in the complexity of optical networks.

On a system side, while optical channel modeling has always been complex, the recent adoption of coherent technologies [11] has made modeling even more difficult by introducing a plethora of adjustable design parameters (as modulation formats, symbol rates, adaptive coding rates and flexible channel spacing) to optimize transmission systems in terms of bit-rate transmission distance product. In addition, what makes this optimization even more challenging is that the optical channel is highly nonlinear.

From a networking perspective, the increased complexity of the underlying transmission systems is reflected in a series of advancements in both data plane and control plane. At data plane, the Elastic Optical Network (EON) concept [12]–[15] has emerged as a novel optical network architecture able to respond to the increased need of elasticity in allocating optical network resources. In contrast to traditional fixed-grid Wavelength Division Multiplexing (WDM) networks, EON offers flexible (almost continuous) bandwidth allocation. Resource allocation in EON can be performed to adapt to the several above-mentioned decision variables made available by new transmission systems, including different transmission techniques, such as Orthogonal Frequency Division Multiplexing (OFDM), Nyquist WDM (NWDM), transponder types (e.g., BVT[1], S-BVT), modulation formats (e.g., QPSK, QAM), and coding rates. This flexibility makes the resource allocation problems much more challenging for network engineers. At control plane, dynamic control, as in Software-defined networking (SDN), promises to enable long-awaited on-demand reconfiguration and virtualization. Moreover, reconfiguring the optical substrate poses several challenges in terms of, e.g., network re-optimization, spectrum fragmentation, amplifier power settings, unexpected penalties due to non-linearities, which call for strict integration between the control elements (SDN controllers, network orchestrators) and optical performance monitors working at the equipment level.

All these degrees of freedom and limitations do pose severe challenges to system and network engineers when it comes to deciding what the best system and/or network design is. Machine learning is currently perceived as a paradigm shift for the design of future optical networks and systems. These techniques should allow to infer, from data obtained by various types of monitors (e.g., signal quality, traffic samples, etc.), useful characteristics that could not be easily or directly measured. Some envisioned applications in the optical domain include fault prediction, intrusion detection, physical-flow security, impairment-aware routing, low-margin design, traffic-aware capacity reconfigurations, but many others can be envisioned and will be surveyed in the next sections.

The survey is organized as follows. In Section II, we overview some preliminary ML concepts, focusing especially on those targeted in the following sections. In Section III we discuss the main motivations behind the application of ML in the optical domain and we classify the main areas of applications. In Section IV and Section V, we classify and summarize a large number of studies describing applications of ML at the transmission layer and network layer. In Section VI, we quantitatively overview a selection of existing papers, identifying, for some of the applications described in Section III, the ML algorithms which demonstrated higher effectiveness for each specific use case, and the performance metrics considered for the algorithms evaluation. Finally, Section VII discusses some possible open areas of research and future directions, whereas Section VIII concludes the paper.

[1]For a complete list of acronyms, the reader is referred to the Glossary at the end of the paper.

II. Overview of machine learning methods used in optical networks

This section provides an overview of some of the most popular algorithms that are commonly classified as machine learning. The literature on ML is so extensive that even a superficial overview of all the main ML approaches goes far beyond the possibilities of this section, and the readers can refer to a number of fundamental books on the subjects [16]–[20]. However, in this section we provide a high level view of the main ML techniques that are used in the work we reference in the remainder of this paper. We here provide the reader with some basic insights that might help better understand the remaining parts of this survey paper. We divide the algorithms in three main categories, described in the next sections, which are also represented in Fig. 1: supervised learning, unsupervised learning and reinforcement learning. Semi-supervised learning, a hybrid of supervised and unsupervised learning, is also introduced. ML algorithms have been successfully applied to a wide variety of problems. Before delving into the different ML methods, it is worth pointing out that, in the context of telecommunication networks, there has been over a decade of research on the application of ML techniques to wireless networks, ranging from opportunistic spectrum access [21] to channel estimation and signal detection in OFDM systems [22], to Multiple-Input-Multiple-Output communications [23], and dynamic frequency reuse [24].

A. *Supervised learning*

Supervised learning is used in a variety of applications, such as speech recognition, spam detection and object recognition. The goal is to predict the value of one or more output variables given the value of a vector of input variables $\mathbf{x}$. The output variable can be a continuous variable (regression problem) or a discrete variable (classification problem). A training data set comprises N samples of the input variables and the corresponding output values. Different learning methods construct a function $y(\mathbf{x})$ that allows to predict the value of the output variables in correspondence to a new value of the inputs. Supervised learning can be broken down into two main classes, described below: *parametric models*, where the number of parameters to use in the model is fixed, and *non-parametric models*, where their number is dependent on the training set.

1) Parametric models: In this case, the function y is a combination of a fixed number of parametric basis functions. These models use training data to estimate a fixed set of parameters $\mathbf{w}$. After the learning stage, the training data can