A Comparison of Antenna Placement Algorithms

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Motivation

- Antenna placement study is generally ignored
- Placing new antennas requires a long, manual effort to complete an antenna placement study, if at all
- Frequency bands change over time requiring new antennas, and therefore need to find new placements
- Parasitic effects due to fixed or mobile platform
- With multiple antennas systems offer interference, and thereby reduce each antenna's efficiency

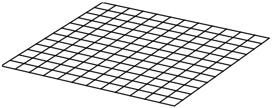
Outline of this talk

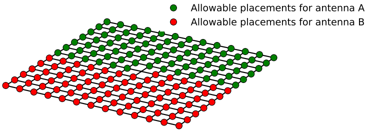
- Part 1: Introduction to the antenna placement problem
- Part 2: Description of stochastic algorithms, their properties and operators
- Part 3: Evaluation of test cases

Part 1: Introduction to the antenna placement problem

Antenna Placement Problem

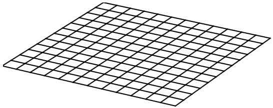
Given, platform $+$ allowable placements of antennas

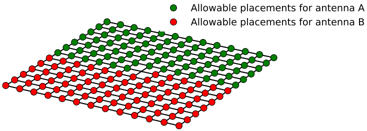




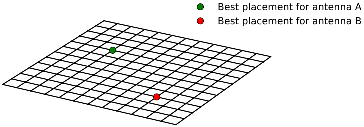
Antenna Placement Problem

Given, platform $\quad + \quad$ allowable placements of antennas





Problem: Find best antenna placements to maximize gain and minimize coupling



Antenna Placement Problem

Given:

- platform P with its surface gridded such that end points represent possible antenna placements
- set of n antennas $A = A_1, A_2, \ldots, A_n$ such that $n > 1$
- for each A_i, L_i denote the set of allowable placements $\in \mathbb{R}^3$ such that $|L_i| = m_i$ and $\forall i, m_i > 1$

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

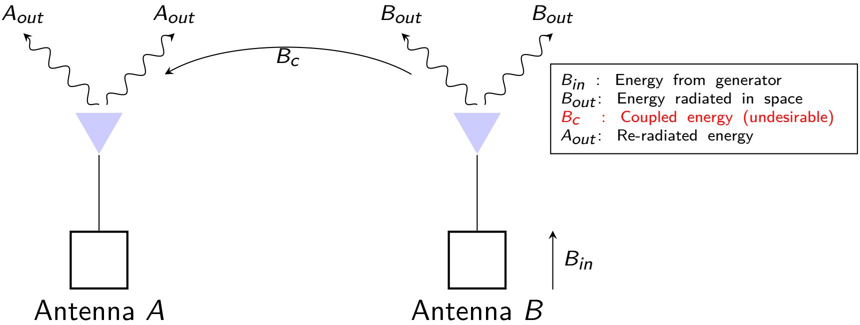
Problem: Find a set of n optimal antenna placements on P to maximize gain and minimize coupling.

Size of search space $= \mathbf{m^n}$, if $m_i = m, \forall i \in [1, n]$

Question: How is a good antenna placement quantified in the context of platform and other antennas?

Mutual Coupling

When two antennas are in proximity, and one is transmitting, the second will receive some of the transmitted energy.



Minimize Mutual Coupling

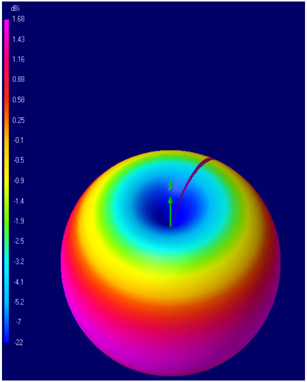
$$F_{MC} = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} CP(A_i, A_j), \tag{1}$$

where

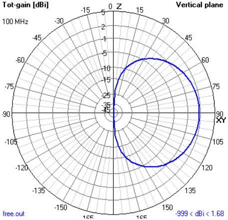
- $CP(\cdot,\cdot) \in \mathbb{R}$ is the coupling between two antennas, and computed using a simulator
- There will be $\binom{n}{2}$ coupling terms

Example: If $n = 3$, then $F_{MC} = CP(A_1, A_2) + CP(A_1, A_3) + CP(A_2, A_3)$

Free Space Gain Pattern



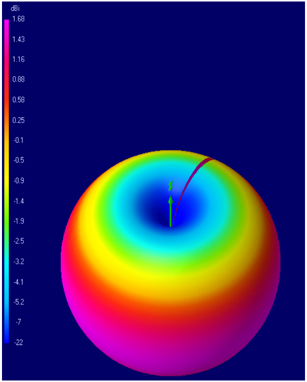
Free-space patten without platform or other antennas



2D view of the free-space gain pattern

This is ideal pattern since there is no interference

Gain Pattern



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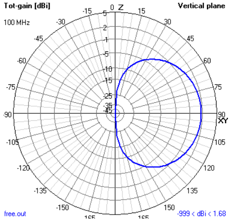
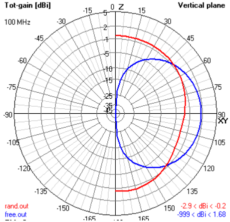


2D view of the free-space gain pattern



In-situ gain pattern for random antenna placements different from free-space gain pattern

Minimize Difference in Radiation Pattern

$$F_{RP} = \sum_{i=1}^{n} \sum_{\theta=0}^{\frac{180^\circ}{S}} \sum_{\phi=0}^{\frac{360^\circ}{S}} \left(FSG_i(S\theta, S\phi) - ISG_i(S\theta, S\phi)\right)^2, \quad (2)$$

where

- S is the step size
- θ, ϕ spherical coordinates in degrees
- $FSG(\cdot,\cdot) \in \mathbb{R}$ is the free-space gain pattern computed by the simulator
- $ISG(\cdot,\cdot) \in \mathbb{R}$ is the in-situ gain pattern computed by the simulator

Fitness Evaluation

Find a placement such that F is minimal:

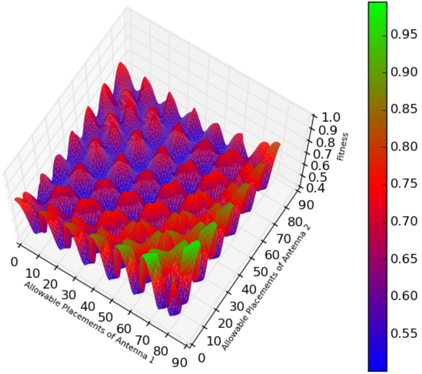
$$F = \alpha F_{MC} + \beta F_{RP}, \tag{3}$$

where α, β are adjustable weights for each of the objectives

Part 2: Stochastic Algorithms

Question: Why use stochastic algorithms?

Multi-Modal Search Space



Search space for one of the test cases evaluated. There are multiple local minimas which makes convergence difficult. z-axis is the combined fitness F

Stochastic Algorithms

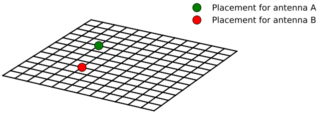
We will consider algorithms which are based on randomization principle:

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

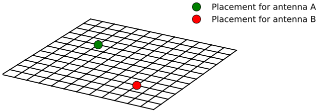
Stochastic Algorithms: Operand

An **individual** is a member of a set of feasible solutions.

- Simulated Annealing and Hill Climbing maintain single individual



- Genetic Algorithm and Evolutionary Strategy maintain a population of individuals



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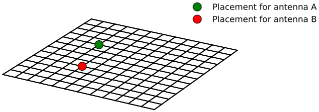
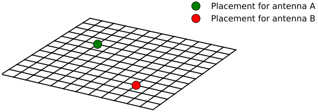
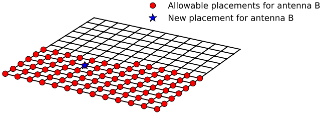


Stochastic Algorithms: Mutation Operator

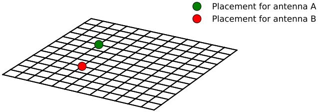
1. Given an individual, select an antenna uniformly at random, let's say antenna B:



2. For antenna B, select any other allowable placement:

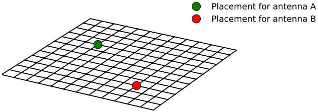


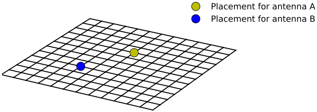
3. Change position for antenna B in individual (antenna A's position remains same):



Stochastic Algorithms: Crossover Operator

1. Select two individuals from population:

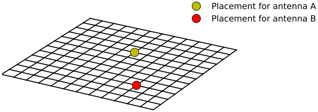


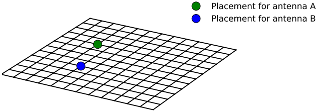


2. Select a crossover point, and swap placements prior to the point:

$$
\begin{array}{lcc|c}
\text{ind}_1: & A & & B \\
& \downarrow & \uparrow & \\
\text{ind}_2: & A & & B
\end{array}
$$

3. Two new offsprings created:





Genetic Algorithm

P $\leftarrow$ generate p random individuals. Compute $fitness(\mathbf{ind}_i), i \in [1,p]$;
$i = 0$;
while $i < gen_{max}$ **do**
    Elitism: Select n_e fittest individuals to add to **P'** ;
    for $(p - n_e)/2$ *times* **do**
        `/* 'select' returns a pair of individuals */`
        $\mathbf{M} \leftarrow select(\mathbf{P}, 2)$;
        if $rand(0,1) < p_c$ **then**
            $\mathbf{O} \leftarrow crossover(\mathbf{M})$;
            Add O to P' ;
        else
            Add M to P' ;
    Uniformly select $p_m \cdot (p - n_e)$ individuals from P, and apply *mutation* operator to each ;
    Update $P \leftarrow P'$;
    Compute $fitness(\mathbf{ind}_i); i \in [1,p]$;
    Update $i \leftarrow i + 1$;

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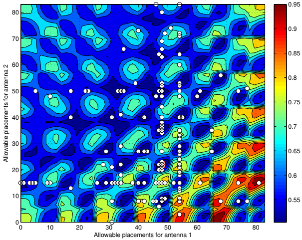

Population for last generation of a run. Search becomes restricted to some local optimums

Evolutionary Strategy

$\mathbf{P} \leftarrow$ generate μ random individuals ;

$i = 0$;

while $i < gen_{max}$ **do**

  Create λ/μ offsprings from each μ individuals by applying *mutation* operator;

  Add all offsprings to **P** ;

  Compute $fitness(\mathbf{ind}_i), i \in [1, \lambda + \mu]$;

  Keep μ best individuals in **P**, and discard remaining $\lambda - \mu$ individuals ;

  Update $i \leftarrow i + 1$

Evolutionary Strategy

P ← generate μ random individuals ;
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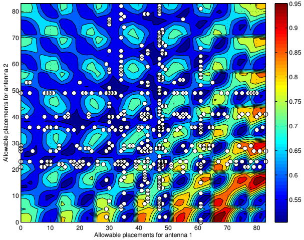

Population with greater diversity in comparison to GA

Simulated Annealing

```
c ← generate a random individual ;
i = 0 ;
while i < i_max do
    n ← mutate(c) ;
    if fitness(c) < fitness(n) then
        if rand(0,1) < e^(−δf/T) then
            /* replace current individual by a higher
               fitness (less fitter) individual          */
            c ← n
    else
        c ← n ;
    T ← T · f_cooling ;
    i ← i + 1 ;
```

Simulated Annealing

c ← generate a random individual ;
$i = 0$;
while $i < i_m ax$ **do**
  n ← *mutate*(**c**) ;
  if *fitness*(**c**) < *fitness*(**n**) **then**
    if $rand(0,1) < e^{-\delta f/T}$ **then**
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  else
    c ← **n** ;
  $T \leftarrow T \cdot f_{cooling}$;
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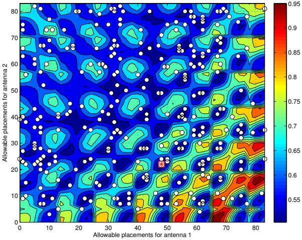

Temperature factor allows search distributed weacross the terrain

Hill Climbing

Initialize $\mathbf{c} \leftarrow$ generate a random inidividual ;
Compute $fitness(\mathbf{c})$;
$i = 0$;
while $i < i_{max}$ **do**
    $\mathbf{n} \leftarrow mutate(\mathbf{c})$;
    if $fitness(\boldsymbol{n}) < fitness(\boldsymbol{c})$ **then**
        $\mathbf{c} \leftarrow \mathbf{n}$
    $i \leftarrow i + 1$

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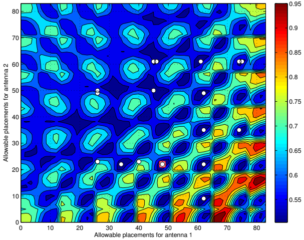


Restricted search due to greedy approach to accept only fitter (low fitness) individuals

Part 3: Evaluation of test cases

Experimental Setup

1. All test cases describe platforms which are representative of real-world use cases like mobile devices, trucks, and cars. If one were to scale up we will expect same behaviour to hold

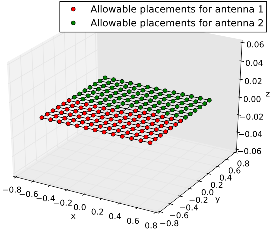
2. We use a popular *NEC2* simulator to get fitness parameters

3. Evaluated the entire search space using an exhaustive algorithm to find the optimal antenna locations which is not ordinarily possible

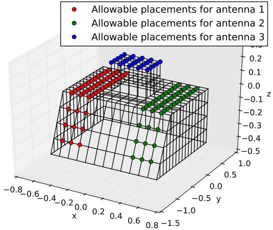
4. Termination criteria was set to be at most 50% evaluations of the search spcae

5. 1000 independent runs of each test case against each algorithm with $\alpha = \beta = 1/2$

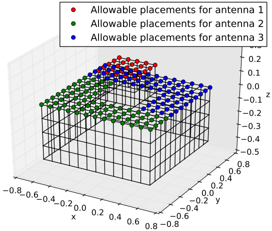
Experiments Test Cases



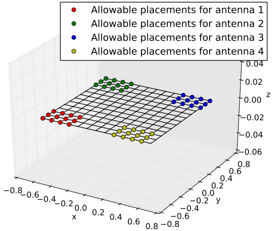
Test Case #1: search space size of 7056 (84x84) allowable placements



Test Case #2: search space size of 50625 (45x45x25) allowable placements



Test Case #3: search space size of 126025 (71x71x25) allowable placements

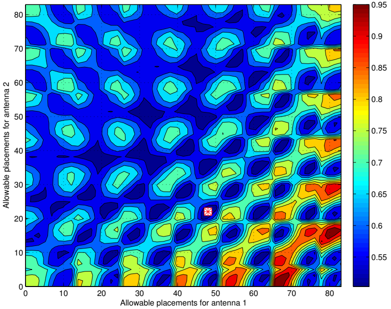


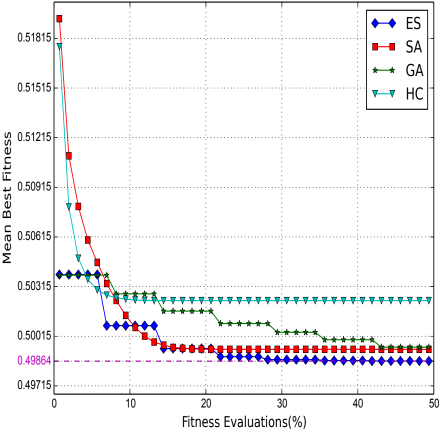
Test Case #4: search space size of 20736 (12x12x12x12) allowable placements

Results - Test Case 1

Sample size = 1000

Algo.	%Evals. vs. exhaust.		Best fitness	
	Mean	Std. Dev.	Mean	Std. Dev.
ES	11.88	10.48	0.49865	0.00009
SA	8.28	4.47	0.49935	0.00163
GA	17.21	15.69	0.49949	0.00182
HC	2.50	2.20	0.50230	0.00501

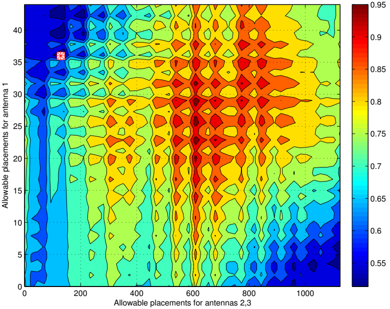


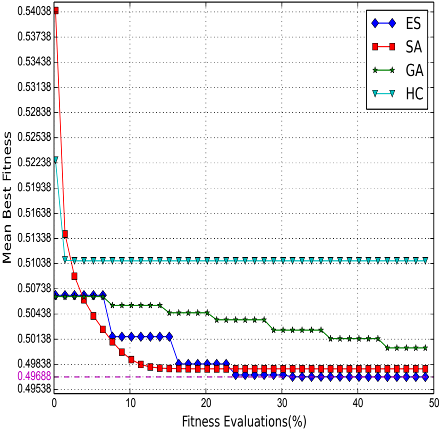


Results - Test Case 2

Sample size = 1000

Algo.	%Evals. vs. exhaust.		Best fitness	
	Mean	Std. Dev.	Mean	Std. Dev.
ES	16.08	7.72	0.49688	0.00000
SA	7.96	3.33	0.49784	0.00233
GA	25.98	15.51	0.50034	0.00341
HC	0.40	0.31	0.51071	0.01305

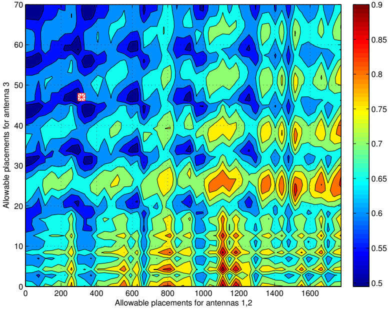


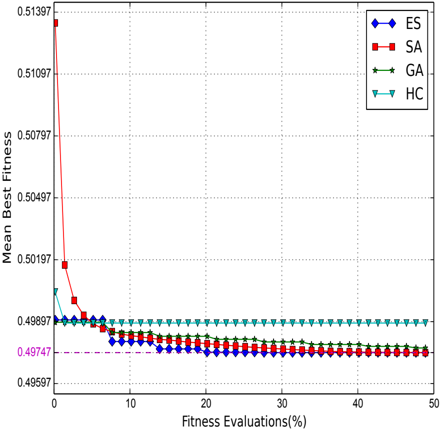


Results - Test Case 3

Sample size = 1000

Algo.	%Evals. vs. exhaust.		Best fitness	
	Mean	Std. Dev.	Mean	Std. Dev.
ES	11.04	6.72	0.49747	0.00000
SA	19.61	11.16	0.49747	0.00003
GA	23.05	16.25	0.49770	0.00038
HC	0.21	0.17	0.49890	0.00182

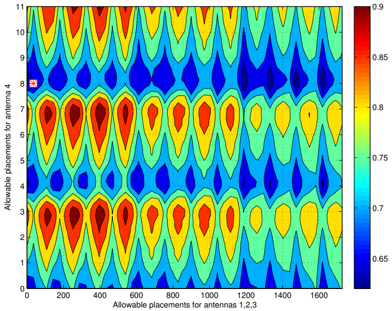


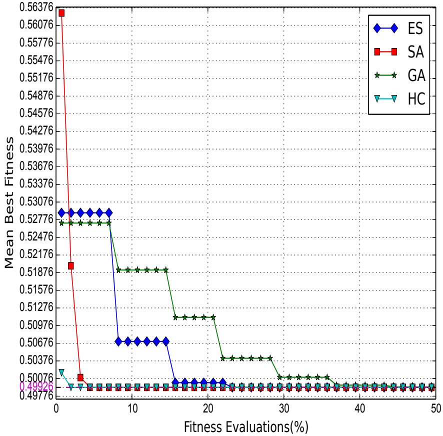


Results - Test Case 4

Sample size = 1000

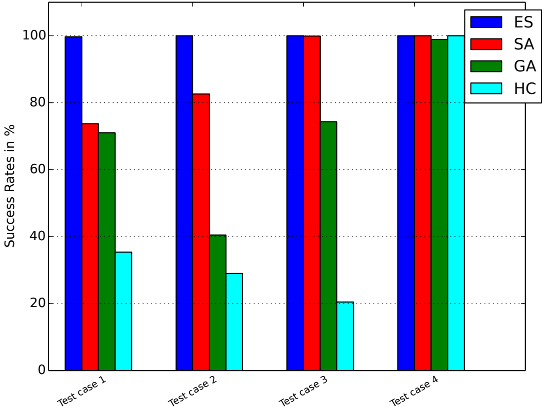
Algo.	%Evals. vs. exhaust.		Best fitness	
	Mean	Std. Dev.	Mean	Std. Dev.
ES	12.48	5.61	0.49926	0.00000
SA	2.76	0.83	0.49926	0.00000
GA	22.42	9.94	0.49934	0.00072
HC	0.44	0.26	0.49926	0.00000





Results - Success Rates

Success rate report the percentage of runs in which the algorithm is able to find the optimum with 50% evaluations as termination criteria



Conclusion

- Formalized the antenna placement problem
- Generic problem formulation to accommodate multiple antennas and platforms
- Optimal placements found using Evolutionary Strategy with at most 25% evaluations of search space with 100% success rate
- Future work - Consider other techniques like *Differential Evolution* and *ALPS*