Outdoor Millimeter-Wave Picocell Placement using Drone-based Surveying and Machine Learning

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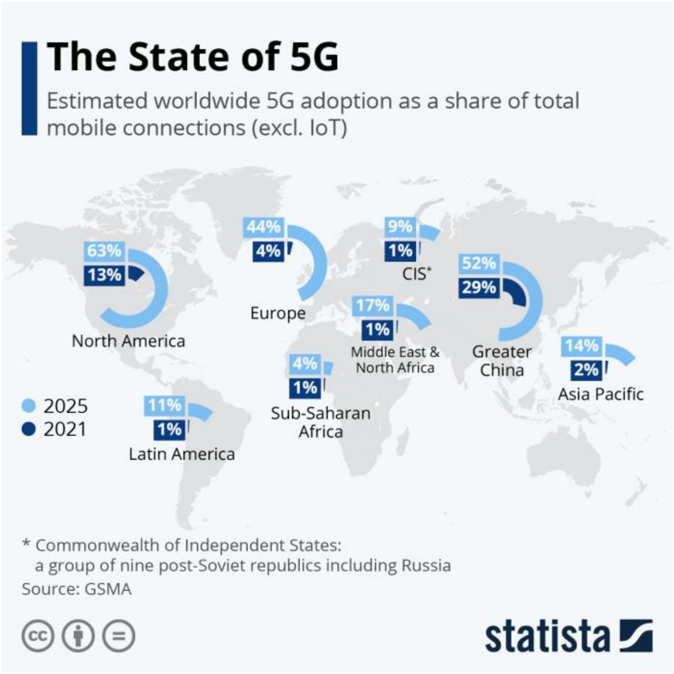
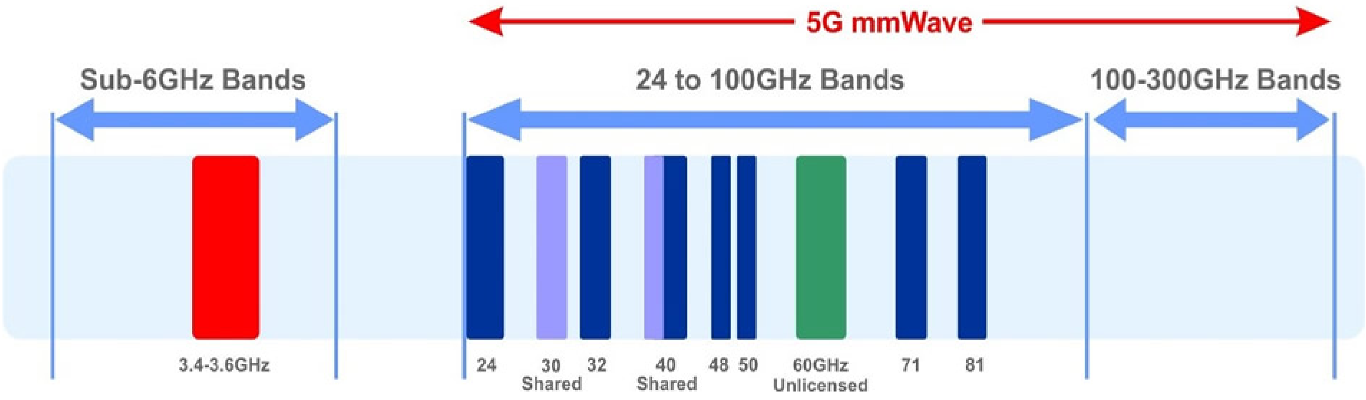
Proliferation of 5G

- 5G use has rapidly increased in recent years and is expected to support massive numbers of smart devices worldwide
- 5G is used for mobile communications, virtual/augmented reality, Internet of Things, autonomous vehicles, etc
- 5G uses millimeter-wave (mmWave) as its major wireless technology and short-range base stations called picocells to provide high data rates





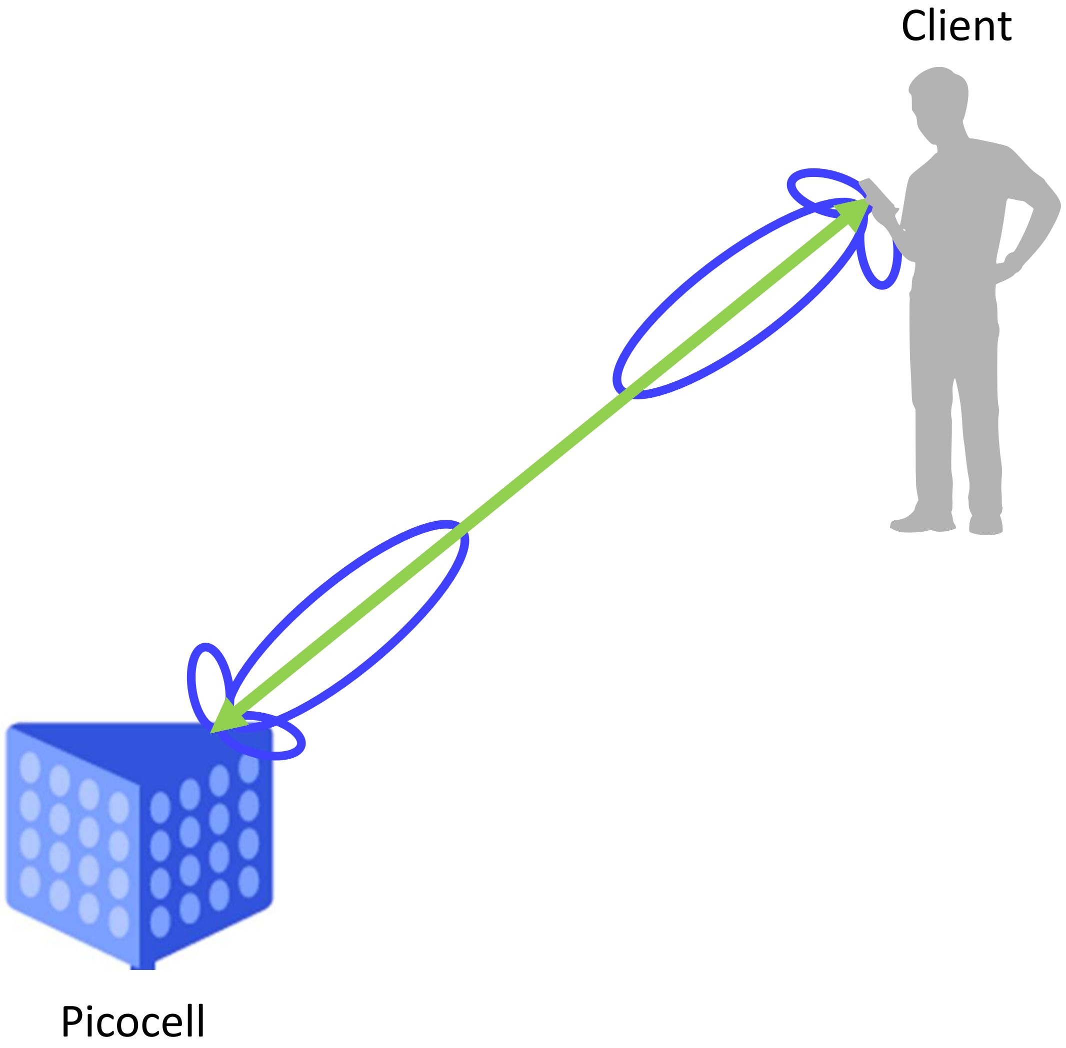
Source: CableFree Networks

Challenges with Picocell Placement

- Line-of-Sight (LoS) paths to picocells are easily obstructed and thus often rely on Non-Line-of-Sight (NLoS) paths

- Finding NLoS paths in outdoor environments can be difficult when many objects do not reflect strongly

- Deployers must find strong NLoS paths for picocells to use when LoS paths are blocked



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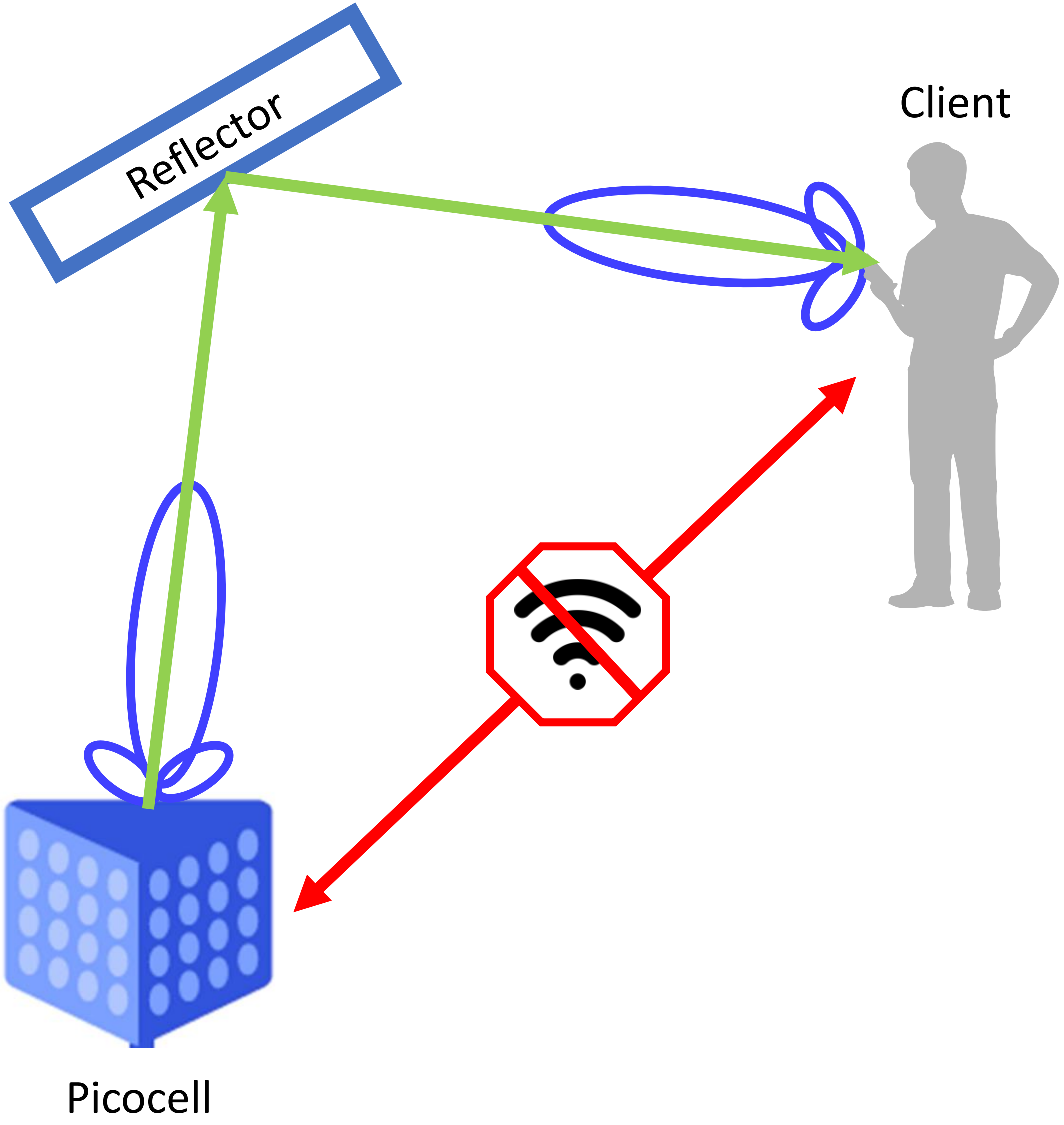
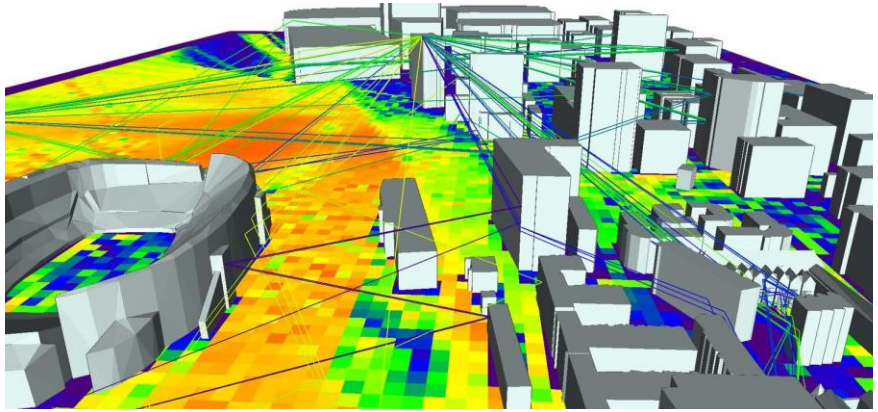


Existing Approaches

- Existing approaches mostly rely on site surveys or propagation models to estimate the mmWave Signal Reflection Profile (SRP) in the environment
- They then use the SRPs to place picocells in a way that achieves high signal strength through NLoS paths
- Site surveys are expensive and time-consuming in large outdoor environments, and propagation models are often unable to represent them at high frequencies
- Past works that aim to reduce survey time are limited to small-scale indoor environments, and do not address issues present in large outdoor environments

"ExterNetworks charges $4,200 for outdoor wireless site surveys up to 100,000 sq.ft."

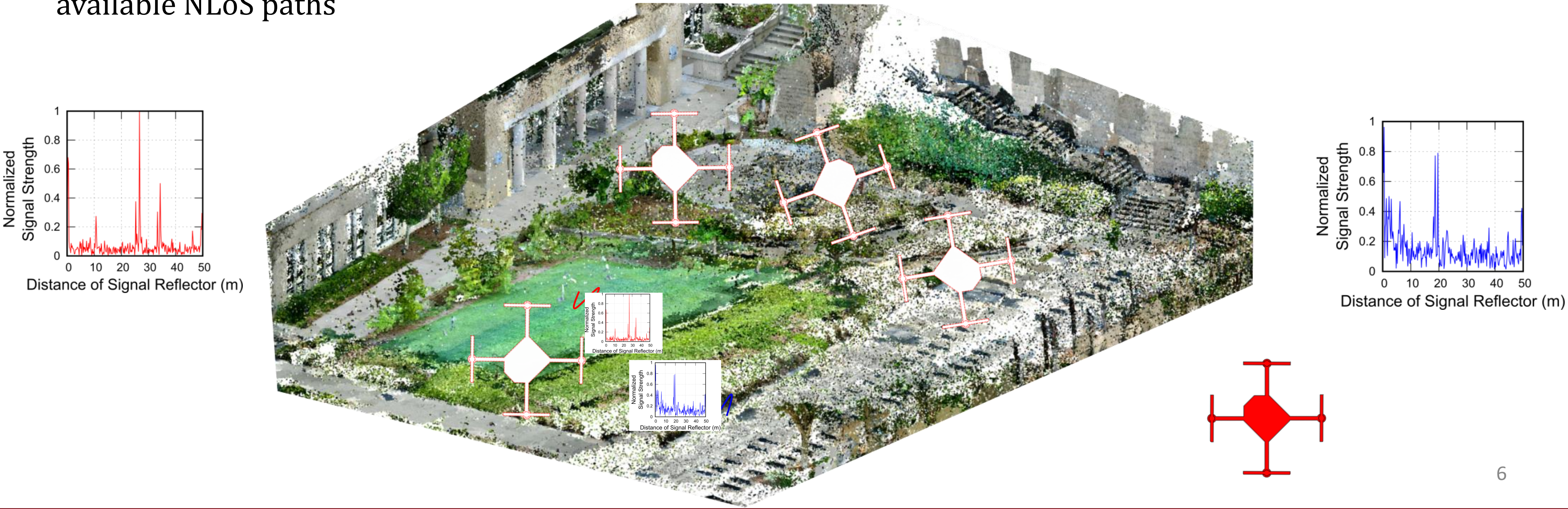
Source: ExterNetworks



Source: Remcom

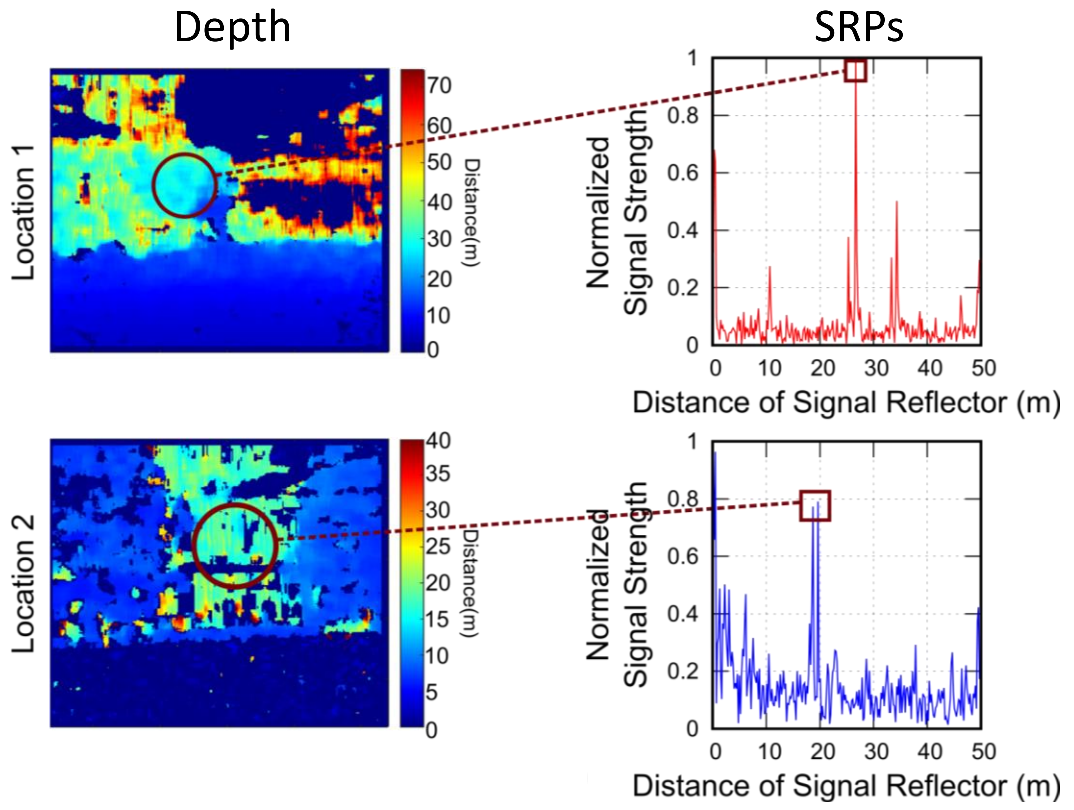
Our Approach: Theia

- Theia aims for easier outdoor surveying and enables deployers to identify near-optimal picocell locations
- Theia leverages visual information to model the complex relationship between visual data and the mmWave SRPs
- Theia utilizes advancements in deep learning and builds a customized deep convolutional neural network
- This enables Theia to predict SRPs from unseen viewpoints and use them to place picocells that maximize available NLoS paths



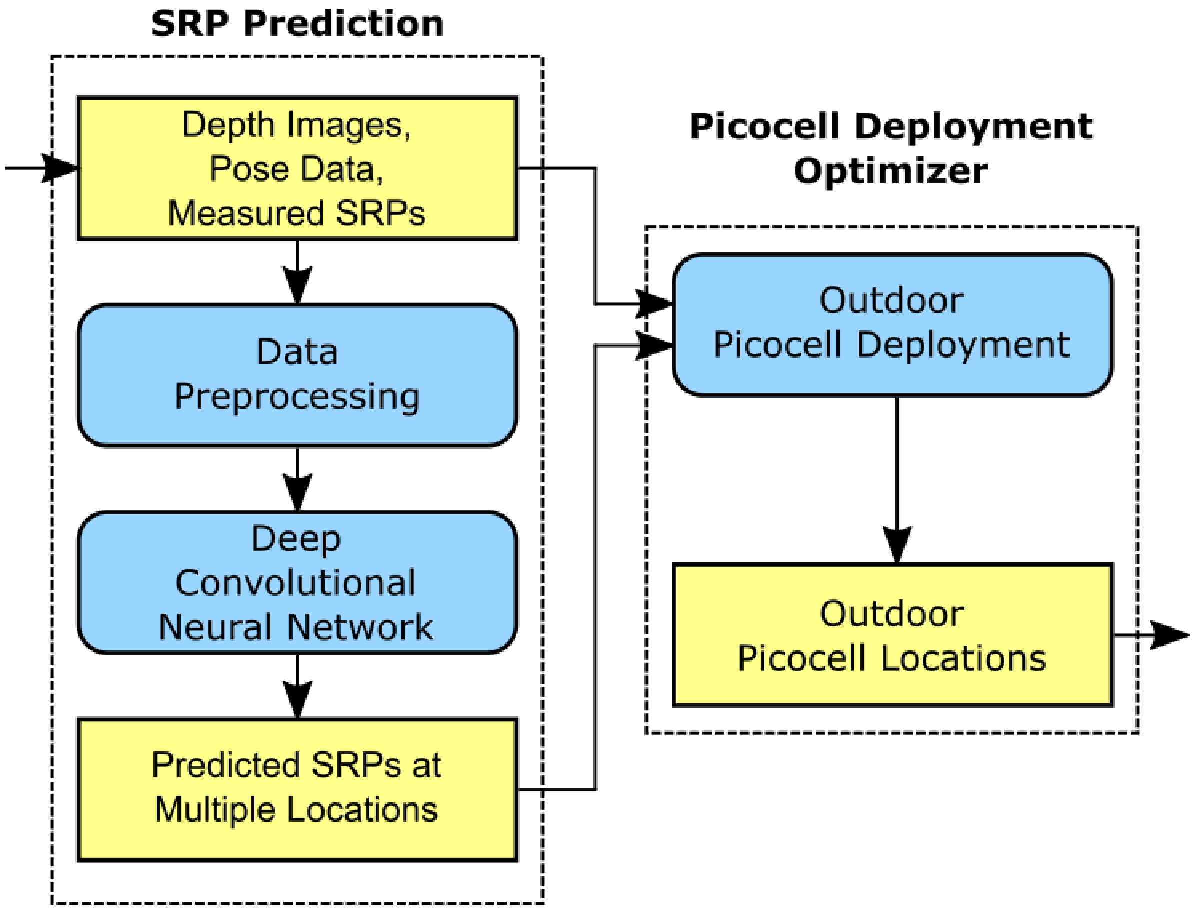
Signal Reflection Profiles

- Using a mmWave transceiver, we send signals at increasing frequency into the environment
- The signal bounces off reflecting points in the environment and returns to the receiver
- With the time of flight of the signal and a Fast Fourier Transform (FFT) we get the reflectors' distance
- With 3 transmit and 4 receive antennas, we get SRPs from 12 virtual channels at slightly different poses



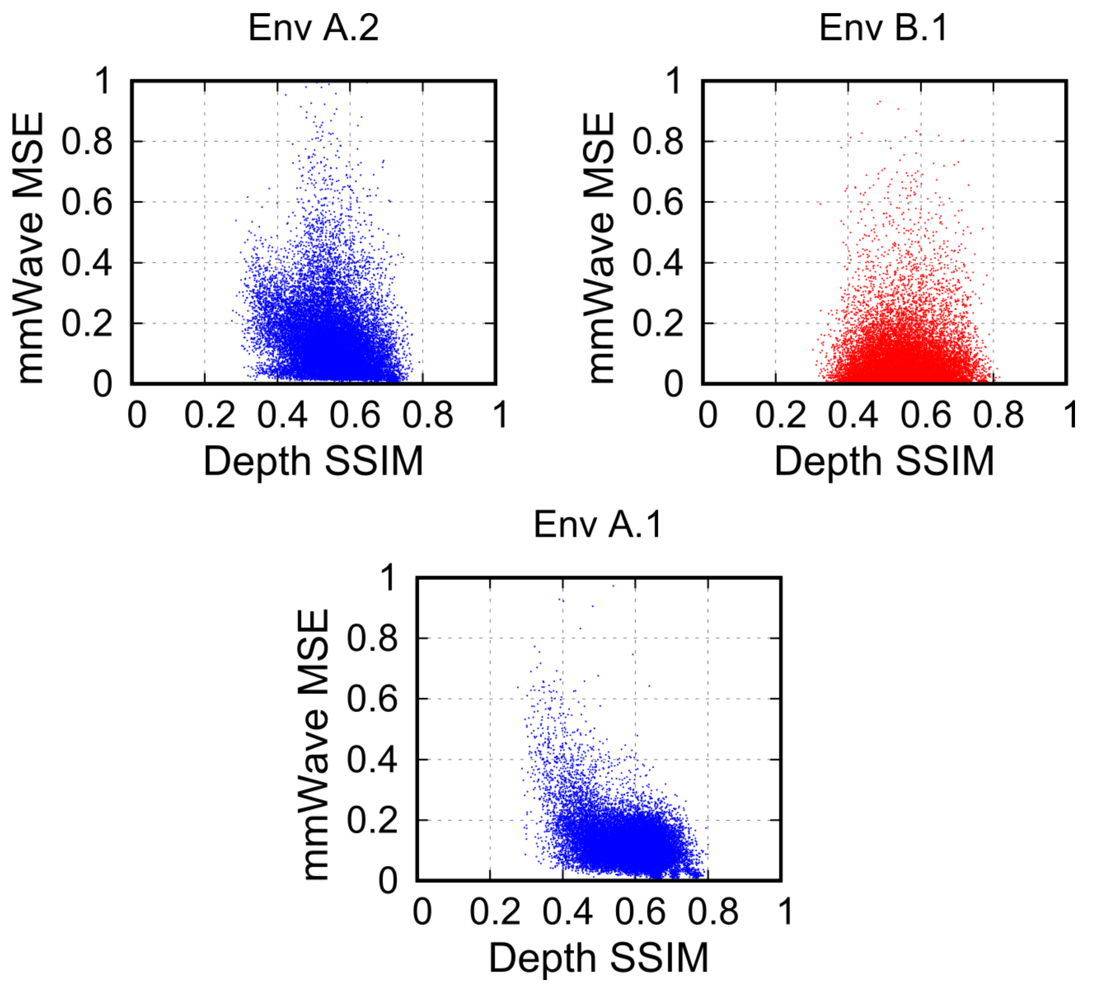
System Overview

- Theia enables deployers to achieve optimal picocell placement with easy SRP prediction
- The drone platform collects depth images, pose data, and SRPs from the outdoor environment
- The depth and pose data is synchronized with SRPs then fed into a Deep Convolutional Neural Network
- The DCNN predicts SRPs at different environmental locations, which are used for picocell placement



Visual to SRP Relationship

- Test Hypothesis: *Similar looking objects produce similar mmWave reflection profiles*
- Compute SSIM between depth images and MSE between corresponding mmWave reflections
- A complex, nonlinear trend cannot be captured by a simple regression-type model
- Differences between environments would make a single model nongeneralizable

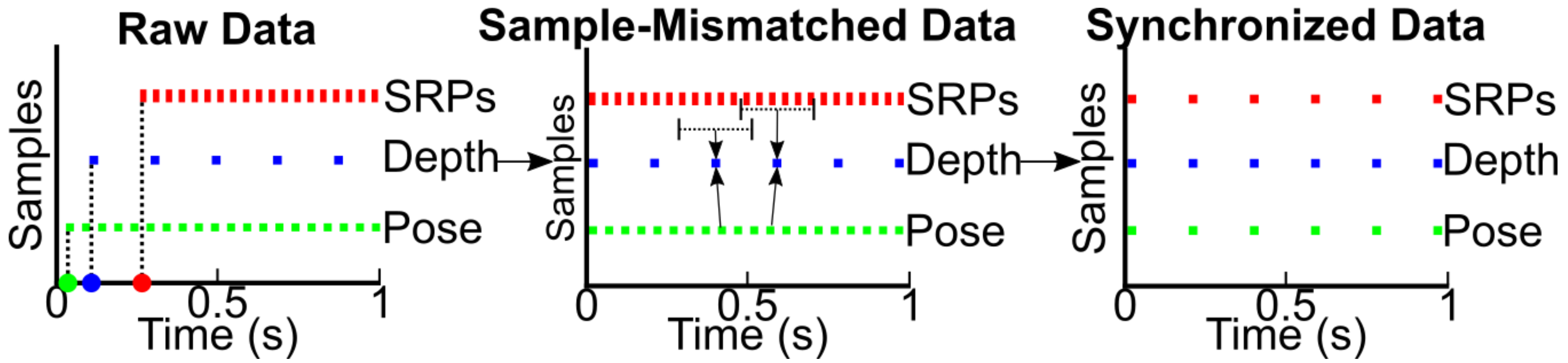


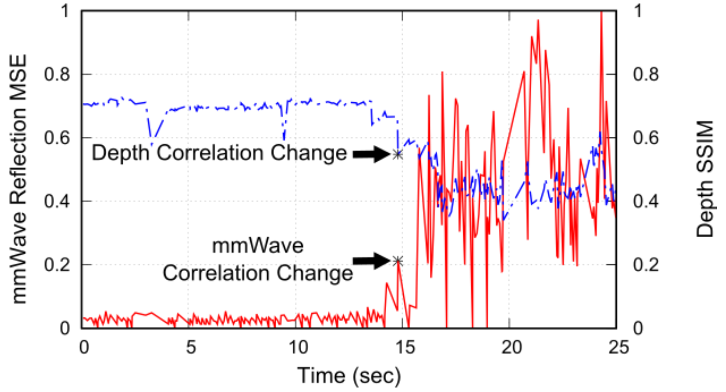
SRP Prediction using DCNN

- Measured SRPs act as low-resolution images, predicted SRPs act as high-resolution images, and positions as labels
- Our problem is in the same vein as the super-resolution problem
- Depth images and antenna pose are fed as input with SRPs at the same pose used as ground truth
- MSE between predicted and ground truth SRPs are used as the loss function

Preprocessing: Data Synchronization

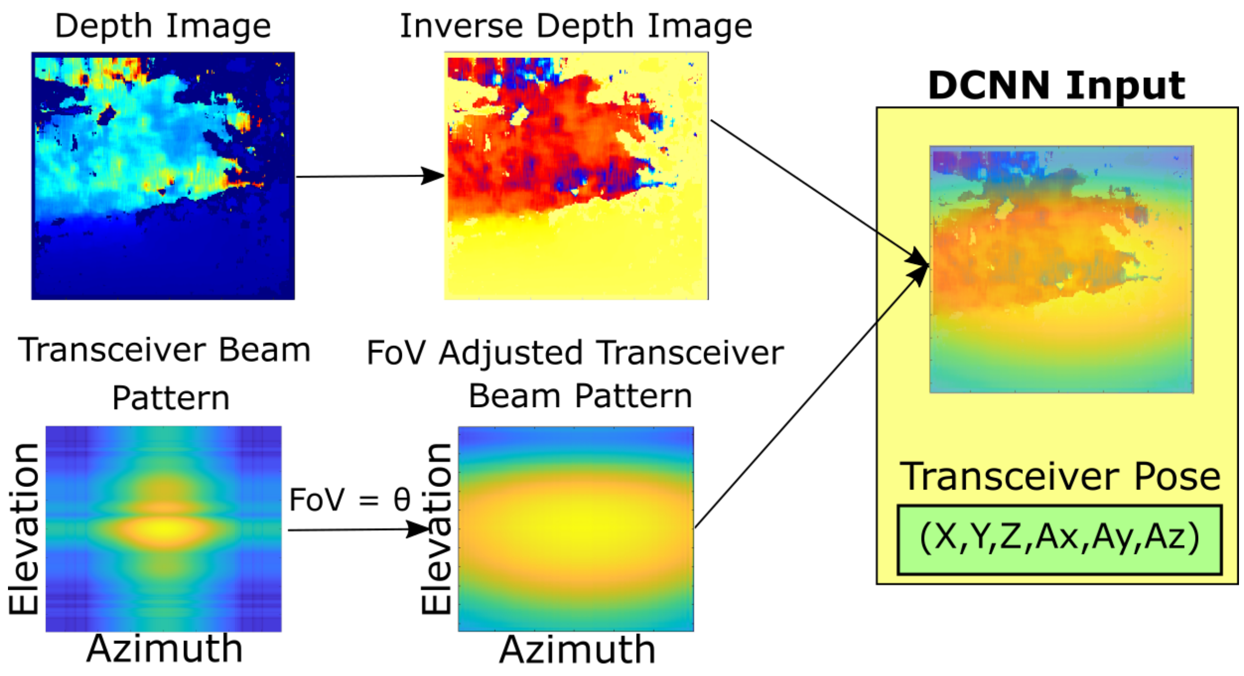
- The different systems start at different times and have different sampling rates, but hardware-level synchronization is not available for our platform, so we implement software-level synchronization
- By recording starting timestamps for each system, we can use the time offset to align the data
- Using interpolation and decimation to match rates, using an overlapping time window for the SRPs





Preprocessing: Constructing DCNN Input

- The transceiver's signal emission (beam) pattern means not all depth information contributes equally
- We first get the Inverse Depth Image (IDI) to prioritize closer objects
- Using the normalized transmit and receive power for different angles, we get a 2D beam pattern matrix
- We adjust the 2D matrix to match the depth sensor's Field of View (FoV), then mask the IDI with this
- We supply the Masked Inverse Depth Image (MIDI) and transceiver pose as input for the DCNN

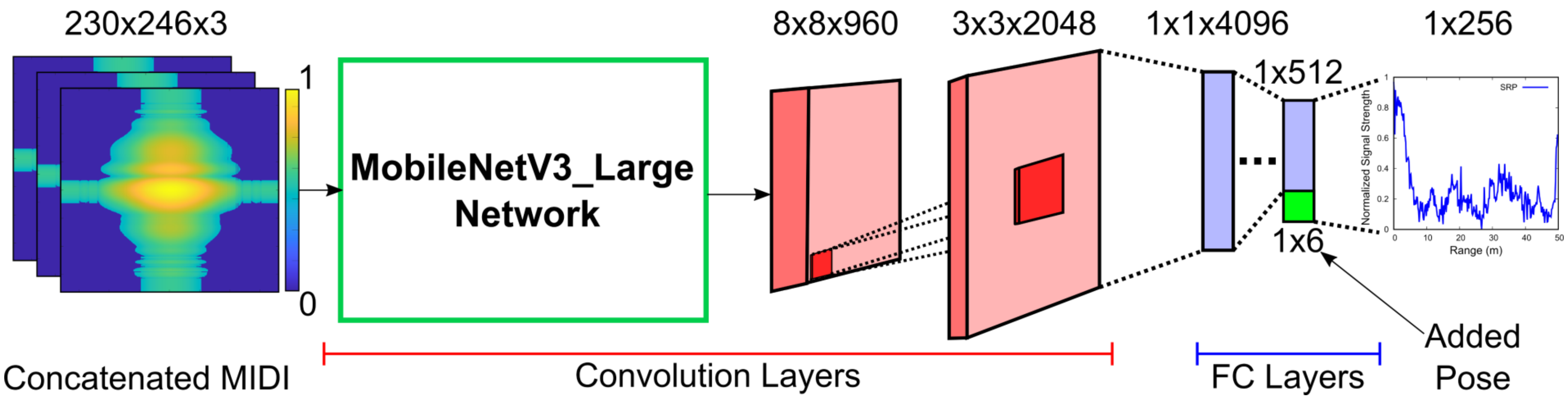


DCNN Model

- We evaluated multiple models as convolution layers, deciding on *MobileNetV3_Large* as it produced the highest performance with the lowest memory and computational constraints

- We concatenate the MIDI for input into *MobileNetV3_Large* for feature extraction, trimming the model after its convolution layers, then feed the output to customized FC layers for regression

- We include the transceiver pose directly into the FC layer to increase the network's generalizability



Picocell Deployment

- Since SRPs provide information about strong reflectors, we can place picocells to best utilize the NLoS paths the reflectors provide

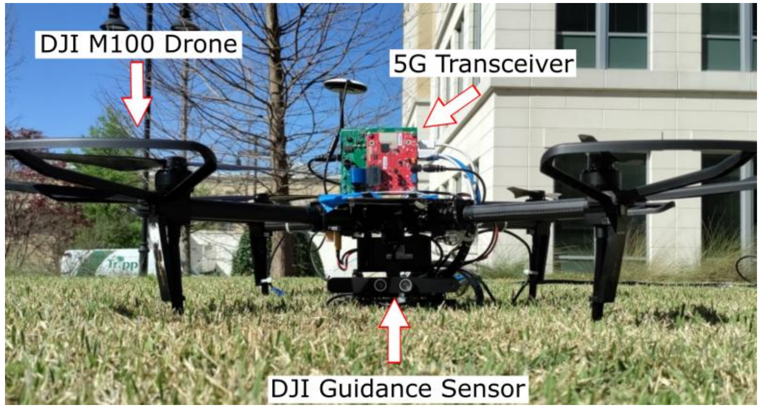
- The placement algorithm uses a Ray-tracing approach to simulate a separate transmitter and receiver and includes realistic reflections from predicted SRPs

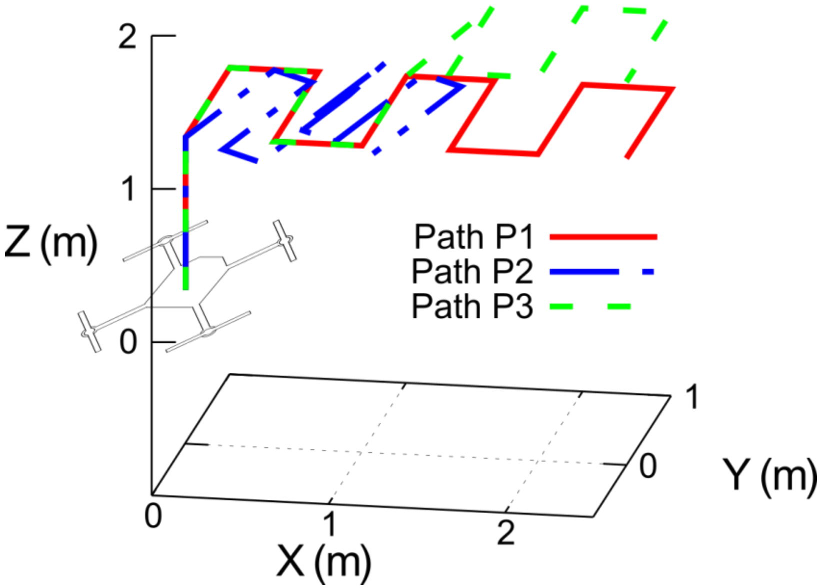
- We use three placement strategies:
  - “Average” aims to provide higher mean throughput to all clients in the environment
  - “Variance” aims to achieve similar signal strengths across the environment
  - “Link-outage” aims to ensure a certain level of signal strength across the environment

Regmi, et al., 2022

Real-world Data Collection

- Hardware Setup:
  - DJI Matrice 100 Drone for flight
  - DJI Guidance System for depth and IMU
  - TI IWR1443BOOST 76-81GHz mmWave transceiver and DCA1000EVM capture card for SRP collection
- We use a 2 meter tethered connection between drone and laptop for safety and data integrity
- Zigzag paths are used with each 10-minute data collection consisting of multiple passes
- Different paths are used to compare path variability

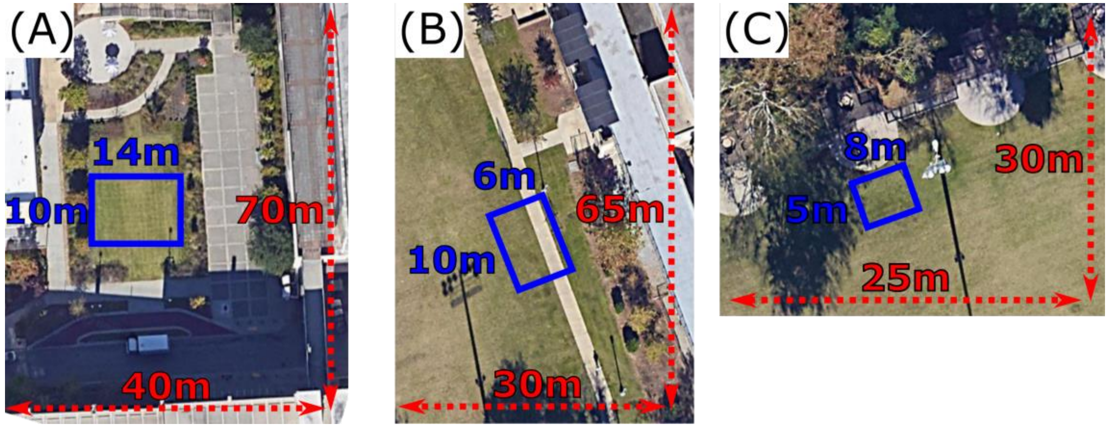




Real-world Data Collection

- Datasets are collected across 6 environments in 3 different outdoor spaces over a period of 4 months
  - Environments A.# are all located in outdoor space A

- We have collected and processed over 44 GB of data with about 144,000 data samples



Environment	Drone Path	Base Yaw Angle	Purpose	Elements of Environment
A.1	P1	0°	Courtyard and Patio	Trees, patio tables, patio seating, stairs, handrails
A.2	P1	90° CW	Courtyard	Trees, benches, glass windows
A.3	P2	45° CCW	Courtyard and Patio	Trees, patio tables, patio seating, stairs, glass windows and doors
A.4	P3	0°	Courtyard and Patio	Trees, patio tables, patio seating, glass windows and doors
B.1	P3	0°	Sports Field	Trees, bushes, benches, fences, glass windows and doors
C.1	P1	180° CW	Sports Field Lounging Area	Trees, bushes, picnic table, fences

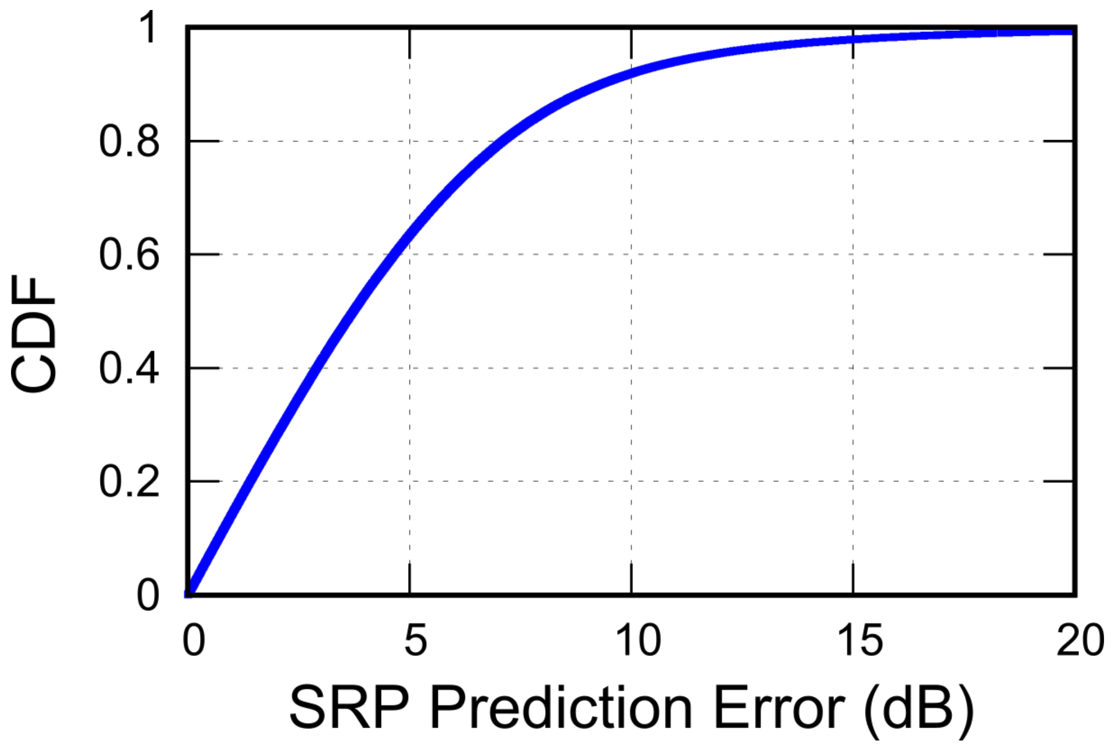
Network Training

- Theia's SRP prediction model is trained with the following parameters:
  - Training time: 1000 epochs, halted after 20 epochs of learning stagnation
  - Optimizer: NAdam with learning rate of 0.005
  - Loss Function: Mean Squared Error (MSE)

- The models are designed and implemented using Python and Pytorch on a server to reduce training time to ~1 hour for each model
  - AMD EPYC CPU @ 2.8GHz
  - 264 GB RAM
  - Nvidia RTX A6000 GPU

DCNN Model Performance

- Trained on datasets from outdoor space A only using 1 virtual channel
- Samples chosen at random with 90:10 train-test ratio (2145 test samples)
- Median error: **3.7 dB**
- 90^{th} percentile error: **9.3 dB**
- *90^{th} %tile error has little effect on picocell placement.*

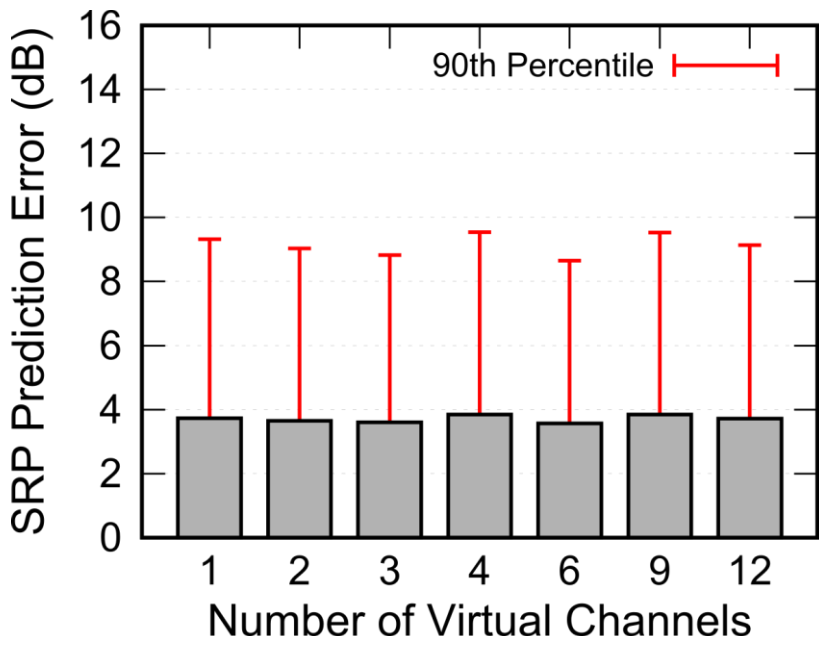


Multi-Channel Surveying

- Trained on datasets using different numbers of virtual channels

- The number of virtual channels has little effect on the median and 90th percentile error

- *Deployers can use any number of virtual channels*

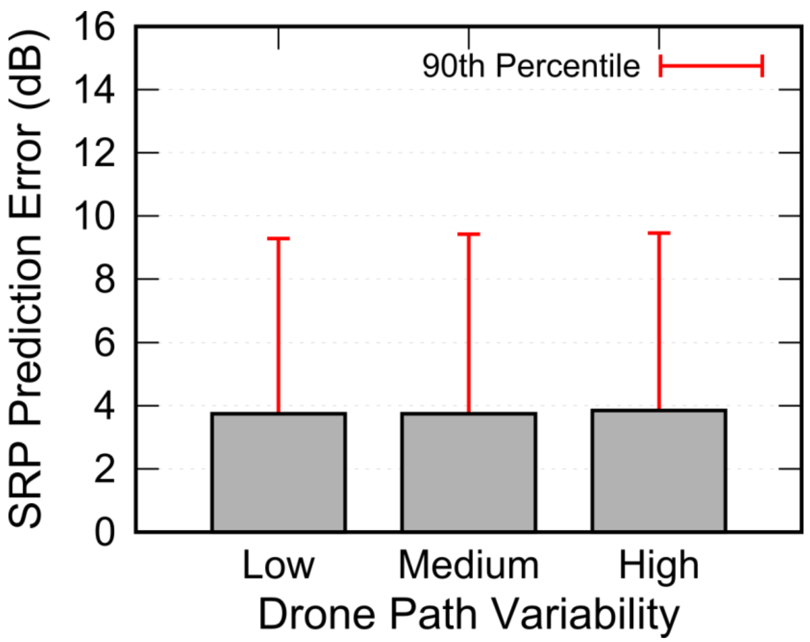


Drone Path Variability

- Trained on datasets using low, medium, and high path variability (Drone paths P1, P2, and P3)

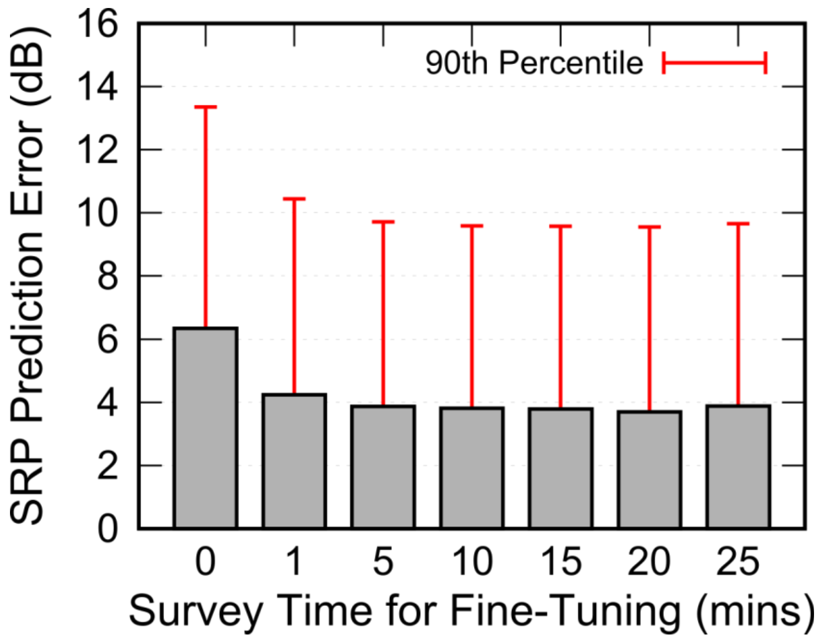
- Errors are within **0.2 dB** for both metrics for all path types

- *Deployers likely won't need to worry about path variability*



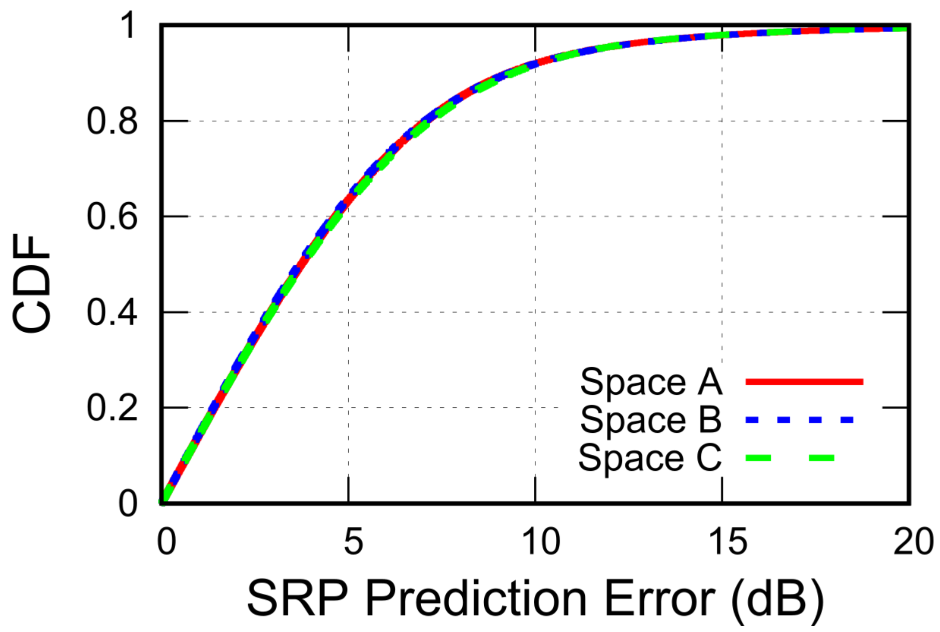
Survey Time Requirement for Fine-Tuning

- The model is initially trained on datasets from environment A.1
- Then the model is trained on samples from A.2 based on survey time, then tested with A.2 samples
- With no fine-tuning, the median and 90^{th} percentile errors are **6.3 dB** and **13.4 dB** respectively
- Just 1 minute of fine-tuning reduces errors to **4.2 dB** and **10.4 dB**, and 5 minutes performs like the base model
- *Deployers will save time collecting new samples*



Generalizability to New, Similar-Looking Environments

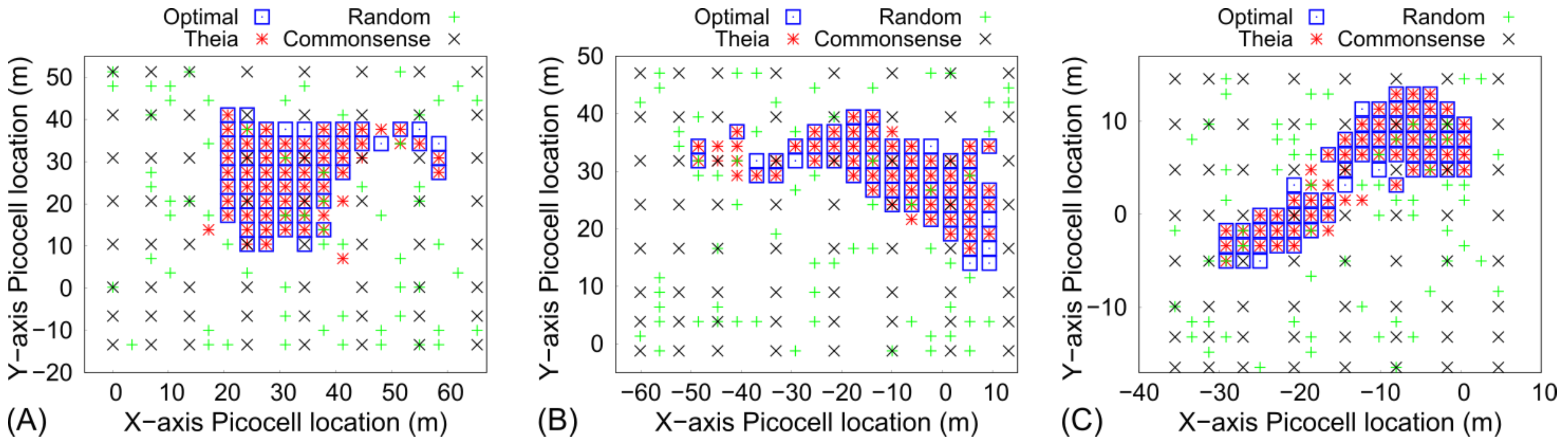
- The model is trained on datasets for each outdoor space
- Despite environmental differences, the model is able to learn with all errors within **~0.1 dB** of each other
- *Theia performs well in new, similar looking environments*



Picocell Deployment Performance

- We build a Ray-tracing method with separate transmit and receive antennas using measured SRPs, using Theia’s prediction error to enable realistic placement errors

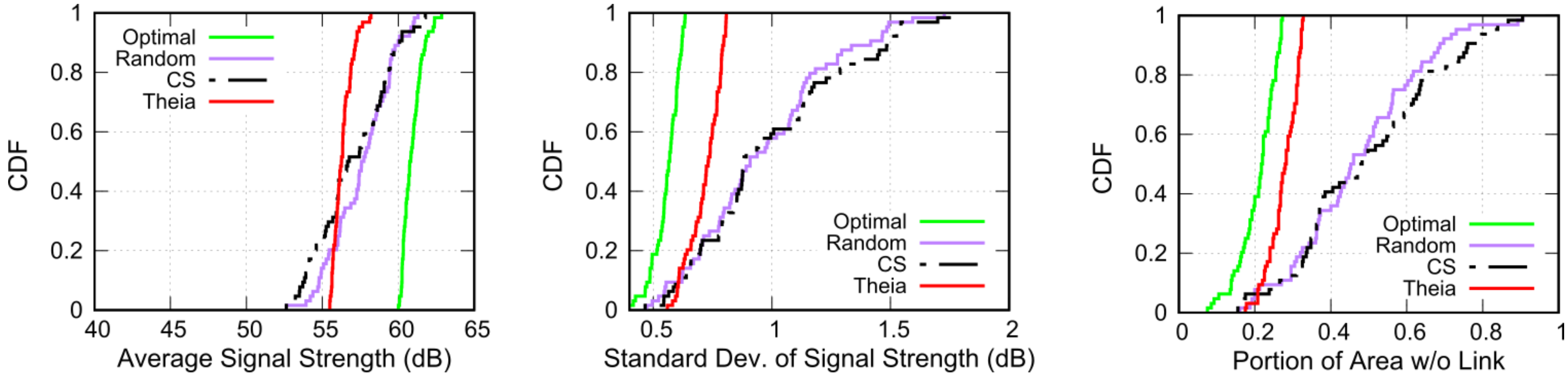
- We also simulate 3 other placements:
  - Random chooses random placements in the environment
  - Common-Sense places picocells at corner locations
  - Optimal is placed assuming zero SRP error



- *Theia performs close to Optimal when placing picocells in outdoor environments*

Picocell Deployment Performance

- We look at the performance of the “average”, “variance”, and “link-outage” strategies for in outdoor space A
- All methods have median average signal strength within **5 dB**, and Theia is able to limit SRP variation to **0.8 dB** and reduce the area without links by **~2.76x** compared to Random and Common-Sense



- *This shows the importance of accurate SRP prediction for deploying picocells in outdoor areas*

Conclusion

- Theia enables accurate mmWave SRP prediction in multiple large-scale outdoor environments
- Theia can fine-tune to new environments with as little as 5 minutes of survey data
- Theia’s SRP prediction accurately estimates picocell placements to enable reliable outdoor mmWave networks

Thank you for your time!

Check out our paper for more results:

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If you have questions: Email to mcdoweli@email.sc.edu