Network-aware path planning for Autonomous Mobile Robots in industrial environments

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IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS) 2025

Agenda

- Motivation and contribution
- Use case simulator
- Network-aware path planning
- Results
- Conclusions and future work

Motivation

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Network-aware path planning

Robot connectivity
Autonomous Mobile Robots need reliable wireless connection (commands, sensor data, coordination)

Path planning
Traditional path planning ignore wireless signal quality when choosing routes

Dead zones
Lost connection can trigger operational stops and and breakdown of operations

Private 5G
Excellent industrial connectivity potential but lacks adaptive planning

Realistic data
Data from 5G models has not been validated against real measurements

Intelligent path planning
Ensure robots maintain mission-critical connectivity throughout their operations

Literature gaps

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Network aware path planning methods still use simple idealized radio models

Advanced ray-tracing tools like Sionna[1] can model complex indoor 5G channels but have not been validated in real-world

Real-world 5G AMR

Different path planning algorithms not compared under a common network testbed

AI-based path planners show promise in network-constrained industrial robot navigation

No unified framework exists that combines validated industrial wireless simulation with multiple path planning approaches

1 Sionna RT: https://nvlabs.github.io/sionna/rt/index.html

Research contributions

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High-fidelity synthetic data generation

High fidelity ray-tracing network simulations with path-planning algorithms, including methods for enhanced synthetic dataset generation.

Network-aware path planning

The extension of A*, CVAE-based and GraphMP implementations that account for dynamic network constraints.

Validation on real world measurements

The validation of simulations against real-world industrial data, achieving strong correlation.

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Real-world use case

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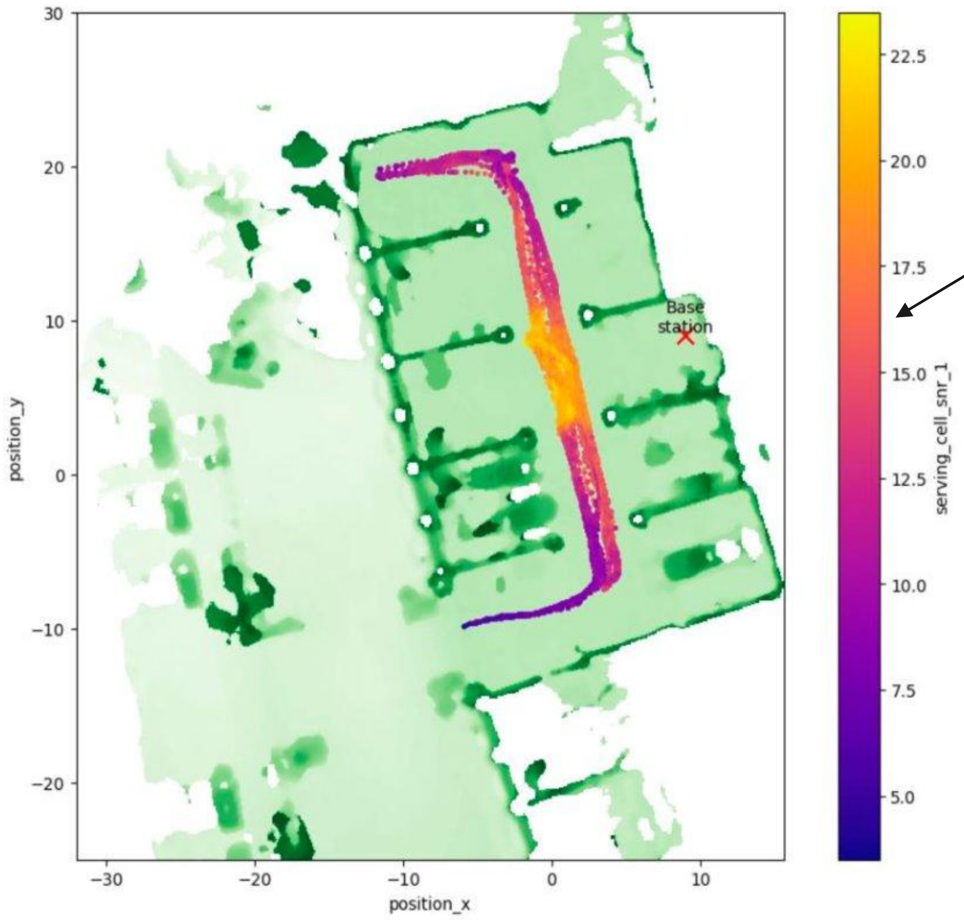


AI4Mobile dataset showing throughput variations from 2.5 Mbps (poor/dark blue) to 22.5 Mbps (excellent/yellow)

Dataset includes SNR, throughput, and latency measurements recorded across a 40×35 m industrial space.

Environment contains metal structures, machinery, and NLOS regions

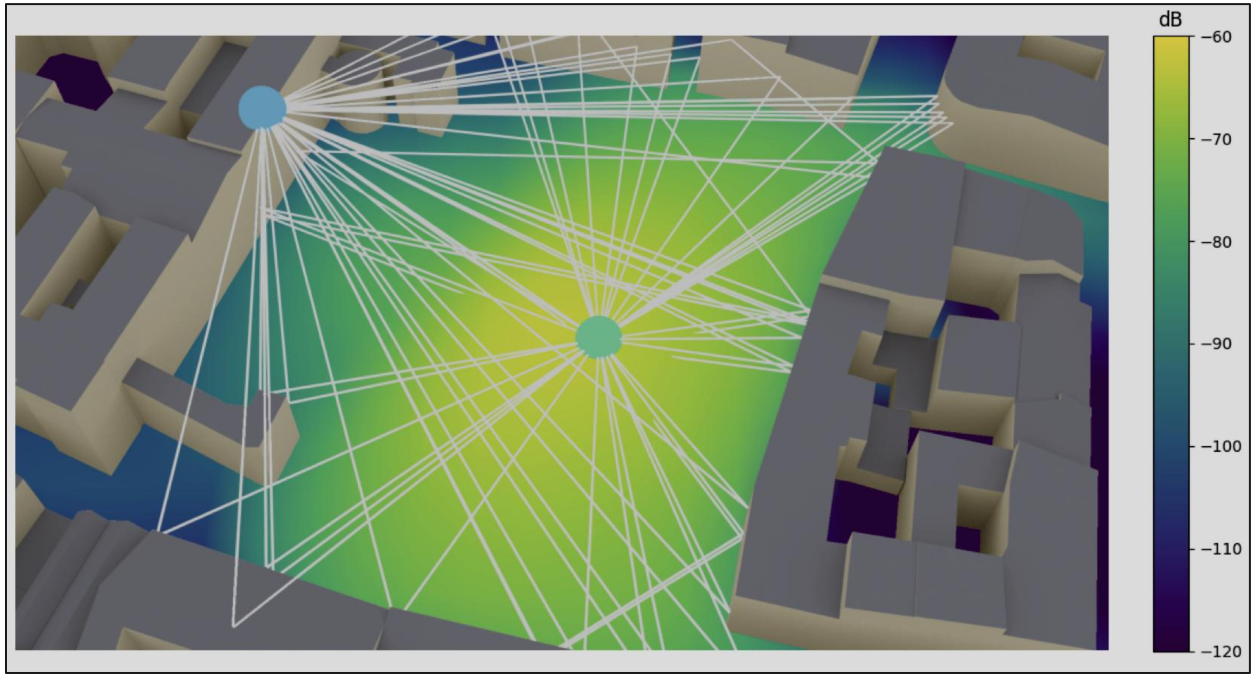
Objective: Match Nvidia Sionna ray-tracing predictions with real data, to then simulate values in other parts of the map

https://ieee-dataport.org/open-access/ai4mobile-industrial-wireless-datasets-iv2v-and-iv2i

Simulation validation

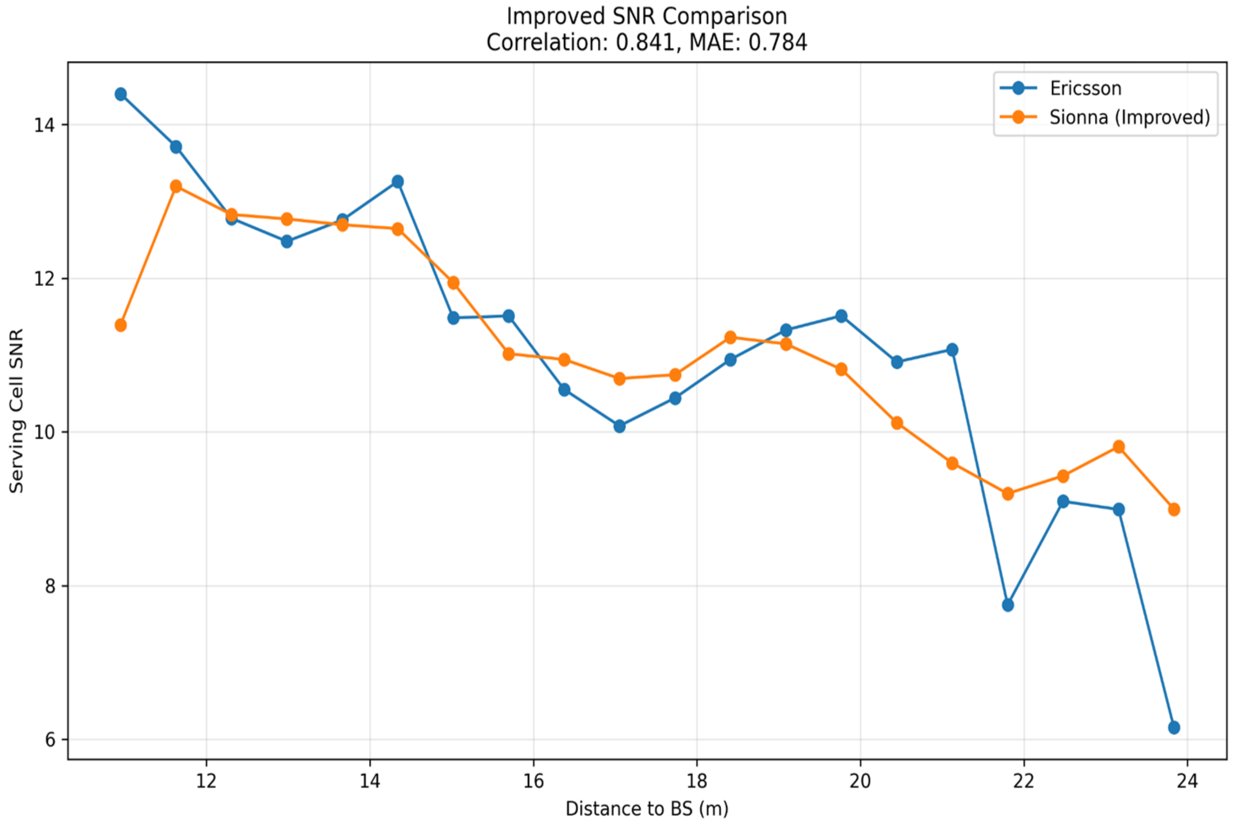
Nvidia Sionna simulator setup

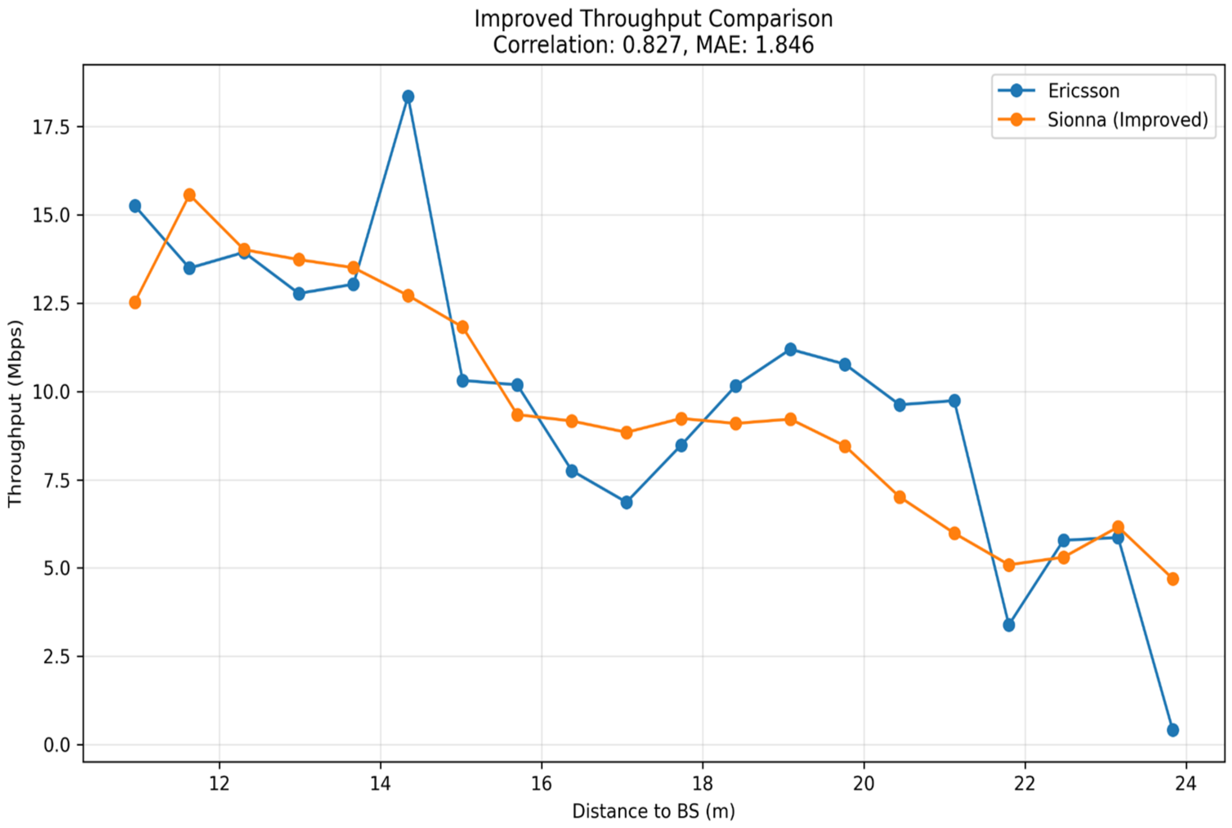
- Simulation parameters aligned with the dataset:
  - 3.75 GHz carrier frequency
  - 100 MHz bandwidth
  - 23 dBm transmit power
  - 4×4 MIMO antenna configuration
- Achieved strong correlation:
  - SNR: $R^2 = 0.87$
  - Throughput: $R^2 = 0.82$
  - Latency: $R^2 = 0.79$

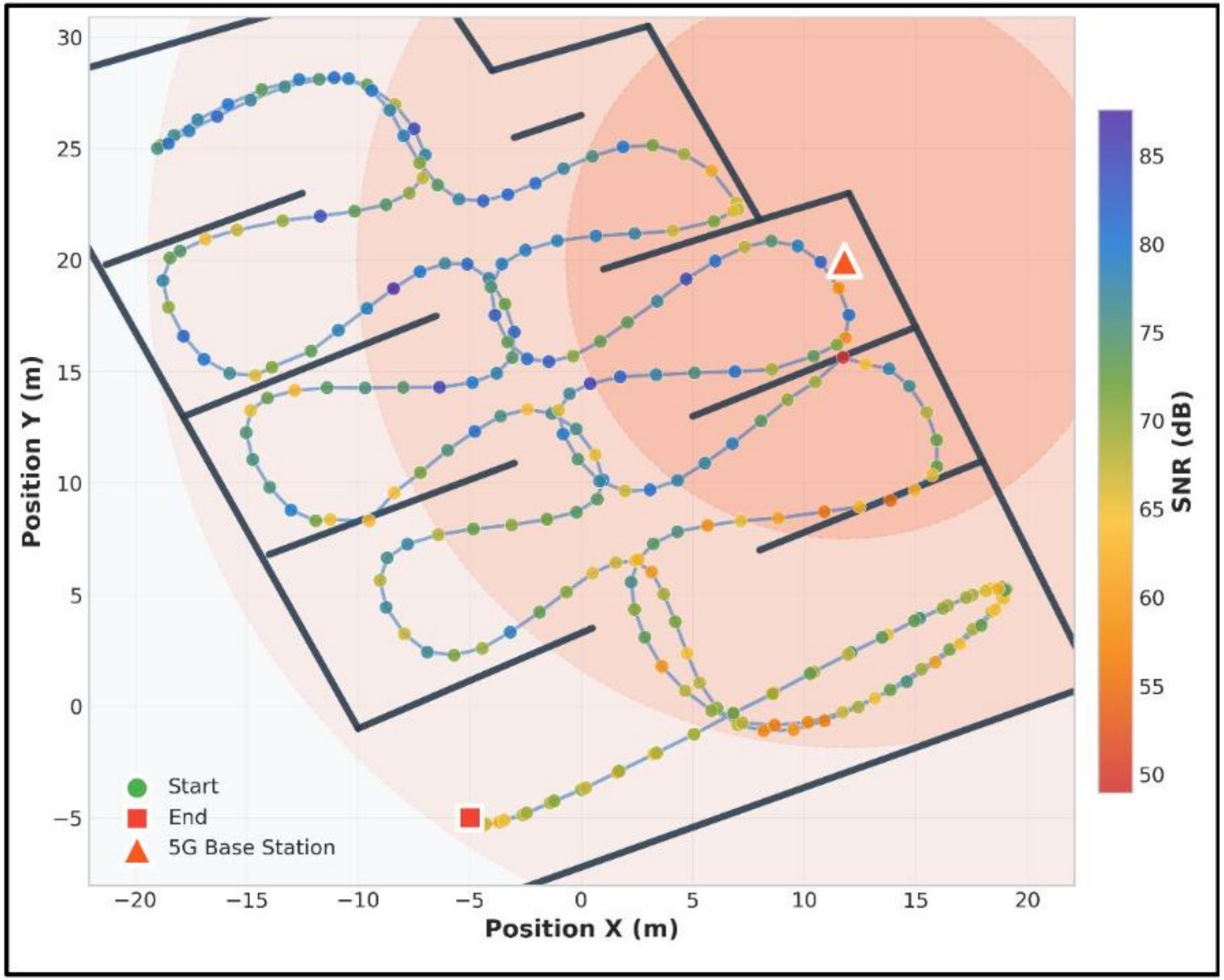


Sionna RT: https://nvlabs.github.io/sionna/rt/index.html

Simulation validation







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AMR path simulation in Sionna framework showing industrial environment with walls, base station, and trajectory with SNR heatmap.

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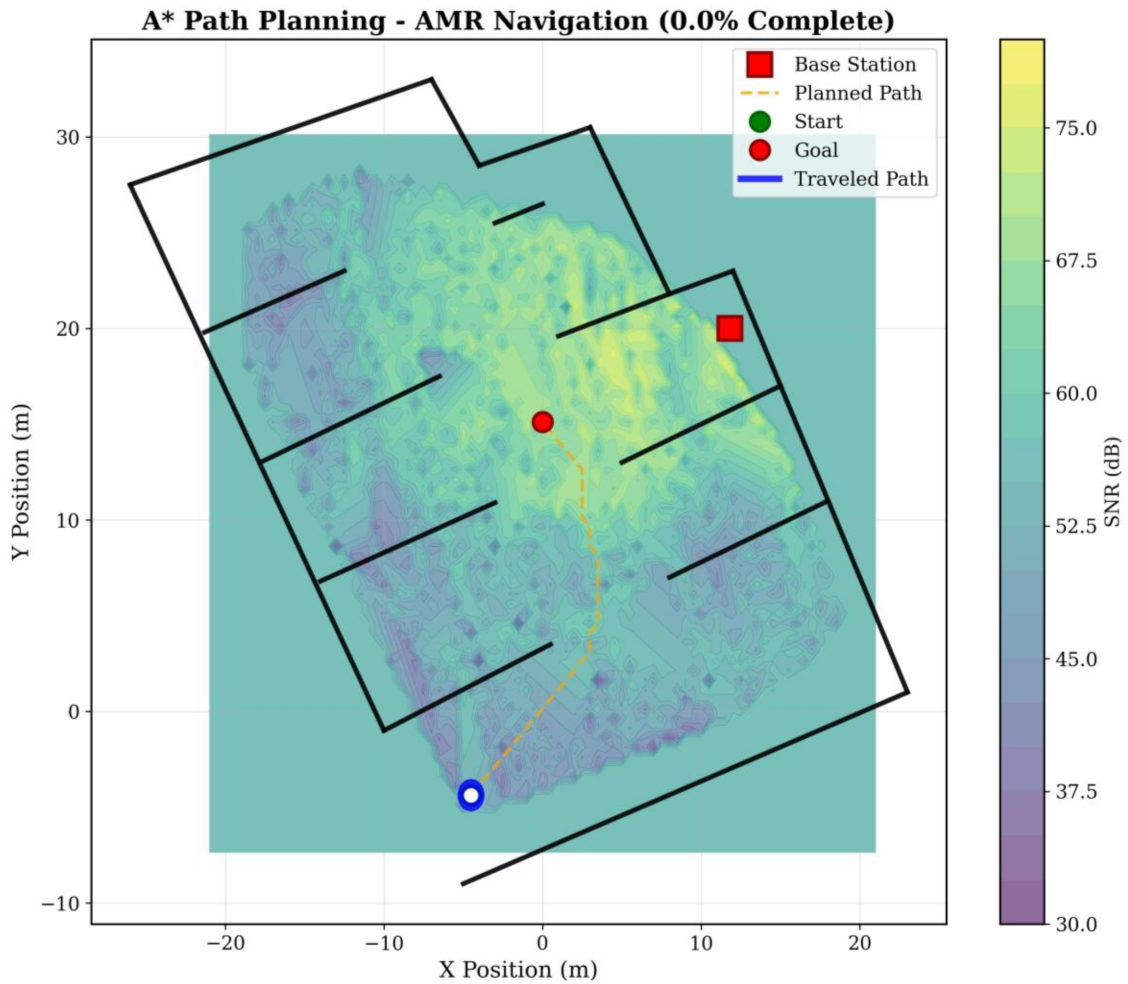
Network-aware A*



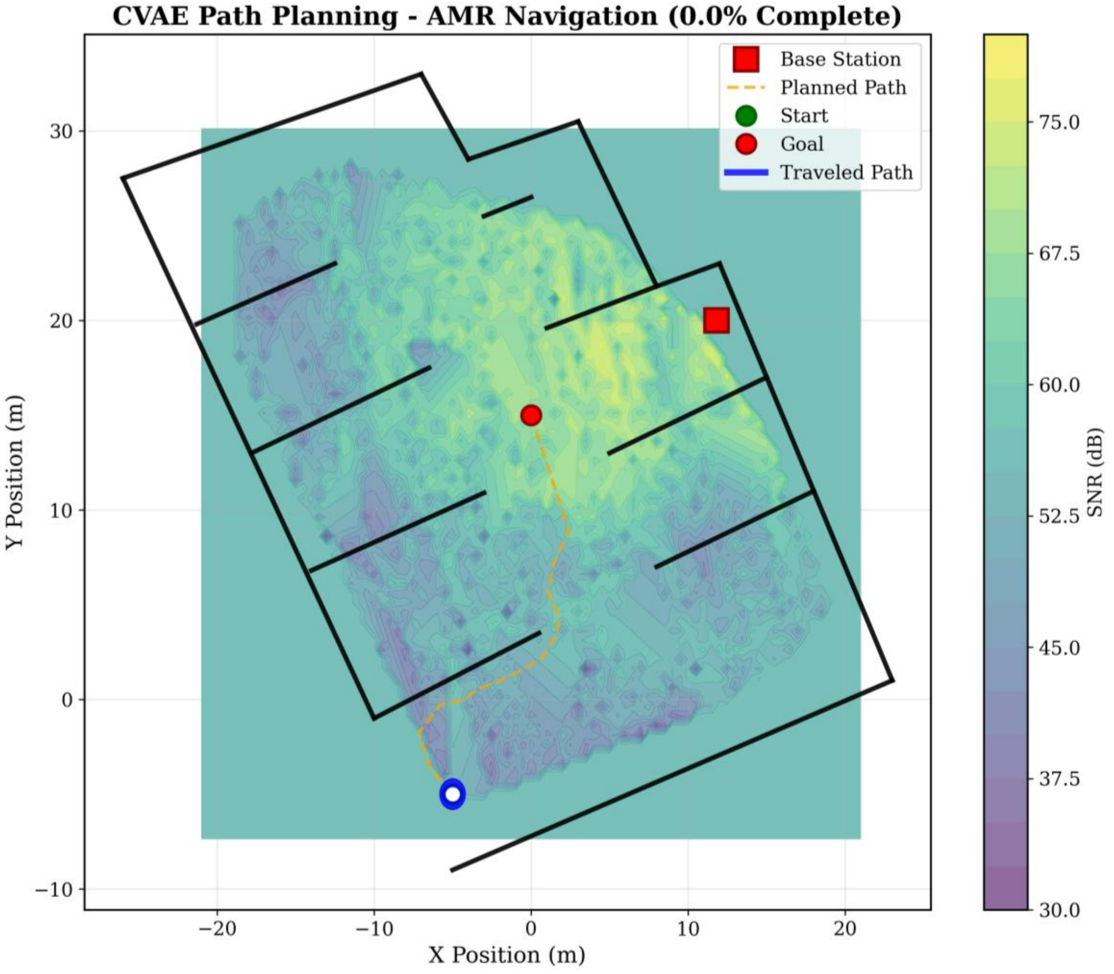
Modify the traditional A* algorithm by incorporating network quality penalties into the cost function for SNR, throughput, and delay constraints.

Validated Network Quality Maps: Sionna-generated network quality maps providing metrics for each location, derived from validated ray-tracing simulation.

Multi-Constraint Optimization: The approach balances path length minimization against network quality requirements through configurable weighting factors.

Performance Characteristics: optimal path length (24.23 m), zero throughput violations, high efficiency (0.851) and moderate planning time (61.81 ms).

Network-aware Conditional Variational Autoencoder



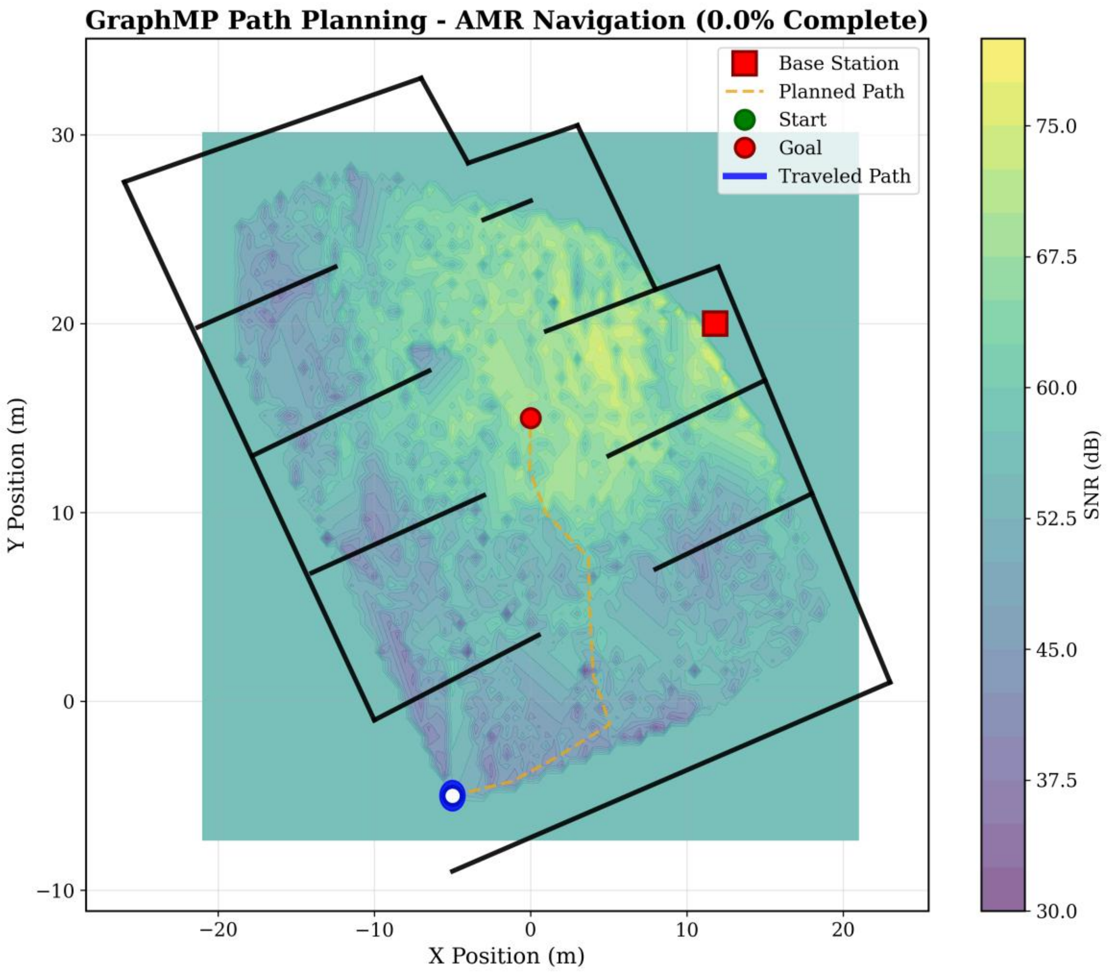
Generative Learning Approach: CVAE learns the conditional distribution directly from 15,000 validated training path examples, enabling probabilistic path generation.

Encoder-Decoder Architecture: The encoder maps observed paths and network constraints to a latent space representation while the decoder reconstructs feasible paths using LSTM with attention mechanisms.

Constraint-Aware Generation: The model emphasizes constraint satisfaction through weighted penalty terms (SNR, throughput, and latency requirements).

Superior Performance: CVAE achieves the highest compute efficiency (0.873), shortest path length (23.61 m), and 73% fewer delay violations compared to A*.

Network-aware Graph Neural Networks



Graph-Based Reasoning: formulates path planning as graph reasoning over network-annotated environments

Dual-Network Architecture: Graph Attention Network (GAT) predicts edge traversability probabilities; Graph Convolutional Network (GCN) estimates heuristic constraints.

Learned Edge Feasibility: The edge feasibility network computes traversability probability using attention mechanisms.

Hybrid Planning Strategy: GraphMP guides A* search using learned predictions, maintaining optimality guarantees though with higher planning time (2287.48 ms).

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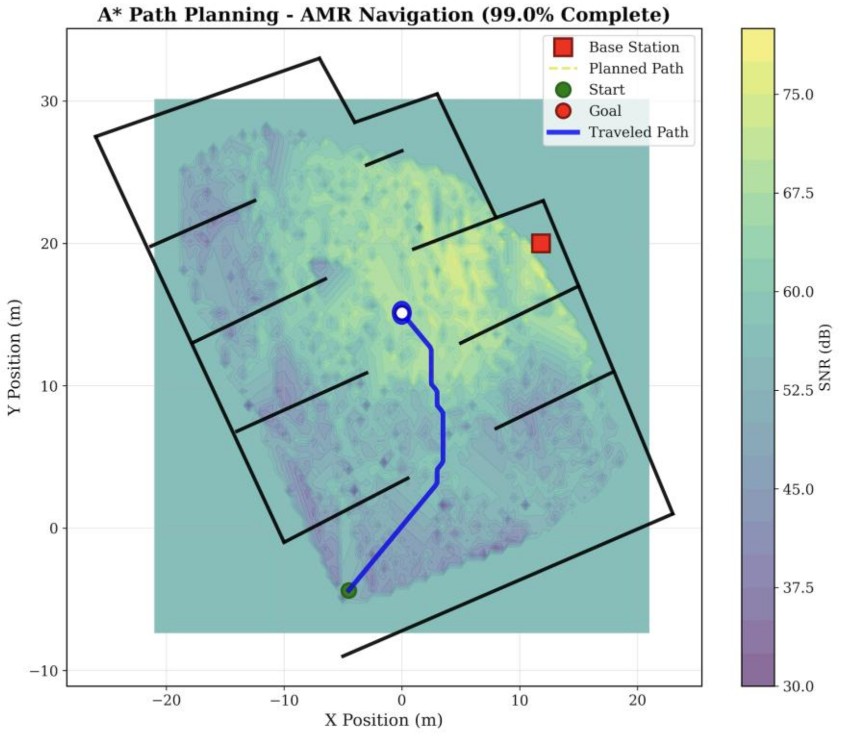
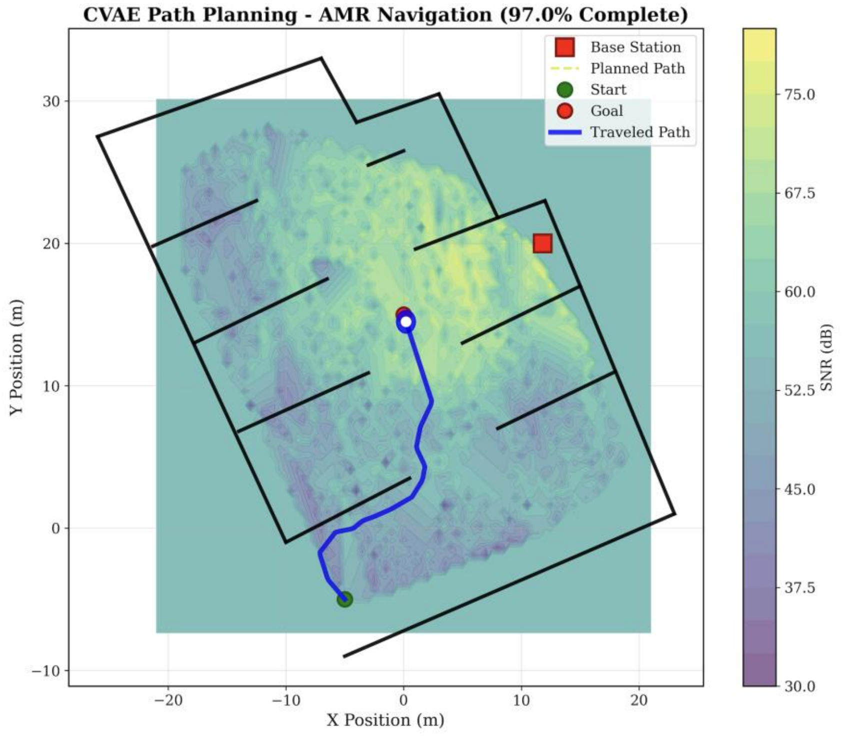
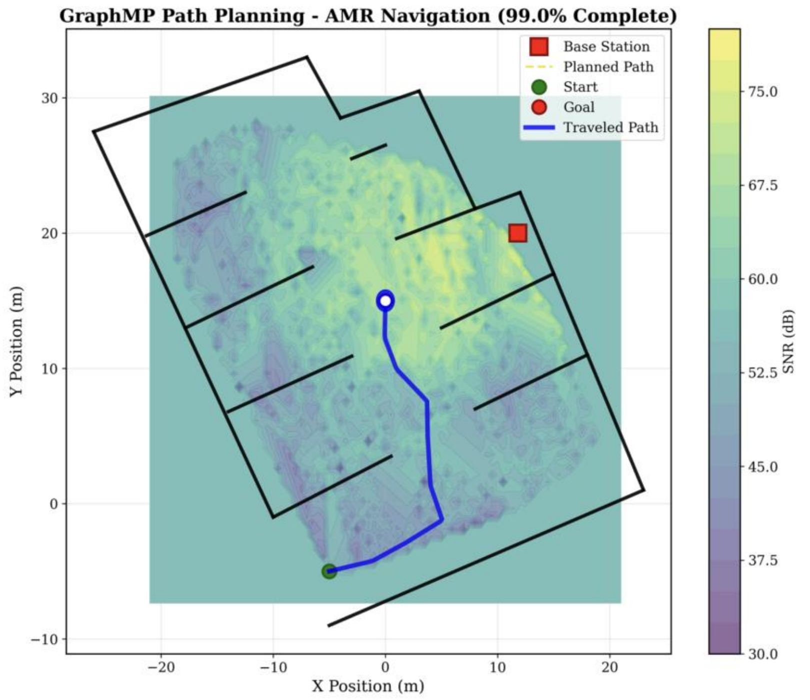






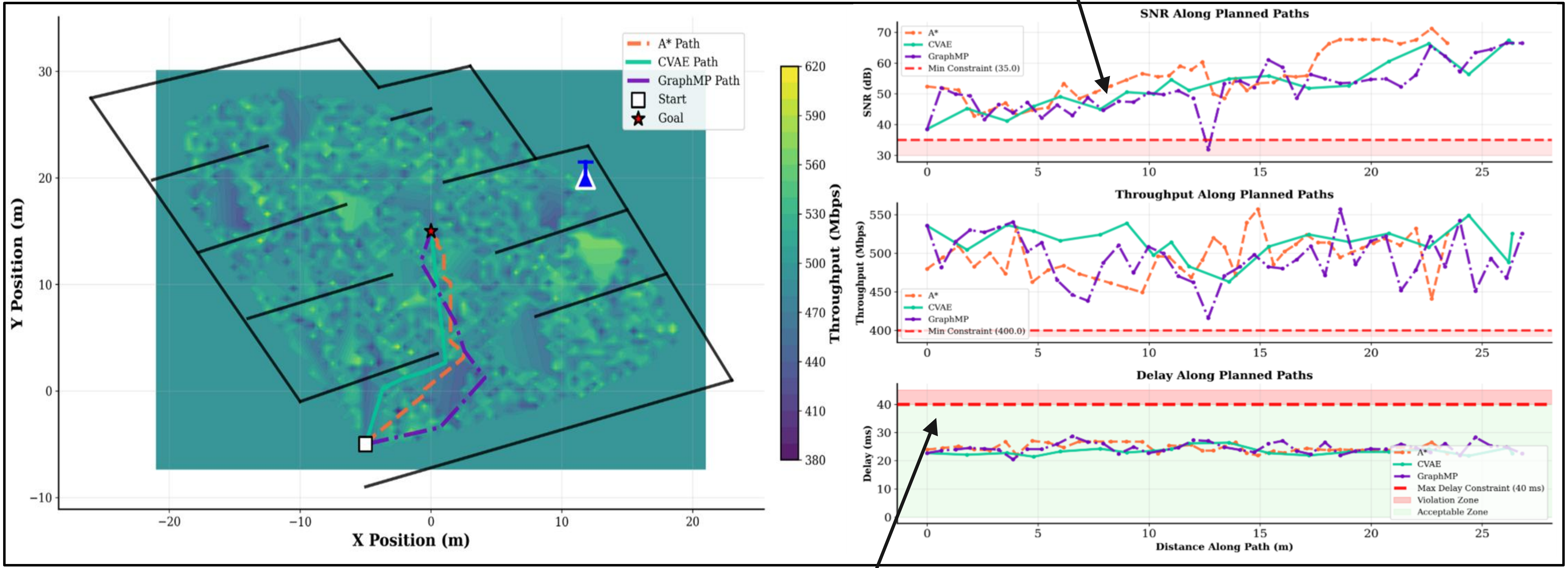
A* performs systematic grid exploration and avoids the lower-left region where the SNR heatmap shows poor signal quality.

CVAE learns that certain areas that look risky on the heatmap actually work fine in practice. CVAE has implicit knowledge about acceptable risk levels and achieves shorter paths.

The GraphMP path shows similar characteristics to A* but takes 37 times longer to compute this path because of extensive preprocessing.

Experimental results

All methods successfully maintain SNR above our 35dB threshold—shown by the red constraint line. They also keep throughput well above 400 Mbps.



Possible to dynamically vary intent requirements that will be met by the algorithms.

Experimental Results

CVAE achieves highest efficiency (0.873) and 73% reduction in delay violations

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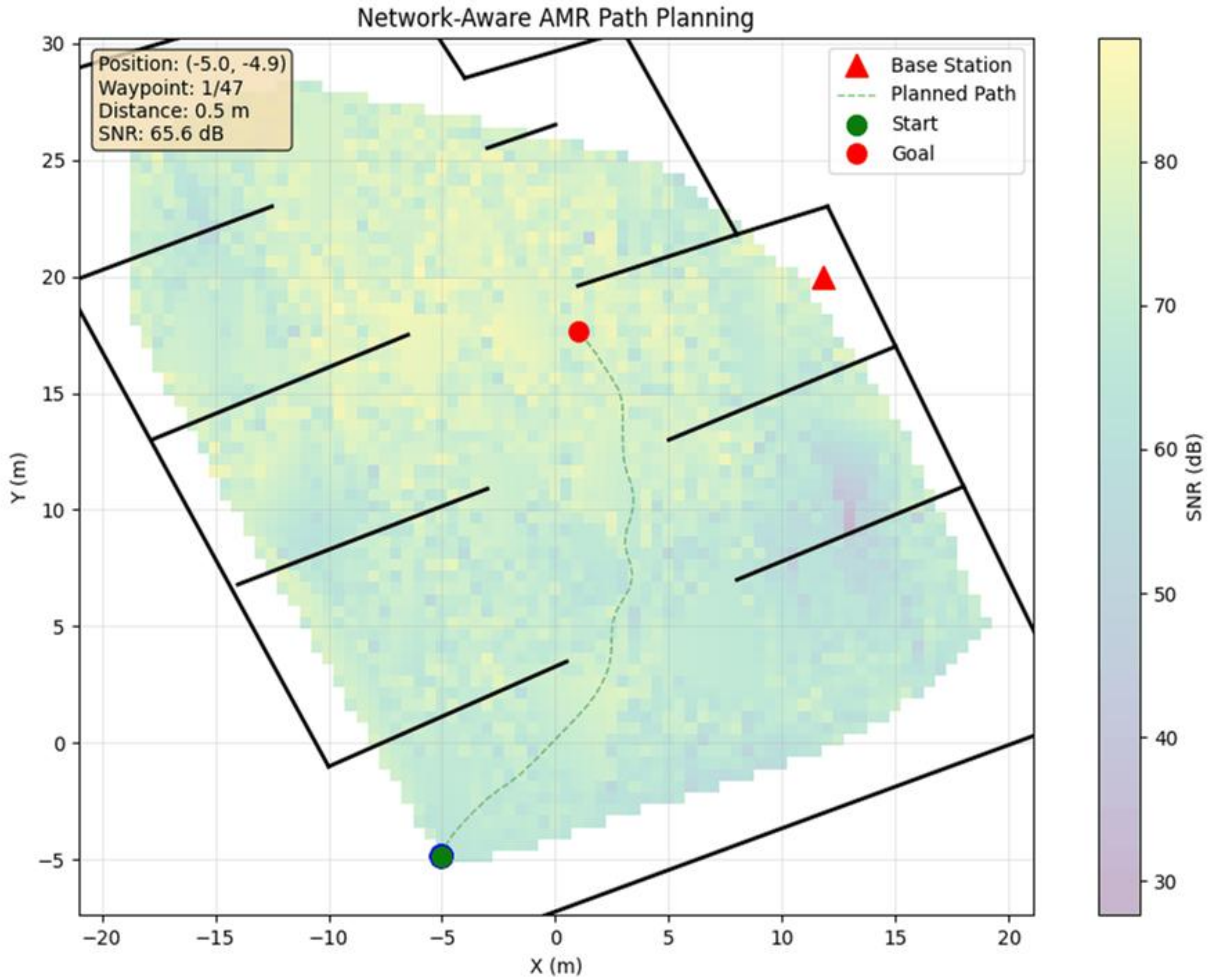
Metric	A*	CVAE	GraphMP	Winner
Planning Time (ms)	61.81	84.11	2287.48	☑ A*
Path Length (m)	24.23	23.61	26.68	☑ CVAE
Compute Efficiency	0.851	0.873	0.773	☑ CVAE
Avg SNR (dB)	55.92	55.62	52.66	☑ A*
Avg Throughput (Mbps)	504.27	498.27	498.05	☑ A*
Throughput Violations	0	0	0	☑ All
Delay Violations	41	15	41	☑ CVAE

A* maintains zero throughput violations with optimal planning time



Network-aware AMR path planning, dynamically traversing high-SNR zones while avoiding low-connectivity regions in a complex industrial environment.

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Key takeaways

Validated Framework: Network-aware path planning that validates Sionna ray-tracing simulations against real-world industrial data

Algorithmic Trade-offs: Our comparative evaluation reveals important performance trade-offs—violations against optimality against computation time.

Foundation for Reliable Navigation: This work establishes a validated foundation for reliable network-aware navigation in industrial autonomous systems.

Future Directions: Environments with mobile obstacles, multi-robot coordination and online learning for adaptive network conditions.

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