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Original article

# Synthesis of phase-only position optimized reconfigurable uniformly excited linear antenna arrays with a single null placement

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ABSTRACT

This paper presents a study on the synthesis of a position-phase optimized reconfigurable linear array antenna with uniform amplitude distributions. The objective is to produce a pencil/flat-top beam pair. In this position-phase method, a pencil beam is duly generated with zero degree phases and phases are varied between −180° and 180° to produce a flat-top beam keeping position of the elements and amplitude excitations common to both pencil and flat-top beams. The amplitude distribution of the elements is kept uniform. The phases as well as position of the elements are optimized by Teaching Learning Based Optimization (TLBO), modified Quantum Particle Swarm Optimization (QPSO) and Symbiotic Organisms Search (SOS) algorithms to produce the beam pair. The simulations are done for two Sets of elements and a null placement is included in one of the Sets. The results obtained using these algorithms are duly compared with each other and it is found that SOS algorithm performed in par with TLBO algorithm in the generation of the radiation pattern parameters and better over TLBO and QPSO in statistical values.



## 1. Introduction

Recent applications in wireless communications systems, namely, radar, satellite and cellular mobile systems show the extensive utilization of reconfigurable antenna arrays. The interest shown in the usage of these arrays in turn reveals the necessity of reduced size, cost effectiveness, etc. These arrays are referred to as the group of elements that are capable of generating dual beams using one or two common parameters while differing in the other parameters. These beams/multiple radiation patterns are in fact generated with the help of a single power divider network. The design and implementation of the feeding network is made simpler when only one excitation is different.

Usually, in these arrays, phase is treated as the differing parameter. One beam is generated using zero degree phases for all the elements and the other beam is generated with phases varying between −180° and 180°. However, both the beams share a common amplitude distribution. These amplitude and phase distributions are generated by many methods and algorithms. Few methods are reported here from the literature. Durr et al. (2000) described the design of multiple radiation pattern array using Modified Woodward Lawson method by switching between various phase distributions while maintaining same pre-established amplitude excitations. Gies and Rahmat-samii (2003) successfully synthesized dual pattern antenna array using excitations that are generated directly by Particle Swarm Optimization (PSO) algorithm. Other algorithms/methods that successfully generated the dual patterns are multi-agent Genetic Algorithms (GA) (Baskar et al., 2004), floating point GA (Mahanti et al., 2007a), GA with fixed dynamic range ratio (Mahanti et al., 2007b), forward-backward matrix pencil method (Liu et al., 2010), factorization of pattern synthesis (Buttazzoni & Vescovo, 2012), etc. There are instances where the position (Elkamshoushi & Wagih, 2011; Vaitheeswaran, 2008) of the elements are perturbed in generating these dual beams. Chen et al. (2008) reported the synthesis of unequally spaced arrays using modified Differential Evolution algorithm. There are instances where non-conventional methods (Yang et al., 2017, 2018) are also in use, especially in large arrays. Literature also shows that evolutionary algorithms have shown better performance than other methods because of their popula-

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tion based probabilistic searches with the capability of escaping from local minima.

Many a times, problem of interference affects the radiation pattern. It becomes essential to include a provision for null placement during the design of an array. Even the literature throws a good amount of light on inclusion of null (Shore 1984; Steyskal et al., 1986; Karaboga et al., 2004; Guney & Onay, 2007; Guney & Basbug, 2008) placement parameter during the design of antenna arrays. Majority of the methods used in the past again sought the support of evolutionary algorithms.

In this paper, a linear antenna array is made to generate a flat-top/pencil beam pair. The amplitudes of all the elements are kept to unity. The position of the elements and the phase excitations are generated using evolutionary algorithms. The phase excitation is kept zero for generation of pencil beam and the phase is varied between −180° and 180° to generate the flat-top beam. Both the beams share the common amplitudes as well as positions of the elements. To undergo the above process, TLBO (Rao et al., 2011, 2015, Tsiflikiotis et al., 2017, Murty et al., 2014), modified QPSO (Sun et al., 2004; Patidar et al., 2017) and SOS (Cheng & Prayogo, 2014; Duman, 2017) algorithms are used. The reason for the usage of these algorithms are because of their success in many recent applications (Rao et al., 2015; Tsiflikiotis et al., 2017; Murty et al., 2014; Patidar et al., 2017; Duman, 2017; Muralidharan et al., 2017; Abdullahi and Ngadi, 2016).

The parameters that are used in this paper are Side Lobe Level (SLL), Half Power Beam Width (HPBW) in pencil beam and Ripple (flat-top portion) and SLL in flat-top beam in Set 1. In Set 2, the same parameters are used as in Set 1 along with the inclusion of a single null in pencil beam. The desired values for all the parameters are shown in Tables 1 and 2.

## 2. Theory

A linear array comprising of 2*N* isotropic antenna elements shown in Fig. 1 is taken into consideration. It is duly made up of variable phase and distance shifters. The far field pattern *FP* generated using these elements is given using the following equation.

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

where $c_m$ and $p_m$ refers to the amplitude and phase excitations of the $m^{th}$ element respectively, $d_m$ is the distance between the position of the $m^{th}$ element and the array center. $\theta$ refers to the angle measured from broadside and $\lambda$ is the wavelength and is assumed unity here. The normalized absolute power pattern (Elliott, 1981) is given by

$$\text{Normalized absolute power pattern} = \frac{|FP(\theta)|}{|FP(\theta)|_{max}} \quad (2)$$

The cost function that is minimized in this problem in Set 1 is given by

$$CF = \sum_{i=1}^{2} w_i (CF_i)^2 + \sum_{j=1}^{2} w_j (CF_j)^2 \quad (3)$$

The first term in the RHS of the above equation deals with the pencil beam and is written as below:

$$CF_i = \begin{cases} C_i^p - C_{i,d}^p, & if \quad C_i^p > C_{i,d}^p \\ 0, & if \quad C_i^p \le C_{i,d}^p \end{cases} \quad (4)$$

where $i = 1$ and 2 refers to the parameters, namely, SLL in dB and HPBW in degrees.

The second term in the RHS of Eq. (3) is for the flat-top pattern and is written as below:

$$CF_j = \begin{cases} C_j^f - C_{j,d}^f, & if \quad C_j^f > C_{j,d}^f \\ 0, & if \quad C_j^f \le C_{j,d}^f \end{cases} \quad (5)$$

where $j = 1$ and 2 refers to the parameters, namely, SLL in dB and the ripple in the flat-top/sector pattern ($-12^\circ \le \theta \le 12^\circ$) in dB.

The terms $C_{id}$ and $C_{jd}$ represents the expected/desired values and $C_i$ and $C_j$ represents the obtained values for each parameter given in the above equations for cost functions. The superscript *p* and *f* denotes the pencil and flat-top beam pattern parameters. The weights $w_i$ and $w_j$ are substituted with unity for all the values of *i* and *j*. For Set 2, an additional parameter null is added along with pencil beam parameters in Set 1. The desired values of all the parameters that are used in the cost function are given in Tables 1 and 2.

## 3. Teaching learning based algorithm

TLBO algorithm (Rao et al., 2011, 2015) is based on the effect of the teacher on the performance of the learners in a class. The output performance is treated in terms of results/grades. The learner's outcome is always influenced by the quality of the teacher. A good teacher will usually assist in betterness of the results or grades of the learners. The overall process of this algorithm is divided into two phases, namely the teacher phase referring to the learning from the teacher and the other phase, namely, the learner phase referring to learning from the learners.

In the teacher phase, at any iteration *m*, let $M_m$ be the mean of the marks of all the students and $T_m$ refers to the teacher. This teacher will move the mean towards its own level, and hence the updated mean will be $M_u$. The output is correspondingly updated as follows:

$$Diff\_M_m = ran_m \ (M_u - TF * M_m) \quad (6)$$

where *ran* refers to a random number lying between 0 and 1, *TF* is the teaching factor which decides to change the mean and its value can lie between 1 and 2. This $Diff\_M_m$ changes the solution according to the following equation

$$x_{new,m} = x_{old,m} + Diff\_M_m \quad (7)$$

**Table 1**
Simulated results for Pencil beam and flat-top beam radiation patterns (Set 1).

| Patterns | Parameters | Desired Values | Obtained values | | |
|---|---|---|---|---|---|
| | | | TLBO | QPSO | SOS |
| Pencil beam | SLL in dB | −20 dB | −20.0936 | −19.9232 | −20.0214 |
| | HPBW | 6° | 6° | 6° | 6° |
| | Directivity in dB | – | 10.872 | 10.807 | 10.999 |
| Flat-top beam | SLL in dB | − 20 dB | −20.0372 | −19.9219 | −20.0281 |
| | Ripple in dB ($-12^\circ \le \theta \le 12^\circ$) | 1 dB | 0.99293 | 1.382 | 0.99133 |
| Fitness values | | | 0 | 0.1579 | 0 |
| Processing time in seconds | | | 1916 | 1005 | 351 |

**Table 2**
Simulated results for Pencil beam and flat-top beam radiation pattern (Set 2).

| Patterns | Parameters | Desired Values | Obtained values | | |
|---|---|---|---|---|---|
| | | | TLBO | QPSO | SOS |
| Pencil beam | SLL in dB | −20 dB | −20.2631 | −19.9643 | −20.4489 |
| | HPBW | 6° | 6° | 6° | 6° |
| | Null in dB ($\theta = -65°$) | −50 dB | −51.0187 | −50.9052 | −55.3485 |
| | Directivity in dB | – | 10.917 | 10.936 | 10.938 |
| Flat-top beam | SLL in dB | −20 dB | −20.1292 | −19.9872 | −20.0263 |
| | Ripple in dB ($-12° \le \theta \le 12°$) | 1 dB | 0.98711 | 1.0998 | 0.98556 |
| Fitness values | | | 0 | 0.0114 | 0 |
| Processing time in seconds | | | 7841 | 4084 | 2158 |

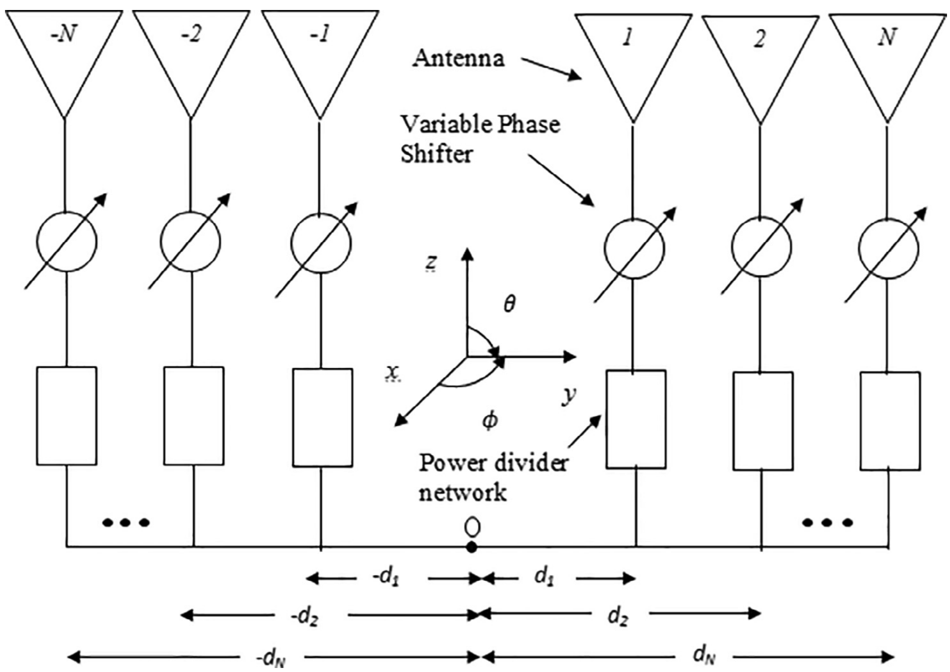


**Fig. 1.** A pencil/flat-top beam reconfigurable linear antenna array.

In the second phase, namely, the learner phase, the learner learns from the others in a random manner with the support of various forms of communications and he also learns more if he receives more knowledge from the others than the one from himself. The modification in the learner is given by the following Set of equations. If $P_n$ is the population size and $f$ is the objective function,

$form = 1 : P_n$

Two learners $x_a$ and $x_b$, where $a \neq b$ are selected randomly

$if\ f\ (x_a) < f(x_b)$

$$x_{new,m} = x_{old,m} + ran_m(x_a - x_b) \tag{8}$$

*else*

$$x_{new,m} = x_{old,m} + ran_m(x_b - x_a) \tag{9}$$

*endif*

*endfor*

Accept $x_{new}$ if it gives a better value.

The overall process of this algorithm is given in the following pseudo steps.

*Step 1*: The problem and its associated parameters are specified along with initialization of the population size, iterations, variables number and the limits of the values of the variables. The population size refers to the group of learners and is 130 for Set 1 and 520 for Set 2.
*Step 2*: The population is initialized randomly. The variables refers to the design variables used in the fitness functions.
*Step 3*: In the teacher phase, the best solution (13 element phase excitations and 13 elements positions) will act as a teacher for that particular iteration. The teacher will try to move the mean from the currently obtained mean towards the best solution, which from now onwards will act as the new mean.
The current solution is updated based on the equation (7). Treat the current solution as the best solution if the fitness values is better than the previous one.
*Step 4*: In the Learner phase, Learners improve their knowledge with the support of their neighbouring learners. Eqs. (8) and (9) holds for this phase.

Stop when the number of maximum iterations is reached, otherwise start from *Step 3*.

The terms *ran* and *TF* affect this algorithm's performance. However, they are not explicitly given or initialized in the simulations and in fact, they are generated randomly in the algorithm itself. Thus this algorithm is easier when compared to many of the algorithms in the past because of its zero requirement of any tuning parameter.

## 4. Modified Quantum Particle Swarm Optimization

QPSO (Sun et al., 2004), a version of PSO utilizes quantum mechanics principles to govern the movement of the particles. Here the particle's state is represented by a wave function instead of the positions and velocities as in PSO. Moreover, the dynamic nature of the particle is highly divergent than that of traditional PSO. Comparing the parameters used in this algorithm (Sun, et al., 2004), there are modifications done in this paper which is shown in the following steps.

*Step* 1: The population (130 for Set 1 and 520 for Set 2) is initialized randomly and the personal best *pb* as well as the global best *gb* values (13 element phase excitations and 13 elements positions) along with the maximum number of iterations are also initialized. *D* is the number of variables and *ps* is the population size.
*Step* 2: Evaluate the fitness values of all the particles.
Step 3: If the current one is better than the *pb*, then the *pb* value is replaced with the current obtained value. This value is designed as the *pb*.
*Step* 4: The above procedure is followed for the overall population and the best fitness value obtained after comparison is chosen as the *gb*.
*Step* 5: The overall mean best of all the particles is obtained using

$$mbest = \frac{1}{ps}\sum_{i=1}^{ps}(\beta * pb + (1-\beta)gb) \tag{10}$$

where $\beta = rand(ps, D)$. To quote the modifications done in this algorithm, the *mbest* here now includes both the terms *pb* and *gb* along with a random factor $\beta$.

*Step* 6: The particle's vector local focus (for the $w^{th}$ dimension of the $i^{th}$ particle) in the $k^{th}$ generation is obtained using

$$x_{iw}^{k} = (ran1_{iw}^{k} * pb_{iw} + ran2_{iw}^{k} * gb_{iw})/(ran1_{iw}^{k} + ran2_{iw}^{k}) \tag{11}$$

*Step* 7: Considering $u = rand(1, D)$ and

$$\propto = (\propto_{max} - \propto_{min}) * \frac{me-i}{me-1} + \propto_{min}$$

where $\propto$ is the contraction and expansion coefficient for controlling the convergence speed. The positions of the $i^{th}$ particle is given by

$$X_{iw}^{k} = x_{iw}^{k} + (-1)^{ceil\left(0.5+ran3_{iw}^{k}\right)*\propto*\log\left(\frac{1}{u}\right)*abs\left(mb-X_{iw}^{k}\right)} \tag{12}$$

$$If\ X_{iw}^{k} < X_{mn}^{k},\ then$$

$$X_{iw}^{k} = rand\left(X_{mn}^{k} - X_{mn}^{k}\right) + X_{mn}^{k} \tag{13}$$

$$If\ X_{iw}^{k} > X_{mn}^{k},\ then$$

$$X_{iw}^{k} = rand\left(X_{mn}^{k} - X_{mn}^{k}\right) + X_{mn}^{k} \tag{14}$$

In this paper, the values of $\propto_{min} = 0.4$ and $\propto_{max} = 0.7$ are used and $ran1, ran2, ran3$ are random numbers that are equal to $rand(1, D)$. The Eqs. (13) and (14) are used to stop the particles from exploding when they by chance move out of the required limits used. Stop the process when the maximum number of iterations are reached or repeat from *Step* 2 again till the maximum number of iterations are over.

## 5. Symbiotic organisms search algorithm

SOS algorithm (Cheng & Prayogo, 2014) depends on the nature of the organisms relying on one another for their existence. It is also described as a relationship between any two distinct species. Usually, the relationships found are *mutualism* between the two organisms in which both mutually benefit, *commensalism* in which one organism gets benefited and the other one unaffected and finally *parasitism*, in which one gets benefited and the other gets harmed.

This algorithm begins with a randomly generated initial population referring to as ecosystem (130 for Set 1 and 520 for Set 2). Each organism (13 element phase excitations and 13 elements positions) with a fitness value is treated as a candidate solution to the problem chosen. This is followed by the mutualism phase which is described as follows.

An organism $X_m$ is matched to another organism $X_n$ in an ecosystem. New candidate solutions for both these organisms are calculated depending on the following equations.

$$X_{nnew} = X_n + rand(0,1) * (X_{best} - M_V * B1) \tag{15}$$

$$X_{mnew} = X_m + rand(0,1) * (X_{best} - M_V * B2) \tag{16}$$

and $M_V = (X_n + X_m)/2$ is the Mutual vector, *rand* refers to a Set of random numbers and *B*1 and *B*2 refers to the benefit factors. The mutual vector is used to increase the survival of the organisms. The organisms are checked for fitness values and their values are updated only, if they are better than the values with which they started this phase.

Similar to the above phase is the commensalism phase, but the difference being $X_n$ attempts to benefit whereas $X_m$ gets unaffected from the interaction between these two organisms. The following equation is used during the interaction process.

$$X_{nnew} = X_n + rand(-1,1) * (X_{best} - X_m) \tag{17}$$

This phase is followed by the parasitism phase, in which an artificial parasite called a Parasite Vector is created by duplicating $X_n$ and modifying the randomly selected dimensions. Now, this Parasite Vector as well as $X_n$ are evaluated to measure their fitness values. The one with the better fitness value will stay further. This algorithm is stopped when the maximum number of iterations is reached.

## 6. Simulation results

To undergo the complete process involved in generation of radiation patterns, the following process is adapted for simulation purposes. Simulations are done using Matlab software.

Here, 26 elements are chosen for consideration with even symmetry option in Set 1. Therefore, it requires only 13 element phase excitations and 13 elements positions which can be flipped and substituted for remaining 13 elements. The phases are varied between $-180°$ and $180°$ and the position of the elements are varied between $0.25\lambda$ and $0.65\lambda$. Moreover, amplitude distribution used here is a uniform one with the value equal to unity. The population size is 130. All the TLBO, modified QPSO and SOS algorithms are used here to provide the necessary excitations and positions.

To investigate the performance of these algorithms with a different population size, Set 2 is considered. Here, an additional parameter, null ($\theta = -65°$) is taken along with other parameters in pencil beam as in Set 1. 26 elements are taken into consideration with a population size of 520 and the above procedure is again adopted here and the positions of the elements are varied between $0.20\lambda$ and $0.70\lambda$. This range chosen is different from the Set 1 in order to reduce the extra burden that the algorithms may encounter while dealing with an additional null placement parameter.

Number of iterations used is 2000 with a total of 10 runs for all the algorithms for both the Sets 1 and 2. This is to make sure that the initial random generation population does not affect the final result. Simulations are done using Matlab software and are run on Intel Core 2 Duo CPU 3 GHz processor and 4 GB RAM in the windows 7 operating system. Figs. 2 and 3 show the dual beam patterns for Set 1 and 2.

### 6.1. Analysis for Set 1

Table 1 shows the values of the parameters obtained using both the algorithms. The values obtained show that the TLBO and SOS algorithm have produced successfully all the parameter values within the desired limits. However, the same is not the case with the modified QPSO, which failed to produce the expected values except the half power beam width. This is sufficient to conclude that TLBO and SOS have performed better than modified QPSO. Fitness values also prove the same. The fitness value of TLBO and SOS is 0, which is well required and again better when compared with the fitness value of QPSO shown in the Table. Again to quote, necessary care is taken here to run these algorithms 10 number of runs in order to avoid any sort of influence the initial seeds produce on the fitness values. Moreover, these algorithms are able to produce the required outputs with the population size just five times the number of variables used.

However, a look at the Table 1 shows that SOS has excelled better than all the others in terms of the time taken. It took just 351 s and this time is very less compared to the time taken by the other algorithms and this is sufficient enough to prove that SOS has excelled itself over the remaining algorithms in overall performance. In addition to the parameters discussed in the fitness functions, directivity is also calculated for the pencil beam. Here also, SOS succeeded in producing the best value.

### 6.2. Analysis for Set 2

The results for the Set 2 are available in Table 2. A similar analysis is done on the simulation results obtained using Set 2 which includes a null parameter in addition to other parameters which are used in Set 1. Here also, TLBO and SOS algorithms have successfully produced all the values of the parameters well within the desired value limits. In addition to the parameters discussed in the fitness functions, directivity is also calculated for the pencil beam. Here, SOS succeeded in producing the best value. Again, the fitness value obtained using TLBO and SOS is 0 which is superior when compared with the value produced by modified QPSO. Similar to Set 1, a look at the Table 2 shows that the time taken by SOS is 2158 s, which is very less when compared to the time taken by the remaining algorithms. Here also, SOS excels over the algorithms. Because of its success, the values of the positions and the phases generated by this algorithm that helped in generating these output results for both Sets 1 and 2 are shown in Table 3. The performance of this algorithm is quite similar to the Set 1 and it is able to produce the expected output with different size of the population also.

As both TLBO and SOS algorithms have successfully produced the expected results, the comparison is now done on the statistical parameters. Table 4 shows the statistical parameters for the best run and Table 5 shows the statistical details of 10 individual runs for all the three algorithms.

Fig. 4 shows the plot drawn between fitness values and number of iterations. It is evident from the Fig. 4 that TLBO and SOS have produced 0 fitness values for the generations of radiation patterns using both the Sets 1 and 2. It is also found that the convergence speed of the SOS algorithm is better than that of the other algorithms. Table 4 shows that the mean of the fitness values produced in the best run by SOS is better than the one produced by the TLBO

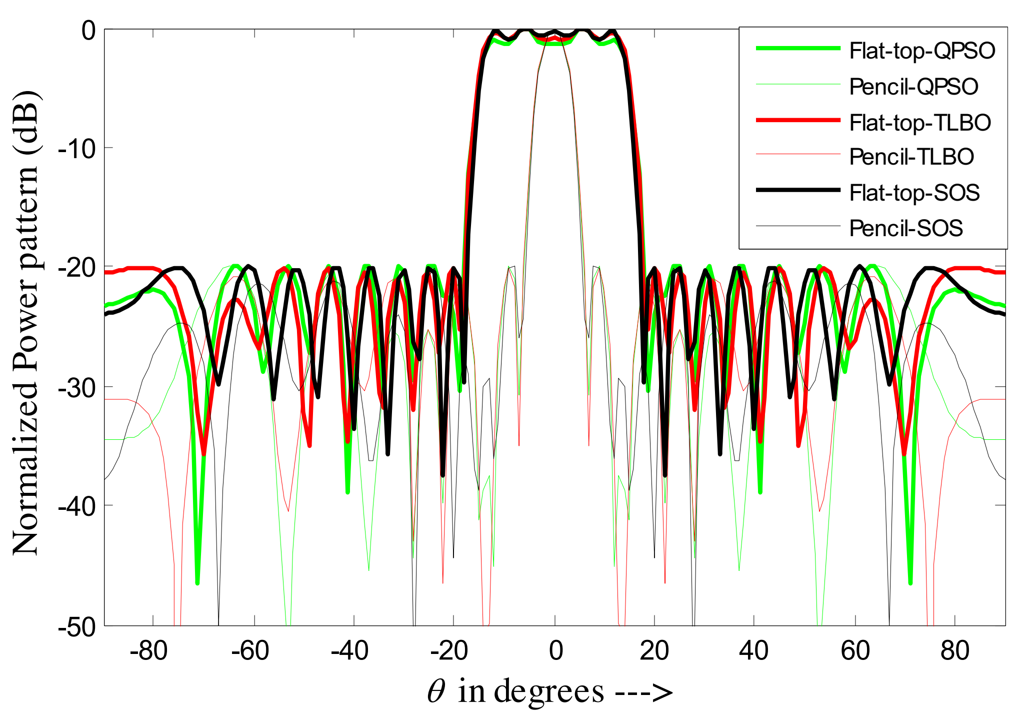


**Fig. 2.** Dual beam radiation pattern for Set 1.

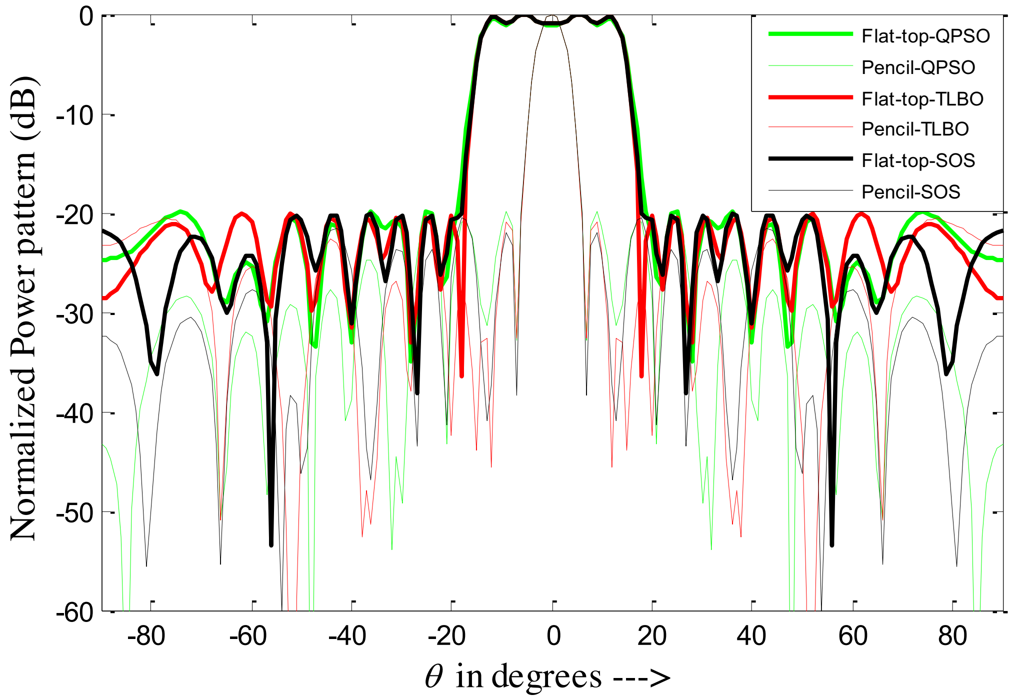


**Fig. 3.** Dual beam radiation pattern for Set 2.

**Table 3**
Position and phase distributions obtained using SOS algorithm.

| Element Numbers | Set 1 | | Set 2 | |
|---|---|---|---|---|
| | Positions in $\lambda$ | Phases | Positions in $\lambda$ | Phases |
| ± 1 | ±0.2500 | −169.8912° | ±0.2490 | 87.9822° |
| ±2 | ±0.5013 | −54.1008° | ±0.5197 | 62.1234° |
| ±3 | ±0.7519 | −179.2458° | ±0.8559 | 178.6482° |
| ±4 | ±1.1354 | −81.6372° | ±1.1041 | 81.4050° |
| ±5 | ±1.4926 | −73.4940° | ±1.4765 | 171.8388° |
| ±6 | ±1.9397 | −61.9272° | ±1.7460 | 174.3642° |
| ±7 | ±2.1907 | −51.7302° | ±2.1425 | 167.6340° |
| ±8 | ±2.5186 | −36.3312° | ±2.3425 | −159.8634° |
| ±9 | ±2.9154 | −37.3338° | ±2.7396 | −170.7822° |
| ±10 | ±3.2764 | −0.0965° | ±3.1475 | −145.3410° |
| ±11 | ±3.8756 | 30.3750° | ±3.7244 | −103.9752° |
| ±12 | ±4.4625 | 68.7456° | ±4.4244 | −56.0826° |
| ±13 | ±5.1125 | 92.8620° | ±5.1234 | −40.8906° |

**Table 4**
Statistical parameters.

| Parameters for the best run | TLBO | QPSO | SOS |
|---|---|---|---|
| *Set 1* | | | |
| Fitness value | 0 | 0.1579 | 0 |
| Mean | 6.794 | 2.108 | 1.284 |
| Standard deviation | 25.35 | 15.48 | 12.73 |
| Median | 0.0253 | 0.1579 | 0 |
| Max fitness value | 371.5 | 272.2 | 289.5 |
| *Set 2* | | | |
| Fitness value | 0 | 0.01138 | 0 |
| Mean | 14.95 | 3.237 | 14.56 |
| Standard deviation | 40.59 | 23.32 | 48.5 |
| Median | 0.03865 | 0.01466 | 0 |
| Max fitness value | 422.9 | 460.1 | 377 |

algorithm for both the sets. Even the other statistical parameters also are in favour of the same.

As 10 runs are done for the algorithms to produce the results to avoid any influence on the initial random values chosen by the algorithms, Table 5 details presents the following details regarding their statistical values. Here also, the mean fitness value and other values are in favour of the SOS algorithm. The worst fitness value for TLBO algorithm in Set 2 is very close to the one produced by SOS algorithm. Overall, it is concluded that SOS showed its supremacy over the other algorithms in the statistical parameters and it is in par with TLBO algorithm in producing the expected radiation pattern parameter results.

**Table 5**
Statistical Details of 10 individual runs for all the three algorithms.

| Parameters for the 10 runs | TLBO | QPSO | SOS |
|---|---|---|---|
| *Set 1* | | | |
| Worst fitness value | 33.2051 | 49.3623 | 19.9097 |
| Best Fitness value | 0 | 0.1579 | 0 |
| Mean of the fitness values of 10 runs | 12.5965 | 16.4831 | 5.4665 |
| *Set 2* | | | |
| Worst fitness value | 1.4242 | 35.0938 | 1.5763 |
| Best Fitness value | 0 | 0.01138 | 0 |
| Mean of the fitness values of 10 runs | 0.3745 | 13.4622 | 0.3201 |

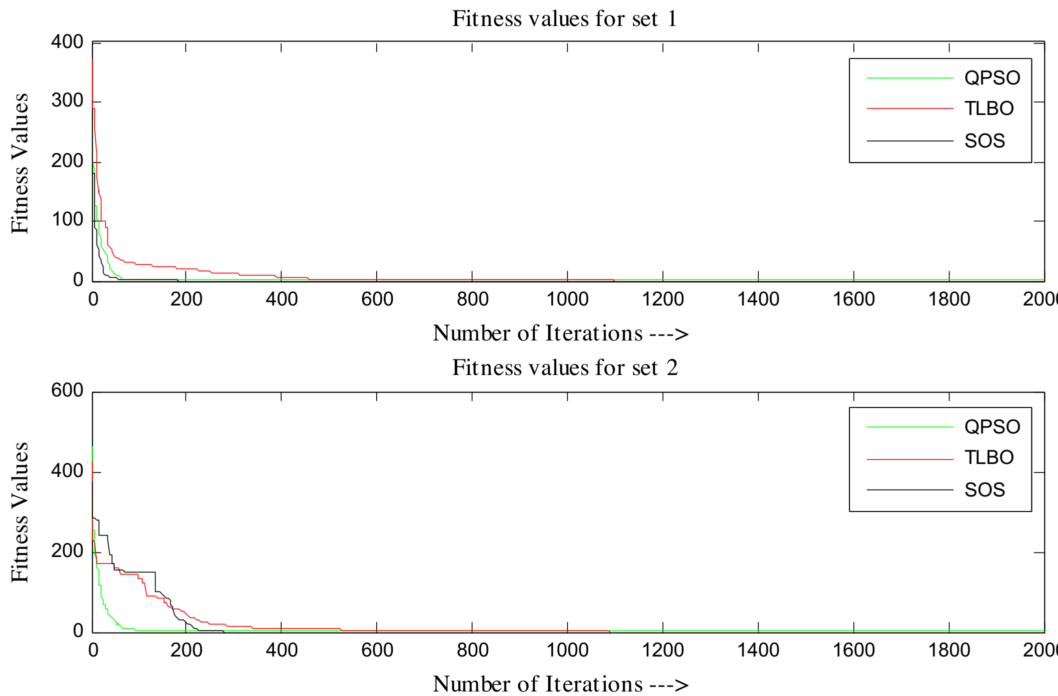


**Fig. 4.** Fitness values versus Number of Iterations for Set 1 and 2.

## 7. Conclusions

This paper presented a design of reconfigurable flat-top/pencil dual beam patterns in uniform linear antenna array. The amplitude distributions and element positions of the antenna elements are kept constant for both the beams. Phase excitations are kept to zero for the pencil beam and they are varied between −180° and 180° for the generation of flat-top beam. TLBO, modified QPSO and SOS algorithms were successfully used for generating the element positions and phase excitations. These algorithms competed with each other in bringing various parameters like side lobe level, ripple value, half power beam width as well as null placement well within the expected value. Both TLBO and SOS algorithms were successful in producing the radiation pattern parameters, and in terms of the statistical parameters, SOS proved to be better than TLBO algorithm. This work can be extended to include other parameters, namely, multiple nulls, more independent nulls, etc., and also to other geometries of antenna arrays.

## Conflict of interest statement

The authors declare that there is no conflict of interest between them and others.

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