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Research Paper

Digitally Excited Reconfigurable Linear Antenna Array Using Swarm Optimization Algorithms

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Abstract: This paper describes the synthesis of digitally excited pencil/flat top dual beams simultaneously in a linear antenna array constructed of isotropic elements. The objective is to generate a pencil/flat top beam pair using the excitations generated by the evolutionary algorithms. Both the beams share common variable discrete amplitude excitations and differ in variable discrete phase excitations. This synthesis is treated as a multi-objective optimization problem and is handled by Quantum Particle Swarm Optimization algorithm duly controlling the fitness functions. These functions include many of the radiation pattern parameters like side lobe level, half power beam width and beam width at the side lobe level in both the beams along with the ripple in the flat top band of flat top beam. In addition to it, the dynamic range ratio of the amplitudes excitations is set below a certain level to diminish the mutual coupling effects in the array. Two sets of experiments are conducted and the effectiveness of this algorithm is proved by comparing it with various versions of swarm optimization algorithms.

Keywords: Reconfigurable Antenna Array, QPSO Algorithm, Digital Attenuator, Digital Phase Shifter, Swarm Optimization.

1 Introduction

MANY times, antenna arrays employed in communications are required to generate different radiation patterns. In connection with this, generations of different patterns [1-10] by one antenna array is more appreciated as it greatly reduces the constraints involved in circuit design, size and cost, etc. In addition to this, it will be a great boon, if the array element excitations involved in the radiation patterns are the same, while differing only in phase excitations. Researchers have succeeded to a great extent in the past in generating these patterns using reconfigurable arrays, thus simplifying the associated design and construction of the feed networks. In spite of that, radiation pattern parameters get affected due to mutual coupling between the elements. Thus, it has been always a challenging task for the researchers to reach the expected goal in generations of these patterns.

Literature review depicts several ways in which the above tasks have been dealt in the past. Bucci *et al.* synthesized the reconfigurable array antennas generating various beams with same amplitudes and different phases using the projection method [1]. Baskar *et al.* utilized the generalized generation gap model Genetic Algorithm [2] for the synthesis of reconfigurable array antennas showing better performance of radiation patterns obtained using discrete phase shifters over continuous realization and subsequent quantization. Gies, *et al.* utilized Particle Swarm Optimization (PSO) algorithm successfully for the generation of multiple beam patterns [3]. Morabito, *et al.* presented a different successful approach to the optimal mask-constrained power pattern synthesis [4], which dynamically reconfigured the radiation pattern by controlling the excitation phases only. Li *et al.* successfully utilized a multiobjective evolutionary algorithm which uses a decomposition approach [5] to

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change the problems of approximation into different single objective optimization problems. An iterative method using phase only control is successfully used in [6].

Further insight into the articles in the literature shows that evolutionary algorithms played a commanding role in handling the fitness functions dealing with antenna parameters. It is found that these algorithms are more adequate to accomplish and are adaptable than other methods in the synthesis of reconfigurable arrays and this makes the researchers rely and adopt the latest developments in the field of evolutionary algorithms. To quote a few, Genetic Algorithm [2, 7, 8, 11], PSO [3, 12, 13], and Differential Evolution [5, 9, 10] are found to be very successful. They have shown their superiority in various beams, namely, pencil, flat top, and cosecant squared beams.

In this paper, Quantum Particle Swarm Optimization (QPSO) algorithm [14-16], one of the variants [14-23] of PSO is utilized for the generation of a flat top beam and a pencil beam radiation pattern simultaneously with common discrete amplitude excitations and different discrete phase excitations of the elements. The reason for using QPSO is that it has proved its superiority in many of the optimization problems in the recent decade.

The parameters that will be controlled are the Side Lobe Level (SLL), half power beam width (HPBW), and beam width at SLL of the pencil beam radiation pattern and the SLL, HPBW, and ripple in the flat top beam of the radiation patterns. Moreover, experiments are also being done utilizing Dynamic Range Ratio (DRR) in order to suppress the mutual coupling effects. This is done by adding a term based on DRR in the fitness function.

In order to evaluate the validity of QPSO algorithm, the simulated results that are obtained using this algorithm are compared with the results obtained from various well-known variants of PSO algorithm, namely Comprehensive learning PSO (CLPSO) [17], Linearly Decreasing Inertia Weight PSO (LPSO) [18], Unified PSO (UPSO) [19-20] and Random inertia weight PSO (RPSO) [18] algorithms. Further details of the variants of PSO are available in the corresponding references mentioned in parentheses above.

This paper is different from the other papers in the sense that both the discrete amplitudes as well as discrete phases are digitally controlled using attenuators and phase shifters. Mutual coupling is duly considered by introducing the DRR parameter. Along with the HPBW parameter, which is usually considered in most of the papers, beamwidth at SLL is considered in addition to HPBW. In addition to the radiation pattern parameters, statistical parameters are also included for comparison purposes.

2 Research Method

The process of generating the radiation pattern of a reconfigurable dual beam antenna array in this paper depends on utilizing common amplitude distributions for both the pencil beam and the flat top beam with the difference in phase distributions. The phases are set to zero for pencil beam, whereas it is varied between -180° and +180° for the flat top beam. Again in this process, the amplitude excitations lie between 0 and 1 and are quantized using a 6-bit attenuator (Power divider network - amplitudes in steps of $1/2^6$) and phases by a 6-bit Variable phase shifter (phases in steps of $360°/2^6$), respectively.

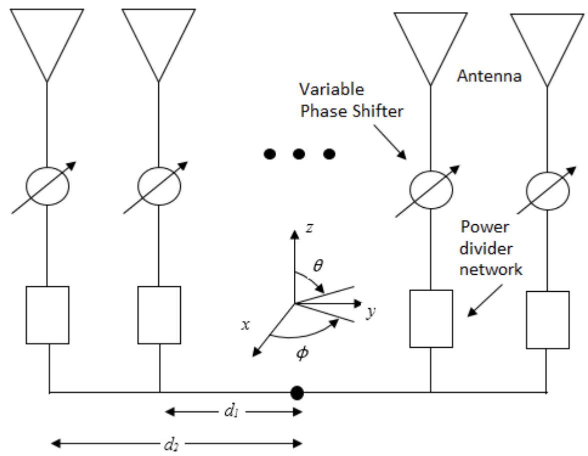

Fig. 1 Geometry of a reconfigurable linear antenna array along the y-axis.

The far-field radiation pattern or array factor of a linear array of $2N$ number of isotropic elements shown in Fig. 1 with even symmetry from the center is written as:

$$F(\theta) = \sum_{m=1}^{N} 2c_m \cos\left(\frac{2\pi}{\lambda} d_m \sin\theta\right) e^{jp_m} \quad (1)$$

where c_m and p_m are the amplitude and phase of the m-th element, respectively, λ is the wavelength, d_m is the distance between the position of the m-th element and the array's center and θ being the angle measured from broadside (−90° to +90°). Because of the nature of the symmetry, only N amplitude and phase excitations need to be optimized. The normalized absolute far field pattern is given by

$$\text{Normalized absolute far field} = \frac{|F(\theta)|}{|F(\theta)|_{\max}} \quad (2)$$

The fitness function that needs to be minimized is given by

$$Fit1 = \sum_{i=1}^{3} (F_i)^2 + \sum_{j=1}^{4} w_j (F_j)^2 \quad (3)$$

The first term in the RHS of the above equation is written as below:

$$F_i = \begin{cases} D_i^{pen} - D_{i,d}^{pen}, & \text{if } D_i^{pen} > D_{i,d}^{pen} \\ 0, & \text{if } D_i^{pen} \le D_{i,d}^{pen} \end{cases} \tag{4}$$

where i = 1, 2, and 3 are the parameters, namely, SLL in dB, HPBW in degrees, and beamwidth at SLL in degrees of pencil beam.

The other term in the RHS of (3) is written as below:

$$F_j = \begin{cases} D_j^{sec} - D_{j,d}^{sec}, & \text{if } D_j^{sec} > D_{j,d}^{sec} \\ 0, & \text{if } D_j^{sec} \le D_{j,d}^{sec} \end{cases} \tag{5}$$

where j = 1, 2, 3, and 4 refers are the parameters, namely, SLL in dB, HPBW in degrees, beamwidth at SLL in degrees, and the ripple in the flat top pattern ($-15° \le \theta \le 15°$) in dB. These parameters and their desired specification values are given in Tables 1 and 2. Moreover, in the above equations, the superscript *pen* represents the specification for the pencil pattern and the superscript *sec* represents the specification for the flat top/sector beam pattern. The term D_{id} represents the desired value and D_i represents the obtained value for each specification parameter. The weight w_j is kept to unity for all the values of j, except when dealing with the ripple value. The weight for the ripple value is chosen to be 10. The reason for choosing a weight for ripple value parameter is to produce a good shape for the flat top portion in the flat top pattern. A new term in the fitness function is added to examine the effects of mutual coupling in terms of Dynamic Range Ratio (DRR), which is given by

$$Fit2 = Fit1 + 10 \times (DR_d - DR_o)^2 \tag{6}$$

where the second term in the above function deals with amplitude DRR which is defined as the ratio of the maximum to the minimum value of the amplitude excitations. DR_d refers to desired amplitude DRR and DR_o refers to obtained amplitude DRR. By reducing this ratio, the differences between the successive excitation amplitudes of the array elements are reduced thus diminishing the effects of mutual coupling. High importance is given to this term by multiplying the differences by a factor of 10.

3 Algorithm Used

Inspired by the flocking behavior of the birds, Eberhart and Kennedy developed the Particle Swarm Optimization technique [12]. In the past decades, this algorithm found itself very much successful in solving a variety of optimization problems in different disciplines. However, because of the problems involved in convergence of the global minimum value, many variations in the steps involved in this algorithm resulted in its new versions and they gathered importance in many fields. One of the versions is the Quantum Particle Swarm Optimization, which is inspired by quantum mechanics behavior. It emerged as one of the best versions of PSO, because of its various advantages like simplified equations in the algorithm, fewer control parameters, quick convergence, etc. In QPSO, the state of the particle is defined by a wave function. This is the primary difference with the PSO in a way that in PSO, the state/position of the particle is defined by the position and velocity of the particle and influenced by social and cognitive factors. The probability that a particle appears in a particular state is obtained from the probability density function, which in turn relies on the potential field.

The QPSO algorithm [14-16, 21-22] is given as follows:

(i). The positions of all the particles in the population are randomly initialized.

(ii). All the particles are appraised based on the fitness values and the personal best *pb* is chosen. If the current value from the fitness function is better (minimal in this problem) than the previous value, then the previous value is substituted with the current one.

(iii). The overall mean best *mb* position of all the particles is given by

$$mb = \frac{1}{P}\sum_{i=1}^{P} pb_i \tag{7}$$

(iv). The above steps are utilized for the complete population and the final obtained best fitness value is regarded as the global best (*gb*), if it's is better than the original fitness value.

(v). The positions of a particle are updated using the following equation

$$x_{ij}^{t+1} = p_{ij}^{t} \pm \beta \left| mb_j^t \right| - x_{ij}^{t} \ln(1/u_{ij}^{t}) \tag{8}$$

where β is the contraction expansion coefficient whose value is chosen as 0.75.

(vi). The particle's vector local focus is given by

$$x_{ij}^{t} = ran1_{ij}^{t} \times (pb_{ij}) + (1 - ran1_{ij}^{t}) \times (gb) \tag{9}$$

(vii). If *ran1*, *ran2*, *ran3*, *ran4*, and *ran5* are the uniform random numbers and X^t_{min} and X^t_{max} are the desired minimum and maximum limits, updating of position of the ***j***-th dimension of ***i***-th particle using (10) and imitate steps (*ii*) to (*vi*) is done till *gb* is acquired.

$$X_{ij}^{t} = x_{ij}^{t} + (-1)^{ceil(0.5 + ran2_{ij}^{t})} \times \alpha \times \left| mb - X_{ij}^{t-1} \right| \times \log(1/ran3_{ij}^{t}) \tag{10}$$

If $X^t_{ij} < X^t_{min}$, then

$$X_{ij}^{t} = X_{\min}^{t} + 0.25 \times ran4_{ij}^{t} \times (X_{\max}^{t} - X_{\min}^{t}) \tag{11}$$

else

$$X_{ij}^{t} = X_{\max}^{t} - 0.25 \times ran5_{ij}^{t} \times (X_{\max}^{t} - X_{\min}^{t}) \quad (12)$$

Equations (11) and (12) are being used to maintain the position within a certain limit in order to avoid any sort of explosion of particles.

4 Results and Analysis

A linear array of 20 isotropic antennas each separated by a distance of half wavelength from its neighboring antennas for the generation of both the pencil beam and the flat top beam radiation patterns is taken for consideration. Since even symmetry is there from the center of the array, it needs only 10 amplitude excitations lying between 0 and 1, and 10 phase excitations lying between –180° to +180° to be optimized. Out of each 20-element vector obtained from the algorithms after minimization of the fitness equations, the first 10 values are scaled to 6-bit discrete quantized amplitude values and the remaining 10 values are scaled to 6-bit discrete quantized phase excitation values. The following settings are used for the simulations with Matlab software. Two cases are discussed below with and without the amplitude DRR constraint.

4.1 Case (i)

The simulations are done for the fitness function *Fit*1 using QPSO and other variants of PSO algorithms. The number of particles in the population is 400 and the total number of iterations is 1000 for all the algorithms along with the same number of function evaluations. The upper and lower boundaries are set to the maximum upper and lower boundaries of the input variable. The variants of the PSO algorithm have the same acceleration constants [2] as well as the same number of maximum function evaluations. In UPSO [19, 20], u is kept equal to 0.2. The equations that are used for RPSO is taken from [18]. For LPSO, the inertia weight is allowed to linearly decrease from 0.9 to 0.4. Since the results depend on the initial seed values of the algorithms, care is taken in such a way that the best results are chosen from a set of 20 results obtained from different initial seed values for all the algorithms. The amplitude excitations are controlled to quantized values using 6-bit digital attenuators between 0 and 1 for both the beam patterns. All the elements' phase excitations are kept at 0° for pencil beam pattern and are varied between -180° and 180° in quantized values for flat top beam using 6-bit digital phase shifters. Table 1 shows the simulated results for Pencil beam radiation pattern and flat top beam radiation pattern without Dynamic range ratio constraint. Fig. 2 shows the corresponding Normalized power pattern.

Table 1 shows that QPSO succeeded completely in producing the expected values of parameters. Even though other algorithms tried using their versatility in bringing their outputs to the expected ones, they were able to bring only a few parameters to the expected value, but not all completely. In other words, the best fitness value became zero only for QPSO algorithm. These values are obtained from the best run out of 20 different runs. Even the statistical parameters also prove that the mean value, as well as standard deviation of QPSO, is best when comparing with other algorithms.

4.2 Case (ii)

The simulations are done for the fitness function *Fit*2 and the settings that are used for Case (i) are used here. Here, the value of the desired DRR is chosen to be 6. The reason for choosing this value is to try out a value of DRR, which is less than or equal to 60% of the max DRR value obtained from case (i). In this case, the mutual coupling effects can be reduced to around 60% in the power patterns obtained from the case (i). Table 2 shows the simulated results for Pencil beam radiation pattern and flat top beam radiation pattern with an expected DRR of less than or equal to 6. Fig. 3 shows its corresponding normalized power pattern.

Table 1 Simulated results for pencil beam radiation pattern and flat top beam radiation pattern without dynamic range ratio constraint.

Patterns	Parameters	Desired values	Obtained values				
			QPSO	CLPSO	LPSO	UPSO	RPSO
Flat top beam	SLL in dB	-25	-25.1434	-24.8844	-24.6882	-24.6987	-24.5328
	HPBW in degrees	45	40	40	38	38	40
	Beamwidth at SLL in degrees	70	66	57	66	56	66
	Ripple (in dB, $-15° \le \theta \le 15°$)	0.5	-0.49805	-0.58095	-0.64739	-0.63558	-0.54872
Pencil beam	SLL in dB	-25	-25.0589	-25.0133	-24.916	-24.5811	-24.6504
	HPBW in degrees	10	8	8	8	8	10
	Beamwidth at SLL in degrees	28	24	24	24	24	26
Both beams	Amplitude DRR	NA	9.8333	10.1667	8.4286	9.1429	11.8
Statistical Parameters for both beams	Global fitness value	NA	0.00	0.0789	0.3215	1.602	0.3642
	Mean	NA	15.99	282.5	47.6	78.47	35.87
	Standard deviation	NA	109.55	370.2	138.8	197.9	122.2

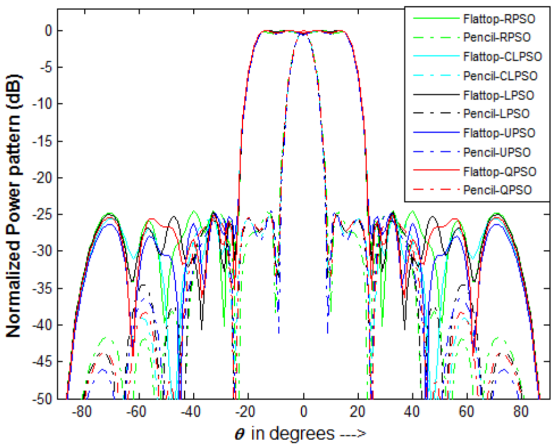

Fig. 2 Normalized power pattern using various PSO algorithms without amplitude DRR constraint.

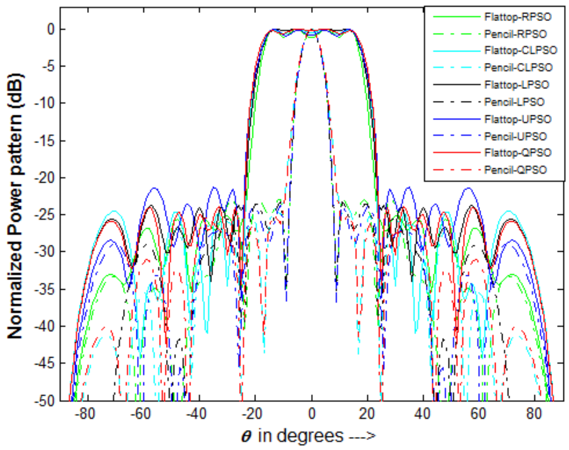

Fig. 3 Normalized power pattern using various PSO algorithms with amplitude DRR constraint.

Table 2 Simulated results for pencil beam radiation pattern and flat top beam radiation pattern with dynamic range ratio constraint.

Patterns	Parameters	Desired values	Obtained values				
			QPSO	CLPSO	LPSO	UPSO	RPSO
Flat top beam	SLL in dB	-25	-23.7467	-24.0594	-23.6042	-21.2734	-24.9585
	HPBW in degrees	45	40	38	38	38	36
	Beamwidth at SLL in degrees	70	57	54	50	59	54
	Ripple (in dB, $-15° \le \theta \le 15°$)	0.5	-0.63766	-0.84962	-0.99267	-0.92022	-1.2816
Pencil beam	SLL in dB	-25	-25.1253	-24.164	-23.2821	-23.7275	-22.9627
	HPBW in degrees	10	8	8	8	8	8
	Beamwidth at SLL in degrees	28	26	26	22	22	24
Both beams	Amplitude DRR	6.0	6.11	6.1	6.11	6.4	6.11
Statistical Parameters for both beams	Global fitness value	NA	1.88	2.906	7.45	17.27	10.38
	Mean	NA	35.56	312.4	34.75	65.94	44.6
	Standard deviation	NA	142.7	361.1	103.9	159.5	109

Table 3 Amplitude and phase distributions obtained using the QPSO algorithm.

Amplitude distribution			Phase distribution in degrees		
Element Numbers	Without DRR	With DRR	Element Numbers	Without DRR	With DRR
1 & 20	0.0938	0.1406	1 & 20	067.500	028.125
2 & 19	0.1563	0.1563	2 & 19	180.000	101.250
3 & 18	0.2813	0.2500	3 & 18	-146.250	135.000
4 & 17	0.3594	0.2969	4 & 17	-118.125	163.125
5 & 16	0.4375	0.2656	5 & 16	-056.250	-129.375
6 & 15	0.6875	0.4531	6 & 15	-016.875	-067.500
7 & 14	0.9219	0.6406	7 & 14	005.625	-039.375
8 & 13	0.8906	0.6875	8 & 13	028.125	-011.250
9 & 12	0.7969	0.7031	9 & 12	073.125	022.500
10 & 11	0.9219	0.8594	10 & 11	101.250	050.620

Table 2 shows that QPSO succeeded in producing many parameters to the expected value. Even though CLPSO matched better in a few aspects, it is the ripple value that made QPSO more acceptable, as it produced the value closer to the expected. These values are obtained from the best run out of 20 different runs. Even the statistical parameters also prove that the mean value of QPSO is best when comparing with other algorithms. The discrete amplitudes, as well as the discrete phase distributions, are shown in Table 3. Fig. 4 shows the plot between Fitness values and Number of Iterations.

Fig. 4 shows the relationship obtained between the fitness values and number of iterations for both the discussed cases (i) and (ii) using QPSO and other variants of PSO algorithms. It is found that the convergence speed of QPSO is best in case (i) and fitness value produced is best in both cases than other algorithms. The mean of the fitness is 15.99 case (i) and 35.56 for case (ii) for QPSO, which is better than others. Moreover, the final fitness values are less for QPSO when compared with other variants of PSO. This also proves that QPSO performed better than other variants of PSO in the design of reconfigurable arrays.

5 Conclusion

This paper dealt with the synthesis of dual beam

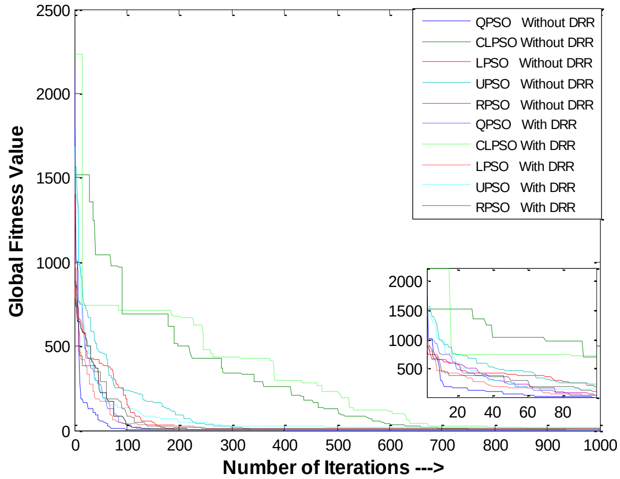

Fig. 4 Fitness values versus the number of iterations using QPSO and other swarm algorithms for cases (i) and (ii).

radiation pattern simultaneously in a linear antenna array constructed using isotropic elements with common variable discrete amplitude excitations and different variable discrete phase excitations. QPSO algorithm was successfully used for the generation of the element's amplitude and phase excitations in quantized values based on the fitness functions. It was compared with few other variants of PSO algorithms for evaluating its performance and the experimental results showed its superiority over other algorithms. The obtained patterns and their corresponding amplitude, as well as phase distributions, greatly simplified the network because of symmetric nature. This also would help in keeping the costs very low as well as resulting in simple control circuitry. In addition to the advantages as well providing the expected radiation pattern parameters, amplitude dynamic range ratio was also considered for the reduction of mutual coupling and the results obtained were considerable to a very good extent. This algorithm can also be applied for the synthesis of multi-beams using non-isotropic elements as well as with other geometries of antenna arrays like circular arrays, rectangular arrays, etc.

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