Neural Modeling of Antenna Array Using Radial Basis Neural Network for Directivity prediction

Abhishek Rawat, R. N. Yadav, and S. C. Shrivastava

Abstract—**In electromagnetic directivity is a figure of merit for an antenna. It measures the power density of an actual antenna in the direction of its strongest emission, relative to the power density radiated by an ideal isotropic radiator antenna radiating the same amount of total power. It is closely related to the phase difference and distance between array elements. A neural network-based solution can exploit the prior knowledge of the radiating system to relate a given directivity distribution with the applied phase and distance between element that must be applied to each radiating element without increase of complexity. In this approach the computation of the directivity is accomplished using three layer radial basis neural network and could be useful to predict directivity for given data set. The result obtained by this network is in excellent agreement with simulation results.**

Index Terms—**Neural network (NN), radial basis function neural network (RBFNN), array antenna, dipole antenna.**

I. Introduction

One of the aims of antenna engineering is to design antennas which transmit most of their radiation in a particular direction. These directional antennas radiate energy in lobes (or beams) that extend outward from the antenna in either one or two directions. The radiation pattern contains small minor lobes, but these lobes are weak and normally have little effect on the main radiation pattern. Directional antennas also receive energy efficiently from only one or two directions, depending upon whether it is unidirectional or bidirectional. The directivity of an antenna refers to the narrowness of the radiated beam. If the beam is narrow in either the horizontal or vertical plane, the antenna has a high degree of directivity in that plane. An antenna may be designed for high directivity in one plane only or in both planes, depending on the application. 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. Thus, the directivity measures how much more intensely the antenna radiates in its preferred direction than a mythical ``isotropic radiator" would when fed with the same total power.

$$D(\theta,\phi)=\frac{U(\theta,\phi)}{U_{avg}} \qquad (1)$$

where $D(\theta,\phi)$ is directivity, $U(\theta,\phi)$ is maximum radiated power and U_{avg} is average radiated power of ideal antenna [1].

The dipole antenna or dipole aerial is one of the most important and commonly used types of RF antenna. It is widely used on its own, and it is also incorporated into many other RF antenna designs where it forms the radiating or driven element for the antenna. The dipole antenna consists of two terminals or "poles" into which radio frequency current flows. This current and the associated voltage causes an electromagnetic or radio signal to be radiated. Being more specific, a dipole is generally taken to be an antenna that consists of a resonant length of conductor cut to enable it to be connected to the feeder. For resonance the conductor is an odd number of half wavelengths long. In most cases a single half wavelength is used, although three, five, seven wavelength antennas are equally valid. In the array of half wave dipole antenna, direction of maximum sensitivity or radiation is at right angles to the axis of the RF antenna. The radiation falls to zero along the axis of the RF antenna as might be expected. The directivity of half wave dipole antenna varies nonlinearly [2] as phase angle or spacing between element changes.

The artificial neural network (ANN) is capable of forming arbitrarily nonlinear design boundaries to take up complex classification task [3]-[6]. Neural networks are extremely useful in problems where the relationship between inputs and outputs is highly nonlinear and not easy to model. An NN can approximate that model because of its ability to adapt its parameters using known input/output pairs. The NN optimizes the weights between its neurons through a training (or learning) process. Once the training has been properly done, the network is able to interpolate results for different inputs. In this paper we use radial basis function neural network for directivity prediction of two half wave dipole antennas.

II. Radial basis Function Neural Network

RBFNN's [7]-[8] are a member of a class of general purpose method for approximating nonlinear mappings. RBF neuron can be trained faster than MLP due to its two stage training procedure. It can be trained with supervised and unsupervised learning. First layer contain the parameters of the basic functions, second layer forms linear combinations of the activation of basic functions to generate outputs. Unlike the back propagation networks which can be viewed as an application of an optimization problem, RBFNN can be considered as designing neural networks as a curve fitting (or interpolation) problem in a high-dimensional space.

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$$y(x) = \sum_{i=1}^{N} w_i \phi(\|x - c_i\|) \quad (2)$$

where the approximating function $y(\boldsymbol{x})$ is represented as a sum of N radial basis functions, each associated with a different center $\boldsymbol{c}_i$, and weighted by an appropriate coefficient w_i. The weights w_i can be estimated using the matrix methods of linear least squares because the approximating function is *linear* in the weights. Approximation schemes of this kind have been particularly used in time series prediction and control of nonlinear systems.

III. Problem Formulation and Generation of Training Data

We are taking two dipole of half wave length and change their phased difference and spacing between them and collect the data (directivity) for 0 to15 deg. These data used for the training of radial basis neural network [9]-[11] and trained it over 0 to 10 deg in the spacing of 0.5, 0.6 and 0.7 wavelength. In MATLAB environment and after successful data training we test it over next 11 to 15 deg. On comparison of neural output with real time output, we find error is limited only up to 0.5 percent. The efficiency of the training is dependent on the training parameters. We are using directivity of array pattern in the neural modeling. The value of the training parameters taken for the training of the present network are as mentioned in Table I.

TABLE I. Training Data

Parameter	**Value**
Total Number neuron	33
Number of hidden layer	1
Learning rate	0.01
SSE	0.019396

IV. Simulation Result

The actual output is directivity of radiation pattern in a particular direction. We collects the data for the best combination for 0 deg to 15 deg phase angle with the spacing of 0.5,0.6 and 0.7 wavelength, and uses 0 to 10 deg for the training. After the training we test the data for 11 to 15 deg in this case network output match with the ideal result. The detail result is given in Table II.

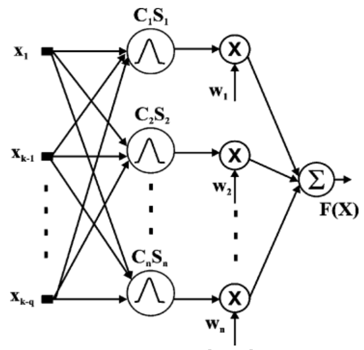

Fig. 1. RBFNN Architechure.

TABLE II: Comparison of Theoretical Output with RBFNN Model Result

Phase differen ce	Directivity At 0.5 distance	Neural model result	Comparativ e error	Directivity At 0.6 distance	Neural model result	Comparative error	Directivity At 0.7 distance	Neural model result	Comparativ e error
0.	3.9606	3.9605	-1E-04	4.8176	4.8176	0	4.9723	4.9724	0.0001
1.	3.9601	3.9606	0.0005	4.8169	4.8168	-0.0001	4.9716	4.9713	-0.0003
2.	3.9597	3.9593	-0.0004	4.8151	4.8151	0	4.9693	4.9696	0.0003
3.	3.9594	3.9592	-0.0002	4.8143	4.8143	0	4.9681	4.9685	0.0004
4.	3.9583	3.9587	0.0004	4.8121	4.8122	1E-04	4.966	4.9658	-0.0002
5.	3.9569	3.9572	0.0003	4.8085	4.8086	1E-04	4.9625	4.9613	-0.0012
6.	3.9561	3.9556	-0.0005	4.8045	4.8045	0	4.9547	4.9563	0.0016
7.	3.9543	3.9543	0	4.8008	4.8004	-0.0004	4.9521	4.9517	-0.0004
8.	3.9520	3.9525	0.0005	4.7957	4.7958	1E-04	4.9473	4.9471	-0.0002
9.	3.9504	3.9500	-0.0004	4.7893	4.7897	0.0004	4.941	4.9410	0
10.	3.9481	3.9482	1E-04	4.7830	4.7828	-0.0002	4.9332	4.9333	1E-04
11.	3.9448	3.9502	0.0054	4.7765	4.7765	0	4.9239	4.9234	-0.0005
12.	3.9426	3.9520	0.0094	4.7687	4.7645	-0.0042	4.9165	4.9028	-0.0137
13.	3.9396	3.9232	-0.0164	4.7595	4.7135	-0.046	4.9075	4.8352	-0.0723
14.	3.9358	3.7717	-0.1641	4.7512	4.5282	-0.223	4.8972	4.6218	-0.2754
15.	3.9327	3.2908	-0.6419	4.742	3.9985	-0.7435	4.8853	4.0491	-0.8362

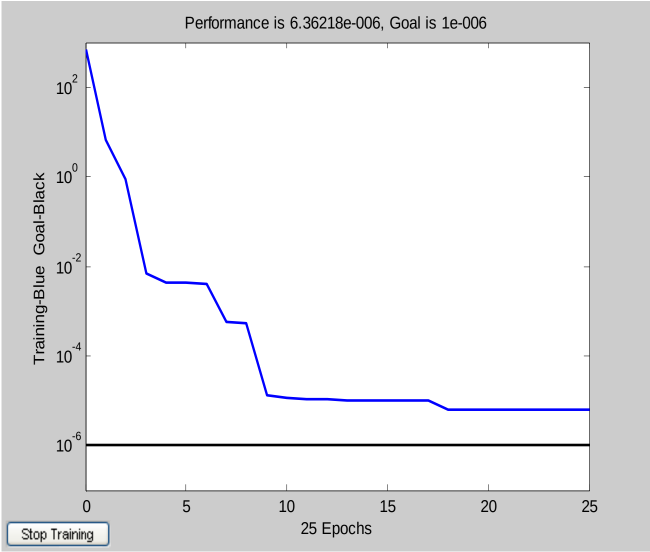

Fig. 2. Training Performance

V. Conclusion

In this paper radial basis neural network based model are applied to predict directivity of radiation pattern in a particular phase angle. The RBFNN model is inherently one type of general regression, which used to predict new results nonlinearly from some training data sets. The results (in table no. II) obtained by the RBNN modeling are in excellent agreement with the simulation results. This method can be used for fault tolerance in space platform applications where replacement of array is not possible. Presently we propose method for two dipole antenna array but same can be extend for large size of antenna array.

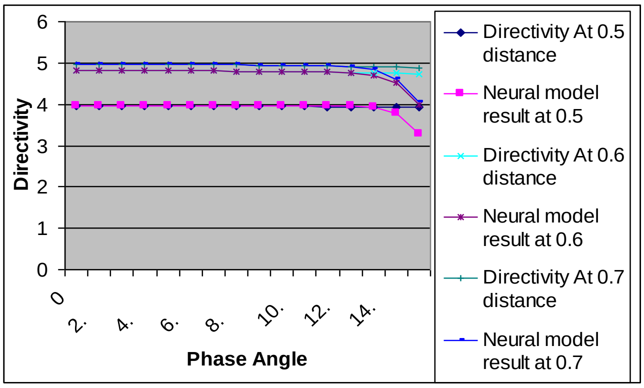

Fig. 3. Training Performance

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