

A Comparison of Antenna Placement Algorithms

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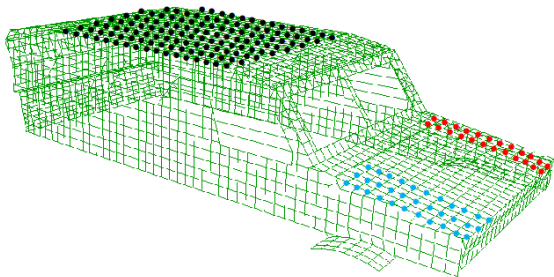
- ▶ Antenna placement on a multi-platform is a manual, and time consuming process
- ▶ Number of possible placements (search space) of antennas becomes exponentially large in the number of antennas to be placed
- ▶ Stochastic algorithms have been used effectively to find antenna designs (*Reference: Hornby, Lohn, & Linden. "Computer-Automated Evolution of an X-Band Antenna for NASA's Space Technology 5 Mission." 2011*)

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How can we automate the process by use of stochastic algorithms?

Antenna Placement Example



- ▶ A_1 has 24 possible antenna placements
- ▶ A_2 has 33 possible antenna placements
- ▶ A_3 has 136 possible antenna placements

Size of search space = m^n

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- ▶ for each A_i , let L_i denote the set of allowable placements locations $\in \mathbb{R}^3$ such that $|L_i| = n_i$ and $\forall i, n_i > 1$;
$$L_i = \{(x_1, y_1, z_1) \dots (x_{n_i}, y_{n_i}, z_{n_i})\}$$

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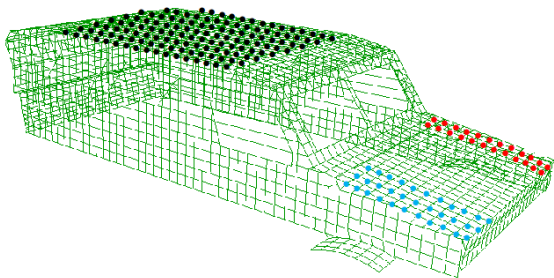
Goal: A set of m optimal antenna locations on P

Stochastic Algorithms

We will consider algorithms which rely on *randomization* principle.

- ▶ Simple Genetic Algorithm
- ▶ Evolutionary Strategy
- ▶ Simulated Annealing
- ▶ Hill Climbing

Representation



A hypothesis is represented by a set of antenna placements. For instance - $((x_1, y_1, z_1), (x_1, y_1, z_1), (x_1, y_1, z_1))$

Evolutionary Strategy

Algorithm 1: AP-ES

Data: Set of placements $L = \{L_1, \dots, L_m\}$; μ ; λ ; gen_{max} - maximum number of generations

Result: H^* from P

```
1 Initialize  $P \leftarrow$  generate  $\mu$  random hypothesis ;
2  $gen_{id} = 0$  ;
3 while  $gen_{id} < gen_{max}$  do
4     Create  $\lambda/\mu$  offsprings from each  $\mu$  hypotheses by applying mutation operator, and
      add all offsprings to  $P$  ;
5     Compute the  $fitness(h_i), i = 1, \dots, \lambda$  ;
6     Keep  $\mu$  best hypotheses in  $P$ , and discard remaining  $\lambda - \mu$  hypotheses ;
7     Update  $gen_{id} \leftarrow gen_{id} + 1$ 
8 end
```

Simulated Annealing

Algorithm 2: AP-SA

Data: Set of placements $L = \{L_1, \dots, L_m\}$; T - initial temperature; i_m - maximum iterations; $f_{cooling}$ - cooling factor

Result: H^* from P

```

1 Initialize  $H \leftarrow$  generate a random hypothesis ;
2 Compute  $fitness(H)$  ;
3  $i = 0$  ;
4 while  $i < i_m$  do
5     Mutation - Apply the operation on  $H$  as stated in Algorithm . Call the
        pertubrated/mutated hypothesis  $C$  ;
6     Compute  $\delta f = fitness(C) - fitness(H)$  ;
7     if  $\delta f > 0$  then
8         Generate a random number  $\epsilon$  using a uniform distribution over  $[0, 1]$  ;
9         if  $\epsilon < e^{-\delta f / T}$  then
10              $H \leftarrow C$ 
11         end
12     else
13          $H \leftarrow C$  ;
14     end
15      $T \leftarrow T \cdot f_{cooling}$  ;
16      $i \leftarrow i + 1$  ;
17 end

```

Antenna Placement Objectives

Antenna Placement Issues

- Coupling among antennas
- Parasitic effects and reflections from the host platform
- Loss of efficiency
- Difficulty conforming to aerodynamic, thermal, other environment factors

Desired Antenna Placement Objectives

- Gain in radiation pattern
- Minimize coupling

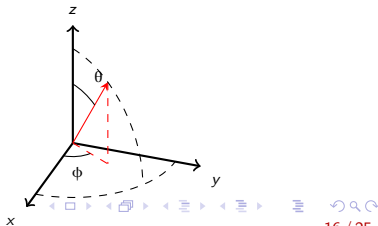
Minimize Difference in Radiation Pattern

Pattern defines the ratio of energy radiated and input energy in a particular direction. For each antenna A_i :

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

where

- ▶ θ, ϕ spherical and cylindrical coordinates
- ▶ $ISG(\cdot)$ returns in-situ gain pattern
- ▶ $FSG(\cdot)$ returns free-space gain pattern



Minimize Coupling

Coupling is the absorption of radiated energy by nearby antennas

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

where

- ▶ $CP(\cdot)$ computes the coupling between two antennas
- ▶ $i \neq j$

Overall Fitness Function

For an hypothesis, fitness is defined as:

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

TODO: about weights

Experimental Setup

- ▶ Create (s) such that each individual is defined by a placement for each of the m antennas
- ▶ Run all individuals through *NEC* simulator¹ to get fitness parameters
- ▶ Apply EA operators
- ▶ Repeat. . .

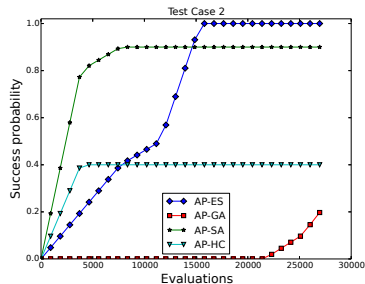
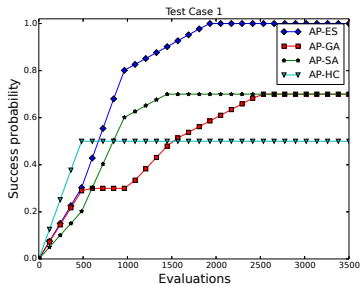
¹<http://www.nec2.org>

Experiments: Test Cases

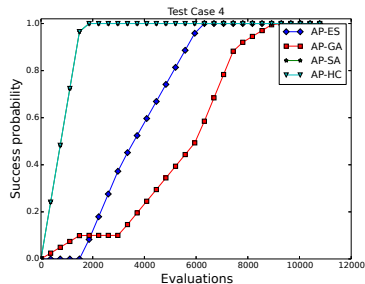
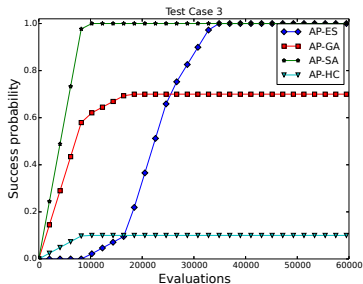
Test Case	Antennas	Total allowable placements
1	2	7,056 (83x83)
2	3	50,625 (45x45x25)
3	3	126,025 (71x71x25)
4	4	20,736 (12x12x12x12)

*Allowable placements for each antenna are provided within parenthesis

Results - Success Probability



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Results: Mean Evaluations

Mean number of evaluations to reach the best solution (over 10 runs):

test case \ method	GA	ES	SA	HC
tc1(7056) ²	2350	1728	667	164
tc2(50,625)	31 680	11 165	1653	174
tc3(126,025)	45 900	26 880	4809	227
tc4(20,736)	6150	4466	423	90

²Total number of possible evaluations within parenthesis

Equivalence of fitness to efficiency

For a particular test case, fitness change of 0.01 is equivalent to either the corresponding value under expected gain (\mathbb{E}_g) column, or difference in coupling (Δ_c).

ID	\mathbb{E}_g	Δ_c (dB)
tc1	872.277	0.5474
tc2	862.082	1.3034
tc3	861.845	1.5180
tc4	871.049	0.5693

$$\mathbb{E}_g = \frac{1}{N \cdot m} \sum_i^m F_{RP}(A_i), \text{ where } N = |\theta| \cdot |\phi|$$

Conclusion

- ▶ Formulation of the antenna placement problem
- ▶ Generic to accommodate multiple antennas and platforms
- ▶ Optimal placements found using stochastic algorithms