Design of 6G Device-to-Device (D2D) Wireless Communication System Using Machine Learning

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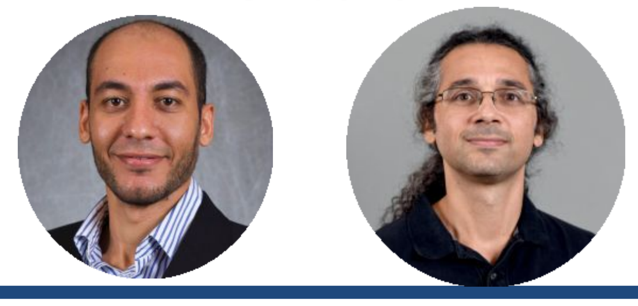
Mentors



Meet the Team

Introduction

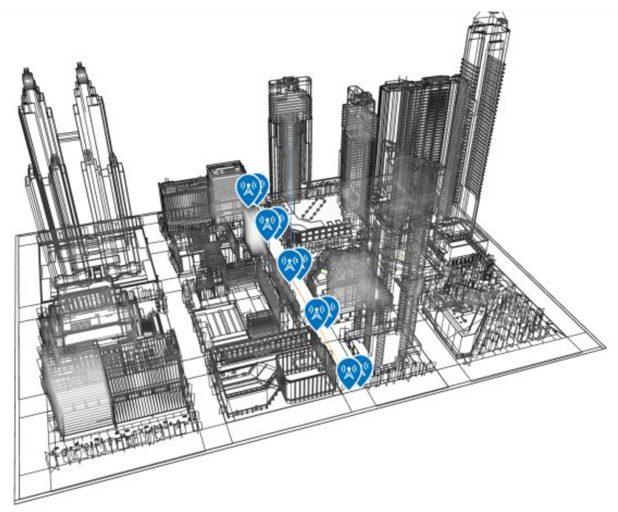
Team NeuralWave's capstone project aimed to enhance Device-to-Device (D2D) wireless communication by improving channel estimation through machine learning (ML). The team used a MATLAB raytracing simulation environment to generate channel coefficients for a realistic urban scenario and tested MATLAB/Python Machine Learning (ML)-based methods against classical Least Squares (LS) estimation. The objective was to show that machine learning (ML) can better capture channel structure, reduce pilot overhead, and improve estimation accuracy, demonstrating a scalable path toward more efficient decentralized wireless networks.

Why it matters?

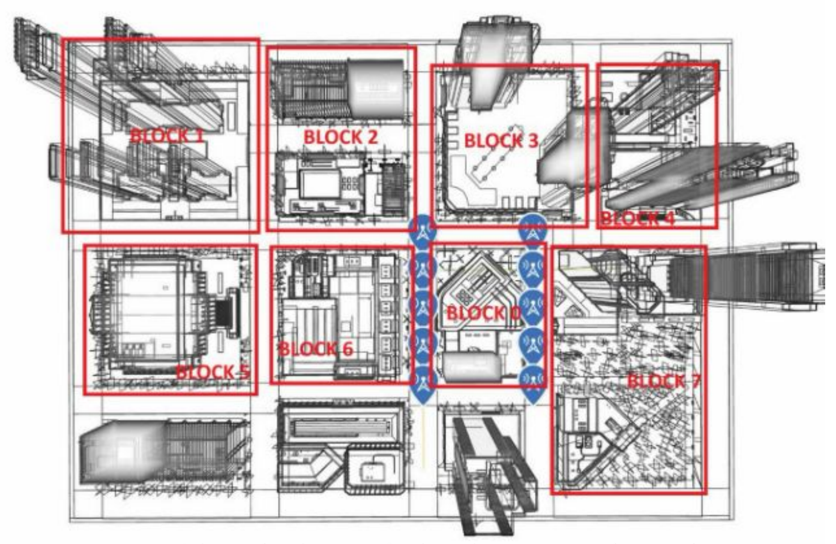
- Every smartphone, drone, and smart device relies on wireless communication to share data instantly.
- As cities, vehicles, and satellites get smarter, networks are becoming overloaded and inefficient.
- Device-to-Device (D2D) communication lets devices talk directly — reducing delays and freeing up network resources.
- Machine Learning (ML) helps these systems adapt automatically to changing environments, by reducing the amount of overhead needed for channel estimation.
- Traditional networks rely on centralized infrastructure; D2D with ML offers a scalable alternative for the next generation of connectivity.
- Future 6G networks could make real-time communication faster, smarter, and more energy-efficient — benefiting everything from emergency response to space communication.

Simulation Environment

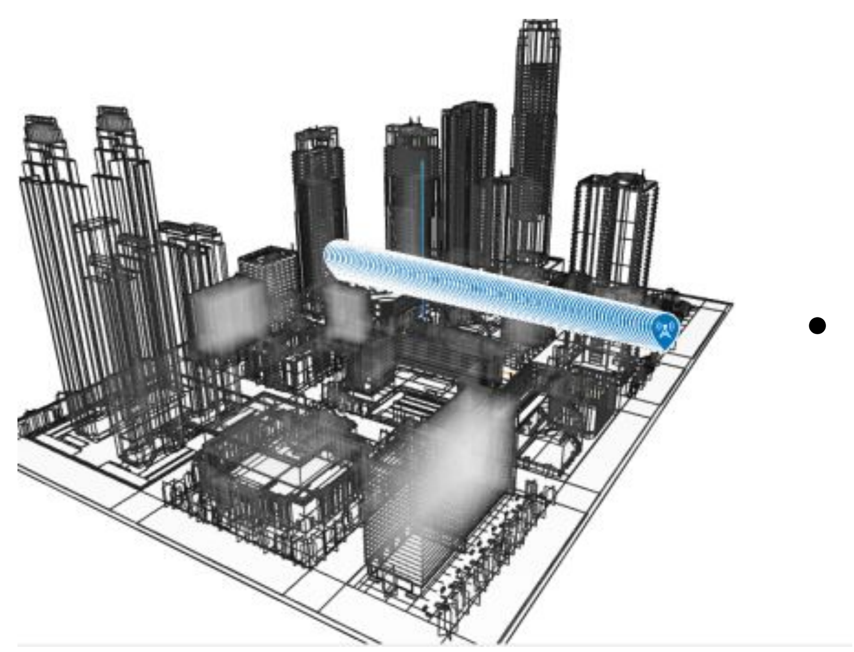
The Matlab simulated city environment with user locations (in blue)



- Simulation placing user devices along a street canyon to capture dense, sidewalk-level deployments and moving users.



- Simulation of city into numbered blocks with sites and route paths, letting us vary condition by block.



- Simulation of 100 x 1 D2D users on one street

Current Limitations

- Requires pilots on every subcarrier (wastes overhead)
- Estimates each subcarrier independently
- Cannot exploit correlation patterns
- Becomes inaccurate at high mobility or low SNR
- Breaks down under nonlinear or real-world impairments

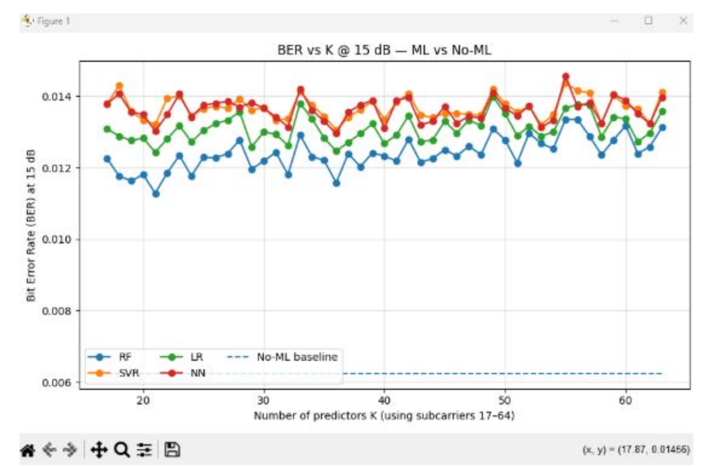
Classical Wireless Channel Estimation Pipeline

Pilot Symbols → Wireless Channel → LS Estimator* → Data Detection

*Least Squares (LS) estimation treats each subcarrier independently, which leads to the limitations above.

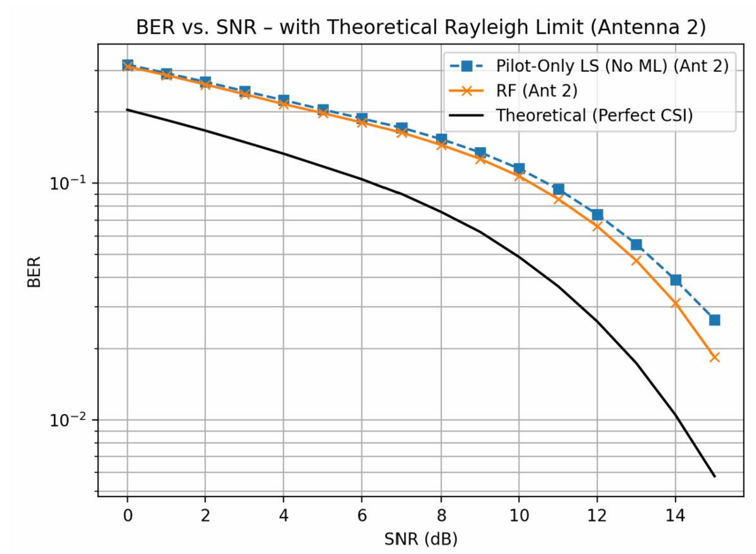
Results

Different ML performance comparison

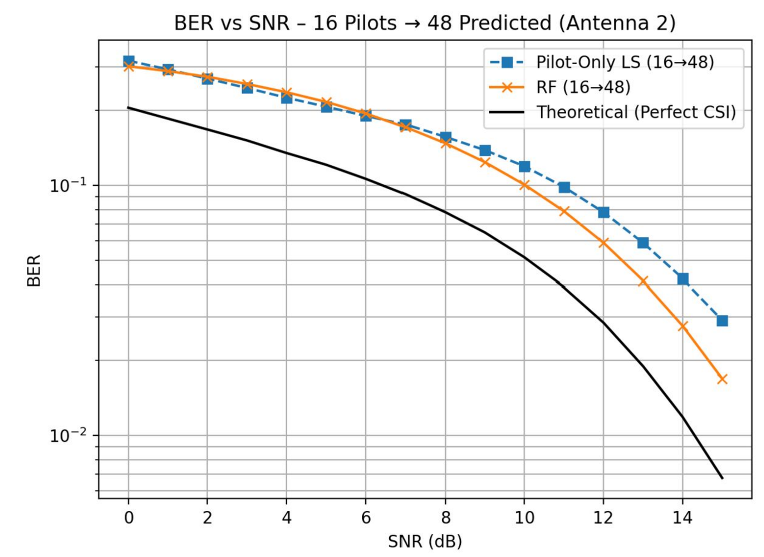


- ML Model ranking & gap to baseline: Random Forest (blue) is consistently the best of the ML models

ML Channel Estimation Performance Highlights

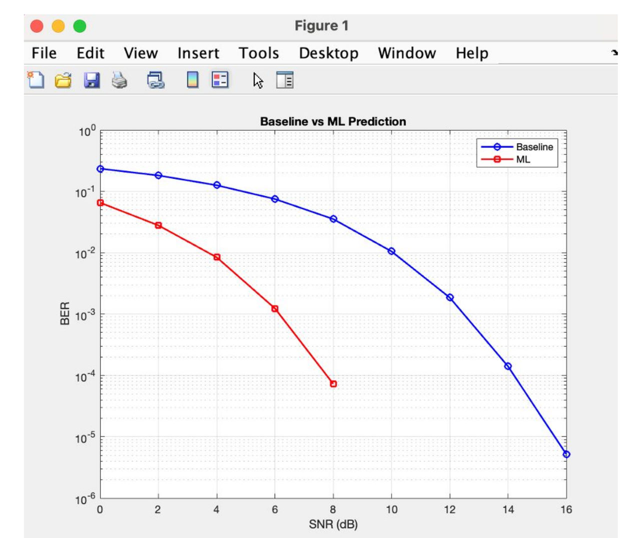


- Model reconstructs unseen subcarrier (63 subcarriers ⟶ 64th unseen)



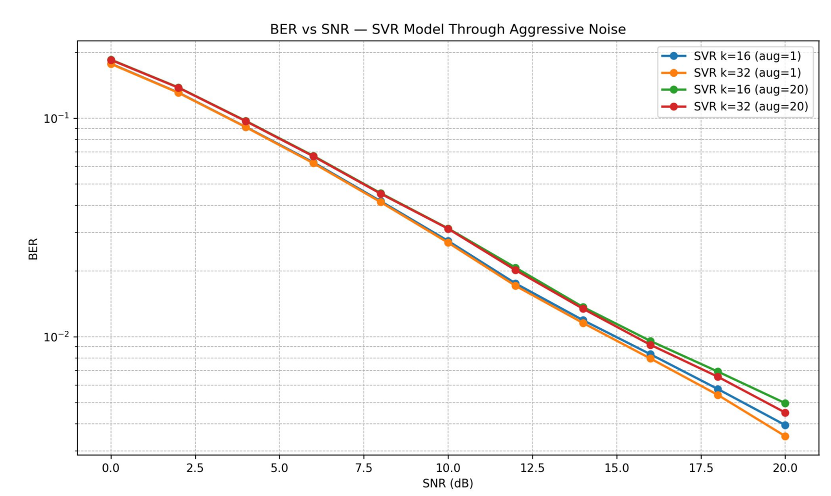
- 16 pilots can reconstruct 48 remaining subcarriers — reducing complexity

Spatial Channel Estimation



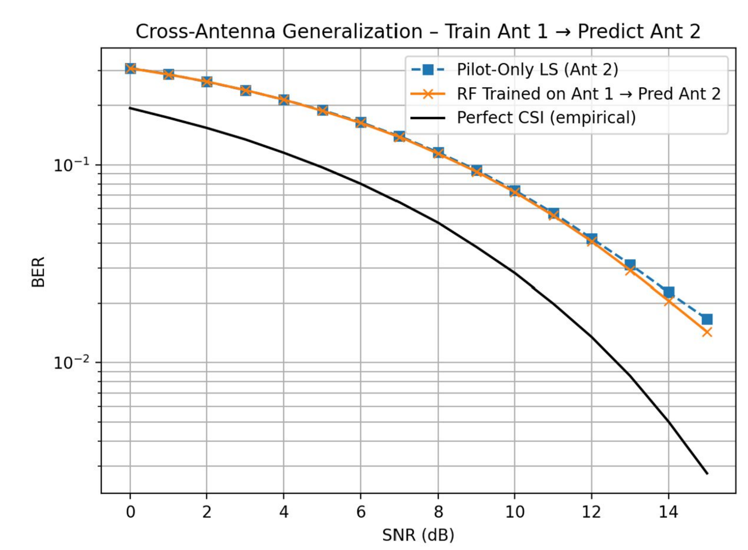
- ML out-performed traditional spatial channel estimation mapping one channel to another given two receivers in different locations.

Model Performance against Noise



- ML Model shows robustness against aggressive noise

Cross-Antenna Generalization



- ML generalizes across antennas, proving it captures true wireless channel behavior — something classical LS cannot do

How ML Improves Channel Estimation

- Learns correlation patterns across subcarriers and antennas
- Reduces pilot overhead by inferring missing subcarriers (16 ➡ 48)
- More robust than LS at medium–high SNR
- Generalizes across receivers — learns real channel structure
- Handles nonlinear or real-world impairments better than classical estimators

Conclusion

- The team created a unified simulation environment through MATLAB and Python that supports channel dataset generation, signal normalization, and noise injections to emulate real-world multipath effects for a simulated city.
- These results confirm the strength of the team's machine-learning framework and confirm that data driven estimation can reduce computational complexity without sacrificing the reliability of the system.
- By combining simulation with accessible visualization for the users, the project aims to bridge classical communication theory with modern data driven design.
- Random Forest performed the best among the machine learning models tested in this project. It consistently improved the BER more than all other ML models.