Paper presented at the 45th European Conference on Optical Communication (ECOC)
Dublin, Ireland, Sept. 22-26, 2019

QUALITY OF TRANSMISSION ESTIMATION AND PERFORMANCE PREDICTION OF LIGHTPATHS USING MACHINE LEARNING

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Keywords: Machine Learning, Quality of Transmission, Performance Prediction, Support Vector Machine, Long Short Term Memory.

Abstract

We show how the quality of transmission can be estimated before lightpath establishment using support vector machine and synthetic data and we illustrate how the long short term memory method can be used for performance prediction after lightpath establishment using field bit error rate data.

1 Introduction

The continuous traffic increase over the years has led to the deployment of WDM optical systems with ever-increasing data rates, capacity and flexibility. Video and cloud applications, as well as emerging 5G and Internet of Things (IoT) applications call for even higher traffic volumes, heterogeneity and dynamicity in optical networks. This will make the potential impact of performance degradation and failure at the link and network levels more severe and the need for flexible and autonomous network management more important than ever. The availability of transponders with monitoring capabilities makes it possible to leverage the potential of machine learning (ML) to design and manage increasingly heterogeneous, dynamic and complex optical networks in a software defined network (SDN) context.

ML algorithms for optical networking applications have been explored in the last years [1]. ML-based methods such as K-nearest neighbours (K-NN), support vector machine (SVM) and random forest (RF) have been proposed for estimating the quality of transmission (QoT) of unestablished lightpaths based on available system and network parameters [2]. A comparative study of ML-based lightpath classifiers realized with a synthetic knowledge base (KB) of 25,600 bit error rate (BER) instances generated using the Gaussian noise model has shown that SVM outperforms RF and K-NN in terms of class prediction's accuracy [2]. Another approach consists in predicting performance metrics such as the BER, signal to noise ratio (SNR) or Q-factor for deployed lightpaths. Performance prediction would allow network operators to respond proactively to performance degradations or potential failures in optical networks. ML methods have been proposed for predicting traffic matrix, lightpath performance and equipment failure [3, 4]. A long short term memory (LSTM) algorithm was proposed to accurately predict ROADM network resource requirements 30 minutes in advance [5].

In this paper, we illustrate the potential of ML in optical networking through two use cases: QoT estimation of unestablished lightpaths using SVM using a synthetic BER database; SNR prediction of an established lightpath using long short time memory (LSTM) and historical field performance data. The remainder of the document is organized as follows. In section 2, the methodology is described in detail. The results are discussed in section 3.

2. Methodology

Fig. 1 shows a general overview of the problem. First, the synthetic BER database used for QoT estimation, as well as the KB of field performance monitoring (PM) data used for SNR prediction, are described. Second, the ML models for QoT estimation and SNR prediction are presented.

2.1 System Setup and data pre-processing

The KB used for QoT estimation was built using the data generation tool based on the Gaussian noise model described in [2]. The tool allows for channel BER estimation as a function of the linear and nonlinear noise contributions, as well as signal and link characteristics. Table 1 lists the signal and lightpath characteristics, assuming uncompensated coherent optical links as shown in Fig. 1. The resulting synthetic KB is increased from 25,600 to 38,400 instances.

The KB used for performance prediction was constituted of field PM data collected at a 15-min sampling rate over 13 months for a PM-QPSK channel at 100 Gb/s in a 1500-km production link of the CANARIE network. During the

Table 1 Optical system and link parameters

Parameter	**Value**
Link length	80 to 7500 km
Span length	80, 100, 120, 150 km
Number of spans	1 to 50
Modulation format	BPSK, QPSK, 16QAM, 64QAM
Channel power	-10 to 5 dBm
Data rate	40, 50, 100 Gb/s

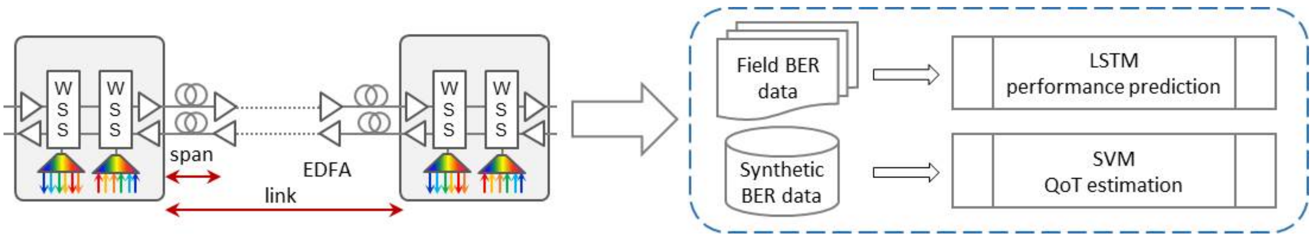

Fig. 1 Overview of the problem and coherent optical link architecture

observation period, the BER varied between 6.2×10^{-3} and 5×10^{-4} with a mean value of 9.32×10^{-4}. The SNR observations computed from the raw BER data are shown in Fig. 2. It is interesting to note that the theoretical BER value calculated using the Gaussian noise model ($\sim 1 \times 10^{-4}$) is consistent with the observed BER values.

An augmented Dickey-Fuller (ADF) test for unique root and a Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for trend stationarity were performed on the time series of PM data using built-in functions in MATLAB (0.05 significance level) revealing that the time series was not stationary (p-values of 0.62 and 0.01 for ADF and KPSS tests, respectively). As stationarity is required with predictive modelling of time series, data transformation was performed on the SNR data to make the time series stationary. Differencing, which is a common data transformation method for removing stochastic trends, was applied to the SNR data. The resulting time series (SNR change vs. time) is shown in Fig. 2. ADF and KPSS tests confirmed that the transformed time series is stationary (p-values of 0.001 and 0.1, respectively).

2.2 Construction of the SVM and LSTM models

2.2.1 SVM model

The SVM model for QoT estimation described in [2] was retrained with the KB of 38,400 instances. For building the SVM model, the KB was split into a training set of 30,720 instances and a test set of 7,680 instances, according to an 80/20 ratio. The library LIBSVM was used in MATLAB for determining the hyper-parameters C and γ to get the best trade-off between accuracy and generalization in a binary classification context using a Gaussian kernel [6]. The best hyper-parameters obtained using 5-fold cross-validation are $C = 1 \times 10^3$ and $\gamma = 1.4$. These values are greater than the respective 64 and 0.088 obtained in [2], resulting in a smaller margin but a less constrained model.

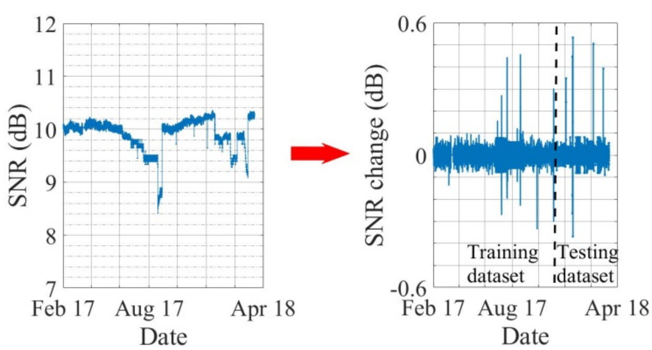

Fig.2 Observed SNR and SNR change vs. time

The SVM QoT estimator trained on the dataset of 30,720 instances provided 99.38% classification accuracy on the 20% test set held out and a 0.43% false positive rate, compared to 99.15% for the dataset of 23,040 instances, and the false positive rate dropped from 0.43% to 0.35%.

2.2.2 LSTM model

The Long Short Term Memory is a type of recurrent neural network which can identify patterns in time series and use them to make predictions. LSTM models use structures called *gates* to control the cell states and a combination with the input information to determine the outputs. In this study, a LSTM model was built with the aim to forecast the SNR change based on historical field data.

For building the LSTM model, the first step was to determine a good size for the training dataset. Three typical split ratios (70/30, 80/20 and 90/10) were considered. The root-mean-square error (RMSE), which is the square root of the average of squared differences between predicted and observed values, was the metric. The lowest RMSE (0.047) was obtained for a 70/30 ratio, which corresponds to training and validation datasets of 9 and 4 months, respectively.

Several parameters come into play in the optimization of the LSTM layer. The number of hidden layers is the number of units in a LSTM cell and the number of epochs is the number of iterations for training the model. The RMSE was computed as the number of hidden layers ranging from 1 to 250 and the number of epochs between 10 and 200. The lowest RMSE (0.027) was obtained with 250 hidden layers and 50 epochs. The adaptive moment estimation function (*adam*) was used as solver. The hyperbolic tangent function (tanh) was used to determine cell states and the sigmoid function was used to compute the gates in the LSTM unit.

3 Results

3.1 SVM QoT estimator

For assessing the performance of the QoT estimator, the synthetic KB was split into datasets of sizes ranging from 1500 to 25,000 instances and the probability for lightpaths in the test dataset to be of good QoT, using the SVM classifier, was determined through the scores returned by the built-in function "*resubPredict*" in MATLAB. Fig. 3 shows the resulting receiver operating characteristic (ROC) curves for the SVM classifier for different KB sizes. The area under the curve (AUC) values show a very good accuracy of 99.5% with a dataset of 10,000 instances. The SVM model allowed estimating the QoT of 15,360 lightpaths in about 0.2 s using a

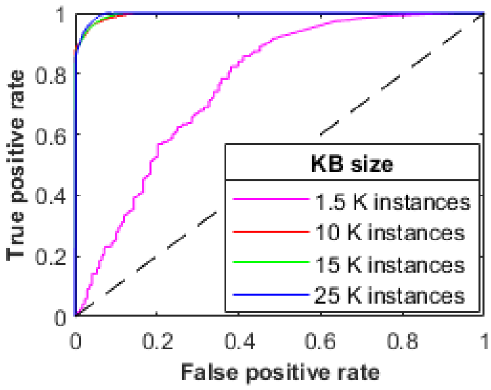

Fig. 3 ROC curves for different KB sizes

Windows 10 system with an Intel® Core ™ i3-3110M CPU @ 2.40 GHz and a 4 GB RAM. The SVM-based QoT estimation tool demonstrated high performance in assessing the class of lightpaths before their establishment in complex and heterogeneous system scenarios.

3.2 LSTM performance predictor

The performance of the LSTM model was assessed with respect to a naive method assuming that the SNR at a given time is equal to the SNR at the previous time step. The RMSE was computed for a prediction range up to 24 hours. The results are shown on Fig. 4. The RMSE increases as a function of the prediction range, as expected, showing a modest advantage for LSTM over the naive method.

Fig. 5 shows the observed SNR for two 24-hour periods in the test dataset, as well as predicted SNR for different forecast horizons ranging from 2 to 24 hours. The objective was to determine if the SNR could be forecast with time scales of several hours. The 12 predicted SNR values were obtained by using 12 different LSTM models, each one trained and used for a specific time horizon, as in [3]. The error bars correspond to the RMSE. The computing time was about 3.3 ms using a Windows 10 system with an Intel® Core ™ i5-3210M processor at 2.50 GHz and a 8 GB RAM. The results show that the LSTM model could predict well the SNR over 24 hours in case a, but was unsuccessful in predicting the SNR drop in case b.

4 Conclusion

In this work, we have explored two ML applications in optical networking. First, the SVM-based QoT estimator shows the potential of ML for fast and automated lightpath provisioning. Second, for the first time to our knowledge, a LSTM model for SNR forecasting based on 13-month historical field data for one lightpath has been presented, with the objective to show the potential of ML in performance prediction of established lightpaths. Further work will be required to optimize the LSTM model with additional input data to search for complex patterns and periodicities in the SNR data that would allow forecasting the performance of established lightpaths with time scales of hours, thus opening the way to proactive maintenance and network automation.

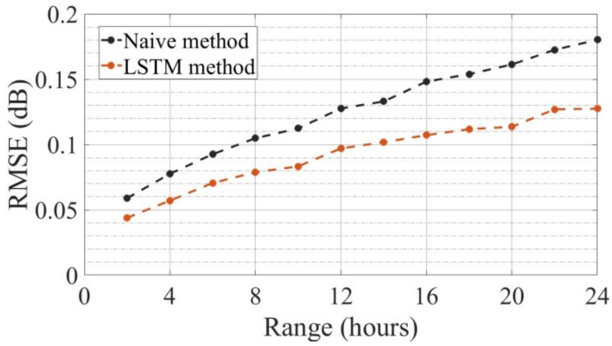

Fig.4 RMSE as a function of prediction range

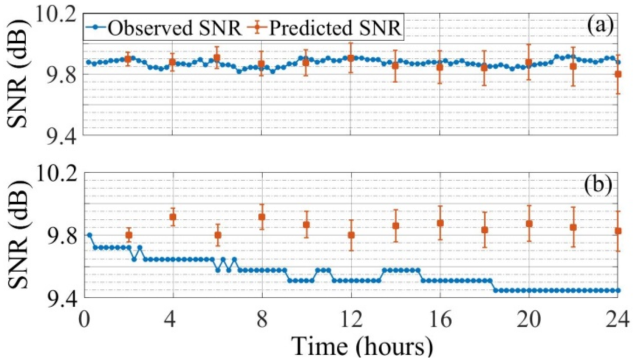

Fig. 5 Predicted vs. observed SNR (a) Jan 5; (b) Jan 17

5 Acknowledgements

This work was supported by the Natural Sciences and Engineering Research Council (NSERC) of Canada under grant RGPIN-2014-05898. The authors thank Thomas Tam and Tao Zhang from CANARIE for field performance data.

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