# 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
- With multiple antennas systems offer interference, and thereby reduce each antenna's efficiency
- Parasitic effects due to fixed or mobile plaform
- Frequency bands change over time requiring new antennas, and therefore need to find new placements

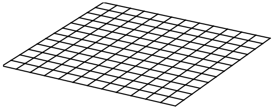
# Outline of this talk

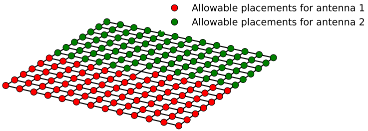
- Part 1: Introduction to the antenna placement problem
- Part 2: Description of stochastic algorithms, their properties and operators
- Part 3: Evaluation of test cases

# Part 1: Introduction to the antenna placement problem

# Antenna Placement Problem

Given, platform + allowable placements of antennas





# Antenna Placement Problem

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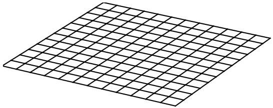
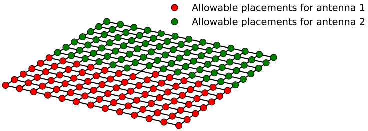
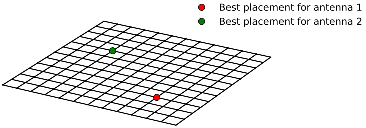





**Problem:** Find best antenna placements to maximize gain and minimize coupling



# 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 $\forall i, m_i > 1$

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

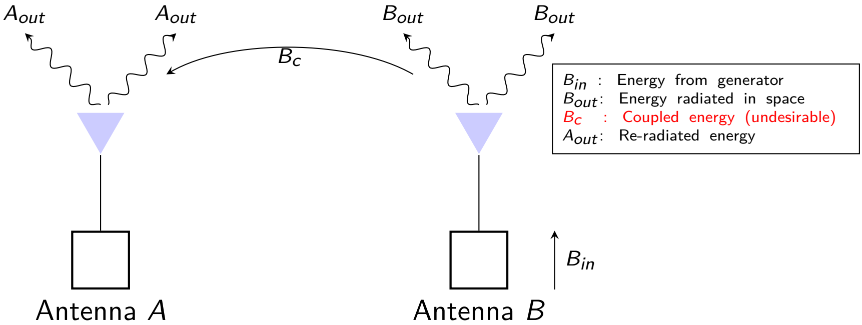
**Problem**: Find a set of $n$ optimal antenna placements on $P$ to maximize gain and minimize coupling.

**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

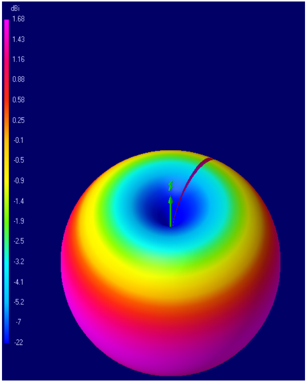
$$F_{MC} = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} CP(A_i, A_j), \qquad (1)$$

where

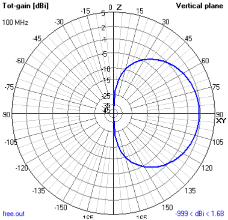
- $CP(\cdot,\cdot) \in \mathbb{R}$ is the coupling between two antennas, and computed using a simulator
- There will be $\binom{n}{2}$ coupling terms

*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



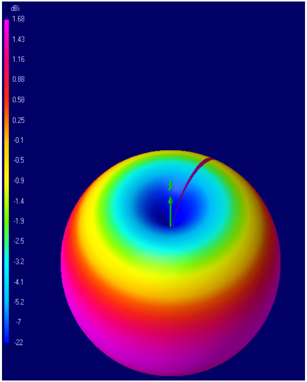

Free-space patten without platform or other antennas



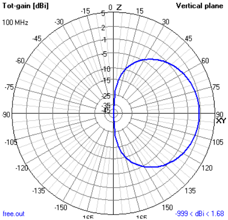

2D view of the free-space gain pattern

This is ideal pattern since there is no interference

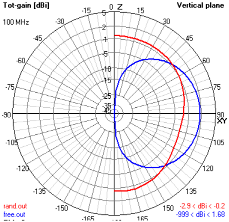
# Gain Pattern




Free-space patten without platform or other antennas




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
- $\theta, \phi$ 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:

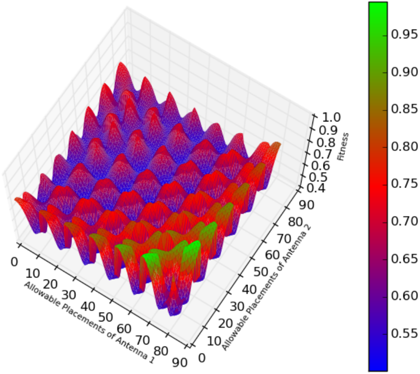
$$F = \alpha F_{MC} + \beta F_{RP}, \tag{3}$$

where $\alpha, \beta$ 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.

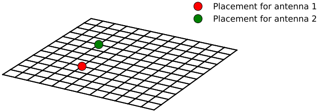
- Genetic Algorithm
- Evolutionary Strategy
- Simulated Annealing
- Hill Climbing

Each algorithm maintains a candidate solution or pool of candidate solutions called population

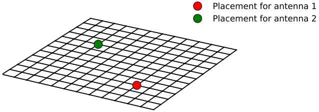
# Stochastic Algorithms: Operand

**Candidate solution** or an **individual** is a member of a set of possible solutions.

- Simulated Annealing and Hill Climbing maintain single individual




- Genetic Algorithm and Evolutionary Strategy maintain a population of individuals

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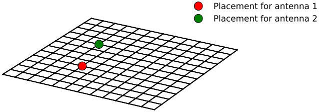
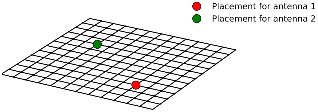
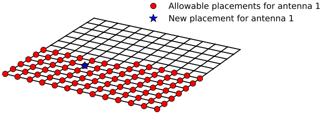


# Stochastic Algorithms: Mutation Operator

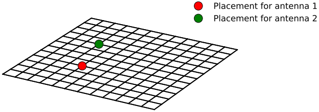
1. Given an individual, select an antenna uniformly at random, let's say antenna 1:




2. For antenna 1, select any other allowable placement:

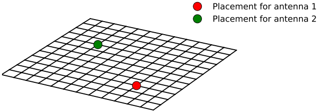


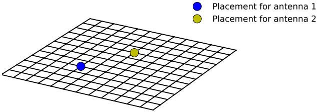

3. Change position for antenna 1 in individual:



# Stochastic Algorithms: Crossover Operator

1. Select two individuals from population:

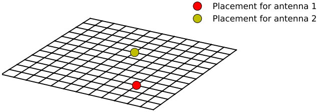


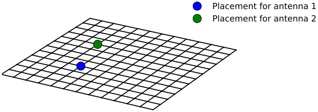




2. Select a crossover point, and swap placements prior to the point:

$$\begin{array}{lc|c} \text{ind}_1: & \color{red}{A_1} & \color{green}{A_2} \\ & \downarrow \;\; \uparrow & \\ \text{ind}_2: & \color{blue}{A_1} & \color{olive}{A_2} \end{array}$$

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 */
        **M** $\leftarrow$ *select*(**P**, 2) ;
        **if** $rand(0,1) < p_c$ **then**
            **O** $\leftarrow$ *crossover*(**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 $i \leftarrow i + 1$ ;

# Genetic Algorithm

**P** $\leftarrow$ generate $p$ random individuals. Compute $fitness(\mathbf{ind}_i), i \in [1, p]$;
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        $\mathbf{M} \leftarrow select(\mathbf{P}, 2)$ ;
        **if** $rand(0,1) < p_c$ **then**
            $\mathbf{O} \leftarrow crossover(\mathbf{M})$ ;
            Add $O$ to $P'$ ;
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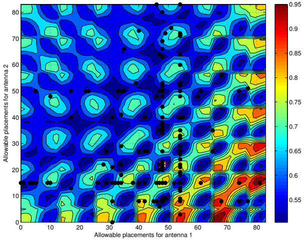


Population for last generation of a run. Search becomes restricted to some local optimums

# Evolutionary Strategy

```
P ← 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(ind_i), i ∈ [1, λ + μ] ;
    Keep μ best individuals in P, and discard remaining λ − μ individuals ;
    Update i ← i + 1
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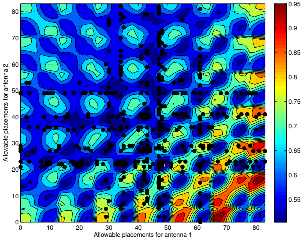


Population for last generation of a run. Notice that search becomes restricted to some local optimums

# 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 ;
```

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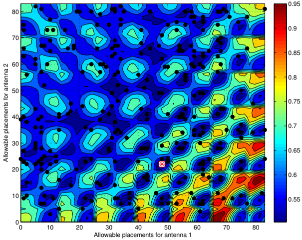


Fluctuation in fitness gradually reduces due to cooling

# 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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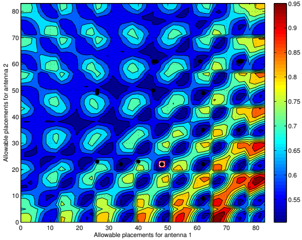



Greedy approach to accept only fitter(low fitness) individuals

# 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

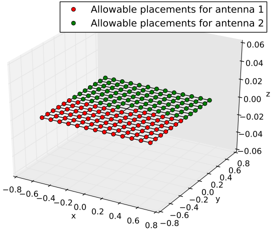
2. We use a popular *NEC2* simulator to get fitness parameters

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

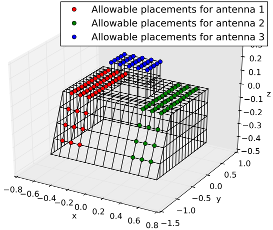
4. Termination criteria was set to be at most 50% evaluations of the search spcae

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

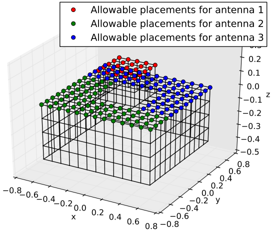
# Experiments: Test Cases



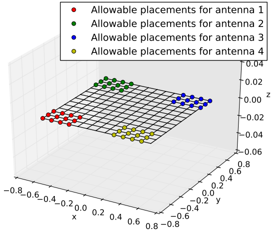

Test Case #1: search space size of 7056 (84x84) allowable placements




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




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

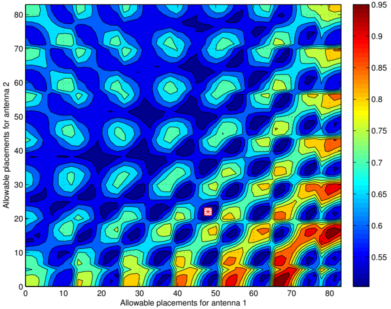


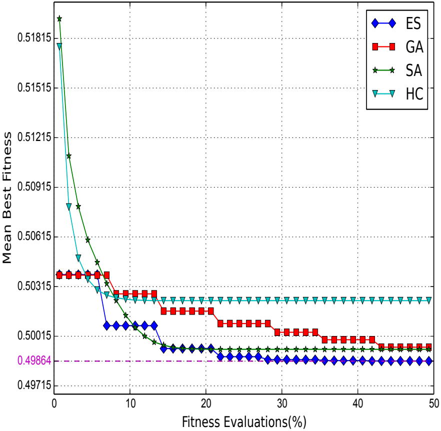

Test Case #4: search space size of 20736 (12x12x12x12) allowable placements

# 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 |
| GA | 17.21 | 15.69 | 0.49949 | 0.00182 |
| SA | 8.28 | 4.47 | 0.49935 | 0.00163 |
| HC | 2.50 | 2.20 | 0.50230 | 0.00501 |

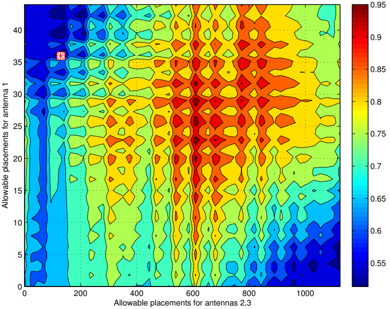


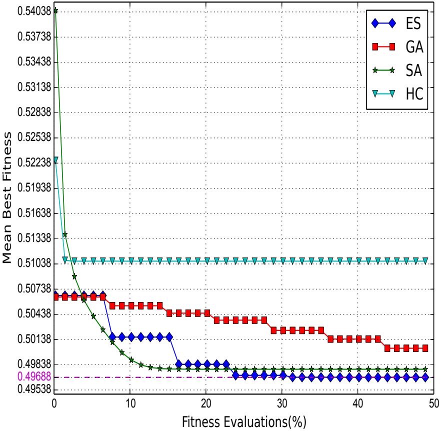



# Results - Test Case 2

Sample size = 1000

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

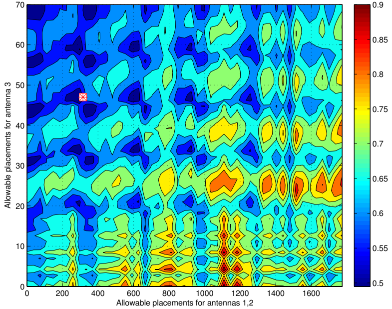


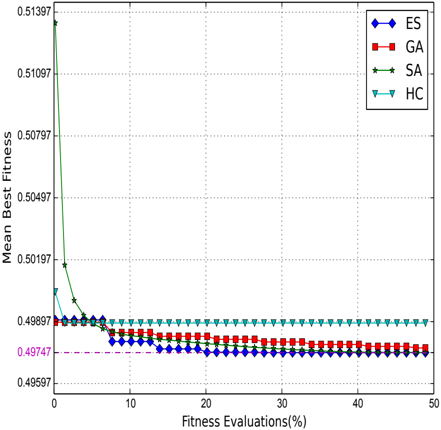



# Results - Test Case 3

Sample size = 1000

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

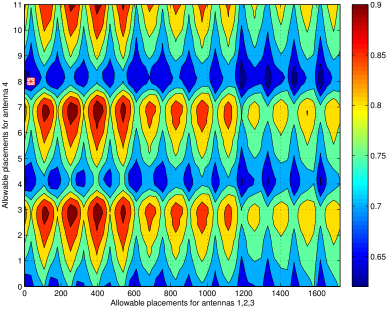


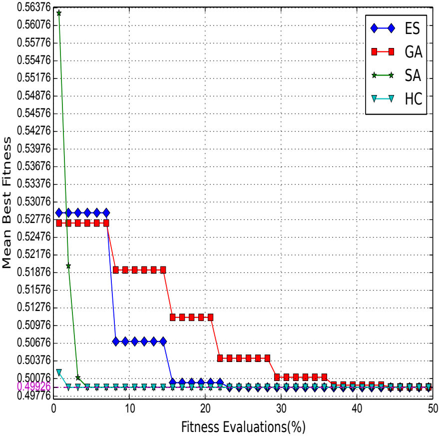



# Results - Test Case 4

Sample size = 1000

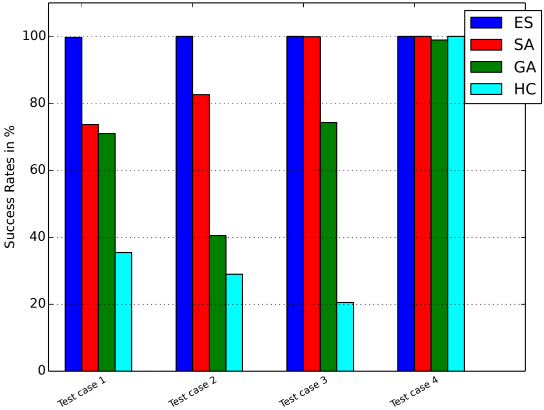
| Algo. | %Evals. vs. exhaust. Mean | %Evals. vs. exhaust. Std. Dev. | Best fitness Mean | Best fitness Std. Dev. |
|---|---|---|---|---|
| ES | 14.11 | 6.17 | 0.49926 | 0.00000 |
| GA | 22.42 | 9.94 | 0.49926 | 0.00000 |
| SA | 2.19 | 0.78 | 0.49926 | 0.00000 |
| HC | 0.43 | 0.40 | 0.49926 | 0.00000 |



# Results - Success Rates

*Success rate* report the percentage of runs in which the algorithm is able to find the optimum



# 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
- Future work - Consider other techniques like *Differential Evolution* and *ALPS*