Application of Machine Learning Techniques in Fiber-Optic Communication Systems

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Abstract: We discuss machine learning applications in different aspects of fiber-optic communications including fiber nonlinearity compensation, optical performance monitoring, cognitive fault detection/prevention, and planning and optimization of software-defined networks.
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1. Introduction

Machine learning (ML) techniques have appeared as a new direction of innovation to address many emerging challenges in fiber-optic communications. ML-based methods are well known to perform exceptionally well in scenarios where it is too difficult to explicitly describe the underlying physics and mathematics of the problem and the numerical procedures available require significant computational resources/time [1]. Over the last few years, we have seen several research works focusing on the application of ML algorithms in various aspects of optical communications such as fiber nonlinearity compensation, data centers optimization, intelligent testing/measurement equipment realization, network planning and performance prediction etc. Recent groundbreaking advancements in deep learning technology have further motivated the researchers to explore true potential of this emerging field in optical networks. In this paper, we review some significant research works pertaining to the use of ML algorithms in fiber-optic communications.

2. Applications of ML methods in optical communications

Figure 1 shows some key applications of ML methods in fiber-optic communications. A short discussion on these works is provided below.

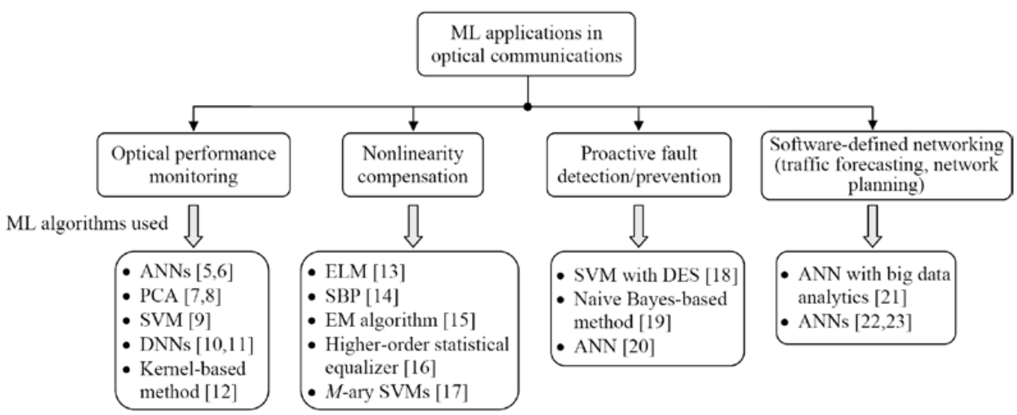

Fig. 1. Some key applications of ML algorithms in optical communications.

(i) Optical performance monitoring (OPM): OPM is regarded as a key enabling technology for emerging software-defined networks (SDNs). By using OPM, SDNs can become aware of actual network conditions and thus dynamically configure various transceiver and network elements parameters e.g. spectrum assignment, transmitted powers, baud rates, modulation formats, forward error correction (FEC) codes, etc. in order to achieve optimum transmission performance [2-4]. To this end, ML-based OPM techniques have gained significant attention recently for enabling cost-effective multi-impairment monitoring in optical networks. Some key ML-based OPM techniques include artificial neural networks (ANNs) [5,6], principal component analysis (PCA) [7,8], support vector machine (SVM) [9], deep neural networks (DNNs) [10,11], and kernel-based methods [12].

(ii) Fiber nonlinearity mitigation: ML-based algorithms have also been applied for compensating fiber nonlinear

distortions. These methods are based on learning the properties of various nonlinear impairments from the observed data and generating probabilistic models of these impairments which are then utilized for either compensating these impairments or quantifying the amount of distortions introduced. Some important ML-based nonlinearity compensation techniques include extreme learning machine (ELM) [13], stochastic back-propagation (SBP) [14], expectation maximization (EM) algorithm [15], higher-order statistical equalizer [16], and *M*-ary SVMs [17] based methods.

(iii) Proactive fault detection/prevention: Reliable operation of an optical network requires incorporation of an early warning and proactive protection mechanism into the network. Recently, several ML-based techniques have been developed for cognitive fault detection/prevention in fiber-optic networks. For example, Wang *et al.* [18] used a combination of double exponential smoothing (DES) and SVM for network equipment failure prediction. Similarly, in [19], proactive fiber damages detection is performed in a coherent receiver by recognizing mechanical stress-dependent Stokes parameters traces using a naive Bayes classifier. In [20], an ANN is trained to learn historical fault patterns in networks and is subsequently used for detecting significant network faults with much better accuracies and proactive reaction times as compared to traditional threshold-based fault detection methods.

(iv) Software-defined networking: ML techniques have also been applied for enabling several critical functionalities in SDNs. In [21], ANNs are used in conjunction with big data analytics for network traffic modeling. Based on predicted traffic volume/direction, virtual network topology (VNT) is dynamically reconfigured in this work. This approach is shown to significantly decrease the required number of transponders at the routers in comparison with static VNT design approaches, thus reducing energy consumption and costs. Similarly, in [22], ANNs are applied for predicting traffic at different spatial locations in a software-defined mobile metro-core network (SD-MCN). The traffic forecasts are then exploited for optimizing online routing and wavelength assignments. Recently, we demonstrated field trails of a ML-based optical network planning framework in SDNs [23]. In this work, a network-scale monitoring database is synthesized storing network configuration as well as real-time information about various signal/link parameters. This information is then exploited for the training of an ANN model which learns the relationship between different signal/link parameters and the known OSNR values corresponding to those links. The trained ANN model is then employed for predicting the performance (in terms of OSNR) of various unestablished lightpaths in SDN for optimum network planning and capacity maximization.

3. Conclusion

In this paper, we discussed how the rich body of ML techniques can be applied as a unique and powerful set of signal processing tools in fiber-optic communications. As optical networks become bigger, faster and software-defined, we will increasingly see more applications of ML and big data analytics in future networks to solve certain critical problems that cannot be easily tackled by conventional approaches.

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