Neural Networks for Synthesis and Optimization of Antenna Arrays

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Abstract. *This paper describes a usual application of back-propagation neural networks for synthesis and optimization of antenna array. The neural network is able to model and to optimize the antennas arrays, by acting on radioelectric or geometric parameters and by taking into account predetermined general criteria. The neural network allows not only establishing important analytical equations for the optimization step, but also a great flexibility between the system parameters in input and output. This step of optimization becomes then possible due to the explicit relation given by the neural network. According to different formulations of the synthesis problem such as acting on the feed law (amplitude and/or phase) and/or space position of the radiating sources, results on antennas arrays synthesis and optimization by neural networks are presented and discussed. However ANN is able to generate very fast the results of synthesis comparing to other approaches.*

Keywords

Neural networks, modeling, optimization, synthesis, antennas arrays, printed antenna.

1. Introduction

In the domain of printed antenna arrays, the synthesis problem consists of estimating the variations of the amplitude and phase feed law and the space distribution of the aerial elements. This provides a directivity diagram as close as possible to a desired diagram specified by a mask [1]. The aim of this optimization is thus to seek for the optimal combination of these different parameters so that the array complies with the requirements of the user and according to precise specifications.

In this domain, many deterministic processing tools for synthesis were developed. Taking into account the diversity of the aims sought after by the users, a general method of synthesis appropriate to all cases is not found, but it is rather found a significant number of methods specific to each class of problem. This diversity of solutions can be used to built up a useful database for a general approach to the synthesis of a given antennas arrays.

We propose here a new approach of stochastic synthesis based on neural networks. This approach is able to model and optimize the antenna arrays system, by acting upon various parameters of the array and taking into account predetermined general criteria. The introduction of this new variant of neural networks represents also an interesting alternative for the printed antenna arrays synthesis.

At the learning step the neural network allows to establish important analytical relations for the modeling and the optimization step of the antenna arrays. There is no restriction on the number of system parameters in input and output. The interest of such system is in the extreme flexibility introduced between the radioelectric characteristics of the antenna arrays. This approach has been carried out only with equally spaced linear arrays [2], [3]. However, it is well known that antenna performance related to beamwidth and sidelobe levels can be improved by choosing the best position or distribution and best excitation coefficients for each element of unequally spaced arrays. Zooghby et al [4] describes the uses of neural networks approach to the problem of finding the weight of one and two-dimensional adaptive arrays. An extension to multibeam arrays synthesis using back-propagation neural networks was given in [5].

In this paper, we present results concerned with the synthesis and optimization of equally or unequally printed antenna linear arrays by neural networks. Thus for the learning step, and in the first application we used an analytical method based on feed laws distribution [6] and in the second application, we used a stochastic method of optimization based on the genetic algorithm [7–9]. The simulation result shows the effectiveness of the proposed method of synthesis.

2. Artificial Neural Networks

The concept of artificial formal neurons is introduced in this paragraph. The architectures of neural networks related to this concept are presented in order to simultaneously highlight their main applications and their multiple functions possibilities.

The artificial neural networks (ANN) are data-processing models inspired from the structure and behavior of the biological neurons. They are composed of inter-connected units which we call formal or artificial neurons [10], [11].

An artificial neuron is an automaton which communicates with its neighbors by weights and is able to activate itself according to the received signals (Fig. 1). Thus, all neurons take their decisions simultaneously by taking into consideration the evolution of the global state of the network. These neurons are connected between them and are set on layers to form a network. To a given inputs' configuration, the network associates outputs' configuration, compared to that which is wished. The synaptic weights (characteristically elements of the neurons) are modified in the network so that, to minimize the obtained error.

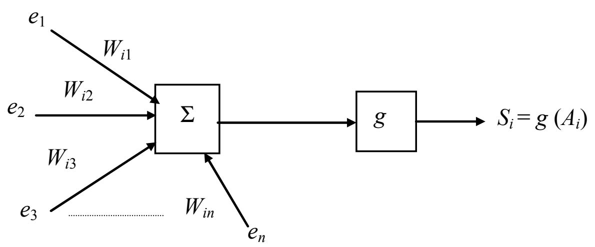


Fig. 1. Scalar product neuron.

$$S_i = g(A_i) \tag{1}$$

with $A_i = \sum_{k=1}^{n} W_{ik} e_k$

where the coefficient W_{ik} is called the synaptic weight of the k towards i connection and e_i input parameters. Generally, the scalar product neuron consists of two successive modules: a linear transformation (the scalar product) followed by a nonlinear transformation g. For the synaptic weights calculation, we proceed with very important step: the learning step.

2.1 Learning Step

The neural networks can change their behavior to adapt themselves to their environment (i.e. the problem), it is what we call the learning. By presenting an ensemble of inputs, the network is self-adjusted by modifying its weighting parameters to produce the desired results.

2.2 Use Step

In this step, we test the performances of the network, because this later will be confronted to situations which are close to the selected examples. With reference to the obtained responses, we will be able to appreciate the quality of the considered network.

In this paper, two distinct architectures are considered; the multi-layers back-propagation network and the RBF network (Radial-Basis Function). They are the most current architectures and the simplest non-linear networks. The abilities of modeling these networks are analyzed.

2.3 Multi-Layer Back-Propagation Network

The multi-layers networks consist of an input layer whose neurons code the information presented at the network, a variable number of internal layers called "hidden" and an output layer (Fig. 2) containing as many neurons as the desired responses. The neurons of the same layer are not connected between them. The learning process of these networks is supervised. The used algorithm for this learning process is known as the Back-Propagation Learning algorithm (BPL). It includes two steps:

- a propagation step, which consists of presenting a input configuration to the network then propagating this configuration gradually from the input layer through the hidden layers up to the output layer,
- a back-propagation step (Fig.3), which consists, after the process of propagation, in minimizing the obtained error upon the whole presented examples,. This is considered as a function of the synaptic weights (W). This error represents the squared sum of distances between the determined responses (S) and the desired ones (Y) for all examples contained in the whole learning process. This process continues in order to recalculate the synaptic weight of the network until the number of epochs is reached or the error is less than the desired goal.

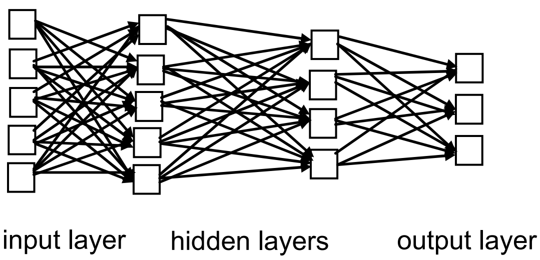


Fig. 2. Multi-layers networks.

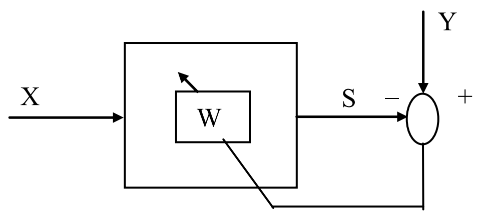
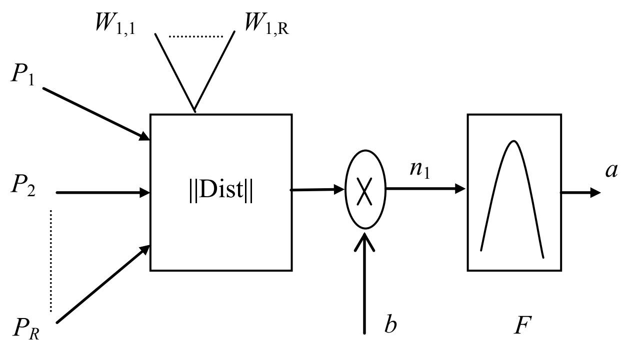


Fig. 3. Back-propagation learning (BPL).

2.4 Radial-Basis Function Network

Fig. 4 represents an RBF neuron with R inputs.



$a = F\,(||W\text{-}P||),\ b)$

Fig. 4. RBF neuronal model.

In this case, the input of the basic radial transfer function is the distance vector between its weight W and the P inputs vector, multiplied by the bias b [11].

The transfer function for a basic radial neuron is $radbas(n) = e^{-n^2}$.

The RBF network is a network with three layers: an input layer, a hidden layer composed of kernel-function and an output layer [12],[13], whose neurons are generally animated by a linear activation function. Each neuron of the hidden layer thus carries out a kernel-function and compares its input with the vector coded in its weights (the prototype vector) and responds by an activation as more intense as the input is similar to the vector.

3. Neural Networks and Antenna Arrays

Let us consider a rectilinear antenna array with P identical sources of directivity diagram $f\,(\theta,\phi)$. Each one localized at X_i position is fed by a complex excitation $w_i = a_i \exp(j\ \psi_i)$. Its radiation diagram is given by [1]

$$F(\theta,\phi) = \frac{f(\theta,\phi)}{F_{\max}} \sum_{i=1}^{P} a_i \exp[j(k_0 X_i \sin\theta\cos\phi + \psi_i)] \quad (2)$$

with k_0 the wave number ($k_0 = 2\pi/\ \lambda$), $\theta,\ \phi$ the angular directions, $a_i,\ \psi_i$ the amplitude and the phase of the complex feed.

The directivity diagram $F(\theta,\ \phi)$ is a function of the two direction angles θ and ϕ. If ϕ is fixed, the diagram $F(\theta,\ \phi)$ could be conformed in the E or H plane. For convenience, we are interested to the synthesis of linear arrays in the $\phi = 0$ plane. In the case of an even number of elements ($P = 2N$) and a symmetrical space distribution, the array has as a normalized directivity diagram following the formula

$$F_s(\theta) = \frac{f(\theta)}{F_{s\max}} \sum_{i=1}^{N} a_i \cos(k_0 X_i \sin\theta + \psi_i)\,. \quad (3)$$

Thus, the synthesis problem consists in approaching the antenna arrays directivity diagram to a desired pattern $F_d\,(\theta)$ by acting on the feed law and/or the space distribution.

The radiation diagram of $f\,(\theta)$ used in our applications is the same as given by Damiano [14]. This diagram is determined for substrate with the permittivity equal to 3.5, thickness equal to 0.159 cm and operating at 5 GHz.

During the learning phase of the neural network, significant analytical relations for the modeling and optimization of the antenna array are developed. A great flexibility between the characteristics of the antenna array: amplitude and phase of feed, space distribution of sources, gain, undulation domain, sidelobe levels.... are thus introduced, since there is no restriction for the system parameters' number in input and output (Fig. 5).

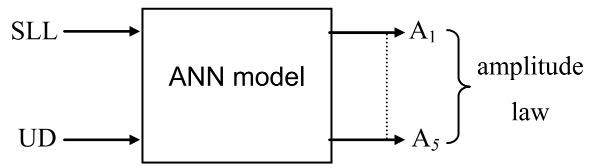


Fig. 5. ANN synthesis model with 2 inputs and 5 outputs.

3.1 Choice of the Neural Network Topology

The network topology must be appropriately selected. It is clear that a single layer network can only solve the problems with linear separations. Thus, it is necessary to have at least an intermediary layer since in practice the nonlinear case often exists. Moreover, there is no precise rule for the choice of the number of intermediary layers (hidden) and the neurons number in each one of these [15].

Choosing a back-propagation network or a RBF network depends on the nature of the problem to solve [16].

3.2 Construction and Validation of the ANN

Generally, the steps of construction and validation of the neural networks are divided into four parts:

- the choice of the network inputs,
- the choice of the network outputs,
- the choice of the studied network architecture,
- tests of the networks selected on new examples close to the learning examples.

Fig. 6 represents the test step synoptic bloc diagram of the developed model by the artificial neural network (ANN).

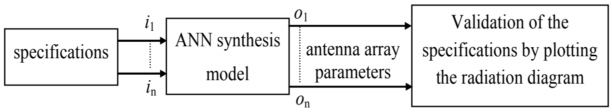


Fig. 6. Synoptic bloc diagram of the RNA model test step.

4. Amplitude Feed Law Synthesis

The printed antenna array synthesis by amplitude law allows reducing the radiation side-lobes level, this level is a function of the amplitude law applied to the array.

In this case, the synthesis problem consists in determining the amplitude coefficients that likely produce a directivity diagram having some properties required by the user beforehand. These properties are generally specified overall from a mask characterizing the desired directivity diagram or only from the side-lobes level (SLL) [17].

In order to reduce the number of unknown factors and as the considered array is symmetrical, the synthesis is carried out on the first half of the aerial elements of the array. However, the elements are equally spaced at the half wavelength.

In this type of synthesis, we apply Tchebycheff distribution laws of feed in order to create a database required to the development of the neural network in its learning step. This database contains a whole of data input/output and corresponds to each input vector: an amplitude feed vector of the array, the corresponding side-lobes level. The construction of the ANN is carried out by an iterative process on the samples of the database built beforehand. Each iteration allows minimizing the mean quadratic error between the ANN outputs and the given samples. The number of training set is equal to 60, and the range of input parameter variations is -62.5 dB ≤SLL≤-10 dB.

4.1 Learning Step

Generally for the choice of the network topology, there is not a general method that allows fixing a topology for a given problem. In this context, we are brought back to a problem that studied the greatest possible number of neuronal architectures. After several tests, we chose a back-propagation network with the following topology:

1 input neuron corresponding to desired SLL,

8 neurons in the hidden layer,

5 neurons in the output layer representing the amplitude law of the first half of the array.

When the network architecture was defined, the learning step allows to determine the synaptic weights connecting the layer neurons by using the algorithm of Levenberg-Marquardt. The choice of such algorithm is that it often converges faster than other methods like conjugate gradient methods [18]. These algorithms consist in presenting of learning examples, i.e. sets of activities of the input and output neurons, to the network. The difference between the network output and the desired output is modified by the synaptic weights of connections until the network produces an optimal desired output. The chosen learning process in our applications is of supervised type [18]. The hyperbolic tangent function is affected as an activation function to the hidden layer and the linear function to the output layer.

4.2 Use Step

This step is called a recognition step or "test", it consists in testing the performances of the neural network. In our application, this step consists in testing the performances of the network to find the feed amplitude to be applied to the printed antenna arrays for each desired sidelobes level SLL.

We noted that our network could recognize even the test examples which do not form part of the learning database. The recognition rate is the ratio between the examples recognized by the network and the whole of the presented examples to the built model by the ANN. The input pattern will be recognized by the network, if the radiation pattern respects the desired sidelobe level or the mask which characterizes the desired diagram (Fig. 8).

Fig. 7a represents the results of the radiation diagram synthesis of the antenna arrays with 10 elements for test input with SLL = – 45 dB. The corresponding learning steps are represented in Fig. 7b.

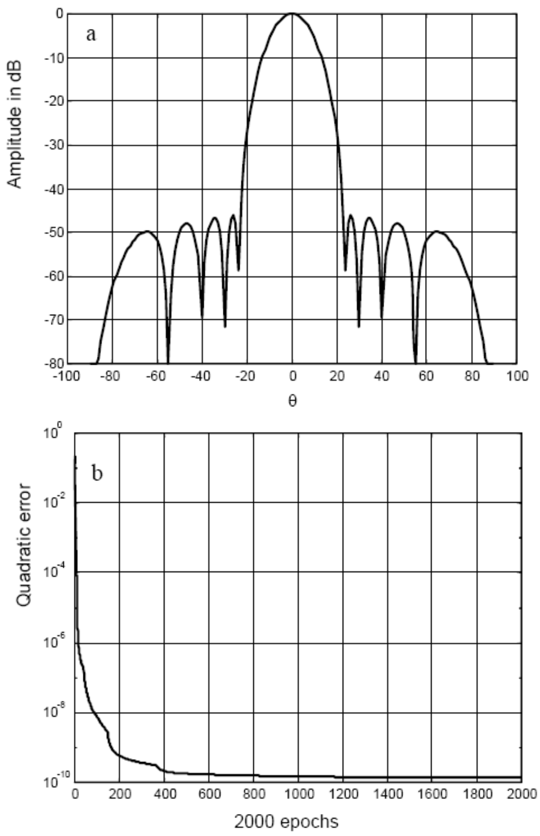


Fig. 7. **a**. Diagram of a 10 elements symmetrical array, SLL = – 45 dB , **b**. Neural network learning step.

With the Tchebycheff method, we normally obtain a constant side-lobes level, but we notice in Fig. 7 that it is not the case. This is due to the fact that we have taken into account the elementary diagram $f(\theta)$ which causes the reduction of the extremes side-lobes.

4.3 Synthesis from a Desired Mask

When the desired directivity diagram $Fd(\theta)$ is specified by a mask, the synthesized diagram must remain within the limits fixed by this mask.

Let us characterize the desired diagram from the half-mask represented by Fig. 8.

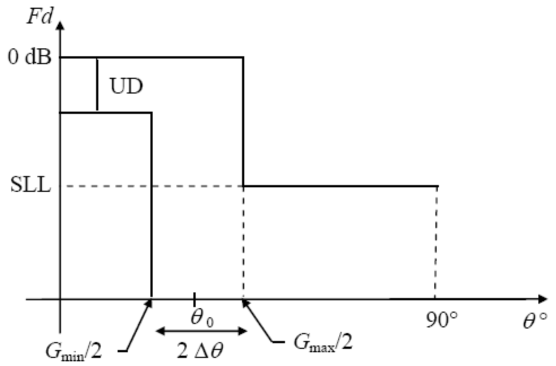


Fig. 8. Half-mask characterizing the desired diagram.

- for $0 \le \theta \le \theta_0 - \Delta\theta$, we define the undulation domain UD,
- for $\theta_0 + \Delta\theta \le \theta \le 90°$, we define the side-lobes level SLL,
- $G_{max} = 2\ (\theta_0 + \Delta\theta)$ represents the mask's maximum beamwidth,
- $G\text{min} = 2\ (\theta_0 - \Delta\theta)$ represents the mask's minimum beamwidth.

The database contains a whole of data (input/output) obtained by simulation starting from the genetic algorithm (GA). In our application, we have used the GA developed by K. K.Yan [19]. Unlike conventional GA using binary coding and binary crossover, this approach directly represents the array excitation weighting vectors as complex number chromosomes and uses decimal linear crossover without crossover site. Compared with conventional GA's, this approach has a few advantages such as: giving a clearer and simpler representation of the problem, simplifying chromosome construction, and totally avoiding binary encoding and decoding so as to simplify software programming and to reduce CPU time consuming. The *Cost* function used here is the same as that given by Audouy [20]:

$$Cost = \sum_{\theta} L(\theta) \tag{4}$$

with $$L(\theta) = \frac{k(\theta) + |k(\theta)|}{2} \tag{5}$$

where $$k(\theta) = (G_{max}(\theta) - |F_s(\theta)|)(G_{min}(\theta) - |F_s(\theta)|) \tag{6}$$

G_{min} and G_{max} represent respectively the masks of minimum and maximum beamwidth.

4.3.1 Learning Step

After several tests, we chose the RBF network, with the following topology (Fig.9).

In our application, the number of training set is equal to 75 and the range of input parameters variations are as follows: –42 dB ≤ SLL ≤ –12 dB, –4.5 dB ≤ UD ≤ –3.5 dB, $13° \le \theta_0 \le 17°$, $0.45\ \lambda \le dx \le 0.6\ \lambda$, with $G_{min} < 20°$, dx being the inter-elements distance.

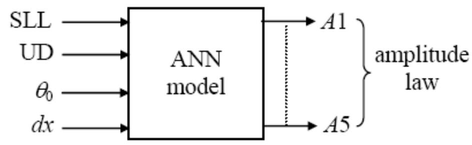


Fig. 9. Representation of the ANN model synthesis: 4 inputs and 5 outputs.

4.3.2 Use Step

Fig. 10 represents the results of the radiation diagram synthesis for a 10-element symmetrical array and for the test vector: SLL = –41.5 dB, UD = – 4 dB, $\theta_0 = 16°$, $dx = 0.55\ \lambda$, the number of testing set is equal to 42 and the recognition rate is close to 90,47%.

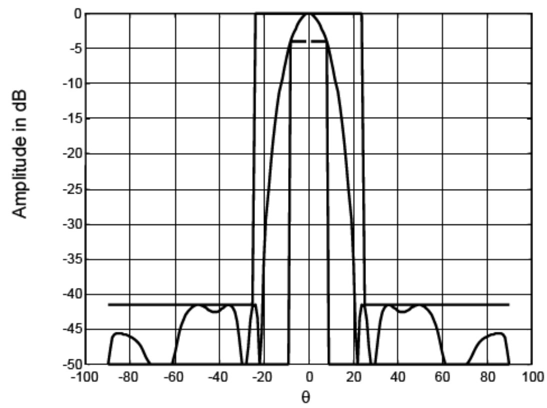


Fig. 10. Diagram of a 10-elements symmetrical array: UD = –4 dB, SLL = – 41.5 dB

We note in this figure that the radiation diagram is contained within the limits imposed by the mask.

In addition, we studied another ANN model by changing the inputs parameters and by keeping the amplitude law as an output.

The inputs parameters are as follows: G_{min}, G_{max} and UD. The database contains a whole of data (input/output) obtained by simulation from the genetic algorithm [7, 17] with a condition as the side lobes must be lower than –20 dB and the inter-elements distance equalizes 0.5 λ.

The number of training set is equal to 75, and the input parameters' variation range is as follows: $12° \le G_{min} \le 20°$; $40° \le G_{max} \le 50°$, -5 dB $\le$ UD ≤ -4 dB.

After several tests, we chose a back-propagation network with the following topology:

3 input neuron corresponding respectively to G_{min}, G_{max} and UD,

12 neurons in the hidden layer,

5 neurons in the output layer representing the amplitude law of the first half of the array.

Fig. 11 shows the radiation diagram generated by the following test vector: $G_{min} = 20°$, $G_{max} = 52°$, UD = –3.5 dB, the number of testing set is equal to 42.

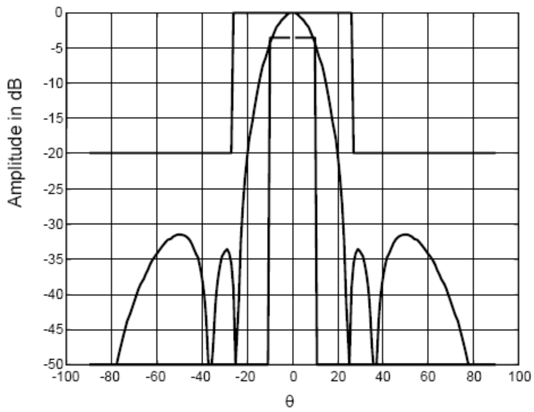


Fig. 11. Diagram of a 10-elements symmetrical array: UD = –3.5 dB, SLL = – 20 dB

We note that the network could recognize all the test examples and that the ANN model has a significant capacity of extrapolation since the results remain valid beyond the domain of the input parameters' variation range. Indeed, the approximation remains acceptable in the [– 5.2 dB, – 3.5 dB] interval for the undulation domain, the minimal beamwidth [12°, 22°] and the maximum beamwidth [38°, 52°] of the main lobe.

5. Synthesis by Feed and Space Distribution Laws

The various characteristics of a periodic array, linear or plane are closely dependent. The feed law determines directivity, the gain and the side-lobes level. In order to introduce more flexibility between these characteristics, the concept of array was gradually generalized. A generalization of the array concept can be described by the aperiodic array.

The problem of synthesis can be generalized here while acting simultaneously on the three array parameters, namely the amplitude, the phase and the space distribution of the sources.

Let us consider a $2N$ elements symmetrical linear array. The synthesis consists in the search of three vectors : the amplitude law $\mathbf{A}=[a_1, a_2, .., a_N]$, the phase law $\boldsymbol{\psi}=[\psi_1, \psi_2, ..., \psi_N]$ and space distribution law $\mathbf{X}=[\Delta X_1, \Delta X_2, ..., \Delta X_N]$, which allows the best approach to the desired diagram Fd.

In our application, the desired diagram is specified from a mask, the database contains a whole of data (input/output) obtained by simulation with the genetic algorithm. After several tests, a RBF network with the following topology (Fig. 12) was retained: The symmetrical antenna array is composed of 8 elements. The number of training set is equal to 45, and the parameters' variation ranges are: – 27 dB ≤ SLL ≤ – 12 dB, – 2.7 dB ≤ UD ≤ – 2 dB, $20° \le \theta_0 \le 23°$ with $\Delta\theta = 6°$.

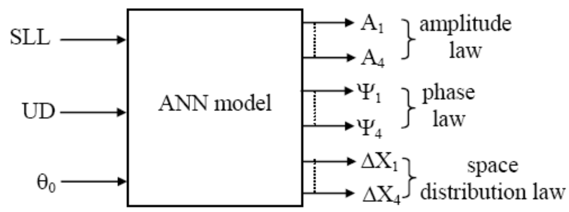


Fig. 12. Representation of synthesis model by the neural networks, 3 inputs and 12 outputs.

Fig. 13 represents the result of synthesis of an 8 elements symmetrical array for the input test data: SLL = – 26.4 dB, UD = – 2.2 dB, $\theta_0 = 22°$, the number of testing set is equal to 30 and the recognition rate is close to 90%.

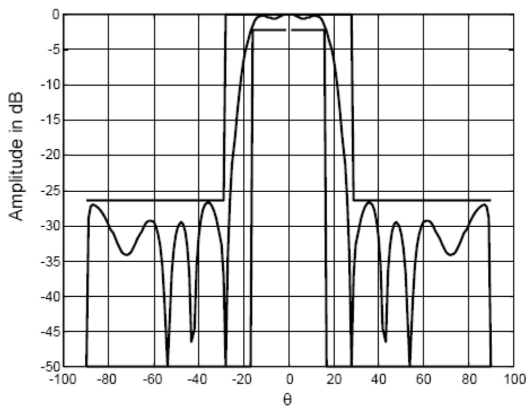


Fig. 13. Diagram of an 8-elements symmetrical array: UD = – 2.2 dB, SLL = – 26.4 dB

5.1 Comparative Study

Fig. 14 represents the synthesized diagram obtained by the ANN and the GA for an 8-elements symmetrical array, and with the mask's parameters: SLL = – 23.5 dB, UD = – 2.5 dB, $\theta_0 = 20°$, $\Delta\theta = 6°$. We note that the two solutions remain comparable with respect to the mask. However ANN is able to generate very fast the results of synthesis comparing to GA which needs much more CPU time and memory.

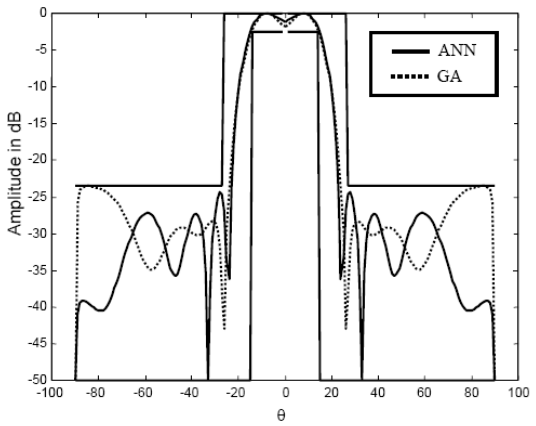


Fig. 14. Diagram of an 8-elements symmetrical array: UD = – 2.5 dB, SLL = – 23.5 dB

6. Conclusion

In this paper, we studied the possibilities of modeling and optimization of the synthesis problem for the printed antenna arrays with the neuronal approach.

Our study was developed in order to solve several problems of printed antenna array synthesis by acting on amplitude and/or phase of feed and/or spatial position, while being based on inputs/outputs samples.

The results obtained are satisfactory and show the interest of the application of the neural networks in the printed antenna array synthesis domain. This interest ensues from their possibilities of approximation, learning, modeling and optimizing the nonlinear models. Indeed, the nonlinear nature of neural networks and their flexibility to produce each characteristic in input and in output, allowed us to clearly show the electromagnetic radiation behavior of the antenna array so modeled. The comparative studies of the results of antenna array synthesis obtained by the neural networks and those obtained by the genetic algorithm enabled us to valid the principles and the synthesis which we developed.

However, the artificial neural networks present the disadvantage that there is not a general rule to define the neural network architecture. In spite of this disadvantage and once the learning process is ended, the ANN allows to provide very fast, a very precise results of printed antenna array synthesis. The precision of the developed model depends on the number of examples contained in the training database. The neural network can of course be built with an experimental data.

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