RESEARCH

Open Access

CrossMark

A novel artificial bee colony algorithm for radar polyphase code and antenna array designs

Xiu Zhang[1,2] and Xin Zhang[1,2*]

Abstract

When designing radar, mobile, or satellite communication systems, optimization problems often come out and need to be handled to accomplish certain requirements. Polyphase code design and circular antenna array design problems are considered in this paper. To deal with the two problems, a novel artificial bee colony (ABC) algorithm is proposed. A population reduction method is used in the proposed algorithm. Large population is initially set for exploration search, while population is reduced to a small one for exploitation search. Moreover, a new boundary repair method is proposed to amend the candidate solutions that violate boundary constraints. It hybridizes four popularly used repair methods in literature. The resulting algorithm is called population reduction and hybrid repair ABC (PRHRABC). Experiments are conducted on the two design problems. Results show that PRHRABC presents promising performance in dealing with the problems compared with standard and a state-of-the-art ABC algorithms.

Keywords: Radar system design, Antenna array design, Artificial bee colony, Boundary repair, Global optimization

1 Introduction

In the design of radar, mobile, or satellite communication systems, optimization problems are usually involved to accomplish certain requirements [1–4]. One example is pulse compression in the radar system design, in which a key issue is to choose appropriate waveform. Polyphase code is an effective method that could do pulse compression. The advantages of this method are their lower side lobes in the compressed signal and easier implementation of digital processing methods. Dukic and Dobrosavljevic [1] modeled the compression problem as a min-max nonlinear non-convex optimization problem. This problem was verified to be a multimodal one with numerous local optima. Another example is the design of circular shaped antenna array. This problem considers N antenna elements placed on a circle of radius r in the x–y plane. All elements constitute a circular antenna array. The objective is to suppress side lobes, minimize beamwidth, and accomplish null control at desired directions by varying current and phase excitations of antenna elements [5].

The aforementioned problems are difficult to handle, and effective algorithms are in great demand. This paper proposes a novel algorithm based on artificial bee colony (ABC) paradigm. ABC contains three bee groups: employed bees, onlooker bees, and scout bees. The initial food sources are supposed to be found by scout bees. Employed and onlooker bees then exploits the food sources in sequence until some food sources become exhausted. Scout bees are sent out exploring new food source in place of exhausted sources. In standard ABC, the number of employed bees is equal to that of onlooker bees. A population reduction method is used in the proposed algorithm. The purpose of this method is to assist explorative search by keeping a large population in the former evolutionary stage and turn to a small population for promoting exploitative search in the latter evolutionary stage. Moreover, a new boundary repair method is proposed to hybridize four commonly used repair methods in literature.

2 Standard artificial bee colony algorithm

This section describes standard ABC algorithm under the assumption that optimization problem is a minimization.

*Correspondence: ecemark@mail.tjnu.edu.cn
[1] College of Electronic and Communication Engineering, Tianjin Normal University, Tianjin, China
[2] Tianjin Key Laboratory of Wireless Mobile Communications and Power Transmission, Tianjin Normal University, Tianjin, China

Springer

Maximization problem can be transformed to minimization by taking the negative.

Initially, a population is randomly created within the search space Ω. The size of population is denoted as N_p. Each solution in population is considered as a food source for honey bees. Besides the evaluation of initialized solutions, their associated fitness values are calculated as follows:

$$fit(\mathbf{x}_i) = \begin{cases} \frac{1}{1+f(\mathbf{x}_i)}, & \text{if } f(\mathbf{x}_i) \geq 0 \\ 1 + |f(\mathbf{x}_i)|, & \text{otherwise} \end{cases}, \quad (1)$$

where $f(\mathbf{x}_i)$ is the function value of solution $\mathbf{x}_i$, $i = 1, 2, \cdots, N_p$.

Employed bee phase. A swarm of employed bees is sent out to search around food sources for making honey. Usually, the number of employed bees is equal to N_p so that one employed bee searches one food source. Candidate solution $\mathbf{v}_i$ produced by employed bee i is implemented by:

$$v_{i,j} = \begin{cases} x_{i,j} + \varphi_{i,j}(x_{i,j} - x_{r1,j}), & \text{if } j = j1 \\ x_{i,j}, & \text{otherwise} \end{cases}, \quad (2)$$

where $\varphi_{i,j} \in [-1, 1]$ is a random number. $j1 \in [1, D]$ is a random integer and D is the number of variables. $\mathbf{x}_i$ and $\mathbf{x}_{r1}$ are different solutions of population. After evaluating $\mathbf{v}_i$, a greedy selection is implemented between $\mathbf{v}_i$ and $\mathbf{x}_i$ as follows.

$$\mathbf{x}_i = \begin{cases} \mathbf{v}_i, & \text{if } f(\mathbf{v}_i) < f(\mathbf{x}_i) \text{ or } fit(\mathbf{v}_i) > fit(\mathbf{x}_i) \\ \mathbf{x}_i, & \text{otherwise} \end{cases}, \quad (3)$$

Onlooker bee phase. A swarm of N_p onlooker bees is sent out. Different from employed bees, an onlooker bee chooses a food source depending on the quality/goodness of that food source. High-quality food sources would attract more onlooker bees, while low quality sources have small chances to be searched. The quality of food sources can be defined according to the fitness of solutions. This behavior is realized by firstly calculating a probability value for each solution, then using roulette wheel selection method to choose a food source. The probability of $\mathbf{x}_i$ is calculated by the following equation:

$$p_i = \frac{fit_i}{\sum\limits_{j=1}^{N_p} fit_j} . \quad (4)$$

After choosing a food source, an onlooker bee produces a modification following (2). Then, a greedy selection is performed between the newly produced solution and the old one.

Scout bee phase. If a food source has been searched for a long time, its nectar amount would not decrease and it might be abandoned by honey bees. In this case, scout bees are send out exploring for new food sources. In standard ABC, a parameter called *limit* is set to determine if

a food source should be abandoned. The abandoned solution is replaced by a randomly created solution. Note that the number that a solution (food source) is searched but not improved is counted as follows:

$$l_i = \begin{cases} 0, & \text{if } f(\mathbf{v}_i) < f(\mathbf{x}_i) \text{ or } fit(\mathbf{v}_i) > fit(\mathbf{x}_i) \\ l_i + 1, & \text{otherwise} \end{cases} . \quad (5)$$

Clearly, standard ABC includes two parameters: N_p and *limit*. The impact of both parameters on the algorithm has been studied on a set of benchmark functions. Studies show that the proper setting of both parameters depends on the characteristics of application problem [6, 7]. Parameter *limit* is not sensitive to the difficulty of problems; $limit = 0.5NpD$ could solve many benchmark functions and thus becomes default setting [6, 8].

In standard ABC, both employed bees and onlooker bees use formula (2). This formula could not fully reflect the behavior of onlooker bees. A new formula is introduced in quick ABC (qABC) algorithm for mimicking the behavior of onlooker bees [9].

$$v_{i,j} = \begin{cases} x_{i,j}^{n\text{best}} + \phi_{i,j}(x_{i,j}^{n\text{best}} - x_{r1,j}), & \text{if } j = j1 \\ x_{i,j}, & \text{otherwise} \end{cases}, \quad (6)$$

where $\mathbf{x}_i^{n\text{best}}$ represents the best solution amongst the neighbors of $\mathbf{x}_i$ and itself. Euclidean distance is used to define neighborhood of a solution. Denote $d(i, m)$ as the Euclidean distance between $\mathbf{x}_i$ and $\mathbf{x}_m$. The mean Euclidean distance of $\mathbf{x}_i$ is computed by:

$$md_i = \frac{\sum_{m=1}^{N_p} d(i, m)}{N_p - 1} . \quad (7)$$

Then, the neighbor of $\mathbf{x}_i$ is defined as the set of solutions with distance $d(i, m) \neq r \times md_i$. Parameter r is "neighborhood radius". When $r = 0$, qABC becomes standard ABC. Experimental results show that qABC improves the convergence performance of stand ABC when r is properly set. Note that r is suggested to be 1 in qABC [9].

3 Population reduction and boundary repair methods

3.1 Population reduction method

The mapping of algorithmic parameter and application problem can be expressed as:

$$N_p^{\text{new}} = g(A, S, N_p^{\text{cur}}) , \quad (8)$$

where A represents the problem attributes; S is the evolutionary state of algorithm; N_p^{cur} is the size of current population. Mapping g is very hard to quantify and is simplified as follows. Consider two problem attributes D and a fixed-budget termination condition. Termination budget is the maximum number of function evaluations (MFE). Based on the search scope, evolutionary status of an algorithm could be divided into exploration, intermediate, and exploitation. Initial population size N_p^{init} has to be

set so that formula (8) could start working. N_p^{init} is related with D by $N_p^{\text{init}} = 4D$. A decreasing step function is taken to approximate g as shown in Fig. 1. The step function is expressed as:

$$N_p = \begin{cases} N_p^{\text{init}}, & \text{if } 1 \leq f_{\text{eval}} \leq \text{MFE}/3 \\ 0.5 N_p^{\text{init}}, & \text{if } MFE/3 < f_{\text{eval}} \leq 2\text{MFE}/3 \\ 0.25 N_p^{\text{init}}, & \text{otherwise} \end{cases} \quad (9)$$

As in (9), MFE is evenly split into three evolutionary stages. In exploration stage, a large population size is used so that the algorithm could perform global search. Then, population size is reduced to half; solutions with high fitness are kept and those with low fitness are discarded. By doing this, elitist solutions survive. In exploitation stage, N_p is equal to one forth of N_p^{init}. Algorithm could search around good solutions and perform local search to attain a promising solution.

Rather than existing researches on algorithmic parameter control methods [8, 10], the proposed population size reduction method could adapt parameters to handle problems with different budget without the interface of users.

3.2 Boundary repair method

Recent study proves that boundary repair methods have great impact on the performance of evolutionary algorithms [11]. Popularly used repair methods in literature include reinitialization, projection, resampling, conservatism, wrapping, reflection, and parent medium [11, 12].

Inspired by previous researches of various repair methods, a new scheme is proposed which is a hybrid of four repair methods: reinitialization, resampling, projection, and parent medium as shown in Fig. 2. In this figure, Par($\mathbf{v}_i$) is the parent of candidate solution $\mathbf{v}_i$, rnd $\in (0, 1)$

Fig. 1 A population size reduction method
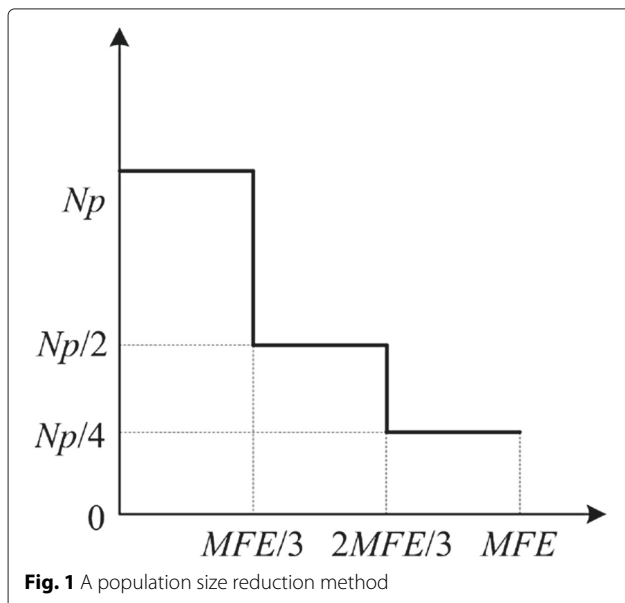
is a random number. Since resampling is firstly recommended, an infeasible candidate solution is repaired first using resampling. However, the computational cost of resampling method cannot be guaranteed. In the worst case, an infinite loop happens if none of the combinations produces a feasible solution. In our implementation, resampling is performed three times at most. For example, if $\mathbf{v}_{i,g}$ is infeasible using (2) or (6), two parents $\mathbf{x}_{r1,g}$ and $\mathbf{x}_{r2,g}$ are resampled no more than three times; if a feasible vector is generated, then repair step is finished and turn to proceed the next individual; otherwise, turn to the following steps.

If $\mathbf{v}_{i,g}$ is infeasible and its associated parent lies in the boundary of search space, reinitialization method is applied. Because in this case, both projection and parent medium methods are the same and cannot generate new gradients, reinitialization instead can create new elements and diversify population. If vector $\mathbf{v}_{i,g}$ is infeasible and its associated parent is feasible but not in boundary, then projection and parent medium methods have equal chance to be selected. Because both methods are good choices, i.e., projection is the second choice and parent medium is suggested in [13], hence each method is assigned a probability 0.5 to be chosen for execution.
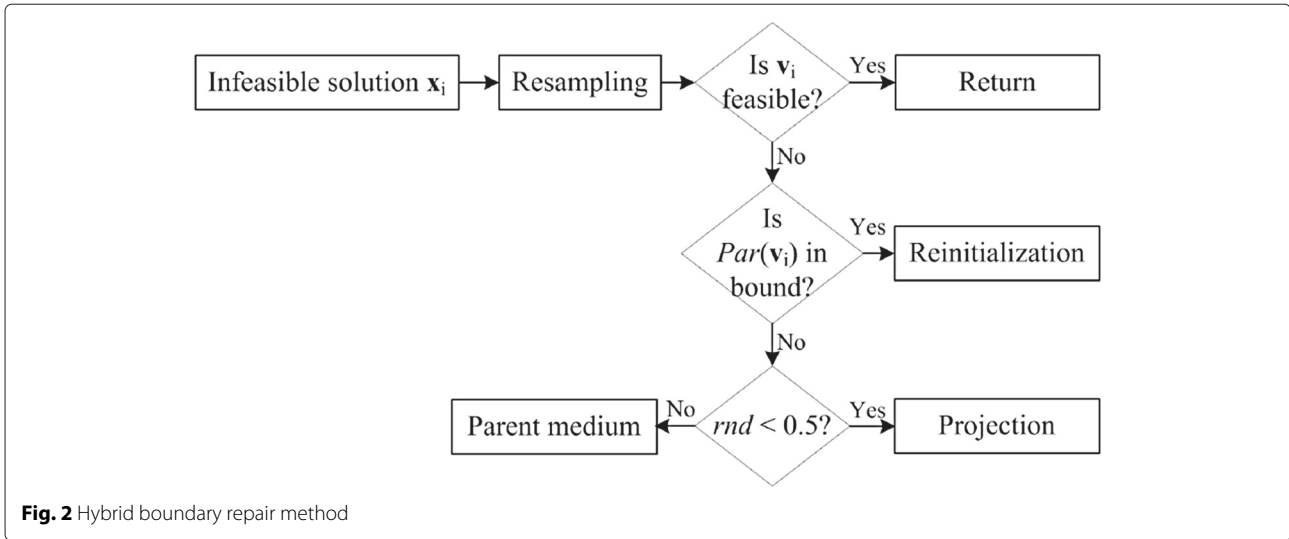
3.3 The proposed algorithm

Population size reduction and boundary repair methods are attached with qABC [9], which is a better imitation of the behavior of honey bees. The resulting algorithm is called population reduction and hybrid repair ABC (PRHRABC). The pseudo code of the algorithm is shown in Algorithm 1.

Algorithm 1 Pseudo code of the PRHRABC algorithm

Require: $f(\cdot)$, *MFE*, D, $\mathbf{x}^{min}$, $\mathbf{x}^{max}$, $N_p = N_p^{init}$, *limit*, r
Ensure: the best solution obtained by the algorithm
 1: randomly create N_p solutions $\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_{N_p}$;
 2: evaluate function values of solutions and their fitness by (1);
 3: set counter $l_i, i = 1, 2, \cdots, N_p$ to 0;
 4: **repeat**
 5:     send out employed bees by (2);
 6:     repair infeasible candidate solutions;
 7:     evaluate candidate solutions and their fitness by (1);
 8:     do greedy selection by (3) and update l_i by (5);
 9:     send out onlooker bees depending on their nectar amounts by (4);
10:     repair infeasible candidate solutions;
11:     evaluate candidate solutions and their fitness by (1);
12:     do greedy selection by (3) and update l_i by (5);
13:     send out scout bees if l_i reaches *limit*;
14:     evaluate candidate solutions and their fitness by (1);
15:     reset l_i to 0;
16:     update N_p by (9);
17: **until** termination criteria are met

Fig. 2 Hybrid boundary repair method

4 Experimental evaluation and analysis

In this section, the proposed algorithm is applied to deal with a polyphase code design and a circular shaped antenna array design problems.

Polyphase code design is often built as a min-max non-convex continuous optimization problem as shown in (10). This model is based on the attributes of aperiodic autocorrelation function and the assumption of coherent radar pulse processing in the receiver [1, 14]. This model contains numerous local optima which makes it difficult to solve.

$$
\begin{aligned}
\min_{x \in \Omega} \ & f(\mathbf{x}) = \max\{\varphi_1(\mathbf{x}), \ldots, \varphi_{2m}(\mathbf{x})\} \\
s.t. \ & \varphi_{2i-1}(\mathbf{x}) = \sum_{j=i}^{D} \cos\left(\sum_{k=|2i-j-1|+1}^{j} x_k\right), \ i = 1, \ldots, D \\
& \varphi_{2i}(\mathbf{x}) = 0.5 + \sum_{j=i+1}^{D} \cos\left(\sum_{k=|2i-j|+1}^{j} x_k\right), \ i = 1, \ldots, D-1 \\
& \varphi_{m+i}(\mathbf{x}) = -\varphi_i(\mathbf{x}), \ i = 1, 2, \ldots, m \\
& \Omega = \{(x_1, \ldots, x_n) \in \Re^D | 0 \le x_j \le 2\pi, j = 1, \ldots, D\}
\end{aligned}
\tag{10}
$$

where $m = 2D - 1$. In this model, variables correspond to the differences of symmetrized phase. The function objective is to minimize the biggest module amongst the samples of autocorrelation function. In this experiment, problem dimension is set to $D = 20$, which is larger than existing studies [14, 15].

As to antenna array design, suppose we consider N antenna elements spread on a circle of radius r in the x–y plane. The N elements constitutes a circular antenna array. The current I and phase excitations of all elements are varied in order to suppress side lobes, minimize

beamwidth, and accomplish null control at desired directions. This problem is modeled as follows [16]:

$$
\begin{aligned}
\min_{x \in \Omega} \ & f(\mathbf{x}) = f_{\text{sll}} + f_{\text{dir}} + f_{\text{des}} + f_{\text{null}} \\
s.t. \ & f_{\text{sll}} = |AF(\varphi_{\text{sll}})| / |AF(\varphi_{\text{max}})| \\
& f_{\text{dir}} = 1/\text{dir}(\varphi_0) \\
& f_{\text{des}} = |\varphi_0 - \varphi_{\text{des}}| \\
& f_{\text{null}} = \sum_{k=1}^{\text{num}} |AF(\varphi_k)| \\
& AF(\varphi) = \sum_{n=1}^{N} I_n \exp[jkr(\cos(\varphi - \varphi_{\text{ang}}^n) \\
& \qquad - \cos(\varphi_0 - \varphi_{\text{ang}}^n)) + \beta_n]
\end{aligned}
\tag{11}
$$

where $N = 12$, num $\in [50, 120]$ is the number of null control directions, φ_0 is the maximum radiation direction, $\varphi_{\text{des}} = 180^o$, I_n and β_n are respectively the current and phase excitation of element n. In this model, I_n and β_n are variables.

4.1 Experimental configuration

PRHRABC and qABC as well as standard ABC are chosen for experiment. The parameter setting for qABC is $N_p = 25$, limit $= 0.5\, N_p D$, and $r = 1$ as suggested in [6, 7, 9]. For PRHRABC, N_p^{init} is set to $4D$, limit $= 0.5 N_p D$, and $r = 1$. For standard ABC, $N_p = 25$, limit $= 0.5\, N_p D$. All algorithms are implemented in Matlab and simulated on a PC with 3.4-GHz four-core CPU and 4 GB of memory. Each problem is conducted 25 independent runs with MFE = 50,000. The source code of PRHRABC can be obtained from the first author upon request.

4.2 Experimental results

The experimental results are shown in Table 1. This table presents the best function values in four kinds of statistics, which are best, median (med), worst, and standard deviation (std). For both polyphase code design and antenna array design problems, PRHRABC obtains better results than qABC and ABC. To gain a statistical view of the

Table 1 Statistics of the best function values found by PRHRABC, qABC, and ABC

	Best	Med	Worst	std	*p*	
Polyphase code						
PRHRABC	1.1035	1.3000	1.4441	0.0885		
qABC	1.1175	1.3454	1.5769	0.0933	0.0199	+
ABC	1.1929	1.3739	1.5226	0.0838	0.0397	+
Antenna array						
PRHRABC	−19.715	−18.590	−17.000	0.7865		
qABC	−19.604	−16.961	−14.892	1.0669	2.77e−5	+
ABC	−18.889	−17.284	−13.719	1.1460	2.14e−5	+

results, Mann-Whitney U test (U test) is utilized with a significant level of α = 0.05. The p values comparing PRHRABC and qABC (or PRHRABC and ABC) are given in the second last column of Table 1. Symbol "+" in the last column indicates cases in which the null hypothesis is rejected, and PRHRABC displays a statistically superior performance by U test. As the p values are less than α for both test cases, we can conclude that PRHRABC significantly outperforms qABC and ABC in this experiment.

The convergence curves of PRHRABC and qABC for dealing with antenna array design are shown in Fig. 3. It is plotted as the median best objective function value found over 25 trials. From the beginning to 14,000 function evaluations (FEs), the performance of the two algorithms is difficult to judge because the convergence lead changes several times. After 14,000 FEs, the proposed PRHRABC attains better solution than qABC and leads the evolutionary process until the end. Thus, the proposed algorithm
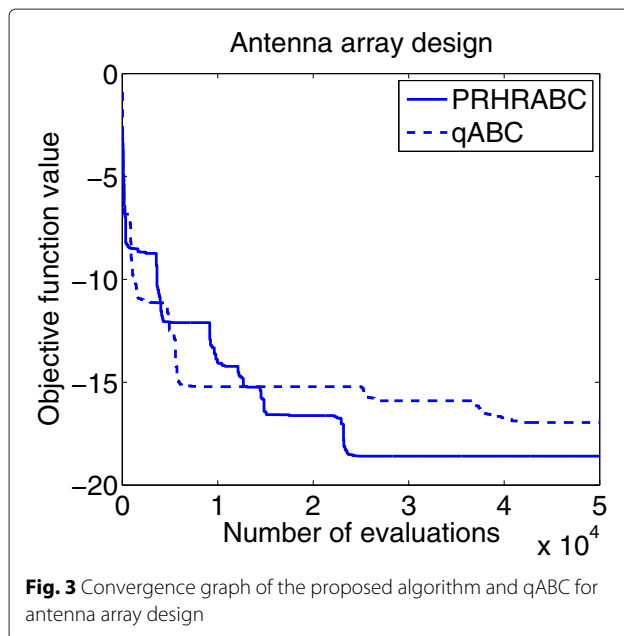
Fig. 3 Convergence graph of the proposed algorithm and qABC for antenna array design

shows good performance to deal with optimization problems in system designs.

5 Conclusions

Optimization problems widely exist in radar, mobile, and communication system designs. These problems are featured with multidimension, numerous local optima, or even NP-hard. Based on the artificial bee colony (ABC) paradigm, this paper proposes a population reduction method and a boundary repair method. Different from previous researches on algorithmic parameter control, the proposed method could adapt parameters to handle problems with different budget setting without the interaction of users. Moreover, a hybrid boundary repair method is used to enhance the reliability of algorithm.

The proposed algorithm is tested on a polyphase code design and a circular shaped antenna array design problems. Standard ABC and quick ABC (qABC), which is a state of the art ABC variant, are chosen as benchmark baselines. Experimental results show that the proposed algorithm significantly outperforms qABC and standard ABC for tackling the two problems. This suggests that the novel algorithm is a good one to solve optimization problems in radar, mobile, and communication system designs.

References
1. ML Dukic, ZS Dobrosavljevic, A method of a spread spectrum radar polyphase code design. IEEE J. Selected Areas Comm. **8**, 743–749 (1990)
2. M Dessouky, H Sharshar, Y Albagory, A novel tapered beamforming window for uniform concentric circular arrays. J. Electromagn. Waves Appl. **20**, 2077–2089 (2006)
3. L Guo, H Deng, B Himed, T Ma, Z Geng, Waveform optimization for transmit beamforming with MIMO radar antenna arrays. IEEE Trans. Antennas Propagation. **63**(2), 543–552 (2015). doi:10.1109/TAP.2014.2382637
4. Y-T Cheng, C-C Chiu, Optimization of the antenna location for relay cooperative system by apso. Wireless Personal Commun. **83**(4), 2485–2495 (2015)
5. MIH Dessouky, A Sharshar, YA Albagory, Efficient sidelobe reduction technique for small-sized concentric circular arrays. Prog. Electromagn. Res. **65**, 187–200 (2006)
6. D Karaboga, B Basturk, On the performance of artificial bee colony (ABC) algorithm. Appl. Soft Comput. **8**(1), 687–697 (2008)
7. K Diwold, A Aderhold, A Scheidler, M Middendorf, Performance evaluation of artificial bee colony optimization and new selection schemes. Memetic Comput. **3**(3), 149–162 (2011)
8. X Zhang, X Zhang, SL Ho, WN Fu, A modification of artificial bee colony algorithm applied to loudspeaker design problem. IEEE Trans. Magnetics. **50**(2), 737–740 (2014)

9.   D Karaboga, B Gorkemli, A quick artificial bee colony (qABC) algorithm and its performance on optimization problems. Appl. Soft Comput. **23**, 227–238 (2014)

10. J Brest, MS Maucec, Population size reduction for the differential evolution algorithm. Appl. Intell. **29**(3), 228–247 (2008)

11. J Arabas, A Szczepankiewicz, T Wroniak, in *PPSN XI*. Experimental comparison of methods to handle boundary constraints in differential evolution (Springer, Berlin, Heidelberg, 2010), pp. 411–420

12. S Wessing, in *Proceedings of the 16th European Conference on Applications of Evolutionary Computation*. EvoApplications'13. Repair Methods for Box Constraints Revisited (Springer, Berlin, Heidelberg, 2013), pp. 469–478

13. J Zhang, AC Sanderson, JADE: Adaptive differential evolution with optional external archive. IEEE Trans. Evol. Comput. **13**(5), 945–958 (2009)

14. AM Perez-Bellido, S Salcedo-Sanz, EG Ortiz-Garcia, JA Portilla-Figueras, F Lopez-Ferreras, A comparison of memetic algorithms for the spread spectrum radar polyphase codes design problem. Eng. Appl. Artif. Intell. **21**(8), 1233–1238 (2008)

15. S Gil-Lopez, JD Ser, S Salcedo-Sanz, AM Perez-Bellido, JM Cabero, JA Portilla-Figueras, A hybrid harmony search algorithm for the spread spectrum radar polyphase codes design problem. Expert Syst. Appl. **39**(12), 11089–11093 (2012)

16. S Das, PN Suganthan, Problem definitions and evaluation criteria for CEC 2011 competition on testing evolutionary algorithms on real world optimization problems. Technical report, Jadavpur Univ. and Nanyang Technol. Univ., India and Singapore (February 2011)