Multiobjective Physical Topology Design of All-Optical Networks Considering QoS and Capex

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Abstract: We present an algorithm to define the physical topology and the specification of the optical devices that should be deployed in a network to minimize simultaneously the total capital cost and the network blocking probability.
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1. Introduction

The problem of physical topology design is to determine which nodes of the network should be connected by means of physical optical links. One can note that the design of an optical network is a multiobjective optimization problem over a multivariable design space [1]. It is multiobjective because the designer must satisfy, simultaneously, several performance constraints such as: capital costs, blocking probability, profits, traffic capacity, etc. To accomplish the design with these constraints, the designer must work in a multivariable design space in order to choose the network devices, routing algorithms, physical topology, node places, node degrees, etc. For these reasons the network topology design (NTD) is an extremely hard problem. Previous works in this field can be classified in two groups according to the techniques employed to solve the problem: those using ILP (Integer Linear Programming) or MILP (Mixed-Integer Linear Programming) formulations [2], and those using heuristics or metaheuristics [3], [4]. The first ones offer optimal solutions but they are time consuming for medium and big size networks, while the others are fast but only achieve suboptimal solutions. Besides, both groups can use either single optimization objective [4] (which is clearly a poor approach for the NTD problem) or multiple optimization objectives [5].

In this paper we propose a multiobjective optimization algorithm for network topology design to solve the physical network topology design problem for all-optical networks. To our knowledge, this is the first paper proposing to solve the network topology design problem taking into account the physical layer impairments and capital costs simultaneously.

2. Problem Description and Representation

We are concerned with the following problem: given the desired node locations, traffic matrix and RWA algorithm, to find the physical topology layout and the proper specification of the optical devices that should be deployed in the network in order to simultaneously minimize total network capital cost and network blocking probability. It was assumed, as design variables, the following network parameters: topological layout, amplifier saturation power and noise figure in Erbium doped fiber amplifier (EDFA) in a per link basis, the isolation factor of all OXC in the network and the number of wavelength per link.

To represent the network topology we define the vector V as: $V = [m_{1,2}, m_{1,3}, m_{1,4}, m_{2,3} ... \ell_S, W]$, where $m_{i,j} = 0$ if the network nodes i and j are not connected, otherwise they are connected using one of the pre-determined available types of optical amplifier in each link, which are given by the integer numbers $(1, 2, .., L_A)$ and they will be defined in section 3-B. The ℓ_S term represents the choice of the OXC isolation factor (ϵ) and the W term represents the number of wavelengths per link.

3. Multiobjective Optimization Algorithm for Network Physical Topology Design

It has been shown that evolutionary algorithms can be used to efficiently solve multiobjective problems. To perform the multiobjective optimization, we used a multiobjective evolutionary algorithm (MOEA) called NSGA-II. The NSGA-II was proposed by Deb *et al.* [1] and is based on genetic algorithms (GA). Our MOEA uses the vector V to form a population of possible solutions for the network, which means different network topologies with different device specifications. Two objectives were considered during the optimization and it envolves the minimization of the network blocking probability (BP) and capital cost (Capex). Each individual of the population is evaluated in terms of BP and Capex. The best individuals are selected based on a dominance rule concerning the two objectives involved in the optimization. The MOEA also performs crossover and mutation operations in the population.

A. Blocking Probability Evaluation

To evaluate the network blocking probability we perform network simulations. Our simulation software uses Shortest Path algorithm for routing and First Fit algorithm for wavelength assignment. It uses the physical layer model described in [6], which takes into account the following effects: ASE noise, amplifier gain saturation effect, saturation of ASE noise in EDFAs and homodyne crosstalk in optical switches. The four wave mixing (FWM) and polarization mode dispersion (PMD) effects are not considered in the present work.

B. Capital Cost Evaluation

In our capital cost model we consider four different sources of costs: a fixed cost for each wavelength used in the network; fiber cable cost and cable deployment cost, which depend on the link physical distance; optical amplifier cost, which depends on the amplifier noise figure and saturation power; and OXC cost, which depends on the node degree, the number of wavelengths in the network and the switch isolation factor. Then, we can define the total network capital cost ($COST_{Net}$) as: $COST_{Net} = COST_{Lambda} + COST_{Amplifier} + COST_{Cable} + COST_{OXC}$. $COST_{Lambda} = \eta \cdot W$, where W is the number of wavelengths per link and η is a constant value that can be inferred from the OLT equipment price. $COST_{Amplifier} = \sum_{i=1}^{N} \sum_{j=1}^{N} C_{amp}(m_{i,j})$, where N is the number of nodes in the network. $C_{amp}(\ell)$ is depicted in Table I. $COST_{Cable} = 2\beta \sum_{i=1}^{N} \sum_{j=i+1}^{N} d_{i,j}$, where $d_{i,j}$ is the physical distance between the i and j nodes if they are connected and zero if they are not connected. β is an input constant inferred from the equipment price. $COST_{OXC} = \gamma \cdot C_{sw}(\ell_S) \cdot W \cdot \sum_{i=1}^{N} G(i)$, where γ is related to the OXC equipment price, $G(i)$ is the node degree of the i node and $C_{sw}(\ell)$ is related to the isolation factor and is defined in Table II.

TABLE I
LABELS AND CAPITAL COST VALUES ADOPTED FOR EDFAS.

Label (ℓ)	**Saturation Power**	**Noise Figure**	**Cost** ($C_{amp}(\ell)$)
1	13 dBm	7 dB	1 m.u.
2	13 dBm	5 dB	2 m.u.
3	16 dBm	7 dB	3 m.u.
4	16 dBm	5 dB	4 m.u.

TABLE II
LABELS AND CAPITAL COST VALUES ADOPTED FOR OXC.

Label (ℓ)	**Isolation Factor** (ϵ)	**Capital Cost** ($C_{sw}(\ell)$)
1	-30 dB	1 m.u.
2	-35 dB	2 m.u.
3	-40 dB	3 m.u.
4	-45 dB	4 m.u.

4. Results

The presence of multiple conflicting objectives in an optimization problem, in principle, implies in a set of optimal solutions (known as Pareto-optimal solutions), instead of a single optimal solution. In the absence of any further information, each point in these Pareto-optimal solutions cannot be said to be better than the other ones [1]. Fig. 1 shows the simulation results for the network cost as a function of the obtained network blocking probability. In this case, we executed the NSGA-II algorithm for 5 different network loads. Each symbol represents a possible solution with its cost and blocking probability, *i.e.* each point corresponds to different network topology with different device characteristics. One can note that the cost increases for lower blocking probabilities and vice versa. Using this figure, the network designer can choose the solution that meets his preferences, according to the project specification. One can also note from the Fig. 1 that for a given blocking probability the cost becomes higher as the network load increases.

Figs. 2(a), 2(b) and 2(c) show examples of the network topologies and devices parameters found by the multiobjective algorithm for a network load of 60 Erlangs. The numbers in parenthesis separated by semicolon represent the link length, output saturation power and noise figure of the amplifiers to be used in the link, respectively. We show three different cases: the best network in terms of blocking probability (Fig. 2(b)), the lowest cost network found (Fig. 2(c)) and the one with a blocking probability of around 1% (Fig. 2(a)). The switch isolation and the number of available wavelength per fiber found for each topology is given in the figure caption. Fig. 2(c) shows that lowest cost network found has a ring topology, as expected. One can also note that to reduce the blocking probability from 1.32% (Fig. 2(a)) to 0.058% (Fig. 2(b)) our algorithm found that it is necessary the addition of 5 more links and 5 more wavelengths ($W = 17$ to $W = 22$) in each link of the network.

5. Conclusion

In this paper we proposed a multiobjective algorithm to solve the physical network topology design problem for all-optical networks. We considered capital cost and network performance in terms of blocking probability as the optimization objectives. The network performance is infered considering physical layer impairments. A case study was performed and the simulation results show that the methodology was successful in obtaining the network

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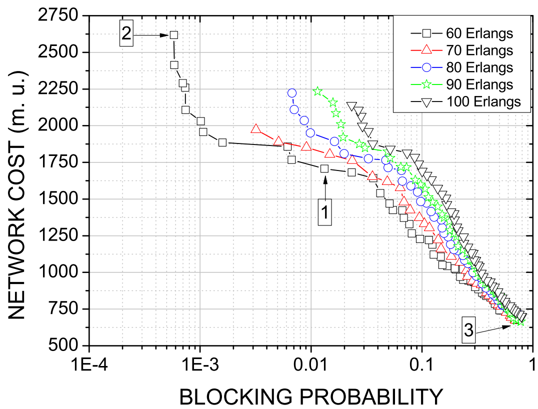

Fig. 1. The optimal Pareto found for five different network loads.

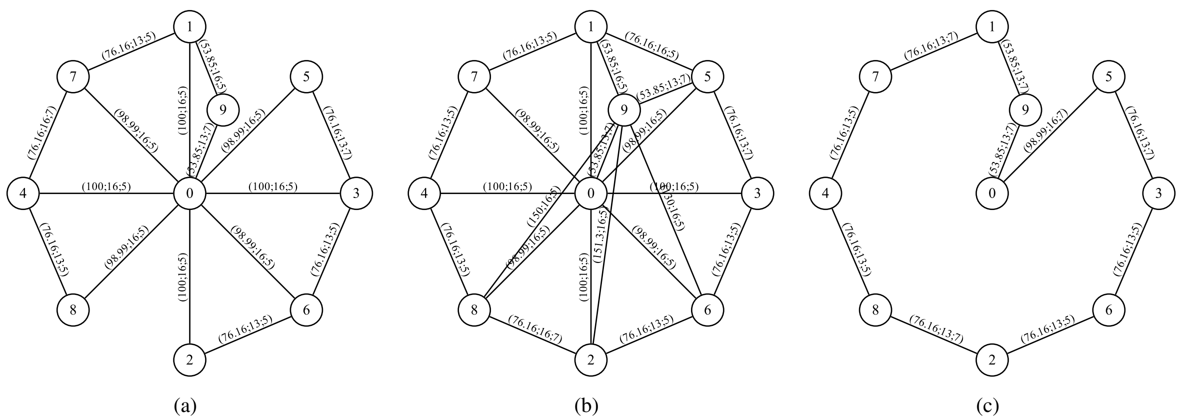

Fig. 2. The best Network topology and devices parameters found for: (a) a network blocking probability around 1%($BP = 1.32\%$, $COST = 1706.7\,\mathrm{m.u.}$, $W = 17$, $\epsilon = -45\,dB$) point number 1 in Fig. 1; (b) for network lowest blocking probability ($BP = 0.058\%$, $COST = 2618.9\,\mathrm{m.u.}$, $W = 22$, $\epsilon = -45\,dB$) point number 2 in Fig. 1; (c) a lowest network cost ($BP = 71.14\%$, $COST = 675.84\,\mathrm{m.u.}$, $W = 4$, $\epsilon = -35\,dB$) point number 3 in Fig. 1.

topology and optical devices parameters for different scenarios. Furthermore, it allows the network designer to choose, among an optimized set, which specific network should be implemented. It is a very powerful tool to analize an important network design trade-off (cost *versus* network performance). It is worth noting that the proposed methodology and algorithm for multiobjective optimization presented here can be used with other capital cost models and other network performance metric. It is not limited to the ones presented here.

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