Routing and Spectrum Assignment Assisted by Reinforcement Learning in Multi-band Optical Networks

Abdennour Ben Terki [(1)], Joao Pedro [(2)], Antonio Eira [(2)], Antonio Napoli [(3)], Nicola Sambo [(1)]
[(1)] Scuola Superiore Sant'Anna, Italy, abdennour.benterki@sssup.it;
[(2)] Infinera, Lisbon, Portugal; [(3)] Infinera, Munich, Germany.

Abstract *Routing and spectrum assignment strategies exploiting Reinforcement Learning are investigated for multi-band optical networks. Generalized Signal to Noise Ratio accounting for Stimulated Raman Scattering is estimated driving modulation format selection. Simulations show that RL may reduce the blocking probability by one order of magnitude. ©2022 The Author(s)*

Introduction

Given the growth of Internet traffic, backbone and metro networks are reaching the saturation of the capacity [1]. The research community is investigating the exploitation of bands beyond C and L (e.g., S and E); thus, the migration toward multi-band (MB) optical networks is considered a valid approach to increase network capacity [2]. In parallel, Machine Learning (ML) is gaining a momentum, e.g., for network optimization purposes, failure prediction and classification. Indeed, over the past years, the usage of ML techniques in optical networks has been investigated for various applications, such as Quality of Transmission (QoT) estimation for unestablished lightpaths [3], failure detection and identification [4] and for network monitoring [5], which show the potential of the different ML models to take part in current and future optical network's control and management planes.

One of the most prominent ML tools is the Reinforcement Learning (RL) technique, which has approved its ability to solve, with accuracy, complex problems in different fields [6]. In optical networks, RL has been used to address the optimization's complexity issues of resource provisioning [7], to exploit the possibility of self-driving network deployment [8], and for the network services restoration in case of failure or disaster [9]. In addition, the reason behind considering RL as an attractive and very competitive solution is that it does not require a training dataset. This ML technique represents a relevant advantage because acquiring accurate data from the network may often be complex. Furthermore, RL still needs to be deeply investigated in the context of MB optical networks.

In this paper, we will consider the scenario of a MB optical network where L-C-S-E bands are active. Then, we investigate several Routing and Spectrum Assignment (RSA) strategies exploiting RL. Given a connection request, a path is computed based on the RL model. Then, a band is selected. The bands are prioritized as follows: C-band first, then L-band, following S-band and finally the E-band. The modulation format selection is performed based on the generalized signal-to-noise ratio (GSNR), which is computed with the open GNPy tool [10][11], accounting for the Stimulated Raman Scattering effect. Then, a portion of the spectrum – within an adequately selected band (e.g., S) – is assigned. The strategies are compared through simulations. Results show that RL may reduce blocking probability by one order of magnitude.

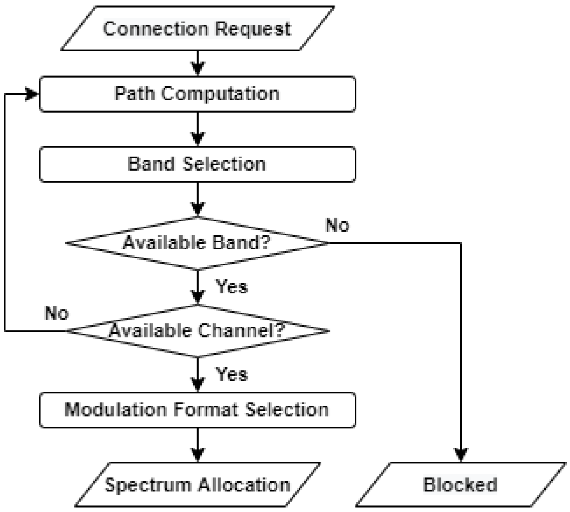

Fig. 1: RSA flow chart

Routing and Spectrum Assignment

The proposed provisioning approach for MB optical networks is illustrated in Fig. 1. The available spectrum per each band is assumed to be the one in [2]. GSNR – computed per wavelength – is the considered figure of merit for QoT estimation. According to the flow chart in Fig. 1, the following RSA strategies exploiting RL are proposed for MB optical networks.

- ***RL-based routing and Highest GSNR spectrum assignment (RL-HighestGSNR):*** Path computation is performed with RL, which explores network topology without any prior knowledge or

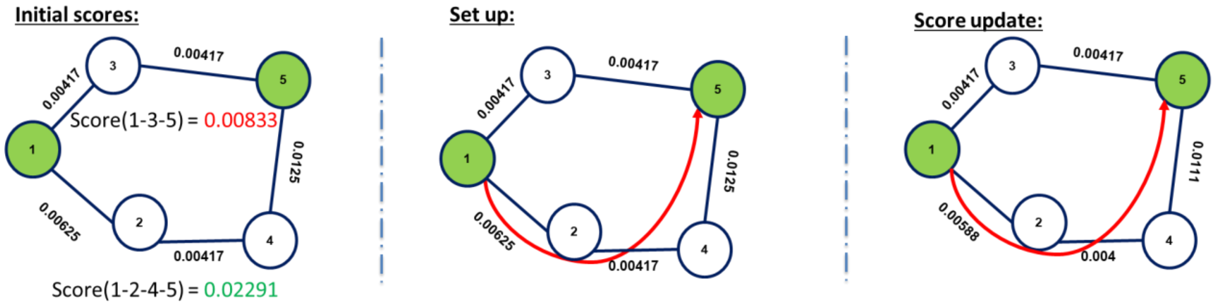

Fig. 2: RL-based strategy steps

training data set. Moreover, RL does not require holding a pre-computed set of routes (e.g., k-shortest paths). RL assigns scores (proportionally to the inverse of the length) to each link. The score of a path, as shown in Fig. 2, is given by the sum of each link's score. The path with the highest score is selected (Path Computation step in Fig. 1). Then, a band is chosen (Band Selection step in Fig. 1). Regarding modulation format selection, we assume fixed symbol rate, thus a lower-order modulation format may require more channels to satisfy the requested bit rate. As an example, assuming polarization multiplexing 16 quadrature amplitude modulation (PM-16QAM) and polarization multiplexing quadrature phase shift keying (PM-QPSK), the latter halves the bit rate, consequently, one channel is required if PM-16QAM is supported or two channels are required if PM-QPSK is supported. After band selection, the strategy proceeds as follows to identify the modulation format. Within the chosen band (e.g., C), the channel *W* with the highest GSNR is considered. Based on the GSNR value, the most-spectral efficient supported modulation format is selected (Modulation Format Selection step in Fig. 1 – e.g., PM-16QAM). Finally, the spectrum is allocated: e.g., one channel on *W* if PM-16QAM is supported, or *W* and an adjacent channel if PM-QPSK only is supported. Once RSA for a given request is concluded, the score related to the links of the computed path is reduced by a penalty *P* in order to discourage the selection of those links, thus, to distribute the traffic over different links.

- ***RL-based routing and Lowest GSNR spectrum assignment (RL-LowestGSNR)****:* Differently from RL-HighestGSNR, within the selected band (e.g., C), the channel *w* with the lowest GSNR supporting the most spectral efficient modulation format (e.g., PM-16QAM) is considered. Then, spectrum is allocated accordingly.
- ***RL-based routing and first fit spectrum assignment*** **(RL-FF)**: Differently from RL-HighestGSNR and RL-LowestGSNR, spectrum assignment is done with first fit (FF).

If no path over all the assumed bands satisfies spectrum continuity constraint, the request is blocked.

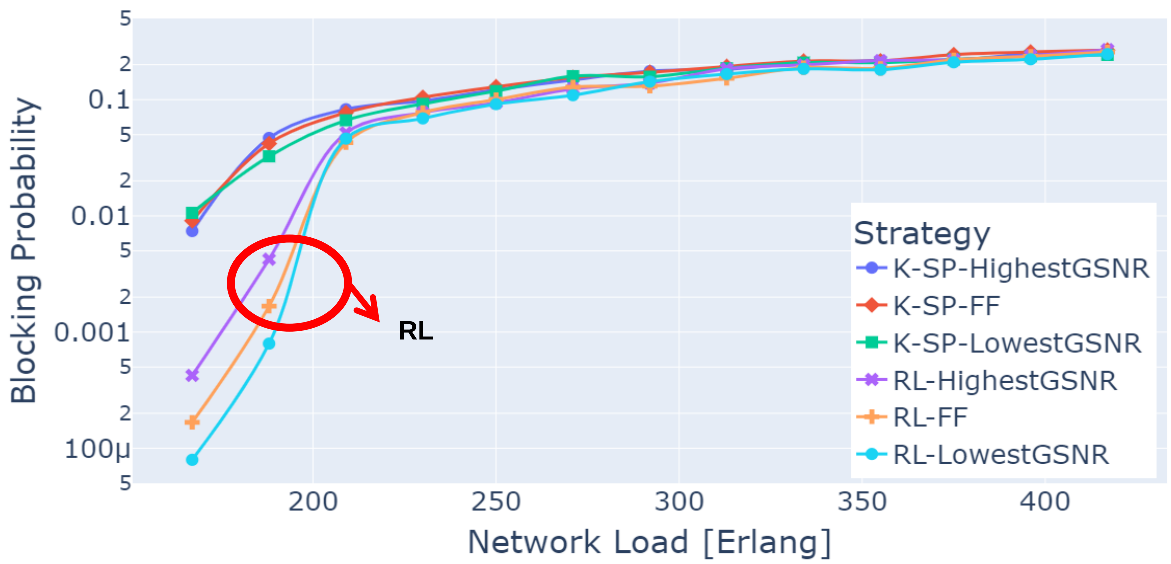

Fig. 3: Blocking probability Vs Network loads for the different RSA strategies.

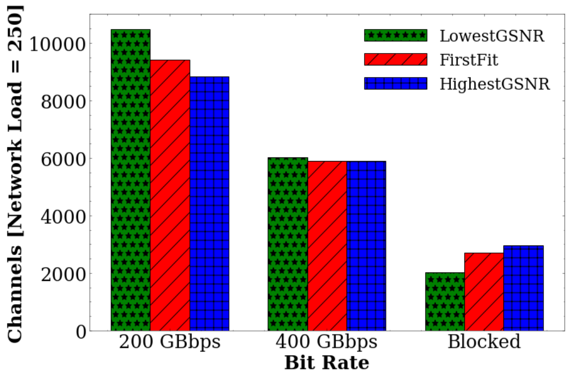

Fig. 4: Number of channels (K-SP-based routing)

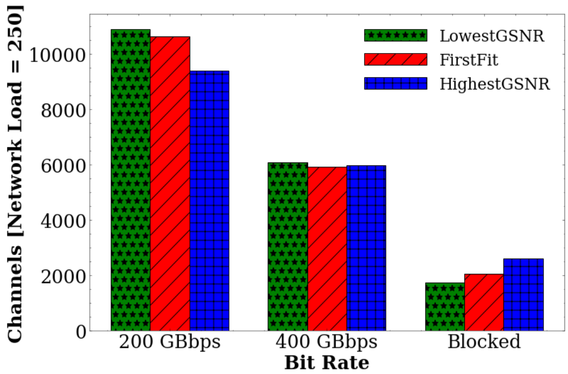

Fig. 5: Number of channels (RL-based routing)

Results

The different RL-based RSA strategies are analyzed through simulations in terms of blocking probability. Japanese network topology [12] of 14 nodes and 44 links is adopted. Traffic follows a Poisson distribution with rate λ. Connection holding time is exponentially distributed with an average of $1/\mu$=1 hour.

Traffic load (λ/μ) is varied with $1/\lambda$. 400-Gb/s requests are assumed. PM-16QAM and PM-QPSK are considered. Requests are switched to 75 GHz when PM-16QAM is supported; otherwise, a single request is provisioned with 2×200Gb/s PM-QPSK channels in 150 GHz. GSNR is computed per wavelength with GNPy [10], and the adopted thresholds are the following: 24 dB for PM-16QAM and 16 dB for PM-QPSK, assuming a symbol rate of 64 GBaud. *P* to reduce scores is equivalent to an increase of 10 km in each link's length of the selected path. RL-based RSA is compared with benchmark strategies based on k-shortest paths: K-SP-HighestGSNR, K-SP-LowestGSNR, and K-SP-FF. With the three benchmark strategies, a set of k-shortest paths is first computed; among them, preference is given to the shortest route; in case of tie, the path maximizing the number of channels satisfying the continuity constraint over the path is selected. Regarding spectrum assignment for the benchmark strategies, similarly to RL-based strategies, K-SP-HighestGSNR is based on the channel with the highest GSNR, K-SP-LowestGSNR is based on the channel with the lowest GSNR (supporting the most spectral efficient modulation format), K-SP-FF is based on FF. Fig. 3 shows the blocking probability at varying the network load for the different RSA strategies. RL can strongly reduce blocking probability: e.g., for a load of 180 Erlang by one order of magnitude with respect to k-shortest. This is due to the fact that RL dynamically updates its view of the overall network thanks to the dynamic update of scores.

Regarding spectrum assignment, independently on the path computation strategy, LowestGSNR achieves the lowest blocking probability. Indeed, LowestGSNR tends to use spectrum with lower GSNR (still attempting to use the most efficient modulation format), thus leaving channels with high GSNR more frequently free. In this way, requests over more critical routes (e.g., the longer ones) may find an available spectrum with acceptable GSNR. Consequently, blocking is reduced. FF presents intermediate performance, while HighestGSNR experiences higher blocking since it may create spectrum fragmentation and may consume high-GSNR channels more quickly, resulting in a worsening performance in terms of blocking probability. Fig. 4 and Fig. 5 show, for a load of 250 Erlang, the average number of channels at 200 Gb/s and 400 G/s deployed in the network, as well as the blocked requests for K-SP-based routing and RL-based routing, respectively. As expected, HighestGSNR reduces the use of PM-QPSK (so the number of 200Gb/s channels). LowestGSNR increases the number of PM-QPSK channels (200Gb/s). Indeed, achieving the lowest blocking, it is able to provision requests that may be blocked with the other approaches. Such requests typically traverse long routes; thus, lower-order PM-QPSK is used.

Conclusions

In this work, we proposed several RSA strategies assisted by Reinforcement Learning (RL) that may strongly reduce blocking probability (e.g., one order of magnitude). Simulations also show that – regarding spectrum assignment – spectrum assignment based on the lowest GSNR may further reduce blocking probability.

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References

[1] "Cisco Global Cloud Index: Forecast and Methodology, 2015–2020," Cisco Systems, 2016.

[2] N. Sambo et al., "Provisioning in Multi-Band Optical Networks," in Journal of Lightwave Technology, vol. 38, no. 9, pp. 2598-2605, 1 May 1, 2020

[3] M. Ibrahimi et al., "Machine learning regression for QoT estimation of unestablished lightpaths," in Journal of Optical Communications and Networking, vol. 13, no. 4, pp. B92-B101, April 2021, DOI: 10.1364/JOCN.410694.

[4] F. Musumeci *et al.*, "Domain adaptation and transfer learning for failure detection and failure-cause identification in optical networks across different lightpaths [Invited]," in *Journal of Optical Communications and Networking*, vol. 14, no. 2, pp. A91-A100, February 2022, DOI: 10.1364/JOCN.438269.

[5] Q. Zhuge et al., "Application of Machine Learning in Fiber Nonlinearity Modeling and Monitoring for Elastic Optical Networks," in Journal of Lightwave Technology, vol. 37, no. 13, pp. 3055-3063, 1 July 1, 2019, DOI: 10.1109/JLT.2019.2910143.

[6] M. H. Krishna and M. M. Latha, "Complexity and Performance Evaluation of Segmented and Recursive Reinforcement Learning," 2021 IEEE 4th International Conference on Computing, Power and Communication Technologies (GUCON), 2021, pp. 1-7, DOI: 10.1109/GUCON50781.2021.9573933.

[7] Bengio, Y., Lodi, A., & Prouvost, A. (2021). Machine learning for combinatorial optimization: a methodological tour d'horizon. *European Journal of Operational Research*, *290*(2), 405-421.

[8] X. Chen, R. Proietti, C. -Y. Liu and S. J. Ben Yoo, "Towards Self-Driving Optical Networking with Reinforcement Learning and Knowledge Transferring," 2020 International Conference on Optical Network Design and Modeling (ONDM), 2020, pp. 1-3, DOI: 10.23919/ONDM48393.2020.9133022.

[9] Z. Zhao et al., "Service Restoration in Multi-Modal Optical Transport Networks with Reinforcement Learning," 2020 International Conference on Computing, Networking and Communications (ICNC), 2020, pp. 204-208, DOI: 10.1109/ICNC47757.2020.9049800.

[10] GitHub repository of GNPy, Nov. 2019, [online] Available: https://github.com/Telecominfraproject/oopt-gnpy.

[11] E. Virgillito, R.-P. Braun, D. Breuer, A. Gladisch, V. Curri, and G. Grammel, "Testing TIP open-source solutions in deployed optical networks," OFC 2022.

[12] M. Salani, C. Rottondi and M. Tornatore, "Routing and Spectrum Assignment Integrating Machine-Learning-Based QoT Estimation in Elastic Optical Networks," IEEE INFOCOM 2019 - IEEE Conference on Computer Communications, 2019, pp. 1738-1746, doi: 10.1109/INFOCOM.2019.8737413.