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Optical Networks Automation Overview: A Survey

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Abstract

The increasing demand for data has driven the advancement of optical networks from traditional architectures to more flexible, dynamic and efficient solutions. This includes technologies like flexgrid reconfigurable optical add-drop multiplexers (ROADMs), variable bandwidth transponders (VBTs) providing different modulation, coding schemes and baud rates. These advancements have brought about new challenges that concerns to the routing and spectrum allocation (RSA), fragmented spectrum, need for rapid and efficient channel restoration, and operation and maintenance management of optical networks. To address these challenges, a dynamic and flexible network requires a highly advanced network operational system (OS) capable of efficiently managing and allocating network resources. It relies on network abstraction, sensors, actuators, and software-defined networking (SDN) to enable algorithms, management, control, and decision-making. Improving the sensing capabilities of the network is crucial. Modern hardware and sensor technology can help forecast fiber breaks, equipment failures, and other potential issues in advance, allowing for proactive actions to be taken. Machine learning (ML) methods have been proposed in the literature to enhance the accuracy of quality of transmission (QoT) estimation, mitigate nonlinearities and provide decisions. This reduces the need for conservative design margins, maximizes the capacity of optical network systems and reduces the investment in infrastructure. Failure management is a critical aspect of optical networks. Providing early-warning and proactive protection is essential. This includes detecting failures, localizing them, identifying the root causes, and estimating their magnitude. Quick response to failures is vital to maintaining network reliability.

Keywords: Network Automation, Machine Learning, Quality of Transmission, Failure Management.

1. Introduction

In this paper I will provide a survey about machine learning applications and algorithms in Optical networks, including themes such as elastic optical networks (EONs), SDN, network abstraction, network data collection (modulation format, OSNR, fiber polarization sensors), algorithms for quality of transmission (QoT) and also optical networks failure management from failure prediction and early detection, failure detection, failure localization, failure identification and failure magnitude estimation. Optical networks have been widely used for traffic transport for several advantages, such as wide bandwidth, low latency, and high anti-interference capability. It links the upper layer services and the underlying physical resources: on one hand, it needs to provision the bandwidth for different service needs; and on the other hand, optical networks involve resources allocation problem in multiples dimensions, such as wavelengths, spectrum slot, and time slot.

This scenario makes optical network operation and maintenance more complicated than other communication networks. If you take into account the convergence of optical network with 5G mobile network and IP networks, it will become more serious. In general, there are mainly three challenges faced by development and operation of optical networks:

- **Network Complexity:** Support to new services, applications and different types of network elements to meet the requirements of 5G networks, cloud computing and IoT (internet of things) [1].
- **Service Complexity:** Support to a wide range of different services such as voice, video, data and cloud computing. Each service has different requirements in terms of bandwidth, latency and reliability. So, different QoS (Quality of Service) requirements make the network design and operation very difficult and challenging.
- **Resource Management Complexity:** Optical networks use a variety of resources such as spectrum, fiber, wavelength, modulation format and baud rate. These resources need to be managed efficiently to meet services demand and reasonable QoT.

Traditional networks' scalability and efficiency are limited by largely static operational and optimization approaches [2]. ML offers a range of methods for essentially adapting to the dynamic network behavior. Although the use of ML in optical networks is still in its infancy, these learning-based techniques offer a promising framework for fault management and end-to-end network automation [2].

The exponential traffic increase from a variety of sources (internet, gaming, Internet IoT, streaming, etc), makes it very challenging for optical networks to handle all this heterogeneous traffic demand. This new great demand cannot be supported by the conventional optical networks. Efficiency, flexibility, and scalability are the requirements for the new optical network. These requirements are met by the EON. The ability to assign spectrum to lightpaths in accordance with client bandwidth needs is present in an EON [3]. The spectrum is split into small slots, and each optical connection is assigned a different number of frequency slots. As a result, compared to the traditional Dense Wavelength Division Multiplexing (DWDM) optical networks, network usage efficiency is significantly improved.

For managing and allocating network resources in a dynamic network environment, a sophisticated network OS is necessary. Optimization of capacity, security and reliability of the network should all be included in the design of such OS. Furthermore, sophisticated machine learning algorithms will be necessary to be implemented on top of the network OS in order to sense and control the network. As a result, the network will be able to perform a variety of functions that are essential for the future network, including self-configuration, self-optimization and self-healing. The network will need sensors to collect data about the network, network abstraction (to hide some aspects while providing crucial data), algorithms to process and analyze the data, and actuators for network control and implementation of actions based on decisions of the algorithms. Abstraction is crucial because it allows the network to streamline complex data and only provide the information that is pertinent to the algorithms that are operating on top of it.

Many options for enhanced performance and optimization are presented by dynamic and flexible optical networks. The presence of VBTs, flexgrid ROADMs, different modulation schemes, coding schemes, symbol rates, all these different parameters provide great flexibility in assigning and managing network resources. However, greater intelligence and decision-making capabilities are required as flexibility increases. To achieve optimum performance, all these different and free knobs require intelligent systems and sophisticated algorithms.

To permit early identification of potential disruptions or impairments, such as a backhoe digging close to the fiber network, network sensing capabilities must also be improved. Early detection of such disturbances enables preemptive action to minimize the huge effects of a potential fiber cut and prevent network outages. Consequently, it can be understood how crucial failure management is in optical networks. It is essential to guarantee the stable operation, ensure the service status, and, in the event of a failure, recover it quickly. Despite its significance, failure recovery still needs intricate and time-consuming human involvement. So, failure recovery automation is a critical component of operators' long-term plans. Optical networks are subject to a few failure modes, divided into soft and hard failure in a general sense.

Soft failures may affect the quality of the services provided on top of such networks by lowering the transmission quality of lightpaths and introducing errors at the optical layer [2]. Filter shifting, filter tightening, filter blocking, and loss increase are examples of soft failures [4].

Fiber cuts, equipment failure, power outages, and/or optical component failures are examples of hard failures (connectors, couplers, splitters, or defects in manufacturing).

In the field of optical networks, artificial intelligence (AI) approaches are being explored and used more often to handle a variety of issues, including traffic prediction, topology design, path calculation, resource allocation, and failure management [2,4]. A direction that shows promise involves using ML to automate failure management operations.

As previously commented, tasks in failure management are separated into two broad categories: active approaches and passive approach methods. Alarm analysis, failure prediction, failure detection, failure identification, failure diagnosis, and failure localization are a few of the sub-tasks that these methodologies can be further broken down into. The following are recent trends that are paving the way towards successful and effective ML applications in optical networks:

• Modern Optical Equipment (ROADMs, transceivers, amplifiers) is now installed with embedded monitoring capabilities such as digital signal processing (DSP) units with embedded neural networks (NN) to combat and/or mitigate nonlinear distortions [5,6].
• The large amount of data available from the optical performance monitoring (OPM) interfaces from this new instrumented network can now be collected and processed in centralized locations thanks to SDN [7].

2. Optical Communications Background

The further an optical signal travels, the more the signal degrades through attenuation, distortion, and loss of timing. Optical signal degradation is caused by many factors including impairments, reflections, linear and nonlinear effects that occur in the fiber cable. Linear impairments include chromatic dispersion (CD), polarization mode dispersion (PMD), polarization dependent loss (PDL) and fiber attenuation. Nonlinear impairments are based on Kerr effect and Inelastic scattering. The CD establishes a phase shift that is dependent of the frequency to the signals, causing the light to spread and creating inter-symbol interference. The imperfections in the fiberoptics cause the two possible polarizations to propagate at different phase velocities. This behavior is mentioned as PMD.

In modern networks, the DSP unit that is present in the coherent transceivers can mitigate both CD and PMD allowing high rates lightpaths to propagate over long distances. Polarization dependent loss (PDL) is the variation of transmitted power based on the values of the signal polarization states. Fiber loss or fiber attenuation is the decrease in signal strength as a function of the transmission distance. There are different types of losses such as absorption (presence of impurities in the fiber), scattering (interaction between light waves with small particles in the fiber), dispersion (caused by CD and PMD), bending and connector losses. There are basically two types of scattering: stimulated Raman scattering (SRS) and stimulated Brillouin scattering (SBS) which will be explained afterwards. The Kerr effect causes the refractive index of the fiber material to change proportionally to the intensity of the electromagnetic field. Nonlinear impairments include cross phase modulation (XPM), self-phase modulation (SPM), XPolM (cross-polarization modulation) and four wave mixing (FWM).

SPM refers to the phenomenon caused by the interaction of the laser beam with the medium which introduces a phase modulation on itself [8]. This is caused by the different speeds of the laser beam components. The index of refraction is changed with optical power level inducing a frequency chirp. The interaction of this frequency chirp with the fiber's dispersion makes the optical pulse spectrum to be broadened.

The XPM is a nonlinear effect due to interactions of copropagating channels. The XPM induces frequency chirping and pulse broadening causing overlapping between channels [9].

XPolM consists in channel crosstalk in DWDM systems due to irregular propagation of state of polarization (SOP) in the core of the fiber due to PMD [9].

FWM in DWDM systems is generated by the nonlinear interaction between two or more co-propagating channels [9]. This interaction creates an additional wave. It occurs in dispersion-shifted fiber (DSF) whose CD is zero at a specific wavelength used for optical transmission.

Inelastic scattering refers to the transfer of energy between the interacting field and the dielectric medium. There are basically two types of inelastic scattering: stimulated Brillouin scattering (SBS) and stimulated Raman scattering (SRS). SRS transfers optical energy from a shorter wavelength to a higher wavelength channel.

SBS consists of a backward scattering. As a wavelength travels along the fiber, there are acoustic vibrations that provide oscillations in the fiber refractive index, causing back-scattering of the transmitted power. So, SBS limits the channel power in optical communication systems.

To increase the system's range in a fiber communication link, several fiber segments with optical amplifiers (OA) are frequently used. Lump amplification is a style of architecture that is frequently employed in long-haul optical networks with more than 10 amplifiers [10].

The Kerr effect, which is how OA noise interacts with the fiber, causes phase variations at the receiver and shortens the transmission range, since SPM can degrade SNR [10,11].

The Gordon-Mollenauer effect or simply nonlinear phase noise (NLPN) are terms used to describe this nonlinear source of noise [12]. The most frequent impairment that makes radio-over-fiber networks perform worse is NLPN. When employing a traditional demodulation grid, the effect of NLPN in the constellation diagram is a shape distortion of the symbols due to symbol overlapping, causing symbol error rate.

Figure 1 provides a summary view of different optical fiber impairments [13].

3. Machine Learning Overview

Machine Learning algorithms may be classified into three different learning families: Supervised Learning, Unsupervised Learning and Reinforcement Learning.

3.1. Supervised Learning

Aiming to identify a function that maps input to output, an agent observes certain input-output pairings in supervised learning. Techniques include logistic regression (predict categories) and linear regression (create continuous predictions, such as an OSNR of a lightpath). The goal is to train a predictive model from a set of input-output pairs which are called labeled examples. A predictive model is a program that is able to guess the output value for a new unseen input. The more common types of supervised learning techniques are:

- **Neural Networks:** It works by trying to mimic the human brain through layers of nodes that are based on inputs, weights, and bias. Application in optical networks range from DSPs with embedded neural networks to combat and/or mitigate for nonlinear distortions, OSNR estimation based on eye-diagram power. An example of an artificial neural network (ANN) consists of an input layer, one hidden layer, and an output layer [1]. Neurons make up the hidden layer and output layer, which compute the output value using the input vector and a nonlinear activation function, respectively. Figure 2 shows an example of ANN. Where x is the input, h is the hidden layer and y is the predicted output.
- **Naive Bayes:** Based on decision trees, the existence of one feature does not impact the presence of another feature in the probability of a particular result. It is used in text classification and recommendation systems. A naive Bayes classifier was employed in optical networks to detect multiple fiber damages, including bending, shaking, tiny hits, and up and down events. It learned from the properties of the observed SOP.
- **Random Forest (RF):** Use multiple supervised learning techniques to make a conclusion. A random forest consists of many decision trees. In optical networks may be used to predict QoT for lightpaths and OSNR monitoring.
- **SVM (Support Vector Machine):** Generally used for data clas-

sification and regression. It is based on a hyperplane that separates the classes of data points. In fiber optic networks SVM has been demonstrated to be effective in reducing NLPN (Non Linear Phase Noise), fiber Kerr effect, laser phase noise, modulator linearity, amplified spontaneous emission (ASE) noise, and linear/non-linear signal detection [14,15]. SVM has a low level of decision complexity and is capable of detecting and de-mapping high order modulations with rotating constellations.

• **K-Nearest Neighbor (KNN):** Data points are categorized according to how closely they are related to other pieces of available data. It is used for recommendation engines, pattern recognition and image recognition. In optical networks can be used to mitigate fiber nonlinearities.

• **The Goal of Multitask Learning (MLT):** A learning paradigm used in machine learning, is to enhance the performance of many tasks when they are generalized. A special type of recurrent neural network (RNN) called long short- term memory (LSTM), first proposed by Hochreiter and Schmidhuber in 1997, is used to handle long time series or sequence data, achieving state-of-the-art performance in many sequence classification problems like speech recognition or natural language processing.

3.2. Unsupervised Learning

Unsupervised learning uses only the input x, whereas supervised learning uses both the input x and the output label y. The algorithm must uncover some kind of structure, trend, or intriguing aspect in the data. In other words, there are neither inputs nor outputs. The data is just a set of examples.

Unsupervised learning has three main objectives: clustering (using K-means to group data into different groups or clusters based on how similar they are), dimensionality reduction which consists in projecting high-dimensional data into a low dimensional space such as principal component analysis (PCA), and anomaly detection.

K-means clustering provides an effective and straightforward unsupervised classification algorithm [16]. With unlabeled data, K-means clustering is frequently used to solve classification challenges. Here, the "K" stands for the number of clusters. In order to reduce the total of the squared error data distance to the centroid, the K-means algorithm divides data into k clusters and assigns each data point to the nearest mean cluster. Figure 3 shows clustered data points grouped into 3 clusters based on their similarity or closeness.

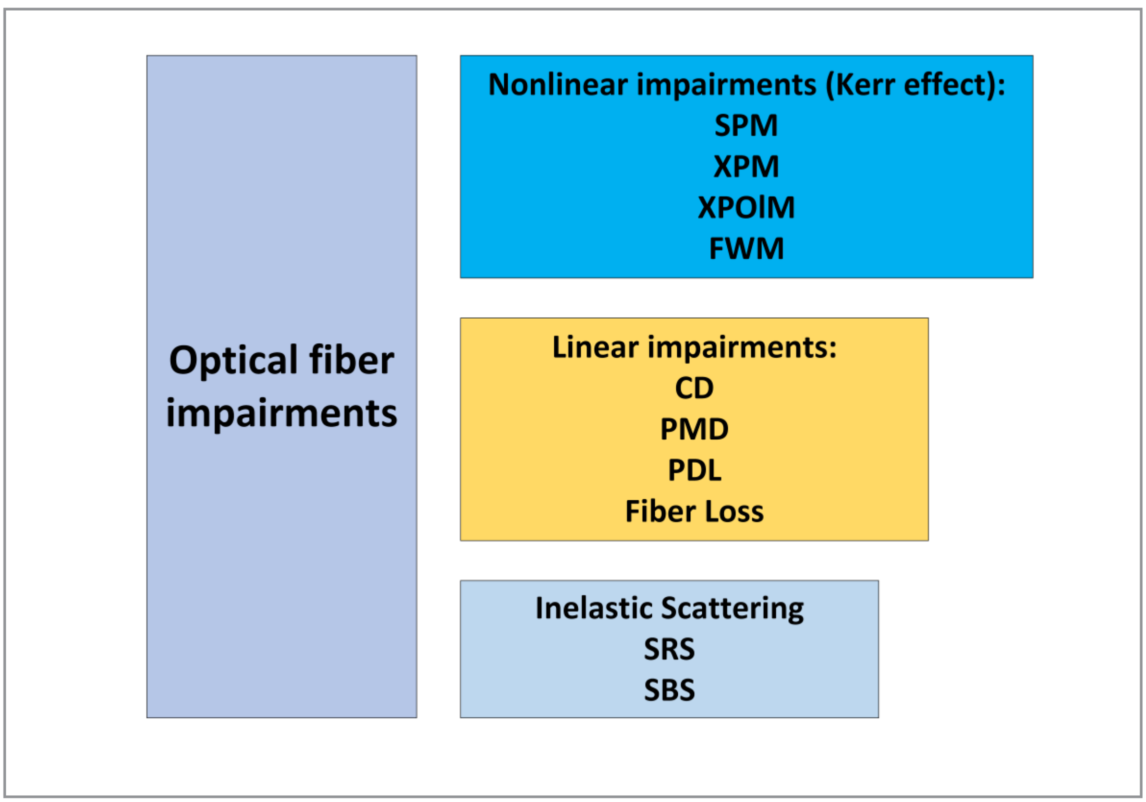

Figure 1: Fiber impairments: SPM, XPM, XPOlM, FWM, SRS,SBS, CD, PMD and PDL.

Almost every industry can benefit from the usage of K-means clustering, from banking to cyber security, document clustering to segmentation of image. It is often used with continuous, quantitative data that has few dimensions. Customer segmentation, document classification, and image segmentation (by attempting to group similar pixels in the image together and producing clusters) are some application cases for K-means.

In optical networks, k-means may be used to mitigate the effects of non-linear impairments on constellation diagrams. Anomaly detection is another task that can be addressed with unsupervised learning. Anomaly is something that differs from the standard. Anomaly is something different from the norm when concerning about it features. In machine learning, anomaly detection is the process of detecting outliers or rare occurrences. It is generally used to detect fraudulent credit card transactions and failures in manufacturing process. In optical networks, anomaly detection shows great potential to detect fiber events, amplifier mal-functioning and spectrum anomaly detection based on constellation images. I personally consider anomaly detection one of the key points for the management of modern optical networks.

3.3. Reinforcement Learning

Algorithms that learn through rewards for preferred actions are known as reinforcement learning (RL) algorithms [17]. It is based on the mathematical decision-making model known as the Markov decision process. The agent's goal is to choose activities that will maximize a long-term indicator of total reward [18]. A series of reinforcements (rewards) or penalties acquired through interactions with the environment help an agent develop an optimal (or nearly optimal) policy [19]. Finding the series of actions that results in the best reward is the goal of training [17]. Training entails learning from one's own experiences rather than from a supervisor or a system.

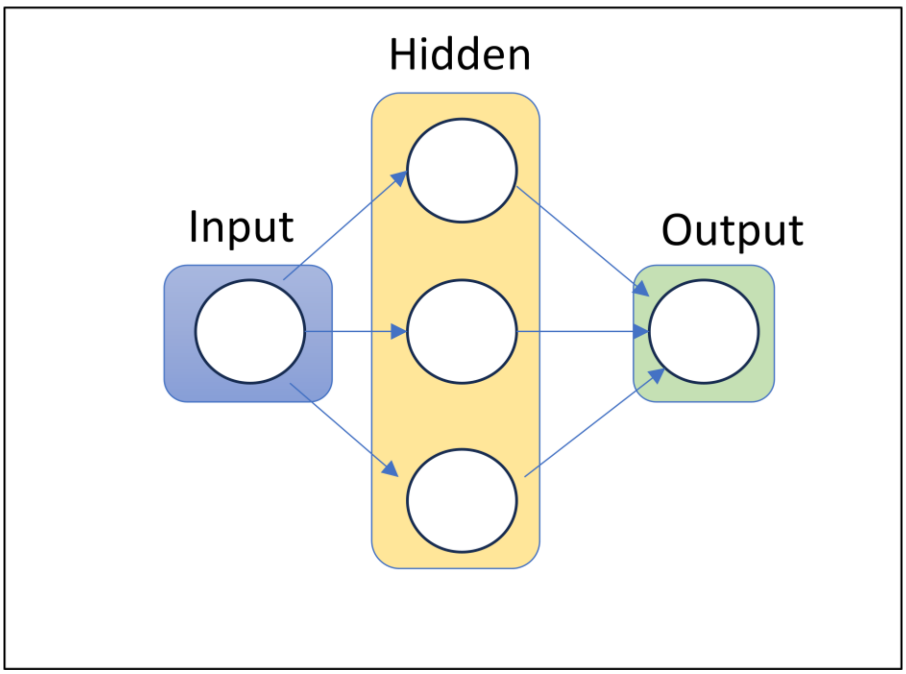

Figure 2: Example of ANN (Artificial Neural Network)

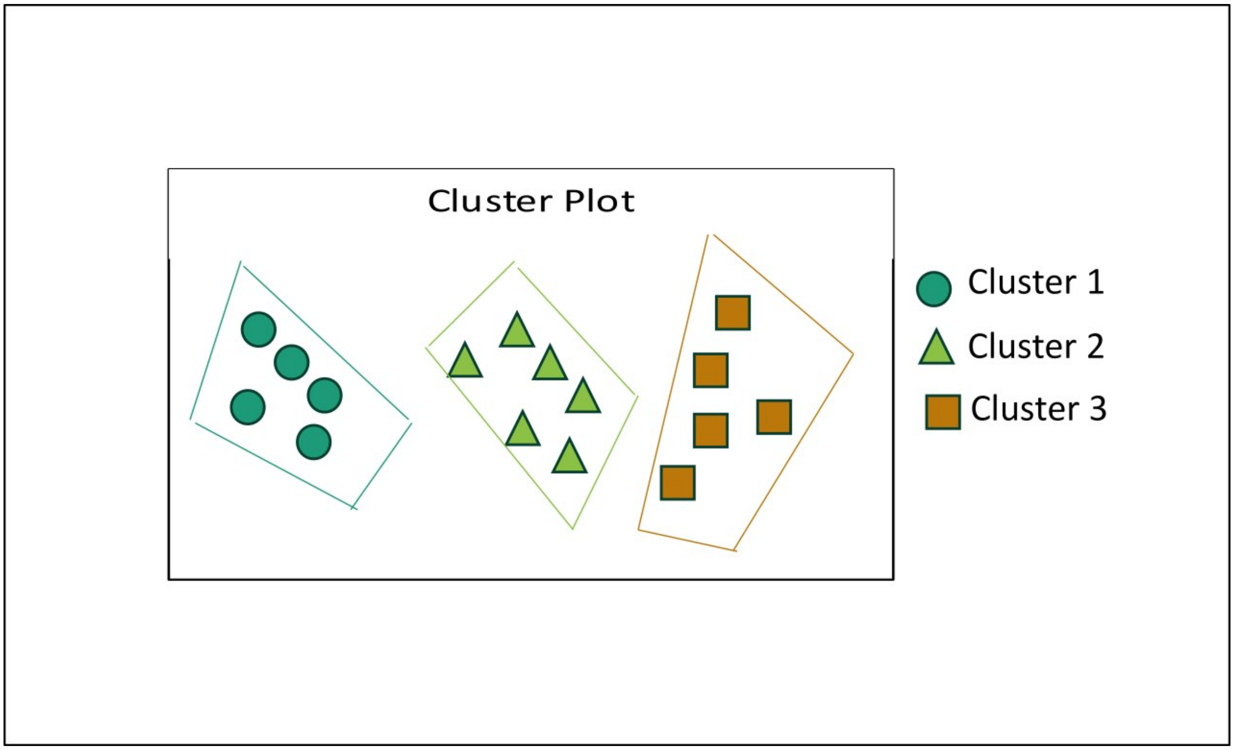

Figure 3: k-means clustering example

Finding the best policy that maximizes the expected return is the aim of interactions with the environment.

A trajectory in RL is the progression of states, behaviors, and rewards or penalties (punishments) that an agent encounters. The agent begins in one state, then after performing an action, it changes to a different state. The agent receives a reward or punishment for its action, and this process repeats. The trajectory ends when the agent reaches a terminal state. By analyzing the rewards it receives for its actions, the agent can learn which actions are more likely to lead to high rewards. The Figure 4 summarizes the idea explained above.

In the case of an SDN controller, the agent is the controller itself and the environment is the network. The controller keeps an eye on the network and develops decision-making skills. Since RL is particularly helpful for network automation and control in the context of optical communication, it has been used at the network layer to automate the resolution of routing, resource allocation, orchestration, and configuration issues.

4. Optical Networks

Existing flexible-grid photonics networks are based on coherent transceivers equipped with DSP (digital signal processing) capabilities. Coherent transceivers rate varies from 100 Gbps to 800 Gbps for medium to long haul distances. These networks are based on photonic control plane in a distributed or centralized approach. The photonic control plane is responsible in setting up and tearing down connections and also responsible in providing means for restoring connections in a backup path due to failures in the network.

Until recently optical networks used to be fixed-grid with fixed spectrum space between channels, typically 50 GHz or 100 GHz. In this scenario, the maximum capacity was of 88 or 96 channels for 50 GHz spacing. Some years ago emerged the flexible-grid networks with the intention of allowing wider spectrum channels to propagate in optical systems as well as minimize the waste of spectrum due to the fixed nature of the fixed-grid networks. With the evolution of the optical coherent transceivers, the transmission rates can vary from 100 Gbps to 800 Gbps depending on the type of the transceiver. A 100 Gbps transceiver can be transmitted in a 50 GHz frequency grid while a 400 GHz transceiver requires 112.5 GHz frequency grid to be accommodated. So, conventional optical networks cannot support this type of transceivers. Only flexible-grid systems can support them.

Current optical networks monitoring are basically limited to the alarms management and performance of the channels are limited to Pre-forward error correction (Pre-FEC) bit error rate (BER) information. There is no visibility for an optical channel or lighpath what and where are the impairments (linear and nonlinear) that most degrade the performance. Network planning is based on offline prediction and not on instantaneous or quasi-instantaneous information. So, QoT of new channels or restoration paths decisions are based on predicted information. So, network planners usually add margins to predictions to minimize risks. This leads to overprovisioning of resources and it is clear that there is limited network automation. In the sequence of this article I will describe what is available on literature to accelerate optical network automation.

5. Optical Networks Automation

In this section it will be described cognitive networks, network OS, sensors, QoT and failure management. First of all, there is a brief description about how ML agents are incorporated in an optical network.

Figure 5 shows the system architecture of optical networks incorporating ML [1]. It is based on an intelligent module made up of Functional Elements (FEs) and a ML agent. The FEs are responsible for information exchange between the network environment and the ML agent where the training is done.

In FEs, the raw data from the optical network is collected by the data collection module, which then preprocesses it into a specific data structure for usage by ML models. ML agents are trained using the gathered, preprocessed network data as well as the network state data from FEs. In optical networks, an ML agent can primarily operate in three paradigms: regression, classification, and decision-making.

5.1. Cognitive Network and Network OS

Recently, it has been suggested that optical networks use cognition to improve network performance [20,21]. By integrating machine learning and reasoning processes into the network's control plane, cognition offers a solution to improve network performance. This allows the network to operate quickly and independently with connection lifetimes as little as a minute. A cognitive network management system senses the current network state conditions, such as traffic and flow patterns, and uses this data to determine how to adjust the network or improve overall performance and offer quick replies to transaction requests. Figure 6 shows how the cognitive network module is a component of the control plane, which affects all network levels [22] (It may reside at distributed or centralized controllers as well as network nodes).

Due to the huge increase in data volume, future network management control systems need to be flexible and quick to adapt. In contrast to the minutes and hours of conventional networks, these dynamics will require network management and control on a time scale as quick as 10ms [22]. Sensing schemes will be implemented where each link and node senses the network (from layers 1 to 3). A centralized or distributed controller can use this information to combine data from various nodes to perform scheduling, complex statistical inference, network reconfigurations, load-balancing, and even more drastic operations like isolating suspicious subnet upon detection of anomalies.

By removing humans from the network management process, cognitive approaches can quickly estimate network state trajectories and optimize network setups and configurations. Learning algorithms can be used to infer the nominal traffic statistics from historical data.

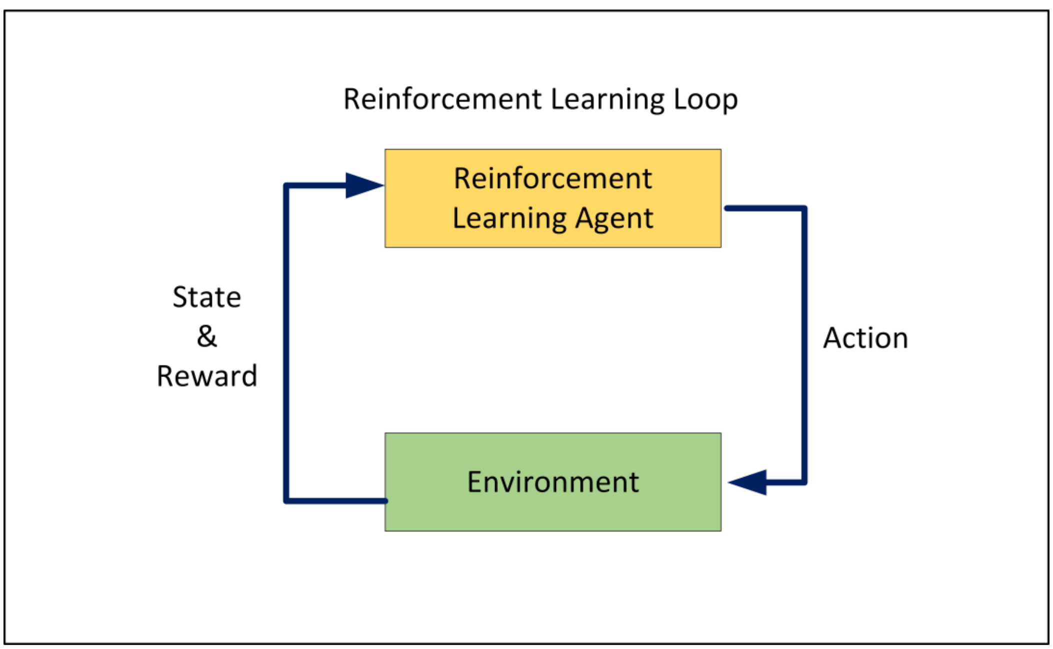

Figure 4: Reinforcement Learning loop

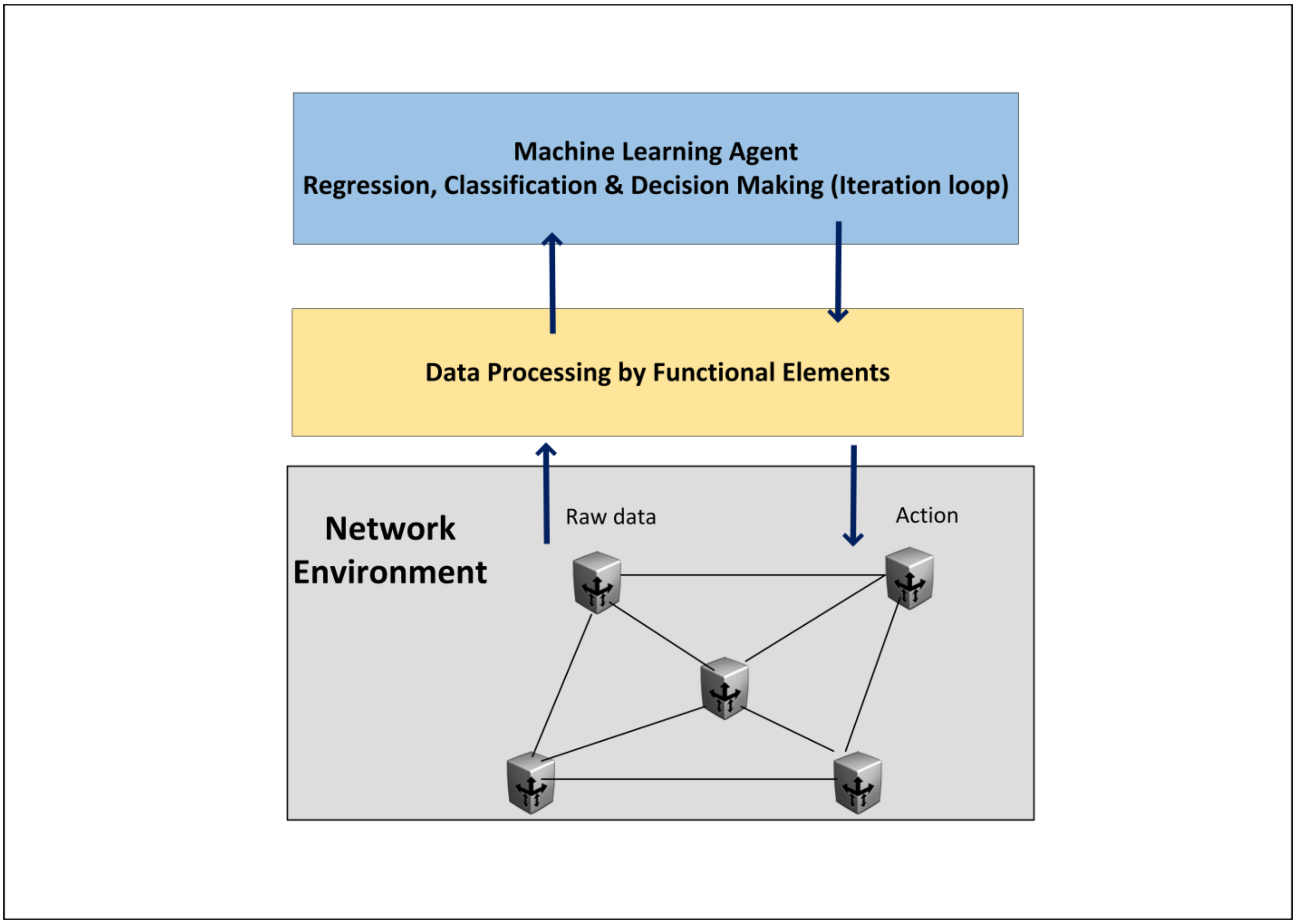

Figure 5: ML System Architecture

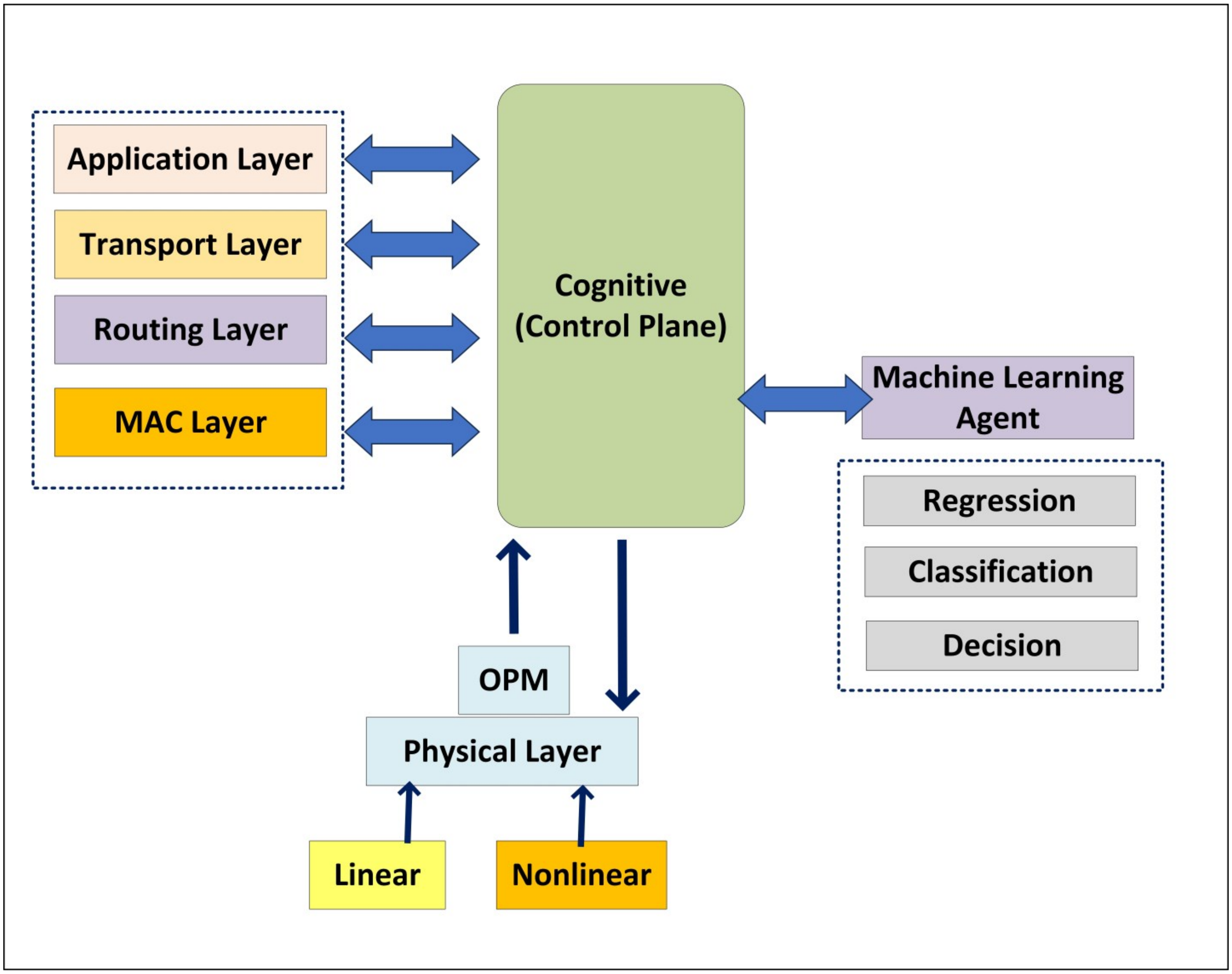

Figure 6: Cognitive Engine as part of Network Control Plane.

A new networking paradigm called Software-Defined Networking (SDN) offers hope for changing the limits of existing network infrastructures [23,24]. First, by separating the network's control logic (the control plane) from the underlying routers and switches that forward traffic (the data plane), it breaks the vertical integration. Second, network switches become simple forwarding devices as a result of the separation of the control and data planes, and the control logic is implemented in a logically centralized controller (or network operating system), simplifying network administration, configuration and policy enforcement [25].

5.2. Sensors

Using a single photodiode and estimating OSNR after photodetection without signal demodulating is one of the simplest methods for performing OSNR monitoring on sensors [26]. The goal is to identify the properties that change as the OSNR and modulation format change. Directly detected (DD) data are used by the OSNR estimator and the modulation format classifier. Several features can be extracted from the power eyediagram that is generated after the photodetector.

The key takeaway is that you don't need all the network's nodes to be equipped with these high-priced optical spectrum analyzers. You can measure something like the variance of the eye diagram and determine how that variation transforms into an OSNR in case you just use a photodiode to capture the eye diagram. One hidden layer of a neural network can be used to estimate OSNR.

Fiber optic sensors have gained considerable interest over the past three decades for their wide range of monitoring applications in a number of sectors, including aerospace, defense, security, civil engineering, communications, and energy. Compared to other forms of sensors, optical fiber sensors offer a number of benefits. These benefits are mostly related to the characteristics of optical fiber, which include its tiny size, light weight, resistance to high pressure and temperatures, electromagnetic passiveness, and others.

By examining the characteristics of light, one can measure many quantities, such as strain, temperature, or angular velocity [27].

Actions (such as re-routing the wavelengths) could be made in advance to lessen the effects of a fiber break in the network in optical communications if there is a sign that the fiber is about to be broken (for example a mechanical excavator is digging close to the fiber plant).

For monitoring on a span-by-span basis, the optical supervisory channel (OSC) can be employed [28]. Customer data is not transported by the OSC. It is only transmitted system maintenance information from the carriers. However, in this single polarization signal, it is feasible to detect the rotation of the OSC channel if the fiber is disturbed. The placement of a single polarization beam splitter is proposed. Consider the two polarization outputs and subtract them. A signal indicates that the polarization is rotating if it is present. You will be able to identify the span that is having issues because this is ended at each amplifier site. This is a cost-effective option.

A coherent receiver was used to implement a proactive fiber damage detection method [29]. Coherent technologies, where the light is frequency and polarization multiplexed by improved modulation formats that carries information not only by the light's amplitude but also by its phase, are the foundation of contemporary high-speed optical communication systems [30].

Many DSP algorithms have been developed and are now frequently used in commercial devices to recover received signal from physical impairments occurring during propagation in the fiber. A naive Bayes classifier was utilized to detect multiple fiber damages, including bending, shaking, tiny hits, and up and down events, with 95% reliability after learning from the characteristics of the monitored SOP. The idea is to make DSP suitable for inexpensive inclusion into coherent terminals. Algorithms that can simultaneously decode data and track SOP were developed to reduce the need for additional hardware in a real-time receiver. DSP is used in coherent technologies with polarization de-multiplexing to compensate for SOP fluctuations and other optical impairments such as CD and PMD.

A threshold is defined, monitored and compared to the Stokes coordinates fiber SOP rotation speed. Pre-trigger and post-trigger samples are given to an ML naive-Bayes classifier if the threshold is surpassed, and it then returns the most likely cause (for example, fiber bending, shaking, hit, or up and down events).

In other work using a threshold-based methodology, anomalous BER trends are identified. To find abnormal BER patterns indicating potential failures along the monitored lightpath, a BER anomaly detection algorithm operating at each network node is proposed. The algorithm uses historical and monitoring BER data statistics as input and returns various forms of warnings and alerts based on whether the current BER exceeds predefined criteria or stays within the boundaries that were predefined [5,31].

LSTM was used in [4, 32] for multitask learning to identify fiber reflection faults that typically arise in connectors or mechanical splices. The LSTM outperformed the conventional OTDR analysis technique in detecting reflecting events with 93% accuracy by learning from the noisy data acquired by the OTDR (Optical Time Domain Reflectometer) and a sequence of signal power levels.

5.3. Quality of Transmission (QoT)

To ensure reliable optical connectivity in real optical network operations, significant system margins are assigned to address all network uncertainties. A lot of network resources are wasted due to these redundancies. Cutting the margins improves network efficiency but calls for precise QoT estimation. As a result, accurate lightpath QoT monitoring can lower performance uncertainty and, as a result, lower the required redundant system margin.

A traditional analytical model that uses a lot of processing power to estimate physical layer impairments yields reliable findings. Regarding the analytical model's complexity, it should be noted that the complex interactions of numerous system parameters, such as input signal power, number of channels, link type, modulation format, symbol rate, and channel spacing, as well as the effects of linear and nonlinear signal (Linear ASE noise of amplifiers, nonlinear noise caused by the fiber Kerr effects, filtering penalties, etc.) propagation impairments, make it more challenging and difficult to predict a precise analytical model [33].

Additionally, if you are not very good at predicting, you will not be able to determine what is your lightpath's quality. Therefore, there will be a lot of spread between your expected performance and the real performance. You must increase your margin to take that spread into account. In its simplest form, the margin is the difference between the pre-FEC BER at the system working point and the pre-FEC BER at the FEC correction threshold. In case it is possible to have an improved and tuned model, the spread between predicted and actual performance is reduced.

And right now, you may apply supervised learning to establish a direct input-output relationship between the quality of the transmission (QoT) measured at the receiver and the corresponding configuration of the lightpath in terms of modulation format, baud rate, and route [33]. Additionally, you can now run with a small margin and just above the FEC correction level. Therefore, ML techniques offer a viable way to automatically forecast if unestablished lightpaths will reach the necessary QoT threshold. Consequently, capital expenditures (CAPEX) can be reduced with ML-based precise QoT estimation. Additionally, every decibel (dB) you have in the planning accuracy is just as useful as a dB in coding gain [28].

OPM is also desired in order to develop accurate ML algorithms that can handle low-margin networks. To prevent major system deterioration and find abnormalities, controllers should be able to access the real-time status of networks via OPM. The monitoring techniques should be able to locate, identify, and recognize optical network faults if they do occur.

Other point with QoT estimatation is the routing and spectrum assignment (RSA) or routing and wavelength assignment (RWA) issues in fixed-grid networks. In addition to ensuring the quality of transmission for the lightpaths, the algorithm that chooses an appropriate path and wavelength/frequency must act quickly to avoid assigning two paths sharing a link with the same wavelength or frequency.

There are several different metrics for the QoT modeling, including BER, Q-factor, signal to noise ratio (SNR), OSNR, and margin [34]. The goal of QoT modeling is to estimate the link performance accurately and build networks with low margin. The QoT estimation requirements differ based on the scenario. Some must determine whether or not one light path can be established, while others require the precise value of the QoT measurements [35,36,37]. For the former, ML classification techniques as KNN, RF, SVM, logistic regression (LR), ANN can be utilized [26]. Convolutional neural networks (CNN), ANN, Gaussian process (GP), network Kriging (NK), and other ML regression techniques can be used for the latter [34].

A summary of the ML-based QoT modeling techniques is presented in the form of a table, along with the modeling targets (OSNR, Q-factor, BER, SNR, margin), the algorithms used to achieve each modeling target, and the input features (modulation format, traffic volume, number of links, link length, FEC, baud rate, CD, average PMD, SPM, noise figure, power, attenuation, etc.) [34].

An ML classifier that predicts whether the BER of unestablished lightpaths satisfies the requirements based on traffic, number of links, route length, and modulation format is examined in [35]. One may think of the proposed classifier as being incorporated into the RSA decision algorithm.

The following methodology was developed in [38]. The required resources (links,wavelengths) are first allocated using a QoT estimator that is based on a mathematical model of the physics of propagation for the deployment of initial demands (greenfield planning). Initially a significant margin m is added. All of the monitored data are collected when lightpaths for the initial demands were established. The QoT prediction for new demands (prediction phase) is improved as a result of the machine-learning algorithm's enhanced input parameters for the QoT model. The margin m' for the design could be lower than the margin m for the original requests. And as new requirements are introduced into the system, the ML algorithm begins to do the training once more, increasing the accuracy of the parameters.

It is demonstrated that it is possible to reduce design margins by feeding a learning process based on a gradient descent algorithm with a collection of measured/monitored data (SNR, power levels, noise figures). Using the SAMBA (semi-analytical model for risk assessment) model and the EGN (extended Gaussian) model, it has been calculated that the QoT prediction error in the brownfield scenario of a Euro- pean backbone network can be reduced from 1.8 dB to 0.1 dB and from 4.2 dB to 0.02 dB, respectively [37]. By expanding this approach, overprovisioning may be further reduced and consequently the associated cost of optical network hardware.

A QoT estimator is proposed by [39]. It is trained using a collection of established lightpaths obtained from earlier off-line simulations over the network under investigation. Compared to conventional analytical/numerical methods, this model lowered the amount of time needed to compute to determine the QoT of a given lightpath. As a result, the magnitude of the typical RWA problem is reduced. For example, a route and available wavelength to establish a lightpath can be handled quickly with a guarantee of QoT for the chosen path. The length of a lightpath is likely to have the biggest impact on the many variables that can affect a lightpath's QoT. As a result, the length of a lightpath is the first factor considered when classifying it. And the SVM-based module only takes over prediction duties if this variable insufficiently determinant. Finally, three areas are defined:

• The lightpath length that is shorter than a predetermined length (inferior threshold) defines the first area. All lightpaths are regarded as high quality in this region.
• The second area is the one that is deemed low quality and is defined over a predetermined threshold for path length (superior threshold).
• The SVM-based module must solve the lightpath performance between the two limitations.

Learning a mapping function between the input features and target values is the aim of SVM. As a result, training, validation, and testing datasets were used to develop SVM. Running prior off-line simulations of an IA-RWA (impact aware routing and wavelength assignment) yielded the training dataset. A radial basis function kernel (RBF) was taken into consideration in order to nonlinearly transfer samples into a higher dimensional space because the relationship between the QoT categories and the lighpaths attributes is nonlinear. The performance of the model was assessed once it had been developed and characterized using various new data subsets.

A long-distance Deutsche Telekom network with 14 nodes was used to evaluate the model. The model improved the R-CBR (Regular Case-based Reasoning) technique by approximately two magnitude orders and reached up to 99.95% success in classification of lightpaths. CBR (Case-based reasoning) is a method for solving new problems by adapting previously solutions that were successful to solve similar problems.

In summary, the idea is to collect data, process it using analytics algorithms in order to provide the actionable intelligence for the process decisions. When all this process were done in hardware and software, those decisions can be moved to the actuators and we have an optical network automation. Based on all described information, the QoT estimation is one inputs to the RSA (Routing and spectrum algorithm flexible networks). The RSA is the algorithm whose function is to find the appropriate route for a channel and allocate the required spectrum for this lightpath. So, an efficient RSA takes into account the physical impairments of the optical channel and selects a route and spectrum information in a timely manner for new channels and for restoration of existing channels. So, in order to plan, deploy and operate the next generation of intelligent optical networks, a simple straightforward and agile QoT estimation before connections and restorations are provisioned is crucial and necessary. The cognitive approach can be based on NN, RF, NK, SVM or any other model previously described. The method basically considers the OSNR, SNR, BER or any other parameter of current lightpaths in a network. So, the measured parameter is compared with the expected/calculated values. So, it is possible to build a cost function and perform a gradient descent algorithm to minimize the cost function. After the calculation converges, the minimized cost function is ready. So, the new lightpath can now be added in the network with lower margins.

Figure 7 illustrates a basic QoT estimator for margin reduction.

By including new variables like lightpath length, amplifier modeling, traffic volume, input from analytical models, and other data, this basic model can be enhanced. The model can also be used to mitigate the chromatic dispersion, polarization mode dispersion, Kerr effect, and other linear and non-linear impairments that alter the shape of symbol points in the constellation diagram of coherent optical signals and establish direct input-output relationships between monitored parameters and desired outputs.

5.4. Failure Management

Failure management's goals include detecting, isolating, and fixing all types of network faults, ensuring the stable and reliable network operation, and meet the service level agreement with the customer [4]. Tasks in failure management can basically be classified into alarm analysis, failure prediction, failure detection, failure identification, failure diagnosis, and failure localization, which are divided into active and passive approaches [40]. Monitoring the network and taking measures to address problems before they become more serious constitute an active strategy. Examples of active methods include:

• **Alarm Analysis:** Examining alarms and alerts produced by the network to spot possible problems before they cause interruptions.

• **Failure Prediction:** Identifying when failures are most likely to occur and taking preventive action to avoid them using data analytics and other tools.

• **Failure Detection:** Identifying when failures occur and responding to them using monitoring tools and techniques. On the other hand, passive approaches involve corrective actions that are carried out following a failure. When using these techniques, the damaged equipment is often diagnosed as having a problem and is then either repaired or replaced (examples include failure identification, failure diagnosis, and failure localization).

Examples of passive methods include:

• **Failure Identification:** identifies the root cause of a failure and pinpoints the machinery or components that require maintenance or replacement.

• **Failure Diagnosis:** involves identifying the problem and choosing the best course of action for fixing or replacing the harmed equipment.

• **Failure Localization:** Finding the precise location where the failure occurred inside the network and responding to it.

A passive approach with minimal extra complexity is shown for localizing errors in optical networks [41]. It is based on raw monitoring information from optical coherent transponders. The fundamental goal of this methodology is to increase availability by speeding up fault localization. As a result, the MTTR (mean time to repair), which takes into account both the time needed to locate the defect and the time needed to remedy it, can be reduced. A list of potential failure scenarios, segment (link) exclusion, and scenario rating by likelihood form the basis of the localization approach known as SFL (streamlined failure localization) which is the localization technique.

According to the approach, more than 90% of failures can be pinpointed without ambiguity. Because a failure can have such severe repercussions in optical networks, failure management is extremely important. Optical networks are essential to many businesses and industries because they efficiently transmit enormous amounts of data over great distances. An optical network failure may result in service interruptions that impact many users, which may result in lost sales, reduced productivity, or even harm to a company's reputation.

Network operators are increasingly looking at improved automation of failure recovery as a critical aspect of their roadmaps for the future since, despite its importance, optical networks failure management still frequently requires complex and time-consuming human intervention [5]. Using advanced statistical and mathematical tools of ML to automate failure management duties is one potential avenue in this area. ML algorithms can be trained to evaluate optical network data in real-time, identify patterns, detect anomalies that could sign possible early stage of failures.

ML algorithms can drastically reduce the amount of time needed to resolve network issues by automating the detection and diagnosis of failures, enabling operators to react to incidents more rapidly and efficiently [4,5,42]. As a result, service outages may be reduced, and optical networks may operate more reliably and effectively overall. In addition, ML can be used to optimize resource allocation and network designs, lowering failure rates and boosting network performance. As a result, ML is turning into a more crucial tool for network operators wanting to increase the performance and reliability of their optical networks.

In summary, using sophisticated statistical and mathematical machine learning tools to automate failure management tasks in optical networks is a promising area. By leveraging ML algorithms, network operators can drastically reduce the time needed to detect and diagnose failures, thereby enhancing network performance and reliability and, ultimately, providing their customers with better service. The use of machine learning (ML) to solve optical network problems has demonstrated considerable potential. Particularly, machine learning (ML) techniques can assist in processing significant amounts of monitoring data and extracting meaningful information from it, such as finding trends and anomalies that can be used for proactive maintenance and fault detection.

For instance, using historical data and current network circumstances, ML algorithms can be used to predict the likelihood of fiber cuts or network equipment failures [43,44]. So, ML algorithms can enable operators to take proactive steps to prevent these problems, such rerouting traffic or carrying out preventative maintenance.

In [44] is presented a methodology for event classification that precede a fiber break based on SOP events. Three ML methods were finally chosen: Kernel SVM, NN and LSTM. Accuracy of the events classification is above 99% for all ML methods with attention to Kernel SVM and LSTM regarding their robustness with smaller training set size.

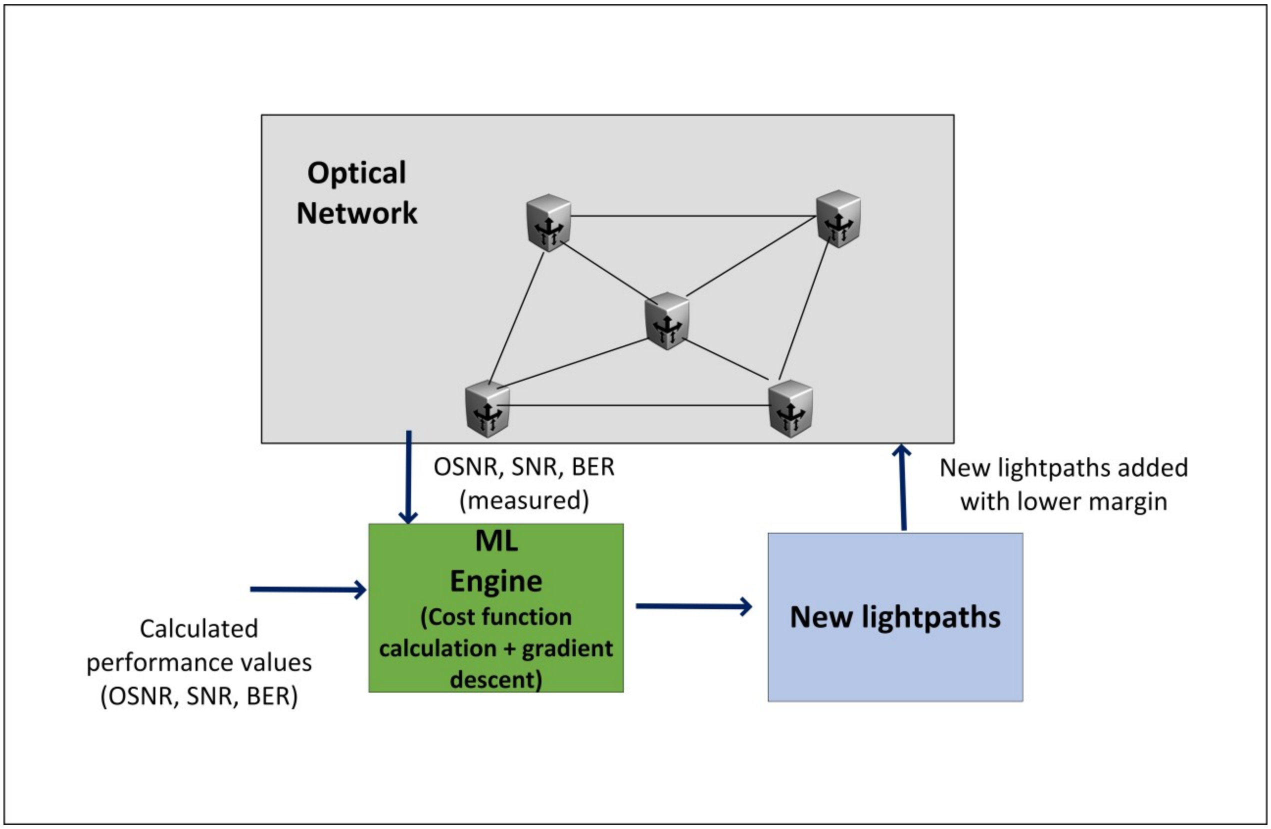

Figure 7: Basic approach to estimate the QoT of an Optical DWDM system.

Effective machine learning applications are being made possible by the most recent technology developments in optical communications. Modern optical equipment has advanced to the point that transceivers, ROADMs, and amplifiers that have built-in monitoring features produce a large amount of data. Using machine learning, this data can be used to automate optical network failure management that is not only based on threshold-based criteria [45]. This architecture is founded on the extensive availability of advanced OPM data and SDN, where a hybrid learning solution is given. This approach combines the benefits of cooperative, unsupervised, and supervised machine learning.

The proof of concept was made based on the typical approach for automated fault management which consists in three main phases in a cycle:

- **Observe:** the NM (network manager) collects telemetry data (OPM data e.g. signal power, chromatic dispersion, PMD) from the nodes on demand
- **Analyze:** ML models analyze the data and identify patterns associated with a specific type of fault such as detection, identification and localization. This phase may also be named Decide. The desired outcome is fed to Act block.
- **Act:** the SDN controller takes action to mitigate the fault. It is responsible to convert the intent into deployment.

The hybrid learning design is explained in the sequence. The data preprocessing block extracts and formats the features to be processed by the ML blocks. Firstly, the features are submitted to the clustering block for pattern analysis where clusters and outliers are identified. Outliers are an indication of probable faults. The learned pattern is fed to the NN block (or other algorithm type) that predicts if the pattern is abnormal or not. In this example a Bayesian neural network (BNN) is applied to the data with the aim of minimizing uncertainties and avoid overfitting. The proposed design can achieve 95% accuracy with just 20% abnormal data for training. Fig. 8 represents this design.

So, thanks to recent developments in logically/management solutions such as telemetry, SDN, and/or orchestration frameworks, these centralized locations can now collect, process and elaborate this large amount of data. So, these advancements make machine learning training models easier to be implemented. Furthermore, by utilizing Network Function Virtualization (NFV) and/or Mobile Edge Computing (MEC), network intelligence (computing capabilities) can now be virtually deployed anywhere [5]. As a result, ML models can be deployed closer to the data source, reducing latency and enhancing the system's real-time response.

In conclusion, these technological advances in optical communication systems have driven new opportunities for efficient and successful machine learning applications in optical network failure management and other related fields.

In [34] ML algorithms are used to identify patterns from data generated by modern optical network elements. Other parts in the optical network failure management process can subsequently be guided by the outputs of these algorithms (regression, classification, or clustering).

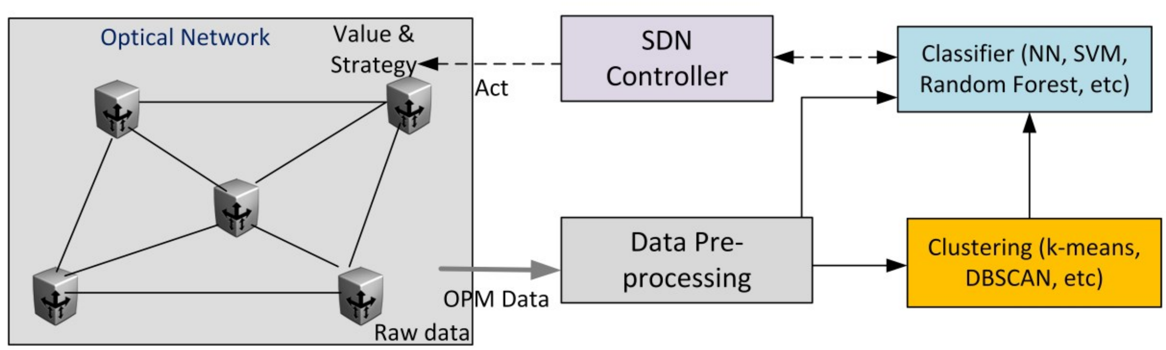

Figure 8. Hybrid learning solution employing unsupervised and supervised ML algorithms to automate network failure management

Figure 8: Hybrid Learning Solution Employing Unsupervised and Supervised ML Algorithms to Automate Network Failure Management.

For instance, a machine learning system may be developed to precisely identify the location of a network failure. The operator can use lightpath rerouting or other approaches to address the issue once the fault location is identified. By identifying patterns and trends in the data, ML can be used to predict and also prevent future failures.

It's important to keep in mind that machine learning is really a part of a more comprehensive optical network failure management process [5]. To make accurate decisions and take the right actions, various pieces of information and expert knowledge must be coupled with the insights and outputs from machine learning algorithms. Optical network failure management (ONFM) covers a variety of tasks that can be broadly divided into proactive and reactive techniques, as shown in Figure 9 [5]. By anticipating failures and taking preventative measures to avoid them, proactive techniques seek to avoid service interruption. These approaches involve realtime monitoring of the network for possible issues and proactively addressing them. For instance, ML algorithms can be used to identify data patterns that indicate a failure is likely to occur, and the network traffic can then be rerouted, or the network can be reconfigured to prevent the failure from happening.

It was developed and tested several ML methods to perform early soft-failure detection and identification in optical networks [46]. The numerical results were obtained based on the experimental setup shown in Figure 10.

Different types of ML anomaly detection classification algorithms, including Binary SVM (B-SVM), RF, Multiclass SVM, and NN with single hidden layer, were utilized to train the failure detection module. The NN method has the lowest complexity, but it provides the lowest accuracy (98.2%) of the three models. In contrast, SVM significantly outperforms NN in terms of accuracy, reaching 99%, however because of the complexity of the SVM algorithm, training the model takes longer. The best accuracy (99.1%) and lowest computational complexity (relative to SVM) are provided by RF, which represents the ideal balance between accuracy and complexity. A multilayer NN that provided 100% accuracy was employed to identify failures.

On the other hand, reactive approaches react to a failure after or while it is happening by immediately initiating recovery procedures to quickly repair or replace the failing equipment. To ensure that service is restored as soon as possible, these approaches may leverage failover and redundancy mechanisms. Reactive strategies can also make use of machine learning (ML) techniques to identify the failure's primary causes and determine the best course of action for recovery.

For failure prevention, continuous monitoring of transmission-quality indicators like BER and OSNR is usually employed. These parameters offer important insight about the network's health and can be used to optimize or fine-tune transmission parameters to keep the required degree of transmission quality. However, merely optimizing the transmission parameters might not always be sufficient to prevent network failures. In some circumstances, it might be necessary to predict failures and implement preventative measures in place before they happen.

In case of a failure, the data retrieved by network monitors and alarms can be used to execute lightpath restoration right away. Using pre-planned or dynamically discovered alternate routes, the process involves promptly identifying and determining the nature of the failure before re-establishing connection along the affected area of the network.

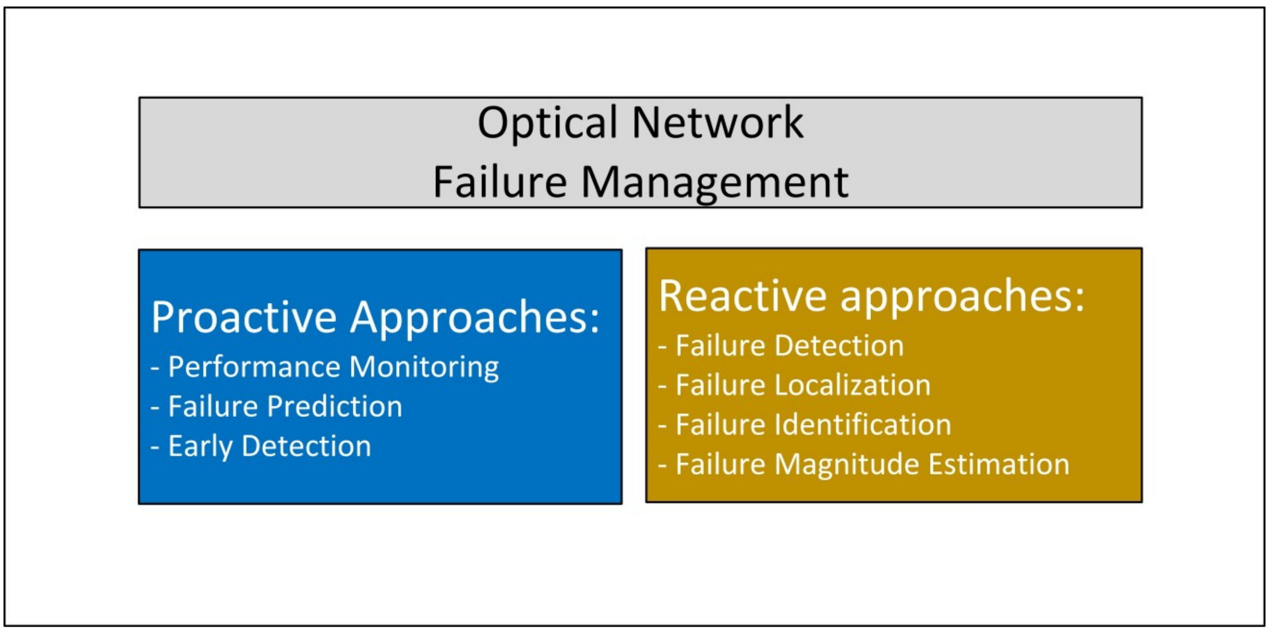

Figure 9: Machine Learning for Failure Management

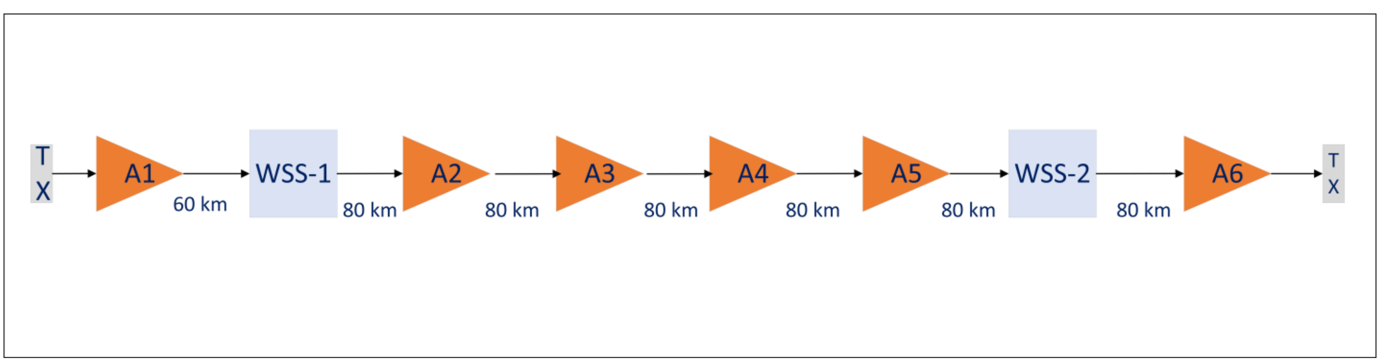

Figure 10: Testbed Setup

Using pre-planned schemes that establish static associations between the primary and backup route is one common approach of lightpath restoration that was outlined in [47]. In this method, backup paths are pre-provisioned with the intention of taking over in the case of a failure. The network automatically switches traffic to the backup link in case of a failure, minimizing the impact on network performance. Pre-planned schemes, nevertheless, might not always be adequate to deal with all failure scenarios, especially those that involve multiple failures or complex and/or mesh network topologies. In these cases, traffic can be rapidly rerouted along available routes through dynamic discovery of alternate paths. This approach consists in a continuous network monitoring and in an identification of alternate paths (alternate routes that are associated with specific fault scenario) that can be selected to bypass failed components or fault segments. The network selects the best available alternate path in case of a failure and reroutes wavelength traffic appropriately [48].

Also, the RSA needs to decide the available path and optimal frequency (considering end-to-end resources and future actions) in seconds and ensure that this path will provide a required OSNR (estimated in real-time based on real-time fiber conditions) for the selected baud rate and modulation.

In summary, tasks in failure management are divided into active and passive approaches. Active methods include alarm analysis, failure prediction and failure detection (identify when failures occur). Passive methods include failure identification, diagnosis, localization and also corrective actions after failure detection. In general sense, ML algorithms reduce the time spent to resolve network issues by automating the detection and diagnosis of fault. Applications range from prediction of fiber cuts likelihood to equipment failure. Also range from failure prevention (BER, OSNR monitoring through OPM) to reactive techniques (failure detection, localization, identification, and magnitude estimation).

Regarding ML techniques, unsupervised learning via anomaly detection seems to be the preferred option for early detection (based on signal power level, BER trends and other metrics). Also, after a failure is detected, ML algorithms can recommend the best course of action (for example: wavelength restoration or retuning). All this is done in a cycle of observation, analysis, and action under supervision of a SDN controller.

5.5. Network Automation and Power Consumption

According to [49], machine learning is on track to use up all the energy being produced, which is an expensive, ineffective, and unsustainable strategy. For instance, it is estimated that during the next five years, the amount of computing power needed for AI would expand by more than a million times, or by a factor of 100, every 100 days [50]. In terms of a sustainable future, what does this mean? Will network automation help to reduce energy use or will it result in higher energy use? AI and ML systems require connectivity within data centers and between data centers. Additionally, more equipment and software running on optical network systems will be necessary. Consequently, more power will be used. However, network automation can help you use resources and energy more effectively. For example, with efficient RWA/RSA algorithms (impairment-aware), new wavelength services or services restoration will only occur if the assignment route is capable to provide services with adequate quality of transmission. In case of not impairment-aware RSA/RWA algorithms, there will be spectrum usage with no service quality and consequently an inefficient use of the optical spectrum.

So, it is necessary to have in mind the energy efficiency criteria when implementing optical network automation. Given the so-called embedded carbon emissions that are produced during the manufacturing of computing gear and optical transport technology, a very well-reasoned solution should be implemented.

In conclusion, there are many obstacles to overcome in the fields of AI/ML and optical transport systems, including the need to consume less energy, less memory, deployment of energy-efficient AI/ML algorithms, use of energy-efficient optical modulation techniques, and make better use of the optical spectrum. All these challenges will foster innovation in hardware architecture, solutions, and also in the field of AI.

6. Results

Table I provides an overview of each described ML algorithm and corresponding reference and metrics.

Name	Ref	Algorithm	Metric
Scheme for proactively detecting fiber damage using a coherent DSP receiver	[29]	Naïve Bayes classifier	could successfully identify "shaking", "bending", "small hit", "up and down" events with >95% reliability over a real-time PDM-QPSK system
Proactive fiber break detection based on SOP monitoring through digital signal processing in a coherent receiver	[42]	Naïve Bayes classifier	event classification can achieve more than 99% accuracy for the testbed conditions
BER analysis for overall failure management (detection, identification, magnitude estimation)	[5]	SVM	classification accuracy depends on window size and overall results may reach 100% accuracy
Detection of fiber reflective faults in connectors and/or mechanical splices with multitask learning based on noisy OTDR data processing	[24]	LSTM	Reflective events detection with an accuracy of up to 93%. The model performs better than a traditional OTDR event analysis method
ML classifier for BER and QoT prediction of unestablished lightpath based on traffic, chosen route and modulation format	[35]	KNN, RF	Based on the reported results, the proposed classifier can be integrated into RSA decision algorithm
QoT prediction based on mathematical model of the physics plus gradient descent algorithm and learning process with two approaches: SAMBA and EG	[38]	SAMBA, EGN	SAMBA reduced QoT prediction error from 1.8 dB to 0.1 dB, while the EGN reduced QoT prediction error from 4.2 dB to 0.02 dB
Lightpath QoT estimation based on a SVM approach for Optical Networks	[39]	SVM	99.95% success in lightpath classification, improving R-CBR technique by over two magnitude orders
Failure localization in optical networks based on a passive method	[41]	SFL	more than 90% of the faults may be directly recognized without ambiguity
Polarization Event Classification based on field measurements	[43]	Kernel SVM, NN, LSTM	Accuracy of the events classification is above 99% for all ML methods with attention to Kernel SVM and LSTM regarding their robustness with smaller training set size
Hybrid learning solution employing unsupervised, supervised and cooperative ML to automate optical network failure management	[45]	Clustering, NN, BNN	With just 20% abnormal data for training, the proposed approach can reach 95% accuracy
Early soft failure detection ML methods based on BER anomaly detection	[46]	SVM, RF, NN	NN: 98.2% accuracy but low complexity;SVM: 99% accuracy but more complexity ; RF: 99.1% accuracy and shows optimal compromise between accuracy and complexity

Table 1: ML Algorithms and Metrics

7. Conclusions

In this paper, it was shown that eye diagrams, constellation diagrams, spectrum information, state of polarization, all this information can be used to implement QoT estimation, combatting NLPN, laser phase noise, non-linearities, margin reduction, equalization, adjusting optical amplification gain, selecting optimal symbol rate and modulation format and optical link failure prediction and failure management. New generation of coherent receivers can provide separated measurement of linear and non-linear noise and also provide power spectrum analysis. Embedded OTDR provides continuously measurement and operation map of the fiber losses and also vibration events based on phase variations. Network automation requires efficient collection and analysis of telemetry information. SDN brings the capability for streaming telemetry which retrieves data directly from devices based on YANG models. So, ML algorithms are able to analyze a large amount of data, make decisions, learn from experience, optimize and make the networks robust, agile, dynamic, and smarter. The availability of accurate and real-time performance assessment and prediction provides us the capability to operate the network with minimum margin. The RSA decision process is being improved and now considers network resources in an end-to-end basis, providing optimum resources provisioning for new services. Services restoration should now consider spectrum, modulation, baud-rate and channel performance all in real-time. The real-time network information also allow us to work with minimum margin and permit the system to raise future or early degradations both for soft and hard failures. In summary, ML algorithms can deal with network control and automation, resource management, QoT estimation, monitoring and survivability. Regarding survivability, some algorithms for failure management were described such as fault localization to reduce MTTR, early detection and failure prediction, failure detection, failure identification and magnitude estimation. For future research, I understand that scientists must consider the impact network automation in the increase of energy consumption and the carbon emissions. It should be considered a model that is energy-efficient, not costly, and sustainable.

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