International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.9, No.11, (2016), pp.45-62
http://dx.doi.org/10.14257/ijsip.2016.9.11.05

Analysis of Performance Parameters of Microstrip Low Pass Filter with Open Stub at 1.08 GHz Using Ann

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Abstract

In the present paper analysis of performance parameters i.e., insertion loss and return loss of microstrip Low Pass Filter with open stub using Artificial Neural Networks has been presented. The Artificial neural network is used in predicting the performance parameters of the low pass filter with open stub as a function of its stub length. Levenberg –Marquardt training algorithms of FFBP-ANN. (feed forward back propagation Artificial Neural Network), Layer Recurrent-ANN and CFBP-ANN (cascaded forward back propagation Artificial Neural Network) has been used to implement the neural network models. Simulated values for training and testing the neural network are obtained by analysing the LPF structure by the use of CST Microwave Studio Software. Comparison of mean square error obtained from different ANN networks concluded that CFBP-ANN gives satisfactory result as compare to FFBP-ANN and Layer Recurrent ANN. The testing of output of neural model is found good agreement with simulated output.

Keywords*-Artificial Neural Networks, Microstrip Low Pass Filter, Feed Forward Back Propagation, cascaded forward back propagation Artificial Neural Network and Layer Recurrent*

1. Introduction

The electromagnetic spectrum is limited and has to be shared for many RF/microwave applications; here filters play important role. In microwave communication systems, low-pass filters (LPF) are often an important component. A microwave filter is a two- port network device used to control the frequency response at a certain point in a microwave system by providing transmission at frequencies within the pass band of the filter and attenuation in the stop band of the filter. A Low-pass filter has many useful properties like easy fabrication, compact size, and very low insertion loss. Hence, it has increased applications in cellular mobile communication and microwave circuits [1]. The emerging applications of filter requires higher performance that's why artificial neural network is used.

Artificial neural networks [2] have been found to be an important technique for the classification and optimization problem. Artificial neural networks have emerged as a powerful learning technique to perform complex tasks in highly non linear dynamic environments. Artificial Neural Networks (ANNs) are computational tools that learn from training, which provide fast and accurate models for microwave modeling, simulation and optimization. ANNs are generally presented as systems of interconnected "neurons" which exchange messages between each other. ANN provides fast and accurate models for microwave modelling, simulation and optimization.

V. S. Kushwah, *et. al.*, [3] had presented the design and analysis of Stub microstrip low-pass filters at 3 dB cut-off frequency 1.4 GHz which gives insertion loss (S21) of -3 dB and return loss of -2.6 dB at cut-off point. Subsequently an artificial neural network model is developed to find out the Magnitude variation of scattering parameters (S-parameters) of microstrip low-pass filter at 1.4 GHz for different dimensions. Robert Mark *et. al.,* [4] had designed interdigital band pass filter and analysed using MLPFFBP and RBF artificial neural networks for desired frequency range between 1.5-3.5GHz. ANN models had been developed and tested for estimating the cutoff frequency of band pass filter and performance is evaluated in terms of mean square error and concluded that RBF network was more accurate than MLPFFBP. S Suganthi *et. al.,* [5] had proposed Chebyshev type microstrip low pass flter using ANN. The low pass flter was designed at cut-off frequency of 2 GHz on a FR4 substrate using HFSS software and then filter design parameters was trained with an ANN optimization technique. Sheetal Mitra *et. al.*, [6] had described the design of S-band low pass filter by using microstrip layout operating at 2.5 GHz for permittivity 4.1 with a substrate thickness 1.6 mm for order n=6. The method of stepped impedance lowpass prototype filter is used to design microstrip filter**.** V. S. Kushwah *et. al.,* [7] had design and analysed the stepped impedance microstrip low-pass filter at cut-off frequency 1.8 GHz which gives insertion loss (S21) of -3 dB at cut-off point. Subsequently an artificial neural network model is developed to find out the Magnitude variation of scattering parameters (S-parameters) of microstrip low-pass filtes at 1.8 GHz for different dimensions.

A number of papers indicate how ANNs can be used efficiently in analyzing and synthesizing various microwave circuits [8-10]. This paper is also an attempt to show that ANNs are computationally much more efficient than EM simulators**.**

2. Design and Data Generation

Low pass microstrip filter using open circuit stub is shown below. The filter is simulated using CST software [11]. Data is generated by varying stub length of filter and keeping other parameters constant, generated data is shown in appendix A and then analysed by different ANN networks.

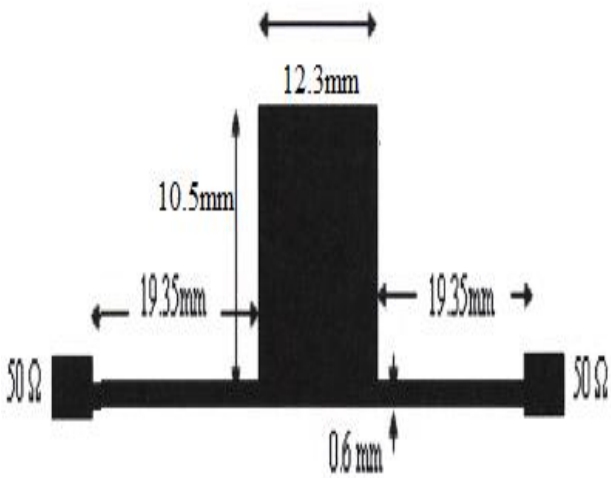

Figure 1. The Designed LPF using CST

Figure 1, shows the geometry of low pass microstrip filter with open stub simulated in CST with the following design parameters *i.e,* Substrate height, h =1.6 mm ,Characteristic impedance, Zo= 50Ω, Pass band ripple = 0.1dB, Dielectric constant, ε_r = 4.7, Cut-off frequency, fc = 1.08 GHz, length of stub , L= 10.5mm and width of stub, W=12.3mm.

The length L and the width W of open stub low pass filter for the specified cutoff frequency are calculated by the relationships mentioned in [1].

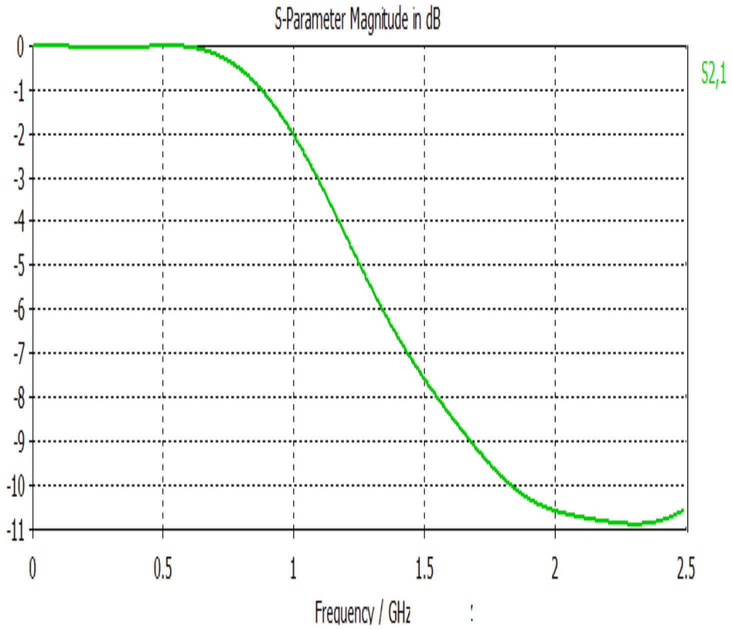

Figure 2. Frequency Response of Low Pass Filter

Figure 2, shows the graph of insertion loss vs. frequency. From the graph, it is concluded that the filter is operated at cutoff frequency 1.08 GHz. At 1.08GHz filter gives 3dB cutoff frequency.

Total 101 values are generated using CST software out of which 91 values are used for training the network and remaining 10 values are used for testing the network.

3. Ann Models for The Analysis Performance Parameters of Mircrostrip LPF

L-M training algorithms of FFBP-ANN (feed forward back propagation Artificial Neural Network), Layer recurrent and CFBP-ANN (cascaded forward back propagation Artificial Neural Network) has been used network for the estimation of different performance parameters (*i.e.*, Return Loss and Insertion Loss) of a microstrip low pass filter.

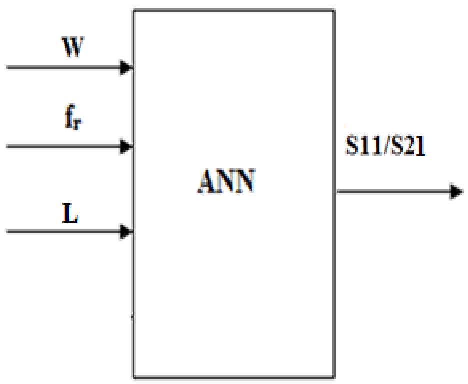

Figure 3. ANN Model for Analysis of Return Loss & Insertion Loss

Figure 3, shows the analysis ANN model. Analysis ANN model has been developed to estimate the return loss and insertion loss of LPF. The parameters *i.e.*, Substrate height, h =1.6 mm , Characteristic impedance, Zo= 50Ω, Pass band ripple = 0.1dB, Dielectric constant, ε_r = 4.7, Cut-off frequency, fc = 1.08 GHz, and width of stub, W=12.3mm

range of stub length 4mm $\leq$ L $\leq$ 14mm range of return loss -1.72dB $\leq S_{11} \leq$ -20.08dB and range of insertion loss -0.16dB $\leq S_{21} \leq$ -5Db.

The different artificial neural networks which are used for analysed the model as follows:

- Feed Forward Back Propagation (FFBP) Neural Network
- Layer Recurrent Neural Network
- Feed Forward Back Propagation (FFBP) Neural Network

3.1. Feed Forward Back Propagation (FFBP)Neural Network

Feed forward neural networks (FNN) have been widely used for various tasks, such as pattern recognition, function approximation, dynamical modeling, data mining, and time series forecasting, [12-13]. A number of different kinds of BP learning algorithms have been proposed, such as an on-line neural-network learning algorithm for dealing with time varying inputs [14], fast learning algorithms based on gradient descent of neuron space [15], and the Levenberg–Marquardt algorithm [16]. They are supervised networks and so they require a desired response to be trained. They learn how to transform input data into a desired response and so they are widely used for pattern classification.

Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons.

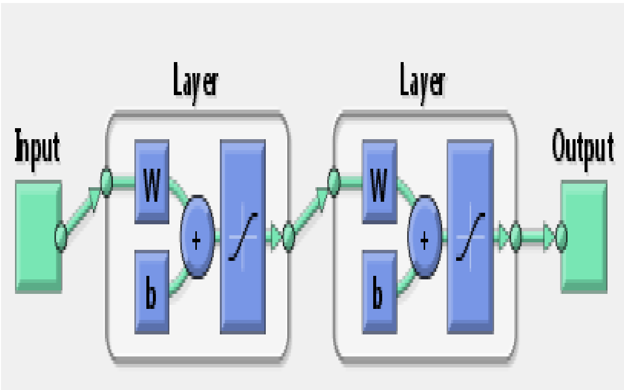

Figure 4. Feed Forward Back propagation Network

Figure 4, shows FFBP-ANN, it consists of 3 input, on hidden layer and two output layer.

3.2. Layer Recurrent Neural Network

Layer recurrent neural networks are similar to feed forward networks, except that each layer has a recurrent connection with a tap delay associated with it. This allows the network to have an infinite dynamic response to time series input data. This network is similar to the time delay and distributed delay neural networks, which have finite input responses.

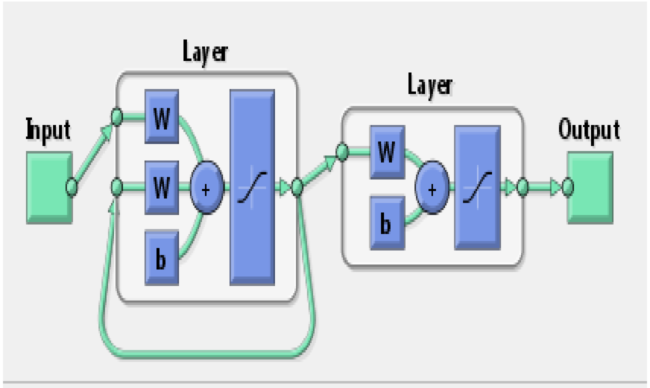

Figure 5. Layer Recurrent Network

Figure 5, shows Layer Recurrent-ANN, it consists of one input, two hidden layer and one output layer with each layer has recurrent connection.

3.3. Cascaded Forward Back Propagation (CFBP) Neural Network

Cascade forward back propagation model is similar to feed forward networks, but include a weight connection from the input to each layer and from each layer to the successive layers. In this network each layer of neurons related to all previous layer of neurons.

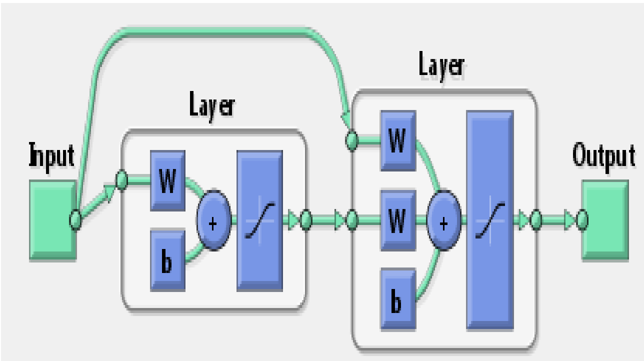

Figure 6. Cascaded Forward Back Propagation Network

Figure 6, shows CFBP-ANN, it consists of one input, two hidden layer and one output layer. In this network each layer of neurons related to all previous layer of neurons.

4. Training and Testing Through ANN

Data is generated by varying the stub length of microstrip low pass filter and then, it is analysed by three different ANN networks using nntool [17].

4.1. Training and Testing for the Analysis of Return Loss Through ANN

Return loss is the loss of power in the signal returned/reflected by a discontinuity in a transmission line or optical fibre. This discontinuity can be a mismatch with the terminating load or with a device inserted in the line. It is usually expressed as a ratio in decibels (dB). Return loss is denoted by S_{11}.

In the model, proposed for the analysis of return loss using FFBP-ANN there are 10 neurons in the first hidden layer. The full set of 86 training input patterns (shown in appendix B) are pass through the neural network for the analysis of return loss.

Table 1. Comparison of Results Obtained using CST and using FFBP-ANN for Return Loss of Low Pass Filter at 1.08 GHz

Length of stub L (mm)	S_{11} (dB) using CST	S_{11} (dB) using FFBP	Absolute error	MSE1
4	-20.08	-19.884	-0.196	0.3841
4.3	-17.44	-17.402	-0.038	0.00144
4.9	-13.97	-14.059	0.089	0.00792
5.4	-11.30	-11.597	0.297	0.08820
5.7	-10.35	-10.367	0.017	0.000289
6	-9.53	-9.494	-0.036	0.00129
6.5	-8.39	-8.397	0.007	0.00004
7.1	-7.22	-7.252	0.032	0.00102
7.8	-5.88	-5.851	-0.029	0.00084
8.6	-4.96	-4.906	-0.054	0.00291

The Table 1, shows the comparison of simulated return loss obtained using CST Software at 1.08 GHz and return loss obtained using FFBP-ANN network for 10 different test patterns and then the Mean Square Error (MSE1) has been calculated followed by absolute error.

In the model, proposed for the analysis of return loss using Layer Recurrent artificial neural network with Levenberg – Marquardt training algorithm and the transfer function tansig. Network has two hidden layers, there are 10 neurons in the first hidden layer. The network is estimating the return loss at the output for the specified inputs. The full set of 86 training input patterns (shown in appendix A) are pass through the neural network for the analysis of return loss.

Table 2. Comparison of Results Obtained using CST and using Layer Recurrent-ANN for Return Loss of Low Pass Filter at 1.08 GHz

Length of stub L (mm)	S_{11} (dB) using CST	S_{11} (dB)using layer recurrent	Absolute error	MSE2
4	-20.08	-19.336	-0.744	0.5535
4.3	-17.44	-17.705	0.265	0.0702
4.9	-13.97	-13.831	-0.139	0.0193
5.4	-11.30	-11.603	0.303	0.0918
5.7	-10.35	-10.539	0.189	0.0357
6	-9.53	-9.618	0.088	0.0077
6.5	-8.39	-8.342	-0.053	0.0028
7.1	-7.22	-7.135	-0.085	0.0072
7.8	-5.88	-6.019	0.139	0.0193
8.6	-4.96	-4.992	0.032	0.0010

The Table 2, shows the comparison of simulated return loss obtained using CST Software at 1.08 GHz and return loss obtained using layer recurrent-ANN network for 10 different test patterns and then the Mean Square Error (MSE2) has been calculated followed by absolute error.

In the model, proposed for the analysis of return loss using CFBP-ANN there are 10 neurons in the first hidden layer. The network is estimating the return loss at the output for the specified inputs. The full set of 86 training input patterns (shown in appendix A) are pass through the neural network for the analysis of return loss.

Table 3. Comparison of Results Obtained using CST and using CFBP-ANN for Return Loss of Low Pass Filter at 1.08 GHz

Length of stub L (mm)	S_{11} (dB) using CST	S_{11} (dB)using CFBP-ANN	Absolute error	MSE3
4	-20.08	-19.929	-0.151	0.0228
4.3	-17.44	-17.382	-0.058	0.00336
4.9	-13.97	-14.038	0.068	0.00462
5.4	-11.30	-11.528	0.228	0.0519
5.7	-10.35	-10.294	-0.056	0.00313
6	-9.53	-9.477	-0.053	0.00280
6.5	-8.39	-8.397	0.002	0.000004
7.1	-7.22	-7.272	0.052	0.00270
7.8	-5.88	-5.887	0.003	0.00009
8.6	-4.96	-4.970	0.01	0.0001

The Table 3, shows the comparison of simulated return loss obtained using CST Software at 1.08 GHz and return loss obtained using CFBP-ANN network for 10 different test patterns and then the Mean Square Error (MSE3) has been calculated followed by absolute error.

Table 4. Comparison of MSE of FFBP-ANN, Layer Recurrent & CFBP for Return Loss of Low Pass Filter at 1.08GHz

MSE1 FFBP-ANN	MSE2 Layer recurrent	MSE3 CFBP-ANN
0.3841	0.5535	0.0228
0.00144	0.0702	0.00336
0.00792	0.0193	0.00462
0.08820	0.0918	0.0519
0.000289	0.0357	0.00313
0.00129	0.0077	0.00280
0.00004	0.0028	0.000004
0.00102	0.0072	0.00270
0.00084	0.0193	0.00009
0.00291	0.0010	0.0001

Table 4, shows the comparison of MSE1, MSE2 and MSE3 obtained using FFBP-ANN, Layer Recurrent and CFBP-ANN respectively for return loss of low pass filter at 1.08GHz for 10 test patterns.

4.2. Training and Testing for the Analysis of Insertion Loss Through ANN

Insertion loss equal to the difference in dB power measured at the filter input and at the filter output. The power measured at the filter input is equal to the measured power when the filter is replaced by a properly matched power meter. Insertion loss is denoted by S_{21}.

In the model, proposed for the analysis of Insertion loss using FFBP-ANN, layer recurrent and CFBP-ANN there are 10 neurons in the first hidden layer.

In the model, proposed for the analysis of insertion loss using FFBP-ANN there are 10 neurons in the first hidden layer. The network is estimating the insertion loss at the output for the specified inputs. The full set of 86 training input patterns (shown in appendix A) are pass through the neural network for the analysis of insertion loss.

Table 5. Comparison of Results Obtained using CST and using FFBP-ANN for Insertion Loss of Low Pass Filter at 1.08 GHz

Length of stub L (mm)	S_{21} (dB) using CST	S_{21} (dB)using FFBP-ANN	Absolute error	MSE4
4	-0.16	-0.168	0.008	0.000064
4.3	-0.20	-0.191	-0.009	0.000081
4.9	-0.30	-0.299	-0.001	.000001
5.4	-0.47	-0.437	-0.033	0.00108
5.7	-0.55	-0.560	0.01	0.0001
6	-0.64	-0.643	0.003	0.000009
6.5	-0.80	-0.798	-0.002	0.000004
7.1	-1.29	-1.156	-0.134	0.0179
7.8	-1.40	-1.441	0.041	0.00168
8.6	-1.75	-1.801	0.051	0.00260

The Table 5, shows the comparison of simulated insertion loss obtained using CST Software at 1.08 GHz and insertion loss obtained using FFBP-ANN network for 10 different test patterns and then the Mean Square Error (MSE4) has been calculated followed by absolute error.

In the model, proposed for the analysis of insertion loss using layer recurrent-ANN there are 10 neurons in the first hidden layer. The network is estimating the insertion loss at the output for the specified inputs. The full set of 86 training input patterns (shown in appendix A) are pass through the neural network for the analysis of insertion loss.

Table 6. Comparison of Results Obtained using CST and using Layer Recurrent-ANN for Insertion Loss of Low Pass Filter at 1.08 GHz

Length of stub L (mm)	S_{21} (dB) using CST	S_{21} (dB)using layer recurrent-ANN	Absolute error	MSE5
4	-0.16	-0.200	0.04	0.0016
4.3	-0.20	-0.223	0.023	0.00052
4.9	-0.30	-0.302	0.002	0.000004
5.4	-0.47	-0.417	-0.053	0.00280
5.7	-0.55	-0.512	-0.038	0.00144
6	-0.64	-0.626	-0.014	0.00019
6.5	-0.80	-0.847	0.047	0.00220
7.1	-1.29	-1.134	-0.156	0.0243
7.8	-1.40	-1.450	0.05	0.0025
8.6	-1.75	-1.794	0.044	0.00193

The Table 6, shows the comparison of simulated insertion loss obtained using CST Software at 1.08 GHz and insertion loss obtained using layer recurrent-ANN network for 10 different test patterns and then the Mean Square Error (MSE5) has been calculated followed by absolute error.

In the model, proposed for the analysis of insertion loss using Cascaded Forward Back Propagation (CFBP-ANN) with Levenberg–Marquardt training algorithm and the transfer function tansig. Network has two hidden layers, there are 10 neurons in the first hidden layer. The network is estimating the insertion loss at the output for the specified inputs. The full set of 86 training input patterns (shown in appendix B) are pass through the neural network for the analysis of insertion loss.

Table 7. Comparison of Results Obtained using CST & using CFBP-ANN for Insertion Loss of Low Pass Filter at 1.08 GHz

Length of stub L(mm)	S_{21} (dB) using CST	S_{21} (dB)using CFBP-ANN	Absolute error	MSE6
4	-0.16	-0.162	0.002	0.000004
4.3	-0.20	-0.199	-0.001	0.000001
4.9	-0.30	-0.290	-0.01	0.0001
5.4	-0.47	-0.446	-0.024	0.00057
5.7	-0.55	-0.556	0.006	0.000036
6	-0.64	-0.644	0.004	0.000016
6.5	-0.80	-0.777	-0.003	0.000009
7.1	-1.29	-1.183	-0.107	0.0114
7.8	-1.40	-1.418	0.018	0.00032
8.6	-1.75	-1.777	0.027	0.00072

The Table 7, shows the comparison of simulated insertion loss obtained using CST Software at 1.08 GHz and insertion loss obtained using CFBP-ANN network for 10 different test patterns and then the Mean Square Error (MSE6) has been calculated followed by absolute error.

Table 8. Comparison of MSE of FFBP-ANN, Layer Recurrent and CFBP-ANN for Insertion Loss of Low Pass Filter at 1.08GHz

MSE4 FFBP-ANN	MSE5 Layer recurrent	MSE6 CFBP-ANN
0.000064	0.0016	0.000004
0.000081	0.00052	0.000001
.000001	0.000004	0.0001
0.00108	0.00280	0.00057
0.0001	0.00144	0.000036
0.000009	0.00019	0.000016
0.000004	0.00220	0.000009
0.0179	0.0243	0.0114
0.00168	0.0025	0.00032
0.00260	0.00193	0.00072

Table 8, shows the comparison of MSE obtained using FFBP-ANN, CFBP-ANN and NARX-ANN for insertion loss of low pass filter at 2.4GHz for 10 test patterns.

5. Result

5.1. Result of Return Loss

The training performance of return loss in case of FFBP-ANN with Levenberg–Marquardt training algorithm and the transfer function tansig is shown in Figure 7 which shows the graph between mean square error and no. of epochs. The minimum MSE is achieved in 42 epochs.

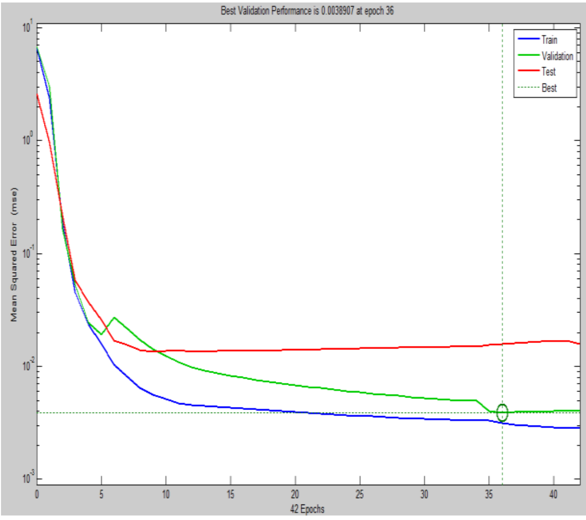

Figure 7. Training Performance of Return Loss & no. of Epochs to Achieve Minimum MSE of FFBP

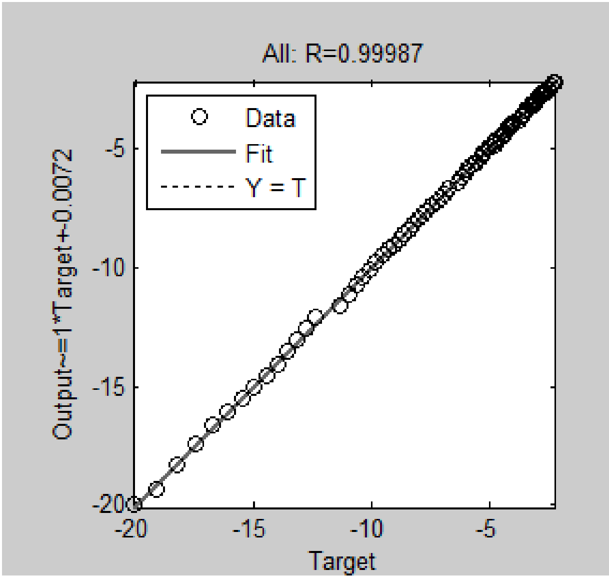

Figure 8: Regression Plot of Return Loss of FFBP-ANN

Figure 8, shows the Regression plot of return loss of FFBP-ANN, which shows the relationship between the outputs of the network and the targets. If the training were perfect, the network outputs and the targets would be exactly equal. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets.

The training performance of return loss in case of Layer recurrent-ANN with Levenberg–Marquardt training algorithm and the transfer function tansig is shown in Figure 9, which shows the graph between mean square error and no. of epochs. The minimum MSE is achieved in 40 epochs.

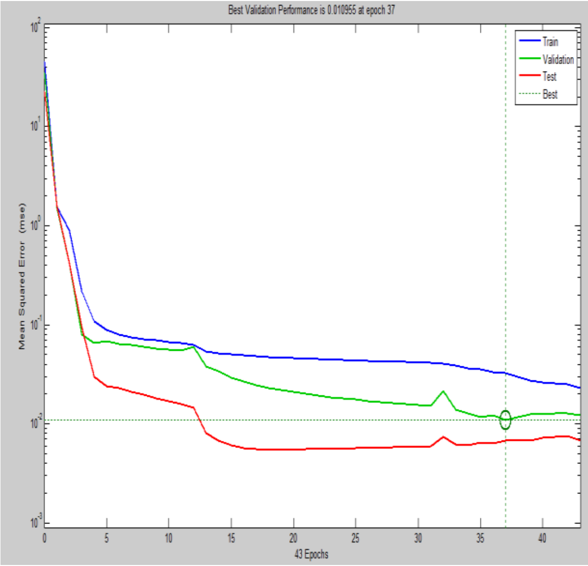

Figure 9. Training Performance of Return Loss and Number of Epochs to Achieve Minimum MSE Level in Case of Layer Recurrent-ANN

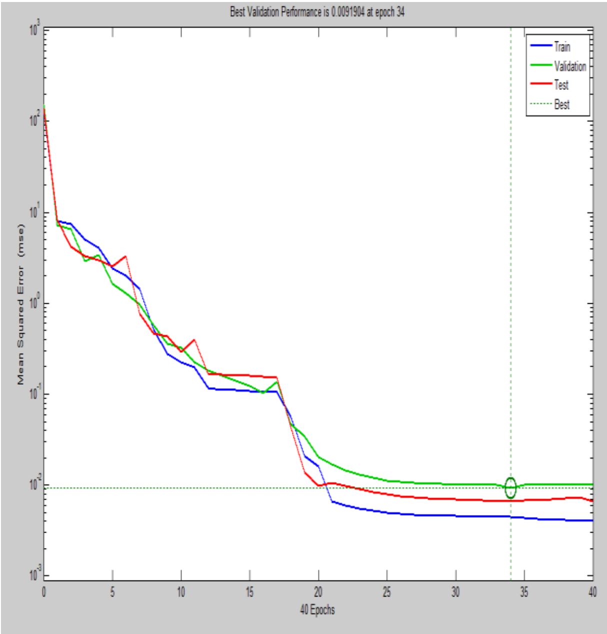

Figure 10. Training Performance of Return Loss and Number of Epochs to Achieve Minimum MSE Level in Case of CFBP-ANN

The training performance of return loss in case of CFBP-ANN with Levenberg–Marquardt training algorithm and the transfer function tansig is shown in figure 10 which shows the graph between mean square error and no. of epochs. The minimum MSE is achieved in 40 epochs.

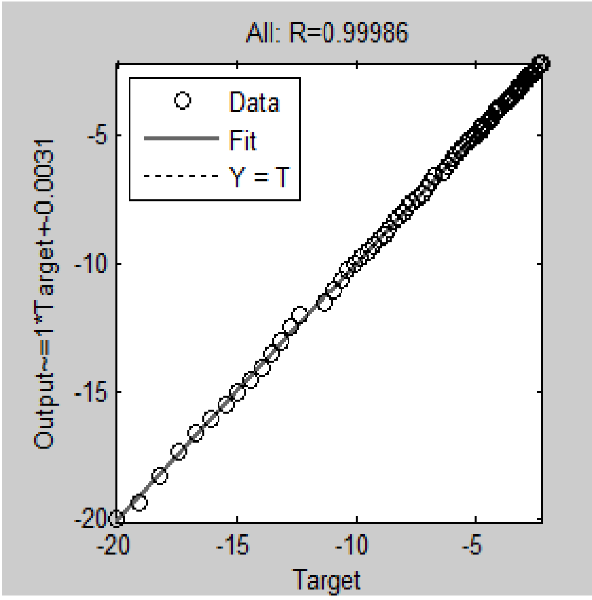

Figure 11. Regression Plot of return loss of CFBP-ANN

Figure 11, shows the Regression plot of return loss of CFBP-ANN, which shows the relationship between the outputs of the network and the targets. If the training were perfect, the network outputs and the targets would be exactly equal. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets.

5.2. Result of Insertion Loss

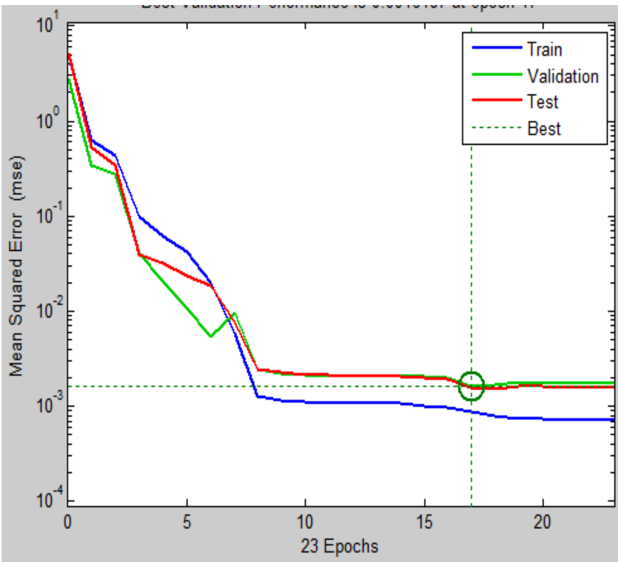

Figure 12. Training Performance of Insertion Loss and Number of Epochs to Achieve Minimum MSE Level in Case of FFBP-ANN

The training performance of insertion loss in case of FFBP-ANN with Levenberg – Marquardt training algorithm and the transfer function tansig is shown in Figure 12, which shows the graph between mean square error and no. of epochs. The minimum MSE is achieved in 23 epochs.

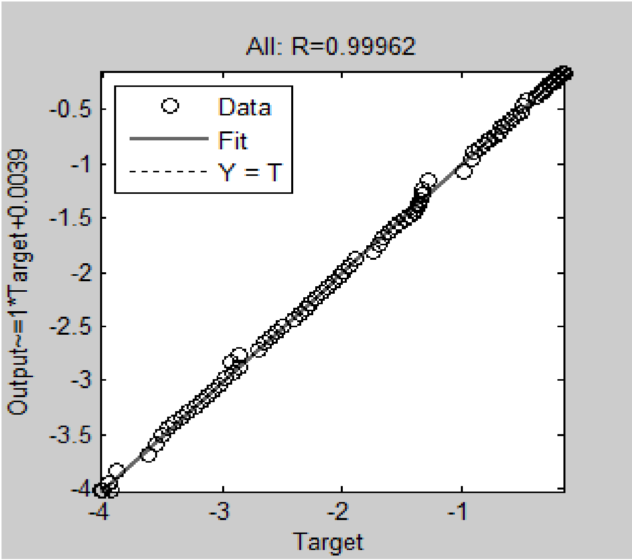

Figure 13. Regression Plot of Insertion Loss of FFBP-ANN

Figure 13, shows the Regression plot of insertion loss of FFBP-ANN, which shows the relationship between the outputs of the network and the targets. If the training were perfect, the network outputs and the targets would be exactly equal. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets.

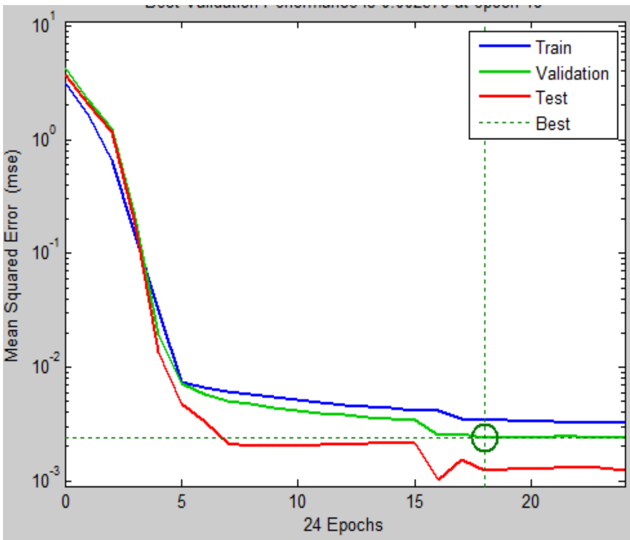

Figure 14. Training Performance of Insertion Loss and Number of Epochs to Achieve Minimum MSE Level in Case of Layer Recurrent-ANN

The training performance of insertion loss in case of layer recurrent-ANN with Levenberg–Marquardt training algorithm and the transfer function tansig is shown in Figure 14, which shows the graph between mean square error and no. of epochs. The minimum MSE is achieved in 24 epochs.

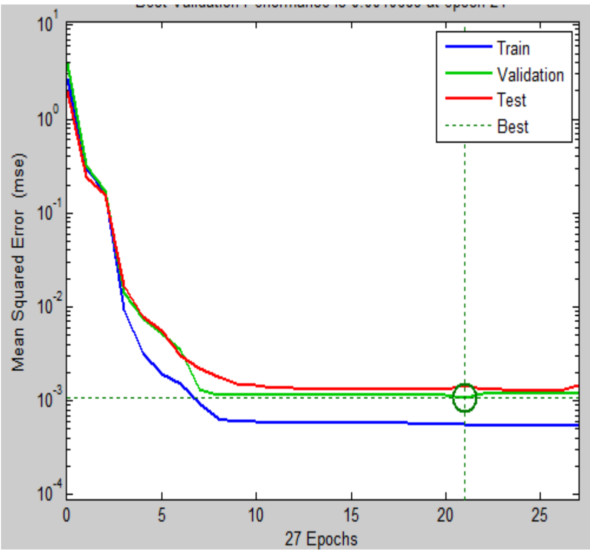

Figure 15. Training Performance of Insertion Loss and Number of Epochs to Achieve Minimum MSE Level in Case of CFBP-ANN

The training performance of insertion loss in case of CFBP-ANN with Levenberg – Marquardt training algorithm and the transfer function tansig is shown in Figure 15, which shows the graph between mean square error and no. of epochs. The minimum MSE is achieved in 27 epochs.

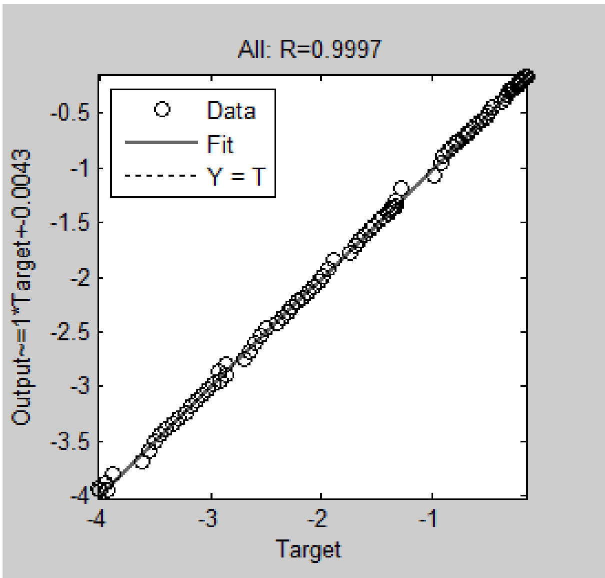

Figure 16. Regression Plot of Insertion Loss of CFBP-ANN

Figure 16, shows the Regression plot of insertion loss of CFBP-ANN, which shows the relationship between the outputs of the network and the targets. If the training were perfect, the network outputs and the targets would be exactly equal. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets.

6. Conclusion

This paper presents the analysis of performance parameters i.e return loss and insertion loss of microstrip low pass filter with open stub using Artificial Neural Network. CST software and ANN tool of MATLAB were utilized for the design and analysis purpose. From Table 4, it is concluded that in the analysis of filter parameter *i.e.*, return loss, mean square error of CFBP-ANN with Levenberg-Marquaradt (LM) training algorithm and tansig as a transfer function is minimum and from Table 8 observed that in the analysis of filter parameter i.e .insertion loss, mean square error of CFBP-ANN with Levenberg-Marquaradt (LM) training algorithm and tansig as a transfer function is minimum. Achievement of such a low value of performance goal (MSE) indicates that trained ANN model is an accurate model for analysing the performance parameters of microstrip low pass filter with open stub.

APPENDIX A

Generated data of microstrip low pass filter with open stub

Inductive length L (mm)	**Cutoff Frequency F_c (GHz)**	**Return Loss S_{11} (dB)**	**Insertion Loss S_{21} (dB)**
4	1.65	-20.08	-0.16
4.1	1.63	-19.1	-0.17
4.2	1.62	-18.23	-0.18
4.3	1.61	-17.44	-0.2
4.4	1.6	-16.73	-0.21
4.5	1.58	-16.09	-0.23
4.6	1.58	-15.5	-0.24
4.7	1.56	-14.95	-0.26
4.8	1.55	-14.44	-0.28
4.9	1.55	-13.97	-0.3
5	1.54	-13.53	-0.31
5.1	1.53	-13.12	-0.33
5.2	1.52	-12.73	-0.35
5.3	1.51	-12.36	-0.38
5.4	1.46	-11.3	-0.47
5.5	1.46	-10.96	-0.5
5.6	1.45	-10.65	-0.52
5.7	1.44	-10.35	-0.55
5.8	1.43	-10.06	-0.58
5.9	1.42	-9.79	-0.61
6	1.41	-9.53	-0.64
6.1	1.4	-9.28	-0.67
6.2	1.39	-9.05	-0.7
6.3	1.39	-8.82	-0.73
6.4	1.38	-8.6	-0.77
6.5	1.37	-8.39	-0.8
6.6	1.36	-8.19	-0.83
6.7	1.36	-8	-0.86
6.8	1.35	-7.81	-0.9
6.9	1.34	-7.63	-0.93
7	1.33	-7.44	-0.99
7.1	1.32	-7.22	-1.29
7.2	1.31	-7.06	-1.33
7.3	1.31	-6.9	-1.34

7.4	1.31	-6.69	-1.35
7.5	1.28	-6.29	1.36
7.6	1.27	-6.15	1.37
7.7	1.26	-6.02	-1.39
7.8	1.26	-5.88	-1.4
7.9	1.25	-5.76	-1.45
8	1.25	-5.63	-1.49
8.1	1.24	-5.51	-1.53
8.2	1.23	-5.39	-1.57
8.3	1.23	-5.28	-1.62
8.4	1.22	-5.17	-1.66
8.5	1.22	-5.06	-1.7
8.6	1.21	-4.96	-1.75
8.7	1.2	-4.69	-1.9
8.8	1.2	-4.81	-1.94
8.9	1.19	-4.71	-1.99
9	1.19	-4.61	-2.03
9.1	1.18	-4.52	-2.08
9.2	1.18	-4.42	-2.13
9.3	1.17	-4.33	-2.17
9.4	1.17	-4.25	-2.22
9.5	1.16	-4.16	-2.27
9.6	1.15	-4.08	-2.31
9.7	1.14	-4	-2.36
9.8	1.14	-3.9	-2.41
9.9	1.13	-3.67	-2.5
10	1.12	-3.6	-2.55
10.1	1.11	-3.53	-2.6
10.2	1.11	-3.46	-2.65
10.3	1.11	-3.4	-2.7
10.4	1.09	-3.24	-2.87
10.5	1.09	-3.22	-2.92
10.6	1.09	-3.18	-2.86
10.7	1.09	-3.15	-2.91
10.8	1.08	-3.12	-2.97
10.9	1.08	-3.06	-3.02
11	1.07	-3	-3.07
11.1	1.07	-2.95	-3.13
11.2	1.06	-2.89	-3.18
11.3	1.06	-2.84	-3.23
11.4	1.05	-2.78	-3.29
11.5	1.05	-2.73	-3.34
11.6	1.04	-2.68	-3.4
11.7	1.04	-2.63	-3.45
11.8	1.03	-2.58	-3.5
11.9	1.03	-2.53	-3.56
12	1.03	-2.48	-3.61
12.1	1.01	-2.3	-3.88
12.2	1.01	-2.26	-3.94
12.3	1	-2.21	-4.02
12.4	1	-2.22	-3.93
12.5	1	-2.18	-3.99
12.6	0.99	-2.18	-4

12.7	0.98	-2.17	-4.05
12.8	0.98	-2.17	-4.09
12.9	0.97	-2.13	-4.15
13	0.96	-2.11	-4.19
13.1	0.95	-2	-4.22
13.2	0.95	-1.99	-4.28
13.3	0.94	-1.99	-4.38
13.4	0.93	-1.96	-4.5
13.5	0.92	-1.93	-4.61
13.6	0.9	-1.88	-4.68
13.7	0.88	-1.85	-4.75
13.8	0.88	-1.81	-4.83
13.9	0.87	-1.75	-4.9
14	0.86	-1.72	-5

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