A Comparison of Antenna Placement Algorithms

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Exhaustive Algorithm

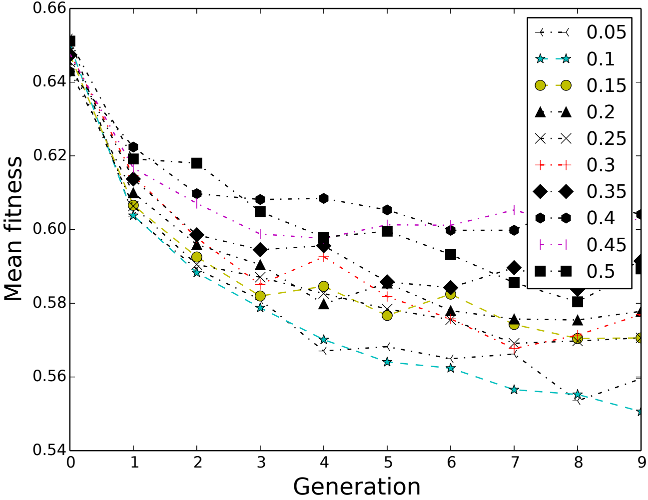
Pseudo code:

```
def exhaustive_search::initialize:
    makeConfigurations(new antenna_configuration,0)

def make_configurations(configuration, count):
    if configuration.length == selected_antennas.length:
        population.push_back(configuration)
        return

    for i in range(0,selected_antennas[count].points.size()):
        if not selected_antennas[count].points.at(i) in configuration:
            configuration.push_back(selected_antennas[count].points.at(i))
            make_configurations(configuration,count+1)
            configuration.pop_back();
```

Parameter Selection - GA



Parameters - GA and ES

Genetic Algorithm

Test Case	Population	Generations	Mutation Prob.	Crossover Prob.	Elitism	Tournament Size
tc1	500	10	0.1	0.6	50	50
tc2	3600	10	0.1	0.6	360	360
tc3	8500	10	0.1	0.6	850	850
tc4	1500	10	0.1	0.6	150	150

Evolutionary Strategy

Test Case	μ	λ	Generations
tc1	70	490	10
tc2	550	3850	10
tc3	1200	8400	10
tc4	220	1540	10

1/7 ratio between and μ and λ[1]. Higher ratios led to higher evaluations per run

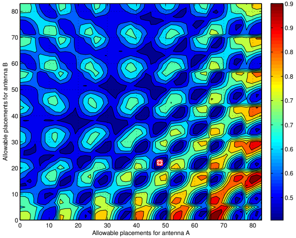
[1] Eiben, A. E., & Smith, J. E. (2003). Introduction to evolutionary computing.

Parameters - SA

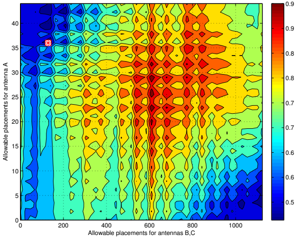
1. Initial Temperature $\in [0.23, 0.27]$
2. Cooling Schedule: Geometric cooling $T_{i+1} = \tau T_i$ $(\alpha < 1)$ where $\tau \in [0.99, 1)$ such that $T_i <= 10^{-4}$ at 50% iterations

Parameter Selection - SA (todo)

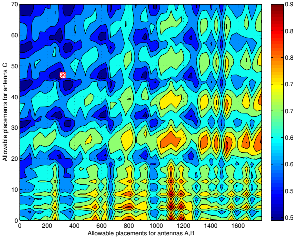
Test Cases - Contour Plots



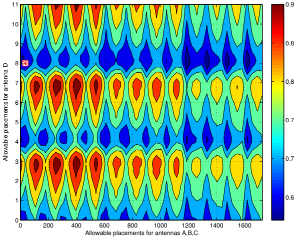
Test Case #1



Test Case #2

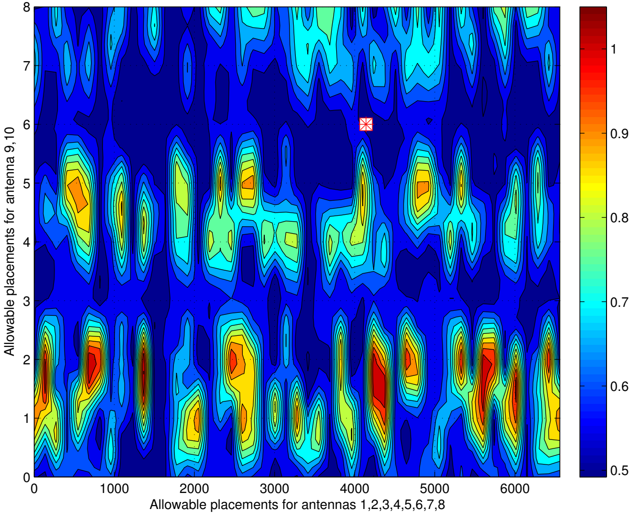


Test Case #3



Test Case #4

Search space for larger problem

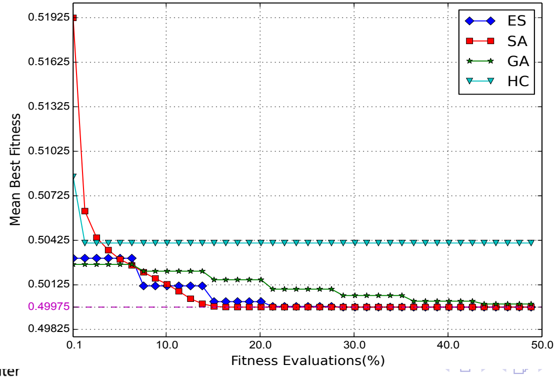


Search space for problem with 10 antennas resembles contours as seen in experiments

Results - Test Case 5

Sample size = 1000

Algorithm	%Evaluations vs. Exhaustive		Best fitness	
	Mean	Std. Dev.	Mean	Std. Dev.
ES	15.11	7.10	0.49975	0.00000
SA	11.58	3.50	0.49975	0.00000
GA	34.08	15.57	0.49977	0.00012
HC	0.13	0.08	0.50407	0.00761



Equivalence of fitness to efficiency

For a particular test case, fitness change of 0.001 is equivalent to either the corresponding value under expected gain ($\mathbb{E}_{\Delta g}$) column, or difference in coupling (Δ_c).

ID	$\mathbb{E}_{\Delta g}$ (dB)	Δ_c (dB)
tc1	9.34	0.055
tc2	9.28	0.13
tc3	9.28	0.15
tc4	9.33	0.057

Differential Evolution

Step 1: Randomly initialize a population

Step 2: Mutation: For each target $x_i^g, i \in \{1, 2, 3 \ldots, NP\}$, a mutant vector is formed for the subsequent generation using:

$$v_i^g = x_{r_1}^g + F \cdot (x_{r_2}^g - x_{r_3}^g),$$

where $F \in [0, 2]$ and r_1, r_2, r_3 are mutually different and also $\neq i$

Step 3: Recombination: Formulate a trial vector as:

$$u_i^{g+1} = \begin{cases} v_{ij}^g, & \text{if rand}() \leq CR \text{ or } j = rnbr(i) \\ x_{ij}^g, & \text{if rand}() > CR \text{ and } j \neq rnbr(i) \end{cases}$$

Step 4: Selection: Compare trial vector u_i^{g+1} and target vector x_i^g, and select the vector which yields a smaller cost function.

Step 5: Termination check

Particle Swarm Optimization

Step 1: Randomly initialize velocity and position of all particles

Step 2: At each iteration, updated velocity as follows:

$$v_i = wv_i + c_1 R_1 (p_{i,best} - p_i) + c_2 R_2 (g_{best} - p_i),$$

where $p_{i,best}, g_{best}$ are positions with best objective value found so far by particle and entire population respectively, c_1, c_2 are weighting factors, $R_1, R_2 \sim \mathbb{U}(0,1)$, w is parameter cooling

Step 3: Position updating

$$p_i = p_i + v_i$$

Step 4: Memory updating: Update $p_{i,best}$ and g_{best}

Step 5: Termination check