attempt at looking for the optimal deployment plan of fiber optics, based on profit. Our method can be considered as a framework that wraps around existing techno-economic models. We employ a Genetic Algorithm (GA), which creates a population of deployment plans, which can then be evaluated through the usual techno-economic approach. The GA then evolves the population of these plans and at the end of the process acts as a decision support tool that advises on the optimal deployment plan, without the need of any human interference in the decision-making process. For comparison purposes, we compare the GA's results with results under other profitable plans. Results show that the introduction of the use of the GA is very advantageous and leads to a significant increase in profit.**

I. Introduction

Fiber optics is a relatively new technology, which many telecom operators have been considering using [1]. Demand for higher bandwidth is rapidly increasing, due to the relevant new ways of using the internet, such as sharing and downloading files, and VoIP (Voice over IP) services. Fiber optics constitutes an answer to the requests of faster internet speeds. However, telecom operators are skeptical in using this technology due to its extremely high cost [2]. Different fiber optic options exist, such as Fiber-to-the-Cabinet (FTTC), Fiber-to-the-node (FTTN), Fiber-to-the-building (FTTB), and Fiber-to-the-home (FTTH), the latter being the most costly. For the purposes of this paper, we do not differentiate among the different options, but we examine a general fiber approach, and thus use the term FTTx.

In order to evaluate the viability of an FTTx investment, techno-economic models are employed. Techno-economic models are tools that companies use for evaluating a project from both the technical and economical point of view. For instance, a construction company that is planning on undertaking a new project would use a techno-economic model to evaluate the technical requirements of the project (e.g., amount of cement, bricks, optimal network design), as well as the economical requirements (e.g., cost, profit).

During the recent years, there have been several works that evaluate the techno-economic benefits of FTTx investments have taken place. Some notable works are [3], [4], [5], which focused on the techno-economic analysis of FTTB and FTTH in municipal areas. Furthermore, the European-funded projects IST-TONIC [6] and CELTIC-ECOSYS [7] have done similar research, producing a high number of papers. In addition, several works have focused on the cost effects of this kind of projects. Typically, this type of works focuses on examining different topologies of a network. For instance, [8], [9] compare different networks in terms of total cost, cost-per-bandwidth and other cost factors. Furthermore, other works take into account the competition that might exist in a country. Such examples are [3], [10], which evaluate optimal deployment starting time based on the existing competition. Moreover, other works have focused on using Geographic Information Systems (GIS) [11] for analyzing the deployment area and thus taking into account the actual topology of a real area [12]. Another interesting approach is to take into account the demographic data of an area (e.g., separate the areas into urban and rural, where each one would have different diffusion rate of the FTTx technology) [13], [12]. Lastly, some little work has taken place on optimizing the topology of the networks by using heuristics [14], [12].

However, a common simplification in the existing literature is in the deployment plans, which are pre-specified by the users of the models. In other words, the authors of such works choose a deployment plan that they consider as a realistic case study, and then use a techno-economic model to evaluate the technical and economic requirements of the given investment. A similar practice is also followed in the industry, where deployment plans are examined based on previous experience of the roll-out of similar technologies. Nevertheless, the chosen plans can be far away from the optimal one and there might thus exist a huge potential for increase in the net profit. To the best of our knowledge, no work has taken place on looking for optimal deployment plans. We find this very interesting, because it constitutes a major disadvantage, since nobody can guarantee that the suggested deployment plan is the most profitable. Given a city of 100 areas, the possible permutations if we assume a 5 year deployment plan are 5^{100}. It is thus obvious that there is a huge number of different deployment plans available and even if we assume a full coverage of the 100 areas in the long run, this cannot necessarily guarantee the highest profit.

The purpose of this paper is hence to demonstrate the benefits of using Computational Intelligence (CI) techniques as part of the techno-economic analysis that takes place for the deployment of Fiber Optic Networks. For the purposes of this work, we are using a Genetic Algorithm (GA), which looks for the deployment plan that returns the highest profit. The GA acts as a *wrapper*, which goes around a given techno-economic model.[1] Therefore, after creating a population of deployment plans for FTTx, each plan's profitability is assessed through the economic model; then the deployment plans are evolved and at the end of the evolutionary process the best one is the suggested plan for the FTTx roll-out. The GA thus acts as a decision support tool, which advises on the optimal roll-out plan.

At this point it should be emphasized that we are not looking for the optimal CI technique for this specific problem, neither do we claim that the GA is necessarily the best algorithm. Since the GA framework wraps around techno-economic models, other CI techniques could be used, as well. However, it is outside the scope of this paper to compare the performance of different CI algorithms on this type of problems. Our purpose is merely to show that a CI technique, such as GA, is crucial to techno-economic analysis, and as such, more research should take place towards this direction.

The rest of this paper is as follows: Section II presents the economic model, which the GA will wrap around. Section III presents the Genetic Algorithm used in this paper. In addition, Section IV presents the experimental design, and Section V presents and discusses the results. Finally, Section VI concludes this paper and discusses future work.

II. Economic model

Before presenting the economic model, we should explain that it falls outside the scope of this paper to present a detailed techno-economic model. Plenty of these models already exist in the literature, as presented in the previous section. Besides, the contribution of our paper is not in presenting a new techno-economic model, but in presenting the GA framework that goes around techno-economic models. For this reason, we leave aside any discussion related to the technical part of the model. On the other hand, because the decisions regarding the roll-out of FTTx are mainly economic decisions, e.g., related to income and cost, we present a detailed economic model. The purpose of this model is to provide information related to the profit that can be made by a FTTx investment, which can then be used by the GA in deciding the optimal (i.e., the most profitable) deployment plan.

[1] Although our framework can wrap around techno-economic models, in this paper we actually only focus on the economic aspects of such models. More details about this follow in Section II.

A. Overview

For the purposes of this paper, we assume that we are interested in deploying FTTx to a city. The same analysis could of course be applied to countries, rather than just cities.

A city can be divided in a number of areas. There can be different definitions of what constitutes an area. At the moment, areas are randomly defined. Each area has three characteristics: population, social category and town. Different areas can have different population. In addition, each area can be categorized by a social category. For instance, an area that is predominantly a business area, can be characterized as such. Other types of social categories can be high-income, medium-income, and low-income. Lastly, an area belongs to a town. In other words, many areas form a town.

The model also has the following parameters:

1) *Rollout customers*. This is the number of potential customers in an area, after we have installed the FTTx network.
2) *Rental services customer percentage*. This is the percentage of customers of the company that use rental services. This percentage can change annually.
3) *Rental services tariffs*. There can be a number of different services. Thus, each different service can have a different tariff. Tariffs can change annually.
4) *Pay as you go (PAYG) services customer percentage*. This is the percentage of customers of the company that use PAYG services. This percentage can change annually.
5) *PAYG tariffs*. There can be a number of different PAYG products. Thus, each different product can have a different tariff. Tariffs can change annually.
6) *Service installation*. This is the service installation charge, which is applied whenever a new customer joins the network. This charge can change annually.
7) *Innovators percentage*. This denotes the percentage of customers that take up new services as soon as they are available. There is a different innovators' percentage per social category. These percentage can change annually.
8) *Imitators percentage*. This refers to the customers that are influenced in their own take-up by the current market share of the services. There is a different imitators' percentage per social category. These percentages can change annually.
9) *Lost customers*. This refers to the customers who have left the network for any reason, e.g., as competition. There is a different percentage per social category. This percentage can change annually.
10) *Interest rate*. This refers to the interest rate of the market, if we were borrowing the investment money from a

bank. This rate can be change annually.

11) *Budget*. This refers to the maximum budget that we are allowed to use annually.
12) *Study period*. This is the total number of years that we run the model.
13) *Rollout period*. The number of years that we plan to have finished the deployment of the network.
14) *No income period*. The number of years we anticipate there will be no income. This is usually the first one or two years of the study period, where we still built the infrastructure, but the services are not yet available to the customers, and thus no income can be made.

In addition, *'deployment plan' is defined as the rollout plan of the network and is given as input to the model*. For instance, given 100 areas, we might decide that we will deploy FTTx in Year 1 in Areas 1-20, then deploy in Year 2 in Areas 21-50, and so on. The model also allows no rollout in an area at all, because for instance that area is isolated and the investment is not worthy. Different deployment plans of course exist, but for now we assume that the deployment plan is given. Thus we run the economic analysis under this assumption. Later, in Section III, we discuss the possibilities of different deployment plans and how we can search for the most profitable one.

Given the above parameters, the following procedure is repeated for the number of years specified in the study period:

(i) Calculate innovator customers
(ii) Calculate imitator customers
(iii) Calculate total customers
(iv) Calculate lost customers
(v) Subtract lost customers from the total customers
(vi) Re-calculate total customers
(vii) Calculate annual revenue
(viii) Calculate annual cost
(ix) Calculate cash flow
(x) Calculate Present Value
(xi) Calculate Net Present Value

Below follows a detailed discussion of the above process.

B. Innovators

As mentioned, innovators are the customers who take up new services as soon as they are available. Therefore, given the innovator percentages per social category, we can calculate how many new customers will take up the new service.

Innovators are only calculated during the first years of the deployment, from the year after the "no income period" until the end of the "rollout period". This is because the innovators are by definition those customers who take up a new service the moment it becomes available. Therefore, after the end of the rollout period, where no new service is offered, there should be no more 'innovators' in any area.

The way of calculating the innovators is to multiply the 'innovators percentage' to the number of new customers ("rollout customers") for the current year. Section II-D provides an example of how to calculate the innovators on an annual basis.

C. Imitators

Imitators are a bit 'slower' in taking up new services. There are again different imitator percentages, which differentiate according to the social category. Imitators can only be calculated in the year after there have been some customers that have taken up the service. This is because imitators are influenced after having seen the service being used by other people. Imitators are calculated as the product of the remaining customers from the previous year multiplied by the 'imitators percentage'. Section II-D provides an example of how to calculate the imitators on an annual basis.

D. Total customers (Step 1)

After having calculated the number of innovators and imitators, we can go ahead and calculate the total number of customers for a given year. This number is given by the sum of innovators and imitators for that year.

Let us give an example in order to make this more comprehensible. The second column of Table I presents the rollout customers per year, for Years 0-2. As we can observe, in Year 0 we roll out to 2 million households, and in Year 1 we rollout to an extra 1 million. We do not roll out to any more customers after Year 1. Also, let us assume that the annual innovators percentage is 10%, and the annual imitators percentage is 5%.[2] Finally, assume that the "no income period" lasts for 1 year, and thus in Year 0 we only install the infrastructure, so *no customers* can take up the services yet. Customers can only start using the network's services from Year 1.

TABLE I
AN EXAMPLE OF HOW TO CALCULATE INNOVATORS AND IMITATORS ON AN ANNUAL BASIS.

	Rollout customers	Innovators	Imitators	Total customers
Year 0	2,000,000	-	-	-
Year 1	1,000,000	200,000	-	200,000
Year 2	-	100,000	90,000	190,000

Thus, in Year 1 we will have innovators, which will be equal to $10\% \times 2,000,000 = 200,000$ customers. Therefore, the total customers that will take up the services in Year 1 are 200,000, and the remaining customers from Year 0 that have not been connected to the company's network are $2,000,000 - 200,000 = 1,800,000$. In the next year, Year 2 imitators start imitating the innovators. Therefore, since there were 1.8 million households from last year that have not joined the FTTx network, 5% of these will be imitators and take up the service: $5\% \times 1,800,000 = 90,000$ imitator customers. In addition, there are new innovator customers from the extra 1 million rollout customers in Year 1. Therefore, Year 2 will also have $10\% \times 1,000,000 = 100,000$ innovator customers. In total, in Year 2 there will be $100,000 + 90,000 = 190,000$ new customers. The same process continues until the end of the study period.

[2] For simplicity, we assume that there is only one social category.

Lastly, while the above simplified example was only using a single social category, the above procedure could be extended to models that have more than one social category. In that case, apart from calculating the total number of overall customers, the model also allows calculating the annual number of customers per social category.

E. Lost customers

Every year a number of customers leaves the company and might join another competitive company or simply decide that does not want to use the FTTx services any more. These are the "lost customers". Different percentages per social category for these 'lost customers' are again allowed. This is because business customers might for instance have higher incentive for looking for better deals more often than a low-income family. The number of lost customers is calculated as the product of the current customers multiplied by the percentage of lost customers.

F. Total customers (Step 2)

Here we re-calculate the total number of customers, after removing the number of lost customers.

G. Annual revenue

The annual revenue consists of three parts: the revenue from the rental services, the revenue from the PAYG services, and the revenue from the service installation charges.

1) Rental services revenue: In order to calculate this figure, we first need to know the number of customers that are using the rental services. This number is given by the product of the total number of customers for a given year, multiplied by the percentage of rental customers. After obtaining this number, we multiply it by the relevant rental tariff.

2) PAYG services revenue: This figure is calculated as above. First we calculate the number of customers that are using PAYG services, which we then multiply by the relevant PAYG tariff.

3) Service installation revenue: As we have said, this is an one time cost for each new customer joining the network. Thus this is defined as the product of the number of the new customers for a given year, multiplied by the service installation charge.

After having obtained the above three figures, we can sum them up and obtain the revenue over a calendar month. However, doing that is not exactly correct, because this assumes that all customers joined the network at the beginning of the year and thus payed a whole year's fees. Nevertheless, this is not necessarily the case. For simplicity, we assume that the revenue increases linearly with time. If all customers had joined the network at the beginning of the year, then the annual revenue would simply be the product of total revenue at the end of the year, multiplied by 12 (months). However, as we said above, not all customers might have joined the network from the very beginning. Thus, in order to get a fair estimate of the annual revenue, we need to take half of the above product (12×[total revenue]), and thus divide it by 2.

H. Annual cost

Annual cost is defined as the sum of the Capital Expenditure (CAPEX) and the Operational Expenditure (OPEX). Both of these are cost figures, which are related to the cost of developing the FTTx infrastructure (CAPEX), and to the ongoing costs for running it (OPEX). At the moment, these values are pre-defined and based on existing research from the literature [15].

I. Cash flow

Cash flow is defined as the difference between the annual revenue and the annual cost. This allows us to have an understanding of what is the net profit or loss every year.

J. Present Value

Present value is the value on a given date of a future payment or series of future payments, discounted to reflect the time value of money. Given an annual interest rate i, the Present Value PV of receiving C monetary units t years in the future is equal to:

$$C_t = \frac{C}{(1+i)^t}$$

In our model C is equal to the cash flow. Hence, every year of the study period, we calculate the cash flow, and then also calculate its PV.

K. Net Present Value

Net Present Value (NPV) is defined as the sum of all PVs over the study period. If this number is positive, then the investment is profitable and is thus worth doing. If, on the other hand, the NPV is negative, then the investment should not take place.

III. Genetic Algorithm (GA)

So far we have presented an economic model that uses a single deployment plan, which is given as input. However, as already explained different deployment plans can be available and nobody can guarantee that the deployment we are using is the most profitable one. For instance, we do not know if we should deploy FTTx in an area in Year 1 or Year 2. Actually, we do not even know if we should be rolling out to that specific area at all. Maybe the cost is too high, and it is not profitable to go there.

These are important decisions that need to be made. Thus we need to evaluate all available deployment plans, so that we can decide which one is the best (i.e. which one offers the highest profit). This is an easy task if we only have a few number of areas, e.g. 5, that we are interested in deploying. However, if we are interested in deploying to a big area with many subareas, or to a whole country, this becomes a very complicated task. For instance, we mentioned in Section I that the possible permutations for a 100 area city, assuming a 5 year roll-out period, are 5^100. Evaluating all different permutations of deployment plans is hence extremely computationally expernsive. We therefore need a heuristic to assist us with the search in this big space.

In this paper, we investigate the benefits of the use of a Genetic Algorithm (GA) to the deployment of Fiber Optic Networks.[3] In the rest of this section, we present the GA we have used in detail.

A. Representation

In our framework, a deployment plan is considered to be a GA individual. A deployment plan is represented as a string of numbers. The length of the string represents the total number of areas we are interested in deploying the network. Thus, if a city is divided in 100 areas, then a deployment plan is a string that takes 100 values. Each position in the string represents a different area of the city. Thus, the first element of the string represents 'Area 1', the second element 'Area 2', and so on. Each element in the string can take values from 0 up to the number of rollout years that the company is planning to deploy the FTTx network. For instance, if the company is planning to deploy the network within 4 years, then the elements of the deployment plan string can take values from 0-4. These numbers represent the year that we are planning to deploy the network in that specific area. Figure 1 illustrates this. As we can see, this figure shows a deployment plan for 100 areas. According to this plan, FTTx in 'Area 1' is going to be deployed in Year 2, in 'Area 2' in Year 1, and so on. Another observation we can make is that different areas can be deployed in the same year (e.g. Areas 2 and 3 are both deployed in Year 1). Finally, we can observe that 'Area 6' has a 0 as a year value. This denotes that FTTx is not going to be deployed at all in that area. It is very important to have this option, because the cost of installing FTTx in some isolated areas might be extremely high, and thus the investment is not worthy in that specific area. The heuristics will thus be also looking to identify those low-profit areas that is not worth deploying FTTx at all.

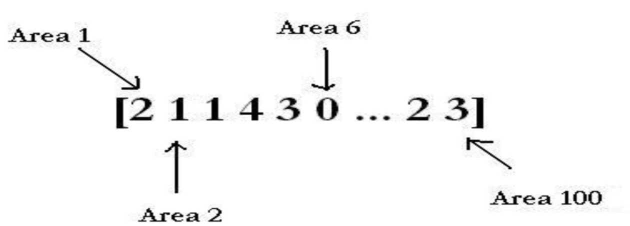

Fig. 1. An example of an individual's representation.

B. Fitness function

Each of the deployment plans of the population needs to be assigned a fitness, in order to measure its performance. The fitness function of a deployment plan is defined as follows:

$$Fitness = NPV \tag{1}$$

In the above equation, the fitness function of the GA is simply the Net Present Value (NPV) of a given deployment plan. Thus, 'fit' GA individuals are the ones that return the highest profit.

C. Constraints

Lastly, there are some constraints that need to be satisfied during the heuristics process. If they are not, then the relevant deployment plan is heavily penalized (i.e. we assign very low fitness to it) and thus has much lower chances of being carried over to the next iterations. The first constraint that needs to be satisfied is forcing the deployment of FTTx in some specific areas, under a specific timeframe. In other words, might believe it is important that FTTx must be deployed in Areas 0, 1 and 23, within the first 2 years. We thus need to make sure that the the Areas 0, 1 and 23 take only the values of 1 and 2. Any other value under these areas is heavily penalized.

The second constraint of our model is related to the annual budget. Earlier in Section II, we mentioned that there is a parameter in the model called budget, which allows to specify the maximum amount of money that is allowed to be spent each year. Therefore, each time we evaluate a deployment plan, we also examine whether the annual cost of that plan exceeds the budget for that year. If it does, then we again assign a very low fitness value to the relevant individual.

IV. Experimental Designs

This section presents the necessary designs for our experiments. Firstly, the dataset we use is an artificial one. We should state that not having real data in this type of tasks does not constitute a problem. On the contrary, this offers us flexibility in creating our own patterns in the data and then asking the GA to re-discover them. The obvious advantage of this is that it allows us to quickly evaluate the performance of the GA, since we can be aware of the optimal deployment plan in advance.

We conduct tests under a city that consists of 100 areas. In addition, *we run tests under both unlimited (UB) and limited budget (LB)*. The reason for using unlimited budget is because of the reason we explained above: UB allows us to know in advance the global optimum, and thus be able to examine how well the GA has performed. This is because when a budget constraint has not been set, the most profitable deployment plan will be to roll-out to all areas in the first year and thus start having income from that year.[4]

The population of each area is a random number drawn from the normal distribution, which ranges from 0 to 10,000 households. In addition, each area can belong to one of the following social categories: business (b), high income (h),

[3] We should again mention that we do not claim that the GA is the best algorithm for our given problem. We are only interested in demonstrating the positive effects of the application of Computational Intelligence techniques, such as GA. The investigation on the performance of other CI techniques has been left as a future work.

[4] For simplification, we do not take into account other constraints, such as man-power. In addition, we assume that under the simplified scenario of UB all 100 areas are profitable and thus it makes sense to roll-out everywhere in Year 1. We consider that compromising in terms of "100% realistic models" is acceptable at this stage, because we are focusing on producing a global pre-defined solution, which allows us to evaluate the effectiveness of the GA.

medium income (m), and low income (l). The distribution of the social categories is as follows: Business category: 3 areas, High-Income category: 10 areas, Medium-Income category: 33 areas, Low-Income Category: 54 areas. As we can observe, there are only a few areas that belong to the business social category. Then there are more areas characterized as a high-income social category, and even more for the middle and low income categories. These demographics must be taken into account by the GA when conducting the search. For instance, it is expected that the diffusion of the new technology will be faster in the higher income areas (this is indeed reflected by the rates of innovators and imitators, as we can see from Table II). This would of course result into higher revenue. A successful GA would thus have to aim to return a plan that gives priority to areas that come from a higher social category.

Table II presents the values of the model parameters. As we have already said, a city is divided into a 100 areas, and the social categories are four: b, h, m, and l. The rental services customer percentage is set to 1, which basically means that there are no PAYG customers in our model. This is done for simplicity. For the moment, we assume that there is only one rental service, which costs 80 monetary units (m.u.) per calendar month (pcm). Moreover, the service installation is set to 150 m.u. The innovators and imitators percentages are different per each social category. We chose to differentiate these percentages for each social category, because we consider it more realistic if the the "richer" areas (i.e., business and high-income) are interested in getting the new technologies faster. The lost customers percentage is set to 5%, under all social categories. The interest rate is fixed for every year, and is set to 10%. Furthermore, as already explained we will be experimenting with unlimited and limited budget. The value of the budget limit is 60,000,000 m.u. per year. Finally, the study period is set to 20 years, where the 1st year is the no income period and the rollout period lasts for 4 years.[5]

We should mention that the annual CAPEX and OPEX costs are set to be the same for each area. In this way, we can investigate whereas the GA has the ability of prioritizing the deployment of FTTx to higher social category areas, which as we have seen have higher innovator and imitator percentages, and thus quicker and higher profit. The CAPEX has been set to 2.5 million m.u. per area, per year, for the first 4 years (rollout period), and the OPEX has been set to 40K m.u., for each area and each year over the whole study period of 20 years. Also, the model takes into account what we call 'dynamic costs'. More specifically, some areas that are geographically close to each other would share the same equipment, such as a connection box; thus, the cost of this equipment would not be calculated until FTTx has been deployed to one of these areas that are geographically close. Therefore, this cost is dynamically calculated by time. *This makes the investigation of optimal deployment plans a harder problem and the use of heuristic optimization is hence imperative*.

[5]We should note that while many of these parameters are at the moment static, future versions of the model could use functions or other exogenous models, which would determine these values. At the moment, we chose not to focus towards that direction, because the aim of this paper was to work on heuristic optimization. Nevertheless, the above does not compromise the significance of our experimental work, since the contribution of this paper is not on the economic model, but on the GA that wraps around it.

TABLE II
ECONOMIC MODEL EXPERIMENTAL PARAMETERS. THE ABBREVIATIONS 'M.U.', 'PCM', AND 'P.A.' REFER TO 'MONETARY UNITS', 'PER CALENDAR MONTH', AND 'PER ANNUM', RESPECTIVELY.

Number of Areas	100
Social Categories	4
Rental Services Customer Percentage	1
Rental Services Tariffs	80 m.u. pcm
PAYG Services Cust. Percent.	0
PAYG Tariffs	15 m.u.
Service Installation	150 m.u.
Innovators Percentage (b, h, m, l)	(0.25, 0.20, 0.15, 0.10)
Imitators Percentage (b, h, m, l)	(0.20, 0.15, 0.10, 0.05)
Lost Customers Percentage (b, h, m, l)	(0.05, 0.05, 0.05, 0.05)
Interest Rate	0.10 p.a.
Budget	UB/LB (60 million m.u.)
Study Period	20 years
Rollout Period	4 years
No Income Period	1 year

Lastly, Table III presents the GA parameters. As we can see, the population is set to 500 individuals. The number of generations is set to 50 and the tournament size is set to 4. The crossover probability is set to 0.9, whereas the mutation probability is set to 0.1.

TABLE III
GENETIC ALGORITHM EXPERIMENTAL PARAMETERS.

Population	500
Generations	50
Tournament Size	4
Crossover Probability	0.9
Mutation Probability	0.1

V. RESULTS

A. Summary Results

In this section we present the average results over 20 individual runs for the GA, for the *fitness of the best deployment plan*. Our purpose is to demonstrate that the introduction of a Computational Intelligence technique, such as GA, can be very advantageous when compared to other techniques that do not use any intelligence. However, a problem that we faced was that there is no benchmark for this type of applications. We thus constructed two different benchmarks that the GA can be compared to, one under unlimited budget (UB), and one under the limited budget (LB) of 60 million m.u. per year. As already explained in the previous section, the global optimum is known under the UB scenario and the best deployment plan is to deploy to all areas in the first year. This is going to be the benchmark for the GA under UB.

On the other hand, in the case of the LB scenario the global optimum is not known. This is of course a more realistic scenario. In order to construct a benchmark solution, we tried to 'imitate' the skeptical of telecom companies when evaluating different deployment plans, by using some 'common sense rules', e.g., a business area is expected to return high profit and thus should be given priority in the roll-out phase. We followed the following simple rules:

- Start deploying from higher to lower social category areas in year t, as long as the cost does not exceed the annual budget limit.
- If it does, continue the deployment from year $t+1$.
- Priority should be given to areas with higher population.

Therefore, while the cost of the deployment to an area does not exceed the annual budget limit, we mark the respective area as ready-to-roll-out. When only a few areas can be deployed in a specific year, we choose the ones with the highest population, because a higher populated area has more potential customers and thus higher potential income. Let us give an example. Under the current experimental design, there are 3 areas designated as business, 10 as high-income, 33 as medium-income, and 54 as low-income. For a 60 million m.u. annual budget limit and a total cost per area of 2,540K m.u. (2,500K [CAPEX] + 40K [OPEX]), each year we can roll-out to a maximum of $\frac{60,000,000}{2,540,000} \approx 23$ areas. In Year 1, we can roll-out to all business and high-income areas ($3 + 10$ areas in total), and there are still 10 areas to be deployed that could be selected from the medium-income category ($23 - (3+10) = 10$). As already explained, these 10 areas are going to be selected based on their population. Hence, the 10 medium-income areas with the highest population are going to be deployed in Year 1. We follow the same practice for all 4 years for the roll-out period. After the necessary calculations, we found that this plan returned a NPV of 4.9899E+08 m.u.

It should of course be mentioned that other plans that could be constructed in a similar 'manual' way and return similar or maybe higher profit. However, a detailed investigation of this falls outside the scope of this paper. Here we are just interested in constructing a deployment plan in a similar manner that telecom companies do, and then compare it to the deployment plans returned by the GA. Nevertheless, in order to see if there could be any 'obvious' solutions that could be better than our benchmark, we created 20,000 random deployment plans and evaluated their performance. We repeated this process for 20 times. The best plan's NPV out of all 20 runs reached the value of 4.8331E+08, which is of course lower than the 4.9899E+08 of our 'manually' constructed plan, and thus decided to use our deployment plan as the benchmark.

Table IV presents the results under the GA, for both limited (LB) and unlimited budget (UB). We can observe that in the case of the UB scenario the GA has found the global optimum. This thus means that the GA is efficient for this type of problems, and can effectively look for the globally optimum solution. In the case of the LB, the average NPV of the GA over the 20 runs is 5.1344E+08, with its best run reaching 5.1507E+08. This indicates that the GA's best deployment plan has improved the profit (NPV) of the benchmark by 3.22%, which should be considered as quite remarkable, especially if we 'translate' this to real-life currency. For instance, if instead 'm.u.' we were using US dollars, a 3.22% difference in the above scenario would mean an increase in profit by around \$17 million. We can thus understand that even 'minor' improvements of 3% are extremely significant in the field of FTTx deployment, because of the high scale of investments that are involved (hundreds of millions, possibly even billions of US dollars). In addition, another important advantage of our approach is that the decision-making process is fully-automated, without the need of any human interference.

TABLE IV
SUMMARY STATISTICS OVER 20 RUNS FOR THE GA, UNDER UNLIMITED (UB) AND LIMITED BUDGET (LB) CONSTRAINT, FOR THE FITNESS OF THE BEST DEPLOYMENT PLAN.

	UB	LB
Mean	5.9274E+08	5.1344E+08
St.Dev.	1.7056E-04	1.7397E-04
Max	5.9277E+08	5.1507E+08
Min	5.9232E+08	5.1163E+08
Global Optimum	YES	Unknown

One last comment that can be made from Table IV is the extremely low standard deviation of the results (1.7397E-04). This is very important, because it denotes that the GA is very robust in this application.

In addition, Figure 2 presents the evolution of the fitness (i.e., the NPV) of the best deployment plan over the 50 generations for the best run of the LB scenario. It is clear that there is a constant learning from generation to generation, which denotes a constant increase in the profitability of the best deployment plan (starting from around 4.35E+08 m.u). The NPV seems to stabilize towards the end of the evolutionary process, around 5.15E+08. We can thus observe from this figure that the evolved deployment plan has 'experienced' an improvement of around 18%, which should be considered as extremely significant.

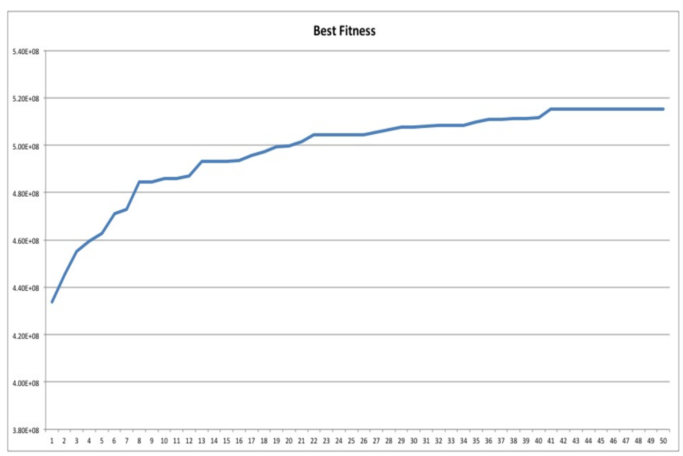

Fig. 2. Evolution of the NPV of the best deployment plan (y-axis) over the 50 generations (x-axis) of the best GA run.

Lastly, the computational times for the 20 runs of the GA under the UB and LB scenarios were 103 and 61 minutes, respectively. This is also very important, because telecom companies can receive high-quality results in a timely manner, which can save them millions in their investments.

VI. Conclusion

To summarize, this paper presented preliminary results from the application of a single Computational Intelligence (CI) technique, namely Genetic Algorithm (GA), to an economic model for the evaluation of FTTx investments. Our aim was to demonstrate the benefits of the use of CI in the decision-making process of deploying FTTx. The reason for wanting to do this was because in both the industry and the literature of FTTx deployments, people choose a deployment plan based on reasons such as experience from previous successful roll-out plans of other, similar infrastructure, or by using 'common sense rules'. We also explained that the deployment plans that telecom companies select can in no doubt be successful and profitable. Nevertheless, we argued that the fact that a plan is successful does not necessarily mean that it is the most successful. Therefore, this paper consists the first attempt in the literature, to the best of our knowledge, of applying a CI technique for looking for the optimal deployment plan of FTTx technology. This is very important, because it allows companies to increase their profit margin and also leads to a fully-automated decision support tool.

We tested the GA under two different scenarios. In the first scenario, which should be considered as a simplified one, we assumed that we had unlimited budget (UB) for the FTTx investment. Since we did not assume any other constraints, this allowed us to know in advance the optimal deployment plan. As a result, we were able to evaluate in a simple and quick way the GA and see if it could reach the global optimum, which it did. In the second scenario, we set a budget limit (LB); the global optimum was now unknown, but we constructed a profitable deployment plan that was going to be used as a benchmark. We also created 400,000 random deployment plans (20,000 plans$\times$20 runs) to see if any of these could return higher profit than our constructed plan and thus replace it as the benchmark. However, none of these random plans had higher profit than our 'manually' constructed plan, and thus compared our plan's performance against the GA. Results showed that the GA returned higher profit of about 3.22%. We explained that this was very significant, because of the nature of FTTx investments, which is in a scale of hundreds of millions or even billions of US dollars. Hence, any type of improvements, even as little as 3% are very significant, because they can secure an increase in profit in a scale of millions. Lastly, further analysis on the GA showed that the algorithm is very robust and is able to return high quality results in a short time.

We believe that the above results demonstrate that the introduction of the GA to the deployment of FTTx is highly beneficial. GA and possibly other CI techniques have the potential of significantly improving the profitability of investment plans, such as the roll-out of FTTx, and we believe that they will have a significant effect in the near future on the area of techno-economic analysis for FTTx investments. Moreover, our framework does not require humans to be part of the decision-making process. This has the obvious advantage that potential errors in the selection of deployment plans are minimized and that the whole deployment process is fully automated, since the GA acts as a decision support tool.

The above lead us to strongly believe that researchers in the field of FTTx deployment should also focus on the application of CI techniques for looking for the optimal roll-out plans. Future work on this area could first of all examine different sets of experimental parameters under the GA paradigm, to examine whereas different setups of the algorithm can further improve the deployment plans' profitability. In addition, other CI techniques should be tested and be compared to the GA results, too. There might indeed exist more effective algorithms that could lead to an even higher increase in the profitability of FTTx investments.

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