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PATTERN SYNTHEISS OF LINEAR PHASE ARRAY USING ARTIFICIAL NEAURAL NETWORK BASED ON PARTICLE SWARM OPTIMIZATION

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Abstract

This paper focuses on the antenna synthesis of uniformly spaced linear phase array using artificial neural network (ANN) based on Particle Swarm Optimization (PSO). The weights of the Artificial Neural Networks (ANN) are trained by Particle Swarm Optimization (PSO). Subsequently the Particle Swarm Optimization (PSO) algorithm is applied in order to select the "global best" ANNs for the future investment decisions and to adapt the weights of other networks towards the weights of the best network. Chebyshev method is used to compare with this approach. Although, Chebyshev method is able to generate perfectly leveled side lobes, PSONN does not have the phenomena of up-swing in edges amplitude of the excitation and grating lobes does not appear in PSONN 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 PSO training is used.

Keywords: Antenna ,Synthesis, Optimization, Swarm, Chebyshev.

توليف الهوائي لمصفوفة الهوائيات الخطية ذات المسافات المتساوية باستخدام الشبكات العصبية الصناعية باستخدام افضلية الحشد الجزيئي

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الخلاصة

هذا البحث يركز على توليف الهوائي لمصفوفة الهوائيات الخطية ذات المسافات المتساوية باستخدام الشبكات العصبية الصناعية باستخدام افضلية الحشد الجزيئي (PSO)، وأيضا تم في هذا البحث وصف بناء اوزان الشبكات العصبية الصناعية باستخدام افضلية الحشد الجزيئي. 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 باستخدام افضلية الحشد الجزيئي 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 باستخدام افضلية الحشد الجزيئي.

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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 a priori selection of antenna type .

The antenna pattern synthesis is an important issue in the design, whether it is traditional antenna, or a new generation of mobile communications in the smart antenna pattern synthesis play an important role. Pattern synthesis is the basis of the space radiation pattern needed to select a group of the appropriate array element value or the right incentives optimize the form of the spatial distribution of the antenna. To change the array antenna radiation pattern methods are three kinds: Adjusting the size of array element incentives, adjust the incentive phase of array elements, adjust the spatial distribution of array elements [1,2,3].

Unfortunately, there is no single synthesis method that yields the "optimum" antenna for the given system specifications .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. In most applications, it is desirable to have both a narrow main beam as well as low side lobes. It would be therefore, useful to have a pattern as optimum compromise between beam width and side lobe level. In other words, for a specified beam width the side lobe level would be as low as possible; or vice versa, for specified side lobe level the beam width would be as narrow as possible [4,5]. As might be expected the optimum beam width-side lobe level performance occur when there are as many side lobes in the visible region as possible and when they have the same level. Dolph recognized that Chbyshev polynomials posse this property, The procedure commonly referred to as Dolph-Chebyshev synthesis equates the array polynomial to a Chebyshev polynomial and produces the narrowest beam width subject to a given constant side lobe level [4,5,6].

Over the last several decades, there has been significant attention paid to the area of array pattern synthesis. In the medium of the last decade, antenna synthesis was started depends on Intelligent systems such that neural network and several global optimization algorithms [1,2,3]. Duan Li et al. (2010) have presented an improved antenna pattern synthesis based on particle swarm optimal algorithm[1]. Sadiq et al. (2005) has used artificial neural networks for optimizing pattern synthesis of a linear phase array antenna [3]. Chuan et al. (2009) have used differential evolution (DE) algorithm with a new differential mutation base strategy, namely best of random, is applied to the synthesis of unequally spaced antenna arrays[7]. Khodier et al. (2009) have used (PSO) method to optimize a linear and circular pattern [8]. Boufeldja et al.

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(2010) have described a new method for the synthesis of planar antenna arrays using fuzzy genetic algorithms (FGAs) by optimizing phase excitation coefficients to best meet a desired radiation pattern [9]. Wentao et al. (2010) have produced investigations on conformal phased array pattern synthesis using a novel hybrid evolutionary algorithm using an improved both genetic algorithm (IGA) and particle swarm optimization (IPSO) [10]. Wentao et al. (2010) have produced an extended particle swarm optimization (EPSO) algorithm for designing conformal phased arrays on the basis array radiation pattern in adaptive beam forming by finding the weights of the antenna array element of traditional particle swarm optimization (PSO) and novel velocity updating mechanism[11].Jeyali et al.(2011) have produced Genetic algorithm optimization method for the synthesis of antenna ants that are optimum to provide the radiation pattern with maximum reduction in the side lobe level. This technique proved its effectiveness in improving the performance of the antenna array [12].

Wang et al. (2011) have produced chaotic particle swarm optimization (CPSO) as novel algorithm explores the global optimum with the comprehensive learning strategy for the equally spaced linear array, unequally spaced linear array and conformal array [13]. Wang et al. (2011) have produced a complex-valued genetic algorithm for synthesis of the radiation pattern of linear antenna arrays[14].

In this paper, the PSONN was introduced to synthesis of uniformly spaced linear phase array in which the weights of the Artificial Neural Networks (ANN) are trained by Particle Swarm Optimization (PSO) because PSO has a probabilistic mechanism and multi-starting points and can avoid getting into the local optimal solutions which show better performance than Chebyshev methods.

2. The Proposed Particle Swarm Optimization Feed-Forward Neural Network (PSONN)

PSO is one of the latest techniques that can be fitted into ANN. A swarm is made up of particles, where each particle has a position and a velocity. The idea of PSO in ANN is to get the best set of weight (or particle position) where several particles (problem solution) are trying to move or fly to get the best solution, which ensures a satisfactory global search and quick convergence, The particle velocity ranges could change adaptively during the optimization process.

In PSONN, the position of each particle in swarm represents a set of weights for the current epoch or iteration. The dimensionality of each particle is the number of weights associated with the network. The particle moves within the weight space attempting to minimize learning error (or Mean Squared Error- MSE or Sum of Squared Error-SSE). Changing the position means updating the weight of the network in order to reduce the error of the current epoch. In each epoch, all the particles update their position by calculating the new velocity, which they use to move to the new position.

The new position is a set of new weights used to obtain the new error. For PSO, the new weights are adapted even though no improvement is observed. This process is repeated for all the particles. The particle with the lowest error is considered as the global best particle so far.

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The training process continues until satisfactory error is achieved by the best particle or computational limits are exceeded. When the training ends, the weights are used to calculate the classification error for the training patterns. The same set of weights is used then to test the network using the test patterns [15-18].

There is no back-propagation concept in PSONN where the feed-forward NN produced the learning error (particle fitness) based on set of weight and bias (PSO positions). The pbest value (each particle's lowest learning error so far) and gbest value (lowest learning error found in entire learning process so far) are applied to the velocity update equation (4) to produce a value for position adjustment to the best solution or targeted learning error. The new sets of positions (ANN weight) are produced by adding the calculated velocity value (equation 4) to the current position value using movement equation (5). Then the new set of positions is used for producing new learning error (particle fitness) in feed-forward ANN. The PSONN learning process is summarized as follows[15,18]:

1. Initialize particle for ANN problem.
2. Calculate fitness value (feed-forwared error or MSE in ANN) for each particle.
3. If the fitness value is better than the best fitness value (pbest) in history, then set current value as the new pbest.
4. Choose the particle with best fitness value of all the particles as the gbest.
5. For each particle, calculate particle velocity.
6. Update particle position (ANN weight).
7. Repeat from 2 if condition not reached.

This process is repeated until the stop conditions are met (Minimum learning error or maximum number of iteration). Compared to BP, learning error is calculated in feed-forward ANN starting from input nodes to hidden nodes and output nodes, then ANN makes a backward pass from output nodes to hidden nodes and input nodes to produce new set of weights.

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 [2, 3, 13,14]:

$$AF(\theta)=\sum_{n=0}^{N-1} w_n e^{jn\psi} \quad \ldots\ldots\ldots\ldots\ldots\ldots eq.(1)$$

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).

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The pattern synthesis with this algorithm can be modeled as shown in Figure 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 Figure2 in which all the responses in side lobe regions are zero. The weights are updated through PSO iteration procedure, which leads to a satisfactory array pattern.

4. Training Neural Networks with PSO

The PSO algorithm is vastly different than any of the traditional methods of training. PSO does not just train one network, but rather trains a network of networks. PSO builds a set number of ANN and initializes all network weights to random values and starts training each one. On each pass through a data set, PSO compares each network's fitness. The network with the highest fitness is considered the global best. The other networks are updated based on the global best network rather than on their personal error or fitness. Each neuron contains a position and velocity. The position corresponds to the weight of a neuron. The velocity is used to update the weight. The velocity is used to control how much the position is updated. If a neuron is further away (the position is further from the global best position) then it will adjust its weight more than a neuron that is closer to the global best [13-17]. *The iterative approach of PSO can be described by the following steps:*

1. Initialize a population size, positions and velocities of agents, and the number of weights and biases.
2. The current best fitness achieved by particle *(p)* is set as *pbest*. The *pbest* with best value is set as *gbest* and this value is stored.

$$v^i(0) = v^i{}_{\min} + rand(v_{\max} - v_{\min}) \quad ,i = 1,\dots,m \quad \text{.........} eq.(2)$$

$$x^i(0) = x^i{}_{\min} + rand(x_{\max} - x_{\min}) \quad ,i = 1,\dots,m \quad \text{.........} eq.(3)$$

$$v^i(t+1) = w * v^i(t) + c_1 r_1 (P^i best - x^i(t)) + c_2 r_2 (g\ best - x^i(t)), i = 1,..,m \text{.......} eq.(4)$$

$$x^i(t+1) = x^i(t) + v^i(t+1) \quad ,i = 1,\dots,m \quad \text{.........} eq.(5)$$

3. Evaluate the desired optimization fitness function *fp* for each particle as the Mean Square Error (MSE) over a given data set

$$E_{tot} = \sum_{i=1}^{N} E \text{.........} eq.(6)$$

$$E_{tot} = \sum_{i=1}^{N} (F_{des} - F_{out})^2 \text{.........} eq.(7)$$

4. Compare the evaluated fitness value *fp* of each particle with its *pbest* value. If *fp* < *pbest* then *pbest* = *fp* and *best xp* = *xp*, *xp* is the current coordinates of particle *p*, and *best xp*

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is the coordinates corresponding to particle *p's* best fitness so far.

5. The objective function value is calculated for new positions of each particle. If a better position is achieved by an agent, *pbest* value is replaced by the current value. As in Step 1, *gbest* value is selected among *pbest* values. If the new *gbest* value is better than previous *gbest* value, the *gbest* value is replaced by the current *gbest* value and this value is stored. if $fp < gbest$ then $gbest = p$, where *gbest* is the particle having the overall best fitness over all particles in the swarm.
6. Change the velocity and location of the particle according to Equations 4 and 5, respectively.
7. Fly each particle (p) according to Equation 5.
8. This process is repeated until the stop conditions are met (Minimum learning error or maximum number of iteration), then stop; otherwise Loop to step 3 until convergence.

Where (i) is the current iteration, r_1 and r_2 are two random vectors with value from zero to one. c_1 and c_2 are positive constants,(w) is the inertia weight. (x^i)represent the position of i^{th} particle. Pbest represents the best previous position (the position that giving best fitness function) of i^{th} particle. The gbest represents the position of the best particle among all the particles in the population; and (v^i) represent the rate of the position change (velocity) for i^{th} particle, 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 . The weights are adjusted to reduce the total error E_{tot} overall output units. Figure 1 shows the PSO training strategy for feed forward neural network.

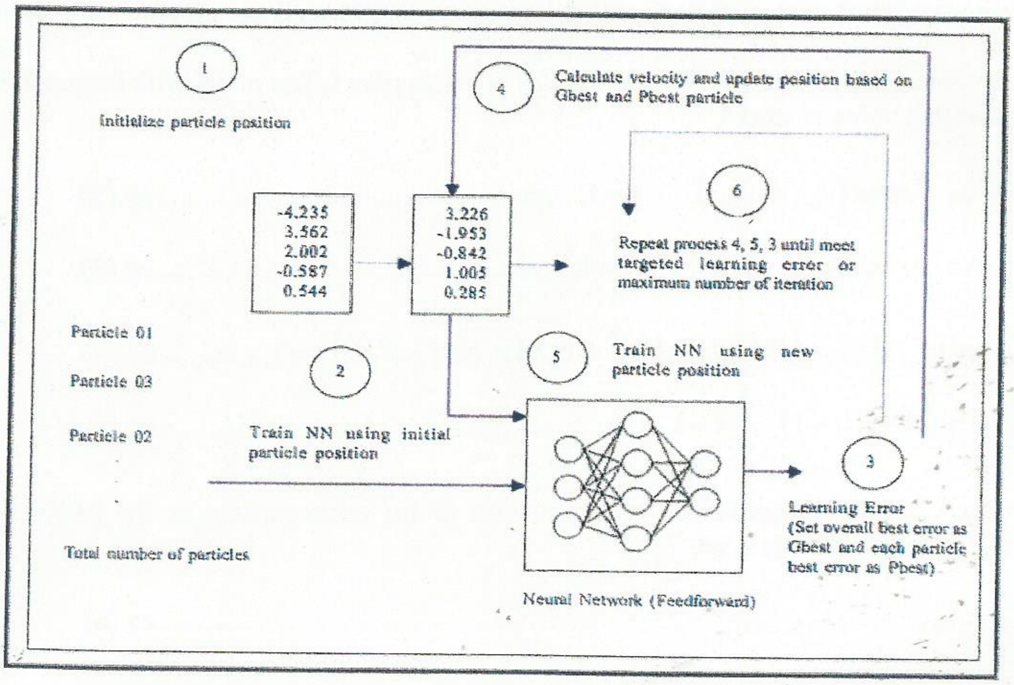

Fig.1 Particle Swarm Optimization Algorithm for Neural Network Training Steps.

5.Results and Discussion

When starting the algorithm shown in Figure 2 with reference pattern (ideal pattern) shown in Figure 3 and initial pattern with side lobe level (SLL) is -20dB shown in Figure 4;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.

Case One:-

In this case the numbers of element are 20 elements and the distance between elements is equal to 0.5λ. Figure 5 shows the relative pattern using PSONN with side lobe level -40dB is obtained, half power beam width is 6.9° compared with chebyshev pattern with the same side lobe level. It is noticed that the results are approximately equal between the two methods. Figure (6) 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.

Case Two:-

In this case the numbers of element are 40 elements and the distance between elements is equal to 0.5λ. Figure 7 shows the relative pattern using PSONN with side lobe level -33dB is obtained, half power beam width is 3° compared with chebyshev pattern with the same side lobe level. Figure 8 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 PSONN. Table 2 shows comparison between the two methods with respect to side lobe level, half power beam width.

Case Three:-

In this case the number of elements are 20 elements and the distance between elements is equal to 0.8λ. Figure 9 shows the relative pattern using PSONN with side lobe level -35dB is obtained, half power beam width is 6° 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 PSONN pattern at this distance. Figure 10 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 PSONN as in the case two. Table 3 shows comparison between the two methods with respect to side lobe level, half power beam width.

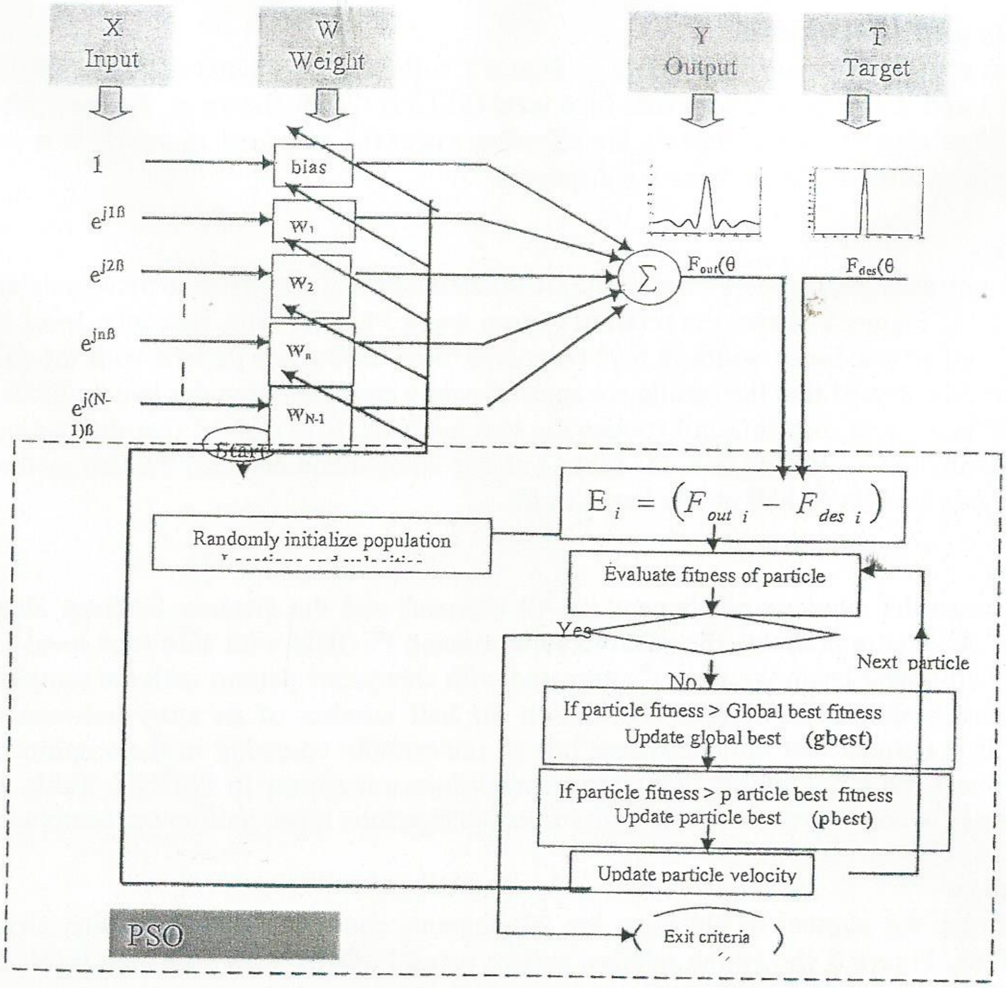

Fig.2 Flowchart of PSONN Model for Pattern Synthesis of Linear Array.

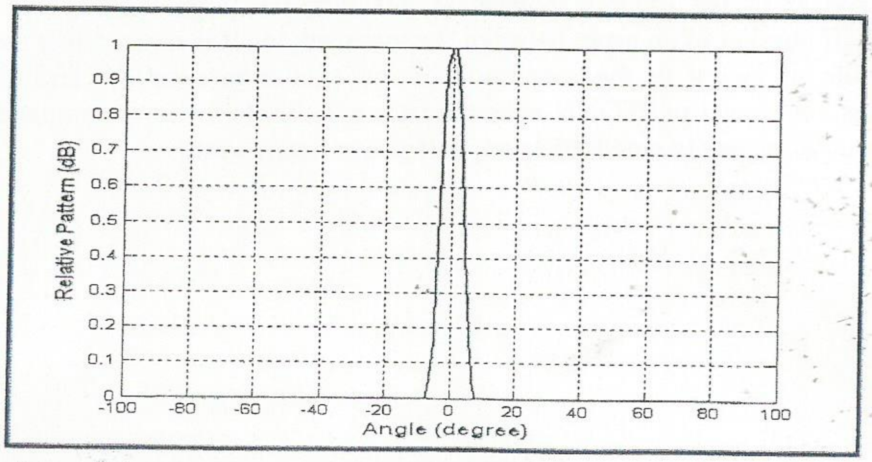

Fig. 3 Ideal Pattern (Reference Pattern) with Side Lobes Regions are Zero.

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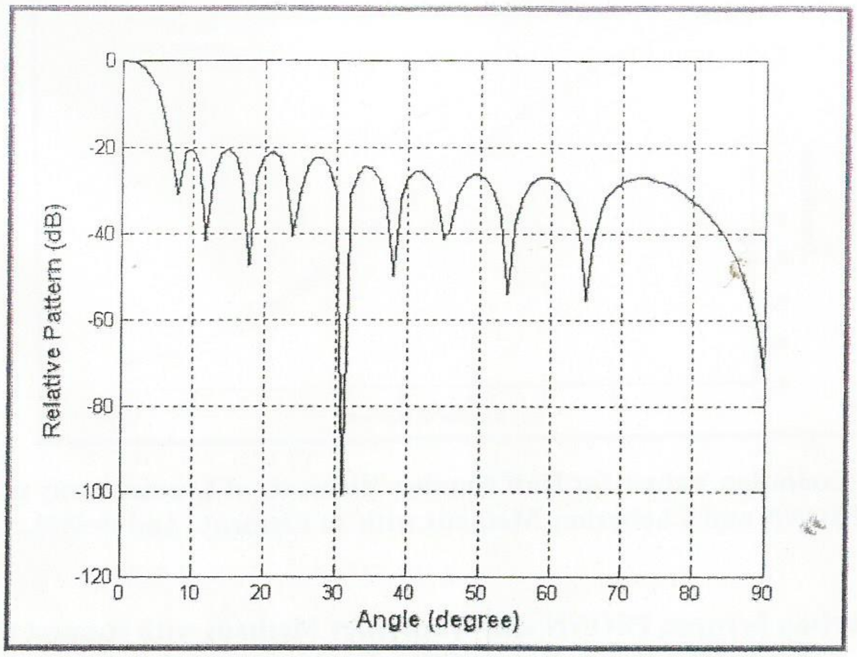

Fig. 4 Initial Pattern with Side Lobes Levels (SLL=-20dB).

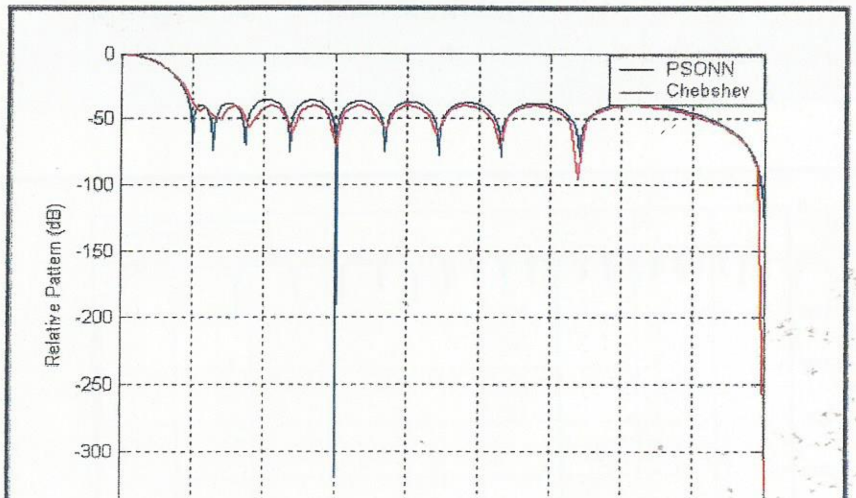

Fig.5 Comparison of the Relative Pattern of Linear Array by PSONN and Chebyshev Methods at SLL =-40dB with 20 Element , and d=0.5λ.

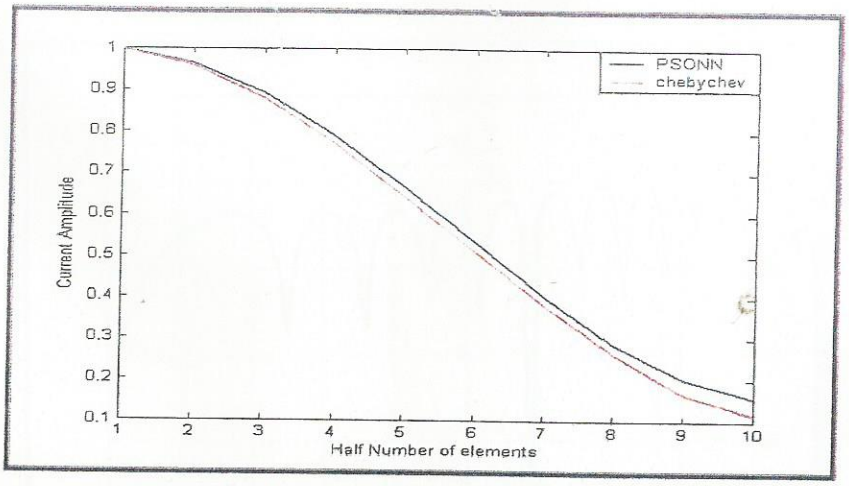

Fig.6 Excitation Values for Half Number Elements of Linear Array using PSONN and Chebyshev Methods with 20 Element , and d=0.5λ.

Table1 Comparison between PSONN and Chebyshev Methods with Respect to Side Lobe Level, Half Power Beam width . For N=40, and d=0.5λ.

Type method	Side lobe level (dB)	Half power beam width (HPBW)
Chebyshev	- 40	7.32°
PSONN	- 40	6.92°

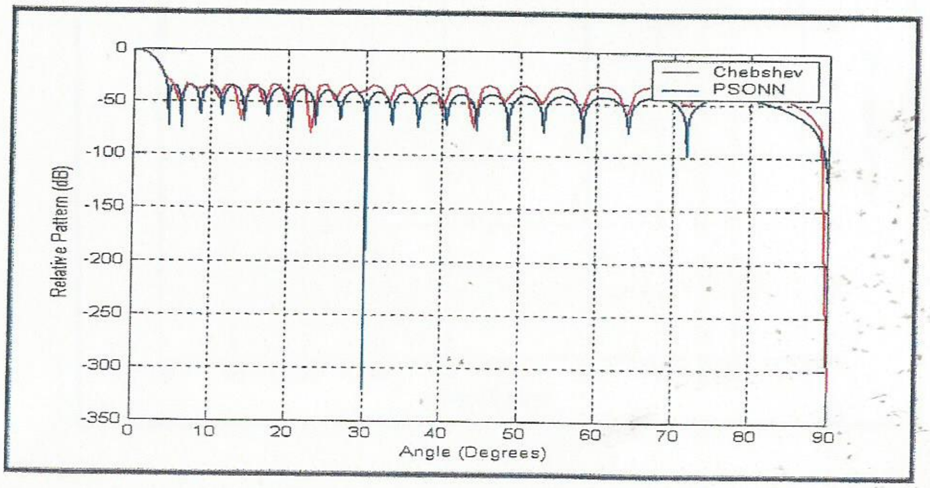

Fig.7 Comparison of the Relative Pattern of Linear Array by PSONN and chebyshev Method at SLL =-33dB with 40 Element, and d=0.5λ.

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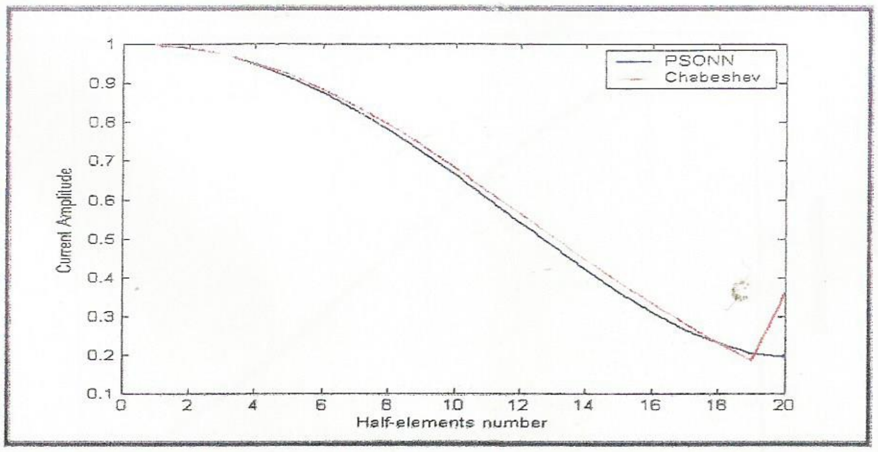

Fig.8 Excitation Values for Half Number Elements of Linear Array using PSONN and Chebyshev Methods with 40 Element , and d=0.5λ.

Table2 Comparison between PSONN and Chebyshev Methods with respect to Side Lobe Level, Half Power Beam Width. For N=40, and d=0.5λ.

Type method	Side lobe level (dB)	Half power beam width (HPBW)
Chebyshev	-33	3.668°
PSOANN	-33	3.32°

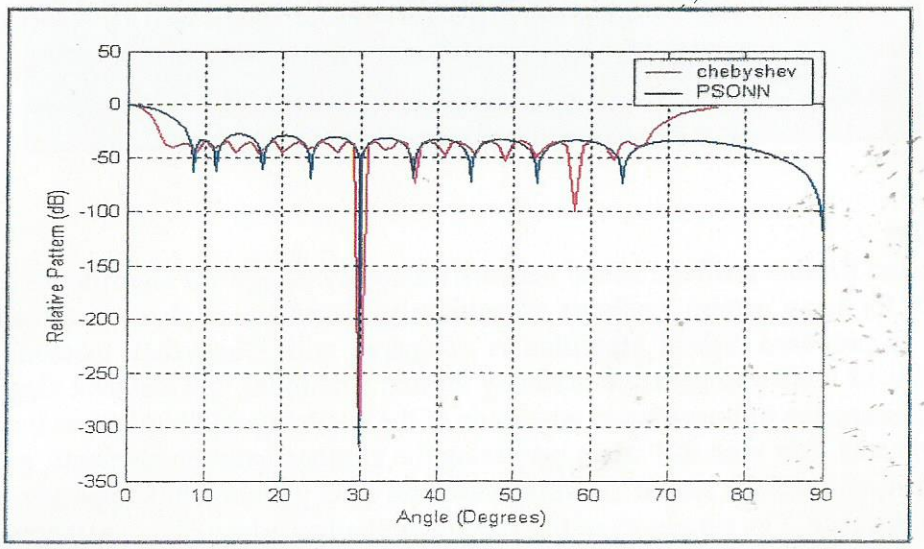

Fig.9 Comparison of the Relative Pattern of Linear Array by PSONN and Chebyshev Method at SLL =-35dB with 20 Element , and d=λ .

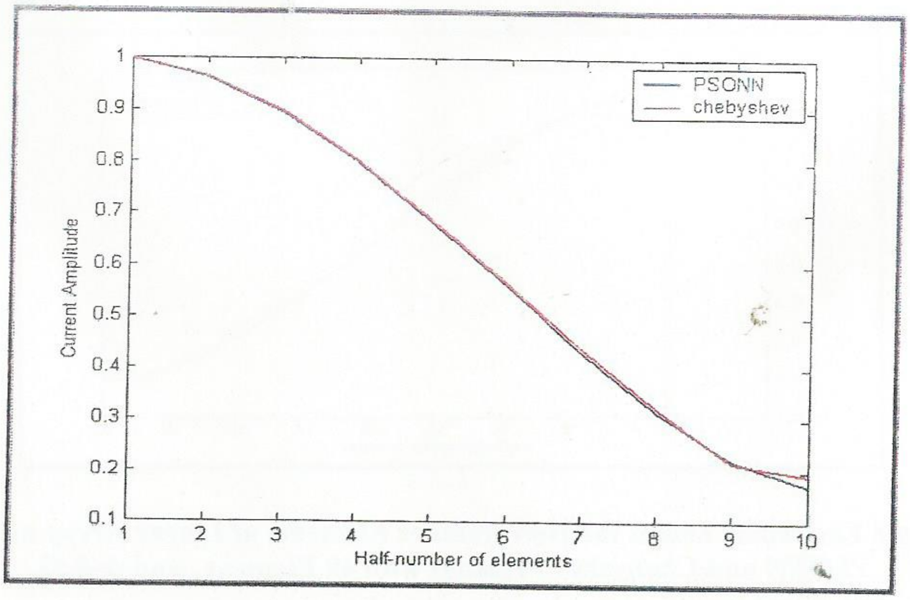

Fig.10 Excitation Values for Half Number Elements of Linear Array using PSONN and Chebyshev Methods with 20element , and d=λ.

Table 3 Comparison between ANN and Chebyshev with respect to Side Lobe Level, Half Power Beam Width for N=20 and d=λ.

Type method	Side lobe level (dB)	Half power beam width (HPBW)
Chebyshev	-35	4°
PSONN	-35	6.32°

6. Conclusion

A simple and flexible artificial neural network trained by using PSO algorithm is proposed as a general tool for array pattern synthesis of uniformly spaced linear phase array antenna. The performance of proposed hybrid algorithm is compared with Chebyshev method. Although, chebyshev method is able to generate perfectly leveled side lobes, the PSONN algorithm 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 based on PSO pattern while appear in chebyshev pattern at that distance. The simplicity of this method will allow arrays to be synthesized quickly.

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