Structure Health Analysis using Smart Fiber Optic Sensor

5.1. Introduction

The neural network method has been developed and adopted for investigating structural health. Cantilever beam structure has been considered to mimic structural problems. The measurement of strain in the beam and locating of the damage in the structure, if present, has been carried out using artificial intelligence. The results of NN method for strain in the beam have been verified with the results obtained from the strain gauge and also obtained from the finite element analysis. The various optical parameters obtained from FOS have been used for training and testing of the neural network model.

5.2. Strain approximation Using Conventional methods

5.2.1. Strain Gauge Method

Strain gauges are the most widely used strain measurement technology. It is generally used in combination with the Wheatstone bridge circuit. In present work, strain gauges are used for validation of the result. V_{ex} is the excitation voltage equal to 3 volt, R_g is the strain gauge resistance equal to 120 ohms, balancing resistances R_1, R_2, and R_3 are taken as 120 ohms. V_{su} voltage is defined as the ratio of voltage difference in voltage of strained and unstrained with excitation voltage. R_L is the load resistance of 120 ohms. Strain gauge factor(G.F) is the ratio of relative change in electrical resistance, to the mechanical strain. In the present work, G.F is taken as 2. Strain values can be obtained by using equation 5.1.

$$\varepsilon = \frac{-4V_r}{G.F(1+V_{su})}\left(1+\frac{R_L}{R_g}\right) \tag{5.1}$$

5.2.2. Finite Element Model

Finite element analysis is one of the most accurate and precise tools used by different researchers and analysts. A model of a cantilever beam having dimensions 24x6 mm^2 cross-sections and length of 180 mm has been considered for finite element analysis. ANSYS 16.1 software is used to develop the model. The analysis of four different models, as given in table 4.1, has been carried out. In the analysis, the solid 20 node 186 element type is used. Material properties include linear elastic, isotropic material with a material density of 2700 kg/m^3. Modulus of elasticity is taken as 70 GPa, and poison's ratio is 0.33. The constraints are provided on one end of the cantilever beam with all degrees of freedom. Loading is applied to the free end of the beam in the negative Y direction. The load is varied, starting from 2N to 10N in the step of 2N. For applying Dynamic loading at the free end of the beam, a loading function is defined in function editor as given in equation 5.2.

$$LoadingFunction = A_L * \sin(\frac{\pi}{2} * \{TIME\}) \tag{5.2}$$

A_L is the amplitude of the loading function and is defined as in equation 5.3.

$$A_L = m_0 e\omega^2 \tag{5.3}$$

Where m_0 is mass of unbalanced mass equal to 0.002 kg, e is the eccentric distance equal to 20 mm, and ω is the angular velocity equal to146 radian/ second. The saved function is selected for applying dynamic ramped loading with a time step size equal to 1. Time at the end of the load step is selected as 20. An additional point load is applied at the middle node of the free end of the beam to obtain variation in the amplitude of beam vibration. After the solution using ANSYS, the axial von-misses strains values at the middle node on the top surface under different loading conditions are obtained.

5.3. Strain approximation using FOS under static loading

5.3.1 Neural Network Methodology

Artificial Neural network (ANN) is an intelligence-based processing structure that is made up of interconnected processing units called neurons. Each neuron transmits a weighted function of its input to the preceding layer of the neuron. The process of transfer of weight is based on the type of training function used in the network. An NN includes three layers: input, hidden, and output layer. Variables are given as a contribution to the input layer, which is associated with the hidden or concealed layer for processing. The concealed layer contains an activation function that ascertains the weight and bias of the variable for investigating the impact of indicators upon the objective factors. The output or yield layer is utilized for anticipating the outcomes with error estimation. In the back-propagation algorithm, at first, the input is engendered to the concealed layer, at that point the shrouded layer proliferates criticism to the information layer to reduce error. Toward the finish of the procedure, it refreshed the weight and bias variables. The back-propagation algorithm is delayed to combine and may cause overfitting. To solve these problems, techniques like Levenberg-Marquardt back-propagation (LM) and Bayesian Regularization back-propagation (BR) are developed for fast convergence without overfitting. Different training functions like LM back-propagation, BR back-propagation, scaled conjugate gradient back-propagation, and resilient back-propagation are available in the Matlab software. In present work, two different training functions, namely Levenberg-Marquardt back-propagation and Bayesian regularization back-propagation, is compared for the approximation of strain values. Levenberg-Marquardt back-propagation algorithm uses the conjugate gradient technique to reduce the sum of squares at each iteration. This algorithm is developed for fast convergence. Bayesian regularization algorithm contains an objective function that includes a residual sum of squares and sum of squared weights to minimize estimation errors for obtaining the required model. In the present study, the training algorithms of LM and BR are compared on the bases of prediction ability in determining the strain values. To compare the performance of both the algorithms, different errors like root mean square error (RSME), mean square error (MSE), mean relative error (MRE) and mean absolute error (MAE) between real and predicted data are analyzed.

An optical output signal from the fiber optic sensor is generated and is fed to the digital oscilloscope for further analysis. Thousand data points are obtained as voltage versus time curve in the time domain. Fast Fourier transform is applied to the signals to convert time-domain signals into the frequency domain signals. Different optical parameters, like the real part, imaginary part, magnitude, and phase, are analyzed using ANOVA (analysis of variance) test. A comparison of the ANOVA test corresponding to 2N to 10N is shown in table 5.1. The signature value equal to 1 shows that the mean difference of corresponding (phase and amplitude) data is significant, whereas a signature value equal to 0 shows that the mean difference of corresponding data (real part, imaginary part, and magnitude) is not significant. The analysis shows that the phase is the only optical parameter that provides variation in the data signal. Thus, a phase shift can be assumed to be proportional to the strain developed on the host material. A direct relationship between phase and intensity of light provides a promising parameter for the prediction of the mechanical phenomenon. Sample *A* is considered as a reference sample, and change in phase and intensity are calculated against the values of this reference sample.

Table 5.1. Signature of ANOVA test corresponding to different loads

Load(N)	**Sample**	**Real part**	**Imaginary part**	**Magnitude**	**Phase**	**Amplitude**
2N,4N,6N, 8N,10N	Sample *B*	0	0	0	1	1
	Sample *C*	0	0	0	1	1
	Sample *D*	0	0	0	1	1

5.3.2. Training and testing of the model

Different cross-validation methods are present which can be used in the machine learning process. Cross-validation is a method of estimating expected prediction error thus helping in selecting the best fit model for a required problem. It also encounters the problem of overfitting of the model. There exist various cross-validation models like the hold-out method, k-fold cross-validation, and leave one out cross-validation and bootstrap method. In the hold-out method, two subsets are formed, one part of the sample is considered for training and another part is tested. A drawback of this model is its dependency on data selection. Output performance is directly affected by changing the training and hold-out subsets. In k-fold cross-validation, the sample is divided into k subsets. One subset is considered for validation and rest subsets are taken for training. In further analysis different subset is taken under validation and rest subset data is considered for training. This process continues until all subsets are analyzed sequentially by the model. The advantage of using this method is that each subset forms a sample for training and validation. This data division reduces the selection bias that is present in hold-out cross-validation.

Leave one out cross-validation is a more generalized form of k-fold method. In this method, each data is considered as the validation set and rest data is taken for training. A similar k-fold sequential analysis is performed to calculate the error for each validation set. The main drawback of this method is that it is expensive and the time of computation is high. Bootstrap is another known method for cross-validation. In this method, random data is selected. The selection of the model is based on the refitting and error estimation of model performance. This process also carries high computation cost and time.

The proposed ANNs undergo training, validation, and testing phases of 1000 combinations of data. Stratification of data for testing and training is done using a hold-out cross-validation method. A Tansig transfer function is used in the hidden layer. Out of 1000 data, 667 data were used for training, and the remaining 333 data were used for testing. Comparison of the LM and BR algorithm is made for sample *A*. The number of neurons in the hidden layer is one of the major parameters which affects the performance of the network. In the present analysis, even numbers of neurons starting from 2 to 30 are considered for both the algorithms. The method of selection of algorithm and the minimum number of neurons in the hidden layer is based on the minimum error criteria regarding RMSE, MSE, MRE, and MAE. A comparison of different errors related to LM and BR algorithms is shown in fig. 5.1. The formulas for error criteria are as follows:

$$MSE = \sum_{i=1}^{N} \frac{(Y_i' - Y_i)^2}{N} \tag{5.4}$$

$$MRE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{(Y_i' - Y_i)}{N} \right| \tag{5.5}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} (Y_i' - Y_i) \tag{5.6}$$

$$RMSE = \frac{1}{2} \sum_{i=1}^{N} (Y_i' - Y_i)^2 \tag{5.7}$$

Where Y_i is predicted output value, Y_i' is the actual output, and N is the number of samples. The objective is to devise the criteria that estimate the number of hidden neurons as a function of input neurons to develop a model for strain prediction. The error values are obtained by varying the number of neurons in the hidden layers of the neural network model using Levenberg-Marquardt and Bayesian Regularization algorithm, respectively. As defined before, different error estimations were made for training the network using the data of sample *A*. Variation in the number of neurons in the hidden layer is taken as 2xn (n=1….15). Error histogram of root means square error as given fig. 5.1a has the lowest error of $1.86e^{-10}$ using ten neurons corresponding to the BR algorithm. Mean square error has the least value of $3.46e^{-20}$ using BR algorithm with ten neurons in the hidden layer (fig. 5.1b). Histograms (fig. 5.1 c, d) show the minimum value of mean relative error and mean absolute error as $4.18e^{-10}$ and $3.46e^{-20}$, respectively corresponding to the BR algorithm again using ten neurons. From fig. 5.1, it is evident that the minimum error for the LM algorithm is obtained by using two neurons in the hidden layer, whereas for the BR algorithm, it is obtained for ten neurons. Using a smaller number of neurons in the network has an advantage of the reduction in computation time. In the present study, the prime focus was to reduce the error in comparison to computation time.

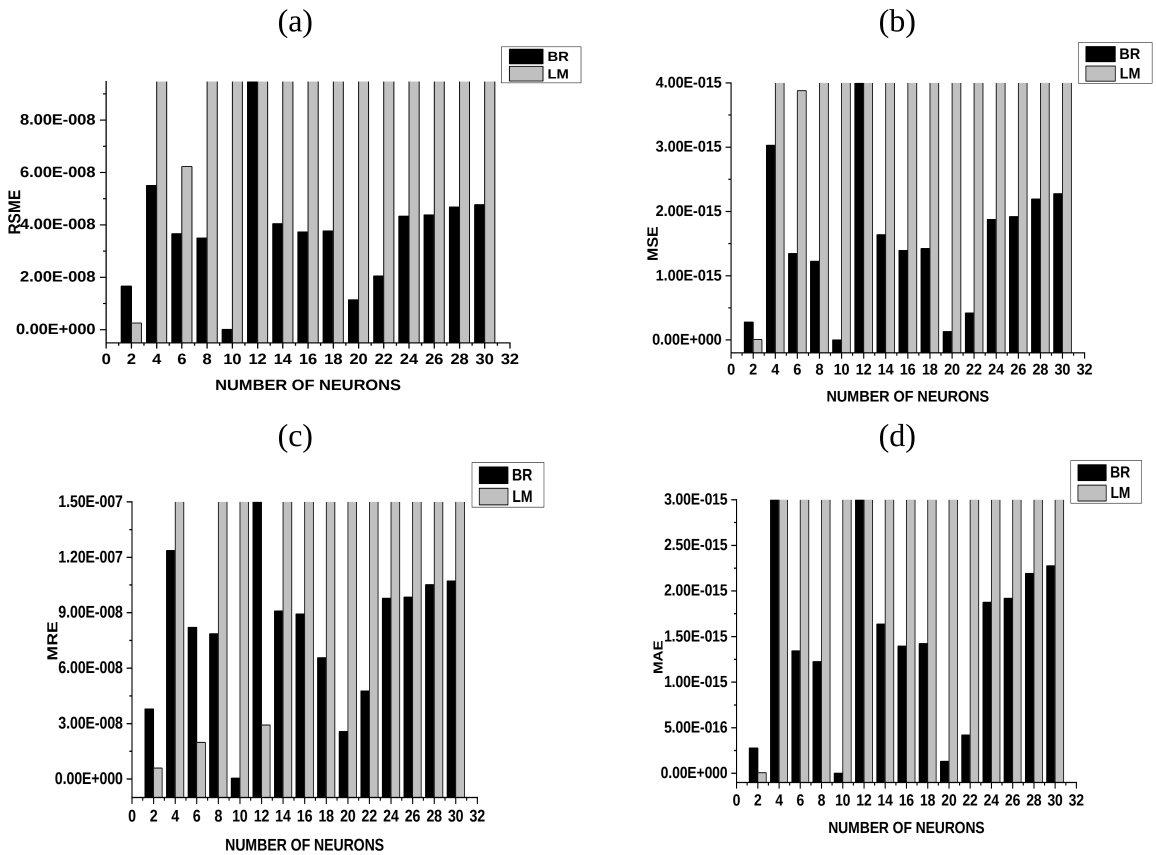


Fig. 5.1. Different error comparison of Levenberg-Marquardt and Bayesian Regularization algorithms (a)RSME histogram; (b)MSE histogram; (c)MRE histogram;(d)MAE histogram

Error using ten neurons in the Bayesian Regularization algorithm is much smaller as compared to using two neurons in the Levenberg-Marquardt algorithm. Hence fixation of the number of hidden neurons is done based on minimum error estimation. Moreover, the Bayesian regularization back-propagation algorithm is selected for training the neural network to verify the strain values.

Regression values are used in this study to evaluate the performance of the artificial neural network. The regression value is estimated as per equation 5.8. Regression analysis of various samples under different loads corresponding to train and test state is shown in fig. 5.2. Regression values are low for both train and test samples, but it increases on increasing the load. All regression values are well within the acceptable range.

$$R = \sqrt{1 - \frac{\sum_{i=1}^{N}(Y_i' - Y_i)^2}{\sum_{i=1}^{N}\left(Y_i' - Y_{avg}\right)^2}} \tag{5.8}$$

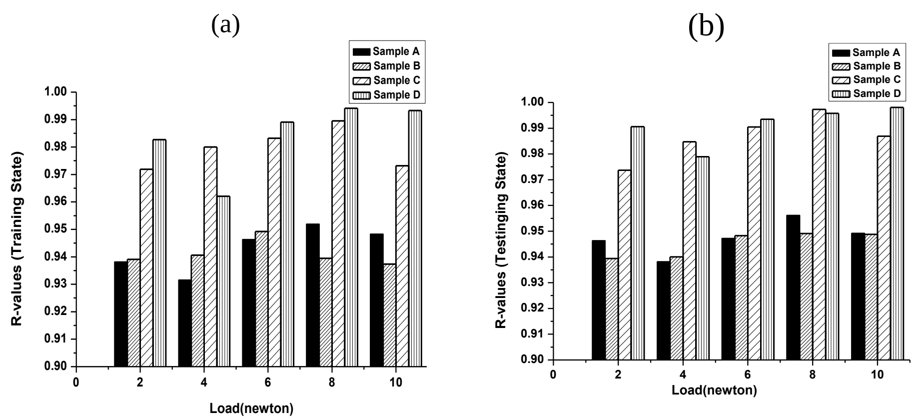


Fig. 5.2 Regression histogram showing variation in sample type at different loads. (a)Training R-value histogram;(b) Testing R-value histogram.

Plots of the regression values related to train and test sets are shown in fig. 5.3. At low loads of 2N and 4N, regression values are low corresponding to both training and testing sets. But the value of regression increases to an acceptable range with an increase in load. The objective of the above least square estimation and regression analysis is to develop a model for strain determination using optical parameters. The schematic of the developed neural network model is shown in fig. 5.3.

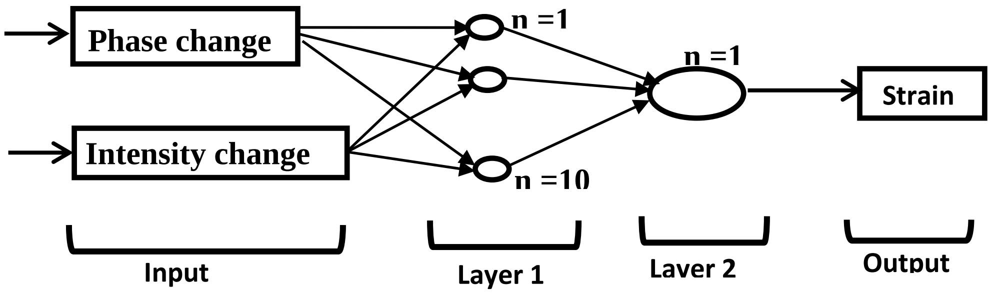


Fig. 5.3 Schematic of neural network architecture for strain detection

5.3.3. Results and Discussion

Fig. 5.4(a) shows the comparison of strain values related to the strain gauge and the finite element method. As seen, the corresponding sample shows good agreement between two methods under consideration at different loads. The relative mean error of different samples is calculated with respect to the finite element model. Fig. 5.4(b) shows that minimum error is 1.09074% for sample *A* and the maximum error is 2.93951% relative to sample *C* and *D*. All errors are well within acceptable limits. Some variations in values of strain gauge measurement give under prediction on increasing load. The reason behind this under-prediction maybe because of the actual strain and the strain transferred to the strain gauge from the host material.

In this section, the comparison of strain values obtained from FEA, and a pre-existing analytical solution given by Haslach [82] have been compared. The analytical solution is based on equation 3.30 of section 3.5 discussed in chapter 3. As shown in fig. 5.5(a), over and under prediction occur in strain values at different loads. Moreover, fig. 5.5 (b) show relative error histogram in which minimum error is

3.05708% corresponding to sample B and the maximum error value is 10.2227% for sample *C* and *D*. This phenomenon of over and under prediction may occur due to dependence of phase change in an optical parameter is affected by the different noise that exists in practical experimentation. The laser source and noise is already discussed in section 3.5 of chapter 3.

In the last section, ANN results have been compared with the results of the finite element model. As is seen in fig. 5.6(a), strain values predicted by the ANN model have higher confidence and accuracy under all loading conditions. Normalize phase change and change in intensity are used as input, and strain values are set as output for ANN modeling. ANN architecture used in the analysis is shown in fig. 5.6. Neural network analysis was performed at 1000 epochs as further training at higher epoch's results in high error variation. Based on minimum error criteria considering four different errors, provide logical reasoning of using the Bayesian regularization back-propagation algorithm in neural network analysis. The mean error histogram is shown in fig. 5.6(b), in which minimum error corresponding to sample *B* is obtained as $3.59e^{-6}$ %. The maximum value of error is 10.2227%, which corresponds to sample *C* and *D*.

(a) (b)

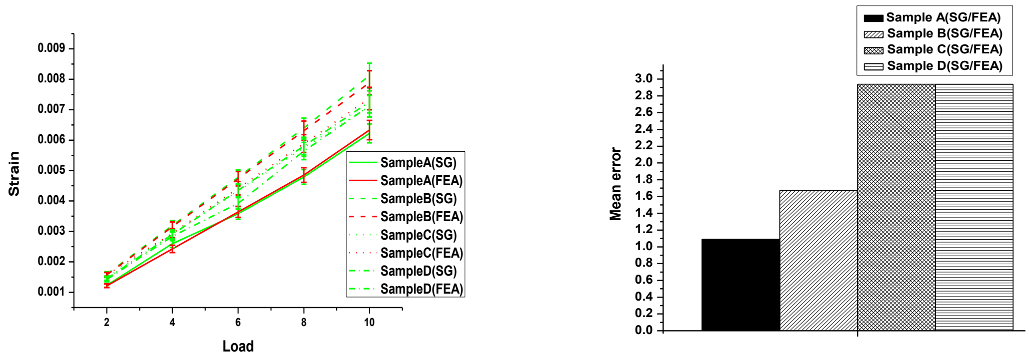


Fig. 5.4 Comparative results of strain gauge and finite element modeling (a)Strain value comparison at different loads, (b) Relative mean strain gauge error histogram

(a) (b)

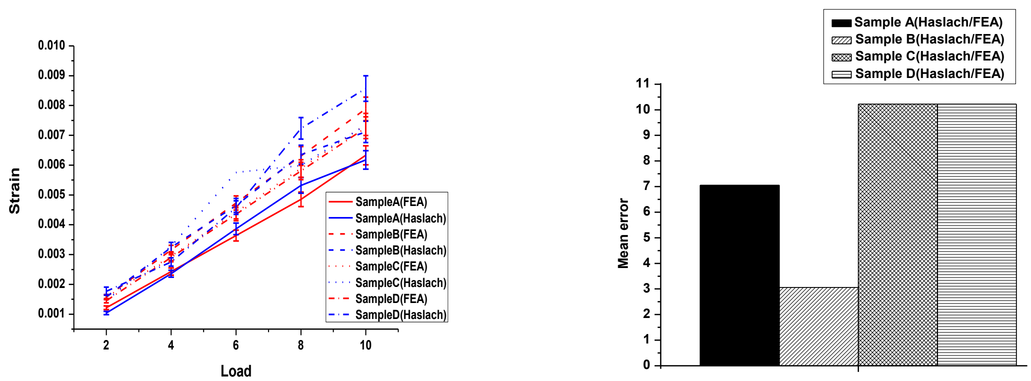


Fig. 5.5 Comparative results of analytical solution and finite element modeling (a)Strain value comparison at different loads, (b) Relative mean strain error histogram

(a) (b)

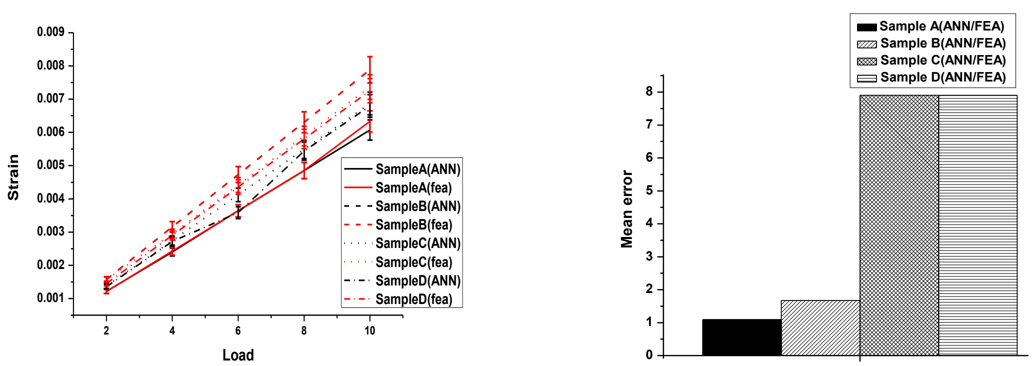


Fig. 5.6 Comparative results of the neural network model and finite element modeling (a) Strain value comparison at different loads, (b) Relative means strain error histogram.

5.4. Strain approximation using FOS under dynamic loading

5.4.1. Neural Network Methodology

As earlier defined in section 5.3.1 network takes variable parameters as input in the input layer, then processing is done and it is transferred to the hidden layer. Hidden layer contains some activation function which explores the weights and bias of variable for prediction of the target values. The output layer is designed to store predicted values with some error estimation. The back-propagation algorithm is applied in the neural network. The major disadvantage of using back-propagation is slow convergence and overfitting. To overcome the problem of convergence two algorithms namely Levenberg-Marquardt and Bayesian regularization are tested, which will be discussed in the following section. To counter overfitting of data set cross-validation is performed. In this study selection of the algorithm is based on the regression analysis and mean square error which is performed on sample A under different loading conditions. A Tansig activation function is used in the network has a range 0 to 1. The function is given in equation 5.9. Normalization of input data is done for obtaining its values in the function range value (i.e. 0 to 1).

$$f(z) = \frac{1}{1 - e^{-z}} \tag{5.9}$$

Analysis of experimental data is performed using a static approach ANOVA. Time-domain signals are converted into a frequency domain signal using a fast Fourier transformation. Analysis of variance is performed using different signal parameters under the Tukey test with a significant value of 0.05. ANOVA tests for the real part, amplitude, and phase show that the sample size of 1000 interquartile range doesn't show much difference in all the different sample categories. Moreover, median values also show a significant difference. The test results are summarized in table 5.2. From this test approach, we can say that significant variation corresponding to the external host occurs only in the real part, amplitude, and phase of the signal. Sample *A* is the reference sample, and change in phase and intensity are calculated based on the reference sample.

Table 5.2 ANOVA analysis under different loading

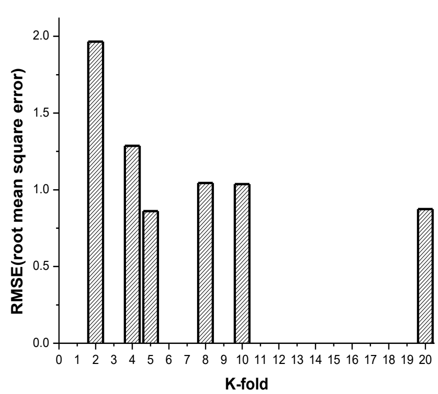
Load(N)	**Sample Type**	**Real Part**	**Imaginary Part**	**Magnitude**	**Amplitude**	**Phase**
2N,4N,6N, 8N,10N	Sample B	1	0	0	1	1
	Sample C	1	0	0	1	1
	Sample D	1	0	0	1	1

5.4.2. Training and testing of the model

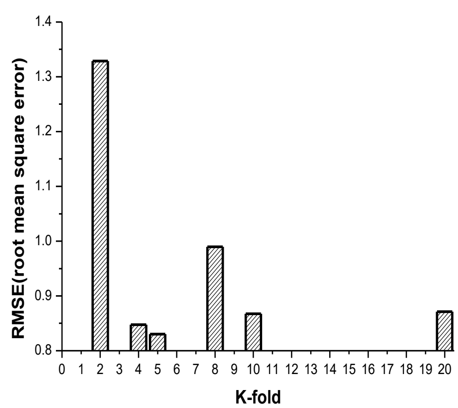
A set of 4000 data corresponding to different samples (*A, B, C, and D*) under specific loading is obtained. Data contains optical parameters like real part, phase change, amplitude, and target strain values. As described in section 5.3.2, the k-fold method (k = 2, 4, 5, 8, 10, 20) is employed for error validation of the neural network model. As the sample size is 4000, therefore, several k-folds are selected to give an even distribution of data in respective subsets. Comparison of Levenberg-Marquardt (LM) and Bayesian Regularization (BR) is carried to select the best artificial neural network model for strain approximation under dynamic loading. The single-layer perceptron model with 10 neurons in the hidden layer is used for model validation.

The selection criterion for the best neural network model is based on the minimum root mean square error (RMSE) and the maximum regression value (R-value) of the model. Fig. 5.7(a) shows a comparison of models based on LM and BR algorithms, where minimum root mean square error is obtained at a k-fold value of 5. Similar results were obtained related to the regression value histogram shown in fig .5.7(b), in which maximum regression value is obtained at k-fold equal to 5. A k-fold value equal to 5 indicates that the best neural network model is obtained if 20% of data is used for testing subset and rest is used in the training subset.

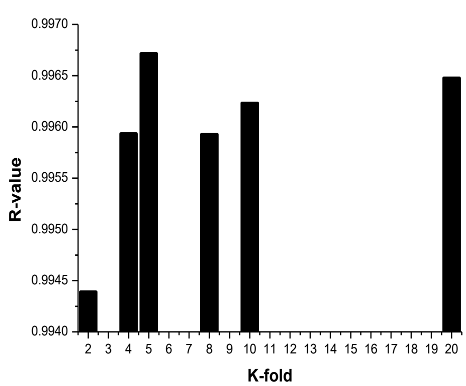
(a)



(b)



(c)



(d)

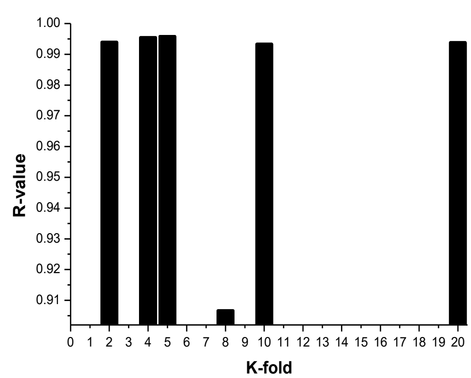


Fig. 5.7 Results of k-fold analysis at different k values: (a) Root mean square error using LM algorithm, (b) Root mean square error using BR algorithm, (c) Regression analysis using LM algorithm, (d) Regression analysis using BR algorithm

Based on the above k-fold analysis, a back-propagation feed-forward single layer perceptron model is developed. Three optical parameters namely the real part, amplitude, and phase are considered as input data and the strain is recorded as an output parameter in ANN design. ANN includes three layers for processing. The input layer takes the input parameters. The next is the hidden layer containing transfer function that helps to adjust the weight and the bias of the variable, thus exploring the effect of predictors upon the target values. The output layer is used for result prediction with error estimation. At the end of the process, test data is used for analyzing the system accuracy. ANN model used in this study is shown in table 5.3, and the block diagram of ANN architecture is shown in fig. 5.8.

Table 5.3. Parameters used in the development of neural network model

The number of neurons of different layers	**Input : 3, Hidden : 10, Output : 1**
Initial weight and biases	Random between -1 and 1
Activation function	Tan sigmoid
Learning rule	Back-propagation
Epoch value	1000
Acceptable mean square error	0.001

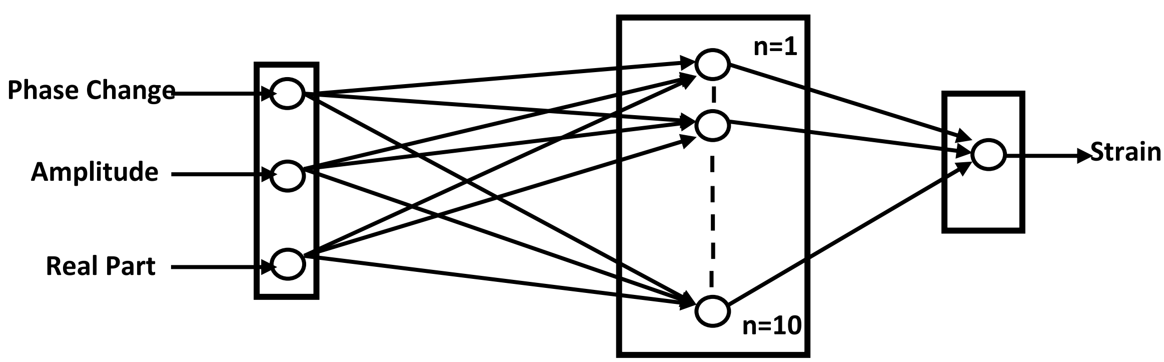


Fig. 5.8. Schematic representation of the neural network model

5.4.3. Results and Discussion

In present work, the cantilever beam structure is considered as a host material for strain determination. Samples based on different notch locations are tested for analyzing strain variations. Samples have fiber optic cables mounted on the surface for obtaining the change in optical signals at different loadings. Dynamic loading is applied using an unbalanced rotating mass at the free end of each sample. The weight pan method is applied to obtain a change in the amplitude of dynamic loading. The loading sequence includes starting from 2N to 10N with an incremental load step of 2N. Amplitude, phase change, and real part of the optical signal are used as input data for the designed neural network. Strain values obtained using finite element analysis are set as target values in the neural network perceptron model. The k-fold analysis provides a logical output for the selection of test and train data. Moreover, the k-fold analysis also eliminates the possibility of overfitting and underfitting conditions. The Bayesian regularization back-propagation algorithm is used in this study for designing the neural network. Testing and training regression values are above the acceptable limit of 90%. Epoch is set to a maximum limit of 1000.

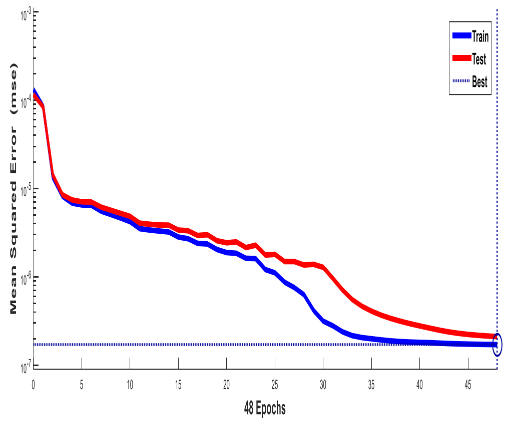
Fig. 5.9 shows the performance plot of the multilayer perceptron model. The performance plot is based on the mean square error of the developed model. It is clear from the fig. 5.9 that the developed model works with high confidence and with the least error values. Mean square error plots of different data set at various loading show that the model well predicts the target values. In fig. 5.9 (a) mean square error for test and train data reduces and became constant after 40 epoch value. For the 4N load in fig. 5.9(b) mean square error reduces initially. But a steep reduction is observed near 50 epochs. A constant value is attained after 200 epoch value. Similarly, in fig. 5.9(c) test and train curves separate near 30 epochs and became constant after 150 epoch values. In fig. 5.9(d) constant reduction in mean square error curve is obtained which became constant at 60 epochs. Fig. 5.9(e) shows a steep reduction in mean square error near 200 epochs and the curve became constant after 450 epoch values.

Table 5.4 presents the obtained values of different ANN parameters used in the analysis. Regression values are analyzed for the acceptability of the developed ANN model. From the table, it is clear that all regression values are very close to 1. Values of data comparison by regression analysis prove that the developed ANN model works well within the acceptable range of regression and standard error. As evident from table 5.4, the regression values obtained for 10N are least and in the acceptable range. Fig. 5.10 shows the strain comparison of various samples under different dynamic loading. Different samples show variation in strain values for analytical and developed neural network models. It is observed that neural network model predictions are more accurate as compared to the analytical solution given by Haslach [82]. The results have been compared taking the target values obtained from strain gauge. Based on the strain analysis following conclusions can be drawn:

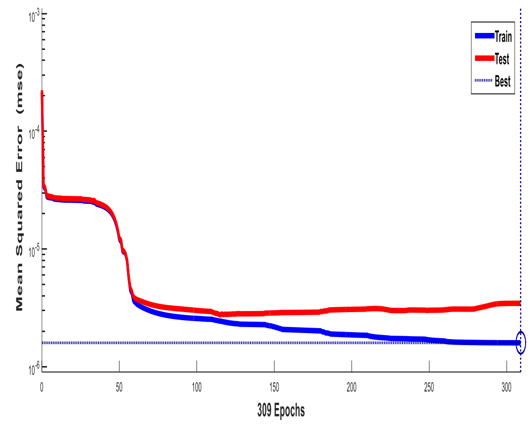
1) Over and under-prediction of strain values are observed using analytical analysis. This random variation occurs because the analytical model was developed to deal with static loading only. Moreover, random variation may be due to the presence of noise factors as defined in section 3.5 of chapter 3.

2) A good agreement in neural network predictions and target values occurs.

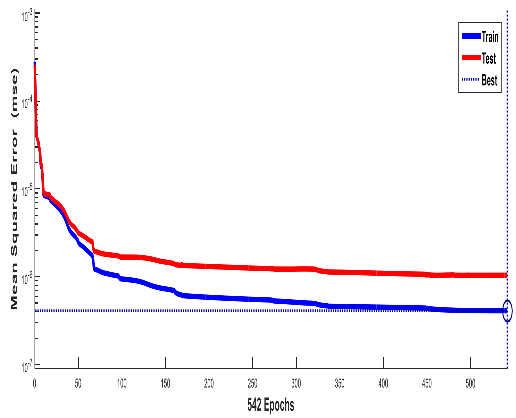
(a)



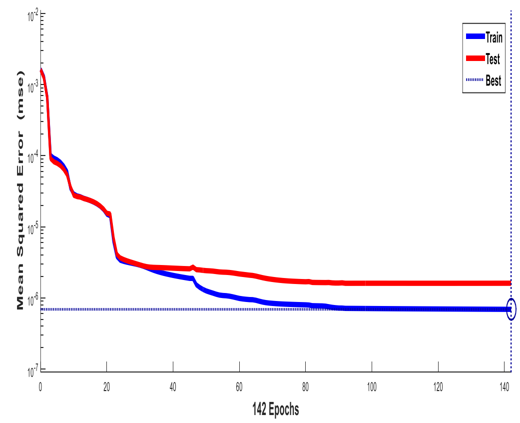
(b)



(c)



(d)



(e)

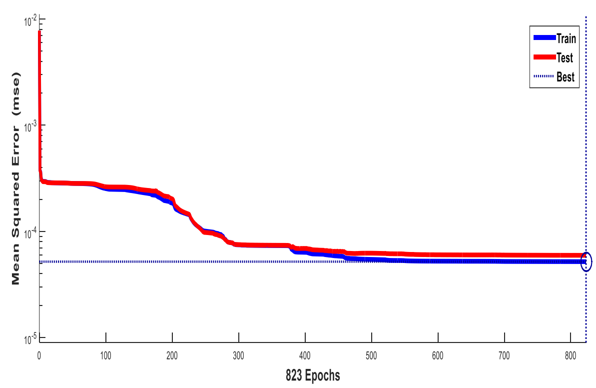


Fig. 5.9. Mean square error plots of data set of different samples at different loadings: (a) 2N, (b) 4N, (c) 6N, (d) 8N, (e) 10N.

Table 5.4 Performance of neural network model at different loads

Load	Training (R-value)	Testing (R-value)	All (R-value)	Epoch	Best training performance
2N	0.99349	0.99166	0.99315	48	$1.7129e^{-7}$
4N	0.98398	0.99662	0.98031	309	$1.5927e^{-6}$
6N	0.99828	0.99548	0.99773	542	$4.0987e^{-7}$
8N	0.99835	0.99619	0.99792	142	$6.6898e^{-7}$
10N	0.93753	0.92414	0.92631	823	$5.1957e^{-5}$

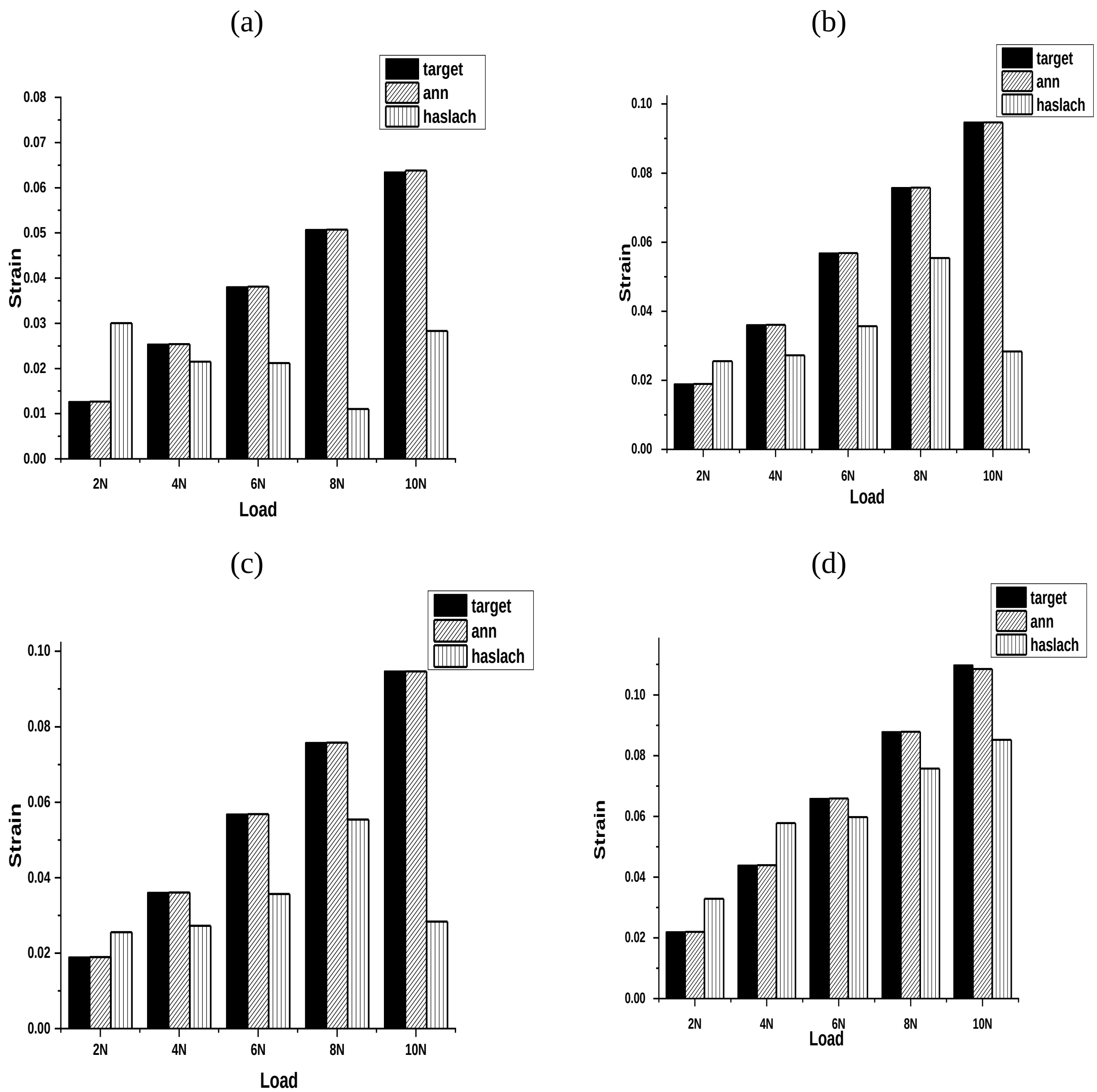


Fig. 5.10. Strain comparison obtained from different methods : (a) sample A, (b) sample B, (c) sample C, (d) sample D

5.5. Damage location analysis

5.5.1. Neural Network Methodology

In this section of the study, a single hidden layer perceptron model is used for damage detection using frequency-domain parameters of the optical fiber sensor as input. Back-propagation is a method to calculate the gradient of the loss function with respect to the weights in an artificial neural network. It is commonly used as a part of algorithms that optimizes the performance of the network by adjusting the weight. In the present study, the two training algorithms namely Levenberg-Marquardt (LM) and Bayesian Regularization (BR) back-propagation are compared on the basis of least square error and regression analysis. The optical signal from fiber optic cable is generated and a fast Fourier transform is performed to obtain the frequency domain parameters. Three basic parameters namely the real part, amplitude, and phase in the normalized form are used as input parameters for the network. To counter overfitting and underfitting of data set, cross-validation is performed. The selection of the algorithm is based on the regression analysis and mean square error under different loading conditions. The schematic of the network used in this study is shown in fig. 5.11.

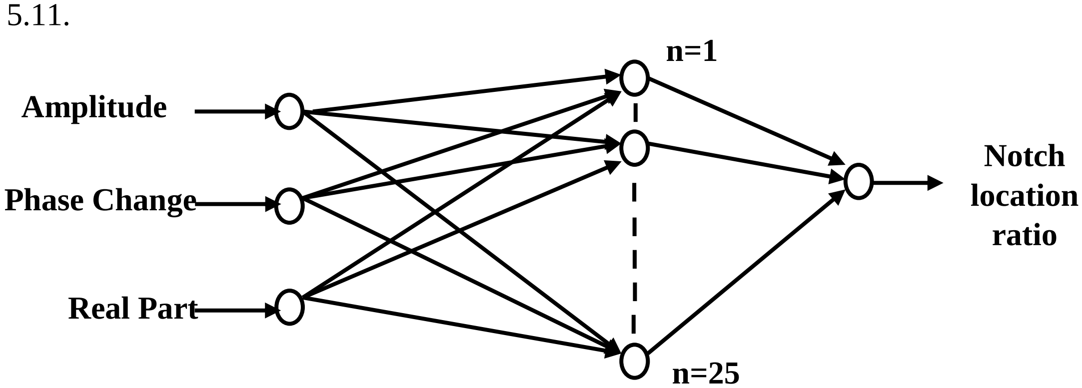


Fig. 5.11. Schematic representation of the neural network model

5.5.2. Training and testing of the model

For damage location problem k-fold analysis is applied on a 30N data set which is taken as a reference data set. A total of 11000 data sets corresponding to 10 different notched and one pristine samples have been obtained. The number of data sets used for the k-fold test is shown in table 5.5.

Table 5.5. Data set for different k-folds

k-fold	Train	Test	Data set per sample type
2	5500	5500	500
4	8250	2750	250
5	8800	2200	200
8	9625	1375	125
10	9900	1100	100
20	10450	550	50
25	10560	440	40
40	10725	275	25
50	10780	220	20
100	10890	110	10

For the selection of the best algorithm, a comparative study of two algorithms Levenberg-Marquardt and Bayesian Regularization has been carried out and the results of the same are shown in fig. 5.12. A single-layer perceptron model with 25 neurons in the hidden layer is used for analysis. The model selection is analyzed on the bases of minimum root mean square error and maximum regression value.

(a) (b)

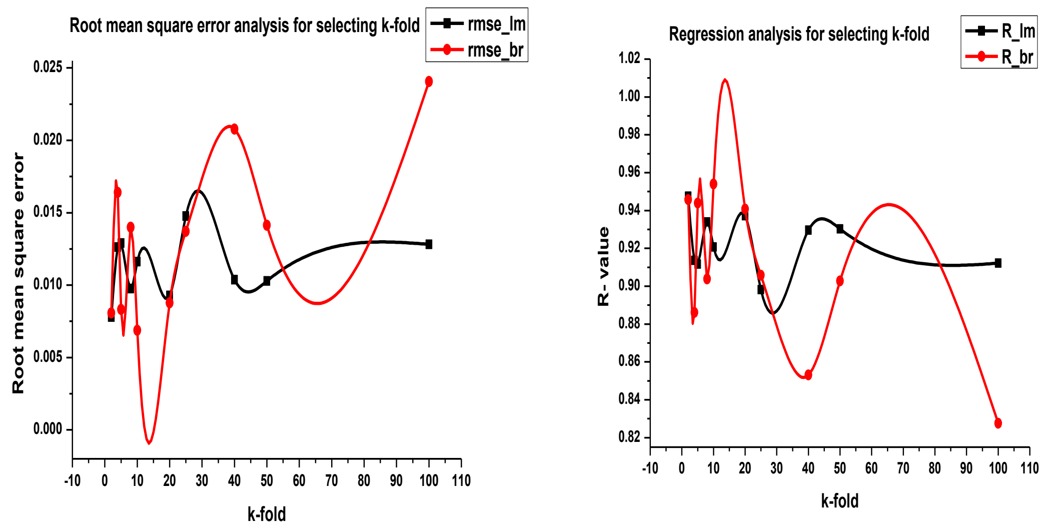


Fig. 5.12. Comparison of k-fold analysis at different k values: (a) Root mean square error, (b) Regression analysis

The minimum root mean square error and maximum regression value corresponds to k-fold of 10. At this k-fold value, the error value is 0.00678 and the regression value is 0.95392. Therefore it is clear that the best model can be obtained using the Bayesian Regularization algorithm with the k-fold value of 10. At k-10 best model is obtained which signifies that 100 data set is to be selected from the 1000 data set for each 11 sample type. Now a random selection of data may lead to a weaker network for damage deduction. Therefore a sequential k-fold analysis is performed in which 1000 data set of each sample type is divided into 10 phases. Each phase contains 100 data set for testing grouped in sequential order. The sequential k-fold output is shown in fig. 5.13. The sequential k-fold analysis shows that phase 1 dataset gives more accurate results than other phase distributions.

(a) (b)

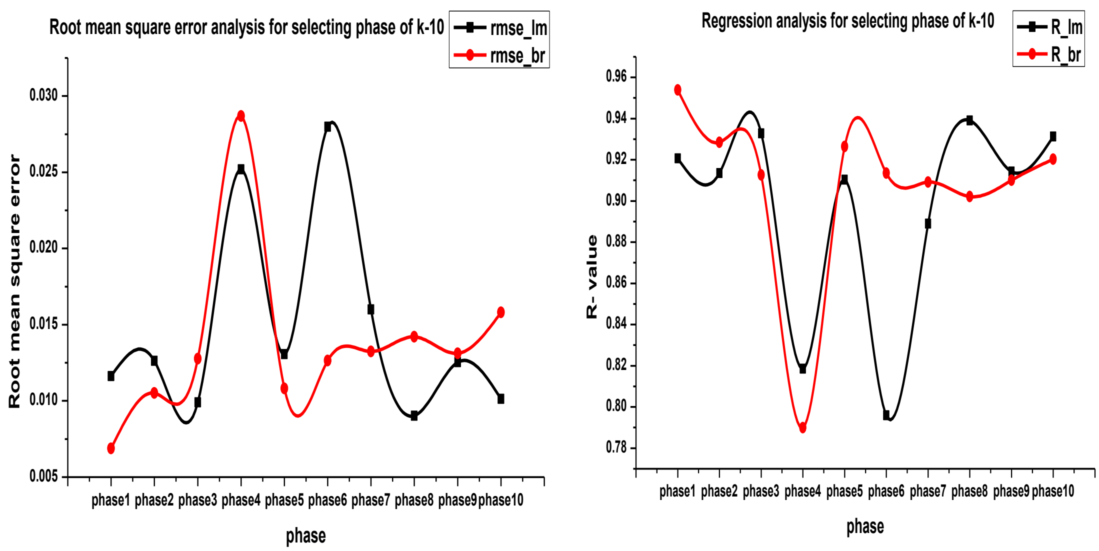


Fig. 5.13. Sequential k-fold analysis at different phase: (a) Root mean square error, (b) Regression analysis

5.5.3. Results and Discussion

In the present work, the cantilever beam structure is considered as a host material for damage detection. Samples have fiber optic cables mounted on the surface for obtaining the change in optical signals at three different static loadings. Amplitude, phase change, and real part of the optical signal are used as input data for the designed neural network. K-fold cross-validation analysis eliminates the possibility of overfitting and underfitting conditions. The Bayesian regularization back-propagation algorithm is used in this study for designing the neural network. Testing and training regression values are above the acceptable limit of 90%. Epoch is set to a maximum limit of 1000. Table 5.6 shows the testing and training of regression values with training performance.

Table 5.6 Performance effectiveness of neural network model at different loads

Load	**Training (R-value)**	**Testing (R-value)**	**All (R-value)**	**Epoch**	**Best training performance**
30N	0.98566	0.98166	0.98315	1000	0.002174
60N	0.99609	0.99662	0.99031	1000	0.000596
90N	0.9753	0.97548	0.97773	1000	0.003197

All regression values are very close to 1 and data comparison by regression analysis proves that the developed ANN model works well within the acceptable range of regression and standard error. The predicted damage location under different loading is shown in table 5.7.

Table 5.7. Comparison of Actual and ANN prediction with percentage error comparison

Actual η	**Predicted η @ 30N**	**%Error @ 30N**	**Predicted η @ 60N**	**%Error @ 60N**	**Predicted η @ 90N**	**%Error @ 90N**
1	0.992	0.776	0.9734	2.629	1.00	0.560
0.0833	0.0875	4.98	0.0824	1.127	0.085	2.11
0.16666	0.162	3.00	0.171	2.790	0.184	10.52
0.25	0.251	0.409	0.245	1.896	0.234	6.495
0.33333	0.294	11.68	0.325	2.573	0.3196	4.20
0.41666	0.418	0.361	0.4178	0.302	0.418	0.363
0.5	0.503	0.68	0.501	0.237	0.506	1.188
0.58333	0.587	0.558	0.582	0.181	0.571	2.109
0.6666	0.663	0.580	0.669	0.3889	0.671	0.618
0.75	0.7495	0.071	0.753	0.378	0.749	0.068
0.83333	0.835	0.217	0.834	0.103	0.83	0.269

The present study shows that an artificial neural network can successfully predict the damage location areas present in a cantilever beam using frequency-domain optical parameters. The initial part of the study defines a sequential methodology for the selection of the best suitable neural network model. The second part of the work shows the damage detection capability of the developed model. Table 5.7 shows a comparison of the notch location parameter (η) and predicted target values under different static loads. Error-values at different loads are within the acceptable range in all the cases. The developed neural network model successfully predicts the damage location areas.