



Unlocking Fast, Accurate, and Generalized Indoor Propagation Modeling at mmWave Frequencies with ML-driven DRaGon Approach

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Abstract—Future 6G networks are expected to support a wide range of industrial applications with stringent requirements on data rates. The millimeter-wave (mmWave) spectrum is a key enabler due to the large available bandwidths. However, propagation at mmWave frequencies is highly sensitive to the surrounding environment, making accurate network planning essential. The quality of network planning critically depends on the underlying channel model. While empirical models are often overly simplistic, ray-tracing approaches provide higher fidelity at the cost of significant computational complexity. Machine learning methods offer a promising alternative by providing the best of both worlds: high accuracy at low computing delays. However, they require large and diverse datasets to map the complexity of mmWave systems, e.g., due to beamforming antenna characteristics. In this work, we transfer the IndoorDRaGon model, originally developed for sub-6 GHz frequencies, to the mmWave domain. To this end, we generate a synthetic large-scale dataset comprising approximately 1.5 billion samples, capturing a wide range of environmental and system configurations. The resulting mmWave-IndoorDRaGon is more than $1000\times$ faster than ray tracing, while achieving a 10 dB reduction in RMSE compared to empirical models. Even on complex, unseen measurement data, the model maintains strong agreement with the measurements, achieving 6 dB RMSE. Finally, we showcase its use in our interactive smart factory demonstrator enabling real-time network analysis.

I. INTRODUCTION

The digital transformation of indoor industrial environments, driven by the principles of Industry 4.0, has given rise to the development of enhanced wireless communication systems, such as 5G and future 6G networks. Modern industrial applications, e.g., time-critical teleoperation of autonomous robots, require extremely high data rates, and robust connectivity across complex indoor environments [1]. 5G millimeter-wave (mmWave) is a promising technology to meet these demands based on large bandwidths not available in sub-6 GHz spectrum [2]. However, the Electromagnetic Waves (EM) propagation at these frequencies is highly challenging due to severe path loss, i.e., strong blockage and weak diffraction, and pronounced angular dependence from directional beamforming employed to compensate the additional power losses [3, 4]. These effects result in frequent shadowing in Non-Line-of-Sight (NLOS) situations with poor signal strength, particularly in dense and dynamic environments such as Indoor Factory (InF) halls. Careful planning of the deployment and configuration of the Radio Units (RUs) is therefore imperative.

Effective planning is contingent upon accurate propagation modeling. However, the complex mmWave propagation cannot

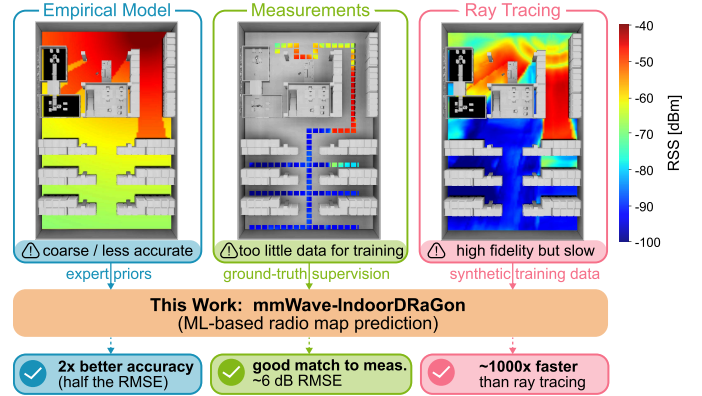


Fig. 1. Bridging the gap between accuracy and computing efficiency in propagation modeling with DRaGon as the basis for efficient network planning

be captured by simplified or overly generic models. Relying on such approaches may lead to significant inaccuracies in coverage estimation, ultimately causing either coverage gaps or unnecessary overprovisioning of network resources. Therefore, advanced and environment-aware modeling approaches are required. As illustrated in Fig. 1, realistic modeling based on ray tracing achieves accurate results at the cost of excessive computational complexity. This inherent trade-off between accuracy and efficiency motivates the need for new modeling approaches. In this context, ML-driven propagation models have emerged as a promising solution for fast and accurate modeling of complex environments. Unlike conventional approaches, these models can implicitly learn propagation effects and material properties without requiring explicit formulation or parameterization. In [5], we introduced the so-called IndoorDRaGon for industrial sub-6 GHz indoor scenarios. In this work, we propose a comprehensive extension of the model to support mmWave frequencies. This extension comprises two main components: (i) generating a large dataset to capture mmWave propagation characteristics, and (ii) extending the feature set with geometry-based information to model directional effects and beamforming-induced angular dependencies.

The remainder of the paper is structured as follows. After discussing related work on propagation modeling in Sec. II, we present the ML-driven propagation model in Sec. III and evaluate its performance in Sec. IV. We then present a demonstrator enabling flexible environmental modifications and real-time Radio Environmental Maps (REMs) computation in Sec. V, followed by the conclusion in Sec. VI.

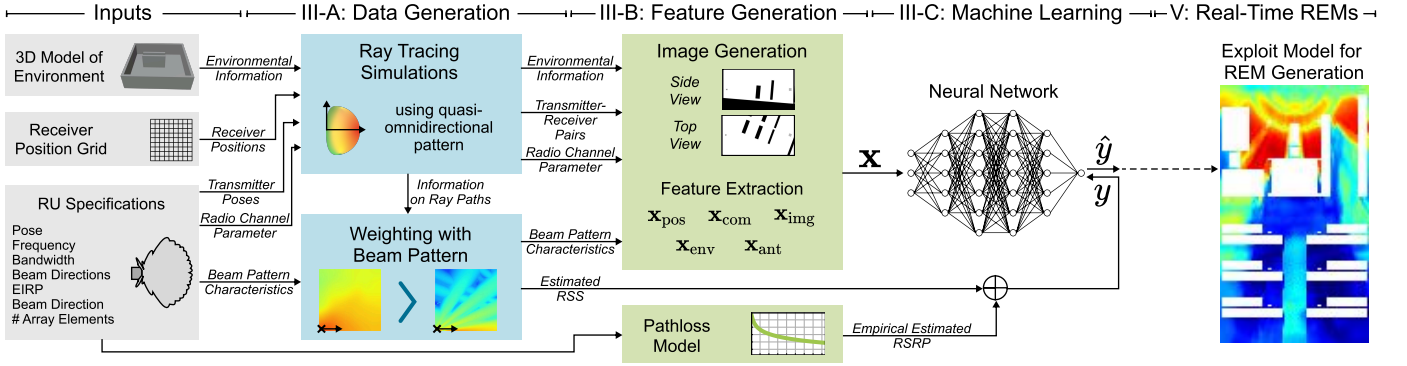


Fig. 2. System architecture of the proposed Machine Learning (ML)-based propagation model for industrial mmWave communication systems

II. RADIO PROPAGATION MODELING IN LITERATURE

Modeling the radio propagation is a fundamental aspect enabling various applications in mobile networks. A wide range of channel models is available in literature, but only with a limited number of models covering mmWave frequencies.

Empirical models are derived from extensive measurement campaigns and are based on statistical analysis of the collected data. These models typically provide a simplified representation of the radio propagation, capturing the average behavior of the channel under specific conditions. They tend to struggle with complex EM wave interactions, due to the absence of explicit environmental modelling. A collection of empirical models for mmWave frequencies is provided in [6].

Deterministic models such as ray tracing simulate the propagation of radio waves by considering the physical interactions (e.g., reflection and diffraction) with the environment [7]. These models can provide a more detailed representation of the radio propagation, but they are computationally intensive and require detailed knowledge of the environment [8].

ML-based propagation models have gained significant attention in recent years as they can learn complex relationships between the input features and the target variable from data, without relying on explicit assumptions about the underlying physical processes [9]. However, the number of models capable of covering both indoor industrial scenarios and Frequency Range 2 (FR2) is limited. In order to model the complex characteristics of the mmWave systems a large amount of data is required. Therefore, some works rely solely on synthetic data without using real-world measurements [10]. Many ML-based models are trained and evaluated on a single scenario, which limits their generalization capabilities to other environments and frequencies. The authors in [11] apply various lightweight ML models, trained on measurements at 28 GHz conducted in a manufacturing lab by using a limited number of features. [12] introduces a Bayesian Artificial Neural Network (ANN) framework for mmWave path loss estimation in outdoor scenarios, considering arrival and departure angles as input features but no environmental information with models being trained separately for Line-of-Sight (LOS) and NLOS conditions and frequencies. In [13], the authors avoid using environmental information by solely relying on features based on channel state information to train an ANN

with measurements at 28 GHz in a small-scale indoor corridor environment. The authors in [14] rely on synthetic data in industry-inspired pseudo-environments to train an ANN for different frequencies, including 28 GHz.

In our *previous work*, we introduced IndoorDRaGon [15] as an ANN-based path loss prediction method for sub-6 GHz networks. In this work, we extend the model to support mmWave frequencies and generalize it to a wide range of industrial indoor environments, including the support of mmWave system characteristics such as beamforming and directional antennas. To this end, we rely on a large, diverse synthetic dataset and a well-designed, multi-domain feature set.

III. PROPOSED ML-BASED MMWAVE MODEL

Our goal is to retrieve a model to accurately predict the Received Signal Strength (RSS) for a given transmitter-receiver pair with respect to the propagation environment and antenna characteristics for mmWave systems. An overall system architecture is illustrated in Fig. 2 with its subsequent steps being explained below.

A. Data Generation for mmWave Propagation Modeling

The performance of ML models strongly depends on the quality and diversity of the training data, requiring comprehensive datasets to achieve high prediction accuracy and robust generalization. However, acquiring large-scale real-world measurement data is costly, time-consuming, and often limited in flexibility. Therefore, this work utilizes synthetic training data generated via ray tracing simulations.

Scenario Generation: To generate a sufficiently large and diverse dataset, various indoor scenarios are considered. Each scenario consists of a 3D environment model including obstacles (e.g., shelves), a specific transmitter pose, and a

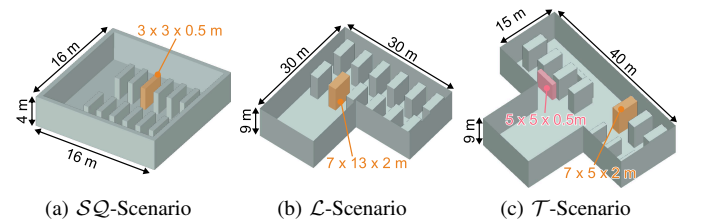


Fig. 3. Indoor environment geometries considered in ray tracing simulations. Each subfigure shows one representative obstacle configuration per geometry.

2D receiver grid at a fixed height. To capture variability in InF hall layouts, three types of environmental geometries are considered: square- ($\mathcal{SQ}$), L- ($\mathcal{L}$), and T-shaped ($\mathcal{T}$), as illustrated in Fig. 3. For each geometry, the model is further diversified by varying the number, shape, and height of obstacles. Specifically, obstacle heights range from 1 to 7 m, while the number of obstacles varies between 0 and 12.

Transmitter and Receiver Positions: For each environment model, a predefined set of transmitter poses, i.e., combinations of position and mechanical orientation, is considered. In total, 15 poses are used for $\mathcal{SQ}$, 10 for $\mathcal{L}$, and 11 for $\mathcal{T}$ scenarios. The considered mechanical orientations span azimuth angles between 0° and 180° and elevation angles of 0° , -20° , and -45° . Initially, a broad forward-facing radiation pattern is employed, approximating quasi-omnidirectional transmission within the front hemisphere. To account for varying receiver heights in factory environments, ranging from ground-level robots to tall machinery, the receiver height is varied between 0.3 and 6 m.

Ray Tracing Configuration: Each unique combination of environment model, obstacle configuration, transmitter pose, and receiver grid height is defined as one scenario. In total, 195 scenarios are simulated using the commercial ray tracing software *Wireless InSite* with the configurations summarized in the following table:

TABLE I. RAY TRACING CONFIGURATION FOR DATA GENERATION

Parameter	Value
EIRP	0 dBm
Center frequency	27.1 GHz
Tx antenna	Semi-omnidirectional (V-HPBW: 90° , H-HPBW: 180°)
Rx antenna	Isotropic
Grid resolution	25 cm
Wall material	Concrete (Lambertian scattering, $s = 0.4$)
Propagation solver	X3D (full 3D)
Max. nrof. interactions	6 / 1 / 0 (reflection, diffraction, penetration events)

Weighting with Different Beam Patterns: At mmWave frequencies, the received power is strongly influenced by the directional characteristics of the transmitter antenna. Beam patterns, defined by their beamwidth and steering direction, determine the spatial distribution of radiated power and thus directly affect the RSS. Consequently, incorporating antenna directivity into the propagation model is essential. Performing ray tracing for multiple beam patterns per scenario is computationally expensive. Therefore, simulations are conducted using a quasi-omnidirectional transmitter, while antenna directivity is incorporated in post-processing by weighting the simulated received power with analytically modeled beam patterns [16]. The beam patterns are parameterized by the carrier frequency, the antenna array size ($M \times N$), and the steering angles (ϕ_{st}, θ_{st}) relative to the mechanical antenna array boresight direction. The directional received power for a transmitter-receiver pair (t, r) is defined as

$$P_{t,r}^{\text{dir}}(\phi_{st}, \theta_{st}) = \max_{k \in \mathcal{K}_{t,r}} (P_{t,r,k}^{\text{sim}} \cdot G(\phi_k, \theta_k; \phi_{st}, \theta_{st}, M, N)),$$

where $\mathcal{K}_{t,r}$ denotes all simulated propagation paths between transmitter t and receiver r , $P_{t,r,k}^{\text{sim}}$ is the simulated received

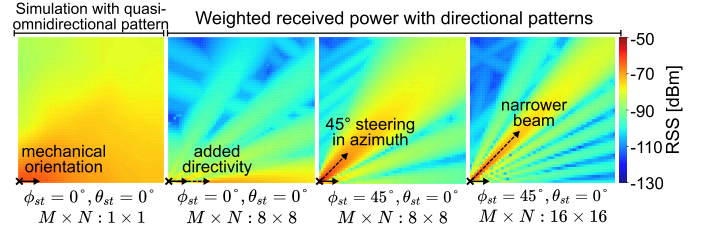


Fig. 4. Received power REMs obtained using the proposed weighting approach for different beam patterns with varying steering angles and antenna array sizes. The RU is mechanically oriented along the x-axis.

power of path k , and $G(\phi_k, \theta_k; \phi_{st}, \theta_{st})$ is the normalized antenna gain in the observation direction (ϕ_k, θ_k) of path k . The antenna gain is applied as a multiplicative factor to the simulated path power and the maximum selects the dominant directionally weighted path.

Fig. 4 shows the resulting RSS REMs after applying the proposed weighting approach for different beam patterns. The quasi-omnidirectional case (left) is contrasted with directional beams of varying steering angles and array sizes. The results demonstrate spatial focusing along the beam direction, shifts of high-power regions due to beam steering, and increased directivity for larger arrays, confirming that the proposed weighting approach accurately captures antenna directivity effects on the spatial distribution of received power.

The semi-omnidirectional simulated scenarios are thus augmented with analytically modeled beam patterns, varying both steering direction and antenna array size to cover a wide range of configurations. Specifically, 1,000 beam directions are considered, mainly spanning azimuth angles from -60° to 60° and elevation angles from -60° to 30° . The antenna array size ($M \times N$) is varied across 8, 12, 16, and 32 elements per dimension, resulting in different beamwidth and directivity characteristics. Combining these variations yields multiple beam pattern configurations per ray-tracing scenario, forming a large-scale dataset of approximately 1.5 billion samples.

B. Data Processing and Feature Generation

The feature generation process is built upon [15], wherein the feature vector is composed of multiple logical sub-vectors capturing position, environmental, image-based, and communication-aware information. In this work, we extend the feature set to cover antenna-related features. The resulting set of 34 features is summarized and described below:

Positional Subvector $\mathbf{x}_{\text{pos}}$ describes the spatial relation between transmitter and receiver, including: relative position differences ($\Delta x, \Delta y, \Delta z$), 3D distance d_{3D} , receiver height z , and angular deviation between the transmitter's mechanical orientation and the direct path ($\Delta\phi_{\text{mech}}, \Delta\theta_{\text{mech}}$).

Communication Channel Subvector $\mathbf{x}_{\text{com}}$ holds physical expert knowledge in terms of calculated path loss based on 3GPP InF SL (sparse clutter, low transmitter height) [17].

Image-based Subvector $\mathbf{x}_{\text{img}}$ provides the ML model with information about the environment structure: For each transmitter-receiver pair, synthetic black-white top-view and side-view images are generated (cf. Fig. 2-B). Numerical features are extracted by splitting the images into three

horizontal and five vertical stripes. The relative amount of obstacle pixels within each stripe is extracted as one feature. **Environmental Subvector** $\mathbf{x}_{\text{env}}$ holds information on the direct path, including: distance of the direct path through obstacles d_{OBS} , number of intersections N_{IS} with obstacles, and distance to the first intersection d_{IS} .

New Antenna Subvector $\mathbf{x}_{\text{ant}}$ holds carrier frequency f , electrical steering angles ($\phi_{\text{st}}, \theta_{\text{st}}$), and horizontal and vertical Half Power Beamwidths (HPBW), which together define the beam pattern. To relate the main beam direction to the receiver, the angular deviation ($\Delta\phi, \Delta\theta$) between the main beam direction and the transmitter-receiver direct path is included. These features enable the ML model to distinguish between different beam pattern configurations and to capture their impact on the received power.

C. Machine Learning Model Adaptation and Training

To model mmWave propagation, we employ an ANN using PyTorch. The architecture is adopted from [15], with an adjusted input layer to match the increased number of features. Hyperparameters are provided in Tab. II. To ensure stable and efficient training, we apply regularization techniques including weight decay, batch normalization, and a learning rate scheduler. As described in the previous sections, our dataset comprises 1.5 billion samples with 34 input features and is divided into 60% training, 20% validation, and 20% test samples. To address Random Access Memory (RAM) limitations, resulting from 66 GB of training data, we rely on the Dask library to efficiently manage and process the dataset.

TABLE II. ADAPTED ANN HYPERPARAMETERS FROM [15]

Parameter	Value
Batch size	1024
Learning rate	0.0001
Weight decay	0.0005
Layer sizes	[34, 512, 1024, 2048, 1024, 512, 256, 128, 64, 32, 1]
Optimizer	Adam

IV. RESULTS

Based on the hyperparameters provided in Tab. II, we trained the ANN using training and validation data. The model was trained for 229 epochs, before early stopping.

A. Performance Comparison and Evaluation

The proposed ML-based model is evaluated on the remaining test dataset, comprising approximately 300 million randomly selected data samples, and compared against traditional channel models. The models under investigation include Friis free-space propagation, 3GPP InF SL [17], and WINNER II B3 [18], both considered under LOS and NLOS conditions. To enable a fair comparison, omnidirectional models are penalized with a 20 dB loss outside the beam to account for directivity. Fig. 5 presents the Empirical Cumulative Distribution Function (ECDF) of the absolute Path Loss (PL) prediction error for the models under investigation. As it can be seen, the proposed model outperforms all other models under investigation. mmWave-IndoorDRaGon achieves a test Root Mean Square Error (RMSE) of 4.25 dB, while the next

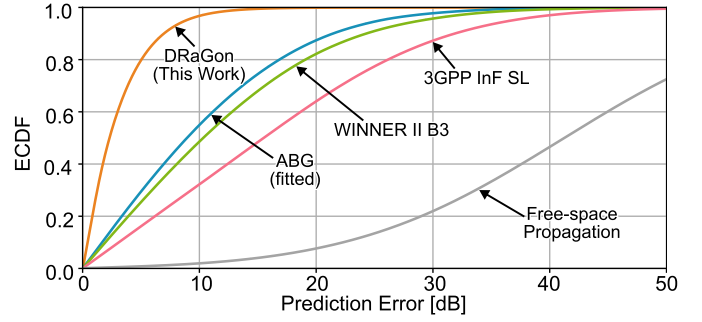


Fig. 5. Comparison of proposed mmWave-IndoorDRaGon model together with empirical benchmark models

best benchmark model is found to be WINNER II with an RMSE of 14.89 dB. 3GPP and free-space propagation models perform worse, with RMSE values of 20.03 dB and 43.64 dB.

To overcome the limitations of empirical models under investigation for our environments, we aim to tailor an empirical model to our data. Most empirical and analytical models can be expressed as *floating intercept*, or *alpha-beta-gamma* (ABG) models, following the equation below:

$$PL = \alpha + 10 \cdot \beta \log_{10}(d_m) + \gamma \log_{10}(f_{\text{GHz}}) \quad (1)$$

where α is the intercept in dB, β is the slope, γ is the frequency dependence. The ABG parameters for the empirical models under investigation are provided in Tab. III together with the parameters found for the fitted model. Our fitted ABG model variant achieves an RMSE of 13.09 dB, outperforming remaining traditional benchmarks.

B. Spatial Prediction Fidelity

To analyze spatial prediction accuracy, a randomly clustered SQ -scenario is considered to compare the ray tracing simulation (ground truth) with the proposed mmWave-IndoorDRaGon model as well as the underlying 3GPP InF SL model. The considered RU is positioned at a height of 3 m on the lower wall, mechanically oriented towards the center of the scenario ($\phi_{\text{mech}} = 90^\circ$, $\theta_{\text{mech}} = 0^\circ$). A single RU antenna beam is considered with steering angles $\phi_{\text{st}} = 44^\circ$, $\theta_{\text{st}} = -6^\circ$ and the horizontal and vertical HPBW measures 18.375° and 6.375° , respectively. The receiver height is set to 2.5 m. 2,557 valid receiver positions are considered.

Fig. 6 presents the ground truth RSS REM alongside the corresponding predictions of the investigated models. A difference REM is included to highlight regions of over- and underestimation. A visual inspection of the results shows that the proposed ML model closely replicates the ground truth REM, achieving an overall RMSE of 3.44 dB. A more detailed

TABLE III. ABG PARAMETER OF BENCHMARK MODELS

Source	Model	α	β	γ
Literature values	Friis Free-space Propagation	32.44	2.00	20
	3GPP InF LOS	31.84	2.15	19
	3GPP InF NLOS SL	33.00	2.55	20
	WINNER II B3 LOS	50.42	1.39	20
	WINNER II B3 NLOS	20.42	3.78	23
This work	Fitted ABG LOS	64.87	1.80	21
	Fitted ABG NLOS	61.13	3.15	21

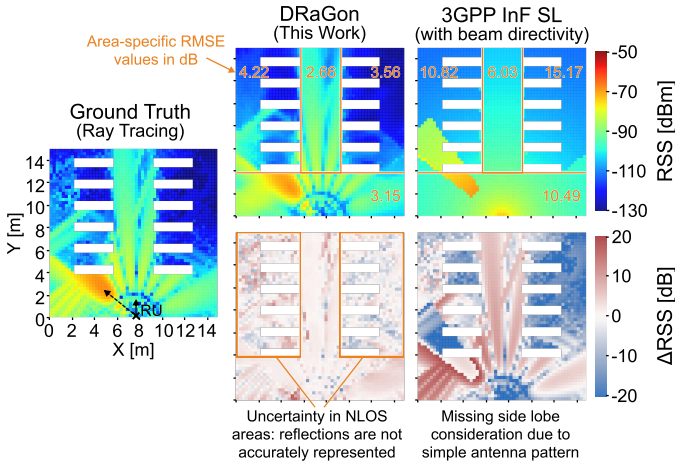


Fig. 6. Visual comparison of RSS REMs for a single RU deployment including area-based RMSE values. Additionally, difference REM are shown to highlight spatial prediction errors.

analysis reveals that prediction accuracy varies across different regions: while the model performs particularly well in LOS areas, larger deviations are observed under NLOS conditions. The difference REM further highlights a notable spatial variability in the prediction error in the NLOS regions, characterized by both over- and underestimation. In particular, in the main lobe’s scenario region, complex propagation effects such as reflections are not fully accounted for, leading to increased deviations from the ground truth.

In contrast, the empirical model exhibits significantly different behavior. Since it can only distinguish between LOS/NLOS and in-beam/out-of-beam conditions, more complex effects such as reflections are not represented at all. As a result, side-lobe effects are not captured at all, and the model performs poorly. This limitation becomes even more apparent in the corresponding difference REM. It can be seen that the model overpredicts the RSS in NLOS regions, while underpredicting in LOS areas, leading to an overall RMSE of 11.21 dB.

Having thus demonstrated that the proposed mmWave-IndoorDRaGon model can closely replicate ray tracing results, the question arises why an ML-based approach should be preferred for network planning. A primary advantage lies in computational efficiency. For the considered scenario, the ray tracing simulation requires a total runtime of 1 h 56 min 23 s (including 20 s for beam weighting) on a *NVIDIA GeForce*

RTX 2080 GPU. On the same machine, our proposed ML-based model enables inference within only 6.5 s, making it **1074x faster than ray tracing**. Note that we only considered a single beam configuration here, whereas practical deployments rely on beam codebooks consisting of multiple beams. While ray tracing must be executed for each beam individually, the proposed approach requires only minor feature updates, allowing efficient reuse of computations.

C. Comparison against Real-World InF Measurements

To validate the proposed model under real-world conditions, we consider a large-scale industrial production scenario from *Fraunhofer IPT* in Aachen, Germany. The factory hall spans 97 m in length, 28.5 m in width, and approximately 10 m in height. The cluttered environment contains more than 50 machine tools and workspaces used across various stages of production. In previous works, the mmWave coverage was investigated by collecting measurements for a single cell [4] and for two cells [19]. The measurement campaigns comprise two RUs mounted at opposite ends of the hall, both mechanically oriented towards the center ($\phi_{\text{mech}} = 90^\circ$, $\theta_{\text{mech}} = -7^\circ$), each illuminating one of the main shop floors. The collected data was filtered, spatially gridded with a resolution of 0.25 m, and sorted according to the connected RU, resulting in a total of 2,167 samples. We employ an antenna beambook consisting of 12 beams (arranged in a 6×2 grid), covering an azimuth range of $[-70^\circ, 70^\circ]$ and elevation angles of -3° and -10° . The horizontal and vertical HPBW are 28° and 10° , respectively.

For each receiver position, the proposed mmWave-IndoorDRaGon model is used to predict the measured Reference Signal Received Power (RSRP) for all beams in the codebook assuming $\text{RSS} = \text{RSRP} + 10 \log_{10}(12 \cdot N_{\text{PRB}})$, where N_{PRB} is the number of physical resource blocks. The final prediction is obtained by selecting the maximum RSRP across all beams. The resulting predicted REMs are shown in Fig. 7, alongside the measurement-based ground truth and a full-scenario prediction. The model achieves an RMSE of 6.35 dB and 6.73 dB for RU 1 and RU 2, respectively. Despite the complexity of the industrial environment and the fact that neither the scenario nor its measurements were included during training, the predictions closely match the measured data. This underlines strong generalization capability to previously unseen real-world deployments. Based on this validated

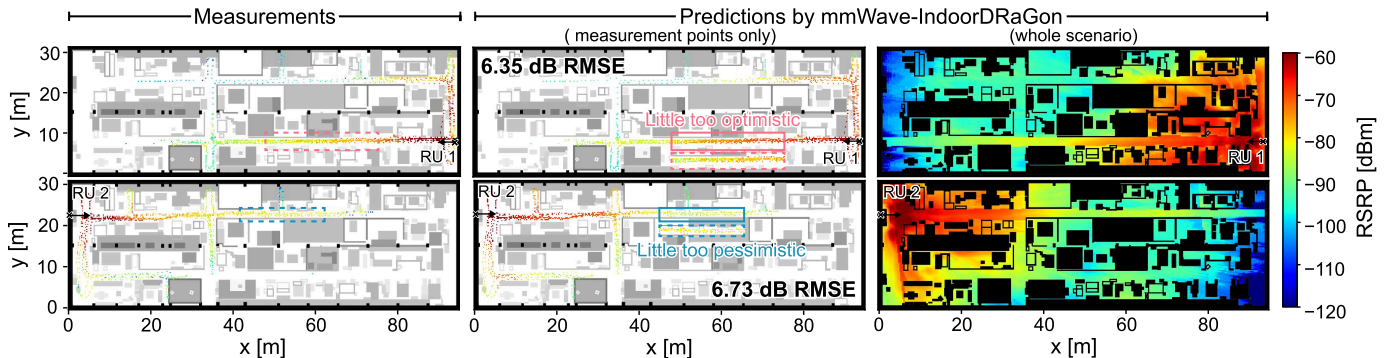


Fig. 7. Comparison of the proposed model with real-world measurements from the *Fraunhofer IPT* factory scenario. The ML-predicted REMs are shown for both RUs together with the measurement-based ground truth and the full-scenario prediction. Note that grayscale levels indicate obstacle heights.

accuracy, the proposed model is further used to infer the RSRP over the entire area, including locations without measurements. Subsequently, scenario exploitation is performed by generating the REM for the complete environment solely based on model inference, without requiring additional measurements.

V. INTERACTIVE SMART FACTORY RAN PLANNER

To demonstrate mmWave-IndoorDRaGon's real-time capability, we developed the *Interactive Smart Factory RAN Planner*, an InF sandbox with live-updating REMs (see Fig. 8). The demonstrator is based on a planar 32-inch monitor that serves as the interactive playground for placing obstacles and RUs in the scenario. The hardware component consists of: (i) the obstacle detection realized using an array of magnetic hall sensors with 1 cm grid resolution, (ii) 3D-printed obstacles of various forms with integrated magnets, (iii) a foil potentiometer for interactive placement of RUs, and (iv) an integrated LED strip indicating active RU positions.

The raw boolean values of the sensor array are transformed into a 3D model (assuming a scenario size of 35 m $\times$ 20 m), which, together with the RU poses and their beam pattern, forms the basis for the feature generation (cf. Sec. III-B). The demonstrator computer is equipped with an *NVIDIA GeForce RTX 5080 GPU*, an *AMD Ryzen 9 9900X processor*, and 64 GB RAM. With these settings, generating a REM for a single RU in a densely cluttered setting takes 1.27 s, considering 3,500 receiver positions and 16 beams. The interested reader is referred to the demo video (cf. QR-code in Fig. 8), which shows the real-time usability of the developed propagation model.

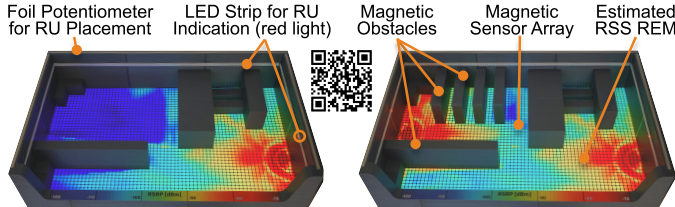


Fig. 8. Illustration of the demonstrator's interactive environment

VI. CONCLUSIONS AND OUTLOOK

In this work, we presented an extension of the ML-based sub-6GHz propagation model [15] feature set to support mmWave characteristics. We generated a large dataset of approximately 1.5 billion synthetic samples across various industrial indoor environments and beam patterns and used it to train an ANN for mmWave path loss prediction. The proposed model outperforms traditional models by 10 dB in RMSE and accurately replicates both ray tracing results and measurement data while reducing computation time by a factor of over 1,000. This enables fast, scalable, and interactive network planning across multiple beam configurations. To demonstrate this, we developed an interactive smart factory demonstrator where users can place obstacles and RUs in real time and obtain live-updated REMs.

In future work, we aim to fine-tune our model using diverse

real-world measurements to enhance its accuracy and generalizability. Additionally, we will investigate the impact of different hyperparameter settings and explore alternative ML architectures to further improve prediction accuracy. We further aim to apply the proposed model to practical radio network planning in industrial environments, as briefly discussed in [20].

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