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Toward Robot-based Validation of Simulated 5G Coverage Maps in an Industrial Context

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Abstract. The deployment of 5G networks in complex industrial environments poses significant challenges, including extensive coverage requirements, intricate physical layouts, and costly infrastructure deployment. Accurate and cost-effective planning is crucial, prompting the use of high-fidelity ray-tracing-based wireless simulators, such as NVIDIA's Sionna RT, to generate predictive coverage maps before physical installation. However, validating these simulations remains critical for practical use. This study presents a comprehensive framework employing autonomous mobile robots integrated with Simultaneous Localization and Mapping (SLAM) capabilities for validating simulated 5G coverage maps. Two distinct scenarios—an indoor research lab and an outdoor urban environment—were modeled in 3D and simulated using Sionna RT, producing Received Signal Strength Indicator (RSSI)-based coverage maps. Empirical validation was conducted with an autonomous robot equipped with a Teltonika RUTX50 5G router, capturing real-world RSSI, Reference Signal Received Quality (RSRQ), and Signal-to-Interference-plus-Noise Ratio (SINR) data, alongside accurate spatial referencing from SLAM. Preliminary results demonstrate alignment between simulated and measured coverage maps, underscoring the viability of robot-based approaches for systematic Radio Frequency (RF) mapping and simulator validation.

Keywords: Mobile Robotics · Wireless Coverage · Simulation.

1 Introduction

The rapid growth of the Internet of Things (IoT) and Industry 4.0 is driving an unprecedented increase in connected devices, with an estimated 42 billion IoT devices by 2025 [1], thereby enabling the emergence of the Industrial IoT (IIoT). These smart industrial applications rely heavily on 5G networks to deliver the massive connectivity, ultra-low latency, and high reliability required for machine-to-machine communication. While 5G offers advanced wireless features—such as massive Multiple-Input Multiple-Output (MIMO) networks combined with efficient beamforming and mm-wave communications, leading to increased spectral

efficiency, as well as smaller cells for improved resource management [22], deploying IoT in complex industrial environments remains challenging due to strict energy constraints on battery-powered nodes, extensive coverage demands, and high infrastructure and operational costs [8]. These challenges are further intensified in large industrial sites often cluttered with obstacles like machinery, walls, and RF-unfriendly materials. Dense and precise infrastructure deployments may therefore be necessary, further increasing deployment and maintenance expenses [22,3].

To optimize deployment costs, accurate simulation tools building digital twins and allowing virtual replication of environment and networks conditions, have become essential for network design and fine-tuning prior to real-world implementation [21,16,24,12]. High-fidelity wireless simulators based on *ray-tracing* become hence the backbone of these digital twins, accurately mirroring site-specific radio propagation characteristics by accounting for reflection, diffraction, and scattering in a 3D defined space [10,6]. Nonetheless, a critical challenge remains: ensuring simulation results that closely match real-world performance, while remaining tractable. Indeed, simplistic models that can be easily computed and implemented, risk diverging from real conditions due to insufficiently accurate representation of complex environmental effects. Manual RF measurements, however, are inherently impractical in large, cluttered industrial spaces due to their time-consuming nature, susceptibility to human error and inconsistency in data collection. To overcome these limitations and efficiently acquire robust ground-truth data, autonomous mobile robots equipped with precise localization and mapping technologies, such as SLAM, present an ideal solution. Robots not only ensure systematic, repeatable, and geo-referenced measurements of critical metrics including RSSI, SINR, and RSRQ, but can also be repurposed from existing robotic fleets within industrial environments, further reducing costs and logistical complexity.

In this context, this paper introduces a robot-based validation methodology, bridging simulation outputs and real-world performance data. The subsequent sections detail our experimental approach and results, demonstrating the utility of robots in ensuring the fidelity and accuracy of simulated 5G coverage maps in IIoT contexts.

2 Ray-tracing based wireless simulators

In this section, we present different network simulators exploiting ray-tracing as well as a comparison between them with our IIoT application insight.

Since ray-tracing computes RF signal paths within a given environment by modeling the interactions with objects, e.g. reflections off buildings or diffraction around corners, it outperforms the accuracy of conventional stochastic channel-based models, especially in radio environments with spatially defined elements and material properties [4,6]. The trade-off, however, is computational complexity: indeed, the higher accuracy of ray-tracing comes at the expense of heavy computation, especially when the number of reflections, diffraction edges, and

scatterers increases [14]. Nonetheless, ray-tracing is the gold standard for 5G network planning especially in cluttered venues like factories and cities, as it explicitly captures multipath and blockage effects that define coverage, the latter being often missed by empirical models. Recent research also explores differentiable ray tracing [10] for optimizing antenna placement or beamforming via gradient-based methods, underlining the ongoing importance of ray-based modeling in beyond-5G networks.

2.1 Considered ray-tracing-based simulators and related strengths

While several wireless network simulators and propagation modeling tools have been proposed both in industry and academia, we here focus on three ray-tracing-based simulators relevant to 5G coverage map estimation, namely NVIDIA Sionna RT, QuaDRiGa, and Remcom Wireless InSite.

Sionna is a recently introduced open-source library for link-level simulation, designed with 5G/6G physical layer research in mind [10]. It features native GPU acceleration and integrates a ray-tracing engine, namely Sionna RT, for environment-specific channel modeling [9]. Notably, it follows the 3GPP 5G New Radio standard and allows rendering of coverage maps for given scenes, facilitating its use as a wireless digital twin tool [12].

QuaDRiGa (QUAsi Deterministic RadIo channel GenerAtor), on the other hand, is a widely used geometry-based stochastic channel simulator originally developed by Fraunhofer HHI [11]. It generates realistic channel impulse responses for multi-cell 5G scenarios, urban macro, micro and indoor factory environments (following the 3GPP TR 38.901), by including 3D spatial consistency and temporal evolution and combines deterministic clusters with randomness to mimic measured channel statistics [11,2]. However, QuaDRiGa does not perform full ray-tracing with exact site geometry; instead, it statistically approximates propagation, which trades off some site-specific accuracy vs. speed and flexibility.

Wireless InSite (WI) by Remcom In contrast, this solution is a commercial high-fidelity ray-tracing simulator that has been a benchmark in propagation prediction for many years [23]. It provides a full 3D electromagnetic ray-optical engine, including advanced models for reflection, transmission through walls, diffraction, and scattering, and has been validated extensively against measurements [17]. WI supports a range of wireless standards (from cellular to WiFi) and offers GPU-accelerated modules (the X3D model) for faster runtime [20].

2.2 Comparison of the considered simulators

Each of the presented simulators presents strengths and limitations in terms of accuracy, computational efficiency, scalability, and real-world applicability.

Accuracy - The two deterministic fine-grain ray-tracing considered simulators, namely Sionna RT and WI, that explicitly model individual propagation paths, generally yield higher accuracy in complex environments, especially in non-line-of-sight scenarios relying heavily on multi-path reflection and scattering, compared to stochastic model-based simulators such as QuaDRiGa. In contrast, QuaDRiGa, as a geometry-based stochastic model, may smooth over such fine-grained effects. As a result, its prediction reflects average expected behavior but not the exact site geometry [11].

Computational efficiency and scalability - Since QuaDRiGa leverages pre-defined statistical models instead of performing per-ray geometric calculations, it is usually faster and more scalable compared to Sionna RT and WI. Indeed, obtaining a high resolution coverage map with WI can take up to hours for a large city scene; the latter can be significantly reduced with Sionna RT thanks to parallel GPU computation [10]. Moreover, if one needs to simulate very large areas or many base stations, a hybrid approach blending the statistical models of QuaDRiGa to obtain a coarse resolution at the network level and the fine resolution ray-tracing capabilities of Sionna RT or WI for a fine resolution of a specific area, might be required [11].

Real-World Applicability - All three considered simulators have already been used to support research activities on 5G and future generations of wireless networks, as well as on network deployment studies. On the one hand, since WI and QuaDRiGa are not as new simulators as Sionna RT, they have been more widely used both in industry to, e.g., identifying coverage holes in urban microcells or optimizing indoor small cell placement [6] and in academia to, e.g. evaluate beamforming and scheduling algorithm under various channel conditions. On the other hand, Sionna RT being an open-source and highly configurable simulator, is quite attractive for academic research and emerging applications like digital twins. Moreover, recent work has compared Sionna’s RT output with real-world data to gauge its fidelity [9], proving its robustness and accuracy.

In summary, ray-tracing-based simulators provide the necessary high-fidelity modeling for 5G coverage mapping in IIoT scenarios, but their performance must be balanced against complexity. For the remainder of this paper, we focus on Sionna RT, given its high accuracy in several real-world applications, including dense networks and/or large areas under study. We also propose a setup to compare Sionna-RT-based simulated measurements against real-world data collected by robot embedding SLAM techniques.

3 Simulated versus Real-World 5G covering map

The primary objective of this study is to establish a comprehensive framework for generating 5G coverage maps using two distinct methodologies. The first approach involves the development of a digital twin environment, enabling the

simulation of coverage maps in a virtual setting [15,19]. The second method entails the acquisition of empirical data collected from real-world environments using appropriate sensing devices [25]. Fig. 1 illustrate the algorithms underlying these two methodologies.

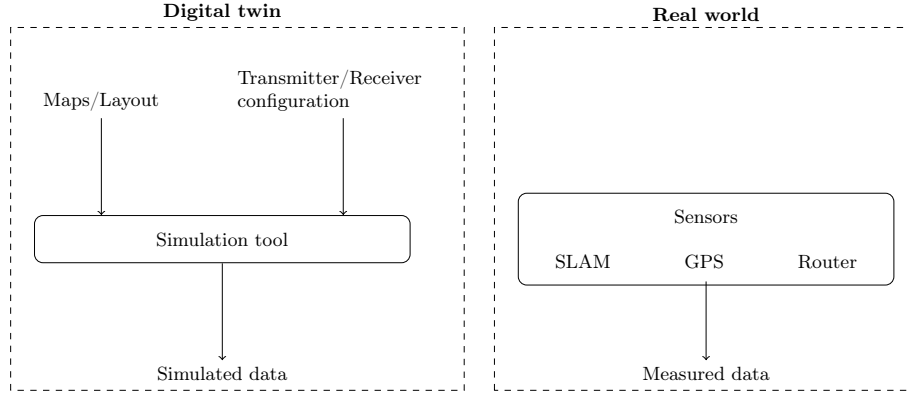


Fig. 1: Digital twin framework (Simulation-based methodology) versus Real world framework (Measurement-based methodology) for generating 5G coverage map

Digital twin framework - Under this framework, the 5G coverage maps, that are predicted by a digital simulator, are expected to be as close as possible to the coverage maps measured in the real world. To that end, the simulations need to be fed with a coherent model of the real world that includes, on one hand, the model of the physical environment alongside with the buildings information (walls, machines...), and on the other hand, the configuration of the communication devices.

Real world framework - In this framework, real data are measured and integrated to build a coverage map that is accurately overlaid onto a 2D spatial representation of the environment under study. The main difficulty of this framework is to accurately locate the performed data collection. In our proposed framework, we propose to exploit SLAM techniques [5], that allow to jointly build a physical map of the environment under study and to locate each measurement, by integrating sensor data such as odometry and obstacles detection. Note that Global Positioning System (GPS), which is not necessary available in industrial indoor setups, can be also added to the SLAM process to improve the localization accuracy, but is not mandatory.

Simulated/Measured data - For comparison reason, simulated and measured covering maps should be similar in terms of represented physical data and precision. We adopt the RSSI as the core metric for coverage comparison due to

its simplicity and standardized definition as the total received signal power (including noise and interference) [18]. RSSI is straight forward to obtain from commercial 5G equipment (e.g., as basic signal strength reading) and can be directly produced by ray-tracing simulations as a sum of received power, ensuring consistency between measured and simulated maps [7].

The subsequent section of this paper details the specific scenarios and procedures employed to achieve and evaluate these results. Ultimately, this research aims to obtain comparable insights by assessing the correlation and consistency between simulated coverage predictions and empirical measurements obtained from physical deployments.

4 Experimental results

In the remainder, we consider two scenarios for evaluation: an indoor research lab environment and an outdoor urban environment. For each scenario, we created a detailed simulation model and ran it with Sionna RT.

4.1 Sionna-based simulated outdoor scenario

The outdoor scenario under study covers several buildings around our research lab located in Douai, France. The different buildings footprints and heights are obtained thanks to OpenStreetMap, see Fig. 2a, and imported into Blender, via the Blender-OSM plugin, to generate a 3D model of the city streets and buildings, see Fig. 2b, similarly as in DITTO’s pipeline [12]. The resulting 3D model is then fed to Sionna RT in a suitable format, namely via the scene description triangulated meshes along with an .xml file containing the material characteristics of each building.

The considered transmitter is a 5G base station positioned on a rooftop at approximately 20 m height, with an antenna pattern following the 3GPP TR 38.901 standard with a vertical polarization. The carrier frequency is set to 3.5 GHz, which is a typical 5G mid-band, and the transmitter power to 30 dBm.

By rasterizing the scene with Sionna RT, we compute a coverage map depicted in Fig. 2c, in terms of RSSI at a pedestrian level of 1.5 m. For the receiver, we used a single isometric pattern antenna with vertical polarization.

4.2 Sionna-based simulated indoor scenario

The indoor scenario under study consists in two classrooms and one corridor of our Research lab in Douai, France. Using architectural floor plans and on-site measurements consolidated via SLAM, see Fig. 3a, we created a 3D model depicted in Fig. 3b that includes major features, such as the walls, along with their thickness and material, doors, glass windows, laboratory benches, metallic cabinets, and even some large machines that are modeled to scale. This model is then fed in Sionna RT to compute the coverage map in terms of RSSI depicted

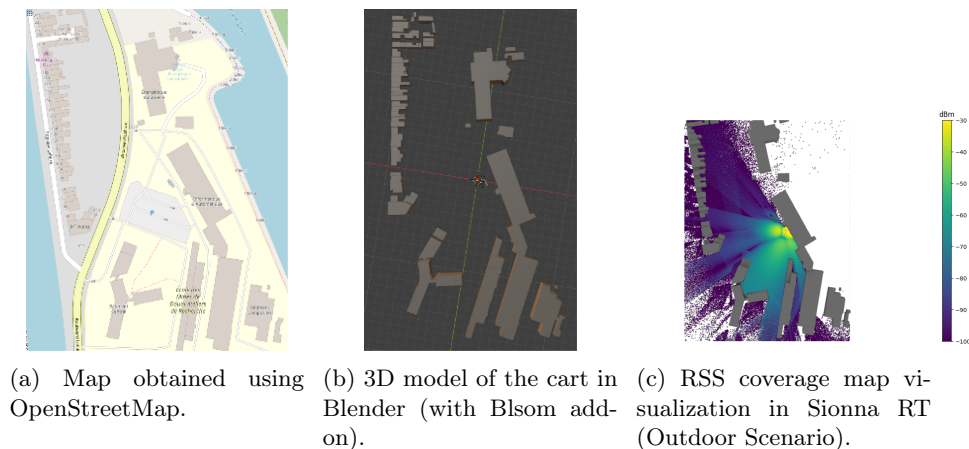


Fig. 2: Simulation process workflow.

in Fig. 3c, similarly as in the outdoor scenario. Note that we here consider a 5G small-cell transmitter following the 3GPP TR 38.901 pattern with a vertical polarization, a carrier frequency of 3.8 GHz and a transmit power of 33 dBm that is located on a desk at 1 m height in one of the classroom.

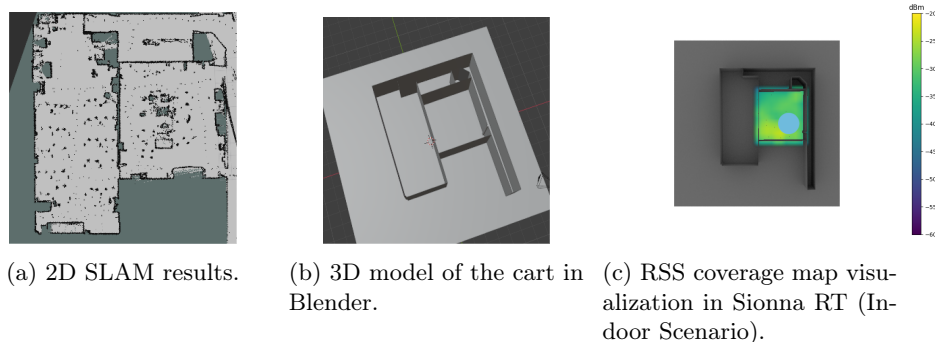


Fig. 3: Simulation process workflow.

4.3 Mobile Robot for Real-World Data Collection

To obtain ground-truth measurements of 5G signal coverage, we deployed an autonomous mobile robot equipped with SLAM capabilities.

As our future objective is to assess the accuracy of Sionna RT, we propose to derive a coverage map from real data that are collected thanks to a Bibus robot, see Fig. 4a, and consider the same indoor scenario as previously presented. More precisely, we installed in one of the classrooms a 4×4 MIMO 5G antenna of gain

of 12.8 ± 0.5 dBi. We further set its carrier frequency to 3.8 GHz and consider a transmission power of 33 dBm.

The robot itself embeds LIDARs to perform SLAM, as well as a *Teltonika RUTX50 5G* router configured in receiver mode to sample network signals and collect three RF-based measurements, namely RSSI, RSRQ and SINR. More precisely, as the robot navigates through the environment, it collects RF-based indicators thanks to the router, along with the timestamp and its current position obtained via SLAM. Hence, this setup effectively creates a geo-referenced signal heatmap of the environment.

The data collection was done in a live 5G network environment for indoor tests. The robot could operate untethered, streaming its measurements to a connected computer in real time. Such an automated mapping approach is aligned with prior efforts in RF mapping using robots [13]. The measured values are transmitted via a message through a topic that contains the adequate positions as well. Upon receiving RSSI data, the node records each RSSI alongside the 2D coordinate of the measurement point

into an internal list. Periodically, the node triggers an interpolation process using the collected data points. It first defines a spatial grid covering the surveyed area based on specified cell sizes. The RSSI values are interpolated over this grid using cubic interpolation, thus creating a continuous spatial distribution of RSSI levels. Following interpolation, visual markers are generated representing each cell in the grid. Ultimately, the interpolation process ensures a smooth RSSI distribution representation, while marker generation translates this data into a visual heatmap accessible in RViz, see Fig. 4b.

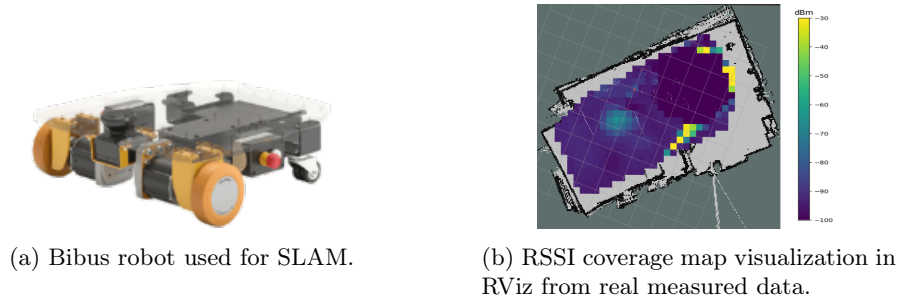


Fig. 4: Simulation process overview.

Several factors may affect the accuracy of the proposed validation methodology. SLAM-based localization can introduce positional errors which impact signal geo-referencing; future work will explore higher-precision alternatives like RTK-GPS or visual-inertial SLAM. Additionally, the limited number of measurement points and reliance on interpolation may cause inaccuracies in RSSI maps; this will be addressed by increasing sampling density and adopting more advanced interpolation, e.g., Gaussian processes.

5 Conclusion and future works

This research introduced a methodology for validating ray-tracing-based 5G coverage simulations using mobile robots equipped with SLAM for spatial referencing. Initial experiments in both indoor and outdoor environments indicate promising alignment between simulation outputs from the Sionna RT simulator and empirical measurements collected by a robot-mounted 5G sensing device. While these preliminary results highlight the potential effectiveness of the proposed methodology, further work is essential. Indeed, with a complete benchmark based on an accurate model of a real-world scenario, it will be possible to clearly compare simulated and measured data.

Future efforts will include detailed comparative analyses with other simulators, such as QuaDRiGa and Wireless InSite, as well as a broader evaluation of RF parameters. This future research aims to strengthen the accuracy, reliability, and applicability of simulation-based 5G network planning in complex industrial environments.

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