A Novel Approach to Synthesize and Analyze Microwave Lowpass Filter using Wavelet as a Preprocessing Unit for Artificial Neural Network

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Abstract - Trendy wireless communication systems have created the demand for compact and multi functional microwave filters with the new approaches for design ,fabrication and also Characterization of filter structures .which has two major components namely analysis and synthesis. This article presents the synthesis of filters using artificial neural network (ANN), addressing the issue of degradation of frequency response in conventional filter due to the rounding off of the order of the filter to the nearest integer value. The proposed ANN based synthesized low pass filter response is validated by fabrication and measurement. But this procedure takes a longer computational time due to exhaustive training sequence for accurate modelling. Hence, a novel neuro-wavelet based synthesis method has been proposed which utilizes the advantage of wavelet basis function in selecting the optimal input vector for ANN so as to reduce the computation time. This method is validated by synthesising a low pass filter which is fabricated on a glass epoxy substrate with a dielectric constant (ε_r) of 4.6 and a thickness of 1.6 mm . The simulated filter responses are validated by the measured results of the fabricated filter. As a result of the analysis, it was found that the filter with this novel approach shows good agreement.

Key Words:Microwave filters, Artificial neural network, Wavelet synthesis, glass epoxy substrate.

I. INTRODUCTION

The emergence of wireless technologies has provided the technocrats and planners an opportunity to improve the quality of life of a common man in respect of healthcare, shelter, telecommunication, man-machine interface, infrastructure and environment.

It leads to an overcrowded frequency spectrum resulting from the continuous rise in the allocated frequencies and a radical change concerning the performance of the electronic modules required (Robert 2006)

Furthermore, the presence of several transmitters operating simultaneously on the same platform with multiple receivers requires very high dynamic range receivers, ultra-clean transmitters and careful attention to the overall electromagnetic compatibility design of the system. This usually requires filtering on both transmitters and receivers to ensure that they do not interfere with each other (Robert 2006).

A filter may present a rather simple geometry, but the use of tuning screws or other devices would make the structure a fairly complex one. As a result, electromagnetic tools are necessary for the rigorous filter electromagnetic (EM) analysis. Unfortunately, to perform yield optimization by using electromagnetic full wave simulators based on FEM or FDTD and their variations do not appear necessary. But essentially, what is needed is a tool which relates the geometrical dimensions (input) to the filter frequency response (output). A neural network is an ideal candidate for such a task.

Artificial neural networks (ANNs) have limited ability to characterize local features such as discontinuities and edges (Jin and Shi 1999, Martell 2000).

Recently, Wavelet analysis has drawn a great deal of attention in both applied mathematics and many engineering disciplines.

In most of the reported literature on wavelet neural network for EM problems the focus is primarily on using the wavelet transform as a replacement for the family of traditional basis function in NN.

In this paper, wavelet decomposition is proposed which is to be utilized to preprocess the input signals before applying them to neural network so as to minimize the training set, thereby reducing the complexity of ANN. In this paper section II explain the importance and literature of wavelet in various fields, section III give the clarity of the method of implementation and section IV discuss the result of this proposed method.

II. WAVELET

In recent years, wavelets have been applied to electromagnetic and semiconductor device modeling for several purposes like packaging, Electromagnetic Compatability (EMC) (Pirinoli et al 2001), and to obtain better convergence in the analysis methods such as FEM, FDTD and point collocation (Cai and Wang 1996). Wavelet is an emerging tool for analysis and synthesis of microwave devices. Wavelet Neural Networks (WNNs) have recently emerged as a powerful new type of ANN (Zhang 1997, Bakshi and Stephanopoulos 1993, Zhang and Gupta 2000), gradient-based techniques (Zhang and Gupta 2000), orthogonal wavelet network for nonlinear functional approximation and nonparametric estimation (Zhang 1997), system identification and control tasks (Sanner and Slotine 1998), and modeling and classification (Echauz 1995).

For all applications involving input data, instead of applying input data directly to the algorithm, a preprocessing stage is applied to the data for efficient representation. Wavelets were used as preprocessing tools for automated neural network detection of EEG Spikes (Kalayei and Ozdamar 1995), ECG spikes (Carranza and Andina 2002), Arrhythmia detection (Strauss 2001), discriminates between different classes of acoustic bursts (Huang and Solorzano 1991). It is used as preprocessing tools for neural network based defect detection in analog and mixed circuits (Viera Stopjakova et al 2005). It is proved that the wavelet preprocessing improves the performance of a Singular value decomposition based denoising application (Bettayeb and Shah 2007) for fuzzy systems (Popoola and Ahmad 2005), an automatic target recognition (ATR) system in recognizing aircraft from high range resolution radar (HRR) signatures (Huether et al 2001), and allows for a speaker-dependent feature set extraction (George et al 2001) .

Recently, applications of wavelets as bases or wavelet-like basis functions are becoming widely used in the solution of electromagnetic modeling problems (Wang et al 1992, Wagner et al 1993, Steinberg and Leviatan 1993, Wang and Pan 1995). Hence, this paper proposes the novel synthesis procedure using a wavelet based preprocessing for a low pass filter using ANN.

III. METHODOLOGY

Conventionally, wavelets are combined with neural networks to form wavelet neural networks for carrying out electromagnetic (EM) analysis (Zhang and Gupta 2000). Wavelet networks are feed forward networks with one hidden layer, and its activation functions being wavelets. By this significant performance enhancement in respect of reduction in memory and computational speed has been reported. Having chosen hyperbolic tangent function as the function for the neural network (NN) so as to synthesis the filter Cauer ladder network form (thenmozhi), the approach of replacing the activation function by wavelets is not attempted. However, the wavelets are used for preprocessing of the input data to the neural network.

The design methodology is to select and transform a suitable wavelet function with the dilation and translation parameters as per the desired response as shown in Figure 3.1. Samples are taken at regular intervals from the desired response that is transformed using the wavelet function with the dilation and translation parameters.

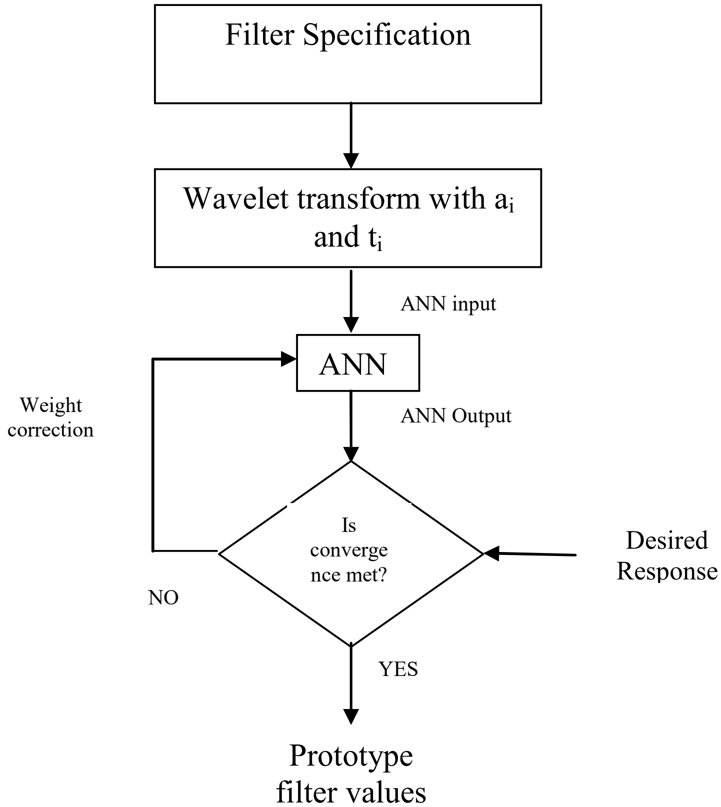


Figure 1 Model development with the help of neural network using Wavelet transform

As it was considered above, preprocessing of the neural network input data can drastically simplify the network architecture, improve its performance, and reduce the number of input vectors needed for the neural network training. Wavelet transform provides high time resolution, and low frequency resolution for high frequencies (low scales); and low time resolution, and high frequency resolution for low frequencies (high scales). That feature is ideal for preprocessing of non-stationary signals (Bremaud 2002). Therefore, wavelet decomposition has been used to preprocess the neural network inputs vectors (Stopjakova et al 2005).

Wavelet transform of a continuous-time signal is defined as

$$W_{x(a,b)} = |a|^{-\frac{1}{2}} \int x(t)\psi\left(\frac{t-b}{a}\right)dt \tag{1}$$

where function $\psi(t)$ is the so-called *wavelet* or *mother wavelet*, defined as

$$\psi_{a,b}(t) = |a|^{-\frac{1}{2}} \psi\left(\frac{t-b}{a}\right) \tag{2}$$

Coefficients a, and b define degree of scaling, and time shift of the mother wavelet $\psi(t)$, respectively. The wavelet coefficients $W_{x(a,b)}$ give a measure of similarity between shifted, and scaled mother wavelet with an input signal $x(t)$.

Symmetry is convenient for the implementation of numerical schemes, while a compact support is essential when complicated boundary conditions are to be enforced. A commonly used wavelet function is the Inverse Mexican-hat function, given by

$$\psi\left(\frac{x-t_i}{a}\right)=\sigma(\gamma_i)=\left(\gamma_i^2-n\right)\exp\left(-\frac{\gamma_i^2}{2}\right) \tag{3}$$

where

$$\gamma_i=\left\|\frac{x-t_i}{a_i}\right\|=\sqrt{\sum_{j=1}^{n}\left(\frac{x_j-t_{ij}}{a_i}\right)^2} \tag{4}$$

where $x= [x_1, x_2, \ldots, x_n]^T$ is the input vector, $t_i = [t_{i1}, t_{i2}, \ldots, t_{in}]^T$ is the translation parameter, a_i is a dilation parameter. This methodology has the following salient features: Desired response need not to be symmetrical, Drastically reduces the number of inputs to the neural network, and minimize the training set, More susceptible to be trapped into local minima, which is caused by the inherent oscillatory property of wavelet functions and Consumes significantly less computational time as compared to neural network synthesis methods. Hence, this Inverse Mexican-hat wavelet function is used with the suitable dilation and translation parameters.

Then the transformed samples are used to train the ANN until the output response is within the specified limit. Outputs from the ANN are suitably equated to the Cauer ladder network forms so as to synthesize the filter coefficients (Valkenburg 1987). The ANN is built of two layers namely the sigmoid layer and the linear layer to train the desired response. In the first layer a tansig function is used to map the neuron's input from the interval (-∞, ∞) to the interval (-1, +1). The tansig is a fully differentiable function, which makes it suitable for the neurons to be trained using back propagation algorithm (The Math Works 1994, Zhang and Gupta 2000). The input-output relationship of the first layer is given by following equations:

$$[A_1]=\tan sig\left([w_1][P]+[b_1]\right) \tag{5}$$

Since tansig (n) ≈ tanh (n)

$$[A_1]=\tanh\left([w_1][P]+[b_1]\right) \tag{6}$$

where, $[A_1]$ is the m x 1 output matrix, $[w_1]$ is the m x n neuron weight matrix, $[P]$ is the $n \times 1$ ANN input matrix and $[b_1]$ is the $m \times 1$ neuron bias matrix. The second layer uses a *purelin* function, which is a linear transfer function that simply passes a neuron's input vectors on to its output, which can be altered only by the neuron's bias. The input-output relationship of the second layer is thus given by

$$[A_2]=purelin[w_2][A_1]+[b_2] \tag{7}$$

Substituting (5) in (7),

$$\left[A_2\right]=\left[w_2\right]\tanh\left(\left[w_1\right]\left[P\right]+\left[b_1\right]\right)+\left[b_2\right] \tag{8}$$

Equation (8) represents the transfer function of the entire ANN. Let s = ([w_1][P] + [b_1]), then the expansion of tanh (s) in the form of infinite continued fraction is given by

Equation (9) represents the transfer function of the entire ANN. Let s = ([w1][P] + [b¬1]), then the expansion of tanh (s) in the form of infinite continued fraction is given by the equations (10) and (11).

$$\tanh(s)=s+\cfrac{1}{\left(\cfrac{s}{3}+\cfrac{1}{\left(\cfrac{s}{5}+.........\right.}\right.} \tag{10}$$

$$\approx s+\frac{1}{s/3} \tag{11}$$

The continued fraction form can be realized as a ladder network consisting of shunt capacitors and series inductors. The ladder network synthesizes the low pass prototype model where the trained ANN weight (w) and bias represents the transfer function coefficients of the filter. The final output is obtained from the following equation:

$$\left[A_2\right]=\left[w_2\right]\times\left(s+\frac{1}{s/3}\right) \tag{12}$$

The elemental values (g) for the inductance and capacitance sections of the low pass prototype filter are calculated from the ANN's optimized weight values by (13a) and (13b).

$$g_l = w_2 \tag{12a}$$

$$g_c = 3\times w_2 \tag{12b}$$

The prototype filter is then scaled for both impedance and frequency to obtain the desired filter. The inductance and capacitance values for the lumped low pass circuit are calculated from the prototype circuit parameters of the 4th order low pass filter and are tabulated in Table 1, as given by

$$L = R_0 g_k/\omega_c \tag{13a}$$

and

$$C = g_k/R_0\omega_c \tag{13b}$$

The electrical lengths of the lines can then be calculated from the following equations

$$\beta\ell = \frac{g_k R_0}{Z_h} \quad \text{(Inductor)} \qquad (14a)$$

and $$\beta\ell = \frac{g_k Z_\ell}{R_0} \quad \text{(Capacitor)} \qquad (14b)$$

where g_k is the prototype value of the filter element and R_0 is the filter impedance, normally 50 ohms.

IV. RESULTS AND DISCUSSION

To show the validity of the proposed neuro-wavelet based filter synthesis methodology, a set of low pass filters representing various orders in a chosen wireless band is designed. A prototype Chebyshev low pass filter response with a cutoff frequency of 1.457 GHz, ripple of -2 dB and an attenuation of 20 dB at 2.1 GHz is taken as a desired response. This wavelet transformed data set is fed as the input to input layer of the neural network. The neural network architecture consisting of two neurons employing tansig function as the input layer and one neuron employing purelin function as the output layer is chosen for training. The neural network is trained with a maximum of 10000 epochs and an error of e^{-5} has been fixed as the performance goal. The time taken for one complete successful training of the ladder network on a 1.7 GHz processor with 1 GB RAM may vary from 1 to 60 seconds depending on the chosen ANN. Figure 2 shows the training curve of the neural network using wavelet transform. This curve represents the relation between the error value and the number of epochs.

It can be seen from the Figure 2, as the number of epochs increase above 120 the algorithm converges to an error of $9.73976e^{-6}$ reaching the performance goal. The training algorithm could escape from the local minimum by the transformed dataset. Since, in this method only the data set is chosen by wavelet algorithm, there is every possibility that the ANN would be trained with insufficient number of neurons for a higher order response resulting in under learning. Thus, it is always necessary to make a decision on the required number of neurons based on the roll off of the desired response. The ANN training algorithm starts with random initial weights and biases, therefore the outputs of each of the training produce different results.

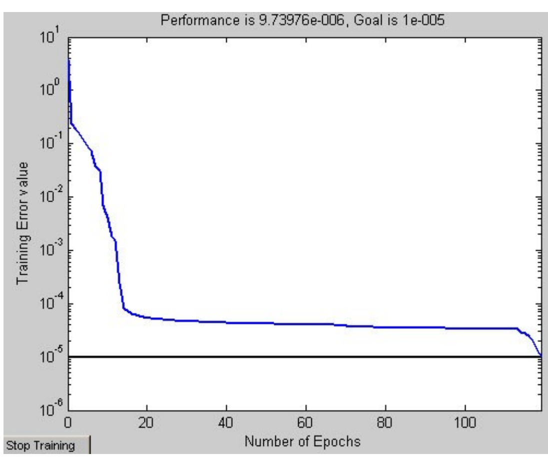


Figure 2: Training error versus number of epochs curve of the ANN

The inductance and capacitance values for the trained 4th order low pass filter of the Neural network using Wavelet transform method is calculated using the equations (13a and 13b) which is tabulated in Table 1.

Table 1 Inductance and capacitance values for the trained 4th order low pass filter using Neural network using Wavelet transform method

Weight values (g_k)	**0.9364**	**2.8092**	**0.9364**	**2.8092**
Inductance values in nH	5.1144	------	5.1144	------
Capacitance values in pF	------	6.1372	-------	6.1372

Figure 3 shows the lumped model of the synthesized 4th order low pass filter using the proposed Neural network using Wavelet transform algorithm. The filter is simulated using ADS 2002C for its RF performance. Figure 4 shows the S-Parameters, namely, S_{21} and S_{11} of the proposed neural network using Wavelet transform based synthesized filter and Chebyshev filter for the same specifications. It is seen from the figure the filter has a pass band ripple -2dB and the return loss 20dB at 2.1 GHz which well coincides with the desired results.

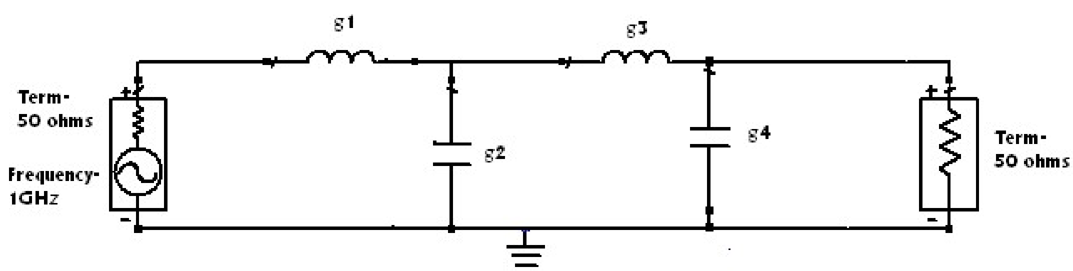
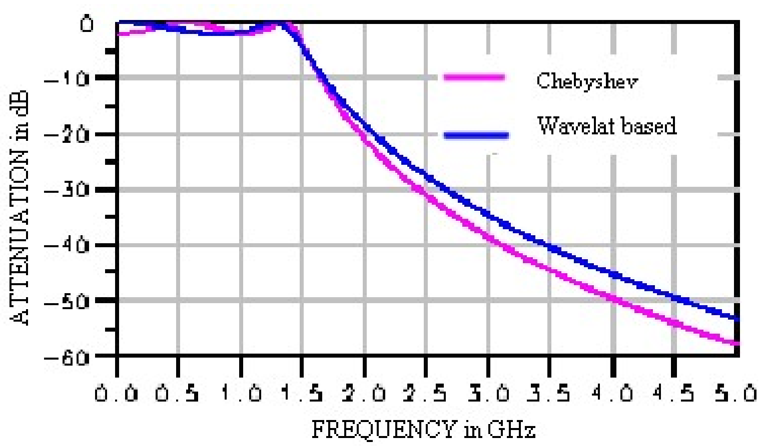
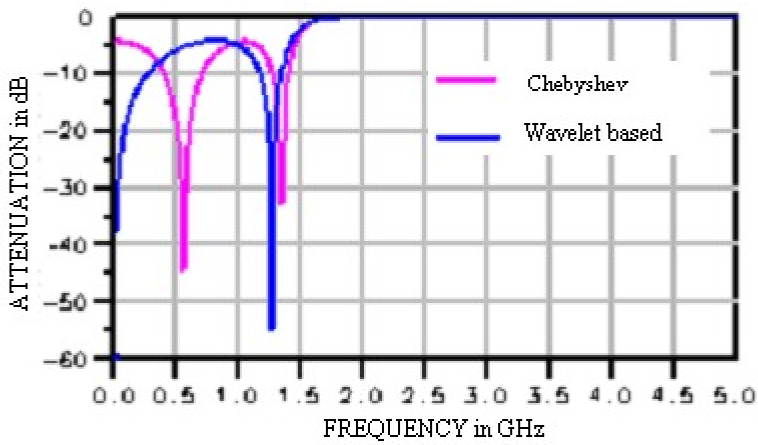


Figure 3: Lumped circuit model for the neural network using Wavelet transform based 4th order low pass filter



(a)



(b)

Figure 4:S21 and S11 versus frequency responses of a Neural network using Wavelet transform based 4th order low pass filter in comparison with Chebyshev filter of the corresponding order

The proposed neural network using Wavelet transform based low pass filter is realized using stepped impedance structure. The selected high impedance (Z_h) value is 90 ohms and low impedance (Z_ℓ) is 10 ohms. The electrical lengths of the lines can then be calculated using the equations (14a and 14b). The layout of the low pass filter was simulated and optimized in ADS 2002C as shown in Figure 5.

The synthesized low pass filter was fabricated on a glass epoxy substrate with a dielectric constant (ε_r) of 4.6 and a thickness of 1.6 mm as shown in Figure 6.

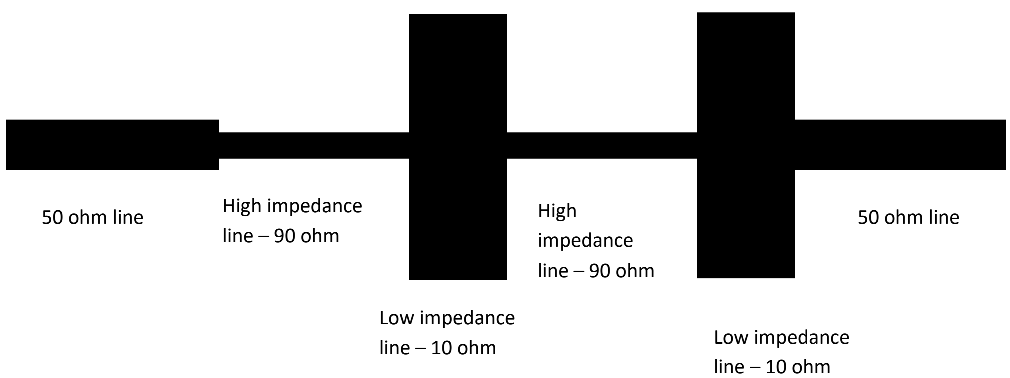


Figure 5: Distributed model of the 4th order Neural network using Wavelet transform based low pass filter

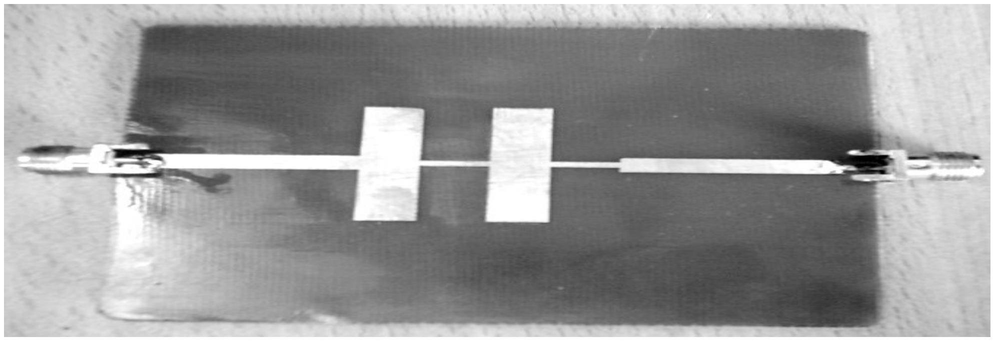


Figure 6 Photograph of the fabricated microstrip low-pass filter designed by Neural network using Wavelet transform Method

The performance of the filter was measured using the Agilent N5230A Vector Network analyzer. The simulated and measured responses of the distributed filter are shown in Figure 7. It is seen that the simulated and measured responses are in good agreement and also it is seen from the figure that the insertion loss of the fabricated model is slightly higher than the simulated model due the loss introduced by the soldering of the connectors and cables used during measurement.

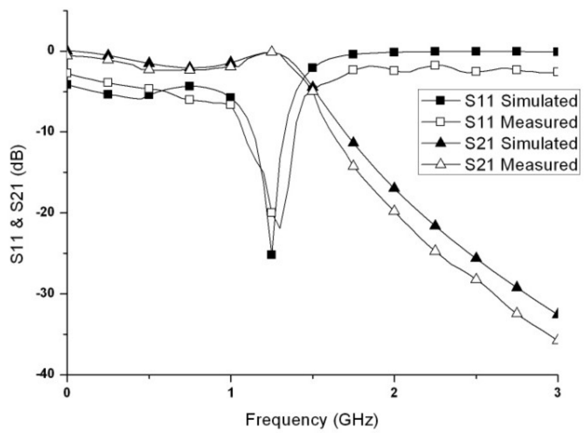


Figure 7: S_{11} and S_{21} versus frequency responses of the Measured and Simulated structures of the Microstrip Low pass Filter

V. CONCLUSION

This paper described the method of designing the neural network using Wavelet transform based low pass filter. The Neural network using Wavelet transform method has been used to model the distributed element parameters and to model the circuit response in terms of the scattering parameters. This method is computationally much more efficient than Electromagnetic (EM) or physics-based model and can be accurate than empirical physics-based models. The design approach was validated through simulation, fabrication and measurement of a microstrip based low pass filter for wireless applications. This proposed method attempts to remove the inherent drawbacks of the ANN approach of filter synthesis in respect of computation time and trapping of solution space into local minima.

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