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Parametric Study and Artificial Neural Network Modeling of Cylindrical Dielectric Resonator Antenna (CDRA)

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ABSTRACT

Parametric studies on Cylindrical Dielectric Resonator Antenna were performed by changing the dimension (radius and height of the cylinder) of the antenna, its material characteristic (permittivity of the dielectric) and feed position of coaxial probe. Resonant frequency of the antenna, its return loss and directivity at resonant frequency were observed for the variation of these parameters in certain ranges. Using these tabulated data, obtained by this parametric study (done using simulation software HFSS), an Artificial Neural Network (ANN) model for the CDRA has been formed and validated.

Keywords: Cylindrical DRA, Parametric study, Artificial Neural Network, Back propagation

1. Introduction

The resonant frequency of the CDRA in fundamental TM_{110} mode without probe feed was found by magnetic wall model [1] as

$$f_{TM110} = \frac{1}{2\pi a\sqrt{\mu\epsilon}}\sqrt{{X'_{11}}^2 + \left[\frac{\pi a}{2d}\right]^2}$$

where X'_{11}=1.841, a=radius of DRA, d=height of the DRA, ε = permittivity and μ=permeability of the dielectric material. But there is no particular close form relation available for resonant frequency of CDRA with probe feed. Relation of dimensions of DRA, ε_r value and position for probe feed with DRA characteristics is also highly non-linear, multivariate and multimodal. So it’s difficult to know the exact resonant frequency of DRA without full wave analysis, often implemented through numerical simulation. Modeling the structure in any commercial software and simulation of the model is quite computation extensive and time consuming. That is why parametric study based neural network model is formed to get a quick and simple analysis for the resonant frequency of the CDRA in order to facilitate its optimization.

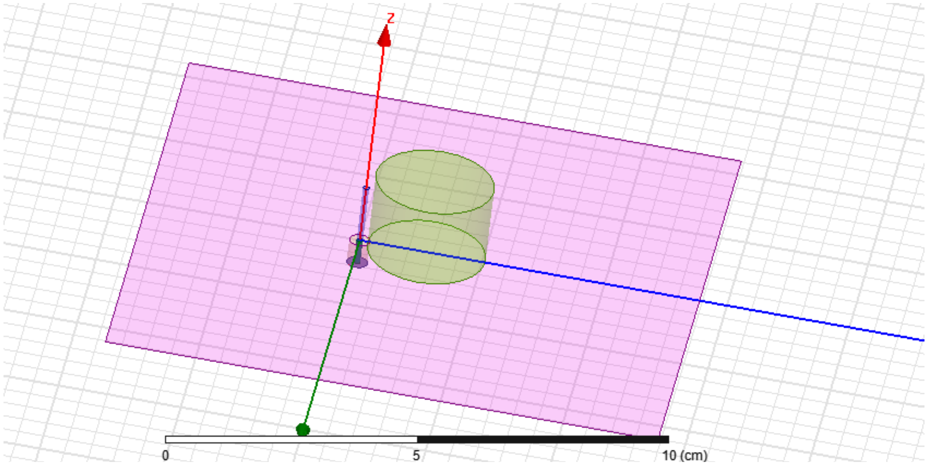

Figure 1: HFSS model of probe fed CDRA

A type of supervised learning algorithm: back propagation, has been used to train ANN in this paper. It uses gradient descent mechanism. This employs a feed forward topology of fully connected neurons (denoted by circles) arranged in a number of layers as shown in Fig. 2. The rms error E is back propagated component wise from last layer to preceding layers to adapt the weights in following manner: $w_{ij}= w_{ij}-\eta\partial E/\partial w$;
where w_{ij}=weight connecting ith neuron of previous layer to j^{th} neuron of present layer, η= learning rate.∂ E/∂ w is determined using chain rule.

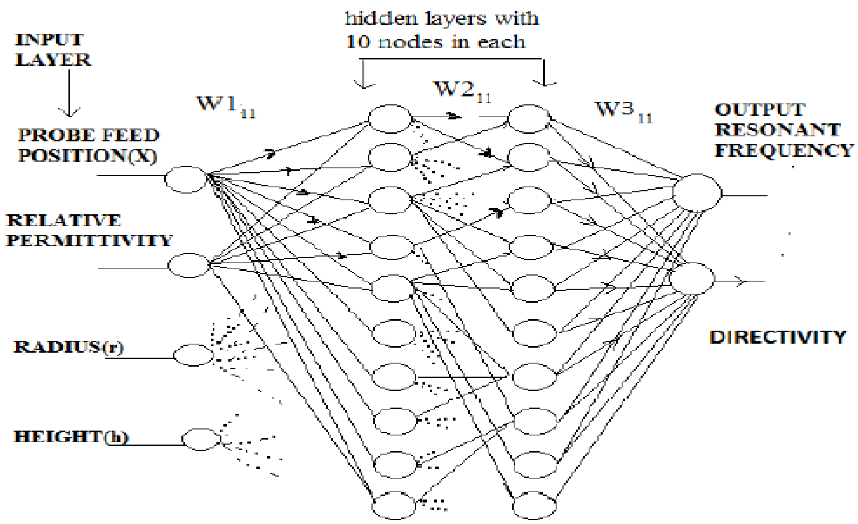

Figure 2: ANN model used (2 hidden layers, 10 nodes per hidden layer).

2. Simulations

Using HFSS model of coaxial probe fed CDRA, 453 samples were collected for different set of values of input variables in the ranges given below and corresponding values of output characteristics were tabulated. Radius of DRA(r): 0.4cm to 2 cm; Height of DRA(h): 0.4 cm to 2.4 cm; Relative Permittivity of dielectric (ε_r): 10.2 to 30; Position for coaxial probe feed(x): 0 cm to 0.3 cm from the outer perimeter of the CDRA. As we changed the relative permittivity value keeping all other parameters constant, the resonant frequency and directivity decreased.

TABLE I. EFFECT OF VARIABLE PERMITTIVITY ON CDRA

Input variables				Output characteristics		
x (cm)	ε_r	r (cm)	h (cm)	Resonant frequency(GHz)	Return loss, RL(dB)	Directivity, D(dB)
0	15	1.2	1.6	2.49	-42.38	6.20
0	20	1.2	1.6	2.19	-21.85	6.13
0	25	1.2	1.6	1.98	-31.06	6.04

With increased distance of probe feed position outside the DRA from its perimeter, the resonant frequency found from HFSS simulation mostly decreased at first and increased then. Return loss and directivity also showed same trend.

TABLE II. EFFECT OF VARIABLE FEED POSITION ON CDRA

Input variables				Output Characteristics		
x (cm)	ε_r	r (cm)	h (cm)	Resonant frequency(GHz)	Return loss(dB)	Directivity(dB)
0.0	15	0.8	1.2	3.62	-28.23	6.20
0.1	15	0.8	1.2	3.57	-18.31	5.68
0.2	15	0.8	1.2	5.80	-22.83	5.75

As the height of the CDRA was increased, the resonant frequency decreased. Return loss also decreased mostly.

TABLE III. FFECT OF VARIABLE HEIGHT ON CDRA

Input variables				Output characteristics		
x (cm)	ε_r	r (cm)	h (cm)	Resonant frequency(GHz)	Return loss(dB)	Directivity (dB)
0	10.2	1.2	0.8	5.34	-42.39	4.42
0	10.2	1.2	1.2	4.86	-28.29	5.03
0	10.2	1.2	1.6	4.67	-21.48	4.39

0	10.2	1.2	2.0	4.60	-24.66	5.30

The resonant frequency increased when radius of DRA≤ height of DRA and decreased when radius of DRA> height of DRA. Return loss value showed same change.

TABLE IV. EFFECT OF VARIABLE RADIUS ON CDRA

Input variables				Output characteristics		
x (cm)	ε_r	r (cm)	h (cm)	Resonant frequency(GHz)	Return loss(dB)	Directivity (dB)
0.1	20	0.8	1.2	3.17	-13.42	5.78
0.1	20	1.2	1.2	3.56	-28.75	5.87
0.1	20	1.6	1.2	2.84	-15.38	5.68
0.1	20	2.0	1.2	3.05	-15.42	4.96

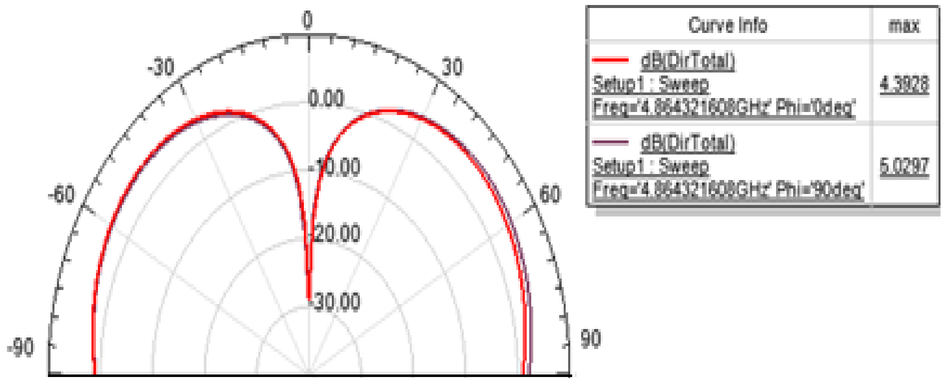

Figure 3: Broadside null radiation pattern of a particular CDRA.

Locating the probe adjacent to or slightly inside the DRA canproduce $HE_{11\delta}$mode and that in the centre of the DRA can produce $TM_{01\delta}$ mode [2]. But while parametric study broadside null radiation pattern ($TM_{01\delta}$) was found for many DRA models with probe outside DRA perimeter. One of which is shown in fig.3.found for a DRA with r=1.2cm, h=1.2cm, ε_r=10.2, x=0cm.CDRA also showed dual band resonant frequency at some values of input variables with fine tuned probe height.

TABLE V. A CDRA MODEL WITH DUAL BAND FREQUENCY

Input variables				Output characteristics					
x	ε_r	r	h	f (GHz), Bandwidth(MHz)		RL (dB) respectively (magnitude)		D (dB) respectively	
0.1 cm	25	2 cm	1.6 cm	2.01,9	3.38,48	13.8	14.7	5.7	5.5

3. ANN Modeling in MATLAB

The modelling of the neural net is done (feeding 453 samples, training and testing) by the help of MATLAB without using its toolbox. As sigmoid activation function is used, values of output variables have been scaled in the range of 0 to 1.Values of input variables have also been scaled between -1 to 1. Momentum has been used to overcome back propagation limitations in the code. Values of initial learning rate η, momentum constant α were chosen by trial and error for better and faster convergence as given below:

η_1=0.32 (for weights connecting input layer to first hidden layer), η_2=0.3(for weights connecting first hidden layer to second hidden layer), η_3=0.1(for weights connecting second hidden layer to output layer);α_1=0.1(for weights connecting input layer to first hidden layer), α_2=0.1(for weights connecting first hidden layer to second hidden layer), α_3=0.075(for weights connecting second hidden layer to output layer).

Convergence up to a relative error of 0.0005 has been considered for training. The trained ANN output was then validated against HFSS generated test data not used in its training. Comparison between the two sets of data for seven such sets of samples is enlisted in TABLE VI and VII.

TABLE VI. COMPARISON OF RESONANT FREQUENCIES

Input variables				Resonant frequency(GHz)		Accuracy (%)
x (cm)	ε_r	r (cm)	h (cm)	From HFSS	From ANN	
0.20	17	1.2	1.6	3.69	3.61	97.9
0.20	20	1.2	1.6	3.48	3.40	97.7
0.30	25	1.2	2.0	3.10	3.18	97.4
0.10	15	0.8	1.2	5.75	5.68	98.8
0.20	13	1.2	1.6	4.15	4.07	98.1
0.10	25	0.4	1.2	5.18	5.21	99.4
0.20	15	0.8	1.6	3.28	3.22	98.2

TABLE VII. COMPARISON OF DIRECTIVITY

Input variables				Directivity (dB)		Accuracy (%)
x (cm)	ε_r	r (cm)	h (cm)	From HFSS	From ANN	
0.20	17	1.2	1.6	4.80	4.87	97.9
0.20	20	1.2	1.6	6.39	6.34	99.2
0.30	25	1.2	2.0	6.60	6.72	98.2
0.10	15	0.8	1.2	5.72	5.68	98.8
0.20	13	1.2	1.6	4.15	4.05	97.6
0.10	25	0.4	1.2	5.60	5.70	98.2
0.20	15	0.8	1.6	5.50	5.42	98.5

4. Conclusions

An ANN model of CDRA is formed here. Future scope of this work is to optimize CDRA for certain characteristics with the help of DE algorithm using ANN model to find the cost function value.

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