Performance Analysis of Rectangular Patch Antenna Design Using Particle Swarm Optimization, Neural Networks Algorithms

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Abstract— This paper deals with the designing of a Rectangular Patch Micro Strip Antenna using a different algorithms such as Particle Swarm Optimization (PSO), Neural Networks(NN).The Simulation time is calculated for the Rectangular patch Micro strip antenna with these algorithms. In this paper the performance comparison of Rectangular patch Micro strip antenna is done using NN,GA and PSO algorithm. The PSO method effectively obtains the less simulation time when compared to the remaining algorithms. The radiation pattern of Rectangular Micro strip antenna is generated using PSO algorithm..

Keywords—*Radiation Pattern, PSO, GA, NN*

I. INTRODUCTION

In wireless communications the role of a Microstrip antenna is very important. Most of the communication systems are using MSA because of its characteristics like Low profile, less weight, low cost and ease of construction. In the designing procedure the MSA have four parts (Patch, Ground plane, Substrate and Feeding part) [1-4] In this paper MSA are applied for given resonant frequency fr = 2.4 GHz, substrate height h = 1.6, and relative dielectric constant for substrate εr = 4.28 The structure of Micro Strip Antenna as shown in Fig.1

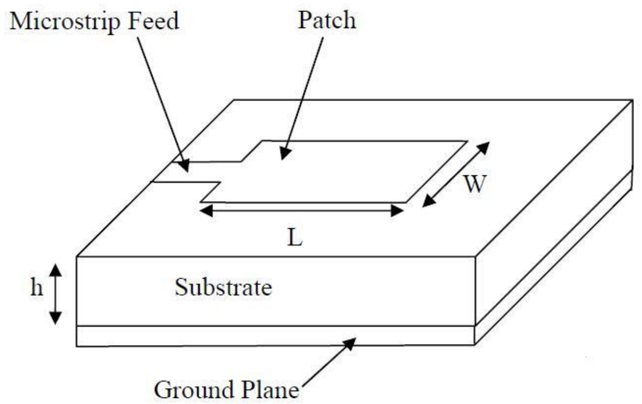

Fig.1 Geometry of microstrip patch antenna

The width of the microstrip patch antenna was computed with the following equation

$$W = \frac{C}{2 \times f_r} \times \sqrt{\frac{2}{\in_r + 1}} \qquad (1)$$

where c is the speed of light (3x108 m/s), fr is the operating frequency of 2.4 GHz and Er is the dielectric permittivity of 4.28.The length of microstrip patch antenna is given by the following equations:

$$E_{reff} = \frac{E_r + 1}{2} + \frac{E_r - 1}{2} \left(1 + 12 \times \frac{h}{w}\right)^{-(1/2)} \qquad (2)$$

where Ereff is the effective dielectric constant and h is the thickness of the dielectric substrate

$$L_{effe}\,(eff\,.length) = \frac{C}{2 \times f_r \times \sqrt{E_{reff}}} \qquad (3)$$

$$L = 0.412 \times h \times \frac{(E_{reff} + 0.3)}{(E_{reff} - 0.258)} \times \frac{(\frac{w}{h} + 0.264)}{(\frac{w}{h} + 0.8)} \qquad (4)$$

In the equation above L stands for length extension.

Therefore, the actual length of the micro strip patch antenna is given by:

$$L = L_{effe} - 2 \times L \qquad (5)$$

The resonant frequency is given by the equation

$$f_r = \frac{1}{2L_{effe}\sqrt{\varepsilon_{effe}}\sqrt{\mu_0 \varepsilon_0}} \qquad (6)$$

In this paper we are designing an linear array for Rectangular Microstrip antenna.This linear array consist of 'N' elements(Antennas) . For this 'N' elements the Electric field is given by[5]

$$E_{array} = \sum_{i=1}^{N} I_i E_i(\theta) e^{jK_0 z_i \cos(\theta)} \quad (7)$$

E_i represents the electric filed of i^{th} element

I_i represents the complex value of current of i^{th} element

$$z_i = (i-1)d \quad (8)$$

d represents the distance between each antenna element

K_0 represents the propagation constant in free space.

The aim of this work is to find the characteristics of MSAfor different algorithms. Section II presents an overview of Neural networks, Section III explains Genetic Algorithm, Section IV deals with proposed algorithm Partical Swarm Optimization Section V is all about result analysis and comparative analysis. Section VI concludes the paper.

II. NEURAL NETWORKS

The Artificial neural networks (ANN) give quick and precise models for microwave modeling, simulation, and optimization. The previous decades has seen a phenomenon development in the improvement of new instruments for microwave CAD. ANNs are computational tools that gain as a matter of fact (training), generalize from past cases to new ones, and unique fundamental attributes from input containing irrelevant information. In the neural network model Radial Basis function(RBFNN0 is used. In this we have two methods Forward side and Reverse side.For the forward neural network with a single hidden layer that uses radial basis activation function for the hidden neurons are called RBFNN[6-8].

The RBFNN model is shown in Fig(2)

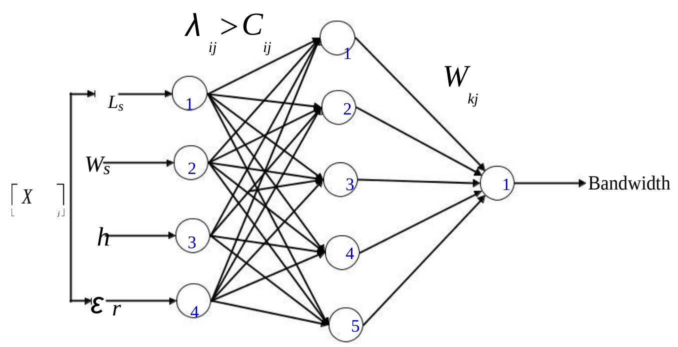

Fig 2 Radial basis function neural network (RBFNN) model

The RBF neural system has both an asupervised and unsupervised segment to its learning. It comprises of three layers of neurons | Input, hidden and output. The hidden layer neurons represent to a progression of centers in the information space. Each of these centers has an enactment work, commonly Gaussian. The initiation relies upon the separation between the exhibited input vector and the center. The further the vector is from the center, the lower is the initiation and the other way around. The generation of the centers and their widths is finished utilizing an unsupervised k-means clustering calculation. The centers and widths made by this calculation at that point shape the weights furthermore, biases of the hidden layer, which stay unaltered once the clustering has been finished[9-10]

III. PARTICLE SWARM OPTIMIZATION

The Particle Swarm Optimization (PSO) is a stochastic calculation, which was produced in 1995 by Kennedy and Eberhart, and the optimization procedure depends on the conduct of swarms (birds and honey bees). The fundamental thought of PSO is the trading of data between particles of the swarm to investigate the hunt space so as to locate an ideal answer for the issue. In this calculation, it is important to make arbitrarily k particles, which frame a swarm. Every particle contains every one of the factors that must be upgraded (amplitudes also, periods of the direct antenna cluster). Every factor must be made inside the predefined run limits. The removal of the particle is given by the total of three vectors, which are acquired by the accompanying perceptions: A particle tends to move a similar way in that it is moving, enduring inertia, which is indicated by w;A particle is affected by the best position found by the particle in the search scenario (memory), indicated by p_{best}(valuable parameter for nearby hunt);A particle is affected by the best position found by the swarm in the pursuit situation (participation), signified by g_{best} (valuable parameter for worldwide pursuit).

Furthermore, two constants ought to be incorporated into the model to consider how a particle believes itself(b) , and how it confides in the particles of the swarm(c). From these perceptions, the speed of the k-th particle can be computed by

$$v_n^k = wv_{n-1}^k + b(p_{best}^k - p_{n-1}^k)u + c(g_{best} - p_{n-1}^k)a \quad (9)$$

$$p_n^k = p_{n-1}^k + v_n^k \quad (10)$$

In the optimization of an antenna array with PSO, a particle is represented by 2*N* variables (amplitudes and phases of the *N* antennas) and stands for a potential set of coefficients that synthesize the desired pattern In matrix form, eq. (9) and eq. (10) can be rewritten as

$$V_n^k = wV_{n-1}^k + b(P_{best}^k - P_{n-1}^k)u + c(G_{best} - P_{n-1}^k) \quad (11)$$

$$P_n^k = P_{n-1}^k + V_n^k \quad (12)$$

$$P_{n-1}^k = \left[|I_1|\delta_1|I_2|\delta_2 \ldots\ldots |I_N|\delta_N \right] \quad (13)$$

$$V_n^k = \left[|\Delta I_1|\Delta\delta_1|\Delta I_2|\Delta\delta_2 \ldots\ldots |\Delta I_N|\Delta\delta_N \right] \quad (14)$$

After the last iteration, the variables of the vector G_{best} correspond to the optimum values of the vector **I** as described.

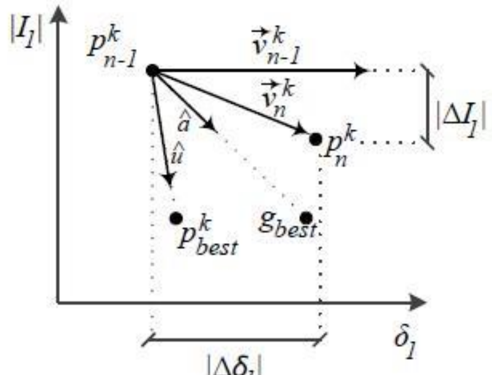

Fig 4 Displacement of a particle in a two-dimensional search space

The PSO is utilized to play out the worldwide inquiry with a specific end goal to recognize an arrangement of coefficients that creates the predefined radiation pattern. The assessment of the fitness of each arrangement of coefficients is required. This is done in light of the assessment of the blunder characterized basically as the contrast between the determined pattern S(Θ) and the synthesized pattern E_{array}(Θ), which is figured with (7)

An extra issue must be considered amid the enhancement of the excitation coefficients, since patterns to be synthesized have specific locales, where unique requirements must be connected. For the principle bar, the particular for the most The investigations that take after considering linear arrays with 10 components consistently separated by 0.5 λ along the vertical heading were considered, where λ is the wavelength in free space. The PSO was introduced with a swarm of 50 irregular particles, with b= 0.5, c = 0.5 and inertial consistent of 0.75. Keeping in mind the end goal to look at the execution of PSO, a similar pattern has been synthesized with GA in this application was viewed as 360 tests of the radiation pattern), which was introduced with a arbitrary population of 50 people (a similar number of particles utilized for the PSO), with hybrid likelihood of 85%, transformation of 8%, and 7% of people regarded as tip top. The points of confinement of variety of the limits were set to [0, 1] for the amplitude and [0, 2π] for the phase. The straight arrays with isotropic components were upgraded more than 200 cycles/generations with the two strategies. A run of the mill instance of beamforming incorporates beam steering and sidelobe concealment. Two cases have been synthesized:

1) Main beam directed to 70° with sidelobe level underneath -23 dB;
2) The same as the above, yet with 30 dB concealment in the rakish locale in the vicinity of 40° and 50°.

The coveted patterns and the aftereffects of the enhancement are appeared in Fig.6 and Fig.7. The outcomes after 200 ages demonstrate that the synthesis with GA does not fulfill the particulars, since the part is a shape that the pattern ought to take after as close as would be prudent, and the blunder is given by

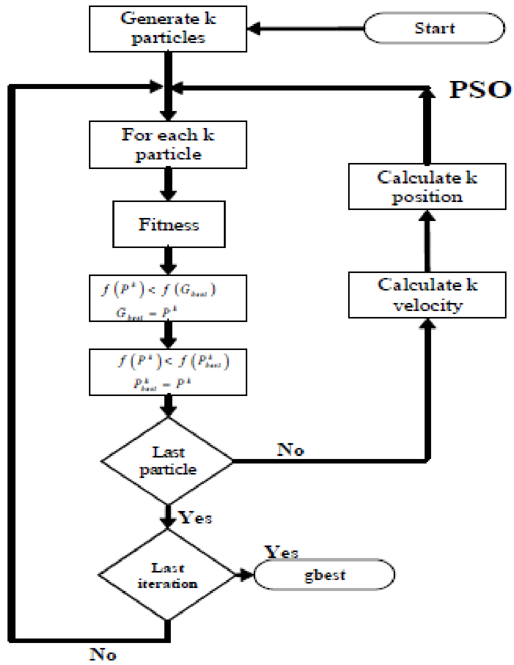

Fig 5.Flowchart of the particle swarm optimization

sidelobes are over the predefined level, though the outcomes got PSO do satisfy the coveted pattern cover. Beam-molded radiation patterns can be utilized as a part of versatile communications frameworks [4] and satellites [1] to give uniform circulation of energy into the cell or on the earth surface. In [4], a squared cosecant pattern with sidelobes level control was determined to get great scope of portable clients what's more, to limit the co-channel obstruction between nearby cells. In this work, the cosecant work was characterized in the interim [96°, 180°] and the standardization edge was set to 106°.

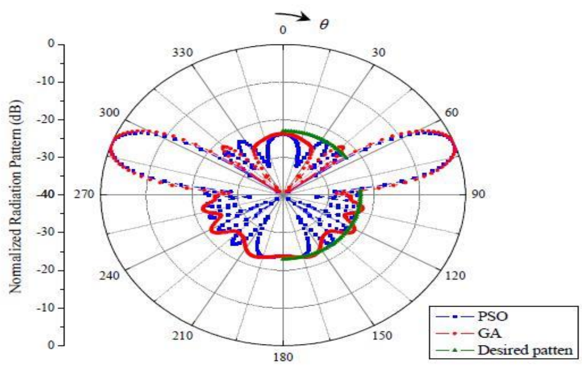

FIG.6- ISOTROPIC ARRAY: PATTERN WITH MAXIMUM IN 70° AND SIDELOBES CONTROL

Considering the instance of patterns for arrays introduced on satellites, the primary beam shape was determined to adjust the spread misfortunes, and it is characterized between [80°, 100°] to cover the earth. For the two cases, the sidelobe level (SLL) ought to be 23 dB beneath the fundamental beam. The coveted patterns and the enhancement comes about are appeared in Fig.8 and Fig.9. Likewise in these cases, GA neglects to join to an ideal arrangement after 200 cycles, while PSO yielded patterns that satisfy the predetermined values.

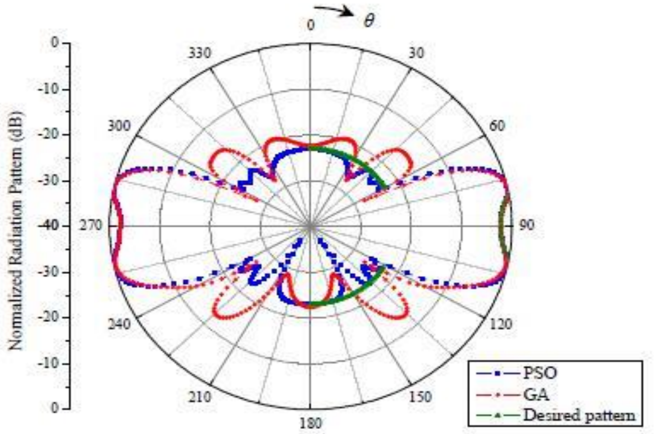

Fig.7- Isotropic array: beam-shaped for uniform power distribution on the Earth surface.

IV. RESULT

Table-I explains the comparative analysis of simulation of Neural Networks, Genetic Algorithm, Particle Swarm Optimization. The simulation time required to synthesize the radiation patterns using various algorithms is as follows, Neural Network algorithm used 142sec Genetic Algorithm used 128sec ,Particle Swarm Optimization algorithm used 54sec, simulation time.

Table-I Performance comparison

Method	Simulation Time(s)	No of cycles/test
Neural Networks	148	402
Particle Swarm Optimization	58	215

V. CONCLUSION

In this paper I designed the Microstrip antenna with the RBFNN with a mean square error value of 7.2334e-029. This paper has exhibited that radiation pattern with entangled shapes could be synthesized by utilizing enhancement techniques. The correlation amongst NN and PSO was acknowledged, where the proficiency of the PSO in examination to GA to upgrade the four diverse radiation pattern shapes were observed.

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