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Optimization of Antenna Arrays for SLL Reduction Towards Pareto Objectivity Using GA Variants

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***Abstract*— One of the most striking aspects of nature inspired algorithms is their capability of reaching a pareto front for a set number of objectives with much lesser computational cost than the classical ones; this is primarily due to the intrinsic intelligence that they inherit from nature. In this paper, as a first example, optimization of linear antenna arrays with dipole element pattern is exemplified for side lobe (SLL) reduction with fixed main-lobe beam width using real coded genetic algorithm (RGA). Though multi goal optimization seems to be possible with proper cost/fitness function formulation in linear arrays, such a task becomes extremely difficult when it comes to planar arrays. This calls for the use of multi objective variants of an algorithm to reach the pareto-objectivity. As a second example, non-dominated sorting genetic algorithm II (NSGA2) is considered as the optimization algorithm for SLL reduction and fixed main-lobe directivity for concentric regular hexagonal antenna arrays (CRHAA). The results show good outcome with respect to side lobe reduction and directivity.**

I. INTRODUCTION

Nature inspired algorithms are those computer algorithms which are inspired by the interactions among the species or living entities as they search for the requirements (like food, room etc.). Evolutionary and Swarm intelligent algorithms are examples of nature inspired algorithms. Among the evolutionary algorithms, genetic algorithm is perhaps the most widespread and robust optimization procedures used in the domain of communication technology. Genetic Algorithms are inspired by natural phenomenon of evolution where the properties of inheritance, accidental changes and survival of the fittest take place in the crossover tool, mutation tool and the selection tool respectively. The term generational means that the solutions (resembling the species) are evolved in iterations. In this paper a broadside linear arrays of dipole elements is considered for optimization as the first example. The phase difference between any two elements is kept zero. The excitation and inter-element spacing of each element are optimized using RGA [6-8]. A cost function is defined, which keeps the SLL at low levels. The dipole antenna or dipole aerial is one of the most important and commonly used types of RF antenna. It is widely used on its own, and it is also incorporated into many other RF antenna designs where it forms the driven element for the antenna. Dipole antenna is constructed with two thin dipole elements that are symmetrically fed at the centre by a balanced two-wire transmission line [1]. There are several types of dipole antennas such as hertzian dipole, half-wave dipole, small dipole [2] etc. Radiation resistance of the half-wave dipole was 73 Ohm which matched with the line impedance [3]. In this paper linear array of dipole element has been taken. There are several parameters by varying which the radiation pattern can be modified. These parameters are geometrical configurations (e.g. linear, circular, planar, spherical etc.), inter element spacing, individual excitations (amplitude and phase) and relative pattern of individual elements [1-9].The non-uniform current excitation and optimal uniform inter-element spacing allows for increased degrees of freedom in design. All these procedures control both peak and average SLL [5]. If the array elements are place symmetry along with the z- axis about the centre of the array, the number of attenuators required and the computational time are halved. Amplitude and inter-element only control is also easy to implement and less sensitive to quantization error [9]. As we shift from linear to planar arrays the need for more complex algorithms is strengthened; in view of this, a multi-objective variant of GA named NSGA2 is used for optimization of concentric hexagonal arrays.

Multiple objective system designing has been the major concern for last few decades. While dealing with system design problems with multiple trade-off parameters, basic modification to be done in the optimization algorithms is in their selection tools, more precisely, the fitness assignment procedures [10]. Other issues those come with this modification are the selection pressure and the premature convergence. Consequently, multiple objective optimization algorithms focus on maintaining the diversity while conducting the search for a set of good solutions. Several approaches of multiple objective optimization algorithms are made since in the past decade. Developments of algorithms have been based on the frameworks [11-14], archiving strategies [15] fitness assignment procedure [16] etc. While dealing with multiple objective problems it is desired that the species having the qualities of performing well in all the circumstances (more-or less, in a trade-off) be focused. Hence, a concept of dominance is developed which may be viewed as a modified selection tool. The next section gives a brief outline of RGA and NSGA2 algorithm; Section III and IV take the optimization examples of linear and hexagonal arrays respectively.

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II. THE USE OF GENETIC ALGORITHM AND ITS MULTIOBJECTIVE VARIANT

Genetic algorithms have been very effectively used in optimization of Antenna designs and areas of Electromagnetics in general [7, 8]. The use of GA has somewhat effectuated the classification optimization solutions as local or global. Algorithmic steps of real coded genetic algorithms (RGA) can be found from [7] which is an excellent treatise on the subject; hence there is no point in repeating those steps here; therefore, only a brief description on NSGA-2 is given here. Goldberg [18] realized the basic objective to carry out successful search for acceptable solutions for MOP. Elitist non dominated sorting based GA (NSGA II) follows not only the same steps of genetic algorithm for single objective, but some additional steps to tackle multi-objective problems. This work utilizes real coded NSGA II [11] for the considered problem and the whole search procedure as applied in this work is listed step by step below:

i. A population of 100 randomized individuals is created maintaining limits of every variable. Each population member is a string of probable current amplitudes (each string is called a "chromosome") one for each ring. Stopping criteria (200 generations), tournament size, crossover and mutation types with individual internal parameters. For this work a simulated binary crossover [19] operator with index to control the spread factor as 2 is opted for crossover operation, and for mutation, polynomial mutation [11] operator with external parameter to control mutation of 2 is opted.

ii. Then non dominated sorting is carried out to record non-domination rank of every chromosome in the population. Until the stopping criteria satisfied the following steps are repeated;

iii. For mating selection crowded distance based tournament selection operator is called for filling the mating pool. This operator operates on a pair of chromosomes, and favors more potential one (less non-domination rank calculated at step ii or v if found, otherwise (if both the chromosomes are at same front) it selects the one which is from relatively less crowded region.

iv. Solutions are combined in a successive pair-wise order to create offspring solutions, which are then individually mutated.

v. The old and new populations are merged, and a non-domination rank is re calculated. Out of these 200 solutions worst 100 solutions based on non-domination rank are discarded. This process by default maintains the elite chromosomes from the past

III. LINEAR ARRAYS OF DIPOLE ELEMENT

Consider a broadside linear array of 2M equally spaced isotropic elements as shown in Figure 1. The array is symmetric in both geometry and excitation with respect to the array center.

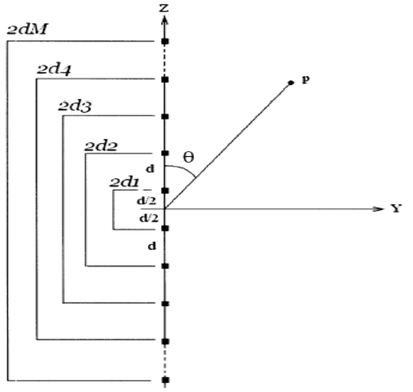


Fig. 1. Geometry of a 2N-element linear dipole array along the z-axis.

For broadside beams, the array factor is given by

$$AF(\theta) = 2\sum_{n=1}^{M} I_n \cos[(\frac{2n-1}{2})kd\cos(\theta)] \qquad (1)$$

where

$\theta =$ Angle of radiation of electromagnetic plane wave;
$d =$ Spacing between elements;
$k =$ Propagation constant;
$2M =$ Total number of elements in the array;

The cost function (CF) for reducing the side lobe level is given below

$$CF = \left|AF(\theta_{msl}, I_n)\right| / \left|AF(\theta_0, I_n)\right| \qquad (2)$$

where θ_0 is the angle where the highest maximum of central angle is attained in $\theta \in [0,\pi]$. θ_{msl} is the angle where maximum side lobe $AF(\theta_{msl}, I_n)$ is attained on either side of main beam. Minimization of CF means maximum reduction of SLL. RGA technique is employed for optimizing non-uniform current excitation weights and optimal uniform inter-element spacing.

As dipole antenna, one of the most commonly used antennas is the half-wavelength ($L = \lambda / 2$) dipole. Because of its radiation resistance as 73 ohms, which is very near to 50-ohm or 75-ohm characteristic impedances of some transmission lines, its matching to the line is simplified especially at resonance. The far-field radiation pattern from a dipole antenna of length L is given by [1]. For the half wave dipole antenna, where $L = \lambda / 2$, the far field radiation pattern of dipole antenna can be given by

$$EP(\theta)=\frac{\cos\left(\frac{\pi}{2}\cos\theta\right)}{\sin\theta} \tag{3}$$

where θ denotes the angle measured from the axis of the dipole to the line of site.

From (2) and (3) the overall total radiation pattern is given by

$$AF_{Total}(\theta)=2\frac{\cos\left(\frac{\pi}{2}\cos\theta\right)}{\sin\theta}\sum_{n=1}^{M}I_n\cos[(\frac{2n-1}{2})kd\cos(\theta)] \tag{4}$$

Here, $EP(\theta)$ is the radiation pattern of individual array elements, $AF_{Total}(\theta)$ is the array factor of linear array of dipole element.

The numerical results for three sets of linear arrays of dipole element designs are obtained by RGA technique. For each antenna array, constraints of the optimization variable are maintained. The best parameters for the RGA are set after many trial runs. It is found that the best results are obtained for the initial population size (n_p) of 120 chromosomes; and maximum number of generations, Nm as 400. For selection operation, the method of natural selection is chosen with selection probability of 0.3. Crossover is randomly selected as dual point. Crossover ratio is 0.8. Mutation probability is 0.15. RGA generates a set of optimal normalized non-uniform current excitation weights and optimal uniform inter-element spacing $(d\in[\lambda/2,\lambda])$ for each set of linear array of dipole element. Sets of arrays considered are of 12-, 16- and 20-elements. Table II shows the optimal results. Table I depicts SLL values and BWFN values for all corresponding uniformly exited linear array of dipole element antenna.

A. *Analysis of Radiation Patterns*

TABLE I. INITIAL VALUES OF SLL AND BWFN FOR UNIFORMLY EXCITED ARRAYS HAVING (I_n =1) AND $\lambda/2$ INTER-ELEMENT SPACING OF LINEAR ARRAY OF ISOTROPIC AND DIPOLE ELEMENTS

Set No.	2M	SLL (dB) isotropic elements	SLL (dB) dipole elements	BWFN (deg.) (isotropic)	BWFN (deg.) (dipole)
I	12	-13	-13.07	19.8000	19.8000
II	16	-13.11	-13.14	14.4000	14.4000
III	20	-13.12	-13.15	11.8800	11.8800

Figs. 3, 4 and 5 depict the optimal radiation patterns of 12-, 16- and 20-element time modulated linear antenna array sets, respectively, with optimal non-uniform excitation weights and optimal uniform inter-element spacing using RGA. From each figure, it is clearly visible that beside noticeable reduction of SLL, BWFN is also well restricted upon optimizing. As seen from the Table II, for optimal non-uniformly exited and optimal uniformly spaced symmetric time modulated 12-element, 16-element and 20-element, linear antenna arrays, SLL reduces to -37.41 dB, -36.25 dB, -39.74 dB, respectively, against -13 dB , -13.11 dB , -13.12 dB, respectively, for corresponding uniform linear arrays

TABLE II. OPTIMAL CURRENT EXITATION COFFICIENS, OPTIMAL INTER-ELEMENT SPACING, SLL AND BWFN FOR THREE LINEAR ARRAY OF DIPOLE ELEMENT SETS

Set No.	$(I_1, I_2 ......I_M)$	Inter-element spacing (λ)	SLL (dB)	BWFN (deg.)
I	0.9348 0.8325 0.6569 0.4564 0.2590 0.1262	0.8485	-37.41	19.8000
II	0.9652 0.9110 0.8064 0.6669 0.5134 0.3620 0.2270 0.1548	0.8713	-36.25	14.4000
III	0.8530 0.8062 0.7564 0.6481 0.5420 0.4283 0.3152 0.2182 0.1379 0.0805	0.8874	-39.74	11.8800

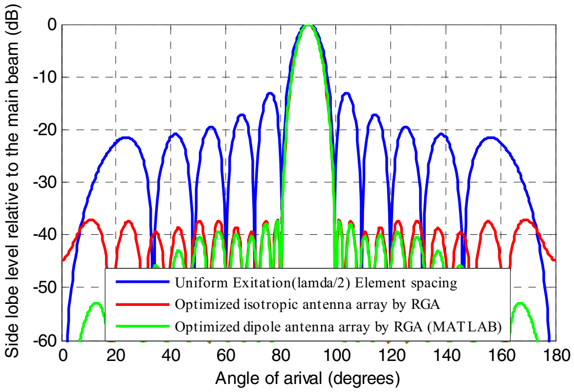


Fig 2. Optimal array pattern obtained by the RGA in case of 12-element linear array of dipole element.

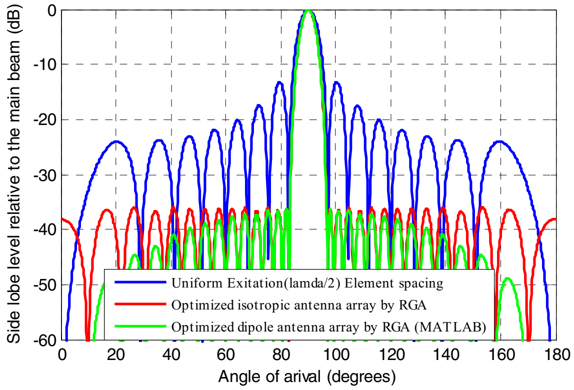


Fig 3. Optimal array pattern obtained by the RGA in case of 16-element linear array of dipole element.

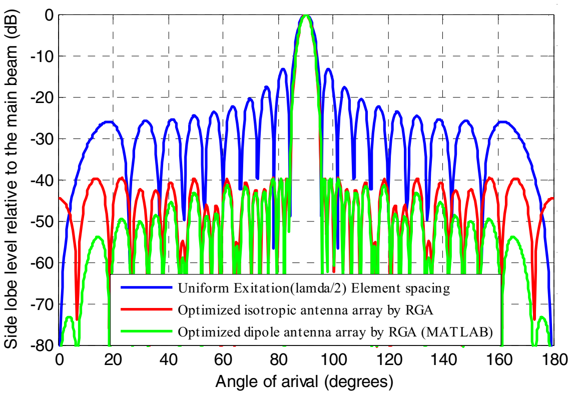


Fig 4. Optimal array pattern obtained by the RGA in case of 20-element linear array of dipole element.

IV. CONCENTRIC REGULAR HEXAGONAL ANTENNA ARRAYS: (CRHAA)

A structure of a CRHAA resting on *x*-y plane is shown in

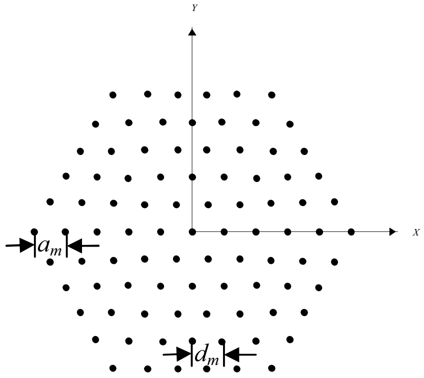


Fig 5 Structure of a CRHAA resting on the *x*-*y* plane.

Let M is the number of the rings on this structure; N_m is the number of elements on the q^{th} sector $\{q=1,2,\cdots 6\}$ of the ring m from the centre; $\{r_{mnq},\phi_{mnq}\}$ be the location of the n^{th}-element on the q^{th} sector on the m^{th} ring according to the cylindrical co-ordinate system; a_m be the inter-element separation between the rings $(m-1)$ and m (a_1 represents the maximum separation of an element of the first ring), and d_m be the inter-element separation on the ring m. The array factor of this array is given as [20]:

$$AF = I_0 + \sum_{m=1}^{M}\sum_{n=1}^{N_m}\sum_{q=1}^{6} I_{mnq} e^{j\frac{2\pi}{\lambda} r_{mnq}\sin\theta\cos\left(\phi-\phi_{mnq}\right)} \tag{5}$$

where $j=\sqrt{-1}$; λ is the wavelength of operating signal frequency; $\{\theta,\phi\}$ represents the angular co-ordinate of any far-field point surrounding the array geometry; I_0 and I_{mnq} represent the complex excitation currents of the centre element and the n^{th}-element on the q^{th} sector on the m^{th} ring, respectively. The parameters of the above expression are inter-related as follows:

$$\begin{aligned} N_m &= \left\lfloor \tfrac{a_m}{d_m} \right\rfloor \\ r_{mnq} &= \sqrt{a_m^2+(n-1)^2 d_m^2 - a_m d_m (n-1)} \\ \phi_{mnq} &= \sin^{-1}\left((n-1)\tfrac{\sqrt{3}}{2}\tfrac{d_m}{r_{mnq}}\right)+(q-1)\tfrac{\pi}{3} \end{aligned} \tag{6}$$

Total number of elements on the aperture is given by $N=1+6\sum_{m=1}^{M} N_m$. This work considers a eight-ring CRHAA with $a_m=d_m=\frac{\lambda}{2}$. Thus, N for this work is 217. For this optimization problem, $I_{mnq}=I_m \forall n\in(1,N), q\in(1,6)$.

The optimization problem is considered as

$$CF=\{SLL,D\} \tag{7}$$

where SLL represents the relative peak sidelobe level of the antenna pattern and D [17] corresponds to the maximum directivity value. Usually, these two parameters are in trade-off and both are very sensitive to the current excitations. Tapering the current distribution will favorably cause suppression of SLL, but will equally cause the fall of D. Hence, this is a multiple objective problem. Both of the parameters are expressed in dB. Usually, a high negative value of SLL and high positive value of D is desired. Using a positive D and negative SLL complicates the design of selection parameter. Rather minimizing $-D$ will serve the purpose and will make the design of selection tool easy, the objective vector is formulated as (1). The entire simulation was carried out using MATLAB software using MATLAB 8.1.0.604 (R2013a) on a Intel® Core™ i5-2500 CPU with processor speed 3.30 GHz and 8.00 GB RAM and operating system Microsoft Windows 7 Version 6.1 (Build 7600). For this work, NSGA2 is run independently for twenty five times and the non-dominated solutions of the combined populations are extracted. Then the most evenly spread twenty five Pareto front representative solutions are reported. The obtained Pareto set for the considered array design problem is depicted in Fig.6 below. Two extreme solutions of the obtained Pareto front are tabulated in Table III. Figures 7(a) through 7(d) depict the excitation profiles and the corresponding radiation patterns of the array geometries corresponding to the extreme points in the obtained pareto-front. Figs 7(b) and 7(d) show upper hemisphere patterns only.

Table III denotes that uniformly excited (isophoric) CRHAA design has an SLL value of -16.92 dB and the corresponding D value is 27.56 dB; Set 1 corresponds to an excitation profile for the considered CRHAA geometry has a dynamic range ratio (DRR) of 3 and which results in an SLL value of -25.93 B and the corresponding D value is 26.94 dB; Set 2 corresponds to an excitation profile for the considered CRHAA geometry has a DRR of 1.01 and which results in an SLL value of -16.91 dB and the corresponding D value of 27.59 dB. Fig 7(a) and 7(c) depict the excitation corresponding to Set 1 and Set 2 of Table III; Fig 7(c) and 7(d) depict the array factors respective to the excitation profiles of Set 1 and Set 2, respectively, for the CRHAA geometry considered in this work. This table denotes that with more tapering of currents (large DRR value), the SLL value drops more, but the directivity also drops. This phenomenon is expected and is similar to the common practice of minimizing the contributions of the far-end elements while minimizing the SLL value. Again D is proportional to the squared sum of the current amplitudes [17], hence, gradual decay in the current amplitudes for far-end elements also causes drop of D-value. It is also interesting to note that the directivity of 'set-2' in Table III is higher than that of an uniformly excited array; this may be attributed to the increase in peak SLL and overall sidelobe levels in 'set-2' with respect to the uniformly excited array.

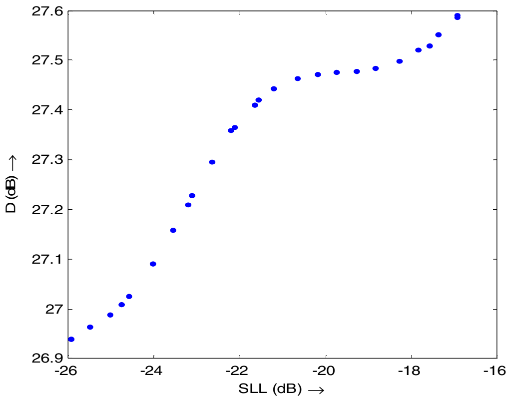
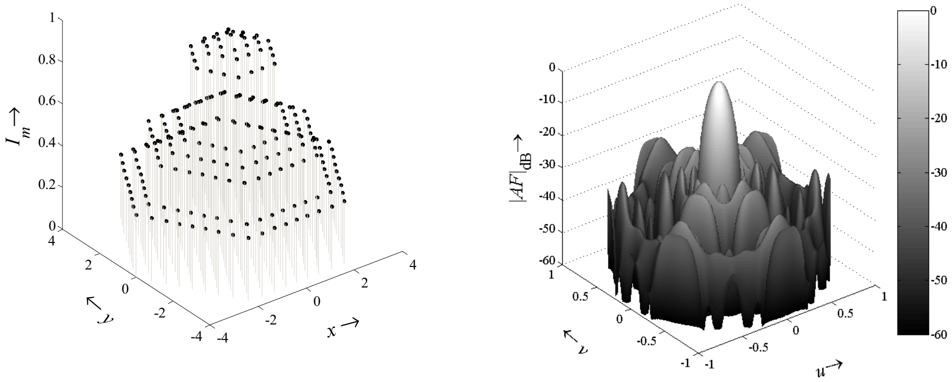


Fig. 6: Obtained pareto front for the pattern optimization problem (1) for eight ring CRHAA design.

The increase in directivity of the mainlobe at the cost of increase in the power of sidelobes is a well-established phenomenon in all forms of antenna arrays including those of uniform spacing and variable amplitudes. It may be further observed that how an inverse amplitude taper is applied, on 'm = 4' of 'set-2' unlike 'set-1', as a resultant of the pareto-optimization process.

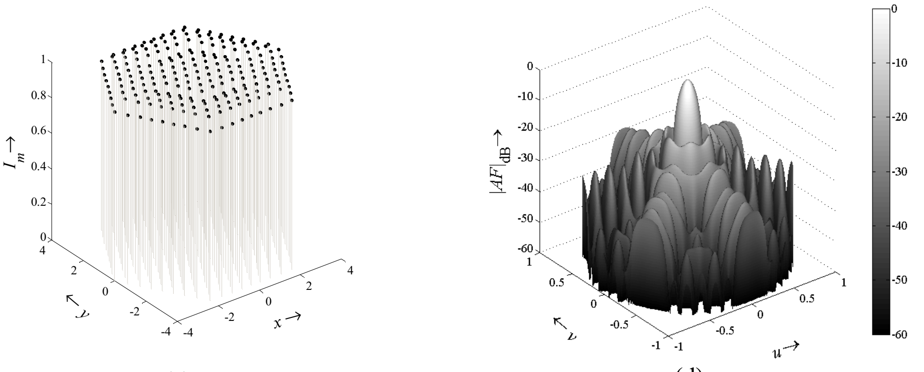
Table III: Current excitation amplitudes and the corresponding pattern parameters for eight-ring CRHAA geometries

	I_0	I_m								Pattern Parameters	
	Centre element	m								SLL	D
		1	2	3	4	5	6	7	8		
Uniform	1	1	1	1	1	1	1	1	1	-16.92	27.56
Set-1 (Lowest *SLL*)	1.00	0.95	0.94	0.89	0.57	0.53	0.49	0.33	0.30	-25.93	26.94
Set-2 (Highest *D*)	1.00	1.00	1.00	1.00	0.98	1.00	1.00	1.00	0.95	-16.91	27.59



(a)

(b)



(c) (d)

Fig. 7. Excitation profile and the corresponding array factor of CRHAA geometries; 7(a) excitation profile of set (1) of Table III; 7(b) array factor corresponding to the current excitations as in 7(a); 7(c) excitation profile of set (2) of Table III; 7(d) array factor corresponding to the current excitations as in 7(c). In this figure $u=\sin\theta cos\phi$ and $v=\sin\theta sin\phi$ where $\theta\in(0,\frac{\pi}{2})$ and $\phi\in(0,2\pi)$.

V. CONCLUSIONS

In this paper the optimal design of non-uniformly excited linear arrays of dipole elements with uniform inter-element spacing has been described using the technique of real coded genetic algorithm. Simulation results reveal that the optimal design of non-uniformly excited linear antenna arrays with optimal inter-element spacing offers a considerable SLL reduction with respect to corresponding time modulated uniform linear arrays with uniform inter-element spacing of $\lambda/2$. For the array sets having 12, 16 and 20 elements, SLLs have reduced corresponding uniform time modulated linear arrays with a very little change in BWFN. The BWFNs of the initial and final radiation pattern remain approximately the same. A bi-objective current-only sidelobe suppression problem for eight ring CRHAA geometries is dealt with. Non-dominated sorting genetic algorithm II (NSGA2) is chosen as the optimizing algorithm. NSGA2 is found to successfully produce a set of well spread trade-off pareto optimal solutions. Future research will be aimed at dealing with other geometries and constraints of many different areas of antenna design and analysis requires a feasible and versatile procedure, being able to perform array synthesis by tuning antenna characteristics and parameters.

REFERENCES

[1] C. A. Ballanis, “Antenna theory analysis and design,” 3rd edition, John Willey and Son's Inc., New York, 2005.

[2] Ramo, Simon, Whinnery, John R., Duzer, Theodore Van, “Fields and Waves in Communication Electronics”, John Wiley & Sons, 3rd Edition, Canada (1994).

[3] Warren Stutzman and Gary Thiele, "Antenna Theory and Design, 2nd. Ed.", 1998, John Wiley and Sons

[4] John D. Krous “Antenna”, Mc GRAW-HILL, Newyork, 1950.

[5] Stephen Jon Blank, Michael F. Hutt, “On the Empirical Optimization of Antenna Arrays” EEE Antennas and Propagation Magazine, 47, 2, April 2005, pp. 58-67

[6] R. L. Haupt, “Phase-only adaptive nulling with a genetic algorithm,” IEEE Trans. Antennas Propagat., vol. 45, no. 6, pp. 1009-1015, Jun. 1997.

[7] R. L. Haupt, and D. H. Werner, “Genetic Algorithms in Electromagnetics,” John Wiley & Sons Inc., 2007.

[8] G. R. Hardel, N. T. Yalapragada, D. Mandal, A. K. Bhattacharjee, “Introducing Dipper Nulls in Time modulated Linear symmetric Antenna Array Using Real Coded Genetic Alorithm,” IEEE Symposium on computers and informatics, pp. 249-254, March, 2011.

[9] K. G uney and a. Akda glı “ null steering of linear antenna arrays using a modified tabu search algorithm, Progress in electromagnetics research, pier33,167–182,2001.

[10] K. Deb, “Multiobjective optimization using evolutionary algorithms”, JohnWiley & Sons, New York, NY, USA, 2001.

[11] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, “A fast and elitist multiobjective genetic algorithm: NSGA-II,” *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002.

[12] Q. Zhang and H. Li, “MOEA/D: A multiobjective evolutionary algorithm based on decomposition”, *IEEE Transactions on Evolutionary Computation*, vol. 11, no. 6, pp. 712–731, 2007.

[13] N. A. Moubayed, A. Petrovski, and J. McCall, “D^{2}MOPSO: multi-objective particle swarm optimizer based on decomposition and dominance”, J.-K. Hao and M. Middendorf (Eds.): *Evolutionary Computation* 2012, Lecture Notes in Computer Science 7245, pp. 75–86, 2012.

[14] K. Li, S. Kwong and K. Deb, “A dual-population paradigm for evolutionary multiobjective optimization”, *Information Sciences*, vol. 309, pp. 50 – 72, 2015.

[15] M. Laumanns, L. Thiele, K. Deb and E. Zitzler, “Combining convergence and diversity in evolutionary multi-objective optimization”, *Evolutionary Computation*, vol. 10, no. 3, pp. 263–282, 2002.

[16] J. D. Knowles and D. W. Corne, “The Pareto Archived Evolution Strategy: A New Baseline Algorithm for Multiobjective Optimisation”, In *1999 Congress on Evolutionary Computation*, pp. 98-105, Washington, D.C., July 1999. IEEE Service Center.

[17] S. Das, D. Mandal, R. Kar and S. P. Ghoshal, “A generalized closed form expression of directivity of arbitrary planar antenna arrays”, *IEEE transactions on Antennas and Propagation*, Vol. 61, no. 7, pp. 3909 – 3911, 2013.

[18] D. E. Goldberg, Genetic Algorithms for Search, optimization, and Machine Learning. Reading, M. A: Addision-Wesley, 1989.

[19] K Deb, R. B. Agrawal, Simulated binary crossover for continuous search space, Complex Systems, vol. 9, 1-34, 2009.

[20] Dong Feng Li and Zhong Lin Gong, “Design of Hexagonal, Planar Arrays Using Genetic Algorithms For Performance Improvement”, In the Proceedings of 2000 2nd Intemational Conference on Microwave and Millimeter Wave Technology, 455-460, 2000.