Efficient Computation of Resonant Frequency of Rectangular Microstrip Antenna using a Neural Network Model with Two Stage Training

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Abstract

Artificial neural networks (ANNs) with two stage training have been proposed for efficient computation of resonant frequency of rectangular microstrip antenna. In the proposed approach in first stage the ANN model trained with empirical relation of resonant frequency with structural and substrate parameters of antenna then in second stage the model has been trained with the actual experimental data. The proposed approach has been validated using experimental published data and compared with results of other models published in different research papers. The result shows that the proposed approach is more accurate than the models developed using experimental data only. The results of the two stage training are in very good agreement with the measurements, and better accuracy than other ANN models developed using experimental data only.

Keywords: *Artificial neural networks (ANNs), computer aided design (CAD), learning algorithms, microstrip antenna, microwave device modeling.*

1. Introduction

During the past four decades, there has been a spectacular progress in microwave technology based microstrip devices and its application to both military and civilian areas primarily due to their simplicity, light weight, low profile, conformability, reproducibility, low manufacturing cost, reliability, ease in fabrication and integration with solid-state devices [1-3]. In military applications, it has played a key role in radar and electronics warfare (EW) systems and for the civil purposes, microwave has greatly helped in the expansion of mobile and satellite communication facilities. The emergent commercial civil and defence market of wireless communication devices over the past decade has led to explosion of interest and opportunities for design and developments of different types of microwave components. The wireless industry emphasizes on the development of components or systems (group of components) in shortest possible time and at low development cost. Modern industrial developments in the design of microwave components suggest the development of fully integrated subsystems that can be fabricated in large numbers. This places the demand of computer-aided-design (CAD) tools for the development of required microwave components and systems. The main objective of microwave CAD is faster and accurate development of components or systems while maintaining their efficiency.

Efforts to lower the cost and reduce the weight and volume of monolithic microwave and millimeter wave integrated circuits (MMIC's) have resulted in high-density circuits where a large number of interconnects are used. With this increased complexity and higher operating frequencies of microwave and millimeter wave devices an accurate and efficient design procedure is required to carry out the device synthesis. In present scenario methods of designing generally used are based on electromagnetic theory but there are some drawbacks of these methods like quasi-static models are valid only at low frequencies or over very short range of frequency and not available for all the devices. Full-wave characterization can lead to accurate results, but at much higher computational expense and they are very time consuming which prevents their use in practical interactive CAD. Many new EM simulation tools are being developed by industries to automate the design process. Some of them are embedding search methods like conjugate-gradient method, quasi-newton method, etc. for optimizing the design parameters. The drawback of these methods is that they require initial guess which should be close to the optimum design otherwise they reach up to local minima. Soft-computing algorithms [4] are reliable alternatives to these methods for getting optimum designs.

In the present paper, an efficient computation of resonant frequency of rectangular microstrip antenna has been presented using new two stage training on ANN model. The ANN model is used with four structural parameters of

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antenna that are thickness of substrata, relative dielectric constant, width and length of patch as input to compute resonant frequency as output. In the proposed two stage training, an ANN model is trained in two stages. In first stage ANN model is trained with the data generated by empirical formula and in second stage with experimental published data to compute resonant frequency of real antennas. Results shows that the proposed approach give better accuracy in compression with the conventional approaches where models are trained with small data sets.

2. Problem Geometry

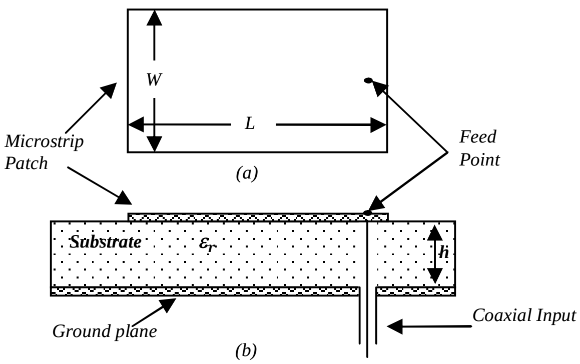

Fig. 1 Geometry of printed rectangular microstrip antenna (a) Top view of microstrip patch, (b) Side view of microstrip antenna with coaxial feed.

Problem geometry has been illustrated in Figure 1**.** A rectangular microstrip antenna of width W and length L printed on substrate of thickness h and relative dielectric constant ε_r. The resonant frequency for different modes of resonance of the printed antenna can be calculated from [1,3].

$$f_{mn} = \frac{c}{2\sqrt{\varepsilon_{eff}}}\sqrt{\left(\frac{m}{L_e}\right)^2 + \left(\frac{n}{W_e}\right)^2} \tag{1}$$

where, f_{mn} is resonant frequency corresponding to mode m and n both belongs to set of positive integers including zero. In the present study only fundamental TM_{10} mode is considered for which *m* is one and *n* is zero. c is speed of electromagnetic wave in free space, L_e and W_e are effective length and width of microstrip patch respectively and ε_{eff} is effective dielectric constant defined as

$$\varepsilon_{eff} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2}\sqrt{\left(1 + 12\frac{h}{W}\right)} \tag{2}$$

The effective length L_e is sum of length of patch L and edge extension length ΔL because of fringing effect can be defined as

$$L_e = L + 2\Delta L \tag{3}$$

and edge extension length ΔL,

$$\Delta L = 0.412h\frac{(\varepsilon_{eff} + 0.3)(W/h + 0.264)}{(\varepsilon_{eff} - 0.258)(W/h + 0.8)} \tag{4}$$

Similarly, one can define effective width W_e.

3. Artificial Neural Networks

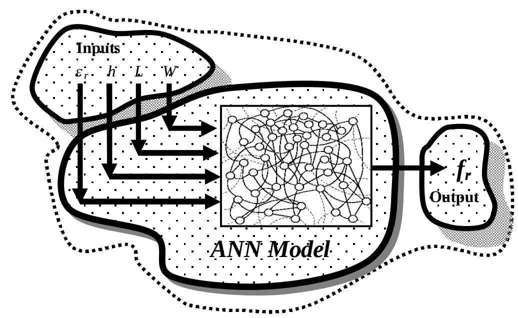

Fig. 2 ANN model with four input parameters and resonant frequency as output.

An Artificial Neural Network (ANN) [5] is a mathematical model which typically emulates certain features of real neural networks found in animal brains. ANN is used in wide variety of problems like information processing, pattern recognition, clustering, classification, image processing and system modeling among others [5, 6]. An ANN models designed in a way in which the animal brain performs a particular task or function of interest with given set of inputs. An artificial neural network has a build in capacity to learn from its environment by undergoing a training session by adjusting its adaptive parameters. According to Hayking [5] a neural network is massive parallel distributed processer that has a nature tendency for storing experiential knowledge and making it available for use. ANN works like an animal brain in two ways, 1) It acquires knowledge through learning and 2) Knowledge is gain or memorized by the means of strength of inter neuron synaptic weights. To realize or design specific function using ANN, large numbers of small processing units known as neurons are used which act as building block of any ANN models. Knowledge is gained by changing the strength of inter neuron synaptic weights and the rule which governs the weight change is known as learning rule or algorithm.

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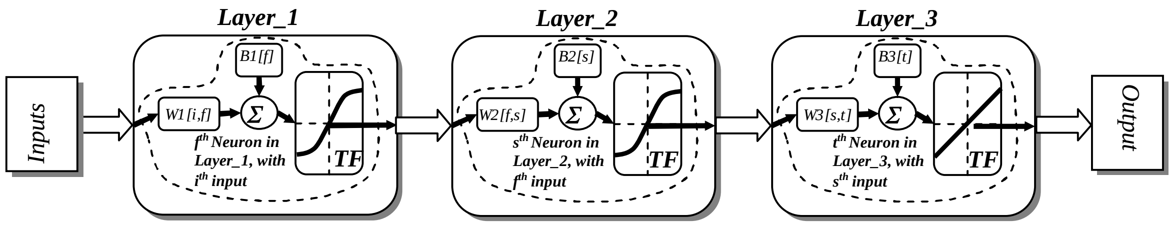

Fig. 3 Final ANN model configuration with two hidden layers and output layer.

4. Two Stage Training

Training is the next step after ANN network is structured for a particular function. In general ANN networks are initialized with random synaptic weight matrix before start of training. There are two main approaches used for training of ANN networks, supervised and unsupervised [5,6]. Supervised approach has been used in present study. In supervised approach network is provided desired output corresponding to the some specific input and these inputs-outputs data pair know as training data pairs or sets. In case of unsupervised approach network has to make its own sense of the inputs without external help. ANN models in supervised learning compares output of models with desired output to compute error or deviation in output, this error is propagated back through the network to adjust synaptic weight matrix in such a way that the error minimizes.

ANN models map input set to output set, these models act as black box which work as function but inside of network is not very clear. Accuracy of model in generating outputs for unseen or test data (data other than used during training) depends largely on training set. To have accurate model training data should be adequate, accurate and uniformly distributed over input range. But in the case of modeling of system where available data is inadequate in size it is very difficult to have accurate ANN models and with small size of training data there are chance of over-learning [5] in which model generate good results corresponding to training data but high errors on test or unseen data. In this paper a new approach has been proposed for training of ANN network when available training sets are of small size. The new approach is named as two stage training. In two stage training, in place of using small size training set directly on ANN model for training, the training is carried out in two stages. In first stage ANN model is trained with data generated from empirical formulas available for system, then the trained ANN model in first stage is used in second stage training to train ANN model second time with available small actual data. Using proposed approach accuracy can be increase with avoiding over-learning problem. Three step algorithm used in the paper is given below:

Algorithm: Two stage training

Step1: Structured ANN model initialize with random synaptic weight matrix.
Step2: Training of model of step1 with data generated from empirical formula.
Step3: Training of trained model in step2 with available experimental or actual data.

In the present study Levenberg-Marquardt algorithm [7,8] is used in step1 and step 2 for training of ANN models. Levenberg-Marquardt algorithm provides a numerical solution to nonlinear function minimizing problems and it is fast and gives stable convergence.

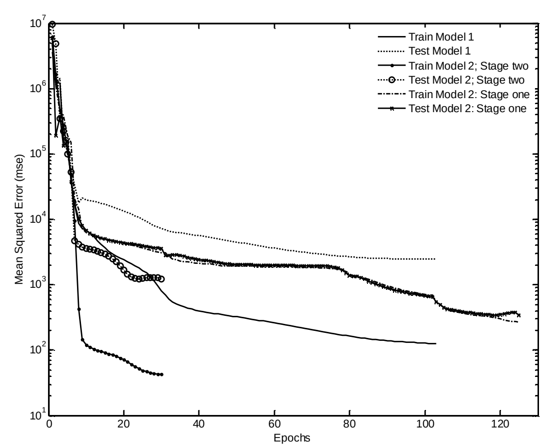

Fig. 4 Performance of ANN models during training.

5. Result and Discussion

For calculating the resonant frequency of rectangular microstrip antenna ANN model is with four inputs and one output as illustrated in Figure 2. Two inputs are substrate parameters that is *dielectric constant* ε_r and thickness of

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the substrate *h* and other two inputs are parameter of printed microstrip patch length L and width W.

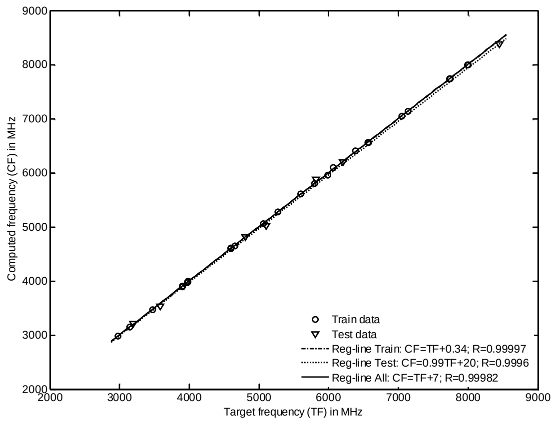

Fig 5. Comparison of computed and target frequency for *Model_1*.

The output of the model is resonant frequency of rectangular microstrip antenna. Hidden layers and the number of neurons in the ANN model has been decided by trial and error approach since there is no straight forward way to determine optimal number of hidden layers and numbers of neurons in corresponding layers. After testing several configurations it is found the most fitting network was $4 \times 4 \times 3 \times 1$. It means 4, 4, 3 and 1 number of neurons in input, first hidden, second hidden and output layers respectively. For hidden layers and output layer the tangent sigmoid and linear activation function was used respectively.

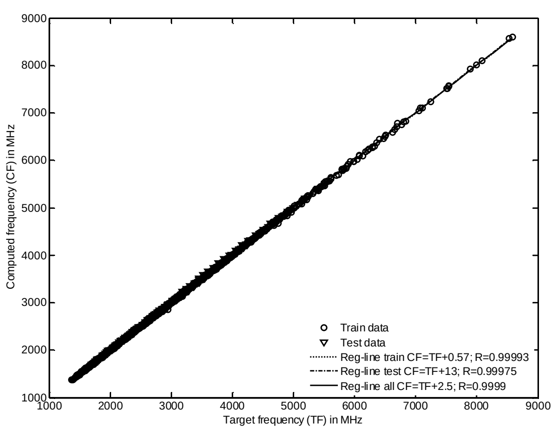

Fig 6. Comparison of computed and target frequency generated from empirical formula for *Model_2* in training stage one.

The final structure of ANN model for the present problem with three layers is shown in Figure 3. In Figure 3 *W1*, *W2*, *W3* are synaptic weight matrix and *B1*, *B2*, *B3* are biasing weight matrix corresponding to three layers. Initially synaptic weight matrix of the ANN model is randomized in range 0 to 1 and this model is referred as *Model_0* untrained model. Then the ANN *Model_0* is trained with two ways, first way referred as *Model_1* in which the ANN model is directly trained with 26 out of 33 sets of experimental data [9,10] given in Table 1. The *Model_1* is conventional way of use of ANN model in microwave device analysis and design [6]. For training Levenberg-Marquardt algorithm is used. *Model_1* is trained with 103 epochs, performance in terms of mean squared error (mse) of *Model_1* during training with epochs is given in Figure 4. In Figure 5 comparison of target (measured or desired) frequency (TF) with computed frequency (CF) and regression (Reg) line equations for training, testing and all data (training+testing) are plotted. In the same figure regression line equations and correlation coefficients R is given, all this proves goodness of model.

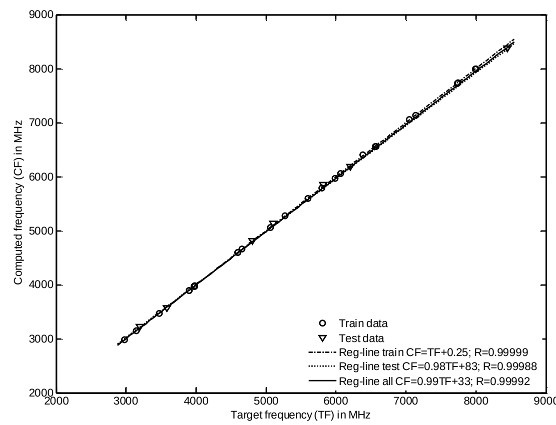

Fig 7. Comparison of computed and target frequency for experimental data [9, 10] for *Model_2* in training stage two.

An innovative training approach has been proposed, named two stage training and the model trained using this approach is referred as *Model_2*. In *Model_2*, in first stage training *Model_0* with same initial synaptic weight matrix which is been used for *Model_1* is trained with the ten thousand set of data generated from empirical formula given in equation (1). For ten thousand sets of data generated by combinations of 10 equally space values of each input and the range of inputs are *dielectric constant* $2.22 \le \varepsilon_r \le 10.20$, thickness of the substrate $0.017cm \le h \le 1.281cm$, length of microstrip $1.0cm \le L \le 3.5cm$ and width $0.776cm \le W \le 2.0cm$. *First stage training is carried out using* Levenberg-Marquardt learning algorithm with 125 epochs performance during training is shown in Figure 4 and comparison of target frequency (TF) with computed frequency (CF) is given in Figure 6. Then the trained ANN model from first stage training is used for second stage training in which 26 out of 33 sets of experimental data

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Table 1: Comparison of two stage training with other methods for resonant frequency and the sum of absolute error between experimental and computed frequencies of rectangular microstrip antenna.

MSA No.	Input parameters W (cm)	L (cm)	h (cm)	ε_r	Target Frequency [9],[10]	Proposed two stage training *Model_2*	Using single stage training *Model_1*	Resonant frequencies computed from different models [11] [12]	[13]	[14]	[1]	[2]	[15]	[16]	[17]	[18]	[10]	[19]
1	0.850	1.290	0.017	2.22	7740	7740.73	7738.98	7804	7697	7750	7791	7635	7737	7763	7720	7717	412	7765
2*	0.790	1.185	0.017	2.22	8450	8378.15	8378.23	8496	8369	8431	8478	8298	8417	8446	8396	8389	488	8451
3	2.000	2.500	0.079	2.22	3970	3970.51	3969.54	4027	3898	3949	3983	3838	3951	3950	3917	3887	510	3977
4	1.063	1.183	0.079	2.55	7730	7728.54	7731.01	7940	7442	7605	7733	7322	7763	7639	7551	7376	1610	7730
5	0.910	1.000	0.127	10.2	4600	4599.59	4599.79	4697	4254	4407	4641	4455	4979	4729	4614	4430	113	4618
6	1.720	1.860	0.157	2.33	5060	5059.57	5057.64	5283	4865	4989	5070	4741	5101	4958	4924	4797	1621	5077
7*	1.810	1.960	0.157	2.33	4805	4820.33	4810.33	5014	4635	4749	4824	4520	4846	4724	4688	4573	1460	4830
8	1.270	1.350	0.163	2.55	6560	6563.85	6563.71	6958	6220	6421	6566	6067	6729	6382	6357	6114	2550	6563
9	1.500	1.621	0.163	2.55	5600	5600.13	5605.94	5795	5270	5424	5535	5158	5625	5414	5374	5194	1769	5535
10*	1.337	1.412	0.200	2.55	6200	6186.56	6198.19	6653	5845	6053	6201	5682	6413	5987	5988	5735	2860	6193
11	1.120	1.200	0.242	2.55	7050	7056.47	7046.91	7828	6566	6867	7052	6320	7504	6682	6769	6433	4792	7030
12	1.403	1.485	0.252	2.55	5800	5793.09	5799.13	6325	5435	5653	5801	5259	6078	5552	5586	5326	3259	5787
13	1.530	1.630	0.300	2.50	5270	5276.32	5269.99	5820	4943	5155	5287	4762	5572	5030	5081	4842	3383	5273
14	0.905	1.018	0.300	2.50	7990	7993.55	7991.80	9319	7334	7813	7981	6917	8885	7339	7570	6822	8674	8101
15	1.170	1.280	0.300	2.50	6570	6562.13	6554.02	7412	6070	6390	6550	5794	7076	6135	6264	5951	5486	6543
16*	1.375	1.580	0.476	2.55	5100	5138.77	5025.30	5945	4667	4993	5092	4407	5693	4678	4830	4338	5437	5193
17	0.776	1.080	0.330	2.55	8000	7991.98	7999.21	8698	6845	7546	7519	6464	8447	6889	7160	6367	8067	7948
18	0.790	1.255	0.400	2.55	7134	7138.02	7129.65	7485	5870	6601	6484	5525	7342	5904	6179	5452	7242	7169
19	0.987	1.450	0.450	2.55	6070	6063.27	6095.75	6478	5092	5660	5606	4803	6317	5125	5341	4735	6103	6026
20*	1.000	1.520	0.476	2.55	5820	5851.25	5884.36	6180	4855	5423	5352	4576	6042	4886	5100	4513	5875	5817
21	0.814	1.440	0.476	2.55	6380	6403.24	6402.49	6523	5101	5823	5660	4784	6453	5122	5396	4729	6546	6515
22	0.790	1.620	0.550	2.55	5990	5972.68	5953.36	5798	4539	5264	5063	4239	5804	4550	4830	4196	5976	6064
23	1.200	1.970	0.626	2.55	4660	4664.26	4652.85	4768	3746	4227	4141	3526	4689	3770	3949	3479	4600	4613
24	0.783	2.300	0.854	2.55	4600	4598.97	4614.29	4084	3201	3824	3615	2938	4209	3168	3446	2921	4603	4550
25*	1.256	2.756	0.952	2.55	3580	3576.74	3531.49	3408	2668	3115	2983	2485	3430	2670	2845	2461	3574	3628
26	0.974	2.620	0.952	2.55	3980	3973.78	3976.60	3585	2808	3335	3162	2590	3668	2790	3015	2572	3955	3956
27	1.020	2.640	0.952	2.55	3900	3895.89	3900.10	3558	2785	3299	3133	2573	3629	2771	2987	2555	3895	3907
28	0.883	2.676	1.000	2.55	3980	3987.09	3989.67	3510	2753	3294	3112	2522	3626	2721	2966	2509	3982	3922
29	0.777	2.835	1.100	2.55	3900	3896.19	3887.43	3313	2608	3147	2964	2364	3473	2554	2823	2356	3903	3747
30	0.920	3.130	1.200	2.55	3470	3470.13	3467.71	3001	2358	2838	2675	2146	3129	2317	2549	2137	3493	3381
31*	1.030	3.380	1.281	2.55	3200	3223.64	3213.48	2779	2183	2623	2474	1992	2889	2151	2357	1983	3197	3123
32	1.265	3.500	1.281	2.55	2980	2977.00	2980.51	2684	2102	2502	2370	1936	2752	2086	2259	1924	2982	2972
33	1.080	3.400	1.281	2.55	3150	3151.93	3153.58	2763	2168	2600	2453	1982	2863	2139	2338	1972	3160	3096
Absolute Errors (in MHz):						327.09	460.00	13136	24097	11539	12322	30669	8468	22572	18148	30504	56698	1393

* Test data set and unmark MSA no. are training data set.

[9,10] given in Table 1 is used with Levenberg-Marquardt learning algorithm for 29 epochs for optimal learning and avoiding over-learning. Figure 4 shows performance and Figure 7 with regression (Reg-) line equations and correlation coefficients R compares computed frequency (CF) with target frequency (TF).

The efficiency of two stage training over single stage training and other conventional methods with published results [11] comparisons are made in Table 1. In Table 1 the proposed approach is compared with results from conventional methods [1, 2], [10], [12]-[19]. It is clear that in the proposed method sum of absolute error is smallest. It is also proved from the Table 1 that accuracy in computation of resonant frequency of microstrip antenna increase by considerable amount in case of two stage training in comparison with single stage training for same initial synaptic weight matrix. Goodness of models can be compared from Figure 5 and 7, correlation coefficients R between target frequency (*TF*) and computed frequency (*CF*) in case of *Model_1* based on single stage training is 0.99997 for training data, 0.9996 for test data and 0.99982 for all 33 (training + test) data set where as in case of *Model_2* based on two stage training correlation coefficients is more closer to one, 0.99999 for training data, 0.99988 for test data and 0.99992 for all 33 (training + test) data set. From above results it is clear that two stage training provides high degree of accuracy in computing resonant frequency and superior to single stage training and other conventional approaches.

6. Conclusions

Resonant frequency of rectangular microstrip antenna has been computed using novel two stage training approach on ANN model. ANN model is used as black box to generate resonant frequency as output corresponding to four input height of the substrate with dielectric constant and dimensions of rectangular patch antenna. In the proposed approach in first stage the ANN model trained with empirical relation of resonant frequency with structural and substrate parameters of antenna then in second stage the model has been trained with the actual experimental data. The results of the proposed approach are in very good agreement with the measurements and shows better

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accuracy than other traditional approaches. The proposed approach offers an accurate and efficient alternative method for the calculation of resonant frequency of antenna. This approach is not limited to the rectangular microstrip antenna it can be easily applied to other antenna and microwave circuit problems. The high-speed real-time computation feature of the proposed approach recommends its use in computer-aided design programs. It is expected that the hybrid approach will find potential application area in electromagnetic engineering and device designs.

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