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 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 getting trapped in local optima. Applying Evolutionary algorithm (EA), a type of stochastic optimization technique, to this problem could greatly improve this process by automatically 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 is work used characteristic mode analysis to compute optimal antenna locations for an antenna placed within 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.

In addition, 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 our problem formulation could vary from a simple rectangular box to an aircraft.

A. Inputs

Our inputs to an algorithm shall 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 let A represent the set of antennas: $A = \{A_1, ..., A_n\}$. For each antenna A_i, let L_i denote the set allowable placement coordinates $\in \mathbb{R}^3$ on P such that $\mid L_i \mid= m_i$, and $\forall i, m_i > 1$:

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

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

Using the inputs, a *candidate solution/individual*, H, is formed by a set of m antenna locations. In other words, a hypothesis is a placement configuration i.e. a set having m placements, one for each of the m antennas, in 3-dimensional space:

$$H = \{(x_1, y_1, z_1), \cdots, (x_m, y_m, z_m)\}$$

The reader should note that the number of allowable placements for any antenna are finite.

B. Fitness Evaluation

The placement optimization aims to find the best individual, H^*, such that the radiation pattern and mutual coupling are optimal. For optimal radiation pattern, we shall minimize the difference between the free-space gain pattern (FSG) of antenna A_i, and its pattern when placed on P and in the presence of all remaining antennas (in-situ gain, or ISG). Thus, for each gain point for A_i we compute:

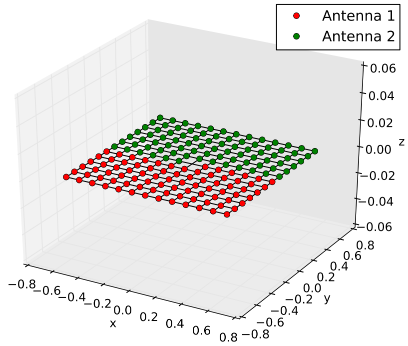

Fig. 1: Test case 1 with two antennas and a square plate. Red dots indicate allowable placement for antenna 1 and green dots indicate allowable placements for antenna 2

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

where θ & ϕ define the spherical and cylindrical coordinates of a field point respectively (see *Section 5 for more information*).

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:

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

The overall optimization for a given placement configuration is to minimize fitness, F, as follows optimal antenna placement for mobile terminals using characteristic analysis:

$$F = \alpha F_{MC} + \beta \sum_i F_{RP}(A_i), \qquad (3)$$

where α and β are constants which satisfy: $\alpha + \beta = 1$.

Radiation pattern and antenna coupling are measured in decibels (dB) which is a logarithmic unit used to express the ratio between two quantities i.e. $10 \cdot \log x_1/x_2$. For radiation pattern fitness 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, expressed in dB. For coupling, the ratio compares the energy absorbed by one antenna when the another antenna is operating nearby. Coupling thus reduces the antenna's efficiency, and undesirable for our antenna placement problem since more energy should be radiated away to establish communication link.

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 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. For arbitrarily large number of antennas, one may need to consider changing the mutation operator to manipulate more than one antenna placement. The mutation operator described in AP-GA is common to all other algorithms compared in this work.

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.

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 an antenna only. Both the antenna and its new placement are selected uniformly at random. *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. Numerous applications have compared simulated annealing with evolutionary techniques. We perform some extra computation to determine initial temperature.

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 for optimization problems.

V. Experimental Setup

We used an open source antenna modeling software called Numerical Electromagnetic Code(NEC) to calculate the fitness of an individual. NEC provides a convenient interface to input details about platform with antennas mounted, and to collect simulation results.

For our purposes, the individual is written to an input file (to be referred as N_{in}) which is used by NEC modeler to

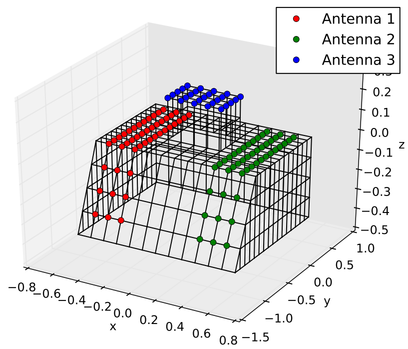

Fig. 2: Test Case 2

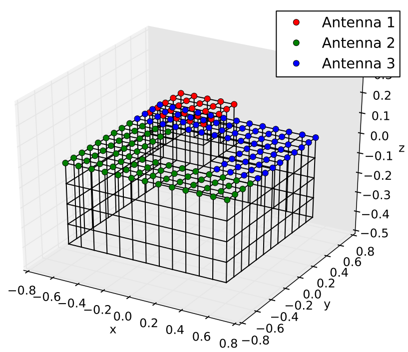

Fig. 3: Test case 3

generate an output file (to be referred as N_{out}). 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 (Figure 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 spherical(θ) and cylindrical(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, m input files would be generated by *EAP* for an hypothesis with m antennas and with only one of the m antennas excited in each input file. Subsequently, NEC would generate m 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

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)

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; m files for free space pattern) output files generated by NEC and performing a summation over squared difference in gain between free-space and in the presence of the platform and antennas (Eq.(1)).

The second fitness parameter - mutual coupling, is generated by inserting the CP card in the $(m+1)th$ file generated by *EAP* . A single file is needed for NEC to generate an output file with mutual coupling results between all possible pairs of antenna placements of an hypothesis.

All test cases were subjected to the same frequency of 100 MegaHertz using the FR card.

VI. 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

[1] Lohn, Jason D., et al. *Evolutionary design of a single-wire circularly-polarized x-band antenna for nasa's space technology 5 mission.* Antennas and Propagation Society International Symposium, 2005 IEEE. Vol. 2. IEEE, 2005.

[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.

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