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1 Executive Summary

In this document, we present State of the Art (SOA) on Machine Learning (ML) assisted Quality of Transmission (QoT) estimation and prediction for efficient control and management of network resources while maintaining Quality of Service (QoS) requirements. We perform SOA analysis on QoT estimation by keeping disaggregated optical network scenario in mind. As ML assisted QoT estimation in disaggregated network scenario is one of the main area to highlight in this report. Hence, we provide a detail description on the evolution of disaggregated optical networks from fully aggregated ones here. In the starting of this report, to lay a foundation, an introductory section emphasizing on the reasons and justification for an end to end QoT estimation, with acceptable QoS in multi-layer networks (MLNs) with optical disaggregation in physical layer is also present.

We also review some of the available mechanisms in literature enabling specific physical layer monitoring systems feeding with relevant information to conduct targeted network performance estimation as well as failure and anomalies detection. In the same section of failure detection, available use cases on MLNs combining different switching technologies are also present. However, design and management of these optical networks is continuously evolving, driven by the enormous increase of transported traffic and drastic changes in traffic requirements, e.g., in terms of capacity, latency, user experience and QoS. Hence, certain QoS mechanisms are required that can manage and act accordingly on these data traffic quality and maintain the QoS requirements specified in Service Level Agreements (SLAs). Considering this in mind, a separate review section on parameters that can affect, specifically traffic prediction and their effect on QoT of existing links, while maintaining end to end QoS requirement of the network is also there.

Concisely, this report is focused on how available monitored physical layer information can be collected and eventually used by the corresponding ML-based optimization strategies in disaggregated network case. Finally yet importantly, since all the ML topics listed above are highly related to each other, this report outlines the connections among them. This task is crucial to identify potential open points and gaps where the research activities within ONFIRE will be oriented.

At the end, we present an overview of research plan, the methodology and time-line to achieve it along with Gantt chart. We also define a separate sub-section on expected results from ESR2 at the end of this report.

2 Introduction

This report focuses on physical layer QoT estimation and prediction in disaggregated optical networks while maintaining an end-to-end QoS in MLNs with optical disaggregation in physical layer. So, we start this section by providing clear definitions for the terms like network, optical network, QoS, QoT and their relationship with each other. Starting with a **network,** the sole purpose of a network is to connect one device with another no matter how far apart they may be. Ideally, it does so without altering or dropping the data. Extending this definition to **optical networks**, they are the telecommunications networks of high capacity. They are based on optical technologies and components, and are used to route, groom, and restore wavelength levels and wavelength-based services. These networks must provide secure, predictable, measurable and guaranteed services.

Several applications are there, which are evolving day by day like 5G front hauling, Industry 4.0 etc. for which service quality is a very crucial aspect and hence needs to be estimated for efficient working of the network [1]. Keeping these applications in mind, a set of technologies for the description of the overall performance of a service by these networks, especially in terms of the user's experience is a basic requirement. To quantitatively measure this quality, several network service related aspects are often considered, such as packet loss, bit rate, throughput, transmission delay, availability, jitter, etc. In general, Quality of Service or QoS is defined as, " *the control and management of a network's data transmission capabilities by giving priority to certain types of time-sensitive and mission-critical data protocols (e.g. audio and video) over the other non-urgent ones*" [2]. Networks consider in this report are optical and hence optical fiber is the medium to transmit and receive data signal. Hence, a detailed knowledge on the transmission quality of these optical connection (or lightpath) through physical layer (optical fiber) is also very important. This can be achieved by calculating a parameter that can guarantee that the established (or unestablished) lightpath satisfies a certain physical layer performance value like BER, OSNR, Q-factor etc. or not. This parameter now defines the transmission quality and is known as, "Quality of Transmission or QoT" parameter.

The level of heterogeneity, both from the types of services to transmission technologies have increased in recent years. Currently emerging multi-vendor based or disaggregated optical network approach is also adding more complexity to these heterogeneous networks in terms of monitoring, reconfiguration based on software adaptable elements and so on. Efficient control and management of network resources while fulfilling user demands and complying with QoS requirements (from management viewpoint) and QoT requirement (from system designer viewpoint) are the main challenges for these networks. A solution for such a scenario may come from cognitive networks. A cognitive network is defined as a network with a process that can perceive current network conditions, and then plan, decide, and act on those conditions. The network can learn from these adaptations and use them to make future decisions, all while taking into account end-to-end goals [3, 4]. Dynamic and agile QoS estimation is the basic requirement for cognitive networks to decide on how to act or not. ML based tools already shown a promising solution for QoS estimation for such cognitive optical networks and is already well explored in literature but not for the case of multi-vendor based disaggregation approach [5, 6]. Accurate QoT estimation while satisfying QoS in these highly disaggregated multi-vendor environment acts as a trigger element for the cognitive networks and hence needs more attention.

The term "disaggregation" in hardware and software is a recognized strategy for achieving efficiency and cost reduction within short reach networks especially datacenter warehouse. More recently, this approach has been applied to high bandwidth inter-datacenter connectivity at transport layer. Telecom Operators look with great interest at this approach, which promises savings that, could make the difference in years of ever decreasing margins on revenues [7]. Basically, this disaggregation allows network operators to select and compose individual nodes of a network, by selecting the most appropriate vendor solutions for each function, for e.g., transponder, Fixed or Reconfigurable Optical Add-Drop Multiplexer (F/ROADM), line system, control, monitoring etc. [8]. At least two levels of disaggregation can be considered at the optical layer:

i. ***partial disaggregation***, where some degree of disaggregation into optical components takes place, while still having some level of aggregation and abstraction
ii. ***full disaggregation***, where every single optical component exposes its programmability through a control interface.

In partially disaggregated case, operator has a freedom to choose only limited functional components within a node. For e.g. transponders from multiple vendor with individual control interface and a single vendor based line system. This approach is an Open Line System (OLS) or disaggregated line system (DLS) approach, where optical hardware (transponders) are from multiple vendors that can be interconnected and controlled by a single common centralized control plane. In case of fully disaggregated systems, opera-tor has the freedom to choose even subsystem blades (each with different functionality), possibly from different hardware suppliers, within in a ROADM architecture. Some more initiatives (e.g., Open ROADM [9] and OpenConfig [10]) are currently working on defining and implementing multi-source agreements for optical whiteboxes. Open ROADM is focused on a multi-vendor optical network based on ROADM and flexible transponders as separate optical nodes. Management and physical level interoperability is specified in detail, including vendor agnostic specifications for commissioning, operation and maintenance procedures. OpenConfig aims to achieve interoperability in the management and monitoring of a multi-level network, realized with different technologies to be able to standardly configure and monitor single networking devices from different vendors [10]. The idea behind introducing the disaggregation and its level here is just to make a basic definition for easy understanding of this introductory section. Both above mentioned levels of disaggregation have their advantages and disadvantages and we will discuss this topic in detail in upcoming section.

From the above paragraph, it is clear that Open ROADM and other variant of it are more specific to optical networks with partial level of disaggregation. QoT estimation, while maintaining end-to-end QoS in these networks is not so much limited because the OLS is under the control of a single vendor and all the components or subsystems like wavelength selective switches (WSS), line amplifiers etc. are seen as a separate system by the same vendor. However, if we take the case for fully disaggregated optical networks, both QoT and QoS estimation is far more complex, since there are multiple vendors in the optical transport layer within the line system at subsystem level. For E.g. ROADM blades are now acting as separate subsystem with multiple vendors. The only condition is the interoperability between different subsystems and interoperability without any power ripples through single wavelength interface (SWI) between transponders from multiple vendor to OLS and through multi wavelength interface (MWI) within disaggregated OLS is also strictly not possible [11]. Apart from these power ripples during interoperability, the nodes cannot be treated as same as for aggregated networks or traditional ones and hence cannot be modelled through analytical models available in literature for QoT estimation [11, 12] affecting QoS also.

From the above paragraphs, following points can be concluded that will also be treated as the main objectives for ESR2 during ONFIRE [13] project.

i. Formulating techniques or extension of already existing analytical models to generate dataset in case of fully aggregated optical networks for QoT estimation
ii. Taking fully disaggregated optical networks as use case, devising cognitive and ML algorithms for deriving decisions with twofold end-to-end objectives: end-to-end QoT and QoS. Accuracy improvement of the proposed tool is also one of the subtask under this task
iii. Experimental validation of QoT estimation tool on experimental dataset collected in multi-vendor environment at Nokia Bell Labs, Germany during secondment of ESR2
iv. Integration of this ML based QoT engine within SDN controller for an end-to-end functionality testing.

3 An Introduction to ML & Disaggregated Optical Networks

This section provides a brief overview of the basics of Machine Learning (ML), its types and the applicable topics within optical networks. This section will also provide an in depth knowledge of disaggregation in optical networks. In this sense, it introduces some of the parameters that ML can estimate or predict from both physical and network layers in optical networks.

3.1 Machine Learning & its types

ML is generally sub-categorized as per the purpose, where it needs to be implemented generally in three types as shown in Fig. 3.1:

i. **Supervised Learning:** Supervised Learning is the one, where one can consider that the learning is guided by a "teacher". We have a dataset which acts as a teacher and its role is to train the model or the machine. Once the model gets trained it is able to make predictions or decisions upon new input data is given to it. Examples of some widely used supervised learning algorithms are regression, random forest, decision tree etc., which are continuous ML algorithms and K Nearest Neighbors (KNN), Naïve-Bayes, Support Vector Machines (SVM) etc. come under categorical ML algorithms.

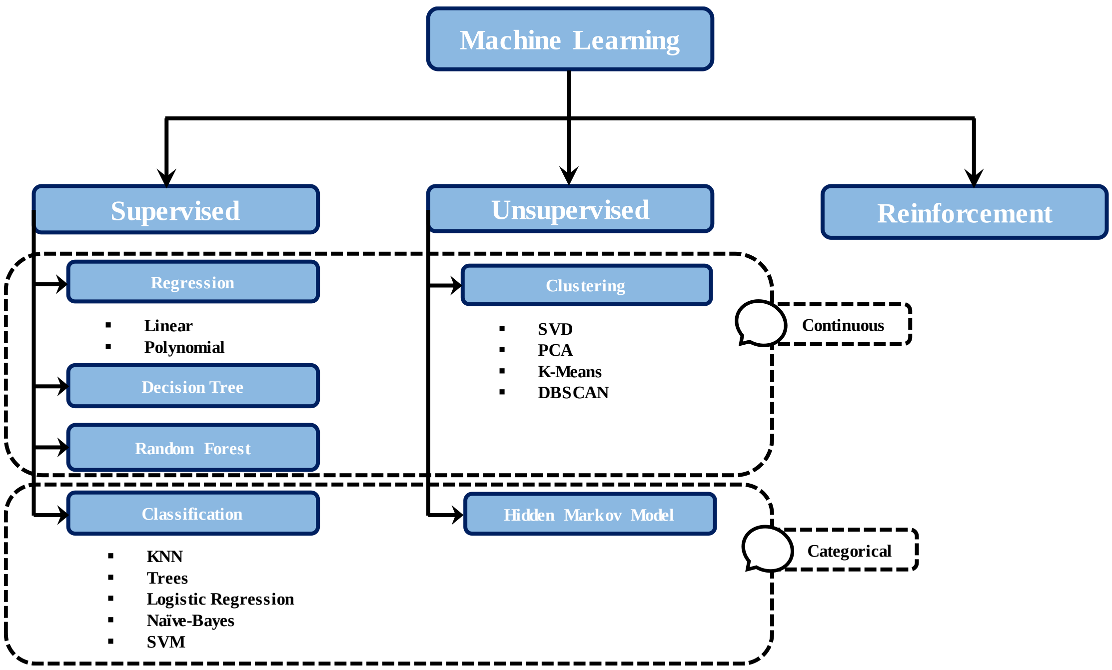


Fig. 3. 1: Types of ML along with representative algorithms

ii. **Unsupervised Learning:** In this ML approach, the model learns through observation and finds structures in the data. Once the model is given a dataset, it automatically finds patterns and relationships in the dataset by creating clusters in it. It cannot add labels to the cluster. Due to that, a hybrid ML term was coined, which means combining both supervised and unsupervised ML. The idea of such hybrid approach is to first grouping/clustering unlabeled data and then adding labels to different groups or clusters.

Some of the examples are Density-Based Spatial Clustering of Applications with Noise (DBSCAN), K-Means, etc.

iii. **Reinforcement Learning:** It is the ability of an agent to interact with the environment and find out what is the best outcome. It follows the concept of "hit and trial" method. The agent is rewarded or penalized according to a correct or a wrong answer. By doing so, relying on the positive rewards the model trains itself. Once the system is trained, it becomes ready to predict a new incoming input data presented to it.

3.2 Disaggregated optical networks and their types

Traditional networks, as shown in Fig. 3.2(a), typically consist of an integrated Wavelength Division Multiplexed (WDM) system that includes transponders/muxponders and the WDM line system. The WDM line system can consist of filters for multiplexing and multiplexing the WDM channels, Wavelength Selective Switches (WSSs) for ROADM, amplifiers, and other functions such as power monitoring, OSC, and OTDR [14]. This integrated WDM system is provided by a single vendor and managed by a proprietary network management system (NMS). Routing and transport switching are provided by dedicated platforms each with its own NMS.

Based on fundamental principles of software-defined networking (SDN) i.e. separating data and control plane, disaggregated solutions have recently been proposed for optical transport networks. Disaggregation aims to separate integrated systems (Fig. 3.2(a)) into functional blocks, enabling the network operator to select best-in-class products for each functional block [14]. Disaggregation at the optical layer is expected to bring benefits to network operators by enriching the offering of available solutions and enabling the deployment of optical nodes that better fit their needs. In fact traditional system vendors are adding SDN management solutions to their Wavelength Division Multiplexed (WDM) transport network portfolio, to abstract and expose resources at a North Bound Interface (NBI) enabling enhanced network programmability and flexibility.

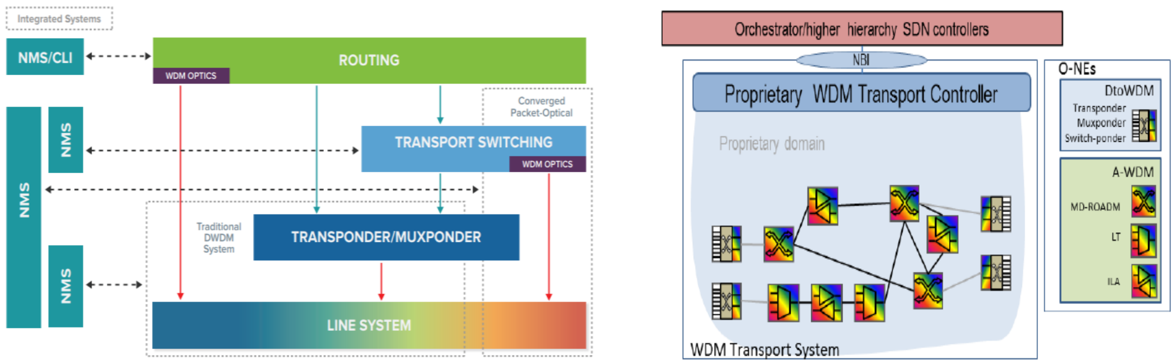


Fig. 3. 2: (a) Traditional integrated WDM system **(b)** Fully aggregated WDM transport system [14, 15]

However, often, these solutions are still dedicated to mono-vendor optical domains and thus imply a black box lifecycle approach: direct access to the control and monitoring of single Optical Network Elements (O-NE) is precluded and is fully mediated by the software provided by system vendor. These solutions are certainly suitable for large optical transport networks due to the complexity of managing physical layer impairments in a vendor agnostic way; but vendor 'lockin' is still present [15]. Fig. 3.2(b) illustrates a simpler mono-vendor WDM transport Systems (WDM-Sys), also known as *fully aggregated* optical system with the introduction of an open NBI for control and management of the whole network in a more flexible way. The term 'disaggregation' in the context of WDM transport network is often used to collectively designate all the operational models in which telecom operators are actively involved in the design, assembly, testing and lifecycle management of the WDM transport Systems (WDM-Sys) deployed in their networks. For a WDM-Sys, the relevant O-NEs are pieces of equipment housing homogenous network functions, possibly made by several shelves or blades, but seen by management and control systems as a single management entity through a suitable OpenAPI, often termed South Bound Interface (SBI). A suitable interconnection of these O-NEs with the addition of a WDM transport controller/management SW makes a complete WDM-Sys (Fig. 3.2(b)): Transponders, **TPs** constitute the 'Digital to WDM adaption layer' (DtoWDM), being in charge of the adaption of digital client signals to analogical 'media channels'; while M-ROADMs, In Line Amplifiers (ILAs) and Line Terminals (LTs) constitutes the actual 'WDM Analog transport layer' (A-WDM).

3.2.1 Levels of disaggregation

As already explained briefly in introduction section of this report, there are two levels of disaggregation either ***partial or fully***. Within these levels, the extent of disaggregation defines its sub levels and are explained with pros and cons of each below [15]:

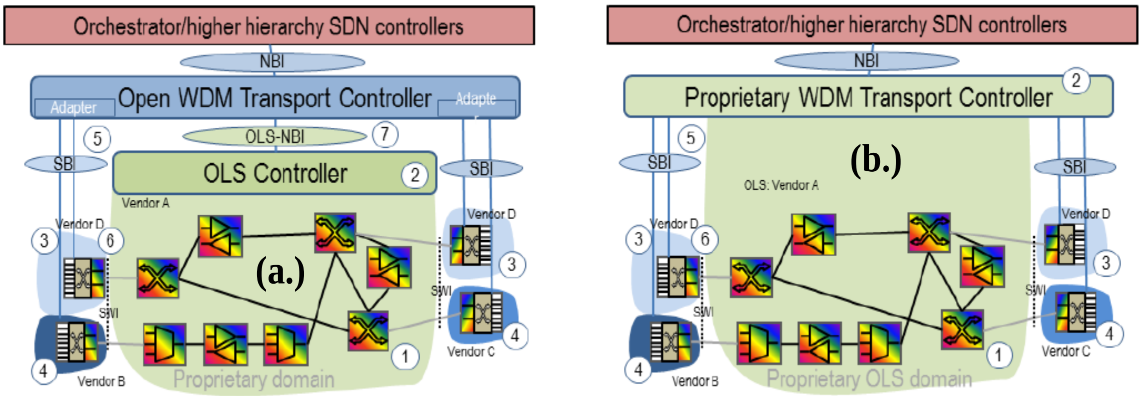


Fig. 3. 3: (a) An Open Line System as part of a partial disaggregated WDM transport system **(b)** Alternative partial disaggregated WDM transport system: OLS and WDM controller are proprietary from a single vendor [15]

i) Partial Disaggregation

There is one line system, which is open to connect with transponders from multiple vendors. In this approach (Fig. 3.3(a) and 3.3(b)), the disaggregation applies to the DtoWDM layer (i.e. to TPs) whose lifecycle is decoupled from that of a mono-vendor and proprietary A-WDM layer. The A-WDM layer remains a proprietary black box analogue transport system (boxes 1-2 in Fig. 3.3) supporting optical channels from external TPs as client signals. This type of disaggregation refers to Open Line System (OLS); the term 'Open' refers to the fact that it is open to be used by any signal, which follows a given behaviour, specified by the Single Wavelength Interfaces (SWI). An OLS-NBI API (box 6 in Fig. 3.3(a)) is needed to configure and report events from the OLS. The standardization of this OLS-NBI is of great help in the process of vertical integration with the Open WDM Transport Controller of the whole WDM-Sys. The rationale behind this approach is that the operational life of an A-WDM is much longer than that of TPs, the latter useful life governed by the continuous increase in capacity needed, requiring a very strong pace of innovation and therefore obsolescence. Furthermore, the multi-vendor environment in the DtoWDM layer leaves to operator the freedom to choose the best supplier for each specific application favouring form time-to-time performance, cost or other metrics. However, with a standard SBI it is possible for the OLS Controller itself to take charge of TPs, thus assuming the role of the controller of the whole system, and eliminating the need for an OLS-NBI and strongly simplifying the integration process and network operations as shown in Fig. 3.3(b).

ii) Full Disaggregation

In full disaggregation scenario, we will discuss two cases as presented by authors in [15]. In the first approach, levels of disaggregation lies in ***O-NEs from multiple vendors***. In this level, O-NEs from both the A-WDM and DtoWDM layers are potentially purchased from different vendors, leaving interworking at the control and data plane to the system integrator as shown in Fig. 3.4(a). Therefore, most of the control intelligence is moved to the WDM controller (necessarily vendor agnostic) which becomes the most critical element of the whole chain, having to face also all the analogue transmission issues (equalization, transient suppression, etc.). Furthermore, detailed specification for both SWI and MWI is needed to support horizontal integration.

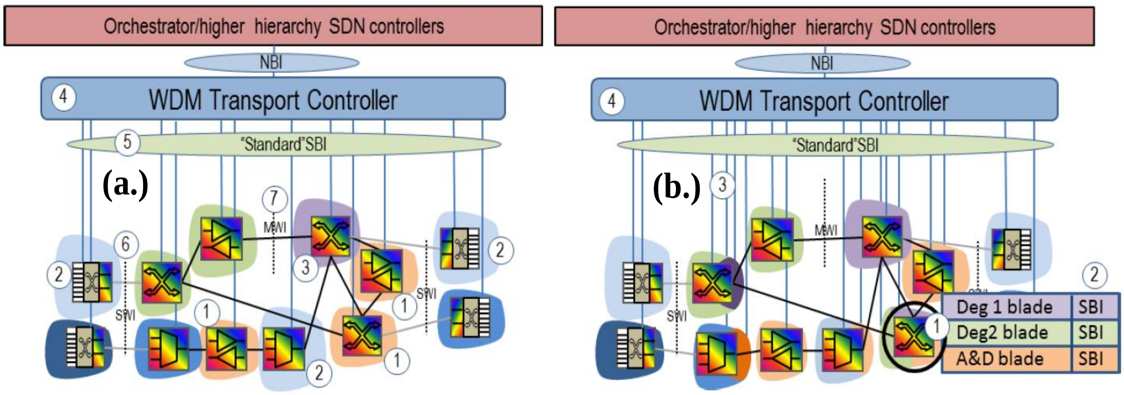


Fig. 3. 4: (a) Fully disaggregated WDM transport system: O-NEs can be from the same (1-2) or from different suppliers **(b)** Full disaggregation: Multi-vendor optical subsystems assembled in O-NEs. [15]

In the second approach presented by authors in the same article, disaggregation level is extended to full extreme in which, ***optical subsystems are from multiple vendors****.* This is the extreme case of disaggregation and it addresses the situation of an ecosystem of exclusively optical, low level functional subsystems (EDFA, WSS, Attenuator, etc.), on separate compatible standardized blades (with control and management interfaces, power supply, cooling etc.) for rack mounting as shown in Fig. 3.4(b). O-NEs like M-ROADM are the assembly of several of these subsystem blades, possibly from different hardware suppliers. Potentially each subsystem could be directly controlled and managed by the WDM transport controller of the whole WDM-Sys. However, this would be at the expense of more complexity in the controller, due to the lower level of abstraction, and a greater number of concurrent communication sessions.

From the above discussion on evolution of disaggregated optical networks from fully aggregated ones, it is clear that there is no interoperability in case of aggregated networks and for the whole network QoS can be easily estimated via analytical models and tools available in literature [44-49]**.** As it can be seen that in OLS approach apart from transponders, full optical domain is under the control of single vendor, hence ensuring end to end QoS within acceptable limits is under the responsibility of the same vendor. To formulate a ML based tool for QoS estimation in such OLS based partial disaggregation environment is possible as the analytical models like GN, E-tool etc. are valid with some additional margin because of the ROADM losses in the node. If interoperability between TPs and OLS through SWI is proper with no or very less power ripples, standards models can be used to calculate QoS parameter. But, for the case for fully disaggregated optical networks (Fig. 3.4), QoS estimation is not as simple as in case of partial disaggregated networks. Because now there are multiple vendors in the optical transport layer within the line system at subsystem level like ROADM blades are now acting as separate subsystem with multiple vendors. Interoperability without power ripples between different TPs - ROADMS pairs at edges through SWI and within ROADMS through MWI is not easy to maintain and this will incur additional random losses and needs to be evaluated **[11]**. Apart from these power ripples, the nodes cannot be treated as same as for aggregated networks and hence limitations are there to model them through analytical models available in literature for QoS estimation.

3.3 Types of parameters estimated through ML in optical networks

Currently, a huge amount of research work is produced within the context of ML-assisted architectures. Those works consider both physical layer as well as network layer. Fig. 3.5 provides a general framework of the devised ML-assisted optical networks. The motivations for using ML-assisted models considering physical layer related aspect and context are due to the fact that the optical fiber nonlinearities do not allow a closed form expression for the optical channel. This has notable implications for the performance predictions of optical communication systems in terms of BER and quality-factor (Q-factor) and for signal demodulation. For the optimal resource selection and lightpath establishment, physical parameters of an optical channel, such as the used modulation format, Chromatic Dispersion (CD), Polarization Mode Dispersion (PMD), Optical Signal to Noise Ratio (OSNR) and Polarization Dependent Loss (PDL), must be estimated (QoT) and passed to the higher networking layer [5, 6] (i.e., control plane). Once these lightpaths are established, performance monitor is also needed for them.

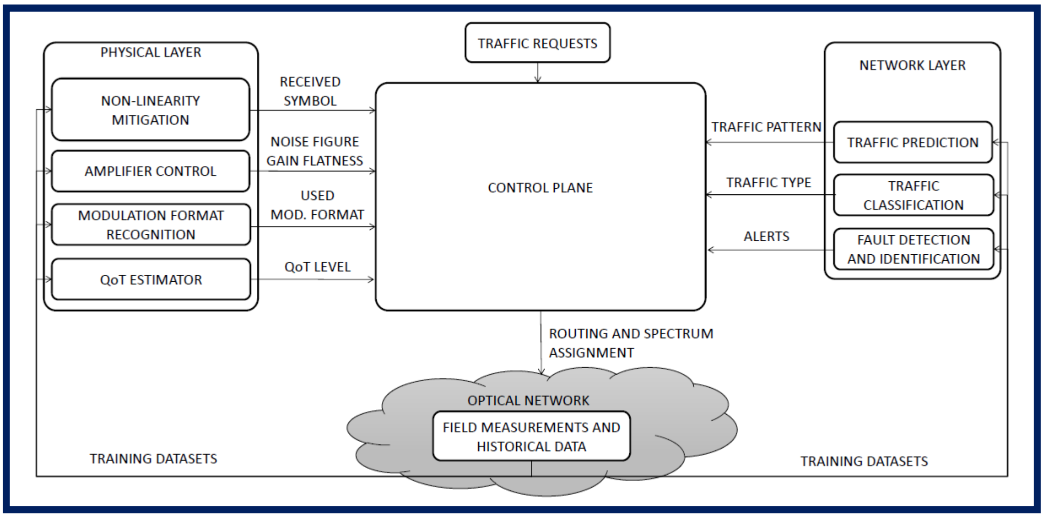


Fig. 3. 5: General Framework of a Machine Learning assisted optical network [5]

This performance monitoring is required to know the current state of the network. That information can be used not only for making immediate decisions but also as an input for forecasting procedures facilitating the execution of proactive action, which helps in improving or sustaining QoS. Apart from this physical layer monitoring and estimation, several other network layer parameters like i.e. current and upcoming traffic requirements, network topology state etc. also contains information regarding the current network. For e.g., the virtual topology is the set of optical connections (or lightpaths) established in a network and it needs to be dynamic to cope up with the changes in the network states. One such use case for dynamic virtual topology reconfiguration in order to better adapt to evolving traffic demands with some objectives like reducing network congestion, end-to-end delay or blocking probability (QoS) or trying to ensure QoT etc. is of our interest and is discussed in section 6. These network monitors providing physical layer quality information along with the network layer parameter values like traffic requirement etc. allow a network designer to build data driven model for more accurate and optimized network provisioning and management (like topology reconfiguration). This evolving data changes like traffic forecasting is possible through ML and hence is a key motivation for exploiting ML advantages within network layers. However, these current optical networks are expected to be operated at much higher utilization than in the past, while providing strict guarantees on the performance parameters, i.e. QoS. While optimization and traffic engineering methodologies are required to achieve these objectives, such complex methodologies may suffer scalability issues, and may involve unacceptable computational complexity [16, 17]. In this context, ML has a wide scope to make a fully automatized network framework that has the capability to do self-configuration and fast decision-making justifying ML usability in such use cases. All this can be done by applying ML algorithms on the extensive data retrieved via network monitors. In such cases, if the optimization is based on ML models, then scalability will not be an issue and the amount of complexity may be comparatively less with respect to traditional traffic-engineered methods. A basic introduction to ML algorithm along with the type of parameters estimated is given in below section.

3.3.1 Parameters estimated in physical layer

Table I overviews some of the ML algorithms for physical layer parameters estimation addressed in the literature as well as listing the considered parameter types which will be more deeply tackled in the upcoming sections. With the advent of advanced modulation formats aiming to increase the spectral efficiency, ranging from 16-quadrature amplitude modulation (16 QAM) to 64 QAM and beyond, the need for robust carrier frequency and phase synchronization becomes crucial. At this point, a precise characterization of amplitude and phase noise of lasers is essential. As for the transmitter side in physical layer, conventional time-domain approaches perform coherent detection in combination with digital signal processing (DSP) to cope with this issue [18, 19], but as higher order modulation formats are implemented, the accuracy of the phase noise estimation is compromised in the presence of moderate measurement noise. Authors in [20] present a framework of Bayesian filtering in combination with expectation maximization (EM) to accurately characterize laser amplitude and phase noise that outperforms conventional approaches. Results demonstrate an accurate estimation of the phase noise even in the presence of large measurement noise.

Additional examples of the use of AI techniques in the optimization of transmitters and lasers include the work in which, the authors use simulated annealing to determine the optimal settings in terms of flatness for optical comb sources for ultra-dense WDM passive optical networks [21]. One more approach, in which the use of ML, genetic algorithms and adaptive control techniques to provide a self-tuning mechanism for mode-locked fiber lasers was, demonstrated [22]. In response to rapid changes of lightpath deployment, Erbium Doped Fiber Amplifiers (EDFAs) suffer from wavelength dependent power excursions, e.g., when a new lightpath is provisioned or when an existing lightpath is dropped. Thus, an automatic control of pre-amplification signal power levels is required, especially in case a cascade of multiple EDFAs is traversed, to avoid that excessive post-amplification power discrepancy between different lightpaths may cause signal distortion. The adaptive adjustment of the operating point based on the signal input power can be accomplished by means of ML algorithms. Most of the existing studies [23-27] rely on a preliminary amplifier characterization process aimed at experimentally evaluating the value of the metrics of interest (e.g., NF, GF and gain control accuracy) within its power mask.

Parameter Type	ML category	ML algorithm	Target variable
QoT estimation	Supervised	RF, NN, DNN, regression with gradient descent, kriging/norm minimization, SVM, CBR	BER, OSNR, SNR and Q-factor
OPM	Supervised	NN, DNN, SVM, kernel based regression	Mod. Format, CD, PMD and OSNR
Optical Amplifier control	Supervised and unsupervised	CBR, NN, Regression, Bayesian regression, Evolution algorithm	EDFA operating point, EDFA power excursion, OSNR
Modulation Format (MF) Recognition	Supervised	NN, KNN, SVM, binary SVM, Bayesian Filtering and some standard approaches of image classification	Type of modulation format along with some threshold limitation on QoT parameter like OSNR, CD and PMD

Table 1: Some relevant physical layer parameters estimated via ML algorithms along with target variable

For the interpolation, authors of [25, 26] adopt a Neural Network (NN) implementing both feed-forward and backward error propagation. Experimental results with single and cascaded amplifiers report interpolation errors below 0.5 dB. An implementation of real time EDFA set point adjustment using the GMPLS control plane and interpolation rule based on a weighted Euclidean distance computation is described in [24] and extended in [27] to cascaded amplifiers. Recently, authors in [28] define a regression problem with supervised machine learning (using a radial basis function) to statistically model the channel dependence of power excursions in multi-span EDFA networks, learning from historical data. It provides the system with accurate recommendations on channel add/drop strategies to minimize the power disparity among channels. Several works has been produced for the joint modulation format and OSNR calculation. For example, Principal Component Analysis (PCA) for dimensionality reduction of captured data, which will take form of an image, SVM, K-Means clustering and several other ML approaches that are already well defined in image classification and identification which we will discuss in detail along with relevant references in QoT estimation section.

As per the relevance with ONFIRE project, QoT estimation and prediction represent one of the most appealing parameters within the physical layer to be explored. In this regard, a myriad of ML algorithms such as variants of Case-Based Reasoning (CBR), random forest classifier, linear regression, Deep Neural Network (DNN) and SVM can be leveraged for the QoT estimation.

3.3.2 Parameters estimated in network layer

Effective provisioning and restoration of lightpaths entail complex operations requiring dynamic data information to attain the most adequate decisions. In this regard, an estimation of users and service requirements may result very desirable for an effective network operation. Indeed, it may avoid overprovisioning network resources. Table II provides some of the ML algorithms related with ONFIRE goals for network layer parameters estimation already explored in literature. Some of the parameters already mentioned are traffic prediction. This relies on time series forecasting, which is a well-developed field in ML. To this end, ML uses Auto Regressive Integrated Moving Average (ARIMA) (or its variant like ARMA, AR, MA etc.) modelling for times series prediction of traffic matrix. For example, the authors in [29], [30] ARIMA method which is a supervised learning method applied on time series data [31]. In both [29] and [30], the authors use ML algorithms to predict traffic for carrying out other functions like virtual topology reconfiguration.

Parameter Type	ML category	ML algorithm	Target variable
Traffic Prediction	Supervised	ARIMA and some modified versions of ARIMA	Traffic Matrix
Failure Detection	Supervised and Unsupervised	SVM, kernel based SVM, Clustering techniques like DBSCAN, K Means jointly integrated with NN, DNN (hybrid), some cognition based methods	List of failures for lightpaths, failure localization at link level, localized set of failures
Path Computation	Supervised and unsupervised	Q-learning, FCM	Optimum path based on origin destination pair request. Assignment of MF is an integral part
VTD	Supervised and Unsupervised	ARIMA, NN, DNN, Non-Negative Matrix factorization clustering	End to end traffic prediction, updated Virtual Topology (VT)

Table 2: Some relevant network layer parameters estimated via ML algorithms along with target variable

On the other hand, for Virtual Topology Design (VTD) and its reconfiguration, using Neural Networks and some unsupervised clustering techniques has shown good potential in literature [33]. Authors presented a prediction module based on NNs, which generates the source-destination traffic matrix. This predicted traffic matrix for the next period is then used by a decision maker module to assert whether the current virtual network topology needs to be reconfigured or not [32, 33]. Authors in [34] reports a cognitive network management module in relation to the Application Based Network Operations (ABNO) framework, with specific focus on ML-based traffic prediction for VNT reconfiguration. However, details on which type of ML has been used and why, has not been mentioned in that work. Within the problem of optimal path computation, both supervised and unsupervised ML approaches can be used. In this context, in [35] it was used Q-Learning and Fuzzy C-Means (FCM) for optimum path estimation for each source-destination pair to minimize burst-loss probability. For the failure detection, previous approaches for estimation were supervised such as Bayesian inference, Network Kriging, SVM, decision tree etc. Recently an end-to-end failure detection and localization (both proactive and post detection) have gathered a lot of attention and we will discuss in details in upcoming sections with references devoted to this topic. The main variation of these approaches from the existing ones is that, they fundamentally work on hybrid ML techniques. Hybrid approach automatically reduces the size of the dataset (real time dataset) and makes the system to predict the failure proactively, so that it can be prevented. Nevertheless, all this comes at the cost of initial preprocessing of the data obtained from the monitoring ports of physical layer devices and periodic refreshing of this data for precise estimation and prediction.

3.4 Recent applications of RL in optical networks

Reinforcement Learning (RL) is a type of ML technique that enables an agent to learn in an interactive environment by trial and error using feedback from its own actions and experiences. Though both supervised and RL use mapping between input and output, unlike supervised learning where feedback provided to the agent is correct set of actions for performing a task, RL uses rewards and punishment as signals for positive and negative behavior.
As compared to unsupervised learning, RL is different in terms of goals. While the goal in unsupervised learning is to find similarities and differences between data points, in RL the goal is to find a suitable action model that would maximize the total cumulative reward of the agent. Below Fig. 3.6(a) represents the basic idea and elements involved in a RL model.

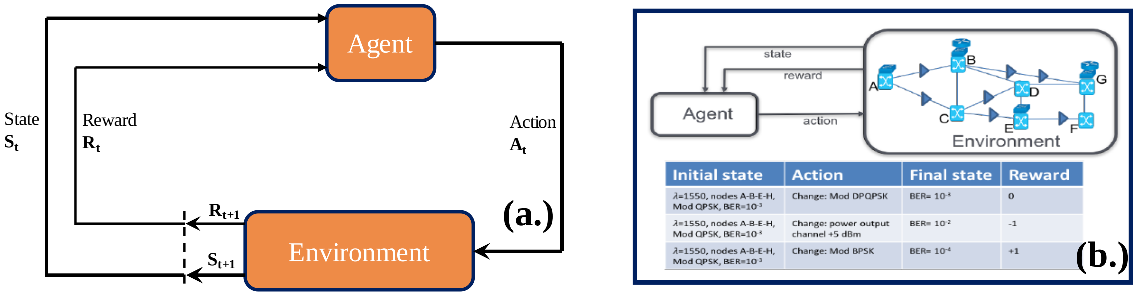


Fig. 3. 6: **(a)** Basic idea and elements in Reinforcement Learning (b) Conceptual view of RL in context to optical network [5]

As already introduced in above section, in RL, a learning agent interacts with its environment by taking actions and receiving information from the environment. This information is the state of the environment and the immediate reward. State information passed to the agent summarizes all currently relevant information about the environment. The reward passed to the leaning agent is a scalar reinforcement that evaluates current and past actions. While interacting with the environment, the agent follows a policy to determine what actions to take.
There are many terms across RL and some key terms that describe the elements of a RL problem are stated below:

- **Environment**: Physical world in which the agent operates
- **State**: Current situation of the agent
- **Reward**: Feedback from the environment
- **Policy**: Method to map agent's state to actions
- **Value**: Future reward that an agent would receive by taking an action in a particular state

RL is used, in general, to address applications such as robotics, finance (investment decisions), inventory management, where the goal is to learn a policy, i.e., a mapping between states of the environment to actions to be performed, while directly interacting with the environment. The RL paradigm allows agents to learn by exploring the available actions and refining their behavior using only an evaluative feedback (i.e., reward). The agent does not just take into account the immediate reward, but it evaluates the consequences of its actions on the future. Delayed reward and trial and error constitute the two most significant features of RL. Fig. 3.6(b) shows a conceptual view of RL in context to optical network in physical layer.

Google recently reported a human level control paradigm leveraging deep reinforcement learning [36]. Specifically, they parameterized a convolution neural network (also known as *Q*-network) that can learn successful policies (Q values) from high dimensional sensory data (*i.e.*, images). Inspired by this work, authors in [37] proposed a Deep-RMSA (Routing, Modulation and Spectrum Assignment), a deep reinforcement learning based self-learning RMSA agent, to realize autonomous and cognitive RMSA for EONs. We structure a deep Q-network consisting of multiple convolution and fully connected layers to learn the best RMSA policies regarding different network states (e.g., connectivity and spectrum utilization) and lightpath requests. The training of the Q-network takes advantage of two key ideas from [36], i.e., deployment of target action-value Q-network and experience replay, for avoiding the divergence of parameters. Further, they tested Deep RMSA with a six node EON topology and the simulation results verify its superiority over the baseline RMSA algorithm. The proposed Deep RMSA successively learns the optimal RMSA policy based on its perception of network states (*e.g.*, topology, spectrum utilization and in-service lightpaths) and the feedback from the environment (*i.e.*, network operations) using deep reinforcement learning. Fig. 3.7 illustrates the schematic of Deep RMSA along with the performance evolution of Deep RMSA w.r.t the blocking probability. Recently, one more work has been presented in the same domain [38]. In that work, a RL-based routing policy modeled as a Policy Network (PN) to improve the profit margin of an infrastructure provider was presented. The obtained results showed that by proactively rejecting low revenue connectivity service requests, the profit margin is improved, when compared to conventional routing policies. To this end, a neural network has been used demonstrating to be able to improve the profit by increasing the link utilization achieving a performance similar to shortest path algorithm approach.

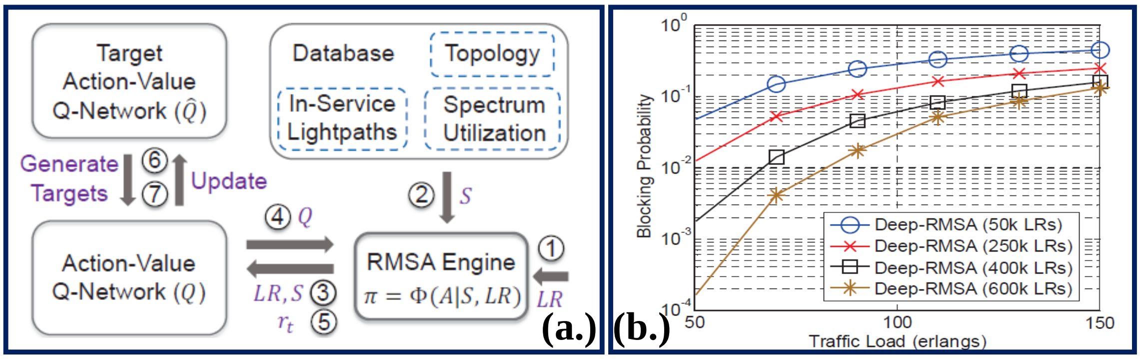


Fig. 3. 7: (a) Schematic of end-to-end Deep RMSA RL model **(b)** performance evolution of Deep-RMSA w.r.t the blocking probability [37]

This is a very preliminary work of applying deep reinforcement learning to solve networking problems and the proposed Deep RMSA design still confronts a number of challenges remaining to be addressed. Firstly, the design of the Q-network and the parameters used for the training process can be refined, such that Deep RMSA can extract better representations of network states and converge to optimal policies quickly even for larger topologies. Meanwhile, different from general learning tasks that can be exactly modeled as Markov decision processes, the actions and rewards of Deep RMSA are also determined by the received lightpath requests in addition to the network states. Therefore, prediction of future lightpath requests is required, and the additional complexity induced as well as the potential oscillation of the learned parameters need to be carefully handled.

In summary, RL is not a new field in ML but in the context of optical networks, it is being adopted quite recently mainly for building efficient routing policies. In this regard, very less research work have exploited in RL so far. This leads to a good opportunity to dig into this field further to explore more possibilities for deploying/devising effective mechanisms improving appealing targets such as the optimal network/resources utilization, efficient routing, etc. while guarantying QoS.

4 ML Assisted QoT Estimation

This section provides a detailed understanding of different types of ML algorithms applied for QoT estimation and prediction, which can be a part of monitoring system or any cognitive framework for end-to-end estimation of some specific parameters depending upon the application.

4.1 Introduction

QoT estimation consists of computing transmission quality metrics such as OSNR, BER, Q-factor, CD or PMD based on measurements directly collected from the field by means of optical performance monitors installed at the receiver side and/or on ligthpath characteristics [5]. QoT estimation is typically applied in two scenarios:

- ***Predicting*** the transmission quality of unestablished ligthpaths based on historical observations and measurements collected from already deployed ones.
- ***Monitoring*** the transmission quality of already deployed lightpaths with the aim of identifying faults and malfunctions.

Linear signal processing algorithms are effective in dealing with linear transmission channel and linear signal detection, while the nonlinear signal processing algorithms, from the ML community, are effective in dealing with nonlinear transmission channel and nonlinear signal detection. The modulation format and the OSNR are key parameters for assessing the performance of optical transmission links. In-band OSNR estimation is especially important in next generation WDM systems, where the channel spacing approaches signal baud rate. For QoT estimation in monitoring scenario, a ML model can be implemented in two ways:

- By tapping some amount of signal at receiving nodes and calculation performance parameters through equipment like Optical Spectrum Analyzer (OSA). After that, the next step is to train the supervised ML model on that tapped data and make prediction on the unseen data. This approach is easy and the only task to be made is to attain a clean dataset that contains all possible information of the network such as path, data rate, number of frequencies used, etc. All those measurements for data collection are done at the deployed OPM points, which have inbuilt costly equipment like OSA operating on per channel basis. Thus, if a large number of OPM points (at every node and egress link) is needed the resulting approach is costly.
- By tapping some amount of signal at nodes (including intermediate nodes) and by using some opto-electronic components (usually cheap), the goal is to extract useful parameters and train ML algorithm on them to predict / estimate the QoT parameter. This second approach is comparatively cheaper than the first one and indeed has been already demonstrated for modulation format as high as 64QAM operating at 32Gbaud with OSNR value ranging from 5 to 30dB [39].

The reason for mentioning the above two approaches is that in ONFIRE project one of the key global objectives is to design a cognitive application framework interfacing with (feasible) monitoring systems to gather physical layer information. Therefore, bearing this in mind, the adopted monitoring system is crucial to eventually achieve an accurate QoT estimation and overall performance. Consequently, the QoT monitoring is a key component and, for many reasons, should be preferably simple and cost-effective.

4.2 Technical Background (SOA)

As optical signals traverse fiber links and nodes and propagate through active and passive optical components towards their destination, they suffer from a number of physical impairments, which degrade the signal quality. These impairments affect each optical channel individually, but they also cause disturbance and interference between co-propagating channels. Hence, as there is no conversion to the electrical domain and consequently, no regeneration at intermediate nodes, the QoT will be affected and might not comply with service requirements. Therefore, in past few years, the impact of physical layer impairments in optical network design and operation has received significant attention [40, 41]. As a result, this interest has led to a set of proposals that, for instance, not only solve the Routing and Wavelength Assignment (RWA) problem in WDM Networks, but also ensure appropriate QoT on the established lightpaths [42, 43]. ML based classifiers promise to provide a mean to automatically predict whether unestablished lightpaths will meet the required system threshold. Moreover, even when lightpaths are already established, continuously monitoring the QoT via measuring (e.g., the received OSNR, BER or Q-factor) allows accomplishing early QoT degradation detection. Leveraging ML processing of monitored data, network operators can activate adequate procedures (e.g., lightpath rerouting, transmission power adjustment, etc.) to maintain the required signal quality.

QoT prediction of unestablished lightpaths is of utmost importance for optimized design of optical networks. These QoT prediction relies on intelligent tools that are either capable of predicting the value of QoT parameter (regression problem) or making a decision, whether a candidate ligthpath will meet the required QoT value or not (binary classification problem). As for the ONFIRE goal, regression problem makes much sense as the predicted values gives some information about the margins and their considerable gap from the extreme limits. However, for both the problems, a detailed dataset capturing essential lightpath characteristics (e.g., length, number of links, modulation format, overall spectrum occupation, etc.) is required. f All these ML models require huge amount of data to be conveniently trained. In such training phase, the dataset generation is likely the most important aspect since its accuracy impacts on the subsequent prediction / estimation results.

4.2.1 Dataset Generation

An appealing and feasible approach relies on training the ML model with the dataset composed by the actual data from the deployed network OPM devices. This indeed is the most basic approach to collect data, and the resulting trained model can estimate closely to actual QoT values. Nevertheless, it is a not an easy approach since if the network net-work has many intermediate nodes, then data collection at each OPM point is not only tedious but also very cost inefficient. Consequently, there is the need of some model or tool that can generate data based on the network topology by accounting all the impairment features starting from ASE noise to nonlinear penalties and side channel cross-talk interference effects.

In this regard, Azodolmolky et al. presented an impairment aware network planning and operation tool for all optical and translucent networks. A key element of that tool is an integrated real-time QoT estimator (referred to as Q-Tool) [44, 45]. This tool combines in a single framework a number of well investigated and verified analytical models previously proposed in the literature. The Q-Tool receives the topology (with its physical characteristics) and a set of lightpaths and then computes their associated Q-factors. The Q-factor is a QoT indicator which is related to the signal's BER, so that a higher value of the Q-factor corresponds to a lower BER. The Q-Tool provides relatively accurate estimates of the Q-factor by taking into account several models of linear and nonlinear impairments of the physical layer, thus being a very useful element in optical network design and control. However, it suffers from a few limitations. One of them is its limitation to 10Gbps ON/OFF keying networks. In addition, the computing time is very high for such Q-tool and is not at all effective in real time estimation.

Poggiolini has proposed in [46] a Gaussian Noise (GN) model. GN model estimates quickly and accurately the OSNR of the optical channels in uncompensated coherent transmission systems. Advanced version of GN model including many other penalty terms for OSNR calculation has also been published by the same author in [47, 48]. Many of the papers used in this report for QoT estimation generates dataset from the GN model or extended version of GN model (EGN). In a recent work the author proposed a new tool known as E-tool (E stands for estimation) to predict QoT parameters [49]. The advantage of using tools like GN model is that they are very fast and convenient to generate the dataset for the aim of training the ML models. Moreover, since they are analytical tools/models, they are flexible i.e., it is simple to change network parameters like traffic, link lengths, route path, etc. The disadvantage is that for the model, the reference results come always from the tool, and such a tool might provide different results compared to the physically collected data from the OPMs. It is worth outlining that until now most of the published research works rely on one of the above reviewed models to generate their datasets.

Since, from the above sections it is clear that, the design of optical networks always relies on a tool to predict the performance parameter for all traffic demands (i.e., quality of transmission) to ensure that the quality of a signal carried on a light path is above a predefined threshold. Any QoT model typically is based on a physical model with input parameters describing network elements. To ensure that all traffic demands in an optical network fulfill their target capacities, network designers add significant margins to the values predicted by the QoT model or tool **[50]**. A significant amount of margins are added to compensate for prediction errors of the QoT model, resulting in network over-dimensioning. These design margins compensate for errors both from the QoT model itself and from the uncertainties of the QoT model input parameters. The latter comes from the incomplete knowledge of the actual parameters of deployed network elements.
In such cases, to lower the design margins by improving the estimation of the performance parameter of a QoT estimator, ML proves to be a promising approach. Couple of research works have recently been published in which many methods were proposed to reduce uncertainties in the input parameters of the QoT tools [50, 51]. A very nice approach has recently published in which, the author does not reduce the uncertainty of the SNR estimation but that of the input parameters of a QoT model by leveraging SNR measurements from coherent receivers terminating previously established light paths [52].

4.2.2 QoT Estimation

A lot of work has already been published in QoT estimation ranging from OPM monitoring based on ML algorithms using asynchronously sampled data to advance ML algorithms such as Deep Neural Network (DNN), SVM, etc. A technique to monitor or estimate Bit Error Ratio (BER) was proposed using high speed asynchronous sampling and on that data a NN is trained to estimate OSNR values for the pre-processed pair of samples [53, 54]. This technique leads to develop joint OSNR monitoring and modulation format identification (MFI) in heterogeneous fiber optic networks. In this work authors pro-posed a new technique named as asynchronous single channel sampling (ASCS) to obtain synchronous samples through a single channel analog to digital converter, which directly represents the cost effective ness of the overall system. Then to reduce processing, principal component analysis (PCA), a dimension reductionality algorithm was also applied in this work. Fig. 4.1 shows the schematic of ASCS proposed by the authors. The proposed technique enables OSNR monitoring for several commonly used modulation formats with mean OSNR estimation error of 1 dB and without requiring any information about the signal type during the online monitoring process. In addition, it successfully demonstrates the identification of unknown modulation formats of the received signals with an overall accuracy of 98.46% [55]. Due to the use of a single low speed asynchronous sampling device in the proposed technique, the implementation complexity and cost of the monitoring devices can be significantly reduced.

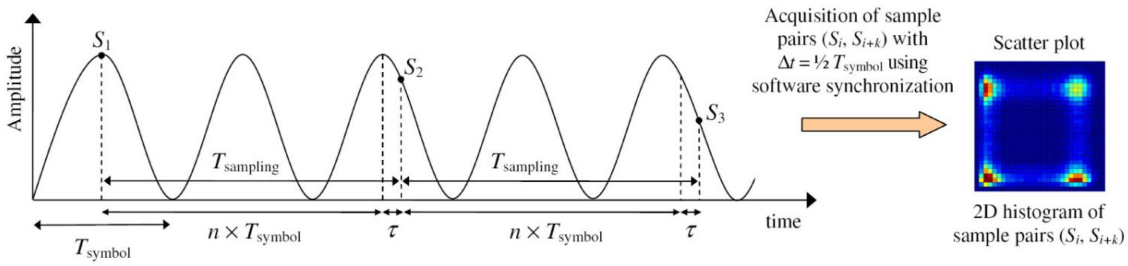


Fig. 4. 1: Schematic of Asynchronous sampling technique [55]

Although this technique has the advantage of asynchronous sampling it does not result adequate since a considerable amount of memory is required to generate the database. Further works addressing the same topic are available in [56, 57], which present similar limitations (i.e., huge data processing and storage). For QoT estimation with regard to monitoring, initially a cognitive Case Based Reasoning (CBR) approach was proposed. It relies on the maintenance of a knowledge database where information on the measured Q-factor of deployed lightpaths is stored along with the route, selected wavelength, total length, total and standard deviation of the numbers of co-propagating lightpaths per link [58]. Whenever a new traffic requests arrives, the most "similar" one (where similarity is computed by means of the Euclidean distance in the multidimensional space of normalized features) is retrieved from the database and a decision is made by comparing the associated Q-factor measurement with a predefined system threshold. As a correct dimensioning and maintenance of the database greatly affect the performance of the CBR technique, algorithms are proposed to keep it up to date and remove old or useless entries. The trade-off between database size, computational time and effectiveness of the classification performance is extensively studied. A technique was shown to outperform SOA ML algorithms such as Naive Bayes, J4.8 tree and Random Forests (RFs) in [59]. Experimental results achieved with data obtained from a real testbed for the same are also discussed in [60].

Similarly, in the context of multicast transmission in optical network, above mentioned is approached and a NN is trained in many research work [61, 62]. These techniques were data-driven for analyzing QoT data of previously established connections for accurately deciding the QoT of the newly arriving multicast requests in metro optical networks. This proposed approach was self-adaptive and relies on the data that are independent from the physical layer impairment. Thus, it does not require specific measurement equipment. This technique also does not assume the existence of a system with extensive processing and storage capabilities. It is also fast in processing of new data, and fast in finding a near accurate QoT model provided that such a model exists. This technique uses features such as the ligthpath total length, the number of traversed EDFAs, the maximum link length, the degree of destination node and the channel wavelength used for transmission of candidate lightpaths, to predict whether the Q-factor will exceed a given system threshold. The NN is trained online with data mini batches, according to the network evolution, to allow for sequential updates of the prediction model. A dropout technique was also adopted during training to avoid overfitting. The classification output is exploited by a heuristic algorithm for dynamic routing and spectrum assignment, which decides whether the request must be served or blocked. The algorithm performance is assessed in terms of blocking probability.

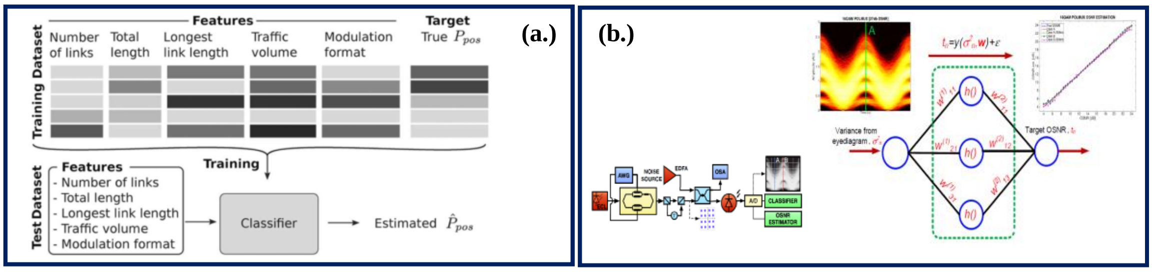


Fig. 4. 2: (a) Machine Learning based classifier approach for QoT estimation of unestablished lightpath [63] **(b)** experimental set up and input feature extraction along with a trained NN regression approach to predict OSNR for Pol Mux 16-QAM [39]

A Random Forest binary (RF) classifier approach was recently adopted, where the goal was to predict the probability that the BER of unestablished lightpaths will exceed a system threshold [63]. The classifier takes as input a set of features including the total length and maximum link length of the candidate lightpath, the number of traversed links, the amount of traffic to be transmitted and the modulation format to be adopted for transmission. Fig. 4.2(a) shows the structure of the binary RF classifier along with the input parameters used for training the model. OSNR monitoring on the basis of State of Polarization (SoP) at monitoring points along with restoration techniques has also been presented [64].

Two alternative approaches, namely network kriging (first described in [65]) and norm L2 minimization (typically used in network tomography [66]), are applied in [67, 68] in the context of QoT estimation. They rely on the installation of probe lightpaths that do not carry user data but are used to gather field measurements. Several heuristic algorithms for the placement of the probes are also proposed in literature [69]. A framework for estimating the QoT of a new lightpath before it is established, as well as for calculating the expected degradation it will cause to existing lightpaths has been thoroughly demonstrated by taking both space and spectrum dependencies [70]. The framework correlates the QoT metrics of established lightpaths, which are readily available from coherent optical receivers that can be extended to serve as OPMs. Past similar studies used only space (routing) information and thus neglected spectrum, while this approach also accounts for the presence on neighbor channels. Recently to reduce uncertainties on the input parameters of ML model has also been discussed by the same authors [71]. Additionally, a data-driven approach using a ML technique, Gaussian Processes nonlinear Regression (GPR), was proposed and experimentally demonstrated for performance prediction of WDM optical communication systems [39]. In this approach, no QoT or E-Tool or any GN model was used. Rather in this work, the complex system dynamics can be captured from measured data more easily than from simulations. Fig. 4.2(b) shows the schematic of the set up used for the dataset generation for ML model. The main benefit with this approach is that, it only uses a photodiode and an Analog to Digital converter (ADC) to extract all the required input parameters.

4.3 Open Problems

This section covers an in depth SOA available in literature for QoT estimation in optical networks. One of the main observation from the above SOA study is that all the literature is manly focused on traditional optical networks and all the models that has been used to generate dataset in the above discussed SOA are valid for such networks only. Although, all these QoT estimation models shows an architecture that how these ML engines can be integrated with SDN for proper management but still limited to traditional networks. The first open problem in all of these above discussed models is that, the vast majority of existing studies adopting ML at the networking level use offline supervised learning methods i.e., ML algorithms are trained with historical data before being used to take decisions on the field. This assumption is often unrealistic for optical communication networks, where scenarios dynamically evolve with time due to traffic variations or to changes in the behavior of optical components and systems caused by aging. Hence, in such dynamic network scenarios, the models to generate dataset, which are presented by authors, are not reliable. In addition, if we use these ML models for the case of fully disaggregated optical networks, these analytical models, might not be valid and hence a deep study of these ML assisted QoS estimation is required in disaggregated networks as well. One of the main reason is that, there are additional losses in the nodes and as already discussed the power ripples through SWI and MWI are not fully suppressible. Hence, we cannot rely on the available models that were used for aggregated environment in case of disaggregated ones and hence a proper investigation is required on the same.

In short, in case of disaggregated optical networks, research work is available mostly in terms of cost savings from operator viewpoint with the level of disaggregation. Some limited research work is also present in autonomic networking with partial disaggregated physical layer but without using ML. This means that ML in disaggregated optical networks for physical layer QoT estimation or an end to end QoS estimation is still very less explored. Hence, formulating techniques or extension of already existing analytical models to generate dataset in case of fully disaggregated optical networks for QoT estimation is one open problem and is primarily look by ESR2 during his research work. Also, taking this as use case of fully disaggregated optical networks, devising cognitive and ML algorithms for deriving decisions with QoT estimation with an end-to-end QoS is also the extension of the above open problem and will also be handled and solved by ESR2 during ONFIRE.

4 ML Assisted Failure Detection

This section provides a basic introduction of fault management system and its key components. One of the key component, which is the failure detection along with its localization by highlighting available use cases in literature, is also present. A basic overview on protection and restoration with control plane interaction is also discussed here.

5.1 Introduction

An optical network comprises a myriad of elements and devices having different types and capabilities and supplied by multiple vendors. As concluded from section 3 that disaggregation at the optical layer is expected to bring benefits to network operators by enriching the offering of available solutions and enabling the deployment of optical nodes that better fit their needs. Nevertheless, as most of the intelligence is now moved to the controller, a more amount of cooperation is required for efficient network performance, without degrading QoS. Networks can be make efficient in terms of QoS estimation, power and cost savings and so on. Even though, failures in the network are purely stochastic and it is very hard to make a network without any failures as failures are random in nature. However, to manage these failures, a tool or system is required, which can proactively or reactively able to manage the failures in the networks. This can be possible if there is a proper coordination and cooperation between controller and network elements and is a bit complex in case of disaggregated networks undoubtedly. A system known as fault management system is implemented for the same. The purpose of fault management system is to provide efficient control, operation, maintenance and preservation of the whole infrastructure.

In general, some option should be there for network survivability in case of faults that are going to happen (or already happened) in the network. Broadly there are two techniques for network survivability under faults: Protection and Restoration. The former allocates and reserves the back-up resources in advance, providing a fast recovering on pre-planned paths, at the expense of an inefficient use of resources. It is generally automatic and is for high priority connections. There is no as such interaction with the control plane as resources are already reserved (due to high priority) to execute the protection strategy. However, the latter makes use of real time availability of resources and hence there is a frequent interaction and cooperation between control plane and network monitoring devices. In optical restoration, the control plane of optical network possess the ability to react to catastrophic events that affects the services configured with the capability of being restored into a different network path. Since, role of control plane is more in restoration as compare to protection schemes, use cases for optical restoration with control pane interaction are presented in upcoming subsection. But, in the partial disaggregated optical networks, additional cooperation between OLS and transponders in spite of control plane interaction is needed to complete the restoration as compare to proprietary optical networks. Frequent performance information and alarms need to be exchanged in order to take the appropriate decisions. Optical restoration is one such case under the broad area of fault management. There are many reasons for fault to happen such as physical degradation modes (e.g., system deteriorations including system aging, connector reuse, etc.) to equipment dynamic modes (e.g., power level spikes, increased spectral tilt due to EDFA, etc.). These failures are detected by alarms, which are raised based on too high QoS parameter, resources not available etc. Fault management is divided into several sub-tasks such as failure or fault detection, its classification and localization up to its repair.

Failures can be either ***hard failures***, that is, unexpected events that suddenly interrupt the established channels; or ***soft failures***, that is, events that progressively degrade the quality of transmission (or both can also happen at same time). Hard failures are detected at the physical layer as they effect the physical channel such as fiber cuts. Soft failures can sometimes be detected at the optical layer if proper testing equipment is deployed, but often require performance monitoring at a higher layer.

5.2 Technical Background (SOA)

Once a failure occurs, the next step is to identify or locate the failure in the in the network along with the reason for the same. Detection of failure can be done locally (distributed) for particular part of the network or centralized leveraging the coordination provide by a SDN controller. When managing a network, the ability to perform failure detection and localization or even to determine the cause of network failure is crucial to rapidly recover from the failure. Handling network failures can be accomplished at different levels, for e.g., performing failure detection allows network operators to only reconfigure the affected lightpaths. Moreover, the ability of performing also failure localization enables the activation of recovery procedures. This way, pre-failure network status can be restored, which is, in general, an optimized situation from the point of view of resources utilization.

Recently a research work has been published that proposed an architecture for optical network fault management with cognitive assurance [72]. Authors introduced the concept of cognitive fault management and elaborated its integration in transport SDN controller. The proposed framework both detects and identifies significant faults, and outperforms conventional fixed threshold-triggered operations, both in terms of detection accuracy and proactive reaction time. Same authors have also published a detailed report of this work along with different ML approaches (from basic level to implementation as a tutorial) in this domain [73]. When managing a network (fault or any system), the ability to perform failure detection and localization or even to determine the cause of network failure is crucial. Failure detection and its localization may enable operators to promptly perform traffic rerouting, in order to maintain service status. Furthermore, determining also the cause of network failure, e.g., temporary traffic congestion, devices disruption, or even anomalous behavior of failure monitors, is useful to adopt for the proper restoring and traffic reconfiguration procedures. Moreover, prompt identification of the failure cause enables fast equipment repair and consequent reduction in overall repair time. Therefore, failure detection is the main part of the fault management system and next section provides the detailed SOA on the same.

5.2.1 Failure Detection

ML techniques have the potential to detect and locate failures by dealing with large amount of information derived from the continuous activity of a huge number of network monitors and alarms. To this end, ML techniques can be adopted either to identify the exact network location of a fault or malfunction or even to infer the specific failure. In this context, approach, named as, “network kriging” was exploited to localize the exact position of the network fault [74]. It was based on the assumption that the only information available at the receiving nodes of the established lightpaths is the number of faults encountered along the lightpath. In the same approach, if unambiguous localization was not achieved, lightpaths probing may be used to provide additional information, which increases the rank of the routing matrix. Similarly, in [75] the measured time series of BER and received power at lightpath end nodes are provided as input to a Bayesian network. This resolves whether a fault is occurring along the lightpath and tries to identify the cause (e.g., tight filtering or channel interference). Apart from Bayesian networks, various clustering techniques to group failed events with non-failed events have been investigated in the literature [76, 77]. Hard failures can cause immediate service disruptions, soft faults gradually degrade the network operations [78]. Thus, powerful anomaly detection and localization schemes are essential for enhancing the availability of optical networks. By detecting these anomalies, an idea about the happening of the failure can be achieved and then there is a scope to proactively handle these failures without having any sort of disturbance in the network.

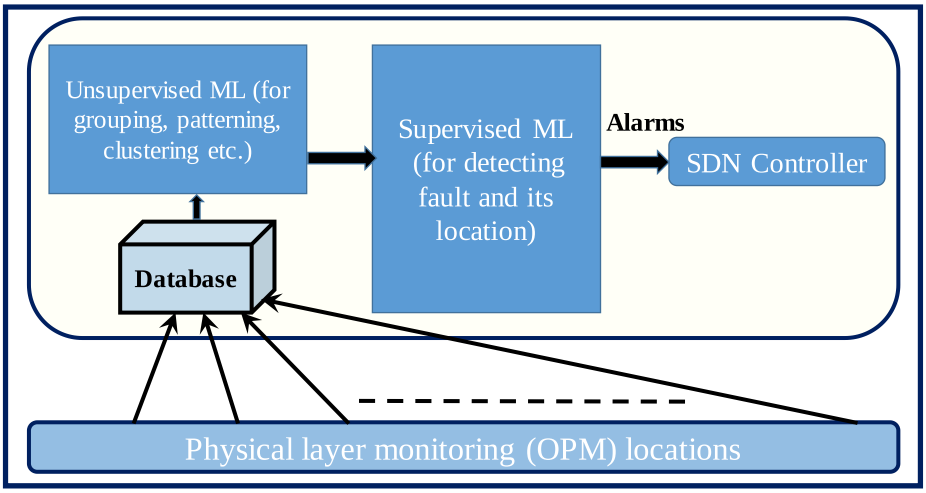


Fig. 5. 1: General schematic of ML approach to detect, locate failure, fault or anomaly in network

Thanks to the rapid advances in ML technology, recent studies have reported a few cognitive anomaly detection algorithms based on the learning of network behaviors [64]. Nevertheless, these algorithms were trained with manually featured abnormal network behaviors and were unable to detect unknown anomalies. Note that, anomalies usually occur infrequently (thus, difficult to collect) but exhibit unique patterns compared with normal network behaviors [79]. An unsupervised clustering algorithm that directly learns patterns of data by exploiting the similarities among data instances would become a promising solution to distinguish anomalies from normal behaviors.

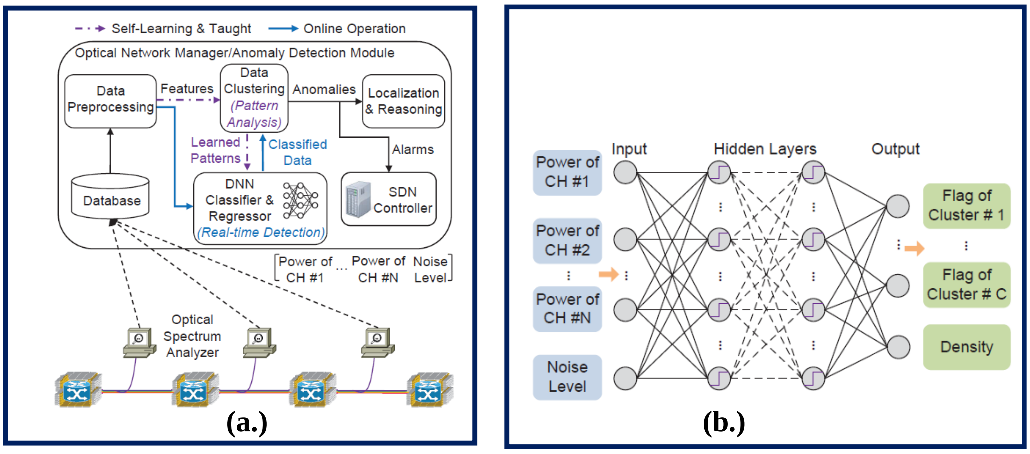


Fig. 5. 2: (a) Anomaly detection framework **(b)** DNN for single point anomaly detection [80]

Recent works on failure detection is more focused on hybrid ML techniques. That is, initially an unsupervised ML model makes some initial filtration or preprocessing like grouping, finding similarity between patterns, clustering etc. to clean data for further feature extraction. Then a supervised ML model is trained on the results from unsupervised ML models to detect the type of failure and even their location. The concept for this type of failure, fault or anomaly detection has attracted many researchers in few years and schematic for the same is shown in the Fig. 4.5. This ML approach can be eventually integrated with a SDN controller to execute the output of the ML for proactively recovering and restoring the (potentially) affected services. Again, the only problem is having a dataset.

Authors in [80], applied the same approach and proposed a scheme that first employs an unsupervised self-learning data clustering module (DCM) to extract the patterns of the performance monitoring data. Then, to facilitate real time anomaly detection, they develop a self-taught mechanism that trains a supervised learning based deep neural network (DNN) based classifier & regressor with the learned knowledge by the DCM. Fig. 4.6 shows the experimental set up and overall schematic approach used by the authors. Then they evaluated the model with an experimental dataset and claimed that with their hybrid ML approach they were able to identify 100% of the anomalies without any prior knowledge of their patterns with false positive rate is only 6.5%. In this work, performance of the proposed self-taught anomaly detection scheme was evaluated with the performance monitoring data collected from a seven node testbed [81] with EDFA malfunctioning, channel misconfigurations, filter narrowing in ROADMS etc. as sources for anomalies.

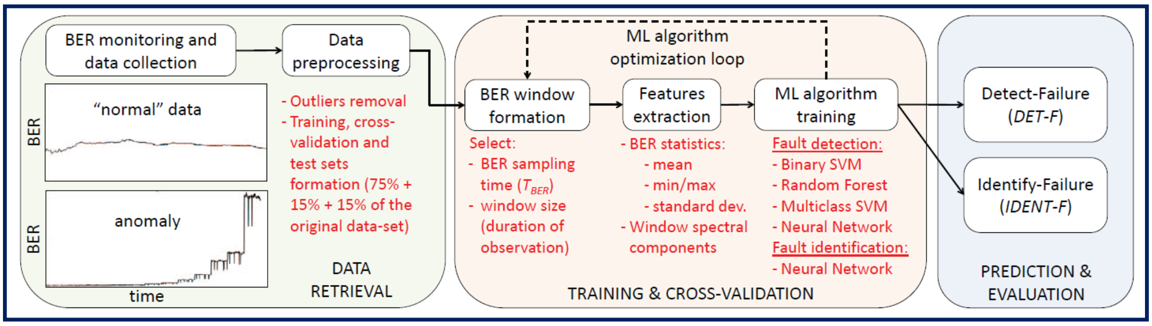


Fig. 5. 3: BER based soft failure detection and identification framework [82]

During network operation, several kinds of soft failures can affect the signal quality and induce anomalies in the BER at the receiver, ultimately leading to packet losses or even service disruption. In this regard, likewise the approach shown in Fig. 2.6, [82] provides a solution for detecting and identifying optical network soft failures. First, BER samples were periodically monitored and collected in datasets. Then, the building blocks of the ML algorithms were implemented as shown in Fig. 4.7. In this approach authors, divides the collected BER samples in a set of windows with some sampling rate. An unsupervised ML approach on each BER window were used to extract some statistical characteristics (i.e., minimum, maximum, mean and standard deviation etc. At the end, a supervised approach, ANN was used to locate fault with 100% accuracy.

From the above, we can state that different types of unsupervised ML classification methods, namely SVM, RF, Multiclass SVM, and NN were performed on the initially preprocessed data for failure detection purposes. Nevertheless, they have not addressed the type of failure and its localization. Here comes the supervised ML approach trained on the results from failure detection step for failure identification to determine the failure cause. A recently published work on soft failure detection and localization in context to EONs was proposed [78]. In this work two techniques, one for active monitoring during commissioning testing and other for passive in-operation monitoring (once lightpaths are in operation) were proposed and demonstrated. Other works have been published on proactive fiber damage (hard failure) detection in real time [72]. This work was further extended to display an end-to-end optical path restoration technique with just in time resource allocation.

4.3 Open Problems

All the above literature presented above states one thing in common, which is, failure detection is highly related to QoT estimation. Hence, all the open problems, which are mentioned in previous chapter on QoT estimation is by default a subtask to be solved for the failure detection problem. In short, failure detection and its localization with the help of the “ML assisted QoT tool” (first open problem of previous chapter) in fully disaggregated optical networks is the second main open problem in this domain for ESR2.

Moreover, as already commented in previous chapter that QoT tools are trained on well-defined datasets. Hence, in practical assets, it is difficult to collect extensive datasets during faulty operational conditions, since networks are typically dimensioned and managed via conservative design approaches, which make the probability of faults negligible (at the price of under-utilization of network resources). One of the solution for this problem is hybrid ML techniques in which, after learning from a batch of available past samples, hybrid ML techniques, could be implemented to gradually take in novel input data and finding some sort of pattern within the dataset, as they are made available by the network control plane. Hence, hybrid ML approaches for failure detection and its localization in disaggregated scenario is an unexplored area and need a proper investigation. This open problem is more or less align with QoT estimation and will be addressed by ESR2 in ONFIRE.

5 ML Assisted Management in Multi-Layer Networks

In previous section, we focus mainly on QoT estimation, failure detection and their inter relationship as how QoT estimation is one of the main criteria to detect failure in many cases. However, at the network layer, several other use cases for ML arise. This section will list a couple of other ML based applications focused more in MLN. Some use cases of ML assisted optimization (network reconfiguration mainly) in context to MLN s (more specifically in IP-over-OTN networks) has also been presented here. The main ML assisted approaches listed in this chapter are traffic prediction and topology reconfiguration based on these predictions for efficient network utilization. The reason for choosing this parameter is because the upcoming traffic not only affects the network topology but it also affects the transmission quality of the established links, which in result affects the overall QoS of the considered network.

6.1 Introduction

Communication networks can be modelled by a stack of layers with a defined client-server relationship between each layers. Each layer has a defined functionality and scope [83, 84]. Each of these network layers may have its own (single layer) fault management or recovery schemes. As will be shown in the upcoming sections, it is important to be able to combine fault management schemes in several layers in order to cope with the variety of possible failures in an efficient way and to benefit from the advantages of the schemes in each layer. It is worth mentioning that implementing a multilayer fault management strategy does not mean that all the recovery mechanisms will be used at every layer. In a multidomain optical network, encompassing core, metro and access network segments (shown in Fig. 6.1(a)), these segments typically work together to support multi-layer services and applications. This heterogeneous, dynamic, and complex mesh of networking stacks, together with future mobility constraints, necessitates smart and end-to-end service oriented software frameworks to augment conventional hardware tools with adaptive learning and decision making across multi-layer and multi-domain network architectures in a cost and energy efficient manner [85].

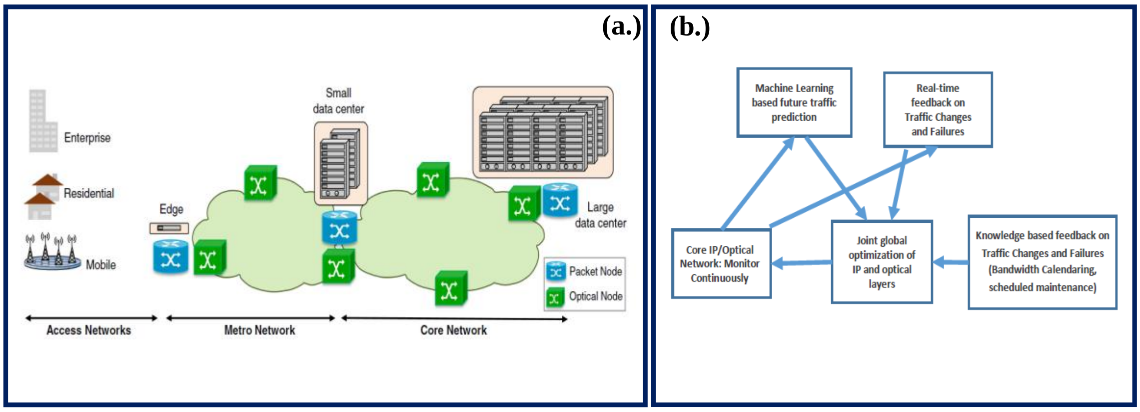


Fig. 6. 1: (a) heterogeneous optical network architecture [73] **(b)** framework for self-optimizing multi-layer networks [92]

As Internet traffic is continuously shifting and changing in volume over time (for instance, due to traffic fluctuation and overall traffic growth), there is a requirement of creating optical networks with the flexibility to reconfigure transmission according to traffic demands. This requires the possibility to set up and tear down Optical transport Network (OTN) layer connections that implement logical links in the higher network layer in real time, which has led to the concept of intelligent optical networks. In addition to allowing the network to adapt to changing traffic demands, this flexibility in setting up lightpaths on demand turns restoration into a viable recovery option. Therefore, in this section, we will see how ML can help to make these optical networks intelligent by optimizing network resources.

6.2 Technical Background (SOA)

To attain effective network utilization without compromising QoS, besides being aware of the current network picture, a basic intuition about potential incoming changes is required. In this current section, these incoming changes are the rate of change of traffic and hence traffic prediction in MLN is considered here. Also based on traffic predictions, efficient and proper network utilization through optimizing virtual network topology in MLN is also discussed with relevant use cases. For. e.g. Fig. 6.1(b) depicts the framework for self-optimizing multi-layer networks (combining packet and optical switching) in a closed loop manner where ML traffic predictions, real time network and traffic measurements, and the awareness about traffic changes and failures are collectively considered to drive joint global optimization for both network layers [92, 35, 39]. Virtual network topologies (VNTs) considers the infrastructure wherein packet-switching nodes (e.g., IP/MPLS routers) are interconnected via virtual links (vlinks) supported by underlying optical connections. This type of dynamic reconfiguration is better for network to adapt to evolving traffic demands with some objectives like reducing energy consumption, network congestion, end-to-end delay or blocking probability or trying to ensure QoT, etc. [86].

6.2.1 Traffic Prediction

Modern communication networks handle continuous variations of traffic. Therefore, it is possible that the network virtual topology is no longer suitable. Reconfiguration of this topology offers many benefits in terms of cost and energy savings, as well as on reducing the set of used resources, depending on the traffic demands [87, 88]. Network traffic is characterized by self-similarity, multi-scalarity [89], long-range dependence and a highly nonlinear nature (insufficiently modeled by Poisson and Gaussian models for example). These statistical characteristics determine the traffic's predictability. Since one of the inherent philosophy of ML techniques is to learn a model from a set of data and 'predict' the future behavior from the learned model, ML can be effectively applied for traffic prediction. Several methods have been proposed for network traffic prediction and can be classified into two categories: linear prediction and nonlinear prediction. The ARMA/ARIMA (Auto Regressive Integrated Moving Average) model and various versions of ARIMA are the most widely used traditional linear prediction methods. Nonlinear forecasting methods commonly involve neural networks (NN) [90, 91]. Literature shows that nonlinear traffic prediction based on NNs outperforms linear forecasting models (ARMA, ARIMA etc.). If we take into account both precision and complexity, the best results are obtained by a Feed Forward Neural Network predictor with multiresolution learning approach. However, most of the research using neural networks for network traffic prediction aims to predict the aggregate traffic value. Nevertheless, for traffic matrix prediction, ARIMA and its variant are still most popular [92]. Since in our case also, which is traffic matrix with VTD, the virtual topology should adapt with the variations in traffic that varies with time, the input dataset is in the form of time-series data. ARIMA is a forecasting technique that works very well with time series data and hence it becomes a preferred choice in applications like traffic predictions and virtual topology reconfigurations. Furthermore, the relatively low complexity of ARIMA is also preferable in applications where maintaining a lower operational expenditure [31].

As already discussed the virtual topology should adapt with the variations in traffic which varies with time, hence an overall ML based model can be implemented, which can forecast traffic and this traffic information can be used by some other ML models to reconfigure VTD. More specifically, the inputs are the real-time traffic matrices observed over a window of time just prior to the current period. To address VTD, use of ML is very practical and helpful as it allows to simultaneously considering a large number of different and heterogeneous service requirements for a variety of virtual topologies, thus enabling fast decision making and resource provisioning. In the next section, we will discuss details of some well-accepted techniques for the same through ML.

6.2.2 Use cases of traffic prediction in MLN

In the literature, as introduced, there are several prediction methods ARIMA, fractional-ARIMA (F-ARIMA), SVM, multilayer perceptron (MLP), and multilayer perceptron with weight decay (MLPWD) [31, 93-95]. Performances of prediction algorithms are based on the type of data input, so we cannot know if a method is better than the other until we try different kinds of input datasets. Maximum of this literature on traffic prediction is on single layer but in the upcoming sub-section; a use case for traffic prediction on multilayer network is presented along with its outcomes [92]. In this approach, a SDN controller collects long-term and short-term traffic and failure data to implement global optimization algorithms, and pushes the required changes to the packet and/or optical network layers as shown in Fig. 6.2 (a).

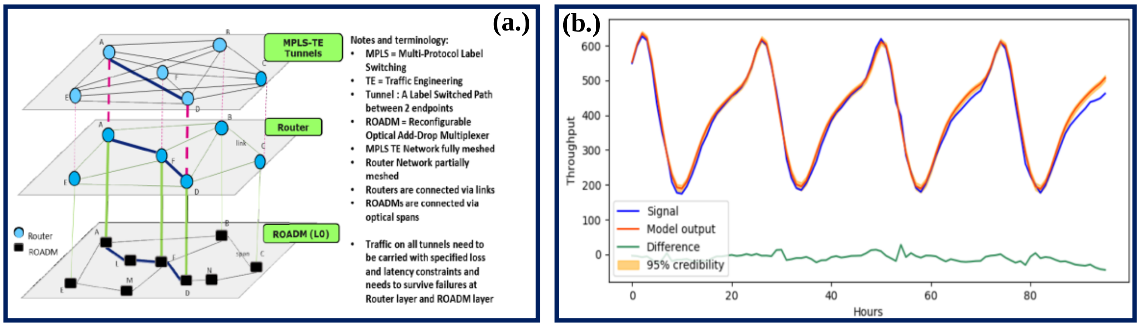
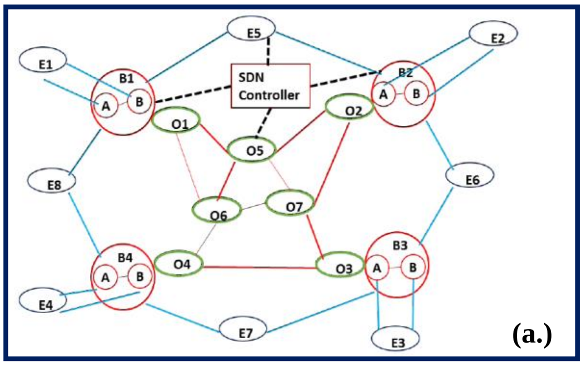


Fig. 6. 2: (a) Layer wise network architecture used for traffic prediction **(b)** Comparison of the total traffic (blue) and a 4-day forecast [92]

An example of the forecasted total traffic for several different forecasting time slots is shown in Fig. 6.2 (b), with the different models combined to form a forecasted trajectory (traffic prediction as a problem of time series forecasting) over four days.



Scenario	# of 100 GE Tails	# of 100 GE Regens	Cost
1. No Machine Learning, IP Layer Optimization Only, fixed IP to Optical mapping	1,000	100	1,040
2. Addition of Machine Learning at long time-scale	910	90	946 (-9%)
3. Addition of Joint Multilayer Optimization with a Fixed IP Layer Topology	810	80	842 (-19%)
4. Addition of Dynamically Changing IP Layer Topology as traffic changes	640	110	684 (-34%)

(b.)

Fig. 6. 3: (a) IP/Optical Network **(b)** Normalized View of Efficiency Gains with Machine Learning [92]

Fig. 6.3(a) illustrates an example of a multi-layer network and its interaction with the SDN controller. E_i represents the packet edge routers, Bi represents packet core nodes and Oi represents optical nodes. The Table within such a figure, Fig. 6.3(b) illustrates the normalized view of the efficiency gains with adopting ML for traffic prediction combined with multi-layer optimization. Another good approach is to mix different methods, as in [94], where the authors built a hybrid model. They concluded that using ARIMA and ANN, for nonlinear time series, is more efficient than using just one method. Using three different data sets, the author concluded that a mixed approach to the prediction could achieve very good results.

6.2.3 Network optimization though traffic prediction

Numerous approaches have emerged through ML, which try to optimize routing based on traffic predictions for efficient utilization of network resources. However, fundamentally virtual network topology is a set of problems that consists of three sub problems:

i. determining the set of lightpaths to be established in the network
ii. assigning network resources for each lightpath, i.e., solving the RWA problem, or the routing and spectrum allocation problem
iii. routing the traffic through that set of lightpaths

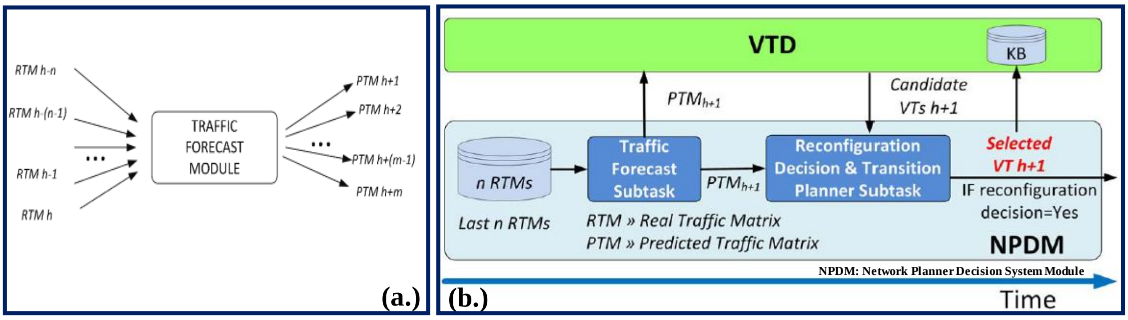


Fig. 6. 4: (a) Traffic forecast module **(b)** overall VTD reconfiguration framework [29, 30]

A full end-to-end cognitive VTD along with reconfiguration has been recently published [29, 30]. The proposed cognitive entity designs and reconfigures virtual topologies by exploiting traffic forecasting solutions and taking advantage of past history. The authors presented that apart from VT reconfiguration, if a traffic forecast demands for reconfiguration, the transition from current configuration to the new one, results in loss of packets and limits network performance in transition phase. The advantage of the proposed method, was in terms of reduced both the operational costs and the resources in operation while maintaining low packet loss ratio. In this work, the VTD and its reconfiguration were done in three steps as shown in Fig. 6.4 (b):

i. the traffic forecast subtask, which predicts the traffic in the near future
ii. the VTD subtask, which determines a set of virtual topologies adapted to the expected traffic in the near future
iii. the reconfiguration decision & transition planner subtask, which analyzes the candidate virtual topologies provided by the previous subtask, and determines whether the current virtual topology should be reconfigured or not, and how to do it

In short, authors proposed, a prediction module based on ARIMA to generate the source-destination traffic matrix. This predicted traffic matrix for the next period is then used by a decision maker module (NPDM as shown in Fig. 6.4(a)) to assert whether the current virtual network topology needs to be reconfigured or not. One more work has gathered a lot of attention recently, in which the authors present traffic prediction in an identical context as previously mentioned i.e., virtual topology reconfiguration, using NNs [32, 33]. A prediction module based on NNs was proposed in this work, which generates the source-destination traffic matrix. This predicted traffic matrix for the next period is then used by a decision maker module to assert whether the current VNT needs to be reconfigured. VNT reconfiguration requires powerful algorithms to analyze large amounts of traffic monitoring data to anticipate, when possible, traffic changes. In this work, big data analytics approach was used to periodically (e.g., every hour) predict traffic. In the case that the VNT needs to be reconfigured, the predicted traffic is used as the input of a VNT optimizer that finds the topology for the next period, thus implementing a decision-making process based on the observe-analyze-act loop as shown in Fig. 5.6 (c).

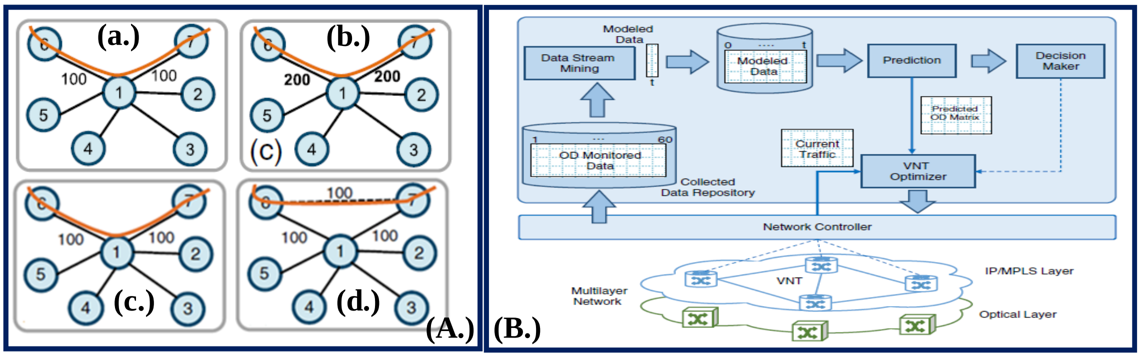


Fig. 6. 5: (a-d) Threshold based (a-b) and proposed (c-d) VNT reconfiguration **(b)** observe-analyse-act loop for VNT reconfiguration [32, 33]

There are some other works in literature, one of which proposes a cognitive network management module in relation to the application based framework with specific focus on ML-based traffic prediction for VNT reconfiguration. However, these approaches do not mention about the details of any specific ML algorithm used for the purpose of VNT reconfiguration [34, 35]. The purpose of mentioning these approaches is that even though ML is not applied in these architectures but a detailed idea of cognitive network management has been presented. In summary, this section introduces that performance of established links get affected, whenever new traffic request arrives. For proper network functioning and efficient resource utilization, prediction of traffic to reconfigure network topologies based on predicted values is required. This will help to proactively preserve the same performance on the existing link, with the arrival of continuously evolving new traffic data request. At the end, we presented some use cases for traffic prediction and use this for network optimization based on topology reconfiguration for a multi-layer scenario.

5.3 Open Problems

As already stated in the introduction part that QoS on established paths gets affected by newly arriving traffic and hence this traffic prediction is very important to minimize this effect and proper network utilization. All of the use cases presented in this section are more focused on MLNs with no disaggregation at optical layer and no use case for MLNs with disaggregated optical transport network is provided. This is because, to the best of our knowledge through SOA literature survey on the same topic, we could not find any use cases for the same. Hence, investigation of these newly evolving traffic requests, their prediction and their effect on QoS of already existed links in disaggregated optical networks is important and is one of the open problem in the same area.

Moreover, scarce attention has so far been devoted to the fact that different applications might have very different timescales over which monitored data show observable and useful pattern changes (e.g., aging would make component behaviour vary slowly over time, while traffic varies quickly, and at different time scales (e.g., burst, daily, weekly, yearly level). Some scope of research work is possible to overcome this challenge that how to make dataset, their timescale to capture specific pattern etc., which can be then used for any problem and not limited to individuality of the problem.

Finally, an important consideration is that, all so far ML-based solutions (either aggregated or disaggregated) have addressed specific and isolated issues in optical communication and networking. Considering that SDN has been demonstrated to be capable of successfully converging control through multiple network layers and technologies, such a unified control could coordinate (orchestrate) several different applications of ML, to provide a holistic design for flexible and dynamic optical networks. In fact, as seen in the Section 3, 4 and 5, ML algorithms can be adopted to estimate different system characteristics at different layers, such as QoT, fault occurrences, RMSA and in Section 5, traffic patterns their predictions along with ML assisted VTD reconfiguration, Many of these approaches are mutually dependent (e.g., the QoT of a lightpath is highly related to the presence of faults along its links or in the traversed nodes), whereas others do not exhibit dependency (e.g., traffic patterns and fluctuations typically do not show any dependency on the status of the transmission equipment but affects QoT of already established lightpaths). Hence, this interdependency and their modelling to get a unified control framework is one such open field, which requires thorough understanding of all the SOA literature presented in section 3, 4 and 5. More research is needed to explore the applicability and assess the benefits of ML-based unified control frameworks where all the estimated variables can be taken into account when making decisions such as where to route a new lightpath (e.g., in terms of spectrum assignment and core/mode assignment), when to re-route an existing one, or when to modify transmission parameters such as modulation format and baud rate to maintain QoS of the network.

6 Research Plan, Methodology, Timeline and Expected Results

Research Plan

This is the preliminary report and is more focused towards choosing the initial steps to achieve ONFIRE goals described at the end of the "introduction" section with respect to ESR2 activities with below defined research plan in Table 3.

Research Plan	
Task#1	**Development of ML based QoT Estimator for "Disaggregated optical networks"**
Subtask	
1.1	Finding ways to generate dataset for ML models
1.2	Checking feasibility of existing analytical models (with additional losses) for dataset generation
1.3	Finding novel ML algorithms for QoT estimation and their accuracy improvement
Task#2	**Extension of the Task#1 in packet-based and in MLN environment**
Subtask	
2.1	Generating dataset, keeping MLN scenario as use case (mainly fault management)
2.1	Finding ways to extend the QoT estimator for packet based networks
Task#3	**Experimental validation of QoT estimator proposed in Task#1 and Task#2**
Subtask	
3.1	Test bed preparation with multi-vendor OTN at Nokia Bell Labs, Germany
3.2	Collection of dataset for training and testing of ML assisted QoS tool
3.3	Checking functionality & reliability of QoT tool on experimental dataset
Task#4	**Integration of QoT tool with SDN controller**
Subtask	
4.1	Finding ways to integrate ML engine within SDN controller at CTTC, Spain
4.2	Selecting the best approach for integration
4.3	Testing working accuracy of model after integration

Table 3: Research plan for ESR2 to achieve ONFIRE objectives

From the above mentioned research plan in tabular form, it is clear that one of the major focused area in ONFIRE for ESR2 is on ML assisted QoT estimator in disaggregated optical networks. ESR2 in ONFIRE project aims at exploiting the flexibility and modularity provided by the disaggregated network paradigm. ESR2 will leverage the benefits of ML to assist the automatizing of the network operations (i.e., by ensuring QoS and QoT estimated through novel ML assisted tools) in both single layer and multi-layer (combining both path and optical switching technologies) infrastructures.

That is why, in this research plan, special attention will be put on ML algorithms for QoT estimation by taking MLNs with disaggregated optical layer as use case with an overall objective of ensuring network's QoS within acceptable limits. The idea of doing that is to take advantage of the large amount of data (e.g., coming from network monitoring elements) to 'learn' from experience and make the network management more agile and adaptive.

Methodology

Task#1 is the major milestone for ESR2 in ONFIRE project. To achieve the objectives of Task#1, ESR2 will use Python and MatLab languages as tools to develop analytical models to generate dataset. Once this is achieve, the next step is to find novel ML algorithms for end-to-end QoS estimation. For this subtask, ESR2 will use python and R languages to build a ML based QoT estimator, while ensuring service quality. One of the main reason for choosing these languages for the development of ML based tool is that, these languages especially Python has abundant of libraries and frameworks that facilitate coding of such model and save development time.

For the experimental validation of model (Task#3), ESR2 will use facilities provided by Nokia Bell Labs, Germany for developing such a disaggregated testbed for data collection. Python and R will again use by ESR2 to test the working accuracy of the model on this experimental dataset. Finally, ESR2 will use testbeds available in CTTC, Spain for integration of this experimentally tested QoT tool with SDN controller.

TimeLine

Please refer to Gantt chart attached at the end of this report.

Expected Results

The first result that will be expected from ESR2 is to successfully develop a ML based model for QoT estimation for disaggregated optical networks. Accurate working possibility of this model from optical to packet-based disaggregated networks and in multi-layer environment will also be expected from ESR2.

As, in the open problem section, accuracy improvement of the QoT estimator is also there. Hence, a percentage increase in accuracy of the proposed QoT tool by reducing uncertainties on the input parameters of the model (by application of error reduction techniques such as gradient descent etc.) is also one of the expected results from ESR2. After proper testing of this model with experimental dataset from multiple vendor based disaggregated network, integration of the same with SDN controller for and end-to-end cognitive framework is the final expectation from the ESR2 and is expected to be done at both Nokia Bell Labs, Germany and CTTC, Spain.

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Gantt chart

Gantt Chart
Research Proposal Timeline for ESR2

Project Name	Project Duration for ESR2	ESR2 Start date	ESR2 End Date		
ONFIRE	31 Months	18-Sep	21-Mar	→	CTTC, Spain
				→	Nokia Bell Labs, Germany

ESR2 Location

Task ID		Task Description	Task Duration (Months)	Start Date (Year-Month)	End Date (Year-Month)	18-Sep	18-Oct	18-Nov	18-Dec	19-Jan	19-Feb	19-Mar	19-Apr	19-May	19-Jun	19-Jul	19-Aug	19-Sep	19-Oct	19-Nov	19-Dec	20-Jan	20-Feb	20-Mar	20-Apr	20-May	20-Jun	20-Jul	20-Aug	20-Sep	20-Oct	20-Nov	20-Dec	21-Jan	21-Feb	21-Mar
1		Development of ML based QoT Estimator for "Disaggregated optical networks"	9	18-Sep	19-Jun																															
Subtask	1.1	Dataset generation	5	18-Sep	19-Feb																															
Subtask	1.2	Scope of using existing models	1	19-Feb	19-Mar																															
Subtask	1.3	Novel ML assisted QoT estimator	3	19-Mar	19-Jun																															
2		Extension of the Task#1 in packet-based and in MLN environment	4	19-Jun	19-Sep																															
Subtask	2.1	Dataset generation for MLNs	2	19-Jun	19-Aug																															
Subtask	2.2	QoT estimator for packet networks	2	19-Aug	19-Oct																															
3		Experimental validation of QoT estimator proposed in Task#1 and Task#2	6	19-Oct	20-May																															
Subtask	3.1	Test bed preparation	3	19-Oct	19-Dec																															
Subtask	3.2	Datast collection	2	20-Jan	20-Mar																															
Subtask	3.3	Experimental validation	1	20-Mar	20-May																															
4		Integration of QoT tool with SDN controller	6	20-Jun	20-Nov																															
Subtask	4.1	Selection of best approach to integrate	4	20-Jul	20-Oct																															
Subtask	4.2	Experimental testing	2	20-Nov	20-Dec																															
5		Thesis preparation & submission	4	20-Dec	21-Mar																															