Application of Machine Learning in Fiber Nonlinearity Modeling and Monitoring for Elastic Optical Networks

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Abstract—Fiber nonlinear interference (NLI) modeling and monitoring are the key building blocks to support elastic optical networks (EONs). In the past, they were normally developed and investigated separately. Moreover, the accuracy of the previously proposed methods still needs to be improved for heterogeneous dynamic optical networks. In this paper, we present the application of machine learning (ML) in NLI modeling and monitoring. In particular, we first propose to use ML approaches to calibrate the errors of current fiber nonlinearity models. The Gaussian-noise (GN) model is used as an illustrative example, and significant improvement is demonstrated with the aid of an artificial neural network (ANN). Further, we propose to use ML to combine the modeling and monitoring schemes for a better estimation of NLI variance. Extensive simulations with 1603 links are conducted to evaluate and analyze the performance of various schemes, and the superior performance of the ML-aided combination of modeling and monitoring is demonstrated.

Index Terms—Coherent optical communication, elastic optical network, fiber nonlinearity, machine learning, optical performance monitoring.

I. INTRODUCTION

NETWORK capacity demand is ever-increasing due to emerging internet applications such as high-definition video streaming, cloud, 5G, internet of things, virtual/augmented reality, and so forth. However, serving as the underlying infrastructure of global communication networks, the capacity of current optical networks based on single mode fiber is approaching the theoretical limit [1]. Commercial products with constellation shaping and strong forward error correction (FEC) techniques are being built to close the gap to the Shannon limit [2]. Space-division multiplexing (SDM) has been actively investigated to scale fiber channel capacity [3], but its commercial deployment for long-haul optical networks is infeasible in the near future. In the meantime, with a higher commercial viability in the short term, elastic optical networks (EONs) have been proposed to intelligently and efficiently utilize physical layer resources in order to increase network capacity and enable dynamic services [4].

In EONs, channel configurations including modulation format, symbol rate, spacing, and launch power can be remarkably diverse, and they need to be fully optimized in order to extract more capacity from the physical layer infrastructure [5, 6]. As illustrated in the EON architecture schematic in Fig. 1, it is essential to have a planning tool capable of providing accurate prediction of link performance (or quality of transmission). A key element of such a planning tool is the estimator of fiber nonlinear interference (NLI) accumulated over signal propagation. On the one hand, modeling of fiber NLI has been widely and deeply investigated. Starting from the nonlinear Schrödinger (NLS) equation, the split-step Fourier method (SSFM) was developed to obtain a highly accurate numerical solution [7]. However, the computation is too intensive for its use in a real-time planning tool. Later, after coherent transmission systems became the mainstream for backbone optical networks, the Gaussian-noise (GN) model was proposed to calculate nonlinear signal-to-noise ratio (SNR) [8], denoted as $SNR_{nl}$. The simplicity of the GN model (and its variants) makes it a

Fig. 1. Optical network architecture of the physical layer.
promising candidate for network planning, even though its accuracy still needs to be improved for heterogenous dynamic links [9]. Another shortcoming of the model-based performance prediction is that the uncertainty of link parameters, e.g. inaccurate measurement of optical power, might lead to further deviations [10].

On the other hand, real-time optical performance monitoring (OPM) is a key building block for future software defined elastic optical networks (EON), which is also depicted in Fig. 1 [11]. In terms of fiber nonlinearity monitoring, a few techniques have been proposed to report nonlinear noise variance based on receiver signal processing. For example, methods aided by machine learning (ML) were proposed in [12, 13] to isolate nonlinear noise variance in the presence of linear noise such as amplified spontaneous emission (ASE).

In this paper, we present the application of ML techniques in the NLI modeling and monitoring for EONs. In particular, we first propose the use of ML to perform the calibration of NLI models to reduce deviations in heterogenous dynamic optical networks. Afterwards, the ML is further applied to combine the NLI modeling and monitoring. To investigate and demonstrate their performances, 1603 links with diverse configurations and link parameters are simulated and an artificial neural network (ANN) is adopted in these schemes. With the proposed ML-aided combination of NLI modeling and monitoring, we show that the estimation accuracy is significantly improved. Finally, the sensitivity of these schemes against the uncertainties in launch powers is evaluated.

The remainder of the paper is organized as follows. In Section II, we briefly introduce the GN models and the noise covariance-based nonlinearity monitoring, which are used in the following studies. In Section III, the application of ML in the NLI modeling is first described, followed by the principle of applying ML to combine the NLI modeling and monitoring. Section IV presents the simulation setup, results and analysis, showing a significantly improved accuracy of the proposed scheme. The paper is finally concluded in Section V.

II. TECHNICAL BACKGROUND

In modern coherent systems, the Kerr nonlinearity effects of optical fiber have become the major limiting factors to further improve the capacity of wavelength-division multiplexing (WDM) systems [14]. The nonlinear propagation of optical signals in a single mode fiber can be modeled by the well-known NLS equation [7]. Considering the averaged random evolution of polarization effects over long distance fiber, the Manakov equation was derived to describe dual-polarization (DP) signal propagations as [15]

\[
\frac{\partial E}{\partial z} = j\frac{8}{9} \gamma |E|^2 E - \beta_i \frac{\partial E}{\partial t} - j\frac{\beta_2}{2} \frac{\partial^2 E}{\partial t^2} - \alpha E
\]

(1)

where \(E = [E_x, E_y]^T\) is the optical field of the DP signal. \(\gamma\) is the fiber nonlinear coefficient, \(\beta_i\) is the first order dispersion coefficient, \(\beta_2\) is the second order dispersion coefficient, and \(\alpha\) is the fiber loss of the optical field. Note that higher-order dispersion coefficients are neglected in Eq. (1).

In general, Eq. (1) does not have analytic solutions. Alternatively, it can be numerically solved by the SSFM, which has been widely used in simulating long-haul optical transmissions. The SSFM approach requires a large number of fast Fourier transform (FFT) and inverse FFT (IFFT), making it extremely computation-intensive for full-filled WDM simulations. Therefore, it is not suitable for network planning applications.

A. GN Model

The GN model and its variants were proposed and extensively investigated in recent years to estimate the accumulated nonlinear noise variance for coherent optical transmission systems [8, 16]. The GN models are derived based on Eq. (1) with a perturbation assumption. In addition, the nonlinear noise is considered as additive Gaussian noise. According to the GN model, the power spectral density (PSD) of the NLI at frequency \(f\) after transmission can be expressed as [8]

\[
G_{\omega}(f) = \frac{16}{27} \int_0^\infty \int_0^\infty G_{WDM}(f_1)G_{WDM}(f_2)G_{WDM}(f_1 + f_2 - f) \cdot \left[ \prod_{k=1}^{N} \exp(-3\alpha_k L_k) \cdot \Gamma_k^{3/2} \right] \cdot \left[ \prod_{k=1}^{N} \exp(-\alpha_k L_k) \cdot \Gamma_k^{1/2} \right] \cdot \exp\left(j4\pi^2 (f_1 - f)(f_2 - f) \cdot \sum_{k=1}^{N} \beta_{2k} L_k \right) \cdot \int_0^\infty \left[ \exp(-2\alpha z) \cdot \exp\left(j4\pi^2 (f_1 - f)(f_2 - f) \cdot \beta_{2s} z^2 \right) \right] dz \left| df_1 df_2 \right|
\]

(2)

where \(\Gamma_k\) is the lumped power-gain placed at the end of the \(k\)-th span, \(L_k\) is the length of the \(k\)-th span, \(\alpha_2\) is the field loss of the \(k\)-th span, and \(N\) is the total number of spans. In this study, we only consider dispersion-uncompensated systems with “link transparency”, which means that the loss of each span is exactly compensated by the optical amplifier at the end of each span. Note that the transmitted signals are polarization-division multiplexed, and each span only consists of a single fiber type.

Based on Eq. (2), we can obtain the variance of the NLI coherently accumulated over different spans. This type of the GN model is referred to as “coherent GN (CGN) model”. Another type of the GN model neglects the coherence among the NLI generated in different spans, and it is referred to as “incoherent GN (IGN) model”. In the IGN model, the total NLI PSD can be obtained by simply summing up the PSD from each span:

\[
G_{\text{IGN}}(f) = \sum_{n=1}^{N} G_{\text{IGN}}^n(f)
\]

(3)

where \(G_{\text{IGN}}^n(f)\) is the NLI PSD based on Eq. (2) over a single span, which can be expressed as

\[
G_{\text{IGN}}^n(f) = \frac{16}{27} \int_0^\infty \int_0^\infty G_{WDM}(f_1)G_{WDM}(f_2)G_{WDM}(f_1 + f_2 - f) \cdot \left[1 - \exp(-2\alpha L) \cdot \exp\left(j4\pi^2 \beta L(f_1 - f)(f_2 - f) \right) \right] df_1 df_2
\]

(4)

Although the IGN model is an approximation of the CGN model, it is reported that the results of the IGN model are also relatively accurate, especially when there exists a large
number of channels [8]. In these scenarios, the IGN model is preferable because of its simple analytical form and low computational complexity. For a small number of channels, however, the IGN model may be inaccurate [8]. In addition, when the WDM configurations and link conditions are highly heterogenous and dynamic, the accuracy of the GN models are found to be significantly degraded [9].

B. Fiber Nonlinearity Monitoring

Coherent optical receiver provides a resourceful platform through digital signal processing (DSP) to build OPM functionalities [17]. For instance, polarization mode dispersion can be monitored based on the coefficients of the adaptive butterfly filter. Meanwhile, ML-aided OPM approaches have been widely investigated. For direct detection systems, ML-based OSNR monitoring schemes based on delay-tap asynchronous sampling [18] and single channel sampling [19] were proposed. For coherent systems, deep artificial neural network (ANN) was adopted to perform OSNR monitoring and format identification simultaneously [20].

Regarding the fiber nonlinearity monitoring, a few techniques have been proposed. In [21], the nonlinearity-induced amplitude noise correlation across neighboring symbols was characterized and employed to aid optical signal-to-noise ratio (OSNR) monitoring in the presence of strong fiber nonlinearities. The fiber nonlinear effects also cause phase noise correlations over neighboring symbols [22]. In [23], ML-based nonlinear noise monitoring using amplitude noise covariance (ANC) and phase noise covariance (PNC) was proposed as illustrated in Fig. 2, and a significant improvement in monitoring accuracy was numerically demonstrated and experimentally verified.

\[
\theta_{ij}(k) = \arg \left( \frac{A_{ij}^*(k) \cdot A_{ij}^\theta(k)}{A_{ij}^*(k) \cdot A_{ij}^\theta(k)} \right) \quad i, j \in \{x, y\} 
\]

where \( A^* \) denotes the complex conjugation of transmitted symbol \( A \).

Following [23], the input features to the ML algorithm include \( R_j \) and \( P_{ij} \), which are obtained by

\[
R_j = 10 \cdot \log_{10} \left( \frac{1}{n} \sum_{m=1}^{6} A_{C(j)}(m) \right) 
\]

\[
P_{ij} = 10 \cdot \log_{10} \left( \frac{1}{n} \sum_{n=1}^{30} P_{C(j)}(n) \right) 
\]

In addition, \( A_{C(0)}(0) \) and \( P_{C}(0) \) are also used as the input.

Reasonable accuracy of the ML-based fiber nonlinearity monitoring has been demonstrated for the system and link cases in [23]. However, due to the limited information in the coherent receiver, it is quite difficult to guarantee the accuracy in more complicated link conditions.

In this paper, we propose a novel framework leveraging ML to combine the NLI modeling and monitoring, and it will be detailed in the next section.

III. PRINCIPLE

A. ML-aided Fiber Nonlinearity Modeling

As mentioned earlier, fast analytical models such as the GN model and its variants provide relatively accurate results for certain links. However, in practical systems with more complex link conditions, their accuracy still needs to be improved. On the other hand, the deviations with respect to the true SNR are found to be related to system configurations and parameters, which implies that it is possible to calibrate the deviations using system parameters [9]. Nevertheless, the deviations are generally caused by high order nonlinearity, and thus could be very difficult, if not impossible, to obtain through an analytical approach. Meanwhile, ML-based approaches have shown the capacity to deliver exceptional performance in scenarios where the underlying physics and mathematics of the problem are too difficult to be described explicitly, and the numerical procedures involved require computational time/resources [24]. Therefore, we propose to use the ML algorithm with system parameters as the input features to perform the calibration function as depicted in Fig. 3. Training the ML algorithm is necessary and critical. Fortunately, large size data sets can be generated using SSFM simulations, whose computation time is reasonable for the offline training process especially when graphics processing unit (GPU) is adopted.

![Fig. 2. Block diagram of ML-aided fiber nonlinearity monitoring.](image1)

![Fig. 3. Block diagram of ML-aided fiber nonlinearity modeling.](image2)
The conceptual block diagram is nonlinear target. In this work, we propose a ML analytical solution with desired performance to achieve this fiber nonlinearities, it is and processing in receiver has limited accuracy. nonlinear noise estimation purely relying on the information available happen due to historical reasons, and inaccurate measurement incorrect link information such as fiber type, which can inaccuracies in practical systems to some extent. First, for link solution developed separately, which is apparently not the optimal B. SSFM results are used as the desired output. The output of the ANN is is number of average gamma and average alpha of the fiber spans, and the parameters of each fiber span. These parameters are fed into the GN model including the WDM configurations and the parameters of each fiber span. These parameters are pre-processed to obtain the input features of the ANN, in order to avoid overfitting problems. Specifically, the input features include span number, maximum span length, average span length, launch power, link length, net chromatic dispersion, average gamma and average alpha of the fiber spans, and number of WDM channels. Note that the set of input features is similar to the one used in [25] to predict residual margin. The output of the ANN is $SNR_{ef}$. In the training process, the SSFM results are used as the desired output.

B. **ML-aided Combination of Modeling and Monitoring**

So far, fiber nonlinearity modeling and monitoring are developed separately, which is apparently not the optimal solution, considering that both of them still suffer from inaccuracies in practical systems to some extent. First, for link models, the input parameters might contain errors caused by incorrect link information such as fiber type, which can happen due to historical reasons, and inaccurate measurement such as optical power. Moreover, some information related to the received waveforms, such as ANC and PNC, might not be available in the models. Then, for link monitoring, the nonlinear noise estimation purely relying on the information and processing in receiver has limited accuracy.

![Fig. 4. Block diagram of ML-aided combination of fiber nonlinearity modeling and monitoring.](image)

The fusion of the link modeling and monitoring schemes is expected to prove more accurate results. However, in terms of fiber nonlinearities, it is not straightforward to develop an analytical solution with desired performance to achieve this target. In this work, we propose a ML-aided fusion of the fiber nonlinearity modeling and monitoring to provide more consistent and accurate results for optical network planning. The conceptual block diagram is illustrated in Fig. 4. A single ML engine can be used to combine the input features of the ML-aided monitoring in Section II.B and the ML-aided modeling in Section III.A.

The ML-aided scheme can be used in any modeling and monitoring methods, and in the following study we employ the GN model, noise covariance-based monitoring, and a feedforward ANN.

### IV. SIMULATION RESULTS AND DISCUSSIONS

#### A. Simulation Setup

The performance evaluations of the ML-based combination of fiber nonlinearity modeling and monitoring were numerically carried out over a wide range of system configurations.

The simulation setup is depicted in Fig. 6. At the transmitter (Tx) side, root-raised-cosine (RRC) pulse shaping with a roll-off factor of 0.14 was applied. The symbol rate ($R_s$) was set to 35 Gbaud. The channel spacing $\Delta f_{ch}$ was 50 GHz. The length of the symbol sequence was $2^{17}$. For the fiber link, doped Erbium-doped fiber amplifiers (EDFA) were employed but the ASE noise was ignored. At the receiver (Rx) side, the center channel was filtered out and processed. Particularly, after chromatic dispersion (CD) compensation, a matched filter was applied, followed by down-sampling to obtain received symbols. Since the Tx laser and local oscillator phase noise was ignored, carrier recovery was not included except that the overall phase rotation caused by fiber nonlinearities was removed. Afterwards, the ANC and PNC

![Fig. 5. Simulation setup.](image)

| TABLE I SUMMARY OF LINK CONFIGURATIONS AND PARAMETERS |
|---------------------------------|---------------------------------|
| Fiber type | SSMF, TWC, ELEAF, PSCF |
| Span length (km) | 10, 20, 30, 40, 50, 60, 70, 80, 90, 100 |
| Span number | 1:1:20 |
| Launch power (dBm) | -4, -3, -2, -1, 0, 1, 2, 3, 4 |
| Modulation format | DP-QPSK, DP-16QAM |
| Total WDM slots | 21 |
| Channel number | 1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21 |

| TABLE II SUMMARY OF FIBER PARAMETERS |
|---------------------------------|---------------------------------|
| Fiber type | $a$ [dB/km] | $D$ [ps/nm/km] | $\gamma$ [1/w/km] |
| SSMF | 0.2 | 16.7 | 1.3 |
| TWC | 0.21 | 2.8 | 2 |
| ELEAF | 0.21 | 4.3 | 1.47 |
| PSCF | 0.18 | 20.1 | 0.9 |
calculations were conducted based on the received symbols. The SNR of the received symbols were considered as the true \( SNR_{\text{ref}} \) since the system only contains fiber nonlinear noise.

In total, 1603 links were simulated to perform the training and test of the ML-based schemes. The selection of the link configurations based on Table I is described as follows. First of all, all the configurations in Table I were randomly selected with a uniform distribution. The fiber types included standard single mode fiber (SSMF), TrueWave classic (TWC), enhanced large effective area fiber (ELEAF), and pure silica core fiber (PSCF). They represent typical fiber types deployed in the field with a wide variety of dispersion, attenuation and nonlinearity coefficient. The parameters of these fiber types are summarized in Table II. The span length was between 10 and 100 km with a step size of 10 km. The span number was between 1 and 20 with a step size of 1. The launch power of the signals was between -4 and 4 dBm with a step size of 1 dB. DP-QPSK and DP-16QAM were both considered. The total number of WDM channel slots was set to 21. We first chose a channel number that was equal to or less than 21. Then this number of channels were randomly distributed in the 21 channel slots.

As mentioned earlier, the waveform propagation simulations were conducted based on the SSMF to obtain received symbols and the true \( SNR_{\text{ref}} \). The adopted ANN has only one hidden layer with 15 neurons, which was carefully chosen to obtain the lowest root mean square error (RMSE) without introducing overfitting. The input features are described in the previous sections and summarized in Table III for clarity.

1123 links were randomly selected to train the ANN and the rest 480 links were used to test the trained ANN. The training was performed using MATLAB R2018a’s neural network toolbox. The logsig and purelin function were used as the activation function (or transfer function) for the hidden and output layers, respectively. In the training phase, the Bayesian regularization learning algorithm was used.

### B. Results of GN Model

Fig. 6(a) and (b) plot the histogram of the \( SNR_{\text{ref}} \) deviation for the IGN and CGN models, respectively. We can see that in the simulated test cases the range of the offset is quite large. The RMSE is 2.14 dB and 2.87 dB for the IGN and CGN models, respectively. This result shows that even though the GN models achieve good results in some certain link scenarios, their accuracy needs to be improved for heterogenous dynamic networks.

### C. Results of GN+ANN Model

Fig. 7 plots the histogram of the \( SNR_{\text{ref}} \) deviation for the GN+ANN models. With the aid of the ANN, the RMSE is reduced to 1.15 dB and 1.02 dB for the IGN and CGN models, respectively, indicating the effectiveness of the ANN in calibrating the GN models.

To illustrate the process of the ANN calibration, in Fig. 8 we plot the deviation versus the number of spans for the links with homogenous 80 km SSFM spans. The WDM system has 11 channels, which are located together without empty channel slots among them. For the IGN model, it is observed that the deviation decreases from \( 3.8 \) dB to \( -0.5 \) dB as the span number increases from 1 to 15. The CGN model manifests a smaller dynamic range since it better approximates the NLE equation as discussed in Section II. Nevertheless, it still changes from \( 3.8 \) dB to \( -1.8 \) dB. Again, we can see that the deviation is correlated to specific link conditions, i.e. span number in Fig 8. Therefore, the ML algorithm is expected to be capable of calibrating the deviation by removing the correlations between the deviation and input features. Indeed, with the ANN, the deviations are within \( \pm 1 \) dB. There are still some residual correlations after the ANN is applied, which means further improvement is possible with more training data and/or stronger ML algorithms.

### Table III

| Features of modeling | Features of monitoring |
|----------------------|-----------------------|
| 1. \( SNR_{\text{ref}} \) from GN model | 11. \( ANC_{ij}(0) \) from Eq. (5) |
| 2. Span number | 12. \( PNC_{ij}(0) \) from Eq. (7) |
| 3. Maximum span length | 13. \( R_{ij} \) from Eq. (9) |
| 4. Average span length | 14. \( P_i \) from Eq. (10) |
| 5. Launch power |  |
D. Results of GN+Monitoring+ANN

Next, the results of the ML-aided combination of modeling and monitoring are shown in Fig. 9. For comparison, the performance of the “Monitoring+ANN” case is also shown in Fig. 9(a) with the same ANN inputs as [23], i.e. noise covariances plus net CD and channel number. The RMSE, which is 0.63 dB, is higher compared with the result in [23] because the system conditions especially the WDM configurations in our link set are much more complicated than the link set in [23]. After we combine the model and monitoring through an ANN, the RMSE values are reduced to 0.23 dB and 0.22 dB for the IGN and CGN cases, respectively. Compared to all the other schemes, the accuracy improvement is quite significant, indicating that using modeling and monitoring together through ML is a promising framework for the development of future optical network planning tools.

E. Results with optical power uncertainty

In practical systems, link parameters normally contain uncertainties due to inaccurate measurement and other reasons. In the last part, we evaluate the performance of the proposed ML-aided schemes in the presence of random offsets in optical powers. The power offsets were generated independently for each span, following a Gaussian distribution with a standard deviation of 0.5 dB. Then they were added to the true launch powers (in dB) before being used as the input of the SNR estimation schemes.

First, the GN+ANN schemes are expected to be less tolerant to the launch power uncertainties because they purely rely on the link parameters to estimate the nonlinear noise variance. As shown in Fig. 9, the RMSE is increased to 1.57 dB and 1.43 dB for the IGN+ANN and CGN+ANN cases, respectively. On the contrary, the link monitored covariances are not affected by the launch power uncertainties. Therefore, we expect a higher tolerance for the combined scheme. Fig. 9 shows that...
the RMSE is only increased to 0.29 dB and 0.31 dB for the two cases, respectively.

![Histogram of SNR deviation for (a) IGN+ANN, (b) CGN+ANN with launch power uncertainty.](image)

![Histogram of SNR deviation for (a) IGN+Monitoring+ANN, (b) IGN+Monitoring+ANN with launch power uncertainty.](image)

**V. CONCLUSION**

In this paper, we report the application of machine learning (ML) techniques in fiber nonlinearity modeling and monitoring. In particular, we propose to use ML to calibrate the deviations that exist in nonlinear models, and then propose to use ML to combine link modeling and monitoring for a better estimation of fiber nonlinear noise variance. Gaussian-noise (GN) model, nonlinear noise covariance, and artificial neural network (ANN) are used as illustrative examples to investigate and compare the performance of different approaches. The RMSE values of the nonlinear signal-to-noise ratio (SNR) for the evaluated schemes are summarized in Table IV. The results show that the proposed ML-aided combination of the link modeling and monitoring delivers a superior performance.

| Input features | RMSE (dB) (Ideal) | RMSE (dB) (with power uncertainty) |
|----------------|-------------------|-----------------------------------|
| IGN/CGN        | 2.14 / 2.87       | n/a                               |
| IGN/CGN+ANN    | 1.15 / 1.02       | 1.57 / 1.43                       |
| Monitoring+ANN | 0.63              | n/a                               |
| IGN/CGN+Monitoring+ANN | 0.23 / 0.22 | 0.29 / 0.31                      |

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