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Artificial Neural Network Synthesis Based Approach For Superdirective Antenna Arrays Design

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Abstract

In this work, a novel technique is proposed to design superdirective antenna arrays using artificial neural network (ANN). A radial basis function neural network model (RBNN) is developed and used to determine the optimal inter-elements separating distance and its corresponding excitation coefficients for a single frequency. The developed model is deployed for designing a three stacked S-shaped monopole antenna array. The simulation result show that a maximal directivity of 10 dBi for a separation distance of 0.16 λ, was achieved.

Keywords—Superdirectivity, excitation coefficients, separating distance, ANN, RBNN.

1 Introduction

Superdirective array antenna have been widely studied in the last decade due to their significant advantage in overcoming the omnidirectional radiation pattern of electrically small antennas (ESAs). In [6], Uzkov showed that the end-fire directivity of N closely spaced isotropic radiators can attain N^2, if each element is excited with proper current amplitude and phase. Such directivity called "superdirectivity". Several methods have been used in the literature to design superdirective arrays. Some of the most famous ones are Yaghjian method [1], Spherical wave expansion based method [2], and network characteristic modes based method [3], etc... All these methods use the same approach: maximizing the directivity by calculating the optimal excitation coefficients, (amplitude and phase) and generally lead to the same results. However, the optimal directivity depends not only on excitation coefficients, but also on separating distance between elements. Hence to reach the upper limit of directivity of Superdirective arrays the optimization should be done both on excitation coefficients and separating distance. A classical method to determine the optimal parameters is to perform a parametric study within a given rang of distances, so at each point, we have to perform a full wave simulation to calculate the far field pattern (since the far field pattern equation for most antennas is not known) and then used it into one of the aforementioned method to optimize the directivity and so on for all distances. Finally we choose the optimal distance that gives the maximal directivity which is a time consuming task. Artificial neural network (ANN) is an effective solution to this kind of problems due to their ability to learn and generalize. Starting from a data base containing a few examples, one can use them to predict accurately the optimal parameters, excitations and separation distance, to achieve superdirectivity.

This paper presents a radial basis function neural network synthesis based approach to design a three elements Superdirective array. Firstly, we present the directivity of an antenna array and how to use the full wave simulation to take into account the mutual coupling effect. After, we present the artificial neural network used in this work and data generation to learn this model. Finally, we applied the developed model to a three stacked S-monopole superdirective array.

2 Directivity of an array antenna

The directivity $\boldsymbol{D(\theta_0, \varphi_0)}$ of an antenna array of N elements in the direction $(\boldsymbol{\theta_0, \varphi_0})$ can be expressed as [1]:

$$D(\theta_0, \varphi_0) = 4\pi \frac{\left|\sum_{n=1}^{N} A_n f_n(\theta_0, \varphi_0) \exp^{(jkr_0 \cdot r_n)}\right|^2}{\int_0^{2\pi}\int_0^{\pi}\left|\sum_{n=1}^{N} A_n f_n(\theta, \varphi) \exp^{(jk_0 \cdot r_n)}\right|^2 \sin(\theta)\, d\theta d\varphi} \quad (1)$$

Where A_n are the complex excitation coefficients, $f_n(\theta, \varphi)$ is the complex far field pattern of the nth element. r_0 and r_n, are the unit vectors in the direction of maximum directivity and in the direction of the antenna array respectively.
Since the far field patterns' equations for most antennas are not known, the full wave simulation radiation pattern is used instead and the following approximation is used [4]:

$$D(\theta_0, \varphi_0) = 4\pi \frac{\left|\sum_{n=1}^{N} A_n f_n(\theta_0, \varphi_0) \exp^{(jkr_0 \cdot r_n)}\right|^2}{\sum_0^{2\pi}\sum_0^{\pi}\left|\sum_{n=1}^{N} A_n f_n(\theta, \varphi) \exp^{(jkr_0 \cdot r_n)}\right|^2 \sin(\theta)\, \Delta\theta\Delta\varphi} \quad (2)$$

Where $\Delta\theta = \frac{\pi}{N_\theta}$ and $\Delta\varphi = \frac{2\pi}{N_\varphi}$ are spherical angle sampling steps and N_θ and N_φ are the number of samples of the simulated far field. The formula (1) is simply the limit of (2) when N_θ and N_φ tend to infinity.
The use of the full wave simulation radiation pattern has the advantage of considering the mutual coupling and the environment effect which is not possible with analytical model.

3 Radial basis function neural network and data generation.

3.1 Radial basis function neural network

Artificial neural network is a mathematical modeling inspired from the human nervous system operation in an attempt to mimic the learning process in human brain.
Radial Basis Function Neural Network is a feed forward neural network. It consists of three layers of neurons: input layer which is directly connected to the input nodes, hidden layer where the input data are processed and output layers which gives the response of the neural network to the input data Figure1. This type of ANN uses a radial basis function as an activation function for the hidden layers, hence the name Radial basis function neural network [7].

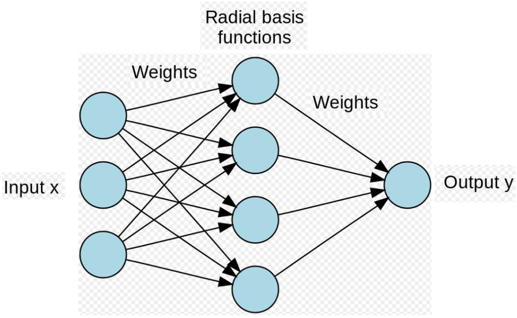


Figure 1. Radial basis function neural network structure.

The effectiveness of these artificial neural network types results from their ability to maps and generalize the relationship between the input and the desired output data.

3.2 Data generation

In order to make our RBNN learn, we have constructed an input-output data set using formula (2). In our case the inputs data is the directivity however, the outputs are the inter-element separation distance ‘d’, (as a function of the wavelength λ) and its corresponding excitation coefficients ‘ A_n’ (Figure 2).

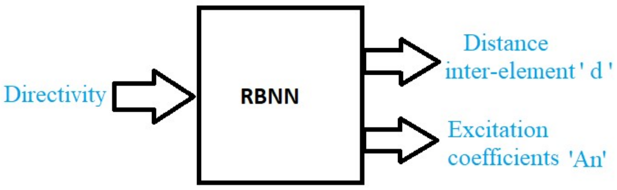


Figure 2. Configuration of the developed RBNN

For a given distance ‘d’, the N elements array antennas was simulated using the commercial CST microwave studio. The obtained far field patterns are then exported into Equation (2) to calculate the directivity for a random complex excitation using a loop program in MATLAB.

4 Application on a three compact super-directive array

4.1 Unit element

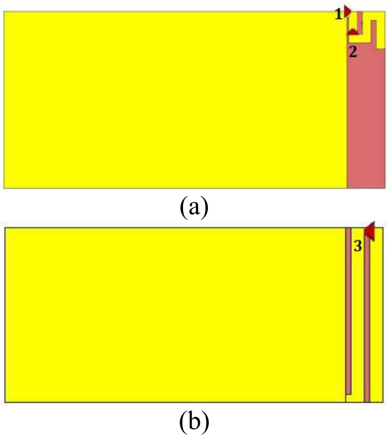


Figure 3. Unit element: (a) Top view, (b) Bottom view.

The unit element used here is a miniaturized S-monopole antenna integrated on a PCB, Figure 1. The antenna is loaded inductively at positions 2 and 3 with $L_1 = 28nH$ and $L_2 = 13nH$, to ensure a wide band behavior [5]. The S-monopole antenna has a resonant frequency of 0.98 GHz and a maximal directivity of 2.71 dBi, Figure 4.

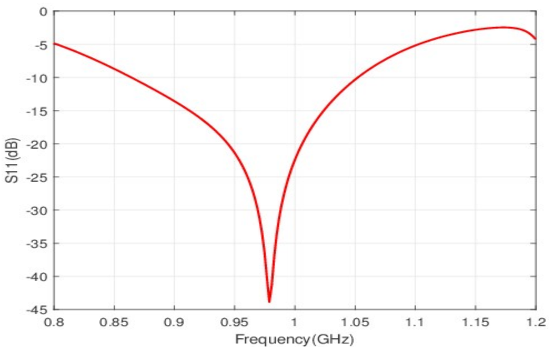


Figure 4. Input reflection coefficient of unit element

4.3 Three elements array synthesis

To verify, the optimization ability of artificial neural networks, the developed RBNN was used to synthetize a three stacked S-monopole antenna array Figure 5.

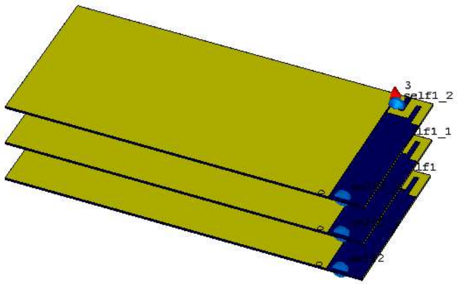


Figure 5. A Three stacked-elements array.

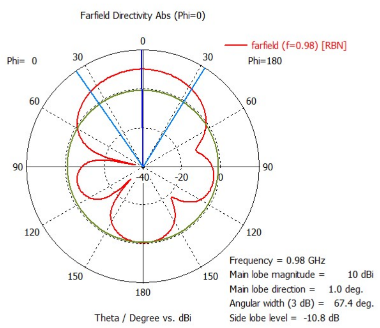
By specifying the desired directivity, the RBNN gives the optimal separation distance between the elements and its corresponding excitation coefficients. It should be noted that the specified directivity should be a realistic and an attainable value according to the type and the number of antennas used in the array. For optimization cases, the specified directivity should be close as much as possible to the maximal attainable limit.

In our case the specified directivity was 10 dBi. The optimal parameters given by the RBNN are depicted in Table 1.

Table 1. Optimal inter-elements distance and excitation coefficients, amplitude and phase (in degree), predicted by RBNN.

d(λ)	$\lvert A_1 \rvert$	φ_1	$\lvert A_2 \rvert$	φ_2	$\lvert A_3 \rvert$	φ_3
0.1595	1	0	0.575	-134.7	0.469	-23.62

With this parameters, a maximal directivity of 10 dBi and a Front to Back Ratio of 10.8 dBi are obtained with a radiation efficiency of 80% Figure 6.



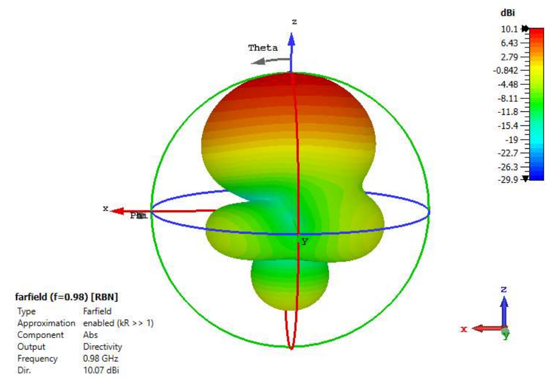


Figure 6. Three stacked-elements array simulated 2D and 3D radiation pattern .

To verify the accuracy of this result, a parametric study was performed within a range of distances [0.01λ, 0.2λ], and a step of 0.01λ. At each point the directivity was optimized using Yaghjian method [1]. Figure7, present the optimized directivity versus the distance inter-elements. From the (figure 7) we can clearly see that the maximal directivity of the array (10.17 dBi) occurs at a distance of 0.16 λ. which is in a good agreement with RBNN predicted result.

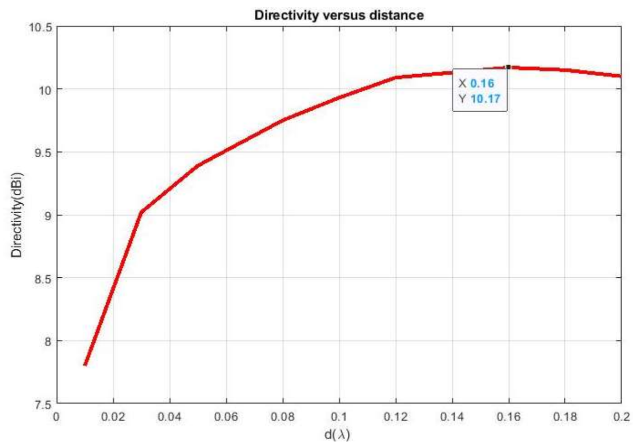


Figure 7. Optimized directivity versus distance

5 Conclusion

In this paper, A Radial basis function neural network synthesis based approach is presented. The developed RBNN is used for designing a three-element Superdirective array. Simulation result show that the predicted parameters give a maximal directivity of 10 dBi. A parametric study was performed to compare the obtained result with RBNN with the optimized ones using Yaghjian method.

6 References

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