

Review Article

Evolutionary Algorithms Applied to Antennas and Propagation: A Review of State of the Art

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A review of evolutionary algorithms (EAs) with applications to antenna and propagation problems is presented. EAs have emerged as viable candidates for global optimization problems and have been attracting the attention of the research community interested in solving real-world engineering problems, as evidenced by the fact that very large number of antenna design problems have been addressed in the literature in recent years by using EAs. In this paper, our primary focus is on Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), and Differential Evolution (DE), though we also briefly review other recently introduced nature-inspired algorithms. An overview of case examples optimized by each family of algorithms is included in the paper.

1. Introduction

Several evolutionary algorithms (EAs) have emerged in the past decade that mimic the behavior and evolution of biological entities inspired mainly by Darwin's theory of evolution and its natural selection mechanism. The study of evolutionary algorithms began in the 1960s. Several researchers independently developed three mainstream evolutionary algorithms, namely, the Genetic Algorithms [1, 2], Evolutionary Programming [3], and evolution strategies [4] (Figure 1). EAs are widely used for the solution of single and multiobjective optimization problems and Figure 1 depicts some of the main algorithmic families.

Swarm Intelligence (SI) algorithms are also a special type of EA. The SI can be defined as the collective behavior of decentralized and self-organized swarms. SI algorithms include Particle Swarm Optimization (PSO) [5], Ant Colony Optimization [6], and Artificial Bee Colony (ABC) [7]. PSO mimics the swarm behavior of birds flocking and fish schooling [5]. The most common PSO algorithms include the classical Inertia Weight PSO (IWPSO) and the Constriction Factor PSO (CFPSO) [8]. The PSO algorithm is easy to implement and is computationally efficient; it is typically used

only for real-valued problems. An option to expand PSO for discrete-valued problems also exists [9]. Other SI algorithms include (i) Artificial Bee Colony (ABC) [7], which models and simulates the behaviors of honey bees foraging for food, and (ii) Ant Colony Optimization (ACO) [6, 10, 11], which is a population-based metaheuristic inspired by the behavior of real ants.

Differential Evolution (DE) [12, 13] is a population-based stochastic global optimization algorithm, which has been used in several real-world engineering problems utilizing several variants of the DE algorithm. An overview of both the PSO and DE algorithms and hybridizations of these algorithms along with other soft computing tools can be found in [14].

Other evolutionary techniques applied to antenna problems include the recently proposed Wind Driven Optimization (WDO) [15]; biogeography-based optimization (BBO); Invasive Weed Optimization (IWO) [16–20]; Evolutionary Programming (EP) [21, 22]; and the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) [23, 24].

An important theorem which is pertinent to the performance of optimization algorithms is the so-called “No

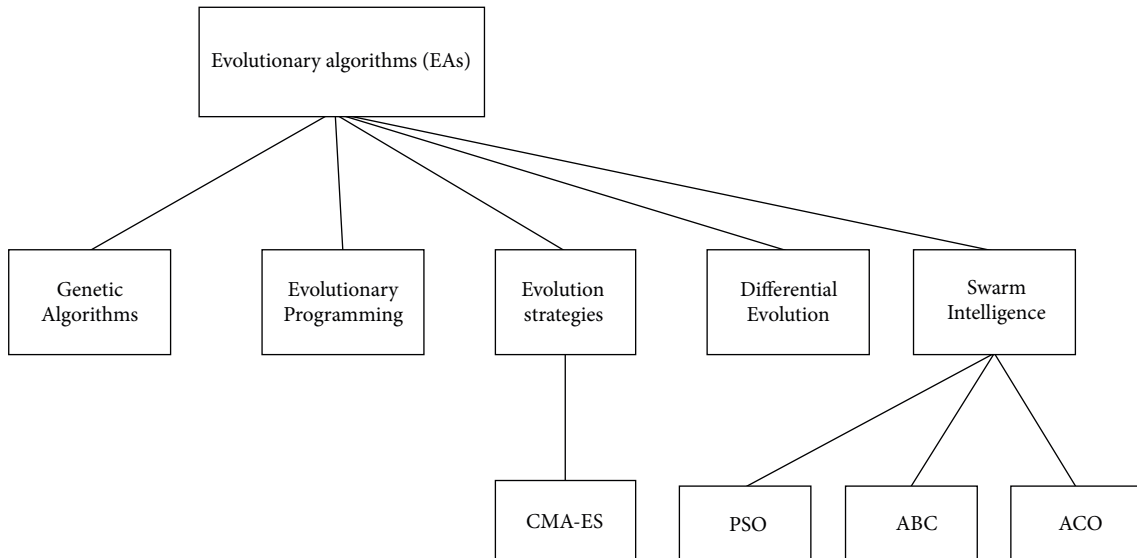


FIGURE 1: A diagram depicting main families of evolutionary algorithms.

Free Lunch” (NFL) theorem, which pertains to the average behavior of optimization algorithms over given spaces of optimization problems. It has been shown in [25] that when averaged over all possible optimization problems defined over some search space X , no algorithm has a performance advantage over any other. Additionally, in [26] the authors show that it is theoretically impossible to have a best general-purpose universal optimization strategy, and the only way for one strategy to be superior to the others is when it focuses on a particular class of problems. It should be noted that a wide variety of optimization problems arise in the antenna domain and that it is not always an easy task to find the best optimization algorithm for solving each of them. Therefore, it is worthwhile to explore new optimization algorithms if we find that they can work well for the problem at hand. Optimization problems arising in the design and synthesis of antennas can benefit considerably from an application of the EAs, which can lead to unconventional solutions regarding position and excitation of the antenna elements in an array. Furthermore, the elements themselves can be geometrically designed by using the EAs.

The purpose of this paper is to briefly describe the algorithms and present their application to antenna design problems found in the recent literature.

Section 2 reviews the Genetic Algorithms (GAs). Section 3 focuses on PSO and Section 4 is devoted to DE. A brief overview of other EA algorithms is provided in Section 5. We describe the algorithms briefly and then present some statistics regarding the use of the algorithms in the literature. Additionally, for each algorithm some representative papers are referenced in the tables. Some open issues are discussed in Section 6, and conclusions are drawn in Section 7.

2. Genetic Algorithms

GAs, the most popular EAs, are inspired by Darwin’s natural selection. GAs can be real or binary-coded. In a binary-coded

GA each chromosome encodes a binary string [27, 28]. The most commonly used operators are crossover, mutation, and selection. The selection operator chooses two parent chromosomes from the current population according to a selection strategy. Most popular selection strategies include roulette wheel and tournament selection. The crossover operator combines the two parent chromosomes in order to produce one new child chromosome. The mutation operator is applied with a predefined mutation probability to a new child chromosome.

A search in the Scopus database shows that there are 65762 conference papers and 94510 journal papers related to GAs from 1977 to 2016. Figure 2 shows the number of papers related to GAs and antennas over the last 15 years. Additionally, the search in the same database using the keywords GAs and Antennas reveals a total number of 2807 papers (both journal and conference). Tutorials and applications of GAs to electromagnetics can be found in [29, 30].

Table 1 lists selected papers that use GAs (mostly binary-coded) for antenna design. Several papers exist in the literature that apply GAs for array synthesis. A binary-coded GA has been applied for linear and planar array synthesis in [31, 32], among others, while a GA that uses decimal operator has been used in [33]. The problem of array thinning has been addressed in the literature using binary-coded GAs in [34], while the array-failure correction problem has been addressed by using the real-coded GAs in [35]. A simple GA has been used for the synthesis of time-modulated arrays in [36]. Different antenna types have been designed using the GAs, for example, wire antennas in [37–40], patch antennas in [41, 42], and RFID tags in [43]. Other GA-type algorithms, such as a mixed integer GA, have also been applied in [44] to several different antenna design problems. An improved GA for the design of linear aperiodic arrays and a binary-coded GA which uses two-point crossover (instead of the usual one point) have been used in [45] for the design of

TABLE 1: Selected journal papers that use GAs for antenna design.

| Problem | Algorithm(s) used | Ref. |
|--|---|----------|
| Thinned arrays | Binary-coded GA | [34] |
| Wire antennas and Yagi-Uda antenna | Binary-coded GA | [37–40] |
| Array synthesis | Decimal operators GA | [33] |
| Array-failure correction | Real-coded GA | [35] |
| Linear and planar array synthesis | Binary-coded GA and hybrid GA with simulated annealing (SA) | [31, 32] |
| Broadband patch antennas and dual-band patch antennas | Binary-coded GA and parallel GA | [41, 42] |
| RFID tags | Binary-coded GA | [43] |
| Time-modulated linear arrays | Simple GA | [36] |
| Linear array design, thinned subarrays, and circularly polarized patch antenna | Mixed integer GA | [44] |
| Linear aperiodic arrays design | Improved GA | [138] |
| Low RCS slot patch antennas | Binary-coded GA and two-point crossover | [45] |
| T-shaped MIMO radar antenna array | chaos genetic algorithm | [46] |
| Quad-band patch antenna | Binary-coded GA | [47] |

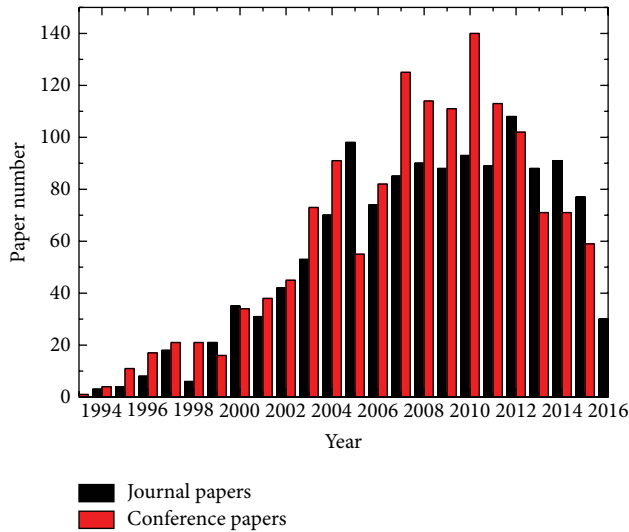


FIGURE 2: Papers using GAs for antenna design from 1993 to May 2016.

patch antennas with low RCS. A GA that combines chaos theory and genetic algorithm is used for designing T-shaped MIMO radar antenna array in [46]. A design procedure based on a GA is given in [47] for optimizing a patch antenna for operation to four frequency bands GSM1800, GSM1900, LTE2300, and Bluetooth.

3. Particle Swarm Optimization (PSO)

In PSO, the particles move in the search space, where each particle position is updated by two optimum values. The first one is the best solution (fitness) that has been achieved so far. This value is called *pbest*. The other one is the global best value obtained so far by any particle in the swarm. This best value

is called *gbest*. After finding the *pbest* and *gbest*, the velocity update rule is an important factor in a PSO algorithm. The most commonly used algorithm defines that the velocity of each particle for every problem dimension is updated with the following equation:

$$u_{G+1,ni} = wu_{G,ni} + c_1 \text{rand}_{1(0,1)} (pbest_{G+1,ni} - x_{G,ni}) + c_2 \text{rand}_{2(0,1)} (gbest_{G+1,ni} - x_{G,ni}), \quad (1)$$

where $u_{G+1,ni}$ is the i th particle velocity in the n th dimension, $G + 1$ denotes the current iteration and G denotes the previous, $x_{G,ni}$ is the particle position in the n th dimension, $\text{rand}_{1(0,1)}$, $\text{rand}_{2(0,1)}$ are uniformly distributed random numbers in $(0, 1)$, w is a parameter known as the inertia weight, and c_1 and c_2 are the learning factors.

The parameter w (inertia weight) is a constant between 0 and 1. This parameter represents the particle's fly without any external influence. The higher the value of w is or the closer it is to unity, the more the particle stays unaffected from *pbest* and *gbest*. The inertia weight controls the impact of the previous velocity: a large inertia weight favors exploration, while a small inertia weight favors exploitation. The parameter c_1 represents the influence of the particle memory on its best position, while the parameter c_2 represents the influence of the swarm best position. Therefore, in the Inertia Weight PSO (IWPSO) algorithm the parameters to be determined are the swarm size (or population size), usually 100 or less, the cognitive learning factor c_1 and the social learning factor c_2 (usually both are set equal to 2.0), the inertia weight w , and the maximum number of iterations. It is common practice to linearly decrease the inertia weight starting from 0.9 or 0.95 to 0.4.

Clerc [8] has suggested the use of a different velocity update rule, which has introduced a parameter K called constriction factor. The role of the constriction factor is to

TABLE 2: Selected journal papers that use PSO for antenna design.

| Problem | Algorithm(s) used | Ref. |
|--|---|--------------|
| Linear arrays design | Original PSO and CLPSO | [50, 51, 63] |
| Profiled corrugated horn antenna design | Original PSO and GA and hybrid GA-PSO | [54] |
| Phased arrays design | Original PSO and GA comparison | [52] |
| Circular array design | Original PSO and DE and GA comparison | [53] |
| Coplanar waveguide-fed planar monopole antenna | Original PSO with MoM | [56] |
| Conformal phased arrays design | Original PSO | [55] |
| Reconfigurable phase-differentiated array design | Original PSO | [57] |
| Multiband and wideband patch antenna design | Parallel PSO/FDTD | [58] |
| Time-modulated arrays design | Original PSO | [59] |
| Infinitesimal dipoles array synthesis | QPSO | [61] |
| Yagi-Uda antenna | CLPSO | [62] |
| Thinned planar circular arrays | Modified PSO | [64] |
| Adaptive beamforming of linear antenna arrays | Adaptive Mutated Boolean PSO | [139] |
| Dual-band patch antenna design | Boolean PSO | [140] |
| Array design | Chaotic PSO | [141] |
| Square thinned arrays | Hybrid PSO and Hadamard difference sets | [142] |
| Linear array design | Feedback Particle Swarm Optimization (FPSO) with nonlinear inertia weight | [65] |

ensure convergence when all the particles have stopped their movements. The velocity update rule is then given by

$$\begin{aligned}
 u_{G+1,ni} = & K [u_{G,ni} + c_1 \text{rand}_{1(0,1)} (pbest_{G+1,ni} - x_{G,ni}) \\
 & + c_2 \text{rand}_{2(0,1)} (gbest_{G+1,ni} - x_{G,ni})], \\
 K = & \frac{2}{\left| 2 - \varphi - \sqrt{\varphi^2 - 4\varphi} \right|},
 \end{aligned} \tag{2}$$

where $\varphi = c_1 + c_2$ and $\varphi > 4$. This PSO algorithm variant is known as Constriction Factor PSO (CFPSO).

The Scopus database shows a total number of 39673 papers from 1995 to April 2016 for PSO related papers (including 19570 journal papers and 18355 conference papers). A refined search for antenna papers reveals 519 journal papers and 515 conference papers from 2002 to May 2016 indicating the popularity of PSO algorithm. Figure 3 shows the distribution of papers on PSO design of antennas from 2002 to 2016.

Table 2 lists selected PSO antenna papers. Introductory and tutorial papers that introduce the application of the PSO for antenna design are [48, 49]. Additionally, the problem of sidelobe suppression of linear arrays using the PSO has been addressed in [50, 51]. A comparison of the performance of the PSO and GA algorithms, as applied to the problem of phased arrays design, has been given in [52], while a comparative study of PSO, GAs, and DE for circular array design has been reported in [53]. A performance comparison of PSO, GA, and a hybrid GA-PSO has been provided in [54], where they have been applied to the problem of designing profiled corrugated horn antennas. The application of PSO to conformal phased arrays design has been shown in [55]. A coplanar waveguide-fed planar monopole antenna for multiband operation has

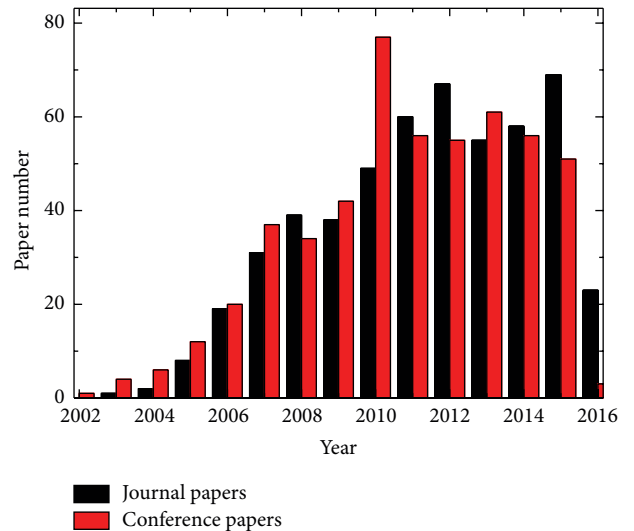


FIGURE 3: Papers using PSO for antenna design from 2002 to May 2016.

been designed in [56] using the PSO algorithm in conjunction with the Method of Moments (MoM). The authors in [57] use PSO for reconfigurable phase-differentiated array design. A Parallelized PSO optimizer has been used in conjunction with the Finite Difference Time Domain (FDTD) which has been employed for multiband patch antenna designs in [58], and the problem of minimizing power loss in time-modulated arrays has been addressed in [59]. Boundary conditions play an important role in the application of the PSO, and the performances of different boundary conditions have been tested on a 16-element array antenna in [60], based

on mathematical benchmark functions. All of the above papers use the original IWPSO or the CFPSO, although several variants of PSO are available. A new PSO variant called quantum PSO (QPSO) algorithm has been proposed and applied in [61] to find a set of infinitesimal dipoles which produces the same near and far fields as a circular dielectric resonator antenna (DRA). The interesting point about QPSO is the fact that it contains only one control parameter. The comprehensive learning PSO (CLPSO) is applied to Yagi-Uda antenna design in [62] and unequally spaced arrays sidelobe suppression in [63]. A modified PSO algorithm has been applied in [64] for the synthesis of thinned planar circular arrays. A Feedback Particle Swarm Optimization (FPSO) is in [65] proposed for SLL minimization and null control of linear arrays. The FPSO is based on a nonlinear inertia weight algorithm.

4. Differential Evolution (DE)

In DE, the initial population evolves in each generation with the use of three operators: mutation, crossover, and selection. Several DE variants or strategies exist in the literature [13, 66] that depend on the form of these operators. The choice of the best DE strategy depends on the problem type [67]. Common DE strategies for the generation of trial vectors include DE/rand/1/bin, DE/rand-to-best/2/bin, and DE/rand/2/bin. In these strategies a mutant vector $\bar{v}_{G+1,i}$ for each target vector $\bar{x}_{G,i}$ is computed by

$$\begin{aligned} & \text{DE/rand/1/bin} \\ & \bar{v}_{G+1,i} = \bar{x}_{G,r_1} + F(\bar{x}_{G,r_2} - \bar{x}_{G,r_3}), \quad r_1 \neq r_2 \neq r_3 \\ & \text{DE/rand-to-best/2/bin} \\ & \bar{v}_{G+1,i} = \bar{x}_{G,i} + F(\bar{x}_{G,\text{best}} - \bar{x}_{G,i}) + F(\bar{x}_{G,r_1} - \bar{x}_{G,r_2}) \\ & \quad + F(\bar{x}_{G,r_3} - \bar{x}_{G,r_4}), \quad r_1 \neq r_2 \neq r_3 \neq r_4 \\ & \text{DE/rand/2/bin} \\ & \bar{v}_{G+1,i} = \bar{x}_{G,r_1} + F(\bar{x}_{G,r_2} - \bar{x}_{G,r_3}) + F(\bar{x}_{G,r_4} - \bar{x}_{G,r_5}), \\ & \quad r_1 \neq r_2 \neq r_3 \neq r_4 \neq r_5, \end{aligned} \quad (3)$$

where r_1, r_2, r_3, r_4, r_5 are randomly chosen indices from the population that are different from the index i and F is a mutation control parameter. After mutation, the crossover operator is applied to generate a trial vector $\bar{u}_{G+1,i} = (u_{G+1,1i}, u_{G+1,2i}, \dots, u_{G+1,ji}, \dots, u_{G+1,Di})$ whose coordinates are given by

$$u_{G+1,ji} = \begin{cases} v_{G+1,ji}, & \text{if } \text{rand}_{j[0,1]} \leq \text{CR} \text{ or } j = \text{rn}(i), \\ x_{G+1,ji}, & \text{if } \text{rand}_{j[0,1]} > \text{CR} \text{ and } j \neq \text{rn}(i), \end{cases} \quad (4)$$

where $j = 1, 2, \dots, D$, $\text{rand}_{j[0,1]}$ is a number from a uniform random distribution from the interval $[0, 1)$, $\text{rn}(i)$ is a randomly chosen index from $(1, 2, \dots, D)$, and CR is the crossover constant from the interval $[0, 1]$. DE uses a

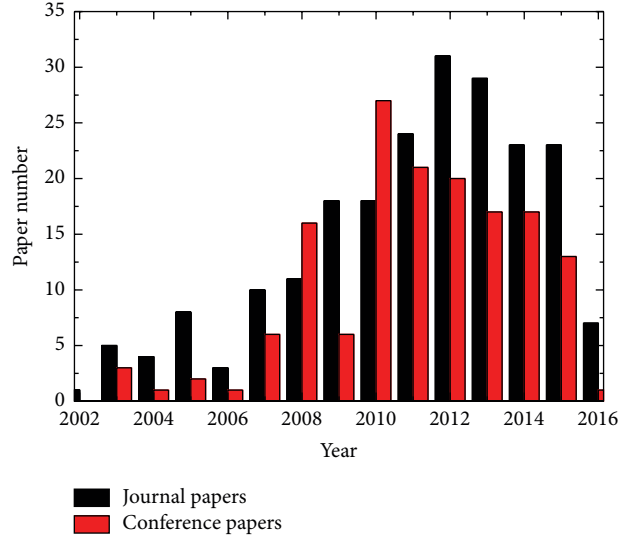


FIGURE 4: Papers using DE for antenna design from 2002 to May 2016.

greedy selection operator, which for minimization problems is defined by

$$\bar{x}_{G+1,i} = \begin{cases} \bar{u}_{G+1,i}, & \text{if } f(\bar{u}_{G+1,i}) < f(\bar{x}_{G,i}), \\ \bar{x}_{G,i}, & \text{otherwise,} \end{cases} \quad (5)$$

where $f(\bar{u}_{G+1,i})$ and $f(\bar{x}_{G,i})$ are the fitness values of the trial and the old vector, respectively. The new trial vector $\bar{u}_{G+1,i}$ replaces the old vector $\bar{x}_{G,i}$ only when it produces a lower objective-function value than the old one. Otherwise, the old vector remains in the next generation. The stopping criterion for the DE is usually the generation number or the number of objective-function evaluations.

A search in the Scopus database reveals 38,097 documents related to DE (27,482 journal papers and 7831 conference papers). A refined search for antenna related papers using the DE shows 221 journal papers and 152 conference papers. Figure 4 shows how the papers related to DE antenna are distributed from 2002 to May 2016.

A general review paper of the use of DE in electromagnetics has been reported in [68], and a book [69] on DE implementation in electromagnetics has been published. Table 3 lists some representative papers for antenna design. The most commonly used DE strategy for antenna design is the DE/rand/1/bin variant. The above-mentioned strategy has been applied, among others, to the problem of linear array design in [70]; synthesis of difference patterns of monopulse antennas in [71]; array pattern nulling in [72]; and conformal array design in [73]. Several other DE strategies have been applied to antenna problems. In [74], the authors have introduced a new DDE/BoR/1/bin strategy for linear array synthesis, while a modified DE strategy (MDSE) has been used in [75] for the same problem. The strategy DE/best/1/bin has been applied in [76–78] for time-modulated array design. Self-adaptive DE algorithms have also been applied to antenna problems, including jDE [79]

TABLE 3: Selected journal papers that use DE for antenna design.

| Problem | Algorithm(s) used | Ref. |
|---|-----------------------------|----------|
| Linear arrays design | DE/rand/1/bin | [70] |
| Linear arrays design | DDE/BoR/1/bin | [74] |
| Linear arrays design and E-shaped patch antenna | jDE [79] | [80–82] |
| Difference patterns of monopulse antennas | DE/rand/1/bin | [71] |
| Array pattern nulling | DE/rand/1/bin | [72] |
| Linear arrays design | Modified DE strategy (MDES) | [75] |
| Linear arrays design | Multiobjective DE | [87] |
| Array design | Improved DE | [143] |
| Shaped beam synthesis | CODE-EIG | [86] |
| Conformal arrays design | DE/rand/1/bin | [73] |
| Horn antenna design and sparse linear arrays synthesis | SaDE [83] | [84, 85] |
| Subarray design | Memetic GDE3 | [88] |
| Time-modulated arrays design | DE/best/1/bin | [76–78] |
| Monopulse antenna with a subarray weighting | Hybrid DE | [144] |
| Yagi-Uda antenna | GDE3 | [89] |
| Low Radar Cross Section (RCS) slot patch antenna design | DE/MoM | [90] |

in [80–82]; SaDE [83] in [84, 85]; and CODE-EIG in [86]. Multiobjective DE algorithms are also another large group of DE algorithms applied to antenna problems. These include applications to linear array design in [87], to subarray design in [88], and to Yagi-Uda antennas [89]. DE algorithms hybridized with other methods are also commonly found in the literature; for instance, the DE has been used with the Method of Moments in [90] for the design of low Radar Cross Section (RCS) antennas.

5. Other Innovative Algorithms

Several new EAs have emerged during the last ten years that are based on different evolutionary models of animals, insects, or other biological entities. Artificial Bee Colony (ABC) [7] is a recently proposed SI algorithm, which has been applied to several real-world engineering problems. The ABC algorithm models and simulates the honey bee behavior in food foraging. In the ABC algorithm, a potential solution to the optimization problem is represented by the position of a food source while the food source corresponds to the quality (objective-function fitness) of the associated solution. The ABC algorithm has been successfully applied to several problems in wireless communications [91]. A number of different variants of the ABC that improve the original algorithm have been proposed in [92]. A search in the Scopus database shows that there are more than 3000 papers on ABC, of which 48 use the ABC for antenna design. These include array design [93–96]; resonant frequency of patch antennas calculation [97]; and RFID tags design [98–100].

Ant Colony Optimization (ACO) [6, 10, 11] is a population-based metaheuristic which was introduced by Dorigo et al. [11] inspired by the behavior of real ants. The algorithm is based on the fact that ant colonies can find the shortest path between their nest and a food source just by depositing and reacting to pheromones while they are

exploring their environment. ACO is suitable for solving combinatorial optimization problems that are common in antennas. The search in Scopus shows more than 10,000 papers on ACO, with 169 papers dealing with the topic of antenna design. The topic of linear array synthesis has been presented in [101]; patch antenna design in [102]; sum-difference pattern synthesis in [103]; and thinned array design in [102]. A modified touring ant colony optimizer has been used for shaped beam synthesis [104] and for pattern nulling in [105–107]. The authors in [108] present a comparative study of simulated annealing (SA), GA, and ACO on self-structured antenna design.

Biogeography-based optimization (BBO) [109] is another later addition to EAs. BBO is based on mathematical models that describe how species migrate from one island to another, how new species arise, and how species become extinct. The way the problem solution is found is analogous to nature's way of distributing species. The search in the Scopus database yielded 654 papers that refer to BBO from 2007 to May 2016 with 40 papers that use BBO for antenna design from 2009 till today. BBO has been applied to Yagi-Uda design [110] and array synthesis [111–117]. Additionally a hybrid DE/BBO algorithm has been used for the design of a reconfigurable antenna array with discrete phase shifters in [118].

Evolutionary Programming (EP) was originally proposed by Fogel in [3]. EP is based on the idea of representing individuals phenotypically as finite state machines capable of responding to environmental stimuli. The representations used in EP are problem-dependent. The most common representation used is a fixed-length real-valued vector. In EP, the vectors evolve but do not exchange information between them. There are no crossover operators but only mutation operators. EP has been applied to several problems in electromagnetics [21, 119, 120]. Among others EP has been applied to patch antenna design [121] and to wideband parasitic dipole arrays [122].

Hansen and Ostermeier [123] introduced the Covariance Matrix Adaptation Evolution Strategy (CMA-ES). CMA-ES is a second-order approach estimating a positive covariance matrix within an iterative procedure. More details about the CMA-ES performance algorithm can be found in [124, 125]. In [23, 24] the authors present an approach for mixed-parameter optimization based on CMA-ES, which is successfully applied in several design problems in electromagnetics. This approach is based on the concepts presented in [22] for EP. The CMA-ES algorithm has been recently applied to design problems in antennas and electromagnetics in general [126–129].

5.1. Other Artificial Intelligence Methods. Other artificial intelligence methods and techniques include Artificial Neural Network (ANN) architectures [130], which are a family of models inspired by biological neural networks. ANNs are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. The applications of ANNs to electromagnetics are a popular topic in the literature [131].

Deep learning is a type of machine learning based on a set of algorithms that attempt to model high-level abstractions in data by using a deep graph with multiple processing layers, composed of multiple linear and nonlinear transformations [132–135]. These methods have dramatically improved the state of the art in speech recognition, visual object recognition, object detection, and many other domains such as drug discovery and genomics [132].

6. Discussion: Open Issues

The choice of the best algorithm for every problem requires the consideration of its specific characteristics. Once the algorithm is chosen, the key issue becomes the selection of the algorithm control parameters, which in most cases can be also problem-dependent. A practical initial approach is to use the control parameters for these algorithms that commonly perform well regardless of the characteristics of the problem to be solved.

For real-coded GAs typical values are 0.9 for the crossover probability and $1/N$ for the mutation probability, where N is the problem dimension. For the binary-coded GA, typical values for crossover and mutation probabilities are [1.0, 0.8] and [0.01, 0.1], respectively.

In the PSO algorithms c_1 and c_2 are set equal to 2.05. For CFPSO, these values result in $K = 0.7298$. For IWPSO, it is common practice to linearly decrease the inertia weight starting from 0.95 to 0.4. The velocity is updated asynchronously, which means that the global best position is updated at the moment it is found.

For the DE, Storn and Price [13] have suggested choosing the differential evolution control parameters F and CR from the intervals [0.5, 1] and [0.8, 1], respectively, and setting $NP = 10D$. The correct selection of these control parameter values is, frequently, a problem-dependent task. Multiple algorithm runs are often required for fine-tuning the control parameters. There are several DE algorithms in the literature

that self-adapt these control parameters. Another question is the selection of the appropriate strategy for the generation of trial vectors, which requires additional computational time using a trial-and-error search procedure. Therefore, it is not always an easy task to fine-tune the control parameters and strategy. Since finding the suitable control parameter values and strategy in such a way is often very time-consuming, there has been an increasing trend among researchers in designing new adaptive and self-adaptive DE variants. A DE strategy (jDE) that self-adapts the control parameters has been introduced in [79]. This algorithm has been applied successfully to a microwave absorber design problem [136] and linear array synthesis [82]. SaDE, a DE algorithm that self-adapts both control parameters and strategy based on learning experiences from previous generations, is presented in [83].

The research domain of evolutionary algorithms is growing rapidly. A current and growing research trend in evolutionary algorithms is their hybridization with local optimizers. These algorithms are called Memetic Algorithms (MAs) [90] that are inspired by Dawkins' notion of meme. The advantage of such an approach is that the use of a local search optimizer ensures that specific regions of the search space can be explored using fewer evaluations and good quality solutions can be generated early during the search. Furthermore, the global search algorithm generates good initial solutions for the local search. MAs can be highly efficient due to this combination of global exploration and local exploitation.

An interesting idea has been presented in [137] where the authors conceptually present the equivalences of various popular EAs like GAs, PSO, DE, and BBO. Their basic conclusion is that the conceptual equivalence of the algorithms is supported by the fact that modifications in algorithms result in very different performance levels.

Finally, another concern that is pertinent to all of the above algorithms is the definition of the stopping criterion. Usually, this is the iteration number or the number of objective-function evaluations. Additionally and in order to avoid stagnation, another criterion could be set for the algorithm to stop after a number of generations when the objective function does not further improve.

7. Conclusion

A brief survey of different evolutionary algorithms and their application to different problems in antennas and propagation have been presented in this review paper. It is to be noted that, among the evolutionary algorithms used in the literature, the GA and SI algorithms are among those most commonly utilized.

The bibliography statistics show that GAs, PSO, and DE are among the most popular algorithms for antenna design. It must be pointed out that several variants of these algorithms have also been employed along with other nature-inspired algorithms that have emerged. Most notably, ABC, ACO, BBO, EP, and CMA_ES have been applied to several antenna design problems. The body of literature on EAs to antenna

design is by now quite extensive and it continues to grow fast with more innovative algorithms. The above presented algorithms have been proven effective in solving specific antenna design problems, although the NFL theorem assures that a best global optimizer does not exist. The search for new algorithms and their application to antenna design problems is an ongoing research process, which is likely to continue unabated for some time to come.

Competing Interests

The authors declare that they have no competing interests.

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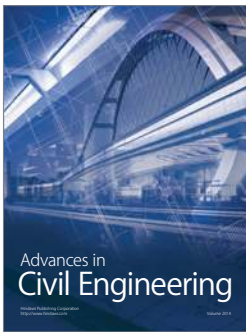
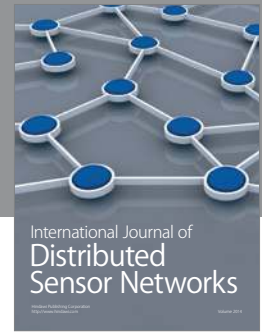
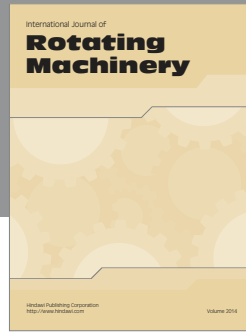
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