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EXPLORATION OF OPTIMIZATION ALGORITHMS FOR OPTIMIZATION OF ANTENNA AND ANTENNA ARRAYS

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Abstract: Optimization of antenna and antenna array is a vital step in design and implementation of any antenna as it helps to achieve required functionality. Optimization algorithm gives a highly precise functional solution to given problem. In antenna designs optimization algorithms help to find required geometry or radiation characteristics. Where as in case of antenna arrays; optimization algorithms are used to configure the element excitation values to achieve required radiation properties. The body of literature on optimization algorithms for antenna design is by now quite extensive and it continues to grow fast with more innovative algorithms. This article synopsizes various optimization algorithms used for optimization of antennas and antenna arrays, which will help designer to select appropriate algorithm according to the design and output characteristics.
Keywords: optimization algorithms, reconfigurable antenna, antenna array, geometry optimization, switches configuration optimization

1. INTRODUCTION

Reconfigurable antenna implementation process has evolved significantly in last few decades. But still the main steps are antenna design, optimization and implementation. Much of the work is presented in literature exploring these steps of implementation in reconfigurable antenna. This paper tries to discuss various optimization techniques used for optimization of reconfigurable antenna and reconfigurable antenna array. Antenna optimization is an important and crucial step in implementation of reconfigurable antenna or antenna array. Objective of antenna optimization is to design a cutting-edge design which is modest in terms of functioning and usefulness. Optimizing a reconfigurable antenna results in finding perfect physical dimensions, minimum no of switches or efficient switch configuration for the given antenna structure to achieve the required reconfigurable operation. Whereas for an array optimization technique leads to arrange the elements and the excitation coefficient values to obtain the expected radiation pattern. Most of the optimization algorithms are designed to find apposite and ideal solution of Maxwell's equations using numerical methods. EM solvers are used to solve optimization problem of given antenna with an objective function to automatically adjust the antenna parameters [1].

Optimization process usually begins with identification and finalization of design variables, which are varied during the optimization process. Selecting few design variables as possible are always preferred while formulating the problem. New variables can be added in terms of new formula or original variables can be replaced depending on the output of optimization. Second step is to define constraints. The constraints are the functional relationships among the design variables and other design parameters such that the physical phenomenon and resource limitations are met. Constraints are always user defined. Next step is to find the objective function in terms of the design variables and other problem parameters. The objective function can be of two types. Either it is to be maximized or it has to be minimized. The final step is to decide bounds on each design variable which will be varied during optimization [2].

Usually optimization algorithms are classified as local or global or considered as deterministic, stochastic or metaheuristic. Both the search techniques try to find solution to optimize given cost function [3]. Local search algorithms start searching the state space from a certain point which is selected using a variety of techniques and repeatedly try to find a better solution in terms of the cost function. If the initial step is wisely chosen; local search algorithms can provide better solution and can be faster than the global search algorithms. As these algorithms are iterative, it is easy to note the best found solution at the current iteration. This helps the programmer select the stop condition. Local search algorithms only provide local optimas dependent on initial conditions, which generally has a much higher cost than the optimas provided by global search algorithms. On the other hand global search algorithms does not require initial solution, also these algorithms find the global optima of the cost function by searching the state space. State space can be discretized to execute in expected time. Deterministic approaches consider analytical properties of the problem and generate a sequence of points that converge to a global optimal solution. Here the output is obtained from the given parameter values and initial conditions. Deterministic Algorithms can move from one solution to other by following specific predetermined rules. Various deterministic algorithms are Linear programming (LP), nonlinear programming, Mixed-integer linear programming problems (MILP) etc. Stochastic algorithms follow probabilistic translation rules. Here output is result of an inherent randomness of the inputs, i.e. the same set of parameters will lead to different results. Stochastic algorithms are preferred over deterministic algorithms due to its properties. Various Stochastic algorithms or metaheuristic are genetic algorithms, and particle swarm optimization, Ant colony optimization, Simulated Annealing, Differential Evolution Bee Algorithms, Particle Swarm Optimization, Tabu Search, Firefly Algorithm, Cuckoo Search etc. This paper presents a review of stochastic algorithms used for optimization of antennas and antenna arrays. It also reviews various parameters optimized to achieve discuss how these algorithms are used to optimize various antennas and antenna arrays.

2. OPERATING PRINCIPLE OF STOCHASTIC OR METAHEURISTIC ALGORITHMS

The principle of some of the optimization algorithms used for optimization of antenna or antenna array is discussed in this section briefly.

— **Random Search Optimization:**

Random Search (RO) optimization is direct-search, derivative-free, or black-box method. It does not require the gradient of the problem to be optimized so can be applied to the functions that are not continuous or differentiable. Implementation of algorithm starts with identification and selection of the "best" state vector or multiple state vectors and then randomly generate a new state vector usually a neighbor of the current "best" state. If this new state is better than the current "best" state, then the new vector is considered as the new "best" state vector. Execution of algorithm is terminated dependent on the stop criterion. Stop criterion is decided by either the no of iterations or under a condition if calculation of further best vector is not possible. The drawback of random search method is that the optimal solution is not always guaranteed. But if large no of iterations are made, then the algorithm can give a better solution to the optimization problem. Hence a trade-off between the no of iterations and quality of the solution is observed.

— **Simulated Annealing**

Simulated annealing (SA) is the first nature-based evolutionary probabilistic algorithms inspired from the annealing (cooling) process in solids. It is a technique without any memory. It discovers global optima in the existence of large numbers of local optima. It is frequently used when the search space is large and discrete. Simulated annealing is a method for solving unconstrained and bound-constrained optimization problems. During execution of the algorithm, a new vector is randomly generated in each of the iterations [4]. The distance of the new vector from the current vector, or the scope of the search, relies on a probability distribution having a scale proportional to the temperature. The algorithm agrees with all new points that reduces the objective or sometimes also agrees with those vectors which increases the objective. Vectors which increase the objective are accepted to stay away from local minima and to discover other potential solutions globally. As the algorithm progresses the annealing schedule decreases the temperature and the search space is also minimized during each of the iteration. Critical part of the SA algorithm is finalization of annealing schedule. In SA there is a trade-off between the computational speed and quality of the solution. Simulated annealing can be preferred in those time bound optimization problems where an approximate global optimum can be accepted instead of precise local optimum [5].

— **Genetic Algorithm**

Genetic algorithm (GA) is a heuristic search algorithm, inspired by Charles Darwin's theory of natural evolution, where the offspring of the next generation are produced from the fittest individuals [6]. The execution of algorithm starts with selection of initial population of chromosomes randomly using an appropriate fitness function, usually each bit in a chromosome corresponds to the parameter to be optimized. The fitness is usually the value of the objective function that depends on the given optimization problem. It is an iterative process, and the population in each of the iteration is termed as generation. In each generation, the fitness of every individual in the population is evaluated. More fit individuals are stochastically chosen from the current population, and each individual's genome is altered (recombined and possibly randomly mutated) to form a new generation. Next iteration of algorithm is then executed with new generation of candidate solutions. Stop criterion of algorithm is selected depending on production of sufficient number of generations or depending on achievement of acceptable fitness level. GA optimization technique is independent of the starting point or initial hence can handle discontinuous and non-differentiable functions. They are also capable of solving constrained optimization problems [7, 8].

— **Ant-Colony Optimization**

Ant-Colony Optimization (ACO) is another population-based and swarm-intelligence based evolutionary optimization technique to find approximate solutions to difficult optimization problem motivated by the foraging behavior of the social ants. Solution of the given optimization problem is obtained through a set of software agents called artificial ants [5]. Here optimization problem is termed as a task to find the best path on a weighted graph in sear of food. The desired condition in optimization is termed as food. The artificial ants increment all build solutions by exploring the graph. The solution interpretation is a stochastic process and is governed by a pheromone model. Pheromone model is a set of parameters related with graph nodes or edges; whose values are changed at runtime by the ants. Even though the individual activity of ants seem to be random, disorganized, and unmotivated but the collective behavior of a colony of ants is very much organized and efficient. This is obvious from the foraging behavior of ant colonies, in which ants find food and without delay bring it back to their nest. The solution of the optimization problem is denoted as pheromone left by the ants while collecting the food and the concentration of pheromone is a parameter to find the solutions. Other ants prefer the route at which pheromone concentration is higher. As Ant-Colony Optimization is based on intelligence and learning it is quite fast and efficient but sometimes it also gives local solution.

— **Particle Swarm Optimization**

Particle Swarm Optimization (PSO) is a population-based and swarm-intelligence- based evolutionary optimization technique motivated by the flocking of the birds and the schooling of the fishes. Particle is considered as the solution of optimization and the properties of particle such as position, velocity are the parameters of the solution [9]. 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. All the positions achieved are evaluated by a fitness function which will signify how well the design criterion is satisfied. The execution ends after predefined iterations. Particle Swarm Optimization is a simple and fast technique as it is based on intelligence and learning but as it is based on random process the results may not be good [10].

— **Differential Evolution**

Differential Evolution (DE) is another population-based evolutionary computational algorithm for the optimization. It uses a differential operator to create a new solution. This algorithm has been widely used in the design and synthesis of antenna as well as switches. In DE optimization problem is treated as a black box that merely provides a measure of quality for given a candidate solution. Solution of optimization is obtained by creating new candidate solutions by combining existing candidate solutions according to its simple formulae, and then selecting the candidate solution that has the best score or fitness for the optimization problem. In each generation the initial population grows using three operators' mutation, crossover and selection. In evolutionary computation, differential evolution (DE) is a method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. Differential Evolution is called as metaheuristic as it makes a few or no assumptions about the optimization problem and can search very large spaces of candidate solutions. However Differential Evolution does not assure to give an optimal solution. The main difference between DE and GA is the use of same operators but in the different ways.

In this method, the selection step is implemented after the mutation and crossover steps and involves both the parents as well as offspring. This method is good in diversification, but it has somewhat less accuracy. DE is used for multidimensional real-valued functions but does not use the gradient of the problem being optimized. Hence it can be used for optimization problems that are not even continuous, are noisy, change over time, etc. [6, 9 and 10]

— **Artificial Neural network**

Artificial Neural network (ANN) is based on biological neural network and is used to estimate the functions dependent upon the large number of unknown inputs. ANN can perform many tasks such as system identification, adaptive control, function approximation and optimization as its execution is inspired form simplified model of neural processing that are used as artificial intelligence in the brain. ANN is the data processing model comprising of nodes. These nodes are called as neurons and the interconnections between them are called weights. Outputs of neurons are generated in proportion with the weights. Neural networks applications are based on software solutions. The learning difficulty in neural networks was expressed in relations to the minimization of loss function. This function is collection of an error and a regularization terms. The error term estimates how a neural network fits the data set and the regularization term is used to avoid the over fitting, by controlling the complexity of the network. Training algorithm can be observed as a function approximation problem to adjust the parameters and to minimize the error function between the network output and the desired output. Common ANN training algorithm used is the Back Propagation which is also known as error back propagation based on error correlation learning rule. It maps input onto the output data. Back propagation neural network algorithm consists of three or more layers which are connected serially with each other such that output of one is connected to input of another [11,12].

— **Artificial Bee Colony**

Artificial bee colony (ABC) algorithm is motivated from intelligent behavior of honeybee swarms. It uses fitness (nectar) values and finds the solution of optimization. Due to the selection criteria employed ABC shows very good performance for local and the global solutions [13].

— **Pattern Search Algorithm**

Pattern Search (PSearch) method is a direct, efficient and derivative-free optimization tool. It searches minima of given function which is usually not differentiable, stochastic, or even continuous. This technique is able to find the solution even though any information about gradient of the fitness function is not provided. To find the solution PSearch algorithm explores a set of points around the existing point whose value of the fitness function is lower than the value at the current point [14, 15]

— **Graph Theory Method**

Graphs are symbolic representations of relationships between different points in a system. They are mathematical tools used to model real life situations, in order to organize them and improve their status. Reconfigurable antennas can also be viewed as a collection of self-organizing parts; graphs are used to model them for optimization purpose. Reconfigurable antenna structure is expressed in terms of graphs and each possible topology is related to corresponding electromagnetic performance to obtain the required frequency of operation, impedance and polarization using predefined graph rules. Graph theory method is used in [16, 17 and18] to reduce the redundancy of antenna structure by reducing no of switches used. Also an analysis of complexity and reliability of antenna structure is done in detail.

Apart from above discussed algorithms some other algorithms like Self-Organizing Maps [19], Hybrid Direct-Newton Approach [20], Space Mapping [21, 22], Response Surface Methodology [23], Multi-task Bayesian compressive sensing [24] and Fruit fly algorithm [25] are also used in literature for antenna optimization.

3. OPTIMIZATION OF ANTENNA AND ANTENNA ARRAY

Various optimization techniques are used for optimization of antenna, which are briefly discussed in previous section; in this section in site is given to the parameters of reconfigurable antenna which are optimized. Mainly optimization technique is applied to achieve the optimized physical dimensions or structure and shape. Optimization is also used to obtain the minimum no of switches or the optimized configuration of switch to achieve the re-configurability. Optimization is also used in antenna arrays to obtain the element excitation to optimize the beam scanning performance. Following table lists various algorithms used for antenna optimization.

Table 1. Optimization algorithms used for Antenna Optimization

No.	Ref.	Antenna optimized	Optimization Algorithm Used	Optimization applied for
1	7	Multi-Port Frequency-Reconfigurable Antenna	Genetic Algorithm	Multiport antenna structure optimization to achieve required band
2	8	Multifunctional reconfigurable antenna	Genetic Algorithm	States of interconnecting switches is optimized. Switches are used to Change geometry to achieve required beam steering, gain, bandwidth and polarization
3	11	Frequency reconfigurable antenna	Artificial neural networks	Used to decide the on/off condition of switches to obtain required frequency
4	12	Reconfigurable antenna	Artificial neural networks	Performance of RF MEMS switch was optimized for reconfigurable antenna application.
5	14	Antenna arrays	Pattern Search Algorithm	To find a configuration for a thinned array which has a normalized SLL
6	15	Linear antenna arrays Algorithm	Pattern Search	Inter-element spacing and excitation amplitudes are optimized to determine physical layout and feeding network of the array so as to obtain required radiation pattern.
7	16	Reconfigurable antenna	Graph Method	Complexity of antenna structure is optimized for desired performance
8	17	Reconfigurable antenna	Graph Method	Complexity of antenna structure is optimized
9	18	Reconfigurable antenna	Graph Method	Redundancy is reduced by reducing no of switches also analysis of complexity and reliability is done
10	19	Reconfigurable antenna	Self-Organizing Maps	Shape of reconfigurable aperture is optimized
11	20	Reconfigurable antennas array	Hybrid Direct-Newton Approach	Antenna array is optimized for obtaining required beam forming and null-steering
12	21	Reconfigurable Antenna	Surrogate-based optimization method-space mapping with inverse difference (SM-ID)	To find antenna geometry corresponding to optimum frequency condition to get minimum reflection coefficient.
13	22	Reconfigurable Antenna	Surrogate-based optimization method-space mapping with inverse difference (SM-ID) and Aggressive space mapping (ASM)	To find optimized frequencies, according to physical dimensions of antenna to get minimum reflection coefficient

14	23	Reconfigurable Antenna	Response Surface Methodology	Physical dimensions are optimized to get required frequency
15	24	Reconfigurable antenna arrays	Multi-task Bayesian compressive sensing (BCS)	Pattern synthesis using element positions and excitations.
16	25	Antenna arrays	Fruit Fly Algorithm	Appropriate excitation coefficient and position for each element for desired radiation characteristics
17	26	Frequency reconfigurable antenna	Genetic Algorithm	States of switch array is optimized to obtain narrow beam pattern
18	27	Reconfigurable antennas	Genetic Algorithm	Search the optimization pattern of the reconfigurable antennas
19	28	Frequency reconfigurable antenna	Genetic Algorithm	Concurrent geometrical and switch-state optimization of a frequency reconfigurable antenna
20	29	Frequency- and Environment-Reconfigurable Antenna	Genetic Algorithm	Geometry optimization for frequency-agile operation and environment robustness
21	30	Reconfigurable antenna	Genetic Algorithm & local optimization	Frequency reconfigurability is implemented through a set of switches connecting the antenna plate to the ground plane the best switch configuration is searched by an exhaustive search.
22	31	Array-fed reconfigurable reflector antenna	Genetic Algorithm	Array, To design the contoured beam and the boosted beam antenna, the excitation coefficients of the individual beam emitted from each array element is computed.
23	32	Pattern reconfigurable antenna	Genetic Algorithm	Optimize combinations of switch configuration on the antenna structure that produces targeted radiation pattern.
24	33	Frequency reconfigurable antenna	Genetic Algorithm	To find minimum number of switches utilized in a planar reconfigurable antenna design
25	34	Reconfigurable antenna	Quantum Genetic Algorithm	States of the multiple-switches is optimized to optimize quantities, such as received signal strength, standing-wave ratio (SWR), or the strength of the transmitted signal in a particular direction.
26	35	Reconfigurable antenna	Genetic Algorithm	To find out a set of beam excitation coefficients and compute the best distribution of the power flux across the coverage area so as to minimize the number of non-served users,
27	36	Reconfigurable reflector array antenna	Genetic Algorithm	Beam scanning performance of a reconfigurable reflector array antenna is optimized. Wide-beam pattern synthesis using genetic algorithm (GA) is carried out.
28	37	Reconfigurable array	Parallel particle swarm optimization	Dual-beam pattern is obtained by directly optimizing the element excitation
29	38	Reconfigurable phased antenna array	Hybrid differential evolution and enhanced particle swarm optimization	Interference suppression and pattern optimization by position-only control using minimum number of mobilized elements for linear- and circular phased arrays.
30	39	Reconfigurable Pixel Patch Antenna	Particle swarm optimization	Impedance matching for a given frequency is optimized by turning the pixels ON or OFF on a rectangular patch antenna
31	40	Frequency reconfigurable antenna	Particle swarm optimization	PSO is applied to the geometry (physical dimensions are changed) in order to find the peak performance design.
32	41	Frequency reconfigurable antenna	Particle swarm optimization	PSO is applied to the geometry (physical dimensions are changed) in order to find the peak performance design.
33	42	Reconfigurable phase-differentiated antenna array	concurrent PSO (CONPSO) and Fitness-Distance-Ratio-Particle swarm optimization (FDR-PSO)	Pencil beam pattern is optimized by finding excitation coefficients of a 20 element array fed by a single power division network
34	43	Reconfigurable annular ring monopole antenna	Particle swarm optimization and artificial bee colony algorithm	Antenna dimensions are optimized using PSO & ABC. Objectives are reducing S11 and enhancing antenna BW.
35	44	Reconfigurable Antenna Array	Particle swarm optimization	Input for digital phase shifters are optimized for interference suppression by controlling the pattern nulls
36	45	Reconfigurable Antenna Array	Hybrid differential evolution with artificial bee colony	To find element excitation to obtain required pattern
37	46	Reconfigurable Parasitic Antenna Arrays	Reduced-order method	Optimization of reconfigurable parasitic arrays for beam forming and null steering to be directly computed.
38	47	Reconfigurable array antennas	Combination of genetic algorithm (GA) and domain decomposition method (DDM) combined with the equivalence principle algorithm (EPA)	To find the optimum positions of the elements in the sparse sub-arrays with minimum side lobe levels.
39	48	Reconfigurable Antenna	Surrogate-based optimization method-Space mapping with inverse difference technique	To find antenna geometry corresponding to optimum frequency condition to get minimum reflection coefficient.
40	49	Reconfigurable Antenna	Self-organizing maps	Physical design is optimized to obtain the required frequency.
41	50	Phased array antenna	Pattern Search Algorithm	Phase distribution is optimized to get required radiation pattern

42	51	Pattern Search Algorithm	Antenna arrays	Phase excitation is optimized to obtain improvement in SLL
43	52	Reconfigurable antennas	Teaching-learning based optimization	Shape of antenna and location of switches is optimized to increase reliability
44	53	Spiral antenna	Artificial Bee Colony	Antenna dimensions are minimized to maximize the gain, conjugate matching, and to maximize the read range.
45	54	Antenna Array	Simulated annealing algorithm	Minimize side lobe peaks by optimizing the elements' position
46	55	Patch Antenna	Genetic Algorithm	Optimization of shape to obtain required frequency
47	56	Rectangular microstrip antennas	Neural Network	Feed position of rectangular microstrip patch antenna is calculated based on feed forward network and back propagation algorithm is presented. Neural network was used to calculate feed position for arbitrary value of width and length. Frequency, length and width as input vector and feed position was as target vector.
48	57	Rectangular microstrip antennas	Neural Network	Neural network approach has been used for calculation of feed position of microstrip antenna for maximum power transfer.
49	58	Circular microstrip antenna	Particle swarm optimization algorithm	Optimal feed position of circular patch antenna to optimized for input impedance matching
50	59	Reconfigurable antenna	Artificial neural networks	Geometrical dimensions are optimized
51	60	Reconfigurable antenna	Simulated Annealing	Shape optimization
52	61	Antenna Array	Simulated Annealing Optimization	Optimize the amplitude of weights coefficients of the elements of the circular array in order to improve the antenna performances and to obtain required beam pattern

Apart from above stated algorithms; in literature recently some more techniques are also observed for antenna optimization which include Wind Driven Optimization (WDO); Biogeography-based optimization (BBO); Invasive Weed Optimization (IWO); Evolutionary Programming (EP); and, the Covariance Matrix Adaptation Evolution Strategy (CMA-ES).

Bibliography study shows that GA, PSO, ABC, ACO and DE are more frequently used algorithms for antenna design. A direct comparison between these methods cannot be done as they all are not demonstrated for a single reconfiguration scheme. But these algorithms have always found useful and effective for optimization of various antennas and antenna arrays. The thrust for new antenna optimization algorithms is a never ending process and research in this context is expected to linger for some more time to come.

4. CONCLUSION

Various optimization algorithms are reviewed in this work. It is observed that the optimization algorithms are applied to reconfigurable antenna for geometry optimization, switch configuration optimization, complexity optimization or feed position optimization to achieve required beam steering, impedance, gain, bandwidth and polarization. For antenna arrays the optimization is applied to search for the best set of beam excitation coefficients for required radiation pattern or for array thinning.

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ISSN 1584 – 2665 (printed version); ISSN 2601 – 2332 (online); ISSN-L 1584 – 2665