Enhancing Closed-Form Based Physical Layer Performance Estimations in EONs Via Machine Learning Techniques

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Abstract *We show that the combination of machine learning methods and analytical expressions can enhance the OSNIR estimation of an optical link of up to 2 dB compared with the use of an analytical expression alone. For this purpose, we exploit seven machine learning algorithms and we examine their OSNIR improvement for 3,000 different operational cases.*

Introduction

The operation of elastic optical networks (EONs) is feasible only via an accurate but, yet, timely knowledge of the physical layer performance across all EON paths. In this respect, a) the Split Step Fourier Method (SSFM) is a very accurate method but it does not return timely results for the overall EON status; b) closed-form solutions can be integrated to EON planning tools and they return results in a useful timescale but mathematical approximations are used[1]; c) experimental measurements are by far the most accurate method but they only provide a snapshot of the network status under the given conditions at a time.

These restrictions lead to a sub-optimal use of the network capacity while the potential of the EON resources is not fully explored including the introduction of operational margins[1],[2]. This underutilisation is evident in[1], that prevents an EON to operate at higher modulation formats and/or line-rates limiting its capacity potential.

So far, Machine Learning (ML) techniques have been used to overcome these remedies[2]-[7]. However, performance estimators relying exclusively on ML techniques may return erroneous results as they are based on the (a) and (c) methods above that only feed the algorithms with performance snapshots.

In prior art, analytical methods in association to ML techniques were reported considering a single ML algorithm[6],[7]. In this work, we propose an estimator that merges a) the performance estimation based on closed-form expressions for the signal to noise plus interference ratio (OSNIR)[8] and b) ML algorithms. The approach we follow is to benchmark against the results obtained from the SSFM method with i) the results obtained solely from closed-form solutions; ii) those obtained solely when ML algorithms are used and iii) the combination of closed-form and ML techniques. This will allow to examine the efficiency and limitations of each method.

In particular, in the alternative (iii), the ML component is engaged only in cases where analytical expressions are inaccurate, e.g. when the accumulated dispersion is low[9], avoiding an averaging between closed-form expressions and ML methods, as this averaging may lead to great discrepancies that ML method cannot tackle.

To carry out the benchmarking, seven well-known ML algorithms were considered to avoid algorithm-dependent conclusions. Moreover, we were not limited to investigate algorithms only for neural networks like in[5]-[7]. The selected algorithms were trained using the results from 3,000 different operational scenarios obtained from the SSFM method[10]. For the training of the algorithms, the combined effect of amplified spontaneous emission (ASE) noise and fiber nonlinearity was taken into account, not only nonlinearity as in[6],[7].

System under investigation

The system under study is illustrated in Fig.1 and consists of N_s spans of SMF and EDFA in tandem. The employed modulation format is PM-QPSK and all the channels are rectangularly-shaped. Using this system, we estimate OSNIR for 3,000 representative combinations of the parameters tabulated in Table 1. The simulated symbols in each case were 8192/channel/polarization. Ideal optical and electrical filters and mux/demux with zero losses are considered. We also ignored the impact of Polarization Mode Dispersion and laser linewidth

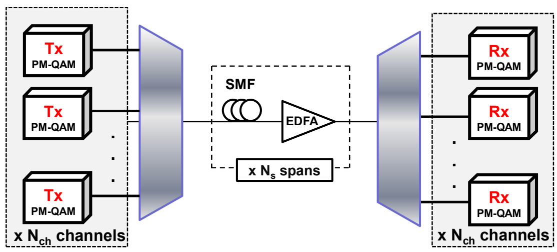

Fig. 1: Examined system.

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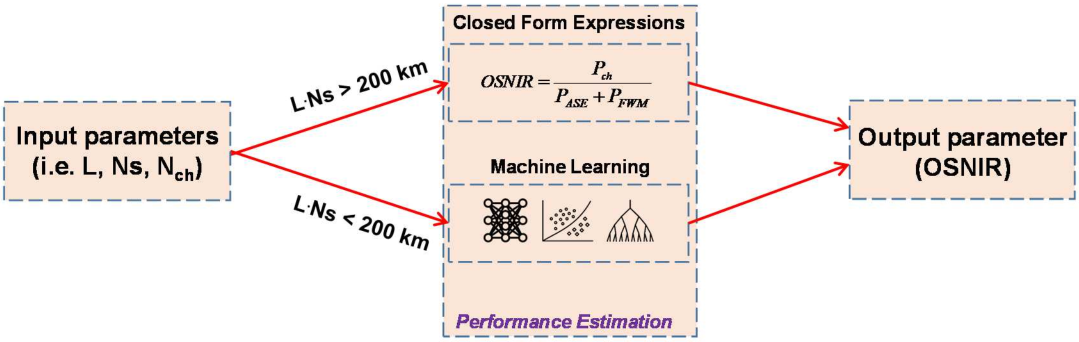

Fig. 2: The proposed method which combines machine learning and closed-form expressions for physical layer performance estimation, *L*: span length, N_s: number of fiber spans.

in order to ensure that the dominant effects that degrade system performance are ASE noise and fiber nonlinearity. Other fiber parameters are D = 17 ps/(nm·km), γ = 1.317 $W^{-1}\cdot km^{-1}$, α = 0.2 dB/km. The amplifier noise figure was set to 6 dB.

Table 1: System parameters used in our study

Parameter	Symbol	Value
Number of fiber spans	Ns	1-50
Span length	L	5, 10, 50, 100 km
Channel bandwidth	B	12.5, 25, 50 GHz
Guard band	GB	0, 12.5, 25 GHz
Number of channels	N_{ch}	3, 9,15
Channel Power	P_{ch}	-10 to +3 dBm

Proposed formalism

The proposed formalism is illustrated in Fig.2. It incorporates the closed-form expression of[8] and seven well-known ML algorithms used for regression purposes, namely Multiple Linear Regression (LR), Multivariate Polynomial Regression (PR), Decision Tree (DT), Random Forest (RF), Support Vector Regression (SVR), k-Nearest Neighbors (k-NN) and Deep Neural Network (DNN). These algorithms were selected as the most appropriate for our problem as they provide high modelling accuracy with reasonable computational time.

Each ML method was trained using the 3,000 combinations of different input-output parameters which were derived using the SSFM. In particular, the parameters of Tab.1 were used as the input and the estimated OSNIR using SSFM was used as the output. The training was performed as follows. First, all 3,000 input-output pairs were shuffled and divided into five datasets, where each dataset contained 1,800 values for training, 600 for validation and 600 for testing. Next, a circular cross-validation rotation between the training, validation and test sub-sets was performed to ensure that all 3,000 values were tested. After that, the ML algorithms were trained whilst the selection of the optimum hyperparameters for each ML method was performed by applying grid search on the validation set. The optimum hyperparameters for each method are shown in Tab.2. Finally, the trained algorithms were applied on the test set and the predicted OSNIR values were compared against the ones computed with SSFM for each of the 3,000 different operational cases in order to calculate the accuracy for each ML algorithm.

Table 2: Optimal hyperparameters for each ML method

Method	Optimal Hyperparameter
Linear Regression	1st order polynomial
Multivariate Polynomial Regression	2nd order polynomial
Decision Tree	depth = 10
Random Forest	depth = 10, number of estimators = 10
Support Vector Regression	C = 15, γ = 0.0011
k-Nearest Neighbors	k = 15, weights = distance
Deep Neural Network	hidden layers = 2, neurons/layer = 32

In the DNN, we considered the use of ReLU[11] as the activation function and Adam[12] as the optimizer. The maximum number of epochs was set to 500 and the training stopped if the loss in the validation set did not improve after 50 epochs.

From Fig.2, we can observe that, based on the operational parameters, either the closed-form expression routine or the ML routine is activated. In particular, the ML routine is enabled in cases where the closed-form expressions are erroneous e.g. in links smaller than 200 km, where the accumulated dispersion is low and the Gaussian Noise assumption is not valid[9]. In all other cases, the closed-form expression routine is activated.

The proposed formalism is independent of the analytical expressions and ML methods used to calculate OSNIR and can incorporate any analytical expression and any additional ML algorithm. Further, the accuracy of the ML methods can be gradually improved over time by feeding them with additional pairs of input-output parameters derived from the SSFM.

The combined solution can be also trained with real data. In this case, the proposed method can reproduce the real transmission channel accounting for additional effects, omitted by the theoretical methods. Finally, the candidate

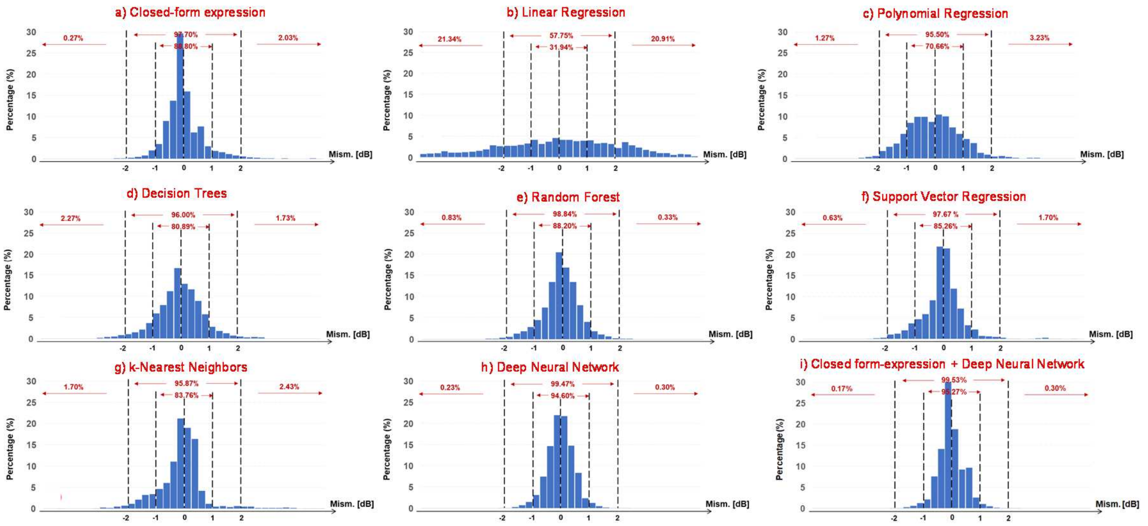

Fig. 3: Histograms of the mismatch in [dB] for all the 3,000 tested values using the closed-form expression of[8] and seven machine learning algorithms. The mismatch is calculated with respect to the SSFM.

solution can serve as an integral part of a Physical Layer Aware, Routing, Modulation and Spectral Assignment algorithm such as[1], due to the very low computational time.

Results

The accuracy of the closed-form expression and the trained ML algorithms is illustrated in Fig.3. In this figure, we show for each algorithm the occurence of the following quantity for all 3,000 cases:

$$Mism\left[dB\right] = OSNIR_{numerical}\left[dB\right] - OSNIR_{estimated}\left[dB\right] \quad (1)$$

where $OSNIR_{numerical}$ denotes the OSNIR computed using SSFM and $OSNIR_{estimated}$ represents the OSNIR calculated with the closed-from and the ML methods.

Evidenty, the DNN (Fig.3h) outperforms all other ML methods showing the lowest mismatch. This effectiveness can be attributed to its complex structure, which allows it to learn more complex patterns between the input parameters (e.g. power, number of channels) and the output quantity (OSNIR). Next, RF (Fig.3e) shows a comparable performance with the closed-form expression of[8], while it outperforms DT (Fig.3d). This is expected, since it combines the results of multiple decision trees, in order to improve the overall accuracy, instead of only one which is included in DT. SVR (Fig.3f) and k-NN (Fig.3g) provide similar performance, however, lower than the DNN and the closed-form formalism. Further, linear regression (Fig.3b) shows the highest mismatch as it fails to capture the relation between the input and output quantities, which is clearly not linear due to the existence of fiber nonlinearity. Finally, the polynomial regression of second order (Fig.3c) shows a significantly lower mismatch when contrasted with linear regression, however, it is outperformed by all other methods. This happens because, in this case, as well, the dependence of OSNIR on all input system parameters is not polynomial.

Next, we select the most accurate ML method, which is DNN and combine it with the closed-form OSNIR expression, following the methodology presented in Fig.2. This synthesis, which is shown in Fig.3i, improves the overall accuracy significantly, as the absolute mismatch is less than 2, 1 and 0.5 dB in 99.53%, 95.27% and 73.29% of the examined cases, respectively. This improvement is apparent when compared with solely the closed-form expression, which shows an absolute mismatch of 2, 1 and 0.5 dB in 97.70%, 88.80% and 65.69% of the 3,000 cases, respectively. Moreover, the number of cases where the absolute error is higher than 2 dB has decreased from 2.30% down to less than 0.5%. Further, the maximum mismatch has downscaled from 5.21 dB to 3.11 dB, which is an important conclusion, as it clearly indicates the feasibility of ML methods on improving the OSNIR estimation.

Conclusions

We examined the potential of seven well known ML algorithms on improving the OSNIR estimations. The combined method which exploited a closed-form expression and DNN was compared against SSFM and reduced the maximum mismatch of about 2 dB, while it also decreased the cases where the absolute error was higher than 2 dB from 2.30% to 0.47%.

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