5G and Satellite Network Coexistence in the FR3 Spectrum

ORBIT Emulation and Machine Learning for Enhanced Spectrum Coexistence

RUTGERS
WINLAB | Wireless Information Network Laboratory

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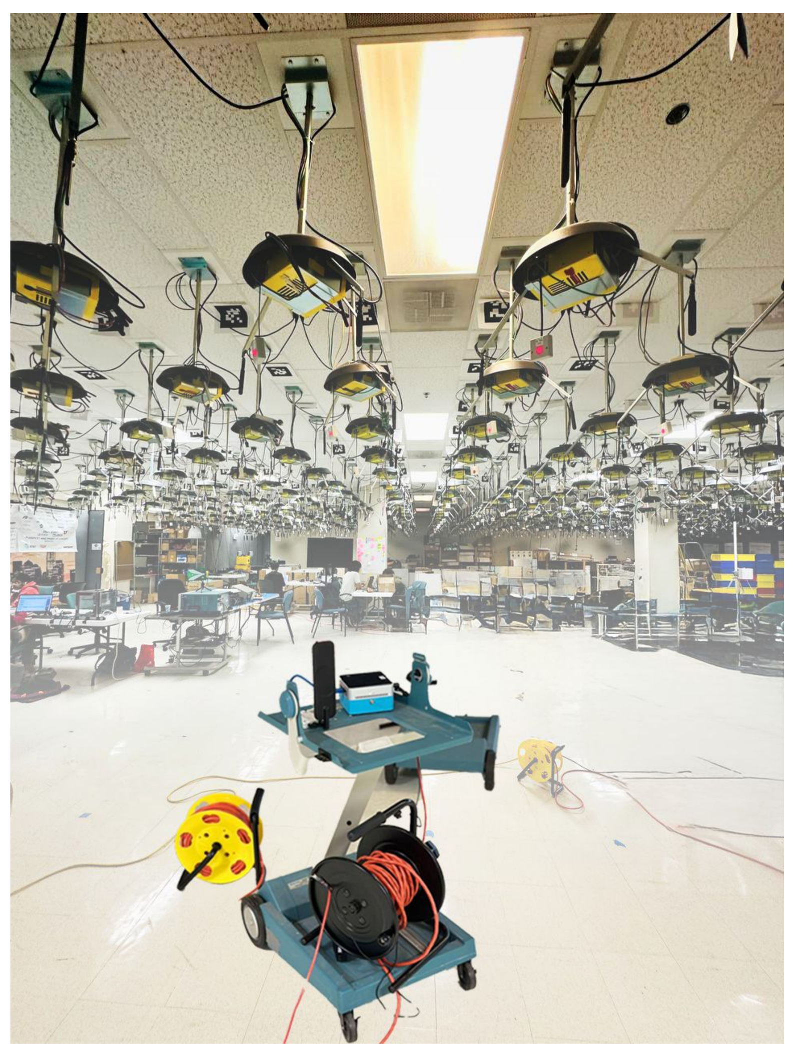
Overview

The deployment of 5G networks in the FR3 spectrum involves sharing bandwidth with existing satellite communications, which can impact signal quality at satellite receiver sites. Therefore, effective interference estimation with minimal resource usage is critical to ensuring the reliability and quality of both communication systems.

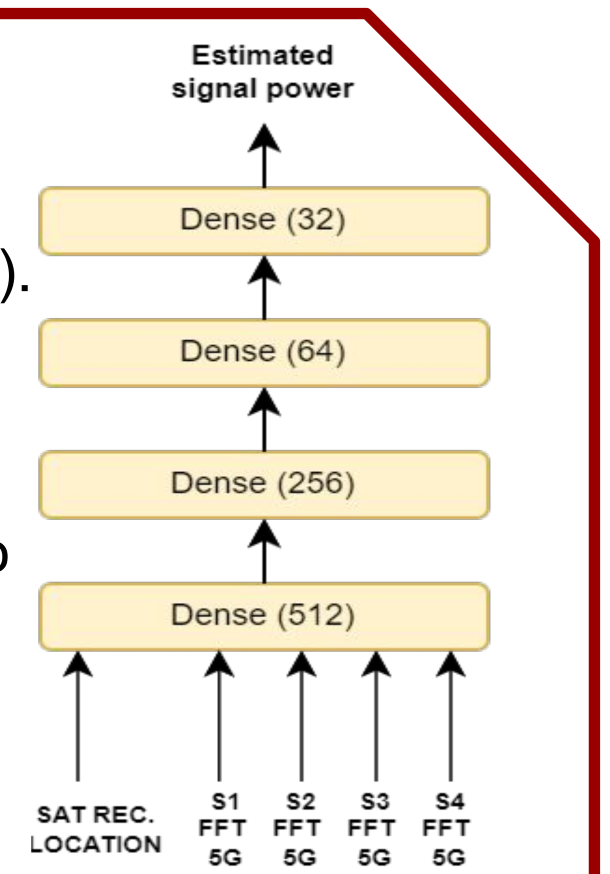


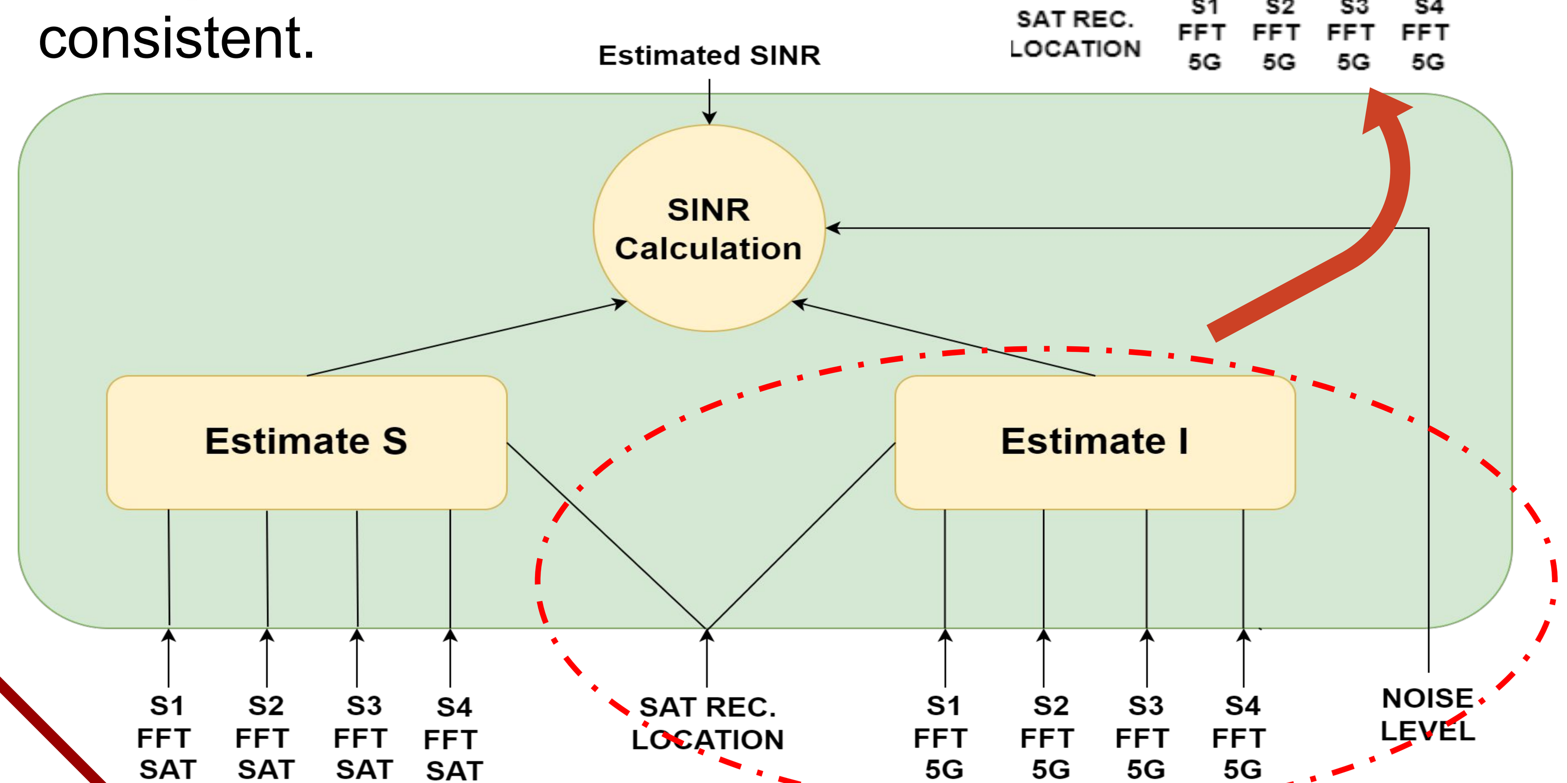
Our approach

- Emulation of coexistence using SDRs on the ORBIT Testbed.
- **Goal:** Accurate interference estimation for every possible satellite receiver location, given FFT measurements from 4 fixed location sensors.
- Supervised approach to construct a neural estimator.
- SINR values at receiver as labels.

Neural Architecture

- The basic block is a **signal power estimator** (universal for all locations).
- Input of the basic block: FFT data, from different satellite receiver location.
- Outputs combined with noise level to provide a final SINR calculation.
- Our model is consistent if and only if the signal power estimator block is consistent.

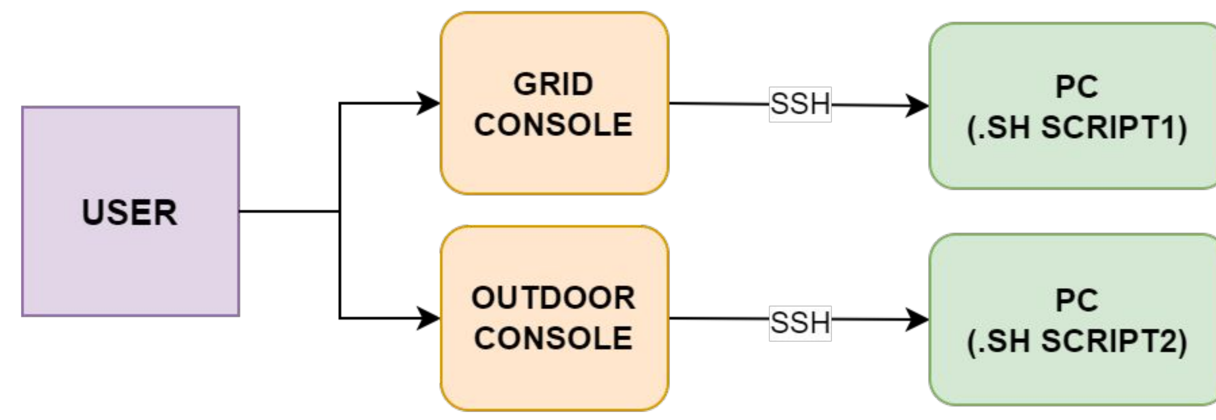


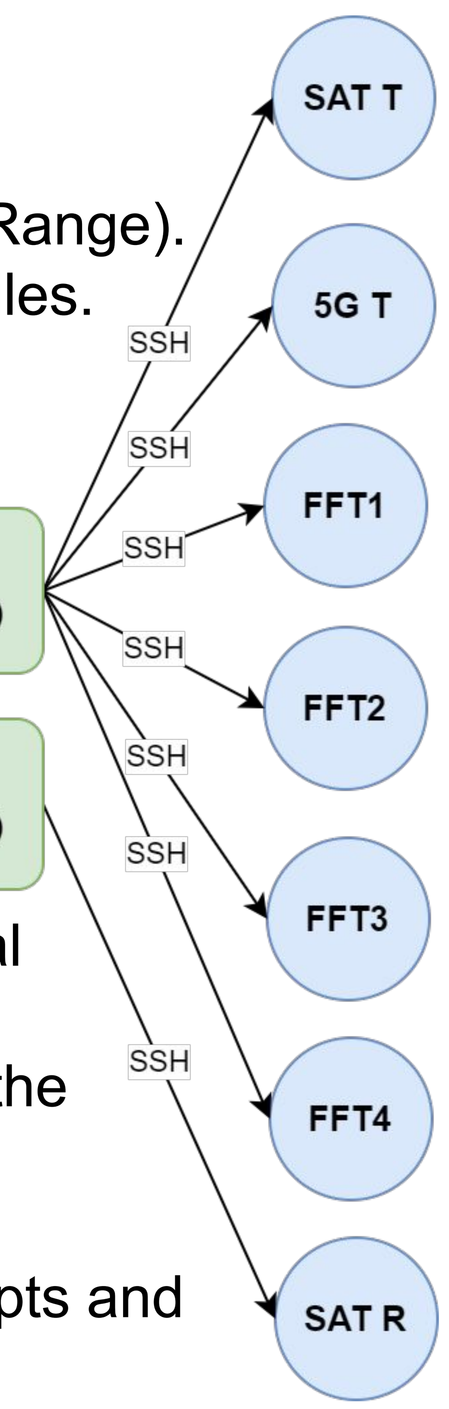


ORBIT Emulation

Implementations in GNU Radio:

- **DVB-S2**, **5G OFDM** Transmitter(in GHz Range).
- **Sensors** logging FFT values to the text files.
- **Satellite Receiver**, with a signal power calculator and a BER tool.

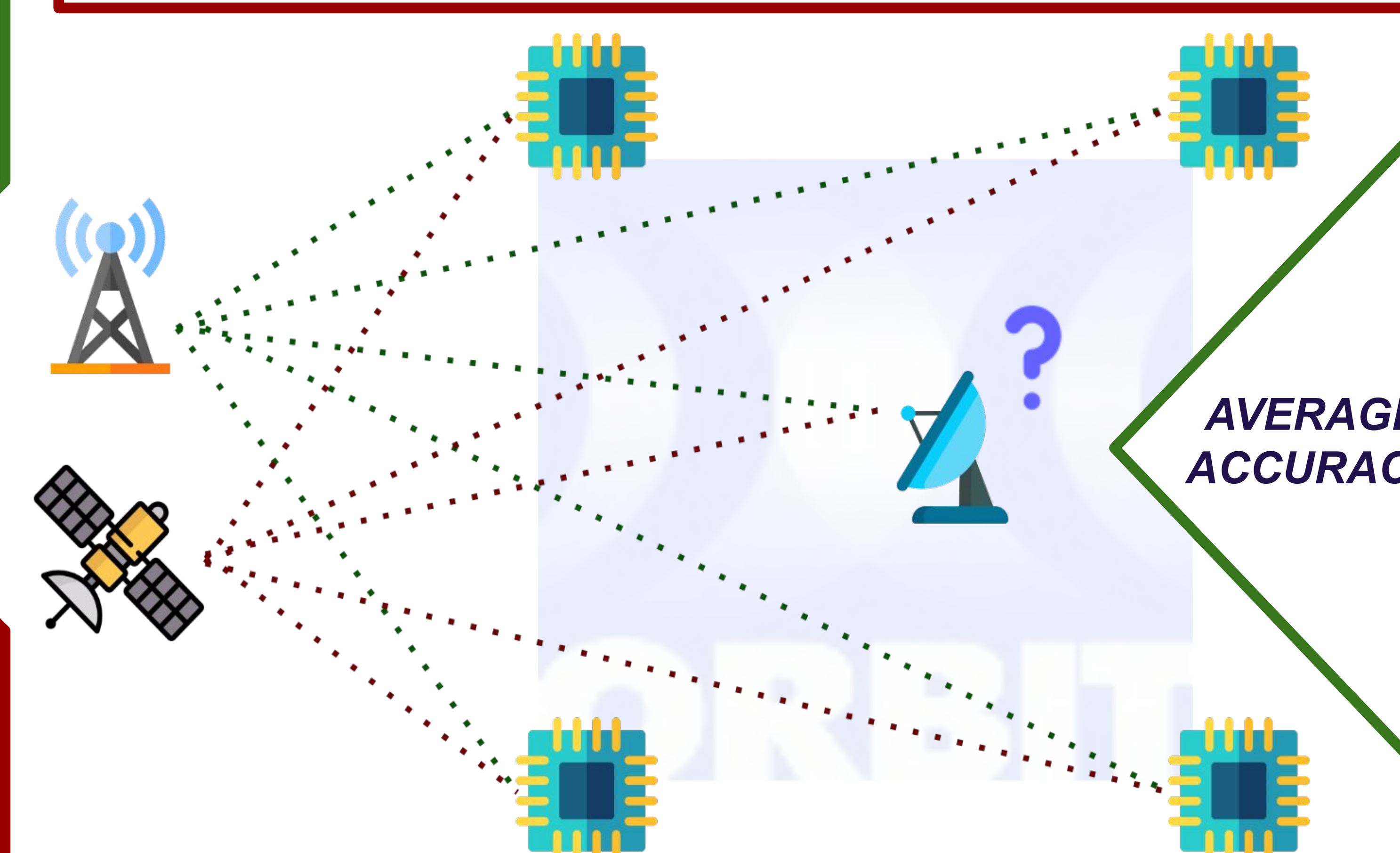




Purpose: Collect training data for the neural universal signal power estimator.

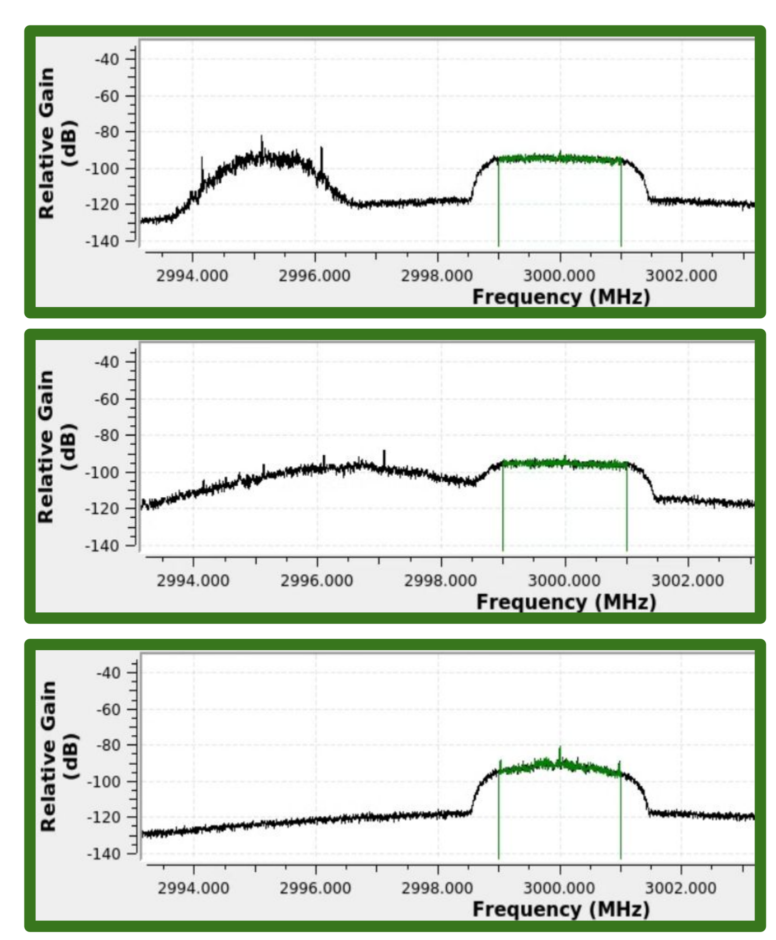
Process: Sequentially activate devices on the ORBIT testbed,

- Collect measurements from text files.
- Automate the process using Bash scripts and timed SSH conncections.



Measurements

- **3000+** iterations (**15** locations).
- Varying 5G transmitter gain and center frequency.
- Varying satellite receiver location.
- Encoding location in (X,Y) coordinates from an origin on the ORBIT testbed.



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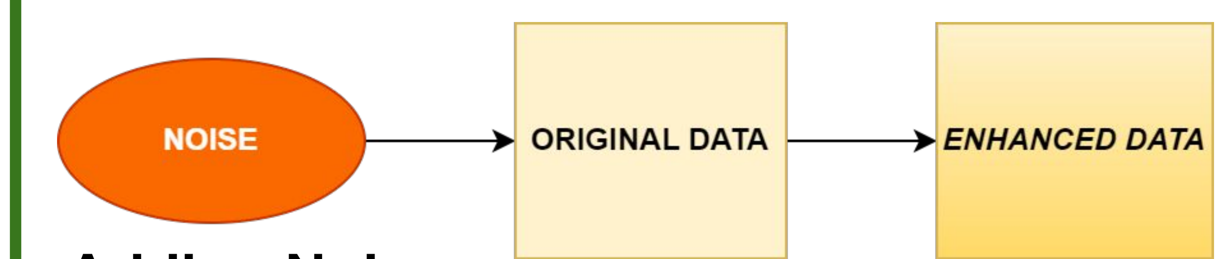
Handling Unseen Locations

The neural network might misinterpret location coordinates as categorical classes, because of the sparsity of data.



Adding Noise:

- Convert discrete coordinates to continuous numerical values (e.g. 7→6.93).
- Combats overfitting.

Measuring the signal quality

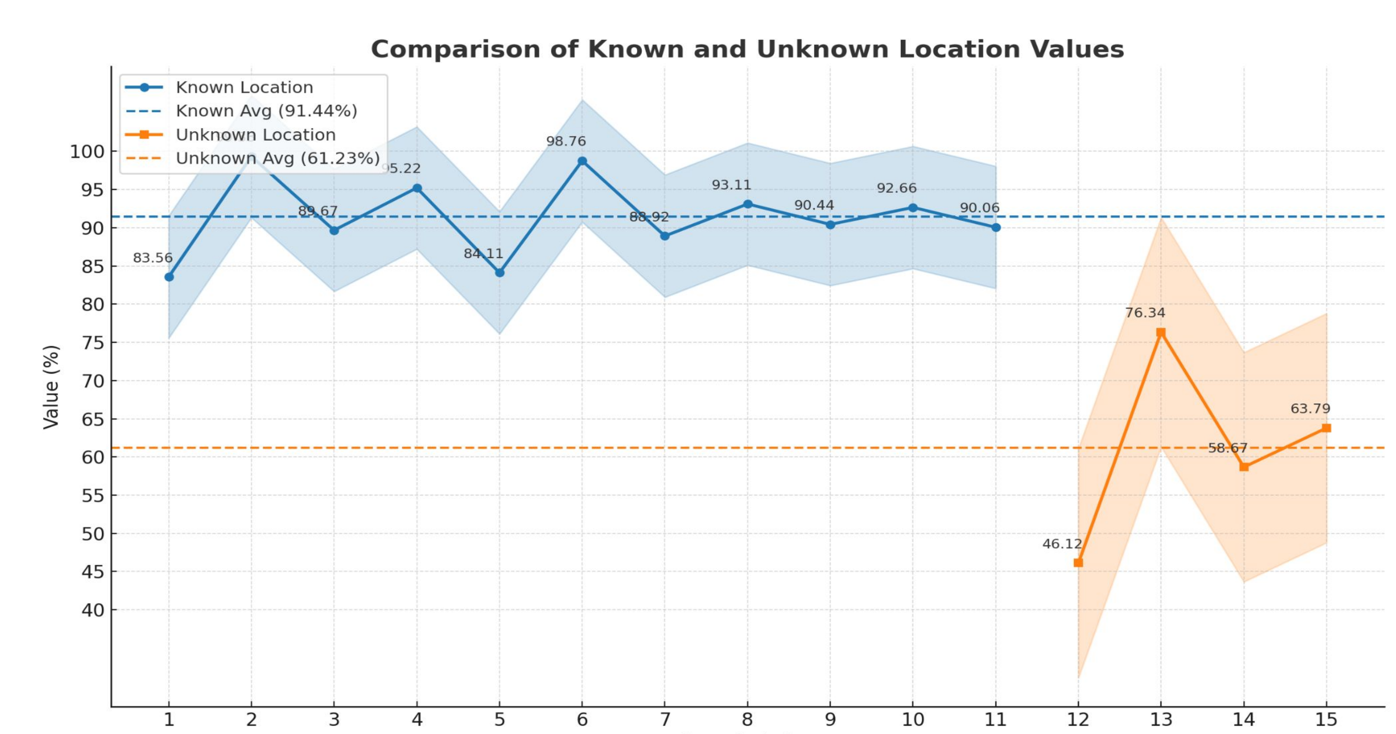
- Our design uses SINR as a label.
- **Defining the threshold**. Using our DVB-S2 demodulator and **BER** tool, we establish the acceptable BER-SINR correspondence.

Evaluation

AVERAGE ACCURACY

Metric: percentage of predictions with deviation ≤10% from the actual value (compared to the total range).

Known locations: 91.44%, **Unknown locations: 61.23**%



Conclusion / Future Work

- Neural mechanisms reliably estimate interference using 4 fixed FFT sensors at different locations.
- High accuracy for known locations.
- Sparse training lacks spatial awareness, but dense measurements could enable a universal estimator.

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