An Adaptive Neuro-Fuzzy Inference System for Calculation Resonant Frequency of Microstrip Dipole Antenna

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ABSTRACT

The accurate computation of the resonant frequency of microstrip antennas is an important factor to guarantee their correct behaviour. To this aim, High Frequency Structure Simulator (HFSS) is commonly used. In this paper, we presented an adaptive neuro-fuzzy inference system (ANFIS) that calculates resonant frequency of the microstrip dipole antennas (MSDAs). ANFIS uses dipole's length and width, the antenna substrate's permittivity value and its size as inputs to calculate resonant frequency. Results obtained by using ANFIS agree quite well with the HFSS results.

I. INTRODUCTION

Technical literature has broadly investigated Microstrip patch antennas (MSPAs). These antennas are lightweight, aerodynamically conformable to aircraft and missile surfaces, compatible with solid-state devices, and simple and inexpensive to construct. Furthermore, by adding loads between the patch and the ground plane (i.e. pins and varactor diodes), one can design adaptive elements containing variable resonant frequency, impedance, polarization, and radiation pattern [1].

Nevertheless, narrow bandwidth is one major drawback of the microstrip antennas. Consequently, printed antennas work efficiently by closely matching their resonant frequency. Therefore, this parameter's accurate evaluation is fundamental in the microstrip antenna design process. A correct evaluation of the resonant frequency requires a rigorous full-wave model [2]. The Finite Element Method (FEM), the Method of Moments (MoM), and Finite Difference Method (FDM) etc. have proved useful for analysis of such antennas by providing rigorous solutions to the present problem. However, this technique requires significant computation and is time-consuming. Recently, studies developed alternative methods for resonant frequency determination using fuzzy logic (FL), neural networks (NNs), and combined adaptive neuro-fuzzy inference systems (ANFIS) [2-4,6].

We developed an adaptive neuro-fuzzy inference system that calculates resonant frequency of the microstrip dipole antennas (MSDAs). Although the MSDAs' resonant frequency greatly depends on the dipole's length, it also depends on the dipole's width, the antenna substrate's permittivity value, and its size (which affects resonant frequency). The past two decades have witnessed significant advances in FL and NNs. Some have unsuccessfully used FL and NN separately to find the MSDA's resonant frequency. The FL system's difficulty stems from constituting correct membership functions and rule base. Insufficient training sets resulted in NNs producing unstable results. The synergism of FL systems and NN produced a system capable of learning, high-level thinking, and reasoning. This tool determines the imprecisely-defined complex system's behaviour. The neuron-fuzzy system's purpose is to apply neural learning techniques to identify and tune the neuro-fuzzy system's parameters and structure. These neuro-fuzzy systems combine the benefits of these two powerful paradigms into a single capsule. Their multi-functionality makes them suitable for a wide range of scientific applications. Their strengths include fast and accurate learning, good generalization capabilities, excellent explanation facilities (formed by semantically meaningful fuzzy rules), and can accommodate both data and existing knowledge about any present problem.

ANFIS can find a model that closely matches the inputs with the target. Fuzzy interface system (FIS) is a knowledge representative where each fuzzy rule describes the system's local behaviour. Viewing FIS as a feed forward network structure where the primary inputs and intermediate results are sent to compute the output allows us to apply the same back-propagation principle in the neural networks. The network structure that implements FIS is called ANFIS and employs hybrid learning rules to train a Sugeno-style FIS with linear rule outputs.

Among the various methodology combinations in soft computing, fuzzy logic and neuro-computing are the most common (hence the tem neuro-fuzzy systems). Such systems play an important role in the initiation of rules from observations. It is a powerful tool for quickly and efficiently dealing with imprecision and nonlinearity wherever it occurs. Neuro-adaptive learning techniques work similarly to neural networks. These techniques allow the fuzzy modeling procedure to learn information about a data set that computes the membership function parameters, allowing the associated fuzzy inference system to track the given input/output data. A neural-type structure similar to a neural network that maps inputs through input and output membership functions and associated parameters can be used to interpret the input/output map. This eliminates the normal feed forward multilayer network's disadvantages (difficult to understand or modify). We explain MSDAs and how to use ANFIS to train a fuzzy inference system that calculates the resonant frequency.

II. MICROSTRIP DIPOLE ANTENNAS

Figure 1 shows the microstrip printed dipole antenna containing a conventional half-wave dipole loaded with two open-circuited stubs. The antenna, printed on a PCB substrate, is fed either by cable, surface mount connector, or printed transmission line. Where 'L' represents length, 'W' is dipole wideness, 'Ds' is distance between the dipole edges and substrate edges, 'h' is the substrate thickness and 'ε_r' is the substrate's dielectric's constant value.

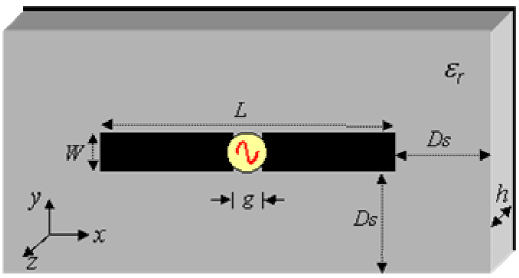

Figure.1. Geometry of the microstrip dipole antenna.

We fixed the space between the symmetrical metal patches on the substrate at 1mm and the antenna is fed from this space. By changing the antenna parameters L, W, h, ε_r and Ds, we obtained 61 antenna configurations, using 51 for training and the rest for testing. Table 1 shows system training and Table 2 shows test data. We used materials used for antenna design such as FR-4, RT/duroid and Rogers TMM. We obtained the antenna substrate's thickness and permittivity values from producer firms' catalogs. We used Ansoft High Frequency Structure Simulator (HFFS) software, based on FEM, to compute and test the data set.

III. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

ANFIS is a multilayer neural network-based fuzzy system [5]. Its topology is shown in Figure 2, and the system has a total of five layers. In this connectionist structure, the input and output nodes represent the descriptors and the activity, respectively and in the hidden layers, there are nodes functioning as membership function (MFs) and rules. This eliminates the disadvantage of a normal feed forward multilayer network, which is difficult for an observer to understand or to modify. For simplicity, we assume that the examined fuzzy inference system has two inputs x and y and one output, the activity. To present the ANFIS architecture, two fuzzy if-then rules based on first order Sugeno model are considered:

Rule 1: If ($x$is A_1) and ($y$is B_1) then ($f_1= p_1x+ q_1y+ r_1$)
Rule 2: If ($x$is A_2) and ($y$is B_2) then ($f_2= p_2x+ q_2y+ r_2$)

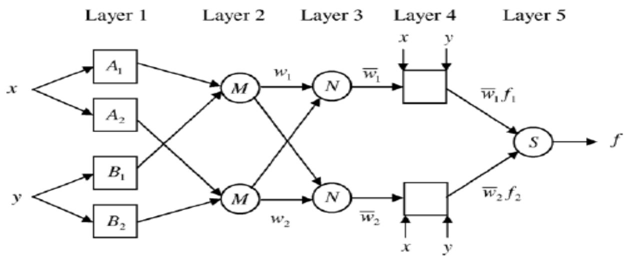

Figure.2 The architecture of ANFIS

Where x and y are the inputs, A_i and B_i are the fuzzy sets, fiare the outputs within the fuzzy region specified by the fuzzy rule, pi, qi and ri are the design parameters that are determined during the training process. In the first layer, all the nodes are adaptive nodes with anode function:

$$o_i^1 = \mu_{Ai}(x), \; for\; i = 1,2 \qquad (1)$$

Where x is the input to node i, and A_i is the linguistic label (low, high, etc.) associated with this node function. In other words, o_i^1 is the membership function of A_i, and it specifies the degree to which the given x satisfies the quantifier A_i. Usually we chose $\mu_{Ai}(x)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0. As the values of parameters $\{a_i, b_i, c_i\}$ change, the bell-shaped functions vary accordingly, thus exhibiting various form of membership functions on linguistic label A_i. Parameters in this layer are referred to as premise parameters.

Every nodes in second layer is a fixed node labeled Π (figure 2), whose output is the product of all the incoming signals:

$$o_i^2 = \omega_i = \mu_{Ai}(x) \times \mu_{Bi}(y), \quad for \;\; i = 1,2 \tag{2}$$

Each node output represent the firing strength of a rule. In layer 3 every node is a fixed node labeled N . The i th node calculates the ratio of the i th rule's firing strength to the sum of rules' firing strengths:

$$o_i^3 = \varpi_i = \frac{\omega_i}{\omega_1 + \omega_2}, i = 1,2 \tag{3}$$

Outputs of this layer are called normalized firing strengths. Every node i in layer 4 is an adaptive node with a node function

$$o_i^4 = \varpi_i f_i = \varpi_i (p_i x + q_i y + r_i), \; i = 1,2 \tag{4}$$

where ϖ_i is a normalized firing strength from layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set of this node. Parameters in this layer are referred to as consequent parameters. The single node in the last layer is a fixed node labeled Σ, which computes te overall output as the summation of all incoming signals:

$$\text{overall output} = o_i^5 = \sum_{i=1}^{2} \varpi_i f_i = \frac{\left(\sum_{i=1}^{2} \omega_i f_i\right)}{\omega_1 + \omega_2} \tag{5}$$

Thus we have constructed an ANFIS system that is functionally equivalent to first-order Sugeno fuzzy model.

HYBRID LEARNING ALGORITHM

From the proposed ANFIS architecture the overall output can be expressed as linear combinations of the consequent parameters. The output f in figure 2 can be written as:

$$\begin{aligned} f &= \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_2}{\omega_1 + \omega_2} f_2 \\ &= \varpi_1 (p_1 x + q_1 y + r_1) + \varpi_2 (p_2 x + q_2 y + r_2) \\ &= (\varpi_1 x) p_1 + (\varpi_1 y) q_1 + (\varpi_1) r_1 + \\ &(\varpi_2 x) p_2 + (\varpi_2 y) q_2 + (\varpi_2) r_2 \end{aligned} \tag{6}$$

Which is linear in the consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2 . To train the above ANFIS system, the following error measure will be used:

$$E = \sum_{k=1}^{n} (f_k - \hat{} f_k)^2 \tag{7}$$

Where f_k and $\hat{} f_k$ are the k th desired and estimated outputs, and n is the total number of pairs (inputs-outputs) of data in the training data set. The learning algorithms of ANFIS consist of the following two parts: (a) the learning of the premise parameters by back-propagation and (b) the learning of the consequence parameters by least-squares estimation [6]. More specifically, in the forward pass of the hybrid learning algorithm, functional signals go forward till layer 4 and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backward, and the premise parameters are updated by the gradient descent. During the learning process, the parameters associated with the membership functions will change. The computation of these parameters is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modelling the input/output data for a given set of parameters. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS.

Therefore, in the present study the proposed ANFIS model was trained with the backpropogation gradient descent method in combination with the least –squares method.

IV. RESULTS AND DISCUSSION

We presented a new approach based on ANFIS to calculate MSDA's resonant frequency. Sixty-one different antenna configurations were obtained by changing the antenna parameters L, W, h, ε_r , and Ds. All substrates were used for this study came from producer firms' catalogs. Resonant frequencies of antenna configurations calculated by used Ansoft-High Frequency Structure Simulator (HFFS).

The data is divided in two parts, 51 for training and 10 for testing. ANFIS used 51 training data sets in 300 training periods. We used triangular membership functions for resonant frequency calculations. Error tolerance was 0 and the output membership function was linear. We used the training data set to train ANFIS, whereas the testing data set was used to verify the accuracy and effectiveness of trained ANFIS model. L, W, h, ε_r and Ds are applied to the inputs of the ANFIS. The output is resonant frequency. After training, 10 testing data sets were used to validate the ANFIS model's accuracy for the resonant frequency. The testing data consisted of different types of material values and varied in size. The ANFIS model's test performance was defined after comparing the simulation results and FIS results.

Table1. Part of the training set used for ANFIS

No	ε_r	h [mm]	W [mm]	L [mm]	Ds [mm]	Simulated Result f [GHz]	ANFIS Result f [GHz]
1	9.20	1.6	3	33	15	3.09	3.09
2	4.40	1.6	2	33	15	4.49	4.49
3	2.1	1.6	3	33	30	6.05	6.05
4	2.1	2.5	3	33	3	5.66	5.66
5	3.27	2.5	3	19	15	6.86	6.86
6	6.0	2.5	3	51	15	2.48	2.48
7	6.0	2.5	4	51	15	2.38	2.38
8	3.27	6.35	4	51	15	2.88	2.88
9	3.27	6.35	5	25	20	4.57	4.57
10	3.27	2.5	5	25	20	5.56	5.56
11	3.75	2.5	3	33	18	4.47	4.47
12	4.40	3	4	25	15	4.73	4.73
13	3.27	1.6	3	51	15	3.34	3.34
14	2.20	2.5	4.5	23	20	6.84	6.84
15	2.20	2	4.5	23	19	7.15	7.15
16	2.20	1.6	3	33	18	5.62	5.62
17	4.90	2.8	2.25	27	12	4.31	4.31
18	3.75	3	4.5	37	16	3.85	3.85
19	5.75	3.5	3	47	22	2.64	2.64
20	8.90	2.54	1.5	23	26	4.48	4.48
21	7.50	0.762	3.25	41	28	2.86	2.86
22	9.20	1.91	1.75	15	8	6.01	6.01
23	4.70	1.27	2.5	17	10	7.34	7.34
24	2.54	3.81	3.5	21	14	6.13	6.13
25	2.2	5.08	4.25	43	12	3.92	3.92

Table.2. Test data set of ANFIS and results

No	ε_r	h [mm]	W [mm]	L [mm]	Ds [mm]	Simulated Result f [GHz]	ANFIS Result f [GHz]	Relative Error (%)
1	3.75	2.5	3.00	33	15	4.46	4.41	1.07
2	4.40	3	4.00	33	15	4.00	3.92	1.83
3	2.10	2.5	4.50	23	20	6.96	6.90	0.83
4	4.9	1.91	2.5	29	16	4.68	4.68	0.12
5	6.0	1.6	3	47	15	2.73	2.68	1.60

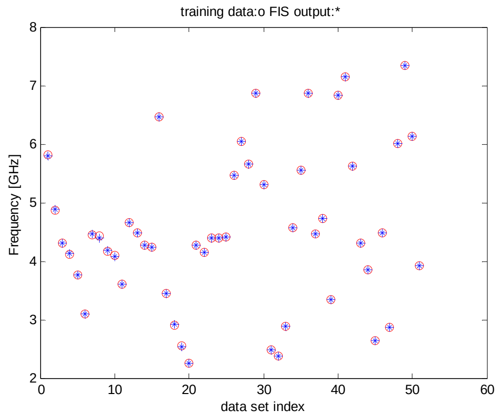

Figure.3.Comparison of training data set results and FIS results for resonant frequency

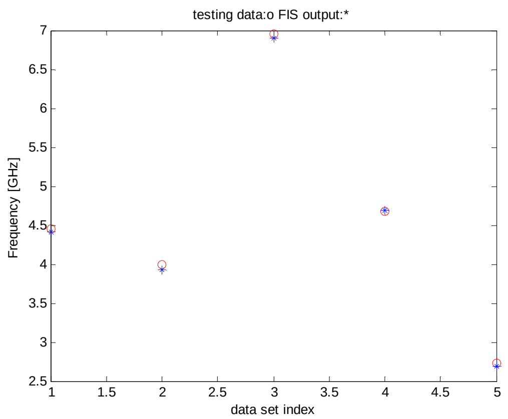

Figure.4.Comparison of testing data set results and FIS results for resonant frequency

In table 1, the simulated result f -labeled column shows the HFSS results while the ANFIS result f-labeled column shows the FIS results. In table 2, the ANFIS model calculates the resonant frequency with 1.07%, 1.83%, 0.83%, 0.12%, and 1.60% with relative error value, respectively. These results show the ANFIS's mean accuracy at 98.91%. While Figure 3 compares the results between the training data set and FIS output, Figure 4 shows the testing data set and FIS output.

V. CONCLUSION

As a consequence, a method based on the ANFIS for computing the resonant frequency of Microstrip dipole antennas has been presented. The hybrid-learning algorithm is used to identify the ANFIS' parameters. The results of the ANFIS are in very good agreement with the simulated. We hope that the ANFIS will find widespread applications in solving antenna and microwave integrated-circuit problems.

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