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High Dimensional Modeling of Microstrip Hairpin Bandpass Filter Using Artificial Neural Networks

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Abstract

Conventional neural network modeling techniques are not suitable for developing models that have many input variables because data generation and model training become too expensive. In this paper, an efficient neural network modeling technique for microstrip hairpin band pass filter that have many input variables is proposed. The decomposition approach is used to simplify the overall high dimensional neural network modeling problem into a set of low dimensional sub neural network problems. A method to combine the sub models with a filter empirical/equivalent model is developed. An additional neural network mapping model is formulated with the neural network sub models and empirical/ equivalent model to produce the final overall filter model. Even, with a limited amount of data, the proposed model can produce much more accurate results compared to the conventional neural network model and the resulting model is much faster than an EM model.

Key words: *Computer-aided design (CAD), high dimensional modeling, Microstrip hairpin band pass filter, neural network, optimization, simulation*

1. Introduction

In microwave communication systems, high performance and small size bandpass filters are essentially required to enhance the system performance and to reduce the fabrication cost. Parallel coupled microstrip filters, first proposed by Cohn in 1958 have been widely used in the RF front end of microwave and wireless communication systems for decades [1]. The advantages of this filter are its planar structure, insensitivity to fabrication tolerances, reproducibility, wide range of filter fractional bandwidth (FBW) (5% to 50%) and an easy design procedure [2–6].

Parallel coupled microstrip filter with $\lambda/2$ resonators are common elements in many microwave systems, their large size is incompatible with the systems where size is an important consideration [7]. The length of parallel coupled filter is too long and it further increases with the order of filter. To solve this problem, hairpin line filter using folded $\lambda/2$ resonator structures were developed [8, 9]. The traditional design of the hairpin topology has the advantage of compact structure, but it has the limitation of wider bandwidth and poor skirt rate due to unavoidable coupling [10]. In addition to small size, high selectivity and narrow bandwidth, good Return Loss (RL) and low cost are desirable features of narrowband bandpass microstrip filters.

Most of the wireless applications are below 3 GHz [11]. In this spectrum, achieving narrow FBW and high quality factor (Q) while maintaining small size and low cost is a challenging task. Using a dielectric substrate with high dielectric constant (ε_r) results in narrower microstrip line. However, a narrower line results in stronger input/output coupling or a smaller external quality factor (Q_e) [12]. Narrow bandwidth and high selectivity demands large Q, which can be achieved through larger gaps between coupled resonators. But increasing gap between coupled resonators directly affects the filter size.

Neural networks have been recognized as useful alternatives for device modeling, where a mathematical model is not available or time-consuming simulation is required. They can be utilized to model multidimensional nonlinear relationships. The evaluation time of a neural-network model is also fast. For these reasons, neural networks have been used for various modeling and design applications [13, 14] including passive microwave structures [15, 16]. Neural networks have not only been used for developing microwave device models, but also have been used in optimization processes, where the neural models are combined with full wave simulation tools [17]-[19].The general idea of neural network based CAD and optimization is to develop neural-network models for EM structures and incorporate the models in circuit simulators. This allows circuit-level simulation speed with EM level accuracy.

In this paper, we focus on neural network based modeling of microstrip filters. Accurate model is essential for the first pass design success. Conventional EM modeling method is the first option to obtain an accurate model. However, the model evaluation time of this method is long, especially when repetitive model evaluations are required. During design optimization, values of geometrical variables are required to be changed many times and each time a complete re-evaluation of the model is required. For this reason, the EM model becomes too expensive.

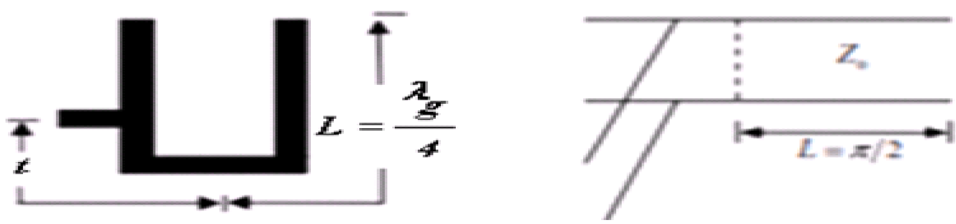
An alternative to the EM model is a neural network model, whose inputs are geometrical variables [13-15], [20-25].The neural network model can provide solutions quickly for various values of geometrical input variables. Due to increasing complexity and variety of microwave structures, the number of design variables per structure is on the rise. In order to develop an accurate neural network model that can represent EM behavior of filters over a range of values of geometrical variables, we need to provide EM data at sufficiently sampled points in the space of geometrical variables [13, 14]. The amount of data required increases very fast with the number of input variables of the model. For this reason, developing a neural network model that has many input variables becomes challenging as data generation becomes too expensive. Therefore, we need an effective method to develop accurate high dimensional neural-network models without requiring massive data.

This paper presents the analysis of microstrip hairpin bandpass filter and also proposes a high dimensional artificial neural network model to determine the S-parameters of the hairpin filter for various frequencies. Performance of the proposed model is evaluated and is compared with EM simulation results and Conventional ANN model.

The remainder of the paper is organized as follows: Section 2 focuses on microstrip hairpin bandpass filter and its design.Section 3 discusses high dimensional ANN modeling for the analysis of microstrip hairpin bandpass filter.Section 4 explains proposed ANN Model for the analysis of microstrip hairpin bandpass filter. Finally, Section 5 summarizes the presented research work.

2. Microstrip Hairpin Bandpass Filter

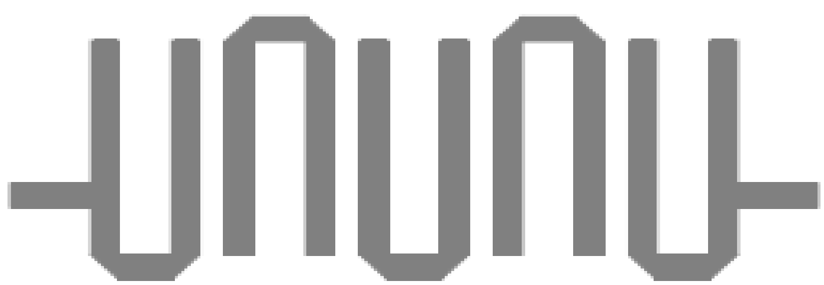
Microstrip hairpin filter is one of the most preferred bandpass filter because of its compact topology and an ease structure. They may conceptually be obtained by folding the resonators of parallel-coupled, half-wavelength resonator filter into a “U” shape. However, to fold the resonators, it is necessary to consider the reduction for coupled-line lengths, which reduces the coupling between resonators [26]. An element of hairpin bandpass resonator and its equivalent circuit are shown in Figure 1(a) and (b) respectively. The advantage of hairpin filter over end coupled and parallel coupled Microstrip realizations, is the optimal space utilization. This space utilization is achieved by folding of the half wavelength long resonators.



(a) Tapped- Hairpin Band Pass Filter (b) Equivalent Circuit

Figure 1. Tapped-Hairpin Bandpass Filter and Equivalent Circuit

Tapped line input and coupled line input are the two types of hairpin structures that are commonly used in filter realization and are shown in Figure 2(a) and (b) respectively. Conventional filters employ coupled line input. Tapped line input has a space saving advantage over coupled line input, while designing the coupling dimensions required for the input and output coupled line is very small and practically not achievable which hinders the reliability of the design. Thus tapped line input is preferred over coupled line input.



(a) Tapped line input 5-pole Hairpin Filter

(b) Coupled line input 5-pole Hairpin Filter

Figure 2. Hairpin Structures

2.1 Design Parameters for Hairpin Filter

For designing a hairpin filter, Full Wave EM simulation is used. For the design purpose the low pass prototype (Butterworth, Chebyshev, and Bessel) is selected according to the design requirement. The equivalent circuit of the n-pole hairpin bandpass filter is shown in **Figure.3**

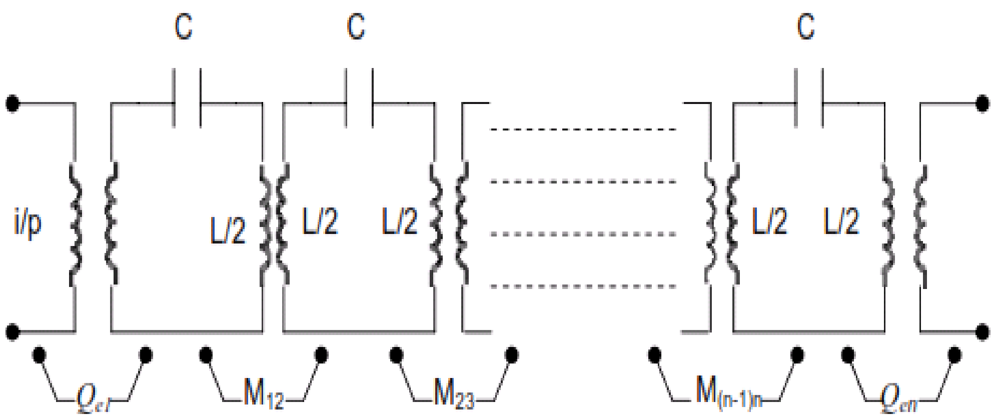


Figure 3. Equivalent Circuit of the n-pole Hairpin Bandpass Filter

As seen from the equivalent circuit of n-pole hairpin filter in Figure 3, each resonator can be modeled as a combination of inductor and capacitor. The mutual coupling coefficient between two resonators is $M_{i,i+1}$, Q_{e1} and Q_{en} are the quality factor at the input and output.

The Coupling coefficient and Quality Factor can be calculated as

$$Q_{e1} = \frac{g_0\, g_1}{FBW} \quad (1)$$

$$Q_{en} = \frac{g_n g_{n+1}}{FBW} \quad (2)$$

$$M_{i,i+1} = \frac{FBW}{\sqrt{g_i g_{i+1}}} \quad \text{for i=1 to n-1} \quad (3)$$

Where FBW is the fractional bandwidth and g_0, g_1, g_2 ……… g_{n+1} are the normalized low pass elements of the desired low pass filter approximation.

If hairpin filter self-coupling effect between arms is ignored, we can calculate the tapped position showing in Figure 1 [12]

$$t = \frac{2L}{\pi} sin^{-1}\left(\sqrt{\frac{\pi Z_0}{2Q_e Z_r}}\right) \tag{4}$$

Where Z_0 is the terminating Impedance, Zr is the characteristic impedance of the hairpin line, Q_e is output/input external quality factor and L is the arm length of hairpin filter.

The arm length L of hairpin filter can be calculated by [12]

$$L = {}^{\lambda_g}/_{4} \tag{5}$$

Where $\lambda_g = {}^{\lambda_o}/_{\sqrt{\varepsilon_{re}}}$, λ_o is the wave length of the filter with frequency f_0 in vacuum.

The effective dielectric constant (**ε_{re}**) of a microstrip line can be calculated using the formula mentioned in [27], which is used in realization of hairpin filter.

Approximate expressions for *W/h of* a microstrip line in terms of Z_c and ε_r, derived by Wheeler [28] and Hammerstad [29]. These expressions provide accuracy better than one percent.

A microstrip hairpin bandpass filter is designed to have a fractional bandwidth of 25% or *FBW* = 0.25 at a midband frequency f_0 = 2.5 GHz. A five-pole (n = 5) Chebyshev lowpass prototype with a pass band ripple of 0.1 dB is chosen. The lowpass prototype parameters, given for a normalized lowpass cutoff frequency $\Omega_c = 1$, are $g_0 = g_6 = 1.0$, $g_1 = g_5 = 1.1468$, $g_2 = g_4 = 1.3712$, and $g_3 = 1.9750$.Having obtained the lowpass parameters; the bandpass design parameters can be calculated using equations (1-3).

The designed parameters of a microstrip hairpin filter are obtained using the above equations. We use a commercial substrate (RT/D 6006) with a relative dielectric constant of 6.15 and a thickness of 1.27 mm for microstrip realization. The hairpin resonators used to have a line width of 2 mm which results in Z_r = 48 ohm on the substrate and a separation of 2 mm between the two arms. The arm length L of hairpin resonator is 14.237mm.The filter is designed to have tapped line input and output. The tapped line is chosen to have characteristic impedance that matches to a terminating impedance Z_0 = 39 ohms. Hence, the tapped line is 2.85 mm wide on the substrate. The tapping location (t) as shown in Figure 1(a) is 5.5mm.The spacing between the resonators are 0.2mm and 0.4mm which gives $M_{1,2} = M_{4,5} = 0.1707$ and $M_{2,3} = M_{3,4} = 0.1427$.

The layout of the final filter design with all the determined dimensions is illustrated in Figure 4.

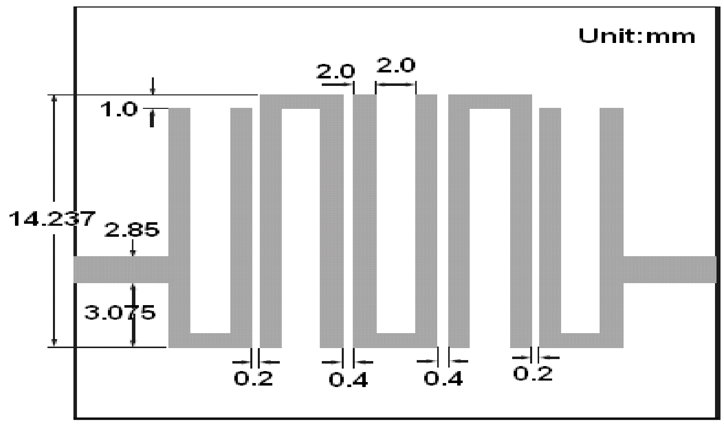


Figure 4. Layout Microstrip Hairpin Filter

3. High Dimensional Modeling

Due to increasing complexity and variety of microwave structures, the number of design variables per structure is on the rise. In order to develop an accurate neural network model that can represent EM behavior of filters over a range of values of geometrical variables, we need to provide EM data at sufficiently sampled points in the space of geometrical variables [13, 14]. The amount of data required increases very fast with the number of input variables of the model. For this reason, developing a neural network model that has many input variables becomes challenging as data generation becomes too expensive. Therefore, we need an effective method to develop accurate high dimensional neural network models without requiring massive data.

Various advanced neural network structures have been investigated for microwave modeling such as knowledge based neural networks [30, 31] for simplifying input–output relationship. It reduces the cost of neural-network training for highly nonlinear input–output modeling problems. However, it does not have the mechanism to address the challenge of high dimensional modeling problems directly.

Modular neural network is an interesting technique, which has the potential to address high dimensional modeling problem because of neural-network decomposition. It has been investigated within the artificial neural-network community for applications such as face detection [32, 33], voice recognition [34], pattern recognition [35, 36], directional relay algorithm for power transmission line [37], problem simplification [38], etc. The modular concept has also been investigated for microwave optimization such as dielectric resonator filters [39], microstrip corporate feeds [40], power amplifiers [41], semiconductor process characterization [42], antennas [43], etc. This technique decomposes a complex neural network into several simple sub-neural-network modules. The modular neural-network technique has been used to improve the learning capability of neural networks. However, the existing modular neural network method is not directly suitable for high dimensional neural network modeling of microstrip filters because it has not been formulated to accommodate the knowledge of microstrip filter formulas. Another problem with the existing neural-network decomposition is the absence of connections between neural network decomposition and microwave filter decomposition.

In this paper, a new method to obtain a complete forward model for filters that has many geometrical variables is proposed. We decompose a filter structure into substructures and develop forward sub models. The inputs of the sub models are geometrical dimensions and outputs are coupling parameters. These sub models are combined with filter equivalent-circuit model to produce an approximate solution of the entire filter. A mapping model is trained and used to make the high dimensional model as accurate as the EM model. The main objective is to develop a high dimensional neural network model, which is too expensive to develop using a conventional neural-network approach. The new method is used to develop complex filter models that hold many input variables. The overall filter is constructed by combining the neural-network sub models, circuit model, and neural-network mapping model. The diagram of the overall high-dimensional modeling structure is presented in Figure 5.

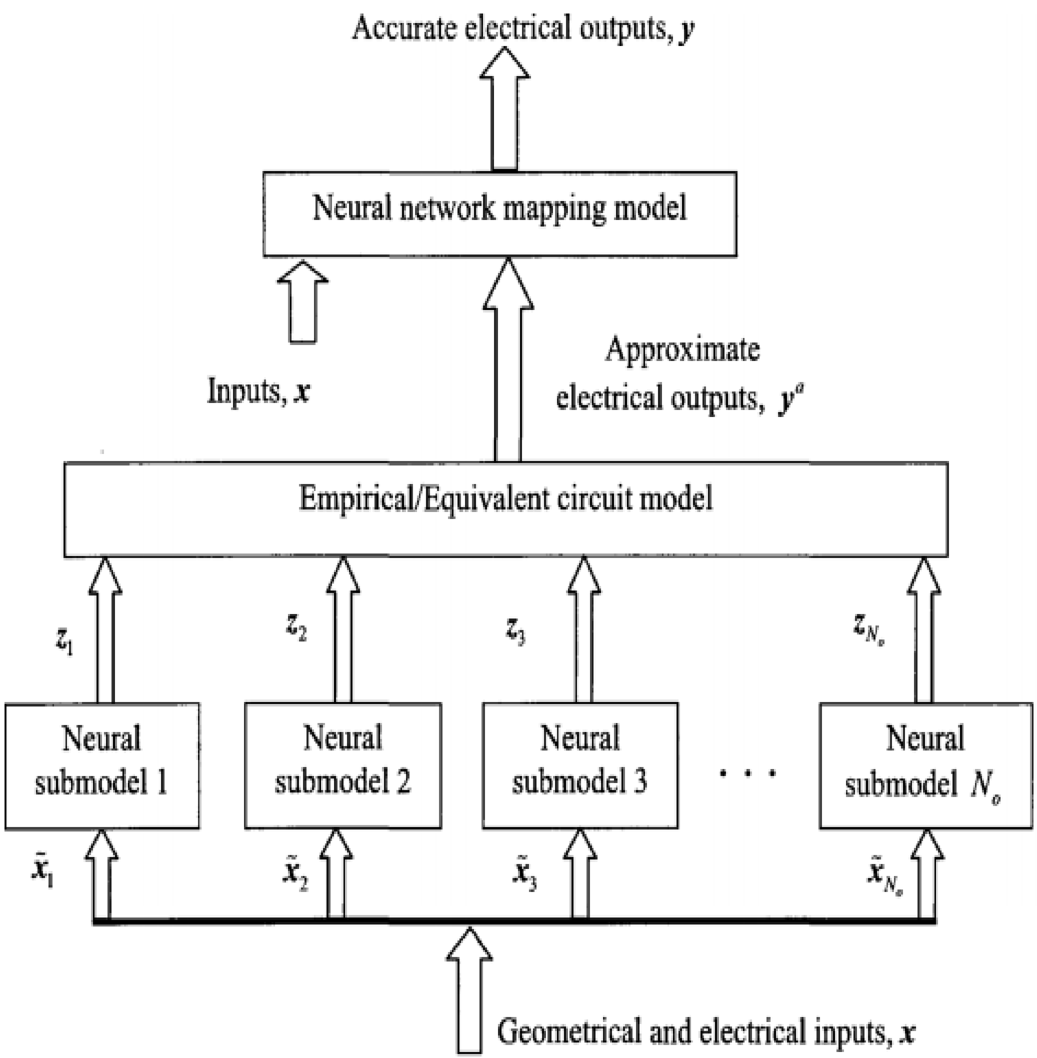


Figure 5. High Dimensional Modeling Structure

The sequence of steps for the overall high dimensional modeling is described as follows:

1. Identify the parts of an overall filter that can be used as substructures. Decompose the overall filter into substructures.

2. Generate training data of the decomposed substructures using EM simulations. Standard sampling approach can be employed for this purpose.
3. Train and test neural network sub models for all the decomposed substructures.
4. If the sub models are accurate, go to Step 5. Else, generate some more data of the sub structures by sampling intermediate points using EM simulation, add those to the existing data, and go to the Step 3.
5. Generate a few data of the overall filter using EM simulation. Sweep the input variables and obtain corresponding output solutions of the overall filter.
6. Combine the neural network sub models and the empirical/equivalent circuit model.
7. Supply the samples of the input variables to the combined neural network sub models and empirical/equivalent circuit model to obtain samples of approximate solution of the overall filter.
8. Using the concept of prior knowledge input, assemble training data for the map ping model. Use the samples of and of Step 7 as the data for the input neurons. Use the samples of that correspond to the samples of as the data for the output neurons. Train the neural network mapping model using some of the assembled data. Test the mapping model with the rest of the data. If accuracy is satisfied, go to Step 9. Else, generate a few more data of the overall filter, add those to the existing data of the overall filter and go to Step 7.
9. Combine the neural-network sub models, empirical/equivalent circuit model, and neural network mapping model, to obtain the overall model of the filter.

4. Proposed High Dimensional Model for the Analysis of Microstrip Hairpin Bandpass Filter

Using the steps discussed in the previous section a high dimensional ANN model is developed and is shown in Figure 6. The developed ANN model is used for analyzing the S-parameters of microstrip hairpin band pass filter for different geometrical and physical parameters.

The S-parameters ($S_{11}$and S_{21}) obtained from EM simulation, high dimensional ANN model and the conventional forward neural model are given in Table 1 and 2 from which it is clear that the results obtained from high dimensional ANN model are better than those of the conventional forward neural model. In order to validate the high dimensional ANN model for the analysis of microstrip hairpin bandpass filter, comprehensive comparisons have been made. The results obtained from high dimensional ANN model is compared with EM Simulated results and conventional forward neural model results and are presented graphically (Figures: 7 & 8).

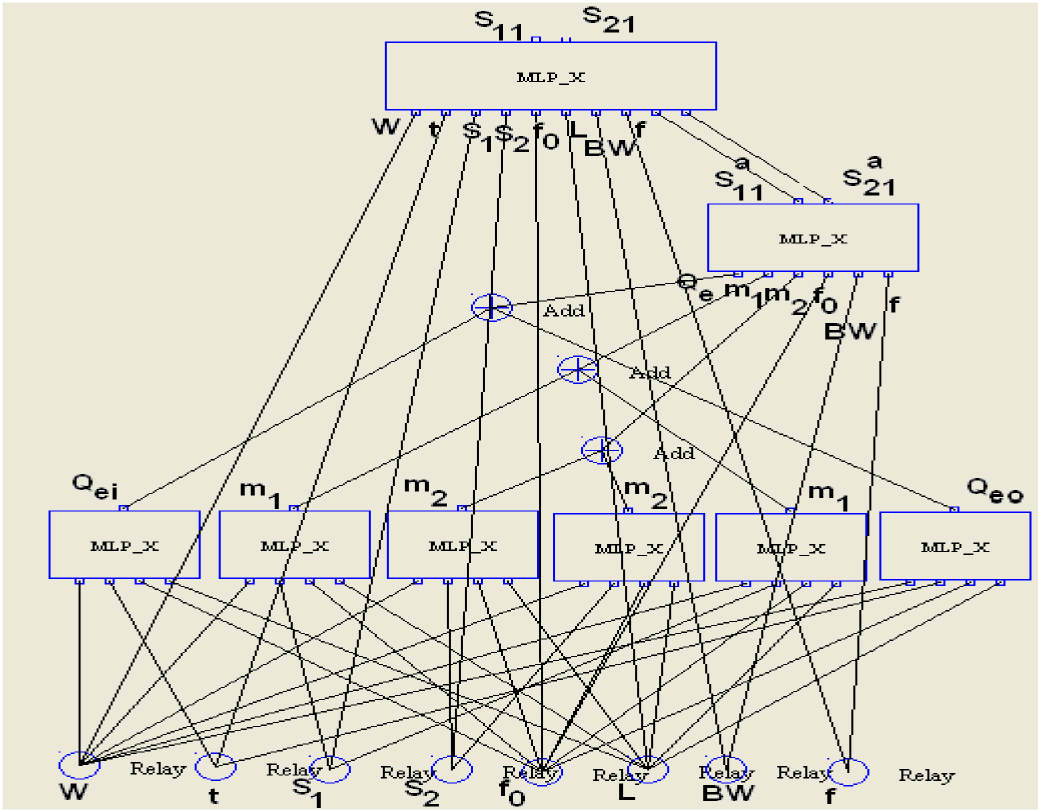


Figure 6. High dimensional Neural Network Model for Microstrip Bandpass Filter

Table 1. Comparison of S_{11} (in dB) for Microstrip Hairpin Bandpass Filter

Frequency (G Hz)	S_{11} in dB		
	EM Simulation	High Dimensional ANN	Conventional ANN
1.624	-1.04798	-1.045978	-0.83114
2.01	-17.8316	-17.83063	-17.0515
2.063	-14.1062	-14.10319	-14.3887
2.549	-0.77539	-0.774386	-0.64218
2.599	-0.64109	-0.64609	-0.50657
2.621	-0.59822	-0.603215	-0.4722
2.804	-0.40939	-0.410393	-0.35272
3.215	-0.30482	-0.309824	-0.30711
3.275	-0.30129	-0.300289	-0.31426
3.399	-0.29903	-0.301034	-0.33802

Table 2. Comparison of S21 (in dB) for Microstrip Hairpin Bandpass Filter

Frequency (G Hz)	S_{21} in dB		
	EM Simulation	High Dimensional ANN	Conventional ANN
1.537	-32.4433	-32.4423	-32.5437
1.641	-21.7712	-21.7752	-21.714
1.821	-3.91559	-3.91259	-4.4896
1.831	-3.67883	-3.67483	-4.15812
2.407	-14.7488	-14.7488	-14.6254
2.832	-46.1849	-46.1809	-46.0332
2.845	-46.6956	-46.6936	-46.5475
2.88	-47.9915	-47.9915	-47.8842
3.299	-56.3798	-56.3808	-56.1816
3.458	-56.6588	-56.6538	-56.8739

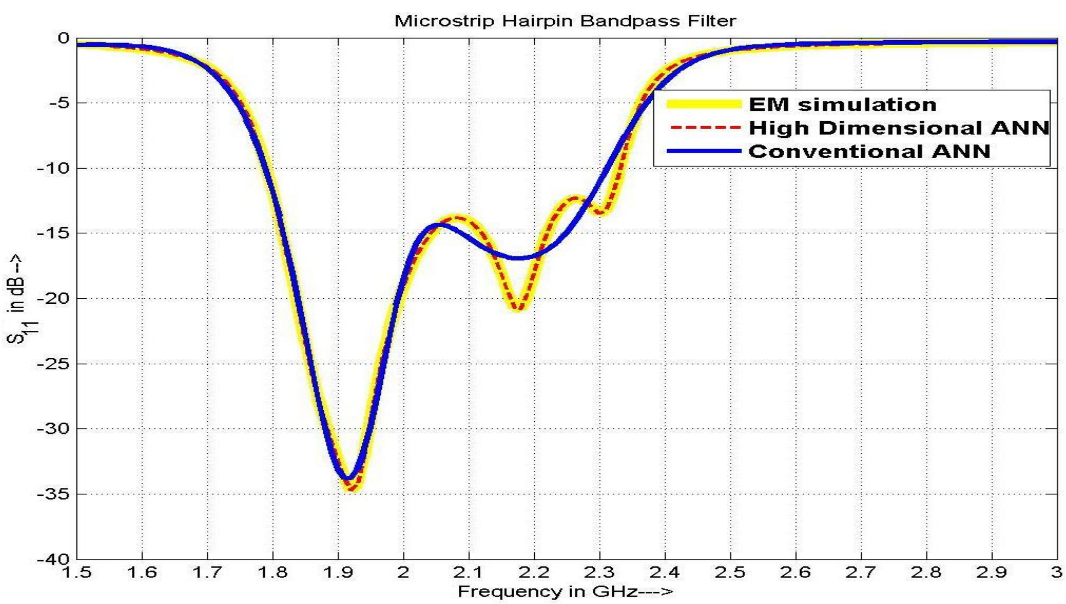


Figure 7. Comparison of Frequency (in GHz) Vs S11 (in dB) obtained using the EM Simulated Results with that of the Neural Model (Conventional ANN & High Dimensional ANN) of a Microstrip Hairpin Bandpass Filter

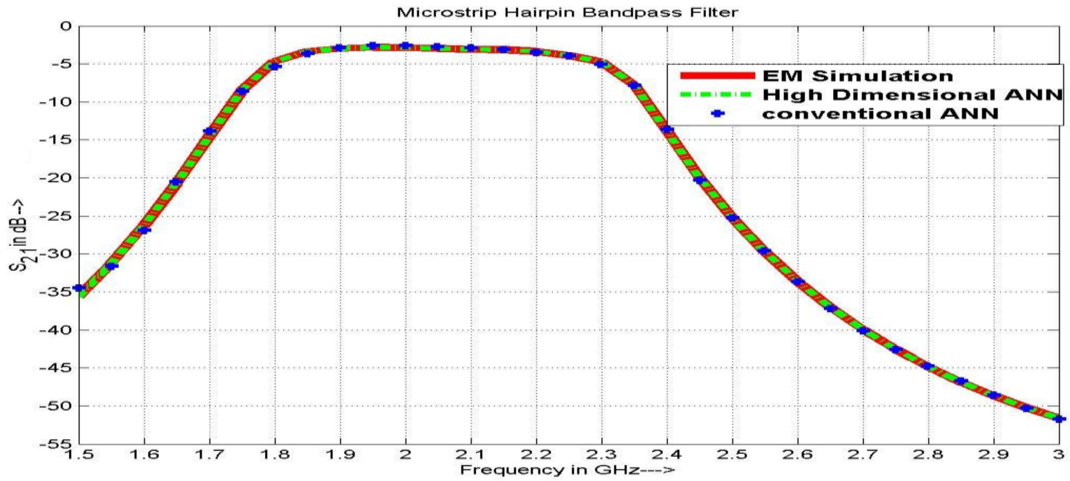


Figure.8: Comparison of Frequency (in GHz) Vs S21 (in dB) obtained using the EM Simulated Results with that of the Neural Model (Conventional ANN & High Dimensional ANN) of a Microstrip Hairpin Bandpass Filter

5. Conclusion

An effective neural network modeling technique for filters that hold many design variables is proposed. It is impractical to develop a neural network model for such structures in the conventional neural network approach. The result shows that the proposed method can be used to produce high dimensional models with few full EM training data, which are usually expensive to generate, compared to the conventional neural network technique. The method is very useful for developing neural network model of microstrip filters that have many design variables. The developed neural network model becomes very useful for fast design optimization of those filters.

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References

[1] Cohn SB, “Parallel-coupled transmission-line-resonator filters,” IRE Transactions on Microwave Theory and techniques, vol. MTT-6, no. 4, **(1958)** April, pp. 223–231.

[2] Matthaei GL, “Design of wide band (and narrow band) bandpass microwave filters on the IL basis,” IRE Transactions on Microwave Theory and Techniques, vol. MTT-8, no. 11, **(1960)** November, pp. 310– 314.

[3] Chang CY, Itoh T, “A modified parallel-coupled filter structure that improves the upper stop band rejection and response symmetry,” IEEE Transactions on Microwave Theory and Techniques,vol. 39, no. 2, **(1991)** February pp. 310–314.

[4] Riddle A, “High performance parallel coupled microstrip filters,” IEEE Microwave Theory and Technology Symposium Digest, **(1988)**, pp. 427– 430.

[5] Akhtarzad S, Rowbotham TR, Johns PB, “The design of coupled microstrip lines,” IEEE Transactions on Microwave Theory and Techniques, vol. MTT-23, no. 6, **(1975)**, June, pp. 486–492.

[6] Pozar DM, Microwave Engineering, 2nd edition, Wiley, New York, **(1998)**.

[7] Collin RE, Foundations for Microwave Engineering, 2nd edition, IEEE Press, Wiley, New York, **(1992)**.

[8] Cristal EG, Frankel S, “Hairpin-line and hybrid hairpinline/half-wave parallel-coupled-line filters,” IEEE Transactions on Microwave Theory and Techniques, vol. MTT-22, no. 11, **(1972)** November, pp. 719–728.

[9] Gysel UH, “New theory and design for hairpin-line filters,” IEEE Transactions on Microwave Theory and Techniques, vol. MTT-22, no. 5, **(1974)** May, pp. 523–531.

[10] Singh K, Ramasubramanian R, Pal S,” Coupled Microstrip filters: Simple Methodologies for improved characteristics, communication systems group,” India EESOF User Group Meeting, **(2005)** November 17.

[11] Bahl IJ, Lumped Elements for RF and Microwave Circuits, Artech House, Boston, London, **(2003)**.

[12] Hong JS, Lancaster MJ, Microstrip Filters for RF/Microwave Applications, Wiley, New York, **(2001)**.

[13] Zhang QJ, Gupta KC, Devabhaktuni VK, “Artificial neural networks for RF and microwave design—From theory to practice,”IEEE Trans. Microwave Theory Tech., vol. 51, no. 4, **(2003)** April, pp. 1339–1350.

[14] Zhang QJ, Gupta KC, Neural Networks for RF and Microwave Design. Boston, MA: Artech House, **(2000)**.

[15] Watson PM, Gupta KC, “Design and optimization of CPW circuits using EM-ANN models for CPW components,” IEEE Trans. Microwave Theory Tech., vol. 45, no. 12, **(1997)** December, pp. 2515–2523.

[16] Bandler JW, Ismail MA, Rayas Sánchez JE, Zhang QJ, “Neuromodeling of microwave circuits exploiting space- mapping technology, ”IEEE Trans.Microwave Theory Tech., vol. 47, no. 12, **(1999)** December, pp. 2417–2427.

[17] Delgado HJ, Thursby MH, “A novel neural network combined with FDTD for the synthesis of a printed dipole antenna,” IEEE Trans. Antennas Propag., vol. 53, no. 7, **(2005)** July, pp. 2231–2236.

[18] Lee Y, Filipovic DS, “ANN based electromagnetic models for the design of RF MEMS switches,” IEEE Microwave Wireless Compon.Lett., vol. 15, no. 11, **(2005)** November, pp. 823–825.

[19] Murphy EK, Yakovlev VV, “RBF network optimization of complex microwave systems represented by small FDTD modeling data sets,” IEEE Trans. Microwave Theory Tech., vol. 54, no. 7, **(2006)** July, pp. 3069–3083.

[20] Narayana JL, RamaKrishna KS, Reddy LP, “Performance Evaluation of Neural Models for the Analysis of GaAs MESFET” Gitam Journal of Information Communication Technology (GJICT), vol. 1, no. 01, **(2008)** July-Dec., pp. 31-41.

[21] Narayana JL, RamaKrishna KS, Reddy LP, “ANN Models for Coplanar Strip Line Analysis and Synthesis” IJCSNS International Journal of Computer Science and Network Security, vol. 8, no. 10, **(2008)** October, pp. 200-204.

[22] RamaKrishna KS, Narayana JL, Reddy LP, “ANN Models for Microstrip Line Synthesis and Analysis” International Journal of Electrical Systems Science and Engineering, vol. 01, no. 03, www.waset.org , Summer **(2008)**, pp. 196-200.

[23] RamaKrishna KS, Narayana JL, Reddy LP, “Performance Evaluation of ANN Models for the Analysis of Microstrip Low Pass Filters” ICGST-AIML Journal, vol. 09, no.01, **(2009)** February, pp. 9-18.

[24] Narayana JL, RamaKrishna KS, Reddy LP, “Synthesis and Analysis of Branch line Coupler using Artificial Neural Network Models” International Journal of Electronics and Communication Engineering, vol. 2, no. 3 **(2009)**, pp. 179-192.

[25] RamaKrishna KS, Narayana JL, Reddy LP, “A Neural Network Modeling Approach for the Analysis of Lange Coupler”, International Journal of Electronic Engineering Research (IJEER), vol. 2, no. 4, **(2010)**, pp. 463– 478.

[26] Zhiqiang G, “A downsized and integrated C-band transceiver for VSAT,” IEEE Microwave and Optoelectronics conference, **(1995)**, pp. 33-36.

[27] Hammerstad EO, Jensen O, “Accurate models for microstrip computer-aided design” ,IEEE MTT-S, **(1980)**, Digest, pp. 407–409.

[28] Wheeler H, “Transmission line properties of parallel strips separated by a dielectric sheet,” IEEE Trans., MTT-13, **(1965)**, pp. 172–185.

[29] Hammerstard EO, “Equations for microstrip circuit design,” in Proceedings of the European Microwave Conference, Hamburg, Germany, **(1975)**, pp. 268–272.

[30] Wang F, Zhang QJ, “Knowledge-based neural models for microwave design,” IEEE Trans. Microwave Theory Tech., vol. 45, no. 12, **(1997)** December, pp. 2333–2343.

[31] Watson PM, Gupta KC, Mahajan RL, “Applications of knowledge-based artificial neural network modeling to microwave components,” Int. J. RF Microwave Computer-Aided Eng., vol. 9, no. 3, **(1999)** May, pp. 254–260.

[32] Urias J, Hidalgo D, Melin P, Castillo O, “A new method for response integration in modular neural networks using type-2 fuzzy logic for biometric systems,” in Proc. Joint Int. Neural Networks Conf.,Orlando, FL, **(2007)** Aug. 12–17, pp. 311–315.

[33] Wang L, Rizvi SA, Nasrabadi NM, “A predictive residual VQ using modular neural network vector predictor,” in IEEE Int. Joint Neural Networks Conf., Montreal, QC, Canada, **(2005)** Jul. 31–Aug. 4, pp. 2953–2956.

[34] Martinez G, Melin P, Castillo O, “Optimization of Modular neural networks using hierarchical genetic algorithms applied to speech recognition,” in Proc. Joint Int. Neural Networks Conf., Montreal,QC, Canada, **(2005)** Jul. 31–Aug. 4, pp. 1400–1405.

[35] Melin P, Mancilla A, Lopez M, Castillo O, “Pattern recognition for industrial monitoring and security using the fuzzy sugeno integral and modular neural networks,” in Proc. Joint Int. Neural Networks Conf., Orlando, FL, **(2007)** Aug. 12–17, pp. 2977–2981.

[36] Li Y, Wang K, Li T, “Modular neural network structure with fast training/recognition algorithm for pattern recognition,” in IEEE Int. Granular Comput. Conf., Hangzhou, China, **(2008)** Aug. 26–28, pp. 401–406.

[37] Lahiri U, Pradhan AK, Mukhopadhyaya S, “Modular neural network-based directional relay for transmission line protection,” IEEE Trans. Power Syst., vol. 20, no. 4, **(2005)** November, pp. 2154–2155.

[38] Anand R, Mehrotra K, Mohan CK, Ranka S, “Efficient classification for multiclass problems using modular neural networks,” IEEE Trans. Neural Networks., vol. 6, no. 1, **(1995)** January, pp. 117–124.

[39] Bila S, Harkouss Y, Ibrahim M, Rousset J, N’Goya E, Baillargeat D, Verdeyme S, Aubourg M, Guillon P, “An accurate wavelet neural-network-based model for electromagnetic optimization of microwave circuits,” Int. J. RF Microwave Computer-Aided Eng., vol.9, **(1999)** December, pp. 297–306.

[40] Horng TS, Wang CC, Alexopoulos NG, “Microstrip circuit design using neural networks,” in IEEE MTT-S Int. Microwave Symp.Dig., Atlanta, GA, **(1993)**, pp. 413–416.

[41] Harkouss Y, Rousset J, Chehade H, Ngoya E, Barataud D, Teyssier JP, “The use of artificial neural networks in nonlinear microwave devices and circuits modeling: An application to telecommunication system design,” Int. J. RF Microwave Computer-Aided Eng., vol. 9, **(1999)**, pp.198–215.

[42] Creech GL, Zurada JM, “Neural network modeling of GaAs IC material and MESFET devices characteristics,” Int. J. RF Microwave Computer-Aided Eng., vol. 9, **(1999)** May, pp. 241–253.

[43] Selleri S, Manetti S, Pelosi G, “Neural network applications in microwave device design,” Int. J. RF Microwave Computer-Aided Eng., vol.12, **(2002)**, pp. 90–97.

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