

## Article

# Digital Twin-Based Ray Tracing Analysis for Antenna Orientation Optimization in Wireless Networks

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## Abstract

Efficient antenna orientation of transmitters is essential for improving wireless signal quality and coverage, especially in large-scale and complex 6G networks. Identifying the best antenna angles is difficult due to the nonlinear interaction among orientation, signal propagation, and interference. This paper introduces a digital twin-based evaluation approach utilizing ray tracing simulations to assess the influence of antenna orientation on critical performance metrics: path gain, received signal strength (RSS), and signal-to-interference-plus-noise ratio (SINR). A thorough array of orientation scenarios was simulated to produce a dataset reflecting varied coverage conditions. The dataset was utilized to investigate antenna configurations that produced the optimal and suboptimal performance for each parameter. Additionally, three machine learning models—k-nearest neighbors (KNN), multi-layer perceptron (MLP), and XGBoost—were developed to forecast ideal configurations. XGBoost had superior prediction accuracy compared to the other models, as evidenced by regression outcomes and cumulative distribution function (CDF) analyses. The proposed workflow demonstrates that learning-based predictors can uncover orientation refinements that conventional grid sweeps overlook, enabling agile, interference-aware optimization. Key contributions include an end-to-end digital twin methodology for rapid what-if analysis and a systematic comparison of lightweight machine learning predictors for antenna orientation. This comprehensive method provides a pragmatic and scalable solution for the data-driven optimization of wireless systems in real-world settings.



Academic Editor: Dimitra I. Kaklamani

Received: 23 June 2025

Revised: 24 July 2025

Accepted: 28 July 2025

Published: 29 July 2025

**Citation:** Yildiz, O. Digital

Twin-Based Ray Tracing Analysis for Antenna Orientation Optimization in Wireless Networks. *Electronics* **2025**, *14*, 3023. <https://doi.org/10.3390/electronics14153023>

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**Keywords:** 6G; digital twin; ray tracing; antenna orientation; machine learning; wireless network optimization

## 1. Introduction

Future wireless communication systems, 5G and 6G, aim not only to provide high data speeds and low latencies but also to create a communication infrastructure that maximizes resource usage, is energy-efficient, and is sensitive to environmental conditions. To achieve this goal, it is of great importance to model channel propagation in a realistic and detailed manner. Especially in complex urban environments, the multipath, reflective, and scattering nature of electromagnetic propagation causes traditional stochastic models to be inadequate. In this context, ray tracing, one of the physics-based deterministic methods, stands out due to its ability to simulate the performance of communication systems in an environmental context with high precision [1].

Ray tracing methods not only perform channel modeling at the link level but also contribute to system-level decision processes such as site-specific coverage analysis, antenna

positioning, and orientation optimization. Especially for 6G systems operating in the millimeter wave (mmWave) and sub-terahertz (sub-THz) bands, such detailed analyses have become inevitable [2]. In this context, the open-source Sionna simulation library developed by NVIDIA provides a GPU-accelerated, differentiable ray tracing-supported environment for physical layer research and enables end-to-end modeling of 5G/6G systems [3,4].

Numerous studies utilizing Sionna have made ray tracing more scalable and realistic, providing more reliable outputs in both channel estimation [5] and link-level decision processes [6,7]. With its integration with classic network simulators like Ns-3 (e.g., Ns3Sionna [6] and Digital Network Twin [8]), multiple connected systems, autonomous vehicle scenarios, and different technologies like Wi-Fi can be simulated under a single roof. Additionally, thanks to the differentiable structure, numerous advanced application areas have emerged, such as learning environmental parameters [9] and RF-based robot navigation [10,11].

This development of ray tracing methods gains a much more powerful dimension when combined with digital twin technology. Digital twins enable the creation of real-time digital copies of physical systems and the performance of optimization, prediction, and control operations on these copies. In particular, digital twins of electromagnetic environments enable the modeling of wireless communication systems in accordance with the real world and greatly increase the accuracy of decisions taken at the system level [12]. In this context, the development of ray tracing-based digital twin platforms is gaining popularity in different areas, such as smart cities [13,14], transportation systems [15,16], robotic applications [10,11], base station placement [17], channel mapping [18], and multi-spectral propagation analysis [19].

Especially in areas with large and complex structures such as campuses, the creation of digital twin-based environments offers significant advantages in terms of optimizing antenna placement and orientation. The angles, heights, and orientation of antennas are critical for both cellular coverage quality and user experience [1,12]. In this context, thanks to differentiable ray tracing and site-specific modeling techniques, these optimization processes can be performed with high accuracy, and maximum efficiency can be obtained from infrastructure investments [4,9].

All of these technological developments, when supported by artificial intelligence (AI)-based approaches, result in more effective and scalable solutions. Machine learning algorithms have demonstrated superior performance over traditional methods in issues such as channel synchronization [20], signal acquisition and decoding [21,22], language model integration on the signal processing chain [23], low-complexity signal detection for high-dimensional MIMO scenarios [24], and early detection systems [25]. AI-enabled digital twin platforms have become real-time decision support systems in network planning, especially in large-scale transmitter placement scenarios (e.g., AutoBS [17]) and through neural networks fed with ray tracing data (e.g., PMNet [18]).

In conclusion, in light of the studies presented in the literature, the integration of ray tracing and digital twin technologies is of vital importance for the planning of 6G and beyond wireless communication systems in a high-performance, scalable, and environmentally sensitive manner. Open-source infrastructures such as Sionna offer researchers a wide range of opportunities both technically and practically in this transition and constitute the cornerstones of future communication systems.

This study presents a unique approach that combines wireless communication performance analysis and machine learning-based optimization over digital twin representations of large-scale university campus environments, which have limited examples in the existing literature. A high-fidelity modeled digital twin of Aydın Adnan Menderes University Central Campus has been integrated into the NVIDIA Sionna platform to define multiple

transmitter and receiver scenarios. In this simulation environment with realistic environmental geometry, key performance metrics such as received signal strength (RSS), path gain, and signal-to-interference-plus-noise ratio (SINR) have been calculated over transmitters with different antenna orientations. Subsequently, under a structure that aims to maximize the quality of user experience (QoE) across the campus, a multi-dimensional optimization problem related to antenna orientations has been addressed by applying different machine learning models such as k-nearest neighbors (KNN), multi-layer perceptron (MLP), and XG-Boost. In this direction, not only have effective antenna azimuthal orientation values been obtained, but a comprehensive benchmark analysis has also been performed by comparing the performance of different machine learning models. The model that gives the most successful results is selected as the final recommendation mechanism of the system. Thus, the processing load and time cost caused by classical trial-and-error-based configuration processes are eliminated, and a fast and effective optimization process based on learning is developed. This integrated approach provides a significant contribution to the literature in terms of both simulation accuracy and effectiveness in decision support systems and introduces a new paradigm in digital twin-supported wireless network planning.

## 2. Materials and Methods

### 2.1. Sionna

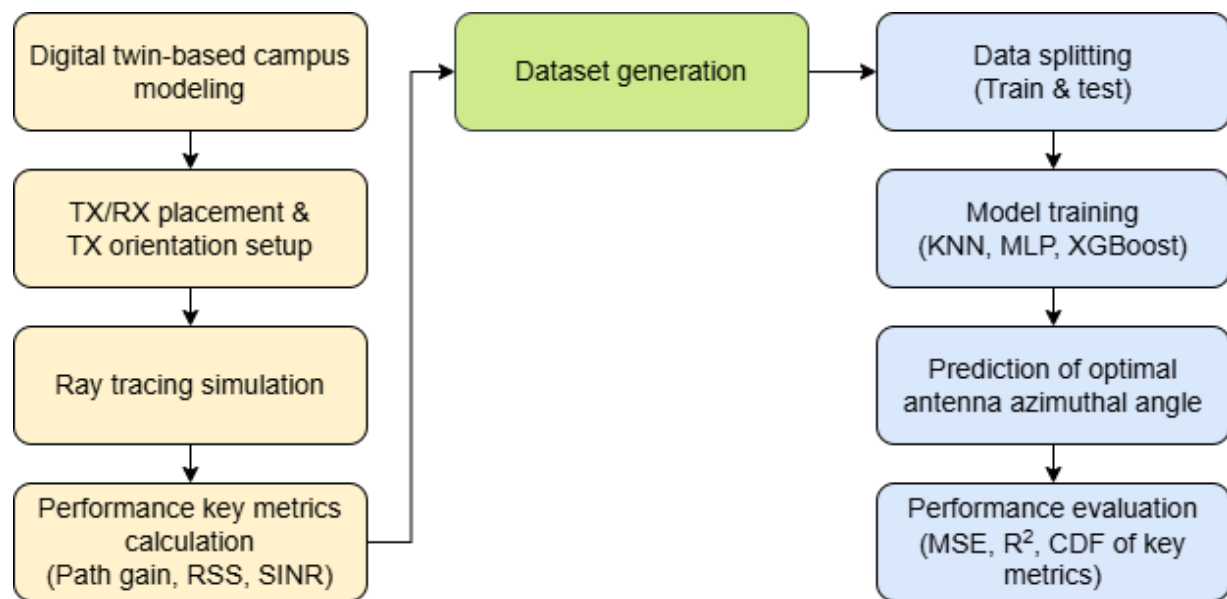
Ray tracing (RT) aims to model point-to-point propagation by determining geometrically exact propagation paths between an electromagnetic wave emission source and a target receiver location. This study conducted ray tracing simulations utilizing Sionna RT, an extension of the open-source radio propagation modeling framework Sionna. Built on Mitsuba 3 [26] and TensorFlow [27], Sionna RT provides a GPU-accelerated, adaptable, and extensible platform for high-fidelity radio propagation modeling. The framework operates natively in Python 3.10 and is entirely compatible with Jupyter notebooks, facilitating reproducible and easily adjustable simulations.

Sionna RT allows the user to create comprehensive simulation setups related to carrier frequency, bandwidth, antenna array geometries, material properties, including relative permittivity, permeability, and conductivity. This information calculates multipath components by tracking the propagation of electromagnetic waves through reflections, diffraction, and scattering events within a 3D scene. Sionna RT generates complete channel information for each transmitter–receiver pair, including path gains, propagation delays, departure and arrival angles.

The open-source 3D modelling tool Blender [28] was used together with the Mitsuba-Blender plugin [29] to produce suitable scene models for Sionna RT. The Blender-OSM plugin [30] was used for realistic environmental modelling as it allows the import of extensive geographic data from OpenStreetMap [31]. This arrangement enables the rapid creation of accurate and site-specific propagation simulations of realistic large-scale scenes.

### 2.2. Workflow of the Proposed Framework

A schematic overview of the end-to-end workflow employed in this investigation is presented in Figure 1. The proposed framework initiates with the development of a digital twin of the campus environment, which functions as the simulation domain for ray tracing-based signal propagation modeling. Various antenna azimuthal orientation configurations are established and simulated to provide essential wireless performance metrics, including path gain, received signal strength (RSS), and signal-to-interference-plus-noise ratio (SINR). The resultant dataset was utilized to train and evaluate various machine learning models for predicting ideal antenna azimuthal orientations. The workflow combines data creation and learning-based evaluation stages to provide a holistic perspective of the methodology.



**Figure 1.** A schematic overview of the proposed framework.

### 2.3. Ray Tracing Scenario Setup

The central campus of Aydin Adnan Menderes University forms the basis of the simulation scene. Using the Blender-OSM plugin, OpenStreetMap’s building layouts, road data, and vegetation information were imported into a comprehensive 3D model of the university. Blender helps polish and refine the imported map data to accurately display important environmental elements such as open spaces, surface materials, and building heights.

All of the materials listed in the ITU-R P.2040-2 recommendation [32] have models available from Sionna. The model for frequency dependency is as follows:

$$\eta' = \alpha f^b, \quad (1)$$

$$\sigma = c f^d, \quad (2)$$

where the constants  $a$ ,  $b$ ,  $c$ , and  $d$  describe the material,  $f$  is the frequency in GHz, and  $\sigma$  is in S/m (where  $\eta'$  is dimensionless) in Equations (1) and (2).

Common construction materials, ground surfaces, and buildings were identified for material properties; relative permittivity and conductivity values were matched for concrete, brick, metal, and ground. The values utilized in Sionna are listed in Table 1 below.

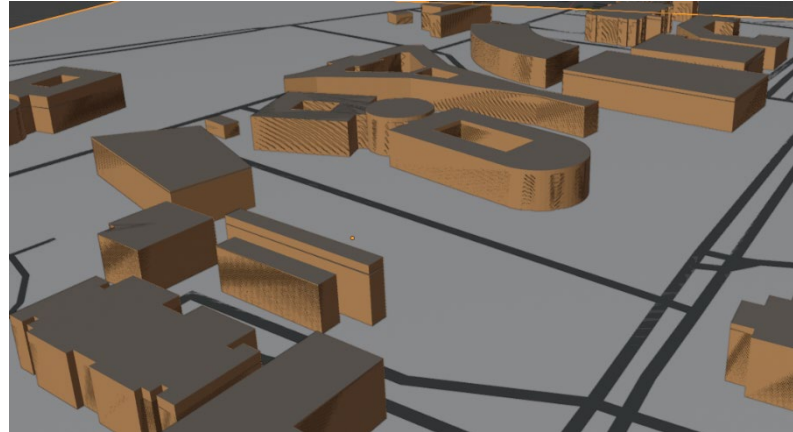
**Table 1.** Material properties.

| Material Class      | Real Part of Relative Permittivity |      | Conductivity [S/m] |        | Frequency Range (GHz) |
|---------------------|------------------------------------|------|--------------------|--------|-----------------------|
|                     | A                                  | b    | C                  | d      |                       |
| Concrete            | 5.24                               | 0    | 0.0462             | 0.7822 | 1–100                 |
| Brick               | 3.91                               | 0    | 0.0238             | 0.16   | 1–40                  |
| Metal               | 1                                  | 0    | $10^7$             | 0      | 1–100                 |
| Ground <sup>1</sup> | 15                                 | −0.1 | 0.035              | 1.63   | 1–10                  |

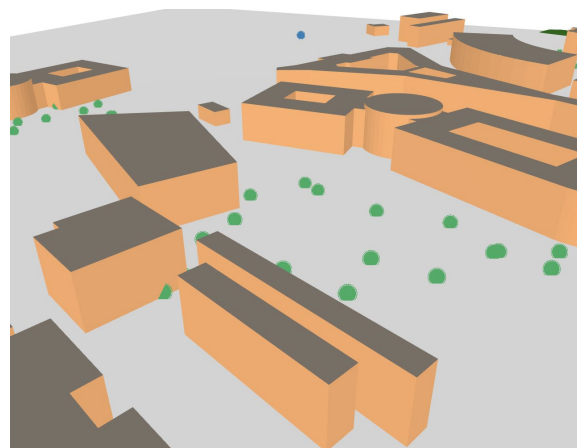
<sup>1</sup> Medium dry ground.

The campus map from OpenStreetMap was processed in Blender, exported to Mitsuba 3 compatible format, and used in Sionna RT for ray tracing simulations, as shown in Figure 2. Using this scene setup, multiple transmitters and receivers were placed along

the signal propagation in the campus environment, as shown in Figure 3. The scenario comprises three rooftop gNBs, each equipped with a single sector antenna. This tri-site cluster mirrors the existing campus deployment, isolates azimuth-tuning effects, and keeps the exhaustive sweep computationally feasible.



**Figure 2.** Three-dimensional scene of the campus on Blender.



**Figure 3.** A transmitter (blue dot) and receiver (green dots) representation in Sionna.

Following the creation of the campus scene, the simulation parameters used to systematically analyze the effects of the angular orientations of the transmit antennas on wireless signal propagation and network performance are given in Table 2.

**Table 2.** Simulation parameters.

| Parameter                 | Value                         |
|---------------------------|-------------------------------|
| Frequency                 | 3.5 GHz                       |
| Number of transmitters    | 3                             |
| Transmitter height        | 30 m                          |
| Transmitter power         | 44 dBm                        |
| Transmitter array type    | Planar array ( $8 \times 2$ ) |
| Transmitter array pattern | TR 38.901 standard            |
| Number of users           | 60                            |
| User distribution         | Uniform                       |
| Receiver array type       | Planar array ( $1 \times 1$ ) |
| Receiver array pattern    | Dipole                        |
| Number of reflections     | 3                             |
| Resolution for rendering  | [1000, 600]                   |

After setting the scenario and simulation parameters on Sionna, the effect of the azimuthal angle changes of the transmitters on multiple users located throughout the campus was simulated using Sionna RT in terms of path gain, SINR, and RSS performance metrics. For this reason, formulas related to performance metrics are included in the rest of the article.

To create a coverage map for a particular transmitter, the path gain  $g_{i,j}$  for each cell  $C_{i,j}$  is calculated using Equation (3). This represents the average signal strength across the cell:

$$g_{i,j} = \frac{1}{|C|} \int_{C_{i,j}} |h(s)|^2 ds \quad (3)$$

In Equation (3),  $h(s)$  denotes the channel coefficients at the coordinates  $s = (x, y)$ . This formula computes the average path gain throughout a cell area by integrating the channel coefficients.

The path gain is transformed into received signal strength (RSS) via Equation (4).

$$RSS_{i,j} = P_{tx} g_{i,j} \quad (4)$$

where  $P_{tx}$  is the transmitter power (in dBm or Watt) and  $g_{i,j}$  represents the path gain in the corresponding cell. RSS reflects the total signal power received at the receiver for a certain cell, which is critical for analyzing network coverage.

The SINR is computed using Equation (5) for each transmitter in the environment to assess the impact of interference and noise on the intended signal:

$$SINR_{i,j}^k = \frac{RSS_{i,j}^k}{N_0 + \sum_{k' \neq k} RSS_{i,j}^{k'}} \quad (5)$$

This formula illustrates that the SINR emphasizes the signal from the target transmitter while treating the signals from all other transmitters as interference. Interference is restricted to the three in-cluster gNBs so that external interference effects can be isolated. The thermal noise power  $N_0$  (W) is determined using bandwidth, temperature, and the Boltzmann constant in the computation of the SINR by using Equation (6):

$$N_0 = B \times T \times k \quad (6)$$

Here,  $B$  is the bandwidth (Hz),  $T$  is the temperature (Kelvin), and  $k$  is the Boltzmann constant  $1.380649 \times 10^{-23}$  J/K.

Emphasizing the effect of changes in the angular orientation of the transmitter antennas on wireless communication performance within the campus environment, the following section offers a thorough analysis of the results after the description of the simulation setup and performance metrics.

## 2.4. Machine Learning Models

This section deploys supervised machine learning (ML) models to transform the high-dimensional dataset produced through ray tracing into a fast, repeatable decision-support engine. By pairing the physical-simulation outputs—path gain, RSS, and SINR—with the corresponding antenna-orientation parameters, we obtain a comprehensive training corpus that recasts the intricate campus-channel behavior as a regression task solvable in seconds rather than hours. The selected algorithms—lightweight k-nearest neighbors (KNN), flexible multi-layer perceptron (MLP), and the tree-based extreme gradient boosting ensemble (XGBoost)—are drawn from the literature for their proven accuracy and complementary trade-offs between interpretability, computational load, and predictive

power. Consequently, orientation optimization that would otherwise rely on protracted trial-and-error loops can be completed within minutes in the digital twin framework, laying the groundwork for the cumulative-distribution and error-metric analyses reported in Section 3.

Building on the feature-engineering workflow and ray tracing data acquisition described in Sections 2.2 and 2.3, respectively, a three-stage machine learning pipeline was adopted. Section 2.4.1 details the model selection and its literature foundations; Section 2.4.2 reports model architectures together with the hyperparameter grids explored; and Section 2.4.3 outlines the large-scale inference sweep used to rank candidate azimuthal configurations.

#### 2.4.1. Model Selection

To ensure that the chosen algorithms spanned the spectrum from very light to state-of-the-art solutions, three well-established methods were reviewed in the literature and positioned within the present study, as summarized in Table 3.

**Table 3.** Used ML models and their role.

| Category         | Model                               | Representative Evidence                                                            | Intended Role                                |
|------------------|-------------------------------------|------------------------------------------------------------------------------------|----------------------------------------------|
| Lightweight      | K-Nearest Neighbors (KNN)           | Outdoor UHF studies have reported <3 dB RMSE when $k \leq 11$ [33]                 | Fast, interpretable lower bound              |
| Intermediate     | Multi-Layer Perceptron (MLP)        | Campus-scale analyses have shown 25–30% error reduction over linear baselines [34] | Flexible capture of moderate nonlinearity    |
| State-of-the-art | Extreme Gradient Boosting (XGBoost) | 3.5 GHz urban trials have yielded the lowest MAE/RMSE among tree-based models [35] | Highest accuracy and built-in explainability |

#### 2.4.2. Model Architectures and Hyperparameters

Table 4 lists the principal implementation settings that were applied after pre-liminary tuning.

**Table 4.** Implementation settings.

| Model   | Feature Scaling      | Key Settings                                                                                                                                                                      |
|---------|----------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| KNN     | StandardScaler       | $n\_neighbors = 7$ ; weights = ‘distance’; metric = ‘euclidean’                                                                                                                   |
| MLP     | StandardScaler → MLP | Hidden layers = [128, 64, 32], activation = ReLU; optimizer = Adam ( $lr = 1 \times 10^{-3}$ ); batch_size = 64; $L2 = 1 \times 10^{-4}$ ; max_iter = 1000; early_stopping = True |
| XGBoost | Raw features         | $n\_estimators = 600$ ; learning_rate = 0.9; max_depth = 6; subsample = 0.8; colsample_bytree = 0.8; reg_lambda = 2; tree_method = ‘hist’                                         |

A fixed random seed of 42 was imposed on all libraries to guarantee verbatim reproducibility. After training, each model evaluated 13,824 randomly generated tilt vectors. The ten best-performing combinations were exported as comma-separated files for downstream analysis.

### 2.4.3. Training, Validation, and Evaluation

Features and targets were obtained and then split into 80% training and 20% test subsets. KNN employed five-fold cross-validation nested within GridSearch; MLP relied on an internal validation split with early stopping (patience = 15 epochs); and XGBoost was trained for all 600 trees without early stopping, with preliminary runs having confirmed convergence.

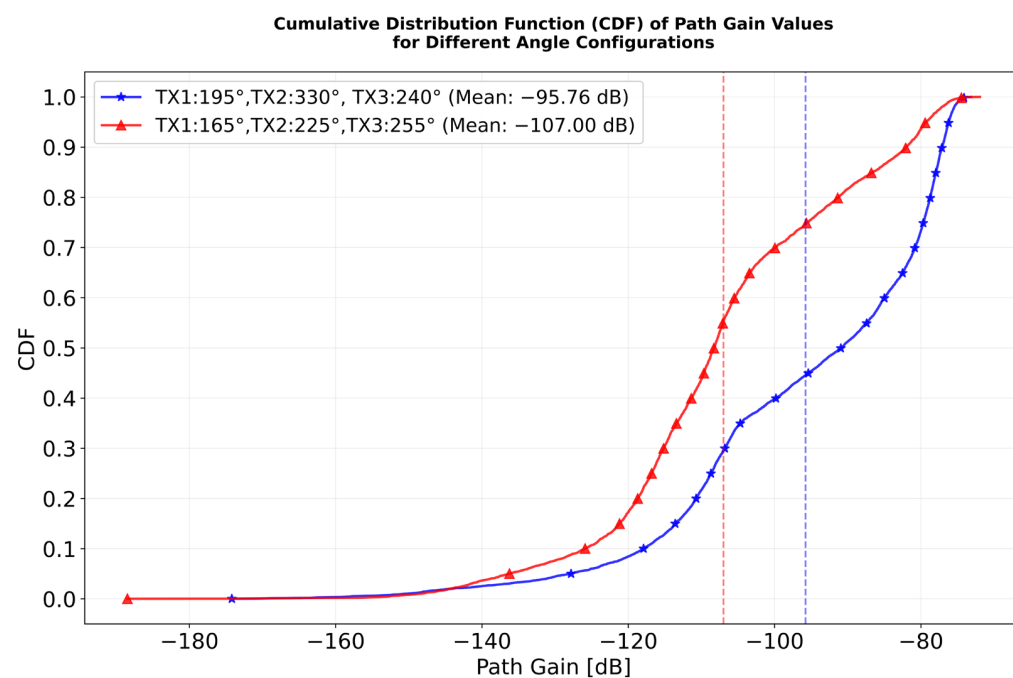
Model fitting minimized the mean squared error (MSE). Section 3 reports the resulting MSE and coefficient of determination ( $R^2$ ).

## 3. Results

### 3.1. Ray Tracing-Based Performance Analysis

In this study, Sionna ray tracing simulations were performed for transmitters located on campus, and the network's coverage map was evaluated and analyzed based on different performance metrics. These metrics are path gain, RSS, and SINR, which directly affect service quality for users in the network.

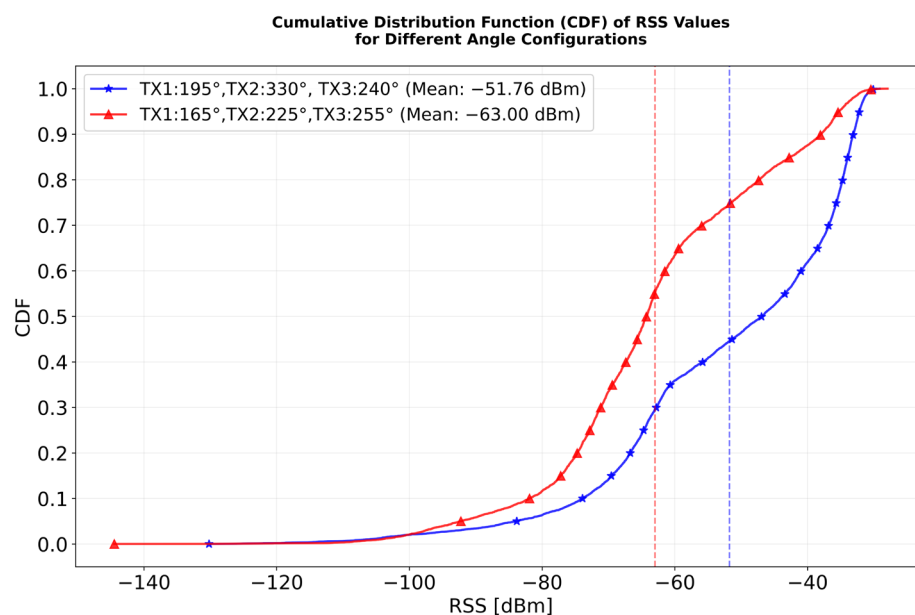
First, 13,824 simulations were performed on Sionna to analyze the performance outputs that the network would experience at different transmit antenna orientations. The optimal antenna azimuthal orientation was evaluated for each transmitter, and the results were recorded based on the experimental results obtained. Figure 4 shows the cumulative distribution of the path gain values corresponding to the two configurations that produced the best and worst mean values. According to this distribution, Configuration A ( $\alpha(\text{TX1}: 195^\circ)$ ,  $\alpha(\text{TX2}: 330^\circ)$ ,  $\alpha(\text{TX3}: 240^\circ)$ ) is located farther to the right than Configuration B ( $\alpha(\text{TX1}: 165^\circ)$ ,  $\alpha(\text{TX2}: 225^\circ)$ ,  $\alpha(\text{TX3}: 255^\circ)$ ) along the entire cumulative distribution function (CDF) curve. In other words, it shows less attenuation and achieves higher path gain values. The difference in propagation is demonstrated by the 11.24 dB difference between the average values.



**Figure 4.** CDF of path gain values for different antenna orientations representing the best and worst configurations.

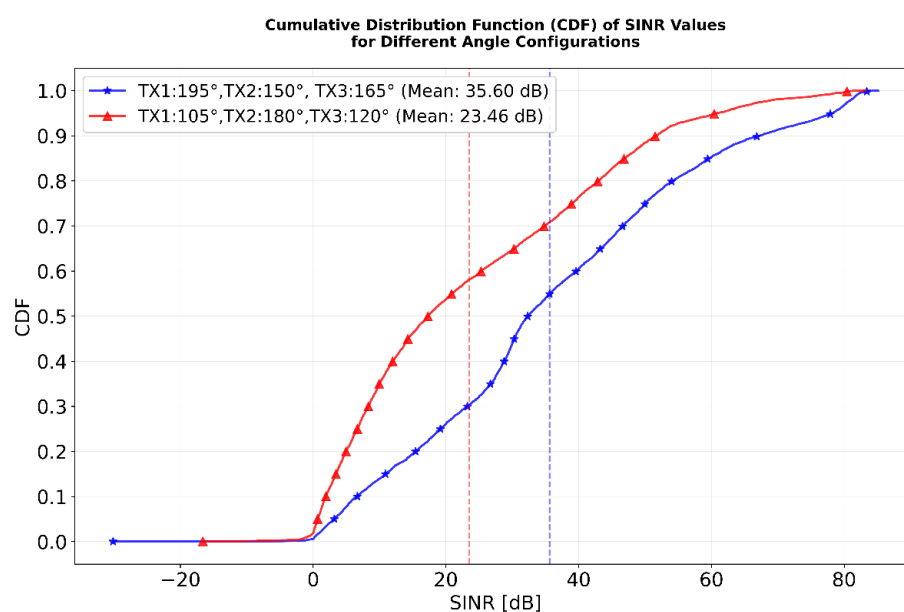
Figure 5 shows the strong correlation between path gain and RSS. The RSS distribution for Configuration A is shifted further to the right than that of Configuration B, indicating

higher signal strength across the network. The 11.24 dBm difference in the averages proves this. A detailed analysis of Figures 4 and 5 reveals that Configuration A provides a better service to all users across the network and improves service for edge users while increasing the received signal strength.



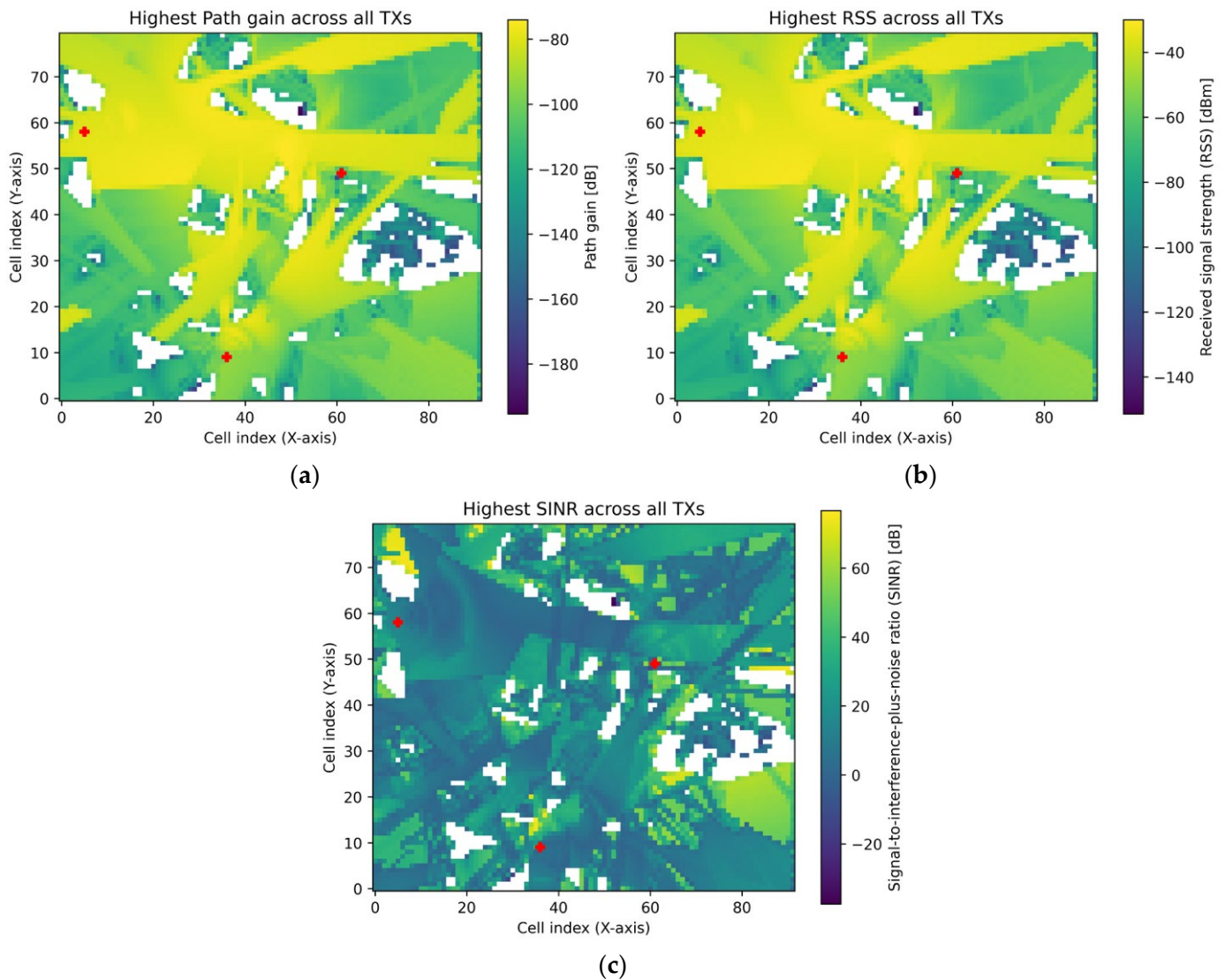
**Figure 5.** CDF of RSS values for different antenna orientations representing the best and worst configurations.

Figure 6 compares the cumulative distribution of SINR values for two different antenna orientation combinations. Configuration C ( $\alpha(\text{TX1}): 195^\circ$ ,  $\alpha(\text{TX2}): 150^\circ$ ,  $\alpha(\text{TX3}): 165^\circ$ ) performed better in terms of SINR, providing stronger signal quality and lower interference levels. There was a 12.14 dB difference across the network compared to Configuration D ( $\alpha(\text{TX1}): 105^\circ$ ,  $\alpha(\text{TX2}): 180^\circ$ ,  $\alpha(\text{TX3}): 120^\circ$ ), which resulted in a higher number of users experiencing lower SINR values and lower signal quality. Configuration C served edge users better, allowing more users to experience higher SINRs.

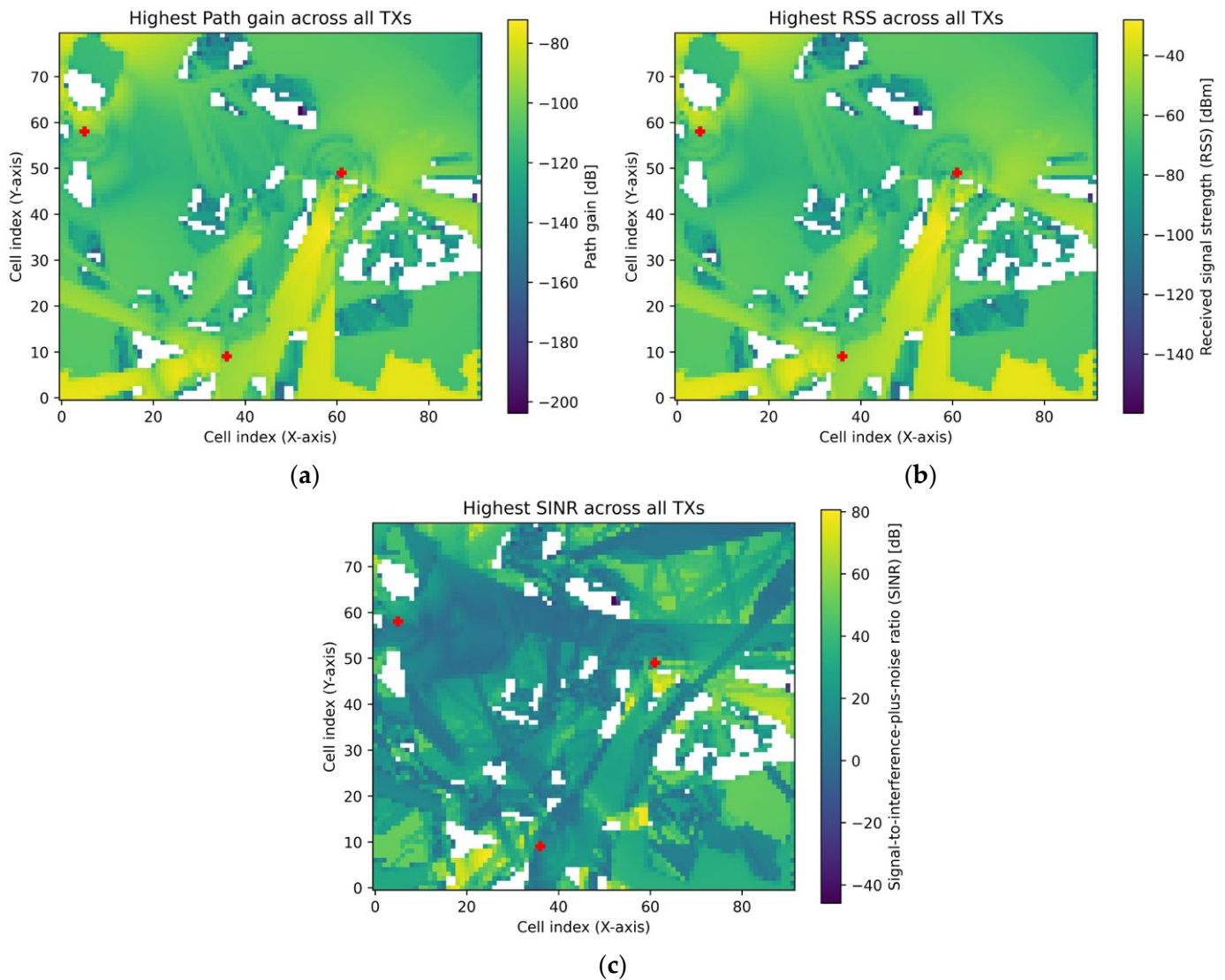


**Figure 6.** CDF of SINR values for different antenna orientations representing the best and worst configurations.

Figures 7 and 8 show the network maps of path gain, RSS, and SINR values for Configurations A and B, representing the best and worst antenna azimuthal configurations for path gain and RSS key metrics, respectively. The red '+' marks in the figures denote transmitter positions, a convention followed throughout all subsequent network maps. The Configuration A maps indicate the optimal azimuthal angle combinations for path gain and RSS performance key metrics. As can be seen in Figure 7, these maps have more high-gain and medium/strong propagation regions than the Configuration B maps. Configuration A is superior in terms of signal strength and robustness against interference. Configuration B is significantly affected by interference, resulting in poor communication quality.

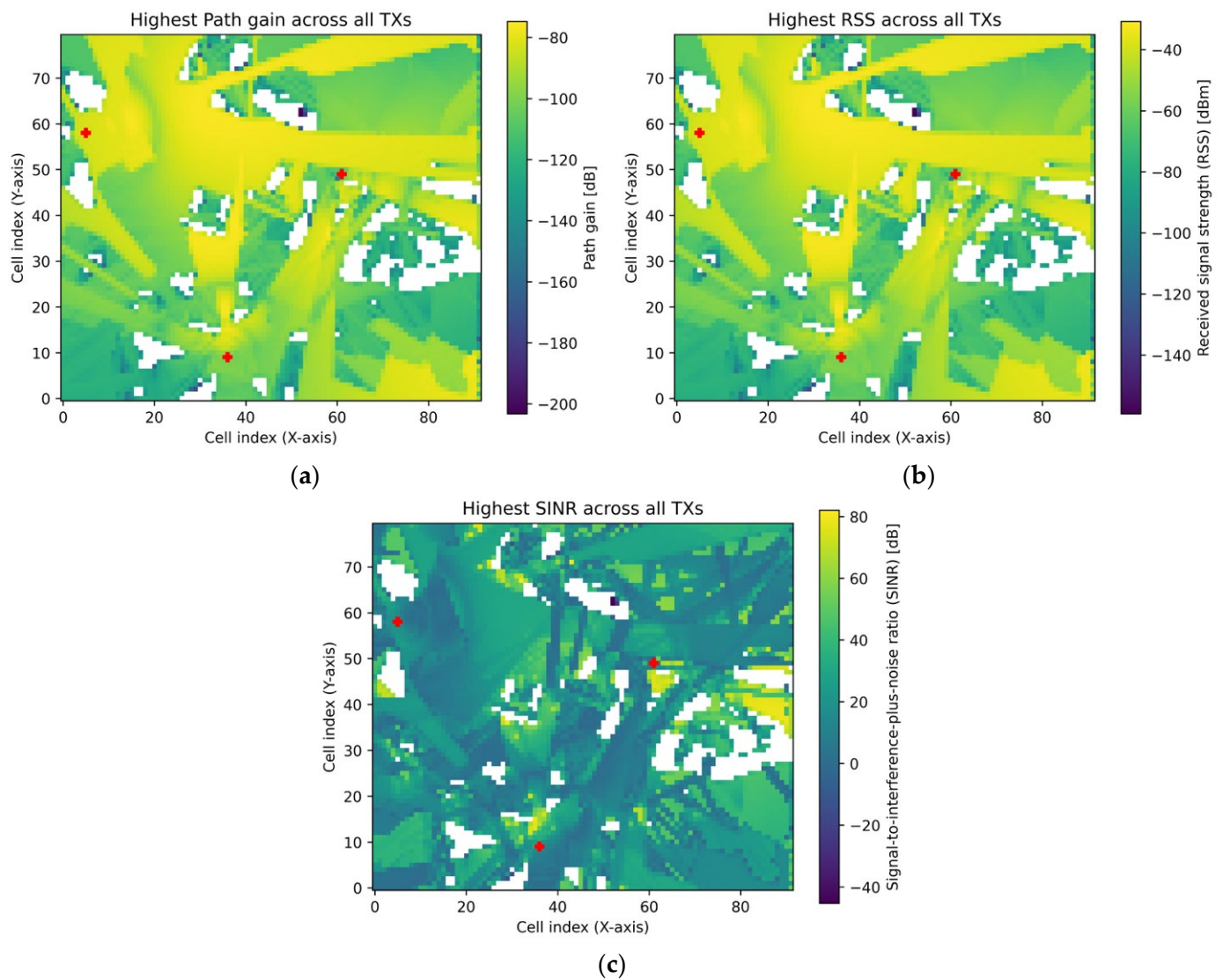


**Figure 7.** Ray tracing maps of the best antenna orientation configuration (Configuration A) for path gain and RSS: (a) Highest path gain map across all TXs; (b) highest RSS map across all TXs; (c) highest SINR map across all TXs.

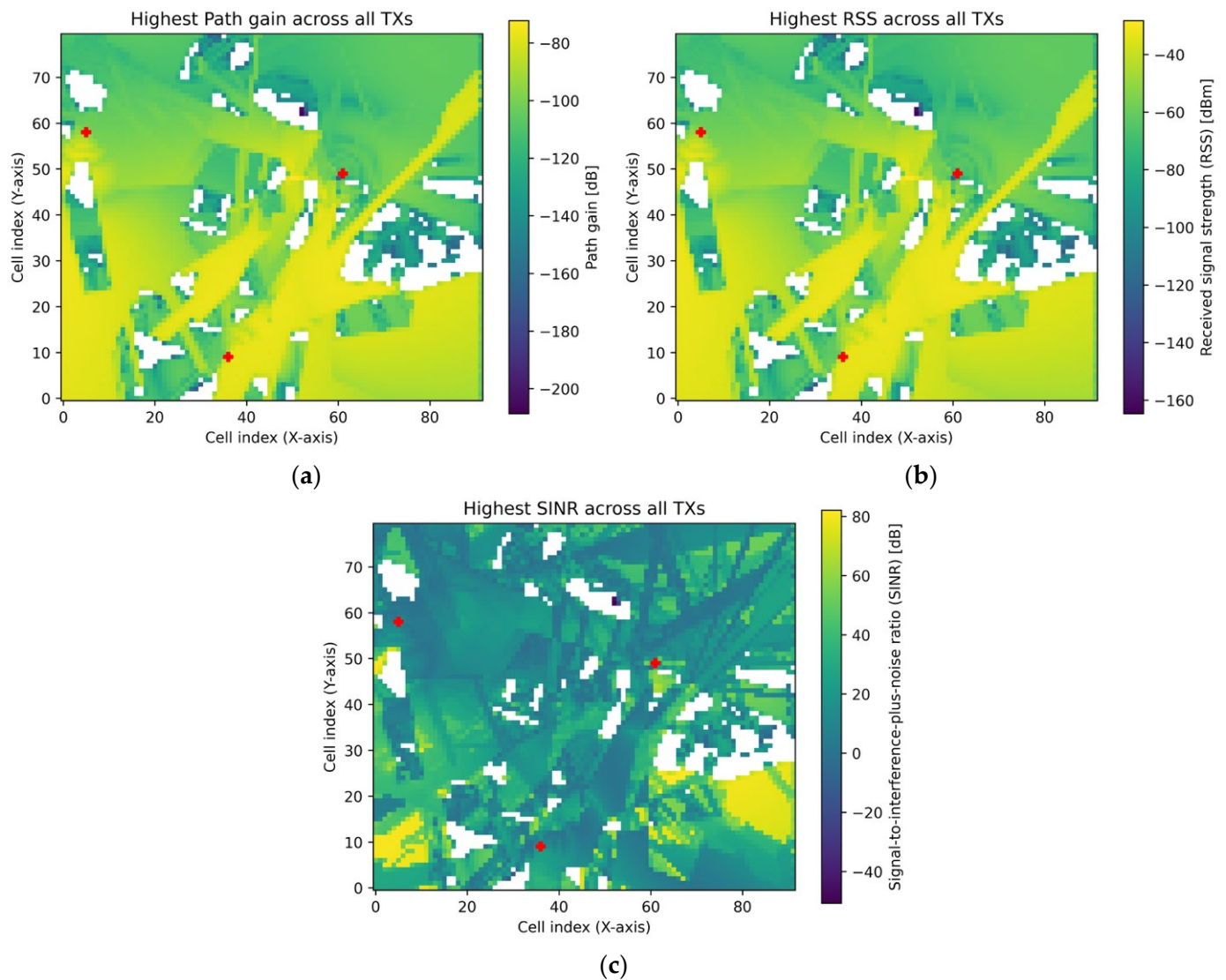


**Figure 8.** Ray tracing maps of the worst antenna orientation configuration (Configuration B) for path gain and RSS: (a) Highest path gain map across all TXs; (b) highest RSS map across all TXs; (c) highest SINR map across all TXs.

Figures 9 and 10 show the network maps of path gain, RSS, and SINR values for Configuration C and Configuration D, representing the best and worst antenna azimuthal configurations for the SINR key metric, respectively. Analyzing Figures 9 and 10 together reveals that Configuration C exhibits stronger signal propagation over a larger area in the path gain and RSS maps. The SINR distributions show that Configuration C achieves higher values in larger regions of the map. In contrast, Configuration D has more fragmented coverage and higher interference levels. Overall, Configuration C offers a more robust and efficient wireless communication solution.



**Figure 9.** Ray tracing maps of the best antenna orientation configuration (Configuration C) for SINR: (a) Highest path gain map across all TXs; (b) highest RSS map across all TXs; (c) highest SINR map across all TXs.



**Figure 10.** Ray tracing maps of the worst antenna orientation configuration (Configuration D) for SINR: (a) Highest path gain map across all TXs; (b) highest RSS map across all TXs; (c) highest SINR map across all TXs.

### 3.2. Performance Comparison of Machine Learning Models

A thorough statistical summary of the projected main performance metrics (path gain, RSS, and SINR) is shown in Table 5, Table 6, and Table 7, respectively, to assess the efficacy of the machine learning models in forecasting signal behavior across diverse antenna angle combinations. This is succeeded by a graphical analysis employing cumulative distribution functions (CDF) to depict the distributional performance of each model.

**Table 5.** Minimum, maximum, and mean predicted values for path gain by each ML model.

| Category             | Min [dB] | Max [dB] | Mean [dB] |
|----------------------|----------|----------|-----------|
| Experimental Results | −174.18  | −73.13   | −95.76    |
| KNN                  | −178.94  | −73.66   | −99.96    |
| MLP                  | −175.29  | −73.71   | −105.59   |
| XGBoost              | −173.08  | −74.13   | −94.87    |

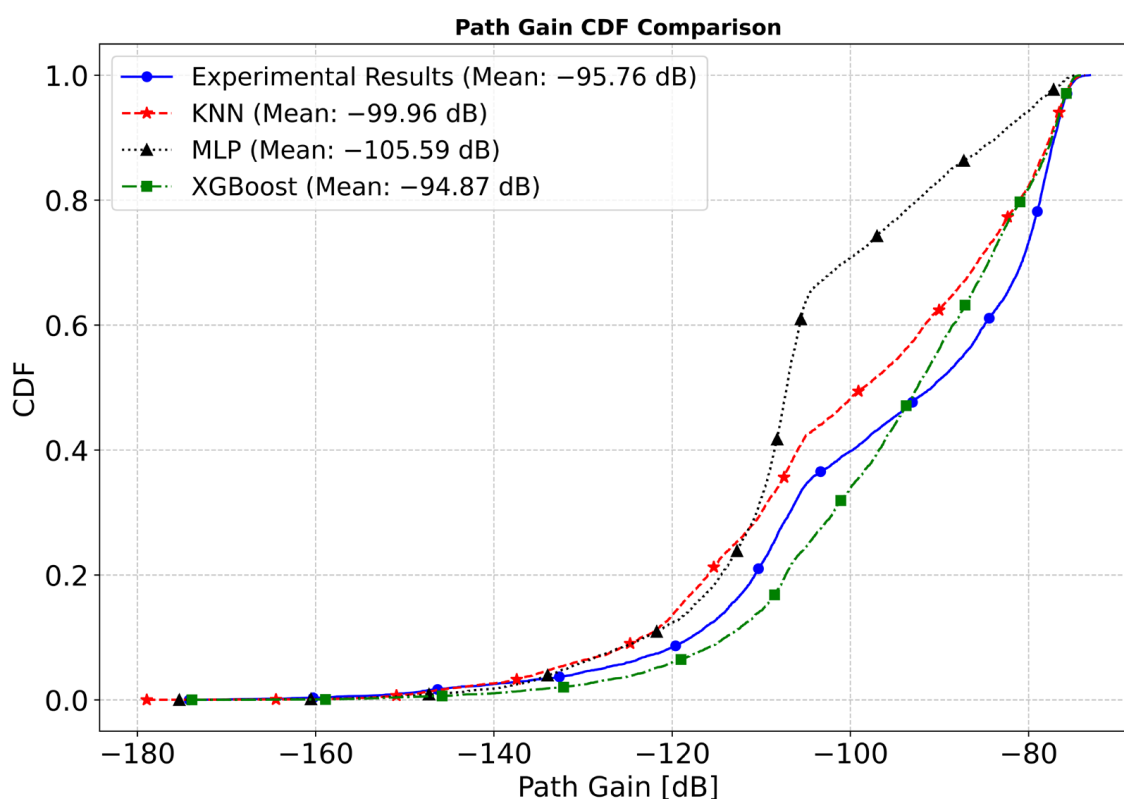
**Table 6.** Minimum, maximum, and mean predicted values for RSS by each ML model.

| Category             | Min [dBm] | Max [dBm] | Mean [dBm] |
|----------------------|-----------|-----------|------------|
| Experimental Results | −130.18   | −29.13    | −51.76     |
| KNN                  | −131.83   | −29.86    | −54.26     |
| MLP                  | −123.41   | −30.06    | −55.97     |
| XGBoost              | −135.16   | −29.60    | −54.20     |

**Table 7.** Minimum, maximum, and mean predicted values for SINR by each ML model.

| Category             | Min [dB] | Max [dB] | Mean [dB] |
|----------------------|----------|----------|-----------|
| Experimental Results | −30.14   | 85.10    | 35.60     |
| KNN                  | −21.32   | 83.33    | 28.64     |
| MLP                  | −21.77   | 83.55    | 30.56     |
| XGBoost              | −20.98   | 83.52    | 36.75     |

Figure 11 compares the path gain prediction performance of the machine learning models KNN, MLP, and XGBoost with the best configuration obtained through CDF. The CDF curves show the path gain distribution corresponding to the optimal combination of each model in the campus network. The values obtained in the experimental results were obtained through a systematic search on Sionna, and the CDF distribution of the path gain for the angle combination that yields the best average path gain is provided. These values serve as a reference for machine learning models and play an important role in model training.

**Figure 11.** Path gain CDF comparison for different ML models.

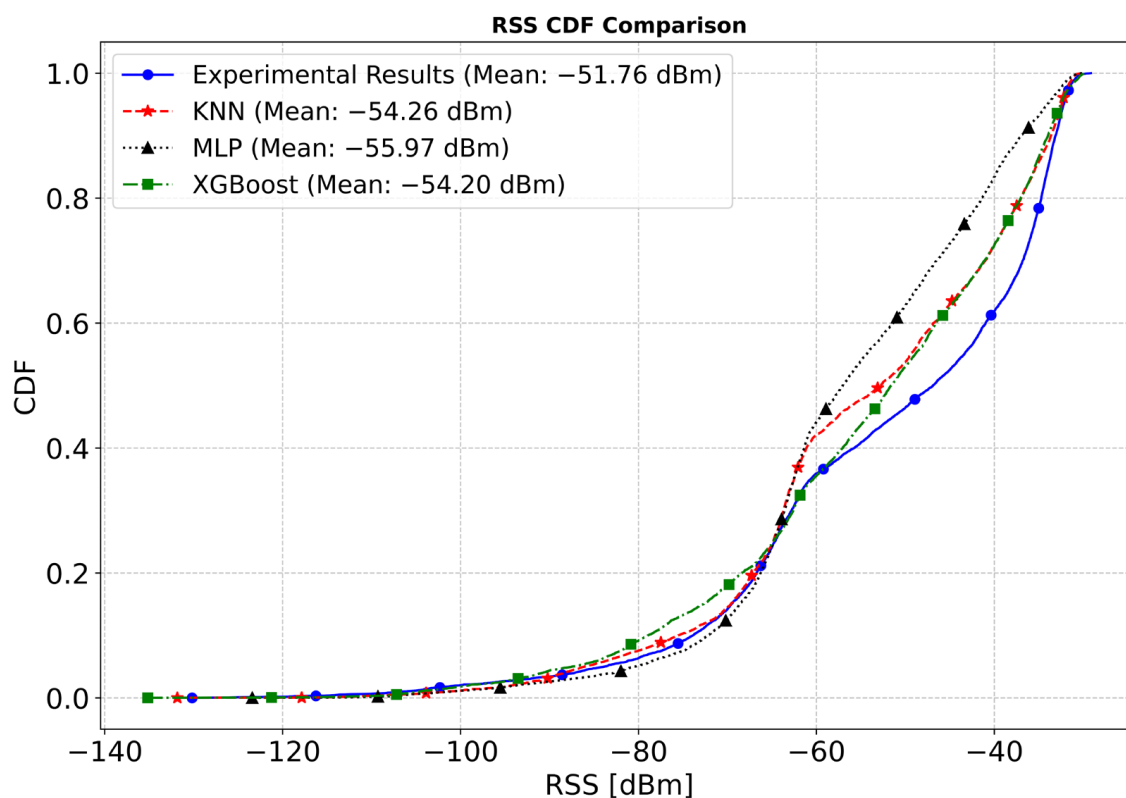
Among the machine learning models, MLP showed the poorest prediction with an average of −105.59 dB. This model's chosen angle combination predicted poor path gain

values and failed to learn the data distribution. When analyzed, the path gain distribution in the network deteriorated, resulting in poor signal quality for many users.

Although the CDF curve of the KNN model closely resembles the experimental curve, it calculates an average path gain value that is 4.2 dB weaker than the experimental results. The high overall distribution similarity suggests that the model found a reasonable combination of angles based on previous experience.

XGBoost provided the highest cumulative path gain values. With an average value of  $-94.87$  dB, XGBoost performed better than the experimental results and identified a better angle combination than the optimum configuration found experimentally.

Figure 12 illustrates the RSS estimate efficacy of the machine learning techniques through the RSS CDF plot. Analysis of the graph reveals that the XGBoost model exhibits the most accurate RSS distribution in relation to the experimental measurements, with several points overlapping the experimental data. While the KNN model produced values comparable to the XGBoost model in certain areas, it exhibited considerable gains at specific spots. The MLP model, conversely, resulted in a greater number of consumers experiencing subpar signal quality compared to the other models and exhibited inferior predictive accuracy.



**Figure 12.** RSS CDF comparison for different ML models.

Figure 13 shows the CDF comparison of the optimal angle configurations of SINR values predicted by different machine learning algorithms and the experimental optimal configuration. The graph shows that XGBoost performed best among the machine learning models. Its CDF curve largely overlapped with the experimental curve, successfully predicting the optimal antenna orientation with an average of 36.75 dB. This performance is higher than the experimental measurement.

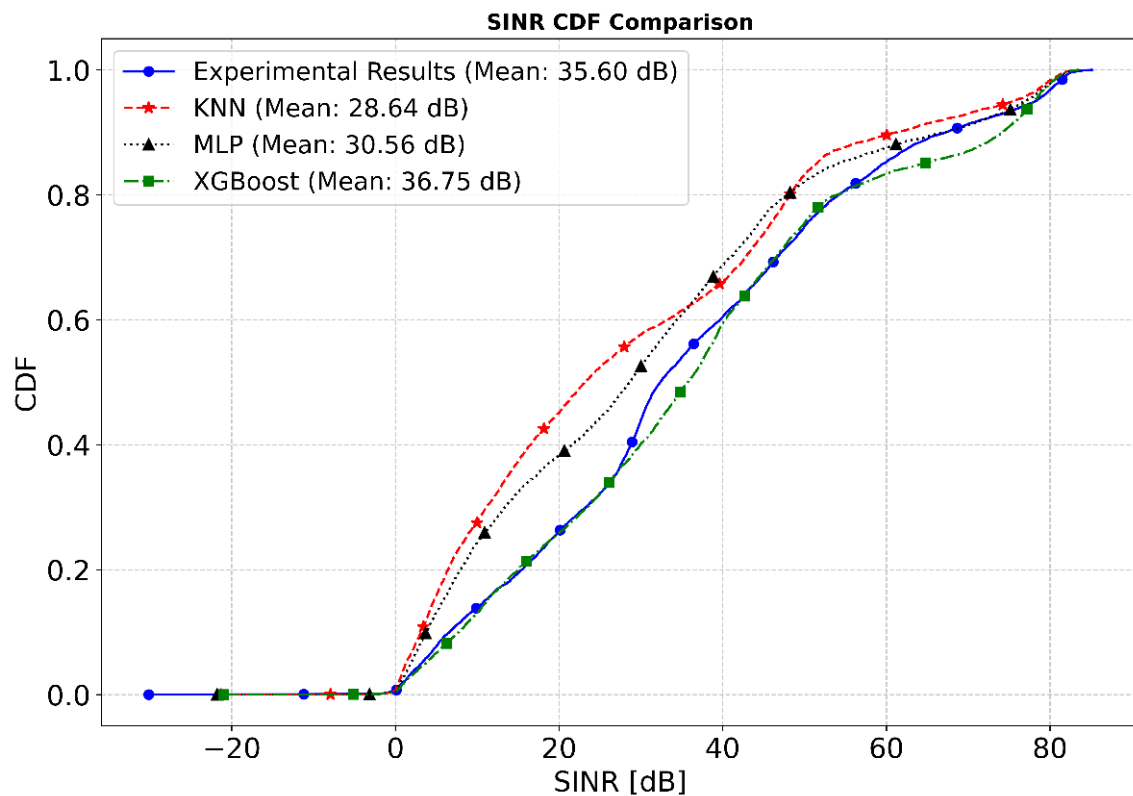


Figure 13. SINR CDF comparison for different ML models.

Conversely, the MLP and KNN models had lower SINR values with their optimal angle configurations and caused high interference in the network. This suggests that these models did not learn the optimal angle combinations well.

As a whole, the machine learning models demonstrate that the XGBoost model not only operates with high signal strength but also with reduced interference. These results confirm the effectiveness of tree-based ensemble learning for selecting the optimal antenna angle configuration to maximize signal strength in complex wireless environments.

Several important inferences were made based on the mean squared error (MSE) and coefficient of determination ( $R^2$ ) values presented in Table 8 when comparing the prediction performance of KNN, MLP, and XGBoost models on three key communication metrics: path gain, RSS, and SINR.

Table 8. Prediction performances for different ML algorithms.

| Performance Metrics | Output | ML Algorithm |         |         |
|---------------------|--------|--------------|---------|---------|
|                     |        | KNN          | MLP     | XGBoost |
| Path gain           | MSE    | 1.5333       | 2.3811  | 0.4483  |
|                     | $R^2$  | 0.554        | −0.0754 | 0.9618  |
| RSS                 | MSE    | 1.5333       | 2.3811  | 0.4483  |
|                     | $R^2$  | 0.554        | −0.0754 | 0.9618  |
| SINR                | MSE    | 1.7528       | 1.8615  | 0.5215  |
|                     | $R^2$  | 0.3008       | 0.2114  | 0.9381  |

Of the three machine learning models evaluated, XGBoost performed best in predicting path gain. It successfully explained more than 96% of the variability, achieving the lowest mean squared error (MSE) of 0.4483 and the highest  $R^2$  score of 0.9618. In contrast, the KNN model was only marginally successful, achieving an MSE of 1.5333 and an  $R^2$  value

of 0.554. The MLP model fell short in this metric, failing to learn the relationships in the data, with an MSE of 2.3811 and an  $R^2$  of  $-0.0754$ .

A similar trend was observed in RSS estimation. XGBoost demonstrated the best performance with an MSE of 0.4483 and an  $R^2$  of 0.9618. The KNN model achieved moderate success with an MSE of 1.5333 and an  $R^2$  of 0.554. In contrast, the MLP model continued its poor performance, falling short in the prediction task. The fact that all algorithms have the same values for path gain and RSS shows that these two metrics are highly correlated in the dataset.

For the more complex prediction problem of the SINR metric, XGBoost again achieved the lowest MSE (0.5215) and the highest  $R^2$  (0.9381). These results demonstrate that the model can produce stable predictions in environments with interference and noise. The KNN and MLP models had MSE values of 1.7528 and 1.8615, respectively, and achieved limited success, with relatively low  $R^2$  values of 0.3008 and 0.2114, respectively.

Table 9 shows that XGBoost completes the entire training process—including hyperparameter search—in the shortest time ( $\approx 1.76$  s). Although the MLP takes longer ( $< 6$  s), this is still negligible for practical use, while KNN, being essentially “training-free,” requires only a 0.44 s cross-validation (CV) pass. Inference latencies are sub-millisecond for all models—0.08 ms for XGBoost, 0.14 ms for the MLP, and 0.23 ms for KNN—more than sufficient for real-time, closed-loop orientation control. Consequently, aside from the one-off cost of the ray tracing sweep, both the training and deployment phases of the learned models are lightweight enough to be integrated seamlessly into network-planning tools.

**Table 9.** Computational cost metrics for ML algorithms.

| Model   | Training Time (s)<br>(CPU) | Hyperparameter<br>Search (s) (CV) | Total ML Time (s) | Inference per Link<br>(ms) |
|---------|----------------------------|-----------------------------------|-------------------|----------------------------|
| KNN     | -                          | 0.44                              | 0.44              | 0.23                       |
| MLP     | 4.60                       | 0.62                              | 5.22              | 0.14                       |
| XGBoost | 1.24                       | 0.45                              | 1.76              | 0.08                       |

Because the experimental optimum is constrained to discrete increments, it may miss a slightly better orientation that lies between two grid points. The XGBoost regressor outputs continuous values and can propose sub-grid refinements, which, once re-evaluated, yield an average performance key metrics improvement over the best grid candidate. Overall, it is clear that the XGBoost model outperforms the others in terms of accuracy and generalization ability. While the KNN model shows acceptable performance in some metrics, it lags behind XGBoost overall. On the other hand, MLP failed to meet expectations under the current data structure and training conditions; extensive hyperparameter sweeps confirmed that stronger dropout or weight decay alleviates the MLP’s negative  $R^2$  but cannot close the gap to XGBoost. The residual deficit stems from the feature landscape itself: with mostly monotonic predictors and a modest sample size, gradient-boosted trees capture the underlying structure more efficiently than dense neural networks. These results demonstrate XGBoost’s ability to reliably predict in wireless communication environments with complex, nonlinear relationships.

### 3.3. Benchmarking Against Conventional Optimization Methods

Automated azimuth tuning is meaningful only if it demonstrably exceeds the speed-versus-accuracy trade-offs of techniques already trusted by network engineers. For that reason, we benchmark the proposed digital twin + XGBoost pipeline against two widely cited baselines:

- An exhaustive simulation grid, which delivers the best accuracy achievable by brute force but is time-consuming [36];
- A 5° KPI-driven hill-climb, the simplest self-optimizing-network (SON) heuristic [37], which is fast yet prone to local-optimum trapping.

This triad of methods spans the spectrum from accuracy-maximized (exhaustive) to latency-minimized, allowing us to quantify both performance and computational burden on equal footing.

The exhaustive grid attains a median SINR of 32.38 dB after a 10 h off-line ray tracing sweep, establishing the simulation upper bound. The on-line hill-climb converges in 6 min but stalls at 21 dB, illustrating its sensitivity to the starting point and temporarily perturbing live KPIs during each trial step. By contrast, the proposed workflow re-uses the same once-per-site ray tracing data and, with only 1.76 s of machine learning overhead, lifts the median SINR to 35.70 dB. Table 10 presents a brief overview that details the median SINR, providing a more precise representation of the central tendency.

**Table 10.** Comparison of orientation-tuning methods.

| Method                | Median SINR (dB) | Runtime |
|-----------------------|------------------|---------|
| Exhaustive Search     | 32.38            | 10 h    |
| KPI-Driven Hill-Climb | 21               | 6 min   |
| XGBoost               | 35.70            | 1.76 s  |

#### 4. Discussion

This study analyzes the effect of antenna orientations on performance metrics in a campus communication environment through ray tracing simulations. Multiple simulations were performed by varying the orientation of the antennas in the x-plane, creating a rich dataset. The path gain, RSS, and SINR values were calculated for each angle combination and were then used to create coverage maps and train machine learning models.

The study subjected the best and worst performing angle configurations—in line with the performance criteria—to thorough investigation. Analytical comparisons were made of the four configurations. Map-based study revealed that some angle combinations gave the user weak coverage and others strong signal propagation and RSS. High path gain and RSS values were found to be produced generally by paths offering wide coverage and homogeneous propagation. Still, the SINR cannot be raised by high signal strength by itself. This is so because the SINR depends considerably on environmental influences and interference.

In the analysis with machine learning models, it was observed that tree-layer learning algorithms such as XGBoost were more successful in predicting performance metrics, while multi-layer artificial neural network models were weak in prediction by requiring more optimization.

For simplicity of analysis, the extent of the study is restricted in this context to x-plane orientations. For more realistic and detailed propagation modeling, nevertheless, it is advisable to extend the antenna orientation to the y and z planes, considering the three-dimensional character of electromagnetic propagation. Furthermore, while this study evaluates fixed user locations, for more realistic and detailed propagation modeling, future work can take into account factors such as mobile users, varying channel conditions, and dynamic environmental structures. Thus, the flexibility and field adaptability of the developed systems can be significantly increased. The present framework provides a static, worst-case snapshot of the campus channel. Incorporating user mobility, temporal channel fluctuations (e.g., weather-induced fading), and evolving urban layouts will be the subject

of follow-on work, leveraging the digital twin's ability to update geometry and re-run ray tracing in near real time.

## 5. Conclusions

This study introduces a framework utilizing digital twin technology and ray tracing to assess and forecast wireless communication performance across different antenna azimuthal orientations. A comprehensive dataset was produced through systematic simulations, enabling the analysis of key metrics including path gain, RSS, and SINR across various transmitter orientations. Machine learning models, including KNN, MLP, and XGBoost, were trained to estimate optimal orientation settings. XGBoost attained superior prediction performance among the group. The results indicate that signal strength measurements alone are inadequate for inferring SINR, underscoring the necessity of interference-aware analysis. The suggested method facilitates effective, data-driven improvement of wireless system parameters in practical settings. This work deliberately restricts the optimization space to azimuth angles; elevation (downtilt) and full three-dimensional steering are beyond the current scope and will be rigorously investigated in future studies. In that expanded framework, a new digital twin and learning-based optimization pipeline will be recreated at mmWave and sub-THz bands, where blockage sensitivity, beam narrowing, and frequency-dependent material dispersion are expected to markedly reshape propagation behavior and the attainable orientation gains. Future work will also extend the digital twin framework to multi-site layouts with dynamic traffic models, thereby capturing external-cell interference and load-coupled effects.

**Funding:** This research received no external funding.

**Data Availability Statement:** The original contributions presented in this study are included in this article. Further inquiries can be directed to the corresponding author.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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