

# A Comparison of Antenna Placement Algorithms

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# Motivation

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- ▶ Antenna placement study is often ignored
- ▶ Placing new antennas requires a long, manual effort to complete an antenna placement study, if at all
- ▶ 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

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

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# Part 1: Introduction to the antenna placement problem

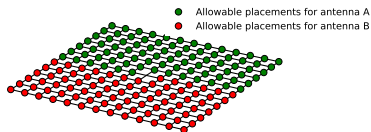
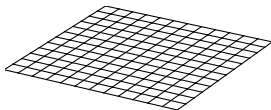
# Antenna Placement Problem

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Given, platform

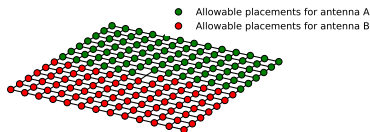
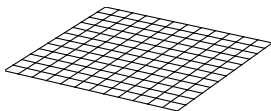
+

allowable placements of antennas

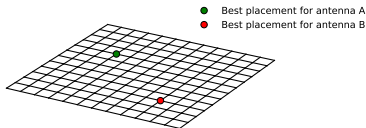


# Antenna Placement Problem

Given, platform + allowable placements of antennas



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



# Antenna Placement Problem

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Given:

- ▶ platform  $P$  with its surface gridded such that end points represent possible antenna placements
- ▶ set of  $n$  antennas  $A = A_1, A_2, \dots, A_n$  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  $\forall i, m_i > 1$

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

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

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

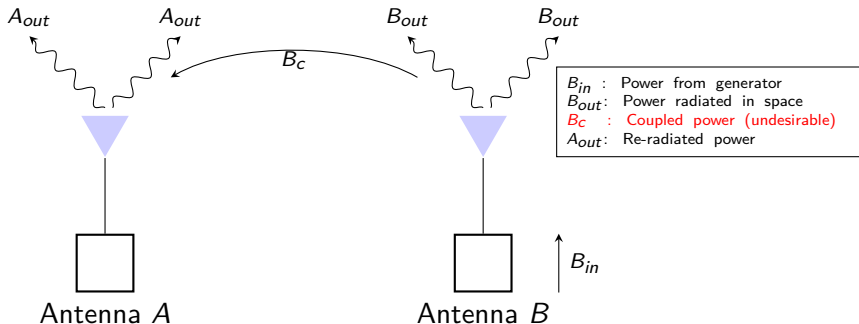
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Question: How is a good antenna placement quantified in the context of platform and other antennas?



# Mutual Coupling

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



# Minimize Mutual Coupling (MC)

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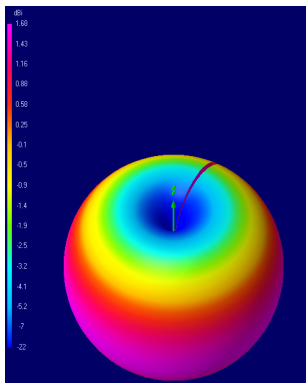
$$F_{MC} = \sum_{i=1}^{n-1} \sum_{j=i+1}^n CP(A_i, A_j), \quad (1)$$

where

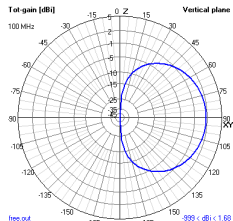
- ▶  $CP(\cdot, \cdot) \in \mathbb{R}$  is the coupling between two antennas, and computed using a simulator
- ▶ There will be  $\binom{n}{2}$  coupling terms

*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 / Radiation Pattern



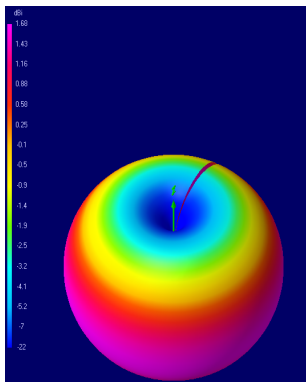
Free-space pattern without platform or other antennas



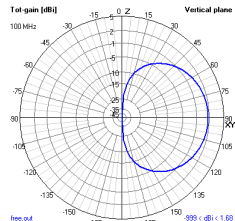
2D view of the **free-space gain pattern**

This is ideal pattern since  
there is no interference

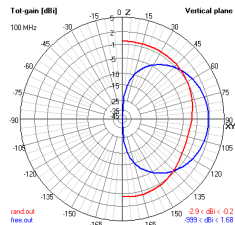
# Gain Pattern



Free-space pattern 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 Gain Pattern (GP)

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

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

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Find a placement configuration such that **fitness**  $F$  is minimal:

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

where  $\alpha$ ,  $\beta$  are adjustable weights for each of the objectives

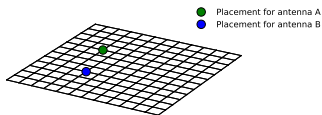
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## Part 2: Stochastic Algorithms

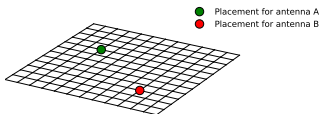
# Individual(s)

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

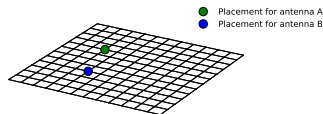
- An algorithm operates on an individual:



- Some algorithms operate on a population of individuals:



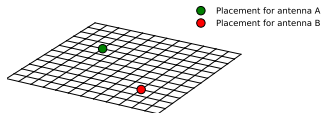
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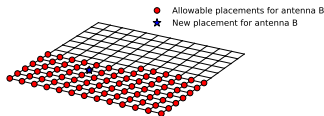


# Mutation Operator

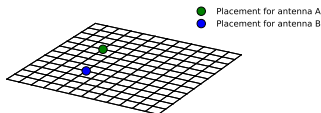
1. Given an individual, select an antenna uniformly at random, say antenna B:



2. Select uniformly at random from other allowable placements of antenna B:

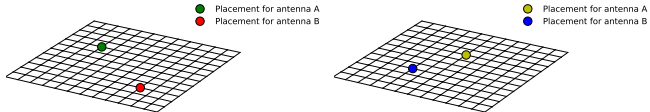


3. Change position for antenna B in individual, whereas antenna A's position remains same:

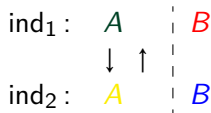


# Crossover Operator

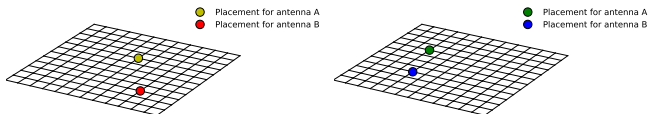
1. Select two individuals from population:



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



3. Two new offsprings created:



# Stochastic Algorithms

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We will consider algorithms which are based on randomization principle:

- ▶ Operate on a population of individuals:

1. **Genetic Algorithm**

2. **Evolutionary Strategy**

- ▶ Operate on a single individual:

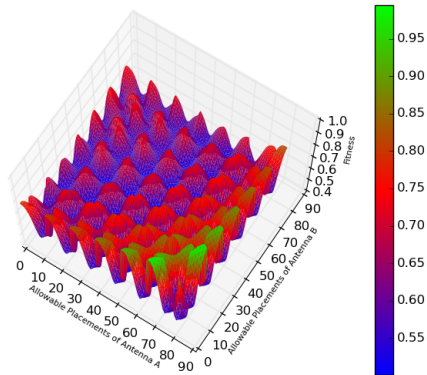
3. **Simulated Annealing**

4. **Hill Climbing**

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Question: Why use stochastic algorithms?

# Fitness Plot



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

# Genetic Algorithm

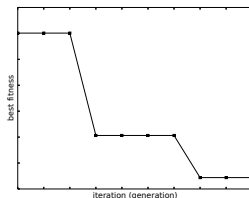
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```

1  Generate initial populaiton  $P_0$ ;
2  Compute fitness of each individual;
3   $i \leftarrow 1$  ;
4  while  $i < gen_{max}$  do
5       $P_i \leftarrow \emptyset$  ;
6      Elitism: Copy some percentage of fittest individuals
          to  $P_i$  ;
7      for  $(population\_size - elites) / 2$  do
8          Select a pair of individuals ;
9          Perform crossover with some probability;
10         Add new or original pair as it is to  $P_i$ ;
11     Apply mutation to a fraction of individuals in  $P_i$ ;
12     Update  $i \leftarrow i + 1$  ;

```

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**Example:** Progress of GA applied fitness minimization problem.  
 Each point shows the fitness of the best individual over iterations.

# Genetic Algorithm

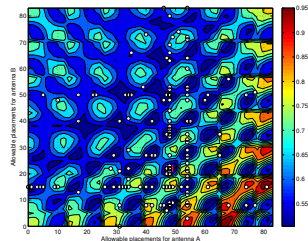
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```

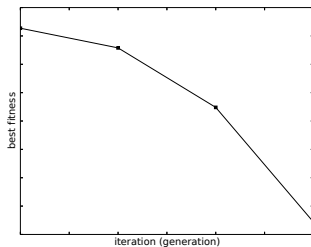
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Fitness of population shown with  $\circ$  for last iteration over the contour plot. Population has less diversity.

# Evolutionary Strategy

- 1 Generate initial population  $P_0$ ;
- 2 Compute fitness of each individual;
- 3  $i \leftarrow 1$  ;
- 4 **while**  $i < gen_{max}$  **do**
  - 5  $P_i \leftarrow \emptyset$  ;
  - 6 Apply *mutation* operator multiple times to each individual in  $P_{i-1}$  to create offsprings ;
  - 7 Compute fitness for all offsprings ;
  - 8 Copy a fraction of  $P_{i-1}$  individuals ordered by fitness into  $P_i$  ;
  - 9 Update  $i \leftarrow i + 1$

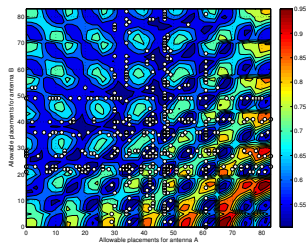


**Example:** Progress of ES applied to fitness minimization problem



# Evolutionary Strategy

- 1 Generate initial population  $P_0$ ;
- 2 Compute fitness of each individual;
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- 4 **while**  $i < gen_{max}$  **do**
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  - 8 Copy a fraction of  $P_{i-1}$  individuals ordered by fitness into  $P_i$  ;
  - 9 Update  $i \leftarrow i + 1$



Fitness of a population shown with  $\circ$  for last iteration. Greater diversity in comparison to GA<sup>1</sup>

[1] Spears, William M., and Kenneth A. DeJong. "Dining with GAs: operator lunch theorems."

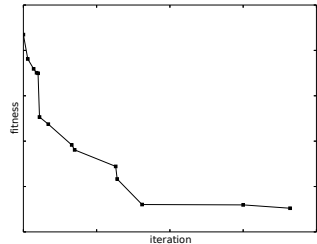
# Hill Climbing

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```
1 Generate a random individual  $ind_{curr}$  ;
2 Compute fitness of  $ind_{curr}$  ;
3  $i \leftarrow 1$  ;
4 while  $i < i_{max}$  do
5     Create another individual  $ind_{new}$  by mutation of
       $ind_{curr}$  ;
6     if  $fitness(ind_{new}) < fitness(ind_{curr})$  then
7          $ind_{curr} \leftarrow ind_{new}$ 
8      $i \leftarrow i + 1$ 
```

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**Example:** Progress of HC applied to fitness minimization problem

# Hill Climbing

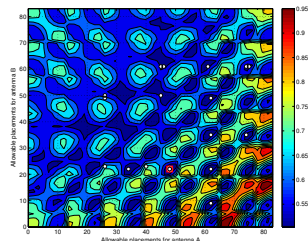
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```

1  Generate a random individual  $ind_{curr}$  ;
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3   $i \leftarrow 1$  ;
4  while  $i < i_{max}$  do
5      Create another individual  $ind_{new}$  by mutation of
         $ind_{curr}$  ;
6      if  $fitness(ind_{new}) < fitness(ind_{curr})$  then
7           $ind_{curr} \leftarrow ind_{new}$ 
8       $i \leftarrow i + 1$ 

```

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Fitness of  $ind_{curr}$  individuals over an entire run shown with  $\circ$ . Search is restricted due to greedy approach to accept only fitter (low fitness) individuals

# Simulated Annealing

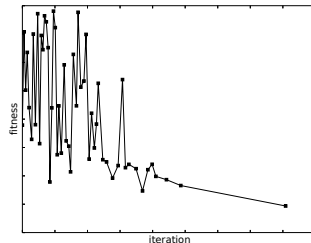
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```

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3   $i \leftarrow 1$  ;
4  while  $i < i_{max}$  do
5      Create another individual  $ind_{new}$  by mutation of
         $ind_{curr}$  ;
6      if  $fitness(ind_{new}) > fitness(ind_{curr})$  then
7          if  $rand() < e^{-\delta f / T}$  then
8               $ind_{curr} \leftarrow ind_{new}$ 
9          else
10              $ind_{curr} \leftarrow ind_{new}$ 
11          $T \leftarrow T \cdot f_{cooling}$  ;
12          $i \leftarrow i + 1$  ;

```

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**Example:** Progress of SA applied to fitness minimization problem.

As iterations increase, worse individuals with lower delta fitness ( $\delta f$ ) are accepted.

# Simulated Annealing

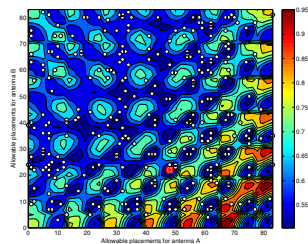
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```

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5      Create another individual  $ind_{new}$  by mutation of
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6      if  $fitness(ind_{new}) > fitness(ind_{curr})$  then
7          if  $rand() < e^{-\delta f / T}$  then
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9      else
10          $ind_{curr} \leftarrow ind_{new}$ 
11      $T \leftarrow T \cdot f_{cooling}$  ;
12      $i \leftarrow i + 1$  ;

```

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Fitness of  $ind_{curr}$  individuals over an entire run shown with  $\circ$ . Search is distributed across the terrain

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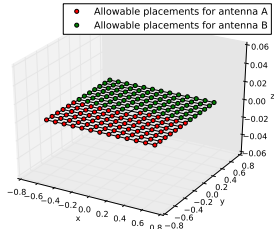
## Part 3: Evaluation of test cases

# Experimental Setup

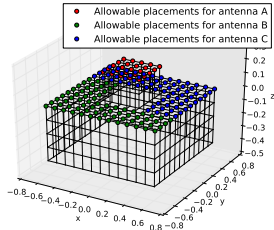
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1. We use a popular NEC2 simulator to get fitness parameters
2. Evaluated the entire search space using an exhaustive algorithm to find the optimal antenna locations which is not ordinarily possible
3. Termination criteria was set to be at most 50% evaluations of the search space
4. 1000 independent runs of each test case against each algorithm with  $\alpha = \beta = 1/2$

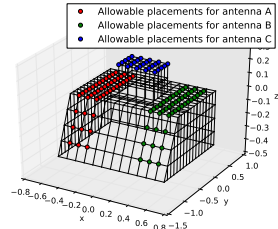
# Experiments Test Cases



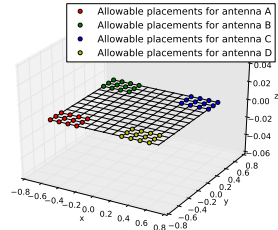
Test Case #1: search space size of 7056 ( $84 \times 84$ ) allowable placements



Test Case #3: search space size of 126025 ( $71 \times 71 \times 25$ ) allowable placements



Test Case #2: search space size of 50625 ( $45 \times 45 \times 25$ ) allowable placements



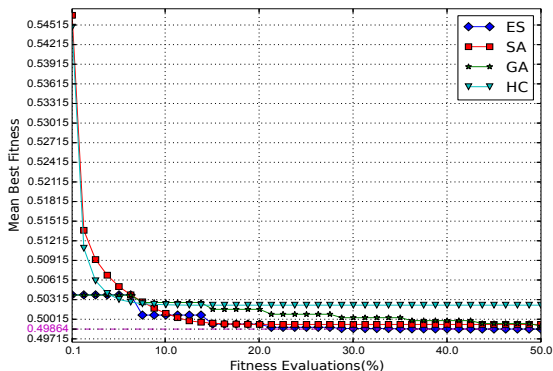
Test Case #4: search space size of 20736 ( $12 \times 12 \times 12 \times 12$ ) allowable placements



# Results - Test Case 1

Sample size = 1000

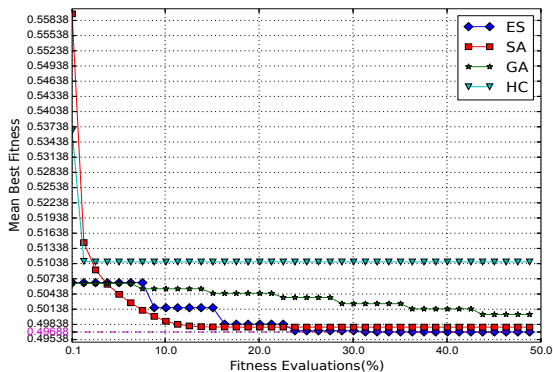
Algorithm	%Evaluations vs. Exhaustive		Best fitness	
	Mean	Std. Dev.	Mean	Std. Dev.
ES	11.88	10.48	0.49865	0.00009
SA	8.28	4.47	0.49935	0.00163
GA	17.21	15.69	0.49949	0.00182
HC	2.50	2.20	0.50230	0.00501



# Results - Test Case 2

Sample size = 1000

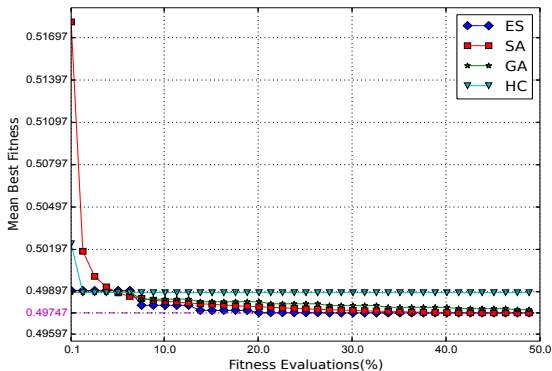
Algorithm	%Evaluations vs. Exhaustive		Best fitness	
	Mean	Std. Dev.	Mean	Std. Dev.
ES	16.08	7.72	0.49688	0.00000
SA	7.96	3.33	0.49784	0.00233
GA	25.98	15.51	0.50034	0.00341
HC	0.40	0.31	0.51071	0.01305



# Results - Test Case 3

Sample size = 1000

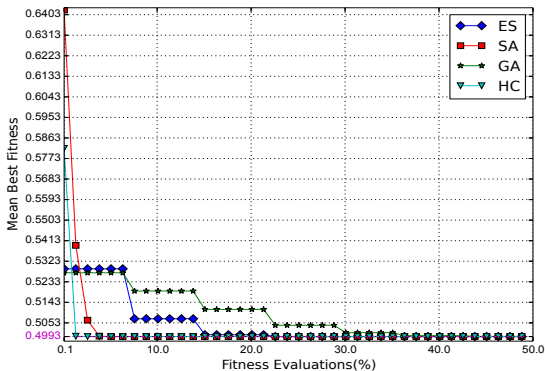
Algorithm	%Evaluations vs. Exhaustive		Best fitness	
	Mean	Std. Dev.	Mean	Std. Dev.
ES	11.04	6.72	0.49747	0.00000
SA	19.61	11.16	0.49747	0.00003
GA	23.05	16.25	0.49770	0.00038
HC	0.21	0.17	0.49890	0.00182



# Results - Test Case 4

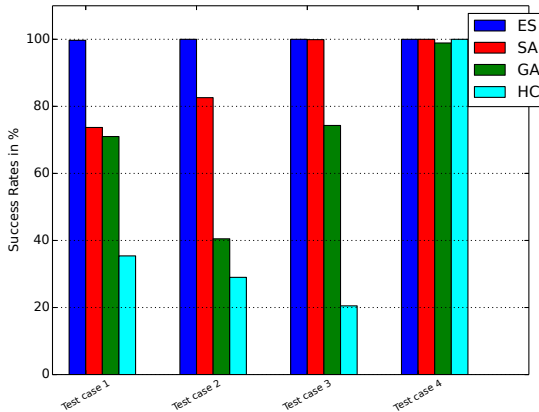
Sample size = 1000

Algorithm	%Evaluations vs. Exhaustive		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* reports percentage of runs in which the algorithm is able to find the optimum with 50% evaluations as termination criteria



# Conclusions

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- ▶ First study to investigate optimizing multiple antenna placement on a single platform using multiple stochastic algorithms
- ▶ Formulated an automated procedure for the antenna placement problem which aims to improve the working of multiple antennas on a platform

# Conclusions

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- ▶ Results show Simulated Annealing was less successful but faster to converge compared to Evolutionary Strategy
- ▶ Evolutionary Strategy was slower to converge but success rate  $\approx 100\%$  with a mean of at most 16% evaluations of search space
- ▶ Algorithms reduce search time to at most 1/4 in comparison to an exhaustive algorithm
- ▶ Future work - Consider other techniques like *Differential Evolution*, *Particle Swarm Optimization* and *ALPS*