Algorithms for Joint Optimization of Link Capacity and Regenerators Placement in Optical Networks

Renan V. B. Carvalho, Carmelo J. A. Bastos-Filho, Daniel A. R. Chaves, and Joaquim F. Martins-Filho

Abstract—In this paper we compare two different approaches to tackle the regenerator placement and link capacity optimization joint problem in translucent optical networks. The former and simpler proposal imposes the same number of wavelengths to all links, whereas the number of wavelengths can be defined for each link in the second proposal. We used the SPEA2 algorithm to perform the multi-objective optimization process in both cases. We compared some of the solutions of the Pareto Fronts found by both proposals and we observed that the constrain on the number of wavelengths in the links leads to more expensive and/or less efficient solutions.

Keywords—Translucent optical networks, Regenerator placement, Link capacity optimization.

I. INTRODUCTION

Translucent optical networks are the ones in which just some of the network nodes present regeneration capability. This solution is a compromise to either all-optical, in which all nodes are transparent, or opaque networks, in which all nodes have regenerators. Translucent networks can achieve a better trade-off between network performance, capital expenditures (CapEx) and operational expenditures (OpEx) when compared to all-optical or opaque networks [1].

One of the main challenges in translucent networks is to properly define which nodes should present regenerators and how many regenerators should be deployed in each one of these nodes. This problem is known as Regenerator Placement (RP) [2]. There are two main strategies to solve the RP problem: islands of transparency and sparse regeneration. The islands of transparency are designed to have transparent subdomains, which means that the nodes within a given island are transparent and the regeneration capability is provided only in the island boundaries [1]. The sparse regeneration refers to a strategic distribution of the regenerators along the network [2]. In general, a heuristic or meta-heuristic method is applied to define the translucent nodes in the sparse approach.

Other important aspect in the optical network design is the definition of the number of wavelengths that should be deployed in each link of the network. If this problem is considered together with the RP problem, one can define the wavelength and regenerator placement (WRP) problem. Carvalho *et al.* [3] proposed to use a multi-objective evolutionary optimizer, called Strength Pareto Evolutionary Algorithm 2

Renan V. B. Carvalho and Joaquim F. Martins-Filho are with Department of Electronics and Systems, Federal University of Pernambuco, Recife, PE, Brazil. Email: {renan.carvalho@ufpe.br, jfmf@ufpe.br}.

Daniel A. R. Chaves and Carmelo J. A. Bastos-Filho are with Polytechnic School of Pernambuco, University of Pernambuco, Recife, PE, Brazil. Email: {darc@ecomp.poli.br, carmelofilho@ecomp.poli.br}

(SPEA2) [4], to solve the WRP problem. This approach is called multi-objective optimization for wavelength and regenerator placement (MOWRP).

In this paper we propose to compare MOWRP algorithms. The first algorithm was proposed in [3] and each link has its traffic capacity scaled individually. The other algorithm places the same number of wavelengths in all network links. We aim to minimize three objectives simultaneously: the network blocking probability (BP), the CapEx to build the network and the number of translucent nodes (TN), which is directly related to the OpEx. These objectives were proposed in [3].

This remainder of the paper is organized as follow: in Section II we describe the problem, the representation of the information and our recent proposed approaches to tackle the WRP problem: MOWRP-R and MOWRP. Besides, we describe the evolutionary algorithm and its parameters. In Section III we describe the cost model, the physical impairments considered in the simulations and the values for the parameters. In Section IV we present and compare the simulation results. Finally, we give our conclusions in Section V.

II. MULTI-OBJECTIVE WAVELENGTH AND REGENERATOR PLACEMENT (MOWRP)

This section presents the representation of the Multiobjective Wavelength and Regenerator Placement (MOWRP) problem and our proposals to solve this problem.

A. Problem Representation

We consider that the optical signals are regenerated using a network element that performs 3R (re-amplifying, re-shaping and re-timing) O/E/O regeneration. We compare two approaches in this paper.

In the first approach (MOWRP-R), the number of regenerators in each network node and the number of available wavelengths in all network links are represented by a vector of integer numbers $\vec{V} = \{v_i\}$, $(i \in 1, 2, 3, 4, \ldots, N, N+1)$, in which N is the number of nodes in the network. Thus, for each integer $i \leq N$, v_i is the number of regenerators deployed in the i^{th} node and the element N+1 defines the number of wavelengths placed in all links of the network.

In the second approach, the number of regenerators in each network node and the number of available wavelengths in each network link are represented by a vector of integer numbers $\vec{V} = \{v_i\}$, $(i \in 1, 2, 3, 4, \ldots, N, N+1, \ldots, N+L)$, in which N is the number of nodes in the network and L is the number of bidirectional links in the network. Thus, for each integer $i \leq N$, v_i is the number of regenerators deployed in the i^{th}

node and for each integer such that $N+1 \leq i \leq N+L$, v_i is the number of wavelengths placed in the $(i-N)^{th}$ link. Therefore, MOWRP-R is similar to the MOWRP, but it has a restriction on the wavelength placement. This means that the number of wavelengths per link is the same for the entire network in MOWRP-R.

B. Proposals to Solve the MOWRP

In this subsection we describe the multi-objective optimizer used to place the regenerators and define the number of wavelengths in the network, in order to minimize simultaneously the network BP, the CapEx and the number of TN. We used the SPEA2 approach to perform the multi-objective optimization. SPEA2 is a multi-objective optimizer based on genetic algorithms [4]. The SPEA2 algorithm has a population of individuals, where each individual is a filled \vec{V} that represents a possible solution for the MOWRP problem. During each iteration, the following genetic operators are applied to the individuals: crossover, mutation and selection. The selection operator is used in two phases: during the environmental selection, in which the individuals are selected from an external archive according to the dominance and diversity criteria, and during the binary tournament, in which the individuals compete to be selected for the next generation. Between these two selection phases, the crossover and mutation are applied to pairs of individuals.

The SPEA2 runs 6,000 iterations in each trial, has an internal population of 100 individuals and an external archive that can store up to 200 non-dominated solutions. We used uniform crossover and mutation. The crossover and mutation probabilities are 0.9 and 0.1, respectively.

III. SIMULATION SETUP AND COST MODEL

A. Simulation Setup and Physical Impairments Evaluations

In order to assess the performance of the two proposals for the WRP problem, we used the SIMTON network simulator [5] to obtain the blocking probability (BP). SIMTON uses the optical signal-to-noise ratio (OSNR) model proposed by Pereira *et. al.* [6] and the pulse broadening of the optical signal described by Bastos-Filho *et. al.* [7]. We assume the same node architecture assumed by Yang and Ramamurthy [2], in which a shared bank of regenerators are available in some of the network nodes.

The network topology used in our simulations is shown in Fig 1. This topology is the Finland topology and presents 12 nodes and 19 links.

We considered the following physical impairments: amplified spontaneous emission (ASE) noise, amplifier gain saturation effect in erbium doped fiber amplifiers (EDFAs), homodyne crosstalk in optical switches (OXC) and residual chromatic dispersion and polarization mode dispersion (PMD) effects in the transmission fiber.

We use the following values for the parameters of the physical layer model [6]: network load of 100 erlangs, fiber loss coefficient $\alpha=0.2\,\mathrm{dB/km}$, maximum pulse broadening $\delta=10\,\%$, transmitter linewidth $\Delta\lambda_\mathrm{Tx}=0.013\,\mathrm{nm}$, first wavelength of the grid $\lambda_\mathrm{i}=1528.77\,\mathrm{nm}$, zero dispersion for

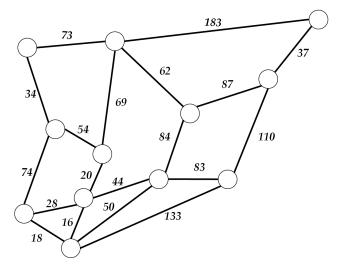


Fig. 1: Finland topology, distances are indicated in km

transmission fiber $\lambda_0=1450\,\mathrm{nm}$, zero residual dispersion $\lambda_{\mathrm{ORD}}=1528.77\,\mathrm{nm}$, switch isolation factor $\varepsilon=-38\,\mathrm{dB}$, optical filter bandwidth $B_{\mathrm{o}}=100\,\mathrm{GHz}$, transmission bit rate $B=40\,\mathrm{Gb/s}$ OOK, compensating fiber dispersion coefficient D_{DCF} (@1550 nm) = $-110\,\mathrm{ps/km.nm}$, PMD coefficient $D_{\mathrm{PMD}}=0.04\,\mathrm{ps/\sqrt{km}}$, transmission fiber dispersion coefficient D_{Tx} (@1550 nm) = $4.5\,\mathrm{ps/km.nm}$, amplifier noise figure $NF=6\,\mathrm{dB}$, multiplexer, demultiplexer and optical switch losses $L=3\,\mathrm{dB}$ each, amplifier output saturation power $P_{\mathrm{Sat}}=20\,\mathrm{dBm}$, transmitter optical power $P_{\mathrm{in}}=3\,\mathrm{dBm}$, compensating fiber slope S_{DCF} (@1550 nm) = $-1.87\,\mathrm{ps/km.nm^2}$, transmission fiber slope S_{Tx} (@1550nm) = $0.045\,\mathrm{ps/km.nm^2}$, transmitter OSNR_{in} = $40\,\mathrm{dB}$ and threshold for QoT criterion OSNR_{Th} = $20\,\mathrm{dB}$.

we are using discrete module for dispersion compensation. The length of the DCF is calculated such that the chromatic dispersion is zero at the wavelength of zero dispersion.

B. Cost Model

Our cost model is composed by two economic variables related to the link and the node CapEx [8], [9]. The CapEx model proposed by Huelsermann *et al.* [8] uses normalized cost values for the WDM links, equipments and OXCs. In this cost model a 10 Gb/s transponder with 750 km reach has a normalized cost of 1 monetary unit (m.u.).

In this paper, the link CapEx is given by:

$$C_{links} = 2\gamma \sum_{l=1}^{L} W_l, \tag{1}$$

in which γ is the capital cost of a 40 Gb/s transponder with a optical reach of 750 km. We used $\gamma = 3.75$ [8]. W_l is the number of pairs of wavelengths placed in the l^{th} link and L is the number of bidirectional links in network.

Chaves *et al.* [9] proposed an adaptation for the OXCs cost defined by Huelsermann *et al.* [8] model. The proposal includes in the cost evaluation the number of OXCs ports. The

node CapEx is given by:

$$C_{nodes} = \sum_{n=1}^{N} [1.4\gamma R_n + (0.05225P_n + 6.24)G_n + 2.5],$$
(2)

in which R_n is the number of regenerators; P_n is the number of OXC ports (determined by the largest number of wavelengths present in the links connected to the node), G_n is the degree of the n^{th} node and N is the number of nodes in network. Thus, the total CapEx C of a given network is given by $C = C_{links} + C_{nodes}$.

IV. SIMULATION RESULTS

The final result for a multi-objective optimization process is indeed a set of solutions the optimizes the trade-off between the conflicting objectives. This set of solution is known as Pareto-front, which is composed solely by non-dominated solutions. Since we considered the optimization process with three objectives, then the solutions of the Pareto-front form a three dimensional surface. In order to facilitate the visualization, we plotted all non-dominated solutions as level curves in a two dimensional space as a function of the number of translucent nodes, as shown in Fig. 2. Fig. 2 shows the Pareto-fronts found by MOWRP-R (open symbols) and MOWRP (solid symbols) in terms of the blocking probability versus the CapEx. One can observe that different symbols stand for different number of translucent nodes.

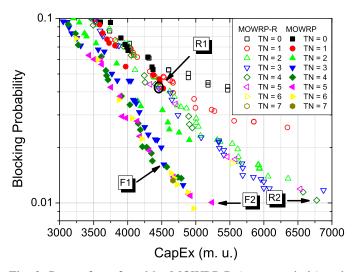


Fig. 2: Pareto-front found by MOWRP-R (open symbols) and MOWRP (solid symbols). The number of translucent nodes are represented by different symbols.

One can observe that for a given number of TN, the solutions found by MOWRP show a lower blocking probabilities and lower CapEx values than the solutions found by MOWRP-R. This means that the Pareto-front obtained by MOWRP dominates the one obtained by MOWRP-R. This becomes more evident for a number of translucent nodes greater than 2 (up-triangle symbols).

For the sake of comparison, we selected two pairs of solutions. The first analysis aims to compare solutions obtained by both approaches for a equivalent CapEx. For this, we selected the RI solution from MOWRP-R and FI from MOWRP, where both present a CapEx of $4500 \, \text{m.u.}$ and a maximum number of translucent nodes equal to three. Table I shows the characteristics of the solutions RI and FI.

TABLE I: Characteristics of the solutions R1 and F1.

Solution	$\sum_{n=1}^{N} R_n$	$\sum_{l=1}^{L} W_l$	CapEx (m. u.)	TN
R1	28	532	4459.71	3
F1	62	516	4530.55	3

The network solution represented by the point R1 in Fig. 2 has: 28 regenerators, 532 wavelengths pairs (28 per link), CapEx of 4459.71 m.u. and three translucent nodes. The network solution represented by the point F1 in Fig. 2 has: 62 regenerators, 516 wavelengths pairs (which means 27 wavelengths pair per link in average), a CapEx of 4530.55 m.u. and three translucent nodes. Figs. 3(a) and 3(b) illustrate the network configuration for the solutions R1 and F1, respectively. Fig 3(b) shows that the solution F1 has 9 links (out of 19) that presents 28 wavelengths or less. One can observe that by increasing the number of wavelengths per link results in a reduction of the number of regenerators required to achieve an optimized performance for a given CapEx. This occurs because it is necessary to use regenerators as wavelength converters. As an example, one can observe that R1 presents less regenerators than F1, although it uses more wavelengths in average in the links. On the other hand, it has smaller number of wavelengths in the links that do not carry a high traffic.

Fig. 4 shows the blocking probability as a function of network load for the solutions R1 and F1. Fig. 4 depicts that the translucent network labeled as F1 presents a lower blocking probability when compared to the solution R1. F1 achieved 54% less blocking for a network load equal to 100 erlangs.

We also compared the lowest cost solution found by both MOWRP-R and MOWRP for a given fixed blocking probability of 1%. Such solutions were labeled as F2 and R2 in Fig. 2. One can note that the solutions are located at the far end of the Pareto-front. The translucent networks labeled as R2 and F2 are shown in Fig. 5(a) and in Fig 5(b), respectively. Table II shows the characteristics of the solutions R2 and F2.

TABLE II: Characteristics of the solutions R2 and F2.

	Solution	$\sum_{n=1}^{N} R_n$	$\sum_{l=1}^{L} W_l$	CapEx (m. u.)	TN
	R2	194	722	6776.07	4
ĺ	F2	192	518	5237.71	5

The network solution represented by the point R2 in Fig. 2 has: 194 regenerators distributed over 4 translucent nodes, 722 wavelengths and a CapEx value of $6776.07\,\mathrm{m.u.}$. The network solution represented by the point F2 in Fig. 2 has: 192 regenerators distributed over 5 translucent nodes, 518 wavelengths and a total CapEx of $5237.71\,\mathrm{m.u.}$. One can observe that in both cases the number of regenerators is almost the same. However, the total number of wavelengths

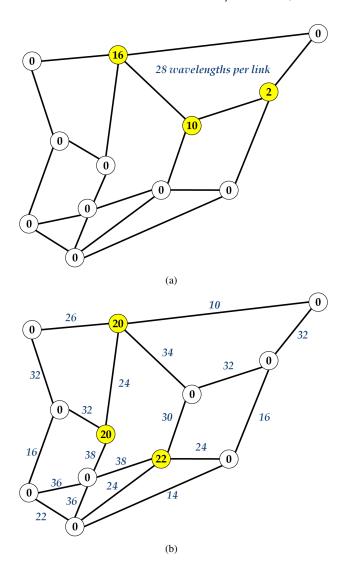


Fig. 3: Network configuration found by solutions: (a) RI (MOWRP-F with CapEx of 4459.71 m.u. and TN=3) and (b) FI (MOWRP with CapEx of 4530.55 m.u. and TN=3).

in network is smaller for the solution F2 (28% less in this case). This may have occurred because the required number of wavelengths to achieve this performance (BP = 1%) forces the MOWRP-R to use a higher number of wavelengths per link (38 wavelengths). Again, MOWRP can allocate more efficiently the wavelengths and reduce the number of transponders in the links which do not need many wavelengths.

Fig. 6 shows the blocking probability as a function of network load for the solutions labeled as R2 and F2 in Fig. 2. Fig. 6 shows that the solutions obtained similar results in terms of blocking probability. The translucent network F2 has 5 translucent nodes, whereas the network R2 has only 4 translucent nodes. As a consequence, the OpEx related to F2 might be higher than the one related to the solution R2. However, the F2 CapEx is 23% lower than the R2 one. This reduction obtained in the CapEx is similar to the reduction in the number of wavelengths (28%). One must remember that the number of regenerators placed in each solution was almost the same (194 for R2 and 192 for F2).

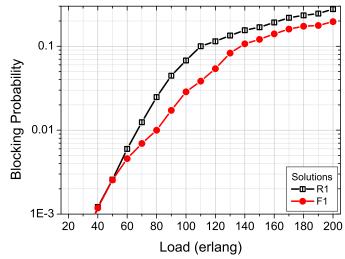


Fig. 4: Blocking probability as a function of network load for solutions R1 and F1.

V. CONCLUSION

In this paper we analyzed two different approaches for solving the WRP problem: MOWRP-R and MOWRP. For the first, MOWRP-R, the same number of wavelengths is installed in all links. For the second, MOWRP, different links are allowed to be equipped with different number of wavelengths. We used the SPEA2 algorithm to perform the multi-objective optimization. The optimization objectives considered were to minimize: blocking probability, number of translucent nodes and CapEx.

We observe that MOWRP outperforms MOWRP-R, since it obtains solutions with lower blocking probabilities, for a given number of translucent nodes and CapEx value.

We also can conclude that when the same number of wavelengths is imposed to all network links, we have more expensive solutions because some of the wavelengths in some links will become idle.

ACKNOWLEDGMENT

The authors thank UFPE, UPE, CNPq and FACEPE for scholarships and grants.

REFERÊNCIAS

- [1] G. Shen and R. S. Tucker, "Translucent optical networks: the way forward [topics in optical communications]," *IEEE Communications Magazine*, v. 45, n. 2, pp. 48–54, Feb. 2007.
- [2] X. Yang and B. Ramamurthy, "Sparse regeneration in translucent wavelength-routed optical networks: Architecture, network design and wavelength routing", Photonic Network Communications, v. 10 n. 1, pp. 39–53, 2005.
- [3] R. V. B. Carvalho, R. F. S. C. Oliveira, C. J. A. Bastos-Filho, D. A. R. Chaves, J. F. Martins-Filho, "Regenerator Placement and Link Capacity Optimization in Translucent Optical Networks Using a Multi-Objective Evolutionary Algorithm", in: Optical Fiber Conference 2012, v. 1. pp. 1–3.
- [4] E. Zitzler, M. Laumanns, L. Thiele, "SPEA2: Improving the Strength Pareto Evolutionary Algorithm for Multiobjective Optimization", in: Evolutionary Methods for Design, Optimisation and Control with Application to Industrial Problems (EUROGEN 2001), pp. 95–100, 2001

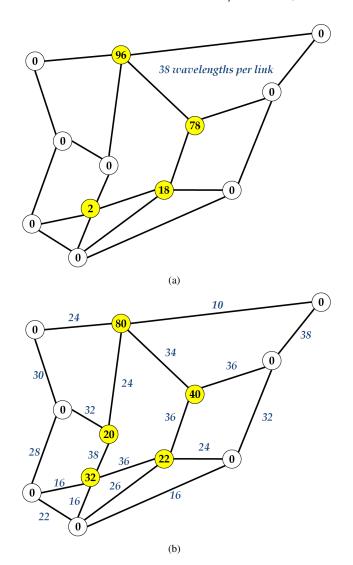


Fig. 5: Network configuration found by solutions: (a) R2 (MOWRP-F with CapEx of $6776.07\,\mathrm{m.u.}$ and TN=4) and (b) F2 (MOWRP with CapEx of $5237.71\,\mathrm{m.u.}$ and TN=5).

- [5] D. A. R. Chaves, H. A. Pereira, Chaves, C. J. A. Bastos-Filho, J. F. Martins-Filho, "SIMTON: A Simulator for Transparent Optical Networks", Journal of Communication and Information Systems (Online), v. 25, pp. 1–10, 2010.
- [6] H. A. Pereira, D. A. R. Chaves, C. J. A. Bastos-Filho, J. F. Martins-Filho, "OSNR model to consider physical layer impairments in transparent optical networks", Photonic Network Communications, v. 18 n. 2, pp. 137–149, 2009.
- [7] C. J. A. Bastos-Filho, D. A. R. Chaves, F. S. F. e Silva, H. A. Pereira, and J. F. Martins-Filho, "Wavelength assignment for physical-layer-impaired optical networks using evolutionary computation", Journal of Optical Communications and Networking, v. 3, n. 3, pp. 178–188, March 2011.
- [8] R. Huelsermann, M. Gunkel, C. Meusburger, and D. A. Schupke, "Cost Modeling and Evaluation of Capital Expenditures in Optical Multilayer Networks", Journal of Optical Communications and Networking, v. 7, n. 9, pp. 814–833, 2008.
- [9] D. A. R. Chaves, C. J. A. Bastos-Filho, and J. F. Martins-Filho, "Multiobjective Physical Topology Design of All-Optical Networks Considering QoS and CAPEX", in: *Optical Fiber Conference 2010*, v. 1, pp. 1–3.

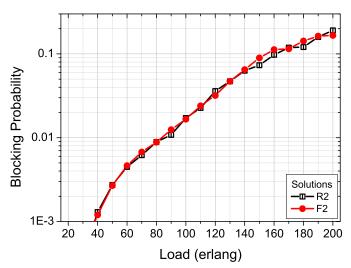


Fig. 6: Blocking probability as a function of network load for solutions R2 and F2.