Machine Learning Approach to Analyze the Different Optical Properties of FBGs

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Research Article

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Abstract

A generalized machine learning (ML) approach is proposed and demonstrated to analyse the various optical properties such as effective refractive index, bandwidth, reflectivity and wavelength of the Fiber Bragg gratings (FBGs). For this purpose, three commonly used FBG variants namely conventional, π phase-shifted and chirped FBG have been taken into consideration. Furthermore, the reflected spectra of those types of FBGs were predicted using a common tool. An exact spectrum was able to reproduce using this proposed model. This simple and fast-training feed-forward artificial neural network can predict the output for unknown device parameters along with the non-linear and complex behaviour of the spectrum minutely.

1. Introduction

Fiber Bragg gratings (FBGs) as one of the important fiber optic components is having many crucial applications in the field of fiber optic communication and sensing [1–3]. The key features of FBGs can be tuned by varying their geometrical parameters. Various types of FBGs are realized and implemented in the field of applications. Conventional FBGs with periodic refractive index (RI) is successfully used for dispersion compensation as well as in a large number of sensors covering various physical perturbations such as acoustic, magnetic, temperature, strain, refractive index, rotation etc. [4–6]. A π phase-shifted FBG can be achieved by little modification on the geometry of the conventional FBG structure. It attributes an ultra-narrow notch in FBG spectrum which can be explored for enhancing the sensitivity and resolutions [7]. Another popular type of FBG is chirped FBG which can be designed by introducing a non-uniform modulation of refractive index along the fiber on the periodic structure. Chirped FBGs (CFBG) is used for FBG interrogation and multiplexing technique along with a high-resolution sensing capability in dynamic measurement. It is also widely used in optical communication due to its dispersion compensation property [8]. These FBGs are characterized by specific properties such as effective refractive index (n_{eff}), central Bragg wavelength (λ_B), reflectivity and bandwidth spectrum. Due to distinct geometrical designs and light propagation mechanisms, each type of FBGs requires dedicated numerical modelling for analyzing the structure [9–11].

Keeping these in mind, we have proposed here a unified analyzing method covering these three widespread FBGs namely conventional FBG, π phase-shifted FBG and Chirped FBG. The proposed analyzing method is developed by exploring the machine learning technique. Owing to the capabilities of extracting essential information from a multitude of datasets, the machine learning technique has brought a thoroughgoing rehabilitation in the field of photonics. Such investigations to simulate the features of photonic components have been reported for these purposes in the last few years [12–16]. The simulation using MATLAB and Artificial Neural Network (ANN) has been put together to compute rapidly and exactly. The main goal is to construct a simple feed-forward multilayer perception (MLP) model which can be trained quickly to estimate the effective refractive index, central Bragg wavelength, reflectivity and the bandwidth of the FBGs. Furthermore, we have demonstrated the machine learning technique using a single ANN model to predict the reflection spectrum of different kinds of FBGs such as

normal, π phase-shifted and chirped FBG accurately for a large amount of data. Moreover, we show how our model can handle the non-linearity and complexity of the output spectrum exactly.

The paper has been organized as follows. Section 2 describes the ANN modelling. Here two different models for predicting the important parameters of FBG along with predicting the reflected spectra of different FBGs have been demonstrated. Section 3 presents the optimization of the epochs. Section 4 describes the different numerical results. The computation performance in terms of computational runtime is shown in Sect. 5 and finally, the paper is concluded in Sect. 6.

2. Fbg Modelling With Ann

ANN, a machine learning technique, is formulated on the structure of the biological neural network. This technique has the potential in solving a complex problem even though the input data set includes errors and are incoherent. Furthermore, it can estimate variables that cannot be measured directly.

The parameters for modelling the FBG have been introduced in this section. The first step to modelling is the identification of the input and output parameters. For the training process of the ANN model, a finite and appropriate labelled dataset is required. We performed a simulation program in MATLAB for generating the dataset (input-output pairs) for this purpose. The MLP architecture is used in this section for generating the dataset. The datasets which have been produced preliminarily plays a key role in developing the ANN model. The precision of the model fully depends on how well the dataset has been lined up to solve the particular problem.

Here, two different ANN models are proposed for analyzing the different optical properties of the FBG and to predict the output reflection spectra of different types of FBGs, respectively.

2.1 Modelling for the analysis of optical properties

In our ANN model, we have taken 5000 data sets taken which are partitioned into 80% training, 10% validation, 10% test data points. The data points consist of input parameters: refractive index of the core and the cladding, periodicity and the grating length, and output parameters: effective refractive index (n_{eff}), Bragg wavelength (λ_B), reflectivity and bandwidth. ANN model consists of 3 hidden layers and 40 nodes/neurons in each layer.

It has been observed that 3 hidden layers with 40 nodes in each layer were reasonable to quickly obtain a stable mean squared error (MSE). Further increase in the number of nodes and layers will increase the computational load and hence be avoided.

Popular "*Rectifier linear unit*" (ReLU) function has been used as an activation function and "*Adam*" optimizer for "gradient descent back-propagation" optimization. Adam optimizer is employed because it adaptatively accelerates the weights and biases of ANN over each epoch, hence provides a proper trade-

off between training time and learning rate. We have trained our model for 100 epochs (iterations) and validated it for 50 epochs.

2.2 Modelling for predicting the output spectrum of different FBGs

To predict the output spectrum of different FBGs using our proposed ANN model, we have taken a total of 10,000 data sets which is split into 70% training and 30% test data points. The data points consist of input parameter: wavelength which has been divided into two different ranges (hence two inputs at the input layer of the model) to maintain the uniform range along the x-axis for all FBGs and output parameters: reflectivity of normal, chirped FBG and π phase-shifted. The model consists of 7 hidden layers. Each hidden layer consists of 500 nodes. The popular "Rectifier linear unit" (ReLU) function has been used as an activation function and "Adam" optimizer for updating of ‘weights’ and ‘biases’ by reducing the ‘loss function’ of the model.

3. Optimization Of No. Of Epochs

Training an ML model in a well-fashioned manner to predict the output for unknown parameters accurately is of paramount importance. To achieve a well-trained model, the number of epochs plays a vital role. The number of epochs with the lowest mean squared error (MSE) is always desirable for this purpose. Here, we have optimized the epochs to train the model meticulously both for the training as well as the validation data set.

To optimize the epoch for analyzing the optical properties, 100 epochs and 50 epochs were taken into consideration for training and validation data set, respectively. From Fig. 3, we can see that as the number of epochs increases the MSE decreases. For the training data set, a constant MSE value was obtained for 50 epochs onwards. In our model, epochs of 100 were considered to make the prediction values closer to the actual values. The model was run until the MSE reaches the stable value i.e., 0.000047. Moreover, as the input dataset was well organized, hence with a smaller number of epochs, the MSE value closer to zero was obtained which can predict the output accurately. While for the validation data set the number of epochs of 50 was considered as the obtained MSE value was very low (0.000014). Due to the less volume of the validation data set i.e., 500, a low MSE value was obtained with relatively a smaller number of epochs as compared to the training stage of learning.

Similarly, for predicting the output spectrum of different kinds of FBGs, 7000 data was used to train the model. From Fig. 4 it can be depicted that, as the no. of epochs increases the MSE loss

Once the model is optimized with stable MSE values, appropriate outputs can be generated with new input data set that has not been used during the training process.

4. Numerical Results

4.1 Analysis of different optical properties of FBG

In this section, we have verified our proposed ANN models. For this, the outputs of the model were assessed for the unknown input parameters. Attention is paid to the effective refractive index, bandwidth, reflectivity and wavelength of the FBG that are the main parameters when used in different sensing applications including multiplexing/demultiplexing.

4.1.1 Effective refractive index (n_{eff})

Figure 4.1.1 shows the scattered plot between the predicted and the actual values of the n_{eff}. The predicted values of n_{eff} were obtained from our proposed ANN model while the actual values from the simulation using MATLAB. Due to the overlapping of the predicted data, a continuous plot can be observed. A linear trained state the well-trained behavior of the model.

4.1.2 Bragg Wavelength (λ_B)

Bragg wavelength of FBG plays a vital role in sensing purposes [17–18]. Accurate measurement of this parameter is of paramount importance in different applications. We have chosen the most useful wavelength range i.e., 1500–1600 nm for this purpose.

Here we have predicted the wavelength of the FBG using our proposed ANN model. Figure 4.1.2 depicts a linear relationship between the actual and the predicted values of Bragg wavelength. This signifies that our model can predict the unknown wavelength accurately. 100 epochs were considered to predict the wavelength accurately.

The demodulation technique of FBG sensors relies upon the detection of the wavelength shift of the sensor peak at the Bragg wavelength. Hence, it is important to analyze the spectral characteristics of the FBG sensor. It was reported that the grating length plays a significant role to design a high-performance FBG based sensor [10]. Therefore, the two most important parameters of the spectrum i.e., reflectivity and bandwidth were considered for further analysis. Well-known coupled-mode equations solved by the transfer matrix method was used to collect the input data.

4.1.3 Reflectivity

One of the most important parameters to fabricate a grating for a particular purpose is the reflectivity of that grating. Reflectivity is the percentage of light reflected at the Bragg wavelength. Reflectivity changes with an increase in grating lengths.

In this portion, the change of the reflectivity has been analyzed using our proposed model with the elevation of the grating length. The result was compared with the simulated result using MATLAB.

The change of the reflectivity with the grating lengths ranging from 1 mm to 50 mm was analyzed as shown in Fig. 4.1.3. Figure 4.1.3 (a) depicts the relationship between the aforesaid parameters using

MATLAB while Fig. 4.1.3 (b) using our proposed ANN model. A good agreement between both results was observed. Reflectivity increases rapidly with an increase in the grating length. The highest reflectivity was observed from the length of the grating of 8.5 mm onwards.

It is worthy to note that, our model can predict the non-linear behavior of the parameters.

Furthermore, the scatter plot between the actual and the predicted reflectivity has shown in Fig. 4.1.3 (c). A linear relationship between the two parameters ensures the well-trained behavior of the model. Due to the coherent nature of the input data set, more data are accumulated over the range of 95 to 100% in the plot.

4.1.4 Bandwidth

Bandwidth is the measure of the reflected signal spectral width. It is usually measured at the full-width half maxima (FWHM). To investigate the grating length dependence on the bandwidth of the FBG spectrum, the grating length ranging from 1 mm to 50 mm was considered. Figure 4.1.4 depicts the relationship between the aforesaid parameters. The tendency is very similar to the results of reflectivity change but in an inverse direction. Here 3-dB bandwidth change shows an exponential decrease over the elevation of the grating lengths. The simulated result is shown in Fig. 4.1.4 (a) while an exact match in the relationship is observed while performing using the proposed ANN model. In case of 1 mm FBG sensor, the bandwidth is around 1.40 nm. The bandwidth reduces as the grating length increases. The grating length reduces to around 1.03 nm at grating length of 5 mm. A constant value of the bandwidth is maintained beyond the grating length of 5 mm.

The scatter plot between the actual and predicted data for the bandwidth is shown in Fig. 4.1.4 (c). A linear relationship between the actual and the predicted values of bandwidth is observed. Hence the well-trained nature of the proposed model is proved.

4.2 Predicting the reflection spectrum of the different FBGs

FBGs are distributed Bragg reflectors that reflect a particular wavelength of light and transmit others. This is achieved by the periodic variation of the refractive index along with the core of the fiber. By changing the periodicity of the gratings, different types of the reflected spectrum of FBGs can be achieved. Chirped FBG is one of these types of FBG having non-uniform periodicity along the length of the fiber [19]. Furthermore, dynamic strain measurement with higher resolution (pico-strain) is an important area of research and development [20]. With normal FBG is quite impossible to breach the limit. π phase-shifted FBG, expected to be used widely in near future is a successful candidate in these aspects. π phase-shifted FBG can be fabricated on a standard FBG by introducing a phase jump at the centre of the grating. Due to the very sharp resonance peak, this type of FBG shows a higher resolution and enhance sensing capabilities [21].

Keeping all these aspects in mind, this section is devoted to predicting the reflected spectrum of three different types of FBG: normal, πphase-shifted and chirped FBG using our proposed ANN model.

The reflected spectrum for three different types of FBGs has shown in Fig. 4.2. The spectra obtained using our proposed ANN model have been compared with those using MATLAB programming. An exact match between these was observed. Hence it can be concluded that our proposed model can predict the output spectrum of different FBGs accurately within seconds, while numerical simulation methods a few minutes.

Moreover, it should be noted that our proposed model can predict the non-linear behaviour and complexity of the spectrum entirely as expected.

Seven hidden layers with 500 nodes in each were used throughout the code, which offers rapid convergence and sufficient accuracy in predicting the output for unknown dimensions. The authors believe that the proposed model may find a wide range of applications in future.

5. Computational Performance

In this section, we have described the computational performance in terms of the ‘runtime’ of our proposed ANN model. For computing using the ANN model, a laptop with Intel Core i7 10th generation, CPU @ 2.30 GHz, 16 GB RAM with GPU configuration: Nvidia RTX 2080 Super Max-Q with 8 GB RAM having Windows 10 operating system. The runtime to train the ANN model fully depends on the parameters such as the size of the input data set, number of the optimized hidden layers, number of the neurons in the layers, number of epochs etc. Here two different models were used for two purposes. For analyzing the optical properties of FBG, 3 hidden layers with 40 nodes in each layer running for 100 epochs were optimized. It took around 23 seconds to train the model with the generated data set. For validation, it took around 1.25 seconds. While for predicting the output spectrum, 7 hidden layers with 500 nodes in each layer running for 2000 epochs were optimized. To train the model it took around 11 mins.. After completing the training process, weights and parameters were saved on the computer. The prediction and analysis were carried out using the already saved weights. Conversely, the numerical simulation using MATLAB requires a few minutes for calculating each point. It may be still taking a long time if a denser mesh is considered.

6. Conclusion

In summary, a supervised machine learning technique using the ANN model has been implemented to accurately predict different parameters of FBG along with the reflected spectrum of different types of FBGs thoroughly. Our proposed models can estimate the effective refractive index, central Bragg wavelength, reflectivity and the bandwidth of the FBG minutely. Furthermore, the output spectrum of normal, π phase-shifted and chirped FBG was predicted exactly using a single model. The hidden layers and the neurons in each layer were optimized to offer rapid convergence with sufficient accuracy in predicting the outputs for unknown parameters. The comparison between the actual and the predicted values of different parameters was shown. A straight-line plot reflects the well-trained behavior of our proposed model. The number of epochs and the neurons in each layer was optimized to avoid the

overfitting and under-fitting problems. Our proposed ANN model can portend within few seconds while it takes a longer time when using MATLAB and other simulation tools. Evidently, the proposed model can predict the complex and non-linear behavior of the spectra. The authors believed that our proposed model could be an alternative to the other simulation tools and have the potential to solve both the forward and inverse problems. To best our knowledge, there are no reports about such ML tools for predicting FBG characteristics. Likewise, this model can be extended to different waveguides to analyze different properties and phenomena.

Declarations

Authors' contributions

Koustav Dey has conceptualised, collected the raw data, did the primary analysis and prepared the manuscript. V. Nikhil has generated the input data set and performed the machine learning programming. Sourabh Roy has analysed the results, drawn the conclusions and finalized the contents of the manuscript.

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Authors Declarations:

Consent to Participate All authors are voluntarily participating for the submission of this research work.

Consent for Publication All authors expressed their consent to publish this research study.

Availability of Code Code is not available publicly at this time but may obtained from the authors upon reasonable requests.

Conflicts of Interest/Competing Interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Compliance with ethical standards

Not applicable

Human and Animals Rights Authors declare no research involving human participants and/or animals was conducted.

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Figures

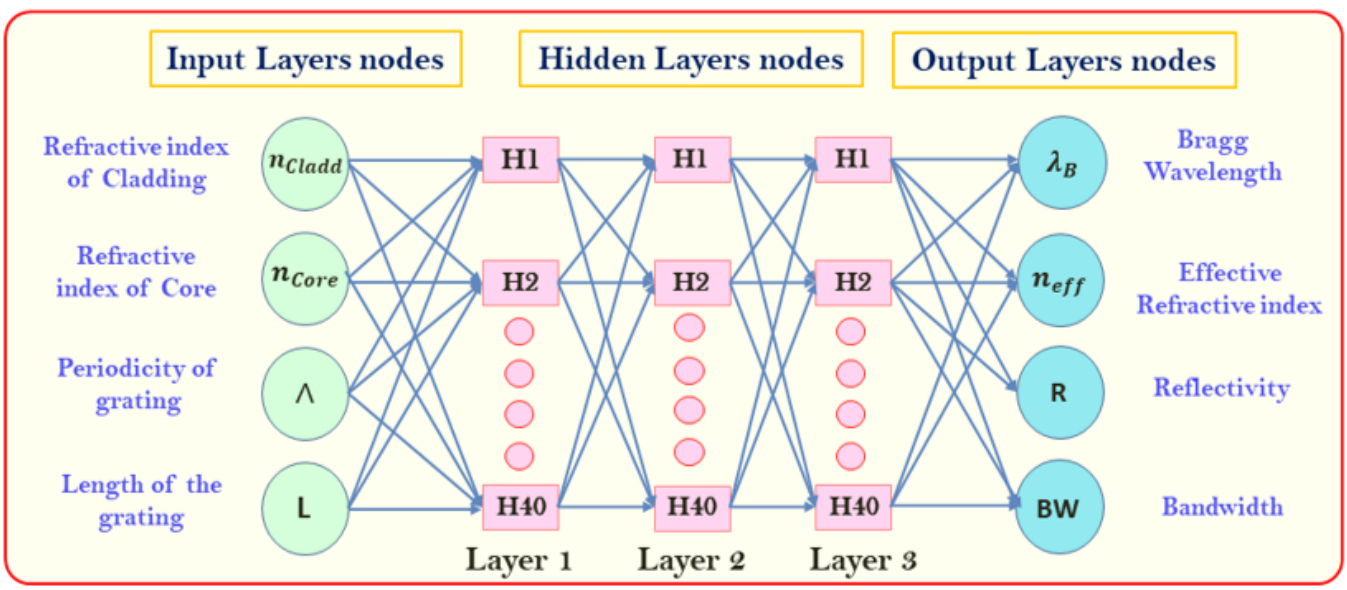

Figure 1

Artificial neural network (ANN) illustration with one input layer (4 input nodes), three hidden layers (40 nodes in each layer) and one output layer (4 output nodes).

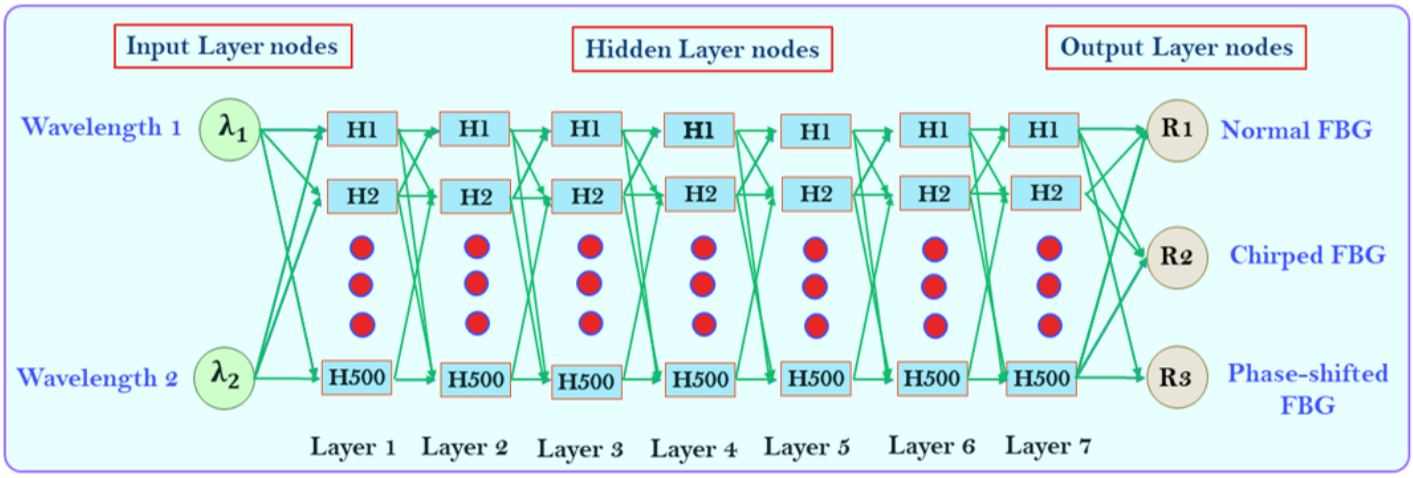

Figure 2

Artificial neural network (ANN) illustration with one input layer (2 input nodes), seven hidden layers (500 nodes in each layer) and one output layer (3 output nodes).

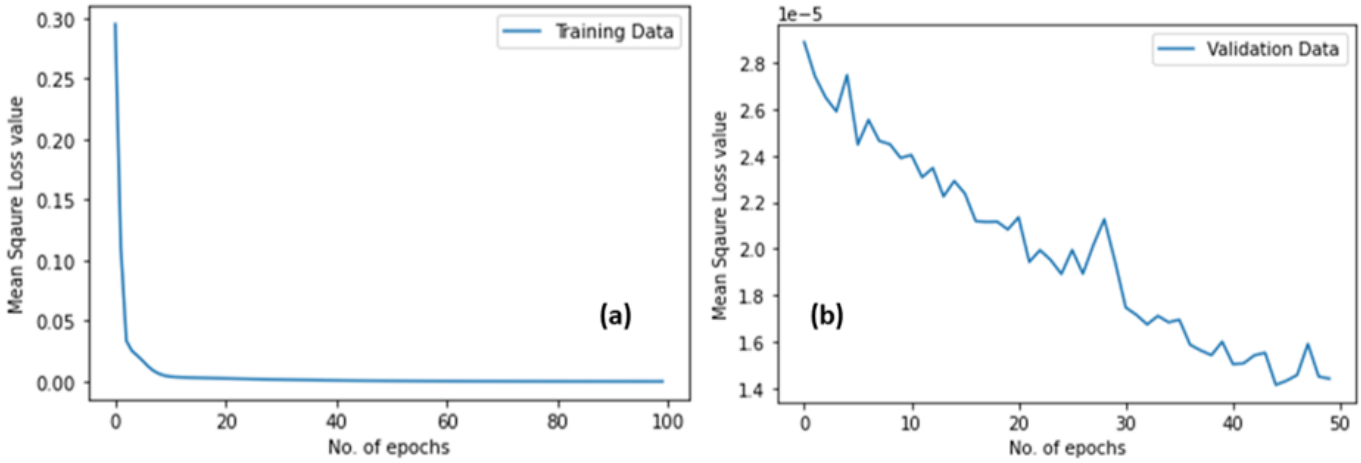

Figure 3

Mean square loss vs. no. of epochs for (a) training data and (b) validation data.

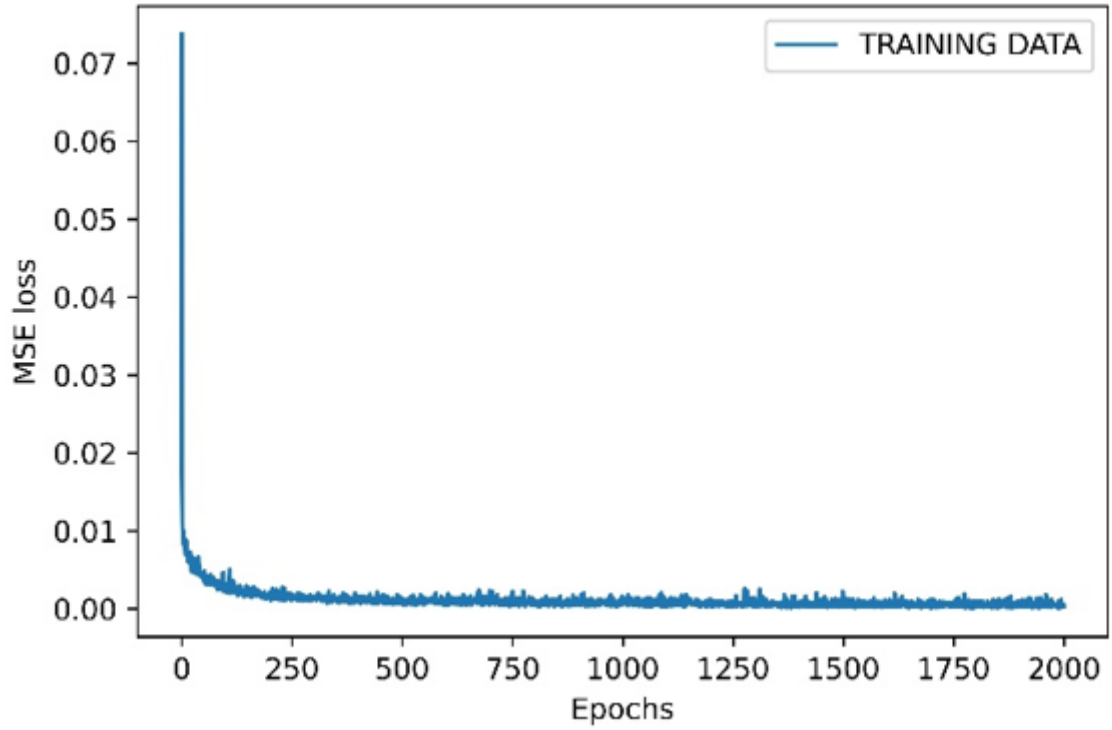

Figure 4

Mean square loss vs. no. of epochs for training data set.

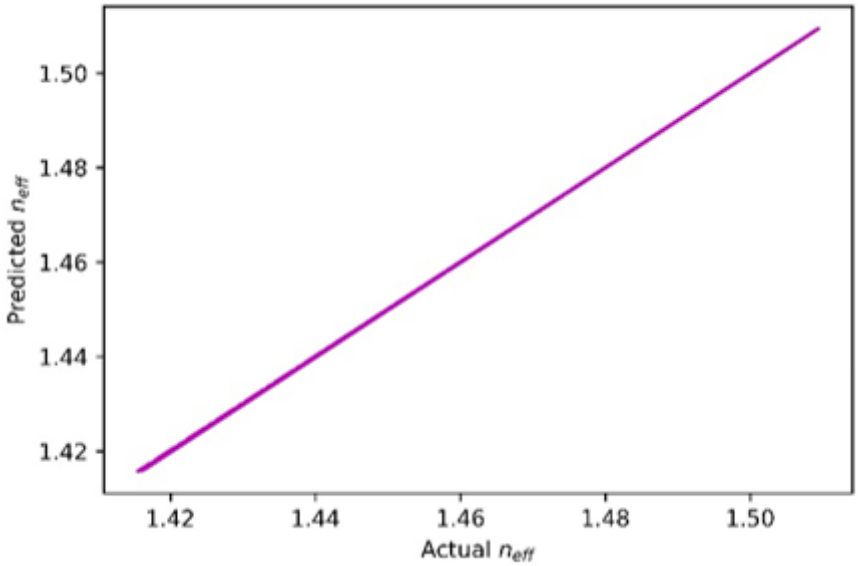

Figure 5

Scatter plot of a training dataset of predicted and actual for neff

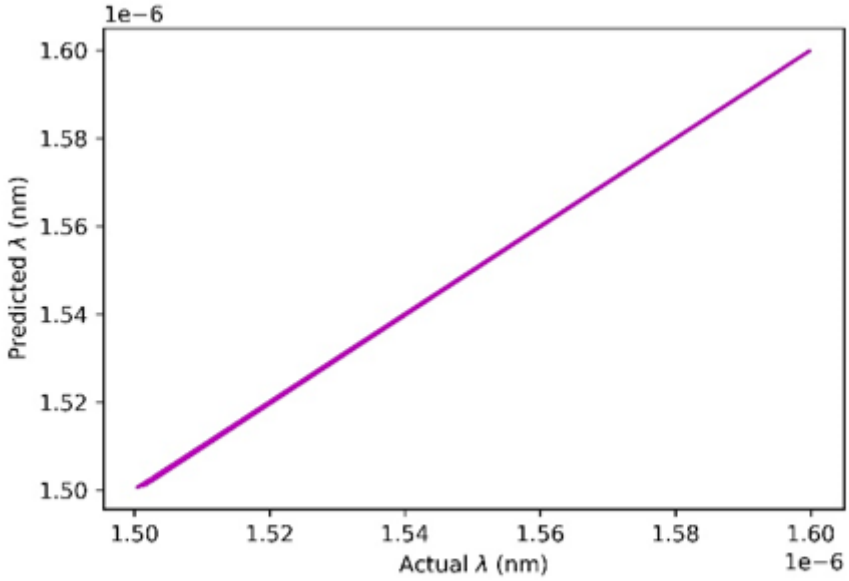

Figure 6

Scatter plot of a training dataset of predicted and actual wavelength.

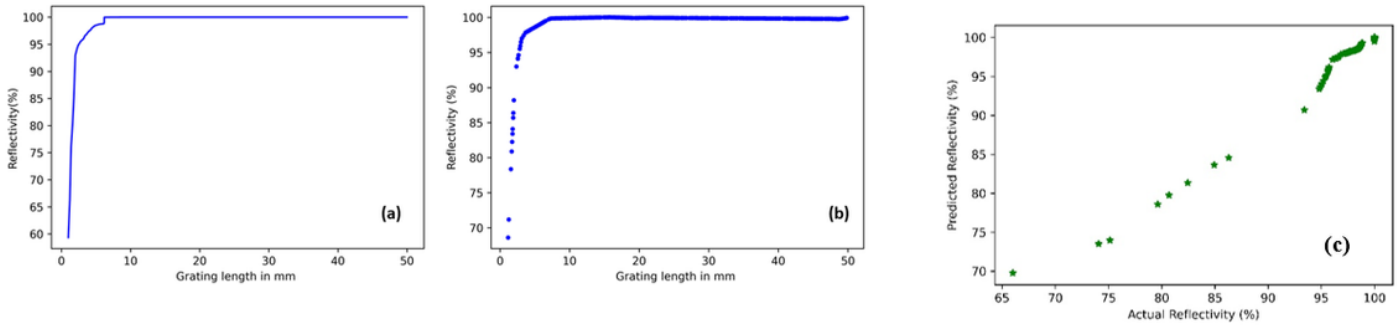

Figure 7

Reflectivity vs. grating lengths of the FBG using (a) MATLAB and (b) ANN model (c) Scatter plot of a training dataset between the predicted and actual values of the reflectivity of FBG.

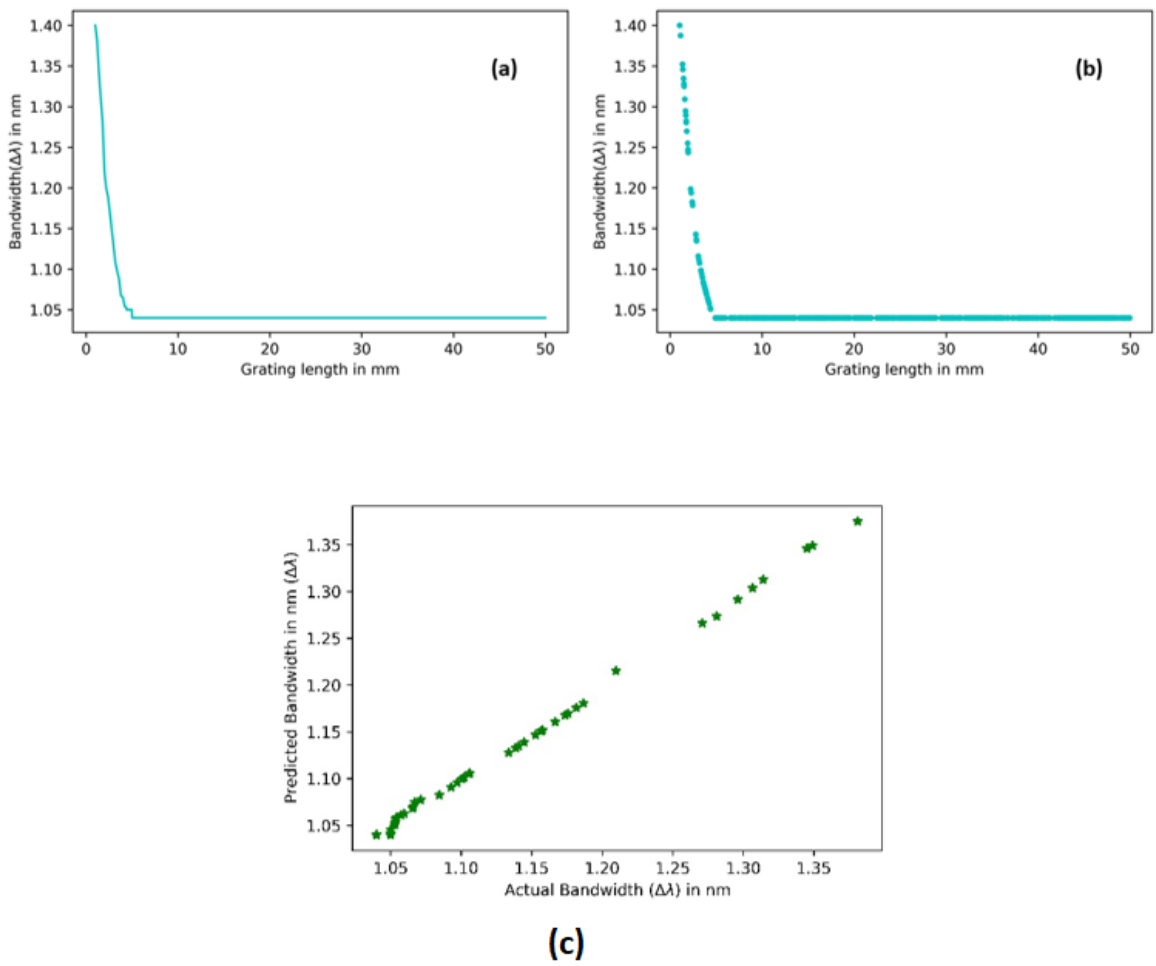

Figure 8

Bandwidth vs. grating lengths of the FBG using (a) MATLAB and (b) ANN model (c) Scatter plot of a training dataset between the predicted and actual values of the bandwidth of FBG.

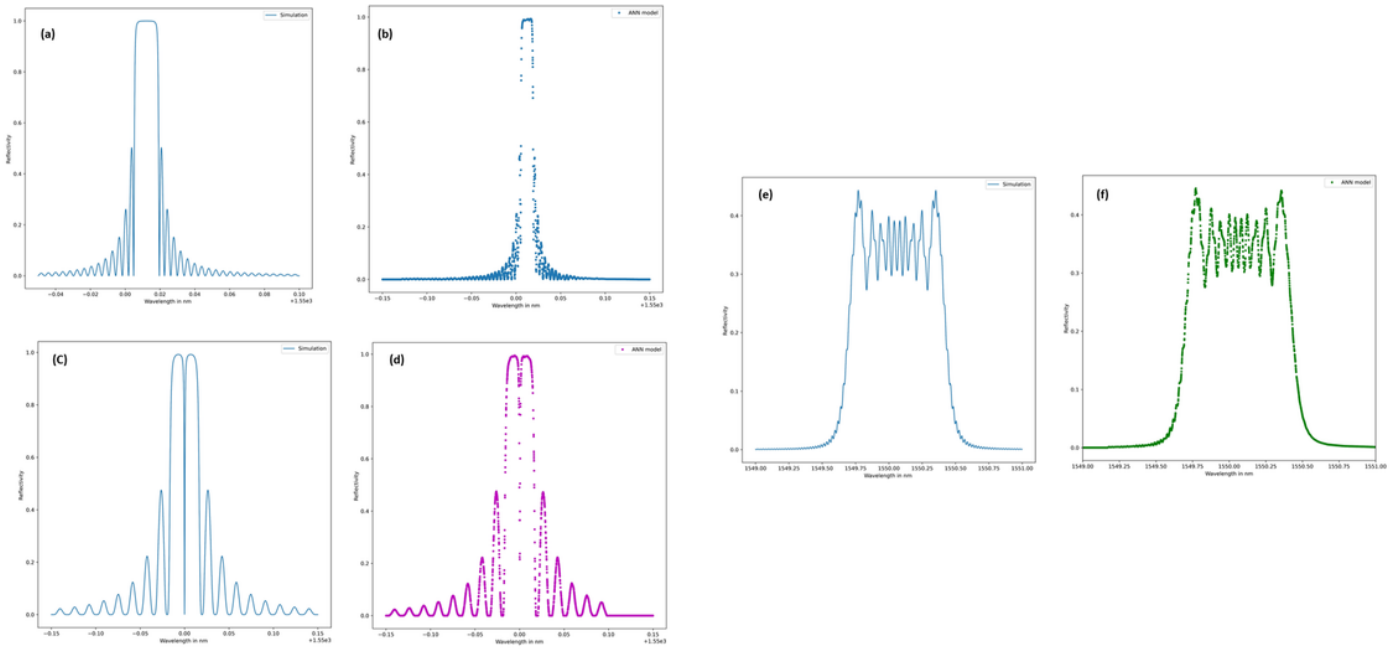

Figure 9

Reflected spectrum obtained using MATLAB and proposed ANN model for (a)&(b) Normal FBG; (c)&(d) πphase-shifted FBG and (e)&(f) chirped FBG, respectively.