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Modeling Of Antenna Array Parameter Using Neural Network For Directivity Prediction

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***Abstract-* In an antenna directivity is very important fundamental parameter. It measures the power density in the direction of its strongest emission, versus the power density radiated by an ideal isotropic radiator (which emits uniformly in all directions) radiating the same total power. Traditional methods used for estimation of directivity are effective but these methods are time consuming. Artificial neural networks are used for the reducing complexity in mathematical procedures and also this method required less time, therefore this method is fast. In this letter, directivity prediction for the collinear short dipole array antenna, parallel short dipoles for yagi uda antenna and short dipole planer array antenna, using radial basis function neural networks (RBF-NNs) are presented and this method compared with feed-forward neural network. Main features of the study are the accuracy and speed for the unseen inputs.**

***Keywords-* Neural network (NN), radial basis function neural network (RBFNN), array antenna, dipole antenna.**

I. INTRODUCTION

In wireless mobile network system most of the time face problems on increase in interference, delay spread and multipath fading resulting from the ever growing communications traffic in a sector. The smart antenna technology, employing antenna arrays along with powerful signal processing, can combat these problems occurred in signalling of an antenna in wireless network. Smart antennas help in reducing the effects of above mentioned signal problems with the help of increasing the directivity and gain, wider coverage range, better spectrum utilization, higher transmission efficiency and improved network capacity.

Prediction of directivity is very important in antenna array design. Conventional numerical methods are time consuming. In this paper we have represent the method of directivity prediction of antenna array for yagi uda antenna using parallel short dipole array, collinear short dipole array and planer array. A fast iterative method for predicting directivity has been presented in this paper. Artificial neural networks (ANNs) utilize simple mathematical tools and are therefore computationally very fast. This paper presents the prediction of directivity for the collinear and parallel short dipole uniform linear arrays in yagi uda antenna, using radial basis function neural networks (RBFNNs).

1.1 Antenna Array-

Antenna arrays are the basic constituents of smart antennas. An antenna array is a set of individual antennas used for transmitting and/or receiving radio waves, connected together in such a way that their individual currents are in a specified amplitude and phase relationship. This allows the array to act as a single antenna, generally with improved directional characteristics. Antenna arrays provide an efficient means to detect and process signals arriving from different directions. Compared with a single antenna that is limited in directivity and bandwidth. After pre-processing the antenna outputs, signals are weighted and summed to give the antenna array beam pattern. An important characteristic of an array is the change of its radiation pattern in response to different excitations of its antenna elements. Unlike a single antenna whose radiation pattern is fixed, an antenna array's radiation pattern, called the array pattern, can be changed upon exciting its elements with different currents (both current magnitudes and current phases).

In an antenna design the antenna transmit most of their radiation in a particular direction.The radiation pattern of most antennas shows a pattern of "lobes" at various angles, directions. In a directional antenna in which the objective is to emit the radio waves in one direction, the lobe in that direction is designed to be bigger (have higher field strength) than the others; this is the main lobe. The other lobes are called side lobe and usually represent unwanted radiation in undesired directions. The power density in the side lobes is generally much less than that in the main beam. It is generally desirable to minimize the side lobe level. The side lobe in the opposite direction from the main lobe is called the back lobe.

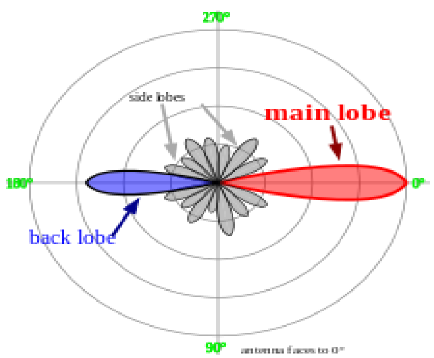

Fig.1. shown here, the largest lobe is called the main lobe. The other lobes are called side lobe.

1.2 *Directivity-*

Basically the directivity of an antenna is defined as the ratio of the maximum value of the power radiated per unit solid angle, to the average power radiated per unit solid angle.

$$D(\theta,\varphi) = \frac{U(\theta,\varphi)}{Uavg} = \frac{4\pi Umax}{Prad} \qquad (1)$$

Where $D\ (\theta,\ \phi)$ is directivity, $U\ (\theta,\ \phi)$ is maximum radiated power and $Uavg$ is average radiated power of ideal antenna.

In yagi uda antenna there are several limitations in parameters. That are reflector length should be 5% longer than dipole length, driven element length should be in between 0.45λ-0.49λ, director spacing in between 0.3λ -0.4λ, radius of director should be in between 0.15λ-0.25λ and separation between driven elements 0.15λ- 0.25λ.

The directivity expression is given for the collinear short dipole and parallel short dipole array are mentioned in (2) and (3). Accordingly, directivity of a uniform collinear short dipole antenna array is

$$D = \frac{3M^2/2}{M - 6\sum_{m=1}^{M-1}(M-m)\left[\frac{cosmkd}{(mkd)^2} - \frac{sinmkd}{(mkd)^3}\right]} \qquad (2)$$

Where M is the number of elements, d is the inter element spacing and $k=2\pi/\lambda$. Directivity of a uniform parallel short dipole array is

$$D = \frac{3M^2/2}{M + 3\sum_{m=1}^{M-1}(M-m)\left[\frac{\sin mkd}{mkd} + \frac{cosmkd}{(mkd)^2} - \frac{sinmkd}{(mkd)^3}\right]} \qquad (3)$$

The directivity for a $(M_x \times M_y)$ short dipole square array in x-y plane having radiation pattern, $E = (1 - sin^2\theta cos^2\varphi)$ is

$$D = \frac{MxMy}{Denom}$$

$$Denom = \frac{2}{3} + 4\sum_{r=1}^{Mx-1}[1 - \frac{r}{Mx}]\left[\frac{sinA}{A^3} - \frac{cosA}{A^2}\right] + 2\sum_{q=1}^{My-1}[1 - \frac{q}{My}]\left[\frac{sinB}{B} - \frac{sinB}{B^3} + \frac{cosB}{B^2}\right] + 4\sum_{r=1}^{Mx-1}\sum_{q=1}^{My-1}\left[1 - \frac{r}{Mx}\right]\left[1 - \frac{q}{My}\right][cos^2 AT \frac{sinE}{E}] + 4\sum_{r=1}^{Mx-1}\sum_{q=1}^{My-1}\left[1 - \frac{r}{Mx}\right]\left[1 - \frac{q}{My}\right][3sin^2 AT - 1][sinEE3 - cosEE2] \qquad (4)$$

Where, $A = rkdx$, $B = qkdy$, $E = \sqrt{(r^2k^2dx^2 + q^2k^2dy^2)}$, $AT = \arctan(\frac{rdx}{qdy})$

1.3 *Neural network model*:

Inspired by research into the functioning of the human brain, artificial neural network are able to learn from experience. These powerful problem solvers are highly effective where traditional, formal analysis would be difficult or impossible .Neural networks can provide robust solutions to problems in a wide range of disciplines, particularly areas involving classification, prediction, filtering, optimisation, pattern recognition and function approximation.

The directivity for the collinear short dipole, the parallel short dipole for yagi uda antenna and short dipole planer array depends on the number of elements *M*, and *d/λ* (as *k=2π/λ*). The operation of the model is based on the prediction of the output after training (learning from the data set). The data sets required for the training of ANNs, are collected from the theoretical (desired) values of directivity obtained using (2),(3) and (4).The process of training updates the weights of the ANN. This is continued till the performance goal in terms of a pre-defined mean square error (MSE) value is achieved. Once trained properly, they can predict the output for unseen inputs and perform effectively in real time. We had found error by using radial basis neural network and feedforward neural network. And we got best result from Radial basis neural network as compared to feedforward neural network as shown in Table I.

1.4 Radial basis neural network:

Radial basis function (RBF) networks are feed-forward networks trained using a supervised training algorithm. They are typically configured with a single hidden layer of units whose activation function is selected from a class of functions called basis functions. While similar to back propagation in many respects, radial basis function networks have several advantages. They usually train much faster than back propagation networks. They are less susceptible to problems with non-stationary inputs because of the behaviour of the radial basis function hidden units.

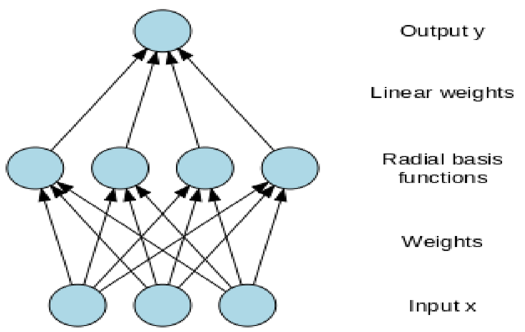

Fig.2. Architecture of a radial basis function network. An input vector χ is used as input to all radial basis functions, each with different parameters. The output of the network is a linear combination of the outputs from radial basis functions.

Radial basis function (RBF) networks typically have three layers: an input layer, a hidden layer with a non-linear RBF activation function and a linear output layer. The input can be modelled as a vector of real numbers. $x \in R^n$. The output of the network is then a scalar function of the input vector$\varphi: R^n \rightarrow R$, and is given by

$$\varphi(x) = \sum_{i=1}^{N} ai\rho(||x - ci|| \qquad (5)$$

Where **N** is the number of neurons in the hidden layer, $\mathbf{c}_i$ is the center vector for neuron i, and a_i is the weight of neuron i in the linear output neuron.

1.5 Feedforword neural network:

The feedforward neural network was the first and arguably most simple type of artificial neural network devised. In this network the information moves in only one direction forwards: From the input nodes data goes through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network. Feedforward networks can be constructed from different types of units, e.g. binary McCulloch-Pitts neurons, the simplest example being the perceptron. Continuous neurons, frequently with sigmoidal activation, are used in the context of backpropagation of error.

II. SIMULATIONS AND RESULTS:

We have been performed for the collinear and parallel short dipole uniform linear arrays for yagi uda antenna (having 8 elements each) and for a 4×4 planar (square) array, by using neural network of radial basis neural network and feedforward neural networ . RBF-NNs and feedforward neural network trained with LM algorithm have been employed for the prediction of directivity. The wavelength λ has been considered as 12.5 cm which corresponds to the frequency of 2.4 GHz. The detail result is given in Table I.

III. CONCLUSION :

This paper presents the modeling of antenna array parameter using neural network for directivity prediction. The paper determines the directivity of antenna using ANN. A neural network based solution can use for the exploit prior knowledge of the radiating system related with a given directivity distribution that must be applied to each radiating element without increasing complexity. It gives excellent result with minimum error.

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TABLE I: 'DIRECTIVITY PREDICTION' FOR INPUT SAMPLES AND ERROR CALCULATED FOR (DTH-DRBF) & (DTH-DFFNN)

	Collinear Short Dipole Array (8-element)			Parallel Short Dipole Array (8-element)			4×4 Short Dipole Planar Array		
d/λ	DTH	DFFNN	DRBF	DTH	DFFNN	DRBF	DTH	DFFNN	DRBF
0.25	6.4467	6.4466	6.4467	8.9661	8.9679	8.9704	10.0513	10.0515	10.0509
		E=0.0001	E=0		E=-0.0018	E=-0.0043		E=-0.0002	E=0.0004
0.50	9.1853	9.1853	9.1853	11.8921	11.8930	11.8931	14.3165	14.3163	14.3164
		E=0	E=0		E=-0.0009	E=-0.001		E=0.0002	E=0.0001
0.75	10.8131	10.8131	10.8131	13.4546	13.4522	13.4537	13.9888	13.9889	13.9888
		E=0	E=0		E=0.0024	E=0.0009		E=-0.0001	E=0
1.00	11.6564	11.6564	11.6564	10.4165	10.4162	10.4166	13.0819	13.0819	13.0819
		E=0	E=0		E=0.0003	E=-0.0001		E=0	E=0

DTH = Theoretical (Desired) Directivity, DRBF = Directivity Predicted by Radial Basis Neural Network, DFFNN = Directivity Predicted By Feedforward Neural Network, E= Error.

V. REFERENCES

[1] Abhishek Rawat, R. N. Yadav, and S. C. Shrivastav,“ Neural Modelling of Antenna Array Using Radial Basis Neural Network for Directivity prediction”, International Journal of Modeling and Optimization, Vol.3, No. 1, February 2013.

[2] Subhash Mishra, Ram Narayan Yadav, and Rajendra Prasad Singh, “Directivity Estimations for Short Dipole Antenna Arrays Using Radial Basis Function Neural Networks”, IEEE transaction, 2015.

[3] Amer Tawfeeq Abed, Hassan W. Hilou,“Directivity in Linear Arrays uniform space and distribution”, Journal 2012.

[4] Rahul Shrivastavaa, Abhishek Rawatb, Yogendra Kumar Jaina, R.N. Yadavc, S.C. Shrivastavac “ Neural Modelling Of Smart Antenna Array Using Radial Basis Function for Beam Shipping of GSM Transmitter”, IEEE 2012.

[5] Mellit, S. Shaari, H. Mekki and N. Khorissi, ”FPGA-based Artificial Neural Network for Prediction of Solar Radiation Data from Sunshine Duration and Air Temperature”,IEEE transaction-2008.

[6]Bratislav MilovanoviC', Zoran StankoviC', Aleksandar StoSiC3 ,“Prediction of the Electromagnetic Field Strength Level using Neural Model” , IEEE transaction 2003.

[7] Rafael G. Ayestaran, Fernando Las- Heras , Luis F. H e r r h,“Neural network-based pattern

synthesis of array antennas with element specification", IEEE transaction 2004.

[8] Jayant D. Sawarkar 1, Umesh L. Kulkarni 2, Dr. Sudhir kumar Sawarkar "Prediction of Short Term Electric Load Using Artificial Neural Network" International Journal, 2010.

[9] S. S. Khade, Suvarna Talatule, S. L. Badjate "Compact Planar Directive Yagi Antenna For WLAN Application" International Journal, April-2013.

[10] Lotfi MERAD, Fethi Tarik BENDIMERAD, Sidi Mohamed MERIAH, Sidi Ahmed DJENNAS, "Neural Networks for Synthesis and Optimization of Antenna Arrays" Journal APRIL, 2007.

[11] R.C. Hansen, Phased Array Antennas, 2nd ed. New Jersey: Wiley, USA, 2009.

[12] R.C. Hansen, "Comparison of square array directivity formulas." IEEE Transactions on Antennas and Propagation, vol.20, issue 1, pp.100-102, 1972.