Active Wavelength Load as a Feature for QoT Estimation Based on Support Vector Machine

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***Abstract*—Reconfiguration procedures in optical transmission systems assisted with artificial intelligence (AI) present an innovative approach towards the mitigation of network resources mismanagement. Regression and classification tools have been studied in recent years with the aim to predict performance metrics such as Bit Error Rate (BER) and Optical Signal-to-Noise Ratio (OSNR). We have generated synthetic OSNR labeled data, which has been used for training a Support Vector Machine (SVM) classifier, in order to predict the OSNR performance upon provisioning a wavelength channel (lightpath). Information on the active lightpaths in the network is used to train the learning model, together with network topology configuration features. Our results demonstrate a 96.2% multi-class classification accuracy to predict QoT of unestablished lightpaths in topology independent (generic) scenarios.**

I. Introduction

Driven by the requirements of 5G services and the infrastructure to support them, the thrive for faster and dynamic network reconfiguration procedures in the optical domain remains latent [1]. In the last decade, compounded solutions relying on software-defined networking (SDN) and network function virtualization (NFV) have proven the feasibility of improving network reconfiguration procedures by restructuring the control and management of resources [2]. However, the re-emergence of cognitive control supported with virtualized instruments pose design challenges to the implementation of future optical control systems. In recent years, studies have reviewed the potential of AI techniques (i.e., Machine Learning (ML)), to support intelligent software-defined optical control systems in enhancing the overall network capacity [3], [4]. In spite of that, this area is still at its infancy, requiring further research.

Because of the irregular nature of nonlinearities encountered in optical networks, controlling the physical effects introduced by these phenomena is rather challenging. Cognitive control will play an important role in learning from the power dynamics in optical transmission systems to mitigate the undesired performance impact in the QoT. Proposals of cognitive control in the optical domain have been surveyed by Mata et al. in [4]. Conceptual analyses have demonstrated the favorable potential of statistical tools to predict, estimate and classify the QoT of lightpaths in optical transmission systems [9-18]. Small in-field experimental studies have also exhibited positive cognition capabilities implemented in software-defined optical control systems [19-21]. In general, a common trade-off exists between learning model accuracy, amount of required data, algorithm complexity, and computational time.

Most of the work done with learning models consisted in offline training approaches, whereas only few live demonstrations of cognitive control systems have been performed. This is mainly due to the technical limitations imposed by networking components to generate large collections of optical data in a fast and dynamic manner. Also, the fact that mainstream monitoring tools are usually allocated only at strategic (*low number of*) points in a network, limits the perspective of analysis towards the interaction of multiple transmissions.

In addition, given the implementation dependent performance of the optical network elements (i.e., routers, amplifiers), learning models tend to not be robust enough to assist *all* control systems, but would only perform reasonably for those systems they were trained for. As a result, we consider relevant the analysis of multiple network features and their role in enhancing QoT prediction. In particular, here we focus on the power dynamics of amplified transmission systems. We present an analysis of the power excursion phenomenon due to the presence of automatic gain controlled (AGC) erbium doped fiber amplifiers (EDFA) in wavelength division multiplexed (WDM) networks equipped with reconfigurable optical add/drop multiplexers (ROADMs). AGC operates by maintaining a constant gain averaged across all wavelength channels in a link. The EDFA amplification process exhibits a wavelength dependent effect that introduces instability among multiple transmitted lightpaths when averaging the gain due to AGC. This phenomenon is commonly mitigated with gain flattening filters (GFFs), by equalizing unequal signal intensities. Due to the static operational nature of filtering, in some cases performance is not optimal, and undesirable power excursions are typically generated during switching operations (i.e., add/drop wavelength channels) [5].

As a use case, following previous work in [6] and [7], we aim to determine the most suitable modulation format to transmit a wavelength channel upon lightpath provisioning. Multiple learning models exist to assist this problem. Among the most common are K-Nearest Neighbours (KNN), Random Forest (RF), and Support Vector Machine (SVM) models. In the literature these have been widely reviewed, without clearly favoring any of them for the binary classification use case. In this work, we use a multi-class SVM classifier to learn from the power dynamics generated by the interaction of various number of lightpaths, taking in consideration their operating wavelength and other network topological features.

In this paper, we present an insight of the capabilities of SVM classifiers to perform multi-class optical parameter-based prediction of QoT. We have used the Optical-MAN emulator introduced in [6] to generate synthetic data for our use case. The emulator is capable of reproducing OSNR degradation and power excursion due to the presence of EDFAs and calculates impairments generated by stimulated Raman scattering. Our SVM model was deployed with the Scikit-learn Machine Learning Python Application Program Interface (API) [8], and was trained to predict the OSNR levels of a wavelength channel upon installation. The remainder of this paper is organized as follows. In Section II, we present the related work in the area of QoT estimation (QoT-E) with classic ML models. Our synthetic data generator and the SVM tool are described in Section III. Experimental procedures and results are discussed in Section IV. We present conclusions and future directions in Section V.

II. Related Work

In this section, we review related work that has aimed to predict and classify the QoT of lightpaths. We include both theoretical and in-field experiments, since both give insights of the potential of integrate learning models to assist future optical control systems.

Barletta et al. [9] considered the use case of deterimining whether unestablished lightpaths meet a required BER threshold. Synthetic data was used for their experiments. They implemented an RF classifier with 100 estimators. The features used for training their model were: the number of links of lightpath, lightpath length, longest link length, traffic volume, and modulation format. Datasets were collected from a single topology, enabling RF to perform with high accuracy with only 1000 training data samples, although they also trained the model with 90 thousand samples. The findings were extended in [10] including a deeper analysis of the challenges imposed by network components in optical networks to the development of cognitive control systems.

Bouda et al. [11] studied the learning capabilities in a multi-vendor scenario. They collected and trained synthetic data on-the-fly, representing the case of an online control system. The learning model used for their studies was based on maximum likelihood principles, correlated with the monitored data. They used many physical layer parameters (i.e., launch powers, fiber span losses of certain links, etc.). An emulated 88-channel system was used to generate data traversing all the spans in their network topology. QoT prediction with 0.6 dB Q-factor accuracy was achieved. They extended their research in [12], presenting an analysis of the network capacity gain due to the implementation of the Q-estimation tool.

Mata et al. [13] have reviewed the potential of SVM to classify lightpaths into high or low quality categories in impairment-aware wavelength-routed optical networks (WRONs), in long haul communication networks. Their results favor SVM with respect to the high accuracy for binary classification. A dataset with 11 thousand samples was used to train the learning model. Nonetheless, they have pointed out the main pitfall of SVM to be the extensive time to train the model, which is indeed a considerable limitation for future control systems. They extended their findings in [14] by comparing the previously implemented SVM model against RF and bagging trees. This time, the new models outperformed SVM in computational time while maintaining a classification accuracy of 99.9%.

Contrasting the results from [13], Aladin and Tremblay studied the potential of an SVM model to classify lightpath QoT into good or bad according to BER thresholds [15]. They also compared the performance of SVM with KNN and RF in terms of computation time and prediction accuracy. By training the learning models with more than 25 thousand data samples, their SVM implementation outperformed the other two candidates in classification accuracy, but with the tradeoff of longer computation time with respect to KNN and RF. As input features for the learning model they considered: total link length, span length, channel launch power, modulation format and data rate. In [16], Tremblay and Aladin show a comparative analysis between the three classifiers, where the results favor SVM with 99.15% accuracy.

Similar to [15], Morais and Pedro compared an SVM model against KNN, logistic regression, and an artificial neural network (ANN) model, to predict the QoT of unestablished lightpaths [17]. They considered 13 different features to train their learning model (i.e., number of hops, spans, link length, span attenuation, etc.). Around 5 thousand samples were used to carry out the learning model training. Their results favor ANN because they achieved 99.9% prediction accuracy with this model. Nonetheless, the other two algorithms performed with an accuracy of 95%. They extended their research work in [18]. This time they concluded that SVM models with KNN, logistic regression could classify correctly 90% of the lightpaths, and ANN continued achieving a classification accuracy of 99.9%.

In [19], Meng et al. used a learning model based on Markov Chain Monte Carlo, achieving a Q-factor estimation error of 0.5 dB. This was a testbed experiment consisting of the integration of a QoT estimator as a module in the control plane of a software-defined small optical network system.

Liu et al. [20] presented an end-to-end testbed with a QoT estimation tool with performance accuracy above 90%. In this study, the learning model used was ANNs. The small testbed demonstrated the potential of cognition on software-defined elastic optical networks.

In [21], Mo et al. studied a deep neural network (DNN) to predict the power dynamics of a 90-channel ROADM system. In their study, a comparison between DNN, ridge regression and RF is presented, favoring DNN with the lowest maximal error (0.8 dB). They performed online training with 6720 training samples. The experiments were carried out in a small testbed, analyzing the effects of power excursions encountered in the amplification process of EDFAs.

Further research is required in this field. We aim to study the features of an optical network that significantly impact the power dynamics in optically amplified transmission systems.

III. System Setup and SVM Classifier Description

In this section, we present the system setup process using the Optical-MAN emulator with the extended optical performance considerations, and describe the SVM model with respect to the documentation in [8].

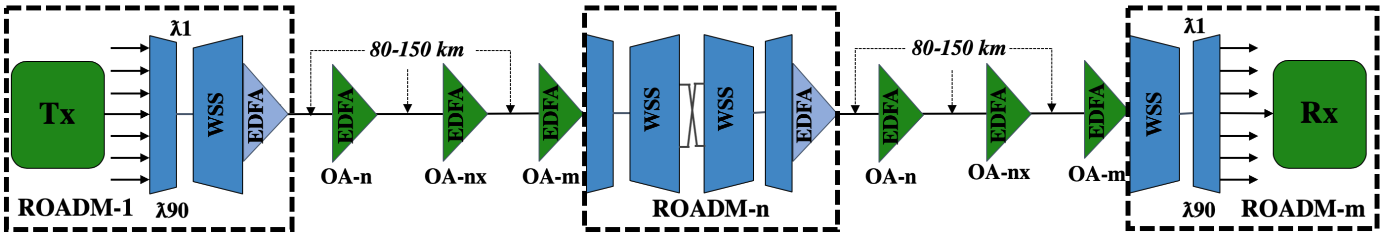


Fig. 1: Linear topology. Deployment may vary in different network settings as per features in Table 1.

A. System setup

In-field optical data generation is a complex and time consuming task. Furthermore, the variation of the topology configuration and the system setup parameters may be limited to the available equipment at the time. The expansion of networking equipment leads to high capital expenses. Despite the use of synthetic data cannot give a definite answer on how a ML algorithm will perform once applied in the field, it enables low cost, fast analysis and understanding of those algorithms, allowing comparisons of their potentials. Afterwards, real data is necessary for validating these tools.

That is why we have developed a customized Optical-MAN emulator, enabling the deployment of virtual optical networks, which have real SDN-enabled control capabilities. The SDN aspects of the Optical-MAN emulator have been described in [6] for single-domain control. For the purposes of this study, we used the emulator to generate synthetic optical domain labeled data, which was used to train and test the multi-class SVM classifier.

The Optical-MAN emulator allows to generate any network topology composed of optically-amplified EDFA links and ROADM nodes, equipped with wavelength selective switches (WSSs) and AGC-EDFAs for pre-/post-signal amplification. End-to-end transmission is enabled for up to 90 wavelength channels in the C-band (1529.6 nm - 1565.2 nm). For this study, we generated multiple end-to-end linear topologies as depicted in Fig. 1, considering multiple combinations of the parameters listed in Table 1.

TABLE I: Topology configuration parameters.

Feature	Value
Number of ROADMs	2 to 8
Number of links	[ROADM number - 1]
Number of fiber spans	2 to 6
Length of fiber span	80 to 150 km
Launch channel power	-10 to 4 dBm
EDFA Preamp gain	Fiber compensation adjustment dB
EDFA Post-amp gain	9 dB

For all system setups, a WSS insertion loss of 9 dB is assumed and compensated by in-line (post-amp) EDFA. The ROADM nodes are interconnected by links composed of several spans. For each linear topology, spans are set to the same length. EDFA preamplifiers are configured to compensate for the span loss. Then, it is assumed that GFFs are used at line amp sites for EDFA gain equalization. However, residual wavelength-dependent gain (WDG) persists, causing undesirable power excursions during wavelength switching (add-drop). Therefore, WDG curves are randomly assigned to each EDFA in all topology configurations, considering different gain settings. An example is shown in Fig. 2, where a post-amp EDFA is assigned a curve with an amplitude range of -/+ 1.5 dB, and a preamp EDFA is assigned a curve with an amplitude range of -/+ 0.4 dB. All subsequent line amplifiers would have similar characteristics, with WDG functions varying in spectral shape and amplitude, as described in [6]. Gain curves were experimentally retrieved from a physical testbed, and the synthetic assignation to the EDFAs for the purposes of this study is just to provide an approximation of the real behavior. Moreover, the power excursions which result from the interaction of wavelength-dependent gain and AGC were modeled with respect to the work in [22], considering the switching functions (add-drop) and the wavelength channel load and the channel configuration (i.e. which channels are active).

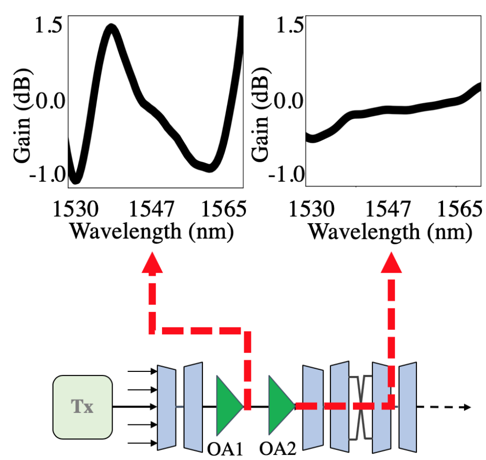


Fig. 2: Different EDFA wavelength-dependent gain functions. Post-amp EDFA is assigned a curve with an amplitude range of -/+ 1.5 dB, and a preamp EDFA is assigned a curve with an amplitude range of -/+ 0.4 dB.

Optical performance monitoring was considered at the receiver end, retrieving power and noise levels for each received wavelength channel. With this data, we were able to compute the OSNR as described in [6], as well as to classify the lightpaths among the multiple modulation format classes. From our previous study, the detection of the feasible modulation format to transmit an unestablished lightpath would enhance the overall network capacity.

B. SVM Classifier Description

For our experiments, we used the toolkit developed by Pedregosa et. al. [8], which consists in an open-source API for ML models in Python. We have implemented the SVM classifier for the multi-class scenario, that can be described as:

$$\begin{gathered}\min_{w,b,\zeta} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \zeta_i \\ \text{subject to } y_i(w^T \phi(x_i) + b) \geq 1 - \zeta_i, \\ \zeta_i \geq 0, i = 1, ..., n\end{gathered} \tag{1}$$

For the given training vectors $x_i \in \mathbb{R}^p, i = 1, ..., n$ in two classes, and a set of labeled training patterns $y \in \{1, -1\}^n$.

Then, the dual of this formulation is described as:

$$\begin{gathered}\min_{\alpha} \frac{1}{2} \alpha^T M \alpha - e^T \alpha \\ \text{subject to } y^T \alpha = 0 \\ 0 \leq \alpha_i \leq C, i = 1, ..., n\end{gathered} \tag{2}$$

where e is a vector of all ones, M is an n-by-n positive semi-definite matrix, $M_{ij} \equiv y_i y_j K(x_i, x_j)$, where $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ is the kernel function.

Last, the decision function is described as:

$$sgn(\sum_{i=1}^{n} y_i \alpha_i K(x_i, x) + \rho) \tag{3}$$

where ρ is an independent parameter. The main regularization parameter of this implementation of SVM is C, which controls the cost of misclassification on the training data. Additionally, the performance is tightly dependent on the kernel function and the kernel coefficient γ. Because it is hard to select an appropriate set of parameters and avoid over-/under-fitting the classifier model, the SVM-API [8] extends a feature for an exhaustive search over specified parameter values for an estimator. This allows for multiple parameters to be trained in parallel (i.e., multiple values of C), to use those that best fit to the final model, enabling higher SVM classification accuracy.

IV. Experiments and Results

In this work, we study the potential of a multi-class SVM classifier to assist the routing and wavelength assignment process of optical control systems, by learning from the power dynamics generated through the interaction of multiple lightpaths in an optical fiber medium. We follow up the use case first presented in [6], where we explore the potential of a QoT estimator to determine the feasible modulation format to be used for unestablished lightpaths. Such flexibility of performance has proven to improve the usage of network capacity and its resources [7]. Four QoT classes are considered as taken from [7]: OSNR $\geq$ 17 dB, $\geq$ 14 dB, $\geq$ 10 dB, corresponding to the feasible modulation formats of 16 Quadrature Amplitude Modulation (QAM), 8QAM and Quadrature Phase Shift Keying (QPSK), respectively. For OSNR $<$ 10 dB we assume the path is below BER threshold. Since we established the minimum OSNR threshold to be 10 dB, below this level we consider that the lightpath is not feasible, classifying it in the *"none"* class.

Our system is capable of reproducing OSNR degradation and power excursions due to the presence of EDFAs and calculates impairments generated by stimulated Raman scattering. The degree of influence is given by the combinations of the parameters in Table 1. Together with that, there is the wavelength-dependent gain introduced by EDFA amplification and the power excursions generated because of it. In contrast with the topological parameters, these physical effects cannot be labeled and fed into the SVM learning model even though they significantly affect the transmission performance. To overcome this learning impairment, we analyze the interaction of wavelength channels under different topological configurations, so the model can indirectly learn from their performance.

The interaction of lightpaths across transmission is highly variable. This results in different effects on individual wavelength channels with respect to the number of active channels and their position in the spectral band. In this work, we analyze the performance of a newly established lightpath into a system with a given wavelength load (WL). That is, setting up a new lightpath when there are N active wavelength channels. In order to train the SVM model, we considered 15 WL scenarios, when N=1, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, and 70. For each value of N we train the system with 7,647 different paths, where the N existing wavelength channels are randomly placed. Then, we compute the OSNR levels of the new channel to be set up $(N+1)$, also randomly selected, and classify it with respect to one of the four QoT classes.

Also, in order to provide relevant data with regard to the wavelength-dependent gain of EDFAs, we have segmented the C-band spectrum into 10 bins, consisting of 9 wavelength channels each, as depicted in Fig. 3. Each bin represents a section of the EDFA gain curve, whose characterization improves the learning process of the multi-class SVM classifier by taking into account the position of the wavelength channels in the spectral band.

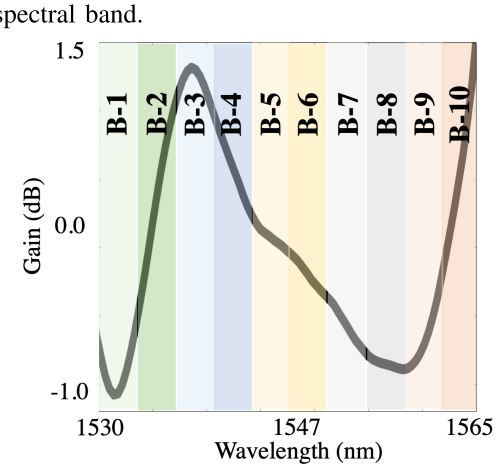
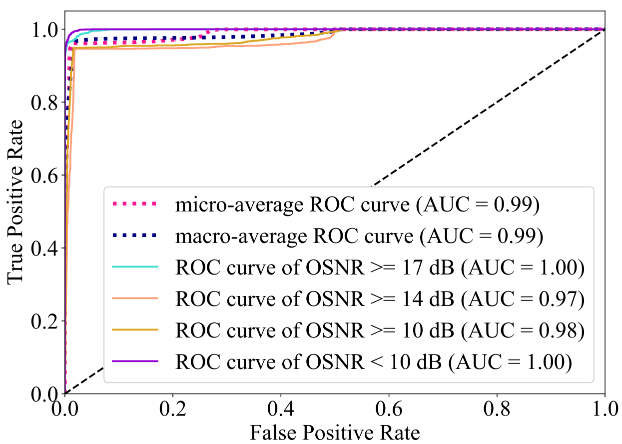
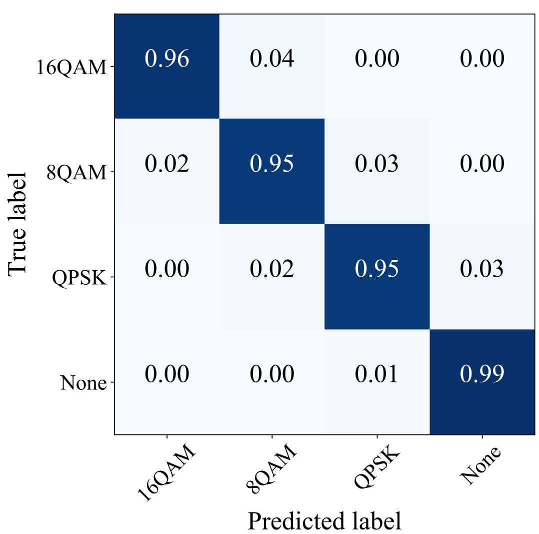


Fig. 3: Segmented spectrum of EDFA wavelength-dependent gain.

Considering these parameters, we have generated 30,588 training samples, for which we balanced the distribution of the training set among the four QoT classes to avoid learning bias. For the test samples, we followed a similar approach, only that this time we considered random WL scenarios (i.e., N is allowed to take any number between 1 and 90). In this way, we were able to analyze the potential of the multi-class SVM classifier to predict OSNR-QoT levels of any WL, without having trained the system for all cases. This gives an insight of the significance of active wavelength channels in a system to predict the QoT of unestablished lightpaths. We generated 7,380 test samples. The total data set adds up to 37,968 samples, which have been separated for training and test data with an 80-20% ratio.



(a) Receiver operating characteristic.



(b) Confusion Matrix.

Fig. 4: Results.

As described in the previous section, the SVM implementation with the Python Scikit-learn API allows for an exhaustive search over specified parameter values for an estimator, allowing for multiple parameters to be trained in parallel, so the model can pick those that give the higher performance accuracy. We have trained the model with the values: $\gamma = 0.001, 0.0001, 1e{-}05$, $C = 10, 100, 1000$, and two kernel functions: radial basis function (rbf) and a polynomial function. Then, we have also used a 5-fold cross-validation for the splitting strategy. For details of the code implementation, refer to [8].

The multi-class SVM classifier is assessed for the four QoT classes; the receiver operating characteristic (ROC) curve and confusion matrix are shown in Fig. 4.a and 4.b, respectively. ROC depicts two metrics of assessment, *i)* contrasting the true positive rate (TPR) against the false positive rate (FPR) of the attempts to predict any of the four QoT classes, and *ii)* the area under the curve (AUC), which uses the value of 1 as the highest possible classification performance. Our results demonstrate an exceptional performance for the case of QoT classes corresponding to 16QAM and below OSNR threshold, whereas a lesser performance is achieved for 8QAM and QPSK. Separately, the confusion matrix depicts the percentage of accurately classified OSNR levels for the four classes, 16QAM, 8QAM, QPSK, and below OSNR threshold (*none*), respectively. The overall accuracy obtained with this tool for the multi-class classification use case was 96.2%. It is important to notice that these results consider generic prediction capabilities, given that the network system topologies used to train and test the learning model were different.

Although the classification accuracy demonstrated exceptional performance, a significant pitfall of this implementation of the multi-class SVM classifier is the computational time required to train the model, given its complexity $O(n^3)$. Because we enabled the exhaustive parameter search function in our implementation, the training process was even longer, taking about 10 minutes in a Linux x86_64 server with 15 Intel(R) Xeon(R) CPU E5-2699 v4 @ 2.20 GHz processors. However, we are keen in continuing exploring SVM in the future, given that this time the classifier was used in the multi-class classification use case, for system setups with widely varied topological configuration settings. Hence, we still consider relevant the study of the multiple relevant features in an optical network concerning the power dynamics, to decrease the computational time required for SVM.

V. Conclusion

We have studied the potential of deploying QoT estimation tools with a multi-class SVM classifier to assist the routing and wavelength assignment module of future optical control systems, in order to improve the management of network resources. Our experiments demonstrated high performance accuracy when using information of the active wavelength channels in a network to train the classifier. We have also given an insight of the potential of this type of learning model to be trained and tested for systems consisting in different topological configurations, overcoming the limitations of system dependent models. Nonetheless, our system still required a number of data samples above 30 thousand, which poses implementation challenges in a physical testbed. Because of that, our future work will concentrate in reducing the number of data samples by analyzing the potential of other optical network features, identifying those that enhance the prediction of unestablished lightpaths.

We will investigate other learning models such as neural networks to assist the multi-class classification scenario and achieve faster training rates. We are also planning to include nonlinear noise effects into the Optical-MAN emulator, so that we can aim at using our learning models on top of physical testbeds. The ultimate goal will be to implement the QoT estimation tool as a module of a real SDN optical control plane.

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