Overview of Quality of Transmission Estimation in Optical Networks

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Abstract—**This paper explores the significance of Quality of Transmission (QoT) estimation in optical networks and highlights the increasing use of machine learning (ML) techniques to enhance QoT estimation accuracy. It presents a survey of literature in this area, categorizing studies into classification and regression algorithms. ML methods are shown to improve QoT estimation, mitigate nonlinearities, and optimize decision-making processes. Ultimately, these advancements reduce the reliance on conservative margins, maximize network capacity, and decrease infrastructure investment. Accurate and real-time QoT information is the foundation for efficient routing and spectral allocation (RSA) systems, it enables proactive failure management, facilitates network reconfiguration, provides inputs for optical line optimization and drives optical network automation.**

Index Terms—**Quality of Transmission, Optical Networks, Machine Learning**

I. Introduction

To guarantee a reliable optical communication system, substantial system margins are allocated to accommodate all network uncertainties. However, these uncertainties often lead to the inefficient utilization of network resources. By reducing these margins, network efficiency can be improved, but this requires a precise quality of transmission (QoT) estimation. Techniques like machine learning (ML) and statistical analysis are being explored for improved QoT estimation accuracy.

A traditional analytical model, while resource-intensive, can provide reliable estimation of physical layer impairments. However, it is important to recognize the complexity involved. The intricate interactions among various systems parameters, such as signal power, number of channels, link type, modulation format, symbol rate, and channel spacing, as well as the effects of linear and nonlinear signal propagation impairments (such as amplifier spontaneous emission (ASE) noise, nonlinear fiber Kerr effects, filtering penalties, etc.), pose challenges in predicting a precise analytical model [1].

In addition, if predictions are unreliable, there will be a significant spread between expected performance and real performance. To account for this spread, a larger margin must be allocated. The margin can be defined as the difference between the pre-FEC BER at the FEC correction threshold and the pre-FEC BER at the system operating point [2]. However, if an improved and finely tuned model can be developed, the spread between predicted and actual performance can be minimized, allowing for more efficient allocation of margins.

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Various methods have been proposed to estimate the QoT by assessing nonlinear impairments in optical links. However, achieving the high accuracy often comes at the cost of computational speed. The most precise technique involves full-fiber propagation simulation using Split-Step Fourier method (SSFM) [3], but it is too computationally intensive for real-time applications. Analytical tools like the Gaussian noise (GN) [4] model offer decent accuracy with faster computation, although they are not accurate as SSFM. Extensions of the GN model and other close-form methods aim to reduce computation time but may sacrifice accuracy. Both simulation and analytical methods require precise knowledge of link parameters [5], [6], leading to less accurate estimations when there are parameter deviations. In contrast, ML-based estimation combines quick computation and high accuracy by training on input features related to the target metric. While the training process may take some time, once trained, the estimation is rapid and suitable for real-time environments.

Selecting the most suitable ML technique for estimating and forecasting lightpath QoT depends on various factors such as the complexity of the optical network, the availability and quality of data, computational resources, and the specific requirements of the QoT estimation task.

This article aims to explore the techniques outlined in existing literature and underscore the significance of rapid and accurate QoT estimation in optical network automation. QoT estimation serves as vital input to cognitive systems, particularly the RSA entity, enabling the design of marginless networks. By facilitating proactive maintenance activities and enabling efficient network reconfigurations, QoT estimation plays a pivotal role in optimizing optical network operations.

This paper is structured as follows. Cognition in optical networks is presented in section II. Section III provides a brief description of ML techniques in optical networks for QoT estimation. Section IV provides an overview of the main QoT indicators as well as a brief description of the main fiber transmission impairments. Section V provides a brief description of the main ML algorithms employed in optical communications. A survey of ML techniques applied in QoT estimation in optical networks is described in section VI for regression and classification categories. It also includes amplifier modeling and open optical networks. Section VII summarizes the survey results and the conclusion is presented in section VIII.

II. Cognition in Optical Networks

As internet usage keeps growing, problems with signal quality and network outages becomes more critical in optical communication systems. This makes it even more important to have network management that can adapt and fix problems autonomously [7], [8]. To help address this challenge, modern coherent transponders are based on advanced digital signal processing (DSP) systems. DSP-based coherent transceivers play a crucial role in enhancing performance monitoring and leveraging machine (ML) learning for QoT estimation in optical networks.

The advancements in optical communications, including technologies like variable bandwidth transponders (VBT), flex-grid reconfigurable optical add-drop multiplexers (ROADMs), various modulation and coding schemes, and adjustable symbol rates, all this offers immense flexibility for optimizing network resources. However, as the complexity and flexibility increase, so does the need for intelligent systems and advanced algorithms to effectively manage and allocate these resources for optimum performance.

The introduction of cognition in optical networks offers a solution to these challenges by incorporating reasoning processes and ML techniques into the network's control plane. This approach aims to enable autonomous and rapid network operation, efficient resources control while meeting signal quality requirements.

Cognition is defined as a capability of the network to observe, plan, decide, and act autonomously, aiming to optimize end-to-end performance and minimize the need for human intervention [9].

A cognitive network management and control system monitors traffic and flow patterns and makes adjustments to the network to enhance overall performance and promptly handle transaction requests [2]. This cognitive approach operates across all network layers and plays a crucial role in decision-making. It resembles a software defined networking (SDN), where SDN controller works with a cognitive decision process to program network nodes. Cognitive processes utilize models fed by monitored network performance to make future decisions automatically and act on the network nodes through adaptable software elements. In addition, coherent transceivers serve as versatile software-driven optical tools. Their DSP ability enables them to electronically counteract propagation challenges and provide a great amount of information such as performance metrics, channel conditions, and spectrum information to the SDN controller.

Cognition systems can optimize routing and spectrum allocation (RSA) decisions by considering various factors such as traffic load balancing, wavelength continuity, and signal quality constraints. By continuously learning and adapting to network dynamics, cognition systems can enhance the efficiency and effectiveness of RSA algorithms, leading to improved network performance and resource utilization.

OPM (optical performance monitoring) provides crucial data needed for QoT estimation. By monitoring network conditions and performance metrics, such as noise levels (linear and nonlinear) and signal quality, OPM feeds into QoT estimation process. ML techniques are increasingly being applied to estimate individual components of optical performance, such as linear and nonlinear noise, extract patterns and trends of data collected, improving the efficiency of OPM processes.

In summary, OPM provides essential data for QoT estimation, while ML techniques enhance OPM accuracy and efficiency. Cognition leverages this data and intelligence to optimize resource management and ensure signal quality, addressing challenges associated with network agility and complexity.

The cognitive network module's function as a control plane component is illustrated in Figure 1, influencing all levels of the network architecture. The cognitive network module continuously monitors the current state of the network, including traffic patterns, link conditions, and overall performance metrics. By analyzing this information, the module can make decisions and implement actions to adapt the network configuration in real-time.

III. ML in QoT Estimation

ML techniques encompasses algorithms designed to discern patterns and behaviors within data, facilitating the creation of models for a range of tasks [10]. These tasks include estimating values based on inputs (regression techniques) and categorizing data into groups (classification techniques). ML has experienced a surge in popularity across various fields, in particular in computer vision, speech recognition, and natural language processing, among others. Numerous articles have been released on the application of ML techniques across fields such as routing and spectral allocation (RSA), QoT estimation, and failure management. These applications demonstrate the potential of ML to enhance efficiency, accuracy, and reliability within optical network operations.

Optical network designers [11] have a longstanding interest in accurate and fast quality of transmission (QoT) estimation. Accuracy is crucial because simulated errors can lead to design margins, which in turn results in overestimated capacity or undesired regeneration. For network planning purposes, whether it is for a greenfield network or the provisioning of a new service in an operating network, computation time of several seconds or few minutes are suitable. However, in the case of online provisioning, extremely fast calculations (sub-second) are required but there can be a tolerance of some estimation errors. This is case for QoT estimation for restoration due to a fault.

In the realm of optical network planning and operation, accurately estimating QoT for lightpaths is necessary. Lightpath restoration in case of network failures, is often automated through the photonic control plane. In order for the lightpath in its future route to be feasible, accurate QoT estimations are essential. This is a feature that is part of networks that encompass impairment-aware RSA. During network reconfiguration, typically done during maintenance window, QoT estimation of the future network state is conducted based on network parameters. Yet, when old equipment is replaced, fiber attenuation values change, and engineers often need to intervene using planning tools in the maintenance window. To streamline this process, networks must evolve to provide real-time QoT calculations. Currently network reconfigurations can take six to eight hours, often involving manual steps such as removing existing lightpaths passing through equipment,

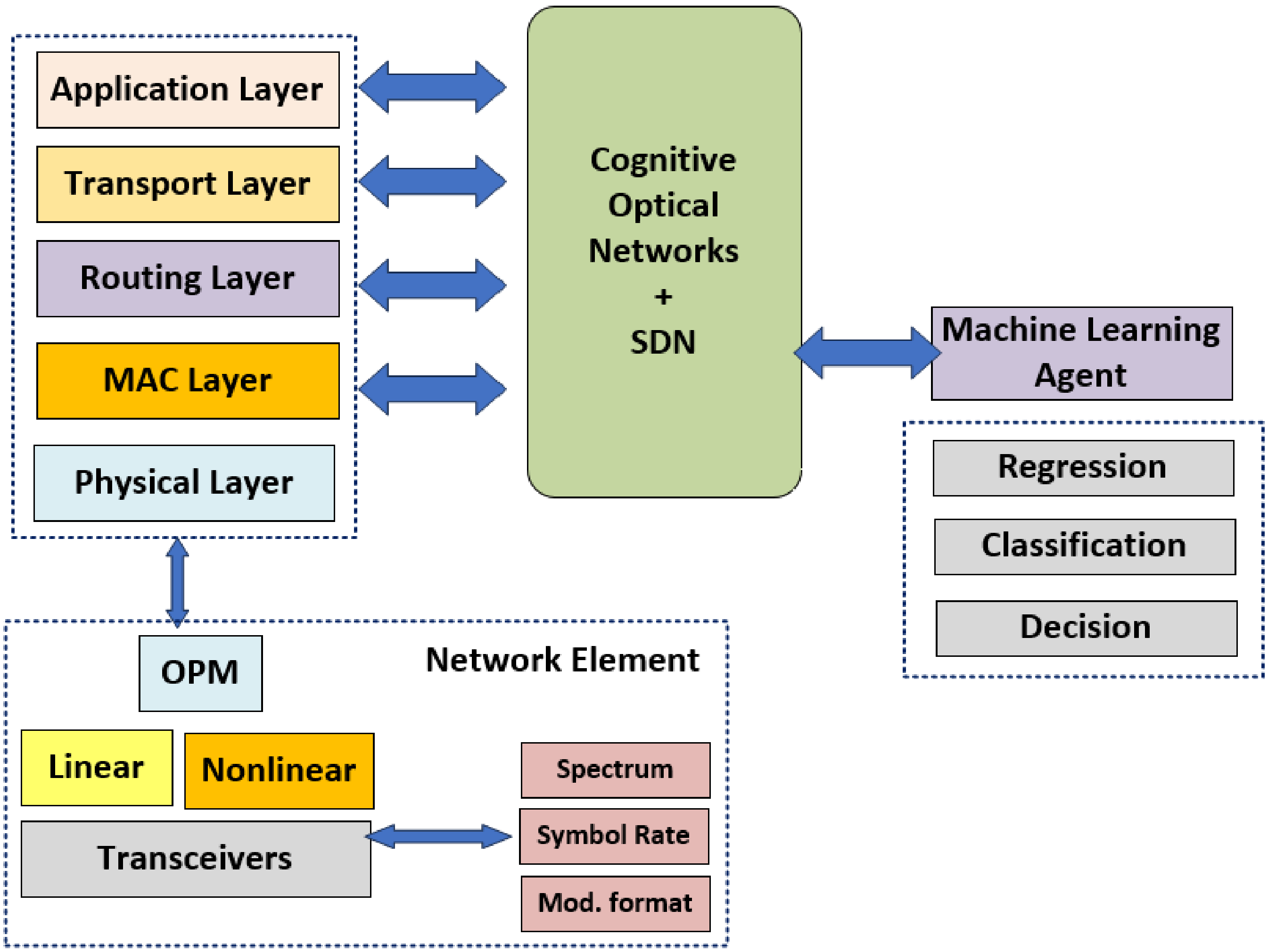

Fig. 1. Cognitive Optical Network

configuring new hardware, and re-establishing traffic flow. Automating these processes, including QoT estimation for future configurations, is crucial for network efficiency and guaranteed continuous service.

Indeed, there are various indicators or metrics used in QoT modeling and estimation, such as BER, Q-factor, signal-to-noise ratio (SNR), optical signal-to-noise ratio (OSNR), generalized OSNR (GOSNR), generalized SNR (GSNR), the margin [11], the error vector magnitude, and the eye diagram characteristics [12]. In sequence there will be a brief description about these metrics. The primary objective of QoT estimation is to accurately estimate lightpath performance and construct networks with minimal margin. However, the specific requirements for QoT estimation vary based on the specific scenario. In some scenarios, the goal is to determine whether a lightpath can be established or not [13], [14], [15]. For such cases, ML classification techniques like K-nearest neighbors (KNN), random forest (RF), support vector machine (SVM), logistic regression (LR), and artificial neural networks (ANN) can be utilized effectively [16]. Accuracy is indeed a common metric used to evaluate the performance of ML classification models [10]. It measures the ratio of correctly classified instances (in this case lightpaths) to the total number of instances. However, it is important to consider other metrics like precision, recall, and F1-score, especially in scenarios where the classes are imbalanced.

On the other hand, in scenarios where precise QoT measurements are needed, ML regression techniques such as convolutional neural networks (CNN), ANN, Gaussian process (GP), network kriging (NK), and other regression techniques can be employed. These techniques enable the estimation of specific QoT metrics with high accuracy, catering to the diverse requirements of QoT modeling in optical networks [11]. Common metrics to evaluate the performance of ML regression models include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), as well as maximum (MAX) and minimum (MIN) errors are commonly used. These metrics help in understanding the accuracy of predictions and setting appropriate margins for the desired level of confidence in the model's output [10].

As previously mentioned, one of the key benefits of having precise QoT estimation is the ability to manage networks with minimal margin. However, it can lead to increased hard failure probability without proper network maintenance practices. To mitigate this, networks need to detect and diagnosis issues, prevent hard failures, and reduce mean-time-to-repair through failure classification and localization. So, QoT information needs also to provide means to trigger early detection and soft failures and not only performance values.

IV. QoT INDICATORS

The quality of light signal traveling through fiber optics can be affected by various factors. These impairments can originate from the fiber itself due to propagation and from the equipment behavior [17]. Fiber-related impairments fall into linear effects and nonlinear effects. Linear effects gradually weaken the signal over distance. Attenuation, chromatic dispersion (CD), polarization mode dispersion (PMD), polarization dependent loss (PDL), are the most common linear impairments and are addressed using optical amplifiers and modern digital signal processing (DSP) techniques in receivers. Nonlinear impairments consist of Kerr effects and inelastic scattering. The refractive index of the fiber material changes in direct proportion to the electromagnetic field's intensity due to the Kerr effect. It includes self-phase modulation (SPM), cross-phase modulation (XPM), and four-wave mixing (FWM). Inelastic scattering consists of energy transfer between the interacting field and the dielectric medium. Stimulated Brillouin scattering (SBS) and Stimulated Raman scattering (SRS) are the two main types of inelastic scattering. Nonlinear impairments are typically mitigated using power equalizers and modeled using equations like Schrodinger or Manakov [17]. Recent research has explored ML solutions for nonlinear impairment mitigation. Amplified spontaneous emission (ASE) noise, wavelength and polarization dependent gain are generated by amplifiers. For ROADMs, besides these previously impairments, it is necessary to include PMD, PDL, filtering effects, insertion loss and crosstalk.

The primary QoT metric of interest is the bit error rate (BER) of the lightpath. This metric determines whether the lightpath is acceptable based on whether the BER falls below a predefined threshold. Modern transmission systems utilize forward error correction (FEC) and the pre-FEC BER is usually used to express the threshold. The BER prior to FEC is known as pre-FEC BER. FEC is a correction technique that adds redundancy to data before transmission.

For a specific modulation format, a well-defined mathematical relationship exists between BER and SNR. Knowing the SNR enables calculation of the expected BER. Similarly, BER and Q-factor can be mathematically linked. Q-factor is a dimensionless parameter that indicates signal quality before applying FEC and is data rate and modulation format independent. Different modulation formats have different sensitivities to impairments and offer varying trade-offs between data rate and Q-factor requirements. As an example, the quadrature phase-shift keying (PQSK) modulation requires a higher Q-factor compared to simpler formats like on-off keying (OOK) for the same BER.

OSNR refers to the optical signal-to-noise ratio, which characterizes the noise introduced by optical amplifiers along the lightpath due to amplified spontaneous emission (ASE), also referred to as OSNR$_{ASE}$.

OSNR is a crucial metric in optical networks, aiding in estimating system performance and providing means to estimate BER. It serves as a key indicator of impairment in optical transmission systems, particularly those employing amplifiers. By knowing OSNR and bandwidth, one can determine Q factor and BER, reflecting the quality of service (QoS) at the physical layer and predicting potential packet losses.

The definition of OSNR as the ratio of signal power to the power of noise within a 0.1 nm bandwidth at 1550 nm is indeed common in optical networks. However, it is important to note that as baud rates increases, leading to wider signals, comparing OSNR becomes more complex. So, defining OSNR as a pure and independent channel baud rate ratio in units of dB, also known as SNR or SNR$_{ASE}$, indeed helps to avoid confusion, particularly when dealing with different baud rate channels.

The design OSNR is determined using the classical formula [18]:

$$\begin{aligned} &OSNR_{Design} = P_{TOP} - N_{Ch} - G - NF - N_R \\ &\text{(average per channel, in dB/0.1 nm)} \end{aligned} \tag{1}$$

where, 58 is a constant related to Planck's constant, the central wavelength of the spectrum and optical bandwidth (12.5 GHz), P_{TOP} is the line amplifier output power in dBm , $N_{Ch}$is the number of channels in dB, G is amplifier gain in dB, NF is the amplifier noise figure in dB, and $N_R$is the number of line amplifiers in dB.

The Design OSNR, while straightforward to calculate based on system parameter specifications (amplifiers gain and noise figure), lacks consideration for all impairments present in a practical system [19] such as ROADM penalties and nonlinearities.

With the introduction of variable baud rate transponders in optical communication systems, a more logical reference may be to define OSNR (dB/0.1 nm) as SNR$_{ASE}$ (dB), removing any discrepancy on a specific channel count or spacing. OSNR can be easily converted into SNR$_{ASE}$ by using the following conversion [19]:

$$SNR_{ASE}(dB) = OSNR - 10 \times \log_{10}(B_o/12.5GHz) \tag{2}$$

where,12.5 GHz is the reference bandwidth, B_o is the spectral width within which the channel under test is defined in GHz, and OSNR is referenced to dB/0.1nm. For example, if the spacing is 50.0 GHz and assuming a classical spacing for a 30-35 Gbaud transponder, the SNR$_{ASE}$ would be approximately 6.2 dB lower than the OSNR.

In optical communication systems, fiber propagation impairments caused by attenuation, chromatic dispersion, and Kerr nonlinear effects can be estimated as additive white Gaussian noise (AWGN). Since all major propagation impairments, such as ASE and nonlinear impairments (NLI), can be represented or modeled as Gaussian disturbances, i.e., as NLI is treated as an additive white Gaussian noise (AWGN) which is statistically independent of ASE noise, the performance of an optical channel can be evaluated using a unique metric called signal-to-noise ratio (SNR). This metric is referred to Generalized

OSNR (GOSNR) which consists in the summation of the linear and nonlinear effects. ITU-T Recommendation 977.1 defines [20] the link GOSNR according to following equation:

$$1/GOSNR = \ 1/(OSNR_{ASE}\ ) + \ 1/(OSNR_{NLI}\ ) \tag{3}$$

where both noise power and signal are referenced to the same optical bandwidth, typically 0.1 nm (12.5 GHz). The OSNR_{ASE} in equation (1) depicts the component of the OSNR caused by ASE noise only. The OSNR_{NLI} refers to the nonlinear distortions. Since the most common coherent technology at the time was 30 to 35 Gbaud 100G DP-QPSK, it made sense to describe GOSNR in terms of 120 channels with 37.5 GHz carrier spacing [18].

Regarding measurement, OSNR evaluation for network performance validation brings challenges such as tight channel spacing in DWDM systems and inaccuracies in traditional OSNR measurements [21] . The traditional method of evaluating OSNR, also called OSNR_{ASE}, faces some challenges. In dense wavelength division multiplexed (DWDM) systems, the close spacing between channels makes it difficult to distinguish the noise floor. Additionally, OSNR_{ASE} mainly considers the ASE noise as the nonlinear interference is primarily in-band. Finally, using the optical spectral analyzer (OSA) to measure the OSNR_{ASE} requires to turn-off adjacent channels which causes disruption in normal operation. So, the concept of generalized OSNR (GOSNR) is introduced [22] , aiming to capture optical impairments more accurately, including linear and nonlinear noise. GOSNR is determined as the OSNR value required to achieve the same BER in a back-to-back transmission scenario, considering both linear and nonlinear impairments [22]. The previous defined concept of GOSNR takes account that [18] the optical line can be modeled using the GN model and that the relationship between fiber nonlinearities and BER in digital coherent systems is predictable.

The rapid movement of coherent technology toward variable bitrates, higher symbol rates, and probabilistic constellation shaping, GOSNR needed to be modified to become the generalized SNR (GSNR), a metric that is independent of channel spacing, modulation format, and symbol rate [18].

Recent papers have proposed to define a new metric called SNR or SNR_{ASE}, similar to OSNR but with the noise bandwidth equivalent to the signal bandwidth. This would make the metric independent of modulation format, channel spacing, channel count, and symbol rate, providing a more comprehensive measurement that accounts for all noise observed at the receiver. Consequently, it provides a unique and comparable modem-independent performance indicator for optical networks.

The relationship between OSNR_{ASE} and SNR_{ASE} is defined in [18] in linear units as follows:

$$SNR_{ASE} = \frac{B_o}{\triangle f}\, OSNR_{ASE} \tag{4}$$

where,

B_o is the optical noise bandwidth (usually 12.5 GHz at 1550 nm) that is used to define $OSNR_{ASE}$

The carrier spacing in GHz, Δf, is used to define $OSNR_{ASE}$ for a system fully loaded.

The power spectral density (PSD) is assumed to be uniform throughout the bandwidth.

The channel's power to the total ASE noise accumulated from in-line amplifiers and NLI as a result of fiber transmission is known as the generalized SNR (GSNR), which is evaluated wholly in the signal bandwidth.

GSNR is defined in linear units as [23]:

$$\frac{1}{GSNR} = \frac{1}{SNR_{ASE}} + \frac{1}{SNR_{NLI}} \tag{5}$$

where, SNR_{ASE} is the channel width independent OSNR previously defined, and $SNR_{NLI}$is the noise generated from the nonlinear interference.

It is worth reiterating that the *GSNR* metric is independent of the modulation format. It is an optical line parameter dependent on spectrum, mainly characterized carrier spacing and symbol rate. The *GSNR* baseline refers to the maximum spectrum occupancy where the calculation is done based on Gaussian noise model.

To meet the evolving demands of network operators, optical networks are transitioning towards full disaggregation, where subsystems operate independently but share common data structures and interfaces. This necessitates interoperability among systems from different vendors, ensuring that physical lightpaths can be provisioned with transponders from different manufacturers. Planning such networks requires physical layer abstraction, often estimated using the GSNR. The total GSNR across multiple domains [24] is calculated considering contributions from ASE noise and NLI, which includes effects like XPM and SPM. XPM is typically treated as a local, statistical effect, while SPM generation within fiber span is stochastic. A localized physical layer abstraction is crucial for planning and managing networks effectively, allowing for a fully disaggregated approach.

When considering a series of optical domains, the total GSNR is calculated by summing the inverses of individual GSNRs as described by [24]:

$$GSNR^{-1} = \textstyle\sum_{i=1}^{N} GSNR_i^{-1} \tag{6}$$

where $GSNR_i$ is the GSNR value of each optical domain.

Most of modern coherent modems employs the effective SNR (ESNR) metric to capture optical performance comprehensively. It accounts for various penalties including linear, nonlinear, modem noise (SNR_M), and other impairments (SNR_I). By encompassing these factors, ESNR provides a holistic view of the signal quality, enabling more accurate assessment and optimization of optical network performance.

The Required ESNR (RESNR) serves as the ESNR limit for a modem, akin to the FEC limit represented in dBQ. Each modem generation and transmission mode may feature its own distinct back-to-back RESNR. It is crucial to understand that, like FEC and dBQ, RESNR remains constant regardless of propagation, making it a fixed value for a given modem generation and transmission format.

In an optical coherent modem, the noise on each received symbol is estimated by comparing it with the estimate of the corresponding transmit symbol. This noise field encompasses contributions from ASE, fiber nonlinearity, decision errors, among other sources. In [25] is estimated the contribution of SNR by using the temporal and polarization correlations imposed on the nonlinear noise by the Kerr nonlinear effects. It accounts for nonlinear noise contributions from cross-phase modulation (XPM), self-phase modulation (SPM), and cross-polarization modulation (XPolM).

At a high level, coherent optical engines consist of three main components: a digital ASIC (DSP), analog electronics, and photonics. The DSP handles signal processing for both receive and transmit directions, including modulation, spectral shaping, and compensation for various impairments. Digital-to-analog (DAC) and analog-to-digital (ADC) conversion operations are included in DSPs. FEC, framing, and encryption are also integrated into the DSP. Coherent modem noise refers to penalties related to compensating for various impairments like polarization dependent loss (PDL), chromatic dispersion (CD), laser linewidth dispersion interaction (laser phase noise), and wavelength tolerance (caused by the number of filters in the path, flexgrid crosstalk, laser frequency drifts) [19]. Figure 2 provides a high-level schematic of the coherent module.

Table I provides a summary of the performance metrics described in this section.

V. ML Techniques Background

In recent literature, there has been a surge of interest in surveys of research using ML techniques in optical networks. While several papers have provided comprehensive overviews of ML applications in optical networks, this paper focus only on studies for QoT estimation. The objective is to analyze and address the current state of the art in this specific use case, aiming to provide insights for future research in this area.

Artificial Intelligence (AI) [10] involves equipping machines with cognitive abilities to execute tasks intelligently, mirroring human-like performance. ML, a prominent AI subset, employs algorithms to detect patterns and behaviors in data, facilitating the creation of models for tasks such as estimation and data categorization. ML has gained significant traction in various fields, especially in computer vision, speech recognition, and natural language processing. ML serves as a catalyst for building cognitive optical networks by leveraging increased data accessibility and computer power. ML techniques are categorized into three families: supervised learning, unsupervised learning, and reinforcement learning [2]. Supervised learning invokes known database information, suitable for classification and regression tasks. Unsupervised learning operates without defined labels, primarily used for clustering and dimensionality reduction. Reinforcement learning adopts a reward strategy, enabling agents to make decisions in complex environments, with Q-learning being a common algorithm in this category.

A. Supervised Learning

Supervised learning consists in training an algorithm to understand the correlation between input and output data by observing labeled examples. These labeled examples consist of input-output pairings, where the output is already known. Techniques used in supervised learning include logistic regression, which predicts categories, and linear regression, which makes continuous predictions, such as estimating the OSNR or the GSNR of a lightpath. The objective is to develop a prediction tool that can accurately forecast the output for new, unseen input data.

There are many different ways to train these models, like:

- **Artificial Neural Networks (ANN) :** influenced by the human brain, these networks use layers of interconnected nodes to process information. These nodes or units, called neurons, are arranged in layers. Each neuron receives information or inputs, adjusts its importance (weights), and adds a small influence (bias) before passing it on. By adjusting these weights and bias over time, the network learns to solve problems. In optical networks, ANNs are used in various ways. For example, they can be embedded in digital signal processing devices (DSPs) to fight signal distortions or to estimate the quality of lightpaths. Three layers make up a typical ANN: the input layer, which receives the raw data, the hidden layer, which processes and modifies the data, and the output layer, which generates the final result [8].
- **Naïve Bayes:** this method assumes that different features (like pieces of a puzzle) act independently. It uses [26] Bayes theorem to calculate the probability of something belonging to a certain category based on various features. It assumes that these features are independent, which is not always realistic. When dealing with complex data, Naïve Bayes can be combined with techniques like kernel density estimation to improve accuracy. It is often used for tasks like classifying text or recommending products. In optical networks, it can be used to identify different types of damage in fibers. This method assumes that different characteristics affecting the signal traveling through a fiber optic are independent of each other, such treating each clue (like low signal strength) as independent evidence for a potential problem (like a fiber bend).
- **Random Forest (RF)**: Numerous [27] decision tree models are generated and combined using the random forest, each with some randomness in how it split data at each step to help prevent all the trees from making the same mistakes. A random subset of the training data is used to build each tree. This helps ensure they learn different patterns from the data. When a new data point arrives, all the trees in the forest vote on its class (like for example spam or not spam). The final prediction is based on the most popular vote. RFs are generally accurate and resistant to overfitting as well as do not need massive fine-tuning. In optical networks, this approach can be used to predict the quality of lightpaths or monitor signal quality.
- **Suport Vector Machine (SVM):** this model is like powerful separators that can divide data points into different categories. They are great for both classification and prediction tasks. In fiber optics, SVMs have been proven to be effective in mitigating various types of noise, such as nonlinear phase noise (NLPN), laser phase noise, fiber nonlinear Kerr efect, modulator linearity issues, ASE noise, both linear and nonlinear signal detection challenges, and de-mapping of high order modulations with rotated constellations [28], [29].
- **K-Nearest Neighbors (KNN):** it works [15] with any kind of data, without needing to guess how the data is distributed.

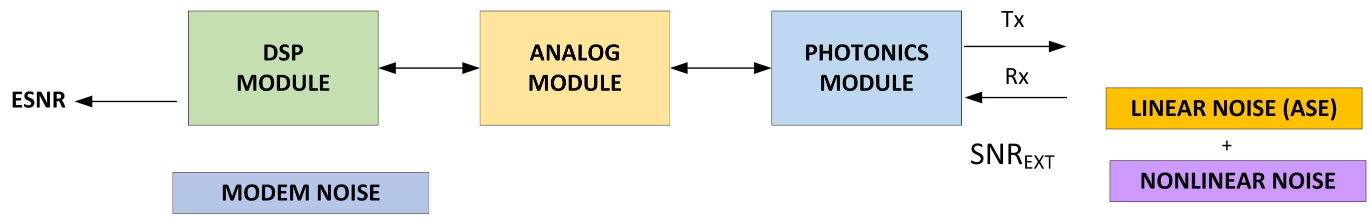

Fig. 2. High level coherent module

TABLE I
OPTICAL SYSTEM PERFORMANCE METRICS

Performance metric	Definition
OSNR	It measures the ratio of optical signal power to the noise (ASE linear noise) within a specified bandwidth (0.1 nm). Its formula considers only the linear ASE noise as impairment. It is dependent on the channel number count (120 channels is commonly used).
GOSNR	It extends the concept of OSNR to account for various impairments, such as nonlinearities, by treating them as additional noise components. NLI is considered as AWGN, statistically independent of the ASE noise. So, GOSNR can be defined as the ratio of the optical signal power to summation of linear and nonlinear noise. But GOSNR is not independent of the baud rate, channel space and modulation format.
GSNR	It is a metric that is independent of channel count, symbol rate (baud rate), and channel spacing. It is the ratio of the channel's power to the total power of all noise sources, including ASE and NLI, within the signal bandwidth.
ESNR	It quantifies the signal quality by considering all penalties (linear and nonlinear), including the modem noise (penalties related for compensating chromatic dispersion, polarization mode dispersion and polarization dependent loss, laser phase noise and wavelength tolerance)

It does not process any data during training. It just stores it. It is known as a "lazy learner" [7] because most of the calculation and computation is done when testing to determine the class of a new input, making it computationally costly for large datasets. When a new data point arrives, it finds the K closest examples in memory and predicts its category based on their majority. The number of neighbors (K) can affect the prediction. A smaller K might be more sensitive to outliers, while a larger K might smooth out details. KNN uses distance metrics, like Euclidean distance, to find the closest neighbors. In summary, it classifies new data points based on their similarity to existing data. In optical networks, KNN can be used to overcome signal nonlinearities.

- **Convolutional Neural Networks (CNN):** it is a specialized neural network type intended for handling grid-like data, such as images [30]. It utilizes operations like convolution, pooling, and activation to obtain features from the input data. Convolution consists in a process of sliding a filter over the input to extract information features, while pooling reduces the dimensionality of the feature map. In pooling, nearby outputs are summarized, often using max or average pooling. Activation functions such as ReLU improve the network's representation capacity through non-linear mapping. CNNs excel at tasks object detection, image recognition, and video translation. In optical communication, [31] where data is often represented as images, CNNs can be used for tasks like channel estimation, equalization, optical signal analysis, and constellation image processing [32]. The typical input images in optical communications are eye diagrams, constellation images, and optical spectrum diagrams.

- **Logistic Regression (LR) :** it is a type of algorithm that uses the logistic function to make predictions [33]. The logistic function always gives a result between zero and one, which can be thought of as a probability. Determining the best parameters for the logistic function is the goal of LR, so that the predicted values are as close as possible to the real values. Once the parameters are set, making predictions for new examples is straightforward using the logistic function. In optical networks, based on the chosen factors and their measurements, the LR model can calculate the probability of the system being healthy or degraded [34].

B. *Unsupervised Learning*

Unsupervised learning [2] focuses solely on input data x, unlike supervised learning, which considers both input x and output labels y. In unsupervised learning, the algorithm aims to identify underlying structures, patterns or interesting aspects within the data with no predetermined output labels. Essentially, there are no specific inputs or outputs; the data is merely a collection of examples. The primary objectives include clustering, where algorithms like K-means group data into groups or clusters based on similarity, dimensionality reduction techniques like principal component analysis (PCA) which maps high-dimensional data into smaller set data, and anomaly detection, which identifies data points that deviate significantly from the typical behavior.

- **K-means clustering**: it is a powerful unsupervised learning classification method commonly used to solve classification problems with unlabeled data [2]. It divides data into k clusters based on similarity, aiming to minimize the total squared error distance to the centroid. This technique finds applications across various industries, from banking to cybersecurity, document clustering to image segmentation. In optical networks, K-mean can address challenges like nonlinear impairments mitigation on constellation diagrams and identification of anomaly detection. Anomaly detection identifies outliers or deviations from the norm, making it valuable for detecting issues like fiber events or amplifier malfunctions. Anomaly detection is crucial for effective management of modern optical networks.

• **Principal Component Analysis (PCA)**: it reduces complexity by identifying the most important patterns in the data and creates a new, smaller set of measurements that capture those patterns. This is like summarizing a long document into the key points. PCA is often used for tasks like finding the main structure in a dataset, reducing noise and making data easier to analyze, and visualizing complex data in fewer dimensions like showing a three-dimensional object in a flat screen. In [35] is described a method that combines data scrambling and PCA for confidentially detecting failures in optical networks. PCA is applied to find patterns, scramble the data and detect errors.

C. Reinforcement Learning

Reinforcement Learning (RL) [32] is a learning method where an agent learns by getting rewards for certain actions it takes. The goal is to make decisions that maximize rewards over time. This learning happens by interacting with the environment, where the agent tries different actions and learns from the outcomes. In RL, the agent follows a policy, which is like a strategy map showing what actions to take in each situation. This process is guided by a mathematical framework called the Markov decision process (MDP), which helps RL algorithms work well. RL is useful in network automation and control, especially in areas like routing, resource allocation, and configuration in optical networks.

D. Recurrent Neural Networks (RNNs)

RNNs are a category of artificial neural network designed to handle sequential data by retaining memory of previous inputs. RNNs handle sequential data by retaining internal states across time steps and can be trained using a technique called backpropagation through time. However, they face challenges like vanishing gradients (loss function derivatives become extremely small, so the weights in the early layers are updated very slowly) or exploding gradients (loss function derivatives grow exponentially, causing the instability and making the learning process to diverge) for long-term dependencies [22]. ML can be even more powerful when we combine multiple learning tasks. This is called multitask learning, and it allows models to learn from each other and improve overall performance.

• **Long Short-Term Memory (LSTM):** on powerful tool for sequential data, like a stream of information, is a special type of neural network called LSTM network. Unlike traditional neural networks, LSTMs [22] have a “memory” that allows them to remember past information and use it to understand current data. This makes them ideal for task like speech recognition or processing long sequence of data in optical networks.

• **Gated Recurrent Unit (GRU):** GRUs [22] is another type of neural network architecture specifically designed for processing sequential data, similar to LSTM networks. They are simpler than LSTMs and require less memory, making them a good choice for situations where computational resources are limited.

Traditional feed-forward neural networks process data only in a forward direction without cyclic connections, making them efficient for learning but not suitable for sequential and variable-length data. RL networks can struggle with very long-term dependencies. When dealing with tasks with long-term dependencies, RNNs might be a better choice. LSTMs networks address these issues as well as vanishing and exploding gradients but require high memory usage due to the presence of multiple memory cells. GRUs networks, which provide a similar solution to LSTM but without separate memory cells, offer a solution that exposes the entire state of the network at each time step. RNNs, particularly LSTM and GRU, are applied in QoT forecasting tasks, aiming to detect performance degradations for proactive maintenance. Univariate models, which use only one input variable, and multivariate models, which incorporate two or more inputs variables, are trained using LSTM and GRU architectures with single lightpath data, showing varied performance across different model architectures. Linear regression models, such as ANNs, sometimes outperform RNNs but are sensitive to outliers in the time series data [7].

E. Evaluation Metrics

In evaluating QoT models, different metrics are employed depending on whether the model is designed for classification or regression [36]. For classification models, accuracy is commonly used, but it may be misleading when classes are imbalanced. So, it is crucial to consider the area under the ROC curve (AUC) [13]. ROC means receiver operating characteristic. AUC provides a more robust evaluation of the classifier performance. It measures how well the classifier distinguishes between positives and negatives instances, irrespective of the chosen threshold.

In regression-based QoT estimator, metrics focus on the distribution of errors between the estimated and actual QoT values [36], [37]. Average error indicates overall performance, while maximum error offers insights into high-probability margins. The cumulative distribution function (CDF) allows for accessing intermediate probabilities while the root mean square error (RMSE) measures the average magnitude of errors. Additionally, the R2 score parameter indicates the proportion of variance in the QoT values that the model can explain. An R2 value of "1" indicates a perfect fit, where the model explains all the variance in the data. Conversely, an R2 value close to "0" suggests the model has little explanatory power. These metrics collectively offer insights into the accuracy and reliability of regression-based QoT estimators.

This paper focuses on the tasks that are crucial for fast lighpath setup and proactive network failure management: QoT estimation for new or unestablished lightpaths and QoT estimation for existing or established lightpaths.

QoT estimation before lightpath establishment involves metrics like BER, OSNR, GOSNR, GSNR and EVM. An accurate estimation requires precise evaluation of linear and nonlinear impairments. Analytical models typically calculate these metrics based on system and link parameters, using methods like the numerical split-step Fourier method or using the Gaussian noise assumption. Using ML can reduce the need for complex calculations and uncertainty in traditional models. These models can be trained with labeled data to predict the QoT of unestablished lightpaths [26]. QoT forecasting for deployed lightpaths becomes challenging in dynamic environments where system parameters fluctuate due to factors like temperature effects or aging. In such cases, analytical models may struggle, and ML techniques can be beneficial. QoT forecasting aims to spot performance issues early by adjusting parameters like modulation format, bit rate, symbol rate, and optical power of the transceivers and take actions in advance before transmission errors occur [26].

ML-based QoT estimators utilize ML techniques to forecast whether the QoT of a candidate lightpath in an optical communication system is above or below a predefined threshold or to estimate the accurate value of a lightpath's QoT. These estimators often rely on artificial neural networks (ANNs) which are highly capable information processing models known by their efficiency in classification and regression tasks when appropriately configured and trained. Despite their effectiveness, constructing ANN models can be challenging due to the complexity involved in their configuration and training process.

Different scenarios [38] demand different QoT estimators, ranging from determining if a lightpath can be established or obtaining specific QoT metric values. In case of determining if a lightpath can be established or not, classification methods like KNN, RF, SVM, logistic regression (LR), and ANN are suitable. In scenarios requiring precise QoT values, ML regression methods like network kriging (NK), Gaussian Process (GP), ANN, and CNN are utilized.

The training process of an ML-based QoT estimation model involves multiple steps, as depicted in Figure 3.

The process begins by gathering data from simulations, experimental setups, or operational networks. This dataset comprises input features (denoted as X) that influence QoT estimation. Feature selection involves cleaning the dataset and identifying the features that have relevant impact. Next, the dataset is divided into three subsets: one for training the model, another for validation, and a third for testing. During the training phase, the model learns to predict QoT values from the training data. In the validation phase, the model's parameters are adjusted to improve its performance. Finally, the model's effectiveness is tested using the testing data to ensure accurate QoT predictions. This learning process applies to various types of ML models, including regression and classification models, and enables the development of accurate QoT estimation systems tailored to specific network scenarios.

VI. Survey of ML-Based QoT Solutions

In this section, it is presented a survey of papers focused QoT estimation using machine learning. The papers are categorized into three groups: Regression, Classification, and Regression based on RNN and ANN.

A. *Regression for BER, OSNR and GSNR prediction*

Techniques using ML for predicting BER, OSNR and GSNR.

In [16], a cost-effective method using a single photodiode to estimate OSNR directly from detected data. This method involves extracting features from directly detected (DD) data, such as the power eyediagram after the photodetector, to predict OSNR. Examining the variance in the eyediagram, it is possible to extract several features. A neural network with just one hidden layer can effectively perform this estimation. This approach eliminates the need for costly optical spectrum analyzers throughout the network. The method for OSNR or GSNR estimation is shown to be independent of the modulation, but it requires training using the specific modulation format intended for transmission.

In [39] is proposed a regression model using a ML algorithm to refine initial QoT estimations. Links and lightpaths are initially allocated using a QoT estimator based on propagation physics, using an initial margin. Based on monitored data collected from this initial deployment (pre-FEC BER, NF, fiber input power), the model is refined by an ML algorithm and new lightpaths are deployed with a lower margin. The ML algorithm increases its accuracy as new inputs or requirements are introduced into the system and consequently, the overall system efficiency is enhanced. The learning process, applied to a European backbone network, significantly reduces QoT inaccuracy for new demands, regardless of initial parameter uncertainties. By using measured data in a gradient descent algorithm, design margins can be lowered, leading to reduced QoT prediction errors. In a brownfield network, the method reduces overprovisioning and equipment costs in optical networks. The method predicts SNR values with typical errors lower than 0.1 dB.

In [40] is investigated Gaussian Process Regression (GPR) for predicting BER in WDM systems. The model learns from measured data under specific system configurations and applies this knowledge to predict performance for new configurations. This approach offers advantages in capturing complex system dynamics more easily than through simulations. Numerical simulations reveal that GPR can accurately predict BER in a four-dimensional input parameter including power, number of spans, symbol-rate and bit-rate. It can predict BER in real WDM systems with 95% confidence interval. So, BER can be accurately estimated in brownfield systems with GPR model trained with synthetic data. Q error is lower than 0.3 dB.

In [37] is explored ML regression to predict the probability distribution of GSNR. Three regression approaches are evaluated using synthetic data generated by simulating network scenarios using the GNPy tool. The study identifies limitations of classification-based approaches and proposes an ML-driven

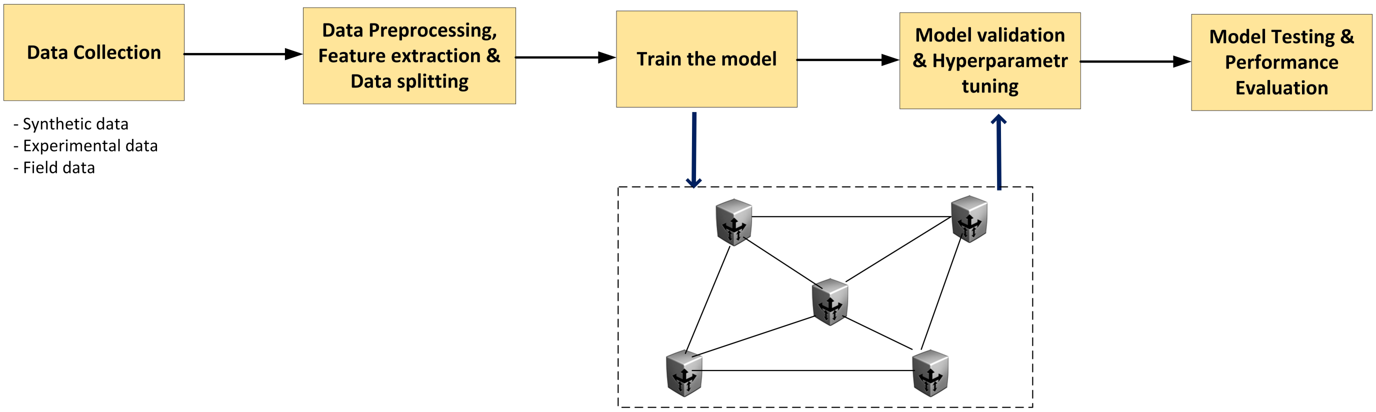

Fig. 3. QoT estimation's training process

QoT estimation method based on regression. It treats the GSNR measure as a random variable (due to amplifier noise figure variation) with a probability distribution function (PDF), considering factors such as traffic load, modulation format, lightpath length, and number of links crossed. Three regression techniques are evaluated for predicting the PDF of the GSNR of a candidate lightpath before deployment. This enables not only determining if a lightpath configuration surpasses a system threshold but also quantifying the proximity of the predicted GSNR to that threshold. This approach achieves a performance cost penalty lower than 0.069, indicating improved accuracy in deployment decisions compared to relying solely on a single estimation point.

In [25] is compared ML (ANNs) with analytical models for QoT estimations. A single hidden layer ANN was employed as the ML algorithm model. For the analytical model, it was considered all contributions involved in the calculation of the SNR such as ASE noise, nonlinear noise (SPM and XPM), and transceiver noise (calculated using the GN model). Per-channel features such as input power, amplifier gain for each channel in the link, as well as equipment and fiber attenuation were taken into account.

B. Classification for QoT prediction

Various techniques use ML for QoT classification of unestablished lightpaths.

In [13] is proposed the use of an ML classifier to forecast whether the likelihood of the receiver BER of a potential lightpath fall within the system's tolerance threshold. Various features such as traffic flow, type of modulation format, total lightpath length, longest link length, and the number of links in the lightpath route are considered. The classifier is trained from BER measurements from deployed lightpaths and from lightpath probes which provide information that normal lightpaths do not provide. Results reveals high accuracy (84%) and the AUC. Transceiver savings can reach 17%.

For a case-based-reasoning (CBR) model [41] experimental results achieved successful classification ranging from 79% to 98.7% with a small knowledge base. CBR is an artificial intelligence approach that tackles new problems by finding similarities with past cases stored in knowledge base (KB). By leveraging the historical KB, the QoT estimator can accurately determine if a lightpath meets the QoT criteria before establishment, enabling a fast decision-making process based on previous experiences.

In [15] is explored the use of knowledge-defined networking (KDN) to enhance network responsiveness and automation. KDN complements SDN by integrating reasoning engines or process and ML algorithms into the networks' control plane. The study focuses on improving the validation process for unestablished lightpaths that is crucial for network operation. Different ML models (KNN, SVM, logistic regression, classification regression, ANN) were trained on network data (span length, transmitted power, bit rate, type of modulation format, number of spans, average length, maximum link length, average span attenuation, average dispersion) to predict whether a lightpath would meet quality requirements. ANN provided better results, achieving 99% accuracy. Output is based on continuous SNR values or two classes of values.

In [42] a new method using SVM has been developed to categorize lightpaths as either high or low quality based on their QoT. The results show that this SVM approach notably decreases the time needed to assess a lightpath's QoT, a critical and crucial aspect of network design, while also slightly improving accuracy. The proposed QoT estimator outperforms previous analytical methods and cognitive proposals in terms of accuracy, achieving up to 99.95% success rate in classifying lightpaths (BER) with better computing time over previous approaches. Several factors influence the QoT of a lightpath, with span length being one of the most impact. Other inputs considered are the total lightpath length, and number of wavelengths.

In [43] is presented a study that employs deep graph convolutional neural networks (DGCNN) to estimate QoT in optical networks. Within a centralized SDN, real-time network state information is collected and stored in a database through OPM. The ML application, integrated with the database, utilizes datasets to train the DGCNN model, which learns to classify unseen network states. The DGCNN achieves convergence to a QoT model accuracy ranging from 92% to 97%.

In [44], the authors explore the application of SVM and ANN classifiers for predicting the QoT of unprovisioned lightpaths. SVM and ANN achieved high classification accuracy initially but decreased when using reduced feature sets. The ANN and SVM model achieved a QoT estimation accuracy of 99.56% and 99.38% when using the full set of features.

In [45] is demonstrated an approach that employs a robust QoT decision method based on pattern recognition techniques, using feedforward NN to analyze data from previously established connections. The method relies on data rather than specific measurement tools or physical layer impairments. The model was trained with different wavelenghts and exhibited high accuracy ranging from 92% to 95%

C. Regression for QoT using RNN and ANN with spectral data

Methods for enhancing QoT estimation in optical networks are explored, including the incorporation of spectral data and utilizing ML algorithms [22]. ML techniques demonstrate high accuracy even when detailed component information is unavailable. It is explored methods to enhance the assessment of QoT in optical communication systems by concentrating on using spectral data to enhance the QoT estimation accuracy. Through experimental investigations, it is evaluated the effectiveness of these enhanced techniques in assessing the performance of an agnostic network. Using ML, QoT can be estimated without precise knowledge of network parameters. Simulated data includes transmission-related features and spectral-related features. Transmission-related features are composed of a transmission vector (modulation format, channel power, channel spacing, symbol rates or baud rates, and total link lengths) and a length vector containing the fiber lengths between the network element nodes. Spectral-related features are composed of a vector containing the power spectral density (PSD) or the total signal power, and a vector containing the channel powers. A LSTM and an ANN based framework are trained on simulated data. LSTM handles variable-length features while ANN processes fixed-length ones. Figure 4 shows the basic structure of the framework. Various ML algorithms including neural networks, support vector regressor, tree structures, and convolutional neural networks, are compared for QoT estimation. The findings indicate that algorithms using spectral features excel with experimental data, reaching impressive accuracy. They achieved R2-scores of over 0.9, meaning they closely predict observed values according to the statistical metric R2. This enables reliable QoT estimation even when detailed component information is unavailable. This approach is very valuable for disaggregated networks where confidential data is not shared.

In [44], LSTM and GRU models were proposed for SNR prediction for 4 days' time-horizon. The LSTM model showed superior performance in forecasting over longer horizons (the LSTM's R2 started low at -0.0148 for a 1-hour forecast but steadily improved, reaching 0.1415 for a 96-hour forecast), outperforming the baseline at 24, 48, and 96 hours.

In summary, the process involves collecting data and processing it using algorithms to generate useful intelligence for decision-making. Once this process is implemented in hardware and software, actuators will execute the decisions, driving optical network automation. QoT estimation is one of the factors considered by the RSA algorithm in flexible-grid networks. The main role of the RSA algorithm is to find the best path for lightpaths and assign the appropriate spectrum for them.

QoT estimation serves as one of the inputs to the RSA algorithm in flexible-grid networks. The RSA algorithm's main task is to determine the optimal route for channels and allocate the appropriate spectrum for the corresponding lightpath.

A well-designed RSA algorithm considers physical impairments and selects routes and spectrum information promptly for both new lightpaths and the restoration of existing ones. For successful planning, deployment, and operation of intelligent optical networks, it is vital to establish a simple, direct, and adaptable QoT estimation process prior to provisioning lightpaths and restorations [2].

The automation approach relies on models like neural networks (NN), RF, NK, SVM, and others. These models consider parameters such as OSNR, SNR, BER, or other relevant factors from existing lightpaths in the network. By comparing measured parameters with expected or calculated values, a cost function is constructed. Using gradient descent algorithm, this cost function is iteratively minimized. Once convergence is achieved, the minimized cost function indicates that a new lightpath can be added to the network with reduced margins, optimizing network performance and resource utilization [2].

Expanding [2] upon foundational model, additional variables such as lightpath length, amplifier characteristics, traffic volume, and other relevant data can be incorporated to enhance its capabilities. This enhanced model can further address issues like chromatic dispersion, polarization mode dispersion, Kerr effect, and other linear and nonlinear impairments. These impairments can distort the shape of symbol points in the constellation diagram of coherent optical signals. By establishing direct input-output relationships between monitored parameters and desired outputs, the model aims to mitigate these impairments and optimize optical signal quality.

Figure 5 shows the basic elements of a QoT estimator. This proposed model can be enhanced by incorporating additional variables that an analytical model work with such as fiber attenuation, spectrum usage and other pertinent data [2]. This enhanced approach is capable of mitigating various impairments in optical communications systems, including polarization mode dispersion (PMD), chromatic dispersion (CD), fiber Kerr effect, and other effects (linear and nonlinear) that affect constellation diagram's shape in coherent optical signals. By incorporating these variables, the model establishes clear connections between monitored parameters and desired results. This enables a more comprehensive understanding of the system's behavior and allows for more effective mitigation of impairments. Additionally, the model's ability to incorporate inputs from analytical models enhances its accuracy and predictive capabilities, making it a valuable tool for optimizing optical communication system performance.

In essence, accurately estimating QoT is vital for flex-grid networks. Real-time QoT estimation is crucial for promptly provisioning new lightpaths and restoring existing ones. Network planning must transition from offline to real-time predictions, utilizing current fiber conditions, amplifier settings,

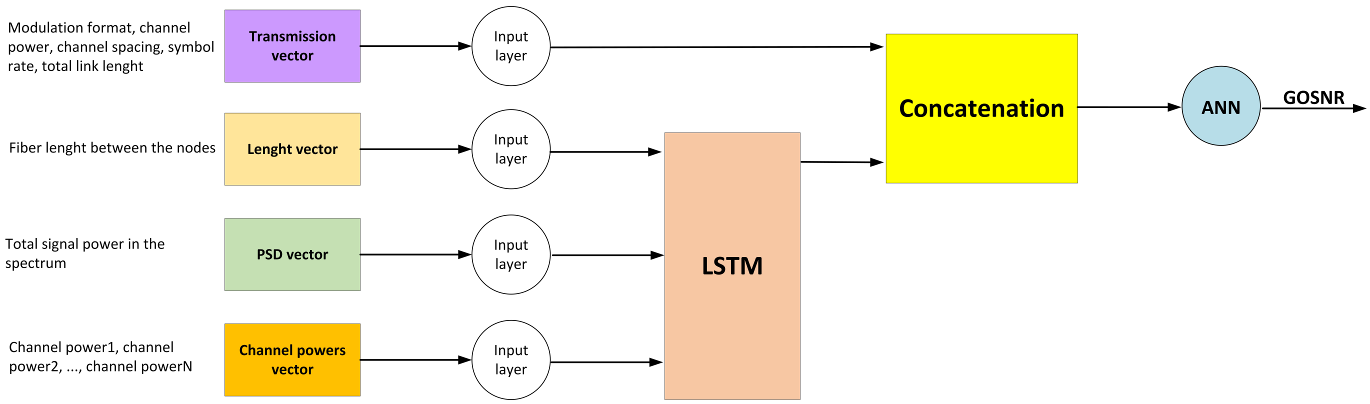

Fig. 4. LSTM QoT estimation framework

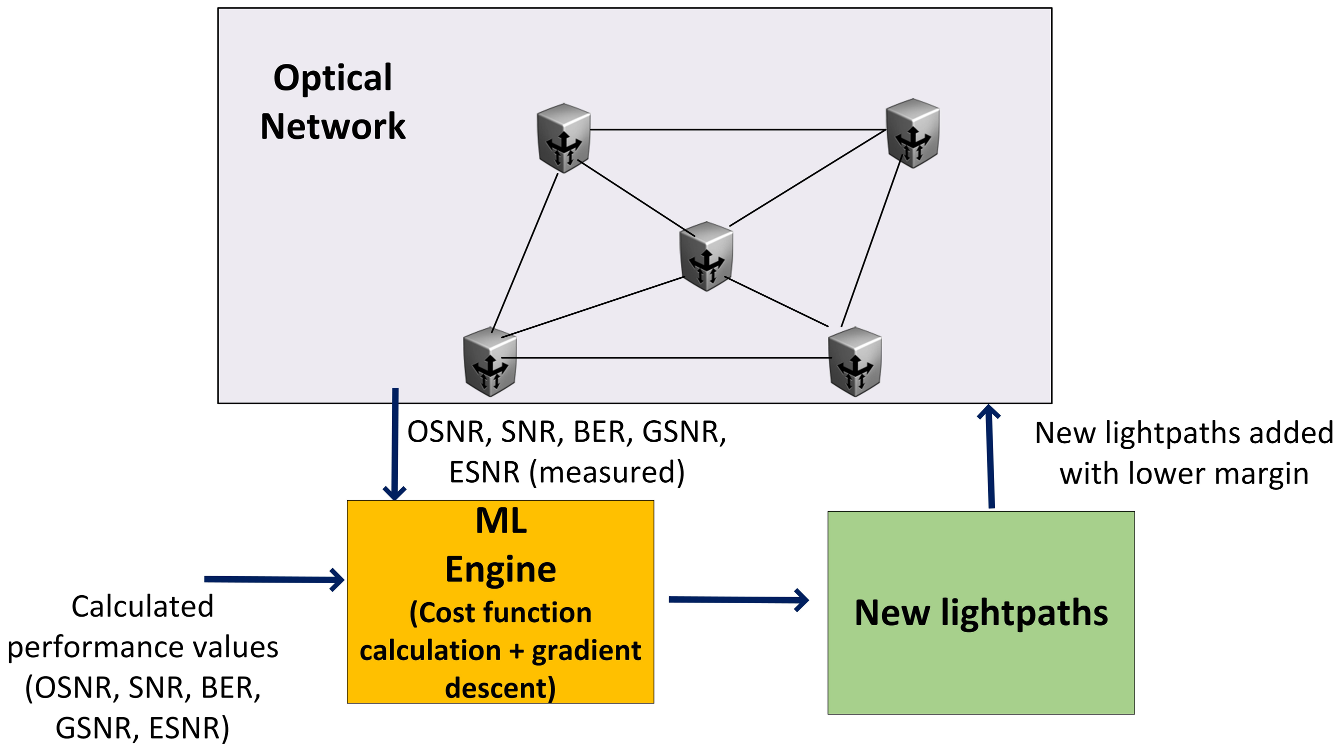

Fig. 5. Basic model to estimate the QoT of an optical comunication system

and network topology. With the introduction of the GNPy (Gaussian noise simulation in Python), which is a vendor-neutral approach for performance prediction, QoT assessment based on GNPy leverages the deployment of disaggregated optical networks. Additionally, accurate QoT prediction aids in early detection of soft failures in optical networks, which go unnoticed and can degrade performance gradually. By leveraging real-time optical data and ML, operators can proactively identify and address faults, moving away from traditional threshold soft failure management.

D. *Novelty in QoT estimation*

Existing methods commented so far for QoT estimation in optical networks primarily rely on regression or classification techniques. These methods play a crucial role in designing and planning optical networks by ensuring efficient resource allocation, reduced margins, and enabling efficient effective failure management. However, in elastic optical networks (EONs), QoT estimation must address fragmentation issues to optimize resources effectively. Dealing with fragmentation issues is an RSA responsibility. But QoT estimation entities needs to handle the complex interplay with RSA and PCE entities in modern optical networks. Additionally, modern QoT estimation should account for challenges like estimating lightpath quality in optical C+L bands, where impairments such as inter-channel stimulated Raman scattering (ISRS) affect signal quality, making the OSNR more frequency-dependent [46].

In [47] is detailed a multi-band transmission (MBT) systems focused on developing fast and accurate models to estimate QoT. Results indicate that the closed-form ISRS GN model offers a satisfactory balance of speed and accuracy. It takes only 0.2 seconds to estimate the QoT for all channels in the MBT systems. The model overestimates GSNR by a maximum of 0.1 dB and underestimates it by 0.4 dB in case of lower launch power scenarios. However, with higher launch power cases, the GSNR estimation error increases to 1.5 dB.

The model demonstrated a maximum overestimation of the GSNR of only 0.1 dB and an underestimation of 0.4 dB only for the lower launch power cases. However, for higher launch power cases, the GSNR estimation error reaches 1.5 dB.

In terms of accuracy, in [48] is proposed a new method called invariant convolutional neural network predictor (IC-NNP) to address challenges in QoT estimation, focusing on variable link configurations and distribution drifting of transmission parameters. The system includes a specialized encoder to combine channel and link details, along with a convolutional neural network to make predictions. In a 72 hours evaluation period, the standard deviation of the SNR prediction error remained under 0.25 dB.

In large disaggregated optical communication systems, enhancing the precision of QoT estimation is vital. In [49] is proposed a methodology based on refining signal power measurements and incorporating additional parameters into the analytical model to reduce QoT estimation errors. The methodology consists in combining data from inline amplifiers and optical channel monitors (OCMs) to estimate gain and noise power of each inline amplifiers to enhance QoT estimation. The standard deviation of the QoT estimation error was lower than 0.25 dB. However, this methodology needs to be automated and QoT results integrated with failure management systems.

E. Amplifier Modeling

The ML techniques described so far focus on predicting BER, SNR or GSNR based on ML techniques consider features such as span length, output power, data rate, modulation format, symbol rate, fiber attenuation as inputs to the model. Modeling optical amplifiers is a crucial key in optical networks. This allows more accurate performance analysis and permit to better optimize network based on traffic conditions.

Amplifier modeling is crucial for understanding and mitigating the noise generated by amplifiers in optical systems, as ASE noise is a major impairment [36]. Modeling amplifiers involves accounting for factors like wavelength dependence and spectral hole burning (SHB), which complicates traditional modeling methods. SHB refers to the phenomenon where certain frequency components of an optical signal experience a decrease in gain or amplification within an erbium-doped fiber amplifier (EDFA). This effect occurs due to interaction between the optical signal and the rare-earth ions within the fiber. Despite the difficulty in accurately predicting SHB effect, a measurement technique was developed in [50], albeit with some limitations.

Therefore, ML techniques are increasingly used to model amplifiers more accurately. In [51] is described a research that focuses on direct and inverse models for amplifiers where direct models map amplifier properties to spectral responses, while inverse models provide settings to achieve target responses. While most papers adopt the data analysis approach, there are cases where the hybrid approach which combines analytical models with data analysis is employed [52] to improve training efficiency.

Despite variations in methodologies, each study focuses on modeling a single amplifier under specific settings. While the reported errors are typically low, they can accumulate in systems with multiple amplifiers, impacting overall SNR in the optical spectrum. So, accurate behavioral modeling of EDFA and Raman amplifiers is a key part in optical performance analysis.

It is sure that the provisioning of optical amplifiers, including their placement, configuration, and operating parameters such as gain, power levels, NF, directly impacts the QoT of the transmitted lightpath. Improper provisioning or suboptimal working points can lead to signal degradation, increased noise, and reduced overall performance. High power levels due to improper provisioning induce nonlinear effects in the optical fiber such as SPM and XPM for example. These effects distort the lightpath signals and affects the QoT.

Few articles described so far the influence of the amplifier provisioning or amplifier working point in the QoT estimation values based on ML techniques. GNPy, the open-source design tool (which will be commented in the next section), considers amplifier parameters such as gain and noise figure. It calculates the GSNR value and the amplifier working points for optimal operation.

F. QoT Estimation in Open and Disaggregated Optical Networks

The successful data center and SDN deployments have fostered the appetite of operators to explore disaggregation in optical networks. SDN offers promising solution to address the complexities involved with coherent transmission, flexible modulation, and programmable transceivers. This means to foster and drive towards full end-to-end vendor neutral interoperable systems. This shift entails disaggregated hardware and software, emphasizing interoperability, and sharing responsibility between vendors and operators. To facilitate this, operators, vendors, consortia, and other entities are collaborating and pushing this to define models for off-the-shelf controllers and an estimator to assess quality of transmission in optical systems. This effort, led by partnerships of operators, vendors and suppliers within the Telecom Infra Project (TIP), aims to simplify deployment, empower system integrators, and provide stable benchmarks for performance decisions in optical network design. The Physical Simulation Environment (PSE) team within TIP is specifically working on developing an open-source QoT estimator to support this endeavor called Gaussian noise in Python (GNPy) [53]. GNPy is equipped with a central engine that evaluates the QoT by factoring in propagation effects. This core engine manages the data flow between various nodes in the network, including fibers, amplifiers, ROADM nodes, and transponders. It relies on JSON or excel files internally converted to JSON, to describe the parameters of each network node. This provides inputs to GNPy calculate ASE noise and nonlinear impairments caused by fiber Kerr effects and inelastic scattering. So, it is necessary to provide the amplifier modeling that accounts the relationship between gain and noise figure. It calculates the GSNR between a source and destination network element node along a specific route, considering signal attenuation through optical fibers, amplification at network nodes, and updated spectral information. GNPy optimizes network operation by calculating optimal levels of launch power and amplifiers operating point.

The accuracy of a GNPy QoT estimation in a multi-vendor open network is demonstrated in [53], [54], [55]. Results show the accuracy of GNPy in predicting GSNR and OSNR values with great accuracy (mean error within 0.4 dB and 1.0 db for OSNR and GSNR values respectively) for channels with different modulations.

In [56], the GNPy open QoT estimator is used as an impairment-aware path computation in multi-vendor optical networks. GNPy module is integrated with the open SDN Controller T-PCE (traffic engineering path computation element) through the development of a REST API that enables the interaction between the two entities. This integration marks the debut of GNPy as open plugin module to support a controller in real-time.

Moving forward, in [57] is presented an open optical architecture centered around on a digital twin of the physical layer within a hierarchical control system. An experimental demonstration is conducted with GNPy as the digital twin of the optical physical layer while ONOS operated as the open SDN controller. This setup showcases the reliability of the control plane, which is decoupled from the data plane, by using GNPy for lightpath QoT estimation and also for amplifier operating point calculations. The reliability is tested through scenarios like automatic failure restoration from fiber cut while network resources are managed by the control plane and lightpath allocations managed by the data plane. So, in [57], the GNPy is leveraged to serve as a dual purpose: by configuring the optical amplifiers, and operating as a QoT estimator and path computation engine, functioning as the intelligence behind the control system. Performance metrics regarding the interactions involved in lightpath restoration are primarily hindered by two-time consuming processes: the lightpath PCE (path computation engine) and lightpath establishment, taking around 4.5 and 6.5 seconds, respectively. However, these durations can potentially be reduced through hardware upgrades and the adoption of next-generation transceivers, improving overall network efficiency and responsiveness.

Figure 6 provides the relationship between the GNPy module and other entities in an open optical network. The architecture consists basically of the optical network controller (ONC), the optical line controller (OLC) responsible for collecting amplifiers information and setting their point of operation, and the GNPy module. Interactions among the modules are done through REST API, and NETCONF and YANG that interact the OpenROADM agents. In [58] is described in detail the workflow of this open optical network architecture, including the open orchestrator.

VII. QoT Performance Metrics overview

The proposal of an ML-based QoT estimator, whether as a classification or regression model, aims to provide an alternative to analytical models. To justify the investment in training and deployment costs, ML-based solutions must demonstrate superior performance in terms of QoT accuracy and computational efficiency compared to analytical models [10].

ML models have shown promise in accurately modeling complex physical phenomena, making them viable candidates for QoT estimation. They can offer faster execution time and require fewer input parameters [15], enhancing efficiency and show robustness with uncertain parameters [22].

The choice between classification and regression models depends on operational requirements. Classification is suitable for checking the feasibility of an optical path, while regression is preferred when the QoT value is needed. Both approaches benefit from assessing estimation errors to facilitate operational margins computation, with regression models offering easier error assessment [10].

Additionally, it is explored how the performance of a QoT estimator is affected by spectral data and recursive ML structures, especially LSTM and GRU [34]. The results demonstrate that algorithms exploring spectral features perform exceptionally well. This advancement can also facilitate the transition to fully disaggregated networks without the need for sharing confidential data. LSTM and GRU are also effective in identifying deteriorations in lightpath performance for up to four days, aiding in proactive maintenance efforts, lightpaths monitoring over time and margin optimizations [7]. In [48] is presented an analytical model for QoT estimation which includes spectral data, amplifier power measurements from a disaggregated optical network leading to an accurate QoT estimation.

Addressing the need for extended capacity in optical networks, in [46], [47] is proposed a QoT estimator that address the need for the use of C + L bands in optical communication systems.

Table II provides an overview of the more relevant described algorithms and their respective performance metrics.

In summary, rapid and precise quality of transmission (QoT) estimation information provides means to design and operate marginless networks, implement proactive failure management, optimize amplifier operation, enable impairment-aware RSA systems, optimize network resources, facilitate the deployment of disaggregated networks, forecast SNR, enable rapid lightpath provisioning and traffic reroute, and drive efficient network reconfiguration, bringing optical network automation to new levels. Figure 7 summarizes the benefits of rapid and precise QoT estimation in optical networks.

VIII. Conclusion

In this paper was presented a survey and an overview on utilizing ML to enhance QoT estimation, a trend gaining momentum in recent years. The described cases consisted in models that evaluate the feasibility of the path (classification models) and models that estimated quantitatively the performance of the lightpath (regression models). It includes techniques such

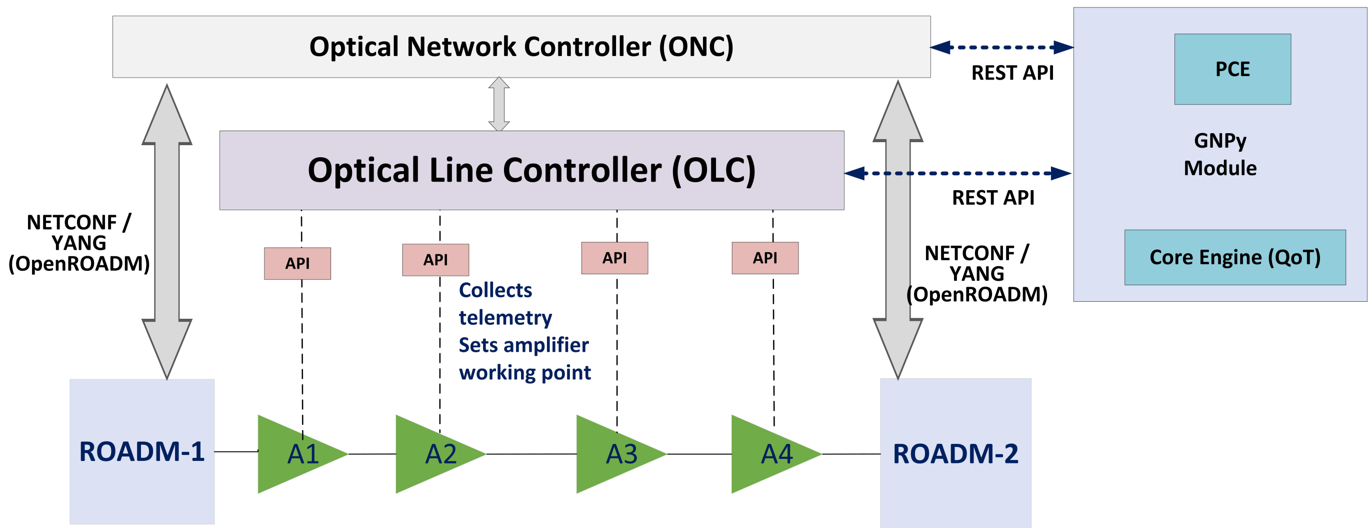

Fig. 6. Open management and control architecture

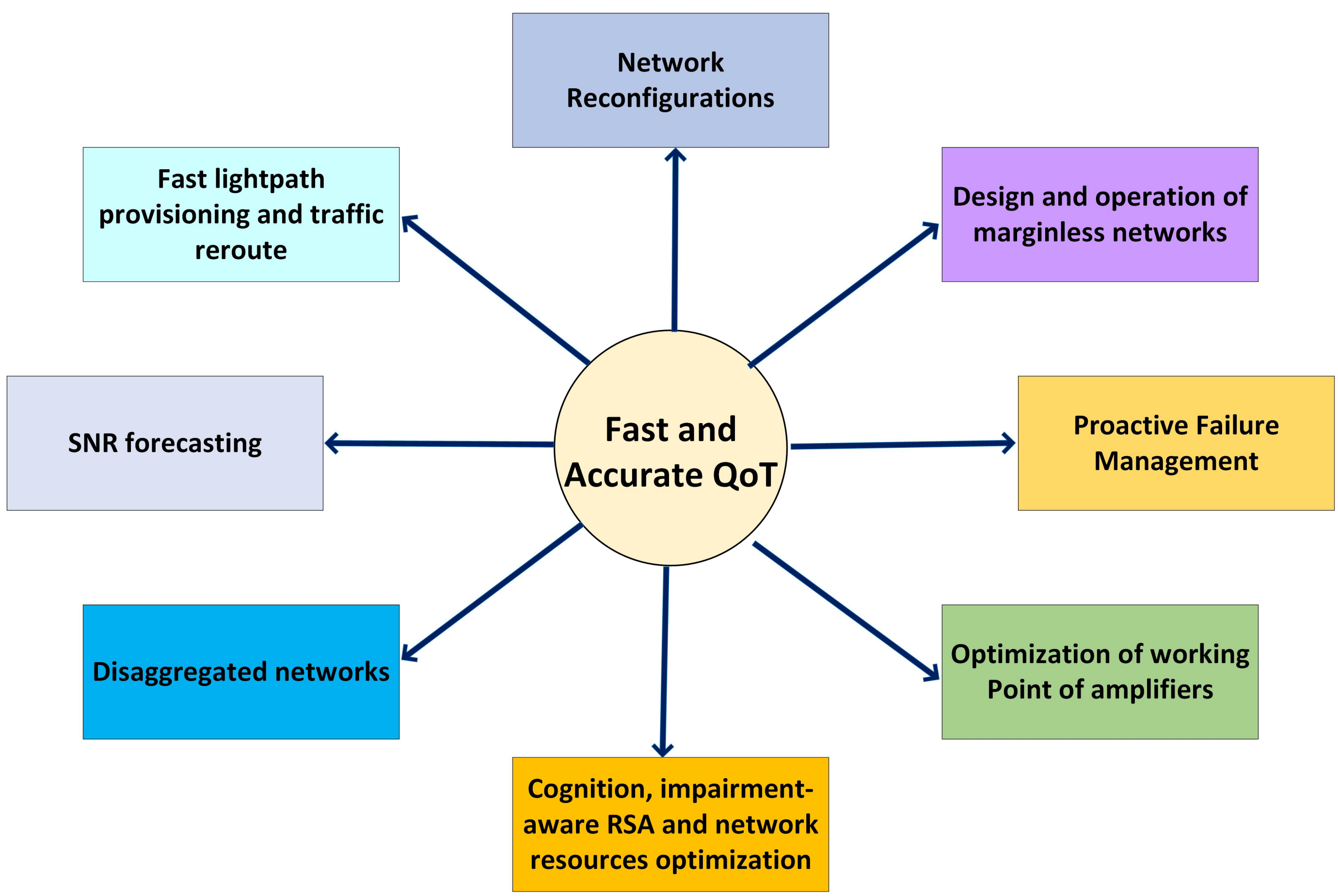

Fig. 7. Drivings of rapid and precise QoT estimation

TABLE II
ML ALGORITHMS AND PERFORMANCE METRICS

Name		Algorithm	Performance
Margin reduction based on gradient descent	[39]	SAMBA, EGN	Typical error lower than 0.1 dB
BER prediction in WDM networks	[40]	GPR	95% confidence interval; Q error lower than 0.3 dB
GSNR estimation based on ML regression	[37]	Regression	Cost penalty lower than 0.069
QoT prediction of unestablished lightpaths	[13]	KNN, RF	Reduction in installed transponders can reach 17%. Classification accuracy reaches 84%
Technique for predicting whether lightpaths meet QoT requirements in impairment-aware networks	[41]	CBR	79% to 98.7%
SNR estimation in a KDN environment	[15]	ANN	Average error of 0.4 dB for regression; 99% accuracy for classification
Lightpaths into high or low quality categories	[42]	SVM	99.95% success rate
QoT estimation in optical networks	[43]	DGCNN	92% to 97% accuracy
BER prediction in WDM networks	[40]	GPR	95% confidence interval; Q error lower than 0.3 dB
QoT estimation of unestablished lightpaths	[44]	ANN, SVM	accuracy of 99.56% and 99.38%, respectively
QoT estimation based on spectral data	[22]	ANN and LSTM	R2 score greater than 0.9
SNR prediction for 4 days' time-horizon	[44]	LSTM	R2 scores reaches 0.1415 for a 96-hour forecast

as ANN, SVM, KNN, RF and RNN techniques such as LSTM and GRU that provide QoT estimation as well as performance forecast.

Accurate and rapid QoT estimation serves as the cornerstone of an efficient optical network infrastructure. The availability of real-time performance assessment empowers network operators to run the network with minimal margin which translates to significant cost savings on network infrastructure and equipment. It works in conjunction with cognition systems, providing to RSA and path computation engine (PCE) systems real-time performance information to make rapid decisions. This translates to faster lightpath provisioning and rapid traffic reroute around outages or failures, minimizing downtime and service disruptions. It enables improved network reliability by enabling proactive network management through early fault detection and performance optimization. Accurate QoT estimation is critical for optimizing optical lines by adjusting the operating point of optical amplifiers in a scenario with different modulations and different symbol rates. It also plays a pivotal role in network operation, maintenance, and reconfiguration activities. Moreover, QoT estimation serves as the foundation for enabling optical network automation, streamlining processes and enhancing overall efficiency.

ML models exhibit potential in improving QoT estimation accuracy, fast response and forecasting lightpath performance degradation. However, there are challenges such as the scarcity of field data. Despite this, ML offers a versatile approach, capable of supplementing or replacing traditional, complex, time-consuming and high-computing modeling methods, with promising results reported in various optical networking fields.

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