

AI-Driven Reconfigurable Intelligent Surface (RIS) System

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Problem:

Urban environments present numerous signal disruptions. Next-generation cell service must excel in both outdoor urban areas and challenging indoor spaces. RF repeaters address dead zones in high-traffic areas but are large and power-hungry.

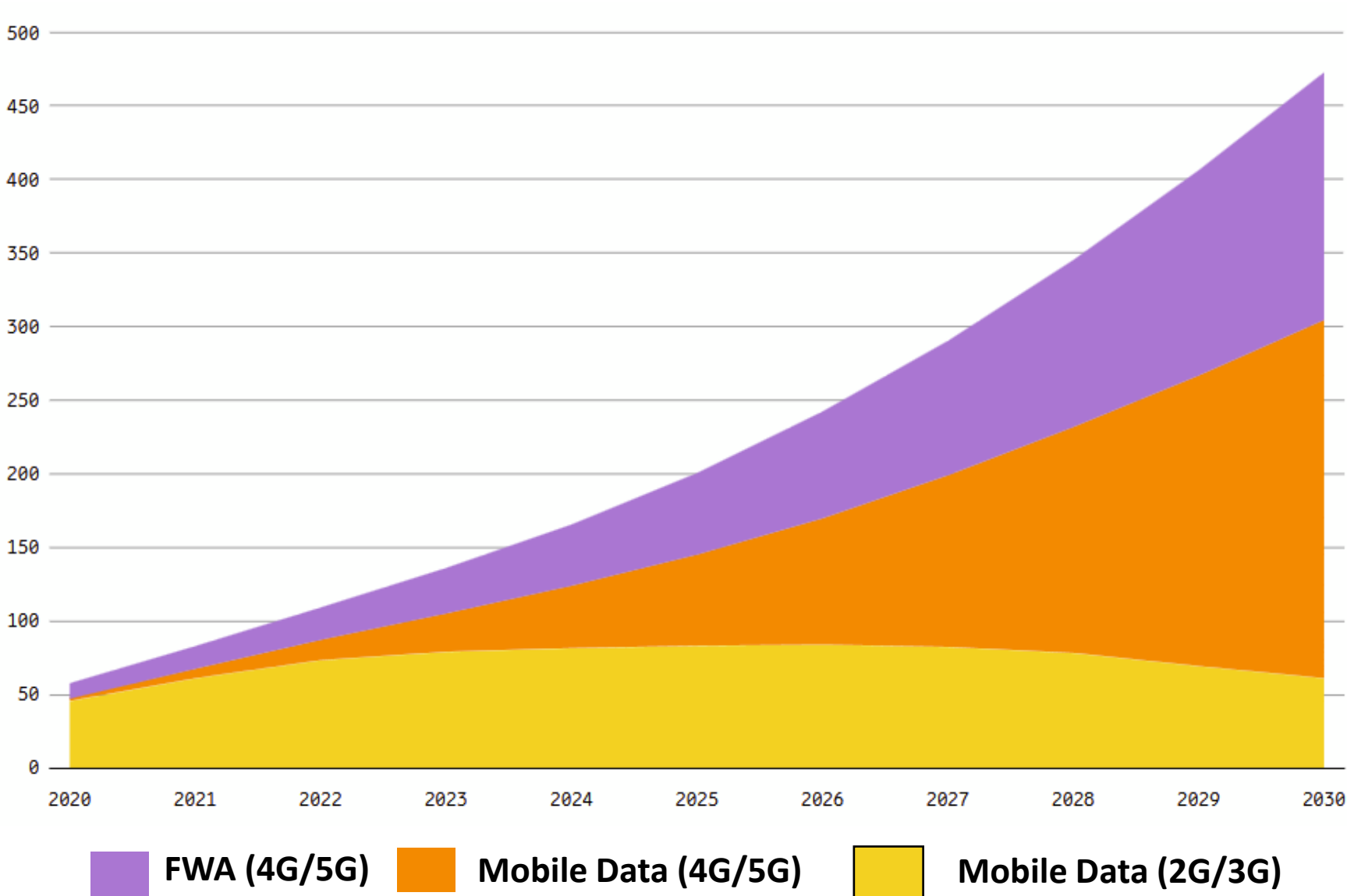


Figure 1. Global mobile network data traffic (EB per month)

Current Solutions:

- Base stations
 - High network range and dynamic beamforming
 - High cost of implementation, power demand, and large size hinder deployment in dense urban areas
- Smart Repeaters
 - Smaller profile allows for flexible deployment
 - Consumes less energy and is more cost-effective than a base station
 - Active signal amplification boosts unwanted noise and degrades signal quality

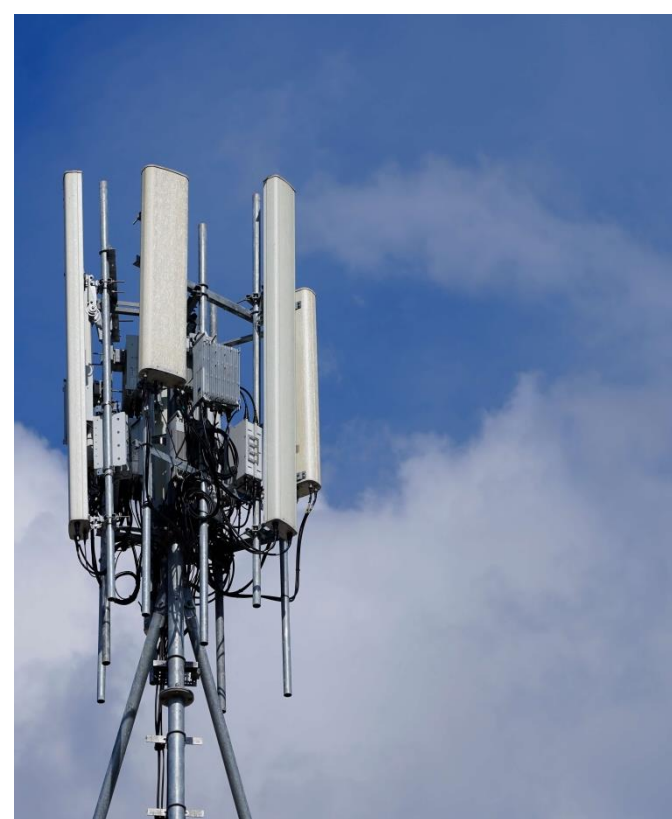


Figure 2. 5G Base Station



Figure 3. Smart Repeaters

Our Solution:

A Reconfigurable Intelligent Surface (RIS) is a surface that can automatically adjust itself to better reflect transmitted signals. Our proposed system uses AI-driven channel estimation to dynamically optimize RIS configuration, enhancing coverage and signal power with minimal energy consumption.

Our Approach:

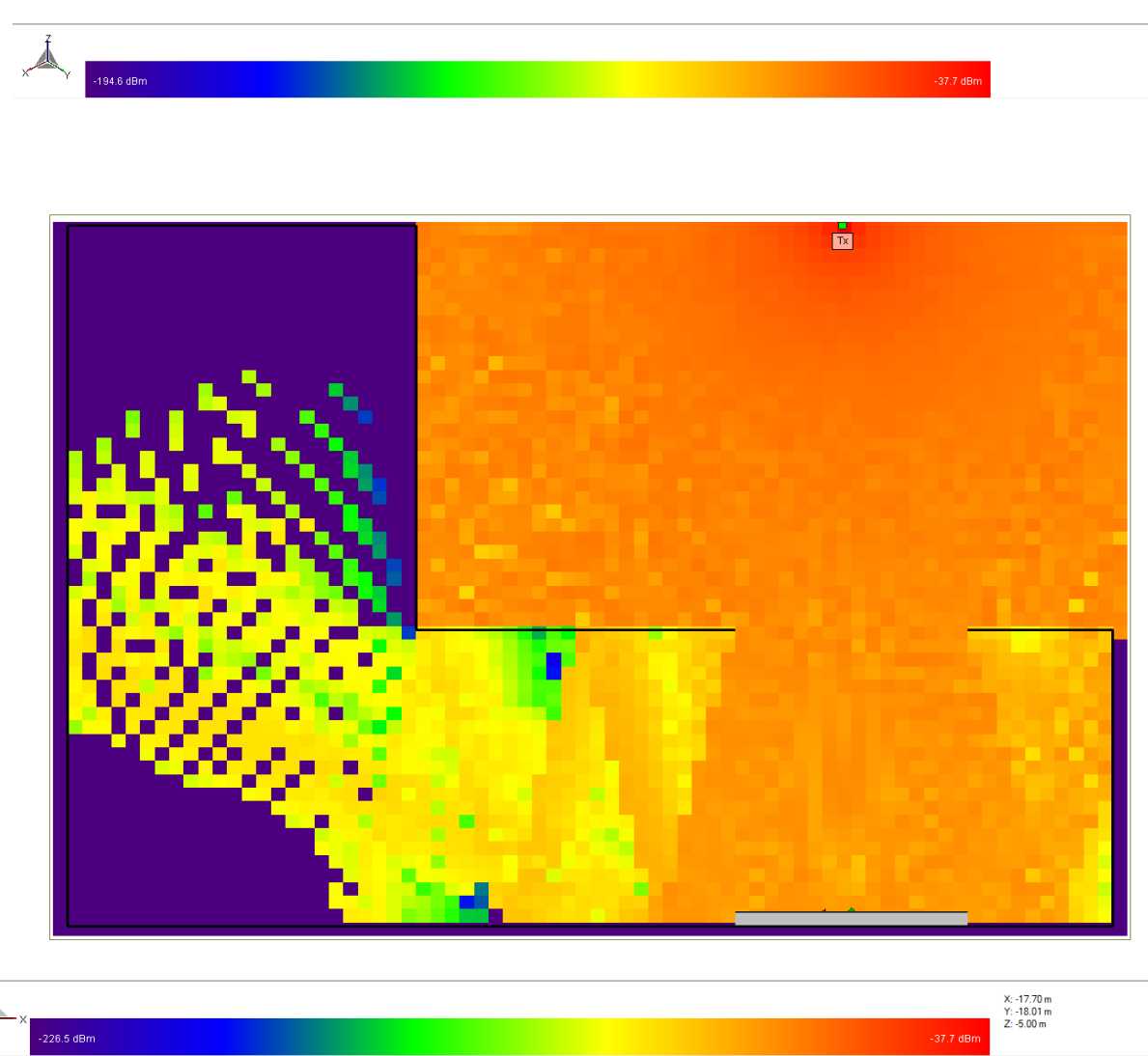
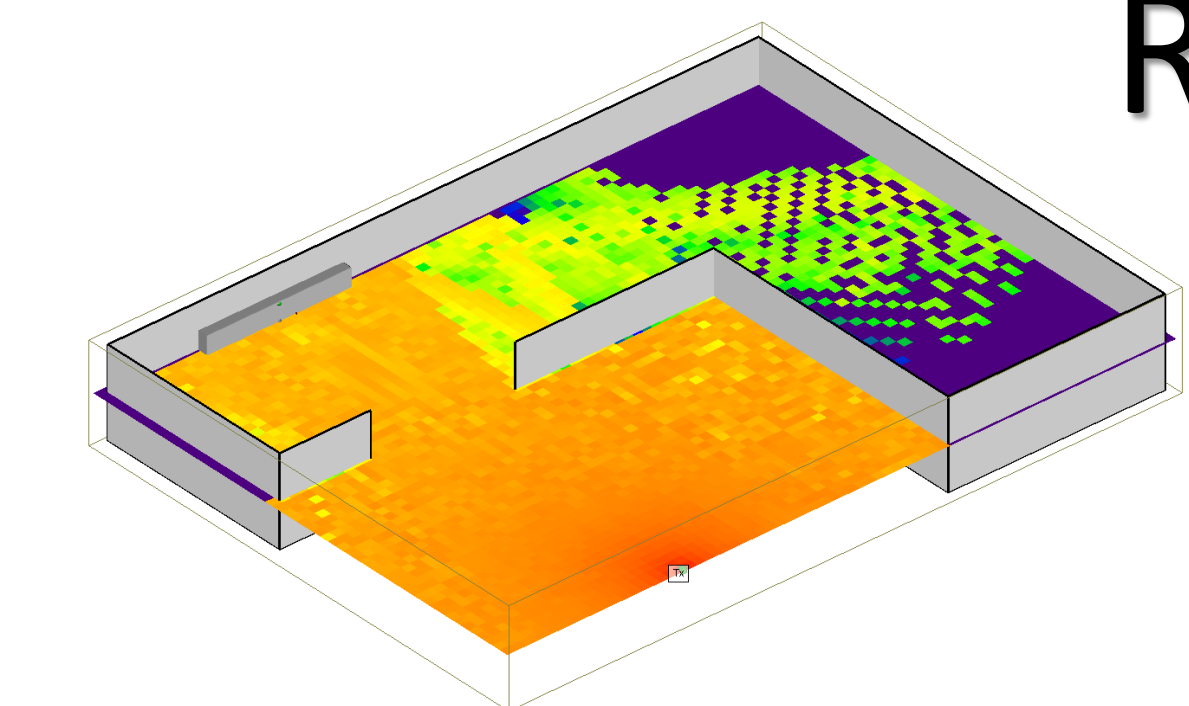
Simulated Scenarios

- Wireless Insite, a ray-tracing software, was used to analyze received power at specific points in the room.
- An automation algorithm in Python was developed to efficiently simulate virtually all possible angles for the RIS, generating a dataset that analyzed the impact of different RIS reflection angles on received power at various positions and was used to train an AI model.

Channel Estimation

- For verification purposes outside of simulation, we tested real-life wireless channels with custom Software Defined Radio (SDR) designs, starting with a copper sheet as a simple reflector.
- The qualifying metrics measured for this design are signal-to-noise ratio, error vector magnitude, and bit error rate for transmitted and reflected signals. All data was collected using Drexel Wireless System's Laboratory's DragonRadio SDR image.

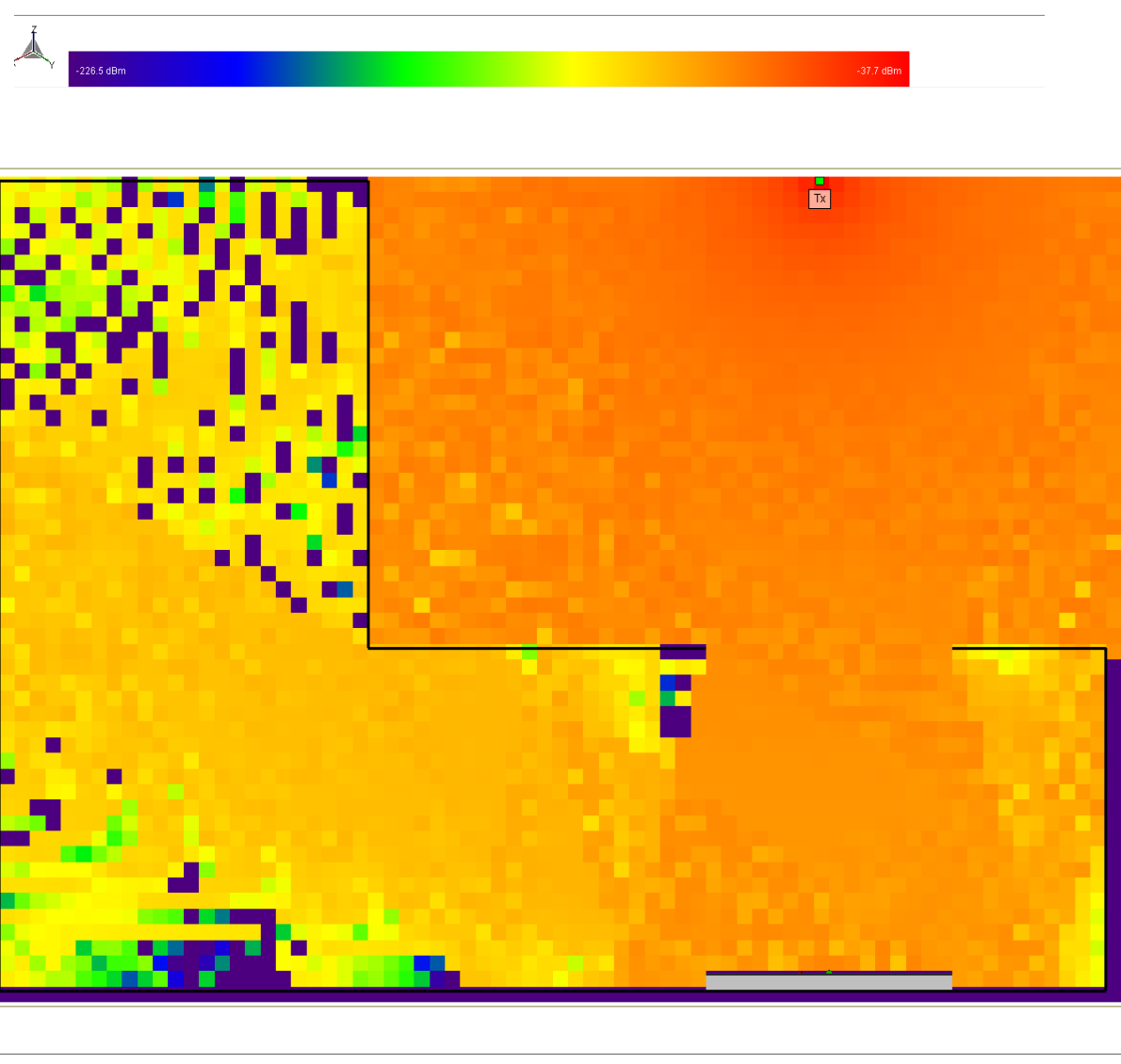
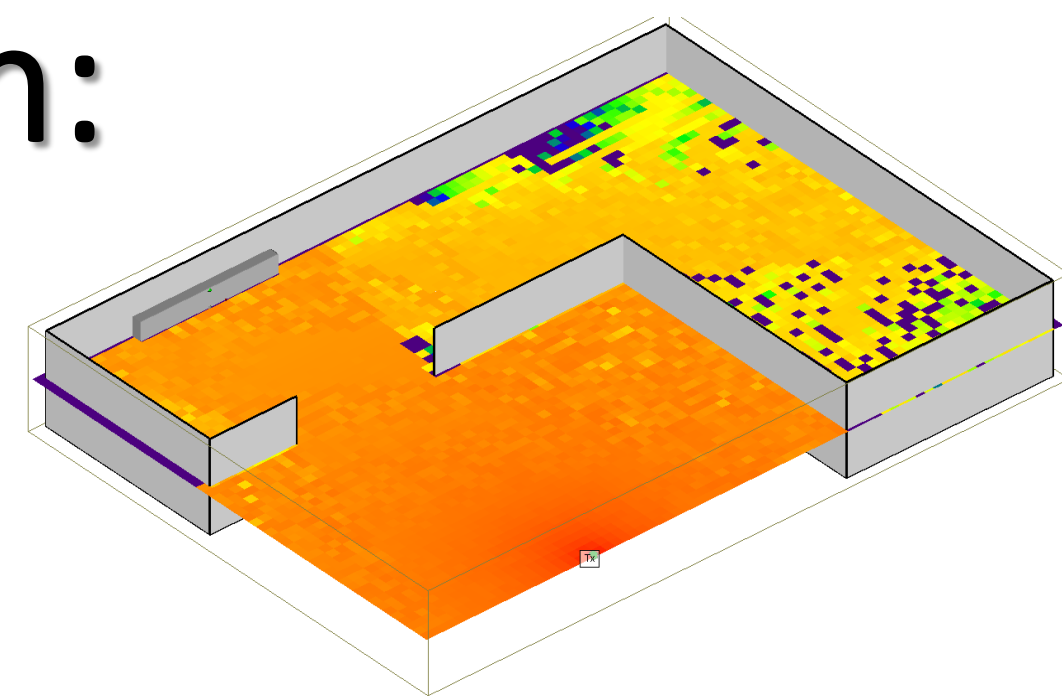
RIS Coverage Simulation:



Figures 4-5: Coverage without RIS



RIS boosts coverage and mitigates dead zones



Figures 6-7: Improved coverage with RIS

Machine Learning

- We implemented Deep Reinforcement Learning Approach using the Deep-Q-Network algorithm to predict the optimal reflection angle that gives maximum received Power at different receiver location within the simulated model.
- The state was defined by receiver's coordinates, while the action space consisted of choosing the reflection angles. The reward function encouraged selecting angles that maximized signal power, rewarding optimal choices and penalizing suboptimal ones. Over multiple training episodes, the model refined its decision-making through exploration and exploitation.

Embedded Design

- Leveraging the direct memory access controller on the STM32 for GPIO buses offloads data transfer tasks from the CPU
- Real-time capabilities of ZephyrOS allow for precise control of antenna adjustments with minimal latency and interference

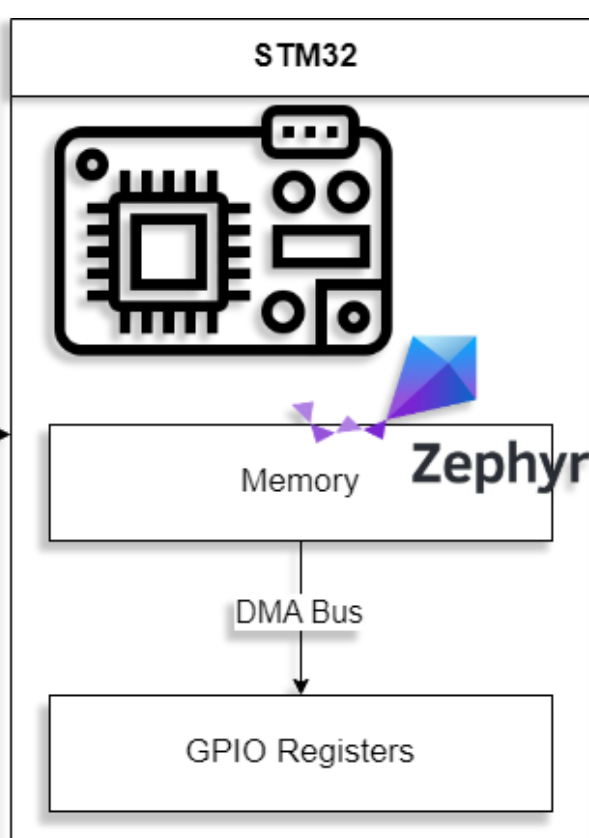
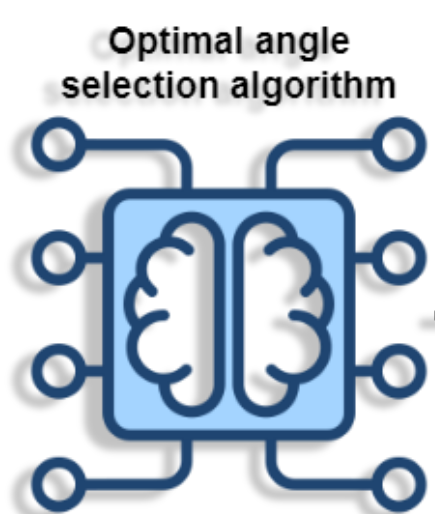


Figure 9. Machine Learning and Control Middleware Overview

Results:

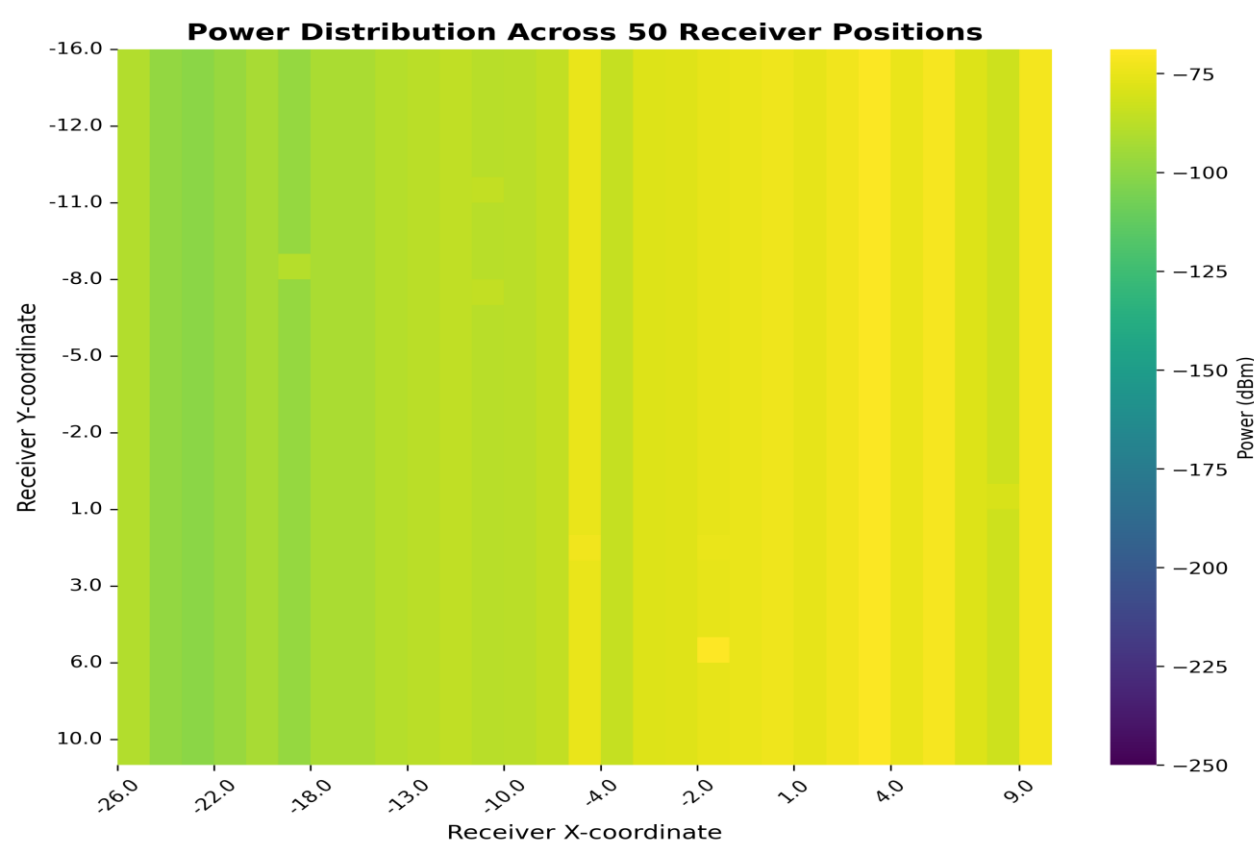
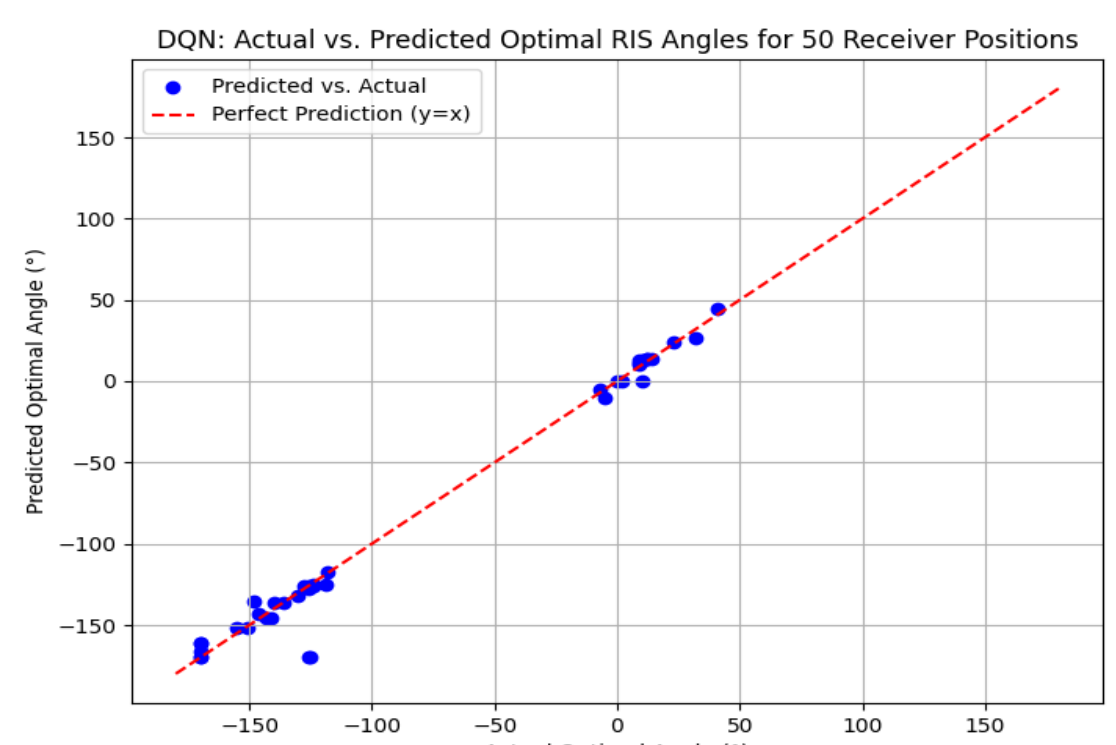
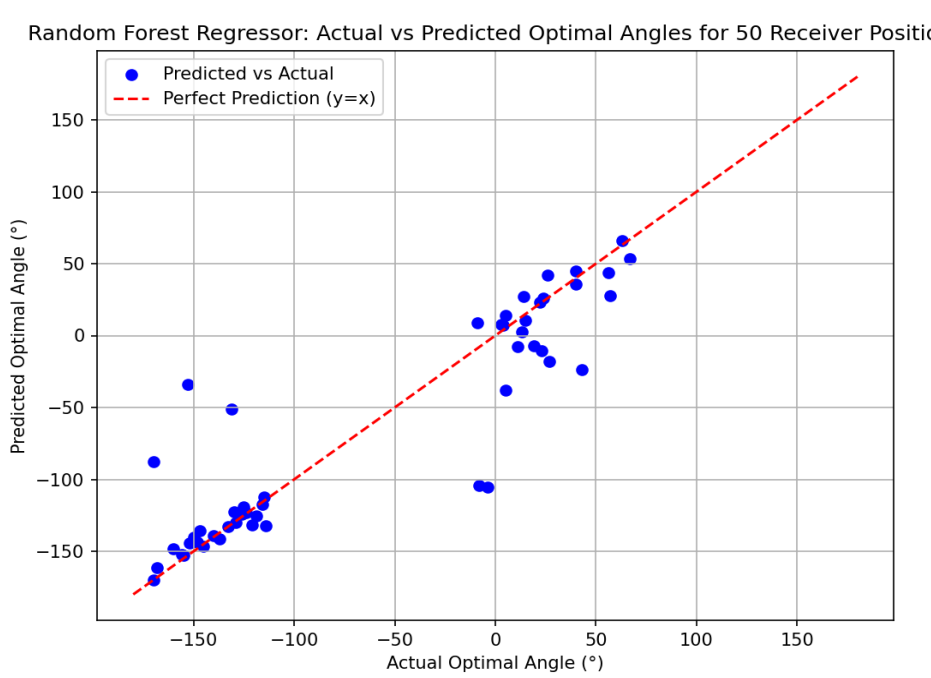


Figure 8: Heatmap illustrating high power distribution across 50 receiver positions after reflecting the RIS based on predicted optimal angle



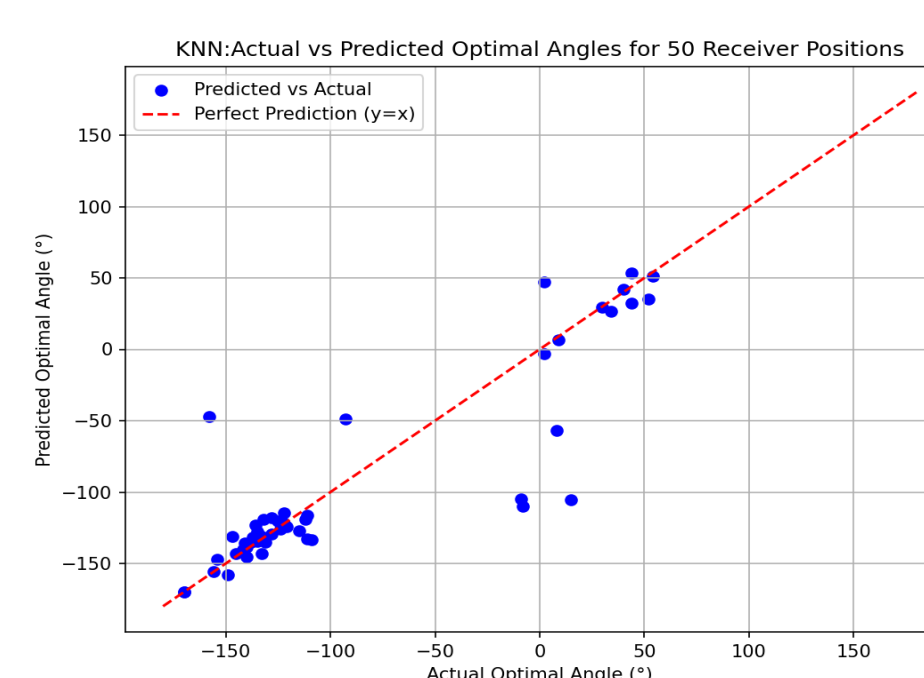
Model Evaluation Metrics (Deep-Q Network):

- MAE (Mean Absolute Error): 5.316°
- RMSE (Root Mean Squared Error): 11.055°
- R² Score: 0.979



Model Evaluation Metrics (Random Forest Regression):

- MAE (Mean Absolute Error): 16.44°
- RMSE (Root Mean Squared Error): 40.25°
- R² Score: 0.8081



Model Evaluation Metrics (K-Nearest Neighbors):

- MAE (Mean Absolute Error): 21.9229°
- RMSE (Root Mean Squared Error): 43.4612°
- R² Score: 0.7200

We also trained two supervised Learning based Random Forest Regression and K-Nearest Neighbors models to predict the optimal RIS angles reflection angles. However, both models showed lower performance compared to Deep-Q Network model.

Future Work:

- We will test our AI model in larger and more diverse dataset across different simulated environments, receiver positions, and channel conditions. Expanding the dataset will help ensure that the model performs well in different real-world scenarios and is not limited to a specific setting
- We will integrate the machine learning model's output with the control middleware to measure end-to-end latency
- We will implement means for synthetic channel estimation by extracting results from the Wireless Insite simulations and porting them into a SDR design to analyze transmission quality with the presence of an RIS under our optimization process

[1] Ericsson, *Ericsson Mobility Report*, Nov. 2024. [Online]. Available: <https://www.ericsson.com/4adb7e/assets/local/reports-papers/mobility-report/documents/2024/ericsson-mobility-report-november-2024.pdf>.
[2] C. Kelly, "Huawei to begin mass production of US-free 5G base stations," *TechHQ*, Sep. 30, 2019. [Online]. Available: <https://techhq.com/2019/09/huawei-to-begin-mass-production-of-us-free-5g-base-stations/>. [Accessed: Feb. 28, 2025]

[3] "Pivotal Commware introduces its Pivot 5G smart network repeater," *Business Wire*, Jan. 7, 2021. [Online]. Available: <https://www.businesswire.com/news/home/20210107005311/en/Pivotal-Commware-introduces-its-Pivot-5G-Smart-Network-Repeater>. [Accessed: Feb. 28, 2025].