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Modeling and Monitoring of Fiber Nonlinearity for Elastic Optical Networks Using AI

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Abstract: To fulfill the rising need for high-capacity and flexible communication systems, Elastic Optical Networks (EONs) have emerged as a possible alternative. However, the growing transmission rates and intricate modulation formats in EONs present substantial difficulties, such as fiber nonlinearity, which may deteriorate signal quality and restrict the network's performance. The fundamental components of EONs are fiber Nonlinear Interference (NLI) modeling and monitoring. Traditionally, they were created and studied independently. Furthermore, for heterogeneous dynamic optical networks, the previously suggested approaches' accuracy must still be increased. In this study, we demonstrate how Artificial Intelligence (AI) is used in NLI monitoring and modeling. We specifically propose to measure the drawbacks of the most current fiber nonlinearity estimates using AI approaches. The Gaussian Noise (GN) framework is used as an instance and Binary Differential-Support Vector Machine (BD-SVM) is used to demonstrate an important enhancement. In addition, we suggest combining modeling and monitoring strategies with AI for a more accurate prediction of NLI variation. Extensive simulations with 2411 connections are done to compare and assess the efficacy of various systems. The results of these simulations demonstrate that the AI-aided modeling and monitoring combo works better than other possible solutions.

Keywords*: Elastic Optical Networks (EONs), nonlinear fiber interference, Artificial Intelligence (AI), Gaussian-Noise (GN), and Binary Differential-Support Vector Machine (BD-SVM)*

1. Introduction

The rapid growth of 5G mobile networks, the Internet of Things (IoT), and cloud services have all contributed to a rise in the need for the capacity and reliability of optical networks, in addition to the emergence of certain brand-new requirements. The technologies of optical networks are constantly developing to accommodate the continually expanding number of internet service consumers [1]. Elastic optical networks (EON) are being developed, which gives network administrators the flexibility to scale up or down resources to make the most use of the available spectrum. A lightpath's excellent transmission quality must be maintained from the Beginning of Life (BoL) to the End of Life (EoL); however, the EON architecture makes this more difficult due to the numerous link and signal configurations. Each connection transmits a substantial volume of data; therefore, even a momentary interruption in traffic flows might have severe consequences [2]. Enhancing optical network reliability is thus crucial. If optical connections are to run at high capability, they must employ network resources more effectively.

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Although a planning tool cannot dependably foresee, a significant design margin is often required to compensate for the difference between the expected metrics and the real value to ensure optimum network performance of the Quality of transmission (QoT). A significant margin might result in the underutilization of the wavelength capabilities. Consequently, a more precise planning tool is required to predict the QoT before link construction or reconfiguration to create a narrow-margin optical network to improve network capacity [3, 4]. Fiber-optic communication systems have evolved into the foundation of international telecommunications networks in the age of ever-increasing data demands. These systems use the special characteristics of optical fibers to efficiently transmit enormous volumes of data across large distances. However, a phenomenon known as fiber NLI offers a substantial challenge to the performance and reliability of these systems as transmission rates continue to rise and cutting-edge modulation schemes are used [5].

Artificial intelligence (AI) systems and entities may mimic biological processes to carry out similar operations for decision-making and learning, with particular emphasis on human cognitive processes. To produce smarter, kinder, and highly responsive to changes in their platform, AI incorporates reasoning and knowledge to deliver databases, environments, and applications rather than sending separate systems for all elements [6]. Fiber nonlinearity becomes considerably more important in the setting of EONs. These networks' elastic properties enable the coexistence of optical channels with various modulation formats and data speeds inside the same fiber. This is made possible by the allocation of variable-sized spectrum resources. This flexibility may have a substantial influence on signal quality and raises the possibility of nonlinear interactions [7, 8]. To address these issues, AI-based methods have emerged as a powerful tool for modeling and tracking fiber nonlinearity in EONs. By using the vast amount of data generated inside the network, particularly Machine Learning (ML) and Deep Learning (DL) algorithms, it may be possible to provide more accurate and useful results [9]. Using AI, fiber nonlinearity may be modeled, enabling the creation of predictive models that can capture the intricate relationships between network characteristics, nonlinearity-induced impairments, and optical channels. These models can effectively forecast the effects of fiber nonlinearity on signal quality by learning from past data and accounting for many elements, including signal strength, modulation format, and channel parameters [10]. In this paper, we use AI modeling and monitoring methodologies for EON fiber nonlinearity.

An optical communication system introduces a data-driven fiber channel modeling technique based on DL. For fiber channel modeling of on-off keying and pulse amplitude modulation of four signals, the research [11] proposed a Bidirectional Long Short-Term Memory (BiLSTM) that was chosen among a wide variety of DL algorithms. The pulse transmission in an optical fiber is described by a nonlinear fourth-order equation. The equation is a generalization of many well-known nonlinear mathematical models introduced in the article [12]. The equation has the distinctive property that any power may be used to change the pulse's intensity and breadth when describing the packing of a wave packet. The study [13] investigated the three integration procedures that were used to extract optical soliton solutions for the extended Kudryashov equations with power nonlinearities: the well-known Kudryashov technique, the novel Kudryashov method, and the combined Riccati formula extension approach.

To compensate for fiber nonlinearities in coherent digital systems, the research [14] introduced for the initial time the use of Long Short-Term Memory (LSTM) neural network topologies. They do numerical simulations using polarization multiplexing for single-channel and multi-channel 16-QAM modulating networks in C-band or O-band communication networks. Numerous possible uses in optical components have been continuously displayed and noticed due to in-depth research and the revealing of the fundamental optical characteristics and new photophysical properties of 2D materials. This has immediately sparked an upsurge in research [15] in the academic community. The unique Resource Assignment RA technique based on dynamic unstructured fuzzy clustering that takes into account both XT and PLIs was suggested in the study [16]. An available resource set will be created using all resource combinations that satisfy the transmission requirements of the services. If the sample size is substantial, fuzzy C-means clustering will be used to achieve more accuracy. The article [17] made progress in this direction. We provide a methodology to specify the reach requirements in an Integer Linear Programming (ILP) paradigm for Routing and Spectrum Assignment (RSA) in an elastic optical network using the probabilistic results of a Machine Learning (ML)-based QoT estimation.

This integrated method eliminates light pathways with unsatisfactory QoT by repeatedly solving the RSA issue by changing the reach restrictions based on the results of a QoT estimate. An alien frequency performance tracking method and ML-assisted QoT prediction for lightpath providing intradomain traffic were empirically shown in the study [18]. Using a 160 Gbaud alien multi-wavelength lightpath, testbed studies show modulation format identification, QoT surveillance, and cognitive routing. The study [19] presented the coexistence of applications that need an immediate reservation (IR) and those that may be scheduled in advance; the difficult Resource Optimization (RO) issue must be managed in Space-Division Multiplexing Elastic Optical Networks (SDM-EONs). Designing more efficient RO tactics has been made feasible by the emergence of AI, particularly ML algorithms. Assuming lightpath topologies may be selected from a sizable (and feasible) set of combinations of routes, modulation formats, Forward Error Correction (FEC) overheads, and baud rates, the research [20] developed an optimization model that solves the Virtual Network Embedding (VNE) issue over EON. The splittable variant of the VNE over the EON issue is solved, which greatly increases the difficulty but is considerably more likely to provide a workable solution.

Following that, the other parts of the study are as follows: Part 2 introduces the methodology, Part 3 introduces findings and discussion, and Part 4 concludes the paper.

2. Methodology

In this part, we will discuss the specifics of our suggested AI-based technique, which includes the GN method, the training of the BD-SVM model, and the implementation in EONs.

2.1. Gaussian Noise (GN) method

In recent years, the GN model and its modifications were presented and thoroughly explored to determine the total nonlinear noise deviation for coherence optical transmission networks. The perturbation assumption is used to generate the GN models from Eq. (1). In addition to this, the nonlinear noise is thought of as an additive GN. After dissemination, the NLI per wavelength at frequencies f may be represented using the GN concept:

$$H_{NLI}(e) = \frac{18}{29}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} H_{WDM}(e_1)\, H_{WDM}(e_2)\quad H_{WDM}(e_1+e_2+e)\left|\sum_{m=1}^{M_T}\gamma_m.\left[\prod_{l=1}^{m-1} exp(-3\alpha_l K_l).\Gamma_l^{\frac{3}{2}}\right].\left[\prod_{l=m}^{M_t} exp(-\alpha_l K_l).\Gamma_l^{\frac{1}{2}}\right].exp\left(i4\pi^2\left(\frac{e_1-}{e}\right)(e_2-e).\sum_{l=1}^{m-1}\beta_2\right).\int_0^{K_m}[exp(-2\alpha_m y)].exp\left(i3\pi^2(e_1-e)(e_2-e).-\beta_{2,m}y\right)cy\right|^2 ce_1ce_2$$

(1)

Where Γ_l is the total energy increase at the ending of the lth period, K_l indicates the span's breadth, α_l denotes the span's field loss, and N_t shows the overall amount of intervals. In this research, we only take into account networks with dispersion-uncompensated "link transparency," thus that suggests the optical enhancement after each span precisely compensates for each span's loss. The same fiber type makes up each span, and the multiplexed polarization-division impulses are sent. The Kerr nonlinearity impacts of optical fiber in contemporary coherence systems have emerged as the primary barriers to further increasing the ability of Wavelength-Division Multiplexing (WDM) technologies.

The variation of the NLI coherence collected across various spans may be obtained using Eq. (2). Coherent GN (CGN) models are one GN model that fits this description. The Incoherent GN (IGN) model is a distinct form of the GN model that ignores the coherence between the NLI produced across various periods. By adding the PSD from each span together, the IGN model's total NLI PSD may be calculated:

$$H_{IGN}(e) = \sum_{m=1}^{M_t} H_{NLI,m}^{1span}(e) \qquad (2)$$

Where $H_{IGN}(e)$ is the single-span NLI PSD according to Eq. (2), which is denoted by

$$H_{NLI,m}^{1span}(e) = \frac{16}{27}\gamma^2\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} H_{WDM}(e_1) H_{WDM} \times (e_2) H_{WDM}(e_1+e_2-e).\left|\frac{1-\exp(-2\alpha K).\exp(i4\pi^2\beta_2 K(e_1-e)(e_2-e))}{2\alpha - i4\pi^2\beta_2 K(e_1-e)(e_2-e)}\right| \times ce_1 ce_2 \quad (3)$$

Despite the technique's resemblance to the IGN model, it is claimed that the model's results are also often true, primarily when numerous channels are accessible. The IGN approach is excellent because of its simple analytical framework and little processing overhead. The IGN model, however, could be off for a small subset of channels. It is also shown that the GN simulations' efficiency has significantly decreased in highly heterogeneous and dynamic WDM topologies and connection circumstances.

2.2. Binary Differential-Support Vector Machine (BD-SVM)

For monitoring fiber nonlinearity in EONs, the Binary Differential-Support Vector Machine (BD-SVM) is a binary classification technique. To distinguish between ordinary noise and impairments brought on by nonlinearity, it uses support vector machines (SVM) and the idea of differential classification. By maximizing a certain objective function, the decision boundary of the BD-SVM is achieved. The BD-SVM decision function equation may be written mathematically as follows:

$$f(x) = siqn(\sum[\alpha_i * y_i * K(x_i, x) + b]) \qquad (4)$$

Where y_i is the class label of the ith support vector (either -1 or +1), f(x) denotes the decision function that provides a class label to an input sample x.

The Lagrange multipliers α_i and bias term (b) are tuned in the training phase of the BD-SVM to determine the selection border that maximum separates the two classes. To maximize the margin among the classes, a quadratic programming issue must be solved throughout this optimization procedure.

The input features utilized for classification in the context of fiber nonlinearity monitoring in EONs might comprise elements like received optical power, OSNR, or other pertinent properties. The BD-SVM model may be taught to distinguish between typical noise that follows a GN model and noise impacted by fiber nonlinearity by utilizing labeled data during training.

After training, the BD-SVM model may be used for real-time monitoring by feeding the characteristics derived from the incoming optical signals. The output of the decision function (f(x)) shows the expected class label, making it possible to spot optical signal impairments brought on by nonlinearity.

Network administrators may benefit from BD-SVM's capacity to manage nonlinearities and accurately categorize the received signals by using them for fiber nonlinearity monitoring. This helps with the precise identification and mitigation of fiber nonlinearity-induced impairments, which enhances the efficiency and dependability of EONs.

2.3. Monitoring of Fiber Nonlinearity

Analyzing the impacts of nonlinear effects on optical signals is a necessary step in monitoring fiber nonlinearity in EONs. The Q-factor, which may be derived depending on numerous characteristics, is often used for tracking fiber nonlinearity. The following equation may be used to represent the Q-factor in EONs:

$$Q = P_{signal} - P_{noise}/\sqrt{P_{noise}} \qquad (5)$$

P_{signal} shows the received optical power of the intended signal. P_{noise} indicates the strength of background interference or noise in the received signal. Network operators may evaluate the quality of the received signals and identify variations from anticipated values by continually monitoring the Q-factor in real time. Due to the distortion of the signal and the resulting rise in noise, fiber nonlinearity-induced impairments are indicated by a drop in the Q-factor.

Other metrics may be used to monitor fiber nonlinearity in EONs in addition to the Q-factor. These include the Bit Error Rate (BER), the received power level, and the Optical Signal Noise Ratio (OSNR). While the BER denotes the number of bit errors in the received signal, the OSNR may be computed as the ratio of the received signal power to the noise power. Fiber nonlinearity may be detected by variations from the predicted OSNR or a rise in BER.

These metrics are generally measured and analyzed at several locations within the network, such as transmitters, receivers, or intermediate nodes, to monitor fiber nonlinearity in EONs. Network operators may detect the start of fiber nonlinearity-induced problems and take preventative action to lessen their effects by comparing the observed data with predetermined thresholds or reference values. To maintain optimum network performance in fiber nonlinearity, these steps may include modifying power levels, improving modulation formats, or putting nonlinear compensation techniques into practice.

2.4. Modeling Fiber Nonlinearity with AI

As was previously indicated, quick analytical models like the GN model and its variations provide findings that are comparatively accurate for certain linkages. Their accuracy still has to be enhanced for use in actual systems with more complicated connection circumstances. The deviations from the real SNR_{nl}, on the other hand, are discovered to be connected to system configurations and parameters, indicating that the discrepancies may be adjusted using system settings. However, the discrepancies are often caused by high-order variability, making it potentially impossible, if not very difficult, to get them by an analytical technique.

However, AI-based methods have shown the ability to provide outstanding results in a range of contexts when the basic mathematics and physics of the problem are too complicated to be understood, and the required mathematical procedures need computer time and resources. As a result, we suggest that the AI algorithm be used to execute the calibration function using system parameters as the input characteristics. The AI algorithm must be trained, which is essential. Fortunately, huge-size data sets may be created using Split-Step Fourier Method (SSFM) simulations, and their computation time is acceptable for offline instruction, especially when Graphics Processing Unit (GPU) is employed.

In this study, the GN model and BD-SVM are given as examples; however, the same architecture may be presented to many NLI systems and AI techniques. Within the system characteristics provided to the GN simulation are the WDM setups and the details of each fiber length. These variables have been previously prepared to offer the BD-SVM's input characteristics to prevent overfitting issues. The attributes of the input include, in particular, the number of spans, the longest possible span, the amount of WDM routes, the initialization strength, the connection width, the mean gamma and averaged alpha of the fiber lengths, the overall span size, the averaged launching strength, and the net chromatic dispersion. It should be noted that the collection of input characteristics resembles the one used to estimate residual margin. SNR_{nl} is the result of the BD-SVM. The intended outcome for the training process is based on the SSFM results.

2.5. Modeling and Monitoring Combined with AI

Fiber nonlinearity modeling and monitoring have been created independently up until now, which is perhaps not the best course of action given that both of them still have some errors in real-world systems. First, erroneous evaluation, such as optical strength, and defective connection details, such as fiber category, may arise for reasons of history and may be included in the input parameters for link models. The transmitted signals' Phase Noise Covariance (PNC) and Amplitude Noise Covariance (ANC), among other information, could not be included in the models. The nonlinear noise estimate used for link monitoring is only accurate to a certain degree. It may only be monitored slowly in noisy surroundings since it solely relies on input to be processed in the receiving device.

It is envisaged that more accurate results would result from combining the link simulation with tracking techniques. To accomplish this goal, an analytical solution must be developed, although it is not simple to do so in terms of fiber nonlinearities. In this study, we propose integrating simulation and tracking of fiber nonlinearity with AI to deliver more accurate and dependable guidelines for designing an optical connection. Fig.1 details the theoretical block structure. The use of an individual AI system, the input features of the AI-aided observation in Part 2-B, and the AI-aided analysis in Part 3-A may be integrated.

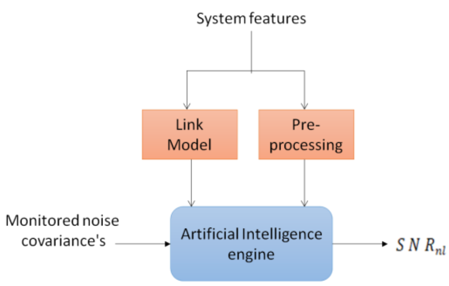


Fig.1. Block diagram for the modeling and monitoring fiber nonlinearity with AI assistance.

In the following analysis, we use a feedforward BD-SVM, the GN method, and noise covariance-based observation. The AI-aided approach may be applied with any modeling and monitoring techniques.

3. Result and Discussion

Here, we evaluate how well the AI-based mixture of numerically conducted fiber nonlinearity simulation and tracking functions is across various system configurations.

3.1 Simulation Findings

To execute the training and testing of the AI-based schemes, 2411 linkages in total were simulated. Following is a description of how the link configurations were chosen using Table 1. All of the configurations were initially chosen at random from a uniform distribution.

Among the readily accessible fiber types were Enhanced Large Effective Area Fiber (ELEAF), Pure Silica Core Fiber (PSCF), Standard Single Mode Fiber (SSMF), and True Wave Classic (TWC). Using a range of variation, amplifying, and nonlinearity characteristics, they reflect typical field-deployed fiber varieties.

Table 1: Description of Link Configurations and Parameters

Fiber type	SSMF, TWC, ELEAF, PSCF
Launch power	-4,-3,-2,-1,0,1,2,3,4
Symbol rate (Gbaud)	37:72:92
Total WDM slots	17
Modulation format	DP-QPSK, DP-16QAM
Span number	1:1:20
Channel number	1:1:17
Span length (km)	10,20,30,40,50,60,70,80,90,100

The characteristics of various fiber types are broken down and presented in Table 2. The diameter of the step was 10 kilometers, and the width of the span went from 10 kilometers up to 100 kilometers. The size of each stage was 1, while the span number ranged from 1 to 20. It should be noted that each link's span length and fiber type were chosen separately; thus, a single link might have a variety of fiber kinds and span lengths. The transmissions' launch power ranged from 4 to 4 dBm, with a step size of 1 dB.

Table 2: Description of fiber parameters

Fiber type	***γ [1/w/km]***	***D [ps/nm/km]***	***α [dN/km]***
ELEAF	1.49	4.5	0.23
TWC	3	2.9	0.25
SSMF	1.5	18.9	0.3
PSCF	10.1	22.2	0.19

Both DP-QPSK and DP-16QAM were taken into account. There were 15 WDM channel slots altogether. Fixed parameters for the center channel included a 24 Gbaud and Fifty GHz spacing. Initially, for each of the additional 15 routes, we chose a channel identifier equal to or lower than 15. The channels in this number were then allocated at random into these slots. Then, each possible channel slot's description of the collection rate/channel distance was separately selected from the three accessible options.

To determine received symbols and the real SNR_{nl}, the SSFM was used as the foundation for waveform dispersion calculations. The SSFM had a 10-meter step size. The adopted BD-SVM contains a single concealed layer comprised of 15 neurons, selected with care to get the smallest Mean Square Error (MSE) without resulting in an excessive amount of fitting. For detail, the input characteristics are listed in Table 3 after being condensed in the earlier sections.

Table 3: Input features to the BD-SVM

Q_{ji}	Features of monitoring
O_{ji}	
$ANC_{vz}(0)$	
$PNC_{vz}(0)$	
Average span length	Features of modeling
Span number	
Launch power	
Number of WDM channels	
Average alpha of fiber spans	
Net chromatic dispersion	
SNR_{nl} from GN model	
Maximum span	
Link length	
Average gamma of fiber spans	

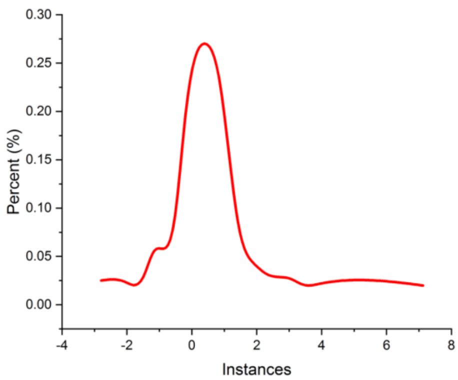
From a total of 2411 linkages, 1688 links were chosen randomly to teach the BD-SVM, and after training, the BD-SVM was put to the test using the balance of 723 linkages. The neural network toolkit in MATLAB R2018a was used for the training**.**

3.2 Effects of the GN Model

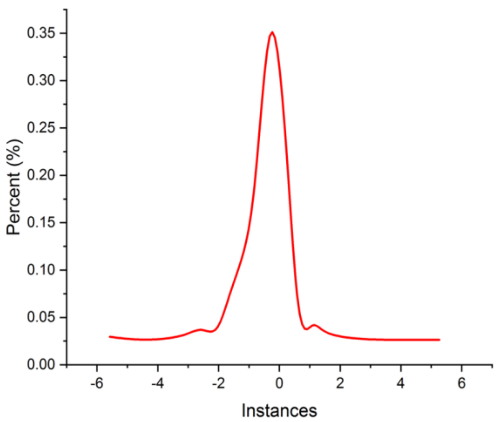
For the IGN and CGN models, we show the histogram of the SNR_{nl} deviation. We can observe that the offset range in the simulated test situations is extremely wide and may sometimes reach >7 dB. This finding demonstrates that although the GN models perform well in certain specific connection situations, they need to become more accurate for diverse, dynamic networks. The persistent positive difference in the CGN estimation is identical to the outcome of past investigations.

3.3 Results of the GN+BD-SVM Model

The histogram analysis of the SNR_{nl} variation for the GN+BD-SVM models is shown in Fig. 2(a) and (b). The BD-SVM helps to minimize the divergence significantly. Most situations for both models are now within 4 dB.



(a)



(b)

Fig.2. SNRnl variation histogram for (a) IGN+ BD-SVM and (b) CGN+ BD-SVM

We exhibit the total SNR_{nl} deviation's Cumulative Distribution Function (CDF) in Fig.3 to calculate the enhancement. The average SNR_{nl} variation for the IGN, CGN, IGN+BD-SVM, and CGN+BD-SVM programs, accordingly, is 3.33 dB, 4.32 dB, 2.82 dB, and 1.65 dB with 95% cumulative chances, demonstrating the efficiency of the BD-SVM in calibrating the GN models.

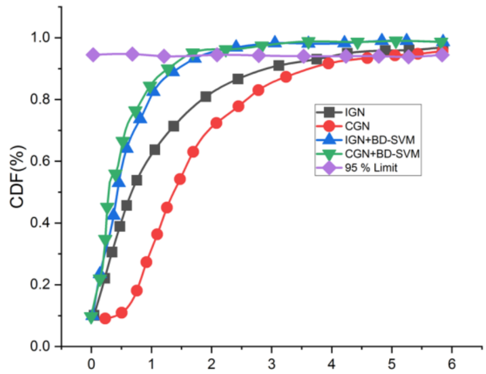


Fig. 3. Average SNR_{nl} variation CDF for the CGN, IGN, IGN+ BD-SVM, and CGN+ BD-SVM systems

For links with identical 70 km SSFM spans, we plot the variance vs. the number of crossings in Fig.4 to demonstrate the BD-SVM calibration procedure. The 11 circuits of the WDM system, each with a spacing of 50 GHz and a symbol rate of 35 Gbaud, are grouped without any open channel slots in between. For the IGN approach, it has been shown thus when the range count increases from 1 to 15; the divergence decreases from 2.7 dB to .5 dB. Because it more closely resembles the NLE solution, as explained in Section II, the CGN model has a lower dynamic range. But it still shifts from ~3.8 dB to ~1.8 dB.

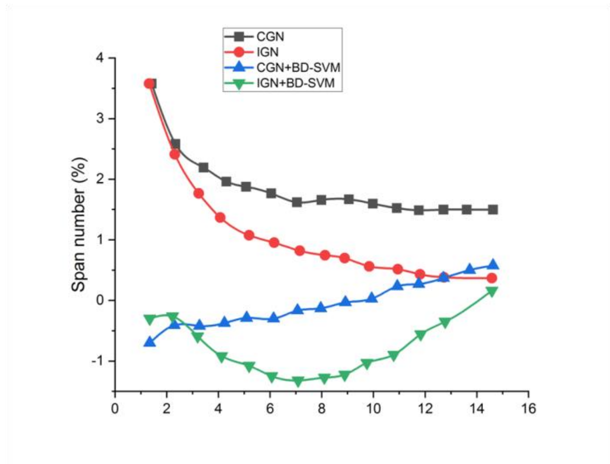


Fig.4. SNR_{nl} variation for different model approaches as a function of spans

Once again, it is clear that the divergence is tied to specific connection parameters, namely the span number. As a result, it is anticipated that the AI algorithm will be able to calibrate by removing associations between the variance and the input properties. The BD-SVM keeps the variations under 1.1 dB. After the BD-SVM is used, there are still some residual correlations, indicating room for improvements with further training information and/or more powerful AI techniques.

3.4 Findings from GN+ Monitoring+ BD-SVM

The outcomes of the modeling and monitoring combined with AI support are then explained. The "Monitoring+ BD-SVM" case's performance is also compared using the identical BD-SVM inputs, namely noise covariance plus net CD and channel number. Since most examples are within 1 dB, we can observe that the accuracy is already reasonably excellent. The accuracy is further enhanced when the model and monitoring are combined using a BD-SVM. Fig.5 shows the CDF of the absolute SNR_{nl} variation to represent the enhancement.

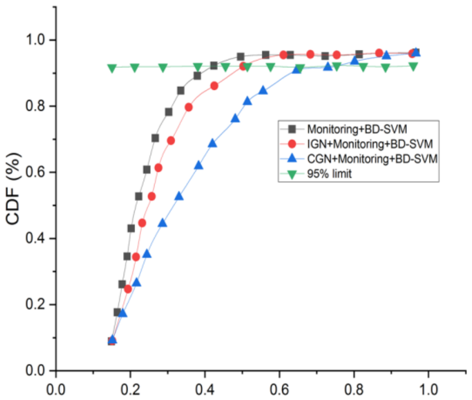


Fig.5. For the CGN+ Monitoring+ BD-SVM, IGN+ Monitoring+ BD-SVM, and Monitoring+ BD-SVM methods, CDF of relative SNR_{nl}variation

The average SNR_{nl} difference for the designs of CGN+ Monitoring+ BD-SVM, IGN+ Monitoring+ BD-SVM, and Monitoring+ BD-SVM, respectively, is .72 dB, .42 dB, and .32 dB at 95% cumulative probabilities. This finding suggests that a practical approach for creating future optical network planning instruments is to combine modeling and monitoring with AI.

4. Conclusions

Elastic Optical Networks (EONs) are severely constrained by fiber nonlinearity; however, using Artificial Intelligence (AI) has shown considerable promise in resolving this problem. We have created novel approaches that lessen the effects of fiber nonlinearity and enhance the functionality of EONs by applying AI algorithms and methodologies. In this research, we provide the modeling and monitoring fiber nonlinearity using AI approaches. For a more precise assessment of fiber nonlinear noise fluctuation, we recommend utilizing AI to integrate connection monitoring and simulation and employing AI to measure the variations contained in nonlinear models. Through in-depth simulations utilizing the GN model, nonlinear noise covariance, and the Binary Differential-Support Vector Machine (BD-SVM), we investigate and evaluate the efficacy of several different methods. Elastic optical networks may perform better when AI uses other mitigation strategies like optical signal processing or new fiber architectures. Future research might examine how AI algorithms could be used with these auxiliary tools to further enhance nonlinear mitigation.

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