

Deep-Quality-EON Classifier

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Abstract—Elastic Optical Networks (EON) provide better spectrum allocation flexibility and scalability than traditional Wavelength Division Multiplexing networks and are suitable to support the increasing demand for Internet traffic. Those are circuit-switched networks that employ routing, modulation and spectrum allocation (RMSA) algorithms to establish optical circuits. To guarantee an efficient operation of these networks it is necessary to be able to monitor its behavior in a dynamic fashion in search of opportunities to improve its control. In this work, we propose Deep-Quality-EON, a deep learning-based model that classifies the efficiency of the resource allocation strategy applied in an EON solely based a snapshot of the spectrum allocation from the network. The deep learning classifier proposed was evaluated in several scenarios and the results obtained are promising, opening a new avenue on the research area of adaptive RMSA algorithms.

Index Terms—Elastic Optical Networks, Routing and Spectrum Allocation, Machine Learning, Deep Learning

I. INTRODUCTION

A great effort is currently being made to develop new technologies that enable higher transmission capacity in transport networks. The current optical networks based on Wavelength Division Multiplexing (WDM) use 50Ghz per wavelength fixed-length frequency grids for transmission and they can not support the increase in internet traffic. In this context, Elastic Optical Networks (EONs) emerged with a more flexible architecture, making efficient use of network resources [1]. Similar to Routing and Wavelength Assignment (RWA) algorithms in WDM networks, EONs use Routing and Spectrum Allocation (RSA) algorithms. The wavelength continuity constraint characteristic of RWA strategies is replaced by the spectrum continuity constraint in RMSA strategies. Besides, another constraint plays an important role: spectrum contiguity, which indicates the need for slots allocated for the same demand to be adjacent. EONS can also accommodate different modulation formats, this adds a new restriction to the algorithm, known in the literature as RMSA (Routing, Modulation and Spectrum Allocation).

However, even with the development of these networks, the investments in infrastructure are growing on a smaller scale than the growth of Internet traffic, and the current oversizing model will not meet future demand. The term capacity crunch was used for the first time at the beginning of this millennium [2], and currently it is highly present in the discussion about the future of the Internet [3]. It occurs when

the resources to provide the desired speed, reliability and other network requirements become insufficient. According to [4], this does not mean a catastrophe for the Internet, but a “new normal”.

Communication networks researchers must propose traffic engineering solutions to postpone the moment when exhaustion will occur. In this context, the circuit blocking rate and bandwidth blocking rate metrics play an important role in measuring the probability of network exhaustion and consequently the efficiency of a traffic engineering algorithm. Several RMSA algorithms were proposed in the literature and their efficiency (blocking rate) is known. All these algorithms have one thing in common, they use fixed strategies such as first-fit spectrum allocation. Getting these algorithms to adapt their strategies to the network state might be the right path to increase their efficiency and extend the network lifespan. The need for adaptation leads to the need for learning, which leads to Machine Learning (ML).

ML is a branch of Artificial Intelligence (AI) with the idea that from relevant data, machines can learn how to solve a specific problem [5]. Many algorithms allow us to do this, such as Support Vector Machine (SVM) and Random Forest. However one particular type has been highlighted in the literature, the artificial neural networks (ANNs). Although proposed in the 1950s, neural networks have gained prominence recently due mainly to the availability of large amounts of data and the increased processing power of computers. Thus, with the increasing complexity of ANNs, a new subclass of algorithms has emerged, named deep learning (DL).

A high number of domains use DL, ranging from image recognition to natural language processing, and several types of neural networks have emerged, such as Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Generative Adversarial Network (GAN) and Autoencoders [5]. For some years now, the planning of optical infrastructure that will support the growing demand for Internet traffic, including EONs, have been using these techniques [6], [7].

In this context, we intend to use the progress made in recent years with the deep learning techniques to evaluate dynamic RMSA problems. We know the uncertainty of future requisitions, which have a stochastic nature. But we expect that a correct representation of the optical network and an adequate machine learning model can make the neural network, after training, acquire enough knowledge to identify how efficiently resources are being allocated. Thus, the question that guides

this research is:

- Is it possible to extract information about the efficiency of a RMSA solution in an EON in real-time?

We believe that by answering this question we can create algorithms that act adaptively in order to make better use of network resources. And, as we will show in this paper, we were able to answer this question satisfactorily.

First we create an ANN that recognizes the RMSA algorithm in an EON. Then we establish a relationship between the spectrum allocation state and the quality of the RMSA solution being used. Thus, we propose Deep-Quality-EON, which evaluates if the resources of the optical network are being well allocated until that moment. In other words, we classify the RMSA strategy according to its efficiency.

We claim that this classifier is an initial step towards the understanding of the relation between the spectrum usage patterns and the efficiency of the employed spectrum allocation solution. Considering that by understanding how the application of an efficient RMSA solution manifest itself in the spectrum usage, it might provide the knowledge to propose new techniques that will allow an efficient adaptive decision making process in the path computation module of an EON control plane.

The rest of the paper is organized as follows: in Section II we present the related work; in Section III we describe the DL model; Section IV presents the results and, finally, in Section V conclusions are drawn.

II. RELATED WORKS

In recent years, much research using machine learning in elastic optical networks has been proposed in the literature, mainly concerning the Quality of Transmission (QoT) estimation, fault management, design of virtual topology and resource allocation, as will be described below.

Estimating signal transmission quality before lightpath establishment is an impressive technique in optical network design. Analytical models often roughly estimate QoT, so networks have to introduce large margins on the power budget of optical circuits, sub-utilizing network resources. In this sense, [8] proposed an ML-based model to determine whether a given route, modulation, and spectrum (RMSA) would have a bit error rate at acceptable level. The features used in the prediction were traffic volume, modulation format, total optical circuit length, most extended link length, and the number of links. In [9], an SDN-based optical network that uses ML mechanisms to predict the optical signal-to-noise ratio (OSNR) of links has been demonstrated. Similarly, [10] made the scenario even more complex by adding multiple domains and proposed a neural network-based EON architecture to estimate lightpath QoT per domain.

Considering the aspect of fault management, packet loss due to problems in the physical layer of optical networks is a significant issue for network operators, as it directly impacts Service Level Agreements (SLAs) and entails financial losses. In this context, [11] proposes two algorithms based on machine learning: BANDO and LUCIDA. The first, located

at the optical nodes, detects BER changes in the links, and communicates to the second algorithm, located in a central controller. This architecture predicted a maximum breach of BER days before the connection was broken, allowing efficient planning for network reconfiguration.

Regarding virtual topology design, in [12] the authors use neural networks to predict traffic to reconfigure the virtual topology of the network. The same research group, in [13], extended the mathematical models and algorithms used in the previous work to the scenario of elastic optical networks, focusing on solving optimization problems related to their design, operation, and re-optimization.

The resource allocation is the area of traffic engineering in which our research fits, so our investigation deep into this topic. In [14] artificial neural networks were used to predict the probability of blocking optical networks using as parameters the topological properties of the network, physical layer information, load, and algorithm used. Although the study was done for Wavelength-Routed Optical Networks (WRONs), the authors suggest that the model can be adapted for EONs.

On the other hand, in [15], a neural network has been implemented to predict the arrival time and the wait time for future connections in EONs. Based on the information from the likely links that will be established, a dynamic spectrum routing and allocation algorithm with satisfactory blocking rates have been proposed.

In [16], [17] the authors propose a data-driven routing model with the objective of minimizing link over-utilization (congestion) through two approaches: i) a supervised learning approach, in which they try to learn the next demand matrix (DM) and optimizing the routing strategy with respect to that DM; and ii) a reinforcement learning approach, in which they try to directly learn a good mapping from observed DMs to routing strategies. The authors did not obtain good results with the supervised approach, claiming that the size of the input and the output impaired the performance of the neural network. On the other hand, as we will observe in our research, we can extract significant information about the allocation spectrum status of the optical network with the correct parameterization of the ML model and with a vast amount of data.

In [18] the authors present a preliminary work of applying DRL to solve the routing problem in EONs, and continue the investigation also addressing the spectrum assignment problem in [7]. In this last work the representation of the spectrum allocation state is simplified due to scalability issues and, inspired by this approach, in our paper we use the whole spectrum in our analysis to avoid any information loss. These works also use deep reinforcement learning, and according to [19] this DL technique tends to have promising results in traffic routing.

On the other hand, the authors of [20] and [21] believe that straightforward representation of the network state can make the learning process of routing more complex. They try to reduce the level of abstraction of the network state through a feature engineering process, in which they leverage

relationships between the links that form an end-to-end path. Basically, they use the idea that according to the bandwidth request of an incoming traffic demand, it is easy to estimate the resulting use of the links after allocating that demand to a specific end-to-end path. So, they provide this knowledge directly to the agent, simplifying their task. This is an interesting way, but evidently there is still the challenge of choose the best routing policy considering the uncertainty of future traffic demands. This approach was evaluated in a simpler scenario than the EONs: in Optical Transport Networks (OTN) using incremental traffic.

According to the papers review conducted, the literature that explores EONs with DL techniques is still incipient and it considers a very simplified scenario. This provides a large margin to be investigated, and this research fits in this context.

III. DL MODEL

We can define the machine learning workflow in 5 stages: (i) Problem formulation; (ii) Data collection; (iii) Data pre-processing; (iv) Model construction and (v) Model validation [22]. In this section, we describe this process in detail.

A. Problem formulation

The initial step of a ML model is to correctly formulate the problem, considering that the training process involves a high cost. Our problem is to identify the algorithm strategy used in an EON based on information extracted from the state of the spectrum, thus it's a classification problem. Among the categories of ML algorithms, supervised learning is useful to solve classification problems. Many algorithms allow us to do this, such as Support Vector Machine (SVM) and Random Forest. However, given the nature of our problem, whose inputs are composed of tens of thousands of attributes, as will be discussed in subsection III-C, artificial neural networks is highlighted as the most promising technique.

First we have to select the classes to be considered in the classification problem. Initially we will classify RMSA algorithms, as will be discussed in subsection IV-A. In subsection IV-C we will classify the samples of the spectrum allocation with respect to the efficiency of the RMSA algorithm, and in this case we will have 3 classes: low, medium and high. To facilitate the understanding of this step of problem formulation we will focus only on the classification of algorithms.

Usually, the literature divides the elaboration of a traffic engineering algorithm into two categories depending on whether it tackles the problems of routing, modulation, and spectrum assignment jointly (in an integrated way) or separately (in a sequentially way) [23].

Algorithms that treat the RMSA problem sequentially seek to divide the problem into parts: (i) initially we chose the route ("R" problem), normally the algorithm chooses the route based on the shortest distance or the k-shortest distances between the origin and destination of the traffic request; (ii) then we must choose the level of modulation that the algorithm will adopt in the optical circuit ("M" problem). Usually, we use the most efficient modulation that meets the Quality of Transmission

(QoT) prerequisites; (iii) finally, in the last step we chose the frequency of spectrum in the fiber, that is, the sequence of contiguous slots that will compose the optical circuit ("SA" problem).

The algorithms that implement the problem in an integrated way try to solve the problems jointly. For example, the Spectrum-Constraint Path Vector Searching (SPV) algorithm and the Modified Dijkstra Shortest Path (MSP) algorithm, proposed in [24], performs the routing and spectrum allocation steps simultaneously.

In this work we use several algorithms following the main approaches found in the literature: (i) K7SP_FF (routing: 7-shortest path; spectrum allocation: the First Fit strategy chooses the lowest index slot in which the range of contiguous slots is capable of meeting the demand [25]); (ii) K2SP_LF (routing: 2-shortest path; spectrum allocation: the Last Fit strategy chooses the highest index slot capable of accommodating the demand [25]); (iii) K5SP_RF (routing: 5-shortest path; spectrum allocation: the Random Fit strategy randomly chooses any slot range to meet demand [25]); (iv) K2SP_BF (routing: 2-shortest path; spectrum allocation: the Best Fit strategy seeks a group of slots of a size closer to the number of slots required by the demand [26]); (v) K4SP_PP (routing: 4-shortest path; spectrum allocation: the Pseudo Partitioning strategy divides high bandwidth and low bandwidth requests at both ends of the spectrum, using First-Fit for some demands and Last-Fit for other demands, for example [27]); (vi) K3SP_DP (routing: 3-shortest path; spectrum allocation: the Dedicated Partition strategy divides the spectrum and each bandwidth demand has a dedicated part of the spectrum, each partition uses one of the strategies mentioned above [27]); (vii) K4SP_AP (routing: 4-shortest path; spectrum allocation: the Acceptance Prone strategy selects the slots based on a cost function that minimizes fragmentation of the spectrum [28]); (viii) K3SP_CS (routing: 3-shortest path; spectrum allocation: The Complete Sharing strategy tries to balance the link-load distribution in the network by always allocating, among the available paths, the lowest possible spectrum to a connection request [27]); and (ix) MADapMSP (this is the MSP algorithm adapted to support levels of modulation, and, as already mentioned, performs the routing and spectrum allocation steps simultaneously. It looks for the shortest possible route (Dijkstra), builds a tree with options to allocate traffic demand and runs through the tree with the Depth-First Search (DFS) algorithm [24]).

We considered 3 signal modulations for each algorithm: BPSK (Binary Phase Shift Keying), QPSK (Quadrature Phase Shift Keying) and 8QAM (Quadrature Amplitude Modulation). Figure 1 shows the bandwidth blocking rates for these algorithms in the scenario described in the subsection III-B.

B. Data collection

In this step, we collect a large amount of representative network data extracted from simulations on which 9 different RMSA algorithms were employed in order to generate data to fit on the previous defined classes.

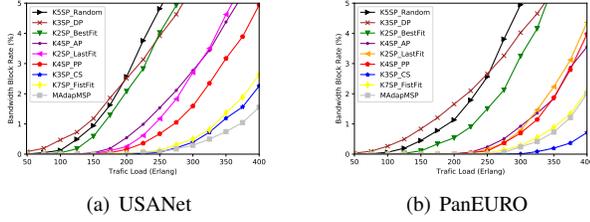


Fig. 1. Bandwidth block rates in USANet and PanEURO topologies.

To guarantee the robustness of our classifier, as we could see in the previous subsection, we selected significantly distinct algorithms: (i) different routing strategies and different spectrum allocation strategies; (ii) and besides this, among the spectrum allocation strategies we consider algorithms that use the type of demand for decision making (for example: K3SP_DP), algorithms not based on the type of demand (for example: K2SP_LF). Moreover, we also considered one-step (for example: MADapMSP) and two-step (for example: K2SP_BF) algorithms.

The ONS simulator was used to generate the dataset [29]. Each simulation was performed five times to generate a 95% confidence interval. The simulator generated 10^5 calls with different granularity levels: 12.5Gbps, 25Gbps, 50Gbps, 100Gbps, 200Gbps and 400Gbps, uniformly distributed. Connection requests follow a Poisson process with the mean holding time of 600 seconds, according to a negative exponential distribution and uniformly distributed among all nodes-pairs.

The topologies considered in the simulations were the USANet with 24 nodes and 86 links, and the PanEURO with 28 nodes and 82 links, shown in Figure 2. Each link has a 4THz band, divided into 12.5GHz frequency ranges, which results in 320 frequency slots on each fiber [30]. The guard band between two adjacent lightpaths is assumed to be of 2 slots to avoid interference between them. Each node in the topology is equipped with sufficient transmitters and receivers with each transmission capacity of up to 32 slots. As mentioned in the previous subsection, 3 levels of signal modulation were considered.

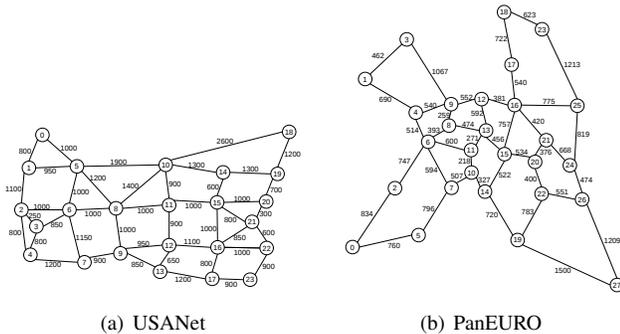


Fig. 2. USANet and PanEURO topologies.

C. Data pre-processing

Data pre-processing is one of the most important stages in machine learning. The first step was to set the network state, and we are inspired by the state of the art research analyzed in section II [7], [16], [20]. According to the number of links and slots mentioned in the previous subsection III-B, we can represent the network as a 86×320 dimension matrix for USANet topology and a 82×320 dimension matrix for PanEURO topology. We adapted the ONS simulator to its output contains this binary matrix, and the value of each cell identifies the occupation of this slot. More specifically: cells with value “1” determine that slot is allocated to some lightpath (including guard bands); and cells with value “0” indicate that the slot is vacant.

By resizing the two-dimensional matrix to one dimension, we obtain a vector with 27,520 positions for USANet topology and a vector with 26,240 positions for PanEURO topology, which represents what we call the network state. The network state is the input of the proposed neural network. In other words, a sample of the USANet topology has 27,520 features, while a sample of the PanEURO topology has 26,240 features.

Each connection request that arrives on the network, if it is accepted, changes its state. We name moment n the arrival of the n^{th} request. And throughout the operation of the network, we get its state at various moments. For this work, we consider 95 network states, evenly arranged between the arrival of the request 5,000 (moment 5,000) and the moment 100,000. The analysis starts with the request 5,000 in order to skip from the transitory phase into the steady phase of the simulation.

The final dataset size can be calculated as follows. Simulations were carried out for 9 algorithms, been evaluated at 18 traffic loads (from 75 to 500 Erlangs with steps of 25), and with 5 random seeds, to ensure statistical variability. For each simulation, 95 moments were collected as previously defined. Finally, the number of samples in the dataset is given below, for each topology, and the whole dataset occupied more than 18GB of disk space.

$$\begin{aligned}
 |dataset| &= algorithms * loads * seeds * moments \\
 &= 9 * 18 * 5 * 95 = 76,950
 \end{aligned}$$

D. Model Construction

Applying deep learning to a problem requires experience to effectively choose optimal hyperparameters and network architecture, like learning rate, batch size, number of layers and number of neurons, which are all tightly coupled. This process requires expertise and extensive trial and error, and there are several approaches to hyperparameter tuning, like Grid Search, Random Search and Auto-ML. Currently, to help us in this complex process, some papers, like [31], give us tips to understand the data and the initial results, so we can select good hyperparameters in a viable time.

Inspired by this and other research [31], [32], our methodology was to develop a simple neural network with few classes to better understand the problem. In possession of this prior

knowledge, we adjust the neural network and the tune the hyperparameters for our most complex scenario. We will not show the steps of this evaluation here due to space issues.

The neural network was developed in Python programming language with the aid of the Keras library [33].

After the fine-tuning, it has: 27,520 neurons in the input layer in the USANet topology or 26,240 neurons in the PanEURO topology, 9 neurons in the output layer (the algorithms), 4 hidden layers fully connected, 100 neurons per layer, a batch size of 10 samples, SGD (Stochastic Gradient Descent) optimizer with learning rate equal to 0.0001, dropout with a probability of 20% and no regularization. We use between the hidden layers the rectified linear activation function (ReLU) and in the output layer the softmax activation function, whose formulas are shown in Equations 1 and 2, respectively.

$$y(x) = \max(x, 0) \quad (1)$$

$$y(x) = \frac{1}{1 + e^{-x}} \quad (2)$$

We use the cross-entropy loss function to compute the loss between the actual classes and the predictions, according to Equation 3, where y_i is the i^{th} scalar value in the model output, t_i is the corresponding target value, and k is the number of classes.

$$Loss = - \sum_{i=1}^k t_i \cdot \log(y_i) \quad (3)$$

Finally, the model validation will be discussed in the next section.

IV. RESULTS

First we show that from a spectrum allocation sample we can extract information from the optical network, more specifically we can identify to which algorithm a sample belongs. Then we created a model based on unsupervised learning to cluster the algorithms into 3 groups: low, medium and high efficiency algorithms. In the following we demonstrate that a spectrum allocation sample can bring information about the use of the network resources and, consequently, whether the optical network will quickly reach an exhaustion state. Finally, we propose Deep-Quality-EON.

A. Classifying RMSA algorithms

We use k-fold cross-validation procedure for estimating the skill of our machine learning model (with $k = 5$). Learning curves based on loss and accuracy are shown in Figure 3 for one of the folds. The model presented good performances in both topologies. In the PanEURO topology, the error was greater than the error in the USANet topology, and we will investigate this in sequence, analyzing the confusion matrix.

The confusion matrix of the NN after training are shown in the Table I and II, for USANet and PanEURO topologies, respectively. In each fold, the neural network was trained with 80% of the samples, while the remaining 20% were used for

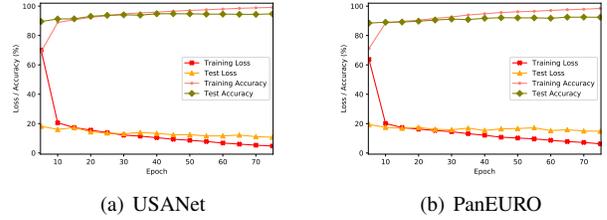


Fig. 3. Training/Test loss and accuracy on our neural network for a fold in each topology (classifying RMSA algorithms).

testing. The confusion matrix shows the rating for all 5 folds, therefore the 76,950 samples were tested and their results are shown in the table. In the confusion matrix the main diagonal represents the algorithms that were correctly classified, that is, the True Positives (TP) and the True Negatives (TN). For example, let's look at the results for the K2SP_BF algorithm in USANet topology:

- The classifier was successful in classifying 8,426 samples as the K2SP_BF algorithm;
- In 124 samples of the K2SP_BF algorithm, the classifier was wrong: 31 of them were classified as the K5SP_RF algorithm, and 93 of them were classified as K2SP_LF algorithm;
- Finally, in 53 samples of other algorithms, the classifier erroneously predicted the K2SP_BF algorithm: 43 of them were from the K5SP_RF algorithm, and another 10 of them were from the K2SP_LF algorithm.

Three fundamental metrics in evaluating a ML model are accuracy, precision, and recall. Precision is most commonly used in problems where False Positives (FP) are considered more harmful than False Negatives (FN). Recall is most commonly used in problems where False Negatives are considered more harmful than False Positive. Our problem does not prioritize FN or FP, so we chose to use accuracy as a metric since it is a good indication of the overall behavior of the model. It is defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

By calculating the accuracy according to Equation 4 we get the accuracy of 94.7% in USANet topology and 92.4% in PanEURO topology. This result shows the ability to identify the routing, modulation and spectrum allocation strategy used in an elastic optical network. Analyzing the tables, we noticed that the algorithms that represent a greater challenge for the classifier are K7SP_FF and MAdapMSP. Although the latter is an integrated type, as discussed in subsection III-A, it uses the first fit logic in allocation strategy. Thus, the confusion between them is plausible.

On the other hand, the classifier showed less accuracy in the PanEURO topology. As we can see in Figure 2, this topology has fewer links compared to the USANet topology and some nodes are more isolated. These characteristics make

the PanEURO topology more restricted, making it difficult for the classifier to recognize the behavior of the algorithms.

Observing the accuracy and loss curves of Figure 3 we realize that training at more times can make the model better learn the difference between the algorithms and improve accuracy. On the other hand, our goal in this first stage was achieved: we were able to extract significant information from a spectrum allocation sample. In the following subsections we will adapt the model to the focus of our research.

B. Clustering the algorithms

The first step in creating a quality classifier of routing, modulation and spectrum allocation strategies is to define which algorithms are efficient and which are not. The algorithms described in the previous subsection and their bandwidth blocking rates (BBR) are well known in the literature, as shown in Figure 1. So, to define the efficiency of an RMSA algorithm we will use the BBR metric. Analyzing the behavior of the curves in Figure 1 in the two topologies we can visually classify the RMSA algorithms into 3 groups. To obtain a mathematical confirmation of this, we resort to the unsupervised learning paradigm (that is, without pre-determined labels), more specifically the K-Means clustering algorithm [34].

We intend RMSA algorithms to be clustered into 3 groups: low, medium and high efficiency algorithms. Thus, we define the number of clusters equal to 3, the inputs of the unsupervised model will be the RMSA algorithms, and the features of each sample will be all the points of the BBR curves presented in Figure 1. The model was developed in Python programming language with the aid of the Scikit-Learn library [35].

As expected, the model has grouped the algorithms K5SP_RF, K3SP_DP and K2SP_BF into one group; the algorithms K4SP_PP, K2SP_AP and K3SP_AP into another group; and the algorithms MAdapMSP, K3SP_CS and K7SP_FF into the third group. Thus, we define the 3 classes of algorithms according to their efficiency. Figure 4 shows a schematic representation of the algorithms in a color scheme: low efficiency algorithms are shown in red; medium efficiency algorithms are in the yellow group; and high efficiency algorithms are represented with the green color.

C. Classifying the RMSA algorithm efficiency from a spectrum allocation sample

In subsection IV-A we created a RMSA algorithm classifier, and in subsection IV-B we divided the algorithms into groups. Now our goal is to create a classifier that identifies if a spectrum allocation sample results from an efficient algorithm. In other words, our expectation is that the model can identify characteristics in the spectrum allocation sample that indicate how efficient the network resources (slots) are being used. So we created a deep neural network similar to the one presented in the subsection IV-A with these 3 new outputs.

We use the same scenario described in the previous analysis. Learning curves based on loss and accuracy are shown in Figure 5 for one of the folds. The classifier obtained excellent results in USANet and PanEURO topologies. As we can see,

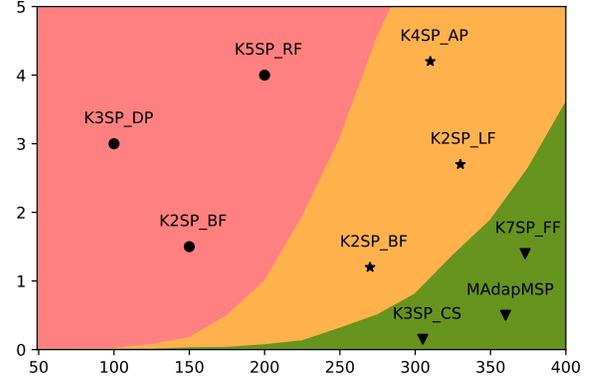


Fig. 4. Schematic representation of the clusters to represent the efficiency of RMSA algorithms.

the results were better than the results of the RMSA algorithm classifier. This occurs because algorithms that present similarities confused the classifier proposed in subsection IV-A. On the other hand, the new classifier easily identifies that a certain spectrum allocation sample indicates whether the resources of the optical network are being well allocated or not.

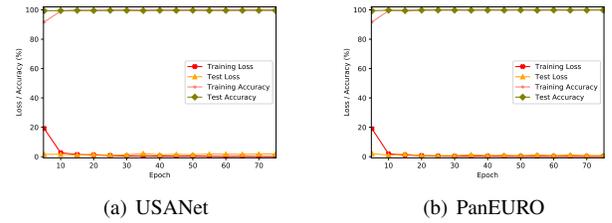


Fig. 5. Training/Test loss and accuracy on our neural network that classifies three classes: low, medium and high efficiency.

The confusion matrices for all samples (i.e. the 5 folds) are shown in the Tables III and IV, for USANet and PanEURO topologies, respectively. And the accuracy according to Equation 4 is 99.5% in USANet topology and 99.8% in PanEURO topology.

To evaluate the robustness of our classifier, we validate it with 5 loads (60, 165, 280, 405 and 520 Erlangs) on a seed that it has not been trained. These loads include not only the range in which the classifier was trained (between 75 and 500 Erlangs), but also loads outside the range. Similar to the discussed in subsection III-C, we use 95 network states, 5 loads and 1 seed, resulting in 1,425 samples for each class algorithm (low, medium and high). The results for all samples are shown in the Tables V and VI for USANet and PanEURO topologies, respectively. By calculating the accuracy according to Equation 4, we get the values 98.4% for USANet topology and 99.0% for PanEURO topology, showing the efficiency of classification even on loads with which the classifier was not trained in a seed that it was not trained too.

TABLE I
CONFUSION MATRIX FOR ALGORITHMS CLASSIFIER IN USANET TOPOLOGY.

		Predicted Class								
		K5SP_RF	K3SP_DP	K2SP_BF	K4SP_PP	K4SP_AP	K2SP_LF	K7SP_FF	K3SP_CS	MAdapMSP
Actual Class	K5SP_RF	8,497	0	43	0	0	0	5	0	5
	K3SP_DP	0	8,550	0	0	0	0	0	0	0
	K2SP_BF	31	0	8,426	0	0	93	0	0	0
	K4SP_PP	0	0	0	8,550	0	0	0	0	0
	K4SP_AP	0	0	0	0	8,448	0	10	68	24
	K2SP_LF	0	0	10	0	0	8,540	0	0	0
	K7SP_FF	0	0	0	0	9	0	7,006	54	1481
	K3SP_CS	0	0	0	0	46	0	35	8,464	5
	MAdapMSP	0	0	0	0	20	0	2058	10	6,462

TABLE II
CONFUSION MATRIX FOR ALGORITHMS CLASSIFIER IN PANEURO TOPOLOGY.

		Predicted Class								
		K5SP_RF	K3SP_DP	K2SP_BF	K4SP_PP	K4SP_AP	K2SP_LF	K7SP_FF	K3SP_CS	MAdapMSP
Actual Class	K5SP_RF	8,489	5	56	0	0	0	0	0	0
	K3SP_DP	0	8,550	0	0	0	0	0	0	0
	K2SP_BF	49	0	8,387	0	0	114	0	0	0
	K4SP_PP	0	0	0	8,545	0	0	0	0	5
	K4SP_AP	0	0	0	0	8,511	0	0	39	0
	K2SP_LF	0	0	0	0	0	8,550	0	0	0
	K7SP_FF	0	5	0	0	0	0	7,689	5	851
	K3SP_CS	0	0	0	0	20	0	25	8,505	0
	MAdapMSP	5	0	0	4	0	0	4,593	29	3,919

TABLE III
CONFUSION MATRIX FOR LOW, MEDIUM AND HIGH EFFICIENCY ALGORITHMS IN USANET TOPOLOGY.

		Predicted Class		
		Low Efficiency	Medium Efficiency	High Efficiency
Actual Class	Low Efficiency	25,541	109	0
	Medium Efficiency	10	25,473	167
	High Efficiency	0	40	25,610

TABLE VI
CLASSIFIER EVALUATION IN UNTRAINED LOADS OF THE PANEURO TOPOLOGY (60, 165, 280, 405 AND 520 ERLANGS).

		Predicted Class		
		Low Efficiency	Medium Efficiency	High Efficiency
Actual Class	Low Efficiency	1,396	28	1
	Medium Efficiency	1	1,417	7
	High Efficiency	1	4	1,420

TABLE IV
CONFUSION MATRIX FOR LOW, MEDIUM AND HIGH EFFICIENCY ALGORITHMS IN PANEURO TOPOLOGY.

		Predicted Class		
		Low Efficiency	Medium Efficiency	High Efficiency
Actual Class	Low Efficiency	25,589	56	5
	Medium Efficiency	5	25,582	63
	High Efficiency	0	10	25,640

TABLE V
CLASSIFIER EVALUATION IN UNTRAINED LOADS OF THE USANET TOPOLOGY (60, 165, 280, 405 AND 520 ERLANGS).

		Predicted Class		
		Low Efficiency	Medium Efficiency	High Efficiency
Actual Class	Low Efficiency	1,395	30	0
	Medium Efficiency	5	1,399	21
	High Efficiency	0	10	1,415

D. Deep-Quality-EON Classifier

Up to this point we have created a classifier that evaluates the efficiency of spectrum usage in low, medium or high. The next step is to validate the performance of the classifier with algorithms in which it was not trained. We chose 3 algorithms for this evaluation: (i) SP_EF (routing: dijkstra algorithm; spectrum allocation: the Exact Fit strategy tries a block of slots that exactly meets the size of the demand, if this block does not exist, the strategy takes the largest available slot block [36]), (ii) K3SP_FLEF (routing: 3-shortest path; spectrum allocation: the First Last Exact Fit strategy creates two groups of pairs: one with disjoint routes in which it uses the FirstExactFit strategy, and another group with non-disjoint routes in which it uses the LastExactFit strategy [27]) and (iii) MAdapSPV (the SPV algorithm performs the routing and spectrum allocation steps simultaneously; it builds a Path Vector Searching Tree (PVTS) and uses Breadth-First Search (BFS) to find the smallest path with spectrum available to allocate demand [24]).

These algorithms were submitted to the classifier and the results are shown in Table VII and Table VIII for USANet and Paneuro topologies, respectively. As we can see, almost 100%

TABLE VII
DEEP-QUALITY-EON EVALUATION
(UNTRAINED ALGORITHMS IN USANET TOPOLOGY).

		Predicted Quality		
		Low Efficiency	Medium Efficiency	High Efficiency
Evaluated Algorithm	SP_EF	1,541	4	165
	K3SP_FLEF	1	1,709	0
	MAdapSPV	1	2	1,707

TABLE VIII
DEEP-QUALITY-EON EVALUATION
(UNTRAINED ALGORITHMS IN PANEURO TOPOLOGY).

		Predicted Quality		
		Low Efficiency	Medium Efficiency	High Efficiency
Evaluated Algorithm	SP_EF	1,508	1	201
	K3SP_FLEF	2	1,708	0
	MAdapSPV	0	6	1,704

of the samples of the K3SP_FLEF algorithm were classified as “medium” in both topologies, while almost 100% of the samples of the MAdapSPV algorithm were classified as “high” in both topologies as well. On the other hand, more than 90% of the samples of the SP_EF algorithm in the USANet topology were classified as “low” and more than 88% of the samples of this algorithm in the PanEURO topology were also classified as “low”.

As mentioned earlier, the bandwidth block rates of algorithms are known in the literature and are shown in Figure 6. These algorithms were also submitted to the KMeans based model of subsection IV-B and, in fact: (i) the SP_EF algorithm was classified as “low”; (ii) the K3SP_FLEF algorithm was classified as “medium”; (iii) and the MAdapSPV algorithm was classified as “high”. Note that from a sample of the spectrum allocation, the classifier was able to recognize the quality of the algorithms.

Then, after this extensive evaluation, we assigned the name Deep-Quality-EON to our classifier. The Deep-Quality-EON can be used as a new metric to classify the efficiency of utilization of optical network resources in real time. Observe that this classifier can be applied by the network control plane at any moment in time, without prejudice to the network operation.

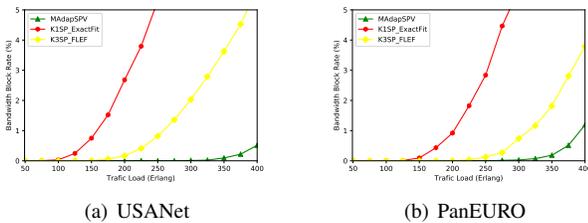


Fig. 6. Bandwidth block rates of untrained algorithms in USANet and PanEURO topologies.

V. CONCLUSIONS

This paper proposes the Deep-Quality-EON, a deep learning model for classifying RSA algorithms into low, medium or high efficiency. More specifically, the model informs in real time if the resources of the optical network are being well used. We evaluated the model in two different topologies and in several scenarios to evidence its robustness.

The contribution of this research is twofold. First, the classifier has immediate applications during the network operation as a tool for decision making, and this brings exciting application possibilities in management and monitoring context.

The second contribution is related to traffic engineering, considering that among the challenges of deploying elastic optical networks, the choice of routing, modulation and spectrum allocation algorithms certainly plays an important role. Currently, the proposed algorithms in the literature use static strategies, and this mechanism does not match the dynamic scenario of an optical network, with dynamic arrivals and departures of connection requests, as well as the uncertainty of future traffic. In this sense, extracting information from a snapshot of the spectrum allocation status of the network opens the way for the development of RSA algorithms that can adapt itself to the network state, making better use of network resources.

In this paper we take the first step towards the understanding of the relation between the spectrum usage patterns and the efficiency of the employed spectrum allocation solution. A future RSA algorithm could evaluate the current strategy performance in real-time and, dynamically change its own strategy. And, finally, another important aspect for future research is explainability, i.e., making the model enable exploitation and interpretation.

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