A Comparison of Antenna Placement Algorithms

Abhinav Jauhri
Carnegie Mellon University
ajauhri@cmu.edu

***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 multimodal 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 nonlinear search spaces to avoid sub-optimal results due to multimodal nature of the search space. Applying Evolutionary algorithms (EA), a type of stochastic optimization technique, to the antenna placement problem could greatly improve determining acceptable antenna placements. Evolutionary algorithms encompass a variety of computer search technologies, with the Genetic Algorithm (GA) being the most well-known. 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 problems have 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. Another related work computes optimal antenna locations restricted to a mobile device. In our work, none of the algorithms discussed have prior information of good antenna placements or type of antennas to be placed on the platform.

It is naught to note that the related problem of co-designing antennas for a given platform (*in-situ* design) using EAs 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 platform for placing multiple antennas could vary from a simple rectangular box to an aircraft.

A. Inputs

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 $| L_i |= m_i$, 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, in Figure 1 $n = 2$ and $m = 83$ for each antenna. Using the allowable placements, l_i, a *candidate solution/individual*, is a placement configuration of n antenna locations, one for each of the n antennas, in 3-dimensional space:

$$\text{Candidate Solution} = \{(x_1, y_1, z_1), \cdots, (x_n, y_n, z_n)\}$$

It is important to note that the number of allowable placements for any antenna are finite and discretized.

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 P and in the presence of all remaining 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 3d space:

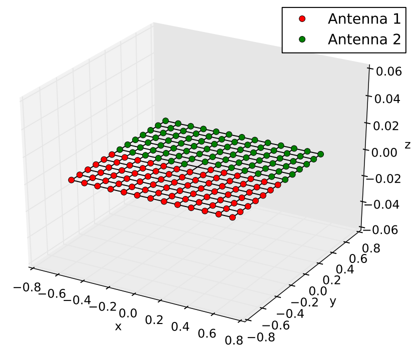

Fig. 1: Test case 1 with two antennas and a square plate. Red dots indicate allowable placements for antenna 1 and green dots indicate allowable placements for antenna 2

$$F_{RP}(A_i) = \sum_{\theta}\sum_{\phi} |FSG_i(\theta,\phi) - ISG_i(\theta,\phi)|^2, \quad (1)$$

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

For the second objective, it is desired to minimize the mutual coupling between the antennas for a given placement configuration because strong mutual coupling reduces antenna efficiency. This is computed in a pairwise manner where the CP function computes the coupling between two antennas:

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

The overall objective for a given placement configuration is to minimize fitness, F:

$$F = \alpha F_{MC} + \beta \sum_{i} F_{RP}(A_i), \quad (3)$$

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 is the ratio of the signal strength of the antenna being tested to 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 algorithms aims to model different DNA operations in nature like crossover and mutation. They have been used extensively as stochastic search procedures for numerous applications.

Operators in our version of GA (referred as Antenna Placement Genetic Algorithm (AP-GA)) are *one-point crossover* and *mutation*. Each pair for one-point crossover operation comprises of an individual uniformly selected from the population and the other individual from a tournament selection. For all experiments, crossover probability was 60% and mutation probability as 10%. The size of the individual is not arbitrarily large, and therefore it was preferred to keep the mutation restricted to just 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 applied to 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, 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. *Mutation* operator is surely applied once on an individual to generate the offspring.

C. Simulated Annealing

Simulated annealing models thermodynamics by including a temperature cooling schedule such that it can accept fitness worsening mutation steps with a probability given by Boltzmann distribution. We used a linear cooling schedule for temperature $T_i = cT_{i-1}$ with $c >= 0.995$. The cooling temperature was adjusted based on the size of the search space.

D. Hill-Climbing

Hill climbing is a greedy search algorithm different from a simulated annealing since there is no cooling schedule. This makes a hill-climbing prone to get stuck in local optimal solutions. However, the ease of implementation and effectiveness in numerous optimization problems makes hill-climbing a popular approach.

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 platform with antennas mounted, and to collect simulation results.

For our purposes, the candidate solution is written to an input file (to be referred as N_{in}) which is used by NEC2 modeler to generate an output file (to be referred as N_{out}).

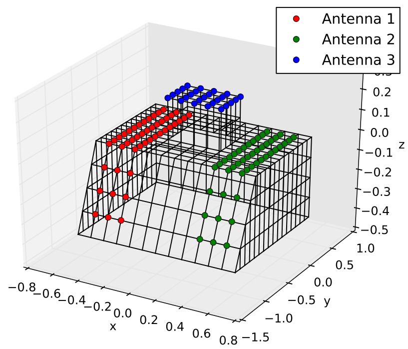

Fig. 2: Test Case 2

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)

The platform and all antennas of an individual are written to N_{in} as a set of wires with a start-point and an end-point in 3-dimensional space.

Figure 2 shows the meshed platform depicting a squared plate with box and a sloped front used in test case 2 of our experiments. The platform and antenna are just a set of tuples similar to w. A square plate with box and sides fixed was the platform for test case 3. Possible antenna locations, for all test cases, are defined by either start-points or end-points of platform wires.

The number of field points in a radiation pattern is determined by the product of total number of unique θ and ϕ values which encompass points in a sphere. All experiments computed the radiation gain over 4140 points i.e.$= \mid \theta \mid \cdot \mid \phi \mid$.

For our placement study, n input files would be generated for a candidate solution with n antennas and only one of the n antennas excited in each input file. Subsequently, NEC2 would generate n output files with performance measures. By exciting one antenna in each input file, we are able to quantify the radiation pattern of an antenna in presence of the platform and other antennas. To determine the free-space gain pattern(FSG) for an antenna, an input file is formed with just the antenna and no platform. F_{RP} is then calculated by *EAP* parsing $2m(m$ files with platform and antennas; n files for free space pattern) output files generated by NEC2.

The second fitness parameter - mutual coupling, is gathered by using $(n+1)th$ file generated. NEC2 generates an output file with mutual coupling results between all possible pairs of antenna placements. If $n = 4$, then there are $\binom{4}{2}$ pairs. All test cases were subjected to the same frequency of 100 MegaHertz.

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

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 to determine fitness for all allowable placements and antennas. 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).

Intuitively, a high mutation rate, referred as p_m in Section IV-A, drives the algorithm into a random search and renders evolutionary aspect of the algorithm weak. It is preferred to have a high value for p_c. For all test cases, *AP-GA* uses $p_m = 0.1$ & $p_c = 0.6$. gen_{max} for *AP-GA* and *AP-ES* is 10.

For similuted annealing, the cooling factor was kept as $1 - \tau$, where $\tau = 0.01 \cdot m_{iters}$. Maximum iterations($m_{iters}$) were about 70% of the total allowable placements of a test case. The initial temperature ranged $\in [0.23, 0.27]$.

The other important observation is of how many number of fitness function evaluations did each algorithm take to find a good hypothesis? Evolutionary strategy and simulated annealing outperformed the genetic algorithm in terms of mean number of fitness evaluations to find the best hypothesis as seen in Table .... The number of evaluations recorded were until the algorithm found the best hypothesis or got stuck at some local optimal hypothesis. Number of function evaluations is more appropriate here rather than the CPU clock time as the time may vary for each machine based on the hardware configuration.

We also visualized the fitness terrain of the best hypothesis followed by each of the stochastic algorithms. Such visualization is a good tool to observe the correctness of the algorithm. For instance, a simulated annealing is prone to have an event of accepting a bad hypothesis with a higher probability initially in the run and this event should happen with low probability as algorithm proceeds. For all simulated annealing graphs in Figures 4, 5, & 6, we observe that the gap between any two consecutive events of such nature increases as the algorithm proceeds in the search space.

The genetic algorithm in Figure 4 accepted a worse hypothesis because of the fact that mutation could happen even in the group of elite hypothesis. The elites were included in the mutation pool to maintain diversity. For evolutionary strategy and hill climbing, the fitness terrain does not have unorthodox patterns. The values in parenthesis for all population based algorithms viz. genetic algorithm and evolutionary strategy, represent the population size. They were kept at approximately the same ratio with the corresponding size of the search space in Table I.

This is not the case, since the top ten hypotheses lie within a small fitness range of $[0.49747, 0.498428]$. As known in general, the hill-climbing algorithm made progress only in the initial phases of the run and got stuck in local optimums for 80% of the runs for test case 3. The purpose for inclusion of such a random search algorithm was to highlight that antenna placements may not be a trivial task to solve with high probability, if the search space is large as in the case of test case 3. For smaller test cases like test case 4, hill-climbing may be appropriate.

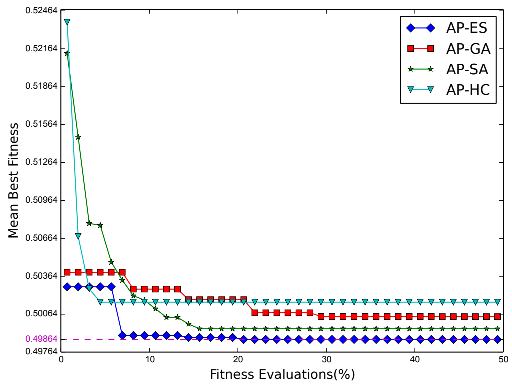

Fig. 3: Test Case 1 Comparison

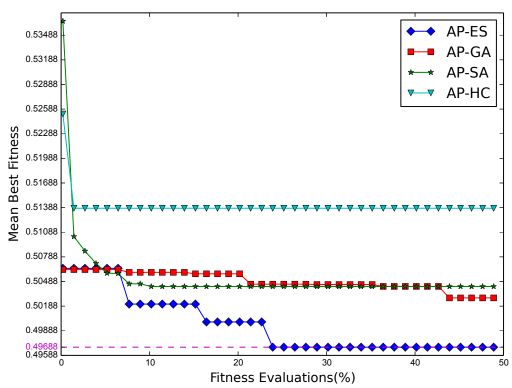

Fig. 4: Test Case 2 Comparison

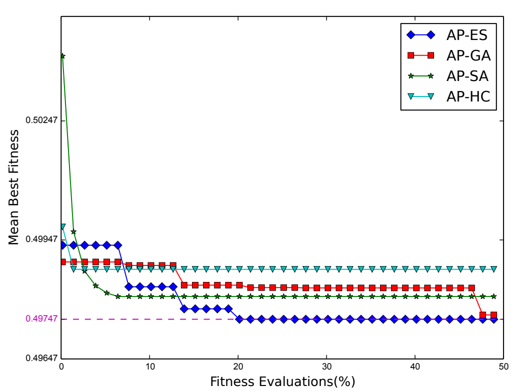

Fig. 5: Test Case 3 Comparison

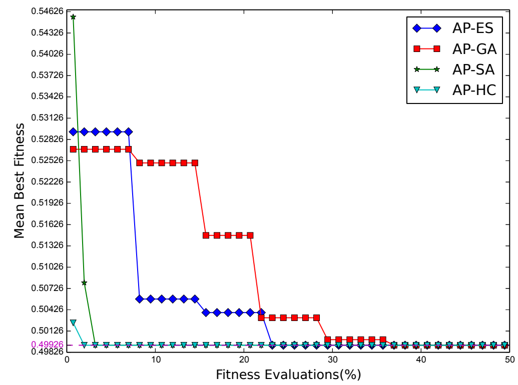

Fig. 6: Test Case 4 Comparison

VII. Conclusion

A comparison of four stochastic search algorithms applied to antenna placement optimization was presented. The results showed that a trade-off space exists: faster, less successful simulated annealing (*AP-SA*) search versus slower, more successful search by evolutionary strategy (*AP-ES*). The other generation-based algorithm (*AP-GA*) did not prove as effective as evolutionary strategy, and also much slower to find the optimal placements. Also, a random search was studied to ascertain that the antenna placement problem may not be effectively solved by a greedy algorithm. Moreover, our methodology 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 need to 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 need to be compared for quality and convergence.

References

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[2] Linden, Derek S. "Wire antennas optimized in the presence of satellite structures using genetic algorithms." Aerospace Conference Proceedings, 2000 IEEE. Vol. 5. IEEE, 2000.