

Antenna array optimization for radio interferometry: towards a machine learning-guided approach

Manal BENSAHLI, M2 intern

Supervised by Ezequiel Centofanti & Samuel Farrens

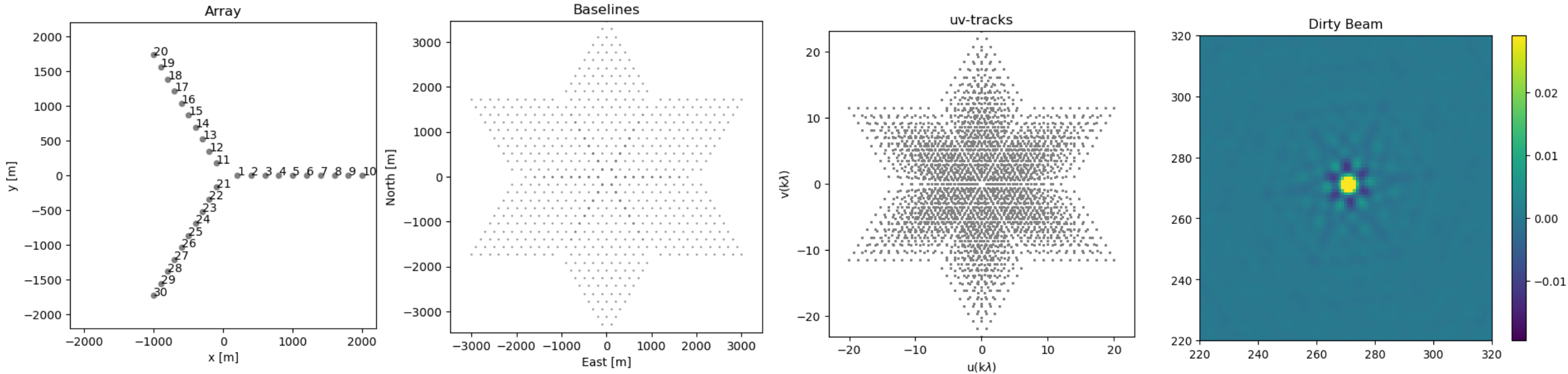
CosmoStat, CEA DAp

Joint ARGOS-TITAN-TOSCA workshop 7th/8th July 2025

Context and scientific motivation

- Radio astronomy : high angular resolution for detailed observations.
- ARGOS project : design of a next generation interferometric array.
- Performance depends on :
 - Antenna placement.
 - UV plane coverage.
 - Beam shape and quality.
- Key challenge : optimize antenna configuraion for specific science cases.

Radio interferometry



- Each antenna pair defines a baseline, which corresponds to a sampled spatial frequency in the uv-plane.
- The uv-plane coverage directly impacts the synthesized beam (PSF) and image quality.
- In Fourier space :

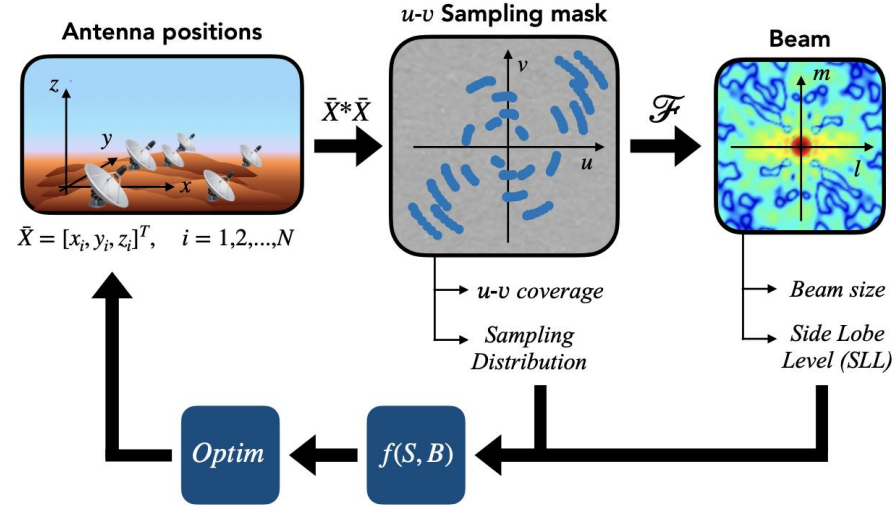
$$\hat{O}(u, v) = \hat{S}(u, v) \cdot M(u, v)$$

- In real space :

$$o(x, y) = s(x, y) * b(x, y)$$

- Goal: Improve uv-coverage and beam quality by optimizing the antenna layout.

Argosim simulation package



- Argosim : tool used to simulate the radio interferometry imaging process, developed at CosmoStat.

Input : antenna positions.

Output : uv coverage, beam, sky reconstruction and metric values.

Used for evaluation and optimization.

- My contribution : integrated new beam metrics, submitted as Pull Request to the main Argosim repository.

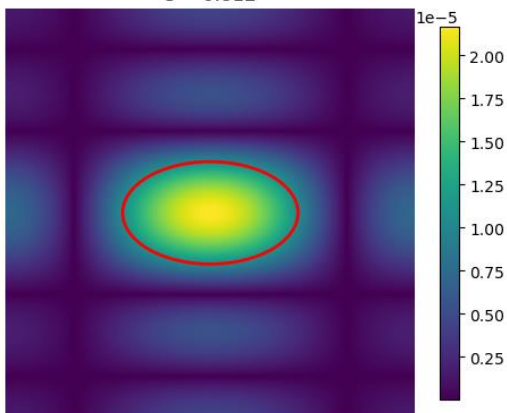
Evaluation metrics

- UV metrics :
 - Number of filled uv-cells.
 - Uniformity.
 - Redundancy (duplicate uv sampels).
- Beam metrics :
 - FWHM (Full Width at Half Maximum).
 - Eccentricity.
 - SLL (Side Lobe Level) in dB.
- Image metrics :
 - MSE = Mean Squared Error between sky model and output image.
 - RMSE = Relative Mean Squared Error (normalized version).
 - SSIM = Structural Similarity Index.

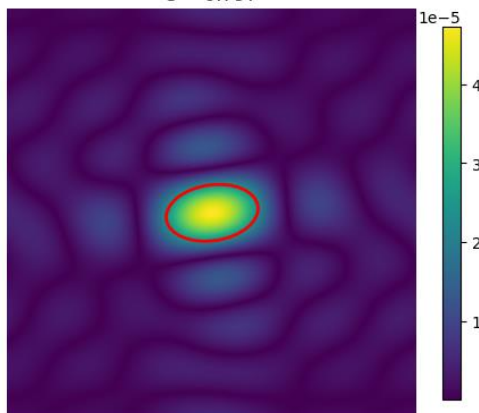
First phase : testing the metrics

- Evaluation of different configurations : Y-arrays, circular uniform array, random configurations.

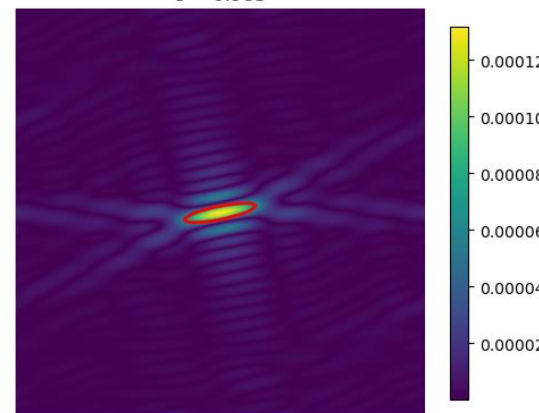
Beam + Ellipse
4x4 (50x100)
e = 0.812



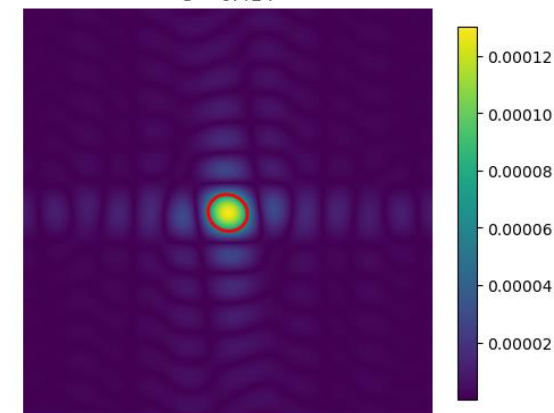
Beam + Ellipse
8x8 (100x200)
e = 0.797



Beam + Ellipse
12x13 (50x900)
e = 0.983



Beam + Ellipse
15x15 (300x300)
e = 0.414



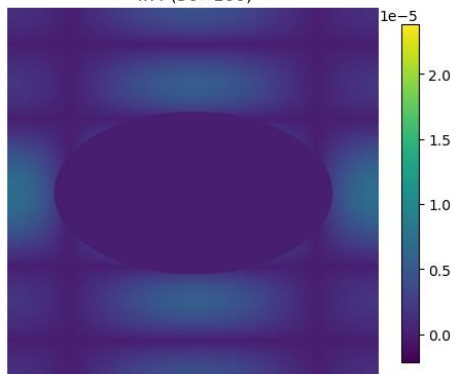
FWHM = (296.60, 173.24)px

FWHM = (156.37, 94.35)px

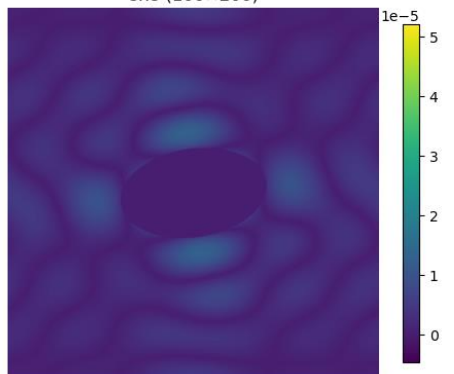
FWHM = (121.27, 22.32)px

FWHM = (67.21, 61.17) px

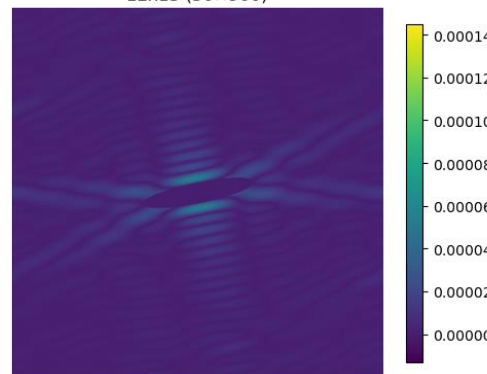
Masked Beam
SLL = -4.7712 dB
4x4 (50x100)



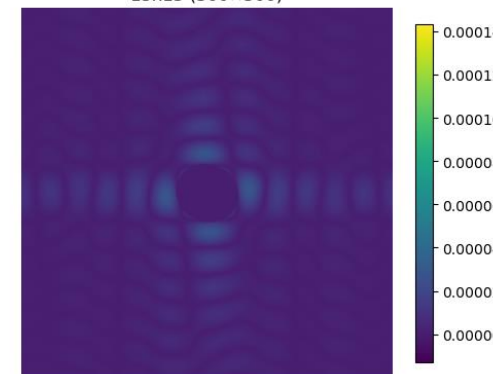
Masked Beam
SLL = -5.6209 dB
8x8 (100x200)



Masked Beam
SLL = -3.7864 dB
12x13 (50x900)



Masked Beam
SLL = -6.4907 dB
15x15 (300x300)

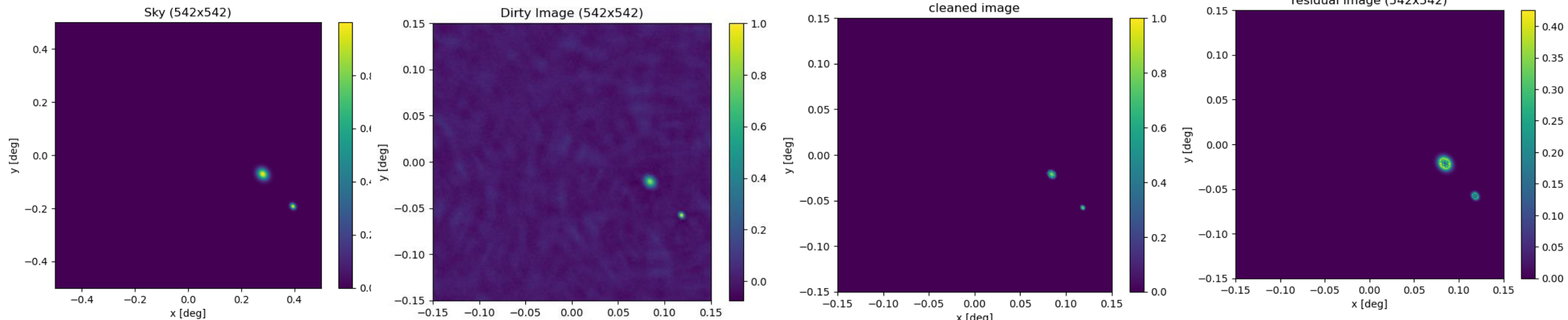


→ Gaussian fit applied to the main lobe of the dirty beam.

→ Eccentricity and FWHM computed from the fit.

Image reconstruction metrics

Y-array

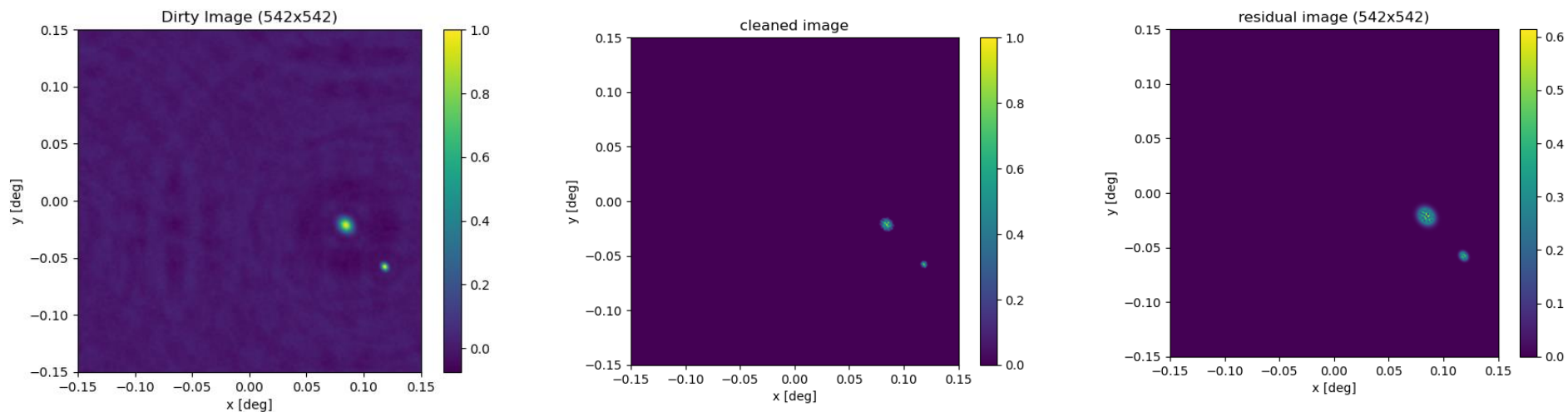
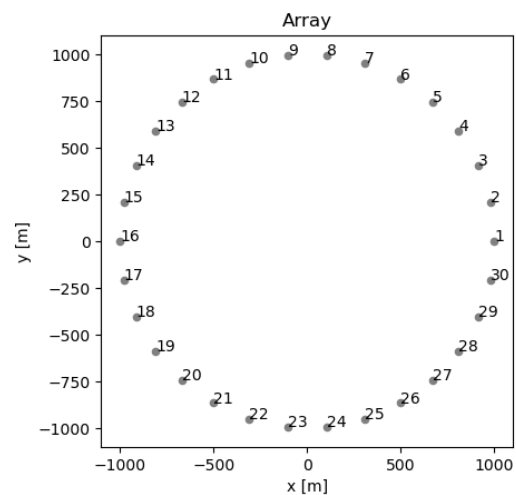


MSE: 0.000227487281945

RMSE: 0.796047374242141

SSIM obs : 0.5143

SSIM cleaned : 0.9933



MSE: 0.000229945891837

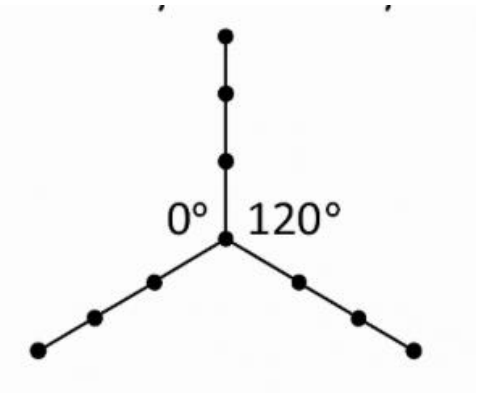
RMSE: 0.975834540958991

SSIM obs : 0.6139

SSIM cleaned : 0.9934

PSO optimization on symmetric Y-array

- Based on : Jin & Rahmat-Samii, IEEE TAP, 2008
- Configuration: 3 arms, symmetric, fixed angles (0°, 120°, 240°).
- Fitness function: maximize the number of filled u-v grid cells.



- PSO : population based algorithm inspired by swarms

Each particle = one Y- array configuration

At each iteration, particles update using :

→ Their personal best (p_best)

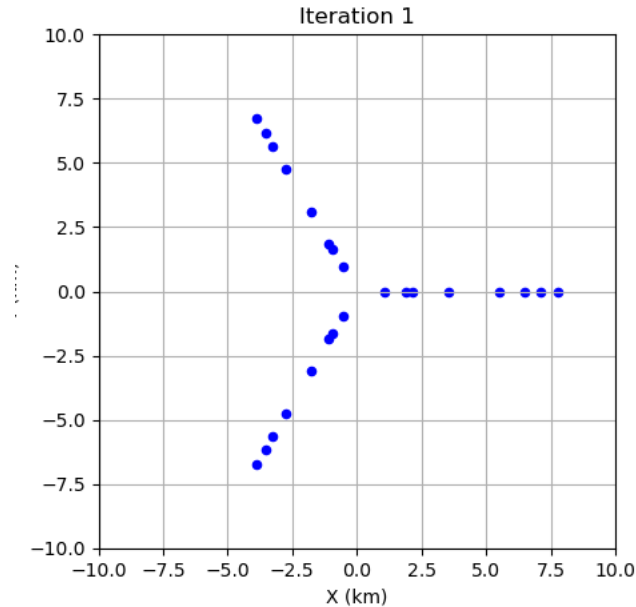
→ The global best (g_best)

→ Velocity and position updates:

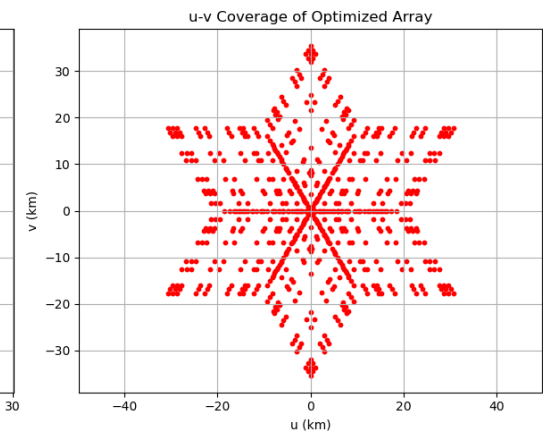
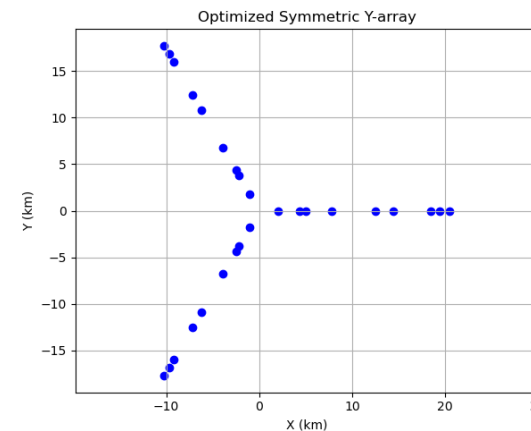
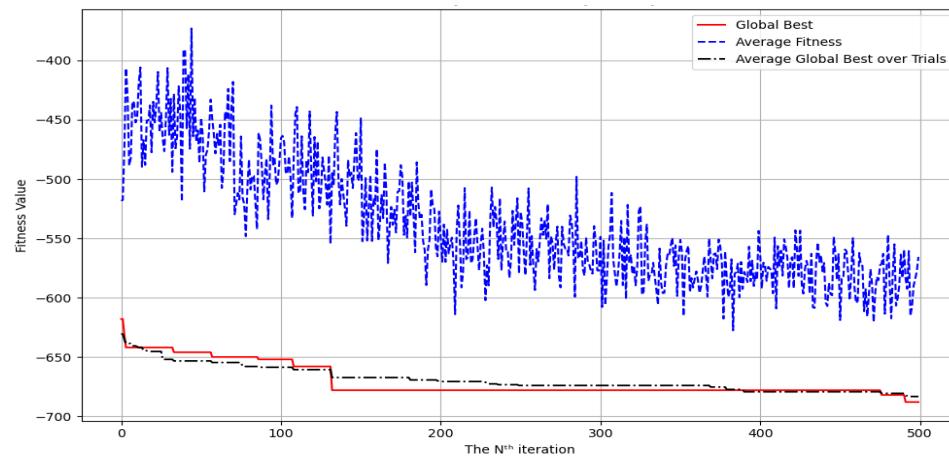
$$v_i(t+1) = w * v_i(t) + c1 * rand * (p_best - x_i) + c2 * rand * (g_best - x_i)$$

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

PSO optimization on symmetric Y-array

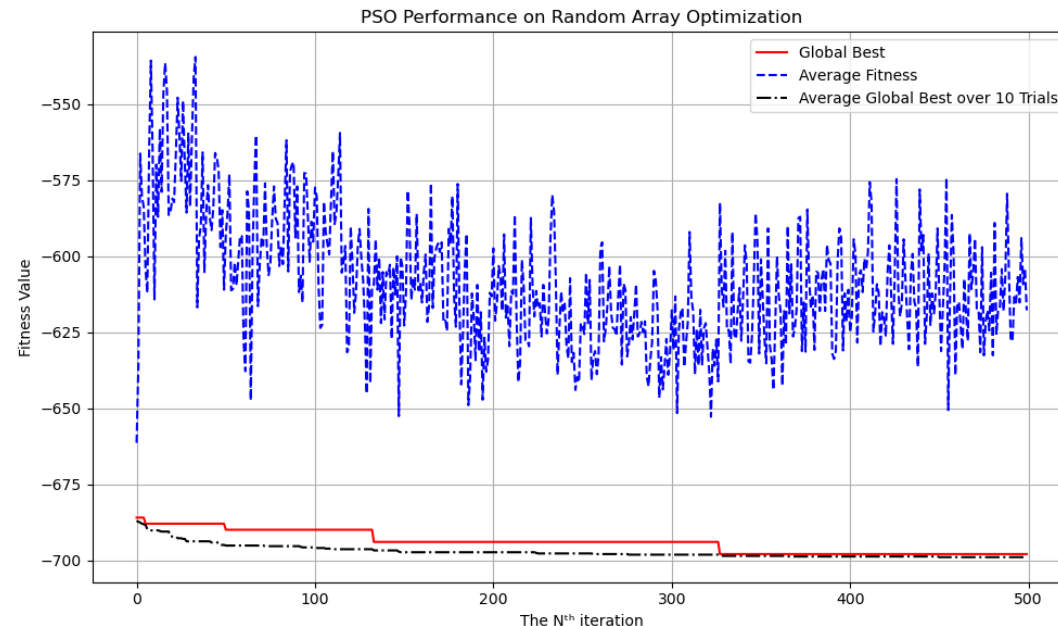
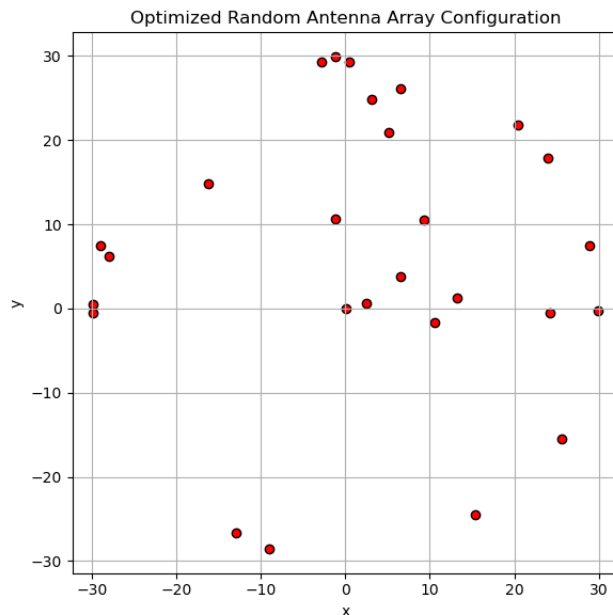


- Results:
 - Good convergence in structured space
 - Visual tracking of g_best evolution
- Limitation:
 - Fixed structure restricts optimization space.



Moving to random configuration

- Each configuration is a 2D vector $X = (E1, N1, \dots, E27, N27)$
- Objective: Optimize positions to improve uv/beam metrics
- Two directions explored:
 1. PSO on 2D coordinates (slower convergence)
 2. Random Forest Regressor to predict metrics from layouts

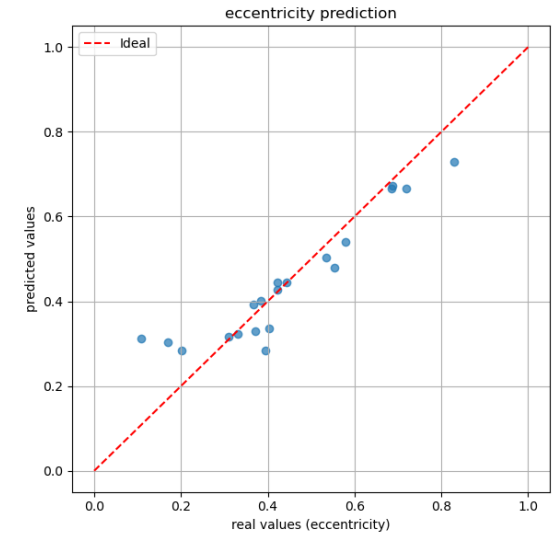
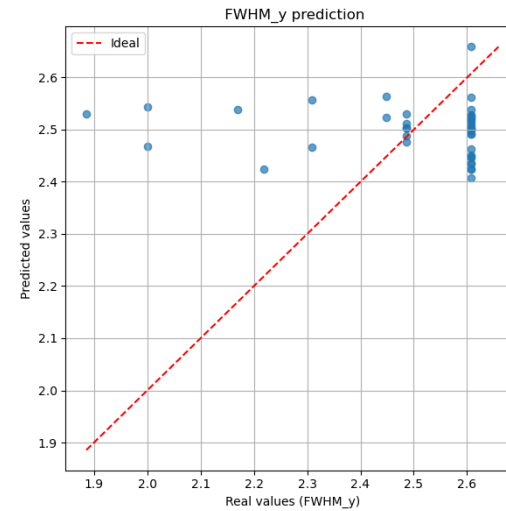
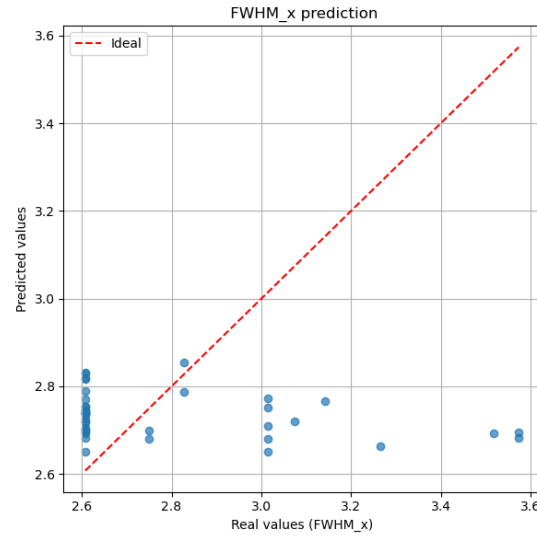
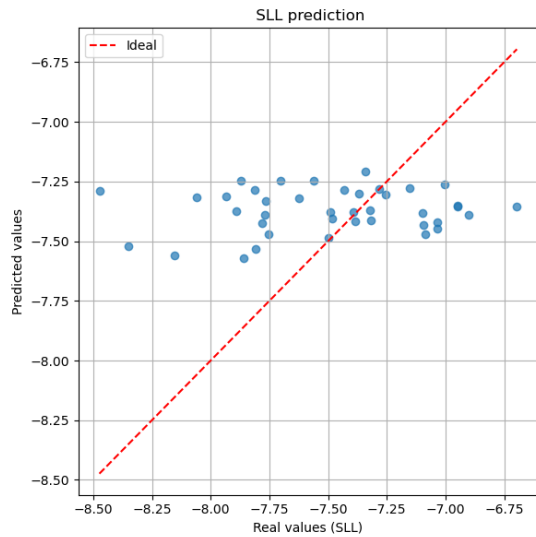


Random forest regressor

- Task: Predict beam metrics (eccentricity, SLL, FWHM) from antenna configurations.
- Dataset: Generated using Argosim (X = positions, y = metric).
- Benefits:
 - Very fast prediction after training
 - Useful for pre-evaluation and filtering

Random forest regressor

- Number of antennas : 30 (freely placed within a 2km * 2km area)
- Training data : 100 configurations



Metric

Mean Absolute Error

R² Score

Interpretation

SLL

0.3418

-0.0773

Poor prediction (weak correlation)

FWHM_x

0.2243

-0.1752

Low accuracy

FWHM_y

0.1478

-0.1269

Similar behavior as FWHM_x

Eccentricity

0.0529

0.8408

Very good prediction

Neural network for objective approximation

- Problem: $f(X)$ from Argosim is non-differentiable.
- Solution: Approximate $f(X)$ with a neural network.
- Once trained, compute gradients: $\partial f / \partial X$.
- Enables gradient-based optimization:
 - $X_{\text{new}} = X - \gamma \nabla f(X)$
- Current status:
 - Dataset preparation in progress

Summary and next steps

- **What has been done:**

- Implemented uv and beam metric computation

- Evaluated structured and random arrays

- Applied PSO on Y-array configurations

- Started ML modeling (Random Forest)

- **Next steps:**

- Train a neural network to learn $f(X)$

- Perform gradient descent using NN

- prediction \rightarrow optimization

Thank you