Reconfigurable Intelligent Surfaces

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Course: Senior Thesis

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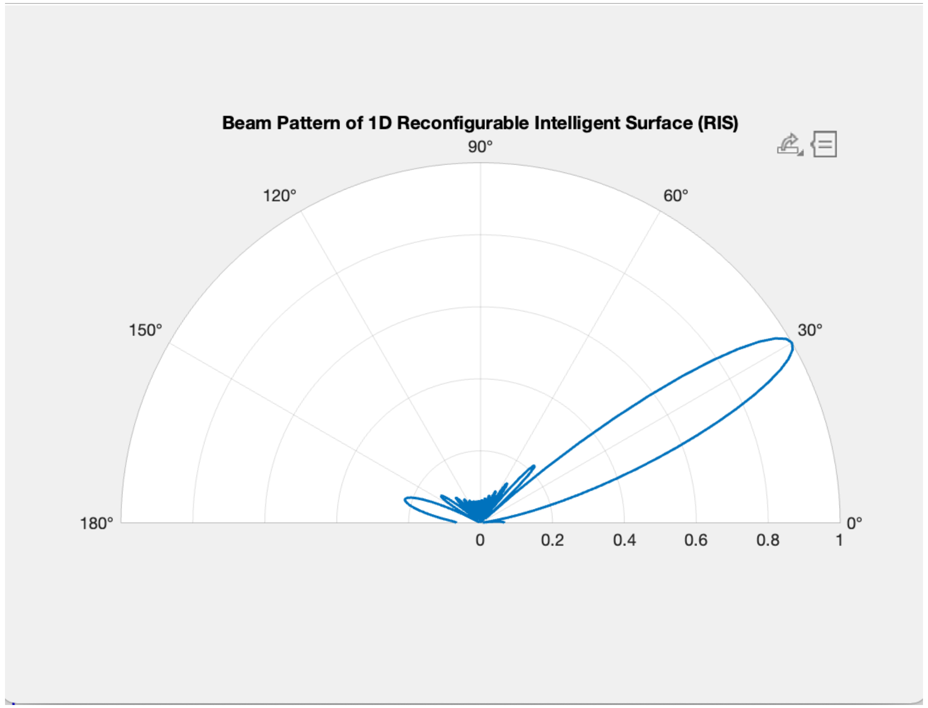
Introduction

- 1D antenna array with N (number of antennas)
- Multiple angle of incidences(**θi)** and only one angle of reflection(**θr**)
- Phase difference (αi) = **π ∗ cos θi**
- Phase difference at the reflection side (αr) = **π ∗ cos θr**

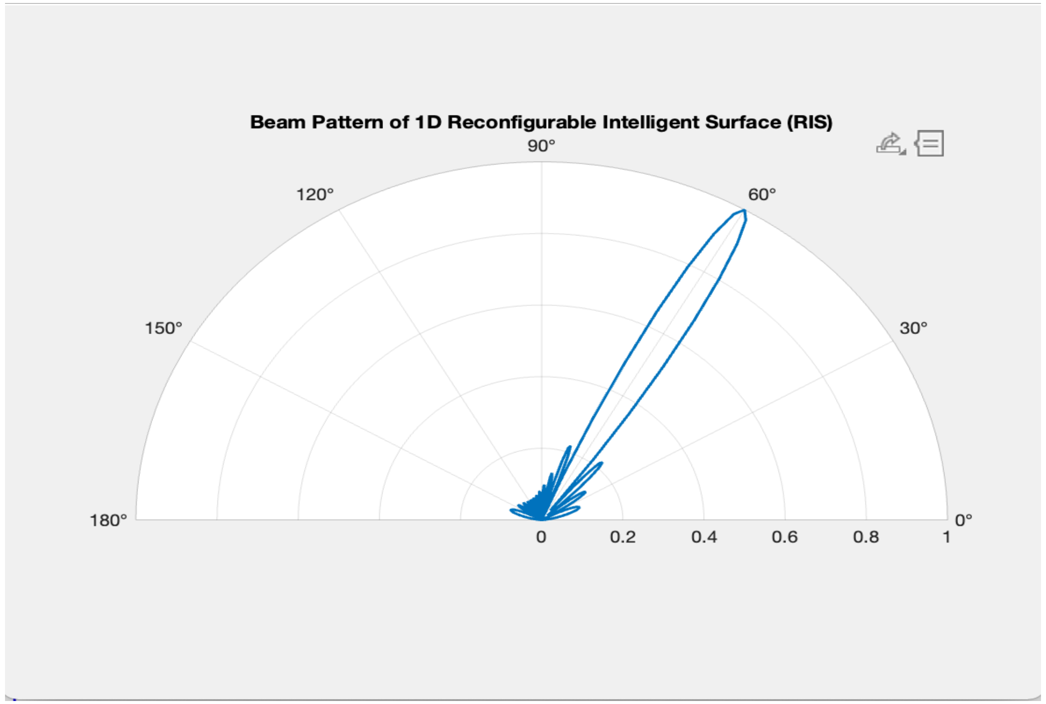
- Electric field strength at each antenna: $E_r = e^{j \cdot (\alpha_r + \alpha_i)}$

Beam patterns at one angle of reflection

- Goal: Creating a beam pattern at multiple angles of incidence with 1 main lobe at the angle of reflection chosen.
- N = 16



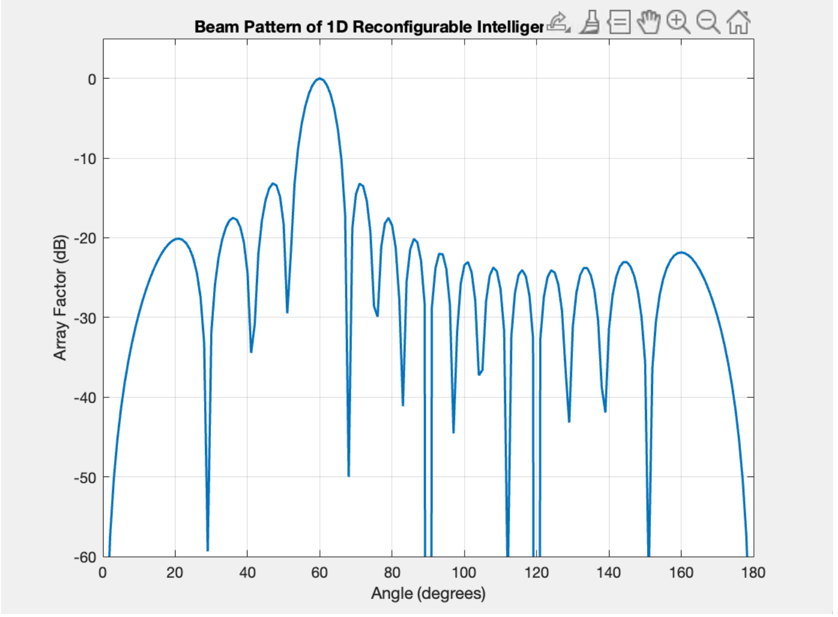
ϴr = 30°



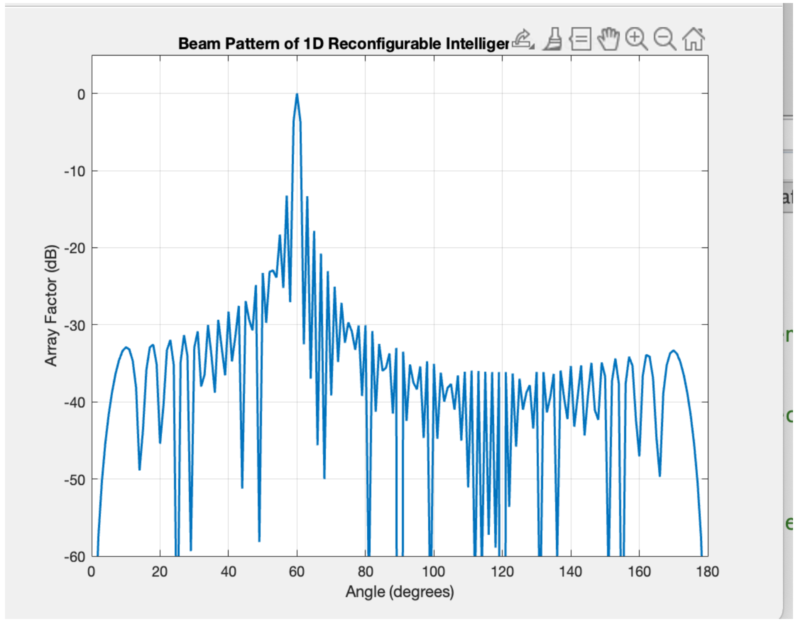
ϴr = 60◦

Effect of increasing N on the beam pattern

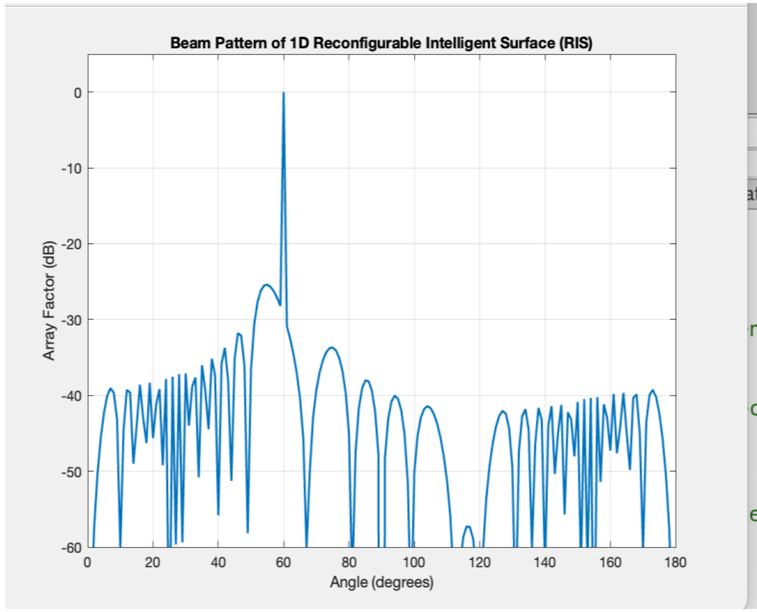
- **Θr = 60°**
- Increasing the number of antennas narrows down the main lobe and side lobes
- Side lobes are reduced hence noises and interferences minimized



N = 16



N = 64

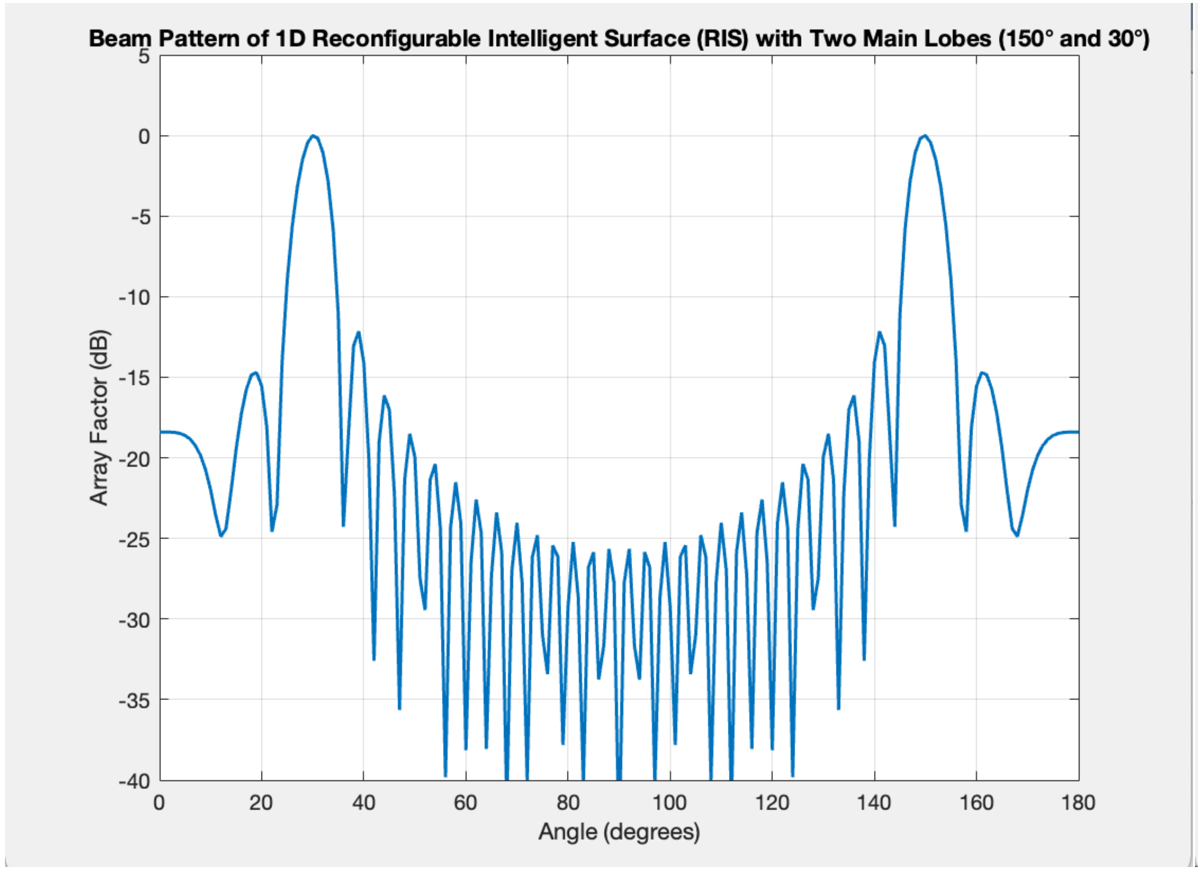


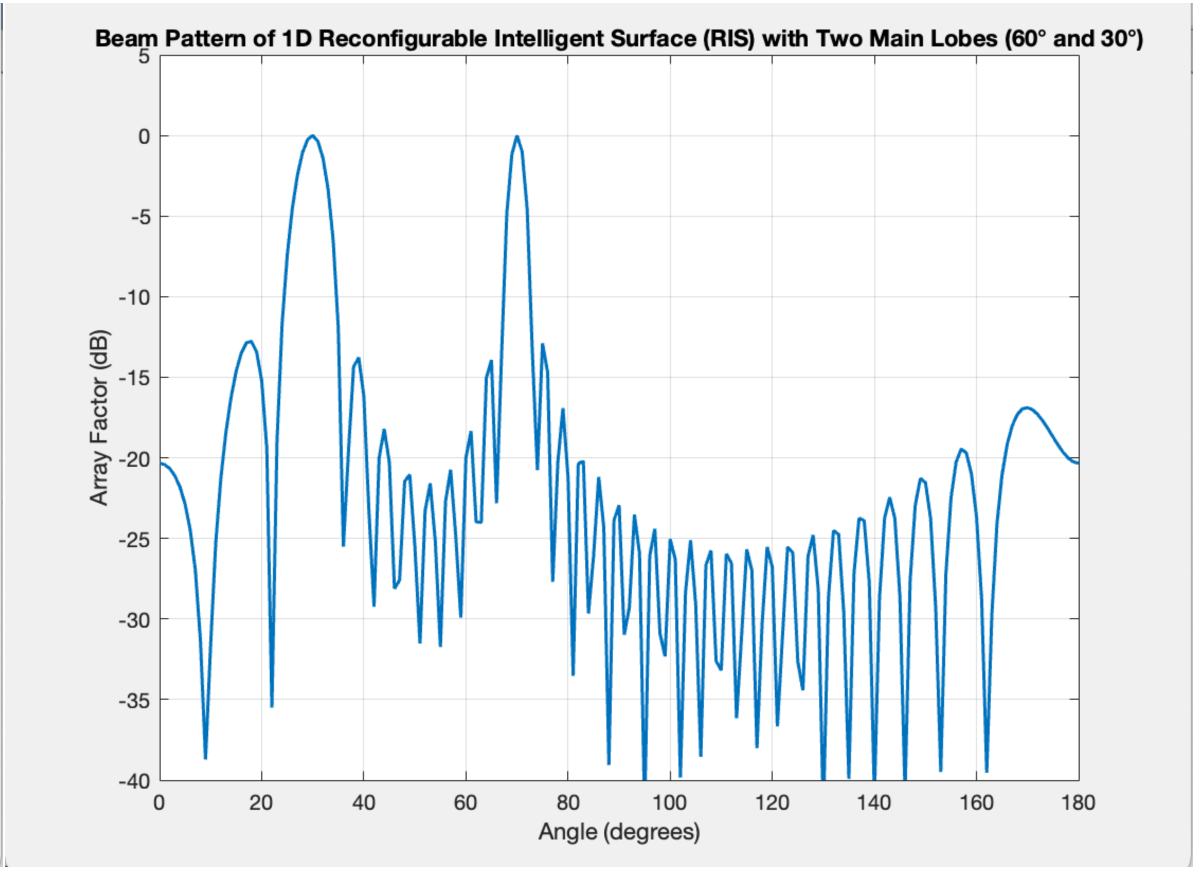
N = 128

Next steps

- Expanding the idea to a 2D antenna array and run the simulations
- Simulate the RIS at 2 angles of reflection or more to see if I can get 2 main lobes. This would be important if there are 2 users

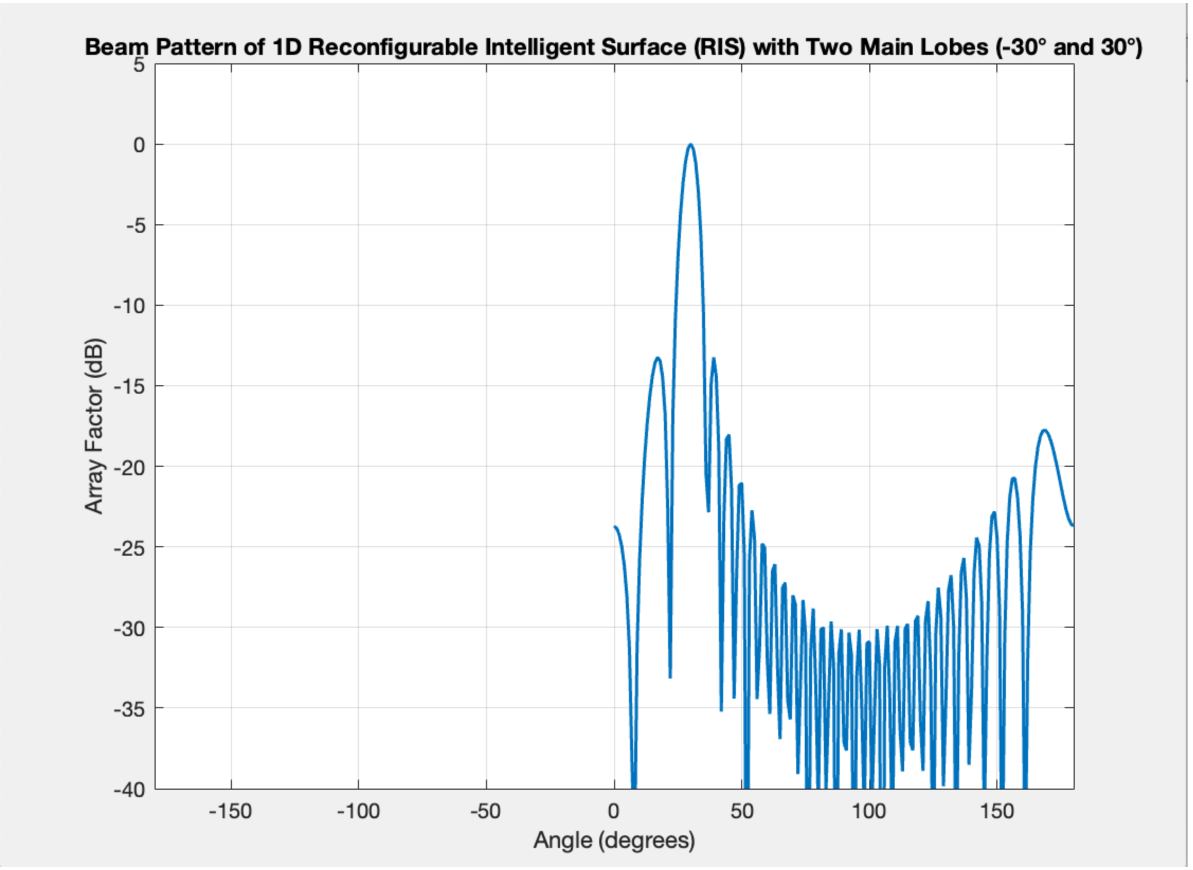
Multiple users



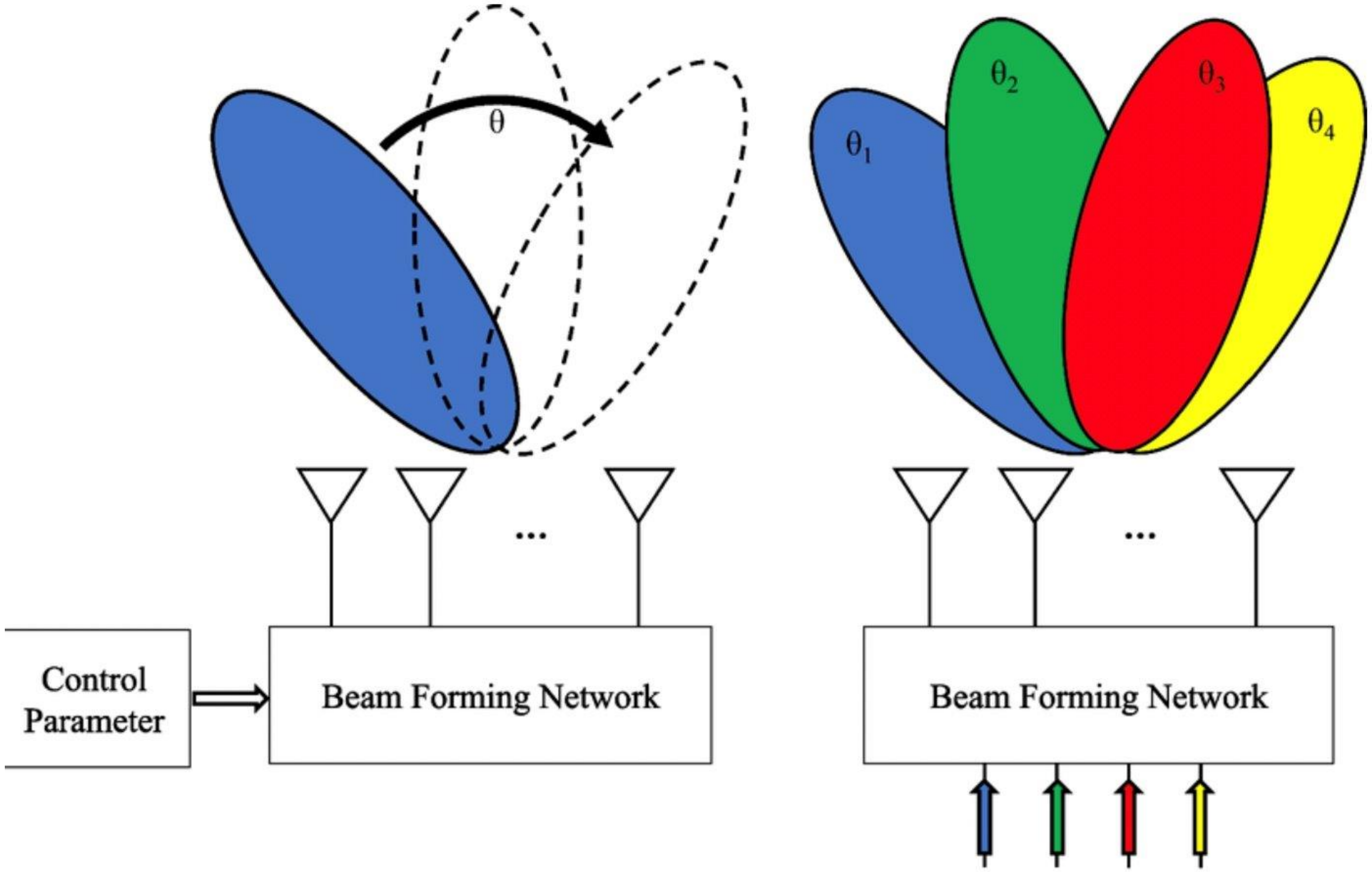


Cont'

Not working for negative angles!



Beam steering

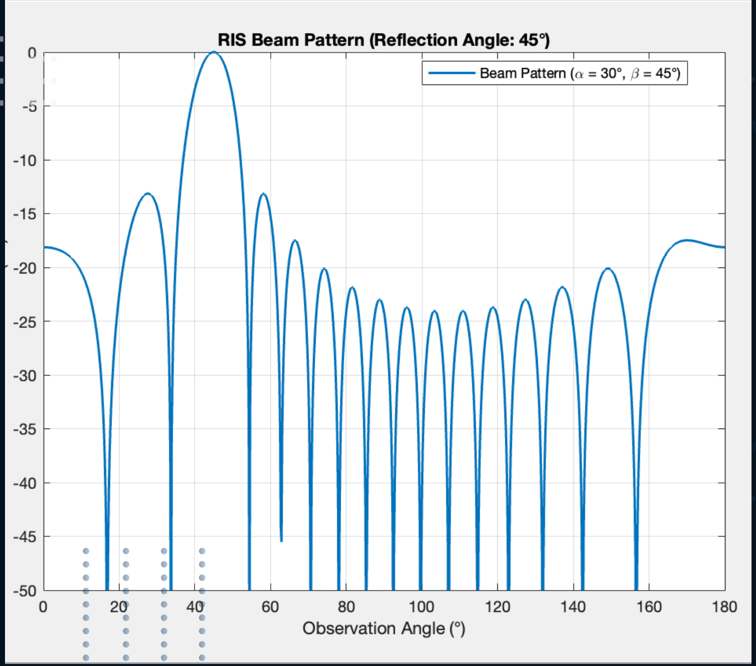


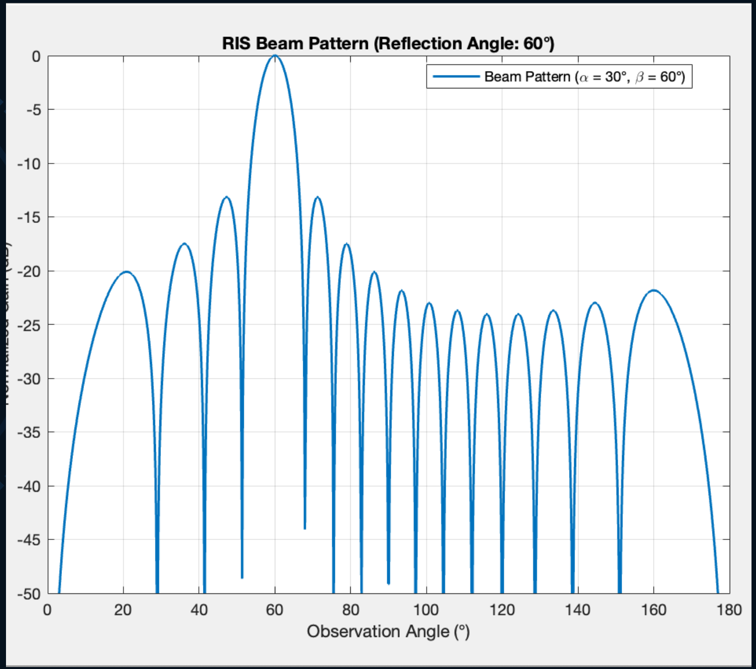
Reflection BeamPattern for RIS

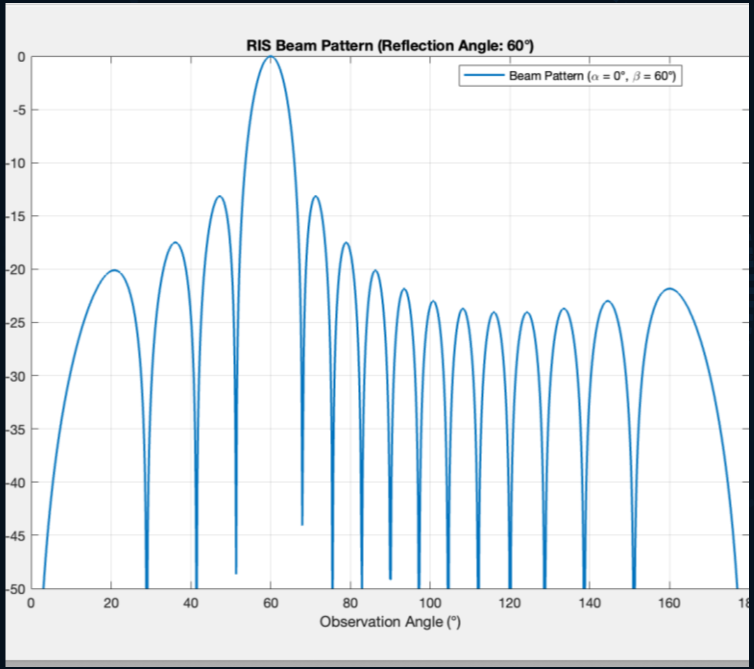
- One incident angle($\boldsymbol{\alpha}$) and one angle of reflection ($\boldsymbol{\beta}$), k * d = $\boldsymbol{\pi}$
- Optima phase shift (γ) = $\boldsymbol{\pi \cos(\alpha) - \cos(\beta)}$
- H1 (TX – RIS) = $\exp(j\pi \cos \alpha)$, h2(RIS – RX) = $\exp(j\pi \cos \beta)$
- Observation steering vector (h_obs(θ) = $\exp(j\pi \cos \theta)$
- Reflected beam pattern (P(θ)) = **|h1' .diag(exp(j.γ)).h_obs(θ)|^2**
- **P_norm(**θ) = $10 \log_{10}[P(\theta)/\max(P(\theta))]$

Beam Pattern Examples

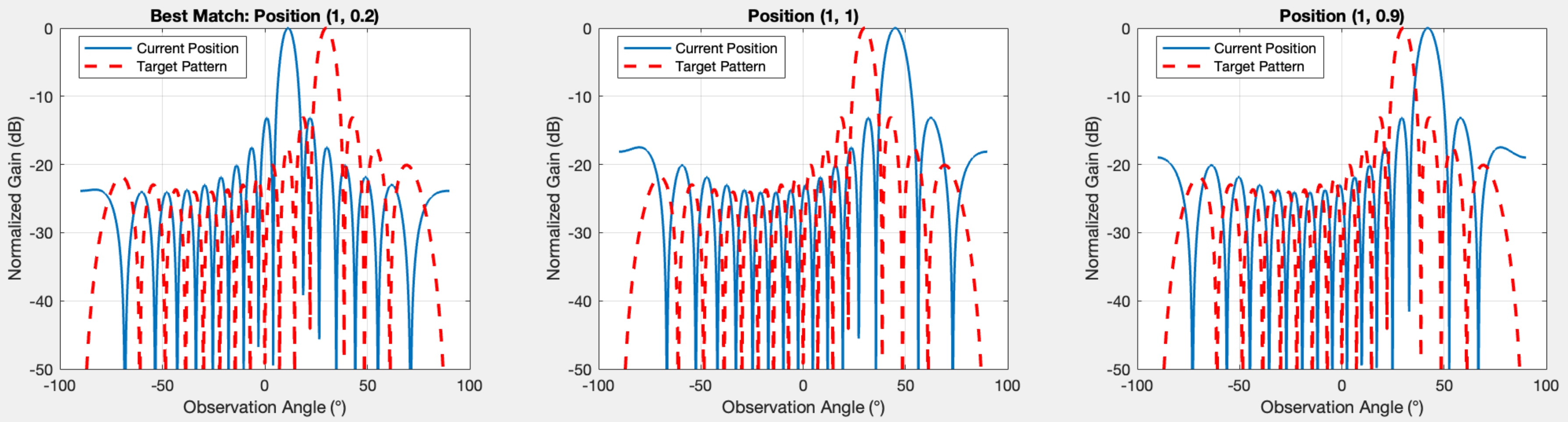
- N = 16, k = 2π , d = ½, λ = 1

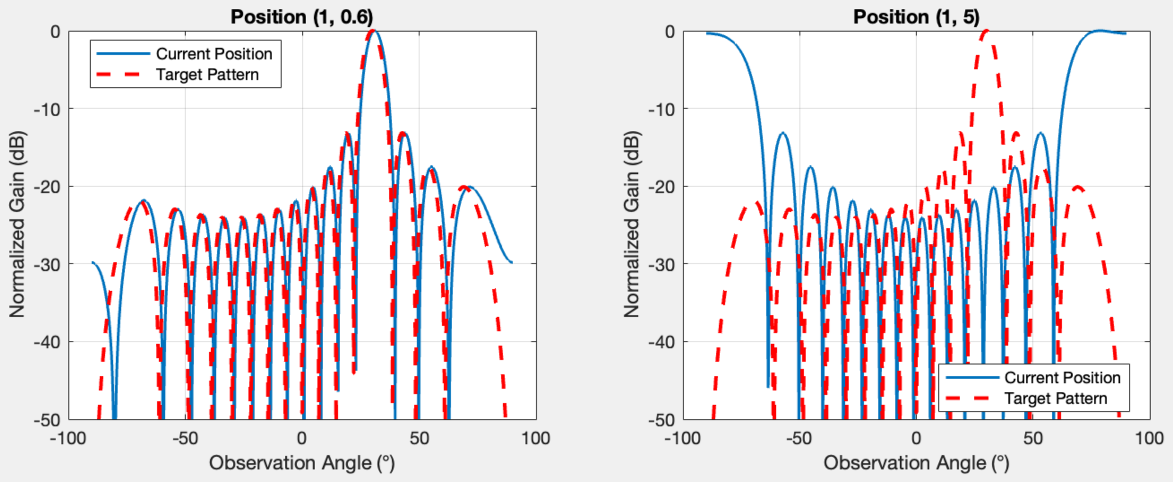






Beamsteering, pre-determined points

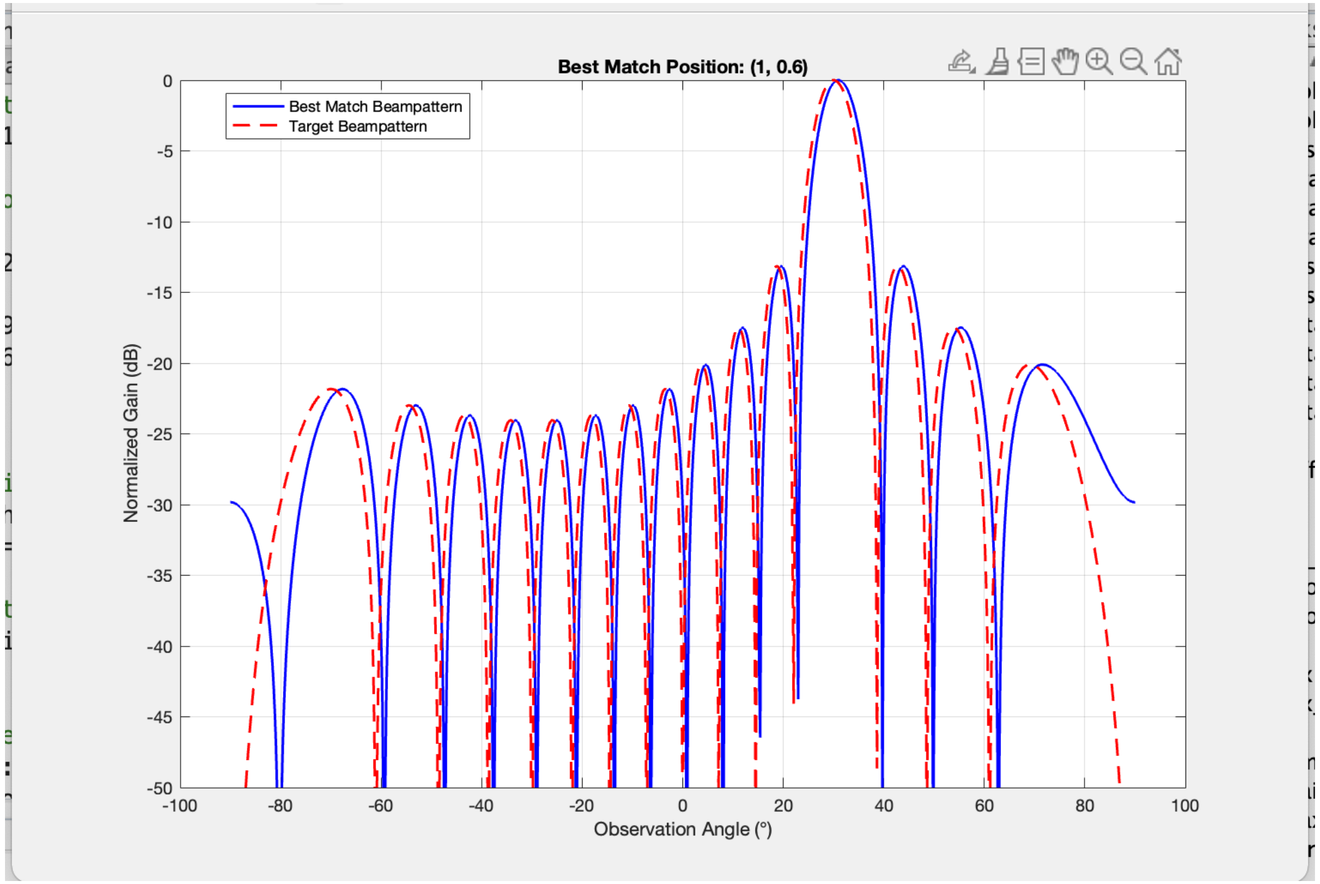




- Incident angle = 0°, intended Beta = 30°
- Intended position is (1, 0.566)
- Pont (1, 0.6) is closest

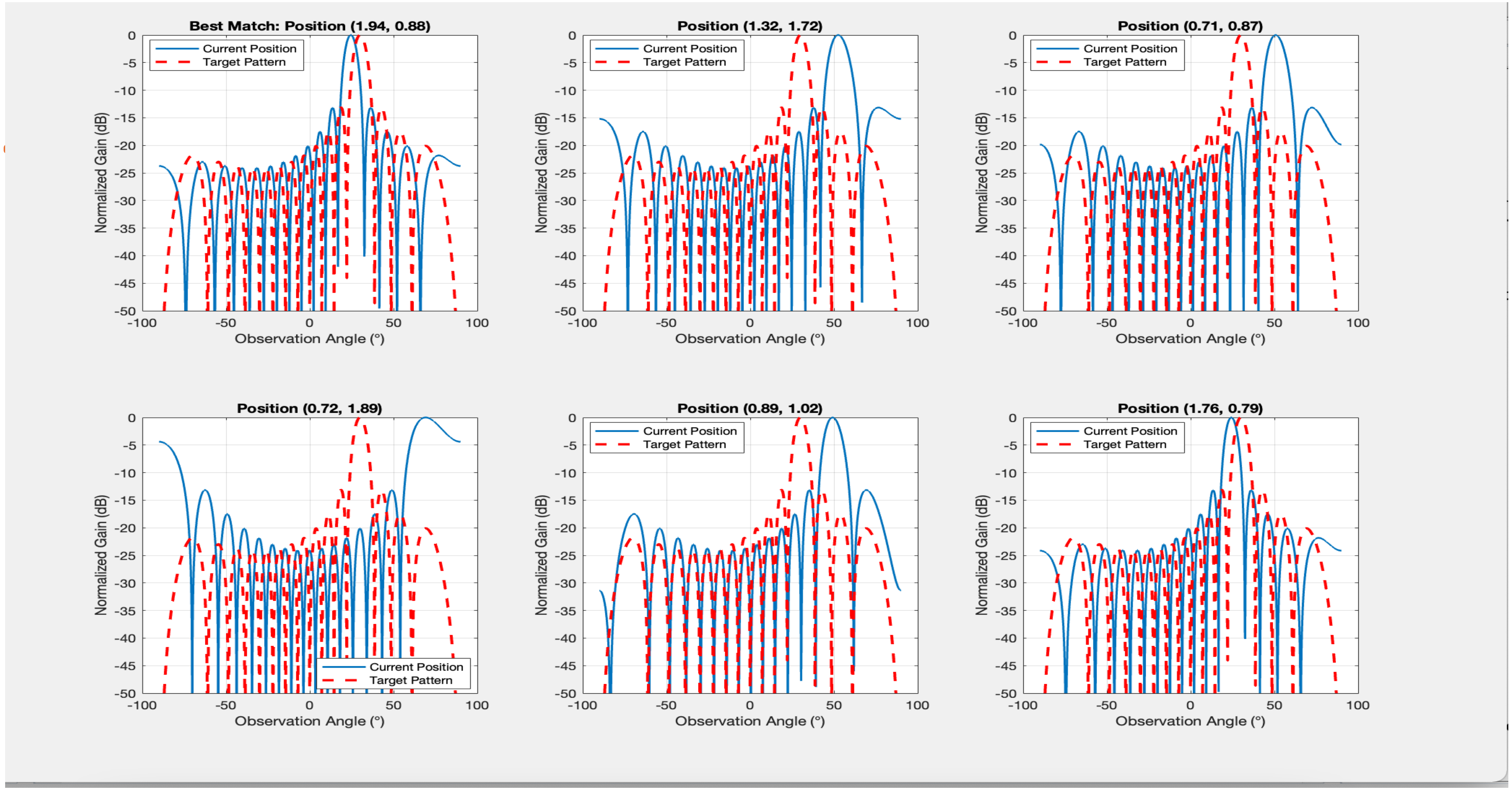
One Beam

- Plotting the beampattern only closest to the desired beampattern:



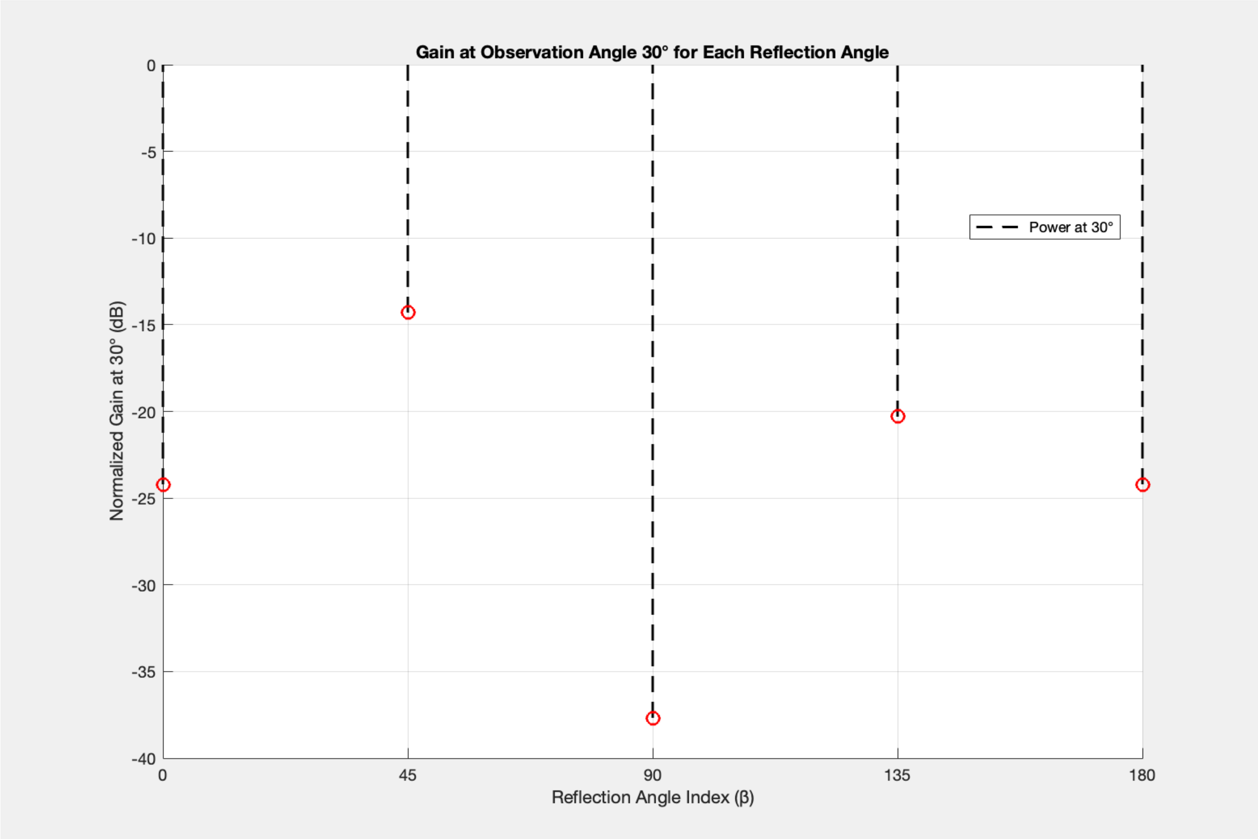
Beamsteering, randomly select points

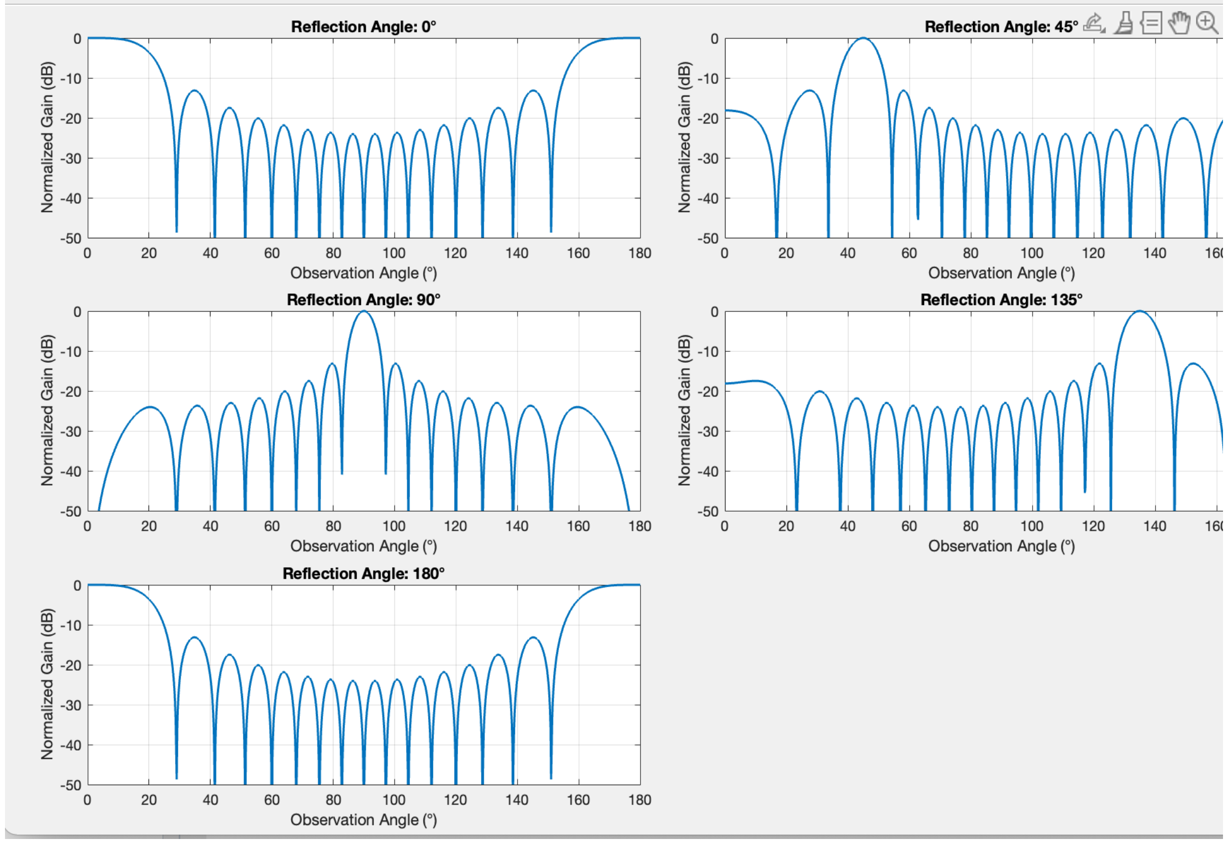
- 5 random points between (0.5 to 2 for both X and Y)



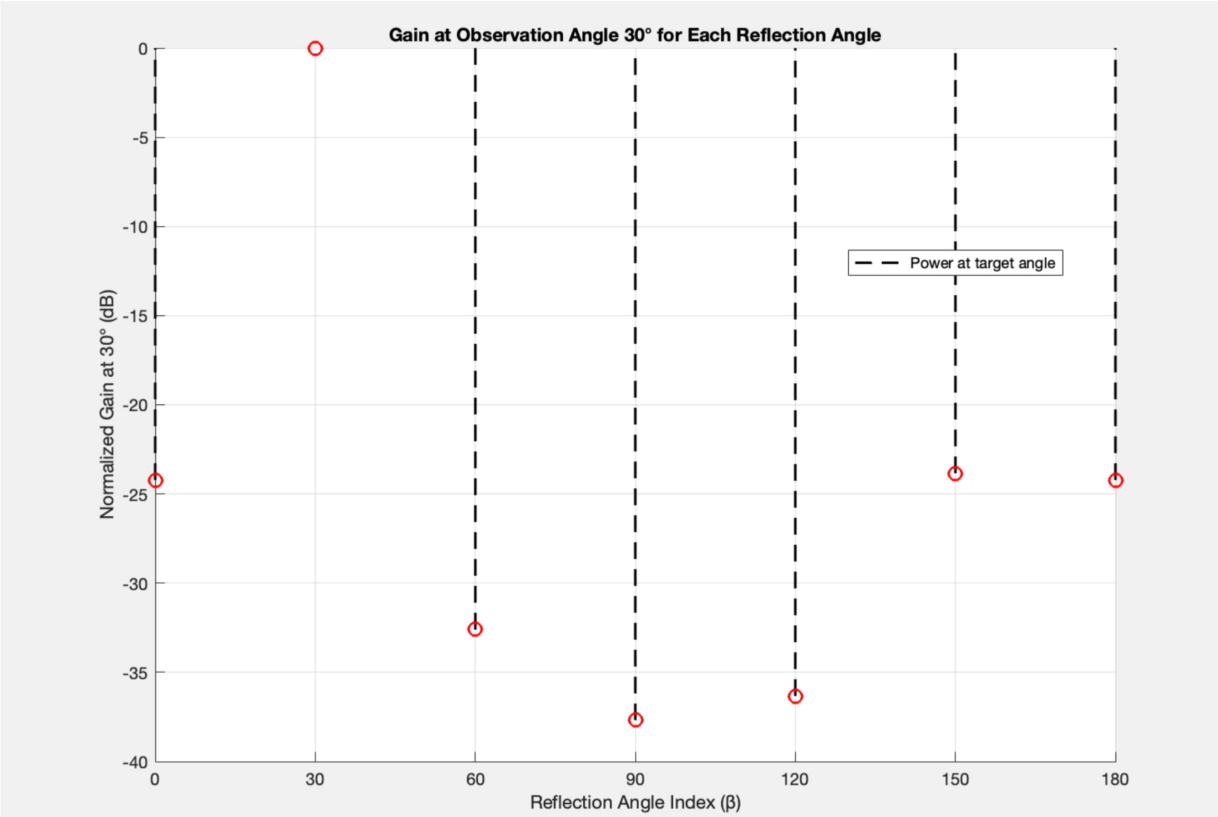
December 1, 2024

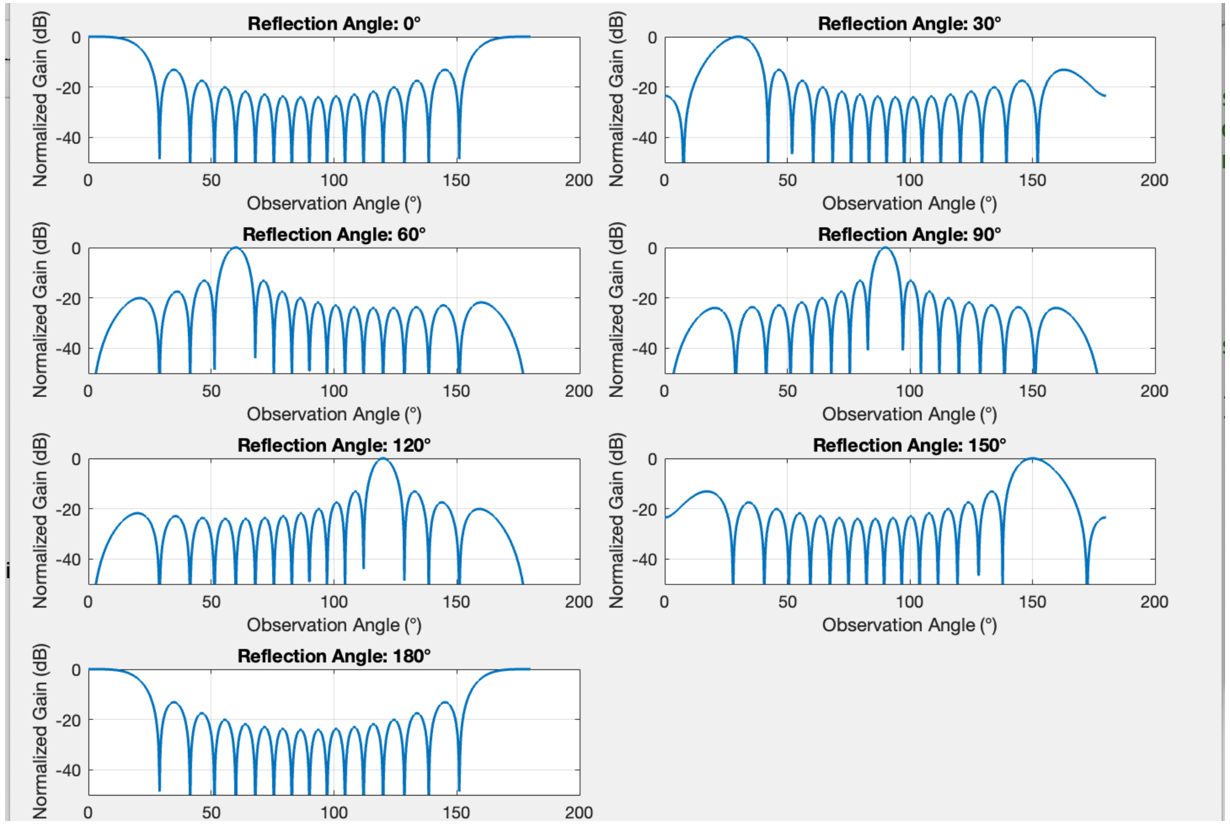
Step angle = 45, Target angle = 30, N =16

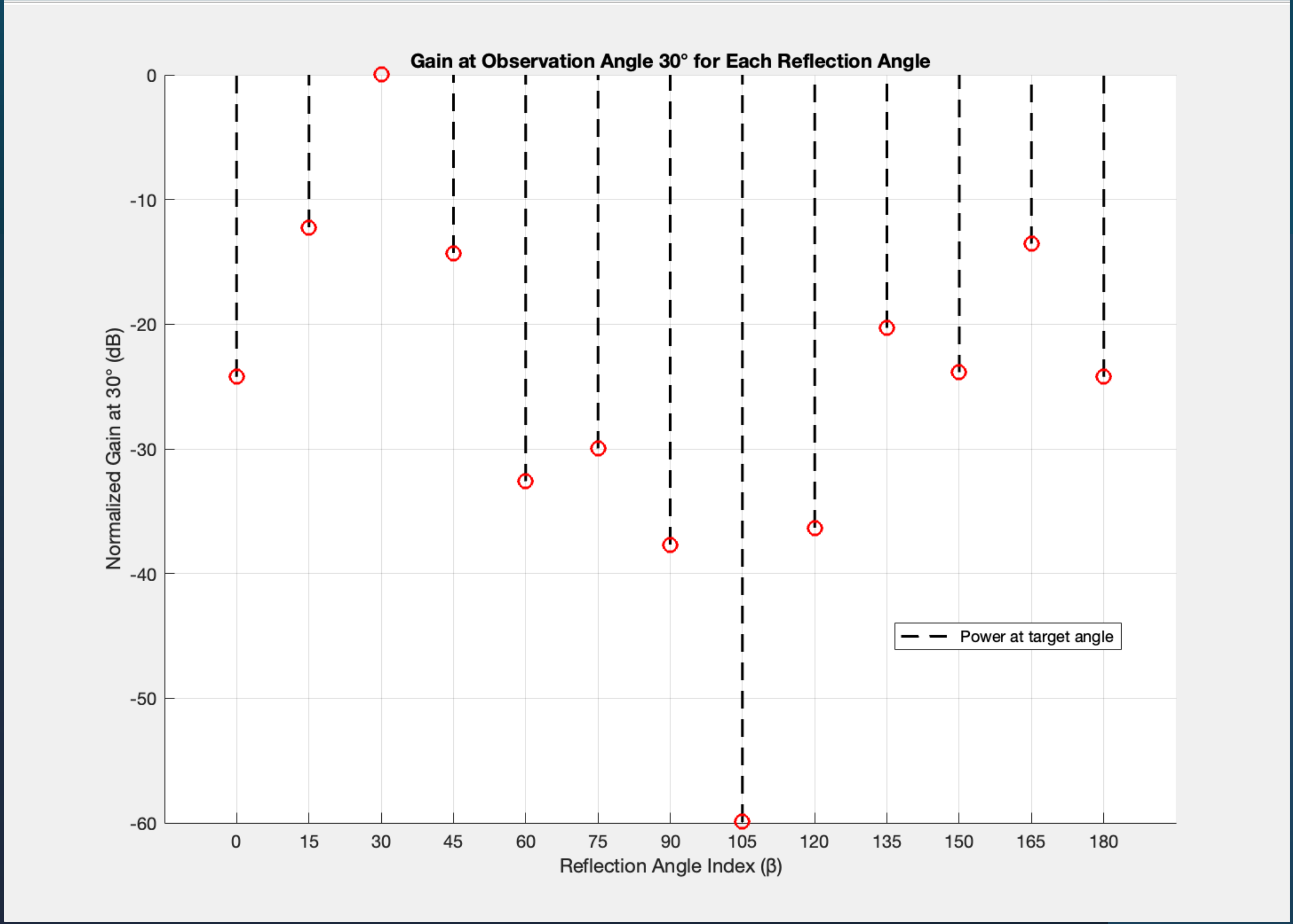




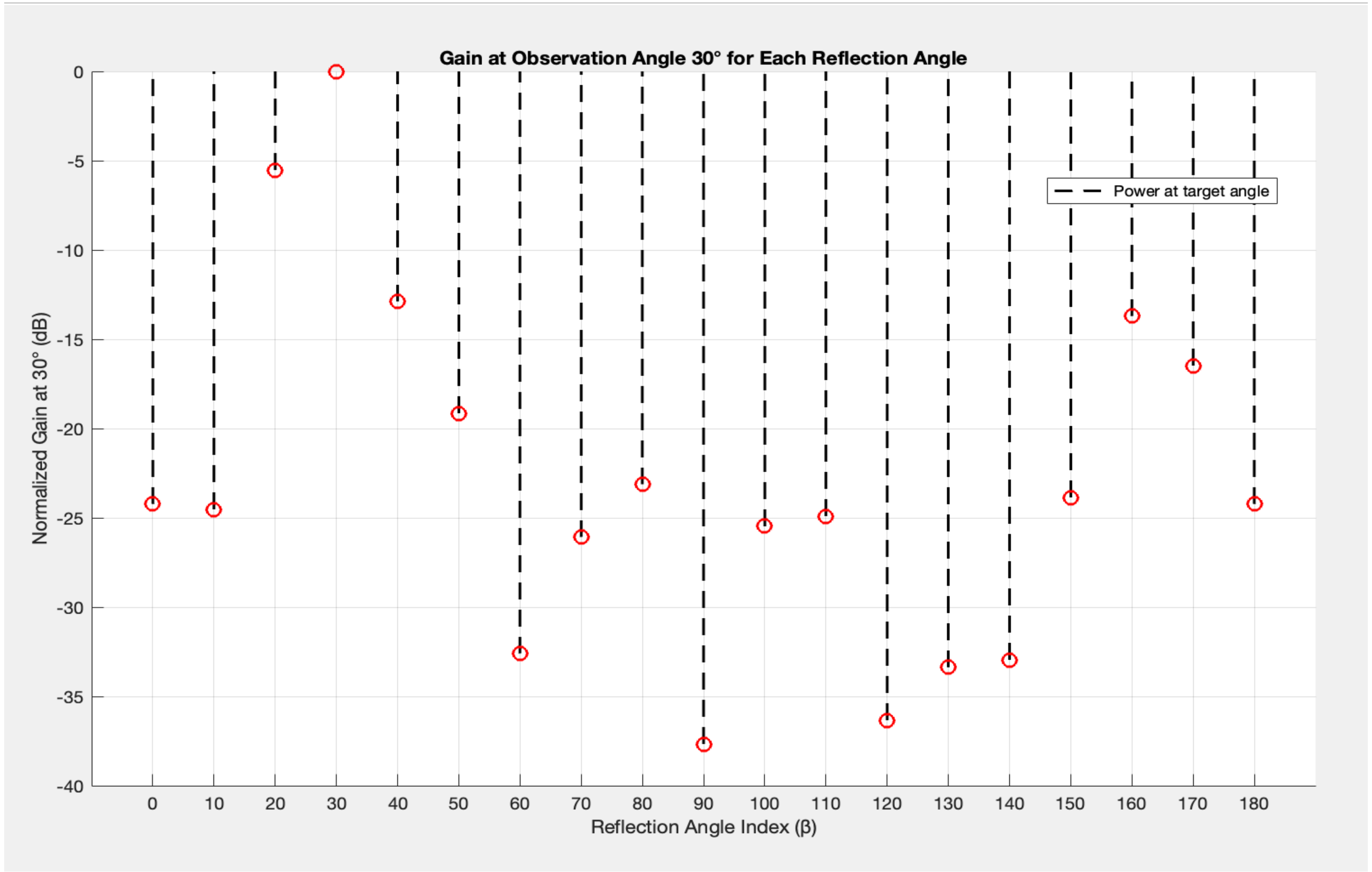
Step angle = 30, Target angle = 30, N =16



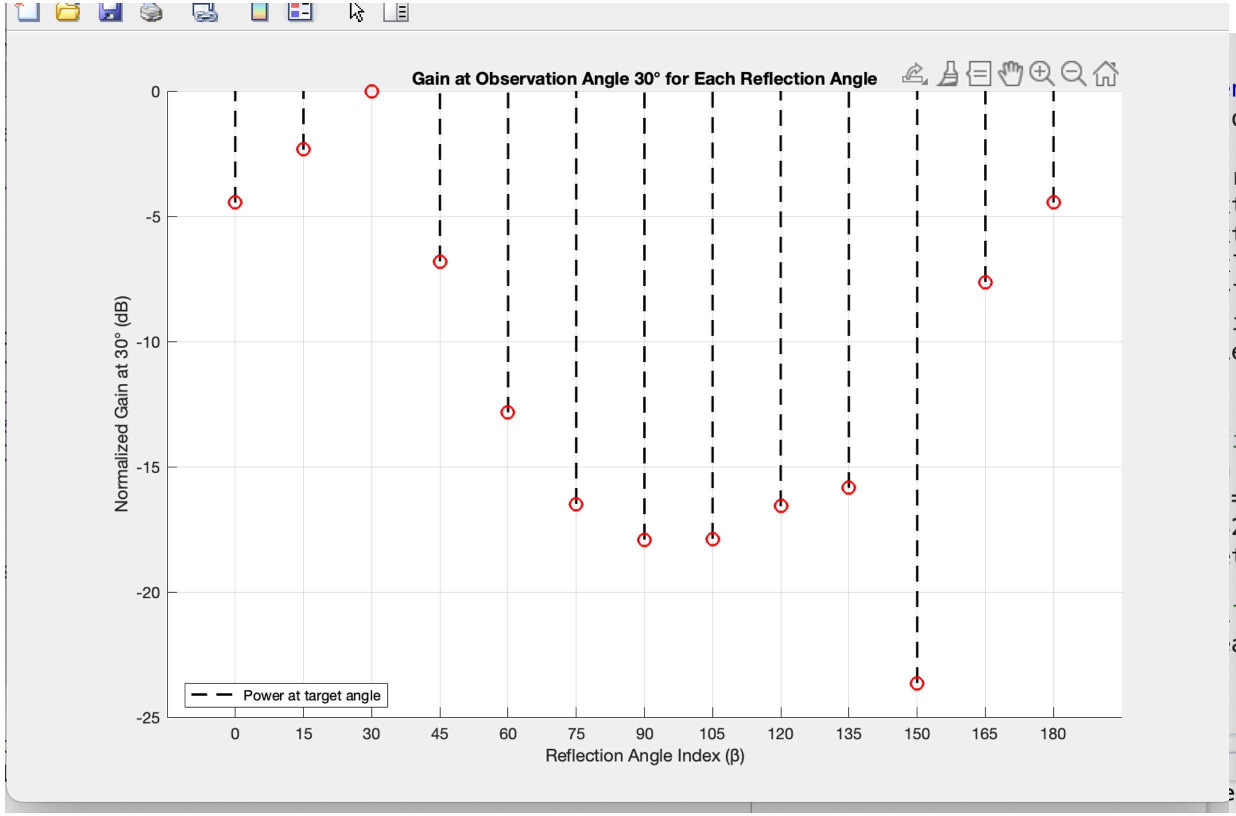


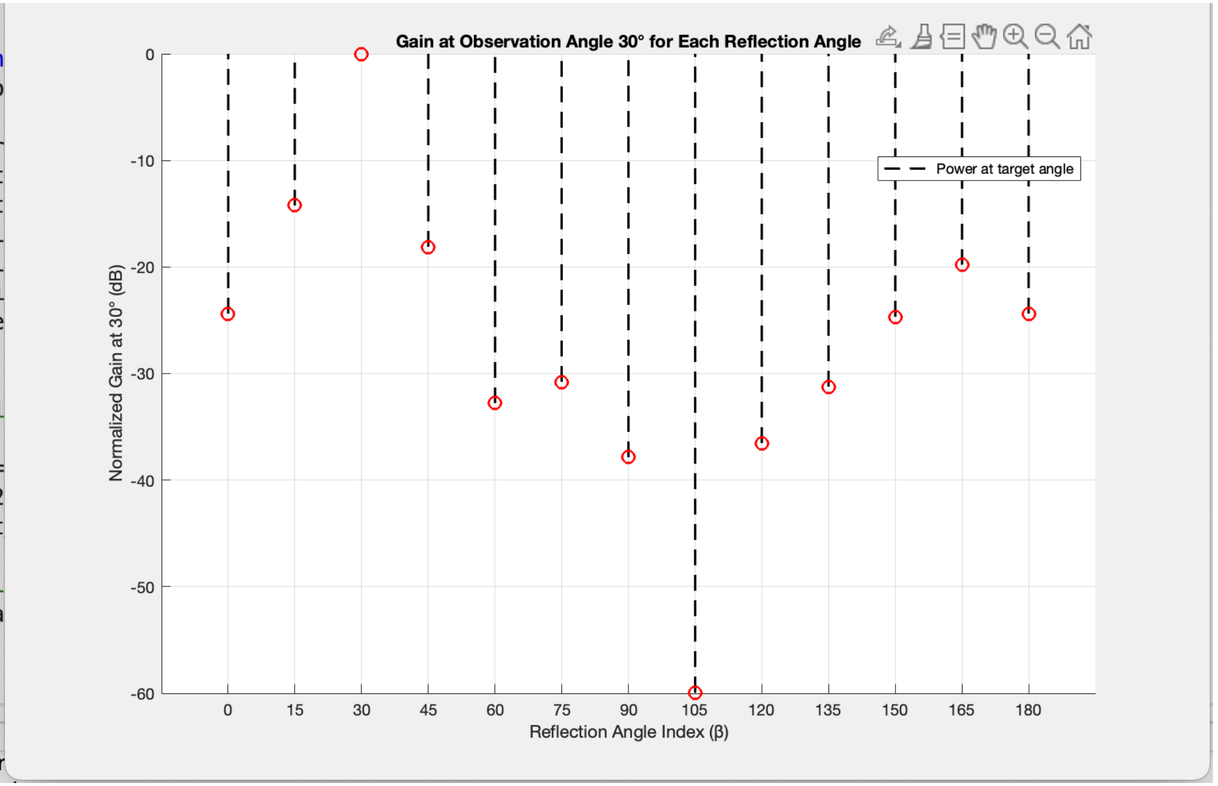

Gain at Observation Angle 30° for Each Reflection Angle
Normalized Gain at 30° (dB)
0
-10
-20
-30
-40
-50
-60
0
15
30
45
60
75
90
105
120
135
150
165
180
Reflection Angle Index (β)
Power at target angle

Step angle = 10



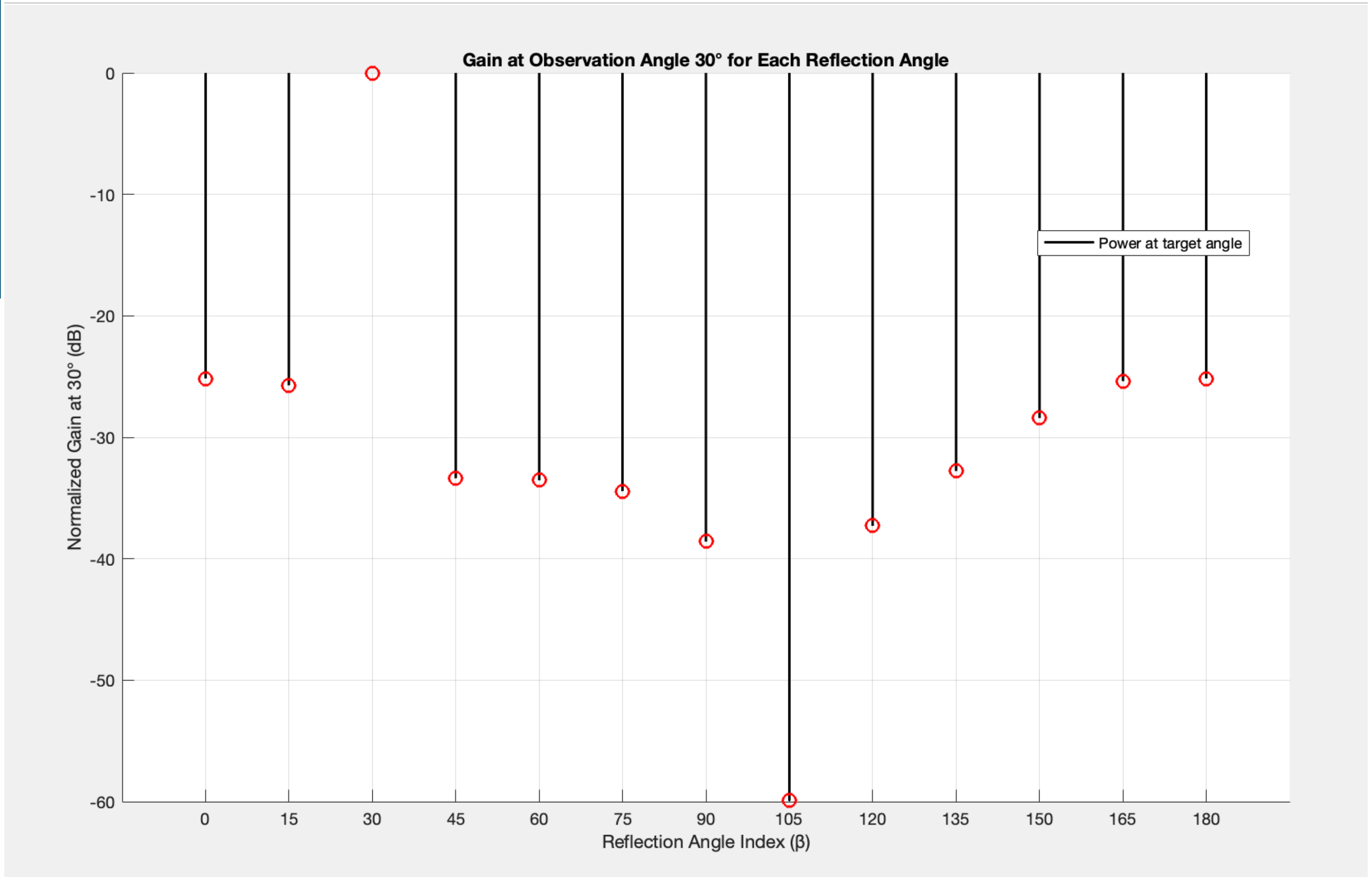
Step angle = 30, N = 8,32





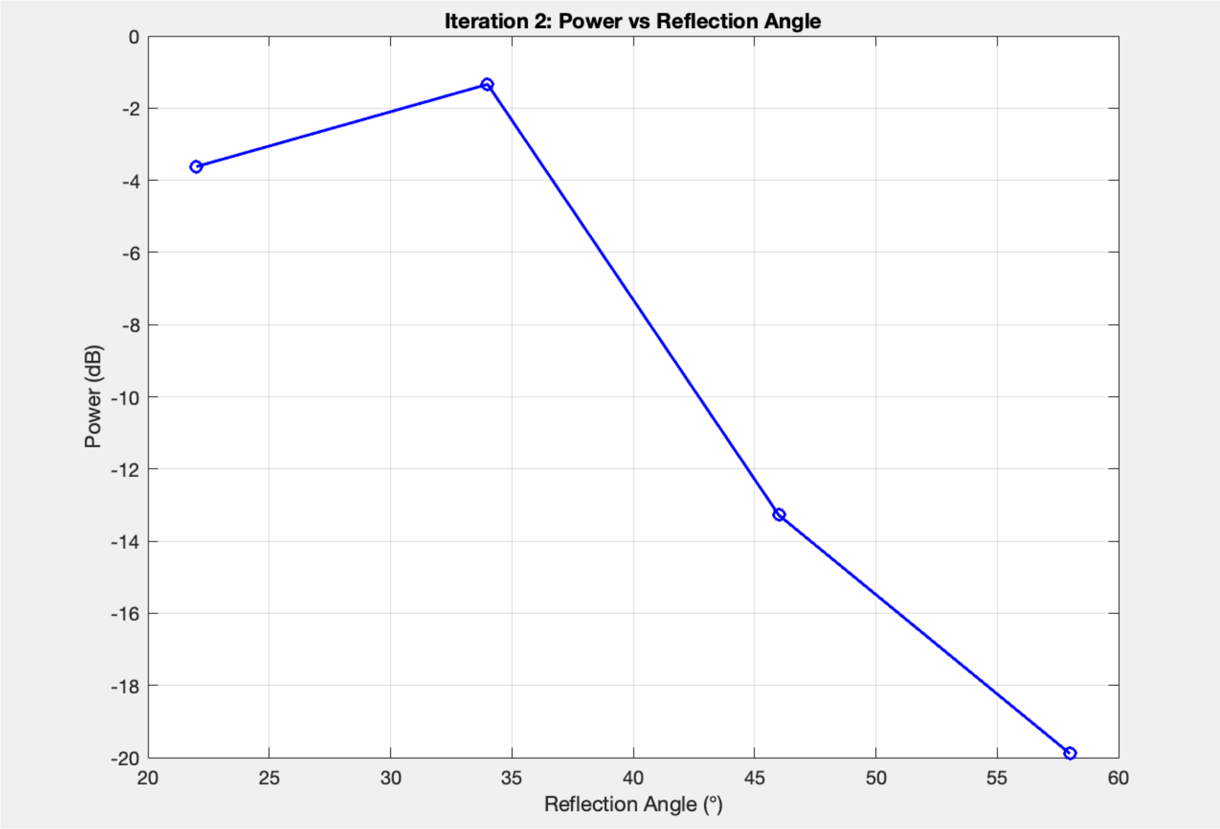
N = 64

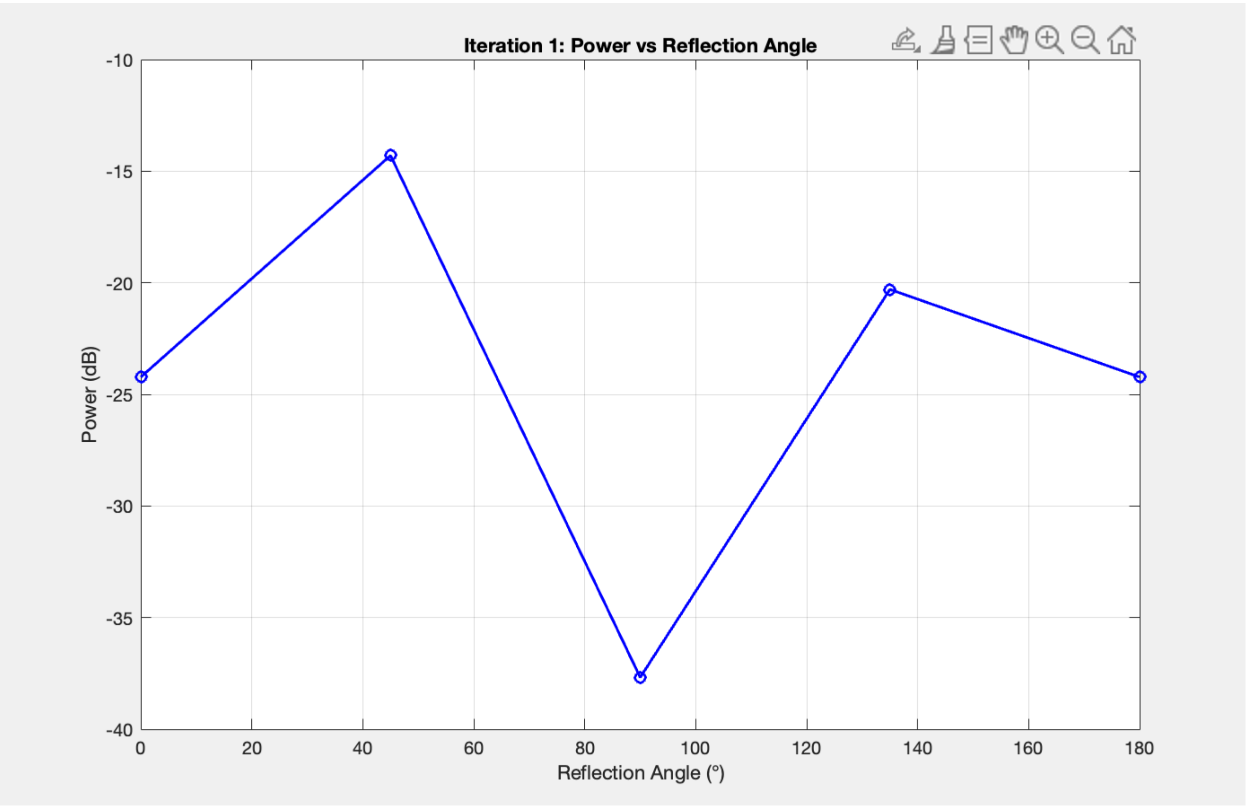
- Increasing number of antennas reduces the power



- Hierarchical Beam Steering

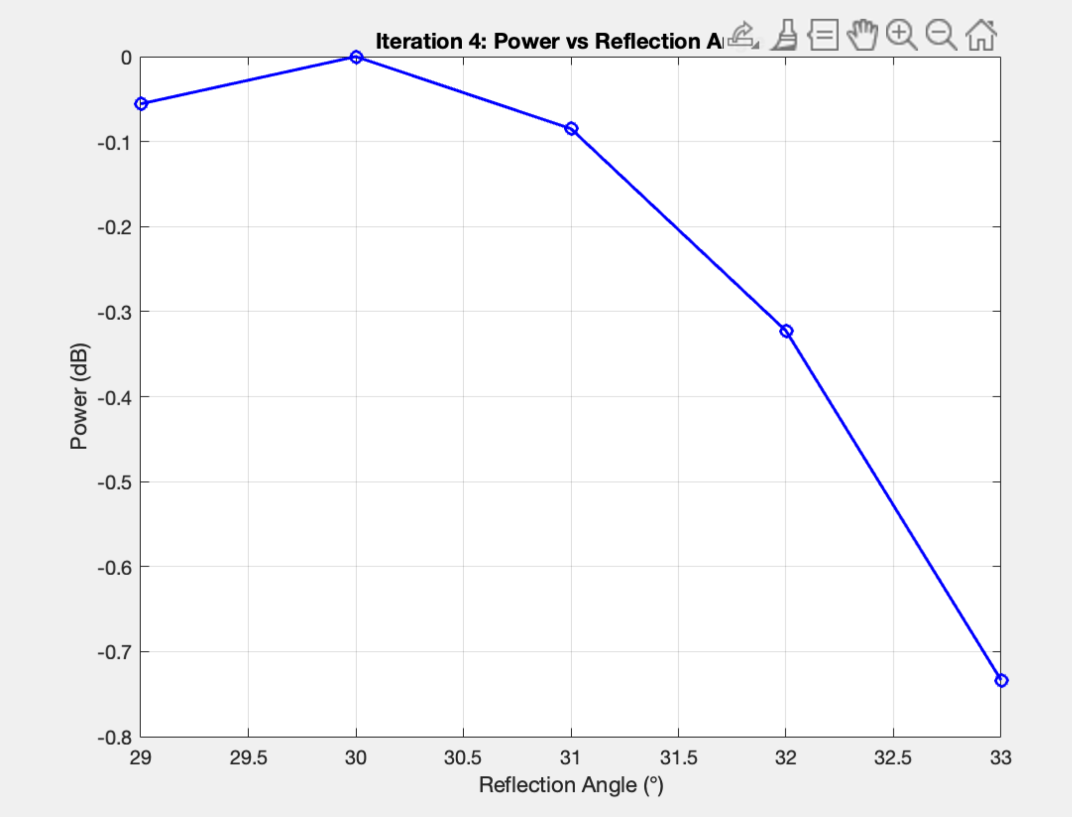
- As of now: setting the maximum number of iterations
- Step = (best angle – previous angle)/2
- New angles = best angle + (- step : step/2:step)



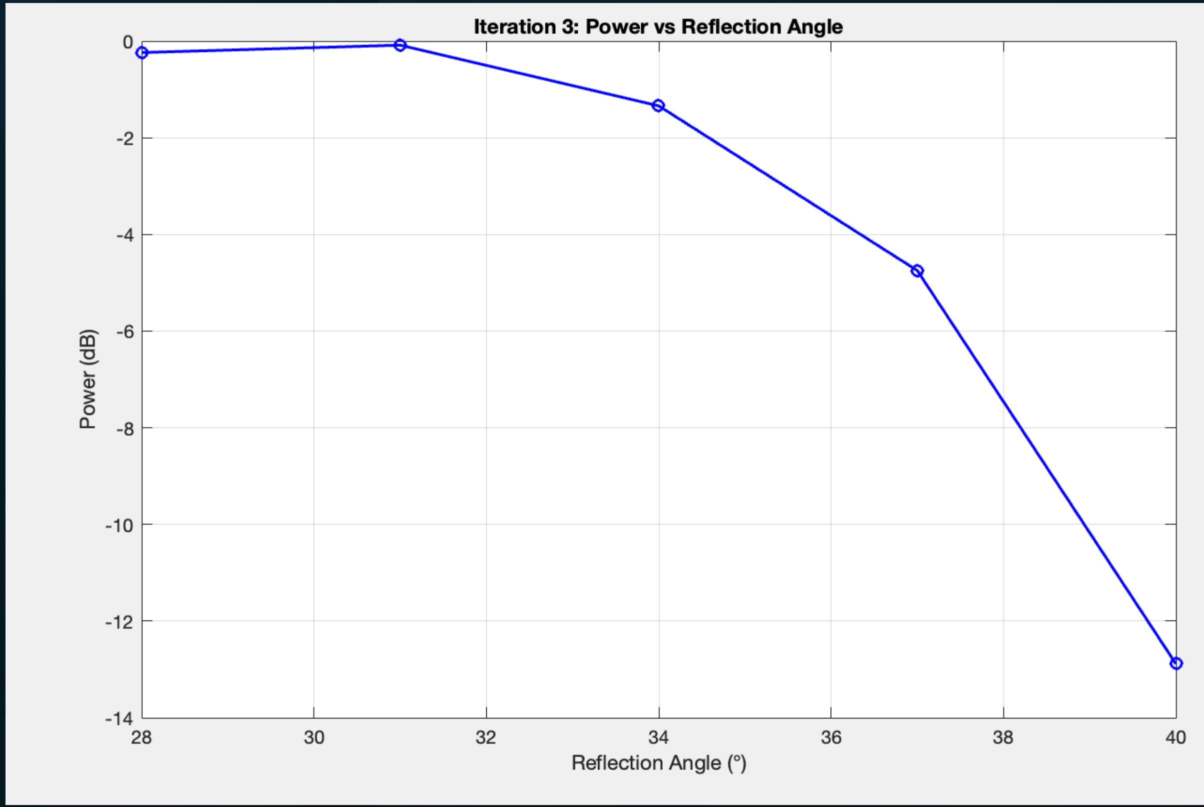


Target angle 30, incident angle

Cont'

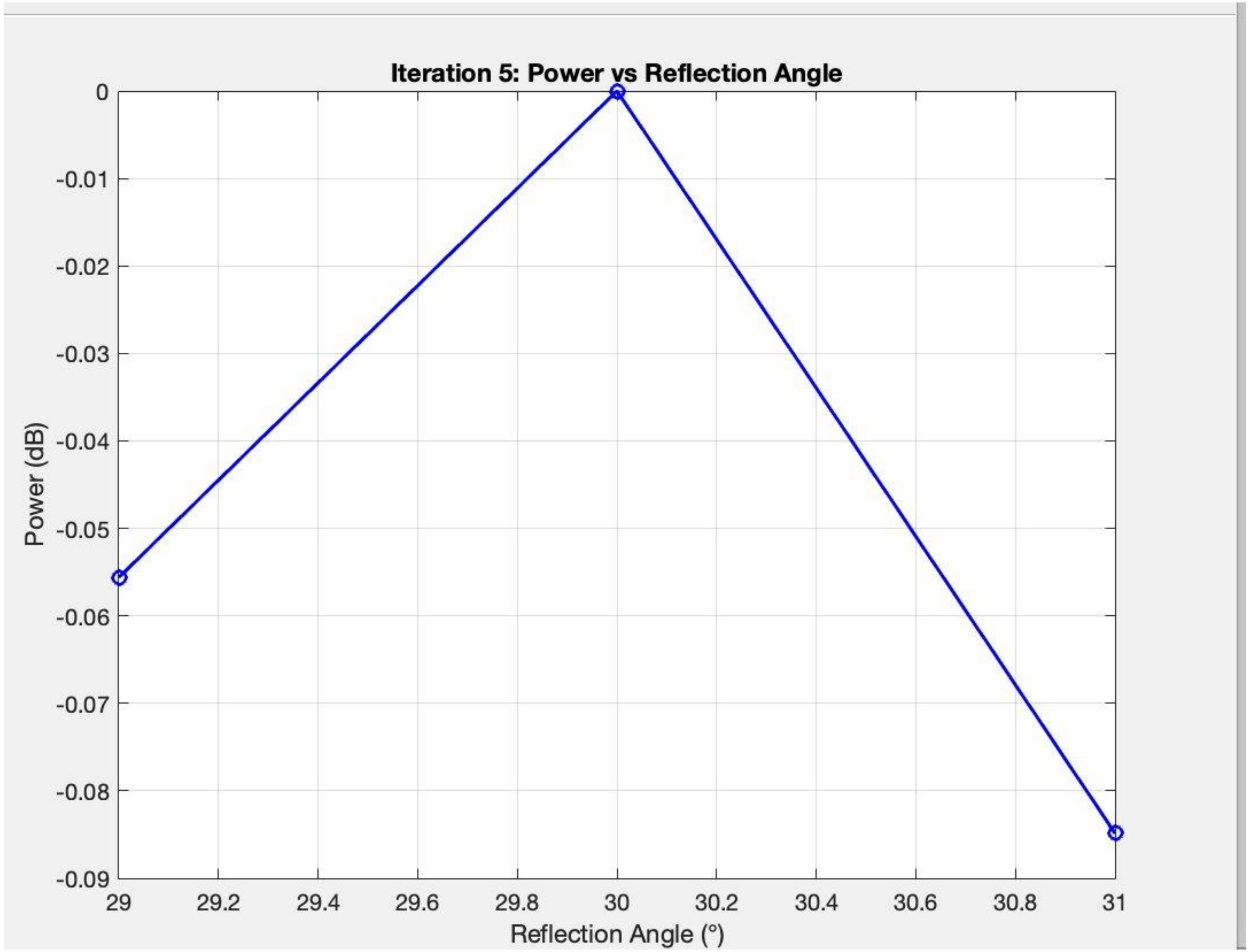


Iteration 4: Power vs Reflection A
Power (dB)
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
-0.7
-0.8
29
29.5
30
30.5
31
31.5
32
32.5
33
Reflection Angle (°)



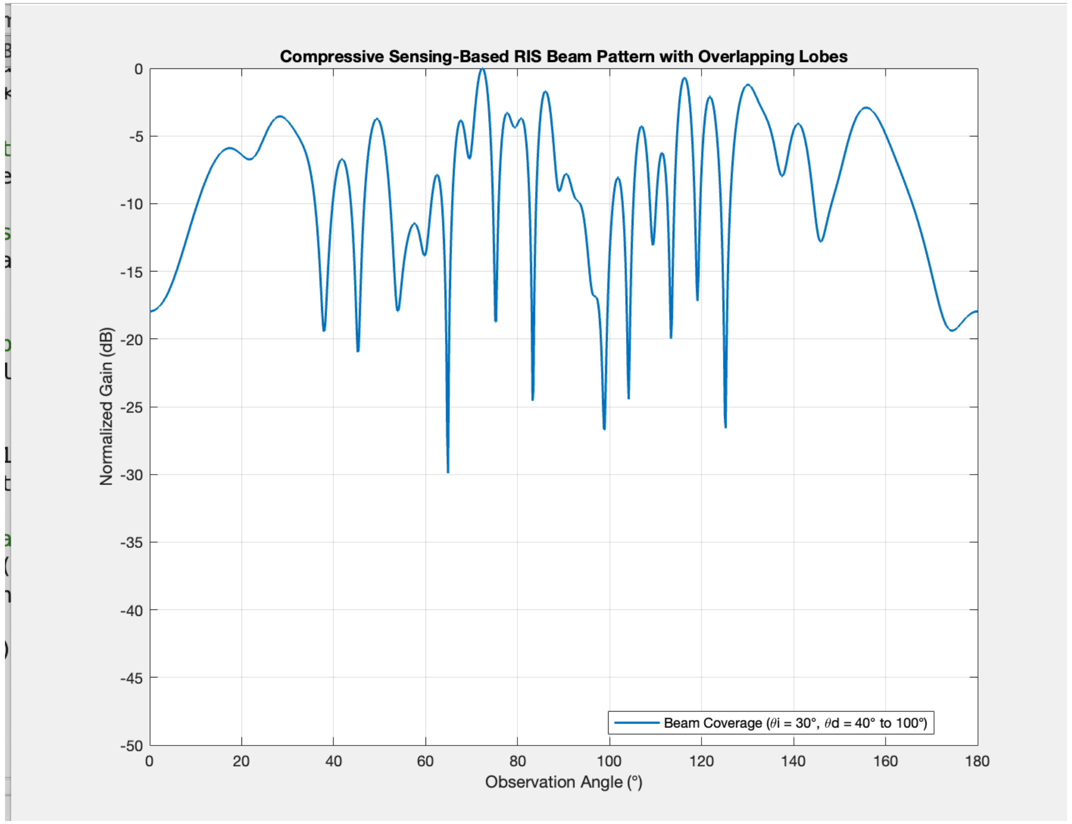
Iteration 3: Power vs Reflection Angle
Power (dB)
0
-2
-4
-6
-8
-10
-12
-14
28
30
32
34
36
38
40
Reflection Angle (°)

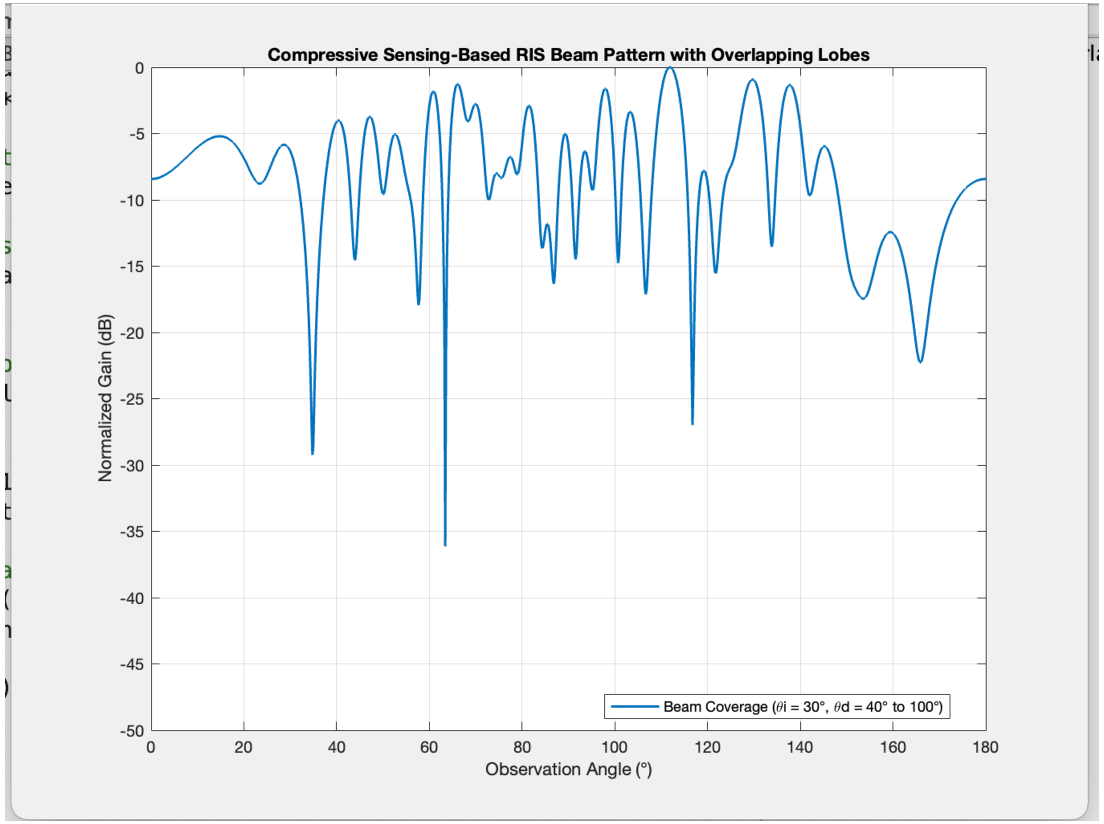
Last iteration



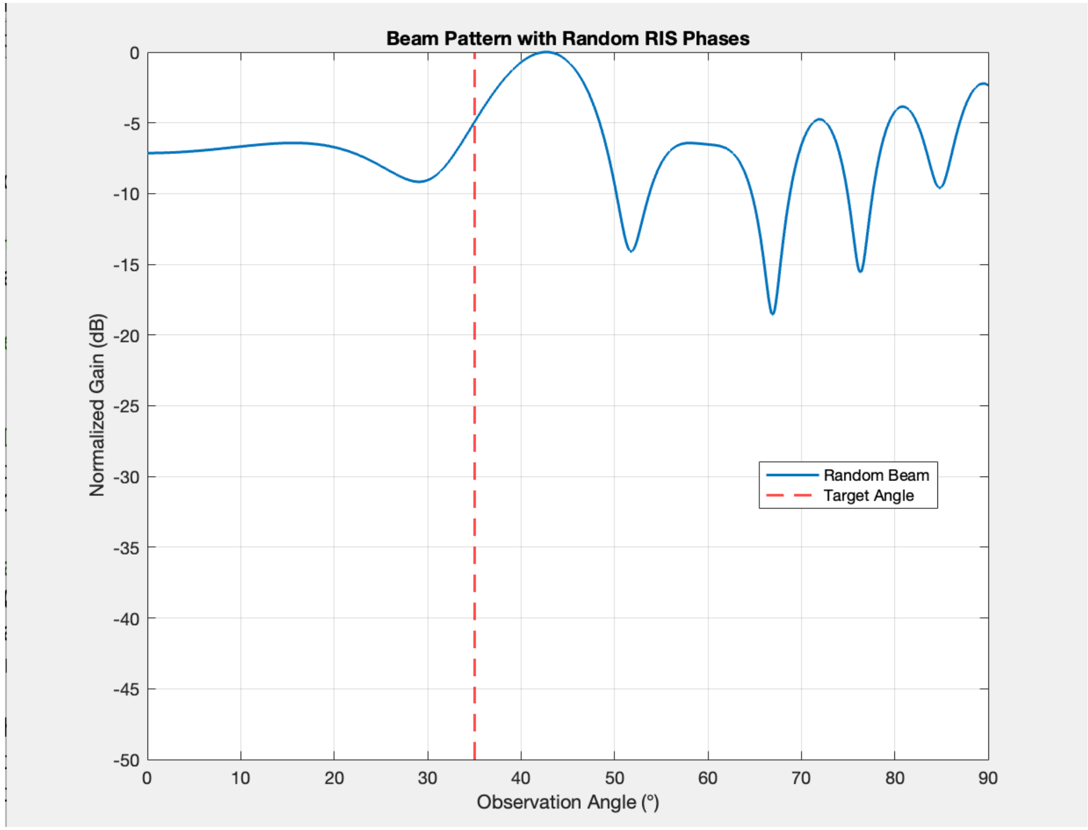
Compressive Sensing

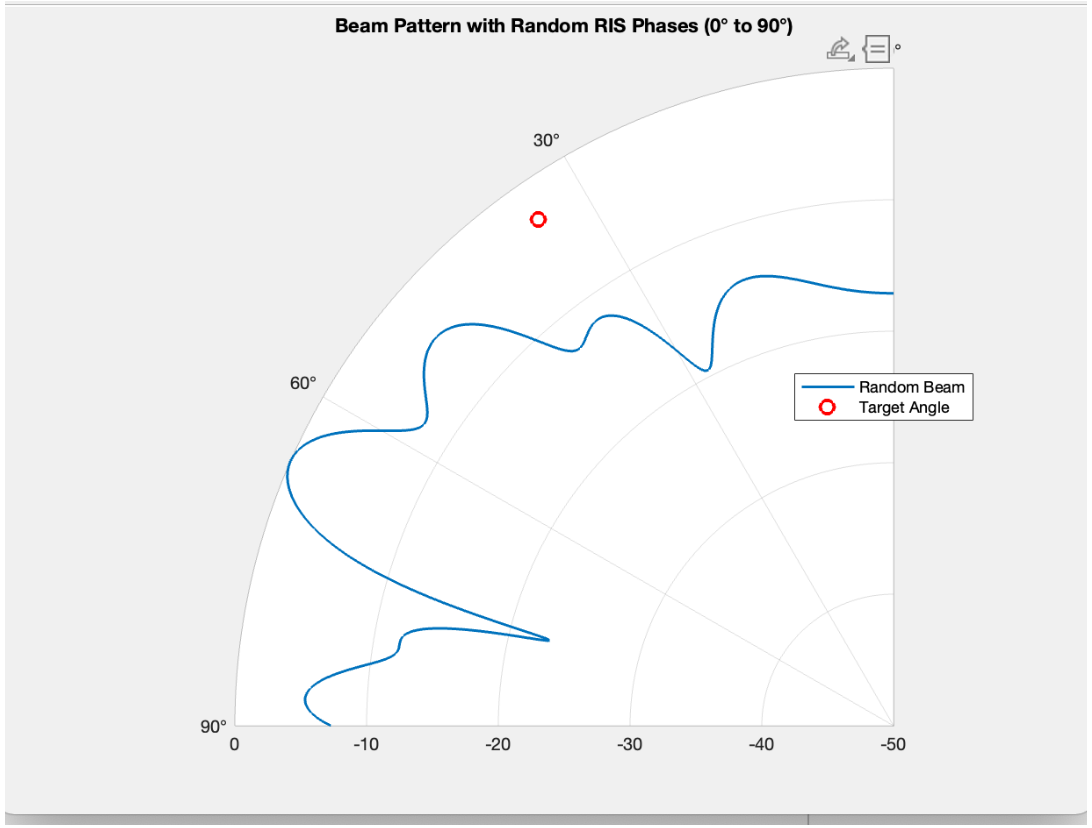
- Form





Random phase shifts



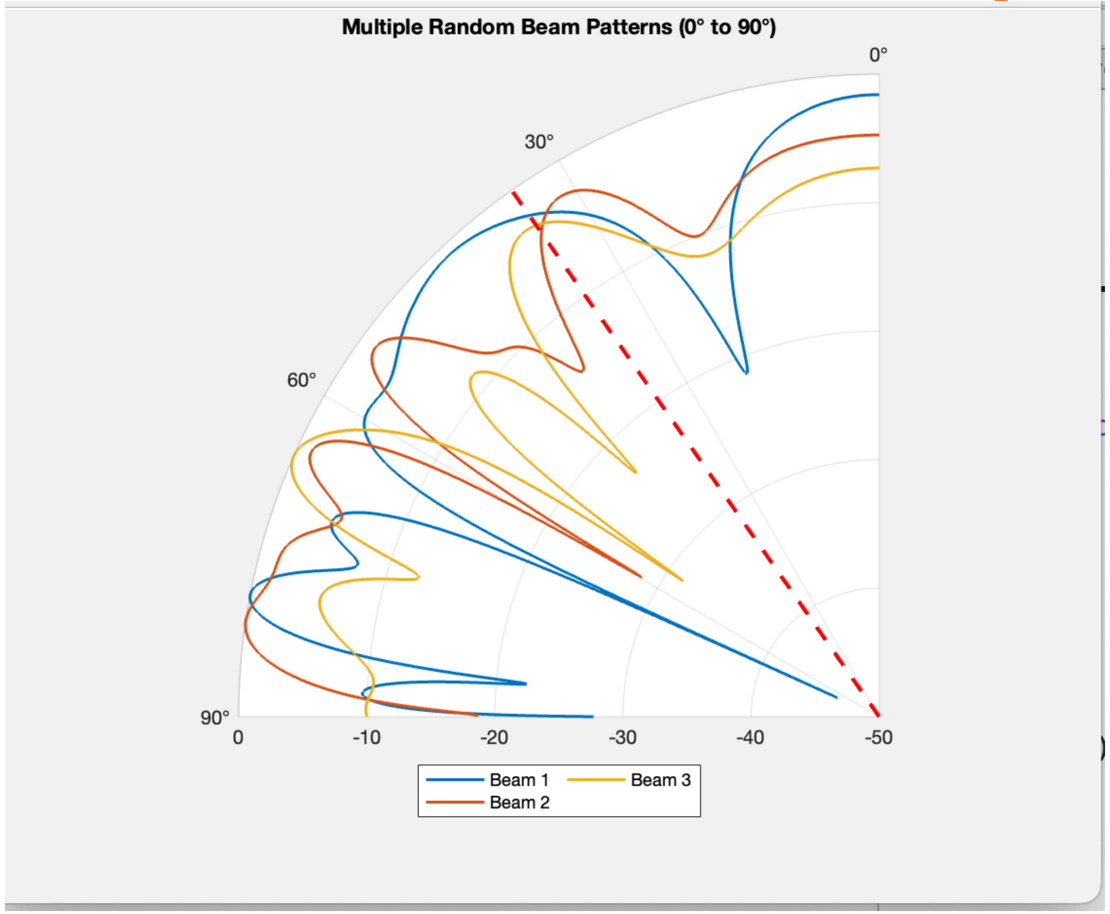


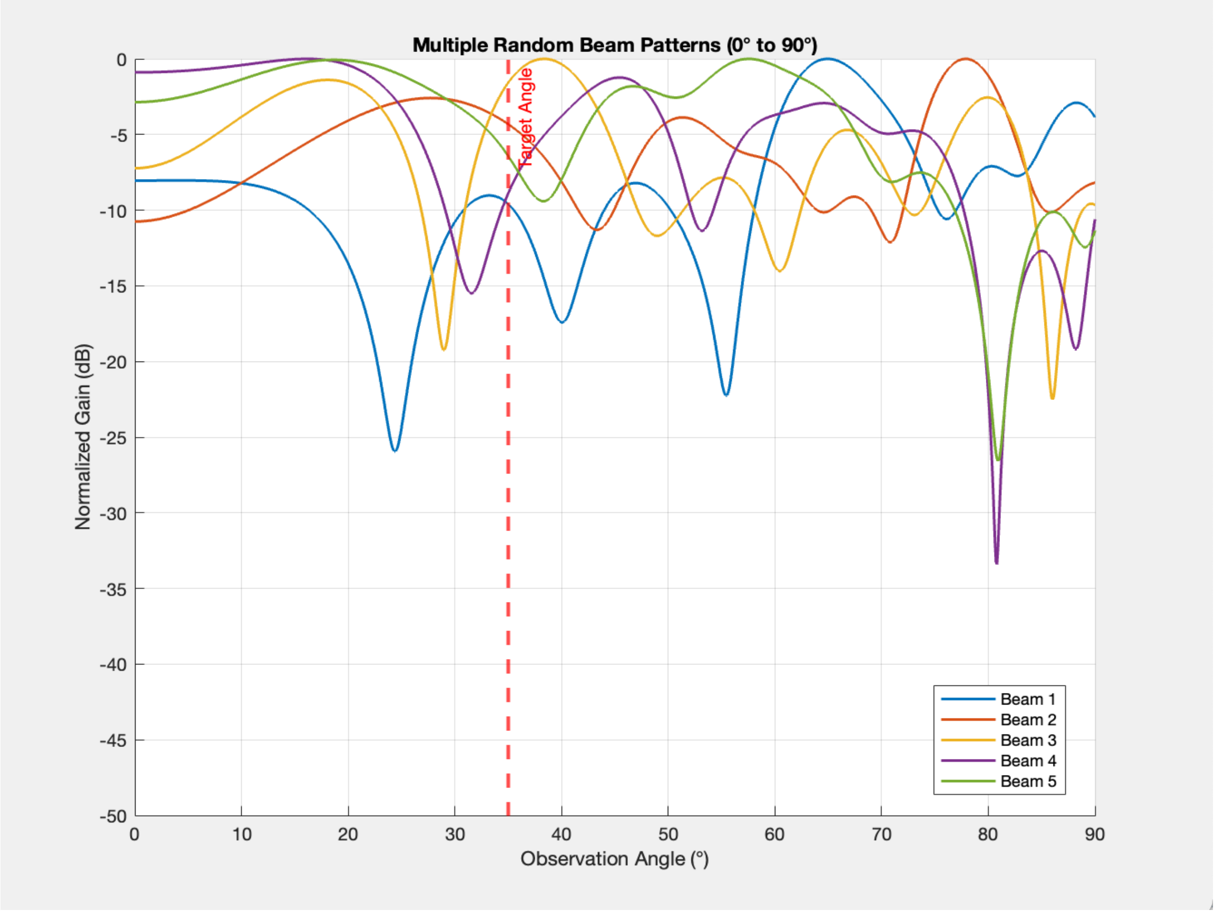
RIS Compressive Sensing

- The phase shifts are randomized and also between 0° and π
- Target angle is 35°

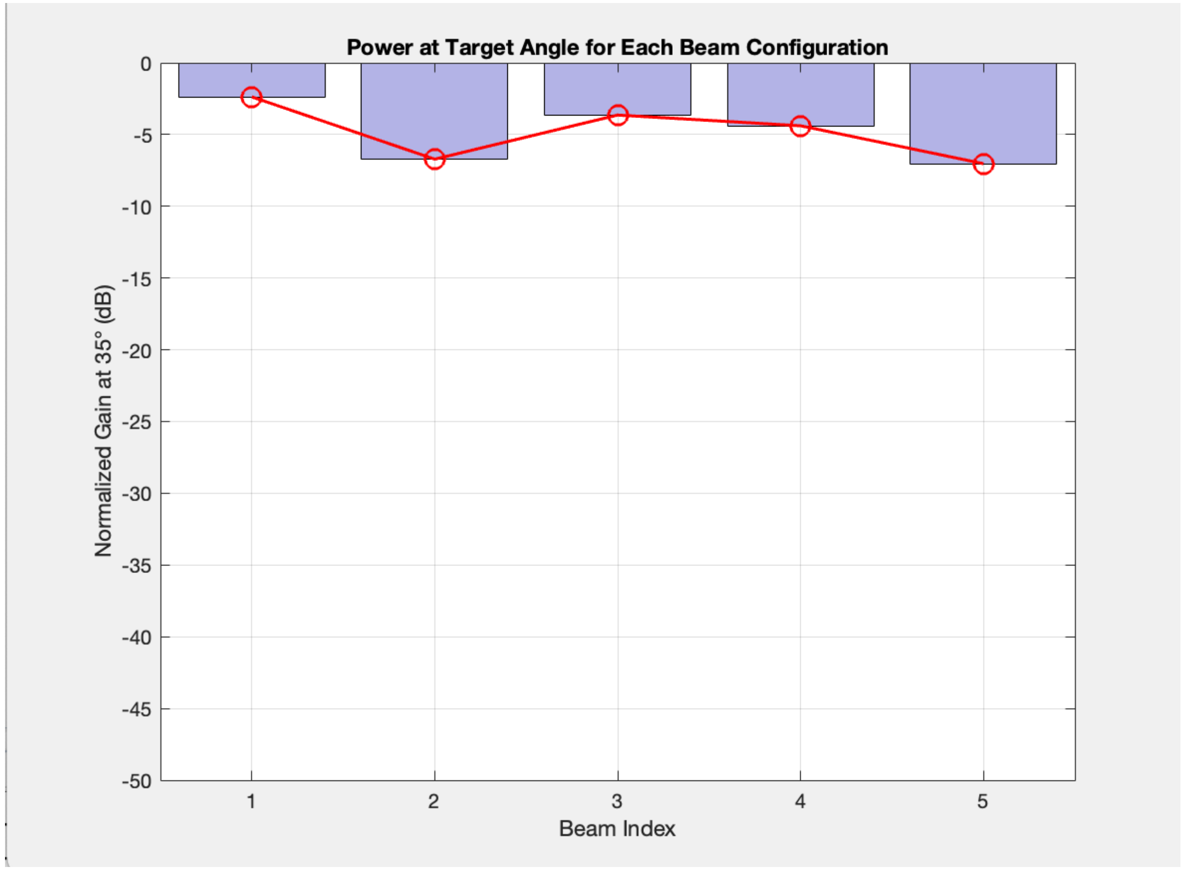
Multiple Beampatterns

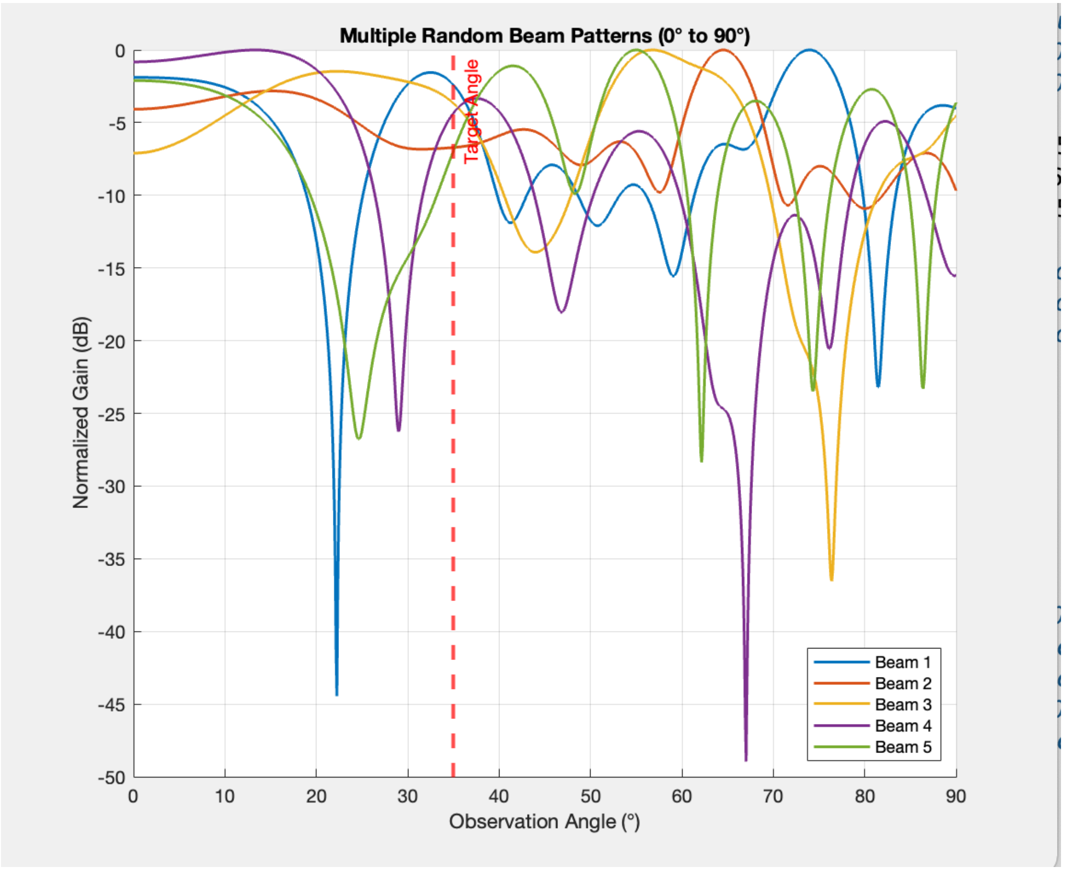
- Multiple iterations
- Target angle of 30°





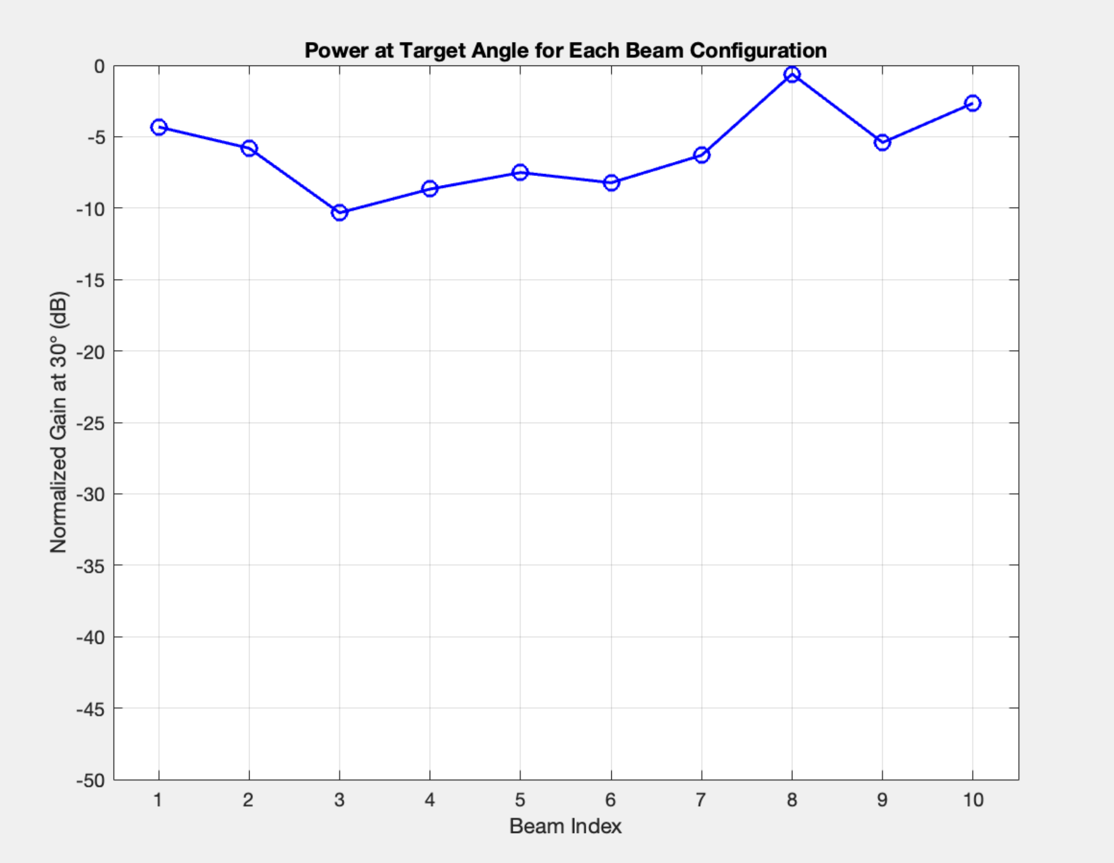
Powers Vs Beam Index



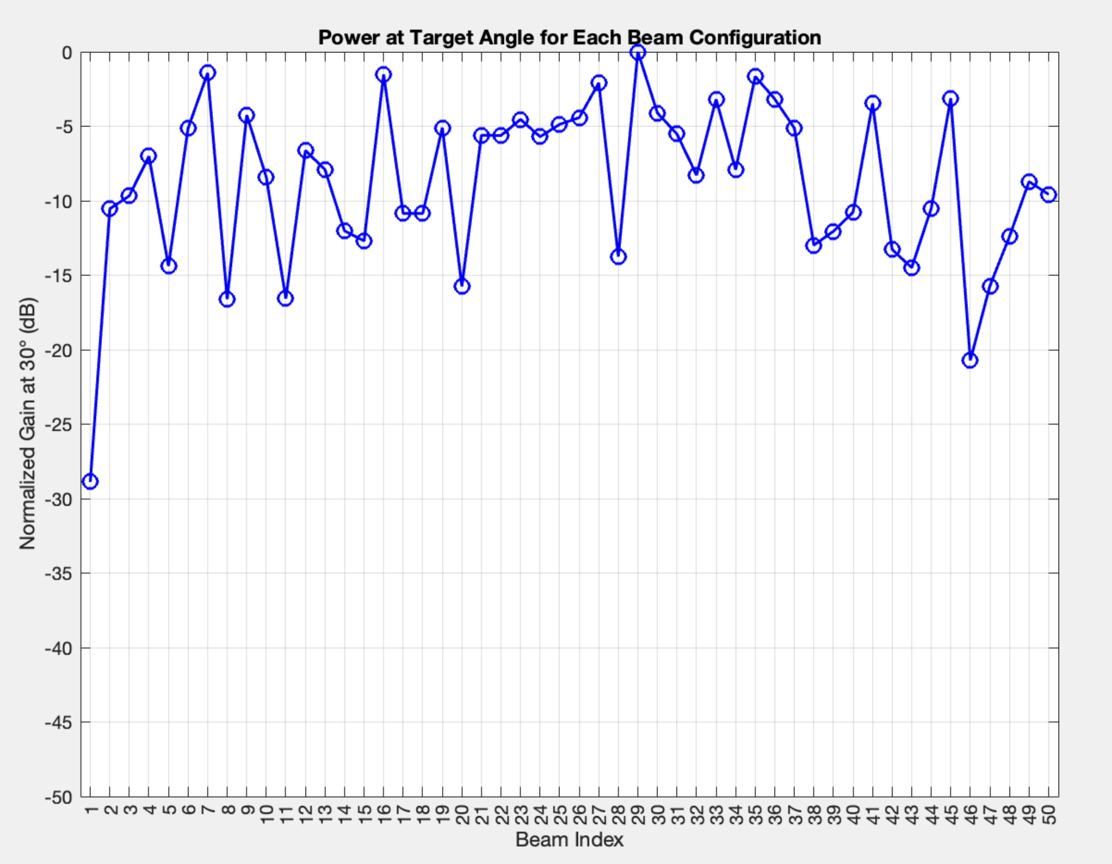


Power vs Beam Index/ Many iterations, one target angle

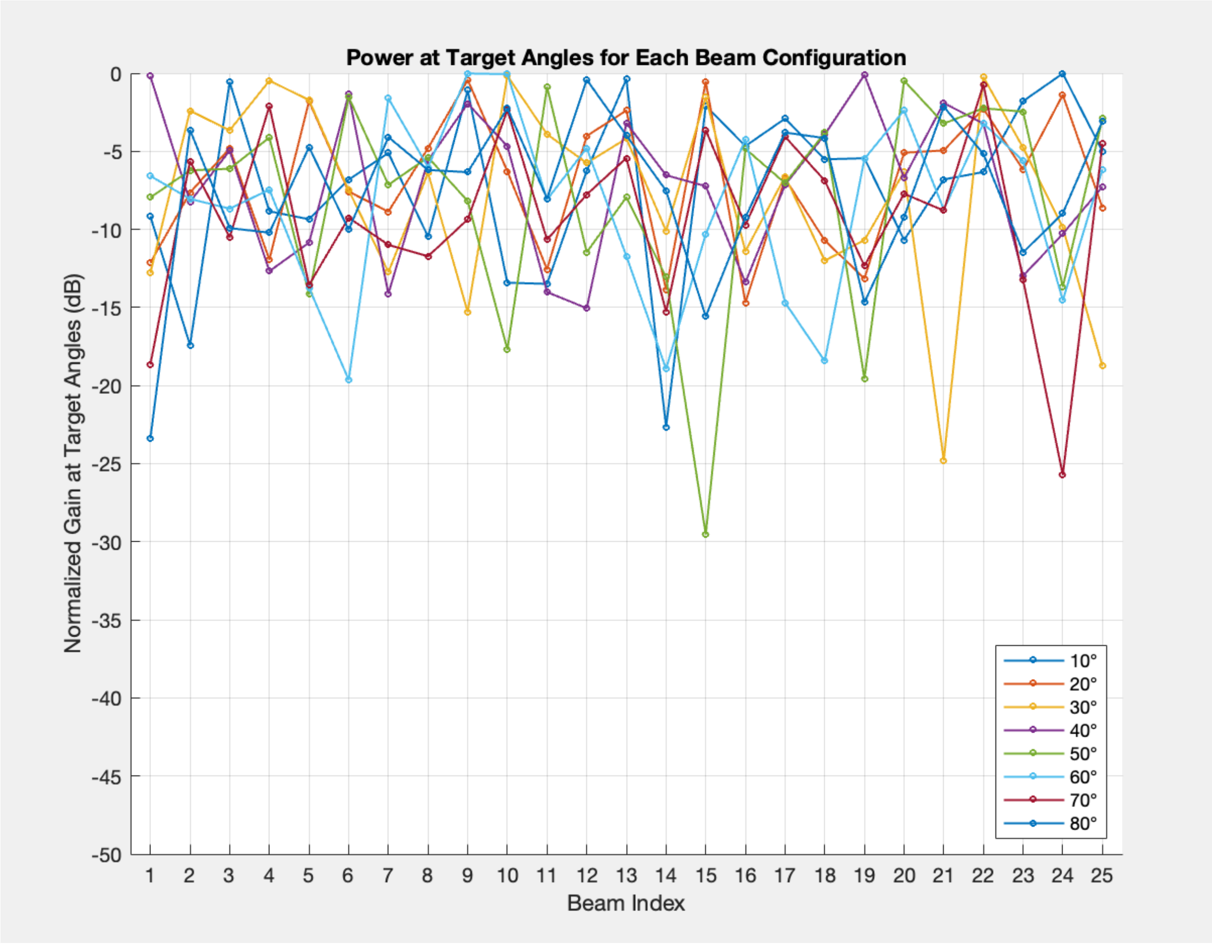
10 iterations

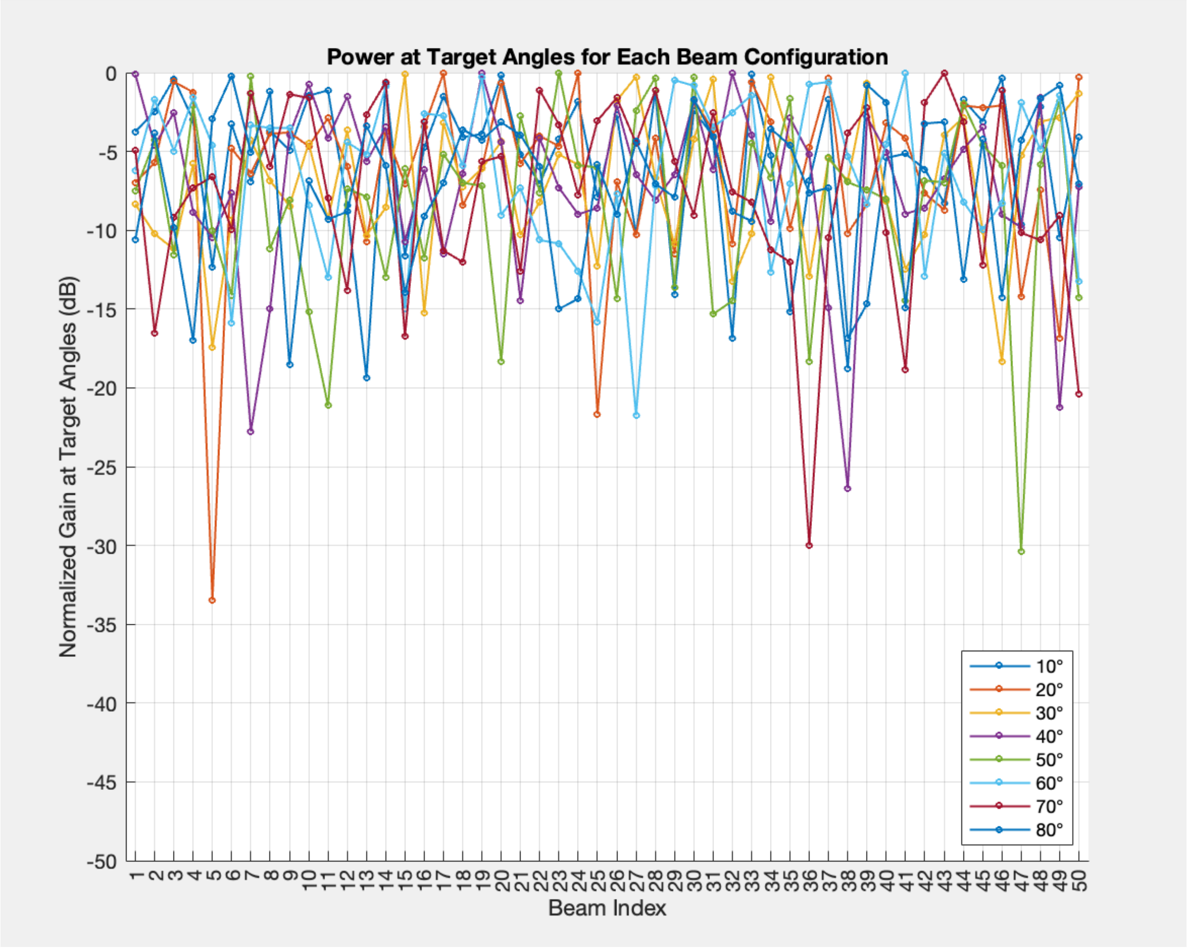


50 iterations

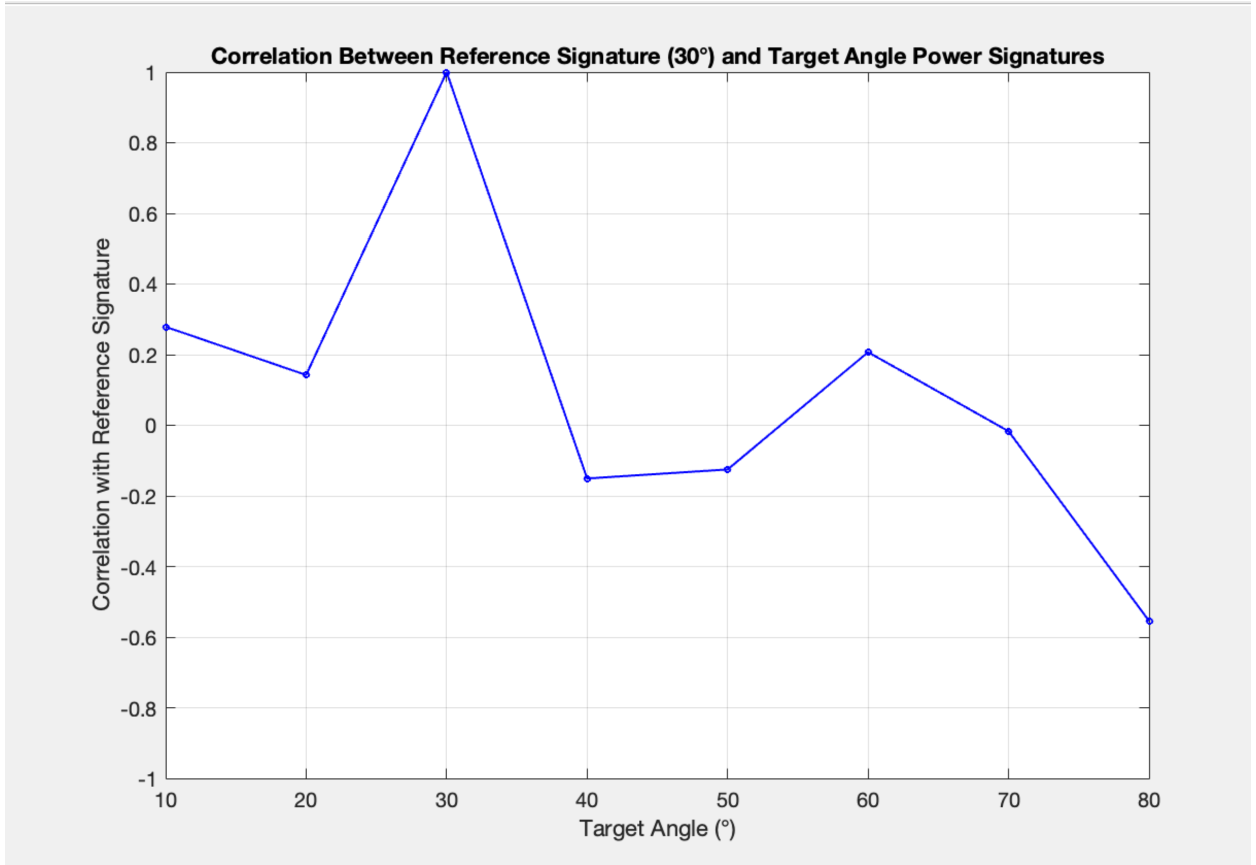


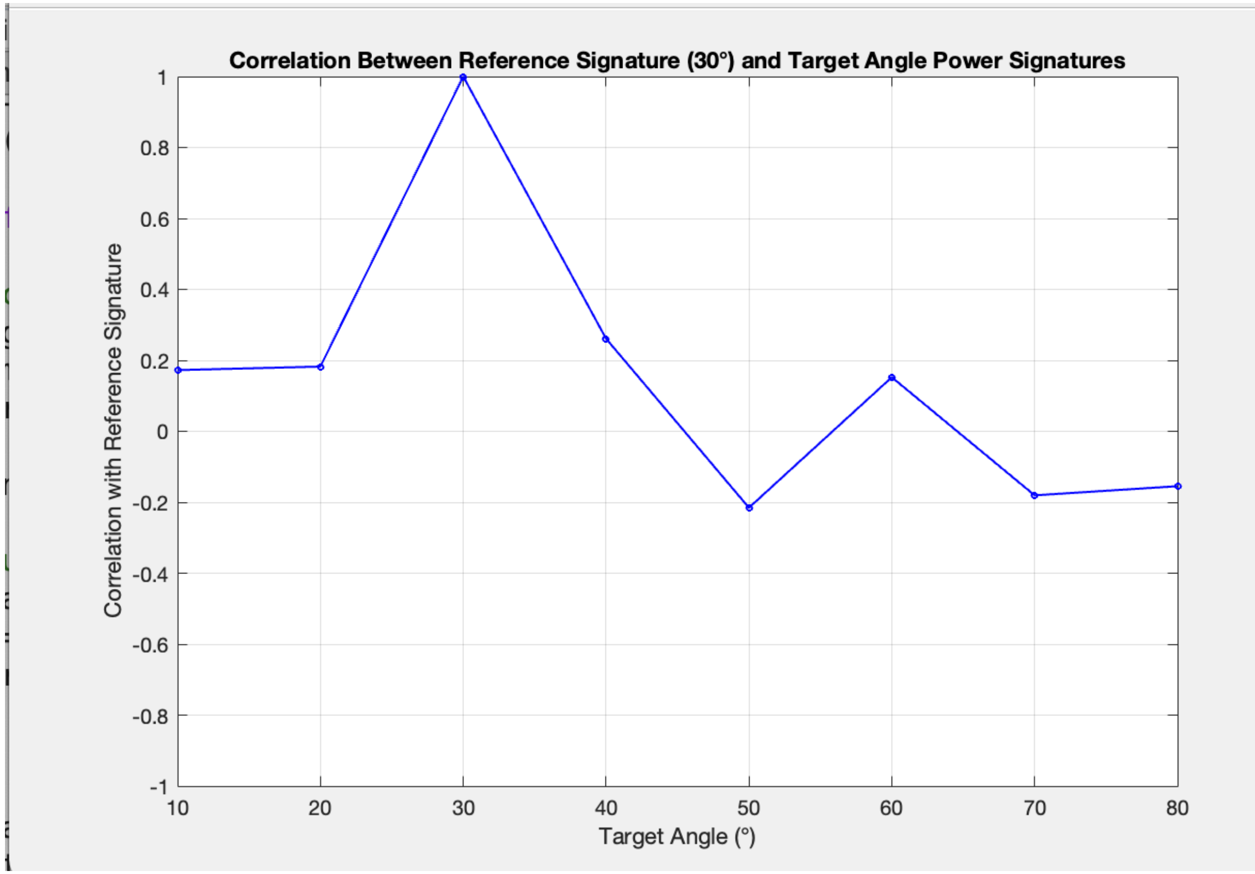
25 iterations vs 50 Iteration



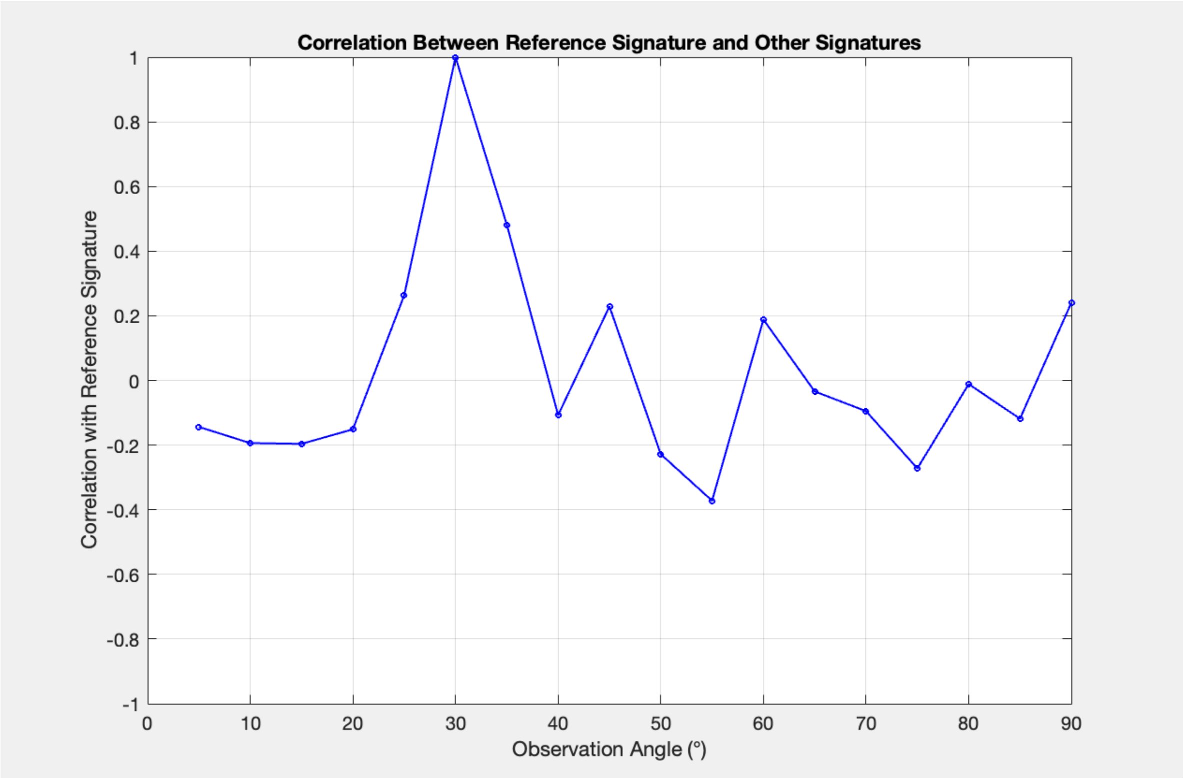


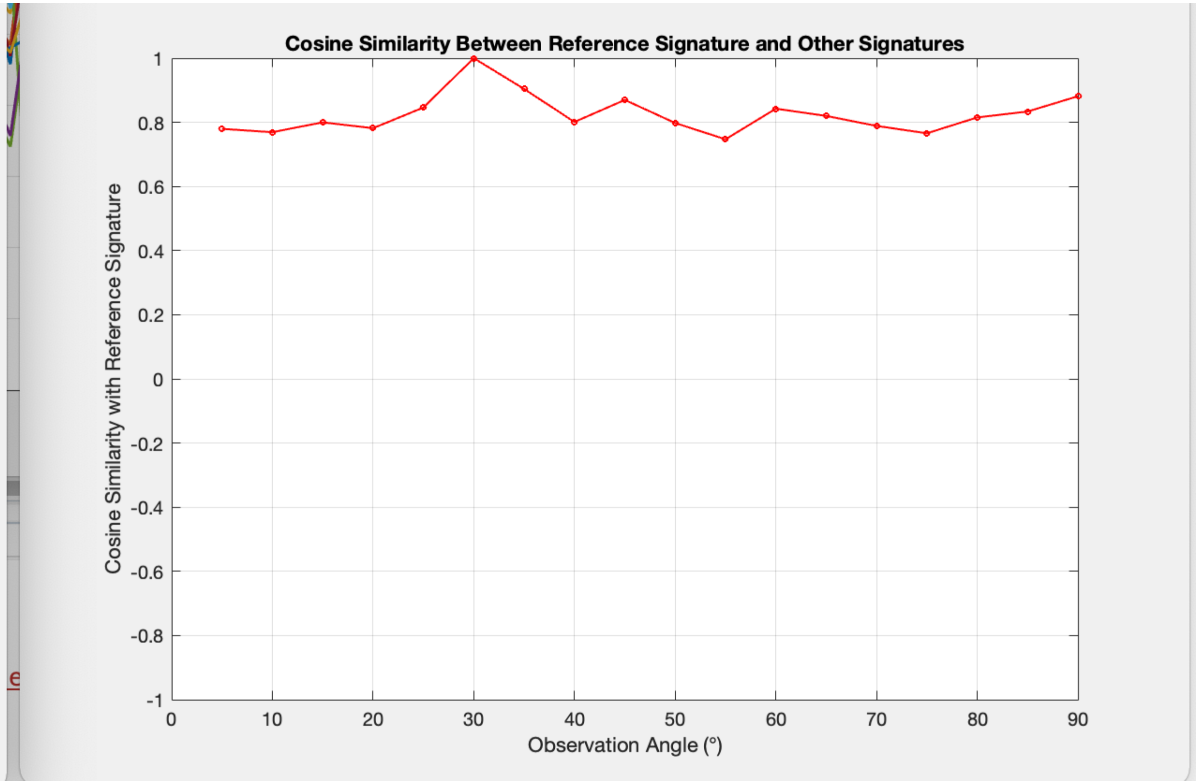
Reference as one of target angles (30 degrees)



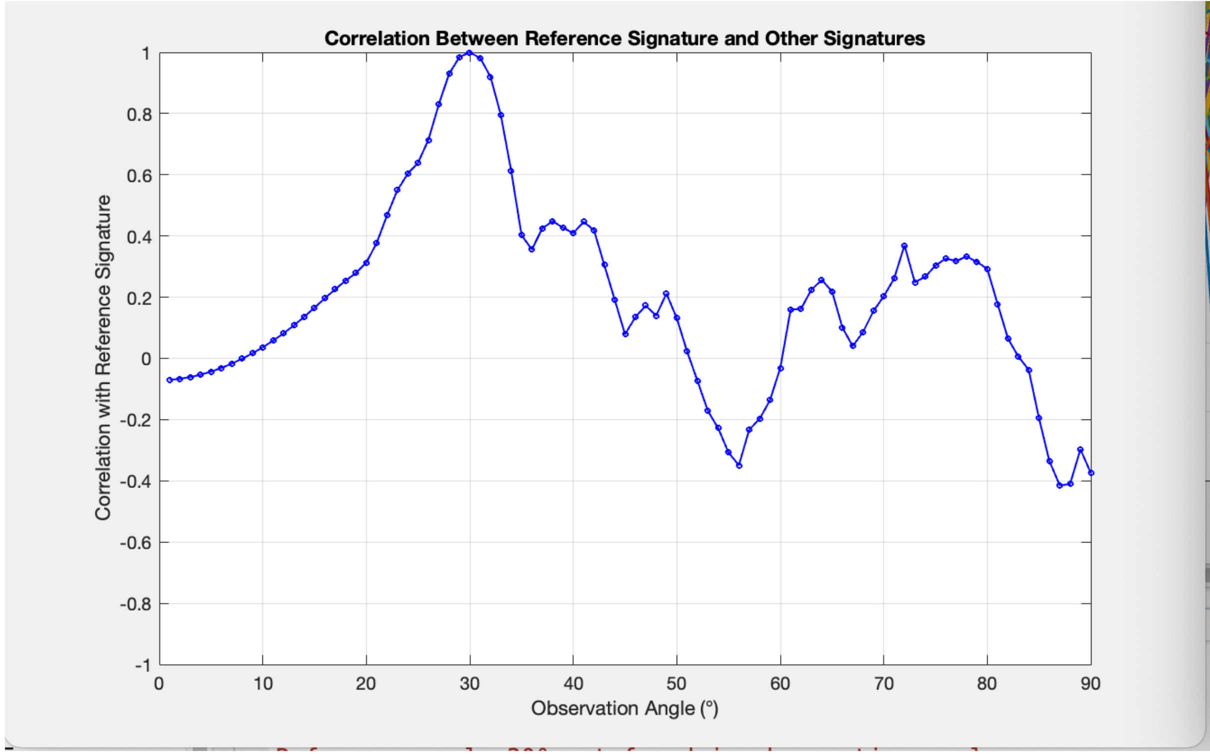


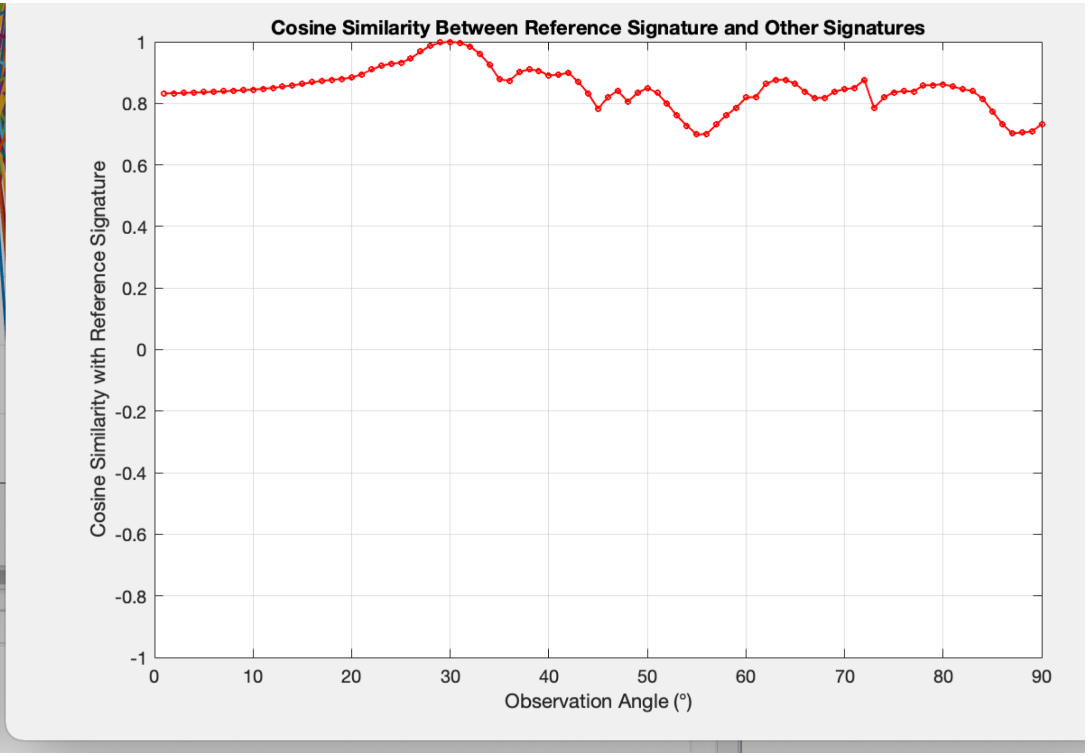
Few angles (18 angles)





Many observation angles (90 angles)

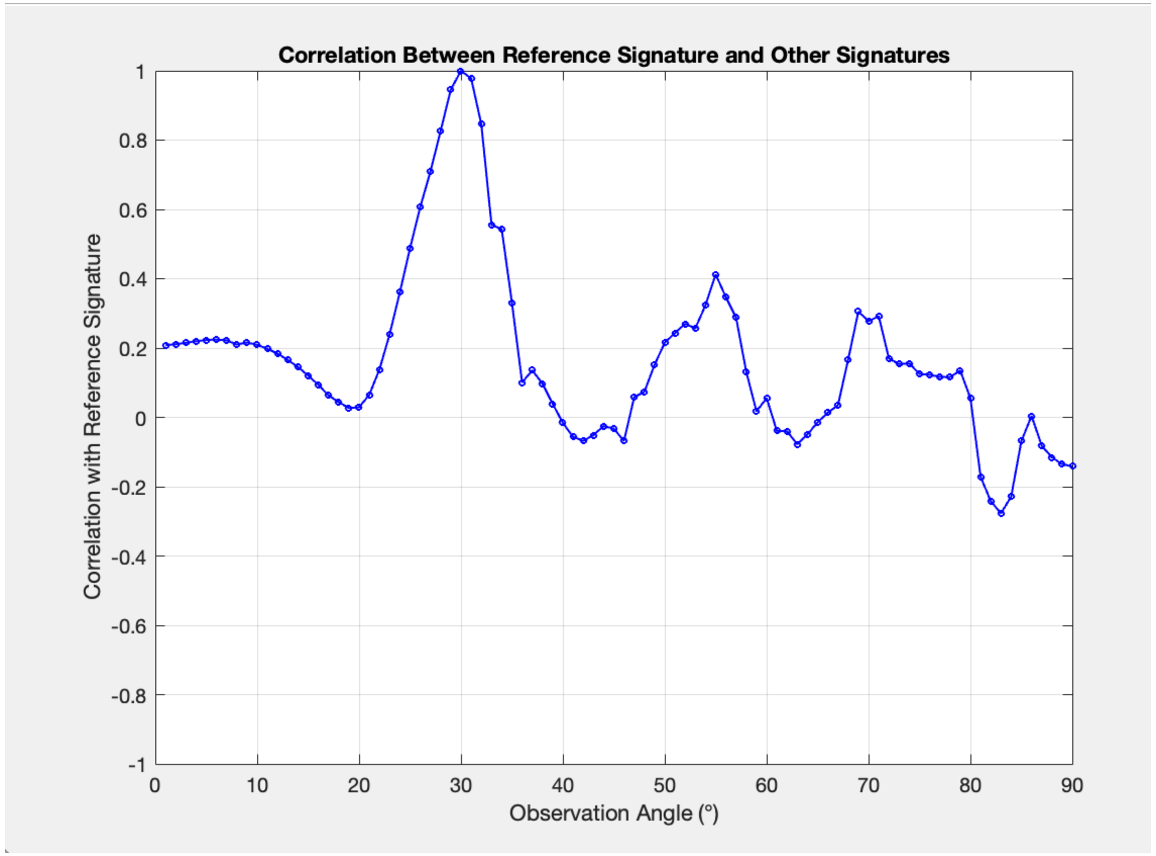




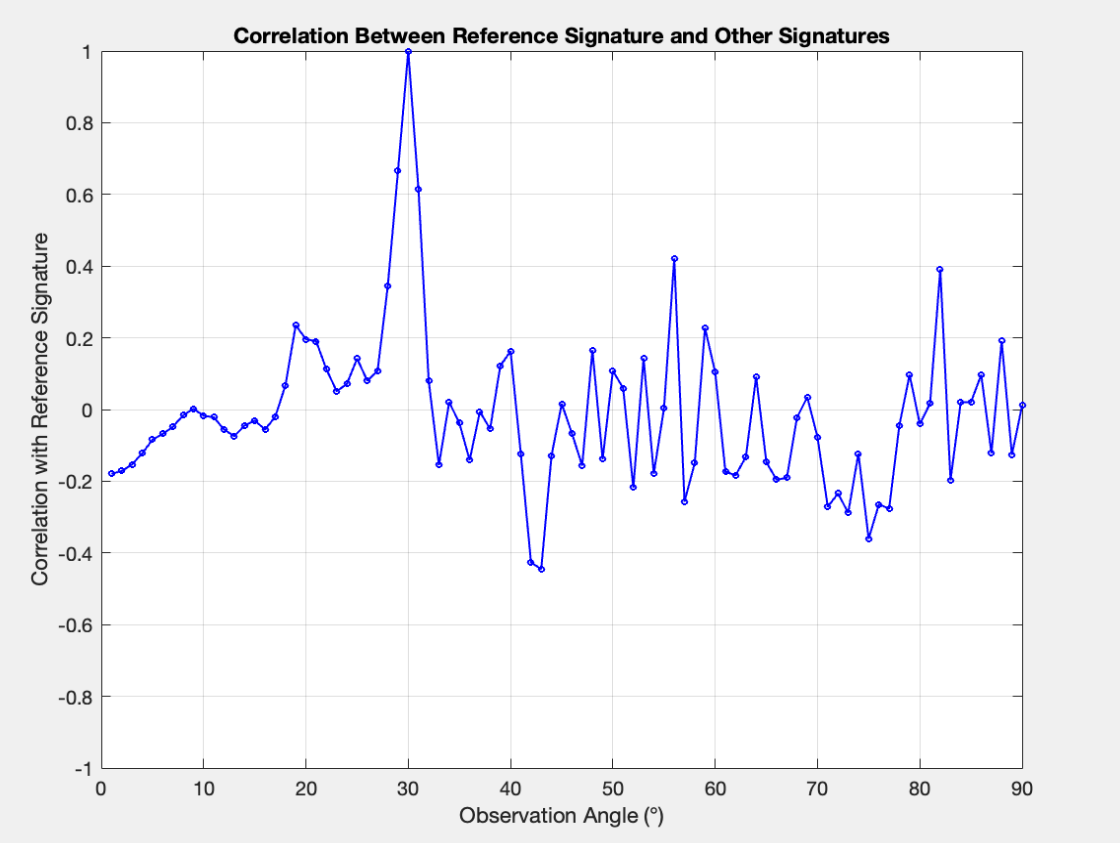
Effect of increasing Number of Antennas (N) on Correlation graph

- Increasing number antennas makes the highest peak isolated from other peaks hence increasing precision and clarity due to the high directivity and directionality
- Number of iterations = 30, reference angle == 30 degrees

N = 16



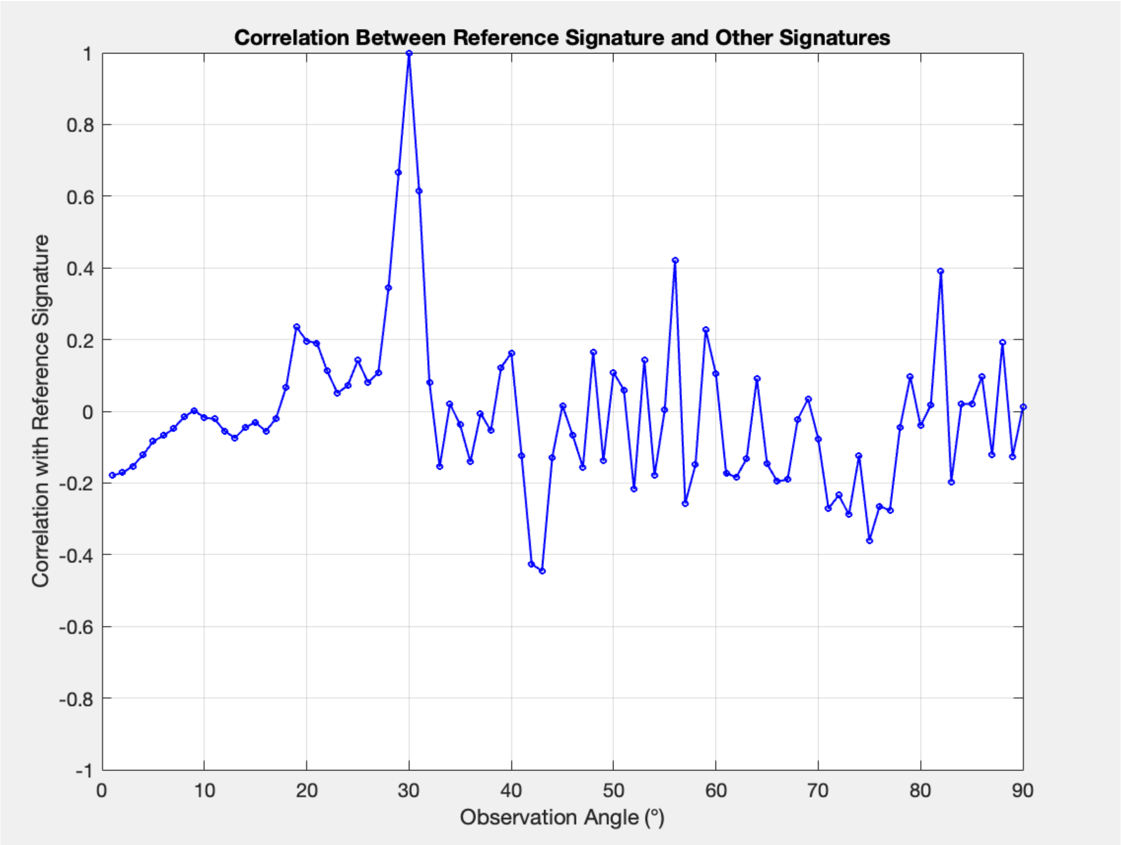
N = 64



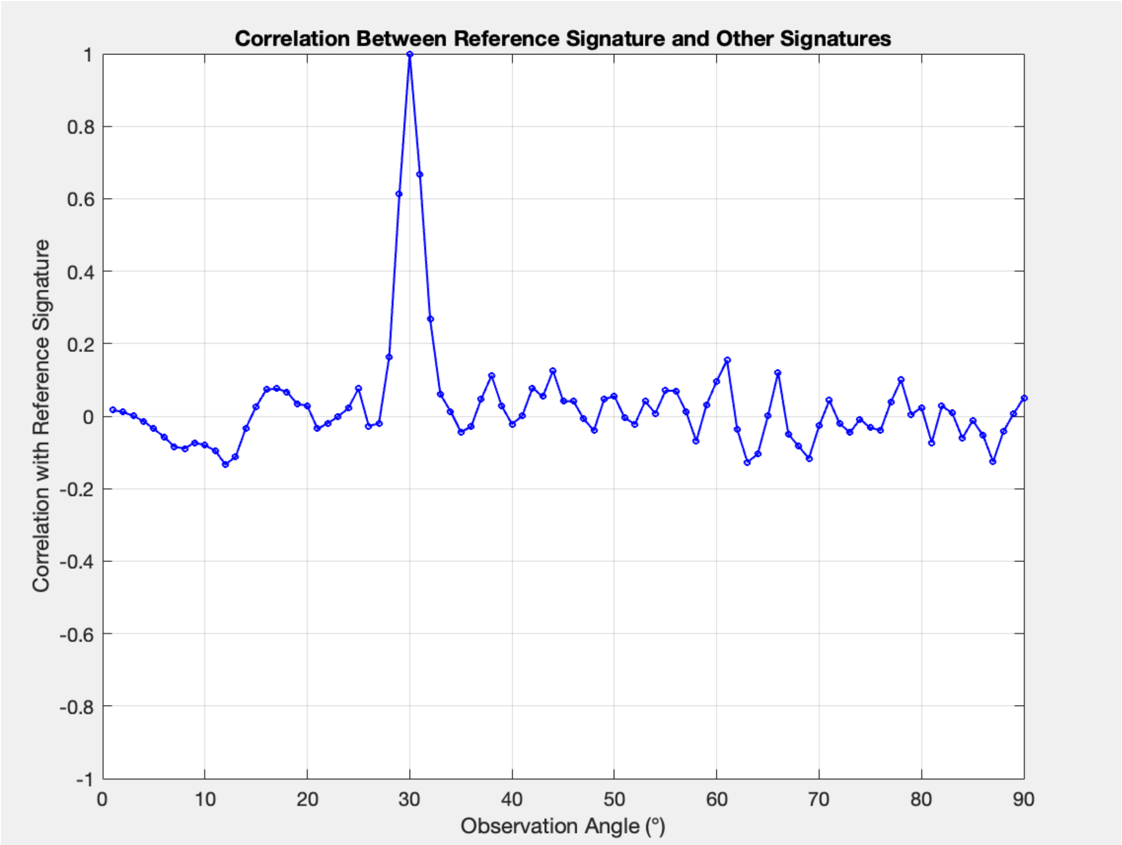
Changing number of iterations

- Increasing the number iterations eliminate the negative correlation values, makes the correlation pattern stable. Increasing iterations also minimiizes others peaks other than the main peak
- N = 16, reference angle = 30 degrees

Iterations = 30



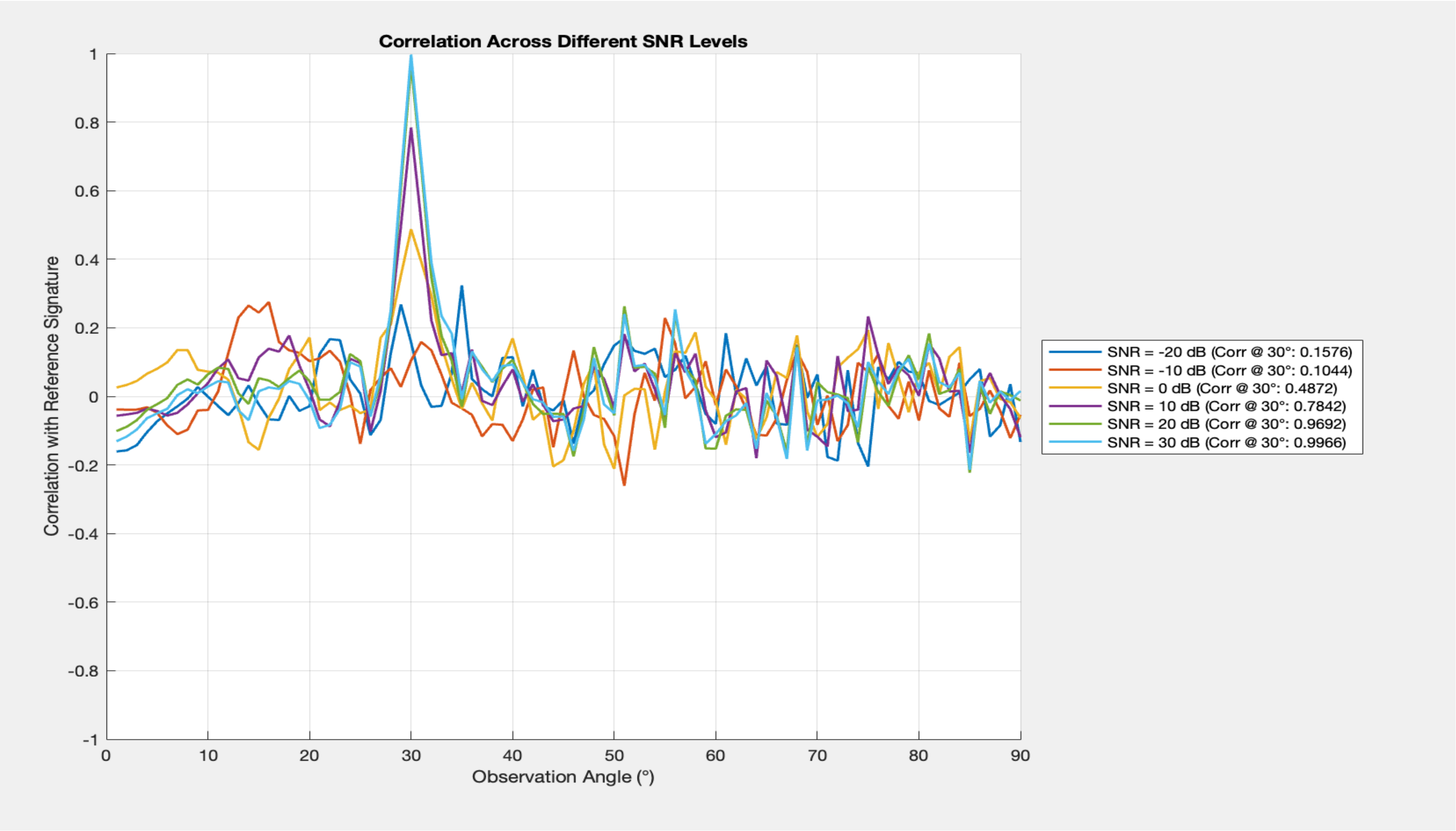
Iterations = 300



- Addition of white gaussian noise to the reference signal to see how the correlation values change for both methods
- AWGN allow us to model real-world fading channel
- Keep SNR, constant and plot the mean squared error curve for different number of iterations
- Keep the number of iterations constant, and plot the mean squared error curves for different SNRs

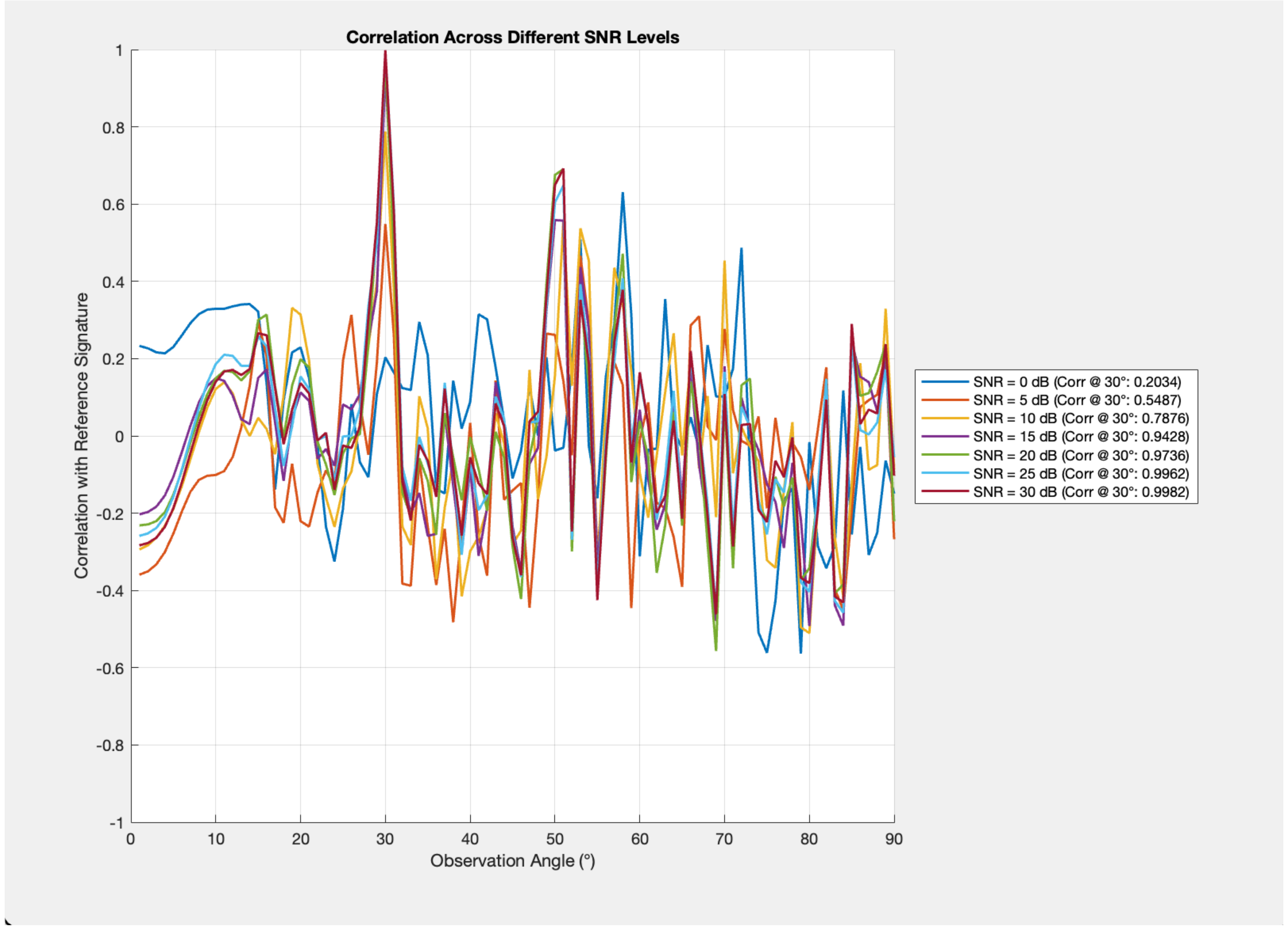
Correlation across different AWGN SNR levels

- Number of iterations = 100, N = 64. Increasing noise level reduces correlation due to signal distortions



- At low SNR, the peak doesn't appear at the target angle
- Multiple high peaks which makes it confusing
- At high SNR, peaks have high correlation and are distinct

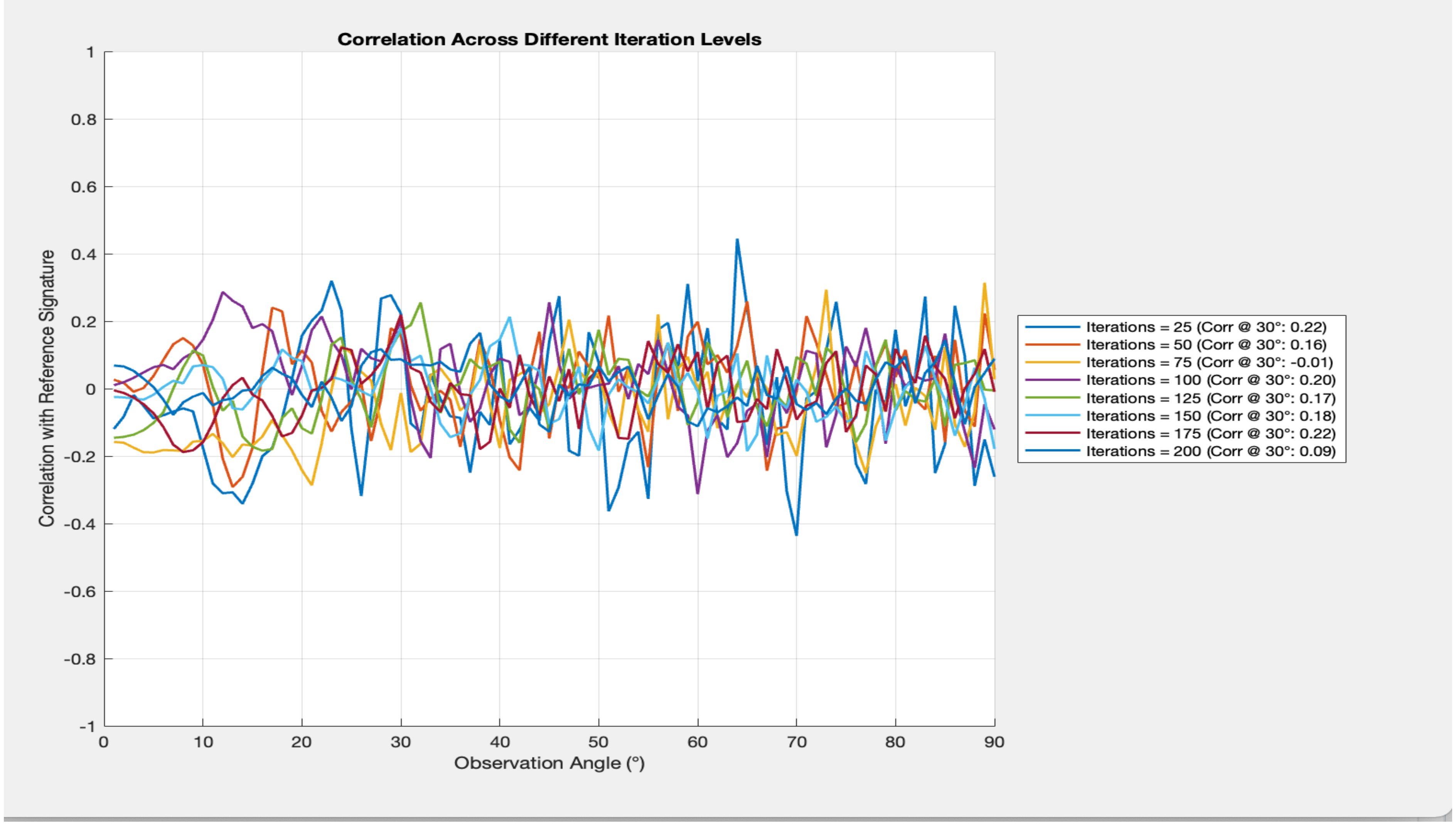
Few number of iterations



- There is still high peaks at high SNR but there are multiple high peaks

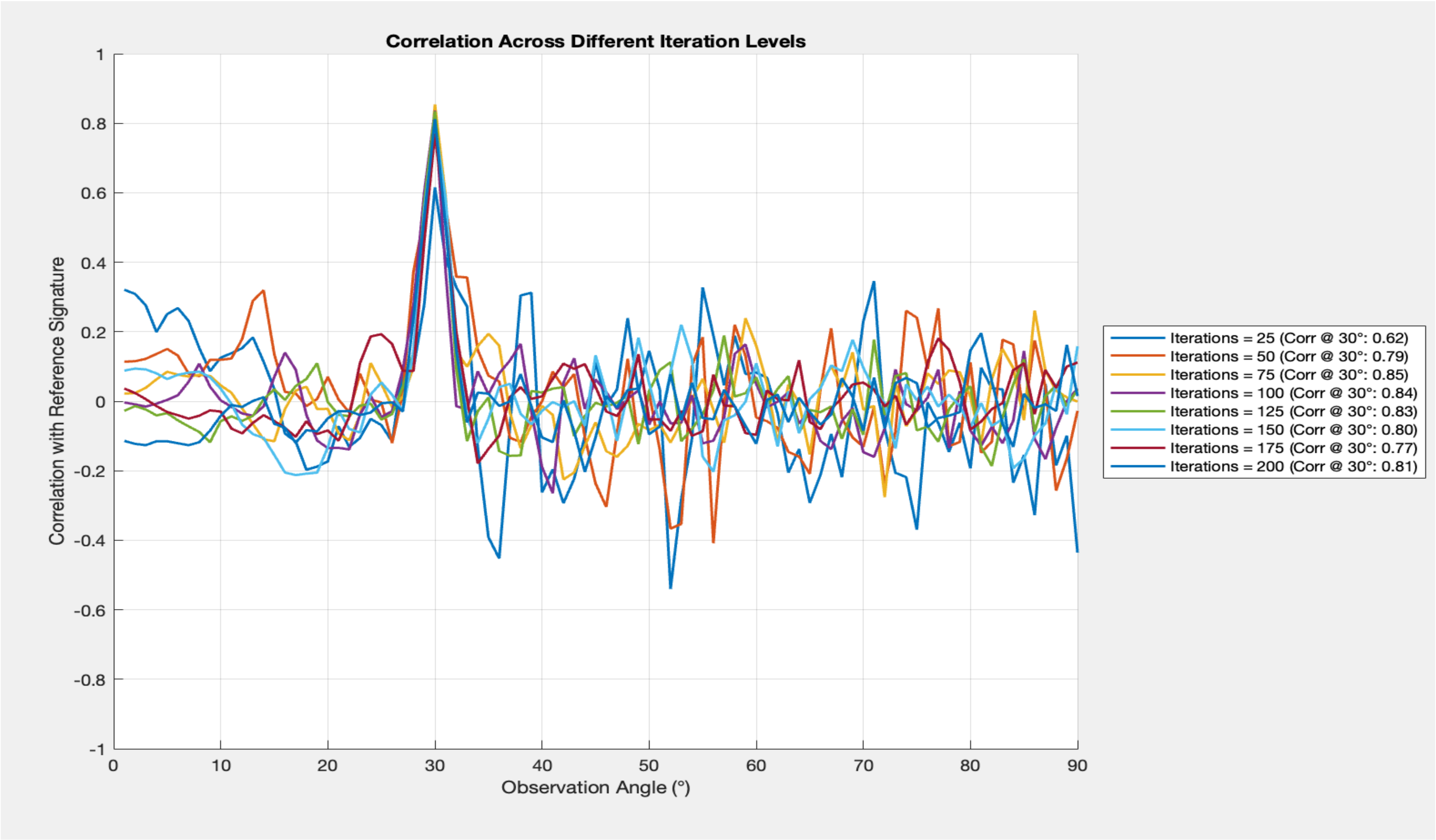
- Evaluating correlation across different number of iterations at different SNR levels

Correlation across different num_iterations



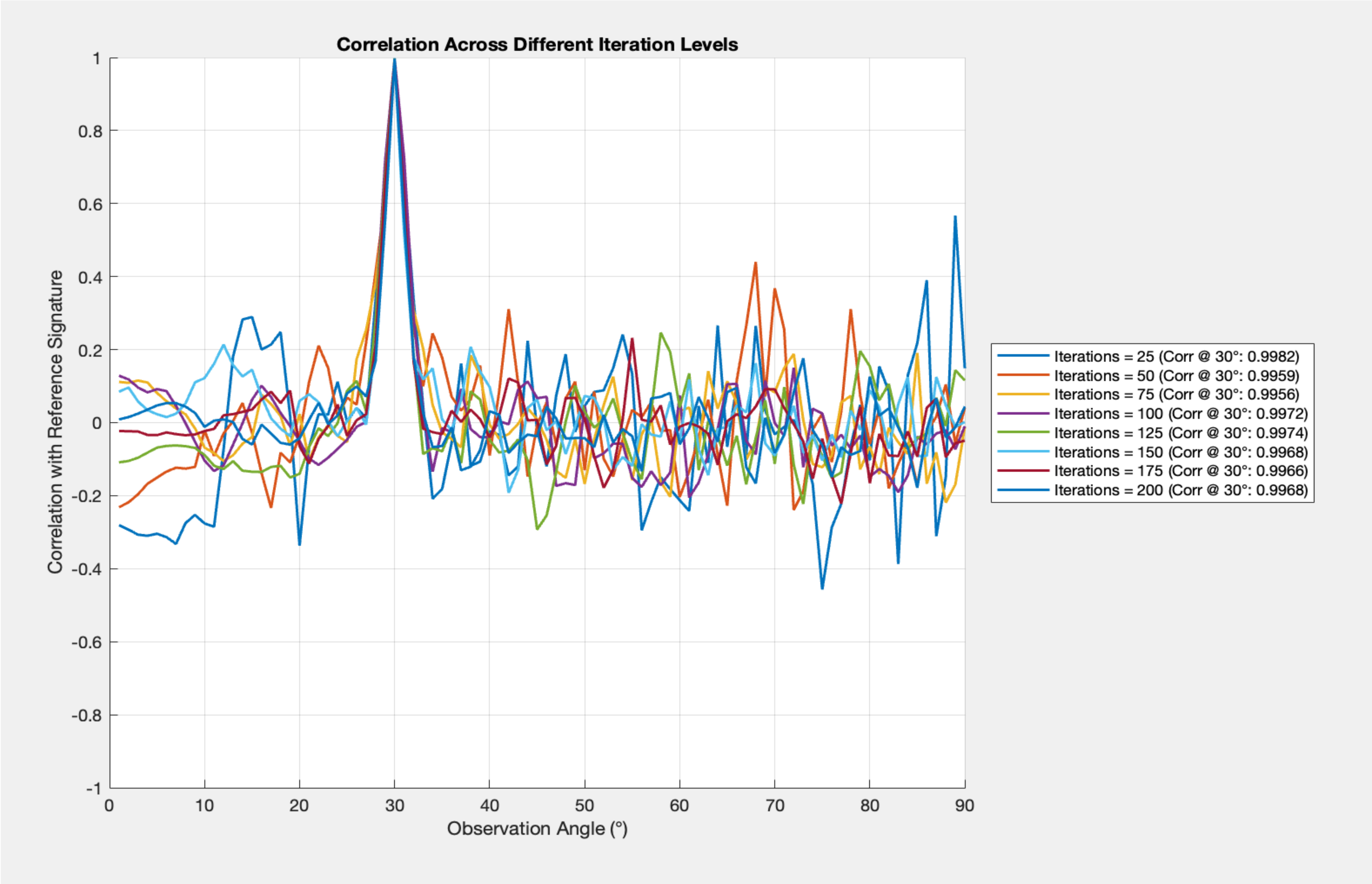
- SNR = -10 dB
- Target angle = 30
- N = 64

Correlation across different num_iterations



- SNR = 10dB
- N = 64
- Target angle = 30
- It doesn't seem like increasing number of iterations necessarily increases correlation
- The angle estimation accuracy has changed too

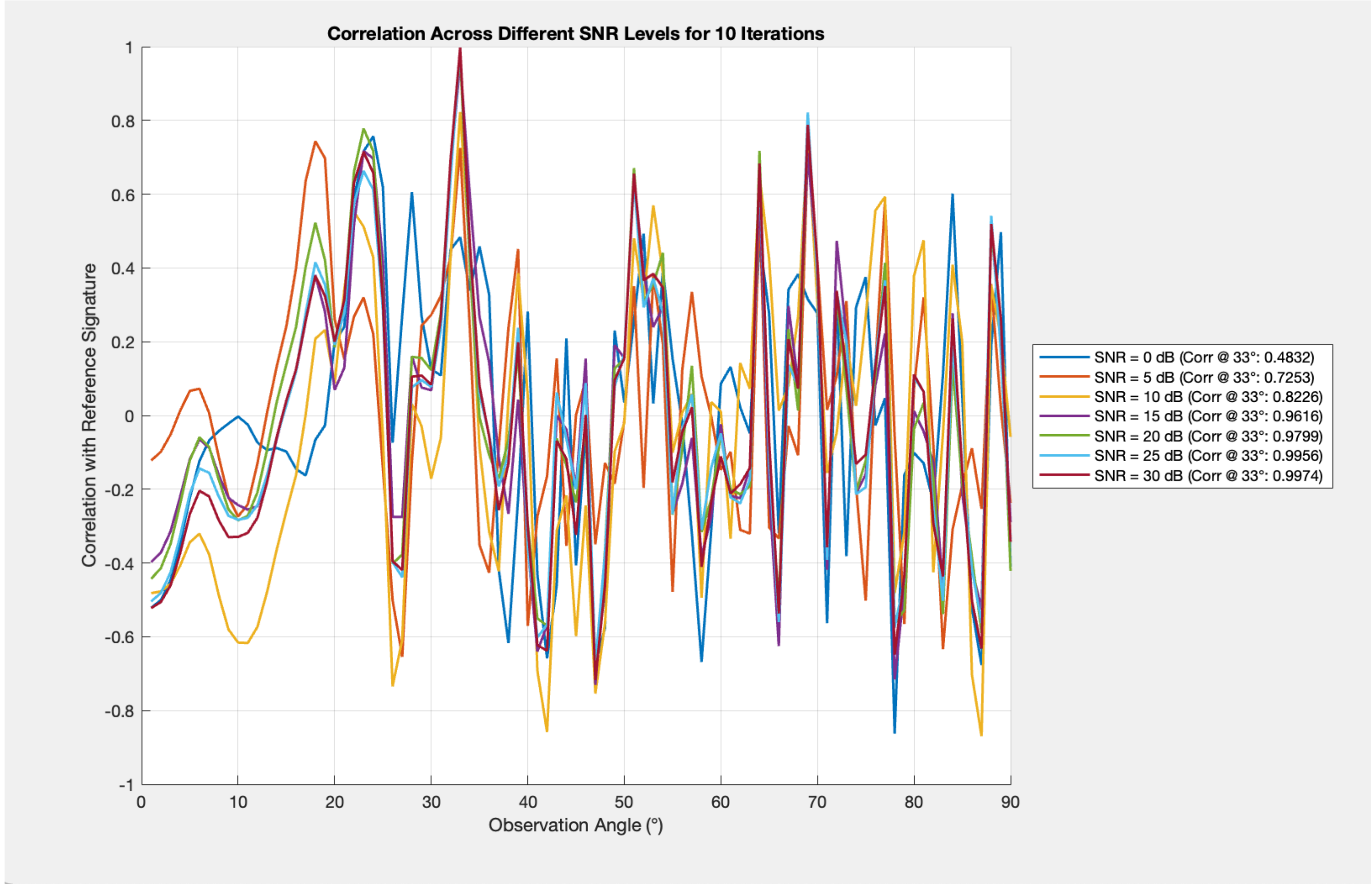
Correlation across different num_iterations



- SNR = 30 dB
- N = 64
- Target angle = 30

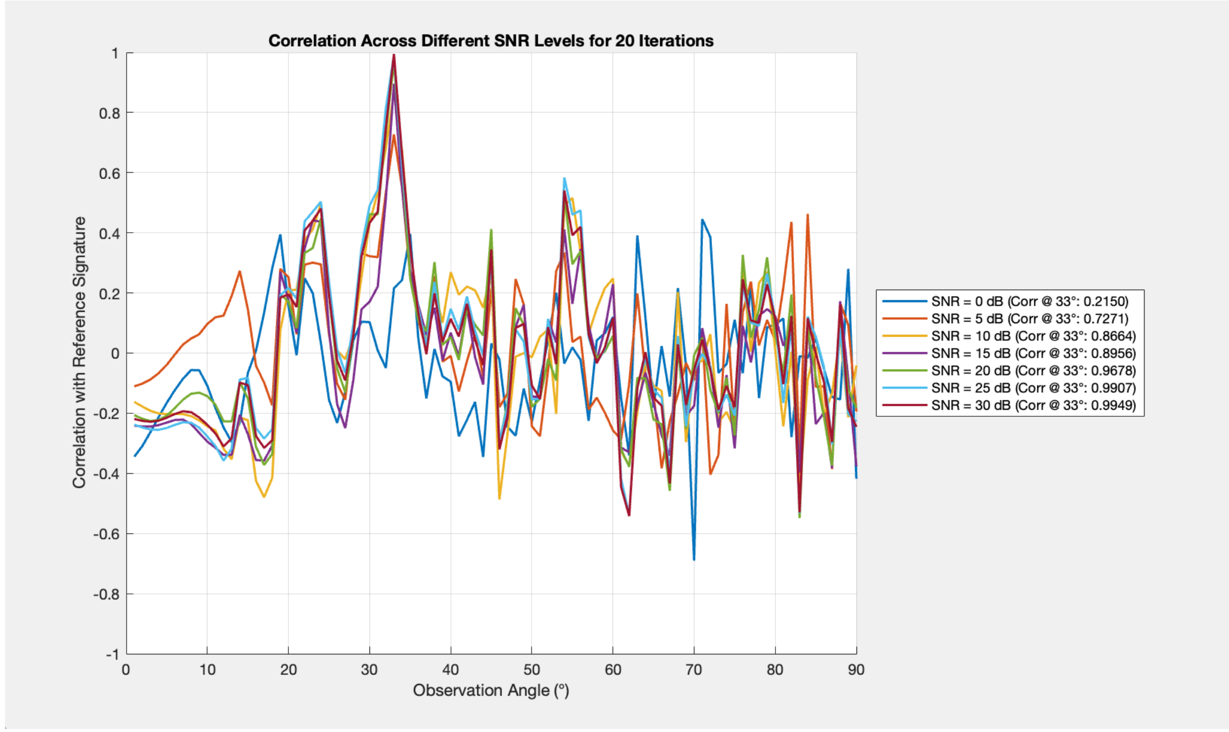
- Evaluating changes in correlation for different number of iterations and SNR
- Ref angle = 33, incident angle = 30, N = 64,

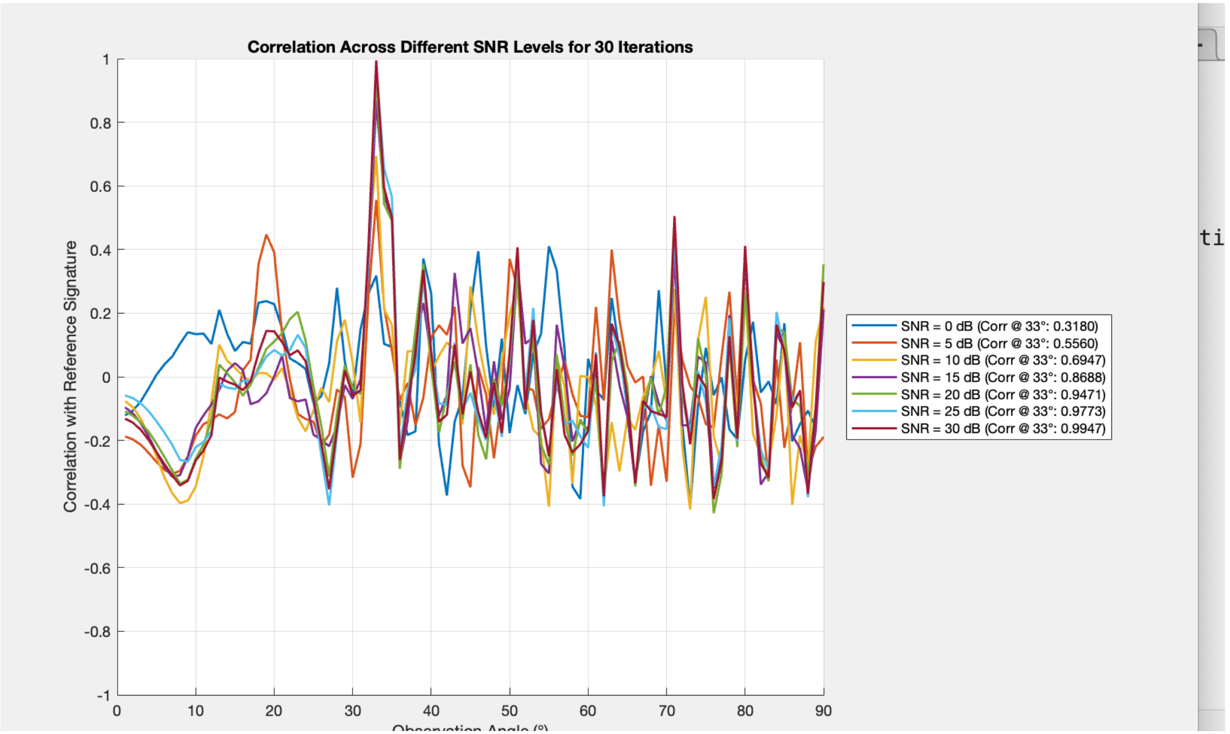
Correlation Variations at 10 iterations



- There are multiple high peaks hence less accuracy in angle estimation

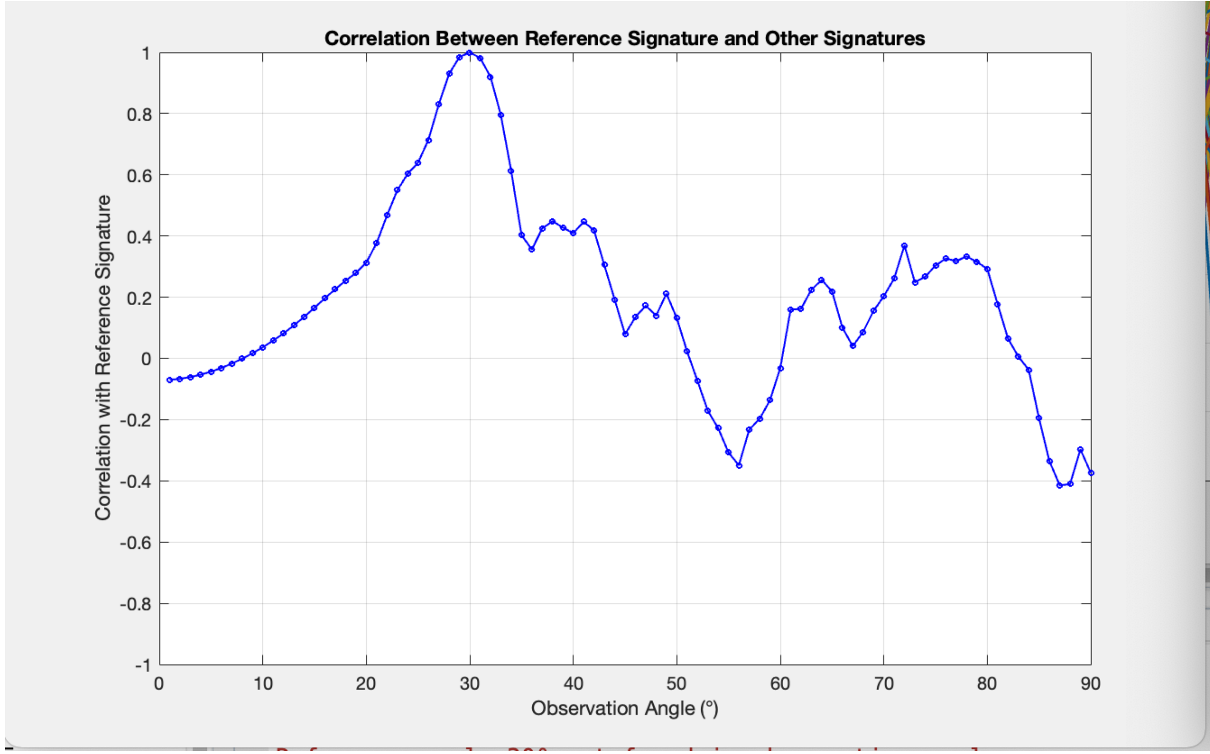
Correlation Variations at 20, 30 iterations

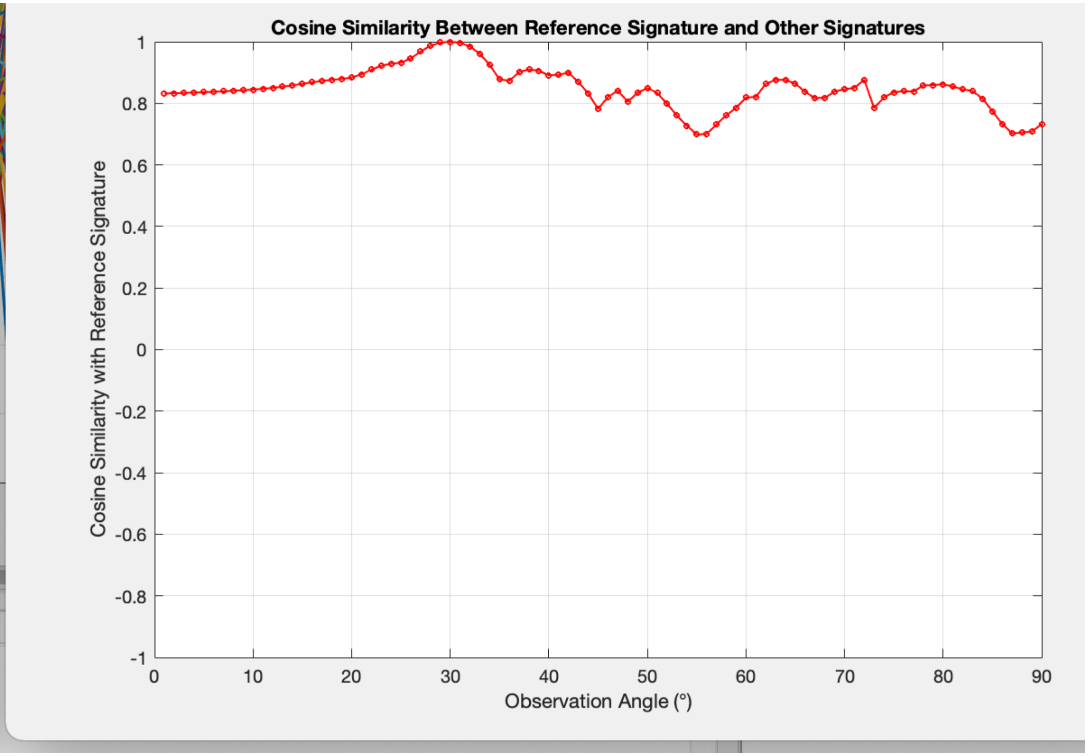




- Meeting with Yasaman

Many observation angles (90 angles)

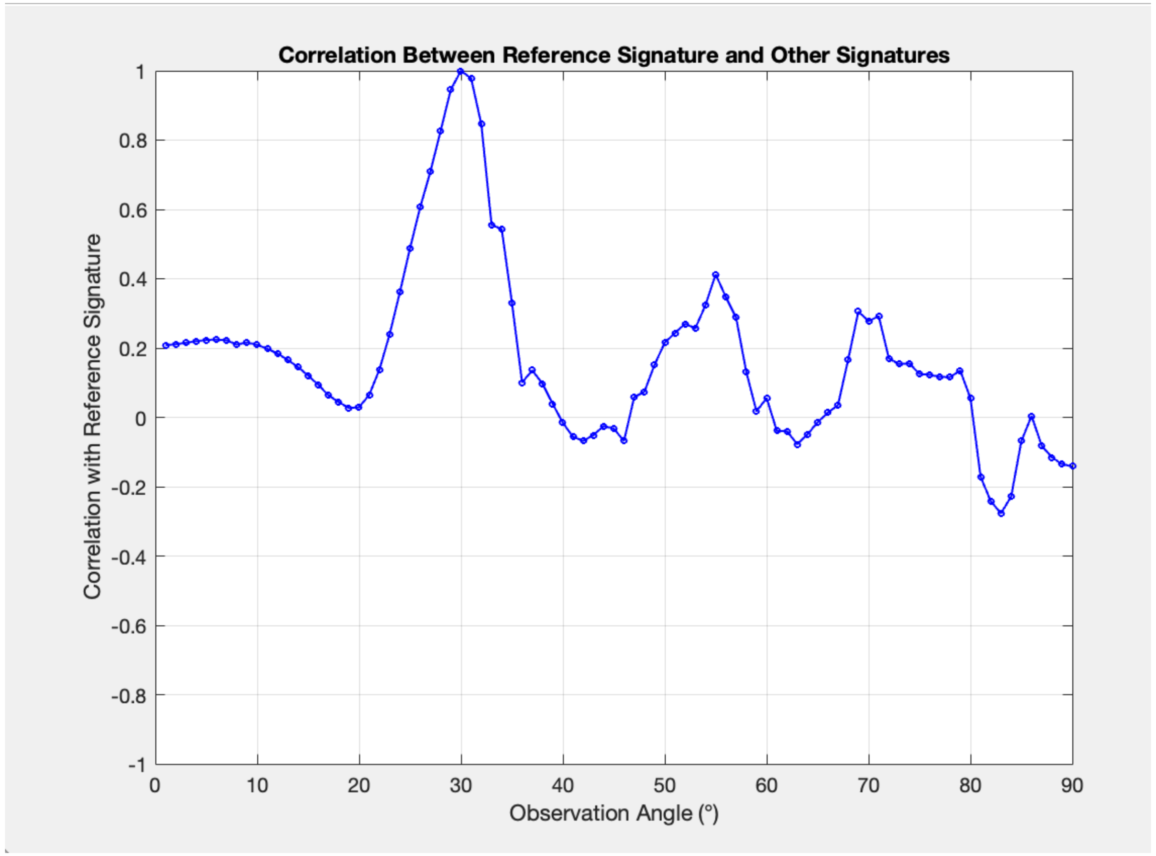




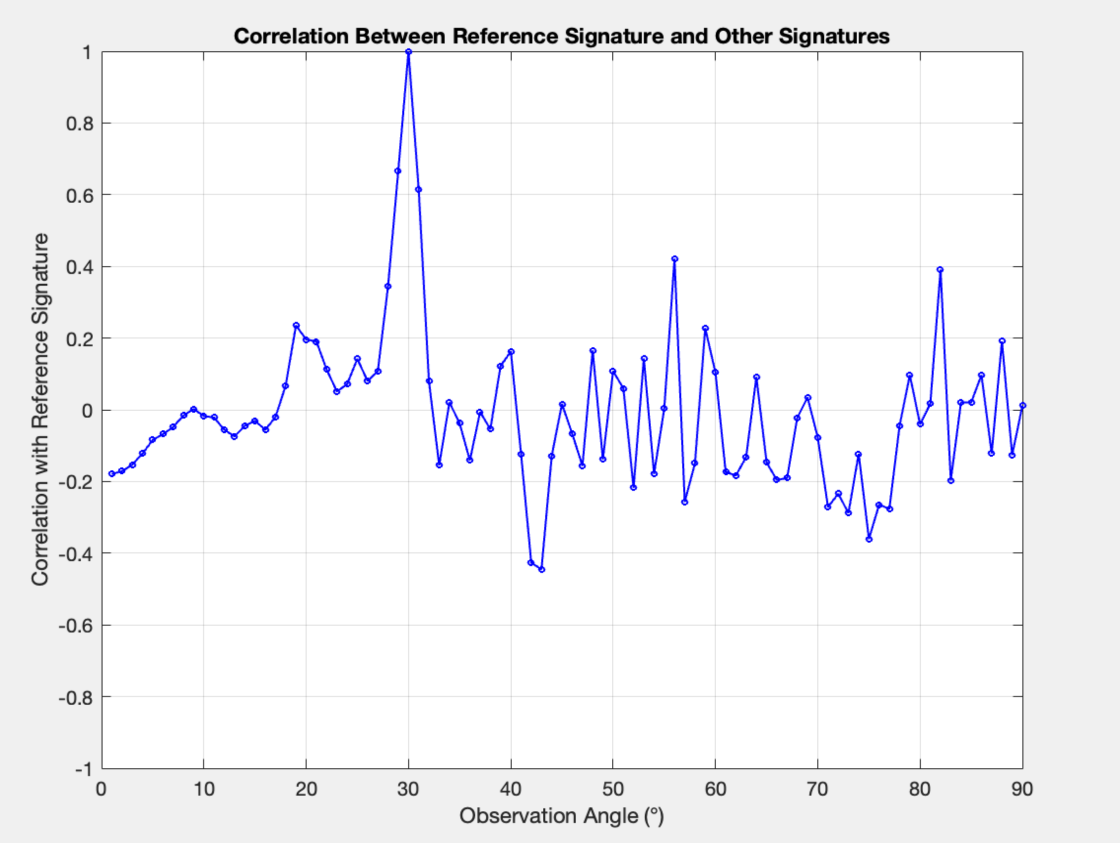
Effect of increasing Number of Antennas (N) on Correlation graph

- Increasing number antennas makes the highest peak isolated from other peaks hence increasing precision and clarity due to the high directivity and directionality
- Number of iterations = 30, reference angle == 30 degrees

N = 16



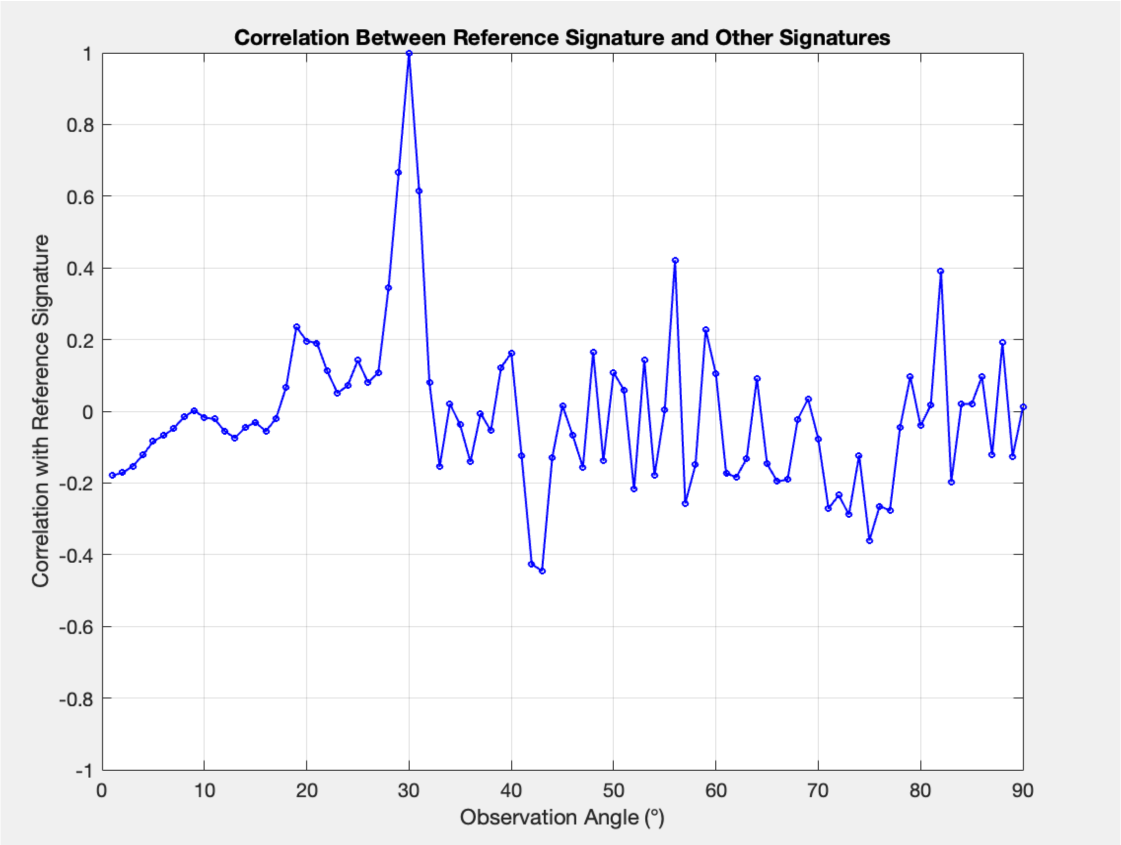
N = 64



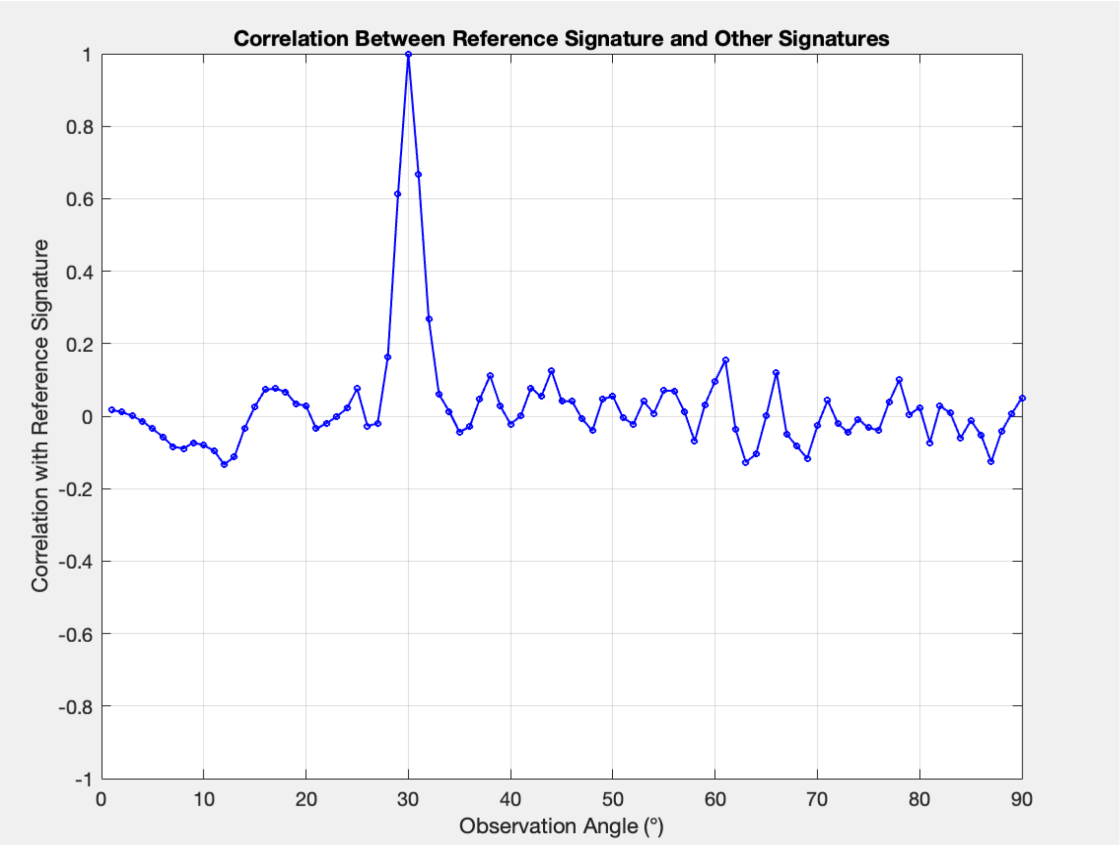
Changing number of iterations

- Increasing the number iterations eliminate the negative correlation values, makes the correlation pattern stable. Increasing iterations also minimiizes others peaks other than the main peak
- N = 16, reference angle = 30 degrees

Iterations = 30



Iterations = 300



Addition of white gaussian noise to the reference signal to see how the correlation values change for both methods

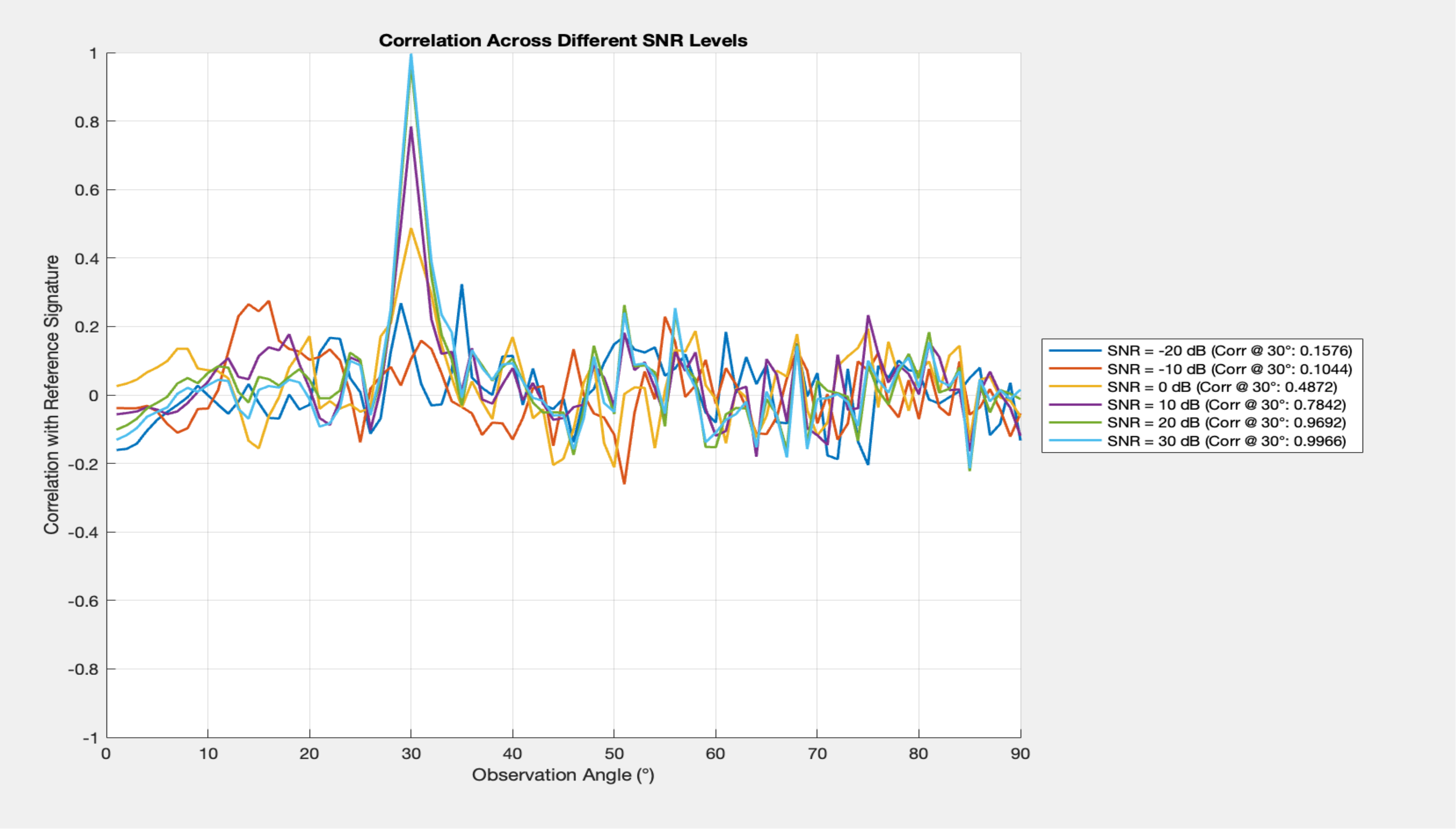
AWGN allow us to model real-world fading channel

Keep SNR, constant and plot the mean squared error curve for different number of iterations

Keep the number of iterations constant, and plot the mean squared error curves for different SNRs

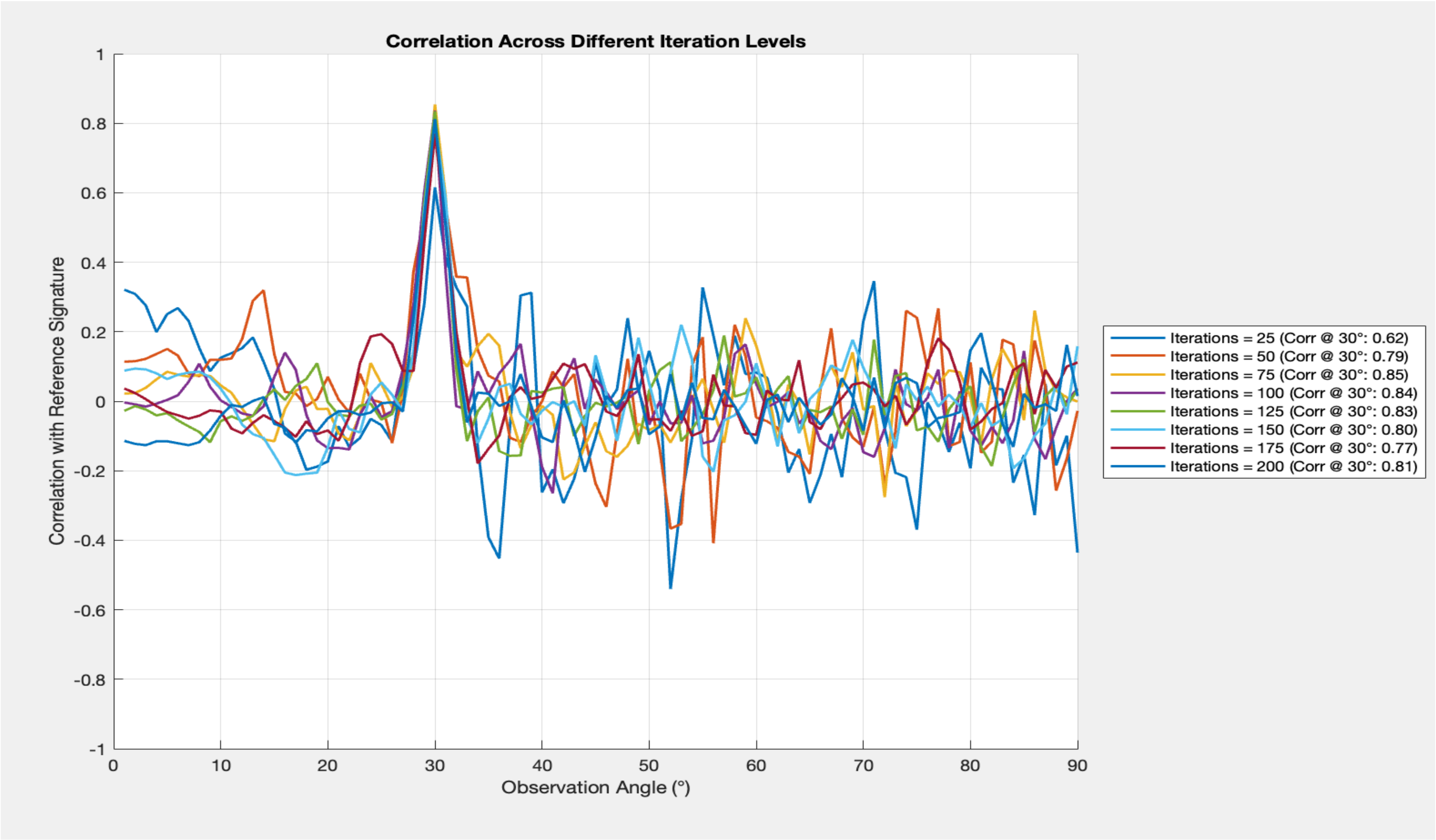
Correlation across different AWGN SNR levels

- Number of iterations = 100, N = 64. Increasing noise level reduces correlation due to signal distortions



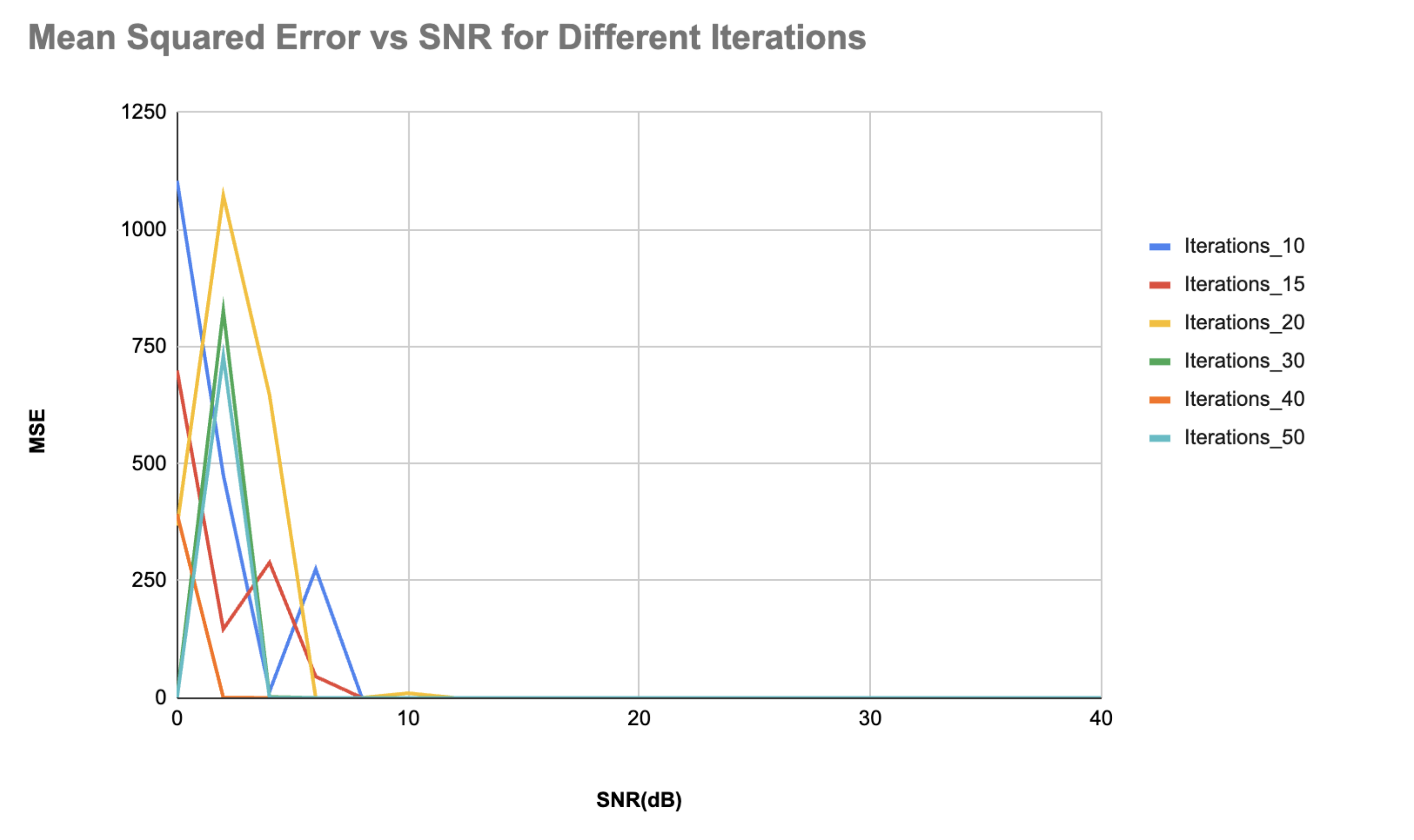
- At low SNR, the peak doesn't appear at the target angle
- Multiple high peaks which makes it confusing
- At high SNR, peaks have high correlation and are distinct

Correlation across different num_iterations

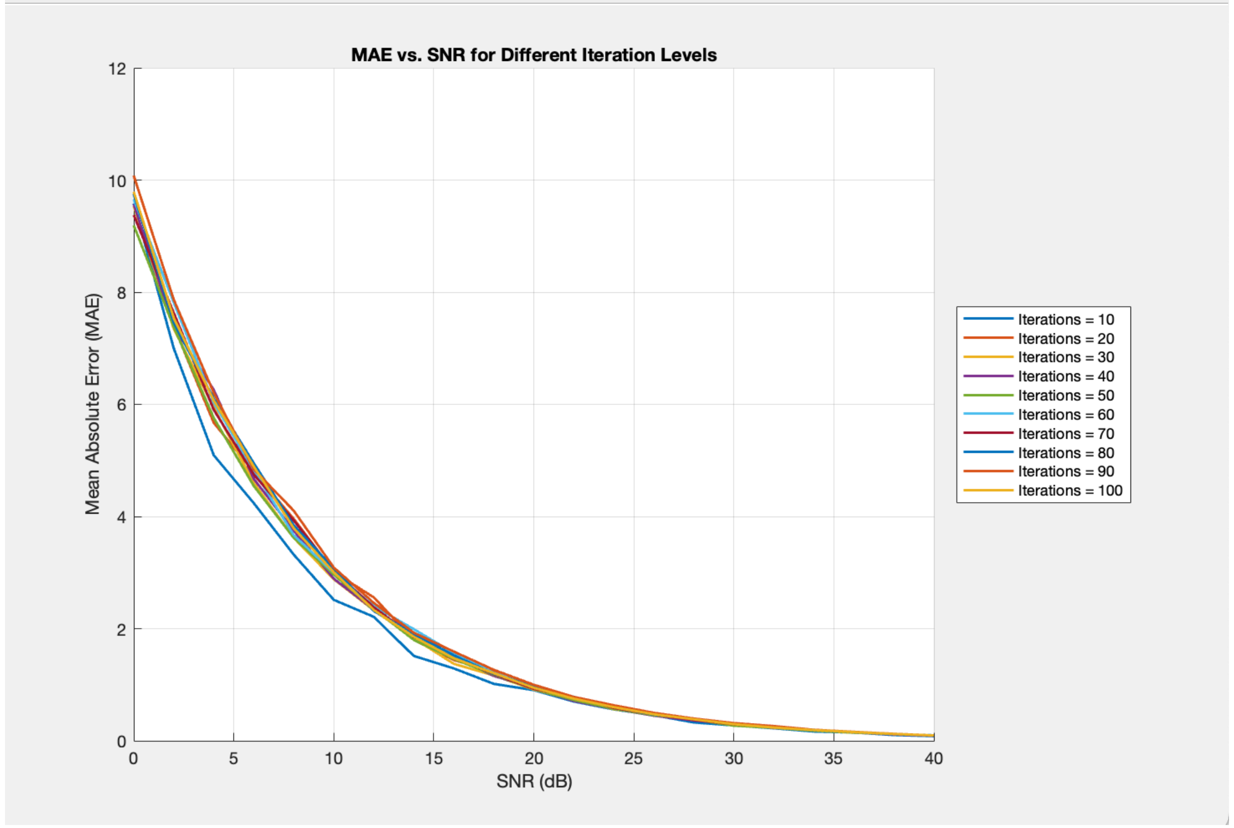


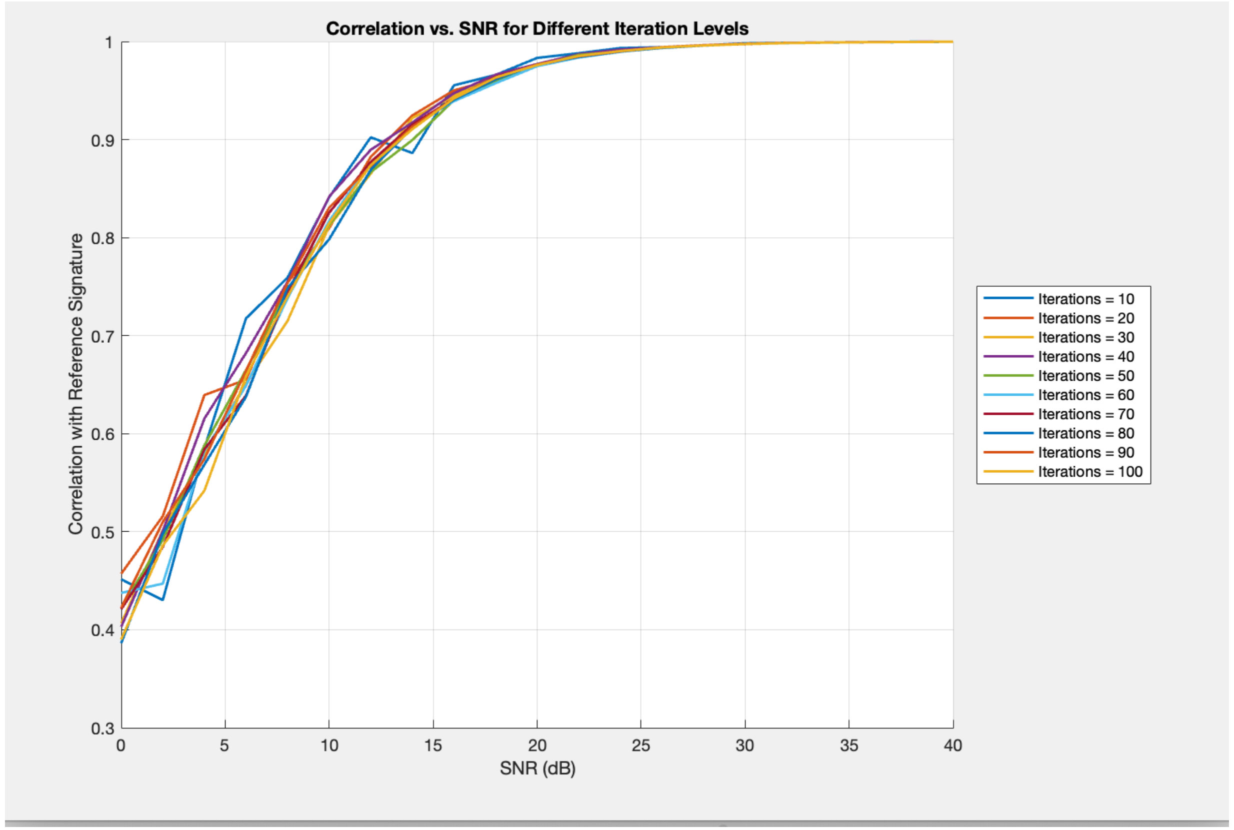
- SNR = 10dB
- N = 64
- Target angle = 30
- It doesn't seem like increasing number of iterations necessarily increases correlation
- The angle estimation accuracy has changed too

MSE vs SNR Graph for different iterations



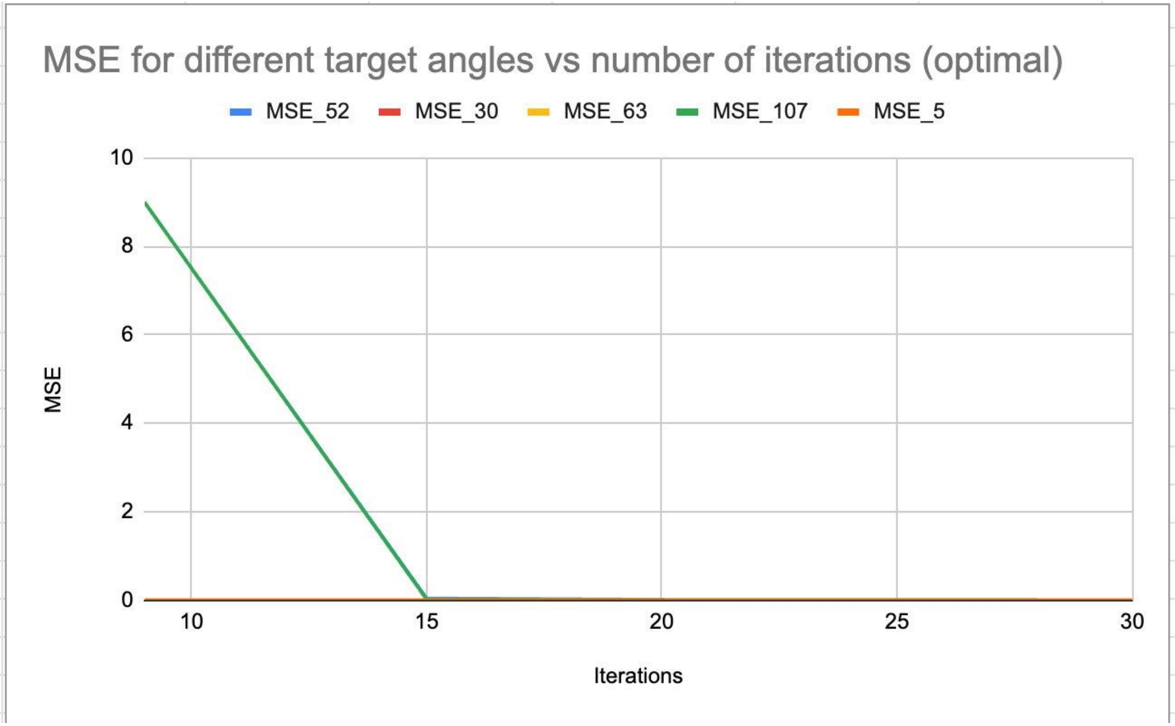
MAE and Correlation for iter/SNR



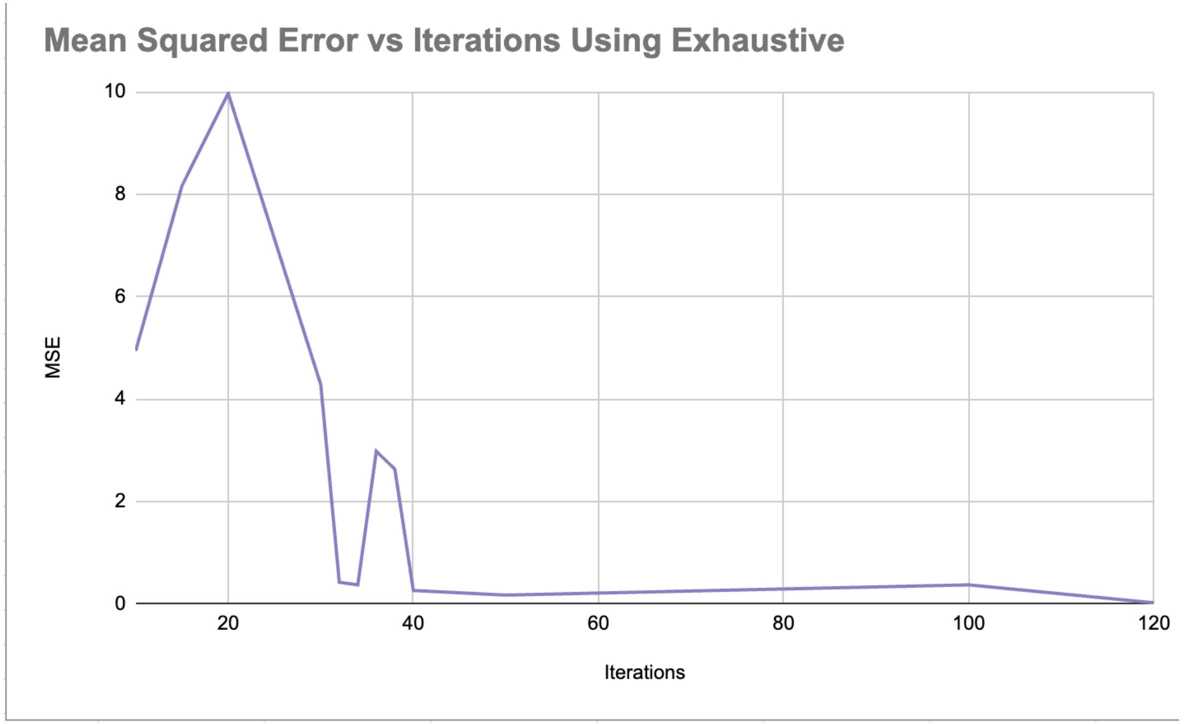


MSE for Exhaustive and Hierarchical

Hierarchical



Exhaustive



New Approach 1, Simple Moving Average

- 1️⃣ **Compressive Sensing (CS)**
- Initial full-angle sweep to find rough user position.
- Periodically re-run if **confidence score drops**.
- 2️⃣ **Hierarchical Beam Searching (HB)**
- Focus search within the CS-detected region.
- Dynamically **prune weak angles early** to reduce overhead.
- 3️⃣ **Confidence-Weighted SMA**
- Smooth angle predictions based on historical estimates.
- Give higher weight to high-confidence estimates.
- 4️⃣ **Adaptive Search Switching**
- If SMA indicates high variance in tracking → switch to **earlier exhaustive search**.
- If SMA is stable → **skip exhaustive search**.
- 5️⃣ **Exhaustive Search (Last Resort)**
- Only used **if hierarchical search and SMA fail** to converge.
- **Uses a smaller search window** than standard exhaustive search.

Approach 2, Gaussian Process Regression

- 1️⃣ **Start with Compressive Sensing (CS) for Initial Angle Estimation**
- This finds an initial **user location estimate**.
- 2️⃣ **Apply GPR to Predict the Next User Angle**
- Train GPR using past beam training data.
- Predict the **next expected user angle** with confidence scores.
- 3️⃣ **If GPR Confidence Score is High:**
- Use the predicted angle for beam steering.
- 4️⃣ **If GPR Confidence Score is Low:**
- Perform **Hierarchical Beam Search (HBS)** to refine the estimate.
- 5️⃣ **If HBS Confidence Drops Again:**
- Use **SMA to stabilize the prediction**.
- If SMA also fails, switch to **Exhaustive Search** for a precise fix.

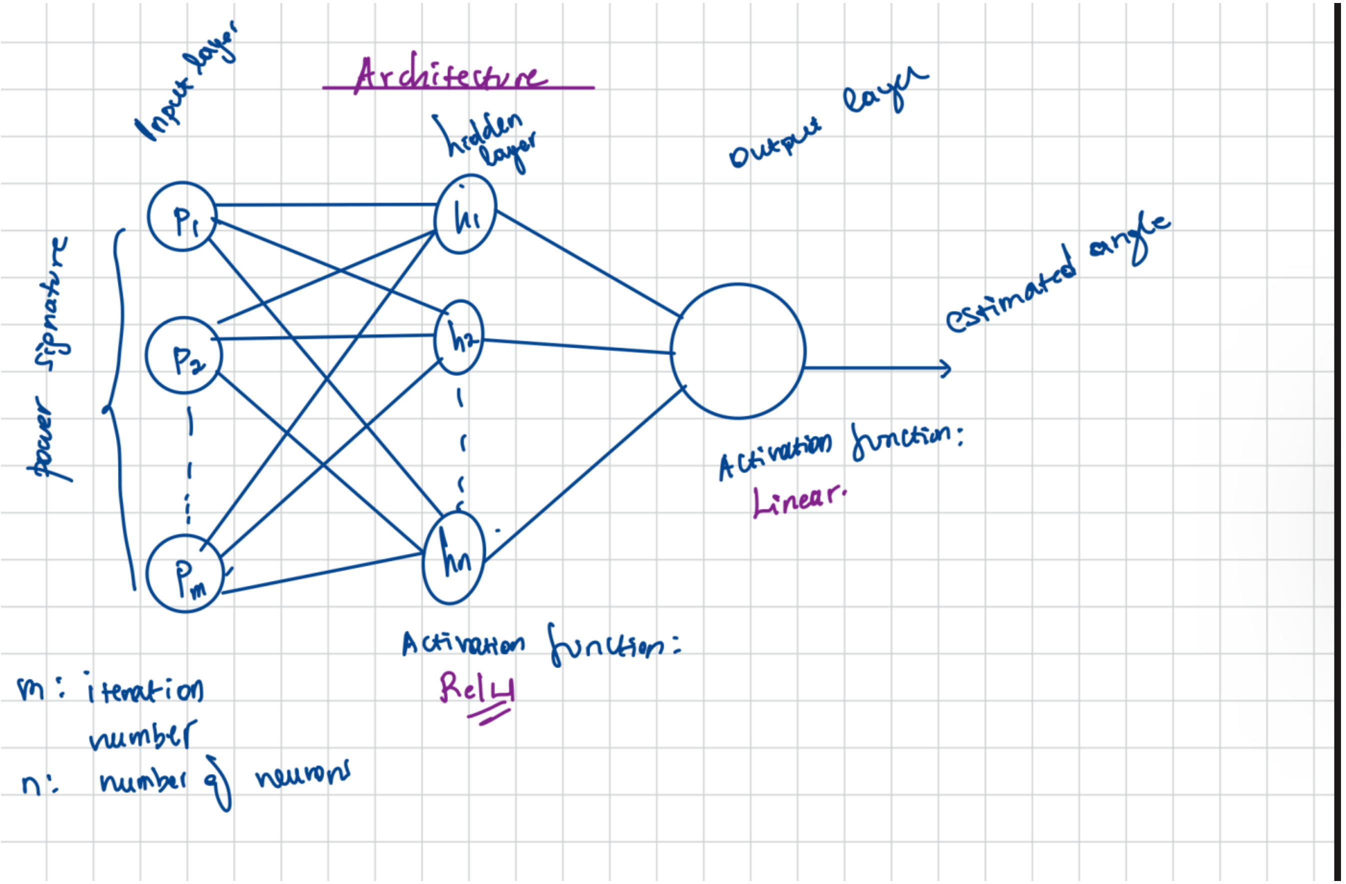
The Neural Network Idea

- **Goal**: Design a regression – based NN model to learn complicated non – linear relationships between the power signatures (both clean and noisy) and their corresponding target angles.
- The power signatures are generated using compressive sensing to mimic a multipath and noisy channel
- Rayleigh Fading channel model: $\boldsymbol{e}^{j\emptyset}$ where $\emptyset = 2 * \pi * rand(N, 1)$
- Tx – RIS channel = $\boldsymbol{e}^{j\emptyset}\boldsymbol{e}^{j*\pi*\cos\theta*(0:N-1)'}$ where θ is incident angle
- Consider Rician channel which considers the dominant path!

Power Signature	SNR Level	Angle label
clean	No noise	10°
noisy	0 dB	10°
noisy	10 dB	10°

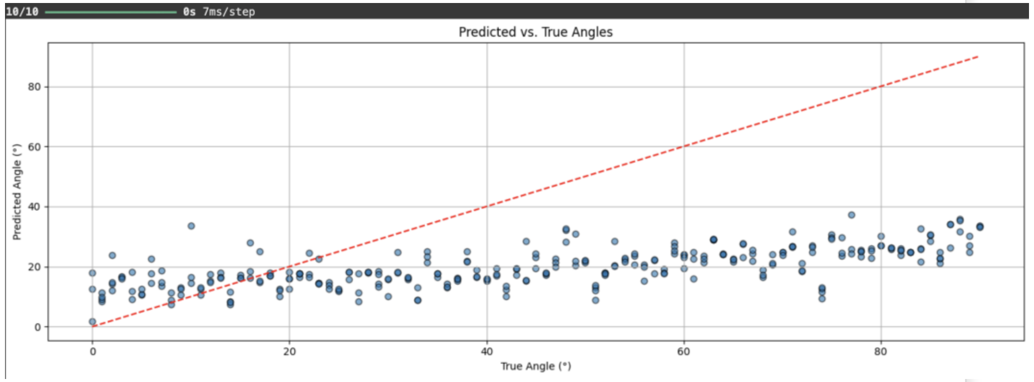
Model Architecture

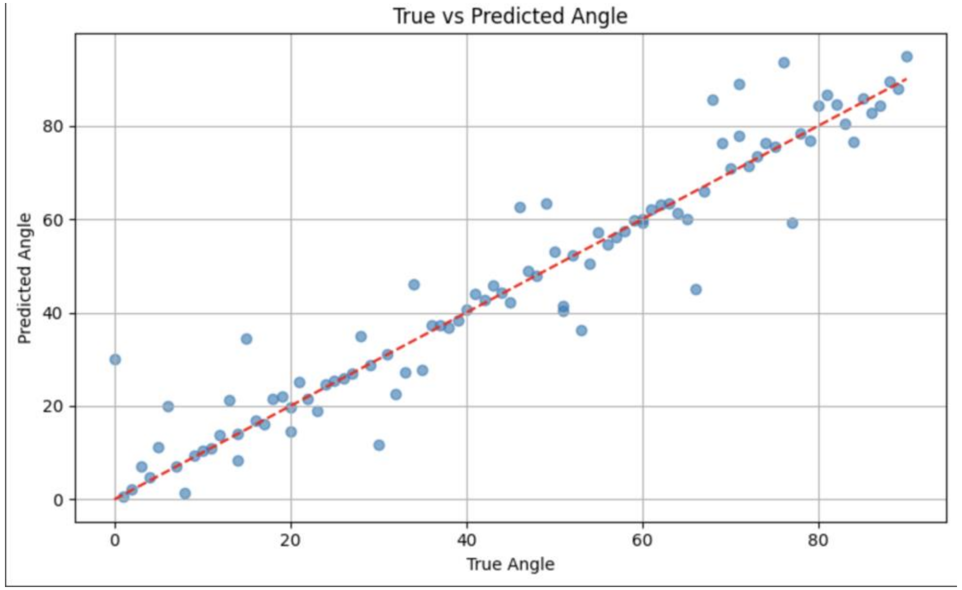
- The Input layer consists of the power signatures
- The activation function for hidden layers is **RelU**: max (0, x)
- Activation function for output layer is **Linear** in order to predict a continuous variable (angle estimation)
- Optimization models : Adam, Stochastic Gradient Descent (SGD)
- Loss function: MSE



Sequential NN (Tensorflow)

- Each layer feeds into the next
- Best used for large datasets with complex patterns
- Input dataset: each angle has 16 rows
- Not accurate as of now

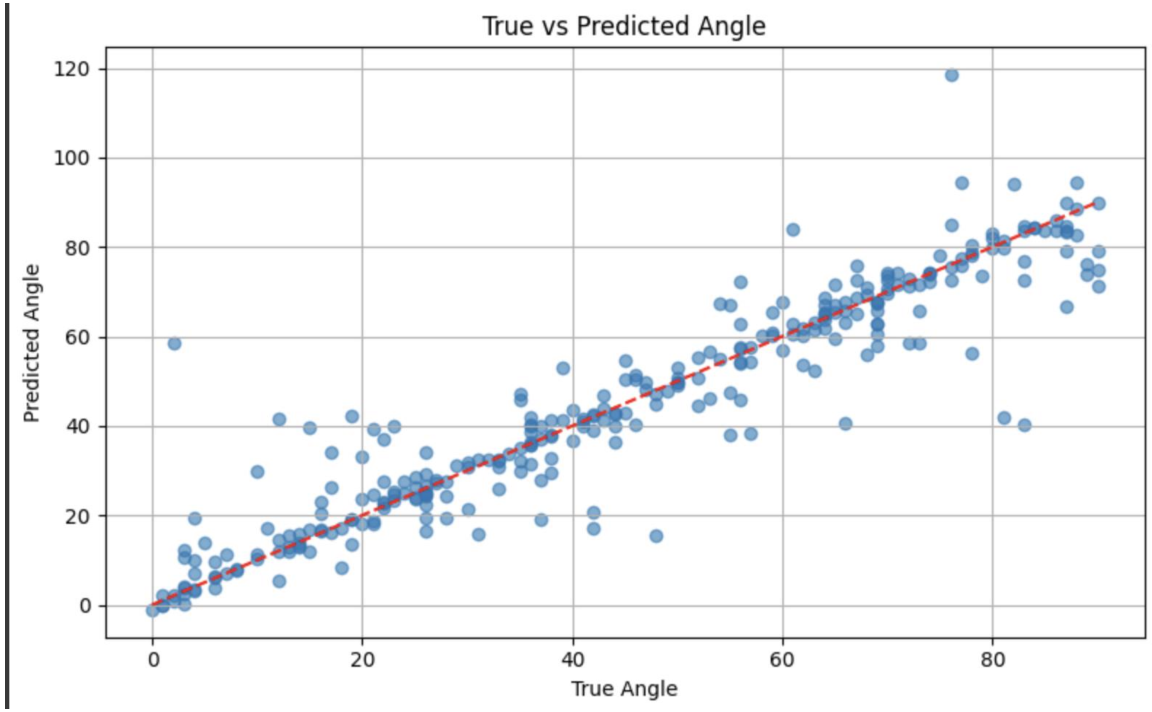




Hidden layers	Final MAE	Predictions
100, 50,25	Training: 1.5 Validation: 5.6	Actual: 41 Predicted: 37.78
		Actual: 74 pred: 24

MLPRegressor (Scikit – learn)

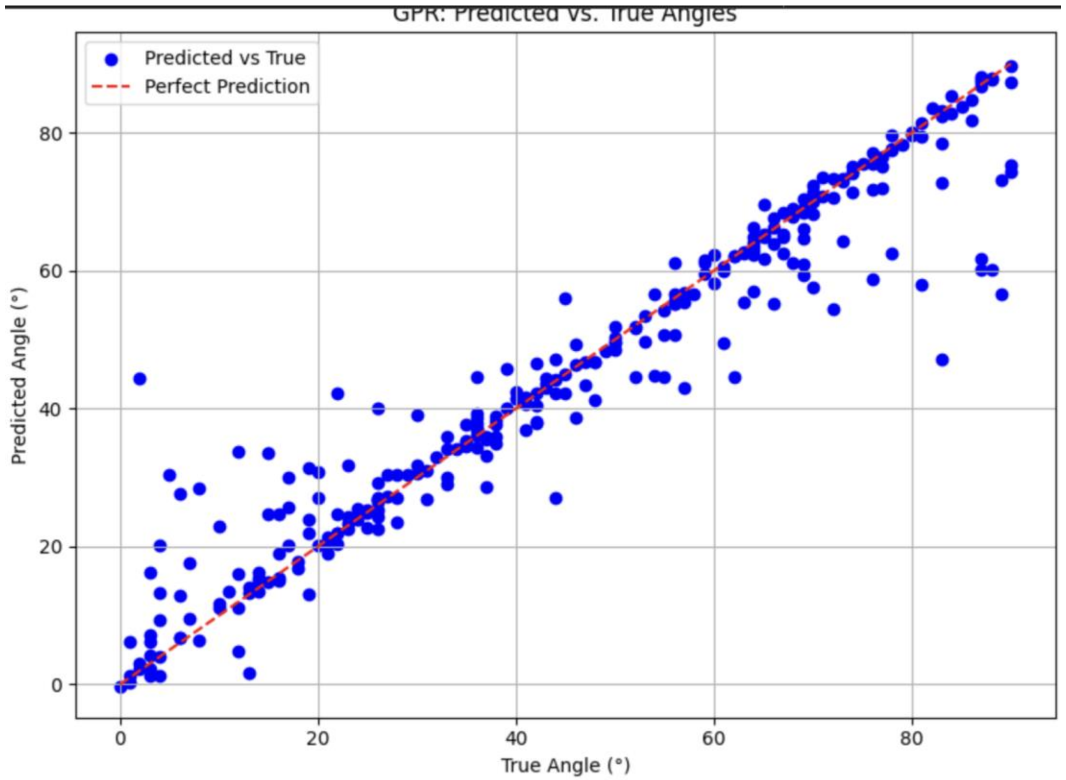
- Multi-Layer Perceptron for regression tasks (predicting continuous variable)
- Training is based on **backpropagation + Adam or LBFGS optimizer**.
- Best for small datasets
- Accurate predictions



Hidden layers	Final MAE	Predictions	
(100, 50)	Validation: 5.28	Actual: 68 Predicted: 70.83	
		Actual: 26 Pred: 25.05	

Gaussian Process Regression (GPR)

- A **Bayesian non-parametric model** that assumes a probability distribution over possible functions that fit the data.
- No layers, instead, GPR defines a **kernel function** k(x,x') to measure similarity between inputs.
- Main component: **Kernel** (e.g., RBF, Matern): defines smoothness/complexity of the function.
- Good for small dataset but works well with noisy and limited data
- **MAE: 4 degrees, MSE: 56.7 degrees**
- **Actual : 68, predicted: 68.9.**
- More accurate



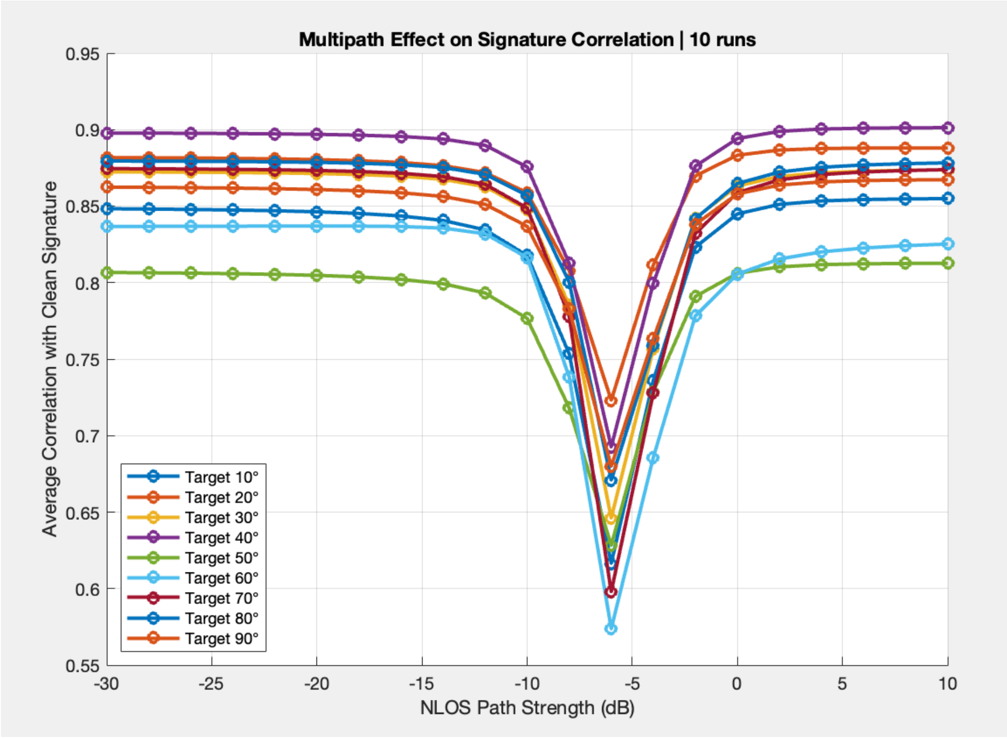
Questions

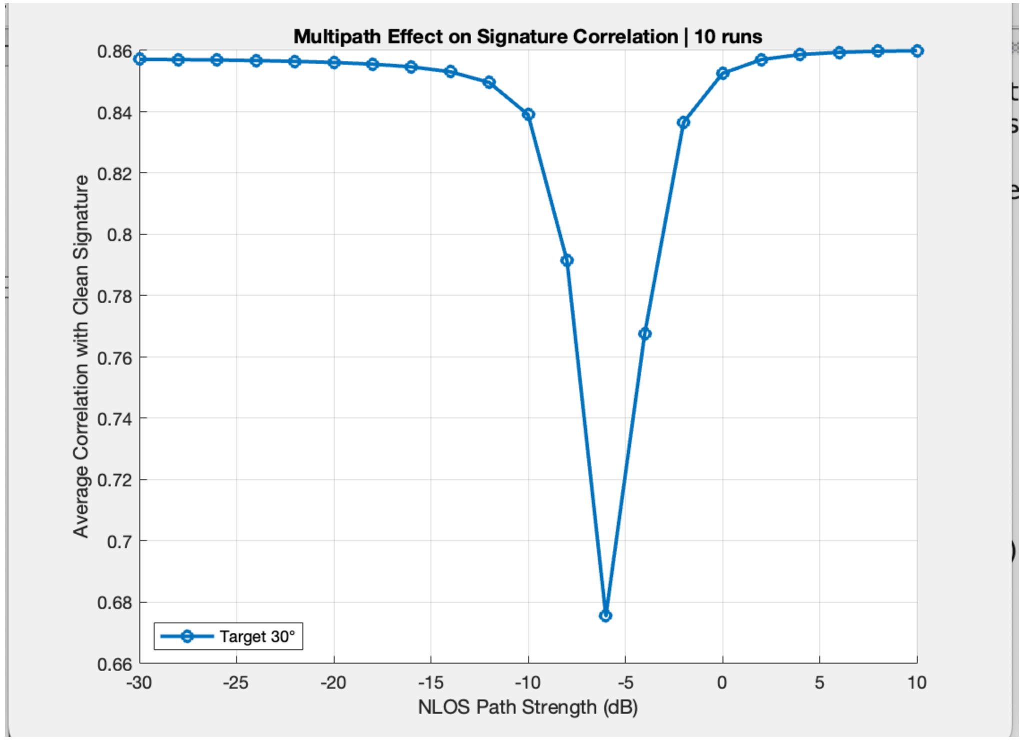
- Generalize well for validation set/unseen data coming from the same datasent
- Testing on new unseen data from different dataset lead to errors
- Any underlying distributions between the environments

- Simulating Multipath Channel

1 LOS + 1 NLOS

- Average correlation between LOS path channel and (LOS + NLOS) channel between RIS and UE
- As NLOS path strength approaches 0 dB, the correlation decreases due to increase in channel uncertainty and complexity
- Past 0 dB, correlation increases coz as NLOS path dominates, because path is less chaotic





Cont"

2. Mathematical View

Let's say the total RIS-to-user channel is modeled as:

$$h_{\text{obs}} = h_{\text{LOS}} + g \cdot h_{\text{NLOS}}$$

Where:

- $h_{\text{LOS}} = \exp(j\phi_{\text{LOS}})$
- $h_{\text{NLOS}} = \exp(j\phi_{\text{NLOS}})$
- $g = 10^{\text{NLOS dB}/20}$

Then the **magnitude squared** of the resulting array factor is:

$$|h_{\text{total}}|^2 = |h_{\text{LOS}} + g \cdot h_{\text{NLOS}}|^2$$

This expands to:

$$= 1 + g^2 + 2g\cos(\phi_{\text{LOS}} - \phi_{\text{NLOS}})$$

At g ≈ 1:

- The cosine term can be positive or negative (random), so the sum fluctuates a lot.
- High **variance** → low **correlation** between iterations.

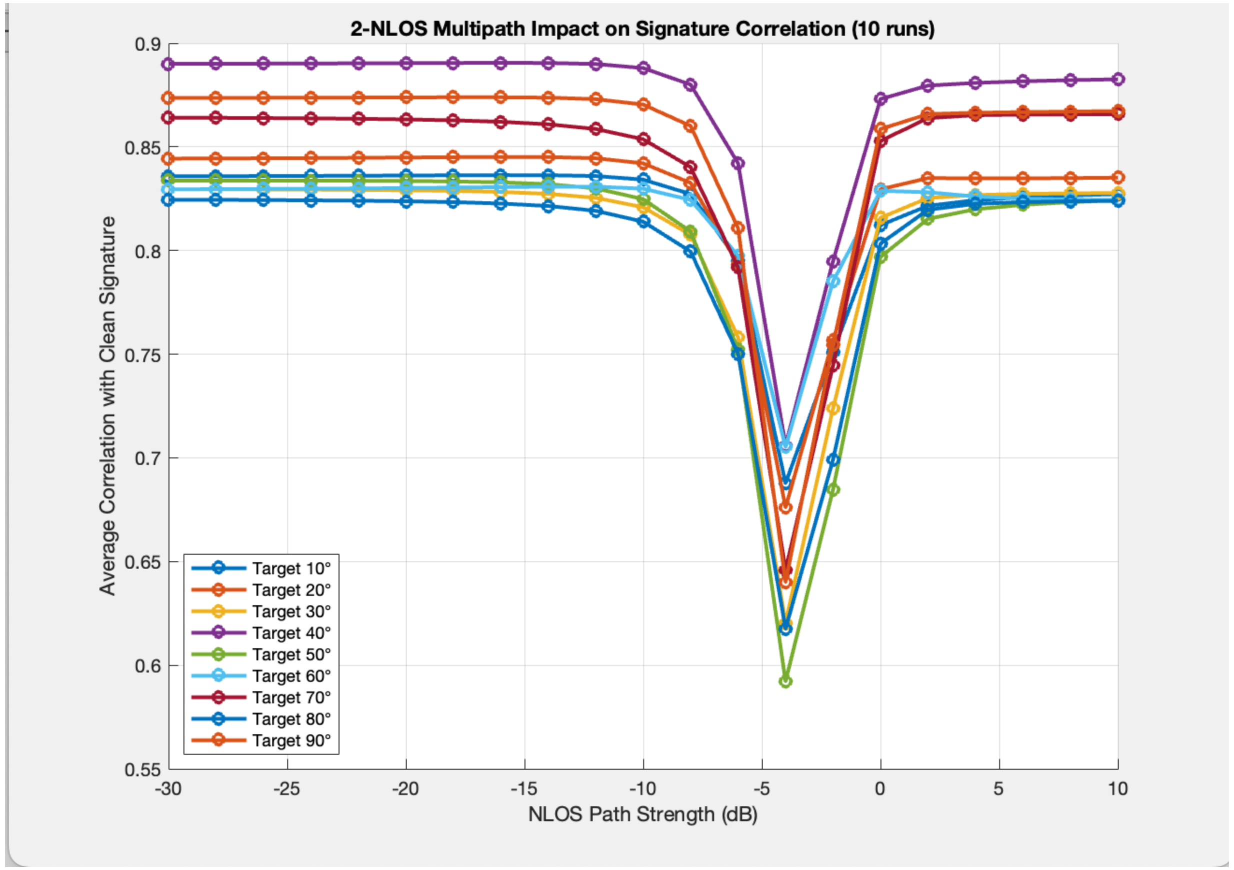
At g ≫ 1:

- g^2 dominates, so the relative phase between paths matters less.
- The pattern becomes dominated by h_{NLOS}, which now drives stability.

Analogy:

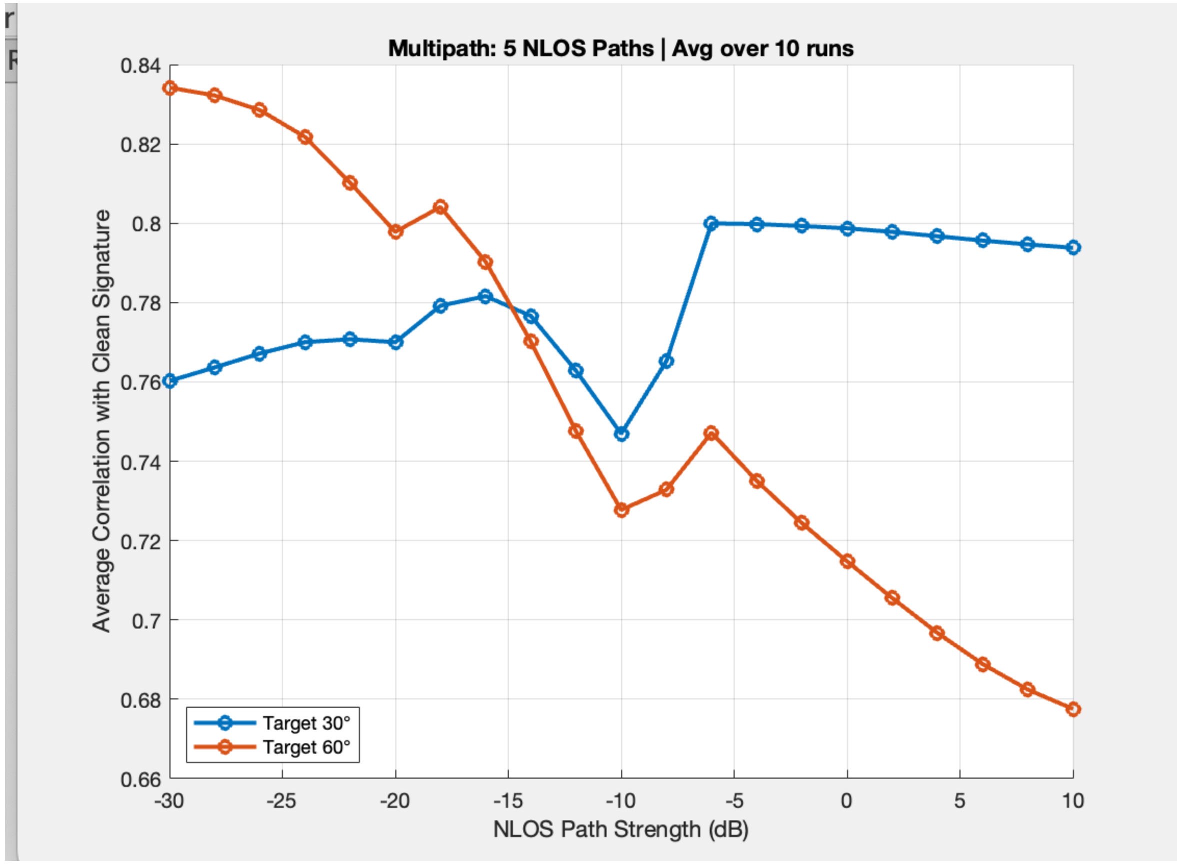
Think of beamforming as shining a flashlight (LOS path). If someone shines a dim torch from (NLOS), the flashlight is mostly unaffected. But when both torches are equally bright and ran flickering, the net lighting is chaotic. If the side torch becomes a floodlight (strong NLOS), it overpowers everything else and becomes the new "reference lighting."

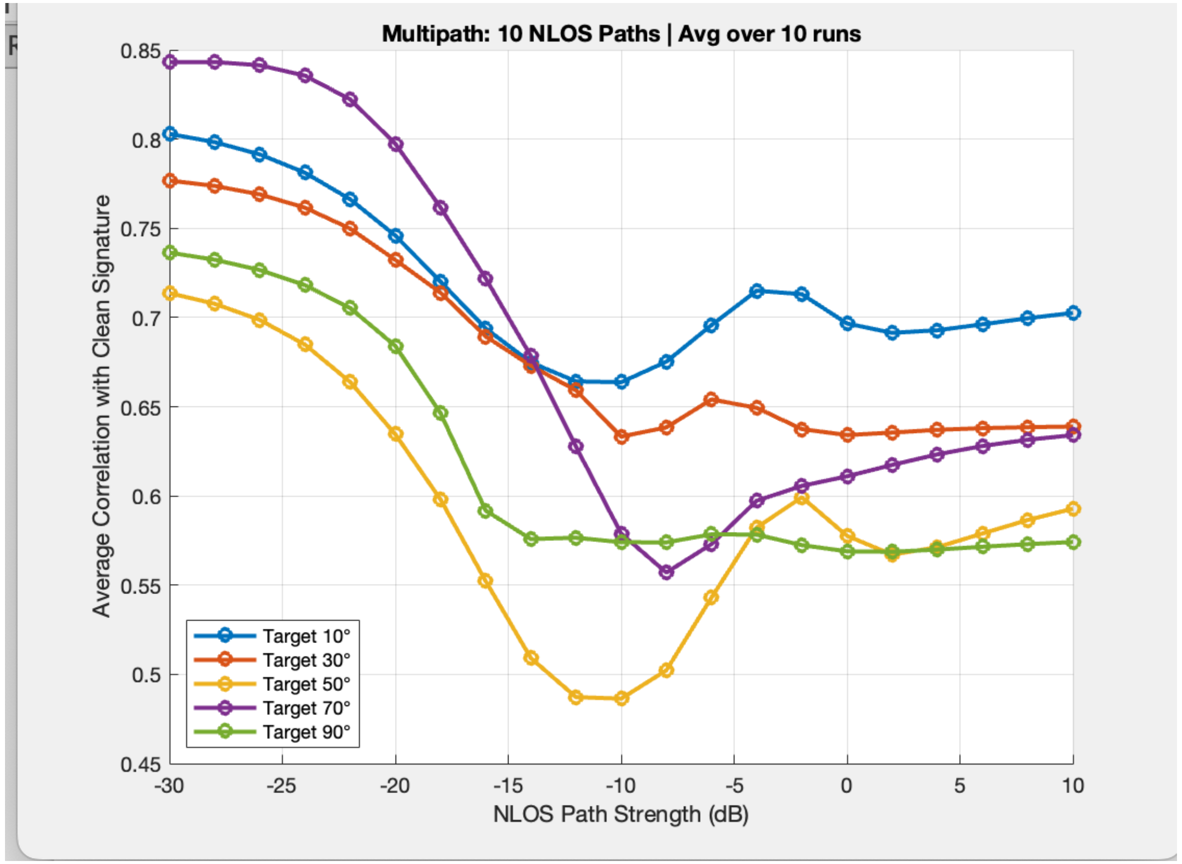
2NLOS, 5NLOS



2-NLOS Multipath Impact on Signature Correlation (10 runs)
Average Correlation with Clean Signature
NLOS Path Strength (dB)
0.9
0.85
0.8
0.75
0.7
0.65
0.6
0.55
-30
-25
-20
-15
-10
-5
0
5
10
Target 10°
Target 20°
Target 30°
Target 40°
Target 50°
Target 60°
Target 70°
Target 80°
Target 90°

MORE NLOS paths



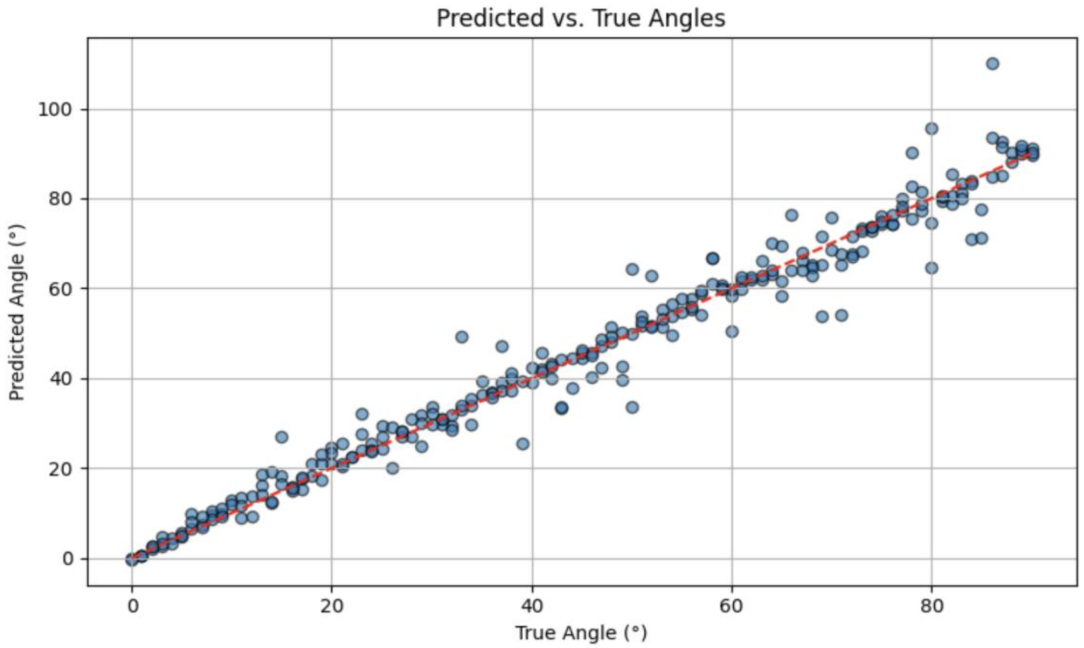


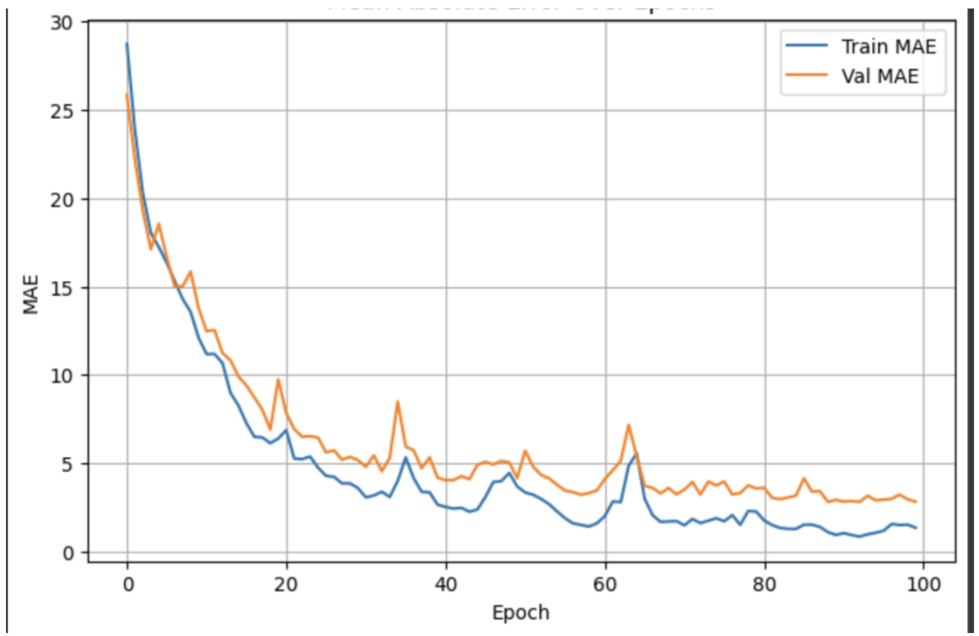
1 NLOS

Sequential

- It's deep Neural Network
- RIS_multipath_signature_dataset

Hidden Layers	MAE	Prediction
100,50,25,1 Adam, lr = 0.01	Training = 1.3553 Validation = 2.8337	Actual = 61 Predicted = 61.65
Dataset1	Training = 1.9268 Validation = 4.0575	Actual = 61 Predicted = 64.5r

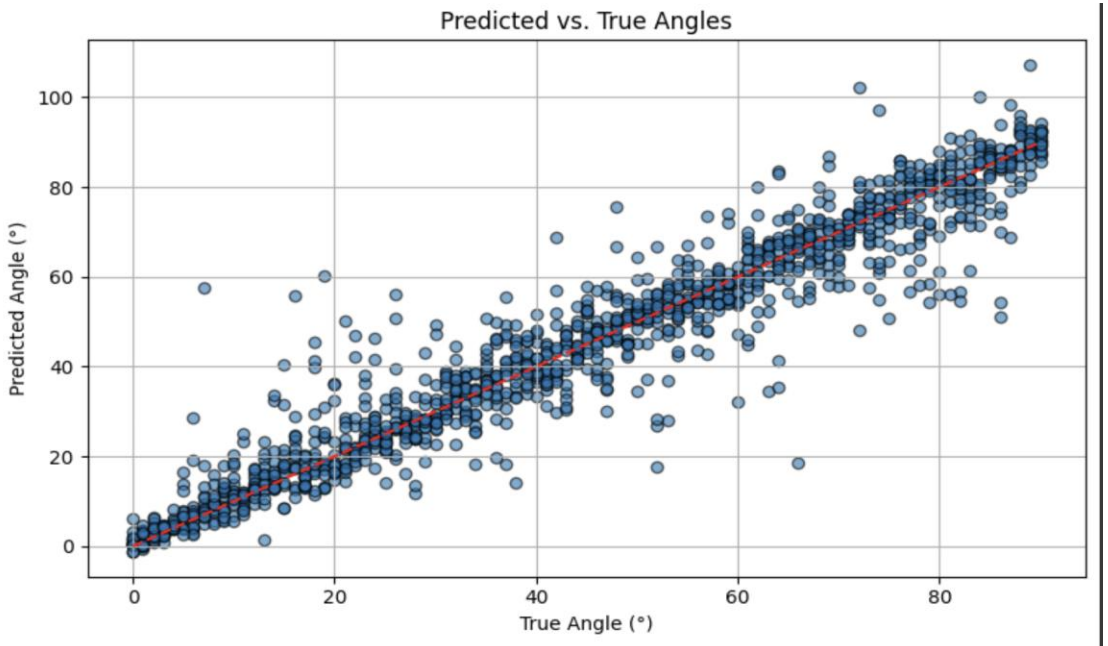


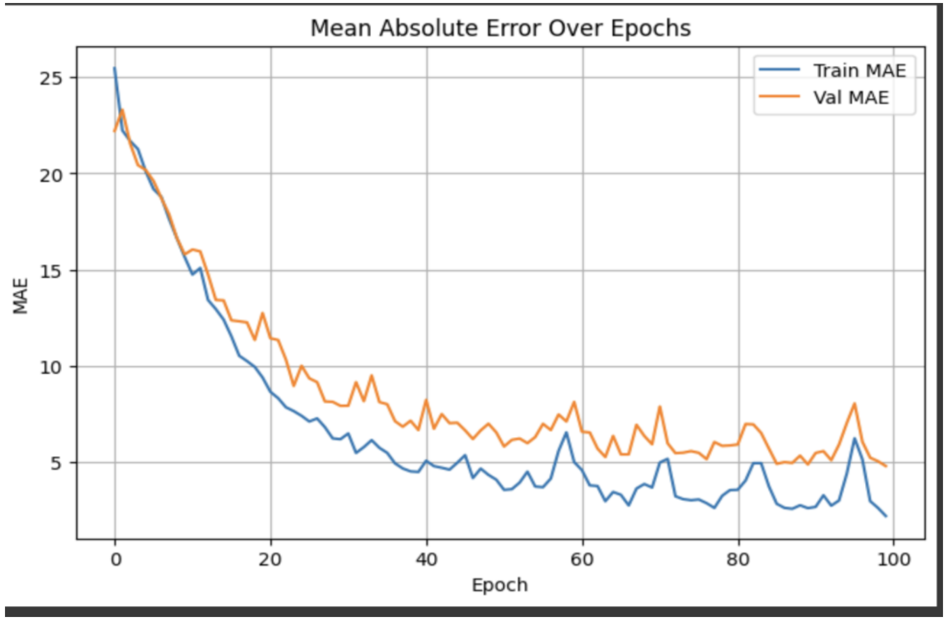


Sequential

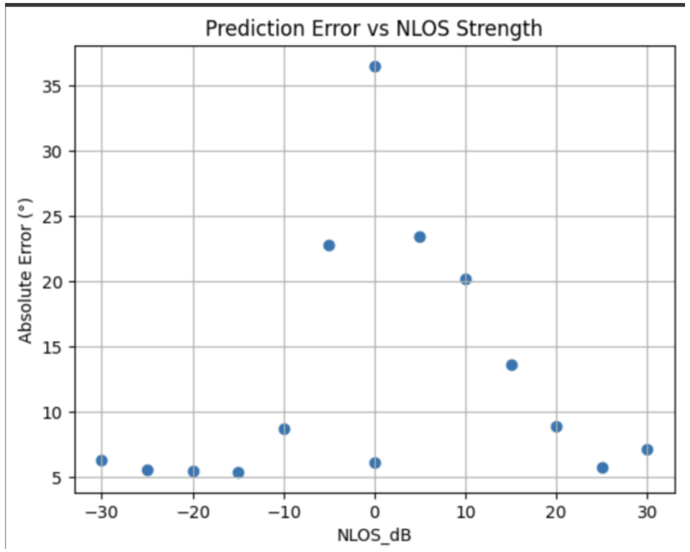
- It's deep Neural Network
- Multiple datasets (5, 1274 rows each).
- Val MAE = 4.79, Train MAE = 2.2

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 50ms/step
✅ MAE: 15.61°
✅ R² Score: 0.000

🔍 Sample predictions:
Example 1: Predicted = 27.96°, True = 30.00°
Example 2: Predicted = 31.26°, True = 30.00°
Example 3: Predicted = 36.47°, True = 30.00°
Example 4: Predicted = 44.86°, True = 30.00°
Example 5: Predicted = 54.92°, True = 30.00°
Example 6: Predicted = 53.78°, True = 30.00°
Example 7: Predicted = 59.03°, True = 30.00°
Example 8: Predicted = 72.80°, True = 30.00°
Example 9: Predicted = 50.93°, True = 30.00°
Example 10: Predicted = 54.74°, True = 30.00°
Example 11: Predicted = 44.72°, True = 30.00°
Example 12: Predicted = 34.32°, True = 30.00°
Example 13: Predicted = 26.59°, True = 30.00°
Example 14: Predicted = 24.69°, True = 30.00°
```





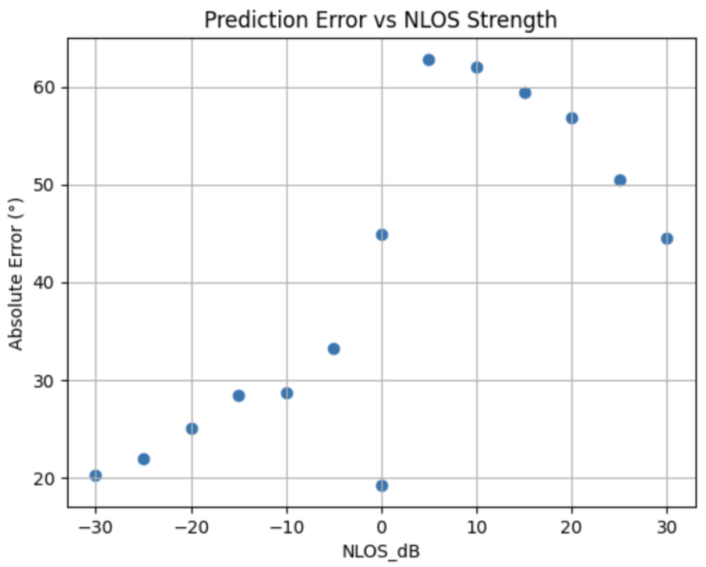
More examples




```
✅ MAE: 13.36°
✅ R² Score: 0.000

🔍 Sample predictions (with NLOS dB):
Example 1: Predicted = 48.34°, True = 48.00°, NLOS_dB = 0.0
Example 2: Predicted = 47.52°, True = 48.00°, NLOS_dB = -30.0
Example 3: Predicted = 50.05°, True = 48.00°, NLOS_dB = -25.0
Example 4: Predicted = 54.95°, True = 48.00°, NLOS_dB = -20.0
Example 5: Predicted = 60.54°, True = 48.00°, NLOS_dB = -15.0
Example 6: Predicted = 66.77°, True = 48.00°, NLOS_dB = -10.0
Example 7: Predicted = 83.47°, True = 48.00°, NLOS_dB = -5.0
Example 8: Predicted = 87.71°, True = 48.00°, NLOS_dB = 0.0
Example 9: Predicted = 84.18°, True = 48.00°, NLOS_dB = 5.0
Example 10: Predicted = 65.40°, True = 48.00°, NLOS_dB = 10.0
Example 11: Predicted = 49.03°, True = 48.00°, NLOS_dB = 15.0
Example 12: Predicted = 40.30°, True = 48.00°, NLOS_dB = 20.0
Example 13: Predicted = 46.26°, True = 48.00°, NLOS_dB = 25.0
Example 14: Predicted = 54.72°, True = 48.00°, NLOS_dB = 30.0
```

```
✅ MAE: 12.57°
✅ R² Score: 0.000

🔍 Sample predictions (with NLOS dB):
Example 1: Predicted = 43.89°, True = 50.00°, NLOS_dB = 0.0
Example 2: Predicted = 43.65°, True = 50.00°, NLOS_dB = -30.0
Example 3: Predicted = 44.46°, True = 50.00°, NLOS_dB = -25.0
Example 4: Predicted = 44.55°, True = 50.00°, NLOS_dB = -20.0
Example 5: Predicted = 44.59°, True = 50.00°, NLOS_dB = -15.0
Example 6: Predicted = 41.25°, True = 50.00°, NLOS_dB = -10.0
Example 7: Predicted = 27.19°, True = 50.00°, NLOS_dB = -5.0
Example 8: Predicted = 13.50°, True = 50.00°, NLOS_dB = 0.0
Example 9: Predicted = 26.58°, True = 50.00°, NLOS_dB = 5.0
Example 10: Predicted = 29.83°, True = 50.00°, NLOS_dB = 10.0
Example 11: Predicted = 36.35°, True = 50.00°, NLOS_dB = 15.0
Example 12: Predicted = 41.11°, True = 50.00°, NLOS_dB = 20.0
Example 13: Predicted = 44.22°, True = 50.00°, NLOS_dB = 25.0
Example 14: Predicted = 42.86°, True = 50.00°, NLOS_dB = 30.0
```

Angles close to 0 or 90



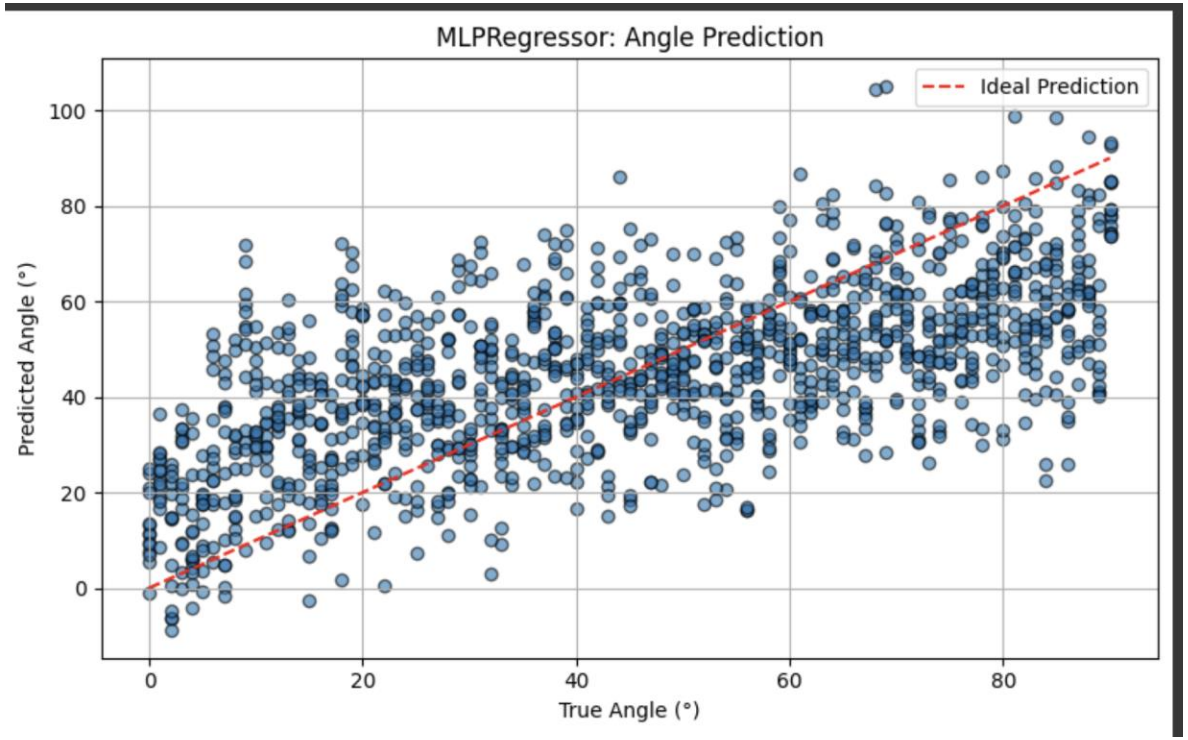

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
✅ MAE: 28.76°
✅ R² Score: 0.000

🔍 Sample predictions (with NLOS dB):
Example 1: Predicted = 52.23°, True = 10.00°, NLOS_dB = 0.0
Example 2: Predicted = 49.16°, True = 10.00°, NLOS_dB = -30.0
Example 3: Predicted = 47.47°, True = 10.00°, NLOS_dB = -25.0
Example 4: Predicted = 43.44°, True = 10.00°, NLOS_dB = -20.0
Example 5: Predicted = 32.75°, True = 10.00°, NLOS_dB = -15.0
Example 6: Predicted = 20.73°, True = 10.00°, NLOS_dB = -10.0
Example 7: Predicted = 13.91°, True = 10.00°, NLOS_dB = -5.0
Example 8: Predicted = 22.69°, True = 10.00°, NLOS_dB = 0.0
Example 9: Predicted = 43.12°, True = 10.00°, NLOS_dB = 5.0
Example 10: Predicted = 37.82°, True = 10.00°, NLOS_dB = 10.0
Example 11: Predicted = 39.24°, True = 10.00°, NLOS_dB = 15.0
Example 12: Predicted = 42.93°, True = 10.00°, NLOS_dB = 20.0
Example 13: Predicted = 47.13°, True = 10.00°, NLOS_dB = 25.0
Example 14: Predicted = 49.99°, True = 10.00°, NLOS_dB = 30.0
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
✅ MAE: 39.83°
✅ R² Score: 0.000

🔍 Sample predictions (with NLOS dB):
Example 1: Predicted = 60.78°, True = 80.00°, NLOS_dB = 0.0
Example 2: Predicted = 59.82°, True = 80.00°, NLOS_dB = -30.0
Example 3: Predicted = 58.14°, True = 80.00°, NLOS_dB = -25.0
Example 4: Predicted = 55.00°, True = 80.00°, NLOS_dB = -20.0
Example 5: Predicted = 51.64°, True = 80.00°, NLOS_dB = -15.0
Example 6: Predicted = 51.40°, True = 80.00°, NLOS_dB = -10.0
Example 7: Predicted = 46.77°, True = 80.00°, NLOS_dB = -5.0
Example 8: Predicted = 35.06°, True = 80.00°, NLOS_dB = 0.0
Example 9: Predicted = 17.18°, True = 80.00°, NLOS_dB = 5.0
Example 10: Predicted = 17.97°, True = 80.00°, NLOS_dB = 10.0
Example 11: Predicted = 20.56°, True = 80.00°, NLOS_dB = 15.0
Example 12: Predicted = 23.15°, True = 80.00°, NLOS_dB = 20.0
Example 13: Predicted = 29.49°, True = 80.00°, NLOS_dB = 25.0
Example 14: Predicted = 35.44°, True = 80.00°, NLOS_dB = 30.0
```

MLPRegressor

- Val MAE = 16.56
- Validation set; actual : 58, predicted = 60.31

```
✅ MAE: 26.01°
✅ R² Score: 0.000

🔍 Sample predictions (with NLOS dB):
Example 1: Predicted = 45.69°, True = 10.00°, NLOS_dB = 0.0
Example 2: Predicted = 43.24°, True = 10.00°, NLOS_dB = -30.0
Example 3: Predicted = 40.11°, True = 10.00°, NLOS_dB = -25.0
Example 4: Predicted = 35.57°, True = 10.00°, NLOS_dB = -20.0
Example 5: Predicted = 31.78°, True = 10.00°, NLOS_dB = -15.0
Example 6: Predicted = 19.26°, True = 10.00°, NLOS_dB = -10.0
Example 7: Predicted = 26.14°, True = 10.00°, NLOS_dB = -5.0
Example 8: Predicted = 42.25°, True = 10.00°, NLOS_dB = 0.0
Example 9: Predicted = 22.10°, True = 10.00°, NLOS_dB = 5.0
Example 10: Predicted = 31.73°, True = 10.00°, NLOS_dB = 10.0
Example 11: Predicted = 39.03°, True = 10.00°, NLOS_dB = 15.0
Example 12: Predicted = 41.66°, True = 10.00°, NLOS_dB = 20.0
Example 13: Predicted = 42.67°, True = 10.00°, NLOS_dB = 25.0
Example 14: Predicted = 42.92°, True = 10.00°, NLOS_dB = 30.0
```

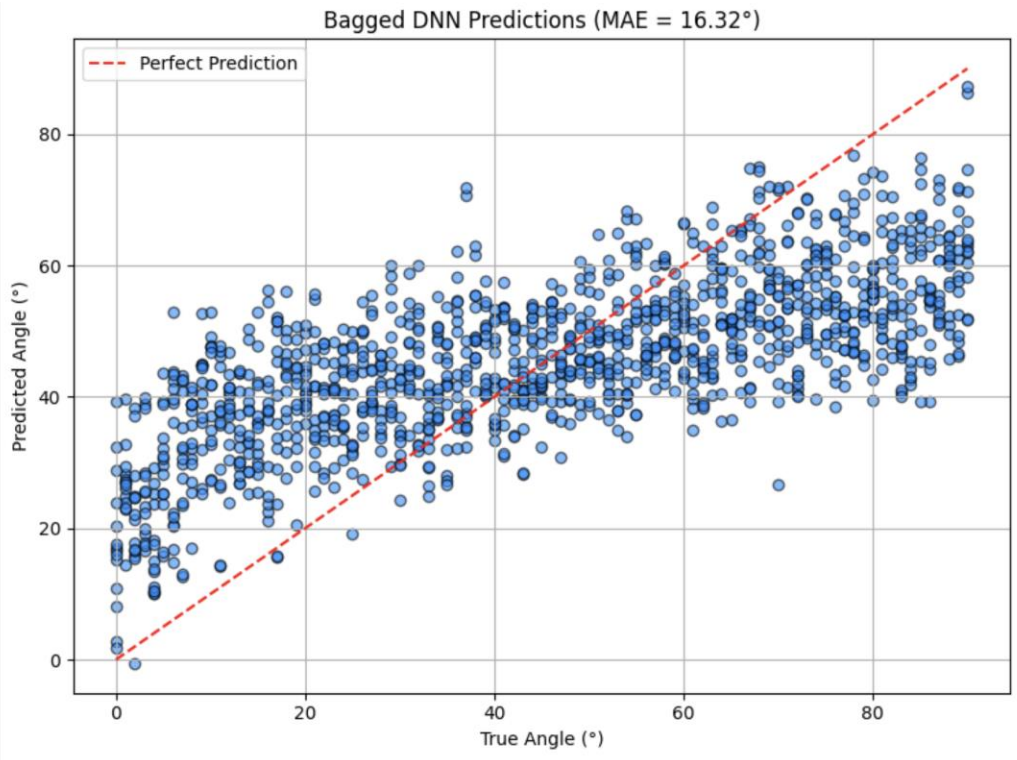


More MLP examples

```
✅ MAE: 8.24°
✅ R² Score: 0.000

🔍 Sample predictions (with NLOS dB):
Example 1: Predicted = 48.74°, True = 48.00°, NLOS_dB = 0.0
Example 2: Predicted = 56.81°, True = 48.00°, NLOS_dB = -30.0
Example 3: Predicted = 57.79°, True = 48.00°, NLOS_dB = -25.0
Example 4: Predicted = 60.21°, True = 48.00°, NLOS_dB = -20.0
Example 5: Predicted = 65.59°, True = 48.00°, NLOS_dB = -15.0
Example 6: Predicted = 72.51°, True = 48.00°, NLOS_dB = -10.0
Example 7: Predicted = 61.49°, True = 48.00°, NLOS_dB = -5.0
Example 8: Predicted = 49.59°, True = 48.00°, NLOS_dB = 0.0
Example 9: Predicted = 38.95°, True = 48.00°, NLOS_dB = 5.0
Example 10: Predicted = 44.28°, True = 48.00°, NLOS_dB = 10.0
Example 11: Predicted = 45.56°, True = 48.00°, NLOS_dB = 15.0
Example 12: Predicted = 48.37°, True = 48.00°, NLOS_dB = 20.0
Example 13: Predicted = 52.24°, True = 48.00°, NLOS_dB = 25.0
Example 14: Predicted = 54.83°, True = 48.00°, NLOS_dB = 30.0
```

```
✅ MAE: 8.97°
✅ R² Score: 0.000

🔍 Sample predictions (with NLOS dB):
Example 1: Predicted = 31.44°, True = 40.00°, NLOS_dB = 0.0
Example 2: Predicted = 33.44°, True = 40.00°, NLOS_dB = -30.0
Example 3: Predicted = 38.91°, True = 40.00°, NLOS_dB = -25.0
Example 4: Predicted = 44.99°, True = 40.00°, NLOS_dB = -20.0
Example 5: Predicted = 50.81°, True = 40.00°, NLOS_dB = -15.0
Example 6: Predicted = 53.53°, True = 40.00°, NLOS_dB = -10.0
Example 7: Predicted = 54.07°, True = 40.00°, NLOS_dB = -5.0
Example 8: Predicted = 42.95°, True = 40.00°, NLOS_dB = 0.0
Example 9: Predicted = 38.62°, True = 40.00°, NLOS_dB = 5.0
Example 10: Predicted = 53.94°, True = 40.00°, NLOS_dB = 10.0
Example 11: Predicted = 47.67°, True = 40.00°, NLOS_dB = 15.0
Example 12: Predicted = 35.24°, True = 40.00°, NLOS_dB = 20.0
Example 13: Predicted = 17.43°, True = 40.00°, NLOS_dB = 25.0
Example 14: Predicted = 27.33°, True = 40.00°, NLOS_dB = 30.0
```

Sequential Ensemble




```
📊 Test Set Performance:
✅ MAE: 3.78°
✅ R² Score: 0.000

🔍 Sample predictions (with NLOS dB):
Example 1: Predicted = 38.70°, True = 48.00°, NLOS_dB = 0.0
Example 2: Predicted = 43.48°, True = 48.00°, NLOS_dB = -30.0
Example 3: Predicted = 43.56°, True = 48.00°, NLOS_dB = -25.0
Example 4: Predicted = 43.43°, True = 48.00°, NLOS_dB = -20.0
Example 5: Predicted = 44.50°, True = 48.00°, NLOS_dB = -15.0
Example 6: Predicted = 45.14°, True = 48.00°, NLOS_dB = -10.0
Example 7: Predicted = 44.68°, True = 48.00°, NLOS_dB = -5.0
Example 8: Predicted = 45.36°, True = 48.00°, NLOS_dB = 0.0
Example 9: Predicted = 43.97°, True = 48.00°, NLOS_dB = 5.0
Example 10: Predicted = 43.02°, True = 48.00°, NLOS_dB = 10.0
Example 11: Predicted = 44.64°, True = 48.00°, NLOS_dB = 15.0
Example 12: Predicted = 45.74°, True = 48.00°, NLOS_dB = 20.0
Example 13: Predicted = 46.26°, True = 48.00°, NLOS_dB = 25.0
Example 14: Predicted = 46.64°, True = 48.00°, NLOS_dB = 30.0
```

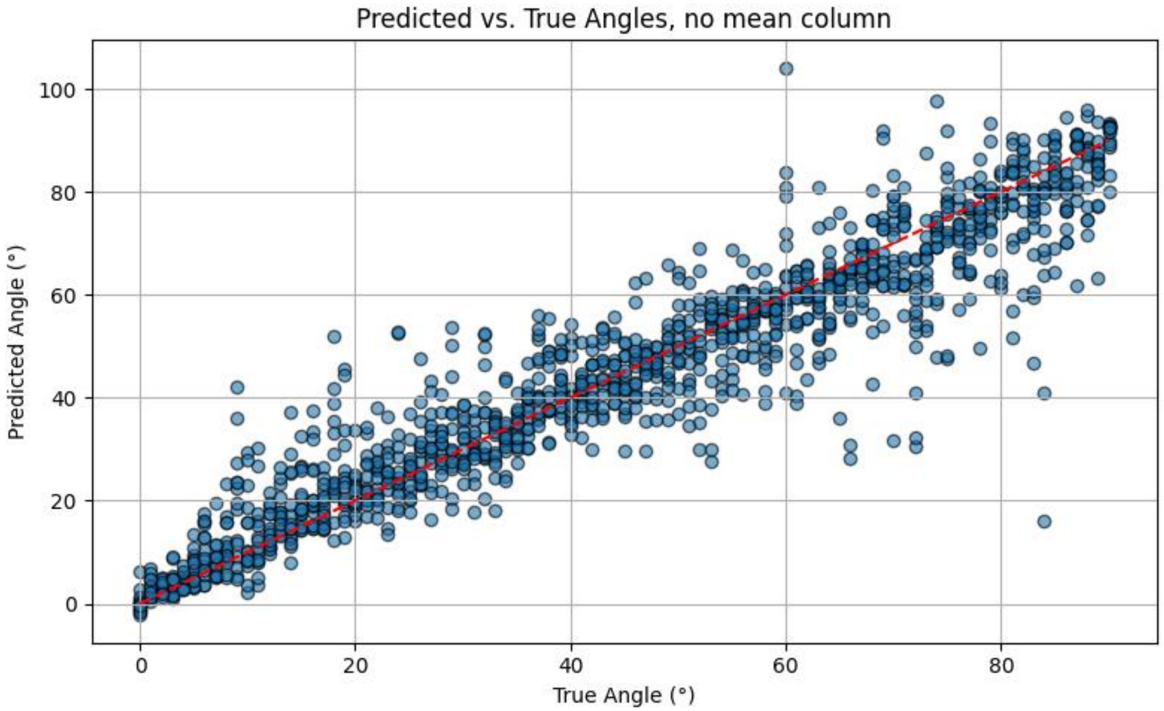
More examples

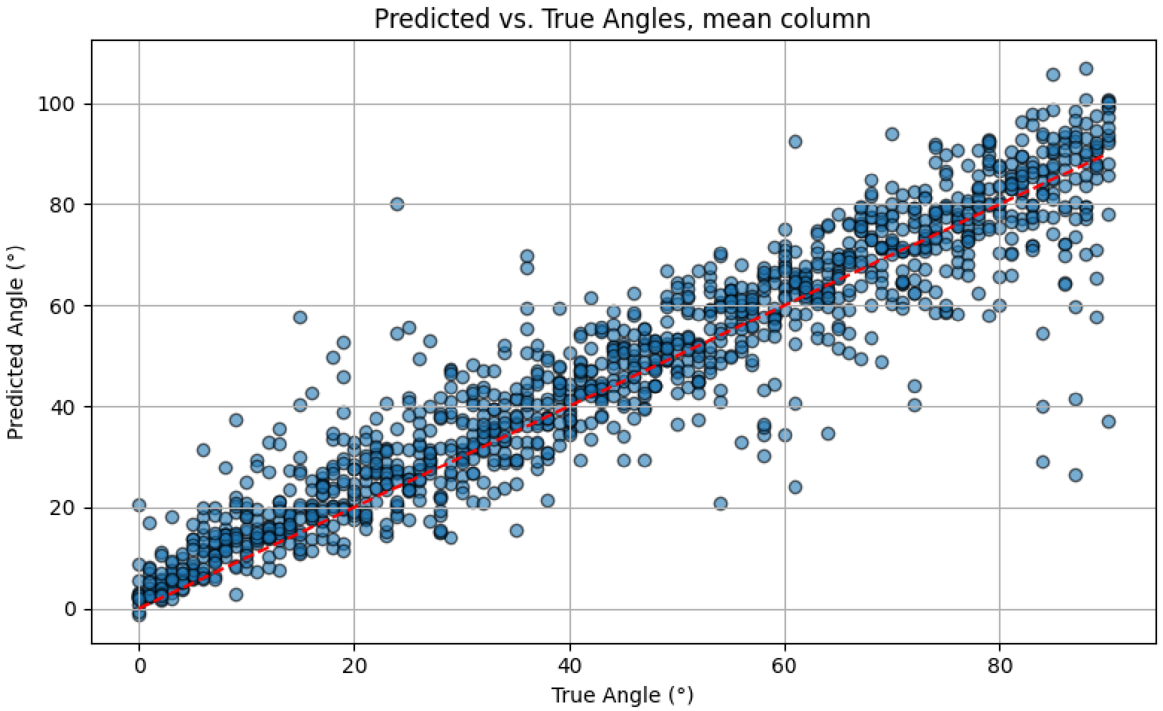
```
📊 Test Set Performance:
✅ MAE: 9.32°
✅ R² Score: 0.000

🔍 Sample predictions (with NLOS dB):
Example 1: Predicted = 42.50°, True = 50.00°, NLOS_dB = 0.0
Example 2: Predicted = 39.73°, True = 50.00°, NLOS_dB = -30.0
Example 3: Predicted = 40.19°, True = 50.00°, NLOS_dB = -25.0
Example 4: Predicted = 40.89°, True = 50.00°, NLOS_dB = -20.0
Example 5: Predicted = 42.22°, True = 50.00°, NLOS_dB = -15.0
Example 6: Predicted = 42.61°, True = 50.00°, NLOS_dB = -10.0
Example 7: Predicted = 34.64°, True = 50.00°, NLOS_dB = -5.0
Example 8: Predicted = 35.05°, True = 50.00°, NLOS_dB = 0.0
Example 9: Predicted = 42.66°, True = 50.00°, NLOS_dB = 5.0
Example 10: Predicted = 53.31°, True = 50.00°, NLOS_dB = 10.0
Example 11: Predicted = 58.53°, True = 50.00°, NLOS_dB = 15.0
Example 12: Predicted = 59.79°, True = 50.00°, NLOS_dB = 20.0
Example 13: Predicted = 59.73°, True = 50.00°, NLOS_dB = 25.0
Example 14: Predicted = 59.66°, True = 50.00°, NLOS_dB = 30.0
```

```
📊 Test Set Performance:
✅ MAE: 29.79°
✅ R² Score: 0.000

🔍 Sample predictions (with NLOS dB):
Example 1: Predicted = 42.26°, True = 20.00°, NLOS_dB = 0.0
Example 2: Predicted = 42.45°, True = 20.00°, NLOS_dB = -30.0
Example 3: Predicted = 42.55°, True = 20.00°, NLOS_dB = -25.0
Example 4: Predicted = 43.90°, True = 20.00°, NLOS_dB = -20.0
Example 5: Predicted = 46.90°, True = 20.00°, NLOS_dB = -15.0
Example 6: Predicted = 52.19°, True = 20.00°, NLOS_dB = -10.0
Example 7: Predicted = 53.76°, True = 20.00°, NLOS_dB = -5.0
Example 8: Predicted = 51.28°, True = 20.00°, NLOS_dB = 0.0
Example 9: Predicted = 47.03°, True = 20.00°, NLOS_dB = 5.0
Example 10: Predicted = 54.93°, True = 20.00°, NLOS_dB = 10.0
Example 11: Predicted = 57.46°, True = 20.00°, NLOS_dB = 15.0
Example 12: Predicted = 55.64°, True = 20.00°, NLOS_dB = 20.0
Example 13: Predicted = 53.82°, True = 20.00°, NLOS_dB = 25.0
Example 14: Predicted = 52.94°, True = 20.00°, NLOS_dB = 30.0
```

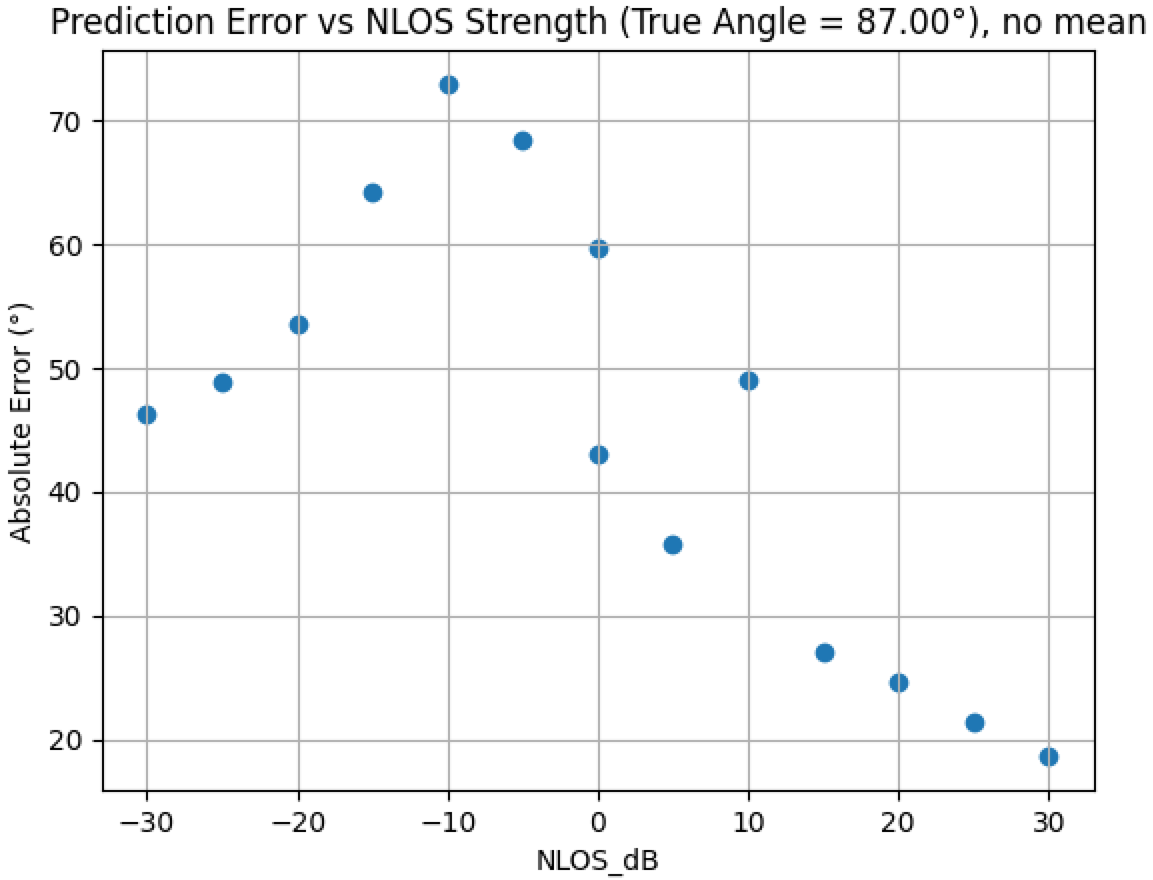
```
📊 Test Set Performance:
✅ MAE: 35.43°
✅ R² Score: 0.000

🔍 Sample predictions (with NLOS dB):
Example 1: Predicted = 47.57°, True = 80.00°, NLOS_dB = 0.0
Example 2: Predicted = 40.79°, True = 80.00°, NLOS_dB = -30.0
Example 3: Predicted = 42.22°, True = 80.00°, NLOS_dB = -25.0
Example 4: Predicted = 43.46°, True = 80.00°, NLOS_dB = -20.0
Example 5: Predicted = 45.99°, True = 80.00°, NLOS_dB = -15.0
Example 6: Predicted = 46.64°, True = 80.00°, NLOS_dB = -10.0
Example 7: Predicted = 45.56°, True = 80.00°, NLOS_dB = -5.0
Example 8: Predicted = 47.72°, True = 80.00°, NLOS_dB = 0.0
Example 9: Predicted = 48.34°, True = 80.00°, NLOS_dB = 5.0
Example 10: Predicted = 45.43°, True = 80.00°, NLOS_dB = 10.0
Example 11: Predicted = 43.28°, True = 80.00°, NLOS_dB = 15.0
Example 12: Predicted = 42.21°, True = 80.00°, NLOS_dB = 20.0
Example 13: Predicted = 42.18°, True = 80.00°, NLOS_dB = 25.0
Example 14: Predicted = 42.52°, True = 80.00°, NLOS_dB = 30.0
```

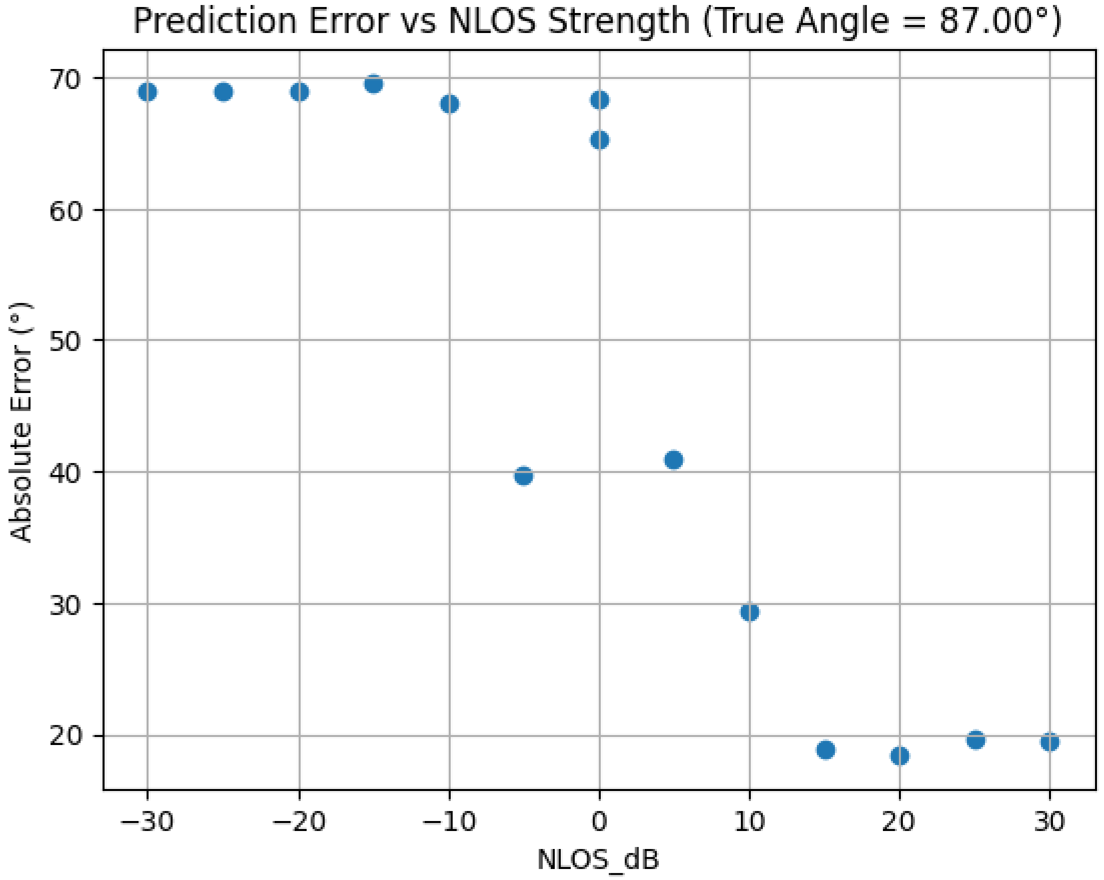
Scatter plots



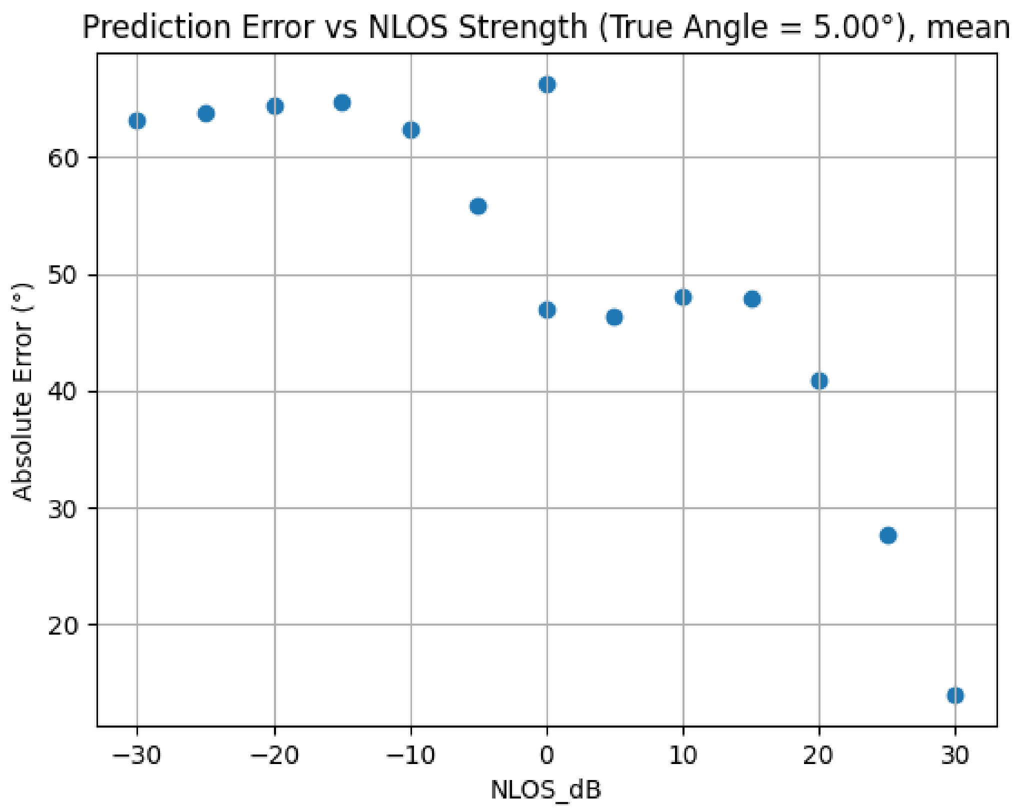


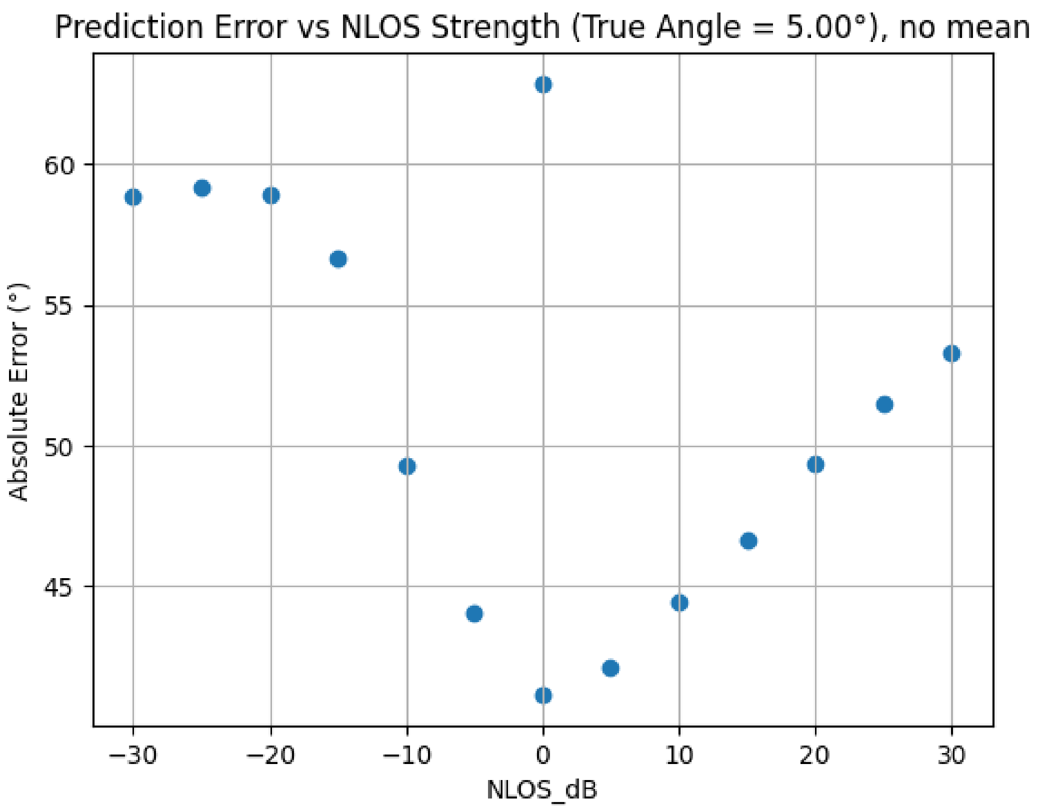
Compare prediction errors



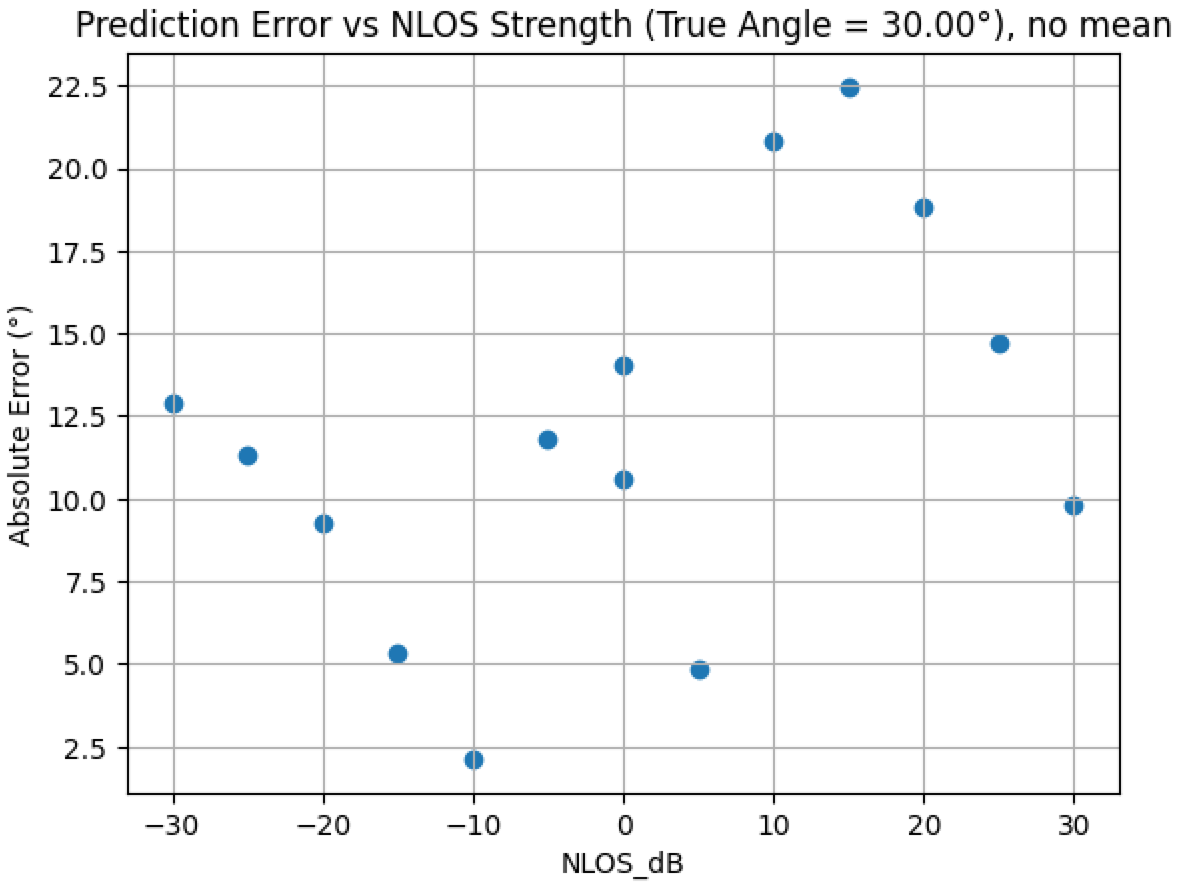


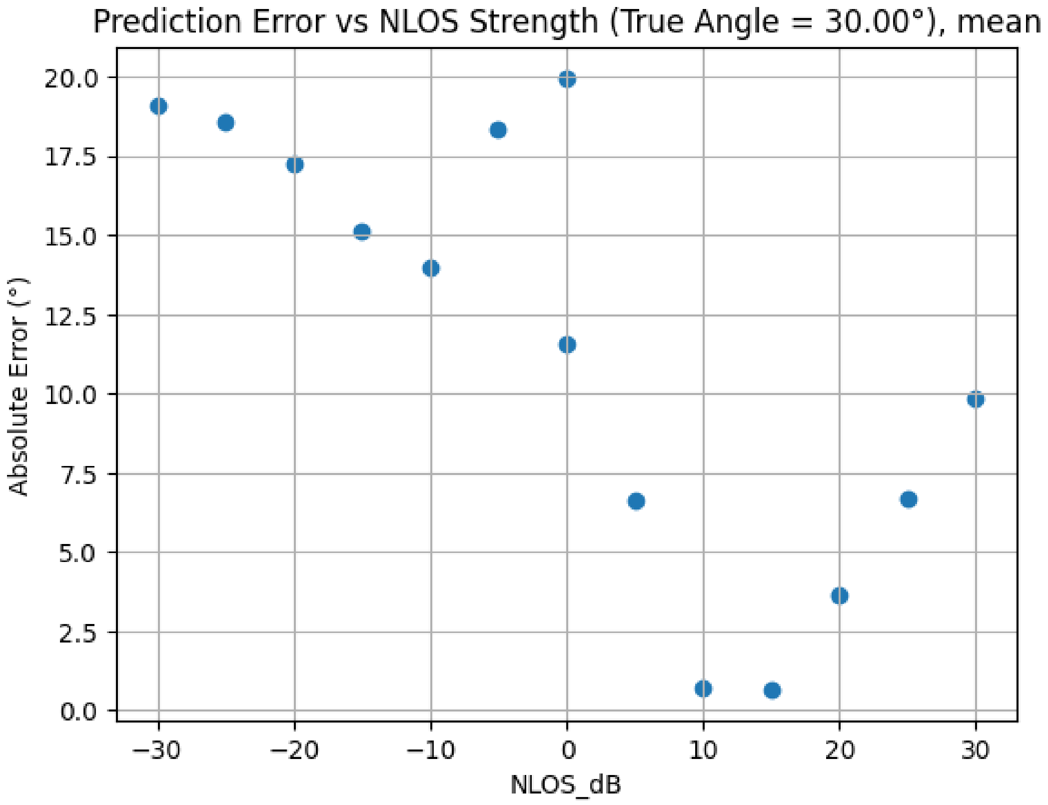
More examples





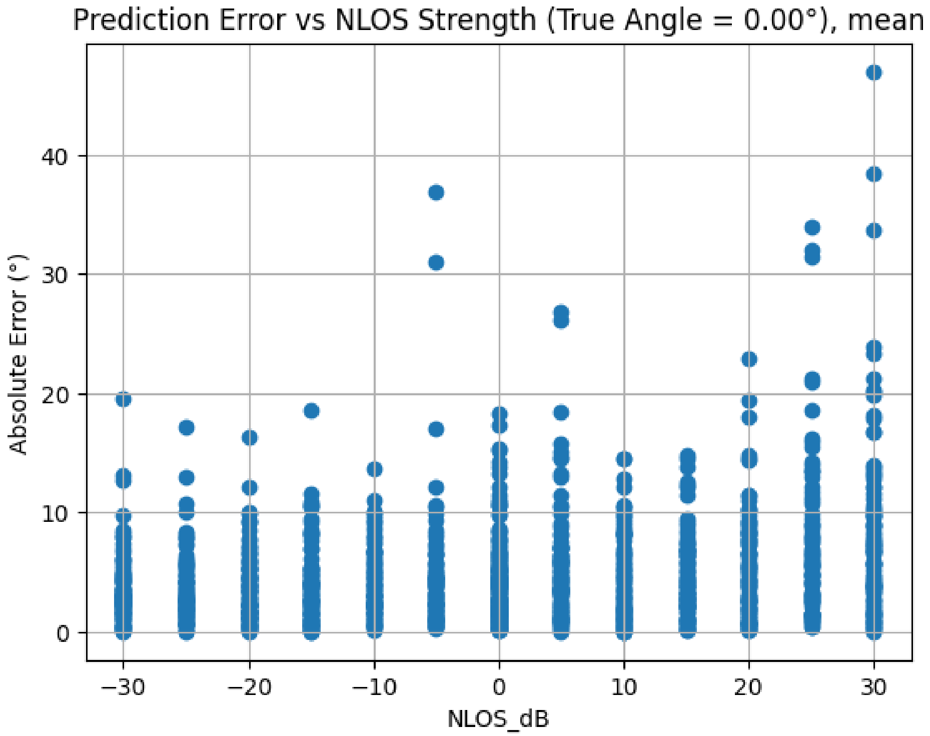
More examples



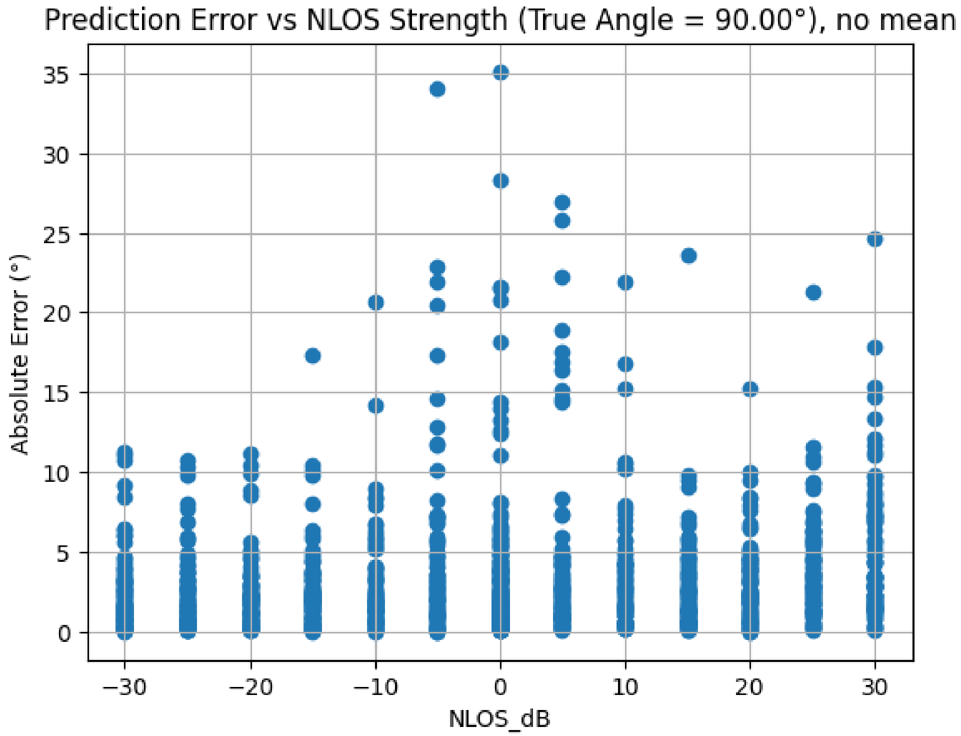


Testing on a dataset

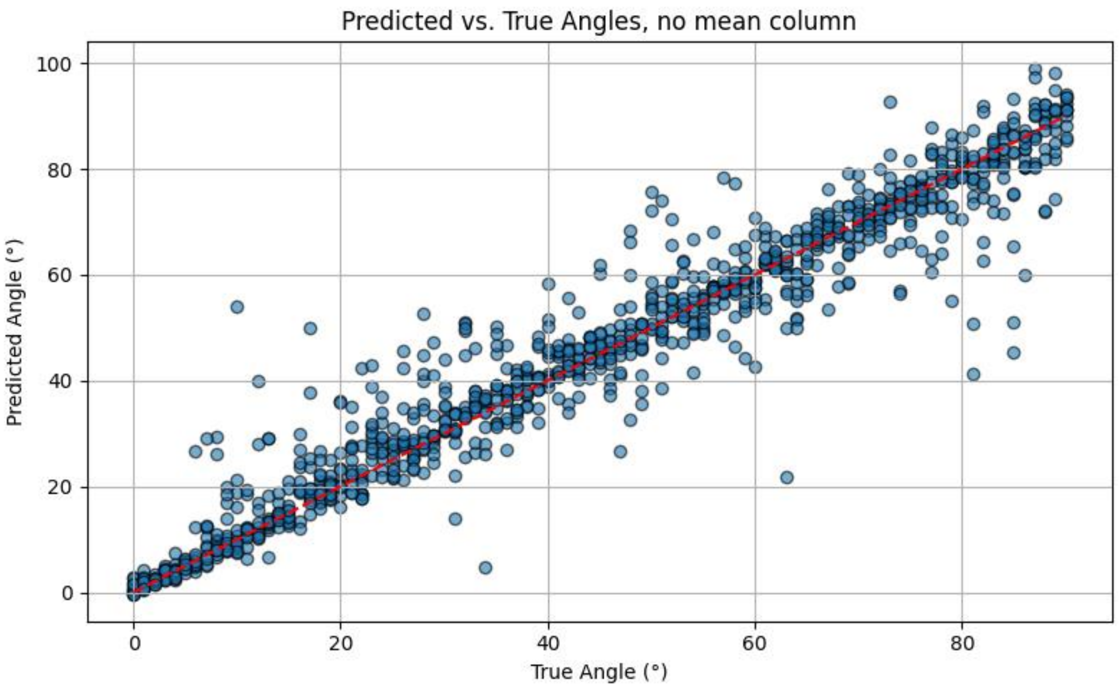
MAE = 4.86

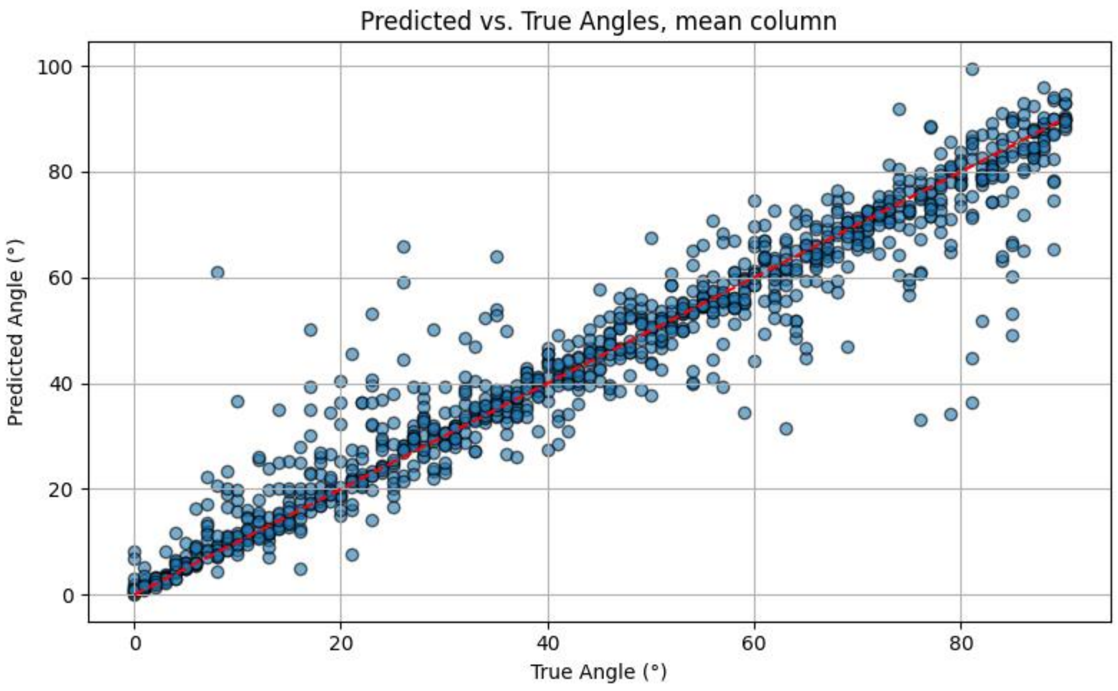


MAE = 3.28

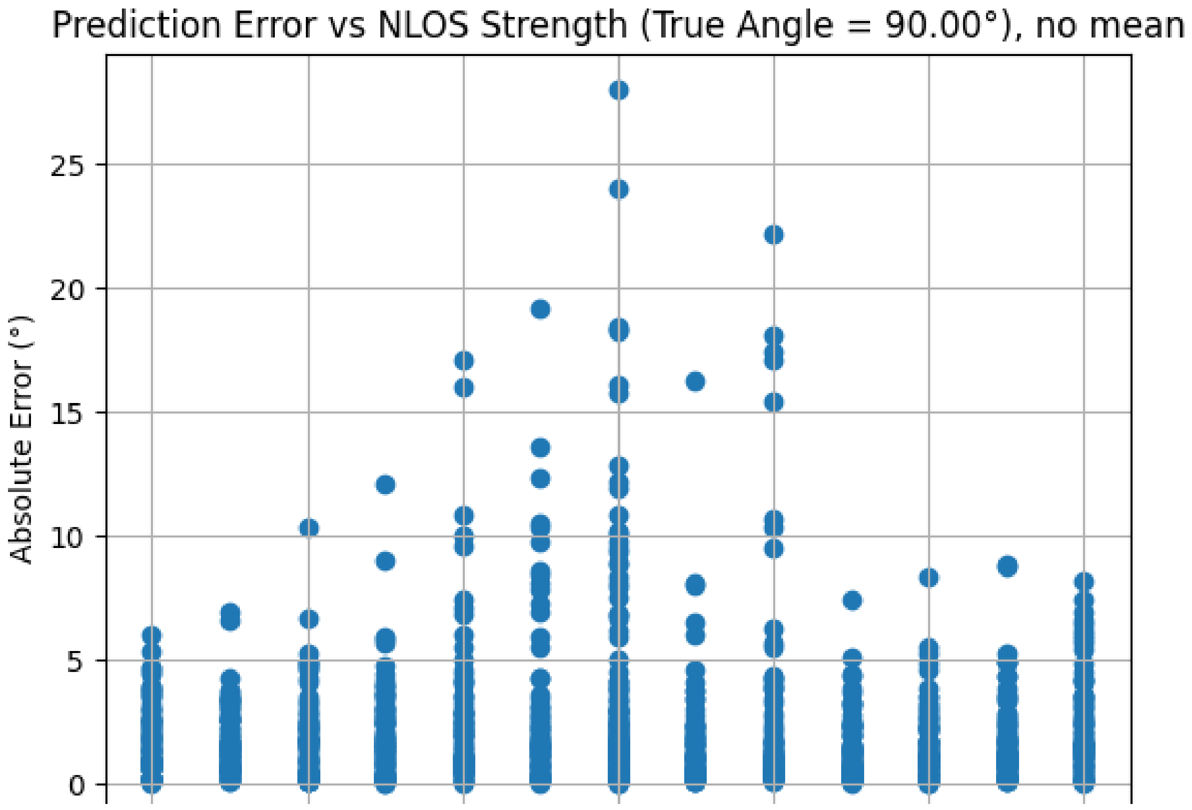


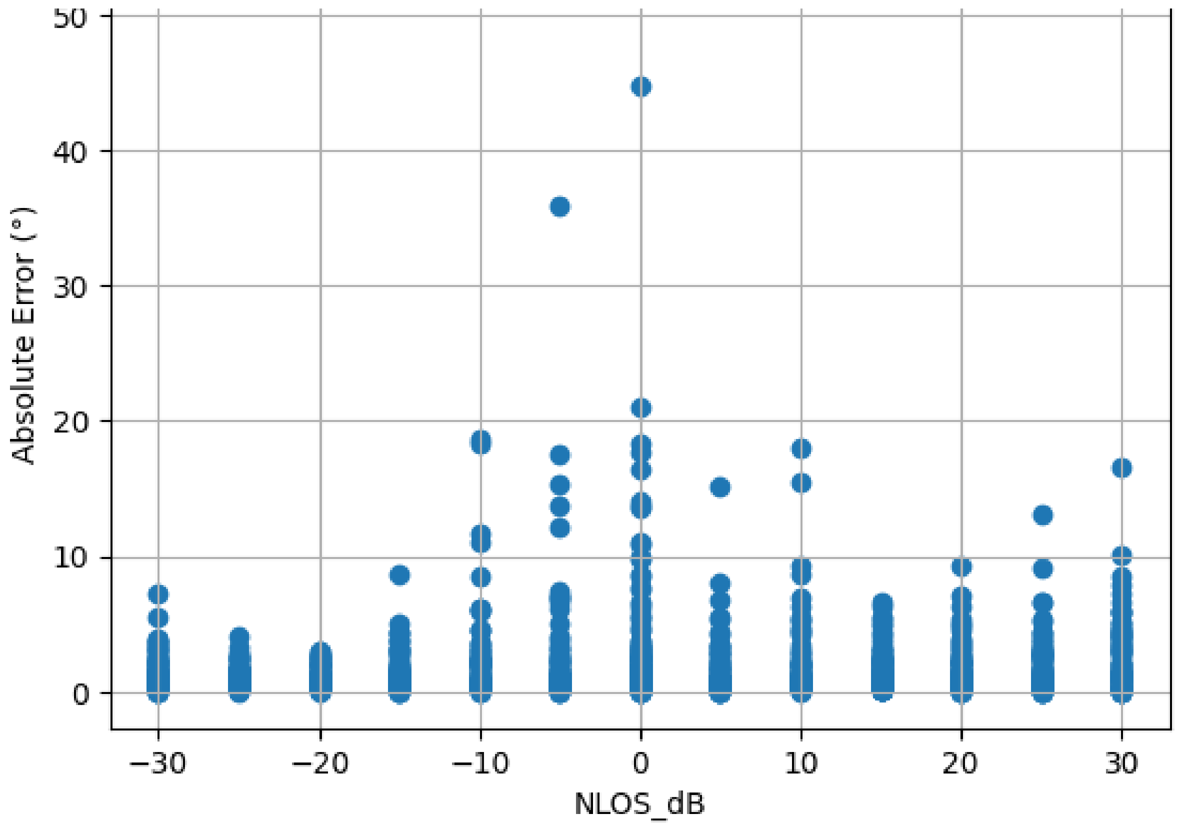
Testing on dataset part of training



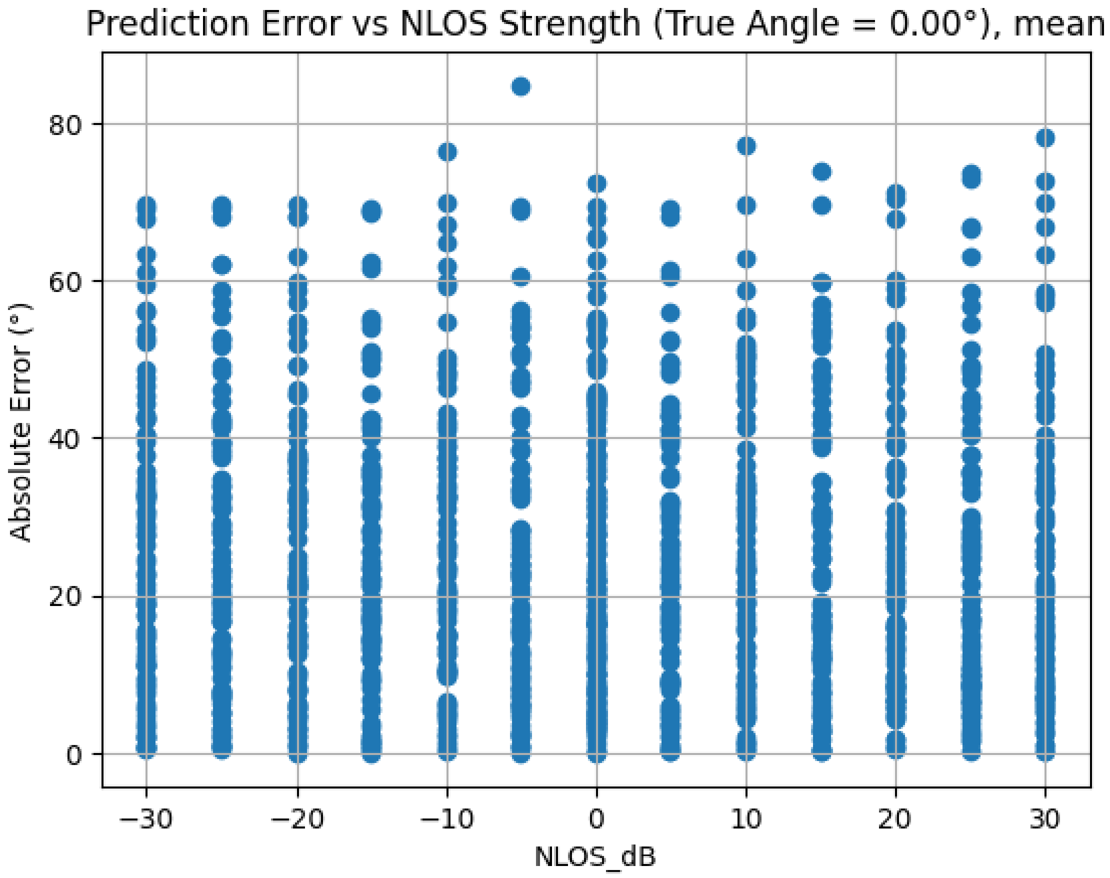


Training set

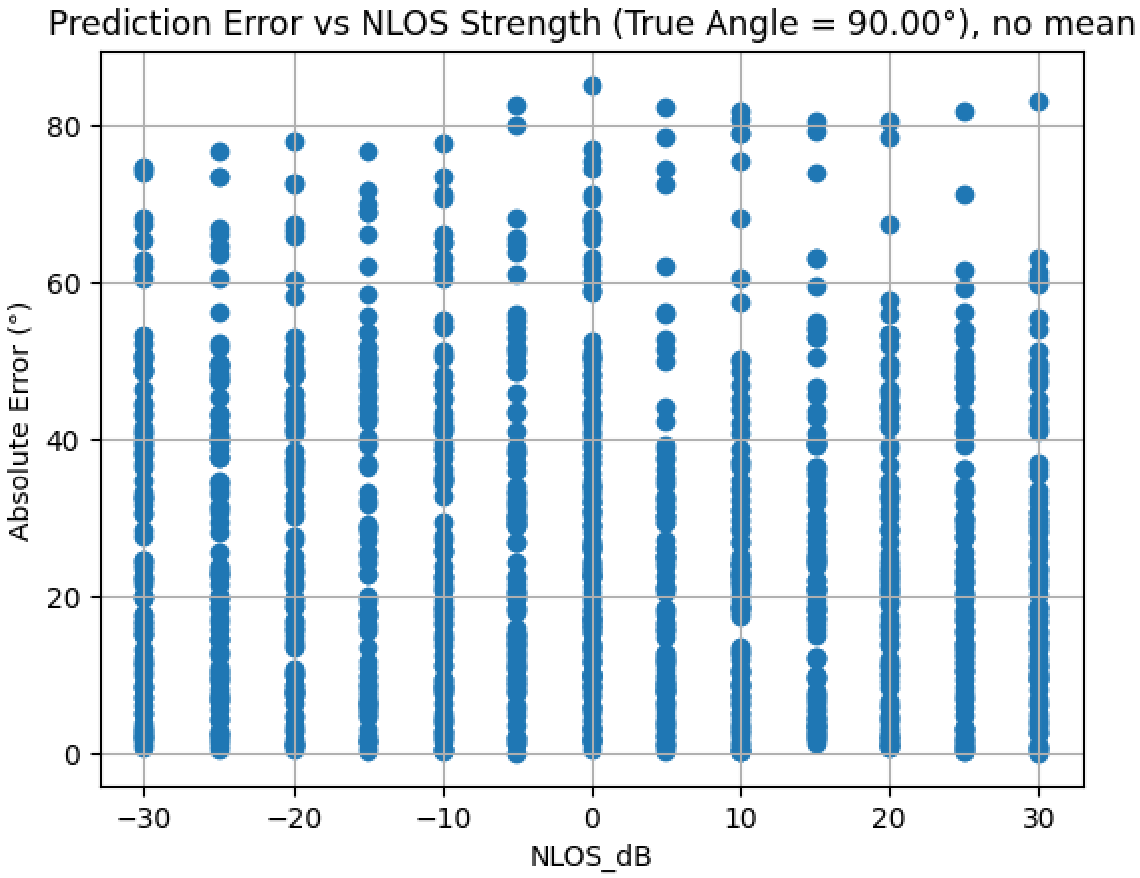




New dataset



Prediction Error vs NLOS Strength (True Angle = 0.00°), mean
Absolute Error (°)
NLOS_dB
0
20
40
60
80
−30
−20
−10
0
10
20
30

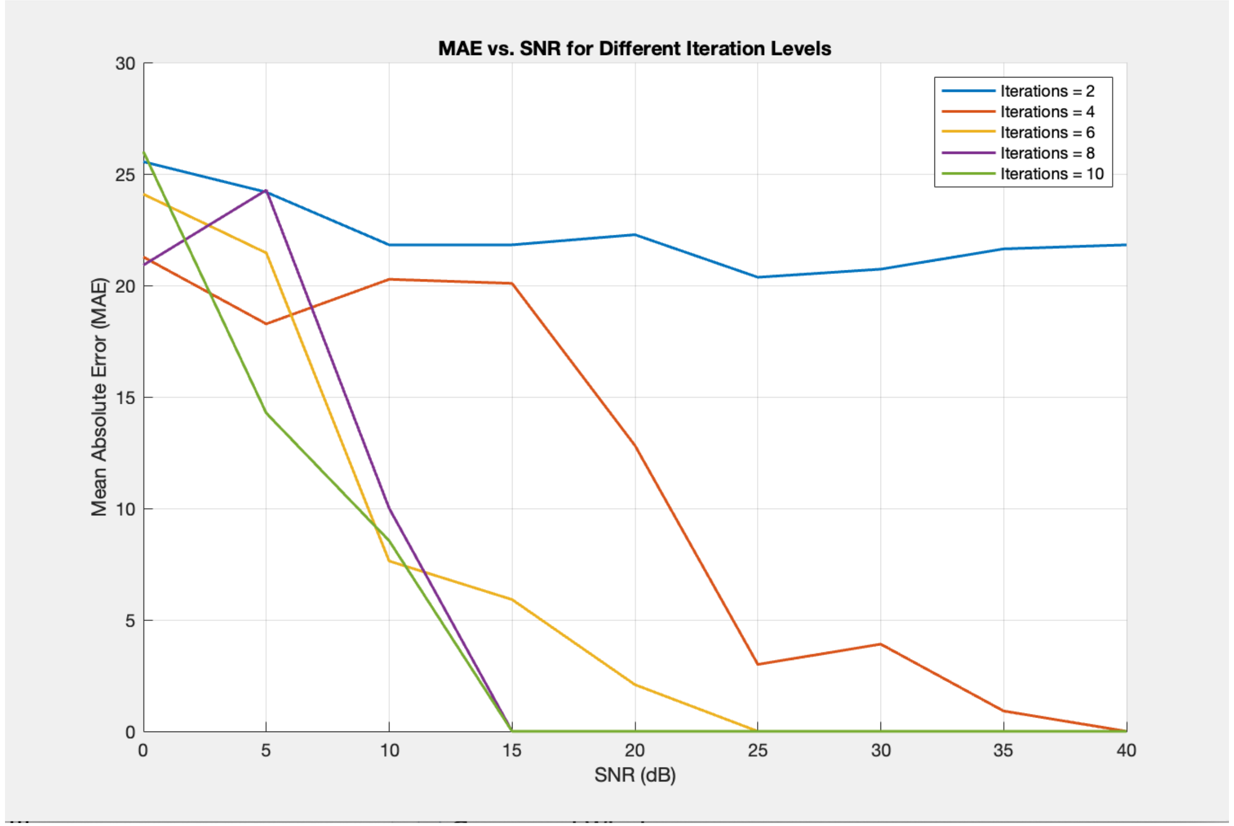


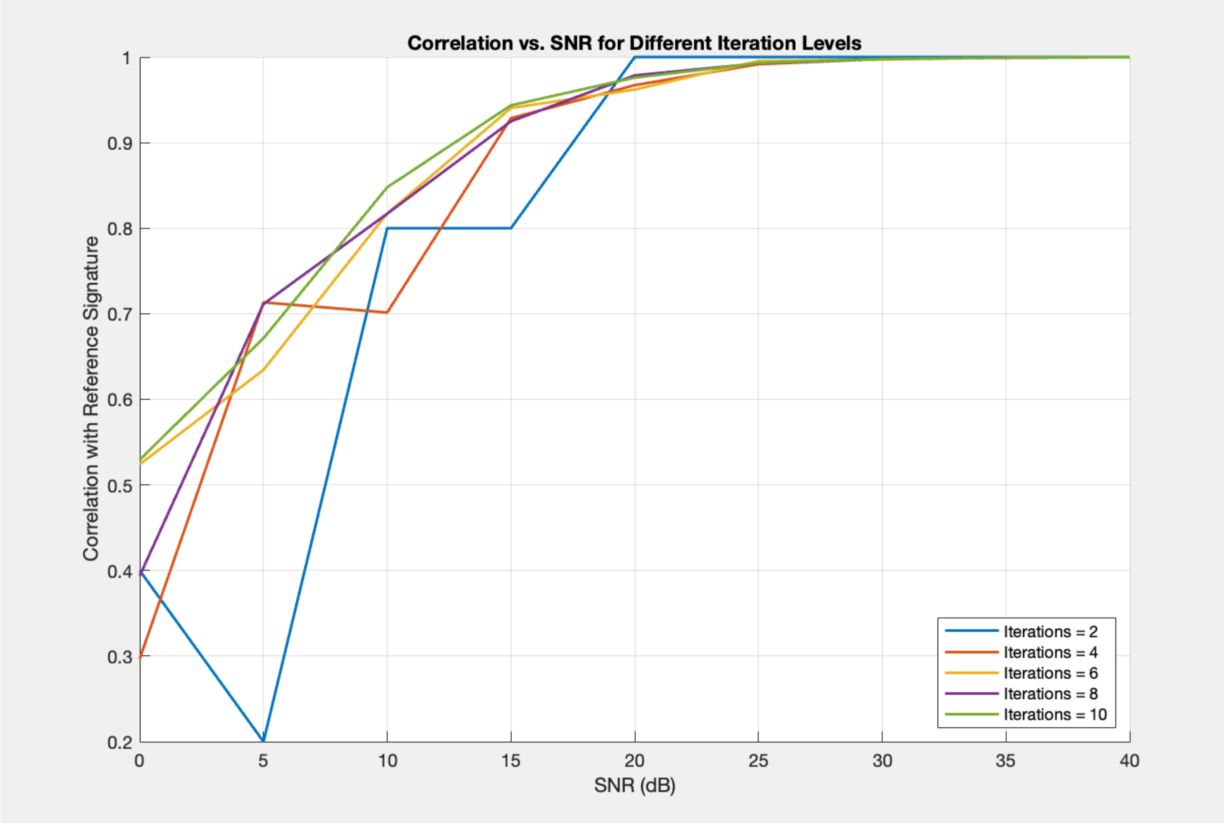
Prediction Error vs NLOS Strength (True Angle = 90.00°), no mean
Absolute Error (°)
NLOS_dB
0
20
40
60
80
−30
−20
−10
0
10
20
30

- Prep for meeting with Ruiyi

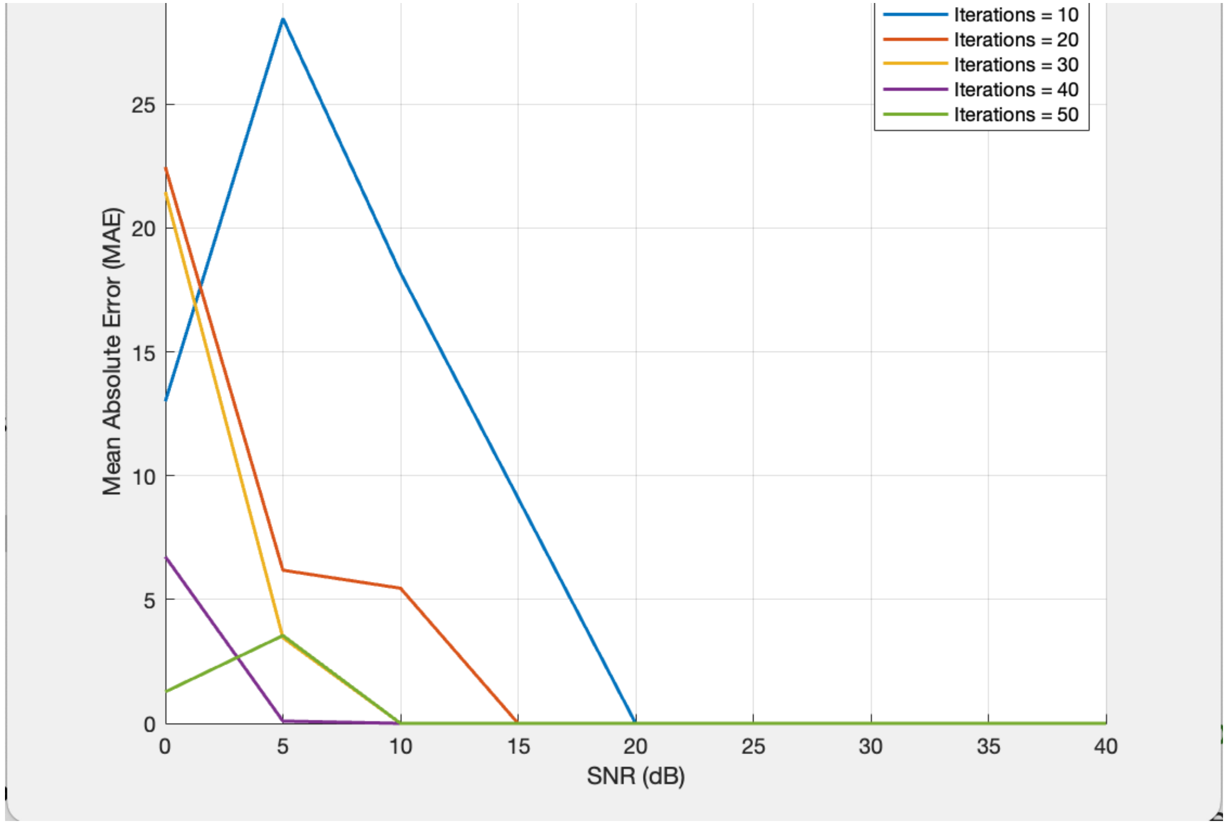
MAE for AWGN SNR vs fewer Iterations

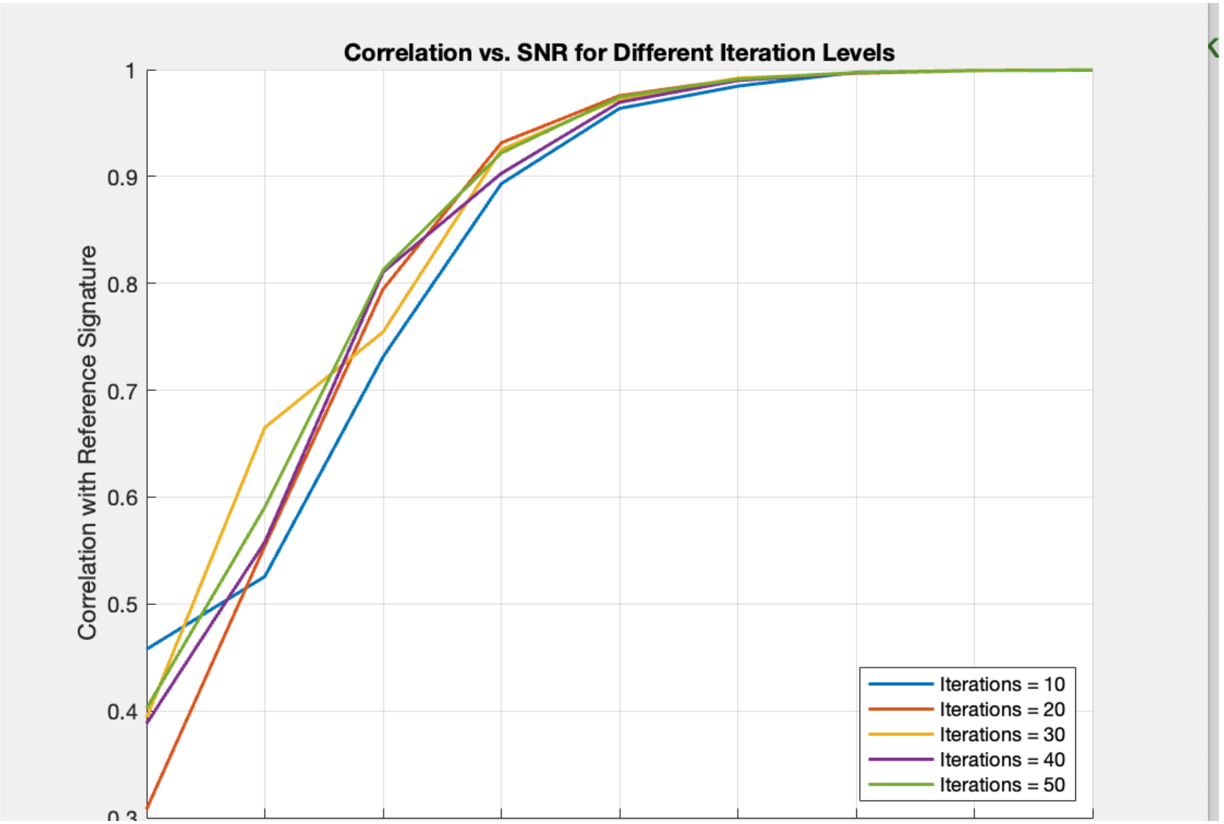
Do average for all angles





More iterations





Multipath channel

Rician Fading

Line-of-Sight (LOS) Component

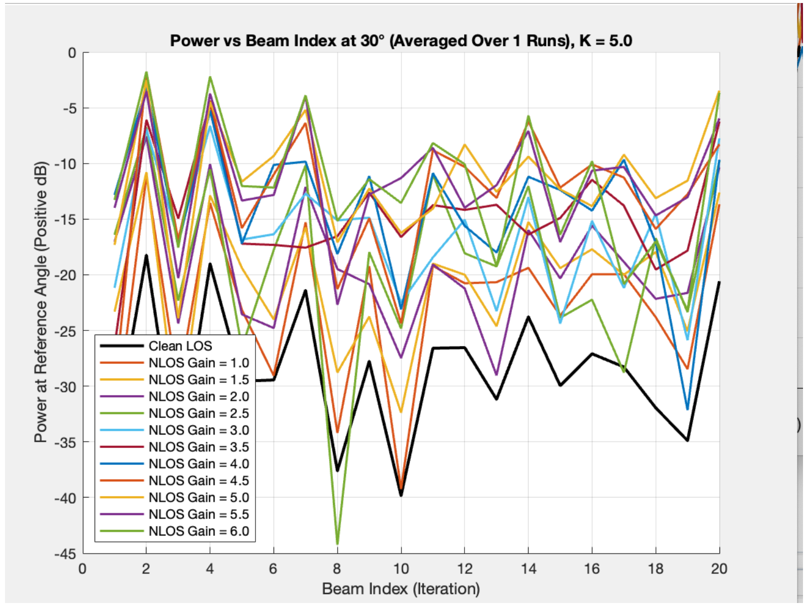
- We model the channel as the sum of a fixed and scattered components

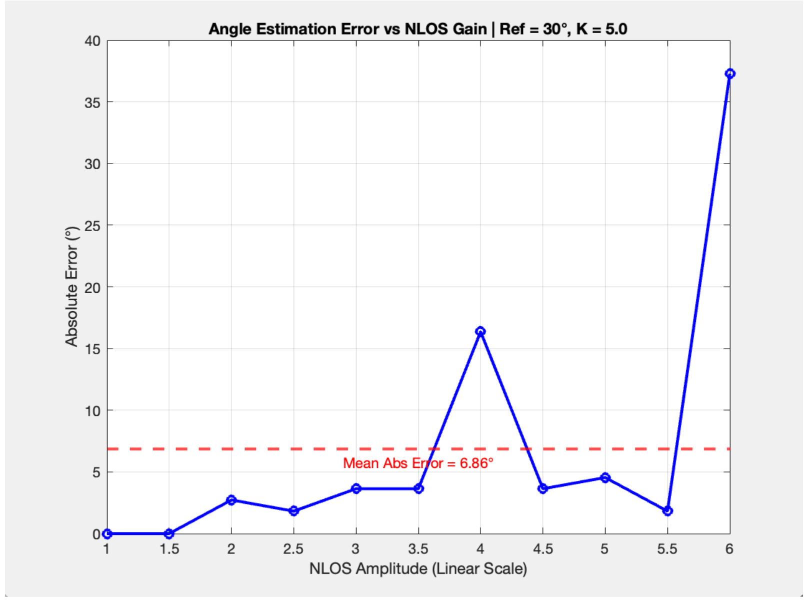
$$\mathbf{H} = \sqrt{\frac{K}{1+K}}\overline{\mathbf{H}} + \sqrt{\frac{1}{1+K}}\mathbf{H}_w,$$

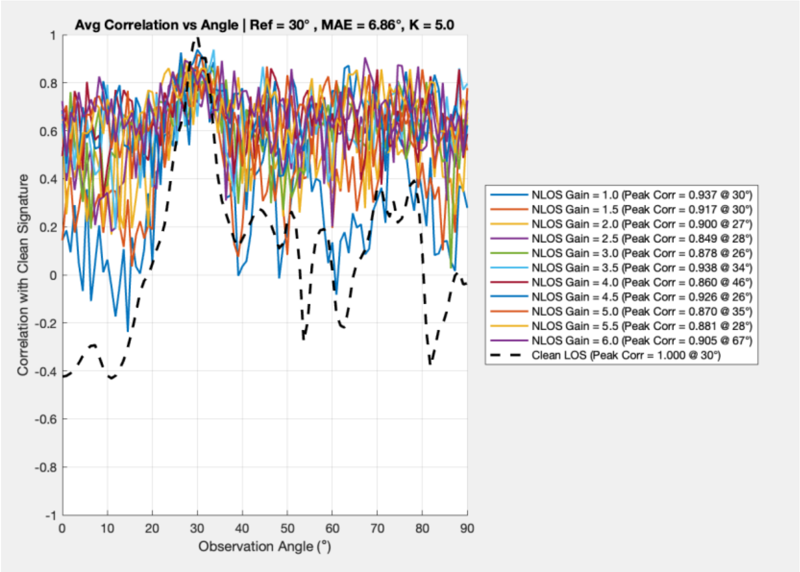
  – $\sqrt{\frac{K}{1+K}}\overline{\mathbf{H}} = \mathcal{E}\{\mathbf{H}\}$ is the LOS component and $\sqrt{\frac{1}{1+K}}\mathbf{H}_w$ is the fading component

  – K is the Ricean K-factor

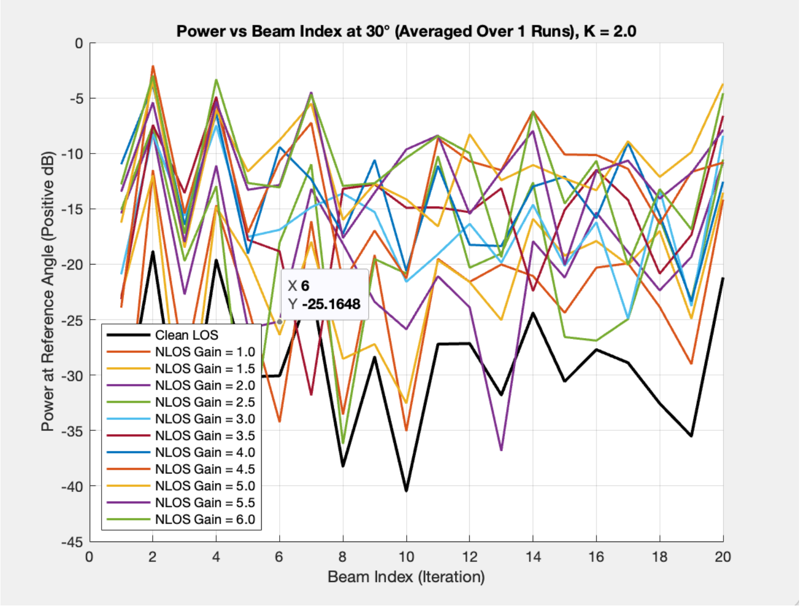
K = 5, iterations = 20

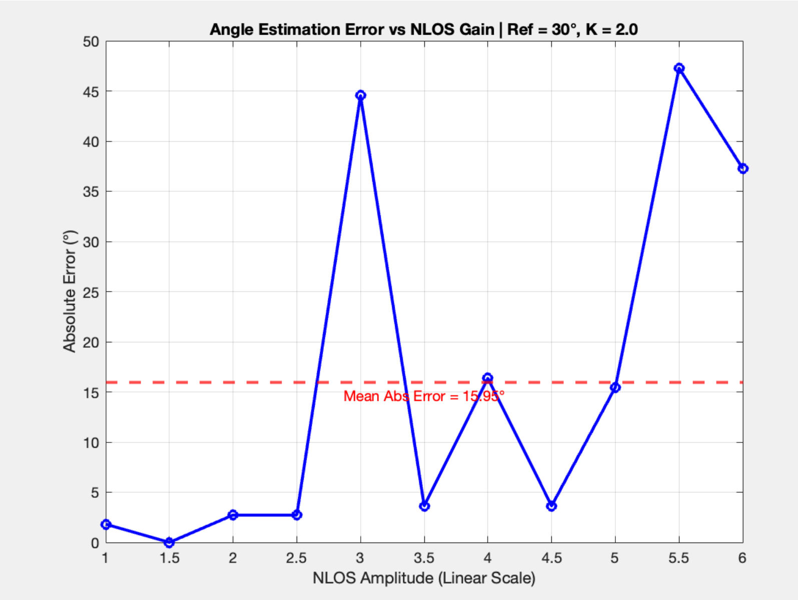


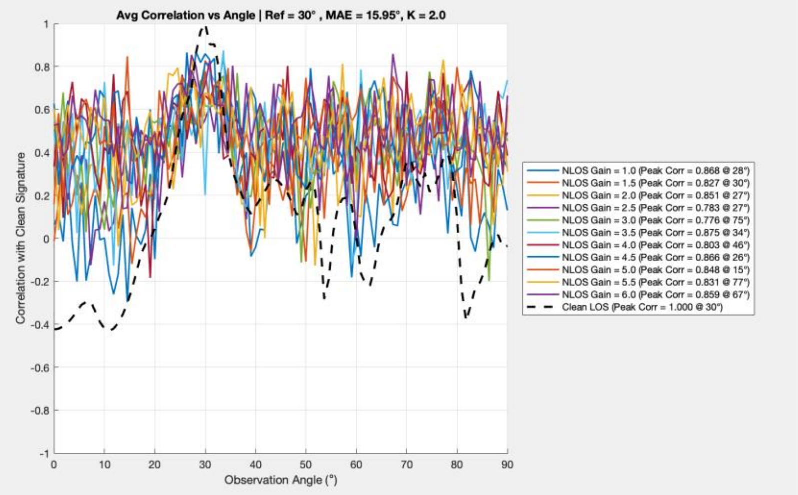




K = 2, iterations = 20

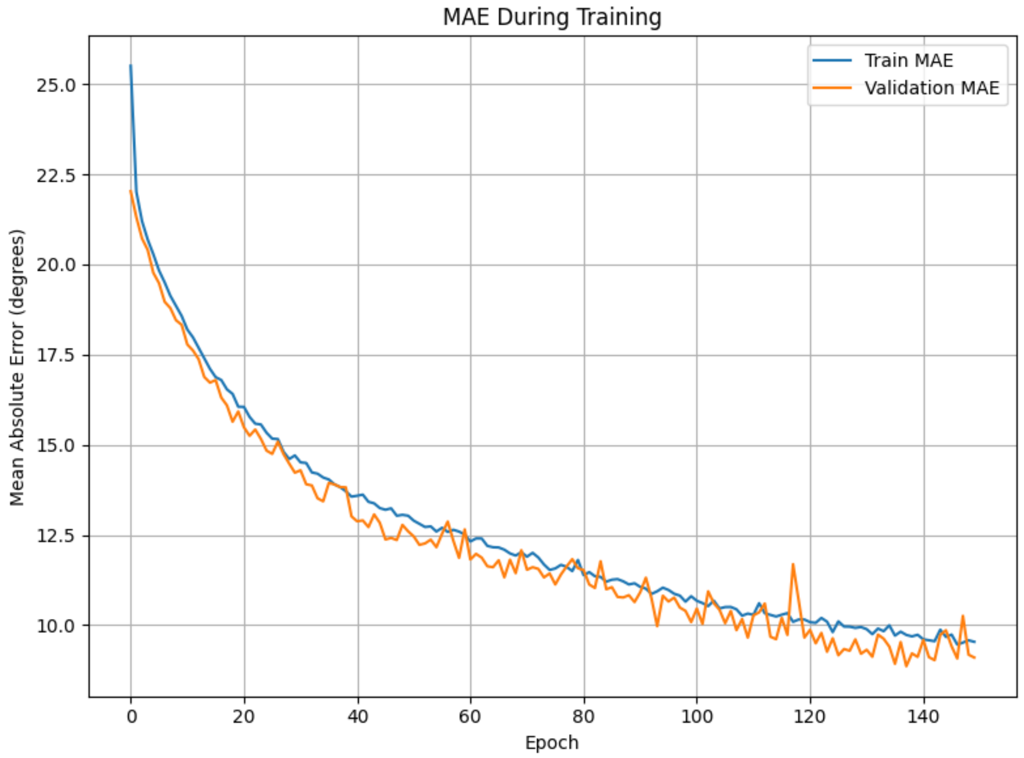


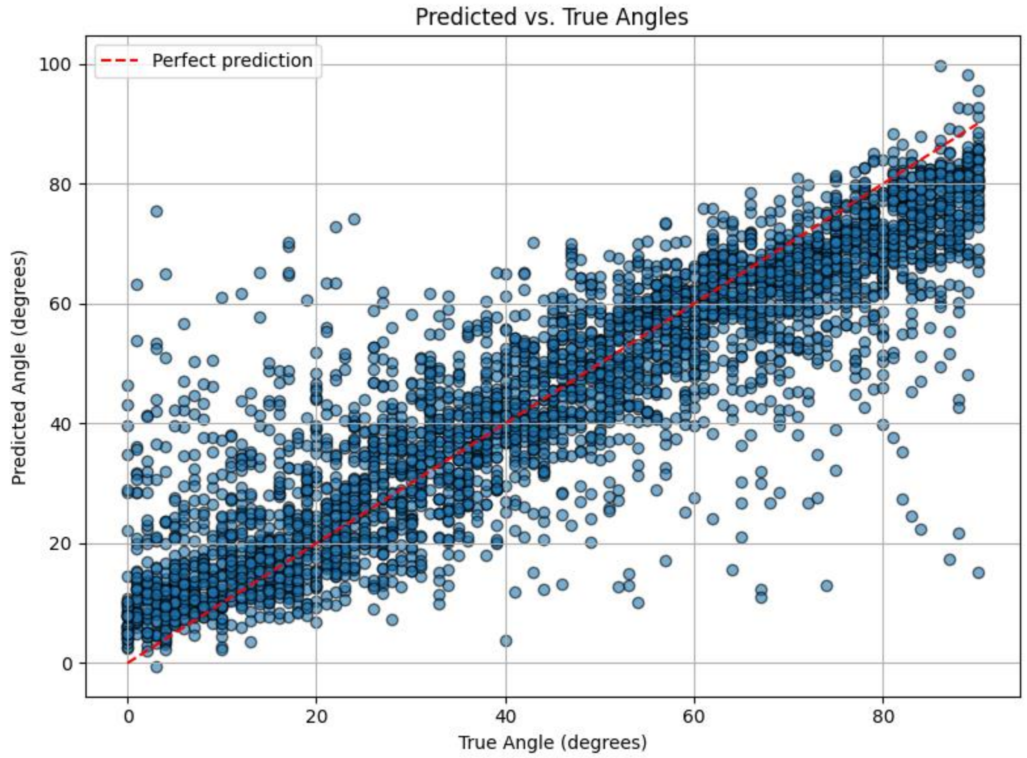




Deep Neural Network

- Activations function = 'relu', K = 2, iterations = 50
- MAE = 8.85 degrees

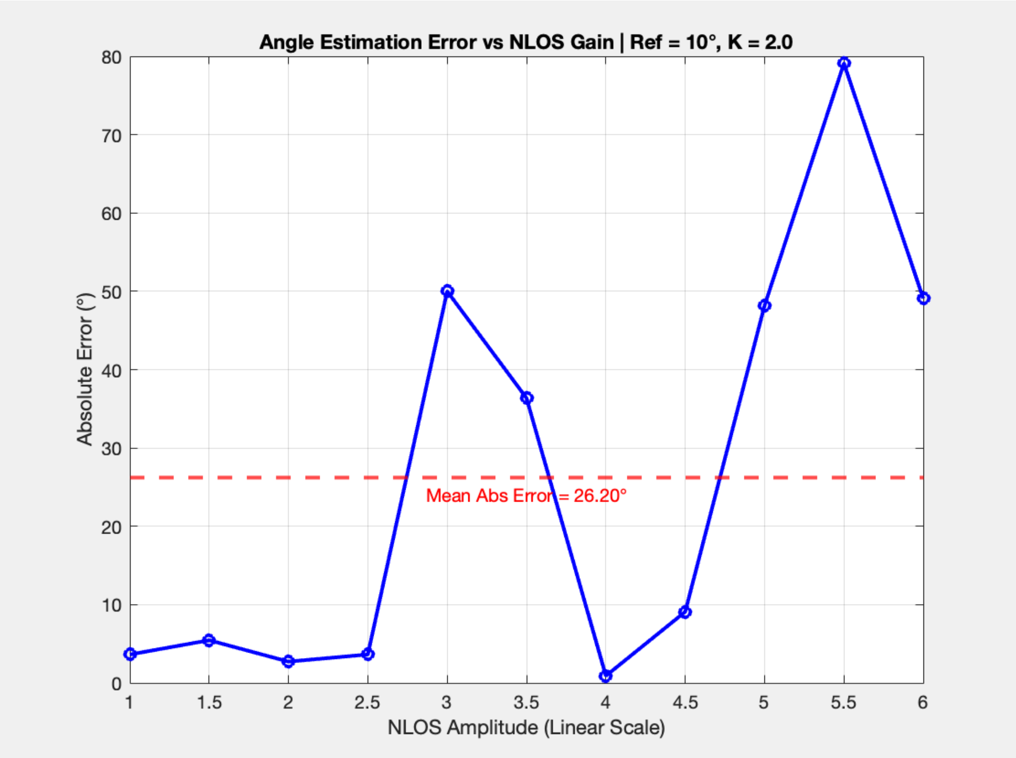


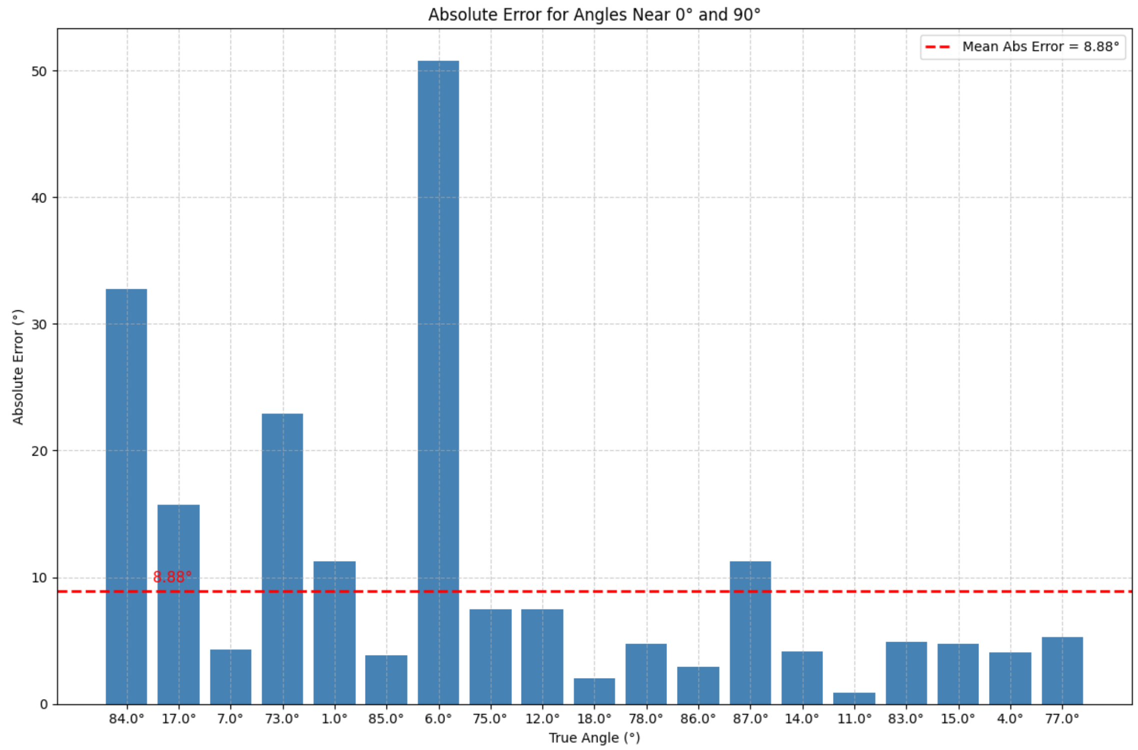


Testing on boundary angles

Correction

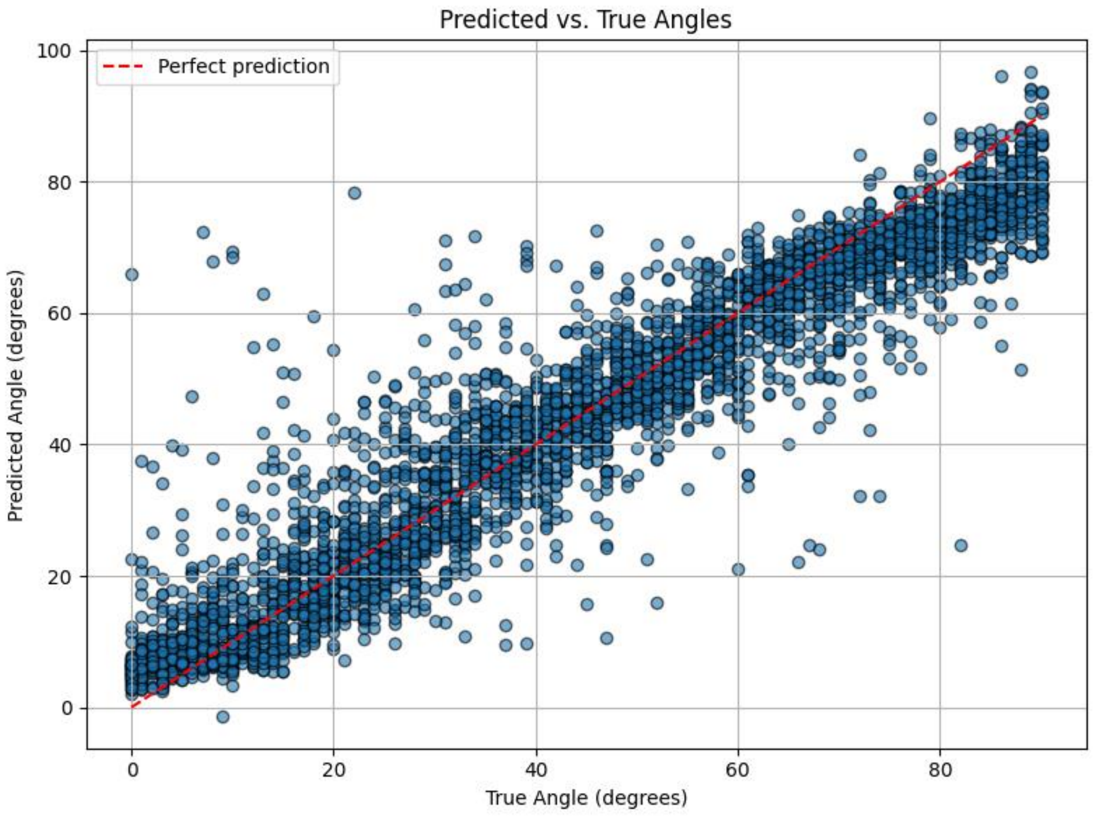
DNN reduce errors



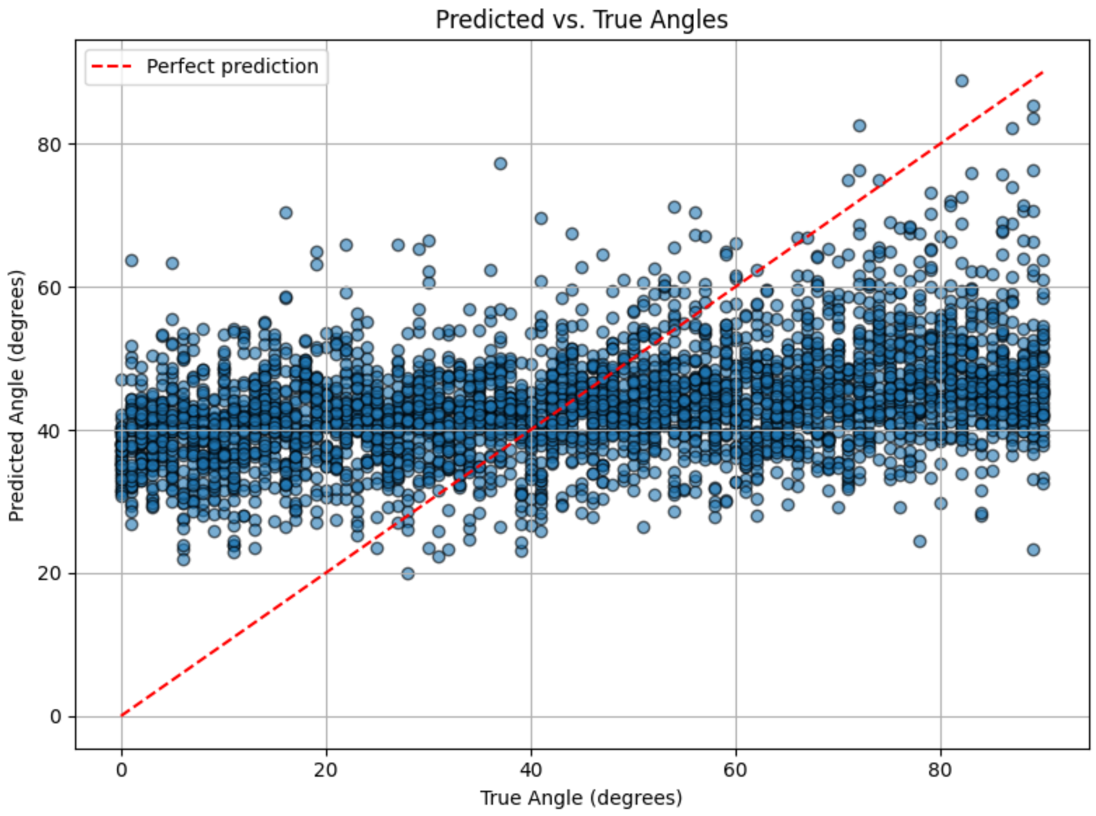


20 iterations vs 100 iterations

100 iterations, MAE = 5.46

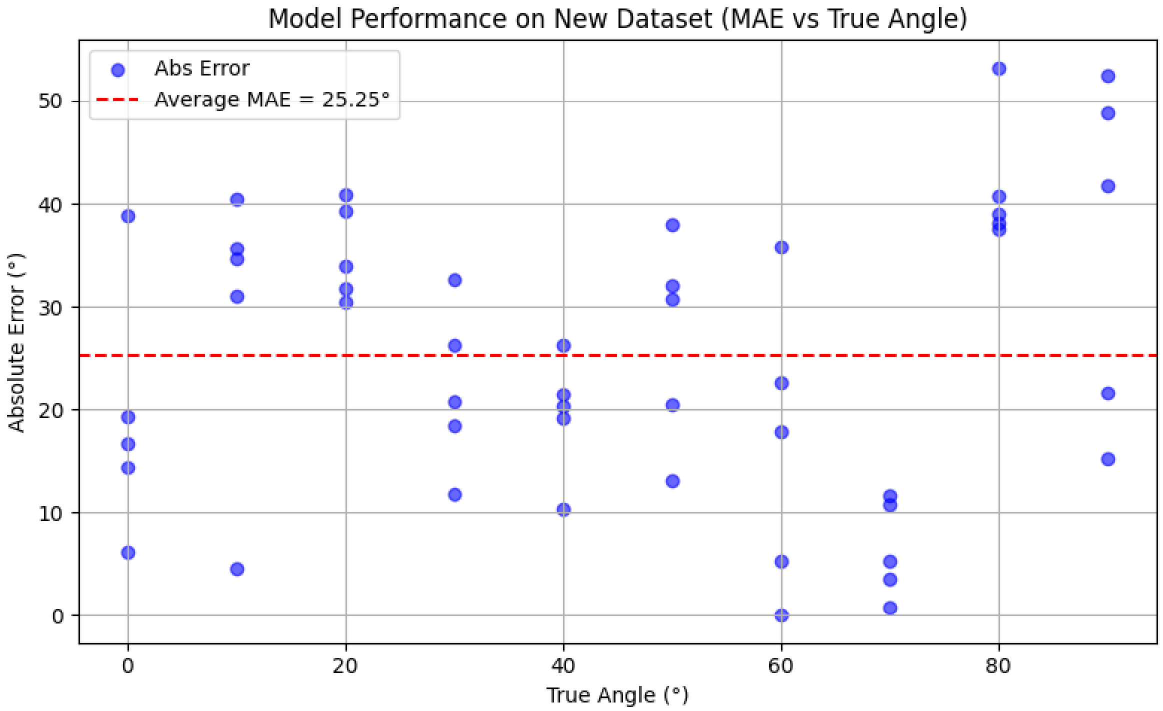


20 iterations , MAE = 20

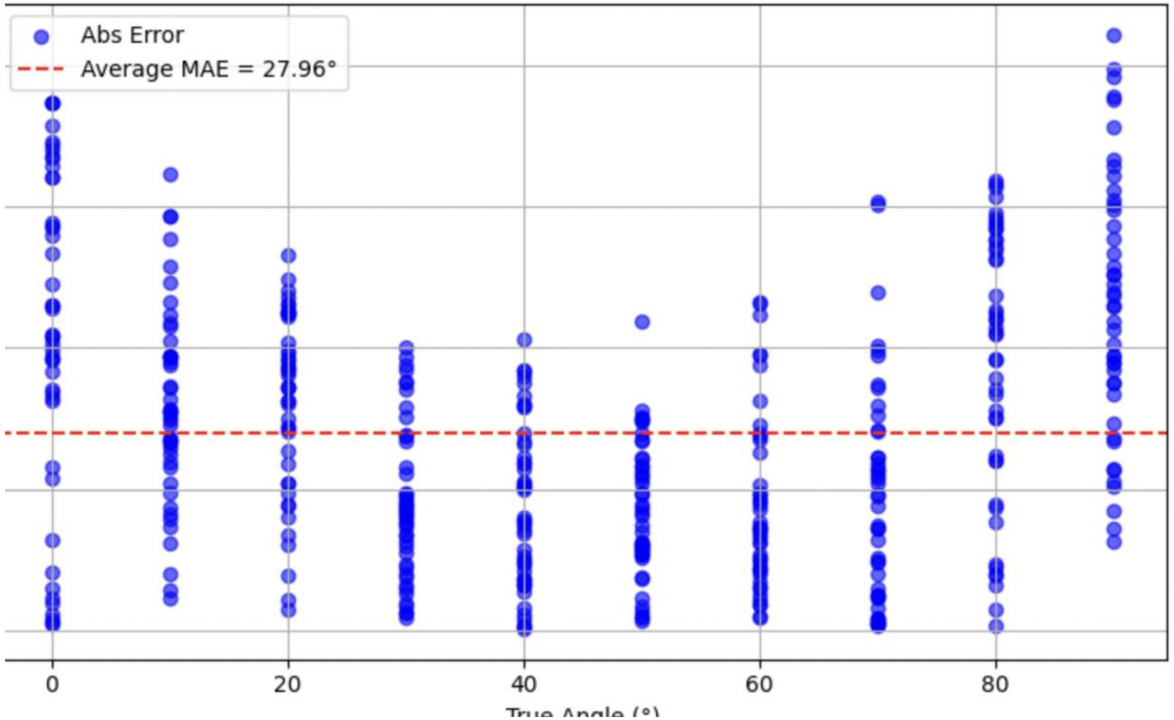


Testing on new unseen environment

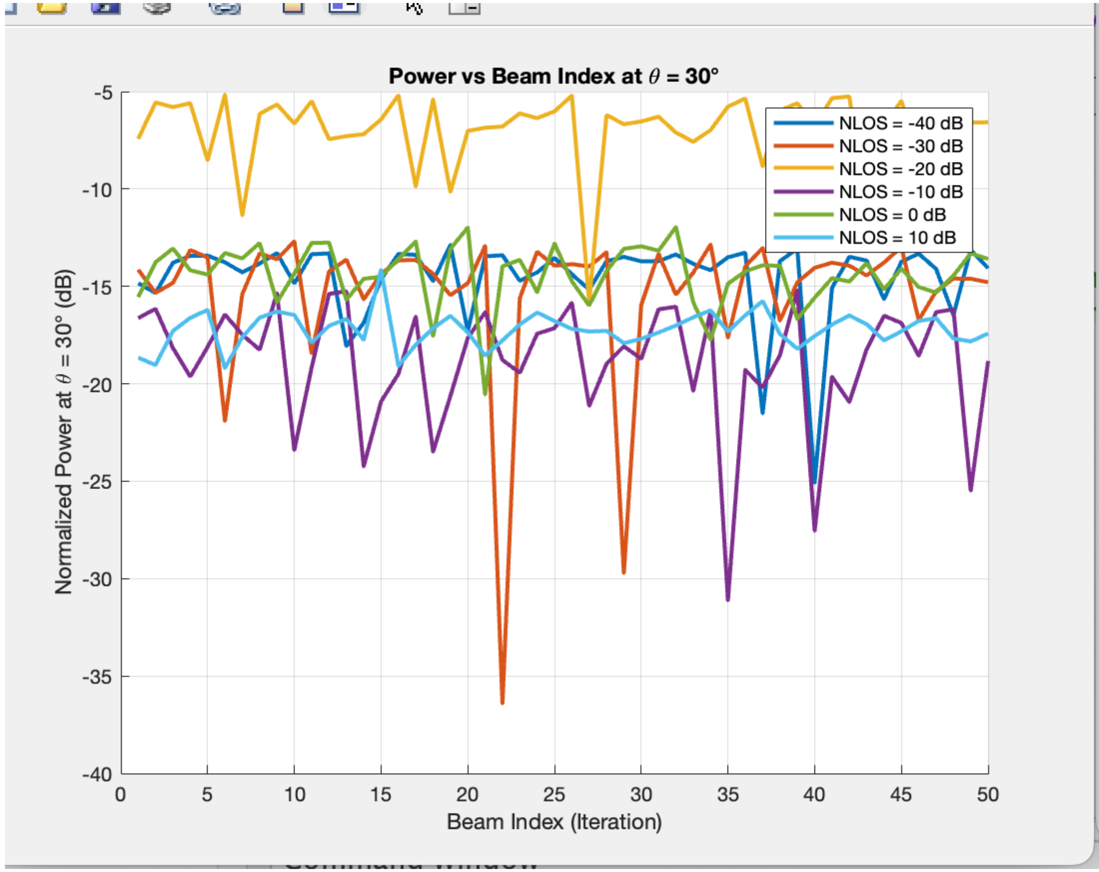
50 iterations

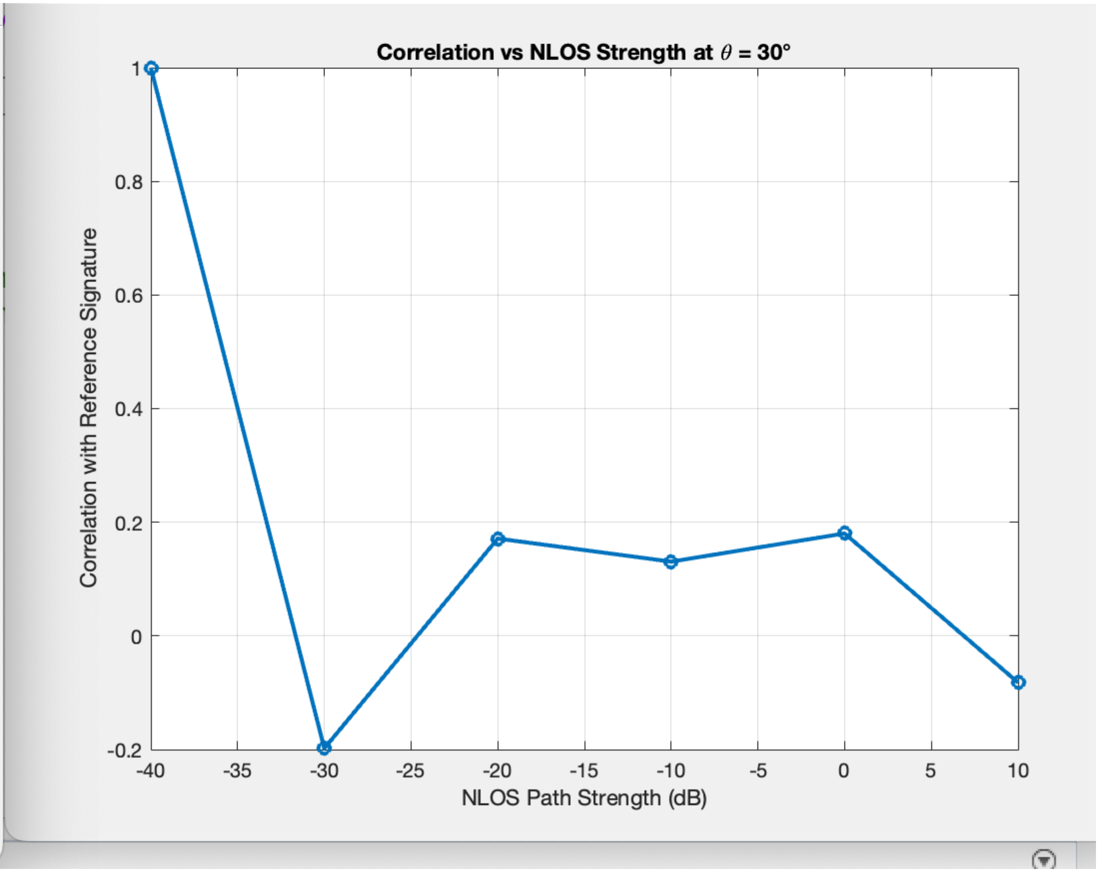


100 iterations



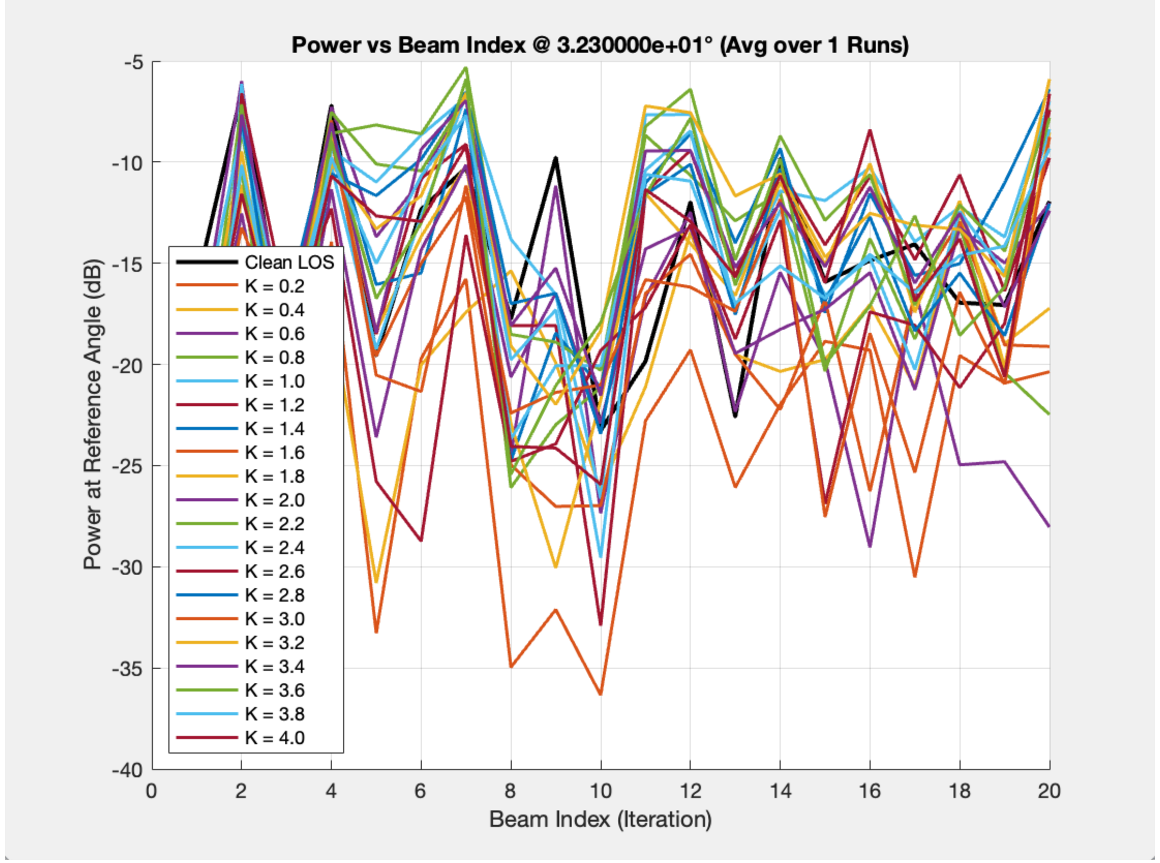
Rayleigh fading channel

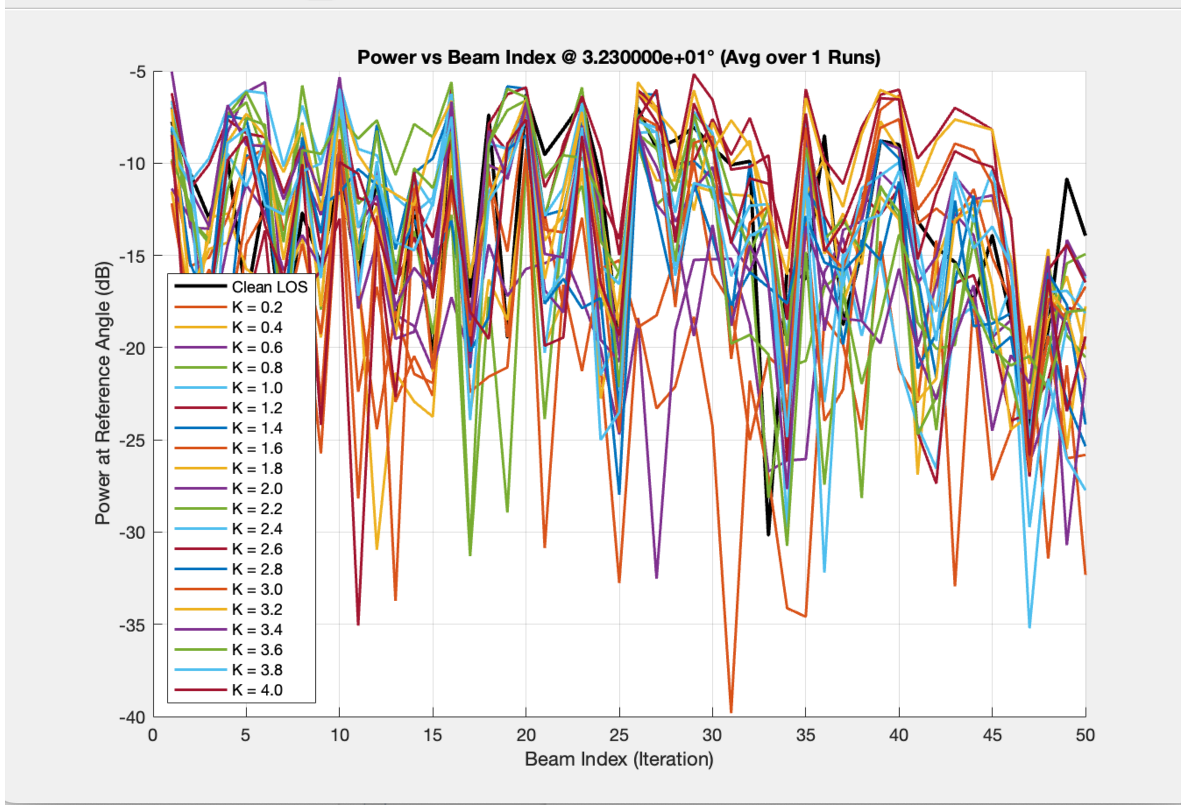




- Matlab Rician Fading channel

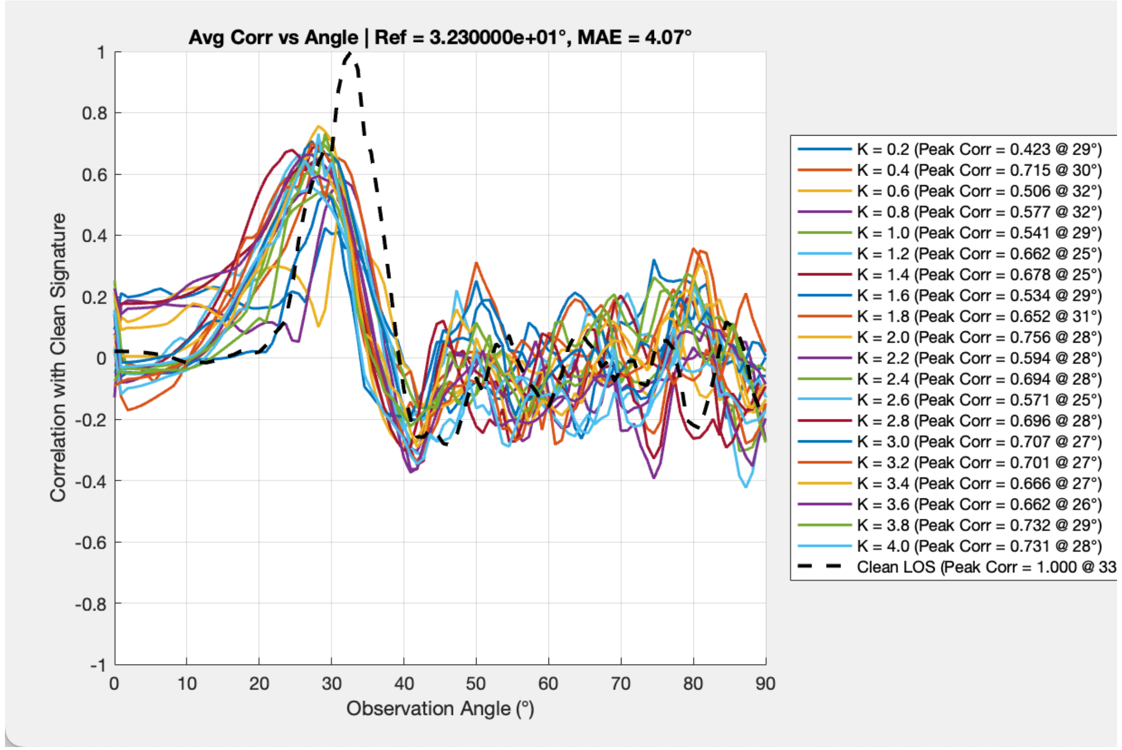
Pure Fading with no noise, Target = 32.3, iter = 60



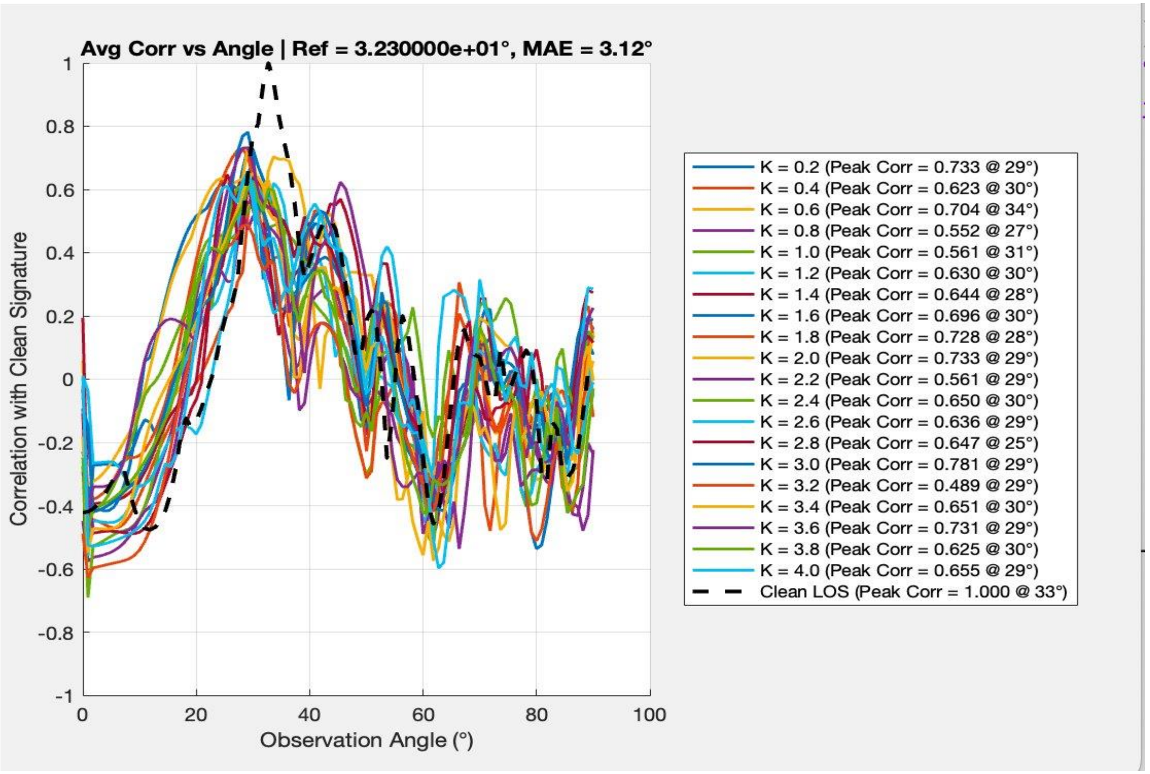


- Correlation has no uniform pattern because the reflections sometimes cause constructive interference or destructive interference

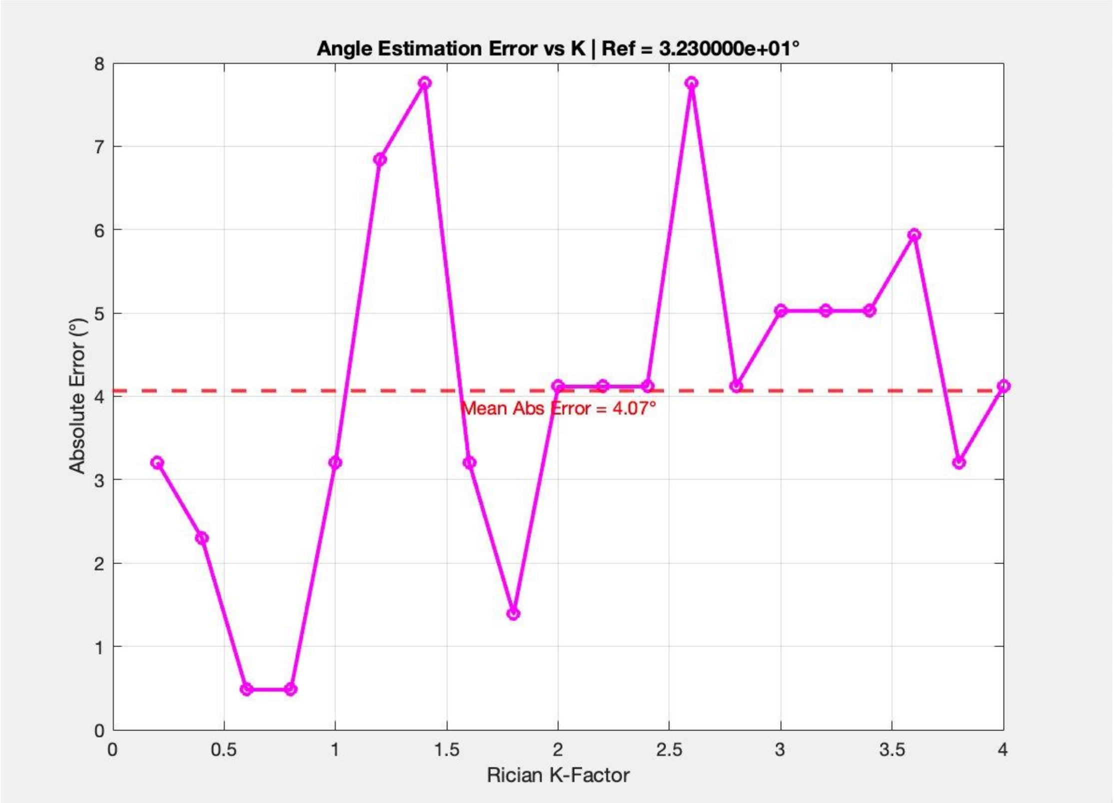
50 iterations



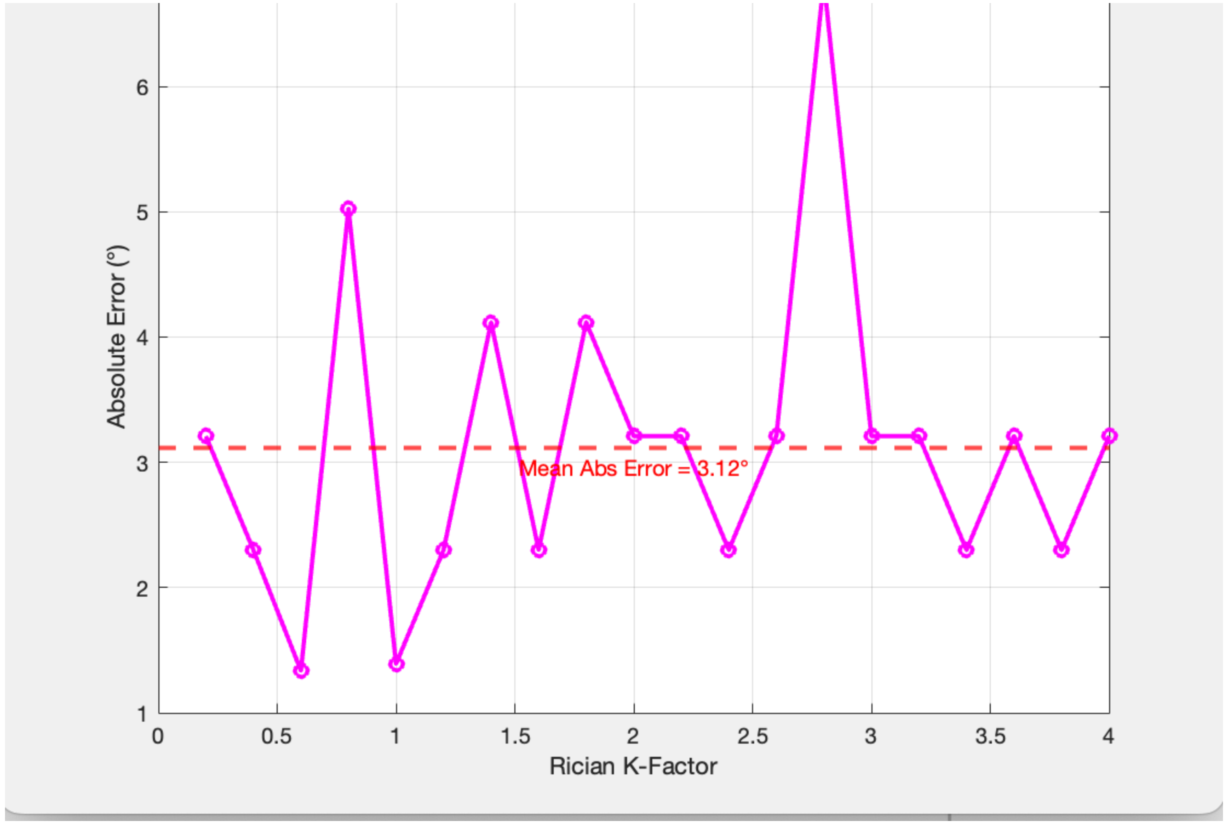
20 iterations



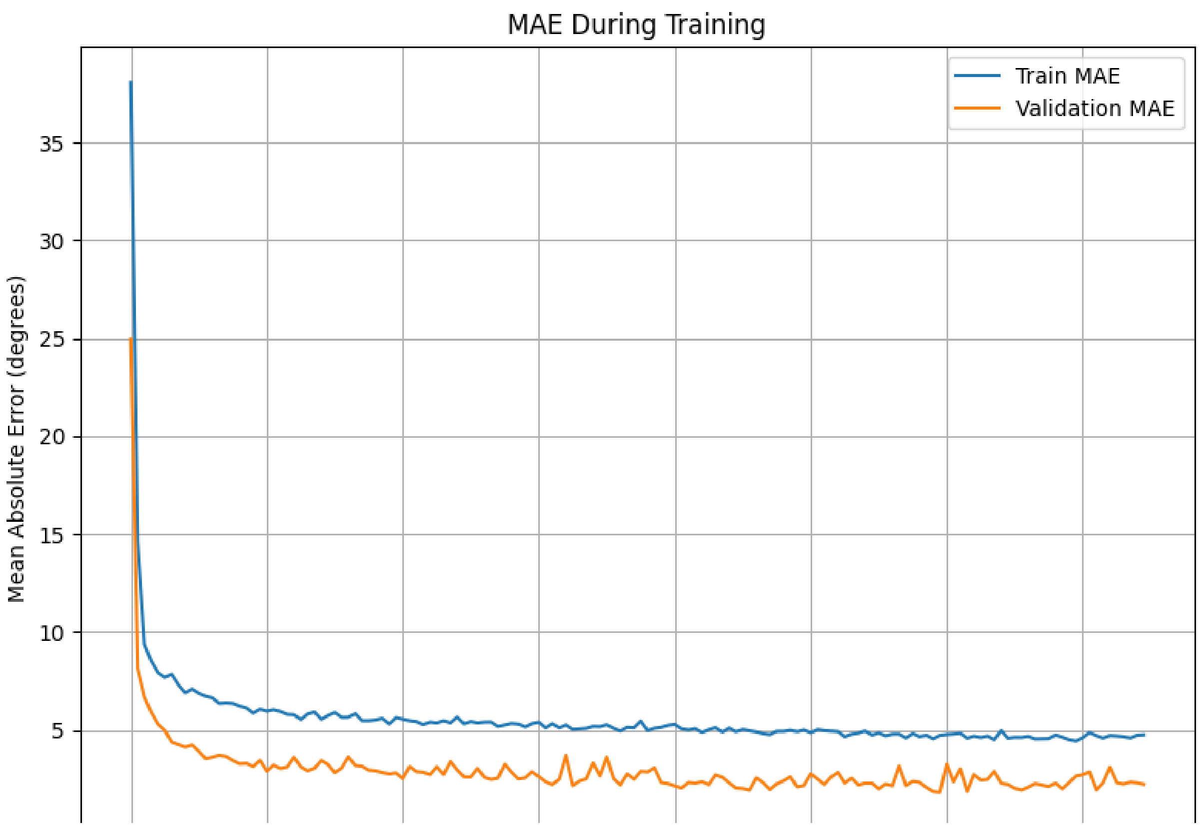
50 iterations

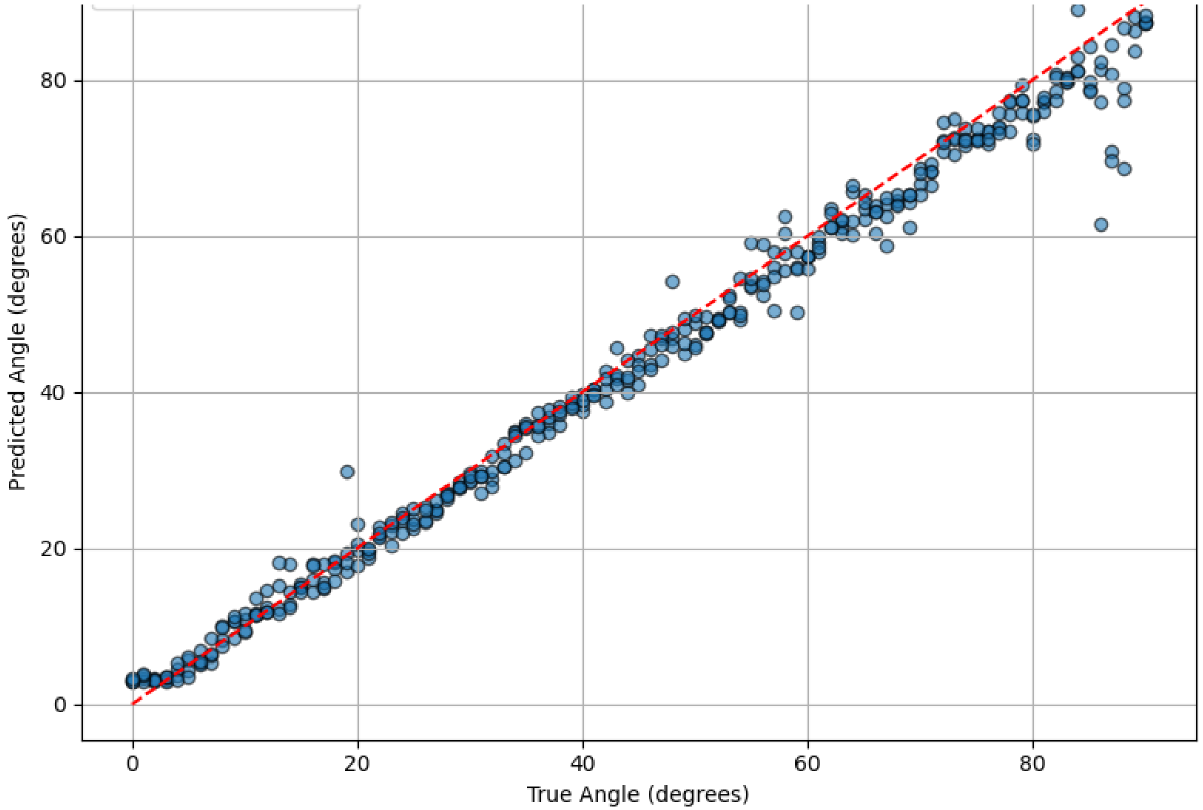


20 iterations

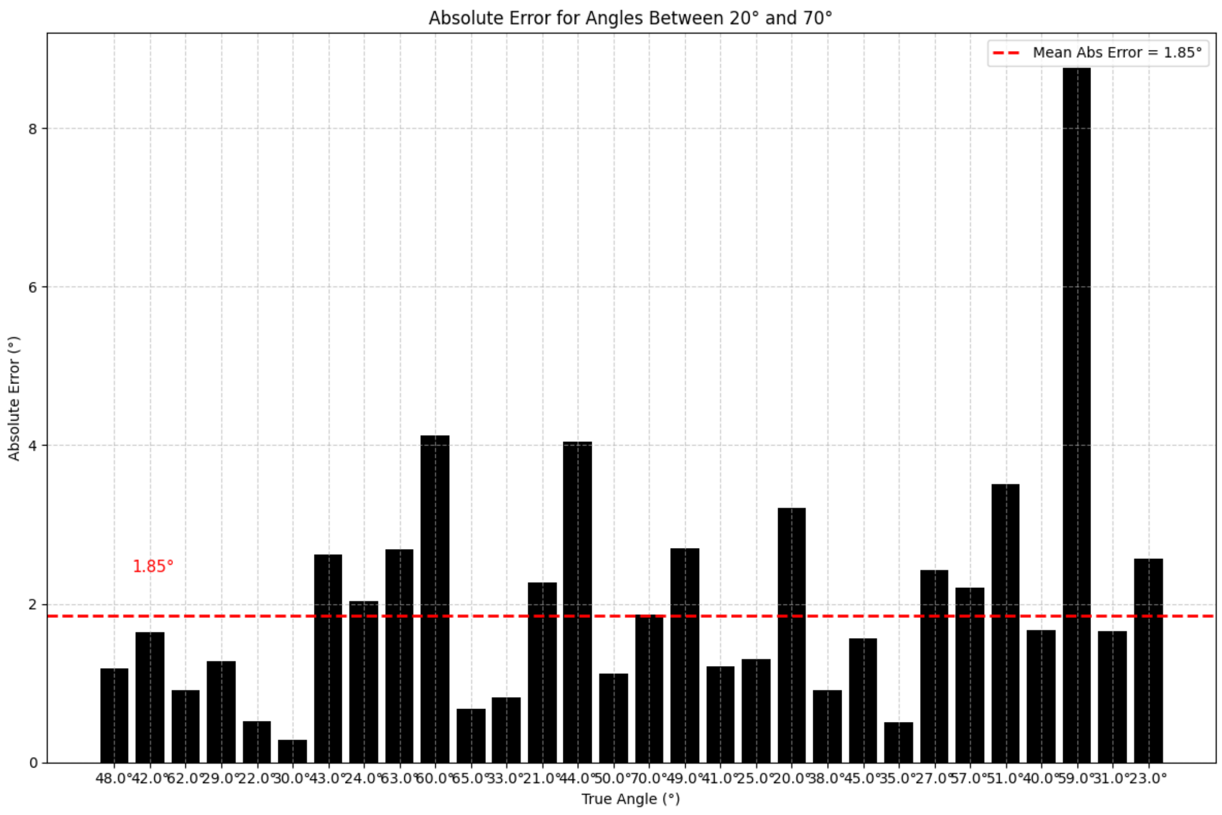


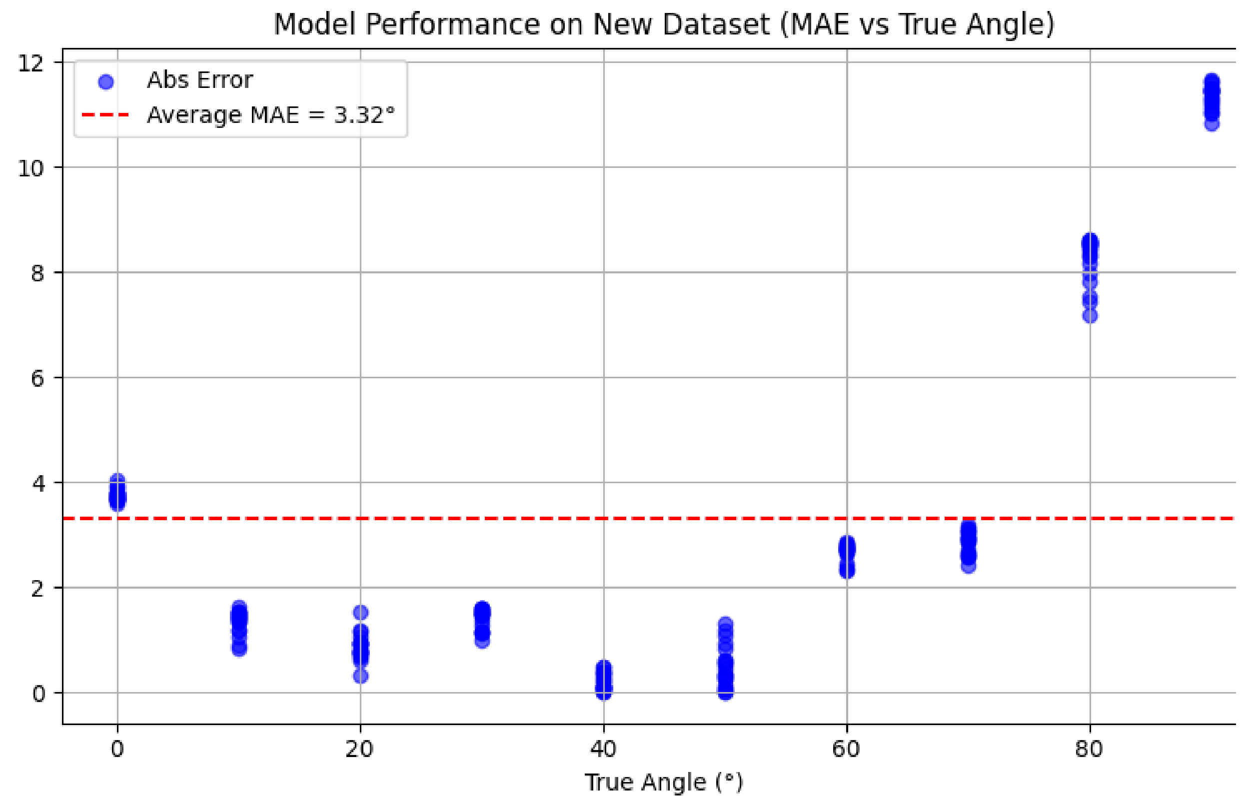
ML, 20 iter, MAE = 2.27

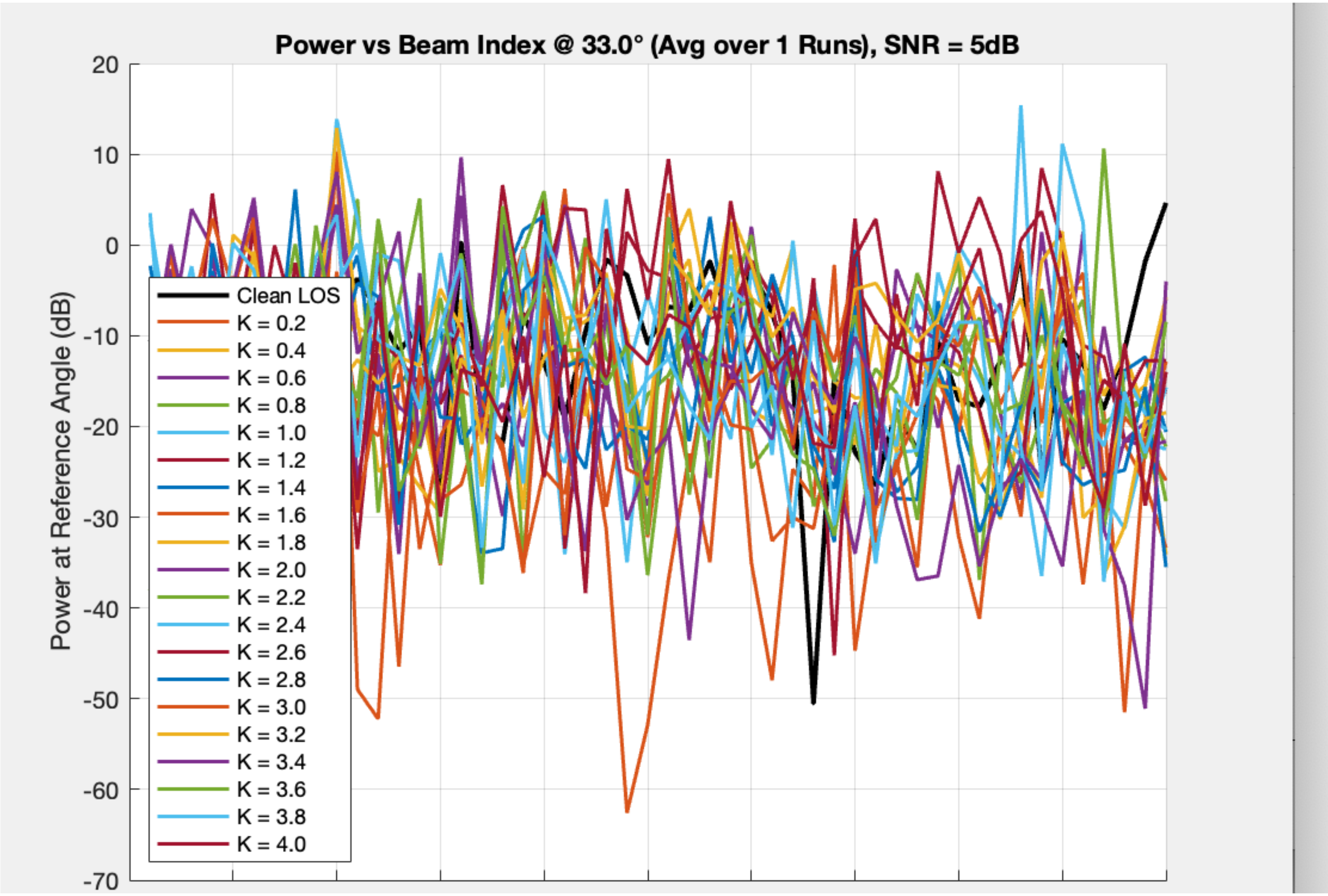




testing

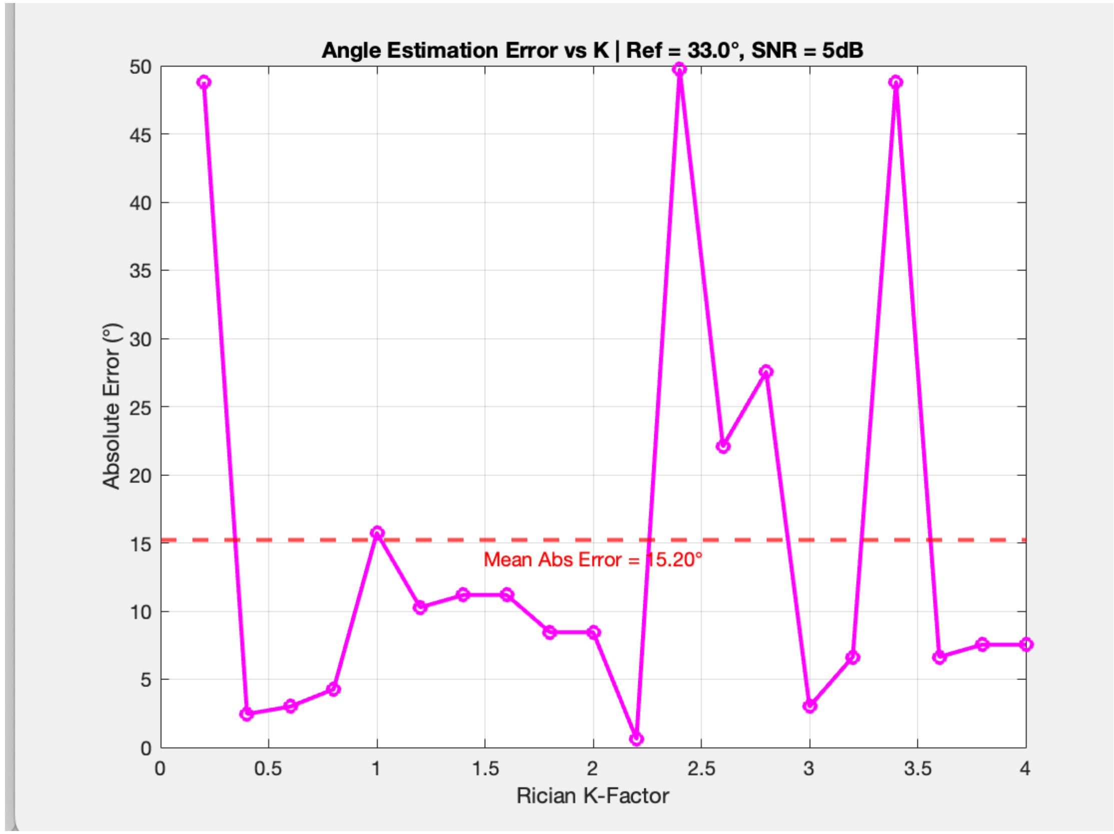

Absolute Error for Angles Between 20° and 70°
Mean Abs Error = 1.85°
1.85°
Absolute Error (°)
0
2
4
6
8
48.0° 42.0° 62.0° 29.0° 22.0° 30.0° 43.0° 24.0° 63.0° 60.0° 65.0° 33.0° 21.0° 44.0° 50.0° 70.0° 49.0° 41.0° 25.0° 20.0° 38.0° 45.0° 35.0° 27.0° 57.0° 51.0° 40.0° 59.0° 31.0° 23.0°
True Angle (°)

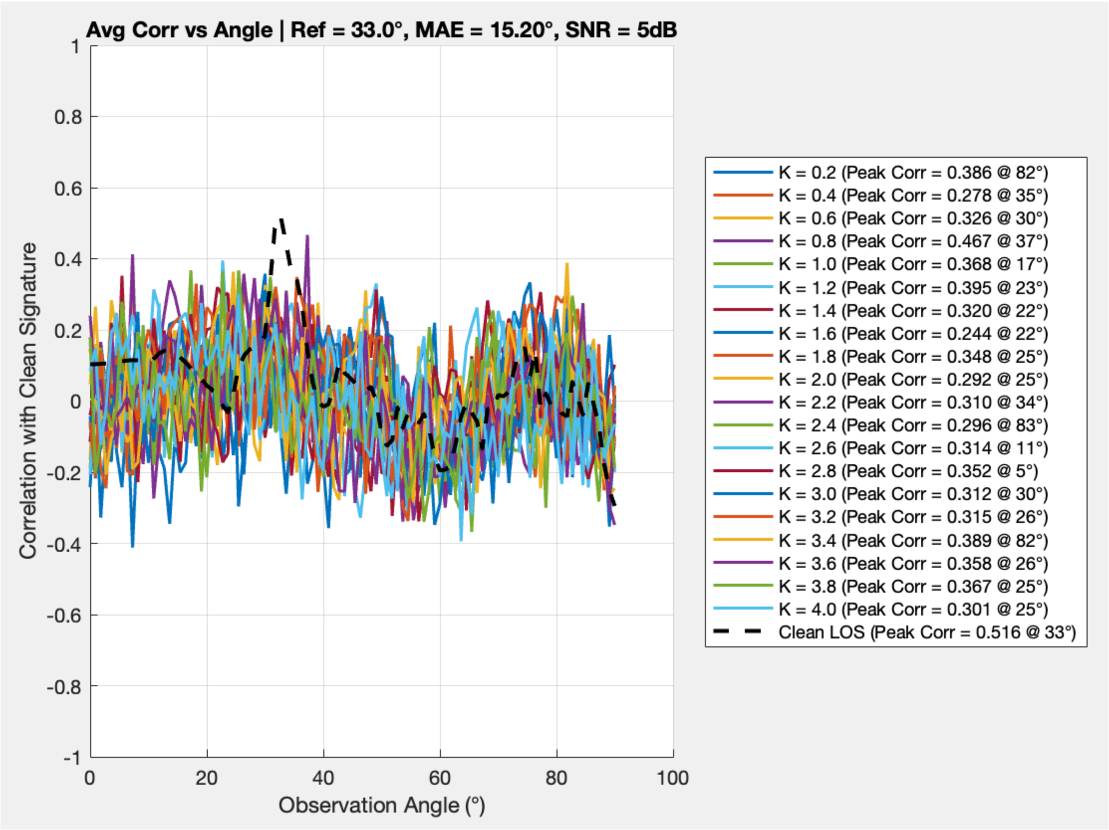

Model Performance on New Dataset (MAE vs True Angle)
Abs Error
Average MAE = 3.32°
0
2
4
6
8
10
12
0
20
40
60
80
True Angle (°)



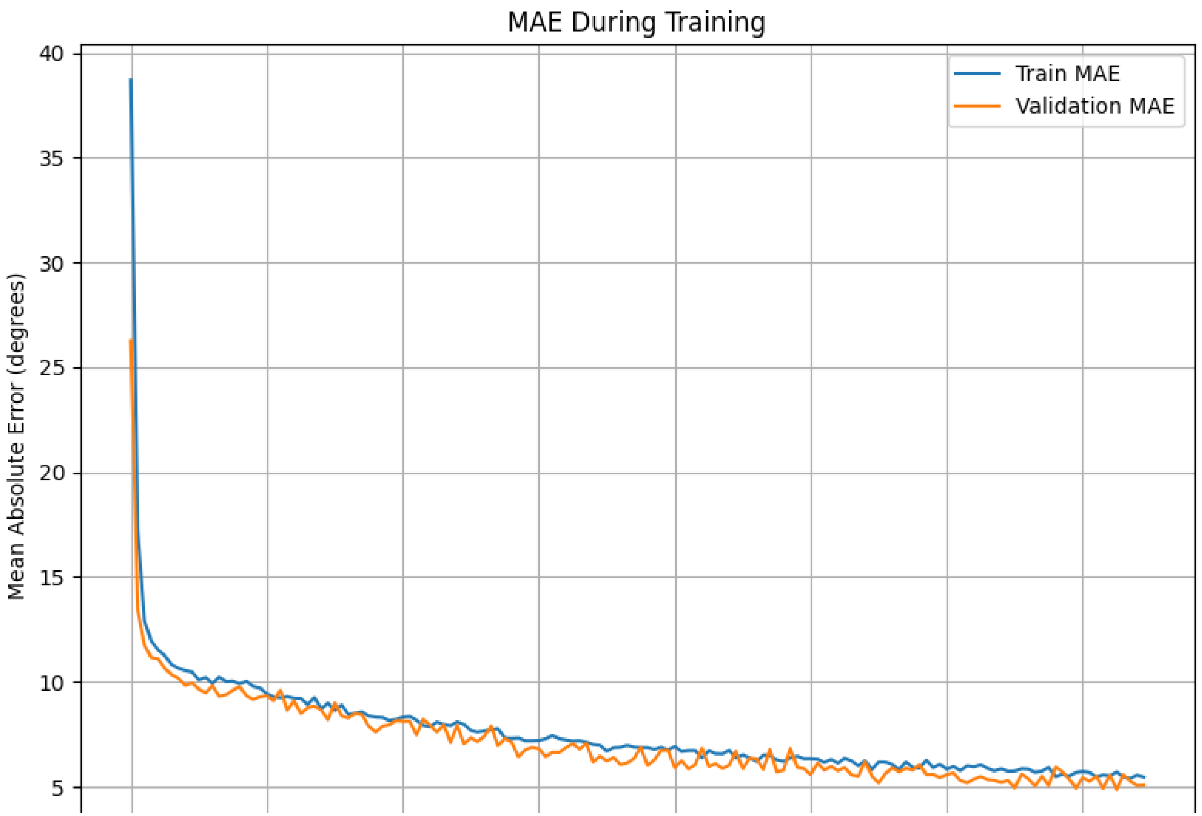
Add noise,
SNR = 5dB

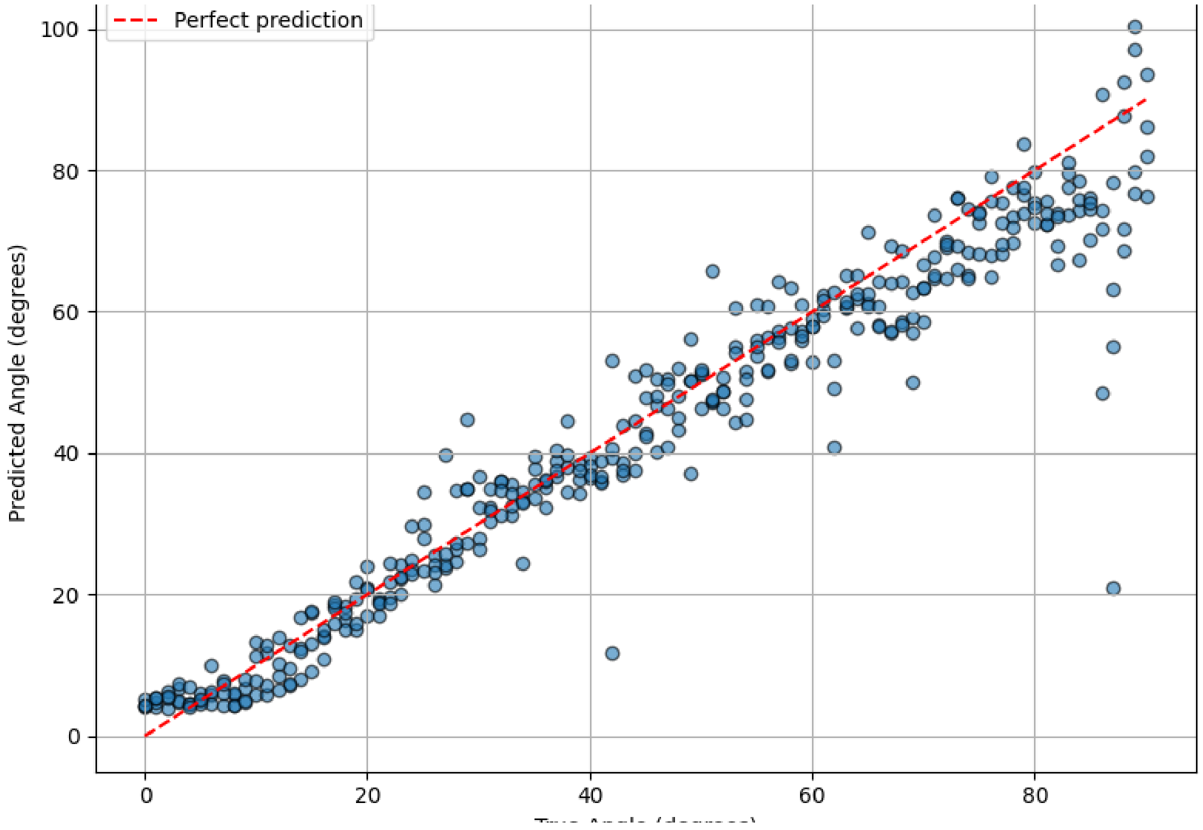
correlation



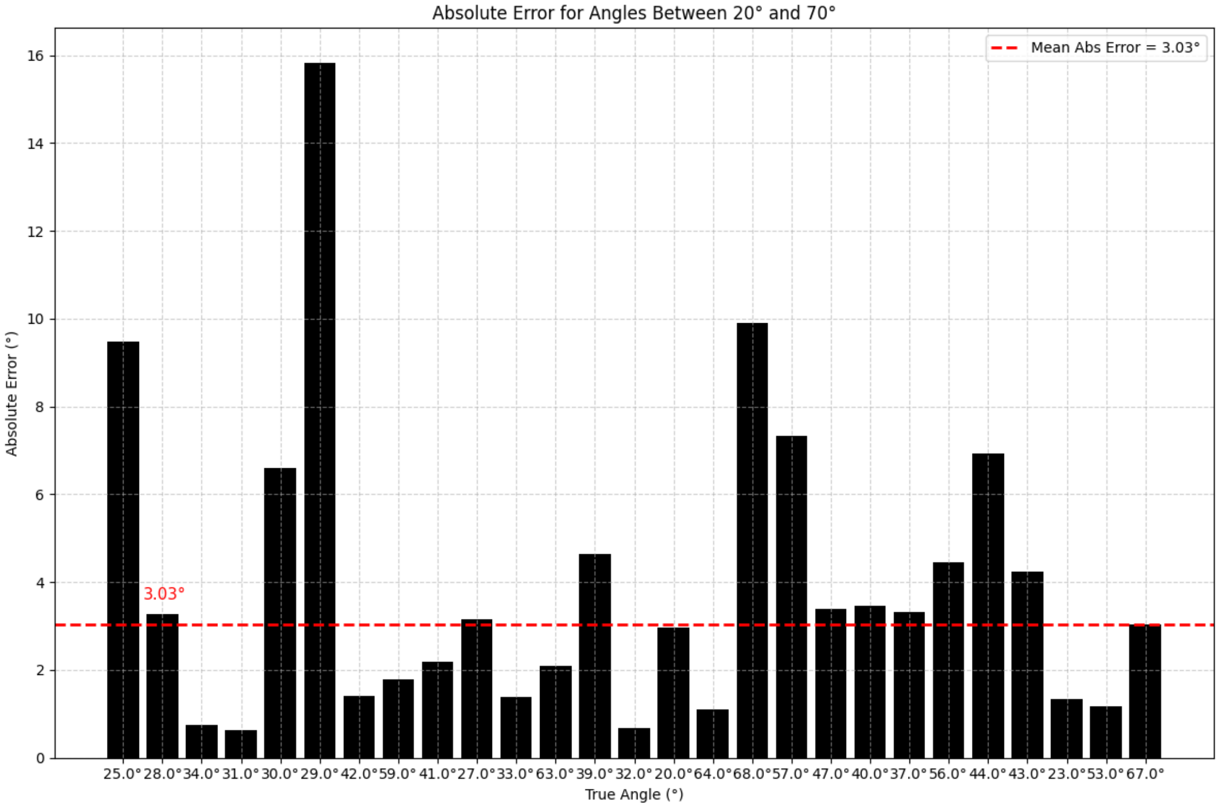


ML for noisy data, MAE = 4.57

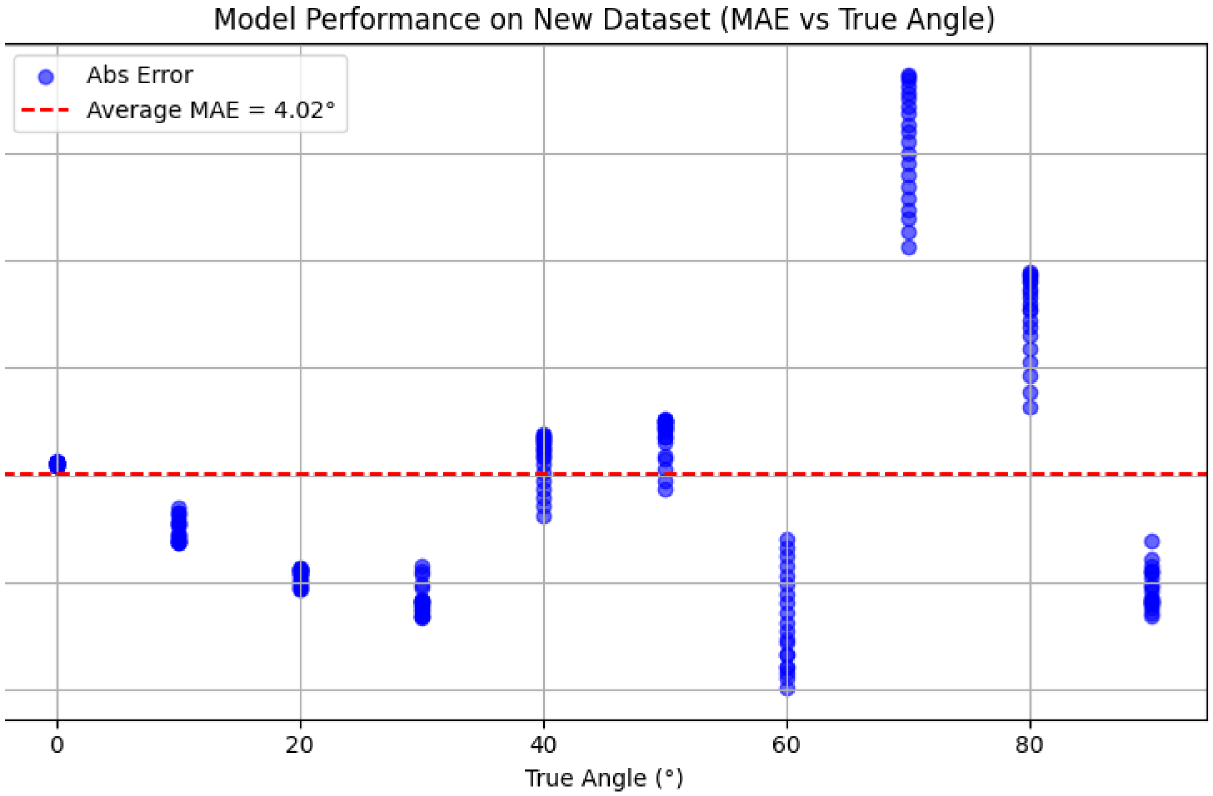




Testing



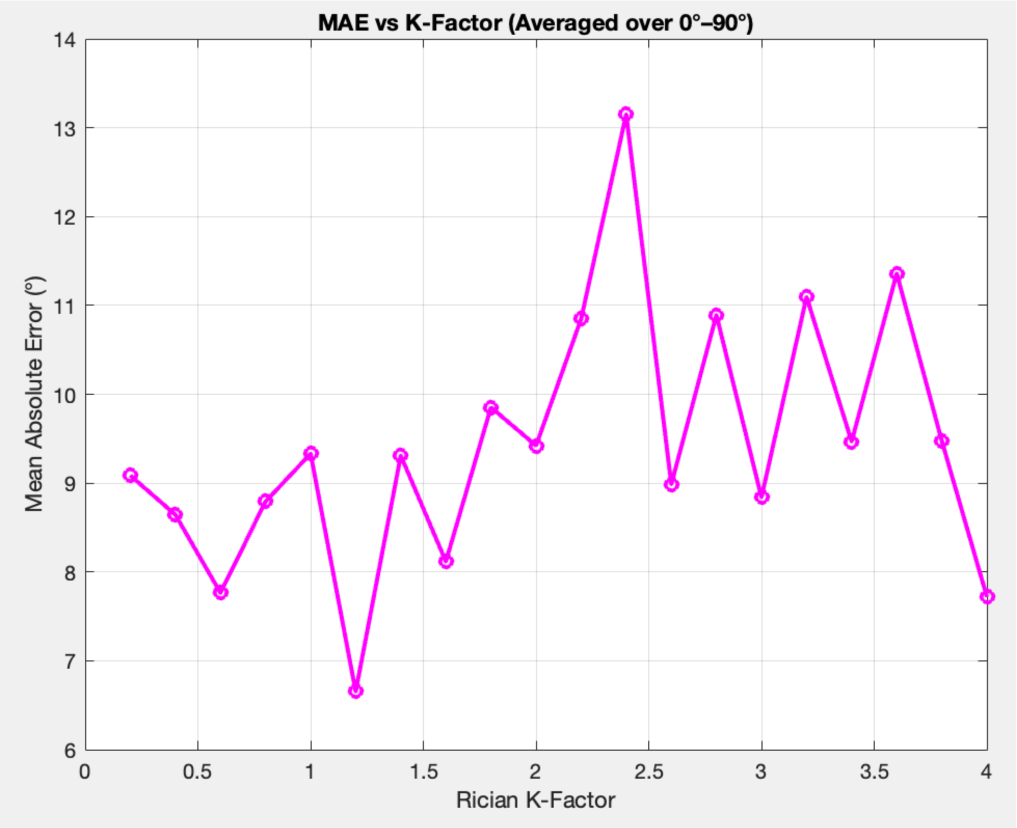
Absolute Error for Angles Between 20° and 70°
Mean Abs Error = 3.03°
3.03°
Absolute Error (°)
0
2
4
6
8
10
12
14
16
25.0° 28.0° 34.0° 31.0° 30.0° 29.0° 42.0° 59.0° 41.0° 27.0° 33.0° 63.0° 39.0° 32.0° 20.0° 64.0° 68.0° 57.0° 47.0° 40.0° 37.0° 56.0° 44.0° 43.0° 23.0° 53.0° 67.0°
True Angle (°)



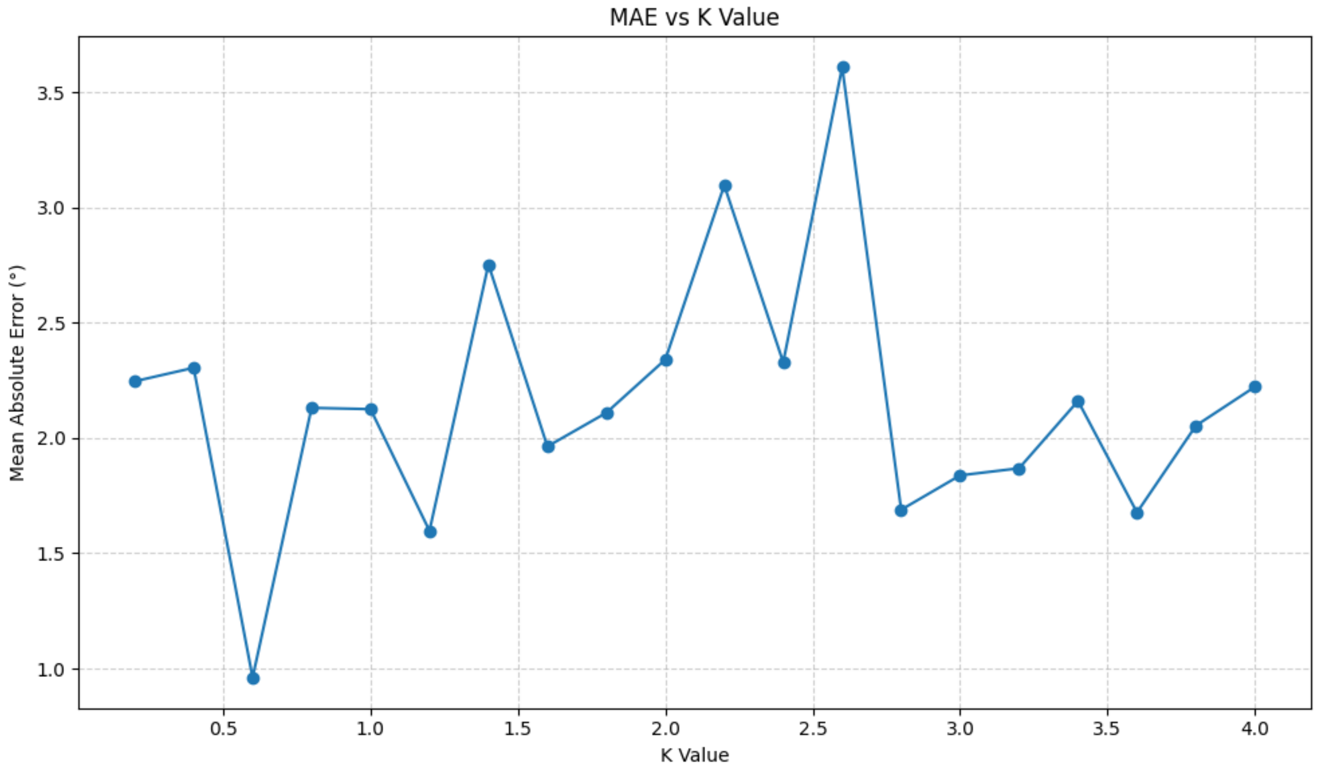
Model Performance on New Dataset (MAE vs True Angle)
Abs Error
Average MAE = 4.02°
0
20
40
60
80
True Angle (°)

Testing all angles, 20 runs

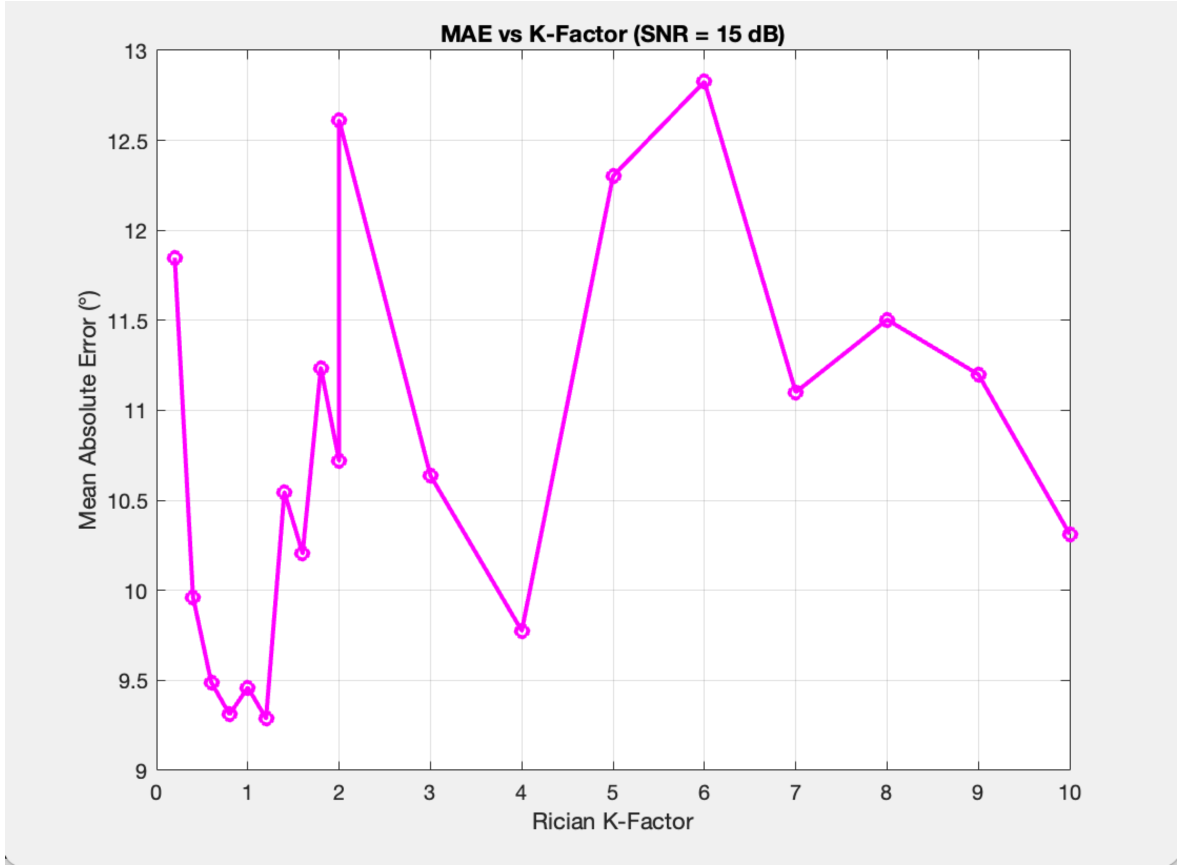
Correlation Method



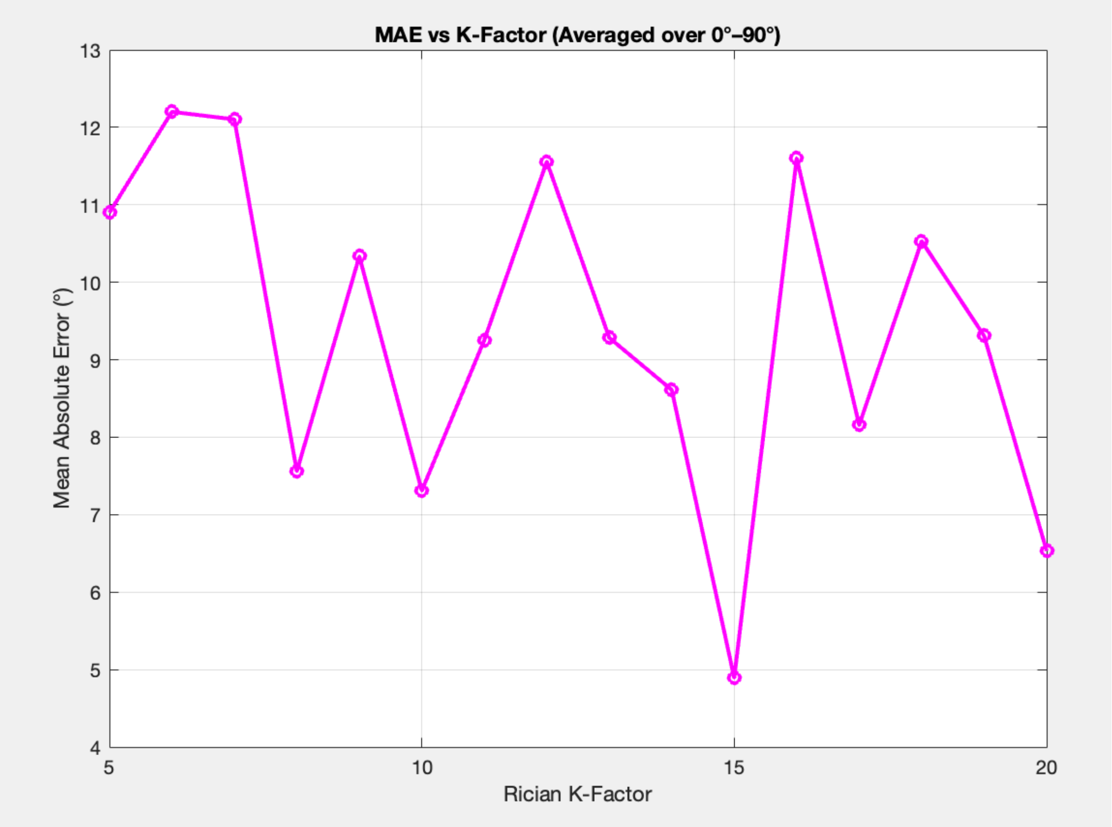
Neural Network method

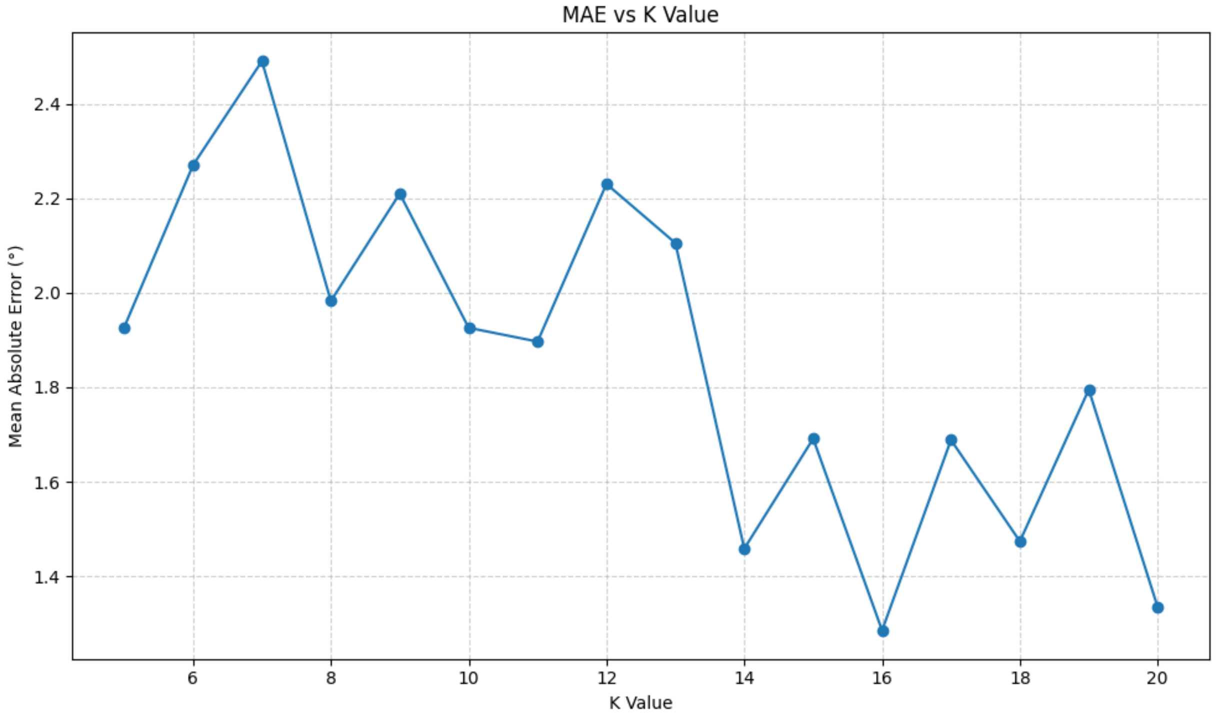


High K - values

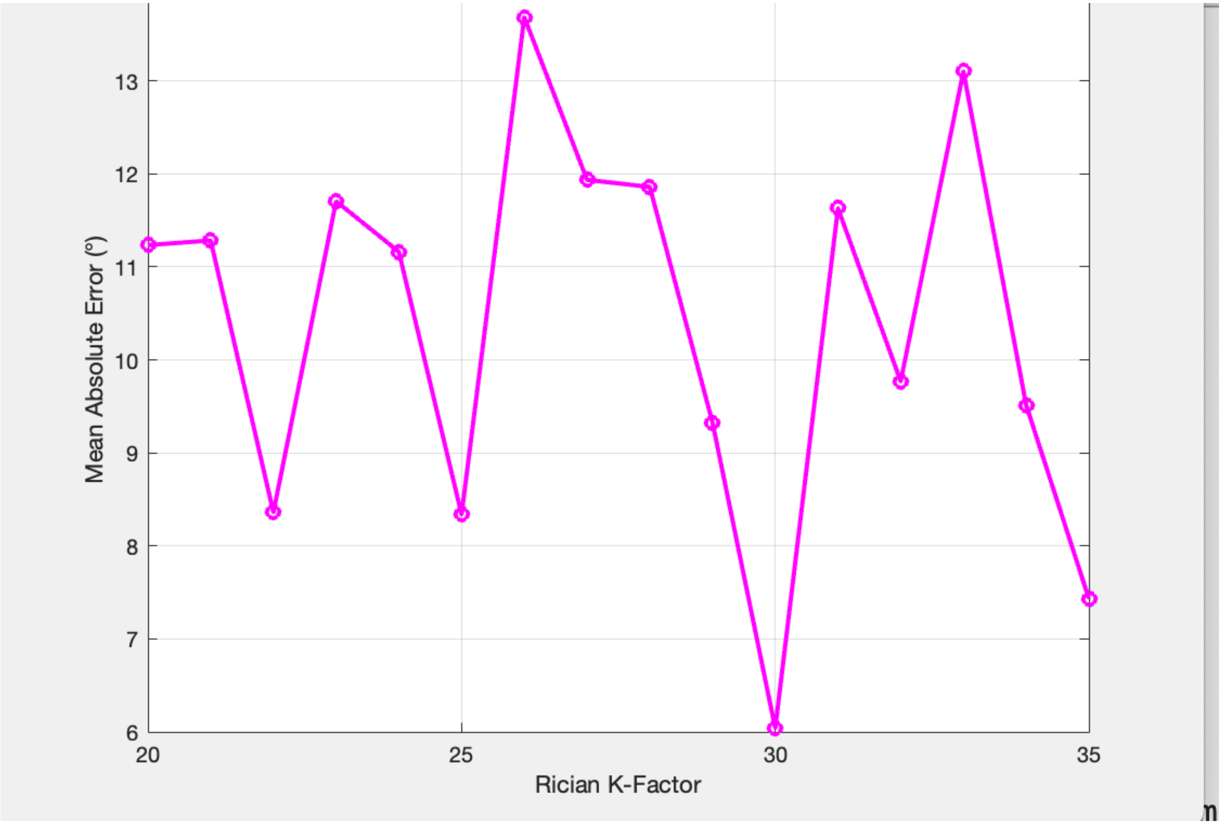


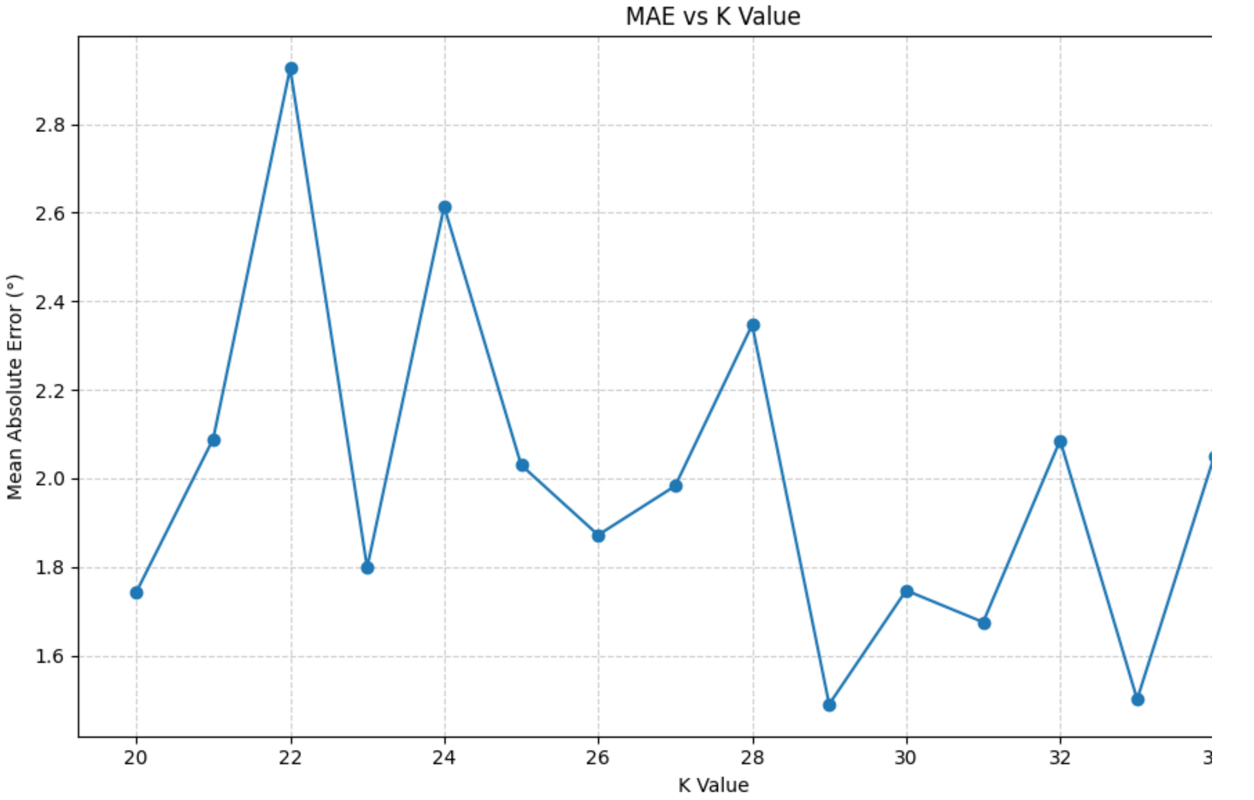
Compare corr and DNN



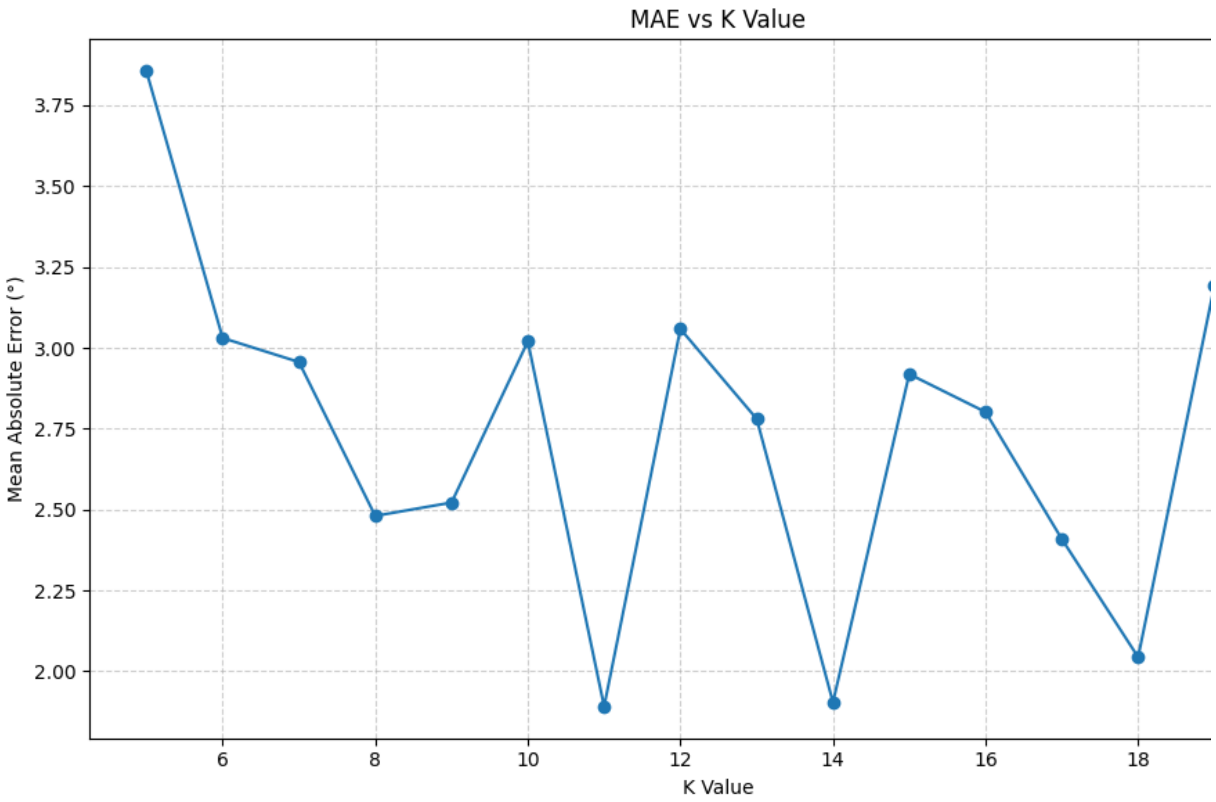


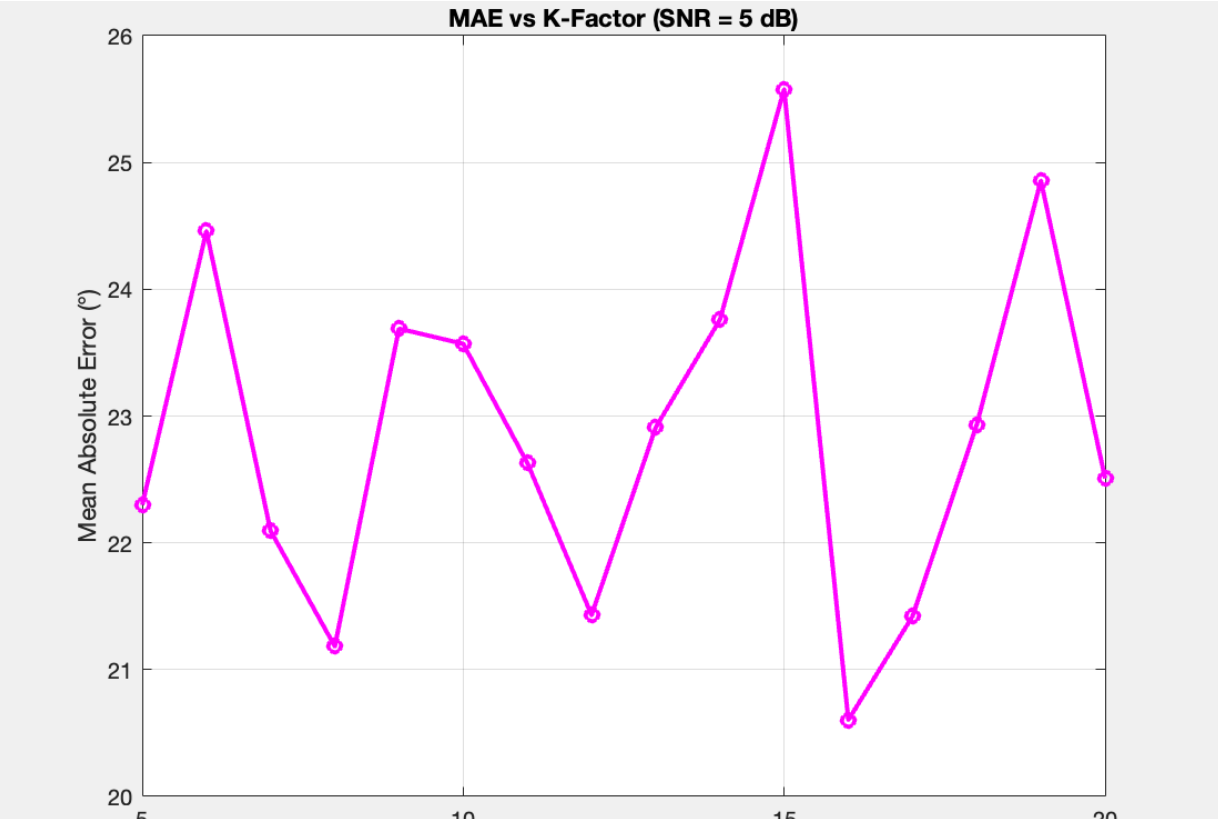
noise

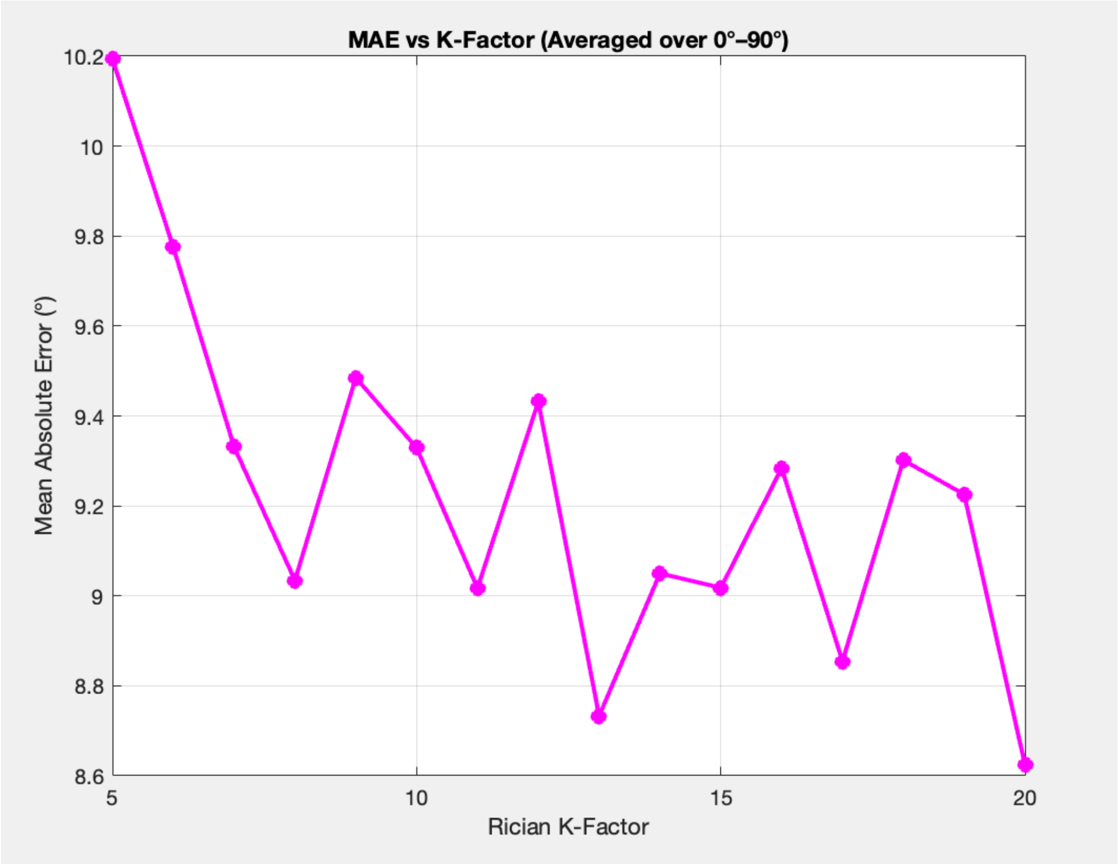

Mean Absolute Error (°)
Rician K-Factor
6
7
8
9
10
11
12
13
20
25
30
35

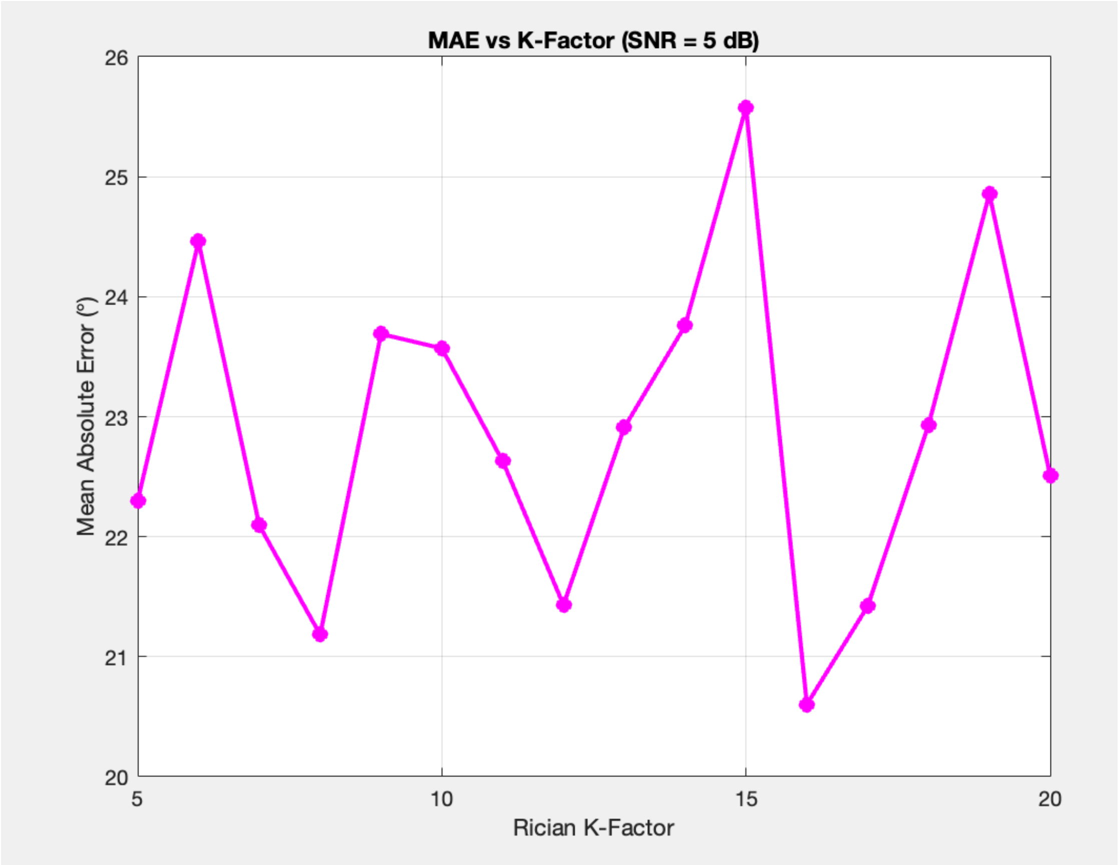

MAE vs K Value
Mean Absolute Error (°)
K Value
1.6
1.8
2.0
2.2
2.4
2.6
2.8
20
22
24
26
28
30
32

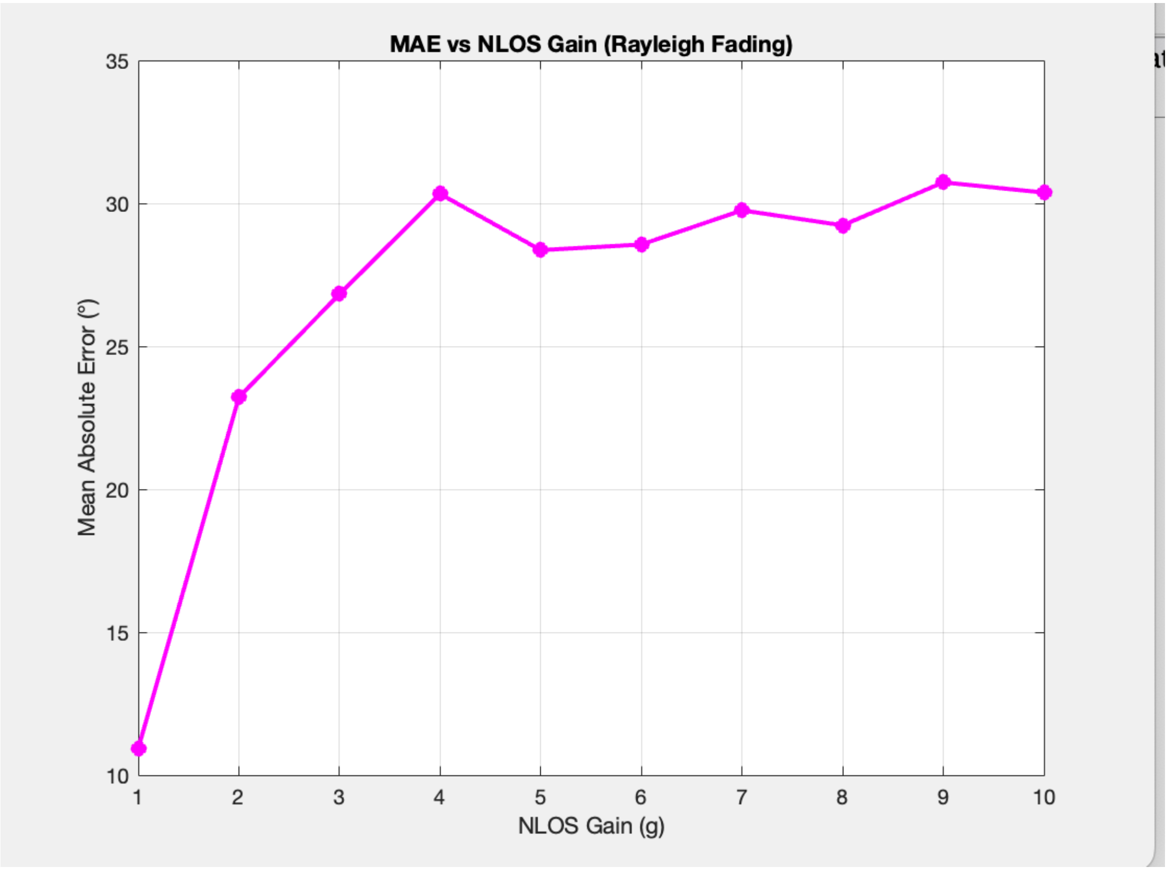
Noise , SNR = 5dB





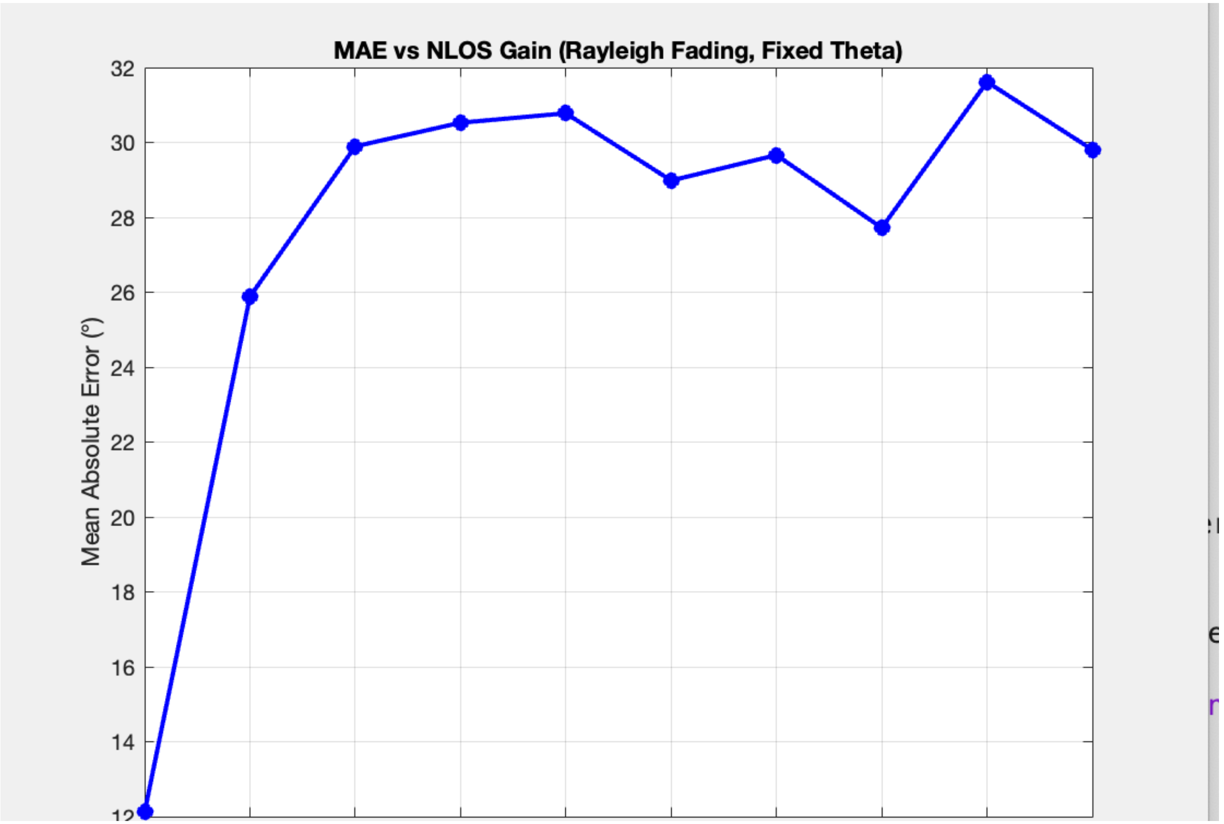

MAE vs K-Factor (Averaged over 0°–90°)
Mean Absolute Error (°)
Rician K-Factor
10.2
10
9.8
9.6
9.4
9.2
9
8.8
8.6
5
10
15
20

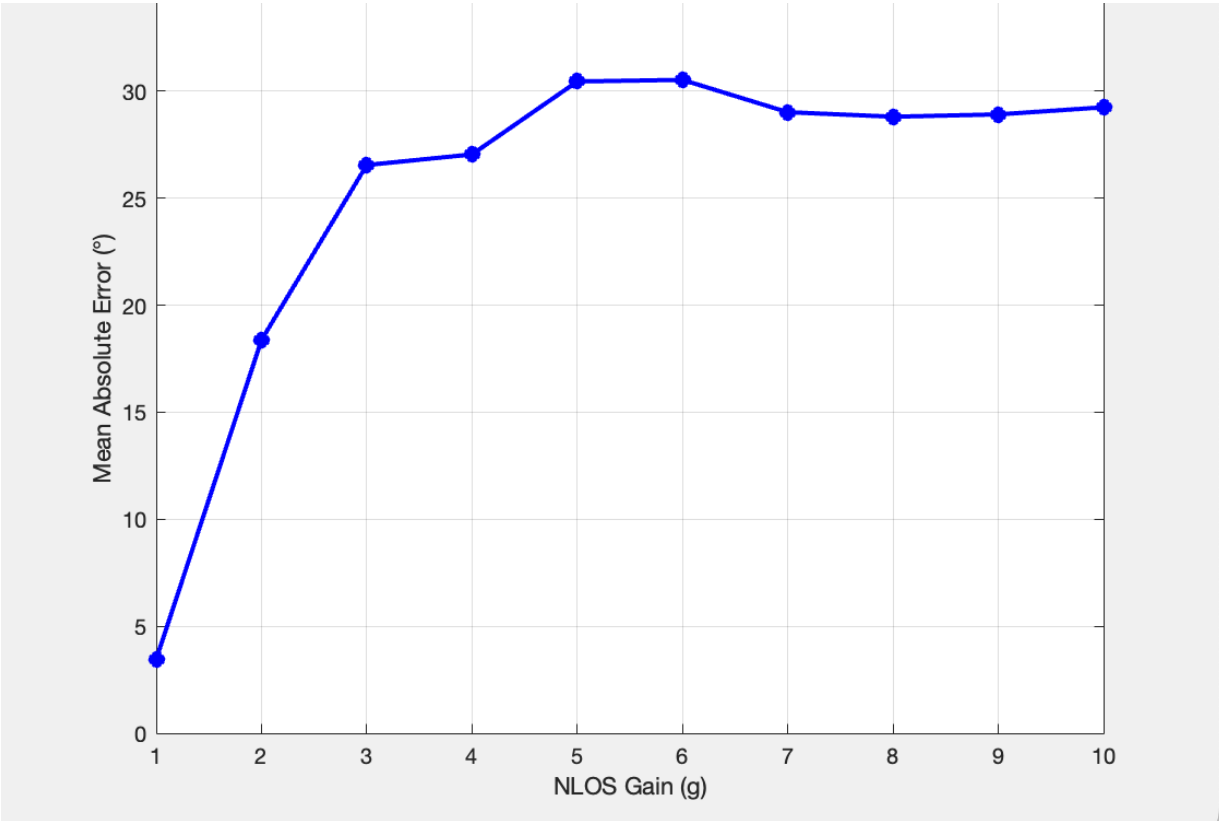

MAE vs K-Factor (SNR = 5 dB)
Mean Absolute Error (°)
Rician K-Factor
26
25
24
23
22
21
20
5
10
15
20



MAE vs NLOS Gain (Rayleigh Fading)
Mean Absolute Error (°)
NLOS Gain (g)
35
30
25
20
15
10
1
2
3
4
5
6
7
8
9
10

rayleigh


MAE vs NLOS Gain (Rayleigh Fading, Fixed Theta)
Mean Absolute Error (°)
32
30
28
26
24
22
20
18
16
14


Mean Absolute Error (°)
30
25
20
15
10
5
0
1
2
3
4
5
6
7
8
9
10
NLOS Gain (g)