



PLANNING AND DEPLOYMENT OF WIRELESS NETWORKS: A DATA-DRIVEN MACHINE LEARNING AND OPTIMIZATION FRAMEWORK BASED ON URBAN MESH AND 5G NETWORKS

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DAI/PRINT Project

This work was developed through the *Doutorado Acadêmico para Inovação* (DAI), funded by the National Council for Scientific and Technological Development (CNPq).

The partner company is based in São Paulo and provides automation solutions for systems through mesh networks, with its main activities focused on smart cities and agritech.

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Reclosers with Mesh Networks

Mesh networks are used to automate and monitor a set of reclosers installed in utility poles from an overhead electric power distribution system



Figure: Recloser

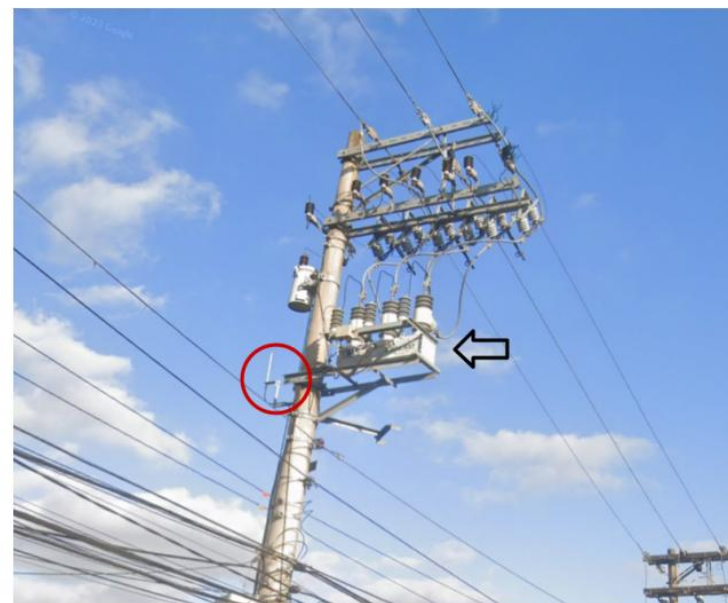


Figure: Overhead electric distribution system with a recloser



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Wireless Mesh Networks

Network components: sink and mesh nodes

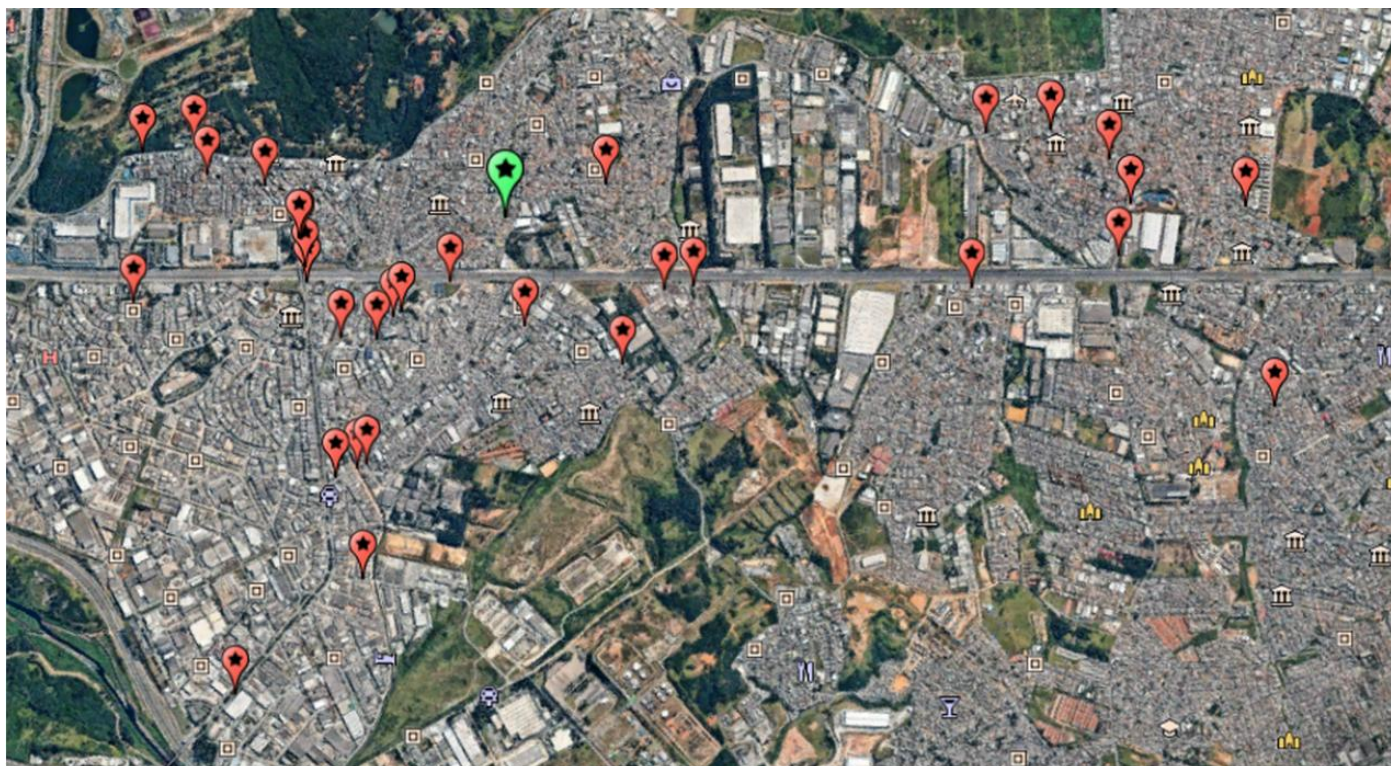


Figure: Recloser network



Planning

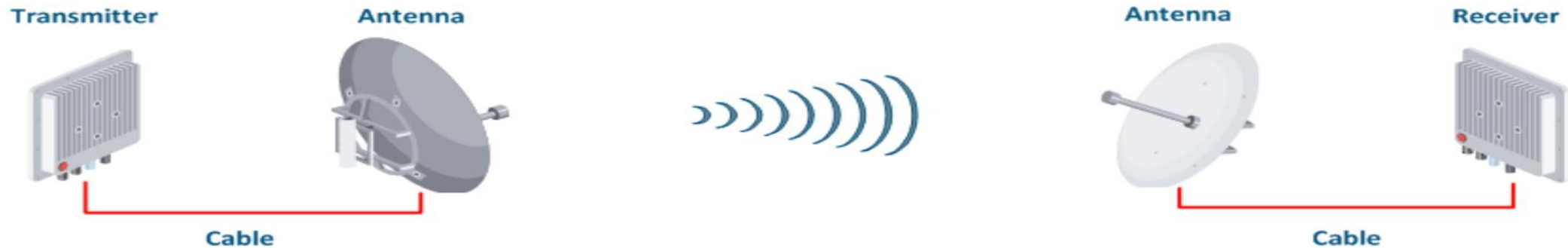


Figure: Point to point wireless link

Estimates the received signal power (signal attenuation):

- Distance and physical obstacles
- Reflections, diffractions and absorption
- Technological parameters



Deployment

Deployment aims to ensure that the wireless network meets the minimum requirements necessary to perform effectively

Through deployment, it is possible to optimize the overall network performance using different quality of service (QoS) metrics

Main QoS metrics:

- Connectivity
- Energy consumption
- Delay
- Fault tolerance



Objectives

- A framework for the planning and deployment of urban wireless networks
- A methodology to predict received signal strength in complex urban environments with an acceptable margin of error
- An optimization approach for wireless network deployment to ensure at least the minimum functionality requirements



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PAPER 1: CASE STUDY

Journals & Magazines > IEEE Access > Volume: 12 ?

Received Signal Strength Indicator Prediction for Mesh Networks in a Real Urban Environment Using Machine Learning

Publisher: IEEE

Cite This

PDF

Marlon Jeske  ; Brunilde Sansò  ; Daniel Aloise ; Mariá C. V. Nascimento  [All Authors](#)

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Comment(s)

Figure: First paper published



Objectives

- Reviewing the state of the art about the received signal strength prediction in urban wireless network
- Predicting the RSSI for urban mesh networks based on machine learning using data collected from the partner company networks
- Comparing the prediction performance using different approaches from literature
- Verifying the relationship between the environment propagation scenario and the signal attenuation



Real-world Data

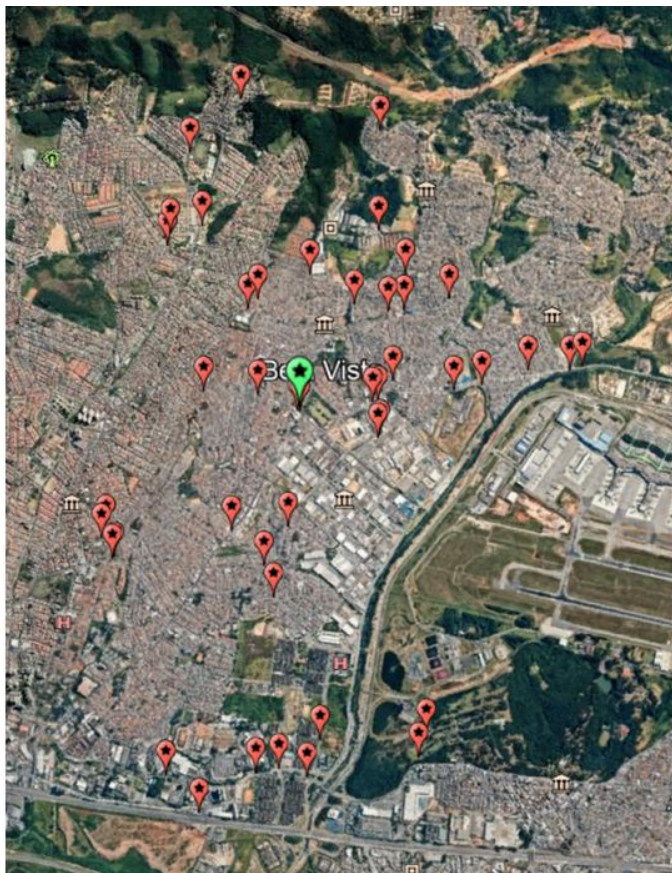


Figure: BVI network

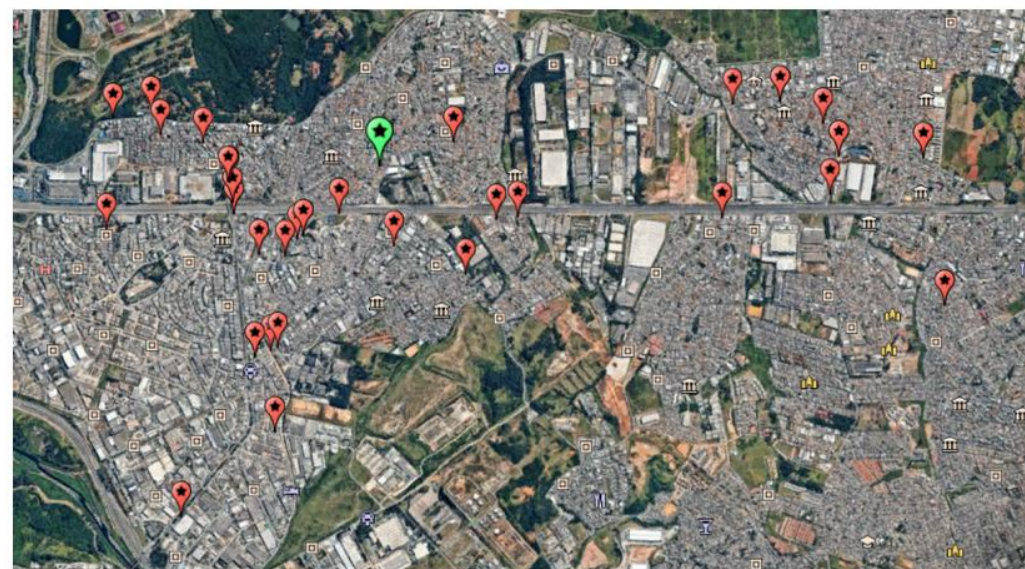
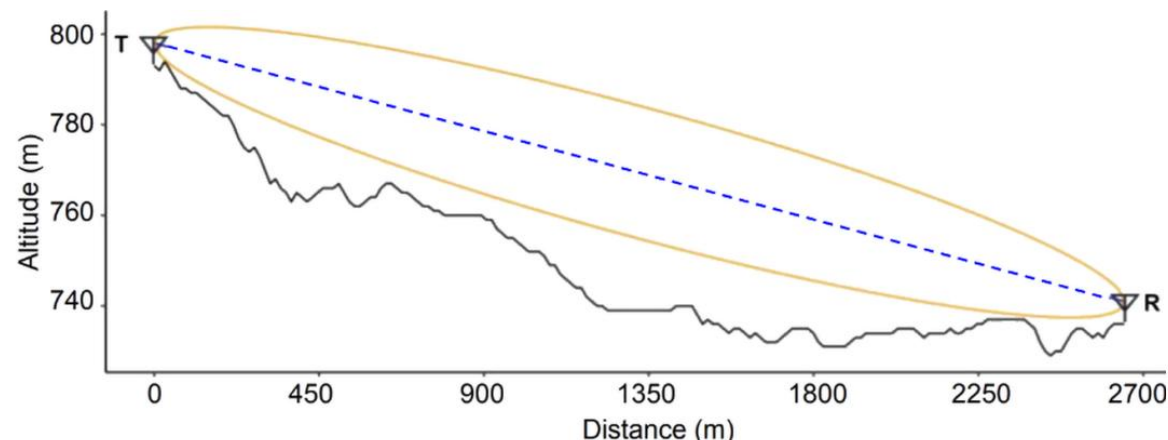


Figure: SLU network



Features and Geographic Data



Features: **Figure:** Elevation profile (black), line of sight (blue), and the first Fresnel zone (orange)

- Effective Height of the Tx and Rx Antennas
- Percentage of Obstruction in the First Fresnel Zone
- Distance from Tx to Rx
- Terrain Elevation Statistics



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Results

Table: Error measurements from prediction models

Models	RMSE (dBm)	MAPE
FSPL	14.6	0.16
FSPL-R	18.2	0.20
Friis	19.9	0.20
Egli	35.5	0.41
Edwards-Durkin	16.5	0.17
Okumura-Hata	52.4	0.63
Random Forest	5.6	0.05
Support Vector Regression	8.0	0.08



Open Questions

- Limitations of traditional and ML models
- Diversity of data and scenarios
- Criteria and motivation for defining the features
- Complexity of the radio propagation environment (attenuation)



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PAPER 2: COMPREHENSIVE FEATURE INVESTIGATION

Journals & Magazines > IEEE Transactions on Antennas... > Early Access ?

Enhancing Reference Signal Received Power Prediction Accuracy in Wireless Outdoor Settings: A Comprehensive Feature Importance Study

Publisher: IEEE

Cite This

PDF

Marlon Jeske ; Daniel Aloise ; Brunilde Sansò ; Mariá. C. V. Nascimento [All Authors](#)

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Figure: Second paper published



Proposal

- Suitable regression model to predict RSRP
- Extensive investigation of feature engineering and ML approaches to predict signal propagation from 62.25 MHz up to 70 GHz (radio/TV to 5G).
- Using real-world data collected from hundreds of base stations located in diverse urban scenarios provided by Huawei
- In-depth feature importance analysis
- Feature selection: a method to significantly reduce the complexity of the ML model by using the feature importance ranking



Literature Review

- ML approaches to predict RSSI or RSRP or Path loss
- From 2012 to 2023
- Urban and suburban environments
- From 62.25 MHz to 70 GHz (from radio to 5G)
- Feature characteristics
- Feature importance



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Three Major Sources of Features

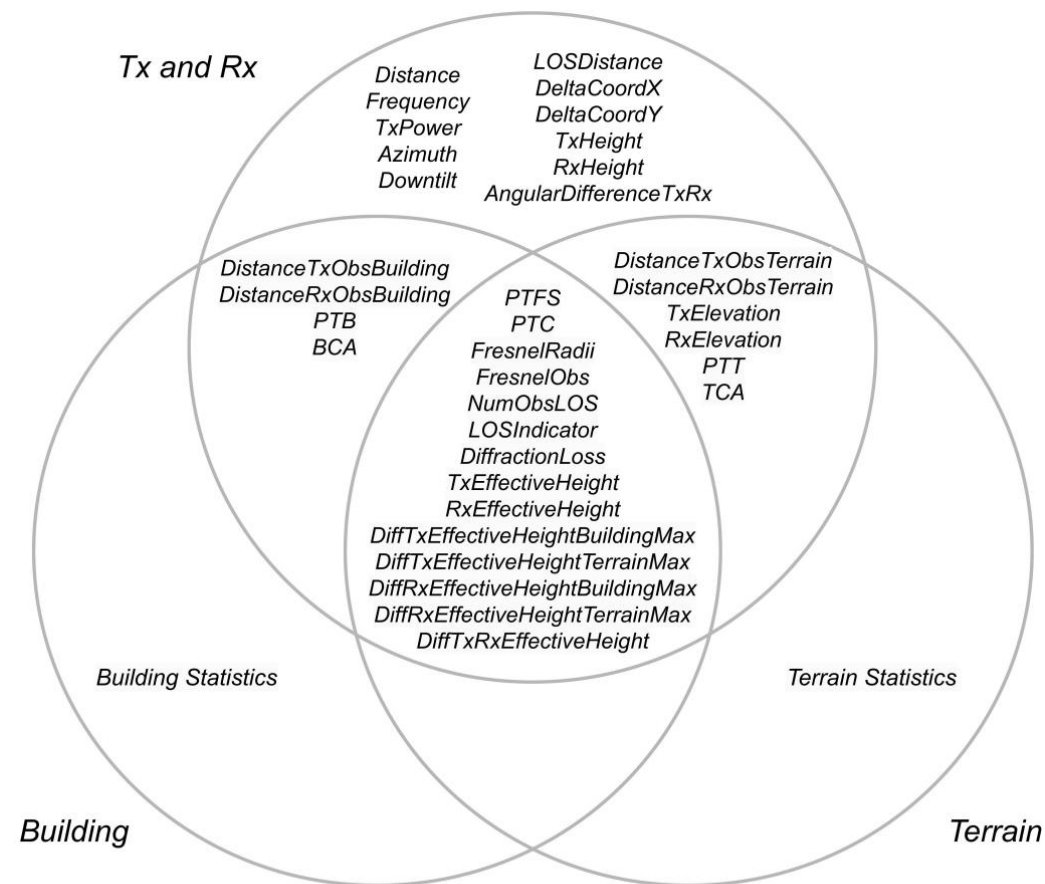


Figure: Venn diagram of the features



Extrapolating to New Scenarios

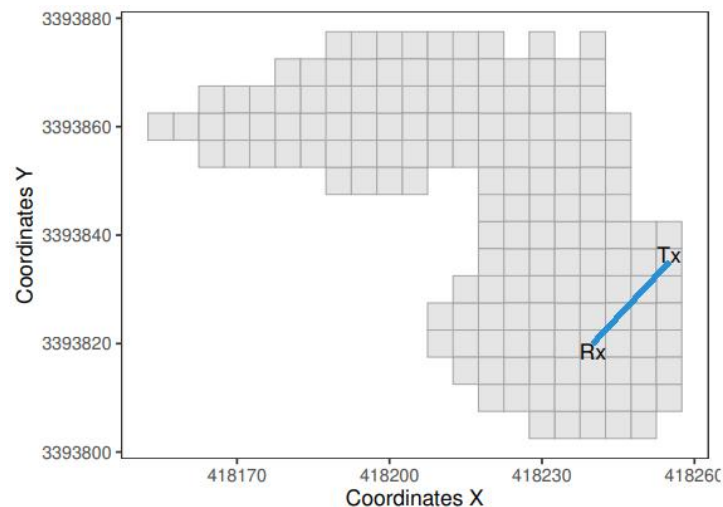


Figure: RSRP measurements

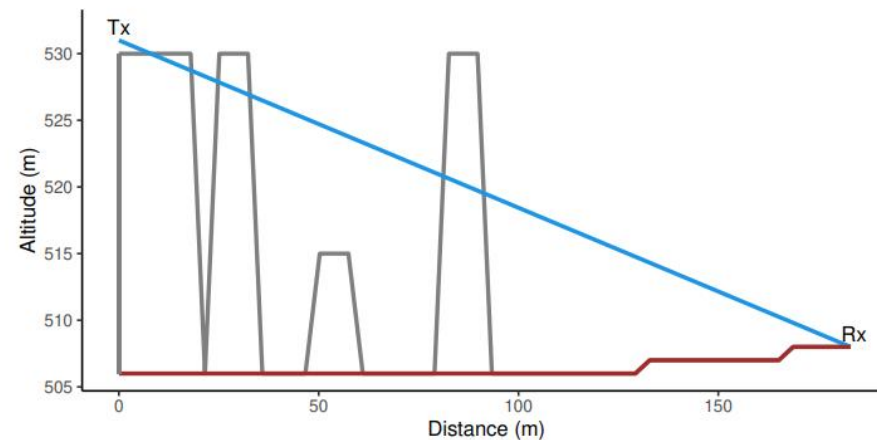


Figure: Path profile

- Dataset provided by Huawei from cellular urban networks
- Tech. parameters and Geographic data
- 326 base stations and 186,635 links (RSRP)



Feature Importance Rank

Table: Feature Importance Rank

Feature	%IncMSE	%IncMSE C	Rank
Downtilt	41.16	6.23	1
Azimuth	40.31	12.33	2
TxEffectiveHeight	28.09	16.58	3
TxHeight	25.25	20.40	4
TerrainMean	23.42	23.94	5
TxPower	23.01	27.43	6
DiffTxEffectiveHeightTerrainMax	22.13	30.78	7
TxElevation	19.62	33.75	8
DiffTxRxEffectiveHeight	19.58	36.71	9
DiffTxEffectiveHeightBuildingMax	18.12	39.45	10
BuildingMax	17.70	42.13	11
AngularDifferenceTxRx	15.77	44.51	12
LOSDistance	15.60	46.87	13
FresnelRadii	15.44	49.21	14
FresnelObs	14.83	51.46	15
BuildingSD	14.77	53.69	16
DiffRxEffectiveHeightBuildingMax	14.28	55.85	17
Distance	14.09	57.98	18
DistanceTxObsTerrain	13.73	60.06	19
BuildingMean	13.42	62.09	20
TerrainMax	12.80	64.03	21
DeltaCoordY	12.14	65.86	22
TerrainSD	11.87	67.66	23
TerrainMin	10.52	69.25	24
DeltaCoordX	10.29	70.81	25



Reduction of Model Complexity

Table: Performance of evaluated regression models

Models	RMSE (dBm)	MAPE (%)
<i>Set-6</i>	6.60	6.1
<i>Set-10</i>	5.32	4.7
<i>Set-15</i>	4.23	3.5
<i>Set-20</i>	4.06	3.4
<i>Set-25</i>	3.72	3.0
All	3.58	2.9

- Reducing the features to 15 or 20 resulted in less than a 1 dBm increase in RMSE
- The ML approach using the 25 most important features produced an error difference of only 0.14 dBm compared to the all features model



Results

- Comprehensive feature discussion (engineering, importance, selection)
- 25 features effectively represent the diverse elements of the radio propagation environment
- Can be adapted for path loss, RSSI, and other signal power measures



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PAPER 3 - DEPLOYMENT VIA MILP FOR RNP

A Mathematical Programming Approach to the Relay Node Placement Problem in Urban Environments



Relay Node Placement (RNP)

Given a 3D urban complex region, the location of sensor nodes, a unique sink, and candidate relays, the problem consists in finding an optimal set of relay nodes considering the following QoS metrics and network constraints:

- Connectivity
- Cost
- Bandwidth
- Energy
- Delay
- Signal Quality
- Fault Tolerance



Urban Networks



Figure: Uniform network

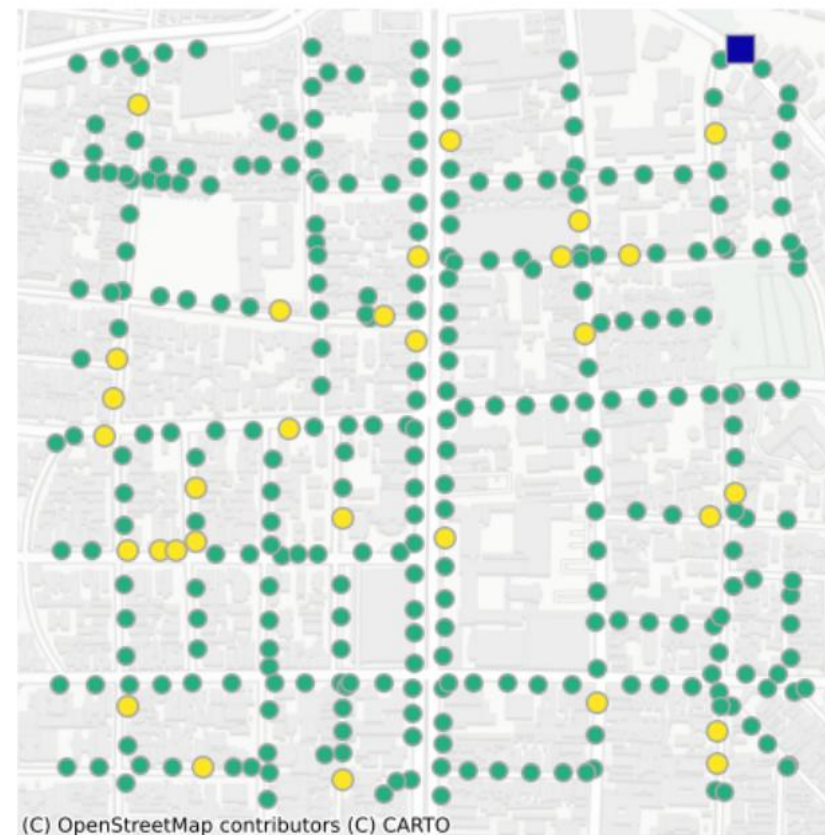


Figure: Random network



Network Connectivity and Initial Network

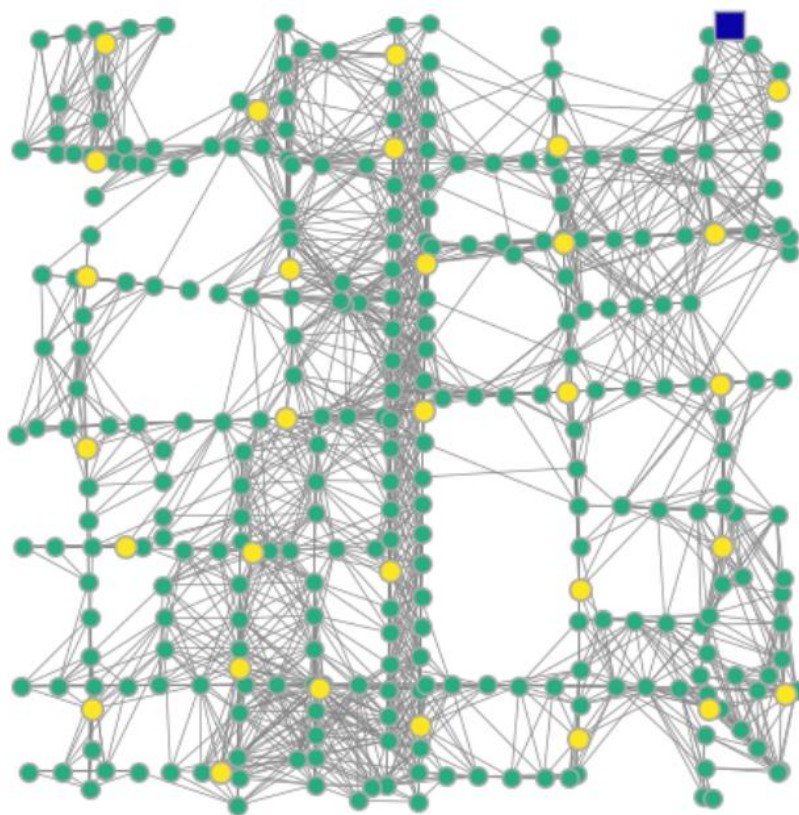


Figure: Network with candidate relays

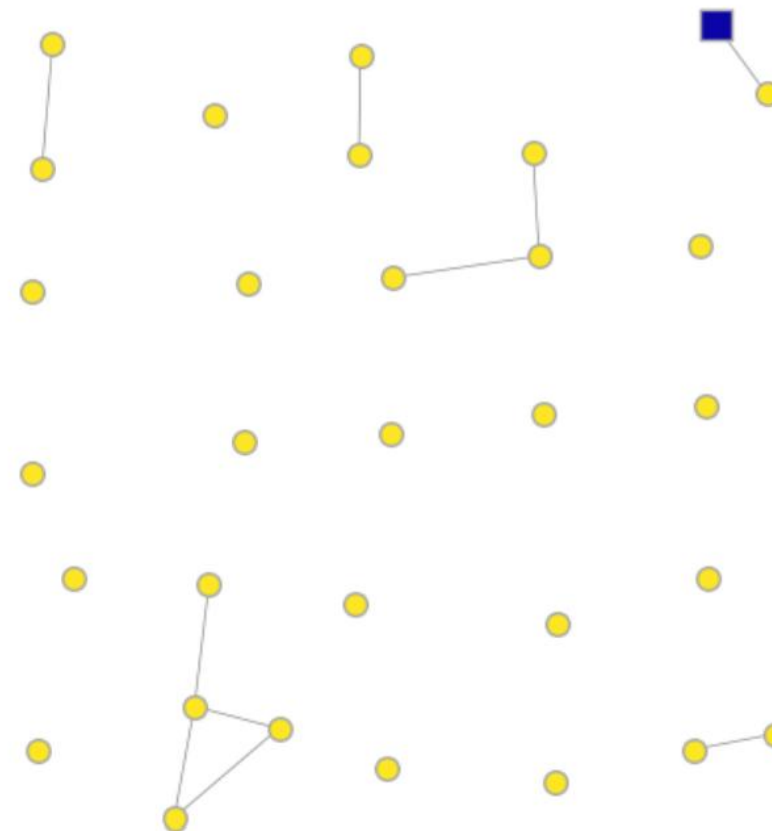


Figure: Initial network



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Graphic Results

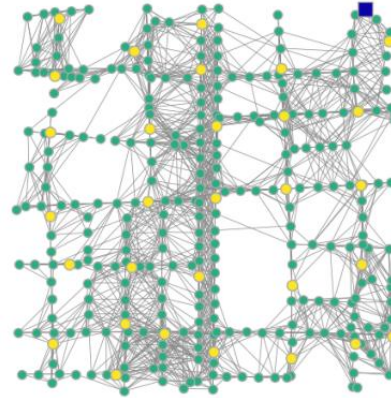


Figure: Network with candidate relays

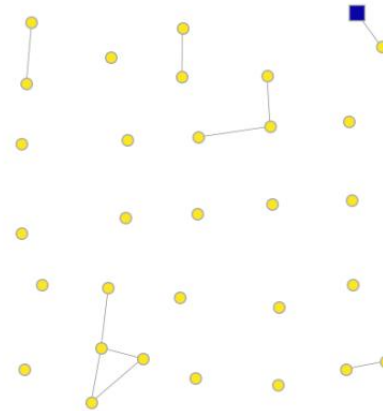


Figure: Initial network

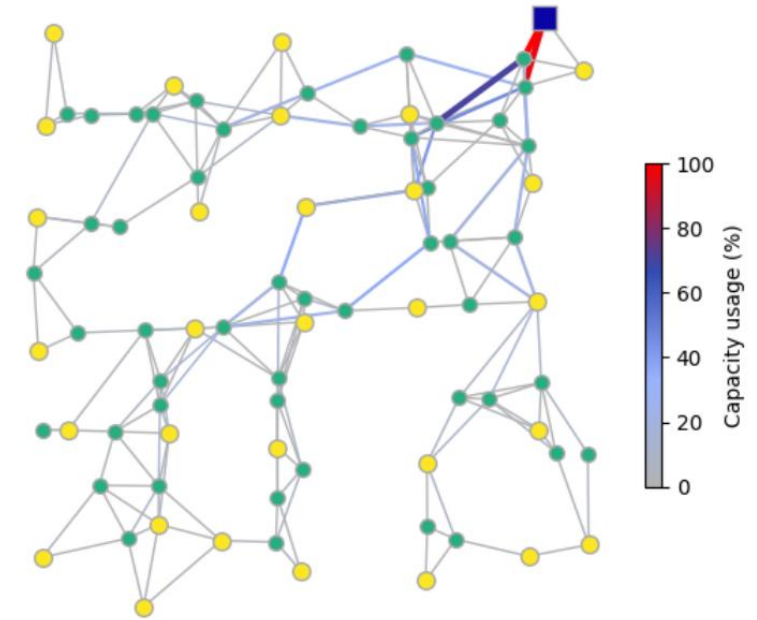


Figure: Optimized network



Conclusion

- A MILP model to RNP for urban WSN
- Critical metrics and fault tolerance against link failures
- Consider the radio propagation environment complexity
- Guarantee of optimal solution with reasonable computational time



Final Remarks

- An approach to guarantee the minimum service requirements and optimize the overall performance of the urban wireless networks
- A machine learning to predict the received signal strength, adaptable for general wireless networks, with improved interpretability and reduced complexity



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