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Pattern Synthesis for Linear Phase Arrays using Artificial Neural Network

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Abstract

This paper focuses on the antenna synthesis of uniformly spaced linear phase array using artificial neural network (ANN), and describes the basics of artificial neural network. Chebyshev method is used to compare with this approach. Although, Chebyshev method is able to generate perfectly leveled side lobes, ANN does not have the phenomena of up-swing in edges amplitude of the excitation and grating lobes does not appear in ANN when the distances between elements are increased.

The basic rule is to alter the weights (current distributions of elements) such that the error between the output values and the target values (desired values) is minimized.

In this paper, single layer feed forward neural network with supervised learning is used. An adaptive linear element algorithm (ADALINE) is used for training artificial neural network.

الخلاصـــــــة

هذا البحث يركز على توليف الهوائي لمصفوفة الهوائيات الخطية ذات المسافات المتساوية باستخدام الشبكات العصبية الصناعية، وأيضا تم في هذا البحث وصف أساسيات الشبكات العصبية الصناعية.استخدمت طريقة جبي شيف للمقارنة مع هذه الطريقة.على الرغم من أن طريقة جبي شيف تستطيع أن تحصل على أي مستوى من مستويات الفصوص الجانبية، إلا أن الشبكات العصبية الصناعية لا تملك ظاهرة التأرجح لقيم التيارات عند نهايتي المصفوفة وكذلك لا تظهر الفصوص الحاجزة عند زيادة المسافة بين العناصر.

القاعدة الأساسية هي تغير في الأوزان (توزيعات التيارات للعناصر) بحيث الفرق بين القيم الخارجة والقيم الهدف (القيم المرغوب بها) اقل ما يمكن.

في هذا البحث تم استخدام الشبكات العصبية الصناعية ذات تغذية باتجاه أمامي وتحتوي على طبقة واحدة مع تعليم مراقب، وكذلك استخدمت خوارزمية التكيفية الخطية لتدريب الشبكات العصبية الصناعية.

1. Introduction

The analysis problem is one of determining the radiation pattern and impedance of a given antenna structure. Antenna design is the determination of the hardware characteristics (length, angles, etc.) for a specific antenna to produce a desired pattern and/or impedance. Antenna synthesis is similar to antenna design and, in fact, the terms are frequently used interchangeably. However, antenna synthesis, in its broadest sense, is one of first specifying the desired radiation pattern and then using a systematic method or combination of methods to arrive at an antenna configuration which produces a pattern that acceptably approximates the desired pattern, as well as satisfying other system constraints. Hence, antenna synthesis, in general, does not depend on an apriority selection of antenna type [1,2].

Unfortunately, there is no single synthesis method that yields the "optimum" antenna for the given system specifications [1]. We will pose the antenna synthesis problem as one of determining the excitation of a given antenna type that lead to a radiation pattern which suitably approximates a desired pattern. The desired pattern can vary widely depending on the application [1,2].

Over the last several decades, there has been significant attention paid to the area of array pattern synthesis. A classic paper by Dolph [3] showed how to obtain the weights for an uniform linear array (ULA) to achieve a Chebyshev pattern, which is optimal in the sense that it yields a minimum uniform side lobe level for a given main lobe width [3]. Taylor modified the ideal pattern by making only the first side lobes approximately equal and by making the far outside lobes decay as sin(x)/x [4]. Other pattern synthesis approaches for ULA's have been presented in literature [5].

In the medium of the last decade, antenna synthesis was started depends on Intelligent systems such that genetic algorithms and neural network. Reference [6] used genetic algorithm for side lobe reduction in the array pattern synthesis. Other pattern synthesis approaches using genetic algorithm have been presented in literature [7]. In other hand artificial neural network (ANN) have been applied in pattern recognition systems, and have been exploited for input-output mapping, for system identification, for adaptive prediction, etc… [8]. By concentrating on neural modeling of antennas and microwaves structures, ANN have been applied to the calculation of resonant frequencies of microstrip antennas, to the computation of complex resonant frequencies of microstrip resonators, to the modeling of microwave circuit, to reverse modeling of microwaves devices, to the calculation the effective dielectric constants of microstrip lines, etc. Moreover, neural network have been applied to the optimization of microwave structures antennas [8].

2. Artificial Neural Network (ANN)

An artificial neural network (ANN) is an electronic system of a hardware or software nature, which is built in accordance with human brain. Therefore, an ANN consists of many simple non-linear functional blocks of a few types, which are called neurons. Neurons are organized into layers, which are mutually connected by highly parallel synaptic weights. The

ANN exhibits a learning ability: synaptic weights can be strengthened or weakened during the learning process, and by that way, information can be stored in the neural network [8].

In this implementation, there are neuron-like processing elements that interact using weighted connection. The output of each neuron element is determined by the input they received. The input to the neural network is a set of values X, the output is given by the set Y and the set of weighted connections between the inputs and the outputs is given by W, in supervised learning, T is the set of target values which defines the desired values for the network. The basic rule is to alter the weights (current distribution for elements) such that the error between the output values and the target values (desired values) is minimized [9].

In this paper, single layer feed forward neural network with supervised learning is used. There are many supervised learning algorithms for single layer feed-forward neural network. These include the least mean square (LMS), the adaptive linear element (ADALINE), the delta rule and the Windrow-Hoff algorithms. These learning algorithms all share the same rule and are slight variations of each other. These algorithms can be applied to any single layer feed-forward NN using a differentiable activation function [9]. In this paper, the adaptive linear element algorithms one of commonly used learning algorithms, is implemented.

3. The Problem Formulation

The problem of array pattern synthesis can be stated as follows: Given the number of array elements and the equal distance between elements, we want to find a set of weights (current distribution for elements) such that the output pattern ($F_{out}(\theta)$) as the same as the desired pattern $F_{des}(\theta)$. The array pattern is given by [1,2]:

$$\mathbf{AF}(\theta) = \sum_{n=0}^{N-1} \mathbf{w}_n \mathbf{e}^{jn\psi} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \mathbf{(1)}$$

where:

AF: is array factor.

$\psi = \beta d \cos\theta$

$\beta = 2\pi/\lambda$ = wave number.

λ: is the wavelength.

d: is the distance between elements.

w_n: are weights of ANN (represented current distribution).

The pattern synthesis with this algorithm can be modeled as shown in **Fig.(1)**. The inputs to the model are the signals of unit amplitude. The signal from each array element is weighted and then summed to give the array output, which is compared with desired array response over an angular range. The reference (desired) pattern $F_{des}(\theta)$, as shown in **Fig.(2)** in which all the responses in side lobe regions are zero. The weights are updated through an iteration procedure, which leads to a satisfactory array pattern. The error between the array outputs and the desired pattern are used to update the weights to obtain the next optimal weight vector.

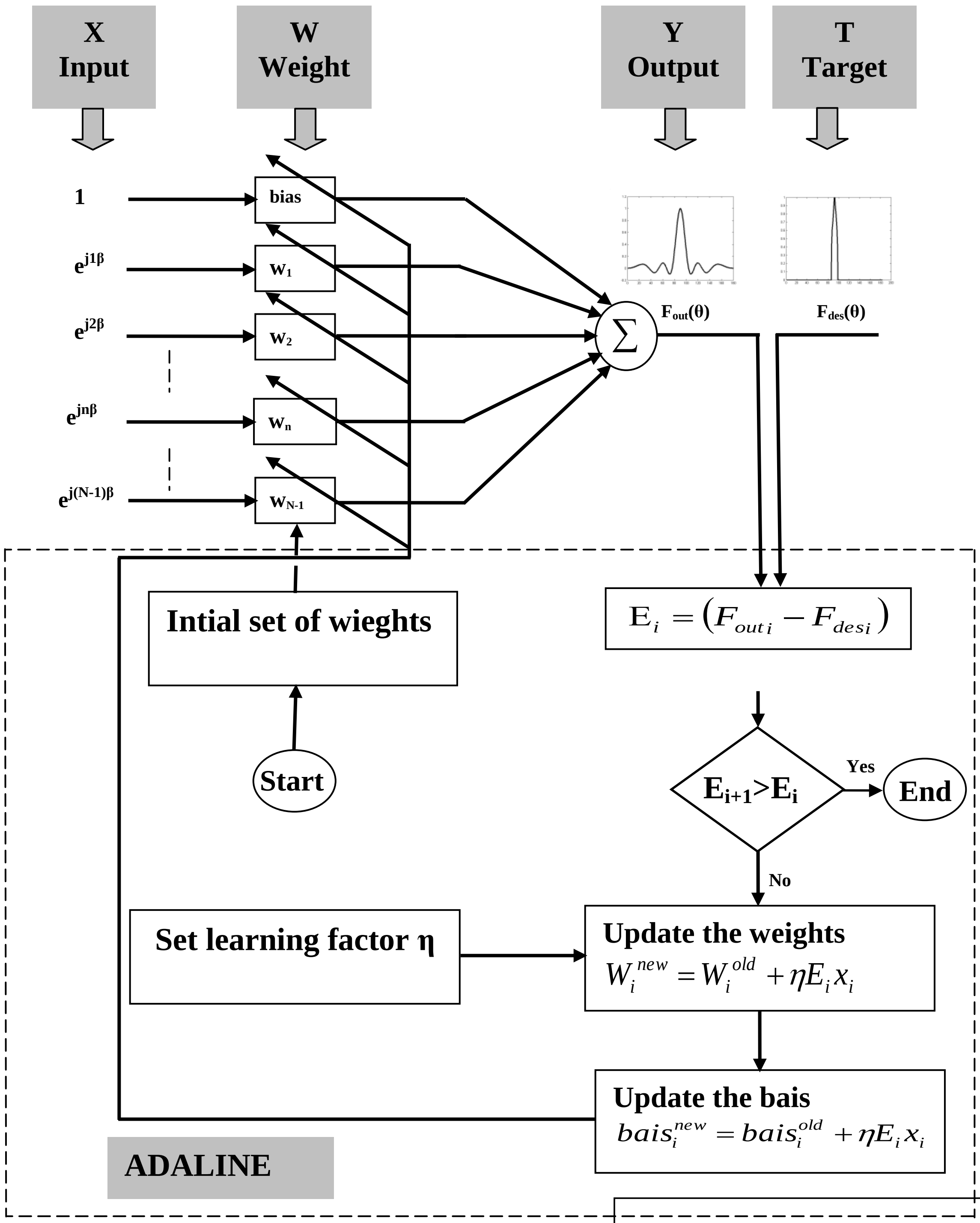

Figure (1) Flowchart of ANN model for pattern synthesis of linear array

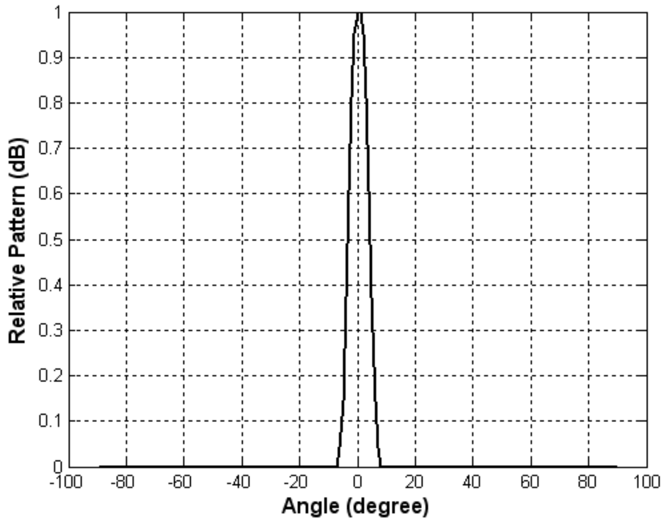

Figure (2) Ideal pattern (reference pattern) with side lobes regions are zero

4. Adaptive Linear Element Algorithm (ADALINE)

In general, an ADALINE can be trained using the delta rule, also known as the least mean square (LMS) or Windrow-Hoff rule. This rule can be used for single layer nets with several output units; an ADALINE is a special case in which there is only one output unit. During training, the activation of the unit is its net input, i.e. the activation function is the identity function. The learning rule minimizes the mean squared error between the output function and the target value. This allows the net to continue learning on all training patterns, even after the correct output value is generated for some patterns [10].

The learning procedure introduced by Windrow-Hoff is a form of supervised learning that can be applied to any single layer feed forward ANN. For given input training pattern elements x_i ($x_i \subseteq X$) and the output elements y_i ($y_i \subseteq Y$), the learning rule for the weights, w_i ($w_i \subseteq W$) is given by iterative formula [8].

$$\mathbf{W_i^{new} = W_i^{old} + \eta\left(F_{des} - F_{out}\right)x_i} \quad \text{.. (2)}$$

where:

η: is a learning coefficient which is problem dependent.

F_{des}: is the desired or target value, and

F_{out}: is the actual value (output pattern) computed by the neuron for input training pattern x_i.

The weights are adjusted to reduce the total error E_{tot} over all output units [8].

$$E_{tot} = \sum_{i=1}^{N} E \quad \text{.. (3)}$$

where:

E_{tot}: is the total error.

The error for a single pattern is given by the sum of squared errors.

$$E_{tot} = \sum_{i=1}^{N} \left(F_{des} - F_{out} \right)^2 \quad \text{.......................................} \quad (4)$$

The error can be reduced by adjusting the weights in proportion to the negative gradient, the direction of the most rapid decrease in the error function, E_{tot} with respect to each weight change. Thus, we obtain an expression for the weight change Δw_i proportional to the negative gradient of the error that is given by:

$$\Delta\omega_i = -\eta \frac{\partial E_{tot}}{\partial \omega_i} \quad \text{.......................................} \quad (5)$$

where:

η: is a positive constant related to the learning coefficient, and

i: is the indicate of inputs.

Taking partial derivatives of each term in the sum gives the following [8]:

$$\Delta\omega_i = \eta\left(F_{des} - F_{out} \right) x_i = \eta E x_i \quad \text{.......................................} \quad (6)$$

The learning rule for bias is given by:

$$bias_i^{new} = bias_i^{old} + \eta E x_i \quad \text{.......................................} \quad (7)$$

5. Results and Discussion

When starting the algorithm shown in **Fig.(1)** with reference pattern (ideal pattern) shown in **Fig.(2)** and initial pattern with side lobe level (SLL) is -20dB shown in **Fig.(3)**. The learning rate (η) takes values ($0.1 <= N\eta <= 1$), where N is the number of elements). To illustrate the effectiveness of the proposed approach, it is compared with Chebyshev method, three cases are discussed.

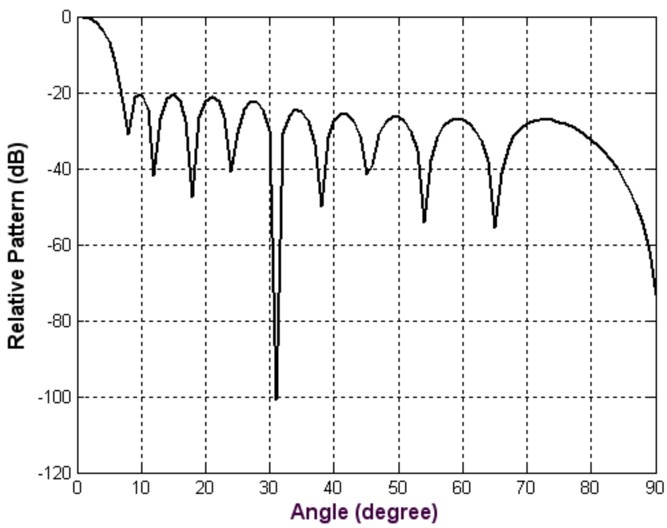

Figure (3) Initial pattern with side lobes levels (SLL= -20dB)

Case One:

In this case the numbers of elements are 20 elements and the distance between elements is equal to 0.5λ. **Figure (4)** shows the relative pattern using ANN with side lobe level -38dB is obtained, half power beam width is 9^{o} and the directivity is 11.8945dB compared with Chebyshev pattern with the same side lobe level. It is noticed that the results are approximately equal between the two methods. **Figure (5)** shows the current distribution between the two methods. It is noticed that the two curves of current distribution are closed to both. **Table (1)** shows comparison between the two methods with respect to side lobe level, half power beam width, and the directivity.

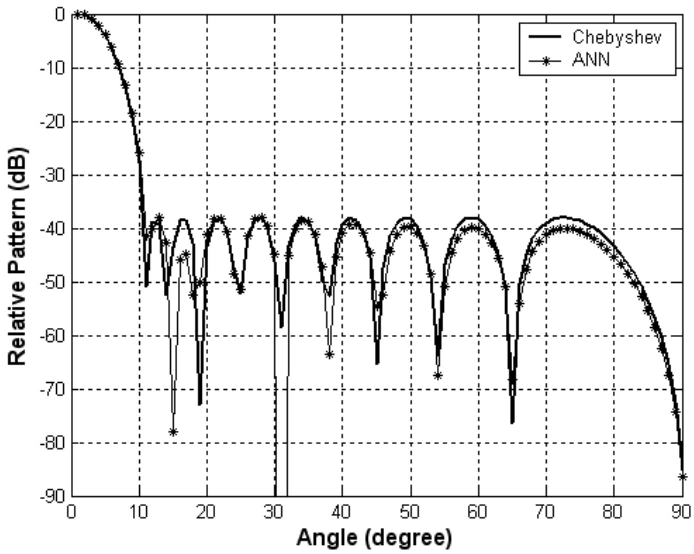

Figure (4) Comparison of the relative pattern of linear array by ANN and Chebyshev method at SLL= -38dB with 20 elements, and d=0.5λ

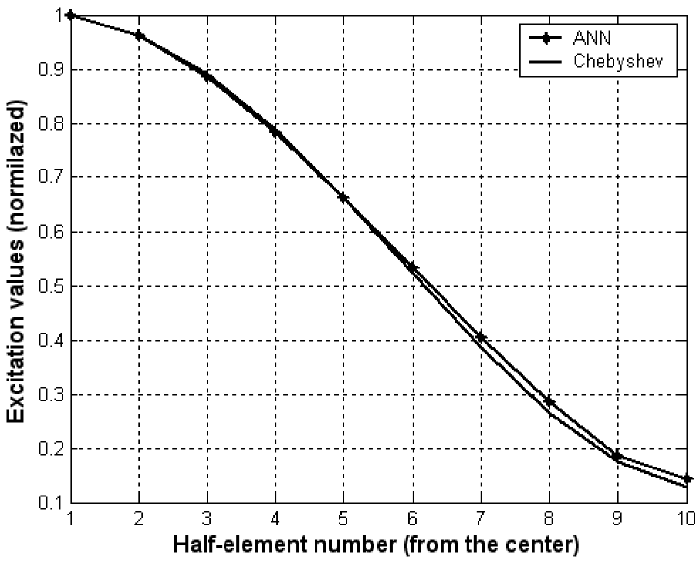

Figure (5) Excitation values for half number elements of linear array using ANN and Chebyshev methods with 20 elements, and d=0.5λ

Table(1) Comparison between ANN and Chebyshev methods with respect to side lobe level, half power beam width and the directivity for N=20, and d=0.5λ

Type method	Side lobe level (dB)	Half power beam width (HPBW)	Directivity (dB)
Chebyshev	-38	8.9^o	11.9641
ANN	-38	9^o	11.8945

Case Two:

In this case the numbers of elements are 40 elements and the distance between elements is equal to 0.5λ. **Figure (6)** shows the relative pattern using ANN with side lobe level -32.4dB is obtained, half power beam width is 5^o and the directivity is 14.9038dB compared with Chebyshev pattern with the same side lobe level. **Figure (7)** shows the current distribution for half number of an array between the two methods. It is noticed that the Chebyshev has an undesirable up-swing in the amplitude of the excitation near the array edges. This phenomenon does not appear in ANN. **Table (2)** shows comparison between the two methods with respect to side lobe level, half power beam width, and the directivity.

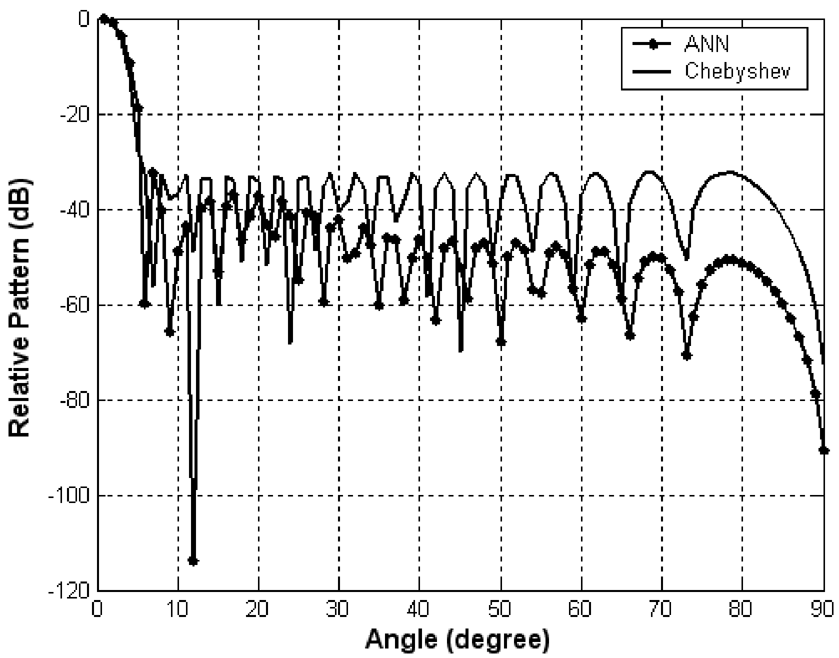

Figure (6) Comparison of the relative pattern of linear array by ANN and Chebyshev method at SLL= -32.4dB with 40 elements, and d=0.5λ

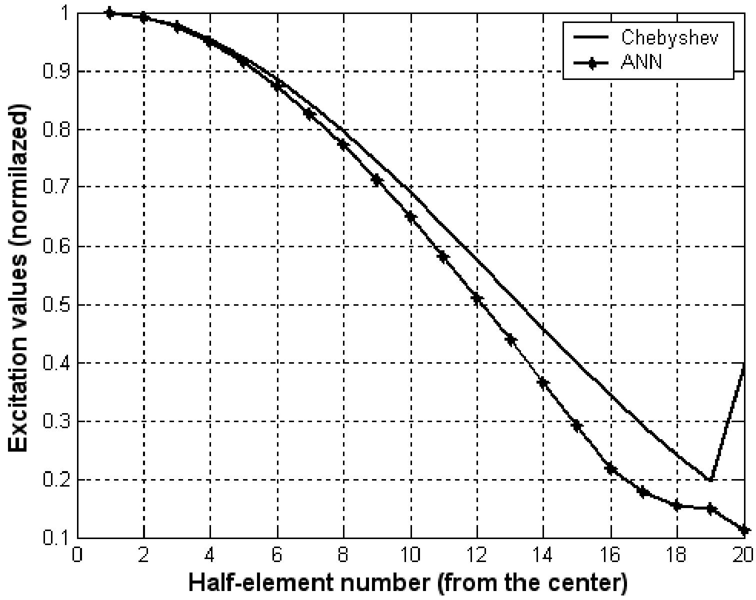

Figure (7) Excitation values for half number elements of linear array using ANN and Chebyshev methods with 40 elements, and d=0.5λ

Table (2) Comparison between ANN and Chebyshev methods with respect to side lobe level, half power beam width and the directivity for N=40, and d=0.5λ

Type method	Side lobe level (dB)	Half power beam width (HPBW)	Directivity (dB)
Chebyshev	-32.4	5^{o}	15.331
ANN	-32.4	5.2^{o}	14.9038

Case Three:

In this case the numbers of elements are 20 elements and the distance between elements is equal to 0.8λ. **Figure (8)** shows the relative pattern using ANN with side lobe level -31dB is obtained, half power beam width is 6^{o} and the directivity is 11.812dB compared with Chebyshev pattern with the same side lobe level. It is noticed that the grating lobe appears at Chebyshev pattern at this distance while grating lobe does not appear in the ANN pattern at this distance. **Figure (9)** shows the current distribution for half number of an array between the two methods. It is noticed that the Chebyshev has an undesirable up-swing in the amplitude of the excitation near the array edges. This phenomenon does not appear in ANN as in the case two. **Table (3)** shows comparison between the two methods with respect to side lobe level, half power beam width, and the directivity.

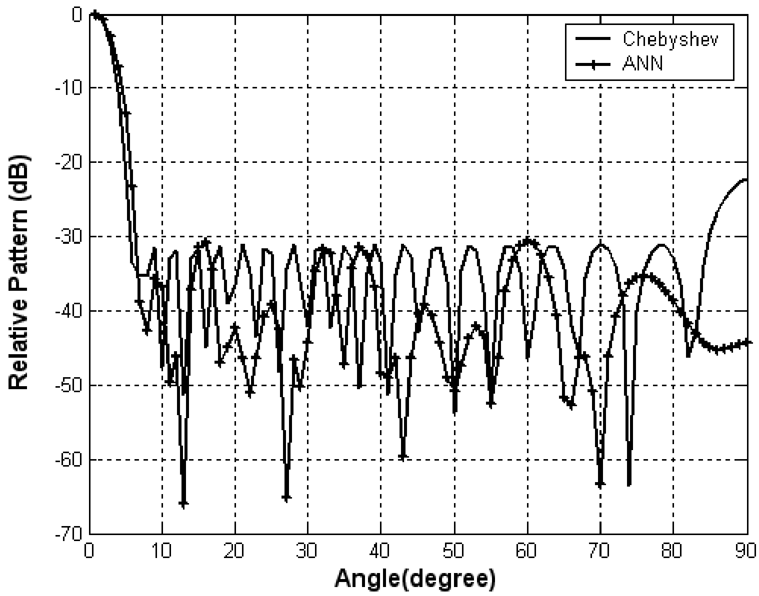

Figure (8) Comparison of the relative pattern of linear array by ANN and Chebyshev method at SLL= -31dB with 20 elements, and d=0.8λ

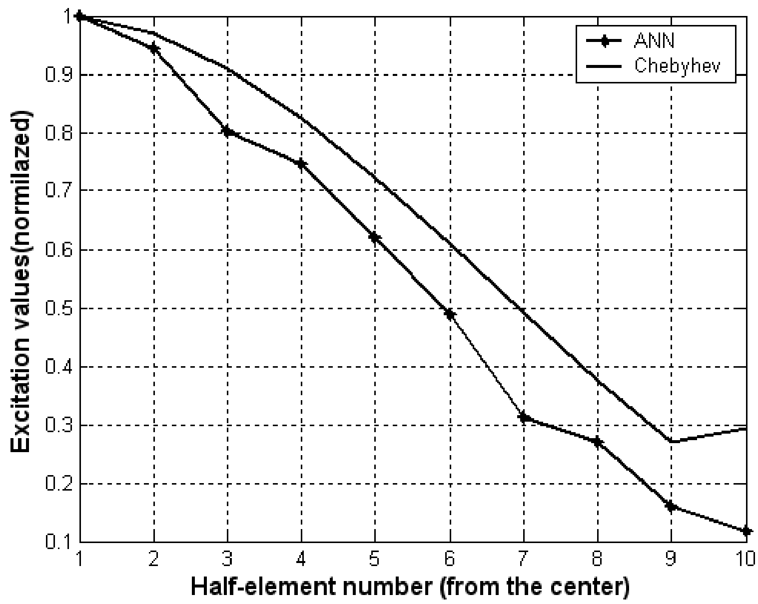

Figure (9) Excitation values for half number elements of linear array using ANN and Chebyshev methods with 20 elements, and d=0.8λ

Table (3) Comparison between ANN and Chebyshev with respect to side lobe level, half power beam width and the directivity for N=20 and d=0.5λ

Type method	Side lobe level (dB)	Half power beam width (HPBW)	Directivity (dB)
Chebyshev	-31	5.6^{o}	12.337
ANN	-31	6^{o}	11.812

6. Conclusion

A simple and flexible artificial neural network is proposed as a general tool for array pattern synthesis of uniformly spaced linear phase array antenna. The performance of proposed artificial neural network is compared with Chebyshev method. Although, Chebyshev method is able to generate perfectly leveled side lobes, artificial neural networks does not have the phenomena of up-swing in amplitude of the excitation in the edges as increasing the number of elements. It is seen that when increasing the distance between elements, grating lobes do not appear in an artificial neural networks pattern while appear in Chebyshev pattern at that distance. The simplicity of this method will allow arrays to be synthesized quickly.

7. References

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