Regenerator Placement and Link Capacity Optimization in Translucent Optical Networks Using a Multi-Objective Evolutionary Algorithm

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Abstract: We present an algorithm to tackle simultaneously the regenerator placement and link capacity optimization problems in translucent optical networks. It can assist a network designer to find a solution that balances cost and performance.

OCIS codes: 060.4254, 060.4256

1. Introduction

The deployment of translucent optical networks is an alternative to either fully transparent or fully opaque networks when it is considered the trade-off between network performance and the capital (CAPEX) and operational (OPEX) expenditures of optical networks [1]. There are two main strategies to design translucent networks: islands of transparencyand sparse regenerationThe latter can achieve better performance with a lower number of translucent nodes in the network. Using the the sparse regeneration strategy, one needs to define which nodes should be equipped with regeneration capability. This problem is known as the Regenerator Placement (RP) problem [2].

On the other hand, it is also important to define the number of wavelengths in each link of the network in order to design properly an optical network. If we consider this problem together with the RP problem, we can define the wavelength and regenerator placement problem (RWP). In this paper we extend our work in [3] (which considered only the RP problem) and propose the use of a multi-objective evolutionary algorithm, called Strength Pareto Evolutionary Algorithm 2 (SPEA2) [4] to solve the RWP considering simultaneously three different objectives (optimization targets): to minimize the network blocking probability (*i.e.* to maximize the network performance), to minimize the CAPEX to build the network and to minimize the number of translucent nodes, which is related to the OPEX. As we are dealing with more than one conflicting objectives, we can define this problem as multi-objective RWP (MORWP). For the best of our knowledge, this is the first proposal to tackle the MORWP.

2. Problem Representation and Experimental Setup

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. The number of regenerators in each network node and the number of available wavelengths in each network link are represented by a vector of integers $\vec{V} = \{v_i\}$, $i \in 1,2,3,4,N,N+1,\ldots,L$, where N is the number of nodes in the network and $L-N$ is the number of 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 $N+1 \leq i \leq L$, v_i is the number of wavelength in the i^{th} link.

In order to evaluate the network performance for the RWP, we used a network simulator to obtain the blocking probability (BP) for each situation. All simulations were carried out by using a call admission control (CAC) that assigns lightpaths based on the Shortest Path routing and First Fit wavelength assignment algorithms. The lightpaths are assessed by a QoT estimator that evaluates the optical signal-to-noise ratio (OSNR) [5] and pulse broadening of the optical signal [5,6]. The signal can be either received or regenerated in a given node of the network only if both OSNR is above a threshold and the pulse broadening is below a predefined value. Otherwise, the given lightpath is blocked. We assume the same node architecture of [2], where a shared bank of regenerators are available in some network nodes. We considered the following impairments: ASE noise, amplifier gain saturation effect, saturation of ASE noise in EDFAs, homodyne crosstalk in optical switches and the residual chromatic dispersion and PMD effects in the transmission fiber. The parameters used in our simulations: network load of 60 Erlang, fiber loss coefficient $\alpha = 0.2$ dB/km, maximum pulse broadening $\delta = 10\,\%$, transmitter linewidth $\Delta\lambda_{\mathrm{Tx}} = 0.013$ nm, first wavelength of the grid $\lambda_{\mathrm{i}} = 1528.77$ nm, zero dispersion for transmission fiber $\lambda_0 = 1450$ nm, zero residual dispersion $\lambda_{0\mathrm{RD}} = 1528.77$ nm, switch isolation factor $\varepsilon = -38$ dB, optical filter bandwidth $B_{\mathrm{o}} = 100$ GHz, transmission bit rate $B = 40$ Gbps, compensating fiber dispersion coefficient D_{DCF} (@1550 nm) $= -110$ ps/km.nm, PMD coefficient $D_{\mathrm{PMD}} = 0.04\,\mathrm{ps}/\sqrt{\mathrm{km}}$, transmission fiber dispersion coefficient D_{Tx} (@1550 nm) $= 4.5$ ps/km.nm, amplifier noise figure $(\mathrm{NF}) = 6$ dB, multiplexer, demultiplexer and optical switch losses $L = 3$ dB each, amplifier output saturation power $P_{\mathrm{Sat}} = 20$ dBm, transmitter optical power $P_{\mathrm{in}} = 3$ 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 $\mathrm{OSNR_{in}} = 40$ dB and threshold for QoT criterion $\mathrm{OSNR_{Th}} = 20$ dB.

Our cost model is composed by two economic variables related to the node CAPEX and the link CAPEX [7, 8]. The node CAPEX is given by $C_{nodes} = \sum_{n=1}^{N}\{1.4R_n + [(0.0522P_n + 6.24)G_n + 2.5]\}$, where R_n is the number of regenerators; P_n is the number of ports (determined by the largest number of wavelengths present in the links connected to the node), G_n is the degree of the node n and N is the number of nodes in network. The link CAPEX is given by $C_{links} = \sum_{l=1}^{L} W_l$, where W_l is the number of pairs of wavelengths in the l^{th} link and L is the number of links in network. Thus, the total CAPEX C of a given RWP is given by $C = C_{links} + C_{nodes}$.

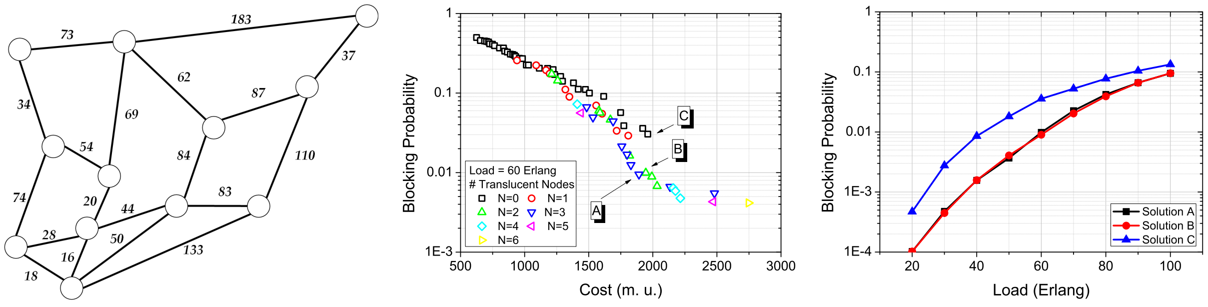
3. Our proposal to tackle the MORWP

In this section we describe the multi-objective optimization algorithm used to find the distribution of regenerators and wavelengths in the network in order to minimize the network BP, the CAPEX and the number of translucent nodes. The SPEA2 algorithm runs a certain number of iterations. During each iteration, the following genetic operators are used: crossover, mutation and selection. The selection operator is used in two phases. The first one is in the environmental selection, that selects the individuals in external archive, according to their fitness. The fitness is evaluated considering the dominance rule and the diversity among the solutions. Then, the algorithm performs the binary tournament in these individuals and randomly chooses pairs to apply the other evolutionary operators aiming to create a new population.

An individual, *i.e.* a filled $\vec{V}$, represents a possible solution for the problem. In each run, the SPEA2 performs $10,000$ iterations. The size of the internal population and the external archive are both equal to 70 individuals. We used uniform crossover and mutation with probabilities equal to 0.9 and 0.1, respectively.

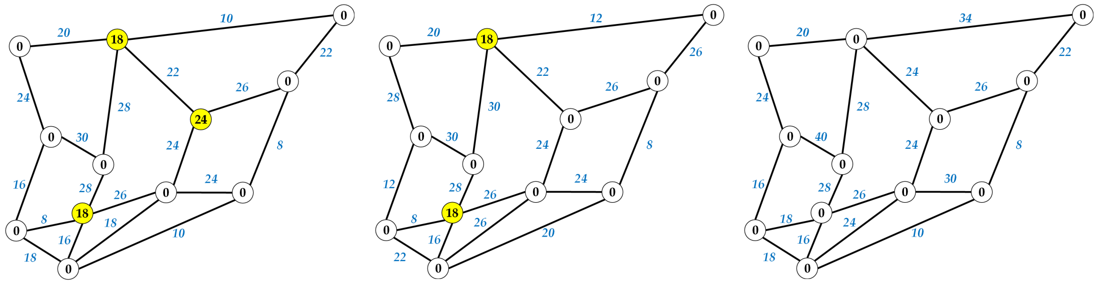
4. Simulation Results

Fig. 1(a) shows the Finland topology used in our simulations. The link distances are depicted in kilometers. Since we are using a multi-objective approach with 3 objectives to solve the RWP, the optimized solution is a set of solutions instead of a single one. This set of optimized solution can be plotted as a 3D surface. However, in order to show the results in 2D we plot the BP as a function of the network cost for different numbers of translucent nodes (N). These results are shown in Fig. 1(b), which shows the best set of solutions found in the end of the SPEA2 execution (*i.e.* non-dominated solutions of the external archive). Each curve represents the best trade-off curve between BP and CAPEX for a given N found by the MORWP. Each point in the graph shown in Fig. 1(b) stands for an optimized solution for the RWP problem. Moreover, all points are obtained simultaneously in the end of the SPEA algorithm. We selected for the sake of comparison three solutions: A, B and C which are properly labeled in the Fig. 1(b). A and B are solutions for translucent networks ($N \neq 0$), whereas C is the transparent network ($N = 0$) with the lowest PB found by MORWP. The solutions A (with 3 translucent nodes) and B (with 2 translucent nodes) show a much lower BP with almost the same CAPEX when compared with solution C. Fig. 1(c) shows the network blocking probability as a function of the network load for the solutions A, B and C. The differences in BP is kept almost constant when the network load is changed. Figs. 2(a), 2(b) and 2(c) show the network configuration for solutions A, B and C, respectively. The numbers in the network links stand for the number of wavelengths found by the MORWP algorithm for the link, whereas the numbers in the nodes represent the number of regenerators. Solution A deploys 60 regenerators and 378 wavelengths, B deploys 36 regenerators and 408 wavelengths and C deploys 0 regenerators and 436 wavelengths. One can observe that the number of wavelengths increases as the total number of regenerators decreases. It occurs due to the reduction of wavelength conversion capacity. Although solution A has a lower cost (1891.97 $m.u.$) than solution B (1960.6 $m.u.$), it has three translucent nodes which can lead to a higher OPEX than B.



(a) (b) (c)

Fig. 1. (a) Network topology, (b) Non-dominated solutions in the external archive and (c) Blocking probability as a function of network load for the three selected solutions.



(a) (b) (c)

Fig. 2. Network configuration of the solutions highlighted in fig 1(b): (a) A, (b) B and (c) C.

5. Conclusion

In this paper we proposed a multi-objective evolutionary algorithm to simultaneously place regenerators in the nodes and define the number of wavelengths in the links, regarding the network performance, CAPEX and OPEX. Our proposed algorithm can assist the design of translucent networks compromising cost and performance.

References

1. G. Shen and R. S. Tucker, "Translucent optical networks: the way forward," Communications Magazine, vol. 45, no. 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," Phot. Netw. Comm., vol. 10, no. 1, pp. 39-53, July 2005.
3. D. A. R. Chaves, C. F .C. L. C. Ayres, R. V. B. Carvalho, H. A. Pereira, C. J. A. Bastos-Filho and J. F. Martins-Filho, "Multiobjective sparse regeneration placement algorithm in optical networks considering network performance and CAPEX," in *ICTON 2010*, pp.1-4, 2010.
4. L. M. Zitzler, E. and L. Thiele, "Spea2: Improving the strength pareto evolutionary algorithm for multiobjective optimization," in *(EUROGEN 2001)*, pp. 95-100, 2002.
5. H. A. Pereira, D. A. R. Chaves, C. J. A. Bastos-Filho, and J. F. Martins-Filho, "OSNR model to consider physical layer impairments in transparent optical networks," Phot. Netw. Comm., vol. 18, no. 2, pp. 137-149, Oct. 2009.
6. N. Zulkifli, R. C. Almeida-Jr, and K. M. Guild, "Efficient resource allocation of heterogeneous services in transparent optical networks," J. Opt. Netw., vol. 6, no. 12, pp. 1349-1359, Dec. 2007.
7. R. Huelsermann, M. Gunkel, C. Meusburger, and D. A. Schupke. "Cost Modeling and Evaluation of Capital Expenditures in Optical Multilayer Networks", J. Opt. Netw. vol.7, no.9, pp 814–833, 2008.
8. 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 *OFC/NFOEC 2010*, vol. 1, 2010, pp. 1–3.