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Optical Performance Monitoring in Fiber-Optic Networks Enabled by Machine Learning Techniques

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Abstract: We review applications of machine learning (ML) in various aspects of optical communications including optical performance monitoring, fiber nonlinearity compensation, and software-defined networking. The future role of ML in optical communications is also discussed.

OCIS codes: (060.2330) Fiber optics communications; (060.2360) Fiber optics links and subsystems.

1. Introduction

Machine learning (ML) is being hailed as a new direction of innovation to address many emerging challenges in optical communications. ML-based algorithms have shown the capacity to deliver exceptional performance in scenarios where the underlying physics and mathematics of the problem are too difficult to be described explicitly and the numerical procedures involved require significant computational time/resources [1]. Recent applications of ML in different aspects of optical communications such as network planning and performance prediction, nonlinearity compensation, data centers optimization, intelligent testing/measurement equipment realization etc., demonstrate quite promising results. Moreover, several groundbreaking developments in deep learning technology over the past few years further motivate the researchers to explore the true potential of this emerging field in future optical networks. In this paper, we discuss some key applications of ML in fiber-optic networks and highlight their advantages over conventional approaches.

2. ML applications in optical communications and networks

Figure 1 shows some significant research works related to the use of ML techniques in fiber-optic communications. A brief discussion on these works is given below.

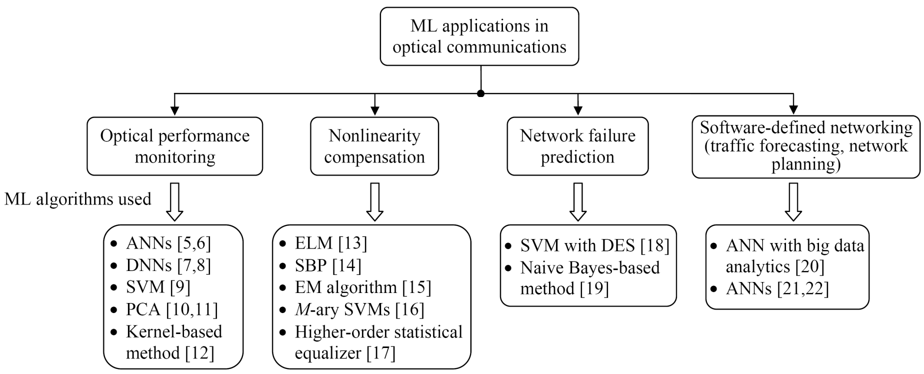

Fig. 1. Some key applications of machine learning in fiber-optic communications.

(i) Optical performance monitoring (OPM): The network architectures in optical communication systems are gradually becoming more complex, dynamic and transparent. Efficient management and reliable operation of such complex fiber-optic networks necessitate incessant and real-time information about different channel impairments ubiquitously across the network, also referred to as OPM [2]. OPM is also considered a key enabling technology for elastic optical networks (EONs). Through OPM, EONs may become aware of actual network conditions and can adaptively adjust different transceiver and network elements parameters such as data rates, modulation formats, forward error correction (FEC) codes, spectrum assignment etc. for the optimization of transmission performance [3]. Unfortunately, conventional OPM techniques have shown limited success in simultaneous and independent monitoring of multiple transmission impairments since the effects of different impairments are often physically inseparable [4]. To remove this bottleneck, ML techniques are proposed as an alternative for realizing low-cost multi-impairment monitoring in optical networks and have already shown tremendous potential. Some important ML-based techniques for OPM include artificial neural networks (ANNs) [5,6], deep neural networks (DNNs) [7,8], support vector machine (SVM) [9], principal component analysis (PCA) [10,11], and kernel-based methods [12].

(ii) Fiber nonlinearity compensation: ML techniques have also been employed for tackling fiber nonlinear distortions in optical networks. These techniques learn the properties of different nonlinear impairments from the observed data and then construct probabilistic models of these impairments which can subsequently be utilized for either quantifying the amount of distortions introduced or for the actual mitigation of these impairments. In [13], we proposed the use of an extreme learning machine (ELM) for the compensation of fiber nonlinearity in coherent optical communication systems. This technique shows comparable performance to conventional digital back-propagation (DBP) method but requires much lower computational complexity. Similarly, Jiang *et al.* [14] proposed stochastic back-propagation (SBP) which outperforms DBP in situations where nonlinear phase noise (NLPN) is the dominant impairment. Other noticeable ML-based approaches for mitigating fiber nonlinearities include the use of expectation maximization (EM) algorithm [15], *M*-ary SVMs [16], and higher-order statistical equalizer [17].

(iii) Network failure prediction: Traditional optical network protection algorithms protect a network in a passive manner i.e. they are unable to forecast the risks and tend to reduce the damages only after a failure occurs. This approach may result in loss of immense amount of data during network recovery process once a failure happens. Therefore, reliable operation of an optical network demands an early warning and proactive protection mechanism incorporated into the network. Recently, a few ML-based algorithms have been developed for advance failure prediction in networks. Wang *et al.* [18] used a combination of double exponential smoothing (DES) and SVM for predicting network equipment failure. Their approach constantly monitors various physical parameters (e.g. power consumption, module internal temperature etc.) of network equipments and then employs DES algorithm to forecast future values of these parameters in the short-term. Next, an SVM-based classifier is used to learn the relationship between forecasted states of various equipments and the occurrence of failure events. This method is shown to predict equipment/network failures with an average accuracy of 95%. Another interesting work in this context is presented in [19] whereby proactive detection of fiber damages is performed by tracking the state-of-polarization speed in a coherent receiver. This approach uses a naive Bayes classifier to successfully recognize the nature of mechanical stresses applied on an optical fiber and can accurately predict fiber breaks before they actually occur.

(iv) Software-defined networking (SDN): ML algorithms are also employed for enabling various functionalities in SDNs. Morales *et al.* [20] used big data analytics in conjunction with ANNs for robust and adaptive network traffic modeling. Based on predicted traffic volume and direction, the virtual network topology (VNT) is then adaptively reconfigured for ensuring required grade of service. In comparison with static VNT design approaches, this method decreases the required number of transponders to be installed at the routers by 8–42%, thus reducing energy consumption and costs. Similarly, Alvizu *et al.* [21] used ML to predict tidal traffic variations in a software-defined mobile metro-core network (SD-MCN). In their work, ANNs are used to forecast traffic at different spatial locations in an optical network and the predicted traffic demands are then exploited to optimize online routing and wavelength

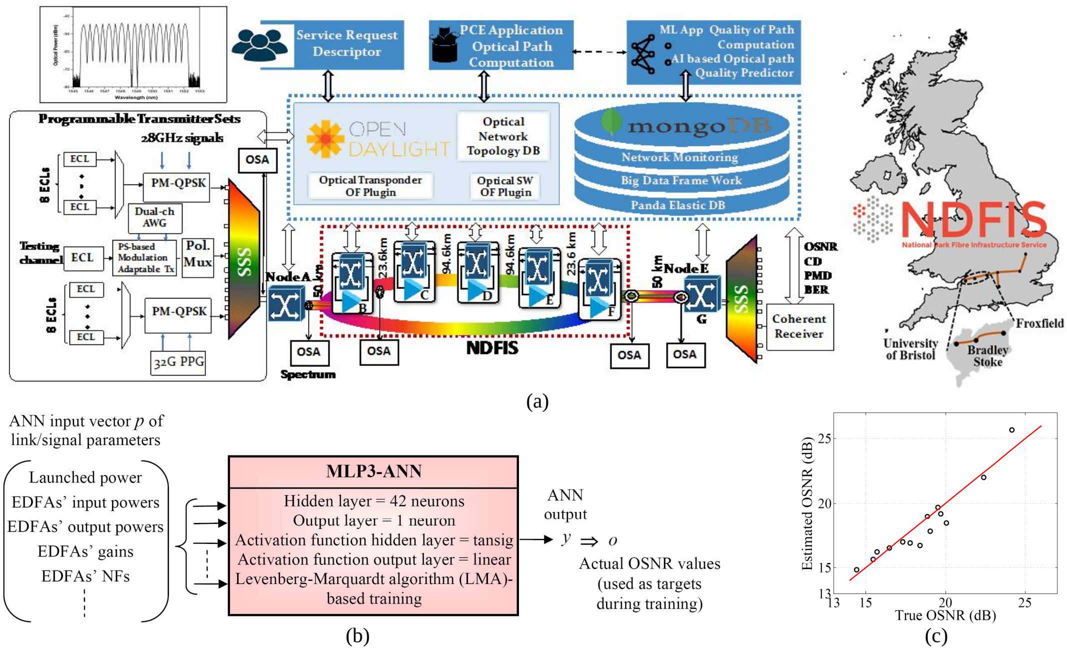

Fig. 2. (a) Field trial demonstration of ML-assisted optical network planning framework in SDNs. (b) ANN model with link/signal parameters as inputs and estimated OSNRs as outputs. (c) True versus estimated OSNRs using the ANN model.

assignments using matheuristics. Due to load-adaptive network operation and dynamic optical routing performed in this approach, energy savings of ~31% are observed as compared to traditional static methods used in MCNs.

In [22], we demonstrated a ML-assisted optical network planning framework in SDNs as shown in Fig. 2 (a). In this work, network configuration as well as real-time information about different link/signal parameters is stored in a network-scale monitoring database. Next, an ANN-based model is trained using this information to learn the relationship between various link/signal parameters and the corresponding known OSNR values for those links, as depicted in Fig. 2 (b). After training, the ANN-based model is able to predict the performance (in terms of OSNR) of various unestablished paths in the network, as shown in Fig. 2 (c), for optimum network planning. We demonstrated that ML-based performance prediction mechanism can be used to adaptively adjust the spectral efficiency and maximize the SDN capacity by employing a probabilistic-shaping (PS) based bandwidth-variable transmitter (BVT).

3. Future role of ML in optical communications

As discussed above, ML algorithms can help solve several diverse problems in optical communication systems. However, it should be noted that many of these issues can be appropriately addressed using conventional DSP-based approaches. Therefore, an important question which needs to be answered is that is there an absolute need for ML-based tools in current/future optical networks? We believe that there are indeed certain scenarios in existing fiber-optic networks in general and future SDNs in particular whereby the role of ML seems mandatory. These cases may include: (i) Systems which exhibit complex dynamic behaviors and whereby analytical models are either hard to derive or the numerical solutions available require very high computational complexity. (ii) As optical networks grow bigger, faster and software-defined, the cross-layer optimization in these networks demands big data analytics, thereby making conventional signal processing tools inadequate for such tasks. ML can play a decisive role in such scenarios since it can inherently learn and uncover hidden patterns and unknown correlations in big data which can be extremely beneficial in solving complex network optimization problems.

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5. References

[1] F.N. Khan *et al.*, "Machine learning methods for optical communication systems," in *Proc. SPPCom*, New Orleans, 2017, Paper SpW2F.3.

[2] F. N. Khan, Z. Dong, C. Lu, and A. P. T. Lau, "Optical performance monitoring for fiber-optic communication networks," in *Enabling Technologies for High Spectral-Efficiency Coherent Optical Communication Networks*, X. Zhou and C. Xie, eds. (Wiley, 2016), Chap. 14.

[3] Z. Dong *et al.*, "Optical performance monitoring: a review of current and future technologies," *J. Lightwave Technol.*, vol. 34, no. 2, 2016.

[4] C. Lu *et al.*, "Optical performance monitoring techniques for high capacity optical networks," in *Int. Symp. CSNDSP*, 2010, pp. 678–681.

[5] F. N. Khan, T. S. R. Shen, Y. Zhou, A. P. T. Lau, and C. Lu, "Optical performance monitoring using artificial neural networks trained with empirical moments of asynchronously sampled signal amplitudes," *IEEE Photon. Technol. Lett.*, vol. 24, no. 12, pp. 982–984, 2012.

[6] F. N. Khan, Y. Yu, M. C. Tan, C. Yu, A. P. T. Lau, and C. Lu, "Simultaneous OSNR monitoring and modulation format identification using asynchronous single channel sampling," in *Proc. Asia Communications and Photonics Conf.*, Hong Kong, 2015, Paper AS4F.6.

[7] T. Tanimura, T. Hoshida, J. C. Rasmussen, M. Suzuki, and H. Morikawa, "OSNR monitoring by deep neural networks trained with asynchronously sampled data," in *Proc. OptoElectronics and Communications Conference*, Niigata, 2016, Paper TuB3-5.

[8] F. N. Khan, K. Zhong, X. Zhou, W.H. Al-Arashi, C. Yu, C. Lu, and A. P. T. Lau, "Joint OSNR monitoring and modulation format identification in digital coherent receivers using deep neural networks," *Opt. Exp.*, vol. 25, no. 15, pp. 17767–17776, 2017.

[9] R. A. Skoog *et al.*, "Automatic identification of impairments using support vector machine pattern classification on eye diagrams," *IEEE Photon. Technol. Lett.*, vol. 18, no. 22, pp. 2398–2400, 2006.

[10] M. C. Tan *et al.*, "Simultaneous optical performance monitoring and modulation format/bit-rate identification using principal component analysis," *IEEE/OSA Journal of Optical Communications and Networking*, vol. 6, no. 5, pp. 441–448, 2014.

[11] F. N. Khan, Y. Yu, M. C. Tan, W.H. Al-Arashi, C. Yu, A. P. T. Lau, and C. Lu, "Experimental demonstration of joint OSNR monitoring and modulation format identification using asynchronous single channel sampling," *Opt. Exp.*, vol. 23, no. 23, pp. 30337–30346, 2015.

[12] T. B. Anderson *et al.*, "Multi impairment monitoring for optical networks," *J. Lightwave Technol.*, vol. 27, no. 16, pp. 3729–3736, 2009.

[13] T. S. R. Shen, and A. P. T. Lau, "Fiber nonlinearity compensation using extreme learning machine for DSP-based coherent communication systems," in *Proc. OptoElectronics and Communications Conference*, Kaohsiung, 2011, pp. 816–817.

[14] N. Jiang *et al.*, "Stochastic backpropagation for coherent optical communications," in *Proc. ECOC*, Geneva, 2011, Paper We.10.P1.81.

[15] D. Zibar *et al.*, "Nonlinear impairment compensation using expectation maximization for dispersion managed and unmanaged PDM 16-QAM transmission," *Opt. Exp.*, vol. 20, no. 26, pp.B181–B196, 2012.

[16] M. Li, S. Yu, J. Yang, Z. Chen, Y. Han, and W. Gu, "Nonparameter nonlinear phase noise mitigation by using *M*-ary support vector machine for coherent optical systems," *IEEE Photonics Journal*, vol. 5, no. 6, 2013.

[17] T. K. Akino *et al.*, "High-order statistical equalizer for nonlinearity compensation in dispersion-managed coherent optical communications," *Opt. Exp.*, vol. 20, no. 14, pp. 15769–15780, 2012.

[18] Z. Wang *et al.*, "Failure prediction using machine learning and time series in optical network," *Opt. Exp.*, vol. 25, no. 16, 2017.

[19] F. Boitier *et al.*, "Proactive fiber damage detection in real-time coherent receiver," in *Proc. ECOC*, Gothenburg, 2017, Paper Th.2.F.1.

[20] F. Morales, M. Ruiz, L. Gifre, L. M. Contreras, V. López, and L. Velasco, "Virtual network topology adaptability based on data analytics for traffic prediction," *IEEE/OSA Journal of Optical Communications and Networking*, vol. 9, no. 1, pp. A35–A45, 2017.

[21] R. Alvizu, S. Troia, G. Maier, and A. Pattavina, "Matheuristic with machine-learning-based prediction for software-defined mobile metro-core networks," *IEEE/OSA Journal of Optical Communications and Networking*, vol. 9, no. 9, pp. D19–D30, 2017.

[22] S. Yan *et al.*, "Field trial of machine-learning-assisted and SDN-based optical network planning with network-scale monitoring database," in *Proc. European Conf. on Optical Commun.*, Gothenburg, 2017, Paper Th.PDP.B.4.