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Modeling Complex Telecom Investments: A System of Systems Approach

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***Abstract*—This paper presents a complex telecom investment problem analysis using system of systems concepts. This is necessary due to problem's multidimensional nature with several interdependences, and the presence of uncertainty and competition. A genetic algorithm is implemented in MATLAB in order to optimize the objective function (operator's profitability) of the formulated nonlinear programming problem. This approach is capable of providing optimal policies (regarding, e.g., services pricing, inception of investment, or revenues reinvestment) in a competitive market helping future investors in decision making by using various emulated strategic plans as reference.**

***Index Terms*—Genetic algorithms (GAs), investment, nonlinear programming problem, optimization, policy, system of systems, techno-economic, telecommunications.**

I. Introduction

INTERNET and generally information and communication technologies (ICT) are assumed as a major factor leading to socio-economic development [1], [2]. ICT can also play a significant role in economic growth [3] and competition [4, Ch. 1.3] for countries, enterprises and individuals. In detail, the use of ICT has a great impact on several fields such as trade, health and education, positively influences wages [5] while creating new job opportunities [6, p. 6 and 7]. On the other hand, ICT can help individuals and enterprises to remain competitive by doing things in a more efficient and effective way [6].

The high importance of Information and Communications Technologies for Europe can be viewed by its action to include Digital Agenda in Europe 2020 Strategy. In this plan, European Union describes its ambitions for 2020 that is "to reach a smart, sustainable and inclusive growth for European Economy" [7, Fig. 1 and Annex 1] and "to exit the crisis and prepare the EU economy for the challenges of the next decade" [8, Europe 2020 Strategy]. Toward this direction, the European Union has already and will continue to provide funds in order to develop a knowledge- and innovation-based "digital" economy [6, p. 3], [9].

Telecom operators who are the main investors of telecommunications networks have thus to exploit the funding opportunities from the one hand and deal with the high uncertainty influencing such deployments. Hence, accurate, quick choices along with budget details and strategy plans need to be constructed on a clear basis. A quick and accurate methodology scheme that will make investors to enhance current methodologies and decide with greater confidence about critical aspects of their investment should consequently be provided.

In the past, several studies, mainly based on a typical techno economic analysis, have been performed dealing with telecom investments [10]–[13]. In the literature, more complex approaches and decision analysis frameworks can also be found, incorporating several methodologies such as real options with analytic hierarchy process [14], forecasting models and diffusion determinants [15], dual objective optimization (maximization of profitability and service level) [16], and dynamic pricing attached to demand forecast [17].

As telecom investments are difficult to be modeled by traditional systems methodologies, given their space and time scale, their multidimensional nature, their complexity, the uncertainties arising from demand and price evolution and the emerging needs of users, new approaches incorporating complexity while keeping computational simplicity are needed. In addition, qualitative issues such as the first movement advantage and externalities deriving from the associated networked economies are even more difficult to be incorporated in a simple and accurate manner. The system of systems (SoS) concept has been proven a valid choice when dealing with such type of complex problems [18]–[23].

Earlier approaches to implement the SoS concept in a techno-economic problem for telecom networks providing a complete and accurate reference to telecom operators and policy makers can be found in [24]. Although this study managed to address the emerging behavior of telecom investments, it could not deal with the complex interdependences of the constituent systems as well as the externalities arising from the associated networked economies.

In this paper, a methodology based on SoS framework is proposed for modeling telecom investments and defining strategies leading to profitability under several constraints. Adaptation and reconfiguration concepts on initial decided strategies are also encapsulated in this framework. To the best of authors' knowledge, this is the first time that such a study is implemented. Having a compact and almost closed-form nature, the proposed framework can be proved an extremely valuable tool for telecom operators.

The rest of this paper is organized as follows. In Section II, the SoS nature of a techno-economic investment is presented having as test pilot a fiber to the curb (FTTC) access network. The telecom investment problem is presented in Section III. The

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SoS constituent systems are modeled in Section IV. The results derived from the implementation of the proposed framework in an FTTC/very high speed digital subscriber line (VDSL) case are illustrated in Section V. Some policy and concluding remarks are given in Section VI and VII.

II. SoS

Before proceeding to the analysis and modeling of this techno-economic SoS, one should list the constituent systems (see Fig. 1). As shown in Fig. 1(a), there are five interdependent systems. The competitor analysis (CA), budget allocation (BU), capital and operational expenses (CAPEX + OPEX), demand forecast (DE), and network externalities (NE). It should be noted that all the constituent systems are able to interact with each other.

The CA is a system that analyses the market, provides information about the base prices of the services, the number of current and potential competitors along with their strengths and weaknesses, possible opportunities for new markets entrance and finally defining strategies [25, Sec. 2]. Budget Allocation is a critical system that actually makes real a techno-economic investment; it quantifies strategy, costs, prices, cash flows, and assets. CAPEX and OPEX are the systems that actually deal with the absolute technical part and the operational part of the telecommunications network. These systems are responsible for the provision of high data rates to the end user. Central offices, local exchanges, switches, and kilometers of fiber, real estate, and installation are some of the elements incorporated in these systems. Demand forecast is a system used to estimate the delivered service success by making various scenarios about service penetration. Finally, network externalities is a critical system describing part of the emerging behavior of SoS telecom networks [26, Ch. 10]. In this study, the dependence of customers' number on external factors such as price is incorporated in the network externalities system. This, along with the rest systems, will define the expected revenues of the network. The described techno-economic SoS roll-out space is encapsulating great uncertainty and time-varying behavior, thus some kind of adaptation is needed in order to fulfill the common mission (revenues maximization). This is mainly achieved by dynamic connectivity among constituent systems of the SoS as can be depicted from Fig. 1(b) [27, Fig. 2] This figure is outlining two different time stamps ($t1$, $t2$) of connectivity among systems, characterized as pre ($t1$) and post ($t2$) investment phases. The inclusion of feedback between SoS outcome (revenues) and BU system, highlights the dynamic and adaptive nature of the SoS. This case is further examined in Section V-B with a portion of revenues to be used on boosting the budgeting strategy. Furthermore in Fig. 1(c), key dimensions of techno-economic SoS [27], [28] are illustrated, in order to identify connectivity, heterogeneity and autonomy in each of the constituent systems. The CAPEX+OPEX system was divided toward accurate description, identifying mainly the difference of machine and human. Following the taxonomy concept, the rest of the systems are also placed in the SoS taxonomy space enlightening variations among them.

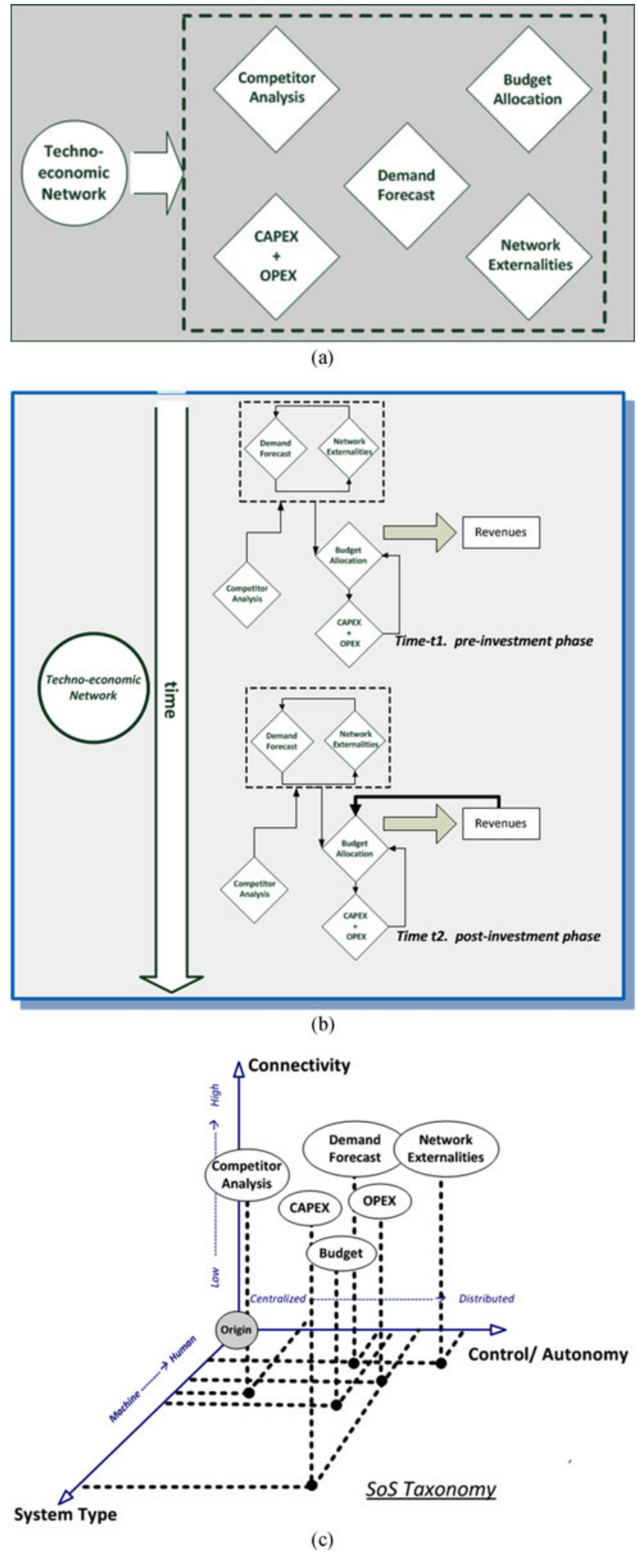

Fig. 1. Technoeconomic network under investigation. (a) Typical representation. (b) Dynamic configuration representation in two different time stamps. (c) Taxonomy-based representation of constituent systems.

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III. Problem Statement

In this section, the problem of a telecommunications network investment from the provider's perspective is stated using the SoS methodology as described in the previous section. The goal is to dynamically allocate the available budget in order to deploy a telecom network while maximizing provider's profit and taking into account several constraints of the considered variables.

As previously described, there are several issues—systems participating in a telecom investment problem. In detail, such investments include capital and operational expenses, services pricing policy, subscribers demand, competition analysis along with public incentives, and budget constraints. Each system of the techno-economic SoS will be modeled in the next section with a specific mathematic formula. All these mathematical representations will be consolidated in one common function that will further represent the main objective of the SoS, which is profitability. By combining the SoS analysis of the previous section, one can derive a simple form objective function *H*(*X*), describing the profitability of the project.

$$H\left(X\right) = \sum_{y=1}^{\text{years of study}} \left(\mathrm{Sub}_y{}^* P_y\right) + \text{Incentives} - \mathrm{BU}_{\mathrm{Total}} \tag{1}$$

where

H(X) the objective Function;

y year under investigation;

Sub_y the subscribers that use the internet service provider (ISP) network the specific year *y*;

P_y the annual price of the provided service at year *y*;

$\mathrm{BU}_{\mathrm{Total}}$ the total available budget for the whole period of study;

Incentives public contribution;

X the array of decision variables.

The objective function in (1) will be inserted along with its constraints, limits, etc., in a Genetic Algorithm (GA) environment in order to be optimized. More specific, GAs [29]–[31] is a stochastic global search method that actually emulates the process of natural selection. It belongs to a large category named evolutionary algorithms (EAs), which is using techniques that are inspired from natural evolution such as mutation, crossover, and selection. The metric that actually points to the proper set of chromosomes is the objective function [32, pp. 1–4]. The objective function is used to measure how the solutions (individuals) are performing. In our case of a maximization problem, the highest the numerical value of the objective function, the highest the result of the appropriate individuals will be. In variants of GAs the fitness function [32, pp. 1–8] is also used in order to transform the objective function into a measure of relative fitness [33, Ch. 1.4]. In our case, we will only use the objective function as measure of suitability. The main characteristic [32, pp. 1–5] of GAs that forced to select them in the proposed framework is mainly the fact that GAs are not searching for a single point, instead they perform a complete search over a population in parallel that is extremely helpful in a complex nonlinear problem (NLP). Stochastic global search methods such as GAs are generally used in NLPs. These methods are fitting perfectly in NLP problems with respect to the size of solution space. Even though computing time is becoming higher following global stochastic methods, multicore computer machines overcome most of the handicaps. In addition, the whole stochastic process includes a sense of probability that actually represents better real-world NLPs. GAs belong to global stochastic methods. More specific, GA simulates natural processes such as selection with some kind of intelligence during the phase of exploitation over the solution space.

The selection of proper parameters and methods of GAs is of high importance affecting its convergence speed as well as the quality of the derived results. Various tests along with exhaustive loops were performed using the MATLAB GA toolbox helping the GA to avoid trapping to local optima. Thus, in order to enhance the reliability of results, 1000 runs of the GA were performed in each optimization substudy. Clustering the gained experience of this pseudoadaptation of GA configuration, authors concluded with great confidence on the parameters and methods over the solution space. Details on MATLAB GAs configuration are shown as follows.

1) *Population*: Initial = 20, in each GA running.
2) *Mutation*: Gaussian type was used (which further decreases in every new generation of GA "children" members).
3) *Crossover Fraction*: Enabled and set to 1.0 (meaning that all the "children" of each GA run are crossover children except of course from the elite individuals*.
4) *Elitism:* Enabled (as mentioned in crossover previously asterisk* characterizing the individuals as elite solutions.)

IV. SoS Modeling

A. CAPEX and OPEX

In order to estimate the required CAPEX needs (number of network components) throughout the study period, simultaneous efforts required on components cost prediction and broadband access forecasting. Components cost is following telecommunication market evolution with respect to substantial learning curves while broadband access forecasts are carried out according to the methodology described in [34, Seq. 3.3]. Next paragraph is allocated in component pricing evolution and demand forecast is evaluated in Section IV-3.

For each component cost prediction, a price curve (learning curve) is calculated representing the component's cost throughout the study period. In fact, the price *P*(*t*) of each network element is assumed to follow the extended learning curve [35, eq. (6.1)]

$$P\left(t\right) = P\left(0\right)\left[n_r\left(0\right)^{-1}\left\{1 + e^{\ln\left[n_r\left(0\right)^1 - 1\right] - \frac{2\ln 9}{\Delta T}t}\right\}^{-1}\right]^{\log_2 K} \tag{2}$$

where *P*(0) is the price of the component in the reference year 0, nr(0) is referring to the units of the component that were sold in the reference year 0, ΔT is the time that is needed for the total production to grow from 10% to 90% of the maximum value and *K* is a learning curve coefficient that actually points to the price reduction that happens when the production volume is doubled. In cases where historical data are available, the parameters *K* and

TABLE I
PARAMETERS BASED ON VOLUME CLASS

Volume Class	$n_r(0)$	ΔT	Example
Old fast	0.5	5	Fiber termination
Mature medium	0.1	10	Fiber cables
New medium	0.01	10	Switches
New slow	0.01	20	Lasers
Emerging medium	0.001	10	WDM*/TDM** components
Straight line	0.1	1000	Cable installation

* Wavelength-division multiplexing (WDM).
**Time-division multiplexing (TDM).

TABLE II
K VALUES FOR COMPONENT GROUPS

Component Group	*K* Value
Civil work	1
Copper	1
Installation	1
Sites and enterprises	0.95
Fiber	0.9
Electronics	0.8
Advanced optical components	0.7

ΔT can be determined using a standard regression analysis. In the analysis presented hereafter, the parameters of the learning curve are stored in a database built within the techno-economic tool, which contains more than 1000 different network components [12, Fig. 2]. The components and subsystems are grouped in several volume classes as presented by [35, Table 7.2]. Example values used for the various volume classes are shown in Table I [35, Table 7.2]. In the same way the *K* parameter is estimated based on type of component or subsystem, reflecting the learning process from other similar components or systems in Table II [35, Table 7.1].

In addition, the volume classes are chosen to cover the two aspects of cost components: the type and maturity of cost components. The definition Old, Mature, etc., stands for the years during which the specific components were offered in the market. The definition Fast, Medium, etc., stands for time in years to grow the total production volume from 10% to 90% of its maximum value. For example, for the components used in the analysis presented herein, the installation or civil work costs are part of the straight line class, fiber cables costs are in the mature medium class, lasers are new slow class components, switches belong to the new medium class and new optoelectronic devices used at the PON architectures under study are emerging medium class components.

In case the components are new and no historical costs exist, *a priori* value has to be chosen. Examples are shown in Tables I and II. Typical values of the learning curve coefficient are from 1 (100%) (meaning no cost reduction) to 0.7 (70%), giving 30% reduction for doubling of production volume. An additional doubling of the production will reduce the cost by 51%. Using the network component prices through the extended learning curve modeling, CAPEX calculation for the FTTC network is now feasible. OPEX is modeled as a percentage (10%) of CAPEX

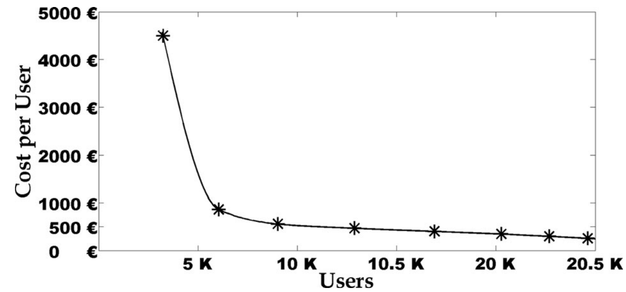

Fig. 2. Cost per user in FTTC network implementation.

[36, p. 111] in order to avoid further increasing the complexity of the problem.

Fig. 2 illustrates the SoS incremental cost (cost per user).The presented curve, obtained using polynomial fitting in MATLAB from simulated data of study [24, Figs. 5 and 6], which further consolidate data also from [12, Fig. 2] and [35, Tables 7.1 and 7.2]. The cost per user can be modeled as a two-session exponential of the following form:

$$\text{Cost per user} = a_1{}^*\exp\left(\beta_1{}^*\text{users}\right) + a_2{}^*\exp\left(\beta_2{}^*\text{users}\right). \tag{3}$$

It is initially high due to large investments and low initial utilization of the network. As the roll out of the network is proceeding and more customers are connected to the network the SoS incremental cost (per user) reduces. The shape of the cost per user function is similar to price curves figures illustrating the additional cost for the implementation of the techno-economic SoS.

B. Budget Allocation

Budget plays an important role in network diversification but also in economic benefits that derive from a telecommunication investment [37, Tables I and II]. An initial amount is given as entry to the algorithm that is split through the years of investment study in order to cover the initial needs as well as split the additional costs of CAPEX and OPEX through the following interaction as shown in Fig. 3.

The aforementioned interaction produces a matrix-based representation, in each GA run, for our reference, as can be depicted in Fig. 4. For the following matrix (indicative example), 15 million Euro(15 M€) budget was used as test case and it was split through years the same way the GA will do based on the aforementioned block diagram. The cumulative sum of the matrix below shows that a total budget of 13.40 million Euros was spent. Residual of 1.60 million Euros was not enough to cover extra network building costs thus disposing did not happen.

The budget used every year, implementing dynamic allocation based on pricing and demand as described in Fig. 3, is calculated as follows:

$$Bi = \text{Adcapex}\,(i) + \text{Adopex}\,(i) \tag{4}$$

subject to pricing and demand, where

B_i budget of each year *i*;

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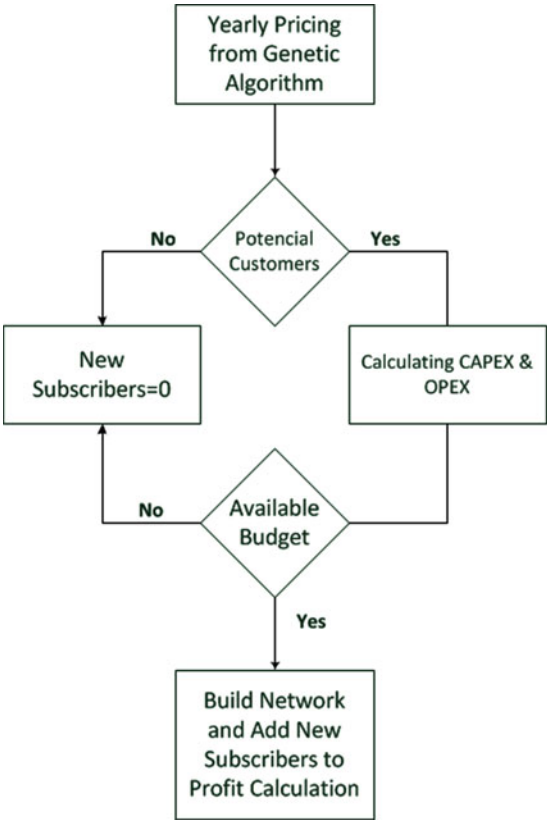

Fig. 3. Block diagram for budget allocation.

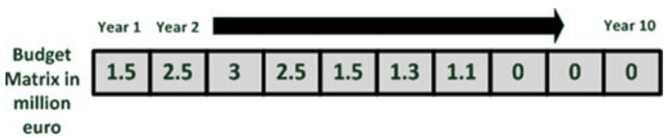

Fig. 4. Budget strategy for 10-year period.

Adcapex*(i)* added CAPEX every year to support new subscribers;

Adopex*(i)* added OPEX every year to support new subscribers.

In particular, the total budget over the study period should not exceed the initial available budget. The simplest functional form satisfying the aforementioned interaction and splitting though year's matrix can be written as follows:

$$\sum_{i}^{\text{years}} Bi \leq \mathrm{BU}_{\mathrm{Total}} \tag{5}$$

$\mathrm{BU}_{\mathrm{Total}}$, initially allocated budget for the investment, for all the study period.

C. Demand Forecast

In order to forecast the broadband subscriptions, a four parameter logistic model as in [34, Sec. 3.3], known as TERA (Techno-Economics Results from ACTS) project, was used. *S* curves are found in various fields such as business and technology. Looking into the anatomy of *S*-curve the shallow start described mathematically as lower asymptote. Then, we have a rapid growth and later the slope arches upwards until it reaches the maximum. This point of maximum growth is called point of inflexion. In business as in our case, the curve starts with a shallow start mainly because of the early adopters of the provided service, then follows a rapid growth meaning that the technology is adopted from many users, and finally, a little growth is maintained that usually indicates saturation and mature market. The aggregate demand for subscriptions is given on [34, p. 24]

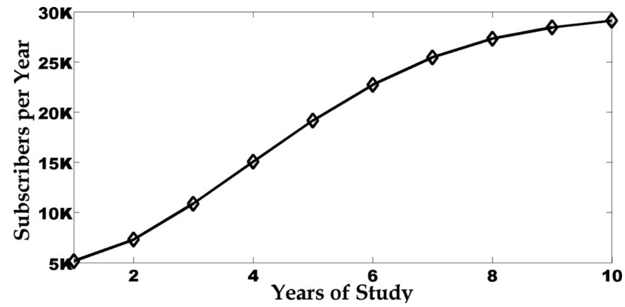

Fig. 5. Subscribers without competition. The presented curve, obtained using polynomial fitting in MATLAB from simulated data by study [24, (2)] having as reference in [34, Sec. 3.3] and selected market saturation equal to 30 K.

$$Y_t = \frac{M}{(1 + e^{\alpha+\beta t})^{\gamma}} \tag{6}$$

where Y_t is the demand (subscriptions) at specific time *t*, *M* is the saturation level or total market potential and α, β, and γ are parameters, which can be estimated by a regression analysis using historical data of existing broadband connections. A schematic representation of *S*-curve is illustrated in Fig. 5.

D. Network Externalities Model (Service Pricing)

Another important point that needs to be carefully modeled is the services price. The annual service price was set as an independent variable whose value is properly chosen by the GA so as covering the investment needs and leading to profitability. However, as indicated by Shy [38, eq. (1)], there is a close relation between the subscription fee *p* (service price) and the number of subscribers *x*

$$p = [1 - \beta x(p)]aNx(p) = aNx(p) - \beta aNx^2\,(p) \tag{7a}$$

where α, $\beta > 0$ price network parameters and *N* potential subscribers. Simplifying the aforementioned equation by adding $b_1, = \beta\alpha N$, $b_2 = \alpha N > 0$ (see Fig. 6), we can rewrite as

$$p = -b_1 x^2 + b_2 x. \tag{7b}$$

As shown in (7b), there are two equilibriums x_L and x_H given by

$$x_L = \frac{b_2 - \sqrt{b_2^2 - 4b_1 p}}{2b_1} \tag{8a}$$

$$x_H = \frac{b_2 + \sqrt{b_2^2 - 4b_1 p}}{2b_1}. \tag{8b}$$

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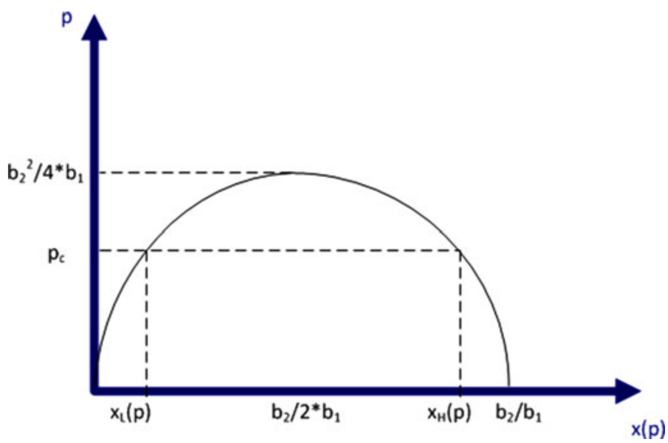

Fig. 6. Shy [38, Fig. 1]. Demand for a network good under network effects as a function of the number of subscribers. Three equilibria are associated with the subscription price as denoted.

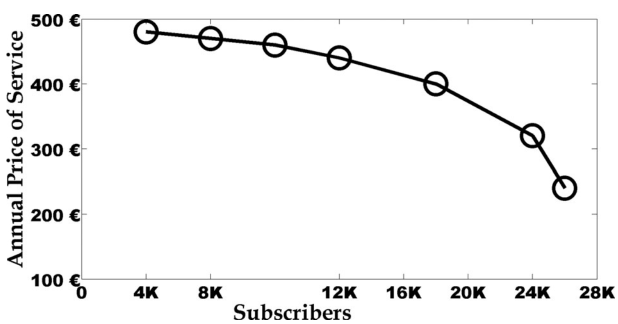

Fig. 7. Price versus demand. Curve fitting was used using simulated data from Rokkas study [24] with ten years extension following Shy [38, (1)] solution as before.

It should be noted that x_L is an unstable equilibrium in the sense that a small increase in the number of subscribers would induce consumers to subscribe. Therefore, the total demand for the network good is given by x_H. It is then straightforward to show that there is an interdependence between the demand model and service price. In fact, one can perform the previously described process [see (6) and (7b)] and use the solution x_L as the saturation level *M* of the demand model. A schematic representation of price–demand is illustrated in Fig. 7.

E. CA, Balancing Market

The CA is an important member system of the SoS dealing with advantages that can be gained depending on the sequence of investors. For example, government provides incentives for new technology deployments. This is usually an important amount of money to cover the initial expenses of network construction.

In this study, a total public funding of CAPEX/2 is assumed. Taking into account a Greenfield case (no infrastructure for the new services is present) and duopoly, the public funding is further distributed to investors according to the following

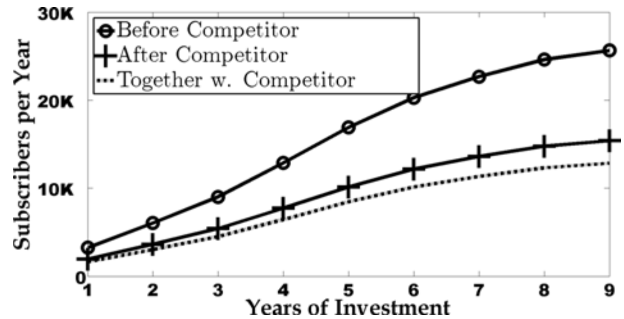

Fig. 8. Subscribers with competition present. The presented curve, obtained using polynomial fitting in MATLAB from simulated data by study [24, (2)] having as reference in [34, Sec. 3.3] and selected market saturation equal to 34 K, with each curve representing the impact of each B factor of (10).

indicative equation:

$$\text{Incenting} = \begin{cases} A1\% * \dfrac{\text{CAPEX}}{2}, X1 = 1, X2 = 0 \\ A2\% * \dfrac{\text{CAPEX}}{2}, X1 = 0, X2 = 1 \\ A3\% * \dfrac{\text{CAPEX}}{2}, X1 = 1, X2 = 1 \end{cases} \tag{9}$$

$[A_1, A_2, A_3] =$ [80, 20, 50] where X_1, X_2 variables correspond to the two operators willing to invest in FTTC network deployments and A_x factors selected toward provision of an advantage to investors willing to start before others. X_1 is attached to the investor under investigation and X_2 is directly attached to its competitor. In detail.

1) $X_1 = 1$, $X_2 = 0$, the operator under investigation starts investing BEFORE its competitor;
2) $X_1 = 0$, $X_2 = 1$, the operator under investigation starts investing AFTER competitor investment;
3) $X_1 = 1$, $X_2 = 1$, the operator under investigation starts investing exactly THE SAME TIME with competitor.

The sequence of investors does not only affect the gained public funding portion but also the number of subscribers that can be attracted by the operator (potential market share). This can be modeled by following equation and depicted in Fig. 8:

$$\text{Subscribers} = \begin{cases} B1\% * \text{Total Available Users}, X1 = 1, X2 = 0 \\ B2\% * \text{Total Available Users}, X1 = 0, X2 = 1 \\ B3\% * \text{Total Available Users}, X1 = 1, X2 = 1 \end{cases} \tag{10}$$

$[B_1, B_2, B_3] =$ [60, 40, 50] where X_1, X_2 variables for the two FTTC network operators willing to invest as shown before at incenting modeling and B_x factors selected toward provision of an advantage to investors willing to start before others in terms of market share.

V. Results

FTTC/VDSL architecture for the last mile is investigated as a case study of the proposed framework. The area is described

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TABLE III
PARAMETER VALUES USED FOR CASE STUDY

Name	Parameters Used	Equation, Figure
Cost per user	$\alpha 1 = 6.158\text{ e} + 04, \alpha 2 = 850.4,$ $\beta 1 = -2.794, \beta 2 = -0.1489$	(3), Fig. 2
Demand	$\alpha = -2.237, \beta = 0.5636, \gamma = 1$ $M =$ solution xL from (8a)	(6), Fig. 5
Service price versus demand	$a = -4.273\text{e-}07$, $b = 0.006487$, $c = 451.9$ a*$x2$ + b*x + c = 0, second-order polynomial	Result solving [see (6) and (7b)], Fig. 7

in terms of subscriber density and geographical characteristics. The area model chosen corresponds to a dense urban area with a surface of 12 km^2 and 5 641 customers per km^2. It is assumed that there is one central office, serving 65 536 customers in total. The total available budget is assumed to be 35 M€ for the whole study period of 10 years maximum. The starting year of operator's investment will be decided by the optimization process using GAs. In order to avoid trapping on local extrema, the GA is running 1000 times. In order to maximize provider's profit at the end of the study period, the following nonlinear programming problem is stated following the objective function that is presented in Section III.

Maximize objective Function *H(x)* [see Section III, (1)], subject to

$$\begin{cases} \text{Incentives [see(9)], Budget [see(5)], Subscribers [see(10)],} \\ \text{Pricing Models [see(6) and (7b)].} \\ \text{Decision Variables Array } \mathbf{X}[\mathbf{0}\ldots\mathbf{12}] \text{ of optimization:} \\ \mathbf{X_0}, \text{Starting Year of Investment,} \\ \mathbf{X_1}, \mathbf{X_2} \text{ as described firstly in (9),} \\ \mathbf{X_3}\ldots\mathbf{X_{12}}, \text{ service price each year of the total} \\ \text{10 of study.} \\ \text{Contraints : } \begin{cases} \mathbf{1 \le X_0 \le 10} \\ \mathbf{0 \le X_1, X_2 \le 1} \\ \mathbf{X_3 \le X_4 \ldots X_{11} \le X_{12}}. \end{cases} \end{cases} \tag{11}$$

The values that were used for the parameters in the equations of Section IV (SoS Modeling) are illustrated in Table III.

Using the estimated parameters along with constituent systems' mathematical models, an optimum strategy for the incremental network deployment (dynamic budget allocation) leading to profit maximization at the end of the study period will be investigated and proposed. The nonlinear programming (NLP) problem is solved as mentioned in Section III using the GA and implemented in MATLAB.

From the derived results, it is deduced that in almost 90% of the cases the FTTC investment is started in the first two years. This is somehow expected and can be attributed to the longer network's operation period leading to increased revenues, and thus, profits. A profitability of ~100 M€ is observed in the majority of the simulation runs. Another interesting result is

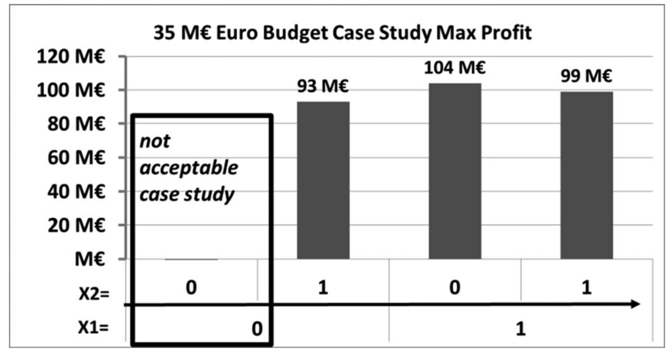


Fig. 9. Maximum Profit of investment with 5 M€ budget. Starting year of investment is 1. $X1 = X2 = 0$ is not a valid assignment in problem since nobody starts investing.

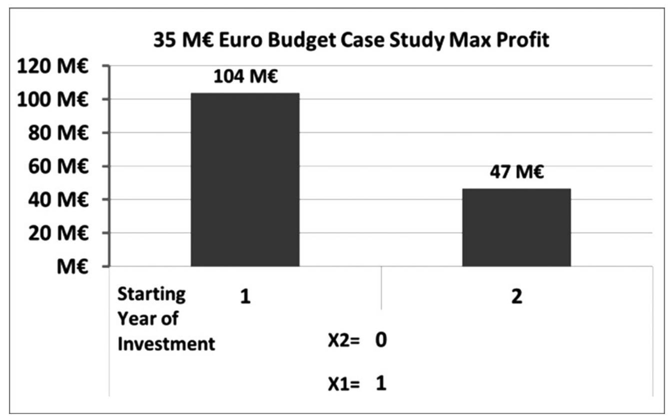


Fig. 10. Pivot chart showing maximum profit for various starting years BEFORE competitor for 35 M€ budget.

that in more than half of the 1000 cases, the operator decides to invest before his competitor. This can be mainly explained by the extra benefits (incentives) received by the first investor. In these cases, a maximum profit of 103 M€ is observed (see Fig. 9). As illustrated in the same figure, a delayed decision (invest after the competitor) results in significant profit losses. An interesting case is the simultaneous investment of both operators, which is the second best choice as the profitability remains in good levels.

It is interesting to note that starting the investment early enough even though the CAPEX costs are high—for new technology equipment—is beneficial for the profit margin. This is attributed especially to market share gained margin and this can be observed in the following figure (see Fig. 10), comparing profit for different starting years of investment.

Another issue that plays a significant role in the maximization of investment's profitability is the services pricing policy during the study period. It should be noted that an extremely aggressive policy was followed in the case of maximum profit described in Fig. 9. According to this policy, the annual price of the services is forced to be reduced each year. In the case of maximum profit, the evolution of annual price of the provided service is depicted in the following figure (see Fig. 11).

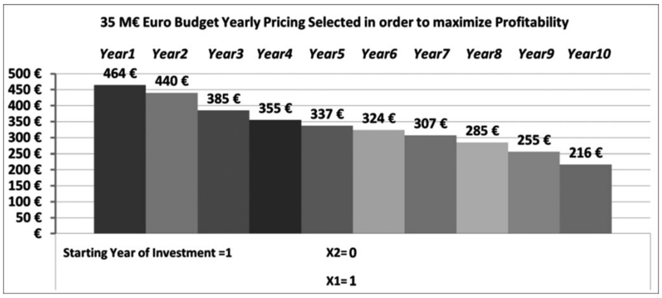


Fig. 11. Yearly pricing selected for 35 M€ budget.

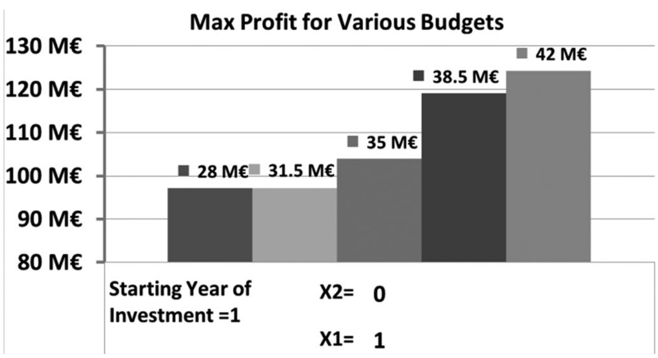


Fig. 12. Pivot chart showing maximum profit when starting at year 1, BEFORE competitor for various budgets.

On the other hand, if the operator decides not to proceed to price reduction, a profit limitation is observed. This was not entirely expected since one would consider that high prices will lead to increased revenues, and thus, to increased profits. However, a thorough look at SoS modeling will reveal that there is no one-way relationship between price and revenues. This can be attributed to the complex interdependence between price and subscribers. A price reduction policy may speed up service adoption, and thus, increase the number of customers, and consequently, the received revenues even in low prices.

Inextricably linked to the pricing policies and the entrance decisions is the extent of network deployment. In the cases of maximum profit where the operator under investigation starts first the investment and follows a price reduction policy, network deployment is extended and almost reaches the end of the study period. On the other hand, in low profit cases, network construction is limited. One more interesting point is that in the majority of cases where we have a significant profit over the years of study, profitability is observed after the fourth year.

A. *Composite Budget Analysis in Order to Capture Dynamic Behavior of the SoS*

The available total budget is a point of great debate and should be further investigated in order to identify possible sensitivities. Toward this direction, a series of simulation runs were performed assuming −20%, −10%, 10%, and 20% budget change, respectively. The obtained results are illustrated in Fig. 12.

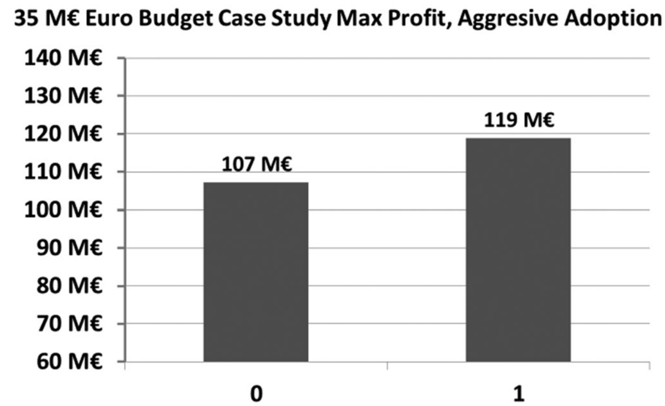


Fig. 13. Maximum profit of investment with 35 M€ budget. Starting year of investment is 1. $X = 0$ equals to after competition investing, and $X = 1$ equals to start investing before competition. Assuming aggressive adoption of market shares.

From Fig. 12, it is deduced that the case of 42 M€ budget leads to the maximum profit. It is straightforward to understand that a bigger amount of budget is required to further expand the network, in order to meet the high demand due to price reduction policy that was followed.

In order to study the combined effect of budget and potential market share, a new series of runs were performed assuming 35 M€ budget and a more optimistic expectation for the potential subscribers depending on the order of investment

$$\text{Subscribers} = \begin{cases} \Gamma 1\% * \text{Total Available Users}, X1 = 1, X2 = 0 \\ \Gamma 2\% * \text{Total Available Users}, X1 = 0, X2 = 1 \\ \Gamma 3\% * \text{Total Available Users}, X1 = 1, X2 = 1 \end{cases} \quad (12)$$

$[\Gamma_1, \Gamma_2, \Gamma_3] = [80, 20, 50]$.

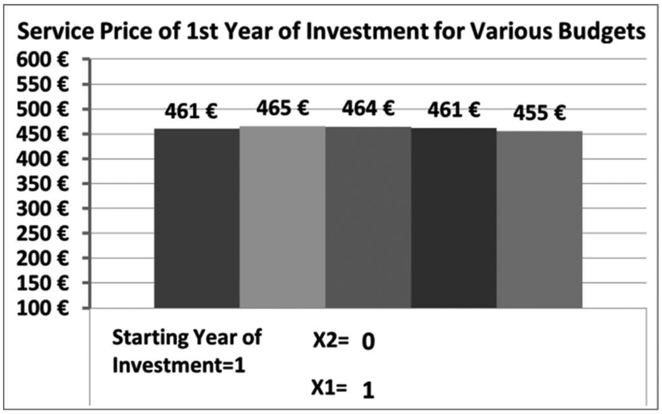
Γ_x factors (similar to β_x) selected toward provision of an advantage to investors willing to start before others in terms of market share.

As shown in Fig. 13, a significant increase in the market share is not followed by a proportional profit (∼119 M€) increase unless it is accompanied by a higher budget. This is expected since the gained market share (more subscribers) cannot be supported due to the limited budget that prevents the construction of required network.

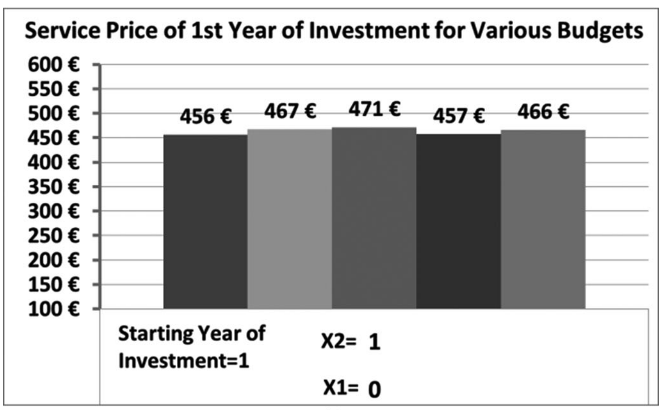
Concerning yearly pricing policy following the starting year of the investment, looking into the gathered data, we can produce the following two different case pivot charts as illustrated in the following figure (see Fig. 14).

The important conclusion from the aforementioned running cases is that all the sequences of prices that produce the maximum profit besides the aforementioned referred safe approach of lowering the value every year also select similar values for all the budgets under study for the first year. This is a low risk approach as it comes up from the results post process showing the lack of any kind of adaptation (either in pricing or network diversification) in the algorithm complex objective Function.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.



(a)



(b)

Fig. 14. (a) Pivot chart showing average price of first year when starting at year 1, BEFORE competitor for various budgets. (b) Pivot chart showing average price of first year when starting at year 1, AFTER competitor for various budgets.

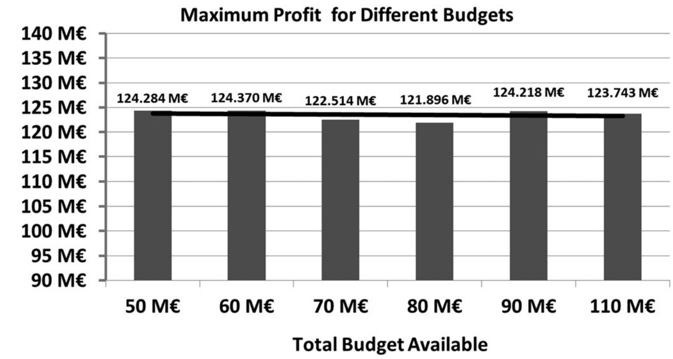


Fig. 15. Pivot chart showing cash flow of the operator under study that selects to get first into the investment the early first year of the total 10 under study.

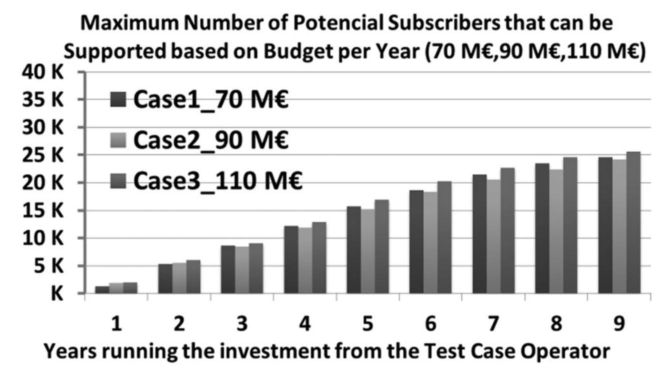


Fig. 16. Pivot chart showing potential subscribers that can be serviced by the operator under study over the years of study period for 70 M€, 90 M€, and 110 M€ budget.

It is also interesting to look into a case study of the aforementioned multiple runs as standalone walkthrough in order to provide a better insight on the information that is encapsulated in the complex objective function and GA decisions. The basic run case of 35 M€ initial budget along with generous incentives produces more than 100 M€ profit, since the operator under study selects to get into the investment before the competitor. More specific the CAPEX+OPEX expenses are up to the seventh year of operation due to the finite amount of operator budget (spends ∼34 M€). After this year, the subscribers that the operator under study can support are kept constant since based on the problem statement no resources can be further allocated due to limited budget. From the aforementioned extended postprocess analysis, it is obvious that CAPEX+OPEX expenses are getting suspended after some years of investment study. This is attributed mainly to the limited available budget. It would be also extremely helpful if any additional information can be extracted concerning the absolute limits in budgeting of the investment under study. This could probably lead to possible saturation observation after exceeding a specific amount of available budget. For the needs of this kind of study, the GA Input was supplied with a set of various budgets, starting from 50 M€ up to 110 M€. 1000 cases for each budget were examined and the data are further presented in the following figures. Fig. 15 presents the maximum profit that can be achieved for various budgets with the operator under study to be the first that gets into the investment. After 50 M€ of budgeting, the profit based on the trend line (also illustrated) is reaching a limit of ∼123 M€. This is a first indication of possible saturation that has to be further examined. To support this statement, the gathered data are getting into a postprocess again and the SoS behavior is observed.

Picking the data that provide the same maximum profit with different starting budgets from the aforementioned illustration (see Fig. 15), the following composite figures (see Figs. 16–19) are produced that enhance the knowledge about the operation of the modeled SoS. Fig. 16 presents the potential subscribers that budget-case investments can support each year for 70, 90, and 100 M€ cases. It is interesting to point out that for budgets of 50 M€ and 60 M€ the CAPEX + OPEX expenses are incurred up to the eighth year of the total study in contrast with the rest higher budget cases where additional money are spent on year 9. Apart from the extra budget that is consumed in these higher budgets, the profit is equal for all the cases under study. More specifically the extra budget (∼10 M€) that is consumed in 110 M€ budget (see Fig. 18) case is actually an attempt to support more subscribers that could lead to more profits based on problem statement. The question that arises is why the extra positions of available subscribers are not covered as can be

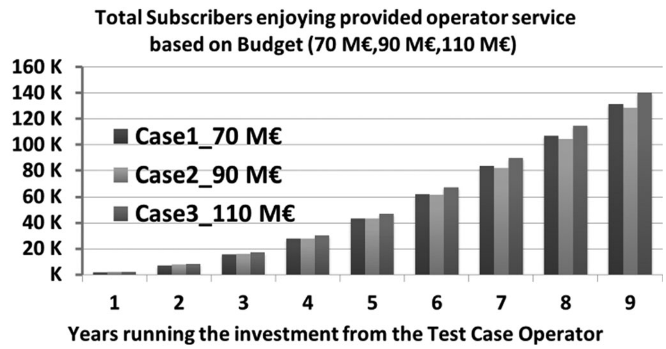


Fig. 17. Pivot chart showing actual subscribers that are using the service by the operator under study over the years of study period for 70 M€, 90 M€, and 110 M€ budget.

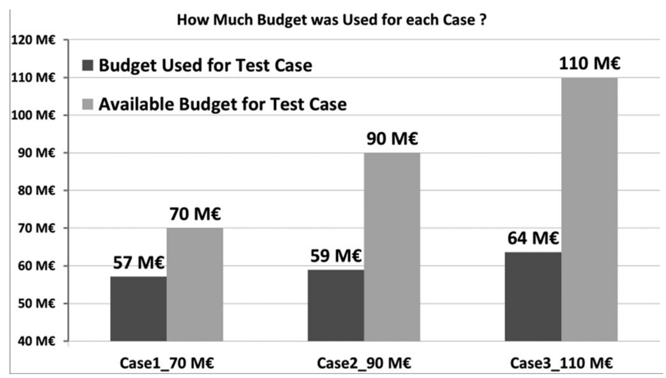


Fig. 18. Pivot chart comparing maximum available budget and actual budget (including incentives) that was used for each case 70 M€, 90 M€, and 110 M€ budget.

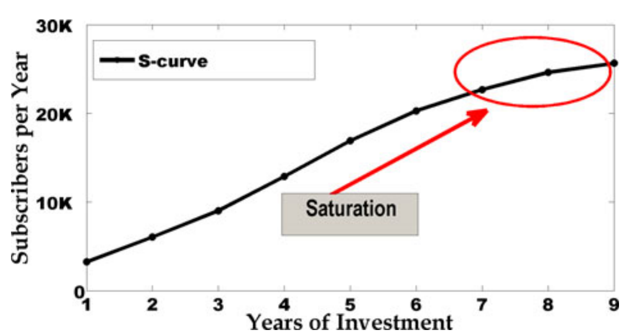


Fig. 19. Market Saturation region indicative plot in sample *S*-curve demand function.

deduced in Fig. 17 and subscribers' number remains well below 140 K. The answer is found in the indicative Fig. 19 where the market saturation case is pointed in the graph. Therefore, based on the Demand Modeling that was employed in the test case, the market saturation is reached earlier than any finite budgeting limitation and actually suppresses the plausible profits.

The lack of any kind of adaptation as mentioned earlier (see Fig. 14) and the problem initial statement with limited budget that led to market saturation, triggered the authors to move to the following additional study section that will cover another

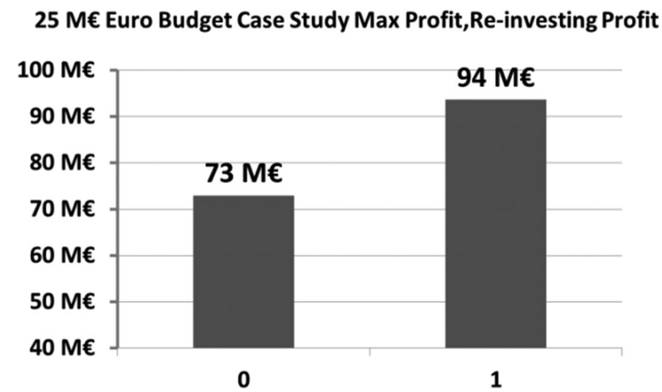


Fig. 20. Maximum profit of investment with 25 M€ budget. Starting year of investment is 1. $X = 0$ equals to after competition investing, and $X = 1$ equals to start investing before competition. Assuming aggressive investment in network construction of yearly profits.

characteristic of SoS, the reconfiguration in order to achieve the higher mission (increase profitability).

B. *Adaptation and Reconfiguration—SoS Emergent Behavior.*

In the analysis of the previous sections, it is assumed that the profits of the investment are shared to the shareholders of the operator's company. However, this strategy is proved to be the worst in terms of available budget. In order to investigate the impact of partial profit reinvestment on both the required available budget and the viability of the project, (4) must be transformed to the following form. Assuming an available budget of 25 M€, a series of optimization runs are performed again

$$\sum_{i}^{\text{years}} Bi \leq \text{BUTotal} + \sum_{i}^{\text{years}} (A\%)^{*}\text{Profit} \qquad (13)$$

$A = [30, 50]$.

From the obtained results, it is deduced that, the maximum profit (around 93 M€) is achieved by reinvesting 50% of the annual profit in network extensions besides the small amount of available budget. The case of starting the investment after competitor is also shown and it produces really low profits (see Fig. 20). This is a high risk case since if the operator under study misses the investment entrance, a severe amount of money for budgeting will be needed in order to gain market share capable of providing adequate profits.

In order to compare the results derived with and without reinvestment, a series of optimization runs are also performed using (4). The maximum profit was ~70 M€, which is much lower than the case of profit reinvestment. This can be easily explained by the fact that low available budget results in limited network deployment. Thus, the growing demand cannot be met by keeping the number of subscribers in low levels. It should also be highlighted that the same conclusions are derived following the advantageous strategies of pricing policy and investment entrance.

This is a clear indication that telecom investments are not static procedures. Contrary, more complicated strategies and adaptive policies should be adopted. This is of high importance, especially in cases where the initial targets are missed over the study period. In order to address such emergent behaviors of the SoS under investigation, it is thus crucial to continuously monitor the defined metrics of effectiveness and performance of a successful investment. Interventions, in terms of pricing policy or percentage of reinvestment, deviating from the initial plan should be performed in order to keep profitability in the desired levels.

VI. Policy Implications

The aforementioned results reveal that policy implications are necessary in order to speed up telecom investments, and finally, converge to digital agenda objectives.

As illustrated, an aggressive pricing policy (annual reduction of services prices) leads to profit maximization since more subscribers are attracted. However, in many cases, such a policy results in operators' cash flow difficulties. Thus, governments should consider the subsidization of some telecom services in order to support telecom operators. Furthermore, price regulations such as price cap regulation applicable to telecom investments should also be considered and investigated.

Another issue that both telecom operators and governments should pay attention to is the incentives that could be provided from the latter. The derived results also depict that the investor who moves first into the investment has a competitive advantage. Although this can be attributed to his ability to gain more market share, this is highly correlated to the fact that the first investor receives more incentives in terms of public contribution. Thus, governments should always investigate the possibility to provide public contribution especially in cases where the risks (e.g., of low demand) are high.

VII. Conclusion

In this paper, a new methodology based on an SoS approach for modeling telecom investments in a duopoly environment was proposed. This allows both the derivation of analytical results for the constituent systems and the planning of appropriate strategies and adaptations improving operator's profitability while addressing market's emergence behavior and uncertainty. A dynamic budget allocation problem was proposed and used in order to identify optimal policies (e.g., for services pricing or revenues reinvestment). The formulated nonlinear programming (NLP) problem of maximizing operator's profit taking into account several constraints is solved using a GA implemented in MATLAB.

As expected, investing before the competitor resulted in higher profitability. It was also shown that an aggressive pricing policy that reduces services price every year led to profit maximization. However, price regulations such as price cap regulation applicable to telecom investments should also be considered and investigated.

Finally, partial revenues reinvestment is in favor of the budget required from the operator. The final strategy that an operator could follow is actually a mixture of corrective actions on an initial strategic plan that could lead to maximum profitability. The resulting optimal policies theoretically maximize the operator's profitability, motivating new network deployments, which, in turn, may lead to socio-economic development.

References

[1] R. Wieck and M. Vidal, "Investment in telecommunications infrastructure, growth and employment? Recent research," *Int. J. Manage. Netw. Econ.*, vol. 2, no. 2, pp. 135–149, 2011.

[2] N. Ahmad, P. Schreyer, and A. Wölfl, "ICT investment in OECD countries and its economic impacts," *Economic Impact ICT—Measurement, Evidence Implications*, Paris, France: OECD Publishing. 2004, pp. 61–83.

[3] P. Koutroumpis, "The economic impact of broadband on growth: A simultaneous approach," *Telecommun. Policy*, vol. 33, no. 9, pp. 471–485, 2009.

[4] S. Dutta, "Global information technology report 2008–2009," World Economic Forum, Geneva, Switzerland, 2009.

[5] S. K. Majumdar, "Broadband adoption, jobs and wages in the US telecommunications industry," *Telecommun. Policy*, vol. 32, no. 9, pp. 587–599, 2008.

[6] European Commission, "Investing today for tomorrow's Europe," European Commission, Brussels, Belgium, p. 1, 2009.

[7] European Commission, "A strategy for smart, sustainable and inclusive growth," European Commission, Brussels, Belgium, p. 1, 2010.

[8] European Commission, "A digital agenda for Europe," European Commission, Brussels, Belgium, p. 1, 2010.

[9] M. R. Vicente and F. Gil-De-Bernabé, "Assessing the broadband gap: From the penetration divide to the quality divide," *Technol. Forecasting Social Change*, vol. 77, no. 5, pp. 816–822, 2010.

[10] B. T. Olsen, D. Katsianis, D. Varoutas, K. Stordahl, J. Harno, N. K. Elnegaard, I. Welling, F. Loizillon, T. Monath, and P. Cadro, "Technoeconomic evaluation of the major telecommunication investment options for European players," *IEEE Netw.*, vol. 20, no. 4, pp. 6–15, Jul./Aug. 2006.

[11] J. Harno, D. Katsianis, T. Smura, T. G. Eskedal, R. Venturin, O. P. Pohjola, K. R. R. Kumar, and D. Varoutas, "Alternatives for mobile operators in the competitive 3G and beyond business," *Telecommun. Syst.*, vol. 41, no. 2, pp. 77–95, 2009.

[12] D. Katsianis, I. Welling, M. Yionen, D. Varoutas, T. Sphicopoulos, N. K. Elnegaard, B. T. Olsen, and L. Budry, "The financial perspective of the mobile networks in Europe," *IEEE Personal Commun.*, vol. 8, no. 6, pp. 58–64, Dec. 2001.

[13] T. Monath, N. Kristian, P. Cadro, D. Katsianis and D. Varoutas, "Economics of fixed broadband access network strategies," *IEEE Commun. Mag.*, vol. 41, no. 9, pp. 132–139, Sep. 2003.

[14] G. N. Angelou and A. A. Economides, "A decision analysis framework for prioritizing a portfolio of ICT infrastructure projects," *IEEE Trans. Eng. Manage.*, vol. 55, no. 3, pp. 479–495, Aug. 2008.

[15] X. Liu, F.-S. Wu, and W.-L. Chu, "Diffusion of mobile telephony in china: Drivers and forecasts," *IEEE Trans. Eng. Manage.*, vol. 59, no. 2, pp. 299–309, May 2012.

[16] M. Karimi-Nasab, S. Dowlatshahi, and H. Heidari, "A multiobjective distribution-pricing model for multiperiod price-sensitive demands," *IEEE Trans. Eng. Manage.*, vol. 60, no. 3, pp. 640–654, Aug. 2013.

[17] B. D. Chung, J. Li, T. Yao, C. Kwon, and T. L. Friesz, "Demand learning and dynamic pricing under competition in a state-space framework," *IEEE Trans. Eng. Manage.*, vol. 59, no. 2, pp. 240–249, May 2012.

[18] K. Tsilipanos, I. Neokosmidis, and D. Varoutas, "A system of systems framework for the reliability assessment of telecommunications networks," *IEEE Syst. J.*, vol. 7, no. 1, pp. 114–124, Mar. 2013.

[19] E. Grigoroudis and Y. A. Phillis, "Modeling healthcare system-of-systems: A mathematical programming approach," *IEEE Syst. J.*, vol. 7, no. 4, pp. 571–580, Dec. 2013.

[20] R. R. Luman, "Upgrading complex systems of systems: A CAIV methodology for warfare area requirements allocation," *Mil. Oper. Res.*, vol. 5, no. 2, pp. 53–75, 2000.

[21] W. A. Crossley and M. Nusawardhana, "Variable resource allocation using multidisciplinary optimization: Initial investigations for system of systems," presented at the 10th American Institute of Aeronautics and Astronautics/ISSMO Multidisciplinary Analysis and Optimization Conf., Albany, NY, USA, 2004.

[22] H. Azarnoush, B. Horan, P. Sridhar, A. M. Madni, and M. Jamshidi, "Towards optimization of a real-world robotic-sensor system of systems," in *Proc. World Autom. Congr.*, Budapest, Hungary, 2006, pp. 1–8.

[23] I. Melgar, C. Mas, M. Sanchís, and M. Gómez, "Optimization of system-of-systems architectures for maritime border control using genetic algorithms," in *Proc. IEEE 36th Annu. Conf. Ind. Electron. Soc.*, 2010, pp. 2880–2885.

[24] T. Rokkas, I. Neokosmidis, D. Katsianis, and D. Varoutas, "Cost analysis of WDM and TDM fiber-to-the-home (FTTH) networks: A system-of-systems approach," *IEEE Trans. Syst. Man, Cybern. C, Appl. Rev.*, vol. 42, no. 6, pp. 1842–1853, Nov. 2012.

[25] C. S. Fleisher and B. E. Bensoussan, *Strategic Competitive Analysis: Methods Techniques Analyzing Business Competition*. Upper Saddle River, NJ, USA: Prentice Hall, 2003.

[26] R. Farr, *Telecommunications Traffic, Tariffs, Costs: An Introduction Managers*., London, UK: P. Peregrinus, 1988.

[27] D. DeLaurentis, "Appropriate modeling and analysis for systems of systems: Case study synopses using a taxonomy," in *Proc. IEEE Int. Conf. Syst. Man Cybern.*, 2005, pp. 86–91.

[28] D. DeLaurentis, "A taxonomy-based perspective for systems of systems design methods," in *Proc. IEEE Int. Conf. Syst. Man Cybern.*, 2005, pp. 86–91.

[29] M. Mitchell, *An Introduction to Genetic Algorithms (Complex adaptive Systems)—A Bradford Book*, 3rd ed., Cambridge, MA, USA: MIT Press, vol. 55, pp. 35–81, 1998.

[30] S. R. Mangano, "A genetic algorithm white paper," Man Machine Interface, Inc., Cleveland, OH , USA, 1993.

[31] D. Beasley, R. Martin, and D. Bull, "An overview of genetic algorithms: Part 1. Fundamentals," *Univ. Comput.*, vol. 15, pp. 58–58, 1993.

[32] A. Chipperfield, P. Fleming, H. Pohlheim, and C. Fonseca, "Genetic algorithm toolbox for use with MATLAB," Department of Automatic Control and Systems Engineering, University of Sheffield, User's Guide, Version 1.2, 1994.

[33] K. A. De Jong, "Analysis of the behavior of a class of genetic adaptive systems," Ph.D. dissertation, Dept. Comput. Sci., Univ. Michigan, Ann Arbor, MI, USA, 1975.

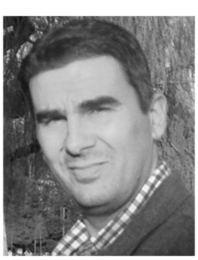
[34] K. Stordahl and K. O. Kalhagen, "Broadband access forecasts for the European market," *Telektronikk*, vol. 98, no. 2/3, pp. 21–32, 2002.

[35] B. T. Olsen and K. Stordahl, "Models for forecasting cost evolution of components and technologies," *Telektronikk*, vol. 4, pp. 138–144, 2004.

[36] K. Casier, S. Verbrugge, R. Meersman, D. Colle, M. Pickavet, and P. Demeester, "A clear and balanced view on FTTH deployment costs," *J. Inst. Telecommun. Profess.*, vol. 2, pp. 27–30, 2008.

[37] S. Negash and L. Patala, "Telecommunication investment in economically developing countries," in *Proc. Southern Assoc. Inf. Syst. Conf.*, 2006, pp. 29–34.

[38] O. Shy, "A short survey of network economics," *Rev. Ind. Org.*, vol. 38, no. 2, pp. 119–149, 2011.



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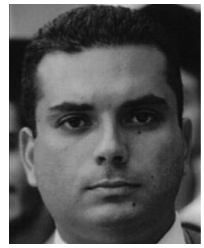

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