A Comparison of Antenna Placement Algorithms

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***Abstract*—Co-location of multiple antenna systems on a single fixed or mobile platform can be challenging due to a variety of factors, such as mutual coupling, individual antenna constraints, multipath, obstructions, and parasitic effects due to the platform. The situation frequently arises where a new communication capability, and hence antenna system, is needed on an existing platform. The problem of placing new antennas requires a long, manual effort in order to complete an antenna placement study. An automated procedure for determining such placements would not only save time, but would be able to optimize the performance of all co-located antenna systems. In this work, we examine a set of stochastic algorithms to determine their effectiveness at finding optimal placements for multiple antennas on a platform. To our knowledge, this is the first study to investigate optimizing multiple antenna placement on a single platform using multiple stochastic algorithms. Of the four algorithms compared on the basis of convergence rates, simulated annealing and evolutionary strategy were found to be most effective in finding optimal placements.**

I. Introduction

Antenna placement on a multi-antenna platform currently involves a manual process that is challenging, time consuming, and may result in sub-optimal placements leading to lowered communication systems' performance. Moreover, the search space is highly complex and becomes exponentially large with regard to the number of antennas to be placed ($|\text{search space}| = m^n$, where m is the number of allowable placements for each antenna and n is number of antennas).

Stochastic optimization techniques have been used extensively for non-convex and non-linear search spaces to avoid sub-optimal results due to multimodal nature of the search space (see Figure 1b). Applying Evolutionary algorithms (EA), a type of stochastic optimization technique, to the antenna placement problem could greatly help determine placements which increase the effectiveness of each antenna. Evolutionary algorithms encompass a variety of computer search technologies, with the Genetic Algorithm (GA) being the most well-known. Moreover, EAs have proven very capable in discovering high performance antenna designs deployed in space [1].

In this work, we have analyzed stochastic algorithms to help determine optimal or near-optimal antenna placements on a platform. The problem has been modeled and simulated using antenna modeling software package called NEC2. The approach is agnostic to specifications of the antenna, and the platform. The algorithmic-set include Genetic Algorithm, Evolutionary Strategy, Simulated Annealing, and Hill Climbing.

II. Related Work

The problem of optimizing the placement of multiple antennas on a single platform has rarely been studied, if at all. The closest research we have found concerns algorithms for locating and configuring infrastructure for cellular wireless networks with the assumption of isotropic radiation pattern [5]. Another related work computes optimal antenna locations restricted to a mobile device. In our work, none of the algorithms discussed utilize prior information of good antenna placements or type of antennas to be placed on the platform.

The related problem of co-designing antennas for a given platform (*in-situ* design) using stochastic algorithms has been investigated in [2] with encouraging results. Because antenna placement bears many similarities to antenna design, we believe that such algorithms will prove effective.

III. Problem Formulation

A. Inputs

A platform for placing multiple antennas could vary from a simple rectangular box to an aircraft. Our inputs to an algorithm comprise of a platform and set of antennas each with allowable placements on the platform. Formally, a platform, P, in 3-dimensional space with its surface discretized into a regular grid with some spacing consisting of potential antenna placement points. Let n denote the number of antennas to be placed on P such that $n > 1$, and A represent the set of antennas: $A = \{A_1, ..., A_n\}$. For each antenna A_i, L_i denote the set allowable placement coordinates $\in \mathbb{R}^3$ on P such that the size of $\mid L_i \mid = m_i$, and $\forall i, m_i > 1$:

$$L_i = \{(x_1, y_1, z_1), ..., (x_{m_i}, y_{m_i}, z_{m_i})\}$$

For example, Figure 1a has $n = 2$ and $m = 83$ for each antenna.

Using the allowable placements (L_i), a *candidate solution* or *individual* is a placement configuration of n antenna locations, one for each of the n antennas, in 3-dimensional space:

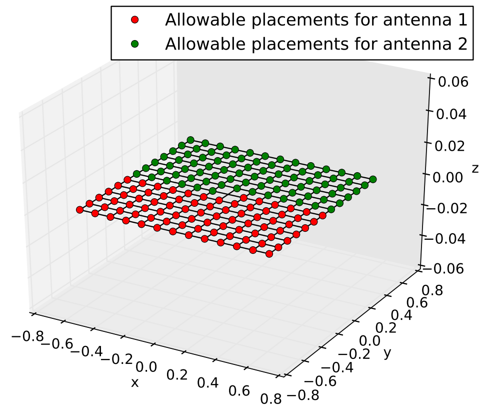
$$\text{Candidate Solution} = \{l_i | l_i \in L_i, i \in [1, n]\}$$

Candidate solutions are the building blocks for each algorithm we evaluate the antenna placement problem on. It is important to note that the number of allowable placements for any antenna are finite.

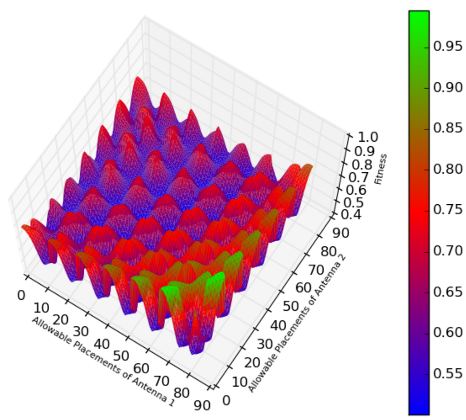
B. Fitness Evaluation

The placement optimization algorithms aim to find the best candidate solution such that the radiation pattern and mutual coupling are optimal. For optimal radiation pattern, we minimize the difference between the free-space gain pattern (FSG) of each antenna A_i, and its pattern when placed on a platform along with all other antennas (in-situ gain, or ISG). Minimizing the difference from the free-space gain pattern will ensure better communication capability. For each antenna A_i we compute multiple field points around an antenna in 3-dimensional space:

$$F_{RP} = \sum_{i=1}^{n} \sum_{\theta=0}^{\pi} \sum_{\phi=0}^{2\pi} \left| FSG_i(\theta, \phi) - ISG_i(\theta, \phi) \right|^2, \quad (1)$$



(a) Test Case 1



(b) Search space for test case 1 with multiple local optimum solutions

where θ & ϕ define the spherical coordinates of a field point.

For the second objective, it is desired to minimize the mutual coupling between two antennas to reduce the overall energy loss. This is computed in a pairwise manner where the CP function computes the coupling between two antennas:

$$F_{MC} = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} CP(A_i, A_j) \tag{2}$$

The overall objective is to find a candidate solution which minimizes the fitness F, defined as:

$$F = \alpha F_{MC} + \beta F_{RP}, \tag{3}$$

where α and β are constants such that $\alpha + \beta = 1$.

Radiation pattern and antenna coupling are measured in decibels (dB) which is a logarithmic unit used to express the ratio between two quantities. For radiation pattern parameter, the *antenna strength* or *gain* shown in Eq.(1), at any given point on a sphere defined by (θ, ϕ) is the ratio of the signal strength of the antenna being tested and a perfectly isotropic antenna. For coupling, the ratio compares the energy absorbed by an antenna when the another antenna is operating nearby. Coupling reduces the antenna's efficiency, and undesirable for the multiple antenna placement problem.

IV. Stochastic Search Algorithms

A. Genetic Algorithm

Genetic algorithm is the simplest of all evolutionary algorithms which aim to model Darwinian evolution and natural selection to evolve a population of candidate solutions. They have been used extensively as stochastic search procedures for numerous applications [3].

Evolution operators in our version of GA are *one-point crossover* and *mutation*. For one-point crossover operation, two individuals are selected with one being uniformly chosen from the population and the other from a tournament selection. For all experiments, crossover probability was 60% and mutation probability as 10%. Intuitively, a high mutation rate drives the algorithm into a random search and renders evolutionary aspect of the algorithm weak. The size of the individual is not arbitrarily large, and therefore it was preferred to keep the mutation restricted to manipulating one antenna placement. Since we have a discrete set of placements (end points of wires of a platform), *mutation's* step size involves a new placement from the set of allowable placements for the antenna. This mutation operator is similar for all other algorithms as well.

For arbitrarily large number of antennas, one may need to consider changing the mutation operator to manipulate more than one antenna placement.

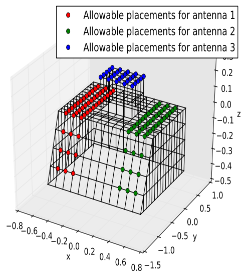
B. Evolutionary Strategy

The evolutionary strategy $(\mu+\lambda)$ is different from a genetic algorithm in the following ways: mutation is the primary operator here for maintaining diversity in the population since there are no crossover operations. Survivor selection is done by selecting only fittest μ individuals to the next generation. A $1:7$ ratio was maintained between μ and λ.

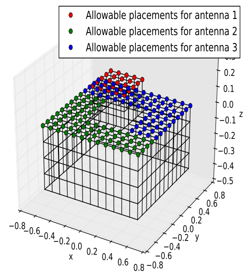
For mutation of an individual, both the antenna and its new placement are selected uniformly at random from the allowable placements while ensuring there is no overlap with any other antenna defining the individual. ES are more effective than GAs since multiple applications of the mutation operator on the same individual (λ times on each of the μ individuals), and preservation of the best individuals help the algorithm to maintain more diversification in the population, and thereby making more useful search.

C. Simulated Annealing

Simulated annealing is a general local search algorithm with a temperature parameter which allows it to accept fitness worsening mutation step with a probability given by Boltzmann distribution. This helps the algorithm to escape local optimum solutions in a multimodal search space. We used a linear cooling schedule for temperature $T_i = \tau T_{i-1}$ with $\tau = f(m_{iters})$. Due to different sizes of the search space, cooling schedule is a function of the maximum iterations (m_iters), which are approximately 50% of the total allowable placements. The initial temperature for SA range $\in [0.23, 0.27]$.



(a) Test Case 2



(b) Test Case 3

D. Hill Climbing

Hill climbing is a greedy search algorithm different from a simulated annealing since there is no temperature cooling schedule. This makes the HC prone to get stuck with locally optimum solutions due to its greedy nature of accepting only fitter individuals. However, the ease of implementation and effectiveness in numerous optimization problems [4] makes hill climber a popular approach for optimization.

V. Experimental Setup

We used an open source antenna modeling software called Numerical Electromagnetic Code (NEC2) to calculate the fitness of an individual. NEC2 provides a convenient interface to input details about the platform with antennas mounted, and to collect simulation results. For our experiments, the candidate solution is written to an input file which is used by NEC2 modeler to generate an output file. The platform and all antennas of a candidate solution are written to the input file as a set of wires with a start-point and end-point in 3D space. Possible antenna locations are defined by either start-point or end-point of a platform wire.

All test cases describe platforms which are replicas of real-world use cases like mobile devices, tanks, and cars. Antennas used on these platforms are used extensively in contemporary microwave systems. Figure 2a shows the meshed platform depicting a squared plate with box and a sloped front used in test case 2 of our experiments. A square plate with box and sides fixed was used as platform for test case 3 shown in figure 2b. For test case 4, the platform was a squared plate as in test case 1 but with four antennas with allowable placements on the four corners of the plate.

For radiation pattern, the number of field points is determined by the product of total number of unique θ and ϕ values which encompass points in a sphere around the antenna. All experiments computed the radiation gain over 4140 points with increments of 4° for θ and ϕ. For all test cases antennas were excited with the same frequency of 100 MegaHertz.

For fitness evaluation of a candidate solution, input files are generated with all specifications of antennas and the platform. NEC2 would use the input files to generate radiation pattern values for all pairs of (θ, ϕ). Similarly, for the second fitness parameter - mutual coupling, NEC2 provides results between all possible pairs of antennas. If $n = 4$, then there are $\binom{4}{2}$ pairs for which mutual coupling is calculated.

[1]Allowable placements for each antenna are provided within parenthesis

TABLE I: Antenna Placement Test Cases

Test Case	Number of Antennas	Number of allowable placements[1]
1	2	7,056 (83x83)
2	3	50,625 (45x45x25)
3	3	126,025 (71x71x25)
4	4	20,736 (12x12x12x12)

VI. Simulation Results

Comparative study of algorithms is based on multiple test cases listed in Table I. Each test case was first evaluated with an exhaustive search algorithm to determine optimal fitness value, and the corresponding candidate solution amongst the entire search space. The results from exhaustive search were also used to normalize fitness function values between $[0, 1]$. For all experiments $\alpha = \beta = 0.5$ in Eq.(3). The termination criteria for a run of an algorithm was either when the global minimum was reached or $0.5 \cdot |S|$, where $|S|$ is the size of the search space, function evaluations were completed.

Genetic Algorithm (GA) and Evolutionary Strategy (ES) operate on a population of candidate solutions at any given iteration as oppose to Simulated Annealing (SA) and Hill Climbing (HC) which operate on one candidate solution. For this reason the mean best fitness in figures 3a, 3b, 3c, & 3d is higher in the initial stages of a run for SA or HC than GA or ES as in a population there is higher probability of creating a fitter individual. In terms of computational time of any algorithm, the bottleneck is the NEC2 simulator. Therefore, the mean best fitness is shown against the percentage of fitness evaluations which is equivalent to the number of runs of NEC2 simulator. In all four test cases, the best candidate solution was found by ES in less than 25% fitness evaluations of the search space.

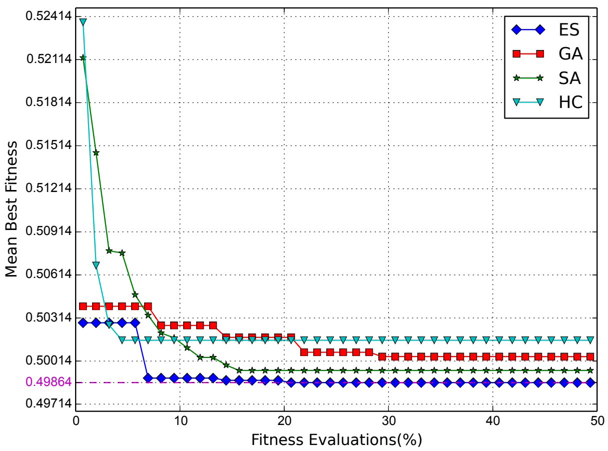
Regions in the plot where the mean best fitness of GA or ES is constant relates to the fitness evaluation of offsprings created by evolutionary operators applied on the population of candidate solutions. For SA and HC, we notice the SA curve crossing the HC curve in all four test cases. This is due temperature parameter of the SA allowing it to accept fitness worsening individuals with high probability initially in the run. However, later in the run the cooling schedule reduces the probability of SA accepting a worse individual. Eventually, SA has a better probability to reach the optimal solution in comparison to the HC.

As known in general, the HC algorithm made progress only in the initial phases of the run and got stuck in local optimums. The purpose for inclusion of such a random search algorithm was to highlight antenna placements may not always be a trivial optimization task as shown in figure 1b. The search landscape for test case 4 always had a lower fitness candidate solution in the neighbourhood, therefore allowing HC to converge quickly.

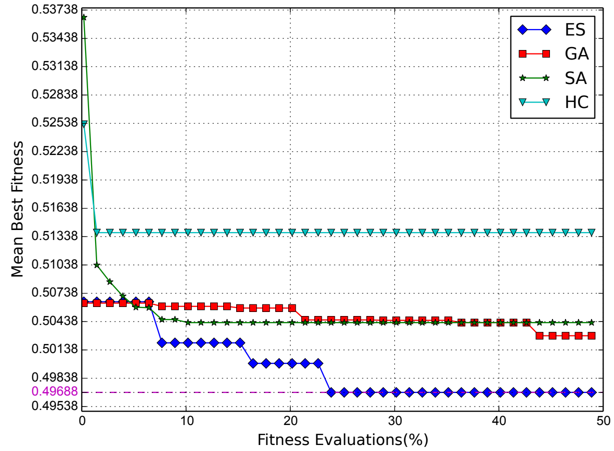
To summarize, Figure 3 shows that ES was successful in finding optimal candidate solutions for all test cases. Alternatively, SA took less number of fitness evaluations to converge but had a lower probability to succeed by finding the optimal solution.

VII. Conclusion

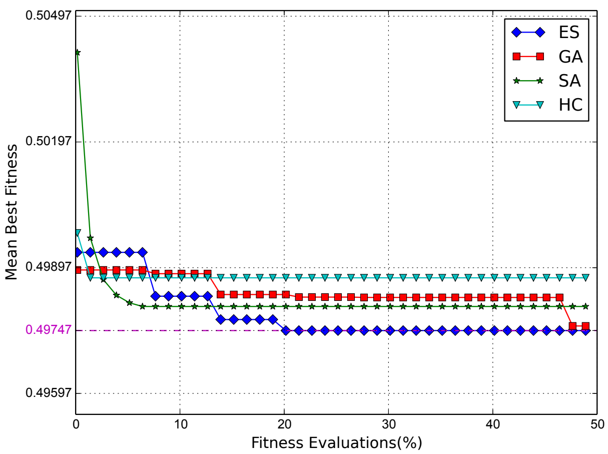
A comparison of four stochastic search algorithms applied to antenna placement optimization was presented. The results



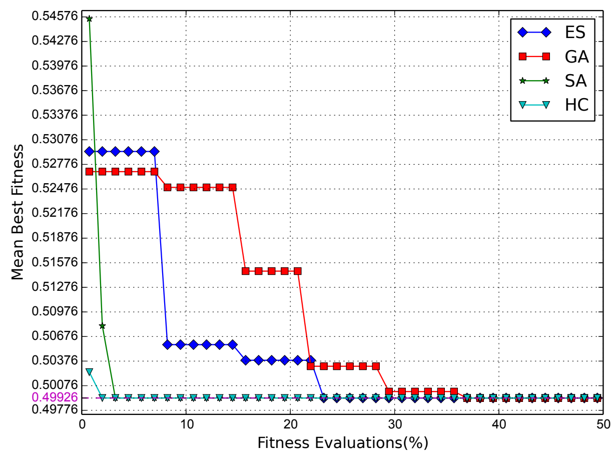
(a) Test Case 1



(b) Test Case 2



(c) Test Case 3



(d) Test Case 4

Fig. 3: Mean best fitness shown for 10 independent runs of each algorithm for all test cases. Global minimum calculated using exhaustive search algorithm for each test case shown in magenta on the vertical axis. The horizontal axis is representative of the percentage of fitness evaluations of the search space. The number of evaluations may not be unique points in the search space.

showed that a trade-off space exists: faster, less successful SA search versus slower, more successful search by ES. GA was not very effective, and also slower to find the optimal individuals. More importantly, our formulation is generic such that it can be applied to any type of a platform which otherwise may be time consuming and expensive in case of large objects like satellites, warships, and aircrafts.

Most of the stochastic algorithms presented here were elementary. More experiments can be conducted for population based algorithms with different population sizes, and to statistically compare how this may affect the performance of the algorithm. Also, bigger search spaces need to be considered with more number of antennas. Other evolutionary techniques like ALPS, and Differential Evolution algorithm can also be compared for quality and convergence.

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