Deep Neural Network for Predicting Supercontinuum Broadening in Chalcogenide Photonic Quasi crystal Fiber

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***Abstract*—Generation SuperContinuum (SC) is a complex nonlinear process caused by chaotic and unstable behaviour, especially simulated by short duration pump pulses when the optical fiber work on the anomalous dispersion region. Understanding the spectral broadening behavior is difficult due to variations in fiber length and input pulse parameters. To address this challenge, we introduce a Deep Neural Network (DNN) to predict the SC spectrum broadening. Remarkably, the DNN provides accurate predictions across different lengths of Chalcogenide (ChG) Photonic quasi crystal Fiber (PQF), achieving a root mean square error (RMSE) of 1.3677 and an R-Squared value of 0.99. Additionally, this DNN significantly reduces the computational time compared to MATLAB and COMSOL Multiphysics software.**

***Index Terms*—Supercontinuum, Deep Neural Network, Chalcogenide, photonic crystal fiber**

I. Introduction

Deep learning (DL) encompasses a range of computational techniques aimed at classification, pattern recognition, prediction, and system optimization using extensive datasets. Recently, an interest has been grown in employing deep learning methods in optical systems, particularly for managing ultrafast dynamics, such as shaping and compression of pulse through neural networks and tailoring SC spectra using genetic algorithms [1]. Moreover, deep learning is a excellent tool to perform the quantitative analysis in complex systems with more number of data parameters. This capability can be effectively utilized to measure the maximum SC spectral broadening for different fiber lengths [2].

The broadband SC has become a versatile and widely utilized light source with important applications in spectroscopy, imaging, and precision frequency metrology. The Generalized Non-Linear Schrödinger Equation (GNLSE) is employed to analyse mid-infrared SC generation phenomena. While this equation provides a solution for SC generation in photonic crystal fibers PQF [1], it does not offer a direct method for selecting the appropriate fiber structure to achieve the desired optical characteristics of SC generation. As a result, researchers often turn to various numerical modeling techniques for fiber structural analysis, such as finite element method (FEM), finite difference time domain and finite integration. These techniques involve discretizing the computational fiber structure into numerous elements to analyze optical properties, requiring adjustments to configurations and frequent simulation iterations. Consequently, the computational time and complexity of fiber structure analysis gets increased [3]. To address this, we propose a deep learning-based model to accurately predict SC spectral broadening with varying lengths of Chalcogenide (ChG) PQF. This model demonstrates more efficient SC broadening spectral behavior compared to traditional simulation tools.

II. METHODOLOGY

The broadband SC is generated by injecting femo-second (fs) pulses of laser through the highly nonlinear and anomalous disperive behavioured ChG PQF, as shown in Fig.1.

Fig. 1. Schematic of representation of SC broadening using nonlinear ChG PQF

In this study, SC spectra are generated using ChG PQFs of varying lengths (3, 6, 10, and 12 mm). The pulse parameters are set to a peak power of 2.5 KW and a pulse width of 80 fs. The SC generation dataset in ChG PQF was created by the authors through extensive numerical analysis using FEM and MATLAB software [4]. The collected SC spectra are then input into the DNN to feature the SC spectral characteristics such as broadening and spatial density, as shown in Fig. 2. The DNN model is trained using the following parameters: 2 hidden layers, 10 hidden neurons, and 10 epochs, with network training based on the Levenberg-Marquardt backpropagation algorithm. During the training phase, 70% of the data is utilized for training, while the remaining 30% is reserved for testing.

III. Results and Discussion

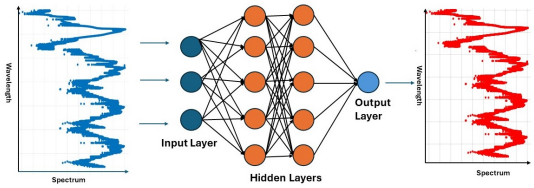

Fig. 2. DNN architecture for behaviour prediction of SC broadening in ChG PQF.

IV. Results and Discussion

In this section, Fig.3 illustrates the SC spectral broadening prediction results for different lengths of ChG PQF. The figure demonstrates a high correlation between the DNN model's predictions and the actual data. Fig.4 (a) and (b) displays the predicted SC spectral broadening for both the training and testing datasets across various PQF lengths of 3, 6, 10 and 12 mm, respectively. The results indicate that the DNN model effectively predicts SC spectral broadening for both datasets.

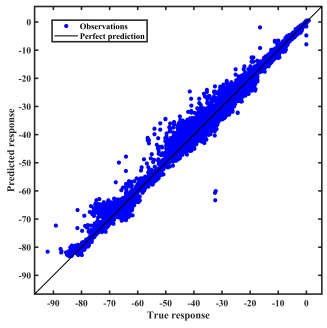

Fig. 3. prediction results of SC spectral broadening for different lengths of ChG PQF.

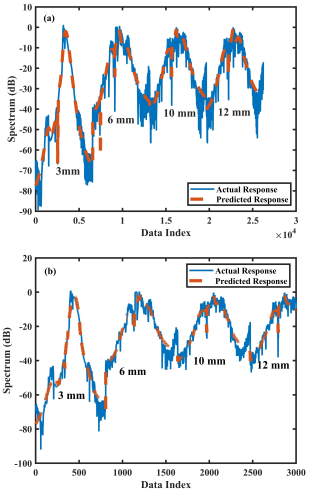

Fig. 4. Prediction of SC broadening (a)training and (b) test dataset

The performance metrics of the DNN are compared with those of other conventional prediction models, as shown in Table.I. The results clearly indicate that the DNN model achieves the lowest RMSE value (1.3677) compared to other methods. Similarly, its R-Squared value (0.99) is higher than those of the other methods.

TABLE I
Performance Measures of Various Prediction Models

Prediction Model	RMSE	R Squared	MSE	MAE
Bi-lateral Neural Network	6.1	0.89	37.296	4.3751
Medium Neural Network	7.5339	0.83	56.758	5.896
Narrow Neural Network	9.5760	0.73	91.699	7.4137
Wide Neural Network	5.64	0.91	31.78	4.3465
DNN	**1.37**	**0.99**	**1.8705**	**0.68856**

V. Conclusion

This study proposes a DNN-based approach for predicting the behavior of SC spectrum broadening across various lengths of ChG PQF. It is noted that the spectral density discontinuities present in GNLSE does not be observed in the DNN findings. The implemented DNN model offers a RMSE as 1.3677 and a R-Squared value as 0.99.

References

[1] S. Sridevi, T. Kanimozhi, N. Ayyanar, S. Chugh, M. Valliammai, and J. Mohanraj, "Deep learning based data augmentation and behavior prediction of photonic crystal fiber temperature sensor," *IEEE Sensors Journal*, vol. 22, no. 7, pp. 6832–6839, April 2022.

[2] M. Karim, R. Rafi, D. Dutta, M. I. H. Upal, and S. Ghosh, "Employing deep learning for predicting supercontinuum generation in chalcogenide planar waveguide," *Optik*, vol. 304, p. 171749, June 2024.

[3] M. Valliammai and S. Sivabalan, "Wide-band supercontinuum generation in mid-ir using polarization maintaining chalcogenide photonic quasi-crystal fiber," *Appl. Opt.*, vol. 56, pp. 4797–4806, Jun 2017.

[4] M. Valliammai, "Efficient wideband supercontinuum generation in mid-ir wavelengths using large mode area quasi-periodic cladding leakage channel fiber with low input energy," *IEEE Journal of Quantum Electronics*, vol. 53, pp. 1–9, Oct 2017.