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Smart Antenna Design Using Neural Networks

Theodoros N. Kapetanakis [1,2], Ioannis O. Vardiambasis [1], George S. Liodakis [1,2],
Melina P. Ioannidou [3], and Andreas M. Maras [2]

[1] Department of Electronic Engineering
Faculty of Applied Sciences
Technological Educational Institute of Crete
Chania, Crete 73100, Greece
{todokape@chania.teicrete.gr, ivardia@chania.teicrete.gr, gsl@chania.teicrete.gr}

[2] Department of Telecommunications Science & Technology University of Peloponnese
Tripolis, 22100, Arcadia, Greece
{todokape@chania.teicrete.gr, gsl@chania.teicrete.gr, amaras@uop.gr}

[3] Department of Electronic Engineering
Alexander Technological Educational Institute of Thessaloniki
Thessaloniki 57400, Greece
{melina@el.teithe.gr}

Abstract: Optimizing antenna arrays to approximate desired far field radiation patterns is of exceptional interest in smart antenna technology. This paper shows how to apply artificial intelligence, in the form of neural networks, to achieve specific beam-forming with linear antenna arrays. Multilayer feed-forward neural networks are used to maximize multiple main beams' radiation of a linear antenna array. In particular, a triple beam radiation pattern is presented in order to demonstrate the effectiveness and the reliability of the proposed approach. The results show that multilayer feed-forward neural networks are robust and can solve complex antenna problems.

Keywords: *Neural Networks, Smart antennas, Antenna arrays, Linear arrays, Beamforming.*

1. INTRODUCTION

Smart antennas have been widely used in mobile and wireless communication systems to increase signal quality, improve system capacity, enhance spectral efficiency, and upgrade system performance. Since the design of smart antenna arrays strongly affects their performance [1]-[2], in this paper we consider multiple main beams as the design criterion for the evaluation of smart antenna array' performance.

The synthesis of an antenna array with a specific radiation pattern is a nonlinear optimization problem, which cannot be effectively treated by traditional optimization techniques using gradients or random guesses [2]-[4]. Especially in complex cases of radiation shapes with multiple main beams and nulls at given directions, there are too many possible excitations and exhaustive checking of the best solution is very difficult [2]. However neural networks (NNs) are capable of solving this kind of complicated and nonlinear search problems [2], [5]-[10], especially in wireless communications.

In general, Multilayer Perceptron (MLP), Radial Basis Function (RBF) and Hopfield-type NNs are the most suitable for use in various smart antenna applications [9]-[10]. Therefore, selection of the appropriate NN configuration parameters, such as the number of neurons, the number of layers, and the training algorithm, is crucial in NN design. Certain characteristics of the NN must be defined before its use, as an adequate structure must be chosen for the network and then trained and tested with a broad dataset for the required application [10].

This paper shows that antenna array design can be dealt with as an optimization problem, training a back-propagation NN to synthesize antenna array patterns for linear arrays. Thus the radiation pattern of a linear antenna array with M elements and with 3 main beams is computed efficiently.

2. FORMULATION OF THE ANTENNA ARRAY PATTERN

In this paper, we will concentrate on finding the current excitations of all antenna array elements, which is the standard technique for designing antenna arrays. If the elements in the linear array are taken to be isotropic sources, the pattern of this array can then be described by its array factor. The array factor for the linear array in Fig. 1 is given by

$$S(\theta,\varphi,\overline{A},\overline{\delta}) = \sum_{n=1}^{M} A_n \cdot \exp[j\,n\,kd\,(\cos\theta\cos\theta_a + \sin\theta\sin\theta_a\cos(\varphi-\varphi_a)) + j\delta_n] \qquad (1)$$

where $\overline{A} = [A_1, A_2, ..., A_M]$, $\overline{\delta} = [\delta_1, \delta_2, ..., \delta_M]$, A_n and δ_n represent the amplitude and phase of the current excitation of the nth array element, $k=2\pi/\lambda$ is the wavenumber, λ is the wavelength, d is the uniform distance between elements, (θ,φ) is the direction of interest, and (θ_a,φ_a) is the direction of the array axis.

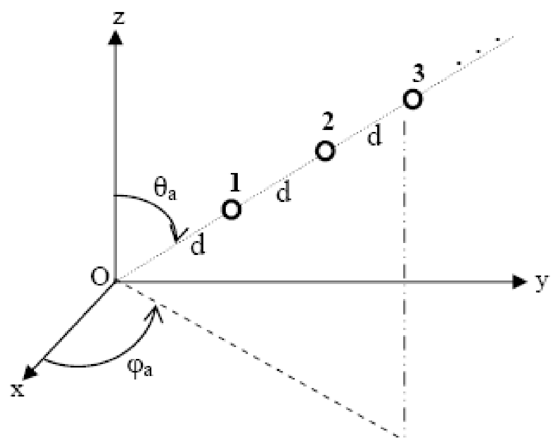

Figure 1: The linear array geometry.

To analyze and synthesize radiation patterns for the linear array of Fig. 1, we develop feed-forward neural networks, which are a widely spread topology with many practical applications in electromagnetics. Especially the MultiLayer Perceptron (MLP) is probably the most famous neural network type, because of its ability to model complex functional nonlinear relationships. An MLP neural network has an input layer, an output layer, and one or more hidden layers, and can realize an infinite set of functions depending on a vector $\overline{w}$ composed of all neural network's weights.

A crucial parameter of the synthesis of an accurate neural network model is the choice of the proper training algorithm. In order to find the best training algorithm, several trials were performed, using algorithms such as, BFGS quasi-Newton back-propagation (BFGSqN), Bayesian Regulation back-propagation (BR), Conjugate Gradient with Powell-Beale restarts (CGPB), Conjugate Gradient with Fletcher-Reeves updates (CGFR), Conjugate Gradient with Polak-Ribiére updates (CGPR), Gradient Descent back-propagation (GD), Gradient Descent with Adaptive learning rate (GDA), Gradient Descent with Momentum back-propagation (GDM), Gradient Descent with Momentum and Adaptive learning rate (GDMA), Levenberg-Marquardt back-propagation (LM), and Scaled Conjugate Gradient (SCG) [9], [11]-[14].

The aim of this paper is to develop two NN models for the analysis and design of a smart antenna array. The first NN model, shown in Fig. 2, is used to calculate the antenna gain $G(\theta,\varphi)$ of a linear array with M elements at a specific direction (θ,φ), for a given set of antenna current weights $\bar{w}$. The second NN model, shown in Fig. 3, is used to calculate the antenna current weights $\bar{w}$ of an M-element linear array achieving specific antenna gain G(θ,φ) values in predefined directions (main beams at θ=40°,100°,135°).

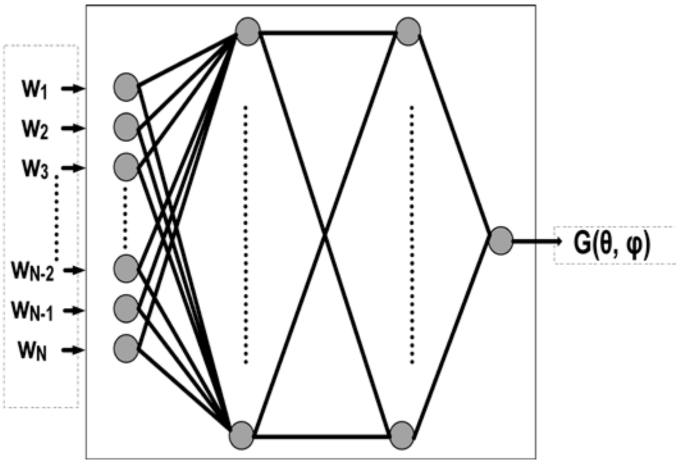

Figure 2: The first NN model having as inputs the current excitations w_m, and as output the smart antenna gain G(θ,φ).

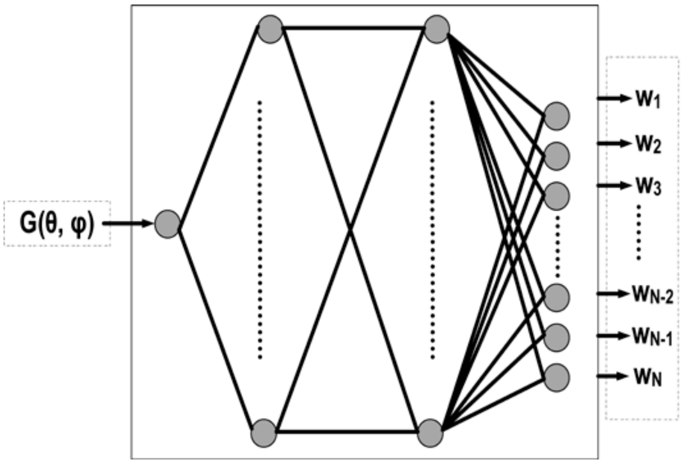

Figure 3: The second NN model having as input the desired antenna gain G(θ,φ), and as outputs the proper current excitations w_m.

Table 1: Errors obtained from the first NN for different learning algorithms.

Learning Algorithm	Mean Square Error			
	NN_1		NN_2	
	Training	Testing	Training	Testing
BFGSqN	8.15×10^{-6}	9.82×10^{-6}	6.62×10^{-3}	7.10×10^{-3}
BR	7.36×10^{-4}	9.31×10^{-4}	5.87×10^{-2}	7.02×10^{-2}
CGPB	2.13×10^{-5}	4.22×10^{-5}	8.56×10^{-2}	9.25×10^{-2}
CGFR	5.67×10^{-5}	4.37×10^{-5}	3.68×10^{-4}	4.39×10^{-4}
GCPR	5.49×10^{-4}	7.53×10^{-4}	3.50×10^{-2}	3.83×10^{-2}
GD	1.27×10^{-6}	2.14×10^{-6}	1.77×10^{-4}	2.14×10^{-4}
GDA	4.73×10^{-5}	5.34×10^{-5}	4.01×10^{-4}	4.74×10^{-4}
GDAM	7.15×10^{-4}	8.87×10^{-4}	2.24×10^{-3}	4.13×10^{-3}
GDMA	3.11×10^{-4}	6.16×10^{-4}	8.12×10^{-4}	8.97×10^{-4}
LM	6.12×10^{-7}	7.03×10^{-7}	2.01×10^{-5}	2.54×10^{-5}
SCG	3.19×10^{-3}	6.98×10^{-3}	3.67×10^{-3}	4.35×10^{-3}

After many trials, it was found that high accuracy was achieved by using one hidden layer with 22 neurons for the first NN model and two hidden layers with 38 and 49 neurons for the second NN model. For both models, the tangent sigmoid activation function was used in the hidden layers, while the training and testing datasets were scaled for inputs and outputs before training between (−1.0, +1.0) in order to accomplish easier learning process.

In order to compute either the radiation field strengths or the antenna current excitations, the NN models using different learning algorithms were fed sequentially and/or randomly with many datasets of antenna currents (w_1, w_2,…, w_N) and the corresponding antenna gain values $G(\theta,\varphi)$ (in order to have 3 main beams at $\theta=40^o$, 100^o, and 135^o). Because of the NN weakness to handle complex numbers, the real and imaginary parts of the currents were used [5]. The Mean Square Error (MSE) between each target theoretical value and its relative actual NN output was used to adapt the NN weights. The adaptation was carried out, after the presentation of each data set, until either the MSEs for all the training datasets are under a given threshold, or the maximum allowable number of epochs is reached.

3. NUMERICAL RESULTS

NNs have been successfully introduced for the antenna radiation pattern synthesis. To obtain models of high accuracy and performance, NNs were trained using 11 different training algorithms. For each learning algorithm, the maximum allowable number of epochs was 2000, and the MSE of the NN models were calculated.

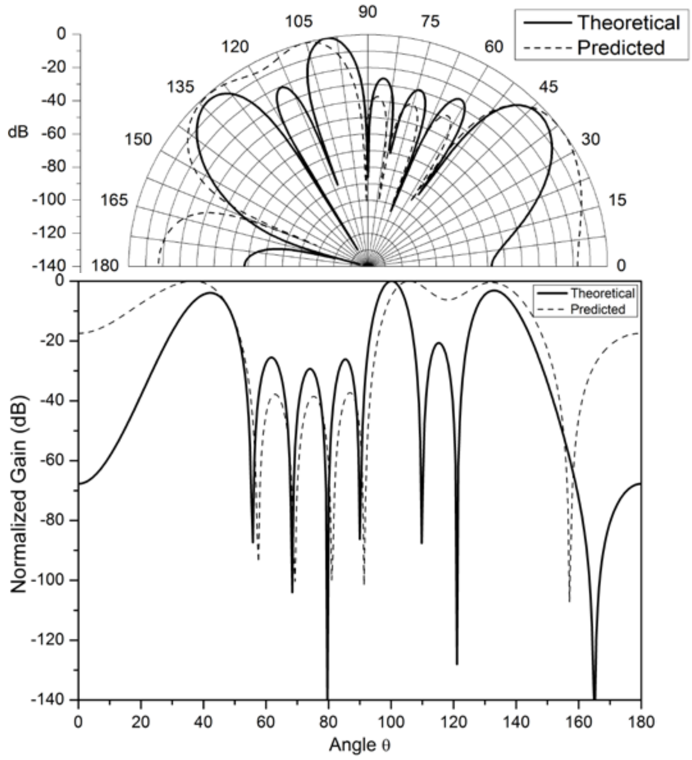

Figure 4: Normalized radiation pattern of a linear array (N=10, d=λ/2, θ_a=0°) with 3 main beams at θ=40°, 100° and 135° (in polar and Cartesian form).

The training and test errors obtained from the NN models trained with different learning algorithms are summarized in Table I. Comparisons of the training and test performances of all learning algorithms reveal that the best results were obtained using the LM algorithm for both models (with MSE less than 3×10^{-5}). These small error values reveal that the NN models trained with the LM algorithm can be used for accurate computations of the current excitations and the field strength of a linear array. Then, in order to validate the developed

NN models, characteristic comparisons between the results of the NN models and the corresponding analytical solutions are given in Figs. 4-6.

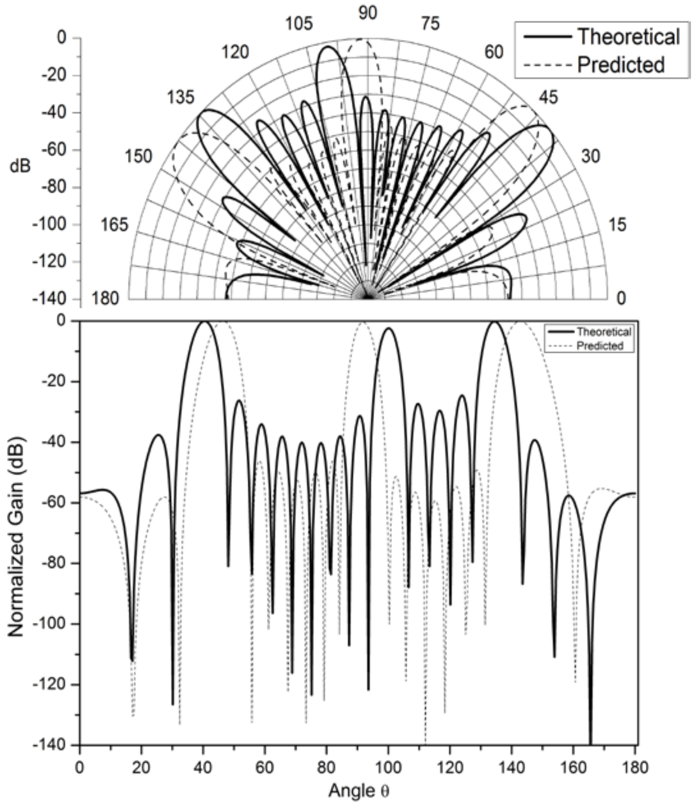

Figure 5: Normalized radiation pattern of a linear array (N=20, d=λ/2, θ_a=0°) with 3 main beams at θ=40°, 100° and 135° (in polar and Cartesian form).

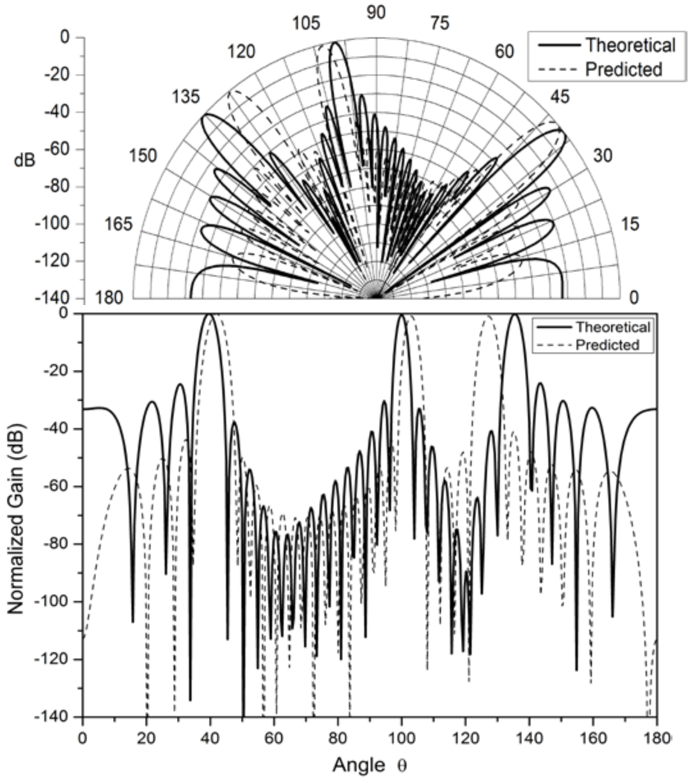

Figure 6: Normalized radiation pattern of a linear array (N=30, d=λ/2, θ_a=0°) with 3 main beams at θ=40°, 100° and 135° (in polar and Cartesian form).

4. CONCLUSIONS

This paper shows that antenna array design and pattern synthesis can be modeled with NNs, where the optimization objective is the maximization of multiple main beams. The good agreement between theoretical and computational results supports the validity of the NN models proposed here. The small error values suggest that the proposed NN models can be used for the accurate computation of the current excitations or the field strength values.

5. ACKNOWLEDGMENT

This work was co-financed by the European Union (European Social Fund-EKT) and Greece (Ministry of Education and Religious Affairs) in the framework of the Operational Programme for Education and Lifelong Learning ("Workplace Learning of Students of T.E.I. of Crete/Department of Electronic Engineering Department" project). The project for WPL of TEIoC students is within the TEIoC's DASTA Structure, including, also, the Liaison Office and the Innovation & Entrepreneurship Unit.

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Proceedings of the

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