A Comparison of Antenna Placement Algorithms

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Contributions

- Formulation of the antenna placement problem
- Evaluation of standard stochastic algorithms on a real-world problem
- Able to achieve global optimum with as low as **25% evaluations** of search space

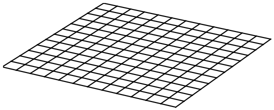
Outline of this talk

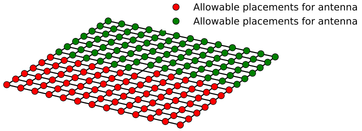
- Part 1: Introduction to the antenna placement problem
- Part 2: Description of stochastic algorithms, and formulation of an instance of antenna placment problem
- Part 3: Results of real world experiments

Part 1: Introduction to the antenna placement problem

Antenna Placement Problem

Given, platform + allowable placements of antennas




● Allowable placements for antenna
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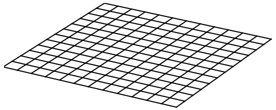
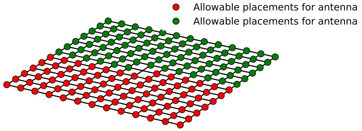
Antenna Placement Problem

Given, platform $+$ allowable placements of antennas




● Allowable placements for antenna
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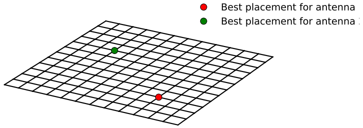
Problem: find best antenna placements



Antenna Placement Problem

Given:

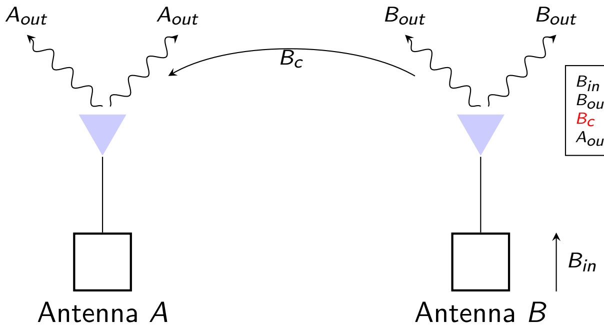
- platform P with its surface gridded such that end points represent possible antenna placements
- set of m antennas $A = A_1, A_2, \ldots, A_m$ such that $m > 1$
- for each A_i, L_i denote the set of allowable placements $\in \mathbb{R}^3$ such that $\mid L_i \mid = n_i$ and $\forall i, n_i > 1$; $L_i = \{(x_1, y_1, z_1) \ldots (x_{n_i}, y_{n_i}, z_{n_i})\}$

Problem: Find a set of n optimal antenna placements on P

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.



B_{in}	:	Energy from generator
B_{out}	:	Energy radiated in space
B_c	:	Coupled energy (not good)
A_{out}	:	Re-radiated energy

Minimize Mutual Coupling

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

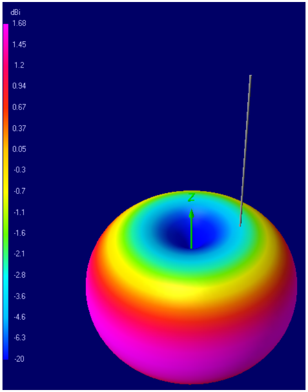
where

- $CP(\cdot,\cdot) \in \mathbb{R}$ is the coupling between two antennas, and computed using a simulator

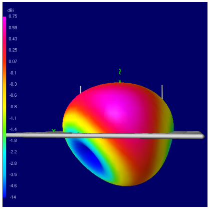
Example: If $n = 3$, then $F_{MC} = CP(A_1, A_2) + CP(A_1, A_3) + CP(A_2, A_3)$

Radiation Pattern

Free-space pattern without platform or other antennas

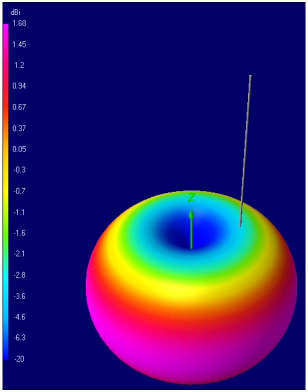


Pattern with platform and antennas (in-situ) similar

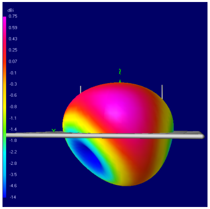


Radiation Pattern

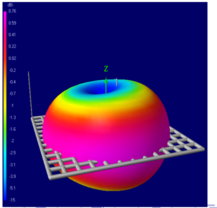
Free-space pattern without platform or other antennas



Pattern with platform and antennas (in-situ) similar



Pattern with platform and antennas (in-situ) similar to free-space pattern



Minimize Difference in Radiation Pattern

$$F_{RP} = \sum_{i=1}^{n} \sum_{\theta=0}^{\pi} \sum_{\phi=0}^{2\pi} \left(FSG_i(\theta,\phi) - ISG_i(\theta,\phi)\right)^2, \qquad (2)$$

where

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

Objective Function

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

Stochastic Algorithms

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

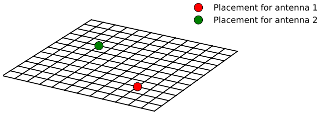
- Genetic Algorithm
- Evolutionary Strategy
- Simulated Annealing
- Hill Climbing

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

Candidate Solution

Also referred as an **individual**

- Pool of individuals



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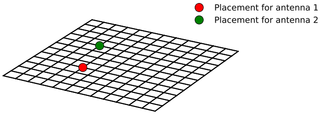
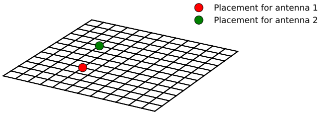
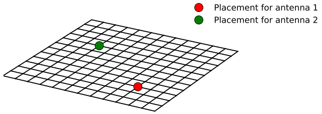


- Single individual

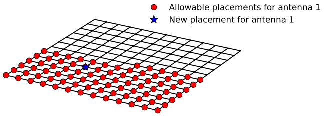


Stochastic Algorithms: Mutation Operator

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

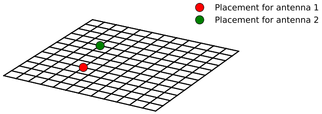


2. For antenna 1, select any other placement:



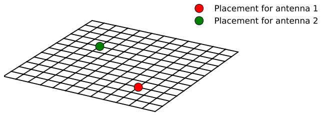
● Allowable placements for antenna 1
★ New placement for antenna 1

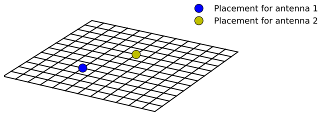
3. Change position for antenna 1 in individual:



Stochastic Algorithms: Crossover Operator

1. Select two individuals from population:

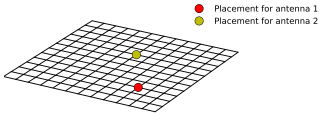


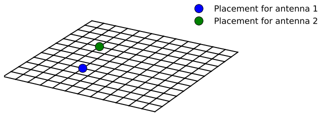


2. Select a crossover point, and swap placements prior to the point:

$$\begin{array}{lcc|c} \text{ind}_1 : & A_1 & & A_2 \\ & \downarrow & \uparrow & \\ \text{ind}_2 : & A_1 & & A_2 \end{array}$$

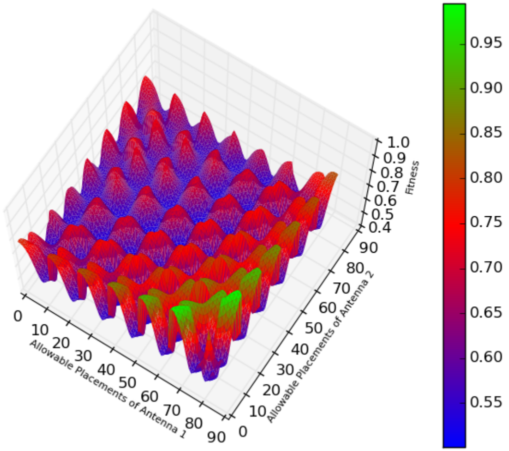
3. Two new offsprings created:





Question: Why use stochastic algorithms?

Multi-Modal Search Space



Genetic Algorithm

```
1  $\mathbf{P} \leftarrow$ generate $p$ random individuals. Compute
   $fitness(ind_i), i \in [1, p]$;
2  $i = 0$ ;
3  while $i < gen_{max}$ do
4      Elitism: Select $n_e$ fittest individuals to add to P' ;
5      for $(p - n_e)/2$ times do
           /* select returns pair of individuals
              */
6          $\mathbf{M} \leftarrow select(\mathbf{P}, 2)$ ;
7          if $rand(0,1) < p_c$ then
8              Apply $crossover(M)$ to get two offsprings
               O ;
9              Add $O$ to $P'$ ;
10         else
11             Add $M$ to $P'$ ;
12     Uniformly select $p_m \cdot (p - n_e)$ individuals from $P$,
       and apply mutation operator to each ;
13     Update $P \leftarrow P'$ ;
14     Compute $fitness(ind_i); i \in [1, p]$;
15     Update $i \leftarrow i + 1$ ;
```

Genetic Algorithm

```
1  P ← generate $p$ random individuals. Compute
   $fitness(ind_i), i \in [1,p]$;
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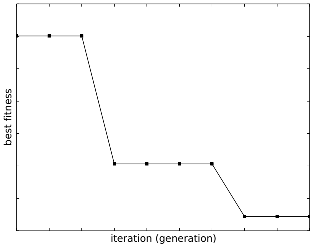

Plateaus suggesting stagnation of search

Evolutionary Strategy

```
1 P ← generate μ random individuals ;
2 $i = 0$ ;
3 while $i < gen_{max}$ do
4     Create $\lambda/\mu$ offsprings from each μ individuals by applying *mutation* operator, and add all offsprings to P;
5     Compute $fitness(ind_i), i \in [1, \lambda]$ ;
6     Keep μ best individuals in P, and discard remaining $\lambda - \mu$ individuals ;
7     Update $i \leftarrow i + 1$
```

Evolutionary Strategy

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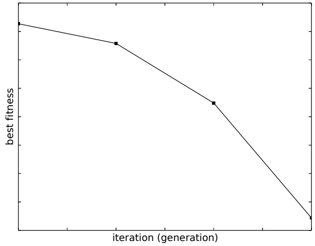

No stagnation in exploration of search space

Simulated Annealing

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

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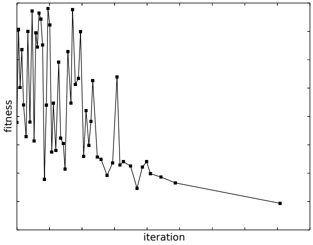

Fluctuation in fitness gradually reduces due to cooling

Hill Climbing

```
Initialize $\mathbf{c}$ ← 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
        $c \leftarrow n$
    $i \leftarrow i + 1$
```

Hill Climbing

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```
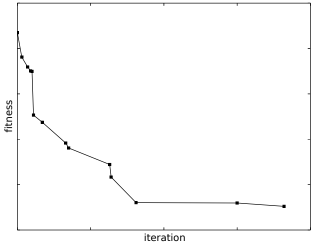



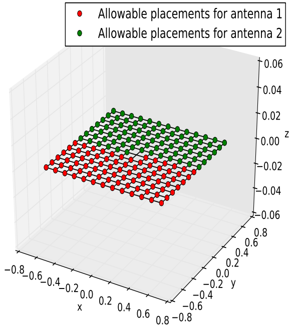
Only accepts fitter individual

Part 3: Results of real world experiments

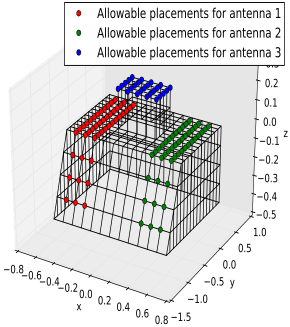
Experimental Setup

1. All test cases describe platforms which are replicas of real-world use cases like mobile devices, tanks, and cars
2. We use a popular *NEC2* simulator [1] to get fitness parameters
3. Evaluate the entire search space using an exhaustive algorithm to find the optimal antenna locations

Experiments: Test Cases

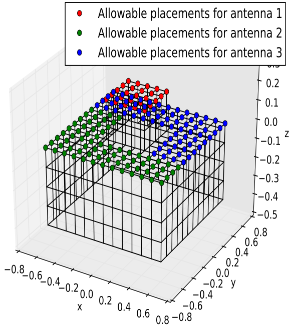


Test Case #1 with 7056(84x84) allowable placements

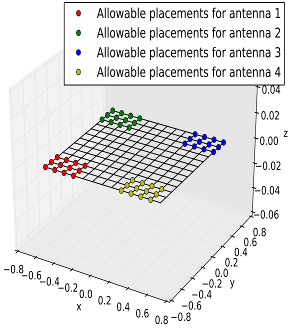


Test Case #2 with 50625(45x45x45) allowable placements

Experiments: Test Cases

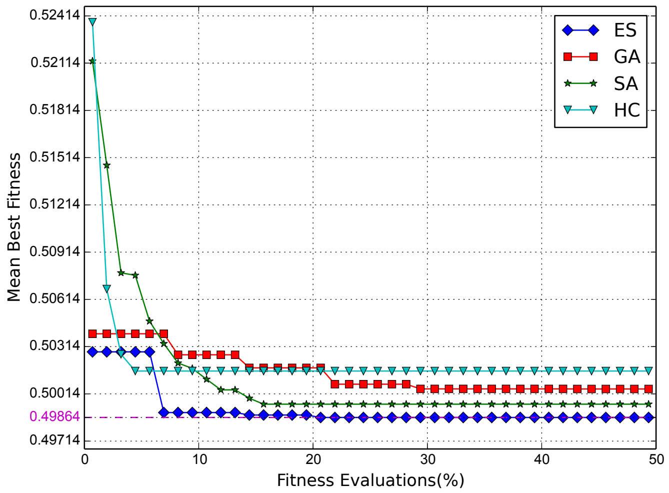


Test Case #3 with 126025(71x71x25) allowable placements

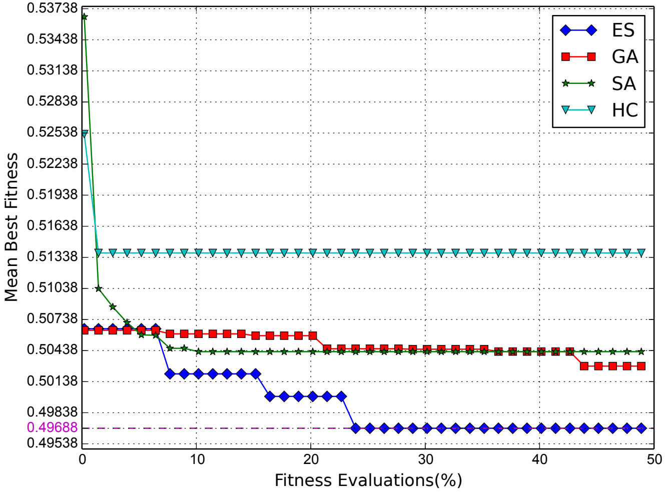


Test Case #4 with 20736(12x12x12x12) allowable placements

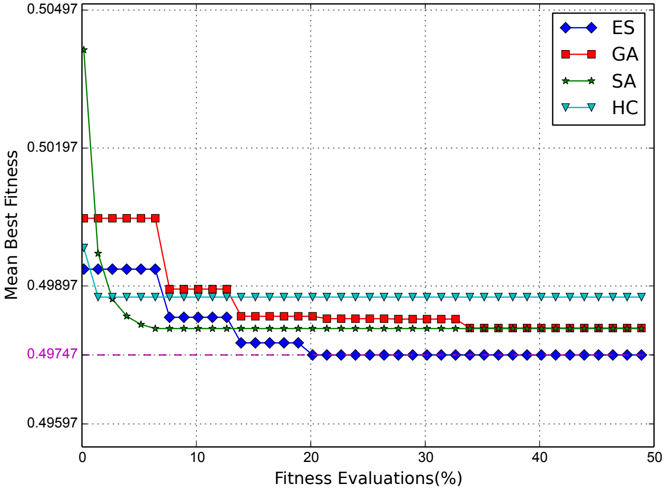
Results - Test Case 1



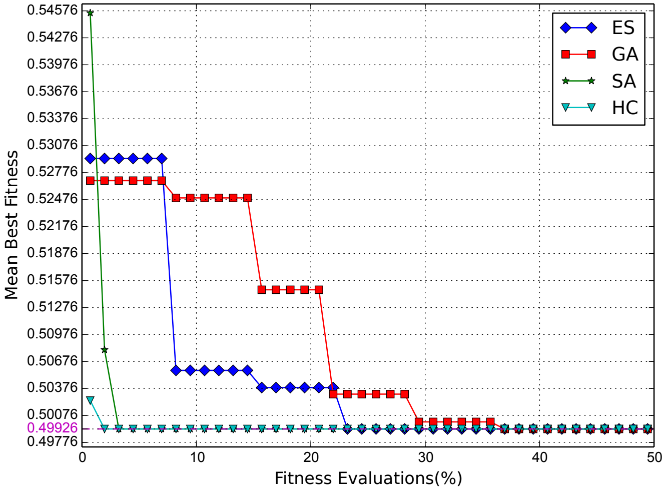
Results - Test Case 2



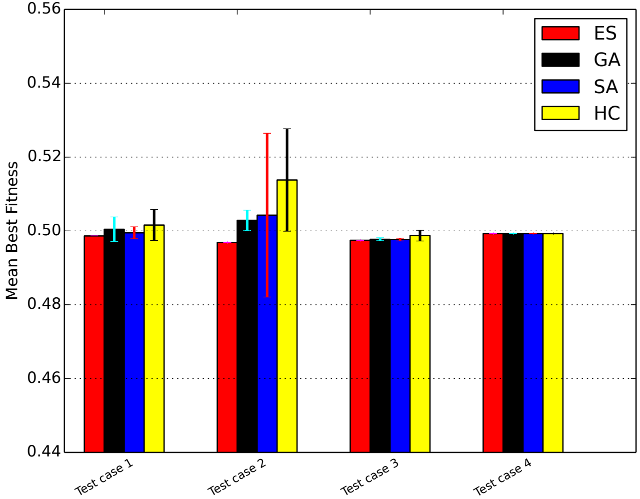
Results - Test Case 3



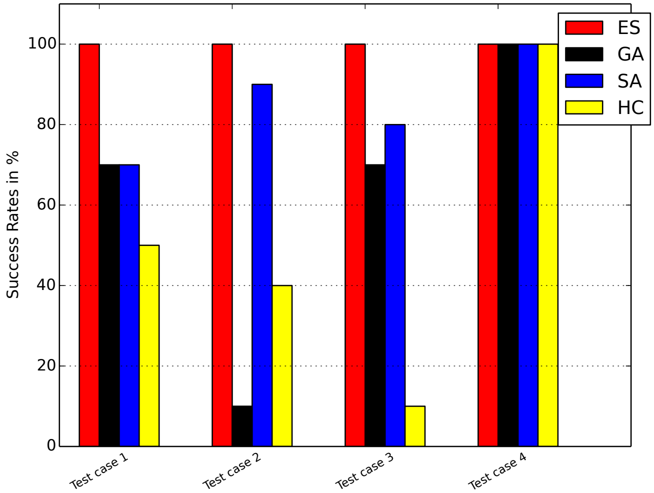
Results - Test Case 4



Results - Mean Best Fitness With Std. Dev.



Results - Success Rates



Conclusion

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