

Artificial Intelligence for Optical Networks

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Abstract: Artificial Intelligence may provide solutions to problems previously not solvable using conventional techniques. In this paper, we discuss potential AI applications related to challenges in optical networks.
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1. Introduction

With the increase of availability and ease of access of performance monitoring data from optical devices and in general network telemetry data, the use of advanced analytics for artificial intelligence (AI) and machine learning (ML) techniques in the context of optical networking seems natural. AI and ML for optical networking have been actively explored in the research community over the last few years [1-5]. However their adoption in the industry is still lagging. In this paper we explore potential use cases for the application of AI techniques in the context of optical networks from the perspective of an hyperscaler. Specifically aspects related to the applicability of AI/ML techniques in the context of network planning, design and operations will be discussed.

2. Network planning and design

Optical networks form the bulk of the traffic carrying part of today's internet and carrier networks. Large investments are required to plan, design, deploy and operate them. Nevertheless, optical networks are generally underutilized as redundant capacity is planned to protect IP traffic and avoid service impact as a result of failures. In addition to this, given the long lead nature of optical network infrastructure (fiber routes, location for space and power for active optical devices), capacity demand forecasting is extremely challenging. Uncertainties in traffic forecasting are usually compensated by positive demand margining which directly negatively affects cost and utilization of the optical infrastructure.

To overcome this scenario, traffic prediction based on recent service demand and mapping it to the existing network for planning and re-configuration would be beneficial in getting the best out of the existing network infrastructure. Add here

After the optical network infrastructure is built, it is important to be able to correctly estimate its capability in terms of achievable capacity and select the most optimal optical design for a given line system. This is usually achieved by means of well known analytical and simulation techniques. However these methodologies allows to obtain accurate results only with a precise knowledge of the technical characteristics of the optical infrastructure, both passive (fiber plants) and active (line system). Such a perfect knowledge can be difficult to achieve, especially at scale, and typically the design uncertainties are managed again by means of margining. A possible way of reducing the impact of such margining is to use ML to develop better models of optical devices exploiting performance monitoring data exposed by them. In this sense, neural network techniques can be used to reduce the uncertainties associated with prediction of tilt and ripple of the gain and noise figure of optical amplifiers and therefore reduce margins. In a similar way, ML models can be used to report linear and nonlinear noise contributions starting from monitoring of performance metrics exposed by coherent receivers. In this context, neural network techniques have been used to estimate nonlinear signal-to-noise ratios of optical signals [6]. The estimation of linear and nonlinear noise components can be used to improve the network modeling and design tools in terms of precision and performance optimization, i.e. balance between linear and nonlinear noise throughout the lifetime of the optical

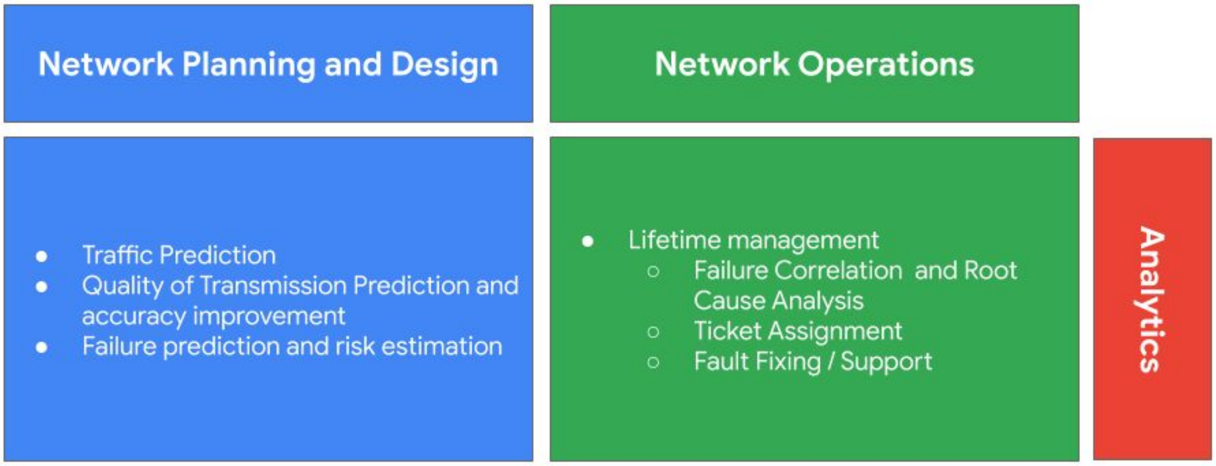

Fig.1 - Opportunities for ML/AI techniques in optical networking

infrastructure. It is worth mentioning that ML in the context of link design should be considered to be as a support technique to well-established analytical and simulative approaches based on physical modeling of optical communications. This is specifically true in the context of green field network design where telemetry used for training models is not yet available. As a matter of fact, quality of transmission estimation does not have stringent realtime requirements during the network design phase. This is not the case for SDN-driven optical restoration, whose benefits compared to IP-layer restoration still need to be proven at scale.

Another potential area of successful adoption of ML techniques is related to failure predictions and risk estimation to properly plan and design the network infrastructure. Historical data on network availability together with performance monitoring data from network devices can be used to improve availability and risk estimations driving an improved network planning. Availability-aware cross-layer network planning requires to test topologies and route traffic according to traffic engineering (TE) policies against random network failures. This operation is computationally challenging as the integration of detailed TE policies requires full networking stack development, and millions of different scenarios need to be simulated/computed to properly test topologies and derive optimized network designs. In this context, ML can help in speeding up network design by helping pruning topologies based with equal availability metrics, or by enabling the emulation of TE application via neural networks based techniques. As for any emulation technique, there is a trade-off between speed and accuracy. Depending on the design objectives, one can trade one for the other. As an example, quick estimation via neural networks can be beneficial in the context of emergency situations, where real time decisions need to be taken (e.g. router drain) for blast radius reduction.

3. Network operations

Apart from network design and planning AI/ML techniques could be used in the context of network operations, i.e. to improve operations and workflows that are taking place when the network is up and running. In this context, ML techniques can be used to take advantage of the large availability of network telemetry which can be used for tasks such as threat detection, failure and root cause analyses and predictive maintenance.
As an example, ML techniques for anomaly detection could be used to detect physical threats to the fiber plants (e.g. construction works) dispatching alarms to network operation centers for mitigation. This is particularly relevant for portion of the infrastructure that are critical from a security standpoint, such as subsea cable landings.

Optical network technologies define standard frame format which contain information for management of the traffic carried. Also, the propagation of faults in the optical network is standardized which would aid in determining the root cause for different failures in the network. However, in real networks, due to the presence of passive components which do not indicate failures and due to the loss of faults as a result of various factors, the deterministic computation of root cause for all the failures in the network may not be possible. In this scenario, identification of probable root cause for failures based on patterns observed in the past would help in fault localization and identification in the network.

Another aspect of fault management is the proactive prediction of faults before they occur in the network. In this context, anomalies and variations in the performance of the network measured in terms of various parameters are strongly correlated to the possible failure in the future. Mapping the performance measurement values in different layers to the normal working conditions of the network and predicting possible faults in the future based on any deviations would be of immense help to network operators to take corrective action and avoid customer churn.

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4. References

[1] Mata, J., De Miguel, I., Duran, R.J., Merayo, N., Singh, S.K., Jukan, A. and Chamania, M., 2018. Artificial intelligence (AI) methods in optical networks: A comprehensive survey. Optical switching and networking, 28, pp.43-57.

[2] Musumeci, F., Rottondi, C., Nag, A., Macaluso, I., Zibar, D., Ruffini, M. and Tornatore, M., 2018. An overview on application of machine learning techniques in optical networks. IEEE Communications Surveys & Tutorials, 21(2), pp.1383-1408.

[3] Boutaba, R., Salahuddin, M.A., Limam, N., Ayoubi, S., Shahriar, N., Estrada-Solano, F. and Caicedo, O.M., 2018. A comprehensive survey on machine learning for networking: evolution, applications and research opportunities. Journal of Internet Services and Applications, 9(1), p.16.

[4] F. N. Khan, Q. Fan, C. Lu and A. P. T. Lau, "An Optical Communication's Perspective on Machine Learning and Its Applications," in Journal of Lightwave Technology, vol. 37, no. 2, pp. 493-516, 15 Jan.15, 2019

[5] D. Rafique and L. Velasco, "Machine learning for network automation: overview, architecture, and applications [Invited Tutorial]," in IEEE/OSA Journal of Optical Communications and Networking, vol. 10, no. 10, pp. D126-D143, Oct. 2018.

[6] A. S. Kashi et al., "Nonlinear Signal-to-Noise Ratio Estimation in Coherent Optical Fiber Transmission Systems Using Artificial Neural Networks," in Journal of Lightwave Technology, vol. 36, no. 23, pp. 5424-5431, 1 Dec.1, 2018.