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Modified and Hybrid Cuckoo Search Algorithms via Weighted–Sum Multiobjective Optimization for Symmetric Linear Array Geometry Synthesis

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Abstract: This study proposes the modified and hybrid cuckoo search algorithms deploying the weighted–sum multiobjective optimization approach in synthesizing symmetric linear array geometry with high directivity, low average side lobe level (SLL), a small half–power beamwidth (HPBW), and/or significant predefined nulls mitigation. The weighted–sum approach optimizes three objective functions simultaneously until the maximum number of iteration achieved. Precisely, the modified cuckoo search (MCS) algorithm is introduced through the integration with the Roulette wheel selection operator, the adaptive inertia weight controlling the positions (solutions) exploration, and the dynamic discovery rate of solutions. Besides, there are also the proposals of hybrid MCS with two popular evolutionary algorithms, which are the particle swarm optimization (PSO) known as MCSPSO and the genetic algorithm (GA) referred as MCSGA. All the modified and hybrid cuckoo search–based multiobjective algorithms go through the weighted–sum approach to generate three optimal decision variables, which are array element excitation locations, amplitudes, and phases, respectively. The optimal solutions obtained through various MATLAB simulations are then compared against corresponding counterparts.

Keywords: Modified Cuckoo Search Algorithm, Particle Swarm Optimization, Genetic Algorithm, Weighted–Sum Multiobjective Optimization, Side Lobe Level Suppression, Half–Power Beamwidth, and Nulls Control.

I. INTRODUCTION

Many studies have been conducted to design and develop an antenna through forming an assembly of radiating elements in electrical and geometrical configuration known as an array. The array is useful in detecting and processing signals arriving from different directions of arrival [1]. Hence, the main aim of performing array geometry synthesis is to determine the physical layout of the array, which can generate a radiation pattern closest to the desired pattern. Precisely, the array pattern should possess high power gain, lower side lobe level (SLL), controllable beam width [2] and good azimuthal symmetry. This can be achieved by determining optimal element locations (with respect to the λ/2 inter-element spacing), excitation current amplitudes and excitation current phases (with a random distribution) applied on the array elements, respectively [3]. Due to their high versatility, flexibility and capability to optimize complex multidimensional problem, modern stochastic algorithm techniques such as genetic algorithm (GA) [4], and particle swarm optimization (PSO) [5], have been applied for antenna array optimization. These evolutionary algorithm (EA) techniques provide better results relatively than the original gradient methods.

II. SYSTEM DESCRIPTION

A. *Modified Cuckoo Search Metaheuristic Algorithm*

Cuckoo search (CS) is inspired by the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds (of other species) [6]. Some host birds can engage direct conflict with the intruding cuckoos. For example, if a host bird discovers the eggs are not their own, it will either throw these alien eggs away or simply abandon its nest and build a new nest elsewhere. In this study, the postulated MCSPSO, MCSGA, and MCS algorithms use the dynamic discovery rate, P_a, and the inertia weight, w. The process of generating new solutions $x^{(t+1)}$ for a cuckoo i, where the Lévy flight integrated with adaptive weight, w can be reinstated as [7]:

$$x_i^{t+1} = w.x_i^t + \alpha \oplus \text{Lévy}(\lambda) \quad (1)$$

where $\alpha > 0$ is the step size related to the scales of the problem of interest while the product $\oplus$ means entry−wise multiplications. The larger w leads to the greater control of exploration or exploitation of host nest positions (solutions) and vice versa. Based on (2), the w is linearly decreased from a relatively large value to a small value through the

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course so that all the proposed MCS−based algorithms have a better performance compared to the fixed w settings.

$$w = w_{max} - [(w_{max} - w_{min}) \times \text{iter}]/\text{maxIter} \quad (2)$$

where w_{max} is the maximum weight and w_{min} is the minimum weight, respectively. Besides, we also apply the dynamic fraction probability, P_a:

$$P_a = P_{a_{max}} - [(P_{a_{max}} - P_{a_{min}}) \times \text{iter}]/\text{maxIter} \quad (3)$$

where $P_{a_{max}}$ is the maximum discovery rate, and $P_{a_{min}}$ is the minimum discovery rate, respectively.

B. Weighted–Sum Approach

In the weighted–sum approach, the authors propose the hybridization of the MCS with particle swarm optimization (MCSPSO) and the MCS with genetic algorithms (MCSGA). These algorithms are directly compared with other stochastic rivals, e.g. hybrid GAPSO, modified CS (MCS), and original CS algorithms, respectively. Technically speaking, the weighted aggregation–based objective function is defined as:

$$Fitness(\text{iter}) = \frac{f_1}{\text{mean }(f_1(\text{iter}=1))} + \frac{f_2}{\text{mean }(f_2(\text{iter}=1))} + \frac{f_3}{\text{mean }(f_3(\text{iter}=1))} \quad (4)$$

For simplicity, it is assumed that the weight given for all objectives f_1, f_2, and f_3 equal to 1.0. The weighted–sum fitness in (8) is normalized through dividing fitness's f_1, f_2, and f_3 in each cycle with their respective mean values of the first iteration primarily to reduce the possible bias caused by differences in terms of magnitude or value for each objective. The resulting optimal location, amplitude, and phase vectors taken from the global minimum value of (4) are declared to be the optimal solutions. Precisely,

$$f_1 = \min\{1/\text{directivity}\} \quad (5)$$

Mathematically, the directivity in terms of beam solid angle can be defined as:

$$D(\theta,\varphi) = \frac{U(\theta,\varphi)}{U_{avg}} = 4\pi\frac{U(\theta,\varphi)}{P_{rad}} \quad (6)$$

where $U(\theta,\varphi) = B_o F(\theta,\varphi)$ is the antenna radiation intensity, and U_{avg} is radiation intensity averaged over all directions. In this study, the directivity is measured in decibel (dB) unit through a formula:

$$D_{dB}(\theta,\varphi) = 10\log_{10} D(\theta,\varphi) \quad (7)$$

On the other hand, f_2 is expressed as:

$$f_2 = \min\left\{\sum_i \frac{1}{\Delta\emptyset_i}\int_{\emptyset_{li}}^{\emptyset_{ui}} |AF(\emptyset)|^2 d\emptyset + \sum_k |AF(\emptyset_k)|^2\right\} \quad (8)$$

The first−term on the right−hand side of the fitness function in (8) focuses on average side lobe level (SLL) suppression whereas the second−term on the right−hand side is used for prescribed nulls control.

Moreover, the fitness, f_3 is stated as below:

$$f_3 = \min\{1 - \text{dynamic range ratio}\} \quad (9)$$

where the dynamic range ratio (DRR) is defined as:

$$\text{DRR} = |\text{max excitation amplitude}/\text{min excitation amplitude}| \quad (10)$$

In this experiment, we assume the $2N$−isotropic radiators are placed symmetrically along the x-axis as below

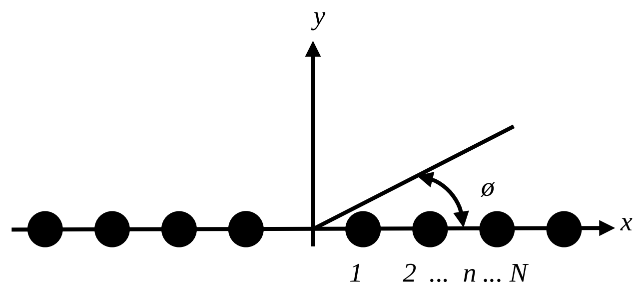

Fig. 1. Geometry of the 2*N*-element symmetric linear array

Theoretically, the array factor (*AF*) for the azimuth plane in Fig. 1 is defined as [1]:

$$AF(\phi) = 2\sum_{n=1}^{N} I_n cos[kx_n cos(\phi + \varphi_n)] \quad (11)$$

where $k = 2\pi/\lambda$ was the wave number plus $I_n, \varphi_n,$ and x_n were the excitation amplitude, phase, and location of the n−th element, respectively. Based on (10), the MCS multiobjective algorithm was postulated to find the optimal $I_n, \varphi_n,$ and x_n values of the symmetric linear antenna array elements with minimum peak and average SLL and/or nulls control. The following is the postulated pseudo–code of MCSPSO hybrid algorithm, which is deployed in this experiment:

```
begin
Let iter denote the iteration number of MCSPSO.
iter ← 1;
Initialize population of host nests with size n at iter=1;
for each iteration
Operate the Roulette wheel selection to obtain the "fittest" host nests with size n;
Generate a new set of solutions (host nests) but keep the Current best (say, i) randomly by Lévy flights incorporating with inertia weight, w, which controls the search ability according to (1);
Evaluate new solution fitness, Fi according to (4);
Get a selected set of host nests among n (say, j) and calculate its fitness, Fj according to (4);
if (Fi< Fj) % fitness minimization%
Replace j by the new set of solutions, i;
end
A dynamic fraction probability, Pa of worse nests is abandoned and a new nest (set of solution) is built;
Keep the best nests with quality solutions;
Let the best nests become as initial particles;
for each particle
Calculate fitness value according to (4);
```

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```
if the fitness value is better than the best fitness value (pbest) in history
Set current value as the new pbest;
   end
end
Choose the particle with the best fitness value of all the particles as the gbest;
for each particle
Calculate particle velocity;
Update particle position according equation;
end
Evaluate the updated current fitness value according to (4);
if the new current fitness value is better than the fitness of pbest;
Set current value as the new pbest;
end
if the new current fitness value is better than the fitness of gbest
Set current value as the new gbest;
end
Keep the best particles with quality solutions;
Rank the solutions and find the current best particle;
end
Post-process results and visualization;
end
```

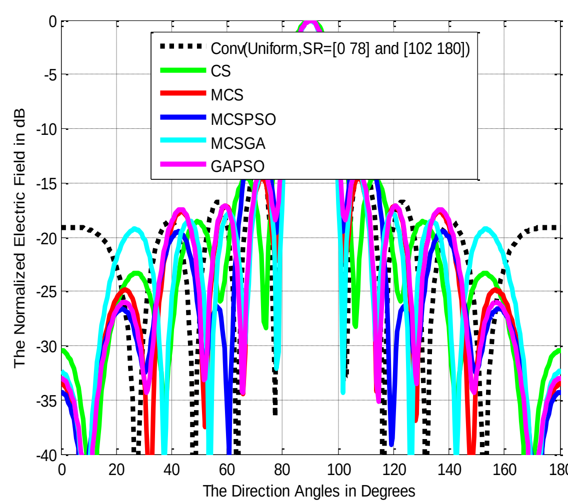
On the other hand, the following is the proposed pseudo–code for the MCSGA hybrid algorithm, which is developed and validated in this study:

```
begin
Let gen denote the generation number of MCSGA.
gen ← 1;
Initialize population of host nests with size n at gen=1;
for each generation
Operate the Roulette wheel selection to obtain the "fittest" host nests with size n;
Generate a new set of solutions (host nests) but keep the current best (say, i) randomly by Lévy flights incorporating with inertia weight, w, which controls the search ability according to (1);
Evaluate new solution fitness, Fi according to (4);
Get a selected set of host nests among n (say, j) and calculate its fitness, Fj according to (4);
if (Fi < Fj) % fitness minimization%
Replace j by the new set of solutions, i;
end
A dynamic fraction probability, Pa of worse nests is abandoned and a new nest (set of solution) is built;
Keep the best nests with quality solutions;
Let the best nests become as initial chromosomes;
Evaluate each individual's fitness according to (4);
Select pairs to mate from best-ranked individuals;
Mate pairs at random;
Apply crossover operator;
Apply mutation operator;
for each chromosome
        Calculate new fitness value according to (4);
if the new fitness value is better than the best fitness value in history
Set current value as the new best chromosomes;
   end
end
Keep the best chromosomes with quality solutions;
Rank the solutions and find the current best chromosome;
end
Post-process results and visualization;
end
```

III. Simulation Results

In the first weighted–sum multiobjective simulation, the postulated MCSPSO, MCSGA, and MCS algorithms with Mantegna's algorithm as the selected α–stable distribution method, host nest (population) = 30, length step factor = $L/100$ or 0.01, and α = 2.0 (Lévy flight Gaussian distribution) are examined on the $2N = 10$ linear array. For uniformity, all the proposed MCSPSO, MCSGA, and MCS algorithms have the dynamic P_a magnitude domain of [0.01 0.25] and dynamic w magnitude domain of [0.95 1.05], respectively. The proposed algorithms are deliberately compared with hybrid GAPSO, and original CS algorithm. Precisely, both the MCSPSO and GAPSO optimizers use the PSO algorithm with the dynamic random particle velocity domain of [–0.1 +0.1]. Moreover, the MCSGA and GAPSO algorithms apply the GA optimizer with the gene crossover probability, P_c = 90% or 0.9, and gene mutation probability, P_m = 10% or 0.1.

According to Fig. 2(a), the normalized radiation pattern for the postulated MCSPSO optimizer outperforms other competitors by having the lowest average SLL suppression and whereas the MCSGA counterpart has the highest intensity or the smallest half–power beamwidth (HPBW) of the main beam. Precisely, the MCSPSO algorithm suppresses SLL between –0.97 dB and –15.20 dB compared to the conventional array within the [120^o 180^o] and [0^o 60^o] regions as can be seen in Fig. 2(b). The HPBW is the angular separation in which the magnitude of the radiation pattern decreases by 50% (or –3 dB) from the peak of the main beam. Fig. 2(c) shows the pattern for MCSGA optimizer has the smallest HPBW, which decreases to –3 dB at 84.825^o and 95.175^o. Hence, the calculated HPBW is 95.175^o – 84.825^o = 10.35^o. Furthermore, the postulated MCSGA array generates a high directivity of 8.4474 dB whereas the MCSPSO counterpart has the slightly smaller directivity of 8.2567 dB, respectively.



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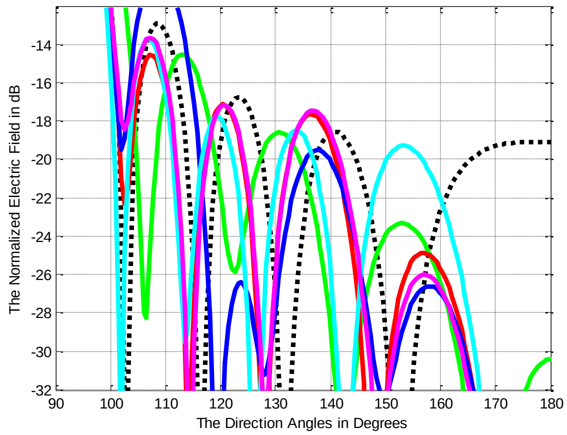

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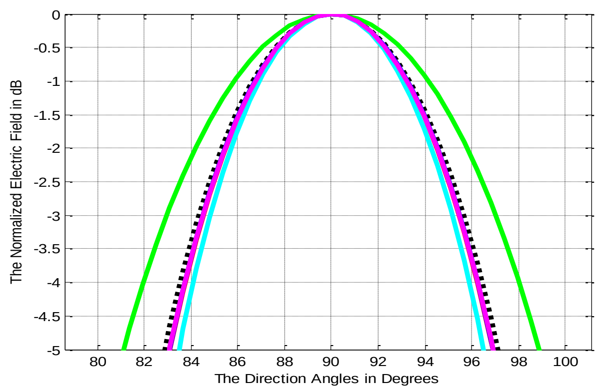

(c)

Fig. 2. Normalized Pattern for Weighted–Sum MCS Hybrids vs. others

As displayed in Fig. 3, the MCSPSO hybrid optimizer produces the lowest weighted–sum fitness, f_{min} of 0.6654 that leads to the best SLL suppression performance. It executes the largest optimal location fluctuations followed by the MCSGA counterpart. Besides, the MCSPSO–based array also generates the lowest optimal amplitude magnitudes for all the $2N$ = 10 symmetric elements as shown in Fig. 4. Furthermore, Fig. 5 portrays that the MCSPSO optimizer produces the biggest optimal phase fluctuations compared to other tested algorithms, respectively.

All the optimal locations, amplitudes, and phases of the MCSPSO optimizer produce a better diversity of excitation components, which increase the linear array beam scanning capability with low side lobes.

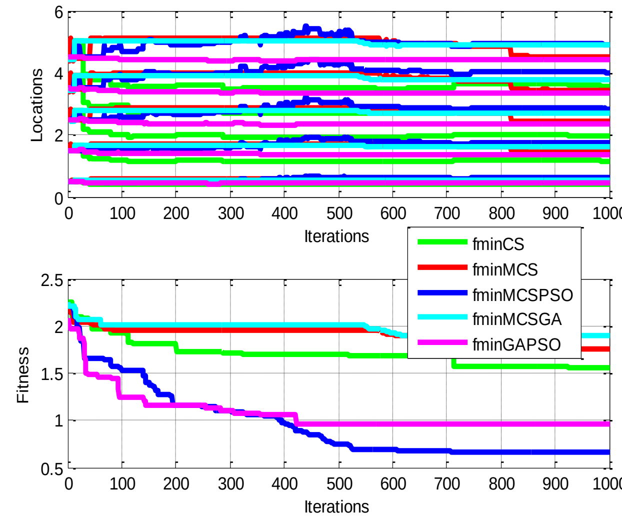

Fig. 3. Optimal Location and Total Fitness Curves for Weighted–Sum MCS Hybrids vs. others

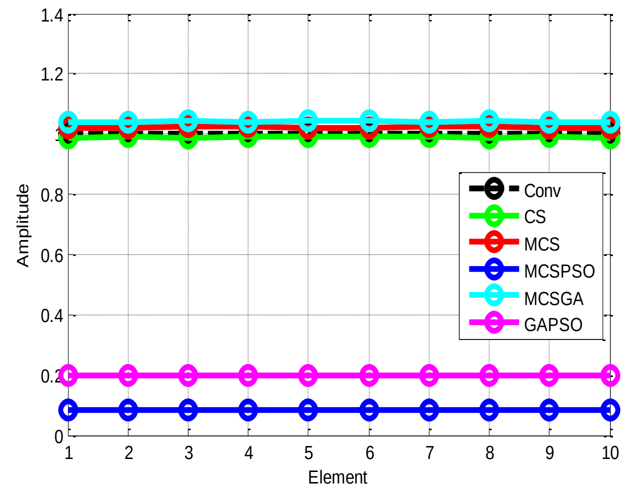

Fig. 4. Optimal Amplitude for Weighted–Sum MCS Hybrids vs. others

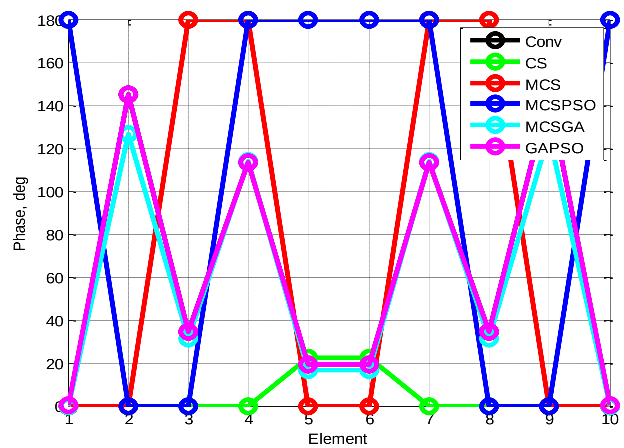

Fig. 5. Optimal Phase for Weighted–Sum MCS Hybrids vs. others

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Table I conscripts the optimal location variations for all the tested weighted–sum optimizers for $2N$ = 10 linear array after 1000 iterations. The MCSPSO hybrid algorithm evidently generates the largest position variations compared to the conventional array which, is between |±0.1119| and |±0.3954| followed by the MCSGA counterpart. Moreover, the MCSPSO array has the lowest optimal excitation amplitude which is 0.0844, hence the biggest amplitude differences compared to the conventional array as tabulated in Table II. Looking on the aspect of the array excitation phase, the MCSPSO hybrid algorithm has the magnitude domain of [0^o 180^o] for all $2N$ = 10 linear array elements. Table III shows that the MCSPSO–based optimizer generates the biggest optimal phase deviations compared to the conventional array, which are between 34.5848^o and 180^o.

TABLE I
OPTIMAL LOCATION FOR WEIGHTED–SUM MCS HYBRIDS VS. OTHERS

Element	1	2	3	4	5
X_n [λ/2]	±0.5000	±1.5000	±2.5000	±3.5000	±4.5000
CS	±0.4055	±1.1638	±1.9590	±2.7393	±3.5674
MCS	±0.4769	±1.4518	±2.4265	±3.4521	±4.5170
MCSPSO	±0.6119	±1.7458	±2.8382	±4.0097	±4.8954
MCSGA	±0.5429	±1.6285	±2.7025	±3.7869	±4.8959
GAPSO	±0.4489	±1.3770	±2.3313	±3.3593	±4.4227

TABLE II
OPTIMAL AMPLITUDE FOR WEIGHTED–SUM MCS HYBRIDS VS. OTHERS

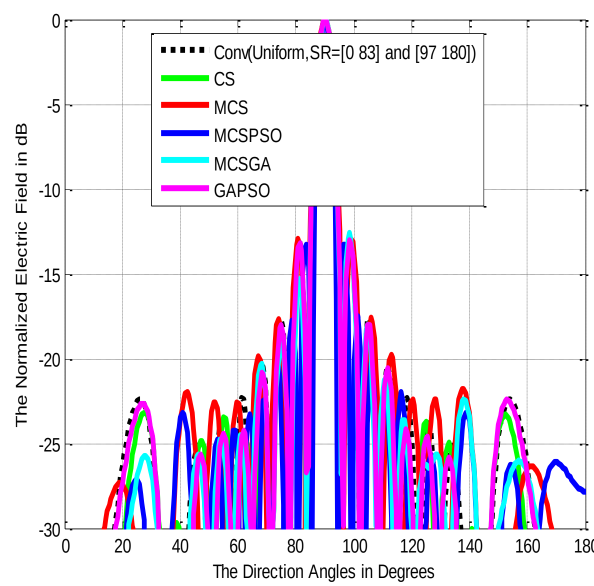
Element	1	2	3	4	5
A_n	1.0000	1.0000	1.0000	1.0000	1.0000
CS	0.9873	0.9906	0.9881	0.9908	0.9911
MCS	1.0195	1.0200	1.0271	1.0241	1.0193
MCSPSO	0.0844	0.0844	0.0844	0.0844	0.0844
MCSGA	1.0378	1.0375	1.0445	1.0388	1.0418
GAPSO	0.2000	0.2000	0.2000	0.2000	0.2000

TABLE III
OPTIMAL PHASE FOR WEIGHTED–SUM MCS HYBRIDS VS. OTHERS

Element	1	2	3	4	5
ϕ_n	0^o	144.8614^o	34.5848^o	113.2354^o	19.0016^o
CS	0^o	0^o	0^o	0^o	22.4561^o
MCS	0^o	0^o	180^o	180^o	0^o
MCSPSO	180^o	0^o	0^o	180^o	180^o
MCSGA	0^o	126.4717^o	31.1931^o	114.1964^o	16.7280^o
GAPSO	0.2285^o	144.8629^o	34.6929^o	113.3098^o	19.1002^o

Secondly, a more substantial simulation is done on the $2N$ = 20 linear array with main beam radiates at the desired direction angle of 90^o and two prescribed interferers at direction angles of 35^o and 145^o, respectively. In this simulation, MCSPSO, MCSGA, MCS and original CS algorithms deploy the Mantegna's α–stable distribution method, host nest = 30, length step factor = L/100 or 0.01, and α = 2.0 (Lévy flight Gaussian distribution). All the MCS–based algorithms have a dynamic P_a magnitude domain of [0.01 0.25] and a dynamic w magnitude domain of [0.95 1.05], respectively. Both the MCSPSO and GAPSO optimizers deploy the PSO algorithm with the dynamic random particle velocity domain of [–0.1 +0.1]. Furthermore, the MCSGA and GAPSO algorithms use the GA optimizer with the gene crossover probability, P_c = 90% or 0.9, and gene mutation probability, P_m = 10% or 0.1.

Fig. 6(a) shows that the MCSPSO–based array outperforms other arrays in SLL suppression particularly between the [0^o 83^o] and [97^o 180^o] regions, respectively. In this case, the MCSPSO hybrid algorithm generates the SLL between 0.047 dB and 3.826 dB below the conventional array as depicted in Fig. 6(b). Moreover, the MCSPSO–based array as in Fig. 6(c) demonstrates the highest radiation intensity at the main beam with the smallest HPBW of 92^o – 88^o = 4^o with the directivity of 11.5831 dB. This is trailed by the MCSGA counterpart with the calculated HPBW of 92.67^o – 87.39^o = 5.28^o, and the directivity of 11.3074 dB. In addition, Fig. 6(d) shows that the proposed MCSPSO algorithm has the significant null mitigation, with the measurements of –70.661 dB nearly at 144.96°, whereas Fig. 6(e) indicates that the proposed MCSGA counterpart has the remarkable null mitigation of –66.126 dB at about 34.95°.



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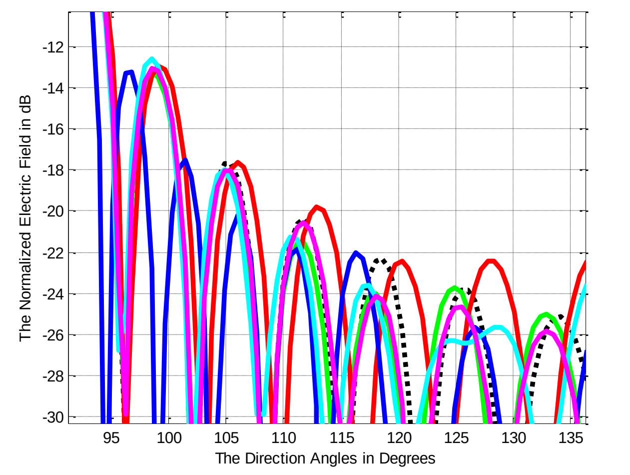

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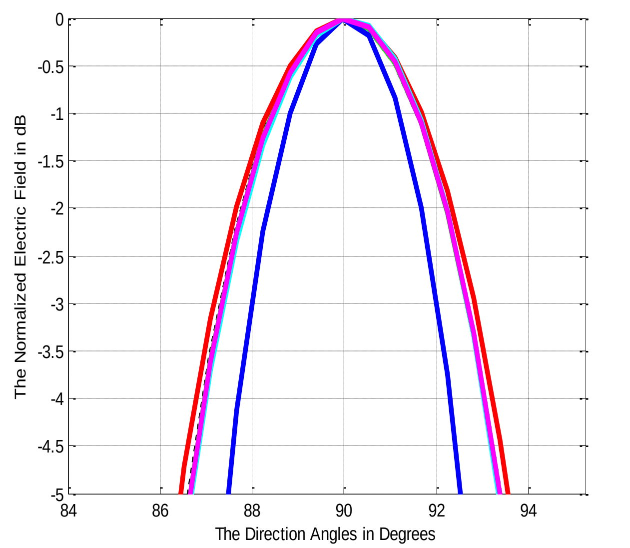

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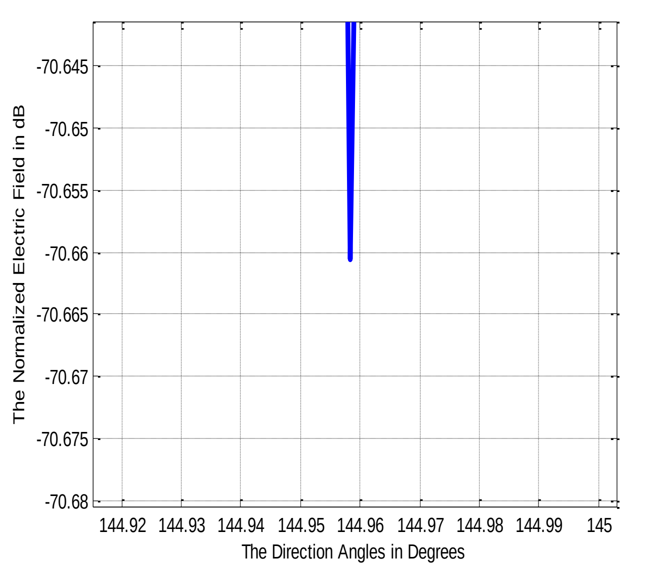

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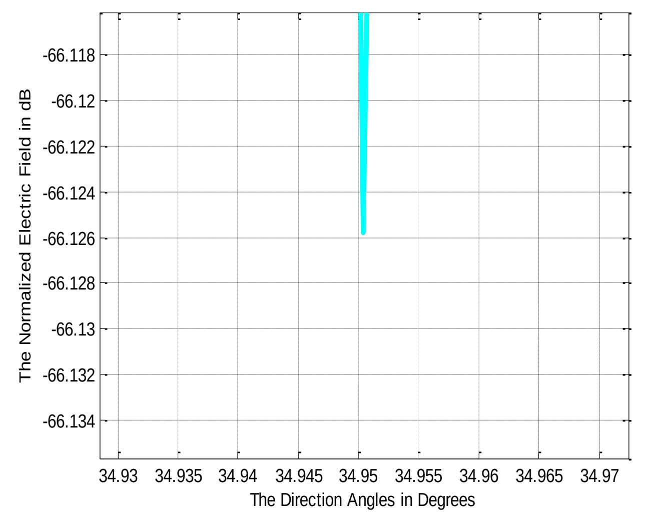

(e)

Fig. 6. Norm. Pattern for Wgt–Sum MCS Hybrids vs. others (Null = [35°, 145°])

Based on Fig. 7, the MCSPSO hybrid–optimizer produces the largest optimal location fluctuations with the lowest weighted–sum f_{min} convergence of 1.0994. Besides, the proposed MCSPSO hybrid–optimizer generates the lowest optimal amplitude measurements for all $2N$ = 20 array elements as shown in Fig. 8. In another aspect, Fig. 9 portrays that the MCSPSO based–optimizer produces the biggest optimal phase variations for the $2N$ = 20 linear array with two prescribed nulls.

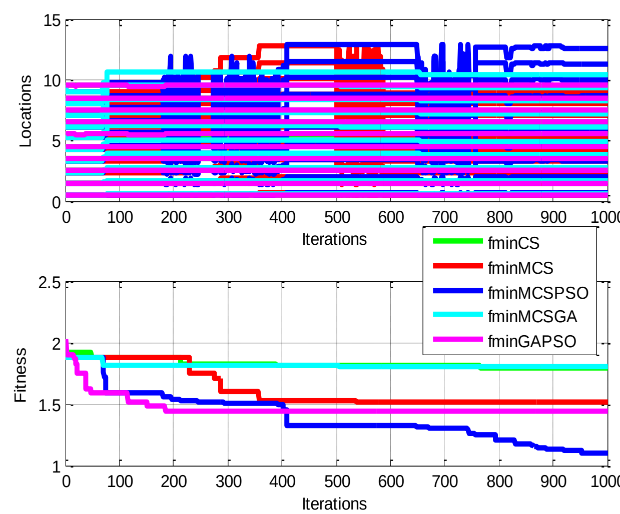

Fig. 7: Optimal Location and Total Fitness Curves for Weighted–Sum MCS Hybrids vs. others (Null = [35°, 145°])

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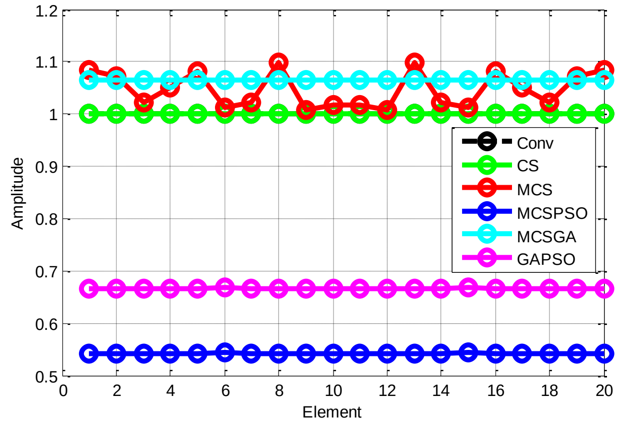

Fig. 8. Opt. Amp. for Wgt–Sum MCS Hybrids vs. others (Null = [35°, 145°])

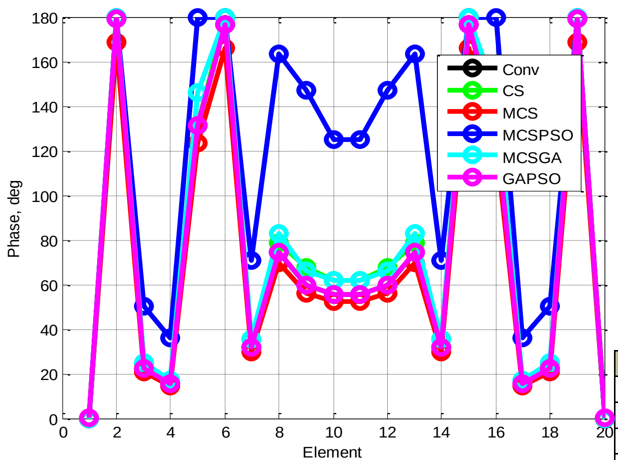

Fig. 9. Opt. Phase for Wgt–Sum MCS Hybrids vs. others (Null = [35°, 145°])

As mentioned earlier, the MCSPSO hybrid algorithm executes the largest optimal location oscillations with the measurements between |±0.1620| and |±3.1255| compared to the conventional array for all $2N = 20$ linear array as enlisted in Table IV. In addition, the MCSPSO hybrid algorithm has the lowest optimal amplitude deviations compared to the conventional array between 0.5427 and 0.5432 for all $2N = 20$ array elements as presented in Table V. As can be seen in Table VI, the MCSPSO hybrid algorithm has the largest optimal phase deviations compared to the conventional array between 0° and 88.9306°. In this case, an element has the excitation phase of 0° and three elements have the excitation phase of 180°. This indicates that the proposed MCSPSO–based optimizer is capable to search the optimal solutions (optimal phases) to the minimum and maximum extents, which improves the scanning capability with low side lobes, a narrow main beam, and well–mitigated nulls.

TABLE IV
OPT. LOC. FOR WGT–SUM MCS HYBRIDS VS. OTHERS (NULL = [35°, 145°])

Element	**1**	**2**	**3**	**4**	**5**
X_n [λ/2]	±0.5000	±1.5000	±2.5000	±3.5000	±4.5000
CS	±0.4996	±1.4969	±2.4978	±3.4928	±4.4918
MCS	±0.4703	±1.4108	±2.3514	±3.2919	±4.2325
MCSPSO	±0.6620	±1.9907	±3.3192	±4.6481	±5.9780
MCSGA	±0.5499	±1.6497	±2.7488	±3.8493	±4.9491
GAPSO	±0.5093	±1.5102	±2.5140	±3.5113	±4.5116
Element	**6**	**7**	**8**	**9**	**10**
X_n [λ/2]	±5.5000	±6.5000	±7.5000	±8.5000	±9.5000
CS	±5.4933	±6.4910	±7.4846	±8.4826	±9.4916
MCS	±5.1730	±6.1136	±7.0541	±7.9947	±8.9353
MCSPSO	±7.3084	±8.6368	±9.9648	±11.2959	±12.6255
MCSGA	±6.0489	±7.1487	±8.2485	±9.3460	±10.4481
GAPSO	±5.5158	±6.5135	±7.5116	±8.5057	±9.5117

TABLE V
OPT. AMP. FOR WGT–SUM MCS HYBRIDS VS. OTHERS (NULL = [35°, 145°])

Element	**1**	**2**	**3**	**4**	**5**
A_n	1.0000	1.0000	1.0000	1.0000	1.0000
CS	1.0004	1.0012	1.0009	1.0003	1.0003
MCS	1.0853	1.0716	1.0213	1.0516	1.0819
MCSPSO	0.5428	0.5429	0.5427	0.5428	0.5427
MCSGA	1.0656	1.0656	1.0656	1.0656	1.0656
GAPSO	0.6666	0.6666	0.6666	0.6666	0.6666
Element	**6**	**7**	**8**	**9**	**10**
A_n	1.0000	1.0000	1.0000	1.0000	1.0000
CS	1.0008	1.0014	1.0002	1.0010	1.0010
MCS	1.0117	1.0228	1.0986	1.0071	1.0161
MCSPSO	0.5432	0.5428	0.5428	0.5430	0.5430
MCSGA	1.0656	1.0656	1.0656	1.0656	1.0656
GAPSO	0.6666	0.6666	0.6666	0.6666	0.6666

TABLE VI
OPT. PHASE FOR WGT–SUM MCS HYBRIDS VS. OTHERS (NULL = [35°, 145°])

Element	**1**	**2**	**3**	**4**	**5**
ϕ_n	0°	179.3495°	22.3307°	15.5222°	131.2926°
CS	0°	180°	24.3387°	17.2827°	131.4126°
MCS	0°	168.6877°	21.0032°	14.5994°	123.4877°
MCSPSO	0°	180°	50.3968°	36.2676°	180°
MCSGA	0°	180°	24.8503°	17.2736°	146.1066°
GAPSO	0.0948°	179.4246°	22.3733°	15.5829°	131.3076°
Element	**6**	**7**	**8**	**9**	**10**
ϕ_n	176.3662°	31.7982°	74.2622°	59.5501°	55.6673°
CS	180°	35.3167°	78.8409°	67.8246°	61.9853°
MCS	165.8818°	29.9079°	69.8475°	56.0100°	52.3581°
MCSPSO	180°	70.7653°	163.1928°	146.8616°	124.8258°
MCSGA	180°	35.3860°	82.6413°	66.2692°	61.9484°
GAPSO	176.3985°	31.8015°	74.3409°	59.6257°	55.7297°

IV. CONCLUSION

Overall, the proposed MCSPSO stochastic algorithm can search further the best host nest (optimal solution) in search space. Hence, this produces a better diversity of optimal solution (array element location, amplitude, and phase). This is driven by the use of value–added attributes, e.g. Roulette wheel selection operator, adaptive w, dynamic P_a, and both the velocity and position of particle iterative effective updating mechanisms in PSO optimizer. As a result, the MCSPSO hybrid algorithm can control more effectively the Lévy flight searching motion (via velocity and position updating processes), and through it can locate the global best host nest (optimal solution) within N–dimensional search space.

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