LSTM Assisted Optical Transmission Performance Analysis over a 493-km Field-Trial

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Abstract: We implement an LSTM-based algorithm to predict and analyse transmission performance and detect anomalies. Cross-validation of the model over two experimental datasets shows high precision of up to 96% for R2 to predict short-term variations.

1. Introduction

Recent trends in low-margin optical networks require accurate quality of transmission (QoT) predictions and comprehensive understandings of transmission link behaviors [1]. Traditionally, analytic models such as permutation models and the Gaussian noise (GN) model have been developed to simulate optical links based on the understanding of optical fiber transmission [2]. Unlike analytic models, ML approaches are able to capture the behavior of a physical phenomenon implicitly, simply through the variations in the time-series data collected from optical networks. Given the high forecasting precision of recurrent neural networks in the sequential data, models such as gated recurrent units (GRU) and long-short term memory (LSTM) have been applied to short-term performance prediction of optical networks [3]. In [4], the Encoder-Decoder LSTM and GRU models have been explored for SNR forecasting and achieved satisfactory forecast accuracy in a supervised learning context, using a single lightpath field KB. However, the current work didn't address the possible reason why the performance variation can be predicted precisely.

In this paper, with open-source data from Microsoft (MS) and the experimental data collected from a field-trial testbed, daily performance variations bear similar patterns, which are fully captured with a single LSTM model. The trained LSTM model obtained from the performance data of an optical channel is cross-validated with multiple optical channels of different links and different networks. The proposed LSTM model predicts performance variations with a precision of up to 96%. The results suggest the daily variations in transmission performance may be related to some common impacts (e.g. temperature) that are shared in both Microsoft networks and our field-trial testbed. The precise LSTM model can be applied to remove daily performance variations, therefore, to reveal the real channel transmission performance. With this information, abnormal link performance degradation can be easily detected to provide knowledge for network operations.

2. Cross-validation of a LSTM model in field-trial data

To evaluate the precision of LSTM models against the link performance variations, two sets of time-series performance data from Microsoft networks and the field-trial testbed are explored.

The data from Microsoft large-scale optical backbone networks in North America has been publicly released (KB-2) [5]. This backbone has 50 optical cross-connects, 100 WAN segments, and 1000 optical channels. The optical fibre primarily consists of LEAF and SSMF with a channel spacing of 50 GHz, and the fibre links range from 5 km to 2600 km [6]. The data set is collected every 15 minutes over a 14-month period for 4000 channels across random 115 optical paths. It provides a variety of scenarios for us to study the temporal behavior of optical channels, the quality of the signal, the correlation among segments, and more.

Additionally to MS open-source data, we collected time-series data over a 493-km field-trial testbed. Fig.1 shows the 493-km field-trial testbed implemented over part of the UK National Dark Fiber Facility (NDFF). In the experimental testbed, the transmitter and receiver nodes are in the lab, and 4 equalized 50GHz-spaced 32Gbaud PM-16QAM signals are generated by 4 Voyager Transponders and launched into the NDFF links, where four transmission wavelengths are 193.45THz, 193.50THz, 193.55THz, and 193.60THz respectively. The Voyager Transponders provide Pre-FEC bit error rates (BERs) for these 4 testing channels. A lab controller is developed to control all the devices such as Wavelength selective switching (WSSs), Voyager Transponders, and facilities through variable communication protocols, which can collect the data automatically. A cloud network configuration and monitoring database (CMDB) is implemented to store the collected data from the field-trial testbed. We

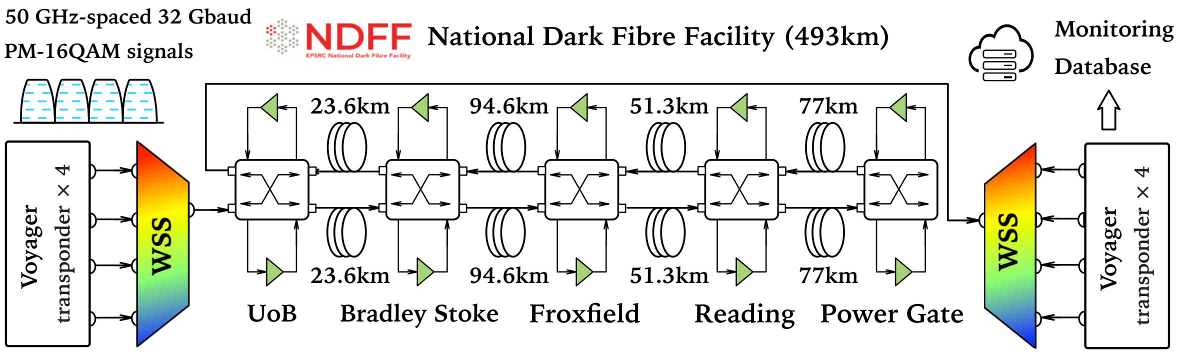

Fig. 1: Field-trial experimental testbed with 4-channel 32Gbaud PM-16QAM signals

collect consecutive 5-days monitoring BER values from the testbed at 1-min intervals, then convert BER values to Q-factor for the performance evaluation using $Q = \sqrt{2} * erfcinv(2 * BER)$.

Figure 2 (a) and (b) show one-week transmission performance variations in the MS optical backbone and NDFF network, and it can be obviously seen that there are periodic trends of the performance variations in both two networks, accompanied by the appearance of two daily peaks. In Fig. 2 (a), the Q factor variation of channel 3493 in the segment 101 from MS open-source data is shown, and it fluctuates periodically in a small range within 0.1dB, and the peak values are basically the same. Fig.2 (b) depicts the performance variations of the data from the field testbed, and the performance of the NDFF network also has a similar periodic variation with a range of 0.3dB. Similar performance variations in the MS optical backbone and NDFF network indicate that the transmission links in these networks suffer some certain impacts such as power supply and human activity, which can be detected.

Based on observed periodic patterns in these two networks, a single ANN model is deployed to predict performance variations. After searching for the hyperparameters to achieve the minimum MSE in the training data sets, the proposed LSTM structure is shown in Tab.1 as [10 × 16 × 16 ×1]. The sizes of two LSTM layers are both 16, and the total number of weights for LSTM is 3281. The best batch size and epoch number are 256 and 40 respectively. To validate the robustness and universality of the implemented model, we trained the model on one of the data sets and test it on the other. In Tab.2, the model trained with MS open-source data achieves high forecasting precision up to 96.81%, also tested in the field-trial data with the R-square score up to 92.64%. Likewise, the model trained with data from the field-trial testbed performs well on MS open-source data without the precision reduced. The different accuracy of the two models on the NDFF data indicates that the LSTM model can learn more obvious patterns from MS data compared with the field-trial data, which is probably because our experimental data are relatively limited, and the long-term monitored data can better reflect periodic performance variations. Cross-validation in two different data sets suggests that the daily variations in transmission performance may be related to some common impacts that are shared in both Microsoft networks and our field-trial testbed, independent to link configurations.

Table 1: The summary of LSTM model

Layer	Shape	Activation function	Parameters
Input	10	-	-
LSTM	16	ReLU	1152
LSTM	16	ReLU	2112
Output	1	-	17
Total parameters:3281; Trainable parameters:3281			

Table 2: Cross-validation on two different data sets

Model trained with MS data			
data set	MSE	MAE	R2
MS data	0.0000	0.0019	0.9681
NDFF data	0.0001	0.0082	0.9264
Model trained with NDFF data			
data set	MSE	MAE	R2
MS data	0.0000	0.0026	0.9638
NDFF data	0.0003	0.0125	0.8029

3. Application of LSTM models

Since the LSTM model can accurately capture patterns in the MS data and field-trial data, it can extract the actual variations in the data, and obtain performance degradation through the difference between the predicted and actual values. Fig.2 (d) and (e) show the performance variation and degradation in the MS data and field-trial data, which can be seen that the link performance is almost a straight line with the periodic variation removed. As shown in Fig.2 (d), the minor performance variation within 0.06dB and the near-zero degradation indicate that the transmission performance of Microsoft optical backbone is extremely stable, which is superior to NDFF network with relatively high performance variation up to 0.3dB shown in Fig.2 (e).

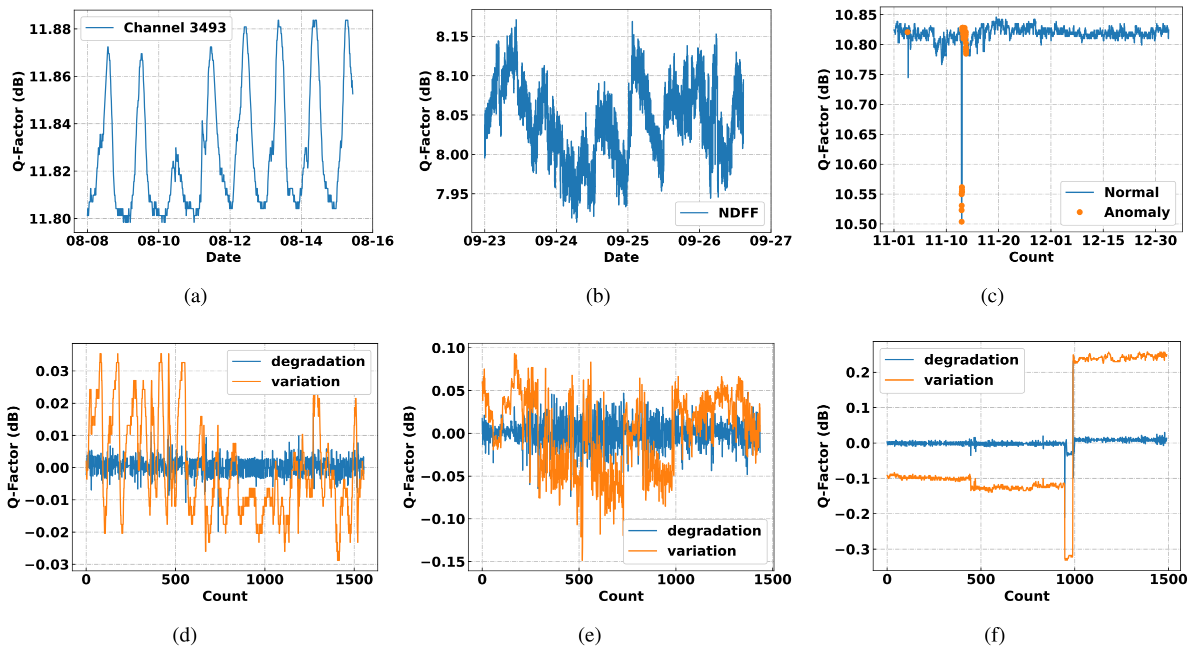

Fig. 2: (a) Performance variation of MS channel 3493, (b) Performance variation of NDFF channel, (c) LSTM anomaly detection in MS channel 2341, (d) Comparison between performance variation and degradation in MS channel 3493, (e) Comparison between performance variation and degradation in NDFF channel, (f) Comparison between performance variation and degradation in MS channel 2237

In Fig.2 (f), one of the reconfigured channels in the MS data is tested with the implemented LSTM model. The result shows that the jump in the transmission performance is caused by the link changes rather than normal performance fluctuation, which suggests that the implemented model can be used to reveal the transmission performance of the channels, with the detected variation patterns eliminated. Fig.2 (c) displays another application of the LSTM model, which is anomaly detection. The strategy of anomaly detection with the LSTM neural network is that the model predicts the future performance trained with previous values over hours or days. If the predicted value is within an acceptable standard deviation, then the performance variations are consistent with the actual situation. Otherwise, performance degradation or jitter occurs with outliers.

4. Conclusion

In this work, we have used the LSTM model trained with MS open-source data and experimental data from the field-trial testbed, and presented transmission performance analysis with recurrent neural networks. High forecasting precision up to 96% of the LSTM model in the Microsoft data and field-trial data reveals similar periodic behavior in the performance variations, and its robustness and universality are confirmed through cross-validation. With these patterns removed, the real transmission performance can be observed. The precise LSTM model can also detect abnormal performance degradation and jitters in the channels.

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