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

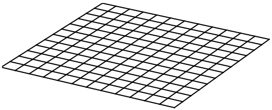
Outline of this talk

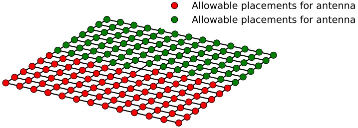
- Part 1: Introduction to the antenna placement problem
- Part 2: Description of stochastic algorithms, their properties and operators
- Part 3: Evaluation of test cases

Part 1: Introduction to the antenna placement problem

Antenna Placement Problem

Given, platform + allowable placements of antennas





Antenna Placement Problem

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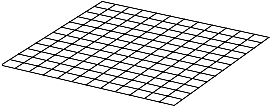
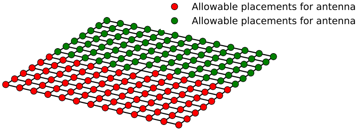
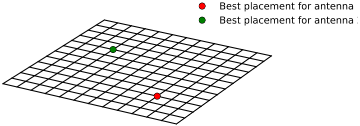




Problem: find best antenna placements



Antenna Placement Problem

Given:

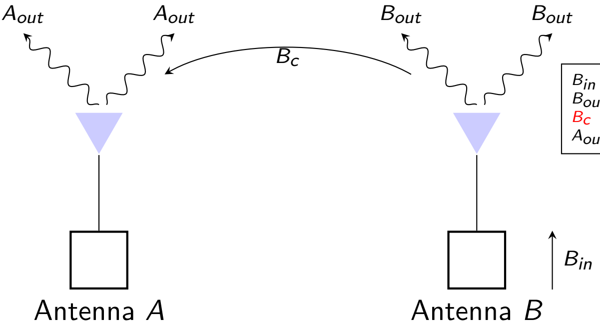
- platform P with its surface gridded such that end points represent possible antenna placements
- set of m antennas $A = A_1, A_2, \ldots, A_m$ such that $m > 1$
- for each A_i, L_i denote the set of allowable placements $\in \mathbb{R}^3$ such that $\mid L_i \mid = n_i$ and $\forall i, n_i > 1$;
 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

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

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

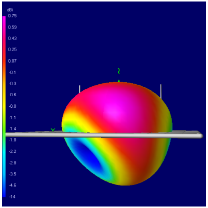
where

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

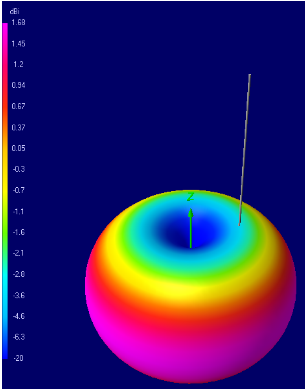
Example: If $n = 3$, then $F_{MC} = CP(A_1, A_2) + CP(A_1, A_3) + CP(A_2, A_3)$

Radiation Pattern

Pattern with platform and antennas (in-situ)

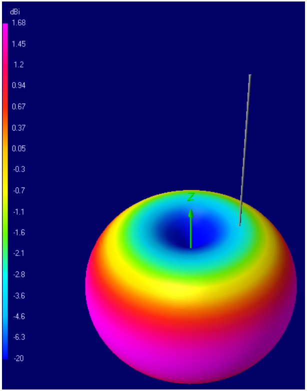


Free-space pattern without platform or other antennas

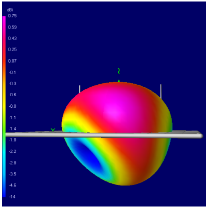


Radiation Pattern

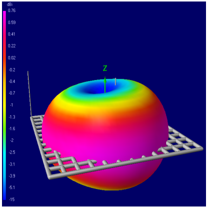
Free-space pattern without platform or other antennas



Pattern with platform and antennas (in-situ)



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.

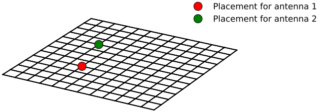
- Genetic Algorithm
- Evolutionary Strategy
- Simulated Annealing
- Hill Climbing

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

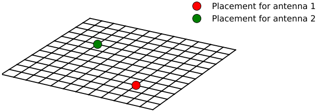
Stochastic Algorithms: Operand

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

- Simulated Annealing and Hill Climbing maintain single individual



- Genetic algorithm and Evolutionary Strategy maintain a population of individuals



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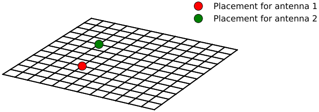
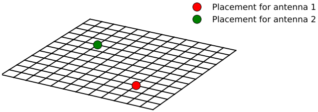
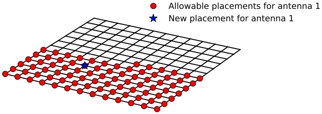


Stochastic Algorithms: Mutation Operator

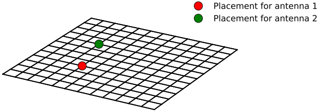
1. Given an individual, select an antenna uniformly at random, let's say antenna 1:



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

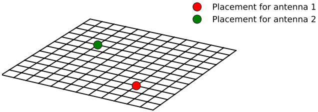


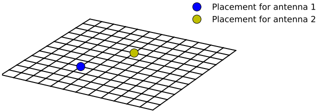
3. Change position for antenna 1 in individual:



Stochastic Algorithms: Crossover Operator

1. Select two individuals from population:

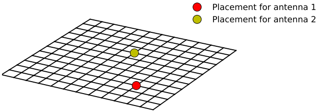


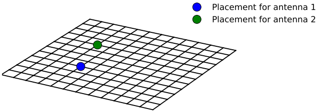


2. Select a crossover point, and swap placements prior to the point:

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

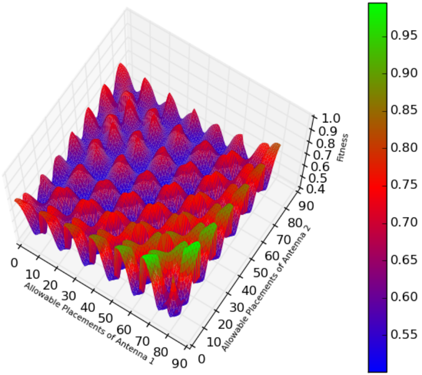
3. Two new offsprings created:





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 (refer Eq. 3)

Genetic Algorithm

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

$i = 0$;

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

  Elitism: Select n_e fittest individuals to add to **P'** ;

  for $(p - n_e)/2$ *times* **do**

    `/* select returns pair of individuals */`

    M ← $select(\mathbf{P}, 2)$;

    if $rand(0,1) < p_c$ **then**

      Apply $crossover(M)$ to get two offsprings **O** ;

      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 $fitness(ind_i); i \in [1, p]$;

  Update $i \leftarrow i + 1$;

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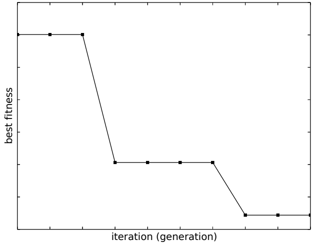

Plateaus suggesting stagnation of search

Evolutionary Strategy

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, and add all offsprings to **P**;
  Compute $fitness(ind_i), i \in [1, \lambda]$;
  Keep μ best individuals in **P**, and discard remaining $\lambda - \mu$ individuals ;
  Update $i \leftarrow i + 1$

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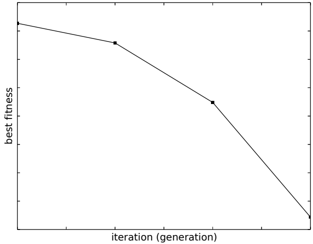


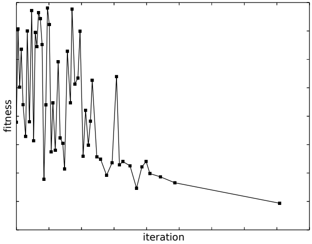
Less likely to stagnate
search space exploration

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
            c ← n
    else
        c ← n ;
    T ← T · f_cooling ;
    i ← i + 1 ;
```

Simulated Annealing

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



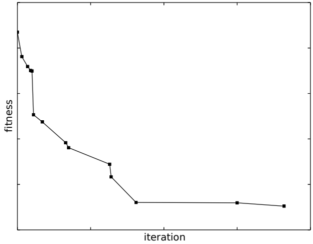
Fluctuation in fitness gradually reduces due to cooling

Hill Climbing

```
Initialize c ← generate a random inidividual ;
Compute fitness(c) ;
i = 0 ;
while i < i_max do
    n ← mutate(c) ;
    if fitness(n) < fitness(c) then
        c ← n
    i ← i + 1
```

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 $fitness(n) < fitness(c)$ **then**
        $c \leftarrow n$
    $i \leftarrow i + 1$



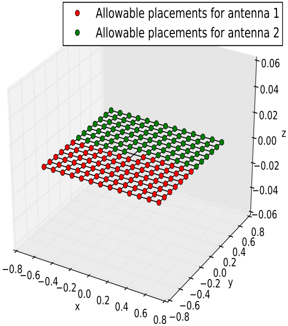
Greedy approach to accept only fitter(low fitness) individuals

Part 3: Evaluation of test cases

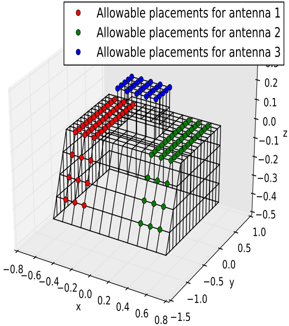
Experimental Setup

1. All test cases describe platforms which are 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

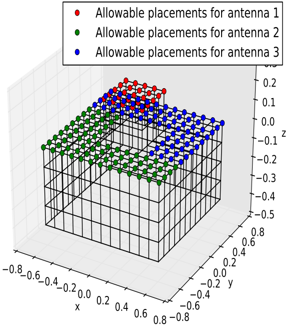


Test Case #1 with 7056(84x84) allowable placements

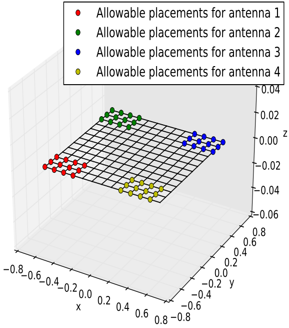


Test Case #2 with 50625(45x45x45) allowable placements

Experiments: Test Cases

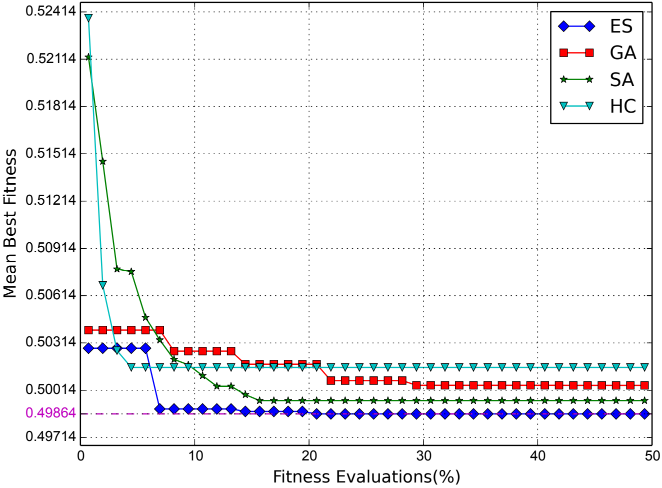


Test Case #3 with 126025(71x71x25) allowable placements

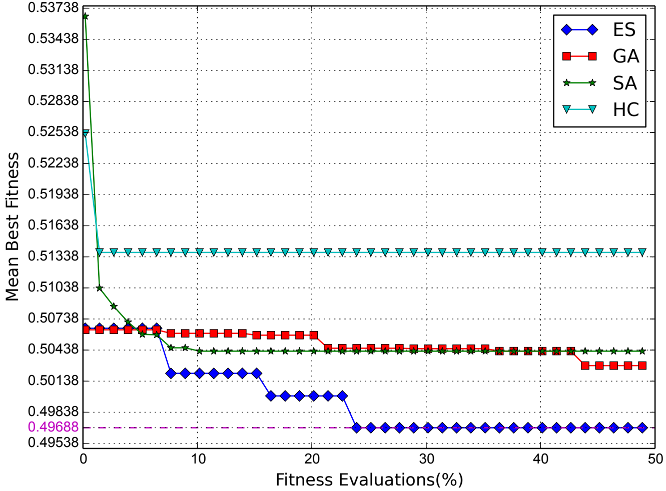


Test Case #4 with 20736(12x12x12x12) allowable placements

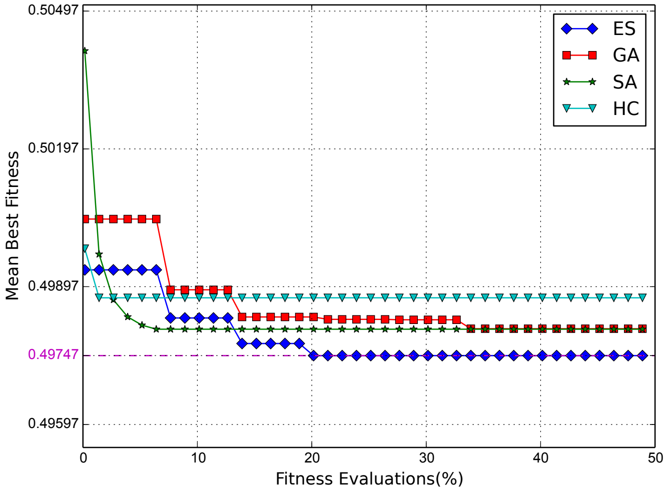
Results - Test Case 1



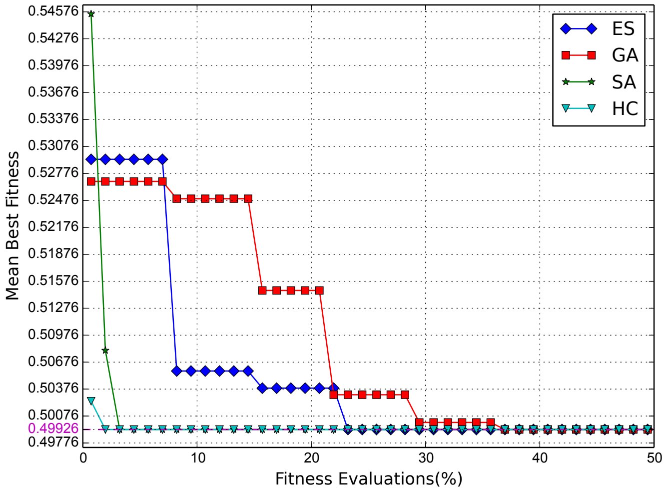
Results - Test Case 2



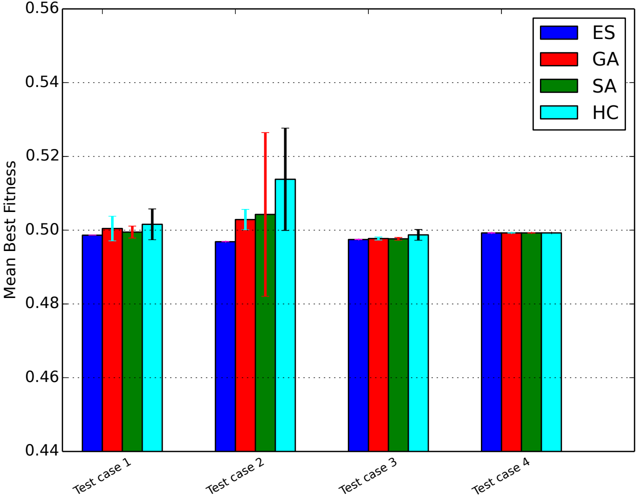
Results - Test Case 3



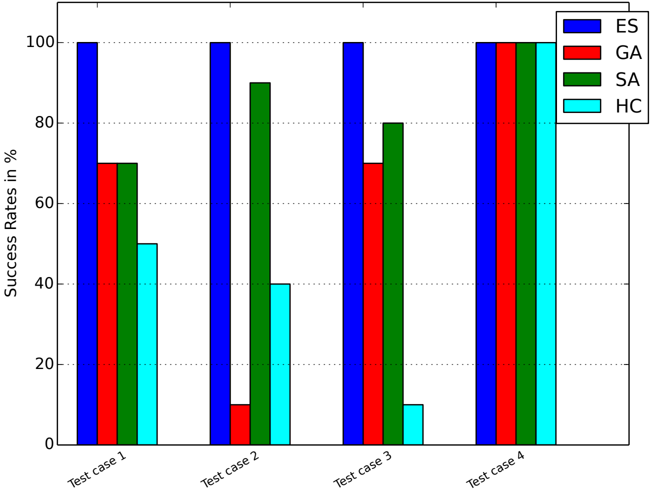
Results - Test Case 4



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 Evolutionary Strategy with at most 25% evaluations of search space