Machine Learning-Assisted Optical Performance Monitoring in Fiber-Optic Networks

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***Abstract*—We review machine learning (ML)-based optical performance monitoring (OPM) techniques in optical communications. Recent applications of ML-assisted OPM in different aspects of fiber-optic networking including cognitive fault detection and management, network equipment failure prediction, and dynamic planning and optimization of software-defined networks are also discussed.**

Keywords—Optical performance monitoring; machine learning; software-defined networks; fiber-optic networks.

I. ML-BASED OPM

Machine learning (ML) techniques have appeared as a new direction of innovation to cope with several emerging challenges in optical communications. ML-based algorithms are well known for delivering exceptional performance in situations where it is too difficult to explicitly describe the underlying physics and mathematics of the problem or the numerical solutions available necessitate substantial computational resources/time [1]. Recently, we have seen an increasing amount of research on the application of ML techniques to various tasks in fiber-optic communications like nonlinearity compensation, network planning and performance prediction, intelligent measurement/testing equipment realization, data centers optimization etc. [2]. Moreover, with the advent of deep learning technology, the researchers are further motivated to explore true potential of this emerging field in different aspects of optical communications.

Optical performance monitoring (OPM) is the estimation and acquisition of various critical physical parameters of transmitted optical signals and network components. OPM functionalities are indispensable for reliable and flexible network operation as well as for improved network efficiency [3]. OPM is also widely regarded as a key enabling technology for software-defined networks (SDNs). Through OPM, SDNs can become aware of real-time network conditions and subsequently adjust various transceiver/network components parameters like launched powers, data rates, modulation formats, spectrum assignment etc. for optimized transmission performance [4]. Over the past few years, ML algorithms have been applied successfully for cost-effective multi-impairment monitoring in optical networks. For example, in [5], we have shown the use of artificial neural networks (ANNs) in combination with empirical moments of received signal amplitudes for low-cost multi-impairment monitoring. Similarly, in [6], joint optical signal-to-noise ratio (OSNR) monitoring and modulation format identification (MFI) in digital coherent receivers is demonstrated by employing deep neural networks (DNNs) in combination with amplitude histograms. In [7], principal component analysis (PCA) and statistical distance measurement based pattern recognition is applied on delay-tap plots for joint OSNR, chromatic dispersion, and differential group delay monitoring as well as identification of bit-rates and modulation formats of the received signals. Other important ML-based OPM techniques include support vector machine (SVM) [8], convolutional neural network (CNN) [9], and kernel-based methods [10].

II. APPLICATIONS OF ML-BASED OPM IN OPTICAL NETWORKS

Figure 1 depicts some key applications of ML-assisted OPM in fiber-optic networks including proactive fault detection/prevention, dynamic planning and optimization of SDNs, and quality-of-transmission (QoT) prediction. A short discussion on them is provided below.

Proactive fault detection/prevention: To enable robust network operation, it is imperative to incorporate an early warning and proactive protection mechanism into the network. ML techniques have recently been applied for advance fault detection in optical networks. In [11], a combination of double exponential smoothing (DES) and SVM is used for network equipment failure prediction. In their work, various physical parameters of network equipments are continuously monitored and the future values of these parameters are then forecasted utilizing DES algorithm. Next, an SVM classifier is employed to learn the relationship between forecasted states of different equipments and the occurrence of failure events. This ML-based method is able to predict network/equipment failures with an average accuracy of 95%. Similarly, in [12], proactive detection of fiber damages is demonstrated by recognizing the mechanical stress-dependent Stokes parameters traces in a coherent receiver with the help of a naive Bayes classifier. This

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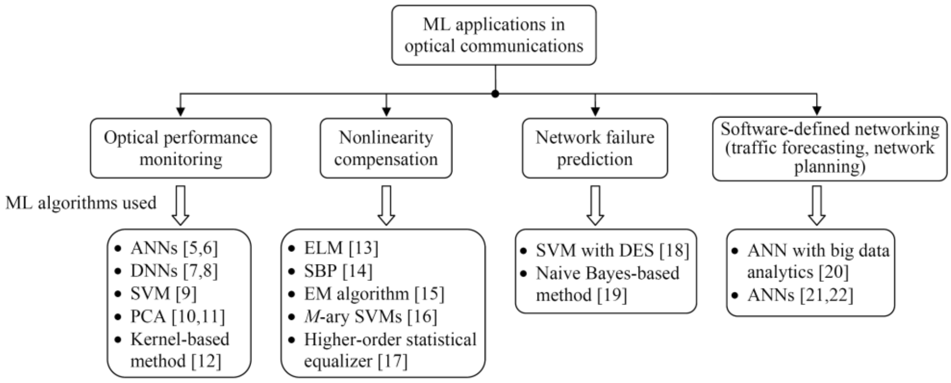

Fig. 1. Some key applications of ML-assisted OPM in optical communications. (Figure is Old. I am currently working on the new version)

approach is shown to predict fiber breaks accurately before their actual occurrence. Another interesting work in this context is presented in [13], where an ANN is used to learn the historical fault patterns in networks for proactive fault detection. In this method, an ANN is trained to learn how the received optical power levels evolve over time under normal or abnormal operation of a network. The trained ANN is then able to detect significant network faults with better detection accuracies and proactive reaction times as compared to conventional threshold-based fault detection approach.

Planning and optimization of SDNs: ML-based OPM can also be used for realizing various functionalities in SDNs. Recently, we proposed a ML-assisted optical network planning framework in SDNs [14]. In this approach, real-time information about different signal/link parameters as well as network configuration is stored in a network-scale monitoring database. Next, an ANN model is trained utilizing this information so that it can learn the relationship between various signal/link parameters and the corresponding known OSNR values for those links. Once the training process is over, the ANN model can be used to accurately predict the performance (in terms of OSNR) of different unestablished lightpaths in the network for optimum network planning. We demonstrated via field trials that ML-assisted OSNR prediction mechanism can be employed to maximize the SDN capacity by using a probabilistic shaping-based spectral efficiency tunable transmitter.

(QoT) prediction: Predicting QoT of lightpaths prior to their deployment is indispensable for optimum design of optical networks. Conventionally, QoT prediction techniques are either based on some sophisticated analytical models which exploit the information about various physical impairments to predict the quality of a given lightpath with good accuracy (at the expense of high computational complexity) or they make use of some simple approximated formulas, enabling fast but relatively less accurate predictions. ML-based QoT prediction methods have recently been proposed as an attractive alternative [15]. These approaches use ML algorithms to learn the relationship between monitored field data and QoT of already deployed lightpaths (obtained through installed OPM devices) to predict the QoT of unestablished lightpaths. Some key ML-based QoT prediction techniques include network kriging [16], case-based reasoning (CBR) [17], SVM [18], ANN [19], and random forest (RF) [15] based methods.

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