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Development of a Data-Driven Mobile 5G Testbed: Platform for Experimental Research

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***Abstract*—The presented 5G testbed aims to prototype an end-to-end mobile data-driven platform for experimental 5G and interdisciplinary research. The testbed design and implementation for both indoor and outdoor are described. 5G introduces more flexibility compared to previous generations of cellular networks for higher performance and flexibility and allows customization for verticals; meanwhile, it brings critical challenges for system security and user experience. Data collection at multiple components on the testbed provides the opportunity for further Artificial Intelligence (AI) based security and performance improvements in various vertical applications. The built data frameworks include data collection, labeling, synchronization, and storing for both near-real-time use cases and non-real-time use cases. This design enables O-RAN compliance through E2 and O2 interface. The outdoor mobility of our 5G testbed allows deployment to places without existing infrastructure. The throughput and latency performance of the testbed is studied. Two data-driven use cases with access to C-Band spectrum in an outdoor environment are studied and evaluated, focusing on the switching between Long Term Evolution (LTE) and (New Radio) NR cell in Non-Standalone (NSA) and antenna direction recognition to enable location aware beamforming separately. The built testbed has a flexible architecture that enables connectivity between the system under test and 5G infrastructure with minimal necessary preparation. The 5G testbed consists of a hybrid design of license-based infrastructure and open-source infrastructure to provide in-depth configurable testing capability and scalable development.**

***Index Terms*—5G, NR, testbed, data-driven, ENDC, outdoor, O-RAN, data framework, C-Band, Machine Learning, KPI, mobile testbed**

I. Introduction

Experimental work in the context of 5G has gained significant attention over the past few years, shifting from simulation-driven research used in previous mobile network generations to system implementation prototyping[1]. This change stems from several factors including the widespread adoption of programmable Software Defined Radios (SDR), network function virtualization (NFV), and subsequent open-source softwarization of mobile network functions through various projects such as Open Air Interface (OAI) [2], srsLTE [3] and Free5GC. Mobile networks' commodity-hardware-driven low-cost deployment enables researchers and parties outside the telecommunications industry to conduct novel 5G-related experiments, significantly accelerating 5G innovation [1][4]. Besides open-source 5G solutions, SDR-based commercial license-based solutions are also being used for 5G research and development. The license-based solutions' well-designed interface offer better stability and make it easier to integrate with other systems and technologies. This paper strives to bridge the gap between emerging research and engineering practice by leveraging the commercial-grade performance of license-based solutions in the context of academic research to benchmark open-source infrastructure components and enable data-driven solutions using our 5G testbed. Compared to controlled indoor experimentation, enabling outdoor experimentation is significant in many use cases of 5G research; it provides a deployment platform that approaches real-world scenarios. However, signal transmission regulations and publicly available spectrum access must be carefully considered for outdoor experiments. Mid-band CBRS and C-Band spectrum are considered for deployment of 5G-cellular systems due to its blend of lower band propagation range and higher band capacity [5]. General authorized access (GAA) of CBRS access provides flexibility to the 5G research community and incentivizes use of Dynamic Spectrum Access (DSA). We utitlize a portion of the 3.4 - 3.8 GHz band for 5G mobile services aimed for secondary users. Outdoor experiments are performed through the access in this band. Outdoor environment provides mid or far field radio propagation environment, and reveals insights and challenges that different with indoor isolated environments, and more close to real-life implementations.

II. Background and Related Work

One of the key enablers of 5G prototyping and experimentation testbeds in the context of mobile networks has been device or software packages providing organized implementation of New Radio (NR) Radio Access Networks (RAN) [6][3][1] and Core Networks (CN) following 3rd Generation Partnership Project (3GPP) or O-RAN standards. Recently, there have been efforts to create large-scale testbeds for LTE network experimentation. Successful examples include POWDER and COSMOS. However, resources providing full-stack end-to-end 5G support capable of cross-layer data collection and intelligent control have not been readily available in these platforms. These capabilities are critical for multi-layer information analysis in an end-to-end carrier-grade 5G environment, enabling reverse engineering for network and protocol layer design analysis vulnerability assessment. Although there is strong demand for 5G applicability within Healthcare [7][8], the Smart Grid and other related areas, there are barriers for non-wireless researchers interested in applying their work to a configurable, open-source, stage-agnostic (Non-Standalone (NSA), Standalone (SA), Frequency Range 1 (FR1) and Frequency Range 2 (FR2)) testbeds without deep 5G knowledge. We designed our 5G testbed not only to enable innovations and research not within 5G or wireless communications, but also to accelerate interdisciplinary research related to 5G and allow researcher to have industry-applicable projects to be deployed and tested without the necessity for external deep 5G knowledge.

Our contribution can be summarized as follows:

1) **Cross layer data framework.** The cross-layer data framework built in the 5G testbed enables data collection, labeling, storing, the Machine Learning (ML)-based model training, deployment to the 5G end to end communications in both near-real-time and non-real-time manner.
2) **Mobile and Outdoor testbed design and configuration.** Outdoor experimentation with traffic from many users in distributed geographic areas can improve the robustness and applicability for building models through the collection of higher-variability data. Deploying the testbed in outdoor environments with a large-scale number of devices and users provides validation results close to real-life user scenarios.
3) **A data-driven and reverse engineering approach to recognize and address 5G performance and security concerns** Two use cases are included to illustrate the testbed's data-driven approach. The switching between LTE and NR cell in NSA is determined by both channel environment and UE implementation.A ML-based model is designed for automated device position recognition and antenna steering.

The outline of this paper is as follows: We describe the 5G testbed prototype in Section III, which includes indoor design and configuration in Section III-A, outdoor architecture and spectrum access in Section III-B, and study of data collection and ML model in Section III-C. Testbed performance assessment is detailed in Section IV followed by the conclusion in Section V.

III. 5G Testbed Prototype

A. Indoor Testbed Design and Configuration

We integrate inter-operable solutions using commercial/license-based and open source software and hardware to create end-to-end 5G network functionality that enables novel research in the 5G sphere.

Fig. 1 illustrates the physical architecture of testbed hardware.

The Amari Callbox Pro (ACP) is a commercially available hardware solution for 5G testing. It acts as a 3GPP compliant eNodeB (eNB), gNodeB (gNB), Evolved Packet Core (EPC), and 5GC, allowing functional and performance testing of NR, Long-Term Evolution (LTE), LTE-Advanced, LTE Cat-M1, and Narrow Band (NB) LTE devices. It also includes an integrated IP Multimedia Subsystem (IMS) server and an Evolved Multimedia Broadcast Multicast Services (eMBMS) gateway for VoLTE and eMBMS testing. Its functionality is software-defined and highly configurable. The ACP enables the creation of a private 5G network within our testbed.

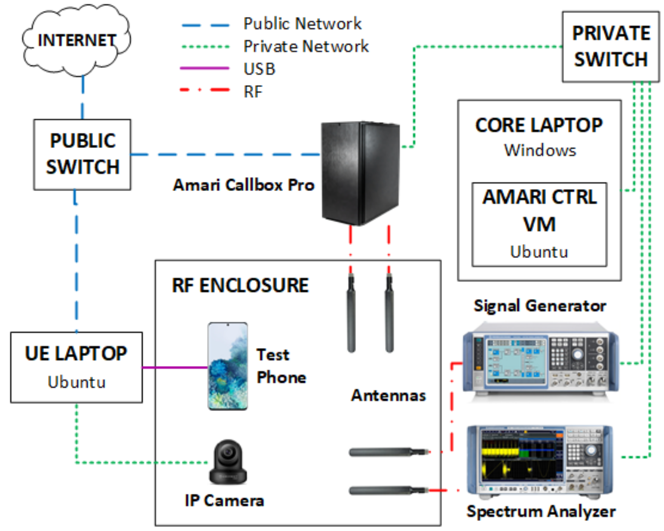

Fig. 1: Overview of Indoor System Architecture

Free5GC is an open-source 5GC integrated into our testbed, connecting with commercial RAN to achieve flexible, distributed, and high-performance end-to-end communications. Free5GC supports standalone mode and can be used for Non-Standalone mode in parallel with adding an in-house developed RAN compatible component.

The Rohde & Schwarz FSW85 Signal Analyzer (FSW) allows for an in-depth examination of the near-real-time RF environment, signal characteristics, as well as LTE and 5G signal demodulation. With its operational frequency ranging between 2Hz - 85GHz, both FR1 and FR2 testing is capable. The FSW enables us to monitor the spectral environment during interference testing, determining signal synchronization and performance in the absence and presence of various interference signals.

The Rohde & Schwarz SMW200A Signal Generator (SMW) allows for continuous wave, additive white gaussian noise, LTE, and 5G signal injection. We use the SMW to inject various crafted interference signals into the 5G physical channel.

A Ramsey 6000 RF enclosure enables over-the-air testing without leaked RF emissions.

As shown in Fig. 1, all network components are connected through network switches and remote control is enabled for the ACP, SMW, and FSW. The ACP is accessed over a secure shell, whereas the SMW and FSW are accessed by a browser using assigned IP.

B. Outdoor Architecture and Spectrum Access

While an isolated RF enclosure allows for environment controlled, interference-free experimentation, outdoor experimentation is necessary to test in environments that mimic real-world channel conditions. A testbed with deployment mobility enables experimentation in outdoor environments and locations without accessible or existing 5G infrastructure.

There are two significant challenges for the outdoor design and deployment in the outdoor environment: RF signal propagation coverage and spectrum access without causing interference to coexisted communications. We added RF components to the front end of the ACP to enable the mobility functionality, supplying power amplification and directional or Omni-directional RF emission dependent on the use case. Front-end amplification is illustrated with the outdoor system architecture shown in Fig. 2.

Fig. 2 describes the 5G NSA system outdoor architecture. Due to the co-existence of LTE cell and NR cell in NSA, the ACP front end is represented with two of its contained software-defined radios. By utilizing SDR0 for 5G NR and SDR1 for LTE, the architecture enables both NSA and SA 5G NR. In the case of SA, only SDR0 is operational. Both Frequency Division Duplex (FDD) and Time Division Duplex (TDD) are enabled with this architecture. In the case of FDD, all four SDR ports are operational. In TDD, channel 1 transmit and receive decoupled to transmitter (TX) ports 1 and receiver(RX) ports 1, respectively. The two TX1 port outputs are routed into power amplifier 1, and the two TX2 port outputs are routed into power amplifier 2. Each power amplifier provides a gain of 35 dB. A multi-channel programmable attenuator is used to control output RF power into the attached antenna. The four attenuator channels correspond to the two Multiple-Input and two Multiple-Output (MIMO) channels of the LTE and NR cells. Output power is chosen based on communication range and potential emissions interference.

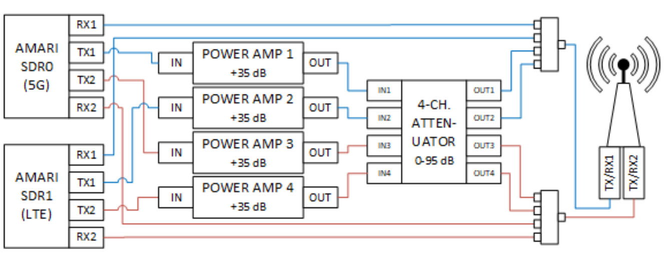

Fig. 2: Outdoor System RF Architecture

In the current E-UTRAN New Radio Dual Connectivity (ENDC) option of NSA, the LTE cell provides a larger coverage footprint while the NR cell provides higher throughput. Cell-steering and switching strategy is decided by channel conditions and UE implementations. The cell-steering between LTE cell and NR cell has a significant impact to user performance. In the performance session, we included the comparison of the expected switching condition for Samsung S20 device. On contrary, at Standalone (SA) option, with only NR cell simplifies the connection of PA and eliminate the complex of cell steering.

Depending on the use case, a MIMO omni-directional or directional antenna is connected to the channel 1 and 2 combiners. The omni-directional antenna provides a maximum gain of 6.2 dBi, whereas the directional antenna offers a maximum gain of 11 dBi. The omni-directional antenna is optimal for use cases with multiple connected devices in a short-range vicinity. In contrast, the directional antenna is attached to a programmable object-tracking turn-table capable of supporting a longer-range link and spectrum reuse in multiple sectors.

For spectrum access outdoor, we analyzed the feasibility of utilizing CBRS and C-Band and addressed the spectrum-based challenges. For current commercial UEs, CBRS (N48) in SA mode is rarely supported; some commercial UEs support C-Band (N78) in SA mode. To access C-Band, we use a GAA tier which is licensed-by-rule to permit open, flexible access to the band. When operating in NSA mode, ENDC allows user equipment to connect to an LTE eNB that acts as a master node and a 5G gNB that acts as a secondary node. Both LTE and 5G band accessibility is required. Eligible ENDC band pairs vary by UEs. The commonly supported ones include LTE B1, B3, B5, B8 + 5G N78. LTE B1, B3, B5, and B8 are often used by primary users for cellular carrier operation and are regulated by the Federal Communications Commission (FCC).

C. Data Collection and Machine Learning Platform

The broadcast nature of wireless media brings various physical-layer security challenges to 5G. Jamming, false base station based man-in-the-middle (MitM) attacks and other threats poses significant vulnerability concerns for 5G communications. The traditional case-by-case security methods become limited and powerless. AI has been explored to mitigate the identified cyber security threats and associated risks with cyber security standards and frameworks [9] [10] [11]. Cross-layer data collection is significant in enabling ML or AI based algorithms and models. When using the platform for deployment scenarios for vertical applications, collected cross-layer data is a critical indicator for system evaluation and can be used for further performance improvements [12] [13] [14].

As a data-driven testbed, a multitude of KPI and RF parameters are collected. In past work we have been able to use collected data to detect and classify the presence of jamming on a 5G UE [15]. Collected data can also be used for reverse engineering design, network capability analysis, etc.

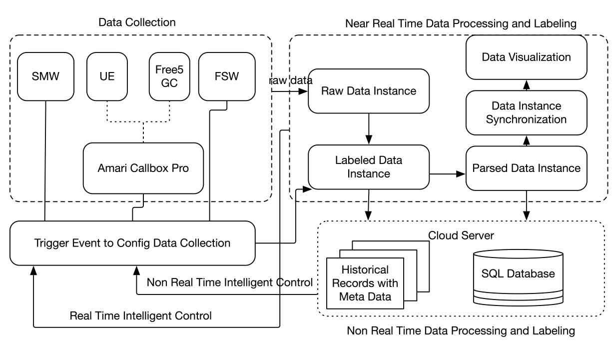

Fig. 3: Testbed Data Collection Process

Fig. 3 explains the closed loop of event-triggering, labeling, storing, synchronization, and real-time deployment of collected data. Data collection and analysis at run time may occupy valuable network resources; we have designed distributed data collection and analysis to minimize the effect of data collection on the communication link. Considering the mobility of UE, the UE log is captured post-run-time. The gNB captures control messages and user plane statistical data associated with a run-time session, storing it in JavaScript notation (JSON) format. The raw .json files captured by the gNB detailing the NR connection are sent to local storage where the current instance of collected data is stored. The rest of the process is carried out in the local repository to minimize computational power usage on the gNB. Labeling information is illustrated with the ”Trigger Event to Config Data Collection” block, which labels raw JSON files and generates parsed data instances. The synchronization block combines the data from all parts to create the association index. Run-time data virtualization is used to monitor NR communication.

All parsed data in local storage is used for near-real-time intelligent control and designed as O-RAN compliance. The ACP doesn't meet the requirement of Distributed Unit (DU) -Center Unit (CU)-Radio Unit (RU) split present in a standard O-RAN base station. However, because of the testbed's designed data framework, the near-real-time processing and labeling utilizes the O-RAN architecture E2 interface. Trained ML-based models located in local storage can be deployed to the RAN and 5GC at run time for optimization.

The cloud server can be located locally or remotely. It saves both historical records with metadata for future labeling and parsed data in a structured way for fast indexing in a Structured Query Language (SQL) database. Data in cloud server is also used for non-real-time intelligent control and designed as O-RAN compliance. The training for near-real-time and non-real-time ML models locate there and interface to near-real-time processing through O2 interface in O-RAN architecture. It is also feasible to deploy the control and configuration directly to the RAN and 5G core at run time.

As with most data-driven models, it is challenging to collect data and resource-intensive to label training data sets with comprehensive information; Labeling is the process of transforming domain knowledge into a format that can be injected into the model. This process directly determines the accuracy and effectiveness of our model. This system enables the creation of ML models based on collected KPI of interest. The system can be configured to generate training data in various configurable channel environments.

IV. Testbed Performance Assessment

In this section we assess performance of the 5G testbed in both indoor and outdoor environments. For the indoor test environment, the performance assessment provides a baseline evaluation of throughput, latency, and various other KPIs for all links comprising the end-to-end 5G testbed. For the outdoor test environment, we focus on two use cases: the first is analyzing factors that affect LTE and NR cell switching in NSA ENDC mode; the second is ML-based device recognition and directional antenna steering. These performance assessments include quantitative evaluation of the testbed and findings inform further research in relevant areas.

A. Indoor Throughput and Latency Performance Assessment

Throughput and latency are two indicators used to quantify system performance; other KPIs can be used for a more detailed assessment. For throughput, we evaluated the performance at different configurations of gNB over a UE. The resulting average value is collected over multiple measurements. The 'traceroute' of computer network diagnostic command is used to observe latency generated over each connection link spanned: tethered IoT to UE, UE to RAN, RAN to core, and core to Data Network (DN). Other performance metrics can be configured depending on the application and use case.

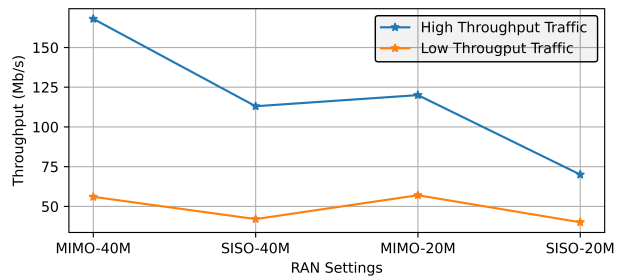

Fig. 4: Throughput at Various Antenna and Channel Bandwidths

Fig. 4 shows the distribution of throughput capacity at different configuration modes. MIMO multiplies the capacity using multiple transmit and receive antennas. As shown in Fig. 4, in both low and high throughput traffic, 2 x 2 MIMO shows an approximate 40% to 50% performance improvement over Single Input Single Output (SISO).

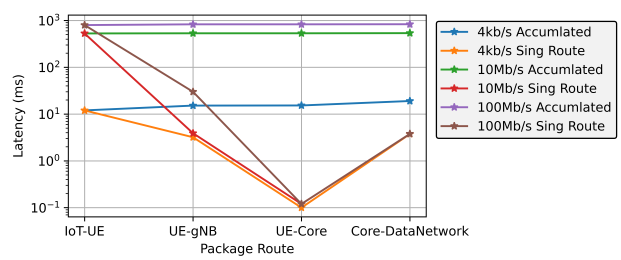

Fig. 5: Latency Evaluation at Different Throughput Levels

Fig. 5 shows the latency for different routes of the communication path. The majority of latency generated is between IoT device and UE due to tethering or hotspotting. The latency caused by the 5G RAN and core is within 5 ms. As throughput increases, the latency generated by the 5G RAN and core increases slowly while the latency due to tethering or hotspotting increases significantly.

B. Analysis of LTE and NR Cell Switching in ENDC NSA

Besides baselining expected performance in various channel conditions, reverse-engineering to uncover system design insights and improve overall performance is another capability of our data-driven testbed. In contrast to our controlled and RF-isolated indoor environment, at outdoor environments, there are multiple random factors contributing to 5G system performance and throughput in outdoor environments. For 5G NSA, the conditions around UE data traffic switching between NR cell and LTE cell are not included in the 3GPP standard; instead, these conditions are non-standard, proprietary, and determined by UE vendors. In the case of malicious actors causing UEs to register to undesired or malicious base stations [16], improper design of NR and LTE cell switching conditions may affect UE performance and cell attachment, or potentially limit cell capacity and disturb network planning for operators. In enviroments with CBRS, C-Band, and other coexisting technologies and services [17], understanding cell switching conditions is critical. Undesired switching between NR and LTE cell is rarely observed when experimenting in an RF-isolated environment due to near-field channel conditions.

The frequency band combination used for outdoor testing is LTE FDD B1 (1930 MHz – 1970 MHz uplink, 2120 MHz – 2160 MHz downlink) and C-Band NR TDD N78 (3469 MHz - 3509 MHz).

TABLE I: Factors for NR & LTE Cell Switching Condition

Coefficient	***Estimate***	***Std. Err***	***t***	$p - value$
Intercept	0.310	0.036	8.510	$< 2e - 16*$
PUSCH SNR	0.0069	0.0004	17.878	$< 2e - 16*$
CQI	0.0797	0.0017	46.276	$< 2e - 16*$
RI	0.231	0.0130	17.857	$< 2e - 16*$
Uplink Pathloss	0.0007	0.0004	2.082	0.0375

R^2 = 0.898

There are multiple factors that determine UE traffic loading between NR cell and LTE cell. Table I shows the regression between potential cell selection factors. Cell ID is the used as the dependent variable. The most relevant factors are selected according to standards and vendor implementation; these include Physical Uplink Shared Channel (PUSCH) SNR, Channel Quality Indicator (CQI), Rank Indicator (RI), and Uplink Channel Pathloss. Since switching is UE specific behavior, most of the information selected is from the uplink channel. Results show that PUSCH SNR, CQI, and RI are the most significant cell selection indicators. Although uplink pathloss is not shown as a significant indicator, it is a confounding variable for both CQI and Cell ID. After removing CQI as the independent variable, uplink pathloss becomes a sigificant indicator; however, R^2 value drops to 0.7634. This indicates that uplink pathloss is a significant indicator for CQI and indirectly affects cell selection. The relationships between uplink pathloss and CQI as well as PUSCH SNR and uplink pathloss are shown in Figure 6.

From Fig. 6, we can see that CQI distribution is affected by multiple factors and varies between LTE cell and NR cell. A possible attack to exploit this result could be increasing the LTE band signal power or adding interference in the NR band to lower channel quality. This exploit can mislead the UE into keeping data traffic on the LTE cell, lowering NR bandwidth utilization efficiency and compromising applications that rely on 5G-enabled low latency and high throughput. There is also

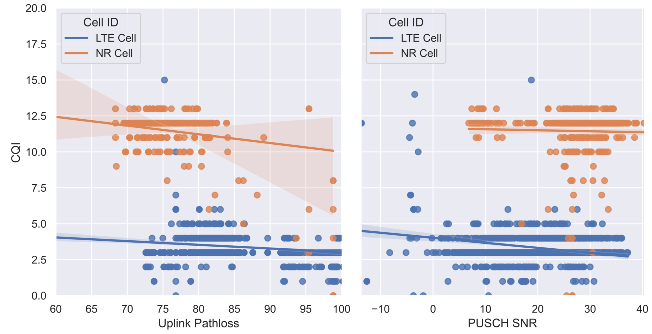

Fig. 6: Relationship Between Uplink Pathloss and CQI

potential for denial-of-service (DoS) if traffic on the LTE cell exceeds capacity. Understanding the regression relationship between factors affecting CQI and cell switching conditions is critical in addressing these vulnerabilities; further investigation is ongoing and results will be included in follow-up publications.

C. Device-Antenna Direction Recognition

Beam-forming in 5G has attracted significant attention. Development and operation of 5G enables the practical implementation of massive MIMO systems with spatial signal processing and adaptive beam-forming (AB). Most research in beam-forming assumes that location information is known; based on this information antenna array direction is adjusted. However, the assumption of device location information may not hold with high mobility objectives. In this section, we explore the device position recognition and antenna steering based on data collected on our 5G testbed. This data can be used to aid implementation of a location-aware beam-forming system. The experiment positions a 2×2 MIMO directional antenna on a turn-table that automatically rotates about the horizontal axis in 15°increments from $-45°$to 30°, where 0°is pointing directly at the object area. Collected data are used for model training to recognize degree changes.

TABLE II: Independent Variables for Antenna

cell_id	dl_bitrate	ul_bitrate
dl_tx	ul_tx	dl_retx
ul_retx	pusch_snr	epre
cqi	ri	ul_phr
ul_path_loss	dl_mcs	ul_mcs
turbo_decoder_min	turbo_decoder_avg	turbo_decoder_max
ue_index	max_ue_index	dl_bitrate_norm

The input parameters included are shown in in Table II. The ML model selected is Random Forest Classifier. The result is based on 3687 records collected over a time period of 553 seconds. The results of the ML model are shown in Figure7. All AUC values are above 0.91. The angle directly facing the object and far end angles have a slightly higher accuracy compared to the intermediate angles. Further investigation and results of this experimentation will be included in follow-up publications.

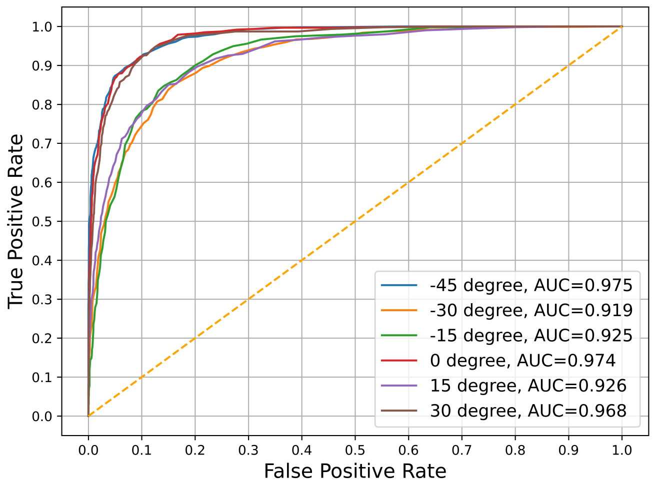

Fig. 7: RandomForestClassifier Antenna Direction Recognition

V. Conclusion

This paper has discussed the design and implementation of a data-driven end-to-end 5G testbed prototype for experimental research in indoor and outdoor environments. Data collection, labeling, synchronization, and storage are designed to provide information for both near-real-time and non-real-time use cases. Overall system throughput and latency performance is analyzed. Use cases for preventing undesired LTE and NR cell switch in ENDC mode and detecting user-antenna direction in real-time are presented, exploring data-driven and reverse-engineering approaches. The results demonstrate high accuracy. Future work includes further investigation of the described use cases, open accessibility of generated data, and deeper O-RAN architecture integration.

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