Performance Assessment of 5G Non-Public Networks for Industrial Applications in Factory and Offshore Settings for Digital Twin Creation

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Abstract—**This paper presents a comprehensive assessment of 5G SA networks deployed in a factory setting and an offshore wind farm at the North Sea. The study focuses on critical use cases such as teleoperated Automatic Guided Vehicles (AGVs) in factories and teleoperated Unmanned Surface Vessels (USVs) in offshore settings. Key performance indicators (KPIs) such as network latency, data rates, and signal quality were measured using advanced network evaluation tools. The results demonstrate that 5G SA networks can meet the stringent requirements of industrial applications. The paper also discusses the challenges of deploying 5G networks in metal-dense factories and dynamic offshore environments, highlighting the importance of practical evaluations in these settings. Furthermore, the study introduces a machine learning-driven framework for signal and Quality of Service (QoS) prediction, leveraging diverse datasets collected in the factory environment. This framework aims to optimize network performance and lays the groundwork for creating a digital twin for factory communication systems.**

I. INTRODUCTION

The fifth generation of mobile networks (5G) introduces a new network architecture, features, and functionalities that promise a significant performance boost over its predecessor, 4G. It targets various verticals, including Industry 4.0, automotive, and healthcare. 5G further pushes the boundaries of peak throughput (20 Gbps downlink, 10 Gbps uplink), primarily through innovations at the physical layer, such as mmWave frequency bands, beamforming, and MIMO technology. For critical and latency-sensitive applications, 5G has enhanced its focus on reliability and latency, specifically targeting Ultra-Reliable Low-Latency Communications (URLLC) use cases. These performance advancements position 5G as a promising technology capable of meeting the stringent and demanding requirements of industrial applications, such as teleoperation and closed-loop control systems [1].

In the Ericsson mobility report [2], it is stated that private 5G networks provide a number of advantages over traditional wireless networks for the manufacturing industry, such as faster decision making and productivity, improved communication for real-time applications, enhanced worker safety and communication and security. As a result, manufacturers are turning more and more to private 5G cellular networks for their challenging use cases.

Non-public networks (NPN) using 5G technology have the potential to meet these high requirements but need to be proven in their applicability in offshore and industrial environments. Recent experiments with 5G networks indicate substantial advantages over current wireless technologies, primarily demonstrated in urban settings due to their emphasis on consumer applications [3]. However, deploying reliable cellular networks in industrial and offshore environments presents significantly greater challenges. These challenges arise from (i) the numerous multipath reflections and angles in metal-dense factories, (ii) the dynamic and unpredictable meteorological conditions at sea. The authors from [4] presented 5G performance measurements conducted in realistic industrial production environments with realistic deployment settings. They concluded that the requirements for very low latencies can be achieved with high reliability guarantees, as required in some of the most stringent industrial IoT applications.

In [5], 5GACIA highlights that industrial environments vary significantly, from discrete manufacturing to process automation, each with distinct requirements. Practical evaluations in these varied settings are crucial to understand the performance and reliability of NPN 5G networks and to determine the most suitable solutions for specific industrial scenarios.

In a typical 5G network, there are thousands of configuration parameters per site. These parameters, often referred to as Configuration and Optimization Parameters (COPs), encompass both hard and soft settings that influence various aspects of network performance, including mobility management, quality of service, and resource allocation. The configurations of 5G setups and industrial environments can vary significantly, as they aim to support various critical use cases with diverse performance requirements. Therefore, it is essential to validate the performance of NPN 5G network deployments under realistic conditions to provide network operators with valuable performance insights and enable them to configure the COPs accordingly. Consequently, there is a clear necessity for more practical evaluations of NPN 5G networks, not only within factory settings but also in offshore environments.

In industrial environments, efficient wireless network operation is critical. As factories adopt advanced technologies like Industrial Internet of Things (IIoT) and Industry 4.0, the reliability and performance of wireless communication systems become essential for seamless connectivity and data-driven operations to support the increasing demands of digitalization, automation and real-time decision-making [6][7]. However, the complexity of these environments, with by dynamic mobility, physical obstructions, and varying network conditions, poses significant challenges to ensure consistent quality of service (QoS) [8]. This paper addresses these challenges by developing a machine learning-driven framework for QoS prediction, using diverse datasets collected in a factory setting. By integrating spatial, temporal, and environmental factors into predictive models, it provides actionable insights for optimizing network performance and lays the groundwork for the creation of a digital twin, enabling real-time simulation and optimization of factory communication systems.

The remaining of the paper is organized as follows. Section II overviews the ValArch5G project. Section III outlines the network requirements, Section IV assesses the performance of the deployed networks, Section V presents the developed digital twin, and Section VI concludes the paper.

II. THE VALARCH5G PROJECT

The ValArch5G project, a Flemish initiative funded by VLAIO, aims to assess the advantages of 5G over existing wireless technologies in industrial applications that require time-critical control. This includes scenarios such as teleoperated maritime drone operations and the teleoperation of Automatic Guided Vehicles (AGVs) in factory settings.

A. Use Cases

In industrial settings, for the teleoperation of AGVs, a remote operator receives images of multiple cameras mounted on an AGV. The teleoperator uses a simple remote interface to actuate the AGV. In-time and reliable reception of the multiple camera feeds is essential to operate the AGV correctly. Moreover, most unmanned surface vessel (USV) operations require a pilot to maintain line-of-sight control. A critical technical challenge in realizing these teleoperated USV applications is ensuring fast and reliable communication between the maritime drones and the ground control station.

One of the project's objectives is to evaluate the performance of a 5G network under more demanding conditions, such as in industrial environments or offshore applications. This initiative aims to expedite the development and deployment of teleoperated vehicles in various applications.

B. 5G SA network deployment

Two measurement campaigns have been conducted in two diverse environments: (1) factory setting at a Bekaert factory [1] where an indoor private 5G SA network of the private mobile operator eBO [2] was deployed, consisting of Nokia Airscale baseband, 4T4R radio unit and an omnidirctional antenna operating in the N77 band (40 MHz TDD: 3880 MHz-3920 MHz) with DDDSU TDD frame structure and 34.5 dBm TX power; (2) Belwind Offshore Wind Farm environment where an outdoor 5G SA network of eBO consisting of a Nokia Airscale baseband, 2T2R radio unit and a Commscope RR-65B-R2 antenna operating in the N20 band (10 MHz FDD: 811-821 MHz DL / 852-862 MHz UL) and 44.6 dBm, was installed on an Offshore Substation (OSS) at the North Sea. Both 5G deployments were 3GPP R16 compliant and used the 5G SA option 2 architecture, consisting of the 5G core (5GC) and a 5G gNB.

In the factory, the gNB was placed in an open manufacturing hall where a lot of industrial equipment was present, such as machines to produce fine steel wire for transmission, transport, and hoist applications as shown in Figure 1. On the gNB, one cell was created using an omnidirectional antenna. An outdoor GNSS antenna was connected for time synchronization.

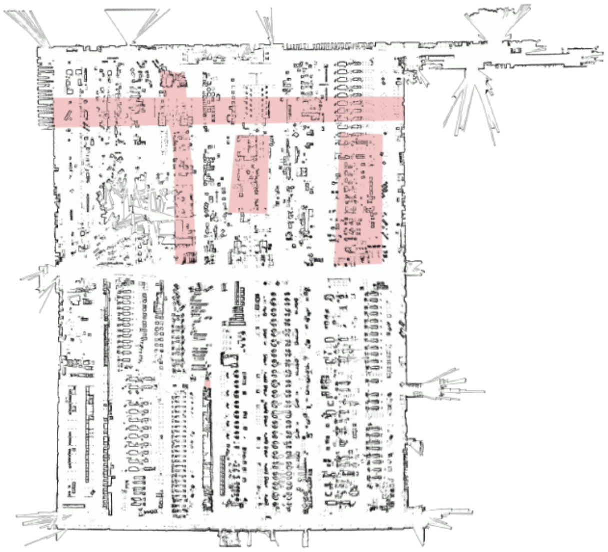

Fig. 1: SLAM generated layout of the factory hall

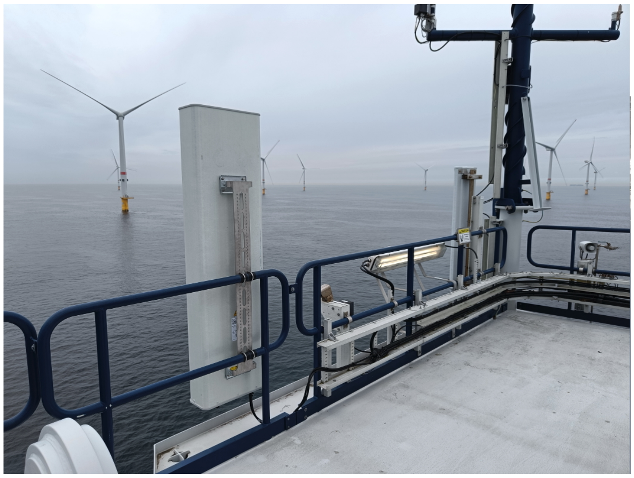

Fig. 2: 5G offshore installation

Regarding the offshore environment, the 5G setup was installed at an OSS in a windmill park in the North Sea, where an outdoor 4 port sector antenna was installed, pointing to the West, as shown in Figure 2 and Figure 3. The coverage area shown in Figure 3 is a theoretical estimate. The red rectangle shows the test area that the authors focused on to collect measurements during the test campaign. Outside the test area, the signal seemed to be substantially low, resulting in poor or no data connection.

III. NETWORK REQUIREMENTS

In order to carefully assess the performance of the deployed 5G networks, a good understanding of the targeted use cases is essential. For the defined use cases, several network requirements have been specified to allow safe and real-time

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[1] https://www.bekaert.com/

[2] https://www.ebo-enterprises.com/

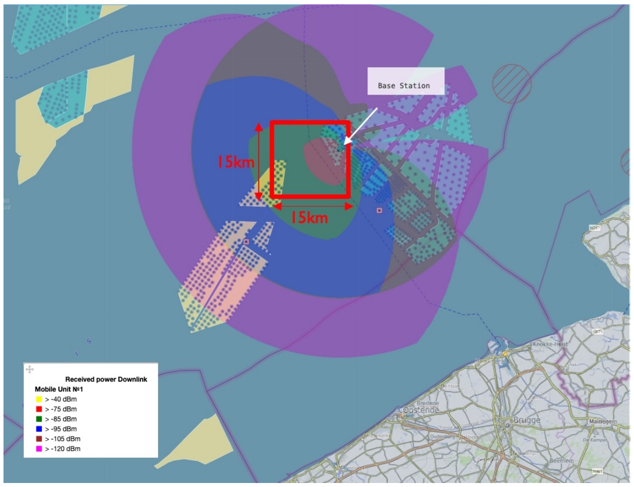

Fig. 3: 5G offshore test area

KPI	Teleoperated AGV (factory)	Teleoperated USV (offshore)
Network latency	$\leq 10ms$	$\leq 50ms$
Datarate uplink	40Mbps	8Mbps
Datarate downlink	124Kbps	500Kbps
Working distance	200m	1km
Speed	1m/s	5m/s

TABLE I: Use Case requirements

operations (Table I).

IV. PERFORMANCE ASSESSMENT OF THE 5G SA NETWORKS

By using advanced network evaluation tools and dedicated hardware, a detailed 5G network performance assessment was done both in the factory environment and on the windmill farm. Several KPIs (Table II) were measured using open source measurement and in-house developed tools. Ping was used to measure round trip time (RTT) latency and IPerf to measure the maximum uplink and downlink throughput for UDP and TCP data streams on the network between the UE and the server, located at the core network. To evaluate the coverage of the private 5G SA networks, the RSRP, RSRQ, and SINR values were collected transparently from the UE using AT serial commands.

A. *Experiment setup*

At both test locations, commercial private 5G SA networks were deployed for the purpose of the project. To assess the feasibility of supporting the defined use cases, end-to-end ground truth network measurements were conducted between an end-device that connected to the 5G network and a Virtual Machine (VM) at the server side. The VM was installed directly at the core network to not create any additional delay, serving as an end-point for round trip time measurements and running an IPerf server for end-to-end throughput measurements.

At the client side, a Quectel RM502Q 5G modem with a SIM card was connected to an embedded PC running Ubuntu, on which several testing tools were installed. A separate 4G/5G router was attached to the PC that was equipped with a SIM card of a public network operator to allow remote connectivity to the system in mobile conditions. Measurement and monitoring data were both logged locally on the device and, if possible, in real-time pushed to a remote database via the public 4G/5G backhaul link. Real-time data was visualized via a Grafana dashboard. Figure 4 shows the two different portable UE cases that have been designed in the context of the project for (a) the factory and (b) the offshore 5G setup evaluation [9].

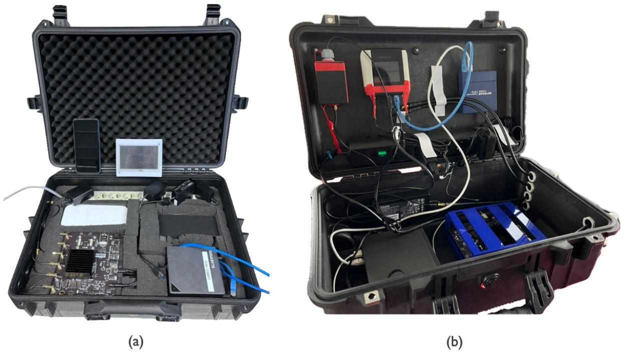

Fig. 4: 5G UE used for (a) the factory and (b) the offshore setup evaluation

Regarding the factory environment, the client device was mounted on a MIR200 robot that was able to drive around the factory hall via teleoperation. The robot was equipped with multiple sensors (laser scanners, depth camera, IMU), providing navigation and environment awareness features. An occupancy grid map was generated for the first time by manually navigating the robot around the entire site where it would operate. During the mapping process, the sensors detected surrounding obstacles, and the data was fused to create a map of the site using Simultaneous Localization and Mapping (SLAM) techniques [10]. The generated map, as shown in Figure 1, is used for subsequent network performance measurements. While moving, the robot published its position to the 5G measurement device at 10 Hz. Further integration was performed to allow the robot to trigger network performance tests at predefined locations in the factory hall.

For the offshore measurements, the client equipment, as described above, was installed in a shielded enclosure that was able to withstand the harsh environmental conditions in the North Sea. The box was mounted on the roof of a vessel used for crew transfer to the windmill farm. Peplink Maritime 20G antennas were installed on the mast and connected via RF cabling. Two antennas were placed for the 5G UE used to test the 5G private test network. An antenna was used for 4G/5G backhauling through the commercial mobile network with an integrated GNSS antenna that was connected to the GNSS device to track the position of the vessel.

B. *Methodology*

During several test campaigns, several KPIs were measured. In the factory setting, the MIR200 was programmed to drive to predefined locations within the factory hall. At each location, the network connection was verified using some diagnostic tool. Upon successful verification, a series of tests were initiated to evaluate the performance of the 5G network. Additionaly, a test was conducted where the signal strength information and UDP DL were continuously monitored from the 5G UE while the MIR200 navigated throughout the factory hall. For the offshore measurement campaign, a similar

KPI	Duration	Tool	Packet size (bytes)
Round trip time (ms)	30s	Ping	56
RSRP, RSRQ, SINR	Continuous	AT commmands	n/a
Max. TCP downlink (Mbps)	30s	IPerf	1300
Max. TCP uplink (Mbps)	30s	IPerf	1300
Max. UDP downlnk (Mbps)	30s	IPerf	1300
Max. UDP uplink (Mbps)	30s	IPerf	1300

TABLE II: KPI test overview

approach was taken, but in that case the vessel was sailing along some trajectories in the test area, for which the tests ran in a continuous loop. Table II provides a summary of the tests in each iteration. Data was reported with a 1s interval.

C. Factory results

Figure 5 shows the heat-map of the collected Reference Signal Received Power (RSRP) values collected by the UE from the eBO private 5G SA deployment at the Bekaert factory. The values were collected while the MIR200 robot with the integrated UE was following a predefined trajectory along the factory corridors. The color gradient in the heatmap ranges from green (representing stronger RSRP values around -75 dBm) to red (indicating weaker RSRP values near -135 dBm). The base station and the antenna are deployed in the middle and lower section of the factory. The area surrounding the base station and antenna exhibits the strongest signal strength, with RSRP values diminishing as the UE moves farther away, particularly towards the upper sections of the trajectory. This pattern reflects the expected signal attenuation due to distance and potential environmental obstructions within the factory. In the upper left and right corners of the factory, the signal quality becomes very weak, resulting in the UE disconnecting from the 5G network. Consequently, no data points were recorded in these areas of the map. This visualization highlights the spatial distribution of signal strength, offering valuable insights for optimizing network deployment. It can aid in enhancing coverage and performance through improved network planning and densification in areas with limited coverage.

Figure 6 presents the empirical Cumulative Distribution Function (eCDF) of throughput for UDP and TCP protocols in both downlink (DL) and uplink (UL) traffic directions from the factory 5G deployment. The UDP DL achieves the highest performance, with throughput values exceeding 900 Mbit/s, while the 90th percentile is 400 Mbit/s. The TCP DL exhibits significantly lower performance, with throughput values mostly below 200 Mbit/s. This reduced performance is attributed to a specific network configuration used during the factory deployment, which impacted TCP DL efficiency. Both UDP UL and TCP UL throughput graphs exhibit a similar trend, with TCP slightly outperforming UDP. This is likely due to the characteristics of the TCP protocol, which ensures more reliable data delivery through mechanisms such as acknowledgments and retransmissions.

D. Offshore results

Figure 7 illustrates the heat-map of RSRP measurements from the private 5G deployment of eBO in the considered offshore environment at the North Sea. The heat-map shows RSRP data over all the test days, while a vessel from GEOxyz [3] was navigating inside the predefined area of interest as shown in Figure 3. As the BS is mounted at an OSS within a windmill park, signal distribution is significantly influenced. Stronger RSRP values (ranging from -80 to -60 dBm, shown in green) are observed near the base station, with signal strength diminishing as the vessel moves farther away, reaching values below -110 dBm (depicted in orange and red). The east & south-east side of the base station is heavily occupied by windmills, which likely obstruct the signal and contribute to weaker connectivity in those areas. Furthermore, the antenna was directed towards the South-West. This map highlights the network's coverage performance and the impact of structural obstructions, providing valuable insights for optimizing the deployment in offshore environments through improved network planning.

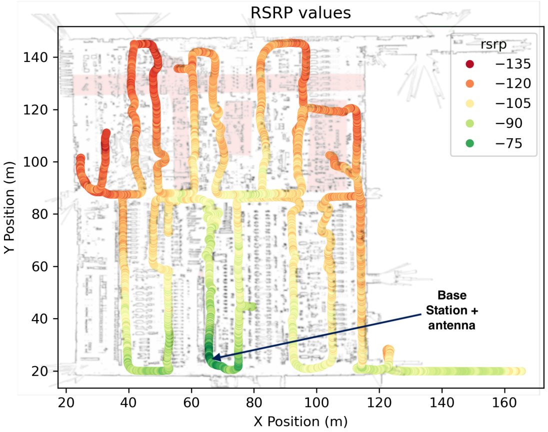

Fig. 5: 5G factory RSRP measurements

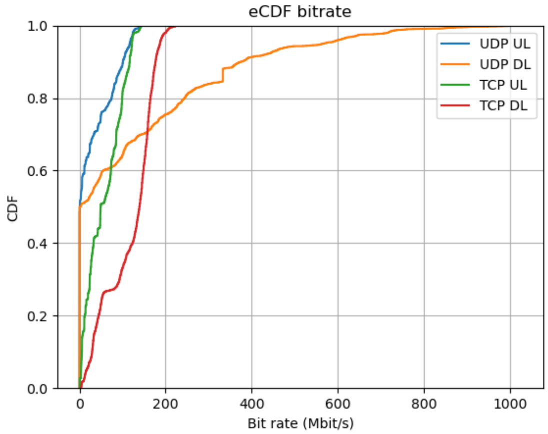

Fig. 6: 5G factory UDP and TCP measurements

The graphs shown in Figure 8 present the eCDF of throughput for both UDP and TCP protocols in UL and DL directions during the offshore 5G network evaluation. A notable observation is that UDP and TCP results follow a similar trend for DL and UL, respectively. For the downlink, both UDP DL and TCP DL demonstrate higher throughput, with the majority of values reaching up to 40 Mbit/s, reflecting the network's performance in delivering teleoperation commands to the vessel. Similarly, in the uplink, both UDP UL and TCP UL can reach throughput values of around 20–30 Mbit/s at

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[3] https://www.geoxyz.eu/en

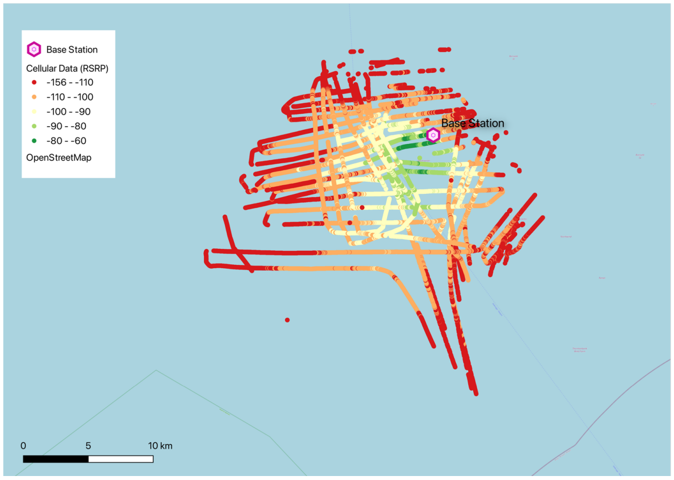

Fig. 7: 5G offshore RSRP measurements

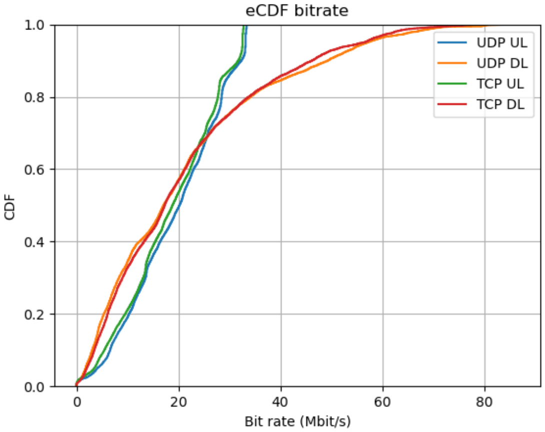

Fig. 8: 5G offshore UDP and TCP measurements

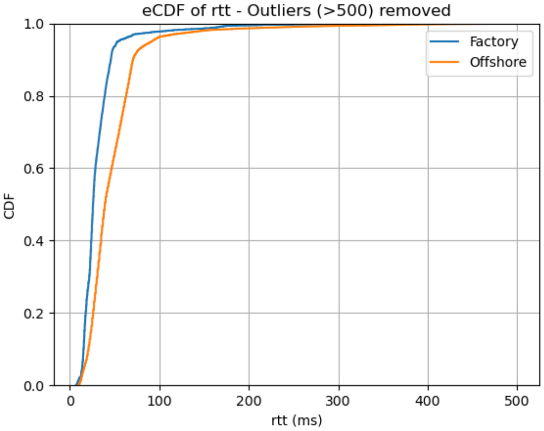

Fig. 9: CDF of RTT measurements for both the factory and the offshore environments

+-50% of the measured locations, which have been proven sufficient for transmitting the required video feed from the vessel towards the teleoperation center, realizing the targeted use-cases.

Figure 9 displays the eCDF of Round-Trip Time (RTT) values for both the factory and offshore environments. Outlier values exceeding 500ms have been excluded for better visualization. Both graphs exhibit a similar trend; however, the factory deployment shows slightly better performance compared to the offshore deployment. Specifically, the median RTT for the private 5G network in the factory is 25ms, while the offshore network has a higher median RTT of 39ms. It is important to note that the two deployments differ in terms of network equipment and environmental conditions, making a direct one-to-one comparison of the graphs impractical.

V. DIGITAL TWIN

Based on the experimental results described in the previous sections, a comprehensive Quality of Service (QoS) mapping framework within the Bekaert factory setting is developed and validated. The primary objective is to model and predict wireless signal metrics and QoS parameters using machine learning techniques and diverse datasets collected under varying conditions. These efforts aim to enhance the understanding and optimization of wireless communication in industrial environments, addressing both static and dynamic operational scenarios. The study utilizes three datasets to assess wireless network performance. Cellular data, comprising 19,703 samples, captures signal strength (RSRP, RSRQ, SINR) and is divided into static (13,574) and mobile (6,129) measurements. Ping data (1,770 samples) provides latency insights via RTT, while iperf data (15,767 samples) evaluates TCP/UDP uplink and downlink performance, including throughput and packet loss.

Due to the superior performance achieved by gradient boosting methods over many different ML problems [11], we opted for this type of algorithm and the XGBoost framework[4]. Four regression tree-based machine learning models were developed for signal metric estimation, differing in input features and dataset segmentation. The first model, trained on static data, predicts RSRP, RSRQ, and SINR using antenna distance and obstacle count from FlandersMake map data. The second model, trained on mobile data, applies similar inputs but focuses on dynamic conditions. The third model adds spatial coordinates (latitude, longitude) for enhanced precision. To mitigate data leakage from sequential samples, the fourth model introduces temporal segmentation in 10-second sequences, improving prediction integrity (Figure 10). Seeing that the fourth model provides the superior performance, the rest of the section focuses on the results derived from it.

The two-step QoS estimator predicts network performance by leveraging the signal estimation capabilities of Model 4 as an intermediate step. In Step 1, the model estimates key signal metrics based on input parameters that include antenna distance, obstacle count, and spatial position (latitude, longitude). By segmenting the mobile dataset into 10-second sequences, this model mitigates data leakage and enhances the temporal consistency of predictions, ensuring that dynamic variations in signal quality are accurately captured. Temporal segmentation further refines prediction accuracy, ensuring that the digital twin accurately reflects the evolving wireless environment of the factory.

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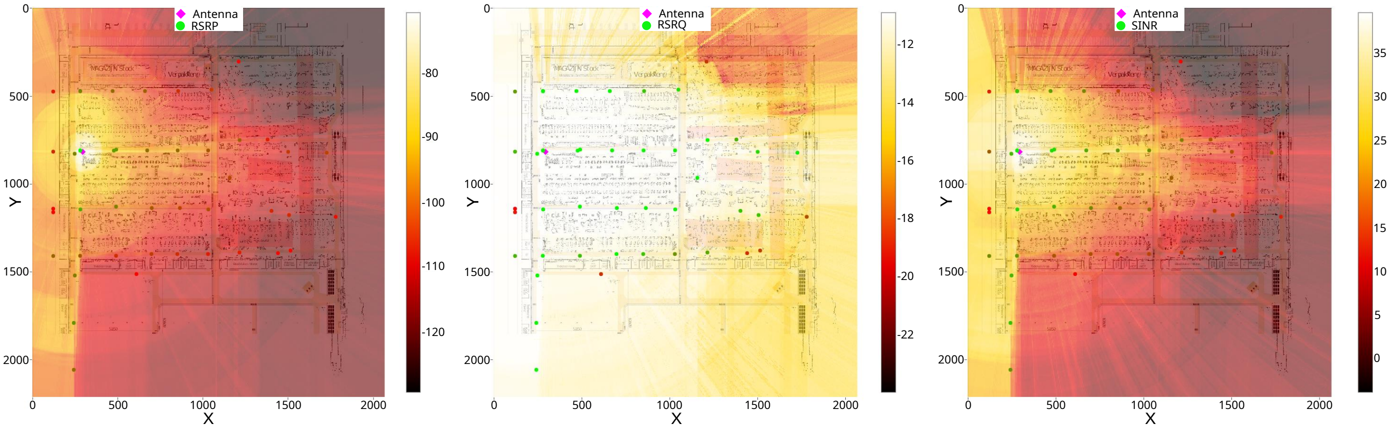
[4] https://xgboost.readthedocs.io/en/release_3.0.0/



RSRP (RMSE on validation set: 3.6698) RSRQ (RMSE on validation set: 0.7970) SINR (RMSE on validation set: 2.5810)

Fig. 10: Signal Metrics from the Fourth Signal Estimation Model

Step 2 uses these predicted signal metrics as inputs to a QoS model, trained on static data, to estimate UDP downlink performance (bitrate, jitter, packet loss). Obstacle maps further refine predictions by accounting for environmental impacts. Root Mean Squared Error (RMSE) is used consistently across both steps for robust performance evaluation. Temporal segmentation and spatial features improve generalization, prevent overfitting, and reflect real-time factory conditions.

This chained approach signal followed by QoS estimation translates radio conditions into actionable network insights, improving prediction accuracy and enabling adaptive resource management. The framework supports scalable deployment in 5G/6G networks, addressing URLLC and massive Machine-Type Communication (mMTC) needs in dynamic industrial settings. While the current model is not expected to generalize to other sites/layouts, this will be part of future work. A similar approach can be used in other sites, and by combining data coming from diverse settings, it is possible to build a model that generalizes better in different environments.

VI. CONCLUSION

The comprehensive performance assessment revealed that 5G SA networks can provide reliable and low-latency communication, essential for critical use cases such as AGVs and USVs. The deployment challenges in metal-dense factories and dynamic offshore settings were addressed, highlighting the importance of practical evaluations in these environments. Furthermore, the introduction of a machine learning-driven framework for signal and Quality of Service (QoS) prediction has shown promising results in optimizing network performance. This framework, along with the creation of a digital twin, enables real-time simulation and optimization of factory communication systems.

For future networks, this approach supports autonomous, zero-touch network management by integrating ML models into digital twins, enabling closed-loop control systems where real-time predictions drive autonomous decision-making. Predictive QoS mapping can dynamically allocate network resources, optimizing performance for time-sensitive applications like autonomous robotics and augmented reality in manufacturing. Additionally, incorporating this framework into digital twins enhances energy efficiency by enabling smarter resource allocation. As 6G networks prioritize sustainability, predictive modeling optimizes power usage, allowing operators to simulate network conditions before implementing changes, reducing unnecessary energy consumption and minimizing the carbon footprint of network operations.

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