

*Full Length Research Paper*

# Reduction of side lobe level in non-uniform circular antenna arrays using the simulated annealing algorithm

A. Zangene<sup>1\*</sup>, H. R. Dalili Oskouei<sup>2</sup> and M. Nourhoseini<sup>3</sup>

<sup>1</sup>Amirkabir University of Technology, Tehran, Iran.

<sup>2</sup>University of Aeronautical Science and Technology (Shahid Sattari), Tehran, Iran

<sup>3</sup>Amirkabir University of Technology, Tehran, Iran.

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**This paper investigates the reduction of side lobe level in antenna arrays. Reduction of side lobe level in antenna arrays has some limitations including fixed width of the beam. We have modeled the side lobe level reduction as an optimization problem using simulated annealing technique for side lobe level reduction of a specific beam width. The advantage of this method compared with other methods is that it can get out of local minimums and converge to the optimized answer. Efficiency of simulated annealing algorithm in pattern extraction of desired circular antenna, which is used frequently in modern telecommunication and radar systems, is investigated and the results are compared with that of genetic and evolutionary algorithms.**

**Key words:** Simulated annealing, antenna array, circular array, non-uniform antenna array, side lobe level.

## INTRODUCTION

Antenna arrays have various applications in wireless and mobile communication systems. In most application antenna should be designed in such a way that it can transmit produced beam in various directions and distances. To fulfill this goal, an array of antennas must be used. Higher transmission power, lower power consumption, radiating beam control, and higher efficiency can be obtained using antenna arrays. Arrays can have different forms such as linear, circular, and planar with different applications, like radar, sonar, imaging, biomedicine and mobile communications (Panduro et al., 2006; Balanis, 1997; Shihab et al., 2008 and Dessouky et al., 2006).

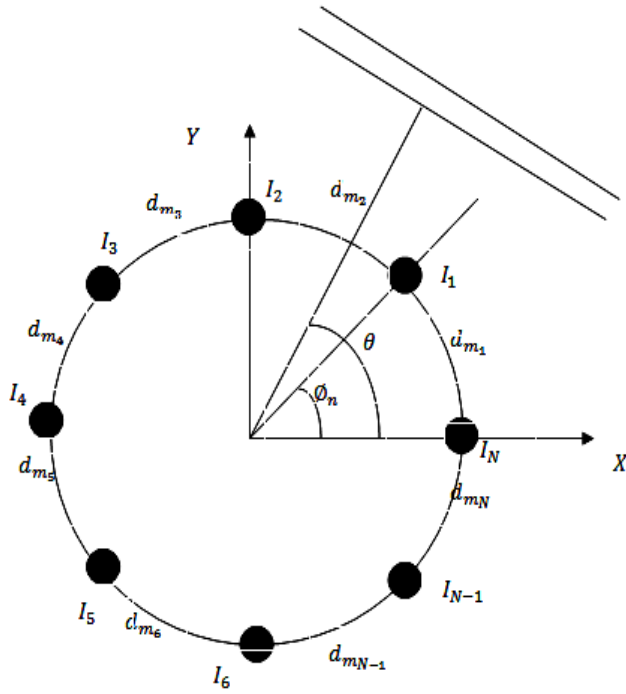
Due to the particular structure of circular antenna,

attention toward circular arrays has increased in recent studies, (Panduro et al., 2006); Shihab et al., 2008; Dessouky et al., 2006; Pathak et al., 2009). In circular antenna arrays with non-uniform distribution, elements are placed on a circular ring with non-uniform distances (Figure 1).

This group of antennas has important functionality with different applications such as radio navigation, air and space navigation, sound tracking, etc (Dessouky et al., 2006; Granville et al., 1994; Locatelli et al., 1994; Ingber, 1993; Aydin and Fogarty, 2004). Recently, antenna arrays have been suggested for wireless communications especially as intelligent antennas. In many studies (Panduro et al., 2006; Balanis, 1997; Shihab et al., 2008;

\*Corresponding author. E-mail: Amirhosein@aut.ac.ir

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**Figure 1.** Structure of an antenna array with  $n$  elements (Panduro et al., 2006).

Dessouky et al., 2006; Pathak et al., 2009) it has been tried to reduce side lobe level as much as possible in non-uniform distribution state. Reduction of side lobe level has ideal influences on telecommunication systems.

Genetic and evolutionary algorithms have been used to reduce side lobe level in paper (Panduro et al., 2006; Shihab et al., 2008). Various parameters such as beam width, and noise sensitivity, and some other factors (antenna gain, radiation pattern, antenna size) should be considered to reduce side lobe level. The objective of this problem is to find the best distances between elements and the stimulation amplitude of each element so that side lobe level is minimal.

Therefore, the problem of finding the best set of distances between elements and their stimulation amplitude can be proposed as an optimization problem. Here, we have used simulated annealing technique to specify the best distances between elements and their stimulation amplitude so that the final produced pattern will have the maximum reduction in side lobe level. Simulated annealing algorithm adds a random aspect to the descent along with the gradient which is controllable by the  $T$  (temperature) parameter. This algorithm allows both transitions to the higher energy state or to the lower energy state; therefore using this algorithm, it is possible to get out of local minimums and get to the global optimized answer. In our experiments beam width and the main beam formation angle were fixed to 50 and 0° respectively.

## PROBLEM STATEMENT

Suppose that  $n$  isotropic elements with interspaces  $d_m$  are placed on the circumference of a circular ring with radius  $a$  on  $x$ - $y$  plane (Figure 1). Assuming that elements are isotropic, it can be concluded that the propagation pattern of this array of antennas can be explained by its array factor.

Array factor for a circular array on  $x$ - $y$  plane is stated as below (2):

$$AF(\theta, I, d_m) = \sum_{n=1}^N I_n e^{jka(\cos(\theta - \theta_0) - \cos(\theta_0 - \phi_n))} \quad (1)$$

In which:

$$ka = \frac{2\pi a}{\lambda} = \sum_{i=1}^N d_{m_i} \quad (2)$$

$$\phi_n = \frac{(2\pi \sum_{i=1}^n d_{m_i})}{\sum_{i=1}^N d_{m_i}} \quad (3)$$

$\theta$  is the angle at which the main beam is generated,  $d_m$  (a  $1 \times 10$  matrix) is the distance between antenna array elements, and  $I_m$ , which is also a  $1 \times 10$  matrix, is the stimulation amplitude of each element.

In the  $d_m$  array, each component  $d_{m_i}$  is the distance of the  $i$ th element from the  $(i+1)$ th one.

$k = \frac{2\pi a}{\lambda}$  is the constant value of the phase difference

between elements,  $\theta$  is the intersection angle of the beam with  $x$ - $y$  plane,  $\lambda$  is the beam wave length, and  $\theta_0$  is the angle at which the main beam has the most propagation. As indicated before, finding the best set of places and stimulation amplitude of the elements can be proposed as an optimization problem. Therefore, to solve this problem using the simulated annealing algorithm, an objective function must be defined through which the simulated annealing algorithm can get to the optimized answer. Assuming that  $\theta_0$  is the angle at which the maximum propagation occurs and  $\theta$  varies in the range  $[-\pi, \pi]$ ,  $\theta_{msl}$  is the angle at which the first side lobe, which is the highest one, is generated,  $BWFN_{desired}$  is the width of the desired beam, which assumed to be equal to the constant value 50, and  $BWFN(I, d_m)$  is the first null beam width, the objective function is stated as follows:

$$f_1 = \frac{|AF(\theta_{ml1}, I, d_m) + AF(\theta_{ml2}, I, d_m) + AF(\theta_{ml3}, I, d_m)|}{AF(\theta_0, I, d_m)} + |BWFN_{desired} - BWFN(I, d_m)| \quad (4)$$

Based on the defined objective function, the best set of  $I$  and  $d_m$  is obtained when  $f_1$  is minimal. Reduction of all side lobes is considered at the same time using the defined objective function.

In this problem, it is also assumed that the circumference of the circle on which the elements are located is constant.

## THE PROPOSED ALGORITHM

The main objective of this work is to maximally reduce side lobes for a circular antenna array in which elements are distributed non-normally. There are some limitations to maximally reduce side lobes in a circular antenna array such as constant width of the desired beam, number of elements and the circumference.

Simulated annealing which is used in this paper is a generic probabilistic met heuristic method for obtaining optimized main point for the desired objective function in a large search space which was first presented by Kirkpatrick in 1983 (Pathak et al., 2009). This method is usually used when the search space is discrete. For some specific problems, simulated annealing technique can be more efficient than searching the whole state space. It may be possible to obtain the best answer by searching the whole space state, but it is not possible considering the time needed for the process. Furthermore, most of the time, we get the answer which is close to the best answer in a specific period of time.

The name and idea of this algorithm has been extracted from the annealing technique in metallurgy. In this process, metal is heated to the melting temperature and then is cooled gradually under control. Heating causes the atoms in the crystalline structure of the metal to leave their primary position (primary positions are considered as local minimums) and place randomly in new locations. Then, in the gradual cooling process, the states with lower energy levels with respect to the primary state of the metal have more chances of converging.

In this technique, any point in the search space is considered as a state with energy  $E$ . when the system transits from one state to another, the probability of accepting the new state is defined by  $P(E_{current}, E_{new}, T)$  which depends on the current state energy, new state energy, and the parameter  $T$ . In this algorithm, if the new state energy is lower than the current state energy, current state to new state transition is done with the probability of 1.

$$\Delta E = E_{new} - E_{current} \quad (5)$$

$$\rho(\Delta E) = \begin{cases} e^{-\frac{\Delta E}{T}} & \Delta E > 0 \\ 1 & \Delta E \leq 0 \end{cases} \quad (6)$$

And if the new state energy is equal to or higher than the current state energy, algorithm accepts this state

transition with the probability of  $e^{-\frac{\Delta E}{T}}$  which is dependent

on parameter  $T$ . At first, this probability has the maximum value and gradually after running the algorithm when  $T \rightarrow 0$ , it tends toward zero. Transition to higher energy states, provides the possibility of getting out of local minimums for the algorithm (Smith et al., 1998; Koulmas et al., 1994; Kirkpatrick et al., 1983).

It can be shown that for any finite problem, the probability that the simulated annealing algorithm will give an answer close to the total optimized answer, with the assumption of no time limitation, tends to zero (Granville et al., 1994; Locatelli, 2001).

It is also possible to use an adaptive neighborhood in this algorithm; so that the neighborhood radius will accept all the states at the beginning and continuing the algorithm it is reduced gradually until converging to the best answer in the end. Simulated annealing algorithm with adaptive neighborhood radius is applicable when the distance between the optimized answer and the current answer is shorter than the step length (Ingber, 1993). The Flow chart of our proposed algorithm for solving side lobe reduction problem is shown in Figure 2.

Based on this technique, it is possible to search the whole state space normally in the primary stages and to reduce the search space to obtain the best answer during the algorithm process. In reference (Aydin and Fogarty, 2004), a number of advantages and disadvantages of the simulated annealing technique have been proposed. This technique has been used for solving major and practical problems such as flow shop scheduling (Low, 2005; Burke et al., 2003), time tabling (Framinana and Schusterb, 2006; Cerny, 1985), travelling salesman (Lin and Kernighan, 1973; Salcedo-Sanz et al., 2004), communication systems (Paik and Soni, 2007; Locatelli, 2000), continuous optimization, and etc.

## RESULTS AND DISCUSSION

The presented algorithm in the previous part was implemented and the results were studied for the design of a circular antenna array with non-normal distribution. In the experiments, to maximally reduce side lobes, the angle with maximum propagation was assumed to be zero at  $\theta_0 = 0$ . The experiments were carried out for different number of elements 8, 10, and 12 and the resulted array factor for each one was reported.

Variation distance value and the coefficient, which was used for gradual cooling in the algorithm, was set to 0.01

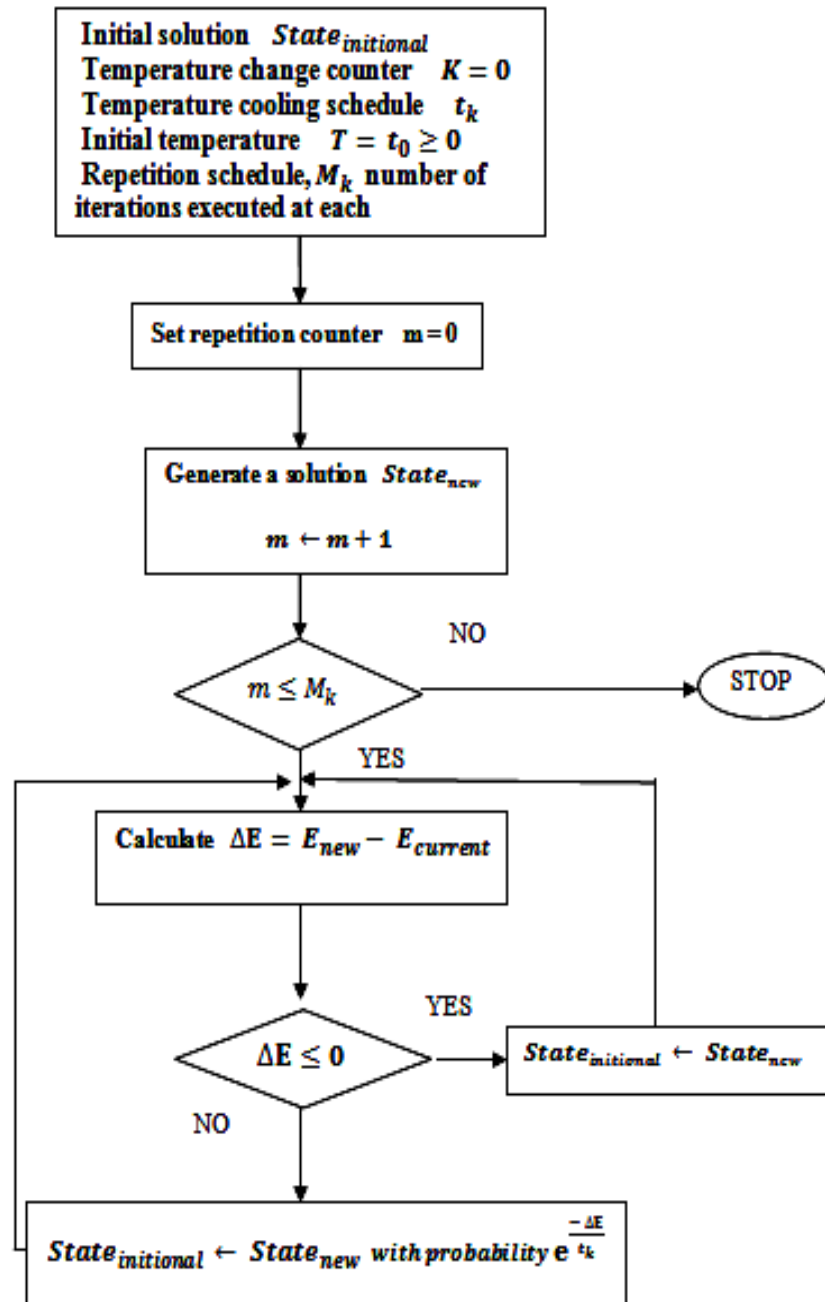


Figure 1. Flow chart for the simulated annealing algorithm.

and 0.7 respectively in the implementation of the simulated annealing algorithm. The algorithm continues until 5 successive output values converge to a unit value. Maximum number of repetitions is assumed to be 10000. As seen in the Figures 3 and 4, for 10 elements, the first side lobe level by using the normal distribution, the genetic algorithm and the proposed algorithm is -7.9, -11.1 and -11.9 dB respectively. In conclusion, by using the simulated annealing algorithm, the side lobe level with respect to the main lobe has 0.8dB reduction in

comparison to the genetic algorithm and 4.1 dB reduction in comparison to the algorithm of normal distribution of elements.

According to the results, superiority of this algorithm in comparison to the genetic algorithm can be observed, because the Genetic algorithm may fall in local minimums while the simulated annealing algorithm can converge to an optimized answer by starting from an appropriate primary point and by some repetitions. In Figures 5 and 6, propagation patterns for an antenna array with 12

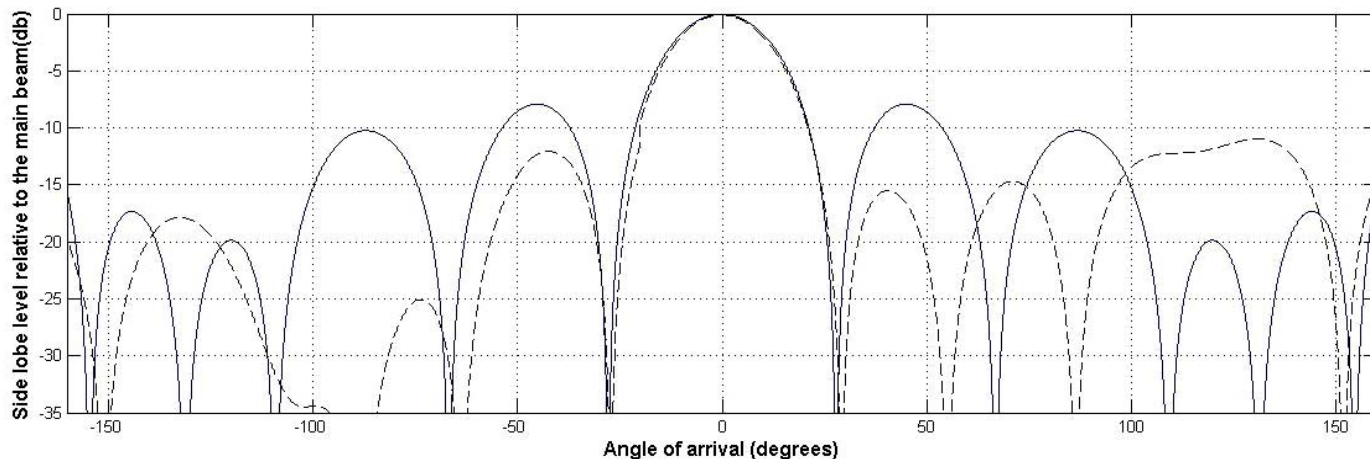


Figure 3. Comparison between propagation patterns of normal distribution ( — ) of elements and simulated annealing algorithms ( - - - ) for an antenna array with 10 elements.

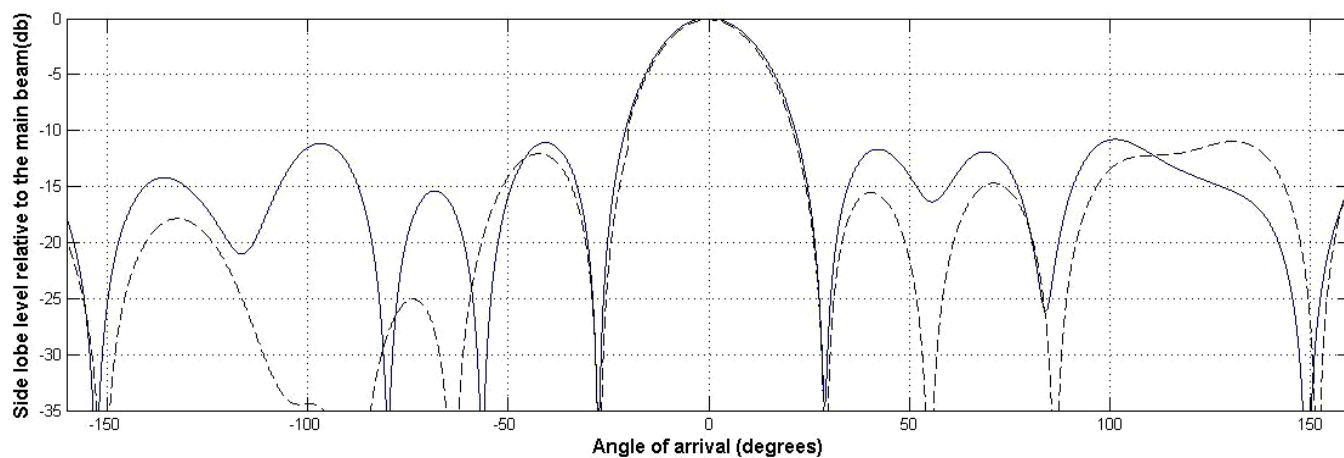


Figure 4. Comparison between propagation patterns of genetic ( — ) and simulated annealing algorithms ( - - - ) for an antenna array with 10 elements.

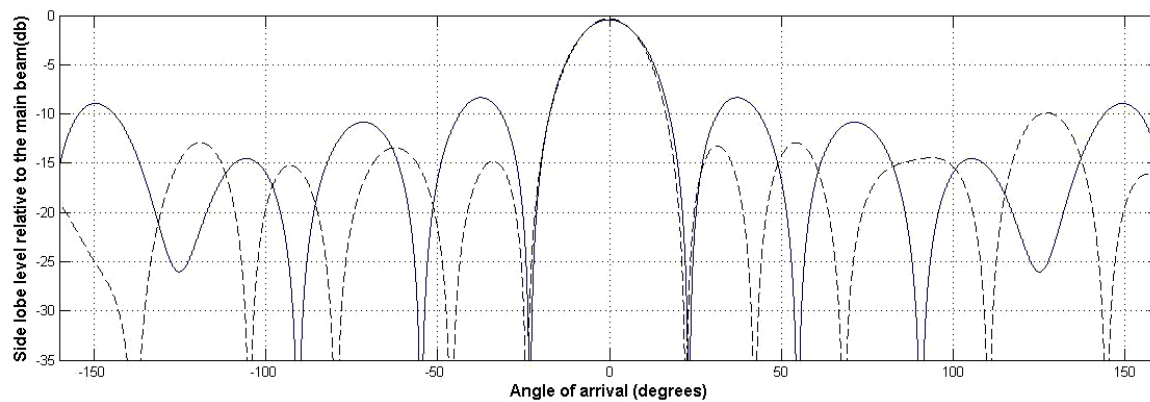
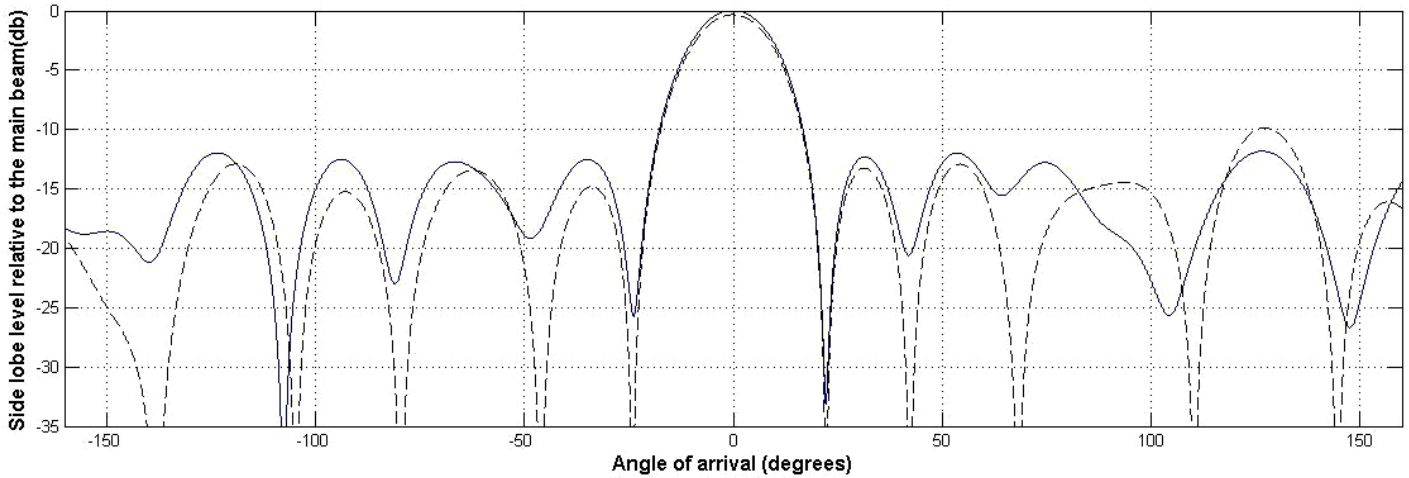


Figure 5. Comparison between propagation patterns of normal distribution of elements ( — ) and simulated annealing algorithms ( - - - ) for an antenna array with 12 elements.



**Figure 6.** Comparison between propagation patterns of Genetic ( — ) and simulated annealing algorithms ( - - - ) for an antenna array with 12 element

**Table 1.** Examples for the non-normal distribution of antenna array elements on a circular surface for two different numbers of elements.

| N  | SLL(dB) | BWFN(deg) | $d_{m_1}, d_{m_2}, d_{m_3}, \dots, d_{m_N}; I_1, I_2, I_3, \dots, I_N$   | Aperture       |
|----|---------|-----------|--|----------------|
| 8  | -10.5   | 71.5      | $0.05961 \lambda, 0.314 \lambda, 0.7763 \lambda, 0.7425 \lambda, 0.6297 \lambda, 0.8969 \lambda, 0.4633 \lambda, 0.5267 \lambda, 0.3289, 0.2537, 0.7849, 1, 1.0171, 0.5183, 0.5176, 0.4612$  | $4.40 \lambda$ |
| 10 | -11.9   | 55.3      | $0.3258 \lambda, 0.4934 \lambda, 0.3505 \lambda, 1.6573 \lambda, 0.6213 \lambda, 0.9948 \lambda, 0.4968 \lambda, 0.2431 \lambda, 0.5878 \lambda, 0.3148 \lambda, 0.9845, 0.3883, 0.4092, 0.9674, 0.6586, 0.5533, 0.5834, 0.6215, 0.4665, 0.6148$   | $6.08 \lambda$ |
| 12 | -15     | 45.6      | $0.5181 \lambda, 0.3665 \lambda, 1.4283 \lambda, 0.8367 \lambda, 0.3249 \lambda, 0.5702 \lambda, 0.4983 \lambda, 0.8135 \lambda, 0.8195 \lambda, 0.4992 \lambda, 0.3595 \lambda, 0.7370 \lambda, 0.1864, 0.5116, 0.2046, 0.6486, 0.7512, 0.8393, 0.5577, 0.4095, 0.5225, 0.4875, 0.4833, 0.8453$ | $7.07 \lambda$ |

elements are shown. In these figures, the propagation pattern obtained from the simulated annealing algorithm is compared with the patterns obtained from normal distribution of elements and the genetic algorithm in Figure 5 and 6 respectively.

As seen in the figures, the first side lobe level is -15 dB for the simulated annealing algorithm, -12.8 dB for the genetic, and -7 dB for normal distribution of elements. Therefore we have 1.2 and 5 dB reduction in first side lobe using simulated annealing algorithm in comparison of genetic algorithm and normal distribution of 12 elements (Panduro et al., 2006).

Results obtained from simulated annealing algorithm for distribution of elements on a circular array with their distance  $\{d_{m_i}\}$ , amplitude  $\{I_i\}$  for a set of 8, 10 and 12 elements are presented. In Table 1, Based on the results,

by increasing the number of elements and the circumference of the circle on which elements are placed, side lobe levels reduce.

## Conclusion

In this paper, simulated annealing algorithm has been used for maximally reducing side lobes in circular antenna arrays with non-normal distribution of elements with the assumption of constant beam width. Simulated annealing algorithm can converge to an optimized answer by starting from an appropriate primary point and by some repetitions. This algorithm can provide the possibility of getting out of local minimums and converging to the local optimized answer by adding a probability aspect to the descent along with the gradient.

Based on the obtained results from the experiments, the efficiency of this algorithm in getting out of local minimums (the genetic algorithm may get stuck in local minimums) and getting to a close optimized answer has been demonstrated.

In conclusion, simulated annealing algorithm shows better efficiency and reduction in side lobes in comparison to the other methods.

### Conflict of Interest

The authors have not declared any conflict of interest.

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