Advances in Deep Learning for Digital Signal Processing in Coherent Optical Modems

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Abstract: We analyze the advances of deep learning in optical coherent modems on the physical layer with respect to modulation design, equalization and signal detection and give an outlook on a combined control and physical layer optimization using neural networks.

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1. Introduction

Since the introduction of the first coherent optical modems based on 40Gb/s, modem line rates have increased to 800Gb/s in 2020 and are targeted to exceed 1Tb/s per wavelength in 2021. The revolution of coherent optics was enabled by the introduction of digital signal processing (DSP) which enabled the compensation of various impairments using cheap digital logic instead of expensive analog optics. The first modems only had a basic DSP functionality compensating for linear effects, such as chromatic dispersion (CD), polarization mode dispersion (PMD) or linear bandwidth limiting effects of the integrated coherent receivers (ICR) [1]. Later transceivers started to employ more sophisticated techniques including the compensation of fiber [2] and component nonlinearities [3] in order to improve the modem performance. The compensation of nonlinearities is a non-trivial problem, since these effects occur along the link in a cascade of various linear and nonlinear distortions with different degrees of intra and inter channel crosstalk, as well as white and colored noise. While Volterra equalizers are general tool to remove nonlinear distortions [4], deep learning using neural networks have been proposed for mitigation as well, possibly offering a superior performance at comparable complexity or a reduction in complexity at comparable performnace [5]. In this contribution, we review the possible use cases for deep learning in coherent optical modems.

2. Deep Learning for coherent optical DSPs

Artificial intelligence is the science and engineering of making computers behave in ways that we thought required human intelligence. Machine learning (ML) is a subset of general artificial intelligence algorithms and is the study of computer algorithms that allow computer programs to automatically improve through experience. As shown in Fig. 1 (left), it can be classified in the three major areas - supervised learning with available reference signals, unsupervised learning, where the learning uses inherent signal statistics for adaptation, and reinforcement learning, which is about taking suitable actions to maximize reward in a particular situation. Depending on the problem which is addressed by machine learning, the type of learning method may vary. Here, deep neural networks using several hidden sublayers are a popular method to apply machine learning and map a higher dimensional nonlinear problems into a digital circuit.

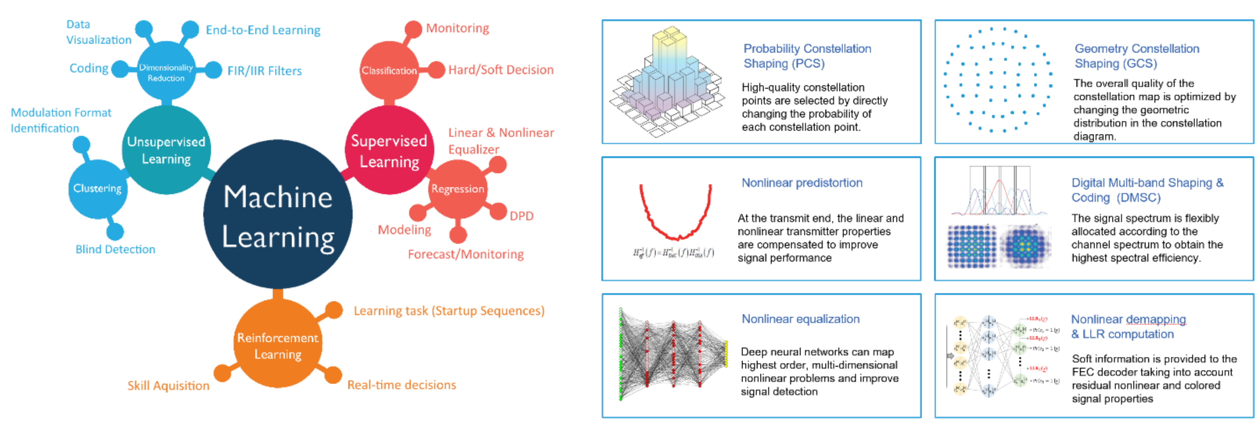

Fig. 1 – Classes of ML applicable to optical communication (left); DSP subcomponents powered by ML (right)

Machine learning can be used in the most abstract form of auto-encoding to take bits at the input and design the complete transmitter and receiver DSP in between as a neural network black box [6]. Although this is theoretically possible, it is impractical due to the inability of the neural network to train fast. Thus, it is more desirable to continue dividing the DSP into subcomponents and for example design synchronization algorithms using classical fast tracking techniques, which were proven to be optimal [1], while using neural networks to address specific, highly complex problems, as outlined in Fig. 2 on the right. Suitable examples include channel matched signal shaping, which takes into account the fiber nonlinearities and is not just purely optimized on an additive white Gaussian noise (AWGN) channel [7]. Fig. 2 illustrates an example of the application of machine learning to constellation design. Fig. 2 (left) shows a classical geometrically shaped 32QAM signal, a design which can also be designed by hand. However, this symbol-wise geometric shaping doesn’t take into account the problem of the optimum bit mapping and is prohibitively hard to compute with classical means for higher order modulations and coding in several dimensions (polarization, time, frequency). Here, machine learning offers a solution for this optimization problem, as shown in Fig. 2 (middle), and provides an alternative 32QAM scheme for the AWGN channel which outperforms the classical cross-32QAM by 0.3dB. Such a 32QAM variant can be a suitable candidate for future 800ZR+ standards [3].

Fig. 2 – Symbol-wise geometric shaping (left); Bit-wise geometric shaping (middle); Performance (right)

Deep learning aided modulation design can be used in combination with digital multi-band shaping in coding and nonlinear power loading [8] to arrive at optimal solutions for this highly dimensional and nonlinear optimization problem, which is quite hard to map using alternative methods. An example is shown in Fig. 3 (left) where the optimum nonlinear power loading with varying bit loading per subcarrier was computed for a multi-carrier system, taking into account the nonlinear crosstalk between the subcarriers, as generated at the transmitter side as a side-effect of the power loading itself. This can be combined with a higher dimensional, machine learned modulation scheme per subcarrier, as shown in Fig. 3 (right) on the example of a 4D constellation with 10 bit/symbol. The transmitter design can be completed using an extreme learning machine enabled nonlinear digital predistortion [9], which can be used for optical transmitter output power maximization in dark fiber links.

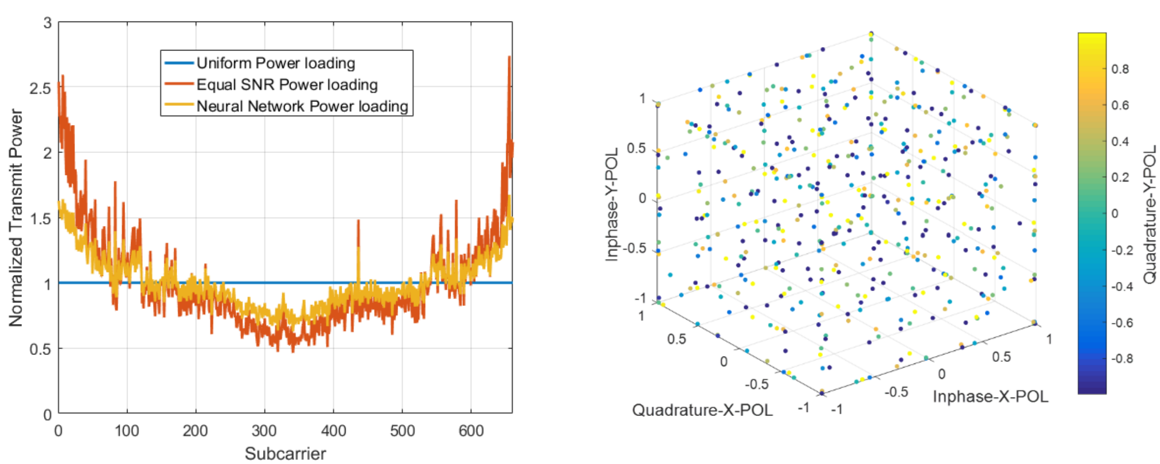

Fig. 3 – Nonlinear power loading (left); 4D modulation design with 10 bits/symbol (right)

At the receiver side, neural networks have been proposed for the compensation of fiber nonlinearities [5,10] and nonlinear component distortions caused by DAC, drivers, the modulator, the integrated coherent receiver and the ADC [11,12]. Here, neural networks have shown the capability to either decrease the complexity of a given problem, as with the example of fiber backpropagation [5] or improve the equalization of a higher order nonlinear task as with the example of nonlinear transmitter imperfections [11,12].

Finally, machine learning can be used to compute the optimum nonlinear demapping of a given multi-dimensional constellation and provide the forward error correction (FEC) with log likelihood ratios (LLR), which are based on the actual residual nonlinear and colored noise characteristics of the signal after the equalization stage [13].

3. Joint modem network optimization

Machine learning has already been productized in optical networks in the domain of network planning, automation, failure prediction or optical performance monitoring [14,15]. However, these methods are still in their infancy, since the learning only includes the control and management layer and feeds back basic settings to each modem, which then establishes a connection based on the isolation calibration and equalization as outlined in Chapters 2-3. As indicated in Fig. 4, deep learning can be used to extend the joint optimization of the network, by introducing a joint AI modem optimization, in which the whole array of modems employing nonlinear shaping techniques is jointly optimized in a given network, taking into the account the completeness of DWDM nonlinear and linear interactions. Neural networks are well suited in order to address this nonlinear and highly multi-dimensional optimization problem.

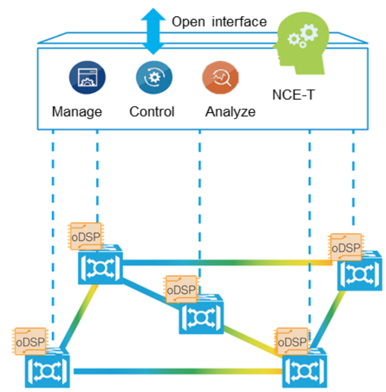

Fig. 4 – AI-powered optical network with joint modem

4. Future evolution of deep learning for DSPs

Machine learning is already part of optical networks on the control and management layer and is progressing to the physical layer as well. Here, we need to distinguish between the more complex real-time tasks like nonlinear equalization and offline optimization problems, such as nonlinear modulation design, which can be offloaded from the power-constrained DSP ASIC in the optical modem to a common CPU or TPU running in the chassis. The increasing complexity of joint modulation and network design will make deep learning a quintessential tool for optical modem & network design.

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