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A Novel Binary Spider Monkey Optimization Algorithm for Thinning of Concentric Circular Antenna Arrays

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ABSTRACT

This paper presents a novel binary algorithm named as binary spider monkey optimization (binSMO) for thinning of concentric circular antenna arrays (CCAA). The proposed algorithm has been adapted from a recently developed nature inspired optimization method, spider monkey optimization (SMO). SMO works in continuous domain and as such is not suitable for application to binary optimization problems. The binSMO algorithm has been proposed with inclusion of logical operators in SMO for binary thinning problem. Thinning of an antenna array reduces the maximum side lobe level (SLL) as well as cost and size of antenna array. Thinning of CCAA can be modelled as 0−1 binary integer optimization problem. The proposed binSMO is used to synthesize CCAA in order to reduce the SLL and at the same time keeping the percentage of thinning equal to or more than the desired level. Simulation examples of two ring and ten ring CCAA have been considered. The novel method binSMO gives reduced SLL as compared to the results available in literature of teacher learning based optimization, biogeography based optimization, modified particle swarm optimization, and firefly algorithm. Moreover, the convergence rate of binSMO is faster than the other methods. The results prove the competence and superiority of binSMO to existing metaheuristic algorithms and it has an ability to become an effective tool for solving binary optimization problems.

KEYWORDS

Concentric circular antenna array; Side lobe levels; Spider monkey optimization; Swarm intelligence; Thinning of antenna arrays

1. INTRODUCTION

The design of antenna is a challenging optimization problem as it involves an objective function and conditions which are highly non-linear and non-differentiable. Classical optimization methods are not good choice for antenna optimization since their performance heavily relies on the initial guess and if the initial guess is not available they may stuck in local minima. Hence, in the recent years, many nature inspired computing (NIC) techniques have been developed and utilized for the design of antennas such as genetic algorithm (GA),[1−5], differential evolution (DE) [6,7], particle swarm intelligence optimization (PSO) [8−13], firefly algorithm (FA), [14−18], biogeography based optimization (BBO) [19,20], and teaching learning based optimization (TLBO) [21] and so on. Introduced by Bansal *et al.* in [22] for numerical optimization problems, spider monkey optimization (SMO) is one such algorithm which is found to be competitive among other NIC techniques. It minimizes the problems like poor exploration of artificial bee colony [23], premature convergence and stagnation of DE [24,25], and problem based tuning requirement of PSO [26]. SMO is based upon the foraging behaviour of spider monkeys, which live in a group of 40−50 individuals. This group is headed by a female leader and is considered as the best fit individual or the global leader. If the global leader is not able to find food, it divides the group into two sub-groups, each sub-group is further headed by the best fit individual of the group called local leader. This process is carried on unless the maximum numbers of groups are formed. When the maximum number of groups are formed, all the group members recombine to form a single group and local leader is updated. This social structure is also known as fission−fusion based social structure as the group is first divided into subgroups resulting in fission and then after fulfilling a certain criteria it is again combined to form a single group or fusion. The main advantage here is that it reduces the direct foraging competition among the group members. As SMO algorithm follows a structured group strategy, so for a single group every newly generated solution is attracted towards best solution providing better convergence. But the population can skip global minima and stuck into local minima because of exploitative tendency. To avoid this, when the solution is not getting updated, the group is divided into subgroups. The formation of new groups result in attraction of new solution toward respective subgroup, hence, increasing the exploration capability. When the maximum number of groups have been formed and solution is not getting updated, all subgroups are combined, balancing the exploration and exploitation capabilities while maintaining the convergence speeds [22].

Concentric circular antenna array (CCAA) find its use in a number of applications which consist of sonar, radar, mobile, and military applications [27–31]. CCAA is favoured as it provides flexibility in array pattern synthesis and its main beam can be scanned in any desired direction. Since CCAA gives nearly invariant azimuth angle coverage, it is also employed in direction-of-arrival applications [8–10]. Uniform concentric circular array (UCCA) is an important configuration of CCAA having element spacing equal to half wavelength with uniform element excitation. UCCA has high directivity but it also suffers from problem of high side lobe level (SLL) [28,31]. High SLL results in interference from undesired directions. One method to reduce the SLL is to make the array aperiodic having non-uniform inter-element spacing. In this, elements have infinite number of ways for placement which adds to the complexity of the system [1].The other technique of reducing the SLL is to employ radially tapered amplitude distribution. However, because of less complexity of the feed network and to maximize the power input, uniform excitation is desired [1].

Thinning is another way of reducing the SLL besides conventional techniques mentioned above. Thinning of antenna arrays is deliberate removal of a subset of active elements in the antenna array so as to maintain radiation properties similar to that of the fully populated array, but using a lesser number of elements in doing so. Thinning of antenna is a binary problem where active elements are denoted as “1” and inactive elements are represented as “0”. Thinning of array not only decreases the maximum SLL but it also reduces the manufacturing cost and weight of the arrays. Therefore, many researchers have employed thinning for the design of antenna arrays. Thinning is a complex problem and hence analytical methods cannot be employed to solve it. In the recent past, several popular optimization algorithms such as GA [3–5], DE [6,7], PSO [11–13], gravitational search algorithm [13], FA [14,17,18], BBO [20], and TLBO [21] have been employed for the design of CCAA using the thinning technique. These methods show good results but some of the methods are continuous algorithms so optimality of results is compromised.

For a binary solution, the basic algorithm working in continuous domain must be modified. Hence in this work, a new binary SMO (binSMO) is proposed which provides the solution in binary search space having logic 0 or 1 values only. In binSMO, the position updating equations of basic SMO algorithm have been modified using logical operators. In this article, the binSMO algorithm is employed for thinning of CCAA.

The next section presents the proposed binSMO algorithm. Section 3 presents the geometry and general design for CCAA along with formulation of fitness function. In the Section 4, detailed discussion about results obtained from the proposed approach in context with thinning of antenna arrays for two- ring and ten-ring CCAA is given. The paper has been concluded in Section 5.

2. BINARY SPIDER MONKEY OPTIMIZATION

SMO [22] is a recently developed algorithm and has been explained in Appendix 1. Inspired from the basic SMO algorithm, binSMO is proposed for binary optimization problems. This approach has been motivated by improved binary particle swarm optimization (IBPSO) algorithm proposed by Yuan *et al.* [32]. They used logical operator for updating the velocity equations of PSO and designed IBPSO. In binSMO, the basic equations of SMO algorithm are modified using logical operators in order to work in binary space. For initialization, a random binary solution is produced using Bernoulli process, using the equation given below

$$SM_{i,j} = \begin{cases} 0, & x < p \\ 1, & \text{otherwise} \end{cases} \tag{1}$$

where $SM_{i,j}$ is the jth dimension of ith spider monkey, p is probability value (taken as 0.5 in our case), and x is a random number in the range of [0,1]. If the random number is less than 0.5, the corresponding dimension becomes 0 and vice versa. After initialization, the positions of spider monkeys are updated using AND, OR, and XOR operators. The modified equations are given below.

2.1 Local leader phase

$$SMnew_{i,j} = \begin{cases} SM_{i,j} \oplus ((b \otimes (LL_{k,j} \oplus SM_{i,j})) \\ \quad + \ (d \otimes \ (SM_{r,j} \oplus SM_{i,j}j))), \ \text{rand} \geq pr \\ SM_{i,j}, \text{otherwise} \end{cases} \tag{2}$$

2.2 Global leader phase

All SMs update their positions by group member experience and experience of global leader. The positions are updated based upon some probability given by the Equation (A4)

$$P_i = 0.9 \times \frac{(\mathrm{fit}_i)}{\mathrm{max\_fit}} + 0.1 \tag{3}$$

where P_i is the probability, fit_i is the fitness of ith SM, and max_fit is the maximum fitness of the group. The position update equation for this phase is given by

$$SMnew_{i,j} = SM_{i,j} \oplus ((b \otimes (GL_j \oplus SM_{i,j})) + (d \otimes (SM_{r,j} \oplus SM_{i,j}))) \tag{4}$$

2.3 Local leader decision phase

$$SM_{i,j} = \begin{cases} SM_{i,j} \oplus ((b \otimes (LL_{k,j} \oplus SM_{i,j})) + (b \otimes (GL_j \oplus SM_{i,j}))), & \mathrm{rand} \geq pr \\ \text{use equation 1}, & \text{otherwise} \end{cases} \tag{5}$$

where $SMnew_{i,j}$ is the updated position of ith SM in the jth dimension, $SM_{i,j}$ is the previous position of ith SM in the jth dimension, $LL_{k,j}$ represents the local leader of kth group in the jth dimension, GL_j is the global leader in the jth dimension, b and d are binary random integers in the range [0,1], and $\oplus$, $\otimes$, $+$ are logical XOR, AND, and OR operators. The pseudo code of binSMO is shown in Figure 1.

```
Initialization Phase
  Set population size.
  Global leader limit and local leader limit.
  Maximum number of groups.
  Perturbation rate.
  Load Binary Optimization Objective function.
    Generate a sol. randomly consisting of binary values using
    eqn. 1.
    Calculate fitness value
    Select Global and Local Leader by greedy search.
  while termination criteria is satisfied do
    /*Local leader phase*\
    Generate new sol. based on equation 2.
    Calculate fitness of new sol.
    Select better sol. based upon fitness of new and old sol.
    /*Global leader phase*\
    Calculate probabilities based on equation 3.
    Generate new sol. based on equation  4.
    Calculate fitness of new sol.
    Select better sol. based upon fitness of new and old sol.
    Update local and global leader position.
    /*Local leader decision phase*\
    if local leader not getting updated
    redirect all members for foraging using equation 5.
    end if
    /*Global leader decision phase*\
    if global leader not getting updated divide the group into two.
    while maximum groups are formed.
      Combine all groups to one.
      Update Local leader.
    end while
    end if
  end while
```

Figure 1: Pseudo code of proposed binSMO

3. FORMULATION OF FITNESS FUNCTION FOR THINNING OF CCAA

In CCAA, the isotropic elements are arranged in M rings with radius r_m as shown in Figure 2. Each ring consists of N_m elements where $m = 1, 2, \ldots, M$. The far-field pattern of this array can be written as [27]

$$E(\theta, \phi) = \sum_{m=1}^{M} \sum_{n=1}^{N_m} I_{mn} \exp[j(kr_m \sin\theta(\cos(\phi - \phi_{mn}))] \tag{6}$$

where k = wave number = $2\pi/\lambda$, λ is the signal wavelength, r_m denotes the radius of the mth ring = $N_m d_m/2\pi$, d_m gives inter-element arc spacing of the mth ring, $\phi_{mn} = 2\pi n/N_m$ is the angular position of the nth element of the mth ring, I_{mn} symbolizes the current amplitude excitation of the nth element of the mth ring, and ϕ and θ are the azimuth and elevation angle, respectively. The phase excitation of all the antenna elements is equal to zero degree.

The aim is to achieve minimum possible SLL by thinning. The fitness function used for designing the antenna is given as

$$F = SLL_{\max} + (T_o^{\mathrm{off}} - T_d^{\mathrm{off}})^2 H(T) \tag{7}$$

In the above equation, $SLL_{\max}$ is the maximum side lobe level, T_o^{off}, T_d^{off} are obtained and desired value of

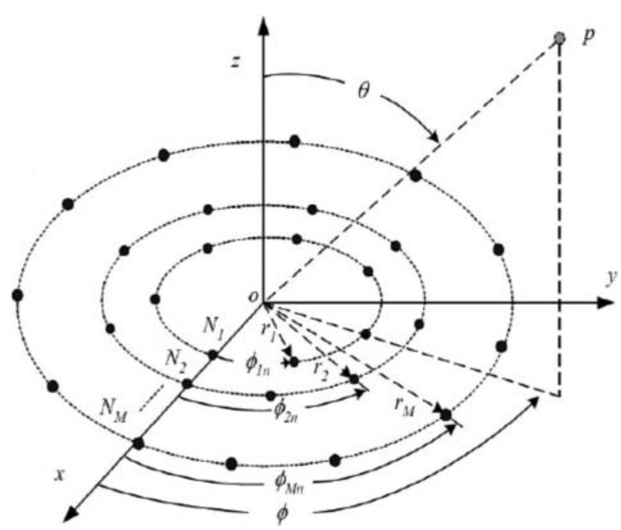

Figure 2: Ideal isotropic CCAA

number of switched/turned off elements. $H(T)$ is the Heaviside step functions defined as

$$H(T) = \left\{ \begin{matrix} 0 & \text{if } T > 0 \\ 1 & \text{if } T \leq 0 \end{matrix} \right\} \tag{8}$$

$$T = (T_o{}^{\text{off}} - T_d{}^{\text{off}}) \tag{9}$$

4. SIMULATION RESULTS AND DISCUSSION

In the order to check the performance and accuracy of the proposed binSMO, it is applied to the design of CCAA. In this work, two different cases of CCAAs are considered for optimization. The first CCAA has 105 elements and these elements are distributed in two rings and for the second case, a CCAA with ten rings is considered having 440 elements in total.

The simulations are performed on Windows 7 PC with 4 GB RAM, Intel core i3 processor and MATLAB version is 7.10.0 (R2010a). The binSMO algorithm has been run for 25 times and best results are reported. The parameters for binSMO are taken as follows.

- Swarm size = 100; maximum number of groups = 10.
- Perturbation rate, pr = [0.1, 0.4] increasing linearly according to the relation:

  $pr_{G+1} = pr_G + (0.4 - 0.1)/\text{maxiter}$,

  where G is the iteration counter and maxiter is the maximum number of iterations.
- Global leader limit = swarm size/2.
- Local leader limit = $[D/2] \times$ swarm size.

4.1 CCAA with two rings

In the first case, binSMO is employed to synthesize a CCAA consisting of two rings. The isotropic elements in inner ring and outer ring are 35 and 70 respectively making the total elements in the antenna equal to 105. The inter-element distance is kept equal to $\lambda/2$. The desired number of elements to be switched off T_d^{off} is kept to 45. The element excitation in different rings of CCAA after optimization is shown in Table 1. Table 2 shows binSMO results for this CCAA along with the results obtained by FA [18] and TLBO [21]. The maximum SLL achieved by binSMO is −19.8325dB with 48 elements switched off. The maximum SLL achieved by TLBO [21] and FA [18] is −18.3611 and −18.26 dB, respectively. The number of switched off elements for TLBO [21] are 45, whereas that for FA [18] are 36. Hence it can be seen that the binSMO has clearly outperformed FA [20] and TLBO [23] in terms of maximum SLL and percentage of thinning. Furthermore, the binSMO like TLBO [21] achieved the results in 150 generations but FA [18] took 500 generations to converge to the results given in Table 2. Figure 3 gives the convergence curve for the binSMO compared with convergence characteristics of TLBO [21] which clearly shows the faster convergence of binSMO as against TLBO [21]. The thinned antenna configuration is shown in Figure 4. The radiation pattern of the binSMO optimized antenna is shown Figure 5 along with

Table 1: Element excitation distribution (I_{mn}) of two ring thinned CCAA obtained by binSMO

Ring #	Element excitation in each ring (0 or 1)
1	01111101100100000101110110010110010
2	1000101000100011111100011110010000111000111011011111111101000101

Table 2: Results obtained by different methods for two ring CCAA

Array	SLL (in dB)	# of switched OFF
binSMO	−19.8325	48
TLBO [21]	−18.3611	45
FA [18]	−18.2600	36

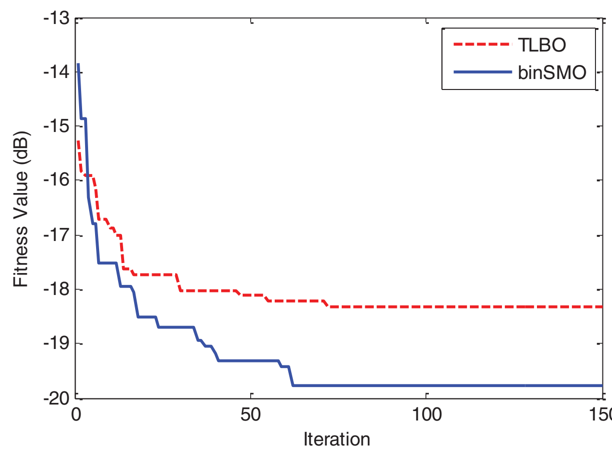

Figure 3: Convergence curves of two ring CCAA using TLBO and binSMO

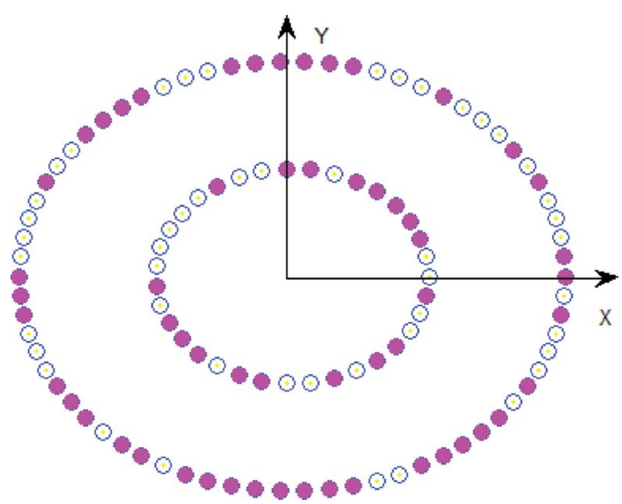

Figure 4: 105 isotropic elements (pink as ON and blue as OFF) in a two ring CCAA

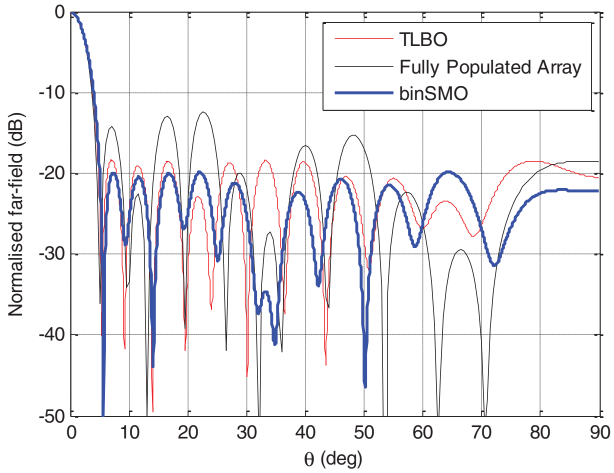

Figure 5: Radiation pattern of fully populated, TLBO and binSMO algorithm for two ring CCAA

the radiation pattern of fully populated antenna and TLBO [21] thinned antennas for comparison.

4.2 CCAA with ten rings

In this subsection, a CCAA of ten rings is considered. The number of equi-spaced isotropic elements in each ring is $8m$ (a total of 440), where m is the ring number counted from the innermost ring 1. The desired number of elements to be switched off (T_d^{off}) is set to 230. The comparison of binSMO results with the results of fully populated uniform array, DE with global and local neighbourhood (DEGL) [7] and modified particle swarm optimization (MPSO) [13] and TLBO [21], FA [17] and BBO [20] thinned arrays presented in Table 3. The value of maximum SLL achieved by binSMO is −27.87 dB and the number of switched off elements are 240. The maximum SLL obtained by uniform array, MPSO [13], DEGL [7], FA [17], and TLBO [21] is −17.37, −23.22, −21.91, 26.15, and −26.24 dB, respectively. Hence, the maximum SLL achieved by binSMO is lower by 10.50, 4.65, 5.96, 1.72, 1.63, and 1.32 dB than the maximum SLL obtained by fully populated MPSO [13], DEGL[7], FA [17], TLBO [21], and BBO [20] thinned arrays, respectively. The convergence characteristics of binSMO and BBO [22] are shown in Figure 6. The optimized thinned ring antenna array is shown in Figure 7. The radiation pattern for the binSMO optimized CCAA is shown in Figure 8.

Table 3: Results obtained by different methods for ten ring CCAA

Array	SLL (in dB)	# of switched OFF
Fully populated array	−17.37	0
binSMO	−27.87	240
BBO [20]	−26.55	224
FA [17]	−26.15	226
TLBO [21]	−26.24	224
DEGL [7]	−21.91	220
MPSO [13]	−23.22	231

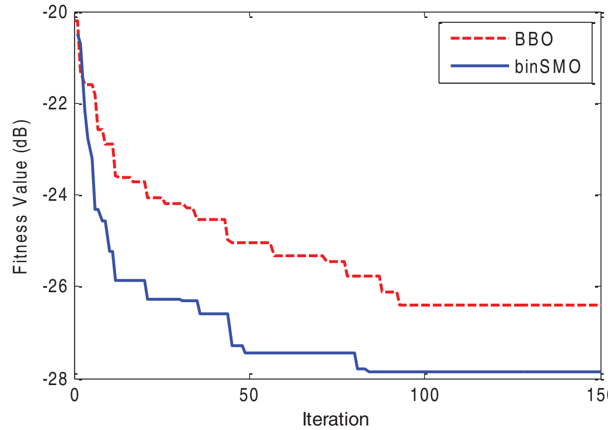

Figure 6: Convergence curves of ten ring CCAA using binSMO and BBO

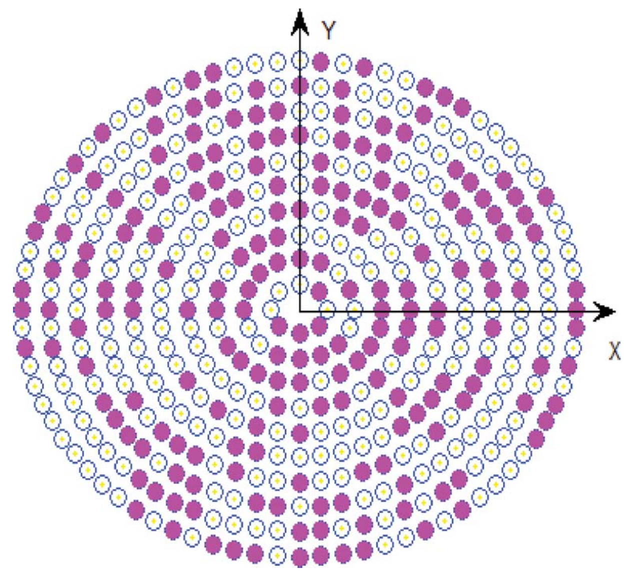

Figure 7: 440 isotropic elements (pink shows ON and blue as OFF) in ten ring CCAA

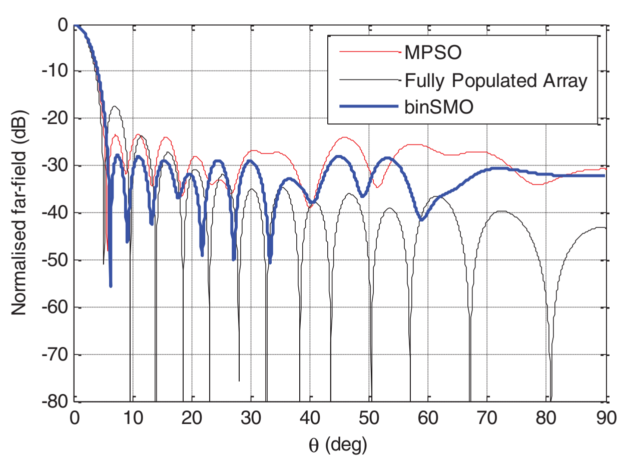

Figure 8: Radiation pattern of fully populated array, MPSO, and binSMO algorithm for ten ring CCAA

Table 4: Element excitation distribution (I_{mn}) of ten ring thinned CCAA obtained by binSMO

Ring #	Element excitation in each ring (0 or 1)
1	10001110
2	1011111100111100
	100000111011011111011111
	10001101100100010000001011010111
	0010111110101100010000010101010000100011
	0100001100100101 10010011 000000001100000011110000
	11001100011101110110101100110000101110100100110010111010
	1001111101101001110101001001100101011110011100110110010000000000
	000110000100010101011010001001010101000000001111000011010101100|00101000
	100001000011100101000011010010100110011010000000000101011101111001010000111010111

For the sake of comparison, radiation pattern of MPSO [13] and fully populated array are also plotted in Figure 8. The element amplitude excitations obtained by binSMO are shown in Table 4.

The optimal results for thinning obtained by binSMO are better than other algorithms. One of the reasons is that the basic SMO has good exploration and exploitation capabilities. Second, binSMO generates binary solutions using logical operators, while in TLBO [21] and FA [17] the values of variables are rounded off to the nearest value to get the binary solution.

5. CONCLUSION

This paper proposes a new binary algorithm (binSMO) based on SMO algorithm working in binary search space. XOR, AND, and OR logic operator has been considered as the key element of moving on to binary search space. In binSMO algorithm, the position of each spider monkey consists of 0 and 1 logic values and these logic values are applied for thinning of CCAA. The simulation results show that binSMO provides good results for both two ring and ten ring CCAA when compared with DEGL, BBO, MPSO, TLBO, and FA. The maximum improvement obtained by binSMO is for ten ring case where the reduction in SLL is by 27% as compared to DEGL [7] antenna array. The proposed method is found to be very effective for binary optimization and can be used for other real-world applications due to fast convergence and less chances to stuck at local minima. Future work includes adapting binSMO for solving binary optimization problems such as linear and planar antenna thinning, sensor deployment in wireless communication, state assignment in sequential circuits, lot sizing problems and feature selection.

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APPENDIX 1. SPIDER MONKEY OPTIMIZATION ALGORITHM

SMO is a swarm intelligent metaheuristic algorithm which has been designed to balance both exploration and exploitation abilities to achieve better optimization of any problem under consideration [22]. In this, new solutions are explored and existing solutions are exploited to achieve optimal results. The main focus on this algorithm is to overcome the drawback of previous algorithms such as premature convergence, stagnation and poor exploration and exploitation. The SMO has seven phases and each phase is explained as follows.

A.1 Initialization phase

Here a random population of N spider monkeys is initialized and each SM acts as the potential solution of the problem under consideration

$$SM_{i,j} = LB_{\min,j} + \mathrm{b}(LB_{\min,j} - UB_{\max,j}) \tag{A1}$$

where $SM_{i,j}$ is the position of ith spider monkey in jth direction, UB_j and LB_j are upper and lower bounds of problem under consideration, respectively, and b is a random number in the range [0,1]. In this phase, the fitness of randomly generated solution is also calculated by using equation below

$$fit_i = \begin{cases} 1 + f_i, \ f_i \geq 0, \\ \dfrac{1}{1 + |f_i|}, \ f_i \leq 0 \end{cases} \tag{A2}$$

where f_i is the objective function value or the problem under consideration.

A.2 Local leader phase

In this phase, position of SM is updated based upon group members experience and experience of local leader. The position update equation is given as

$$SMnew_{i,j} = \begin{cases} SM_{i,j} + \left(\left(b*\left(LL_{k,j} - SM_{i,j}\right)\right) \right. \\ \left. + \left(d*\left(SM_{r,j} - SM_{i,j}\right)\right)\right), \ \text{rand} \geq pr \\ SM_{i,j}, \ \text{otherwise} \end{cases} \tag{A3}$$

where $LL_{k,j}$ gives the jth dimension of kth local group leader, $SM_{r,j}$ represents jth dimension of rth SM such that $r \neq i$, d is random number in the range $[-1,1]$, and pr is the perturbation rate.

A.3 Global leader phase

All SMs update their positions by group member experience and experience of global leader. The positions are updated based upon some probability given by Equation (A4):

$$P_i = 0.9 \times \frac{(fit_i)}{\text{max\_fit}} + 0.1 \tag{A4}$$

where P_i is the probability, fit_i is the fitness of ith SM and max_fit is the maximum fitness of the group. The position update equation for this phase is given by

$$SMnew_{i,j} = SM_{i,j} + \left(b*\left(GL_j - SM_{i,j}\right)\right) + d*\left(SM_{r,j} - SM_{i,j}\right) \tag{A5}$$

where GL_j is the global leader in the jth dimension.

A.4 Local leader learning phase

The position of local leader is updated and best fit individual in the local group is considered as the updated local leader. If local leader is not getting updated after some predefined number of times, local leader count is incremented by 1.

A.5 Global leader learning phase

The position of global leader is updated and best fit individual in the group is considered as the updated global leader. If global leader is not getting updated after some predefined number of times, global leader count is incremented by 1.

A.6 Local leader decision phase

In this phase, if the local leader count becomes equal to or greater than a predefined threshold (called local leader limit), then the position of all group members is updated based on equation given below

$$SM_{i,j} = \begin{cases} SM_{i,j} + \left(\text{b}\left(LL_{k,j} - SM_{i,j}\right)\right) + b\left(GL_j - SM_{i,j}\right), \ \text{rand} < pr \\ LB_{\min,j} + b\left(LB_{\min,j} - UB_{\max,j}\right), \ \text{otherwise} \end{cases} \tag{A6}$$

A.7 Global leader decision phase

This is the final phase of SMO algorithm and in this phase if the global leader count becomes equal to or greater than a predefined threshold (called global leader limit), the group is divided into sub groups. When the maximum number of groups is formed, the global leader combines to form a single group and position of local leader is updated.

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