Horizon Europe Framework Programme

CENTRIC

Towards an AI-native, user-centric air interface for 6G networks

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D5.4 Final CENTRIC PoC demonstrator

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ABSTRACT

This deliverable documents the development and final results obtained with CENTRIC's proof-of-concept (PoC) demonstrators during the project lifetime. It contains the description of three testbeds developed in WP5 of CENTRIC, which have been used to enable 4 different PoCs in which AI techniques applied to different PHY functionalities in the air interface have been validated. In addition, a description of the dissemination actions undertaken with the different PoCs is provided.

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Executive summary

This deliverable reports the outcome of task T5.3 – "CENTRIC over-the-air PoC of AI-AI technologies" throughout the project's lifetime. CENTRIC has developed three testbeds for validation of AI-AI techniques, and 4 different AI techniques for the air interface have been validated using them.

The first testbed developed consists of a setup to perform and record over-the-air (OTA) transmissions performed at sub-terahertz (sub-THz) frequencies. The testbed uses Keysight's signal generation and digitization hardware, VDI up- and down-converters and horn antennas, as well as Keysight's signal design and analysis software. This setup has been used to enable the demonstration of neural network- (NN-)based channel estimators developed by Keysight and Interdigital, which are shown to largely outperform a classical channel estimation benchmark. Using the testbed, this PoC has been leveraged for dissemination at three different events during the first half of 2024: the ETSI Research Conference in Sophia Antipolis, the Mobile World Congress (MWC) in Barcelona, and the EuCNC conference in Antwerp.

The second testbed that CENTRIC has implemented consists of an Open Radio Access Network (O-RAN) testbed using commercial equipment. The testbed uses Keysight's signal generation and RF channel emulation hardware to emulate 5G transmissions over channel responses obtained from NVIDIA's Sionna ray-tracer. The emulated transmissions are received by a commercial O-RAN radio unit provided by Taiwanese company LITEON. The IQ samples recorded by the radio unit can then be fed to a Linux computer with a graphical processing unit (GPU) for AI-based processing. This setup has been used to develop two different PoCs in CENTRIC. In the first of them, the testbed has been used to emulate the transmissions from two users towards a MIMO-equipped base station in a ray-traced scene. The recorded received signals have then been fed to NVIDIA's multi-user MIMO neural receiver developed in the context of CENTRIC's task T3.4. The results obtained from the testbed show that a neural receiver trained based on synthetic simulation data shows excellent performance when processing RF-emulated received signals. In addition, they showcase that finetuning the neural receiver with data collected form the same site in which it is deployed can further improve its performance. The second of the PoCs consists of the validation of an AI model performing sensing based on 5G NR sounding reference signals (SRS). Using 3D modelling tools, a virtual model of an indoor environment in which human targets move around has been produced. Using ray-tracing, this virtual model is employed to model the effect of the movement of the human target on the received signals. The received signals are then fed to the AI model which performs the tasks of target localization, presence detection, and activity detection. Both of these PoCs have been showcased in multiple events, such as MWC'24 and MWC'25, or the upcoming IEEE International Conference on Machine Learning for Communication and Networking, to be celebrated at the end of May 2025.

The third and final testbed has as goal the validation of techniques related to closed-loop MIMO systems, particularly suited towards large MIMO orders such as in massive MIMO systems. Using Keysight's multi transceiver platform, DL transmissions from a gNodeB to a user equipment are emulated. Using this testbed, a PoC of the AI-based CSI compression use case has been enabled. In it, the testbed emulates DL transmissions from which a UE obtains

channel estimates. These channel estimates are then fed to an AI model, assumed to be deployed at the UE, that compresses them into a low-dimensional representation. Subsequently, a reconstruction AI model, assumed to be deployed at the gNodeB, reconstructs the CSI originally obtained by the UE. The reconstructed CSI is used to precode a subsequent downlink transmission, and the effectiveness of the precoder obtained from the compressed and reconstructed CSI is evaluated. This PoC is still in its last stages of development, and will be showcased at the upcoming EuCNC conference to be celebrated in the beginning of June 2025.

The testbeds and PoCs reported in this deliverable constitute the platforms from which the datasets published in the upcoming CENTRIC deliverable D5.5 will be obtained.

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Keysight Technologies	Carles Navarro Manchón	Writing of Sections 1 & 4, contribution to Sections 2 & 3, and Editorial Review

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Abbreviations

AI	Artificial Intelligence
AI/ML	Artificial Intelligence / Machine Learning
BLER	Block Error Rate
BS	Base Station
CSI	Channel State Information
DL	DownLink
FDD	Frequency Division Duplexing
gNB	gNodeB
GPU	Graphical Processing Unit
IQ	In-phase / Quadrature
LDPC	Low-Density Parity Check
MIMO	Multiple-Input Multiple-Output
NMSE	Normalized Mean Squared Error
NN	Neural Network
O-DU	O-RAN Distributed Unit
ONNX	Open Neural Network Exchange
O-RAN	Open Radio Access Network
O-RU	O-RAN Radio Unit
OTA	Over-The-Air
PHY	Physical Layer
PoC	Proof of Concept
PUSCH	Physical Uplink Shared Channel
RF	Radiofrequency
SGCS	Squared Generalized Cosine Similarity
SRS	Sounding Reference Signal
TDD	Time Division Duplexing
UE	User Equipment
UL	UpLink
WP	Work Package

1 Introduction

The fundamental goal of CENTRIC is to research, design, develop, and validate artificial intelligence- (AI-)based techniques for the air-interface of future 6G mobile communications. Working towards that goal, work packages (WPs) 2, 3 and 4 in the project have been dedicated to proposing new AI-enablers, AI-based PHY techniques, and AI-based protocols respectively. The role of WP5 is to propose validation methodologies for these techniques and, to fulfil that, the implementation of some of the methods in testbeds including real hardware and RF modulated transmissions is a fundamental task.

While computer simulations play a fundamental role in prototyping and achieving an initial assessment of a particular technique, the actual performance of a method when implemented in a real system can deviate greatly from the performance predicted by simulations. When the techniques to be assessed are data-driven methods, such as is the case in AI models, the disparity between the results observed in the simulation realm and those observed in practice can be even larger, as the operation of the method itself is completely dependent on the data to which it is exposed. Synthetic data obtained from simulation models will inevitably suffer from the simplifying modelling assumptions needed to make the simulator computationally practical. Hence, to achieve a trustworthy assessment of a given AI-based method, training of the model with realistic data and evaluating it in realistic conditions is an unavoidable step.

For these reasons, the development of proof-of-concept (PoC) demonstrators involving real radiofrequency (RF) hardware is one of the main goals of WP5 in CENTRIC. The development of testbeds capable of hosting PoCs of some of the AI-based methods researched in CENTRIC fulfils two important goals of the project:

1. To enable validation and benchmarking of a subset of the PHY techniques developed in WP3 in conditions much more realistic than those that can be replicated in computer simulations.
2. To enable the collection of datasets of measurements obtained in the testbeds that can be used for training and evaluation of AI-based air interface techniques.

In this deliverable, we report the outcome of the experimental validation efforts undertaken in WP5 of CENTRIC. We present the testbeds that have been developed in the project, along with the PoCs that have been enabled by them. We report the KPIs assessed by the different PoCs, as well as the dissemination actions that have been carried out with them.

In order to provide in this report a full, comprehensive view of all the PoC work done in CENTRIC, this deliverable has been written in the form of an update of deliverable *D5.2 - Early version of CENTRIC PoC Demonstrator*. Hence, some of the contents –mainly those corresponding to PoCs developed in the first half of the project—have been left unaltered or with minor modifications with respect to the content of D5.2. Nonetheless, we clarify next which parts are new to the present D5.4 deliverable, and which ones have been inherited from the preliminary D5.2 deliverable. The remainder of this deliverable is structured as follows:

- In Section 2, we present the three testbeds that have been developed in the project, detailing their hardware and software components. The first two testbeds, detailed in Sections 2.1 and 2.2, where developed during the first half of the project and, consequently, where already reported in D5.2. The testbed documented in Section 2.3 is fully novel content of D5.5
- Section 3 describes the 4 PoCs that the project has developed. The setups of the PoCs are detailed, the results obtained with them are discussed, and the different dissemination activities carried out with the PoCs are presented. PoC1 and PoC2 where developed in the first half of the project, consequently the text describing them only presents minor updates with respect to the content of D5.2. The updates are mostly related to dissemination actions. The description of PoC3 and PoC4 in Sections 3.3 and 3.4 is fully new to D5.4, as these PoCs where developed in the second half of the project.
- Section 4 draws conclusions from the work so far, and outlines plans for further work in the rest of the project's lifetime.

2 Description of CENTRIC Testbeds

In this section, we detail the components of the three testbeds that WP5 of CENTRIC has so far developed:

1. A testbed performing OTA transmissions at Sub-THz frequencies (144 GHz).
2. An O-RAN testbed using commercial components and emulating ray-traced transmissions with an RF channel emulator.
3. A closed-loop MIMO testbed aimed for experimentation with massive MIMO techniques.

2.1 Sub-THz OTA testbed

This testbed is aimed at investigating AI/ML functionalities in the physical layer in terms of their suitability of implementation and performance. For this purpose, the testbed is comprised of the necessary hardware and software to generate and receive high fidelity, high bandwidth 5G waveforms in the radiofrequency domain. Additionally, the different components can be used to apply different channel conditions to said signals and/or perform over-the-air (OTA) transmissions.

These capabilities render the testbed fit to generate and record data in the RF domain that can be used to train and test AI/ML models in a much more realistic manner than using the synthetic data coming from simulations.

The hardware present in the testbed is the following:

- Arbitrary waveform generator M8195A [1]:
    - Used as an RF transmitter. It can play arbitrary 5G waveforms with a variety of configurations though several independent channels. Is a rack unit accompanied by the AXIe chassis (M9502A) [2].

Figure 1: M8195A Arbitrary waveform generator in a M9502A AXIe chassis

    - Digital-to-Analog converter resolution: 8 bit
    - Bandwith: 25 GHz
    - Number of channels: 4
    - Maximum sample rate: 65 GSamples/sec
- Digitizer M8131A [3]:
    - Used as a RF receiver. It can digitize up to 4 independent RF signals.

Figure 2: M1831A digitizer in a M9502A AXIe chassis

- Analog-to-Digital converter resolution: 10 bit
- Bandwith: 6.5 GHz
- Number of channels: 4
- Maximum sample rate: 16 GSamples/sec

- D-Band up/downconverter from VDI (WR5.1 CCU/CCD) [4]:
    - Used to convert intermediate frequency RF signals into or from D-Band (110-170GHz). The combination of VDI upconverter and downconverter makes it possible to investigate the behaviour of RF signals in Sub-THz frequencies while employing hardware (signal generators, digitizers, etc…) designed for lower frequencies.

Figure 3: VDI's WR5.1 compact converter

- Frequency range: 140 – 220GHz
- Number of channels: 1

- D-Band waveguide amplifier from VDI (WR5.1 AMP) [5]:
    - RF amplifier needed to inject more power to the D-Band signal after the upconverting process.

Figure 4: VDI's WR5.1 waveguide amplifier

- D-Band horn antennas from VDI (WR5.1 HA) [6]:
  - Pair of antennas designed for D-Band RF signals. Needed to radiate the signals to the air.

Figure 5: VDI's WR5.1 horn antenna

- Vector Signal Generator PSG E8257D [7]:
  - High fidelity signal generator up to microwave ranges. Used in the testbed as local oscillator to feed the up/downconverters

Figure 6: Vector Signal Generator PSG E8257D

  - Baseband bandwith: 80MHz
  - Number of channels:
  - Frequency range: 100kHz – 44GHz

The software present in the testbed is the following:

- PathWave Vector Signal Analysis (VSA) [8]
- PathWave Signal Generation [9]
- PathWave System Design [10]
- O-RAN Studio [11]

2.2 Commercial O-RAN testbed

This testbed is aimed at investigating communications systems based on open radio access network (O-RAN) implementations and their possible expansions and improvements. More precisely, uplink transmissions are investigated leveraging one of the main components of the testbed: a commercial O-RAN Radio Unit (O-RU).

Employing a commercial Radio Unit to develop Proofs of Concept (PoCs) means the results derived from this testbed are valid in real-world scenarios, facilitating their prospective deployment. The testbed is capable of transmitting 5G waveforms in the RF domain, apply arbitrary channels and propagations to said signals and receive via the commercial O-RU, which will output baseband in-phase / quadrature (IQ) samples that can be treated and processed with AI/ML algorithms.

The hardware present in the testbed is the following:

- Open RAN Studio Player and Capture Appliance S5040A [12]:
  - Unit that can act as an emulated O-RAN Distributed Unit (O-DU). It allows to control commercial O-RU units in both uplink and downlink, make recordings of IQ samples, replay, and inspect them. It also acts as triggering and synchronization hardware for the different elements of the testbed.

Figure 7: Open RAN Studio Player and Capture Appliance S5040A

- RAN Radio Unit FlexFi from LITEON [13]:

- Commercial O-RU unit from the Taiwanese company LITEON. It is used in the testbed to digitize input RF signal into IQ samples in the baseband domain. The use of a commercial O-RU in the testbed is crucial to understand the validity of AI/ML algorithms in real-world scenarios where hardware impairments are present.

Figure 8: LITEON’s FlexFi O-RU

  - Bandwidth: 100MHz,
  - Frequency: 3300 to 5000 MHz
  - Power: Rx 24 dBm, Tx 24 dBm
  - Rx Configuration: 4 Ports.
- Vector Signal Generator VXG M9484C [14]:
  - High fidelity and high bandwidth signal generator. Used to emulate 5G transmitters.

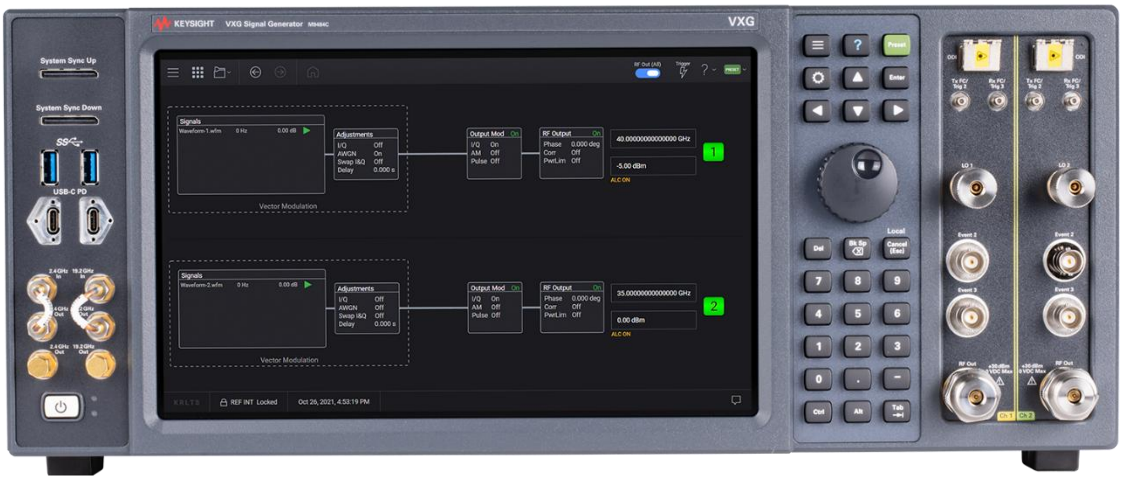

Figure 9: VXG M9484C Vector Signal Generator

  - Bandwidth: 2.5GHz,
  - Frequency: 9kHz to 54GHz
  - Waveform Playback Memory: 4096 MSamples
  - Tx Channels: 2

- Signal Analyzer MXA M9020B [15]:
    - High fidelity signal analyzer. Used to inspect and calibrate RF signals across the testbed.

Figure 10: MXA M9020B Signal Analyzer

-
    - Bandwidth: 160MHz
    - Frequency: 10Hz to 5GHz
    - Rx Channels: 1
- Real-time RF Channel emulator PROPSIM F8800A [16]:
    - Real-time RF channel emulator. Used to emulate arbitrary propagation environments and channels. Can use 3GPP defined channels or custom channel impulse responses coming from ray-tracing or geometric tools. Multiple input/output ports allow for MIMO emulation.

Figure 11: PROPSIM F8800A Real-time RF Channel emulator

    - Frequency range: 3MHz – 7.25GHz
    - Bandwith: 200MHz
    - Number of channels: 64 TRx
- AI server, alias Claude
    - Linux based computer with GPU and fibre optic input to run AI/ML applications.
    - RAM: 64GB
    - GPU: NVIDA 4090RTX

The software present in the testbed is the following:

- PathWave Vector Signal Analysis (VSA) [8]
- PathWave Signal Generation [9]
- O-RAN Studio [11]
- Sionna Ray-Tracer [17]

2.3 Closed-loop MIMO Testbed

A third testbed has been developed during the second half of the project. The primary purpose for this testbed is to enable the prototyping and assessment of PHY signal processing algorithms related to closed-loop multiple-input multiple output (MIMO) communications. Contrary to the O-RAN commercial testbed previously presented, where the emphasis was put in compliance with 3GPP standards via the use of a commercial radio unit, this testbed focuses instead on allowing for signal transmissions over a large number of parallel RF channels. This enables the assessment of MIMO techniques over channels that have dimensions of the same order as to those encountered in 5G and beyond. Importantly, the fact that prototyping hardware and software tools are used instead of commercial equipment for the emulation of both the gNB and the UE makes it possible to investigate closed-loop MIMO algorithms, as the processing used by both sides of the transmission can be customized by the testbed user. Such level of flexibility is difficult to accomplish with commercial equipment (e.g., a commercial gNB) as vendors would typically limit customization options for the user.

The testbed relies on two main hardware components: a multiport RF transceiver that can synchronously modulate or digitize signals over a large number of ports, and the RF channel emulator already presented in the testbed of Section 2.2. These, together with a suite of signal generation and processing tools, as well as an effective automation framework, constitute the key elements. All of them are detailed below:

- Multi Transceiver RF Test Set (MTRX) E6464A [18]:
    - Scalable RF test platform hardware that provides up to 64 Vector Signal Analyzer (VSA) and up to 64 Vector Signal Generators (VSG) in a single instrument.
    - Frequency range: 450—7250 MHz
    - Bandwidth: 200 MHz
    - Up to 16 independent RF local oscillators

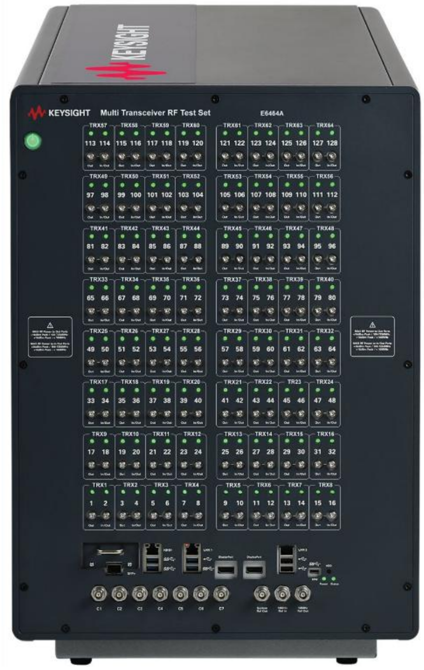

Figure 12: Multi Transceiver RF Test Set (MTRX) E6464A [18]

- Real-time RF Channel emulator PROPSIM F8800A [16] (see Section 2.2 for details).

The software utilized in the testbed is the following:

- PathWave Vector Signal Analysis (VSA) [8]
- PathWave Signal Generation [9]
- PathWave System Design [10]
- KS8400B PathWave Test Automation [19]

3 Proofs of Concept

In this section we present the four PoCs that have been enabled by the testbeds introduced in Section 2, namely:

- PoC1: An AI-based Channel Estimator for sub-THz frequencies, which uses the testbed described in Section 2.1.
- PoC2: A site-specific multi-user MIMO neural receiver, enabled by the testbed introduced in Section 2.2.
- PoC3: A validation of AI-based Sensing using 5G NR SRS, implemented using the testbed described in Section 2.2.
- PoC4: An AI-based CSI Feedback Compression model for Massive MIMO systems, developed based on the closed-loop MIMO testbed presented in Section 2.3.

3.1 PoC1: AI-based Channel Estimation for sub-THz Frequencies

The first step in AI-based air interface is widely agreed to be the substitution of individual processing blocks of current systems with AI/ML models that could potentially outperform them. Within the system, the receiver is the main focus of this substitution. Figure 13 depicts all the blocks susceptible of being replaced in “stage 1”:

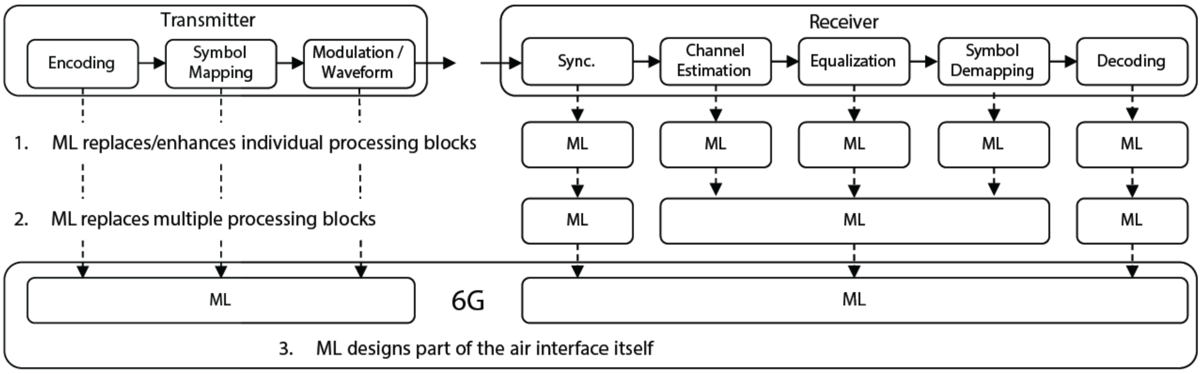

Figure 13: Roadmap of the inclusion of AI/ML in mobile communications systems [20]

This PoC has been implemented based on 2.1 Sub-THz OTA testbed. In this implementation the aim is to validate the suitability and performance of an AI-based channel estimator. More precisely the channel estimator under study should be able to deal with 144GHz carrier channel and 1.5GHz bandwidth signal.

3.1.1 Setup and design

The setup is the following:

1. M8195A acts as a 5G waveform generator. It produces a continuous 5G downlink signal with numerology 5, 1.5 GHz bandwidth and 5 GHz of carrier frequency i.e. in intermediate frequency.
2. The signal produced by the M8195A is fed into the VDI upconverter. The PSG acting as a LO is configured with a sinusoidal tone of 23.16GHz. The VDI converter is configured

with a harmonic factor of 6, bringing the carrier frequency after upconverting to 5 + (6*23.16) = 144GHz

3. The 144GHz signal is amplified with the VDI waveguide amplifier and radiated to the air via the horn antenna.
4. The horn antenna attached to the downconverter receives the signal and feed it into the downconverter, which is configured with the same LO and configuration as the upconverter. The output of the downconverter has a carrier frequency of 5GHz.
5. Finally, the intermediate frequency signal is digitized by the M8131A and 20ms of transmission are recorded. The recorded signal is used as an input in a 5G simulation inside Pathwave System Design.

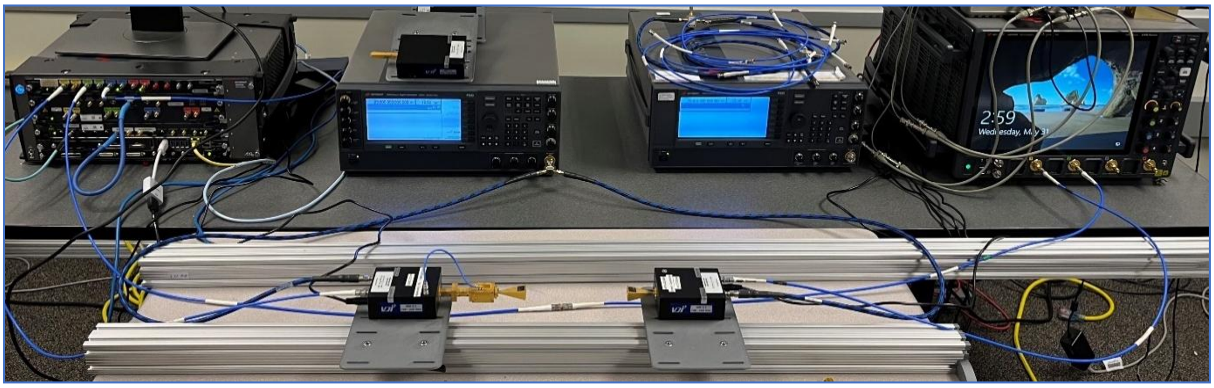

Figure 14: Picture of the testbed used in PoC1

3.1.2 Assessed KPIs and Results

The results in this PoC are taken from the performance of an AI-based channel estimator. After being used as a replacement of the baseline channel estimator, the BLER performance of the whole receiver system is monitored as the main KPI.

Three different models are evaluated:

1. Keysight channel estimator: this NN-based model was designed by Keysight in the early stages of the PoC development. The model is not fully optimized for performance.
2. InterDigital channel estimator: a NN-based channel estimator developed and optimized by Interdigital.
3. InterDigital channel estimator + equalization: extension of the previous model including equalization operation.

The BLER achieved in the testbed with the different models is depicted in Figure 15, where we use as benchmark for the NN-based models a classical MMSE channel estimator.

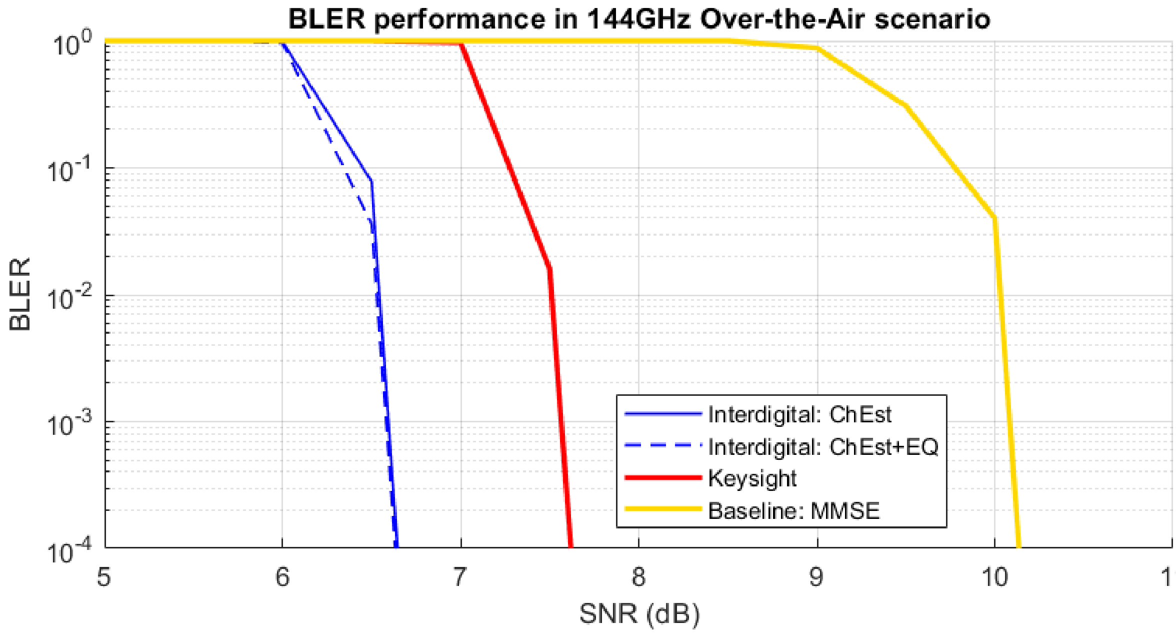

Figure 15: BLER performance of the receiver when using different channel estimators

The results obtained confirm the superiority of the AI-based receiver components as compared to the traditional baseline. The unoptimized Keysight model already presents a gain larger than 2 dBs in SNR with respect to the benchmark, and this gain is further increased by the InterDigital models. Interestingly, there doesn't appear to be a significant gain by including equalization in the operations to be performed by the AI model. Further investigation will be needed to design a model that can leverage joint channel estimation and detection to yield higher gains.

3.1.3 Dissemination

PoC1 has been utilized as a tool for dissemination of CENTRIC's research in several industry events and conferences since the beginning of 2024. Specifically, different versions of the PoC have been showcased at the following events:

- ETSI Artificial Intelligence (AI) Conference - Status, Implementation and Way Forward of AI Standardization (5—7 of February 2024, Sophia Antipolis, France).
- Mobile World Congress (MWC) 2024 (26—29 of February 2024, Barcelona, Spain) (Figure 16)
- 2024 EuCNC & 6G Summit (3—6 of June, Antwerp, Belgium) (Figure 16)

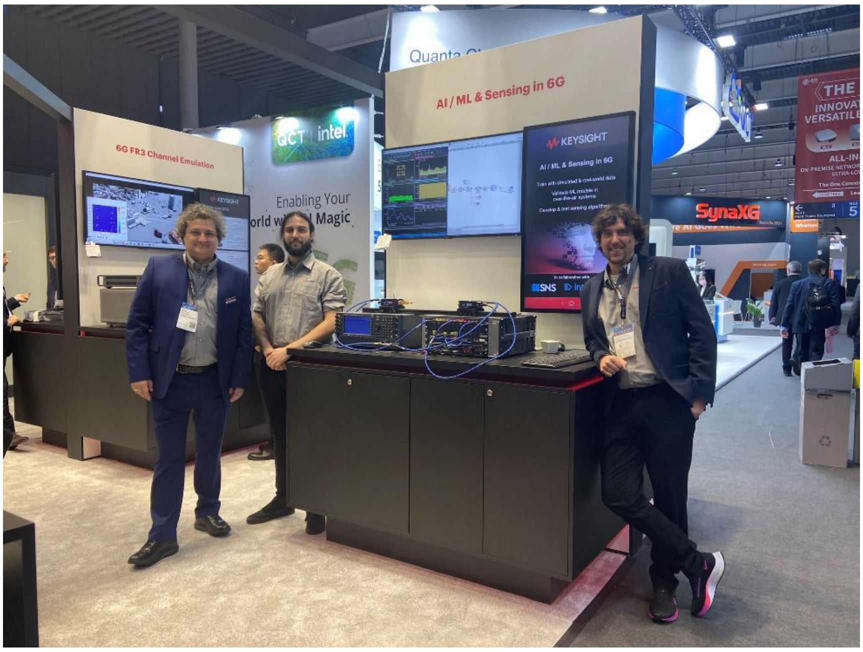

Figure 16: PoC1 being showcased at MWC'24 (Barcelona, February 2024)

Figure 17: PoC1 being showcased at EuCNC'24 (Antwerp, June 2024)

3.2 PoC2: Site-specific Multi-User MIMO Neural Receiver

In contrast with PoC1, the roadmap towards AI-native communications includes "stage 2", depicted in Figure 13, where more than one processing block is replaced by an AI/ML model. This model takes care of all the processing operations at once without explicit output of the intermediate results. This creates a trade-off between modularity and performance.

In this context NVIDIA has developed what they coined a “Neural Receiver” which performs the operations of channel estimation, MIMO equalization and symbol demapping. Except for LDPC decoding and synchronization, the Neural Receiver performs all the baseband operations needed in a real base-station.

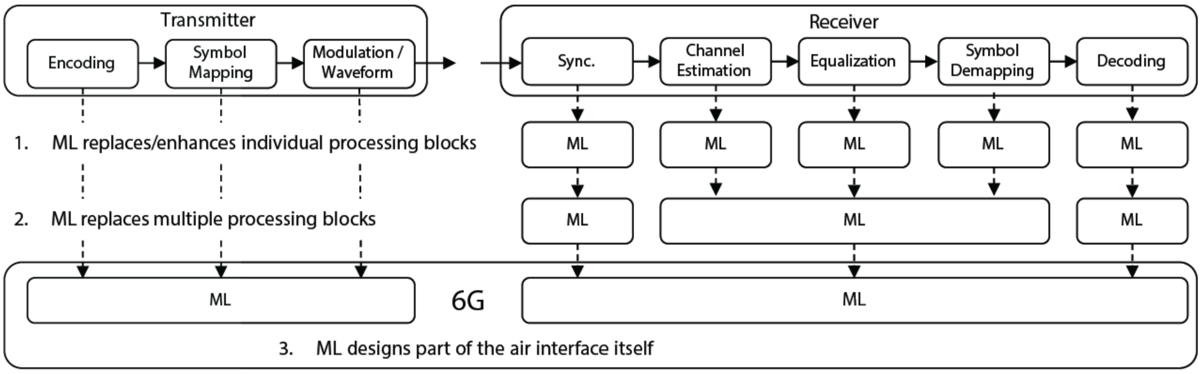

Figure 18: Roadmap of the inclusion of AI/ML in mobile communications systems [20]

This Proof of Concept has been implemented based on the commercial O-RAN testbed presented in Section 2.2. In this implementation the aim is to validate the implementation and functionality of the Neural Receiver as part of a real-world receiver connected to O-RAN hardware. The presence of hardware brings new challenges that are extremely difficult to model in simulations. For this reason, deployments of AI-based receivers in this testbed renders the results valid in real-world scenarios.

3.2.1 Setup and design

The setup of the PoC is depicted in Figure 19:

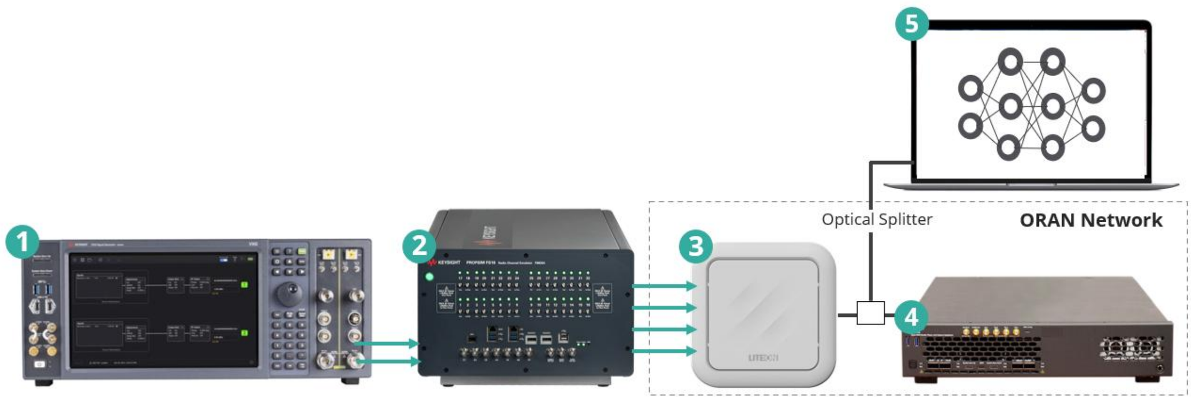

Figure 19: Graphical representation of the testbed used in PoC2

1. VXG generates two independent 5G waveforms to emulate two independent UE data streams.
2. The transmitted signals from both UEs are fed into the channel emulator PROPSIM where they will undergo real time RF channel emulation. The channel impulse responses used in the PoC are generated by Sionna RT. More precisely, two independent trajectories around a digital map of the area of “Fira de Barcelona” were

simulated and their propagation ray-traced. Each simulated trajectory is applied to one signal.

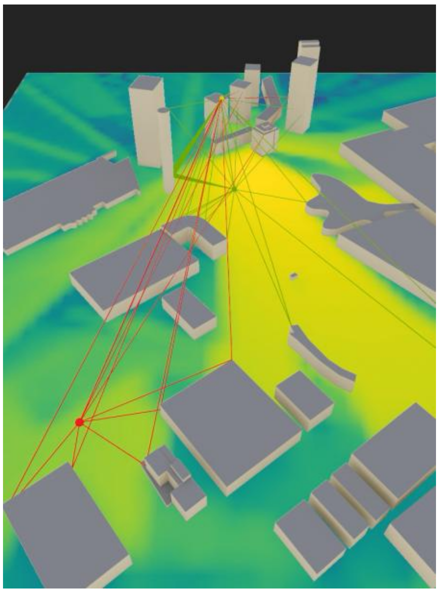

Figure 20: Snapshot of the propagation scenario simulated in Sionna's Ray-Tracer [17]

3. The channel-affected signals are summed and outputted via four ports of the PROPSIM and inputted to the commercial O-RU

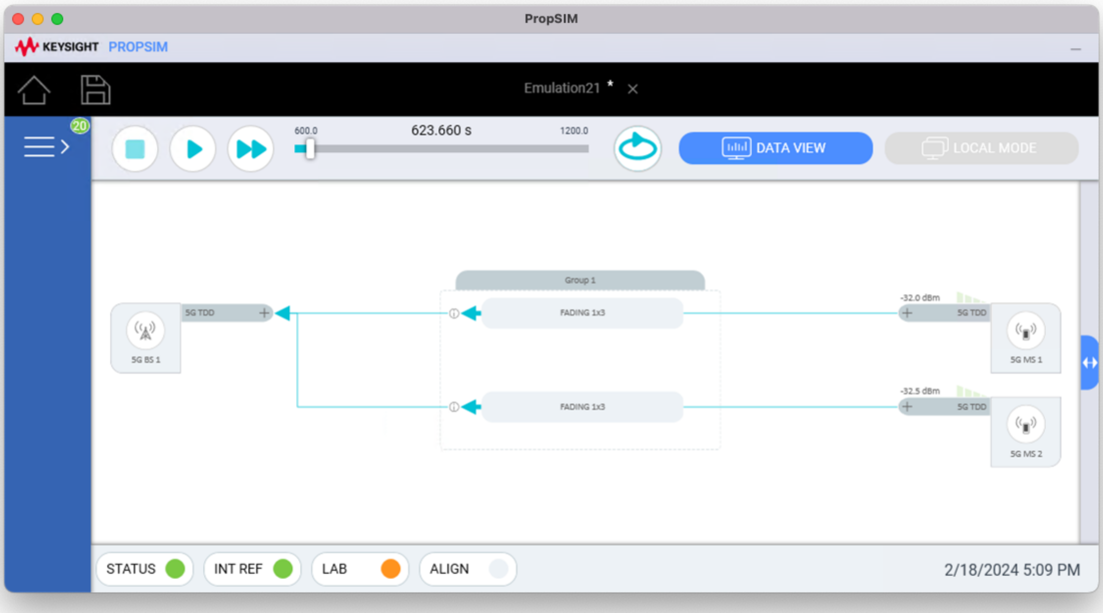

Figure 21: Snapshot of Channel Emulation in PROPSIM

4. The O-RU is controlled via the S5040B, which sends control-plane messages to the O-RU indicating the time instant and bandwidth that needs to be digitized. The O-RU converts RF signals to baseband, perform analog-to-digital conversion, cyclic prefix

elimination and FFT. At the output of the O-RU, IQ samples of the received constellations are fed into the S5040B via one end of an optical splitter for recording and inspection.

5. The second end of the optical splitter is connected to Claude. Inside Claude there are two versions of NVIDIA´s Neural Receiver:
    a. Neural Receiver trained with 3GPP models i.e. CDL channels
    b. Neural Receiver finetuned with the CIRs coming out of the SionnaRT

   This two Neural Receivers consume the live IQ stream coming out of the O-RU and output the predicted LLR values that are then inputted into a standard-compliant LDPC decoder. The bit outputs of the LDPC decoder are used to check the CRC values of each transport block. A failed CRC check will flag the transport block as an error and use it to compute Block Error Rate (BLER) in a live fashion.

3.2.2 Assessed KPIs and Results

The results in this PoC are taken from the Neural Receiver performance, its suitability to be deployed along with hardware and its performance gains when finetuning approaches are applied.

To assess the performance of the Neural Receiver, the selected KPI is the BLER after the LDPC decoder. PUSCH throughput measured in slots per second (slots/s) will help measure the speed at which the AI server can process slots compared to real-time processing.

The results Figure 22 and Figure 23 show the BLER vs SNR of a 3GPP-compliant standard receiver and the two different versions of the Neural Receiver in setups with 3 and 4 antennas, respectively.

On one hand, it is easy to check that the Neural Receiver performs exceptionally better than the baseline receiver even when consuming IQ samples from a real-world O-RU. This proves the potential of employing an AI-based receiver even outside simulations and theorical environments.

On the other hand, the site-specific version of the Neural Receiver shows better performance than the version trained with 3GPP stochastic models. The finetune effort was miniscule compared to a normal training process. Given that the complexity of the site-specific receiver is the same as the general version, this performance gap comes at the small cost of finetuning.

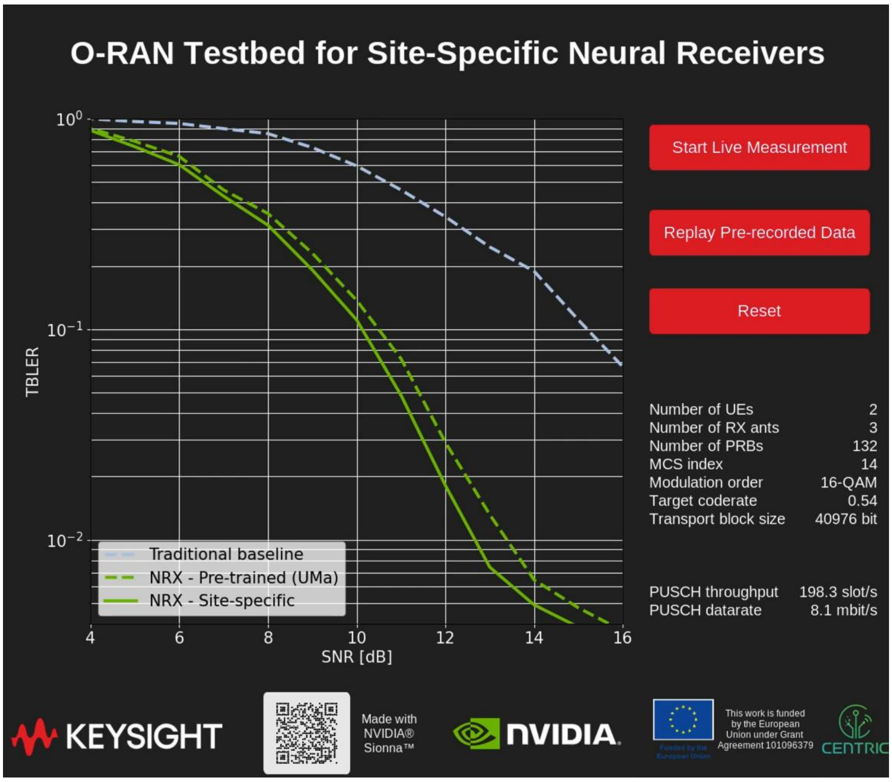

Figure 22: BLER performance of the different versions of the Neural Receiver and baseline receiver vs SNR levels. Case with 3 Rx antennas.

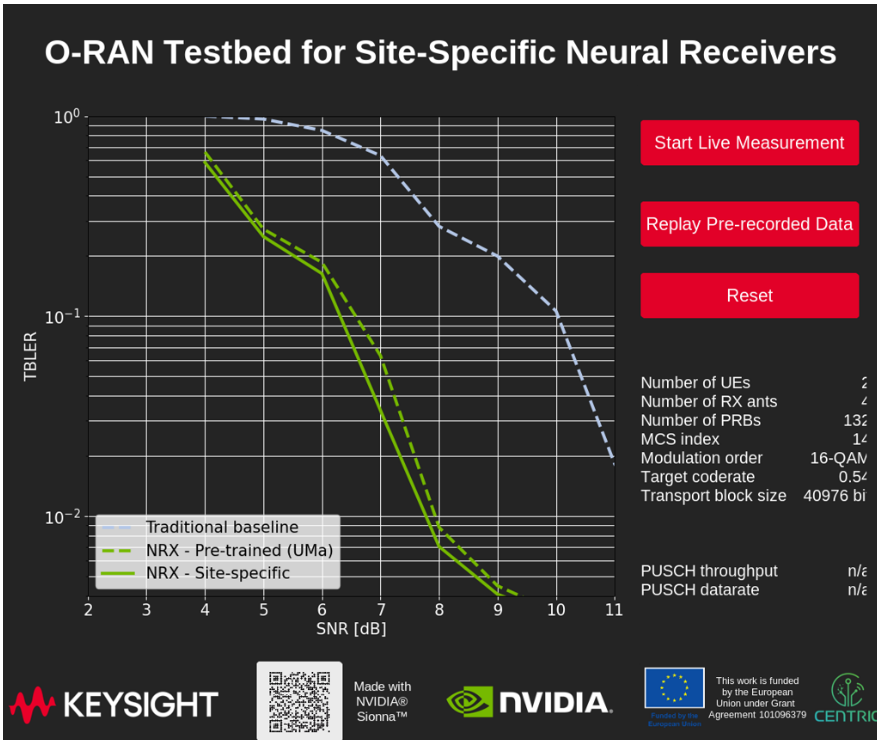

Figure 23: BLER performance of the different versions of the Neural Receiver and baseline receiver vs SNR levels. Case with 4 Rx antennas.

3.2.3 Dissemination

PoC2 has been disseminated at the following events:

- Mobile World Congress (MWC) 2024 (26—29 of February 2024, Barcelona, Spain) (Figure 24)
- 2024 EuCNC & 6G Summit (3—6 of June, Antwerp, Belgium) (Figure 25)

In the first event, the Neural Receiver was evaluated with 3 Rx antennas, as in Figure 22, whereas at EuCNC the setup was upgraded to process signals received at 4 Rx antennas (Figure 23).

In addition, this PoC will be showcased in the upcoming IEEE International Conference on Machine Learning for Communication and Networking (IEEE ICMLCN), to be celebrated in the end of May in Barcelona, Spain. It has been accepted for demo exhibition in a joint effort with PoC3. An extended abstract of the demo will also be published in the conference proceedings and IEEExplore.

Figure 24: Booth at MWC'24 showcasing PoC2 (Barcelona, February 2024)

Figure 25: CENTRIC booth at EuCNC'24 showcasing PoC2 (Antwerp, June 2024)

3.3 PoC3: AI-based Sensing using 5G NR SRS

One of the main novel features expected in the 6G air interface is the introduction of sensing capabilities integrated concurrently with the communication signals transmitting the user data. The concept, coined as joint / integrated sensing and communications (JSAC / ISAC), intends to, on the one hand, leverage 6G signals to perform sensing operations on the users and environment and, on the other hand, to utilize the acquired sensing information (e.g., position and speed of users) in order to enhance communication performance. ML and AI techniques are expected to play a pivotal role in accomplishing these goals, either by helping design the sensing waveforms, by providing advanced processing capabilities in order to derive sensing information from the signals, or by helping incorporate contextual information obtained via sensing to improve communication services.

To demonstrate the potential and analyse the performance of AI techniques in this important 6G use-case, CENTRIC has developed a PoC that enables the benchmarking of an AI model that performs sensing and classification of human targets in an indoor environment based on 5G NR standard-compliant sounding reference signals (SRS). For this purpose, the commercial O-RAN testbed introduced in Section 2.2 has been used to enable the use case as presented next.

3.3.1 Setup and Design

As previously mentioned, the setup relies on the commercial O-RAN testbed reported in Section 2.2, in a setup highly similar to that used for PoC2. The setup is illustrated in Figure 26, and we describe the different elements next.

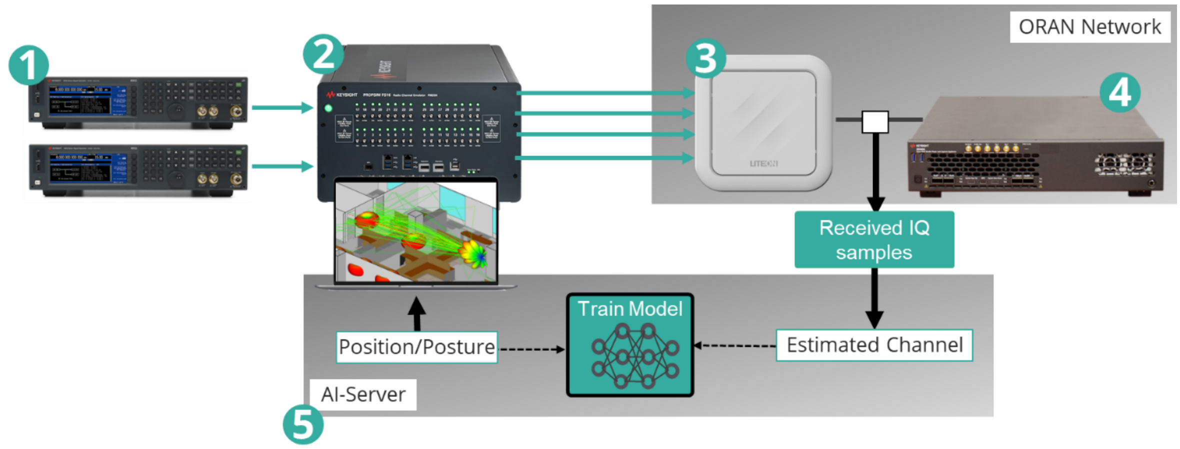

Figure 26: Block diagram of the setup for PoC3

1. RF signal generators are used to generate the RF 5G-NR signal containing the SRS that will be used for the sensing tasks. In the modeling of the system, 2 UEs transmit orthogonal SRS. The IQ samples are generated using Keysight's Pathwave Signal Generation software [9] and are modulated into RF frequency using either a VXG signal generator [14] with two output channels or using two single-channel MXG N5182B [21] signal generators, depending on the available hardware. The signals have a bandwidth of 100 MHz and are modulated at a carrier frequency of 3.7 GHz.
2. The generated RF signals are fed to PROPSIM F880B [16] channel emulator, which emulates the propagation of the signals through an indoor office environment in which 2 UEs communicate with 4 spatially-distributed receive antennas (more details on the modeling of the channel are provided below). Hence, PROPSIM outputs for RF signals.
3. The output of the channel emulator is then fed to the LiteOn O-RU [13], equipped with 4 antenna ports. The O-RU performs basic demodulation of the 5G signal, by digitizing it, removing the cyclic prefix, and performing fast Fourier transform operation. The resulting IQs are then fed, using an optical splitter, to both the O-DU emulator S5040A [12] and to a server with AI processing capabilities.
4. The O-RU is controlled via the S5040B, which sends control-plane messages to the O-RU indicating the time instant and bandwidth that needs to be digitized. At the output of the O-RU, IQ samples of the received constellations are fed into the S5040B via one end of an optical splitter for recording and inspection.
5. The other end of the optical splitter is fed to the AI server, which delivers them to the AI model performing sensing and classification of targets. The role of the AI model is further detailed below.

We turn the attention now to the modeling of the environment that is emulated by the channel emulator to replicate a sensing use case. The targeted environment is modeled using a 3D-modeling tool (Blender) that replicates an office-like scenario, as illustrated in Figure 27. The 3D modeling tool is also used to have high-fidelity models of humans moving around the scene and performing two different actions: walking and remaining stationary. The virtual model is annotated with the RF material properties of the different elements. Sionna's ray-tracing tool [17] is used to generate channel responses between both UEs and all the RX positions. The two UEs are placed on cafeteria-like tables, whereas the reception points are distributed in space at a height close to the ceiling level. As the human moves around the room, they perturb the RF channel in a way that is dependent on the human location. This, in turn, will perturb the SRS that are output to the channel emulator, and these distorted signals will be the features used by the AI model in order to estimate the position of the target, as well as its corresponding action (walking / stationary).

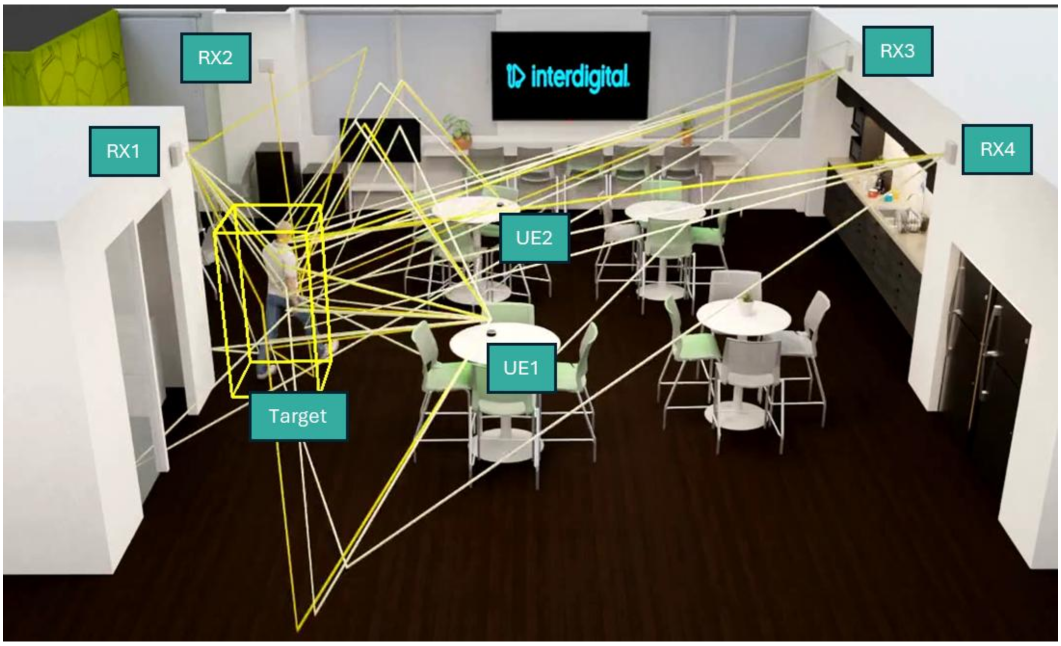

Figure 27: Snapshot of the 3D modeling of the indoor office environment, depicting rays calculated by the ray-tracing tool

The AI model used to solve the sensing and activity classification tasks was developed by InterDigital, and is not reported here for confidentiality reasons. It accomplishes three different tasks: 1) it detects the presence or absence of a human in a room (presence detection), 2) when a human is present, it estimates its location (target localization), and 3) it detects whether the human is walking or is stationary (activity detection). We report next some indicative results of the performance that it achieves at the different tasks.

3.3.2 Assessed KPIs and Results

In order to assess the performance of the AI model under test, the following KPIs are used:

- For the target localization task, the root mean squared (RMS) 2D position error is used as KPI.
- For the presence and activity binary detection tasks, accuracy of the predicted label in percentage are used as KPIs.

While the evaluation of the AI model has so far been restricted to the emulated office-like scenario, and testing of it in a diversity of environments would be needed in order to achieve more detailed conclusions, we can report here the following results in the evaluated case:

- In terms of location accuracy, the model achieves an RMS position error of around 16 cm.
- In both binary classification tasks of human presence detection and human activity detection, the accuracy of the model exceeds 90% of the evaluated snapshots.

A snapshot of the GUI used to visualize the results of the model is provided in Figure 28.

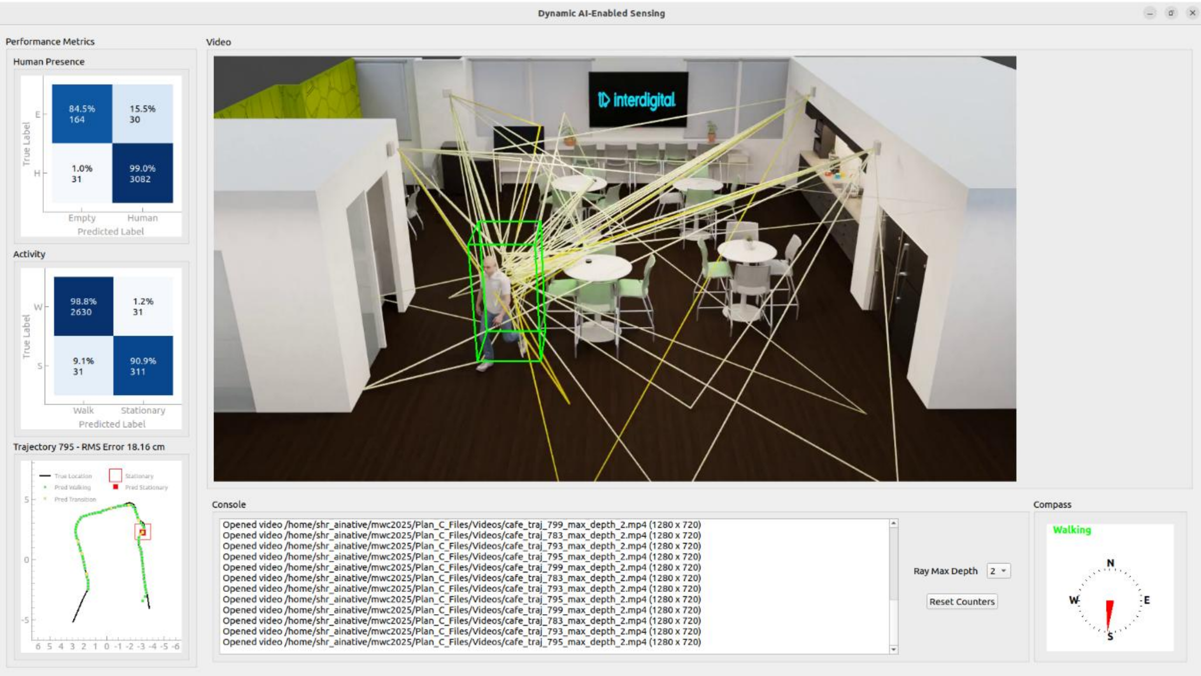

Figure 28: Snapshot of the AI sensing model GUI, illustrating the results obtained

3.3.3 Dissemination

For PoC3, the following dissemination action has been already implemented:

- The setup and results of PoC3 where showcased at InterDigital’s booth in MWC’25 in Barcelona, celebrated early March 2025. A picture of the InterDigital and Keysight staff present at the event is provided in Figure 29.

In addition to the presence at MWC, PoC3 has been accepted to be showcased at the Demo Exhibition in the upcoming IEEE International Conference on Machine Learning for Communication and Networking, which will take place in Barcelona the last week of May 2025. In addition to this, an extended-abstract of the demo will be published with the conference proceedings and in IEEExplore. It should be mentioned that at this conference PoC3 will be showcased jointly with PoC2, leveraging the fact that they both require the same hardware setup. This fact illustrates the flexibility and wide applicability of the commercial O-RAN testbed developed in the project, which allows to validate and benchmark AI models for highly different tasks: baseband receiver processing in PoC2, and sensing tasks in PoC3.

Figure 29: The InterDigital booth showcasing PoC3 at MWC'25 in Barcelona (March 2025)

3.4 PoC4: AI-based CSI Feedback Compression

The last PoC developed in the context of the CENTRIC project deals with one of the air interface functionalities where adoption of AI techniques is expected to come earlier into 3GPP standards. Indeed, RAN1 in 3GPP developed a study item in release 18 titled *Study on Artificial Intelligence (AI)/Machine Learning (ML)* [22] in which the introduction of AI/ML techniques for the air interface of the 5G evolution was studied using three illustrative use cases:

- Channel State Information (CSI) feedback enhancement
- Beam management
- Position accuracy enhancements

These three use cases where agreed to spearhead the introduction of AI in the air interface. While the study was restricted to these three use-cases, it aimed as well to draw general conclusions on AI model management for other uses cases as well.

In PoC4, we focus on the first of these three use cases: CSI feedback enhancement. In a nutshell, the problem is illustrated in the left-hand diagram presented in Figure 30, and relates to the acquisition of CSI used for beamforming at the gNB, which is particularly relevant in the case of massive MIMO capable gNBs. When acquisition of CSI at the gNB using channel reciprocity in a TDD system is not possible (either due to the system being FDD or due to non-reciprocity of the UL and DL channel), the DL CSI must be acquired by the UE based on the transmission of downlink pilots signals –typically channel state information reference signals (CSI-RS). Once the UE has estimated the CSI, this has to be fed back to the gNB via an uplink channel. The transmission of such CSI, if done uncompressed, would imply a large overhead in the uplink transmissions, particularly in the case of high-dimensional MIMO channels. Hence, compression and quantization of this CSI is required before the information is fed back to the gNB. In 5G NR, different CSI encoding schemes based on codebooks (Type I and Type II codebooks) have been proposed. However, the overhead vs accuracy tradeoff of such compression schemes leaves room for improvement, particularly as the dimensions of massive MIMO channels grow large.

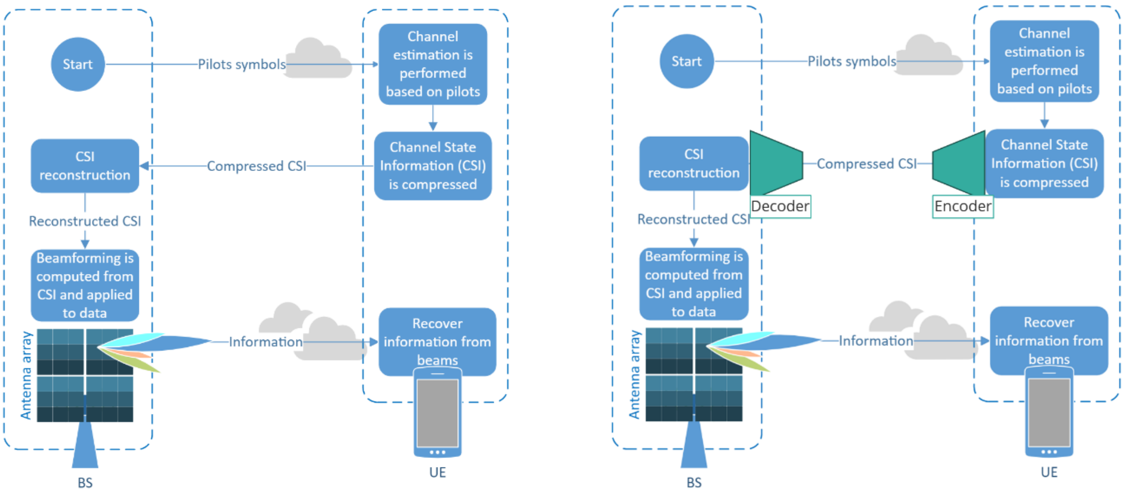

Figure 30: Diagram illustrating the CSI feedback procedure in 5G NR. Left: traditional compression. Right: AI/ML based compression and reconstruction

It was hypothesized that the use of AI models for compression of the CSI at the UE side and reconstruction at the gNB side could outperform the 3GPP standard Type I and Type II codes. The concept is depicted in the right-hand diagram in Figure 30, where two AI models have been introduced at the UE and at the gNB sides. Typically, the two models together should form an autoencoder (see Figure 31), that is, a neural network which aims to encode its input into a lower-dimensional representation, called the "Latent Space Representation", and then reconstruct the original input based on such latent representation. The first layers of the autoencoder, prior to the latent representation, are typically called the "Encoding Network", whereas the layers following the latent representation are called the "Decoding Network". In its application to CSI compression, the Encoding Network is deployed at the UE, and takes as input the (possibly pre-processed) CSI estimates obtained by the UE. The encoding network encodes these CSI estimates into a low-dimensional representation (latent space representation) which is then fed back to the gNB via UL transmissions. Upon reception of this compressed CSI representation, the gNB uses this as input to the decoding network, which reconstructs as faithfully as possible the CSI originally obtained at the UE side.

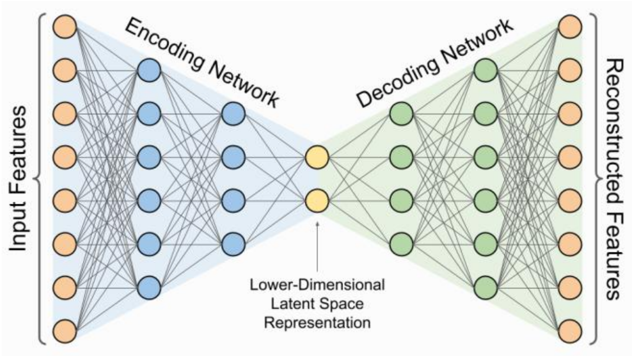

Figure 31: Representation of a typical Autoencoder NN architecture

Our goal in PoC4 is to construct a hardware-in-the-loop testbed that can, in the lab, validate and benchmark different AI models for CSI compression under 3GPP channel models. As a test case, the CSI compression models developed by NOK in the context of Task 3.4 in WP3 of CENTRIC will be used.

3.4.1 Setup and Design

The setup of this PoC is based on the closed-loop MIMO testbed presented in Section 2.3, and is illustrated in Figure 32. The MTRX multi transceiver platform takes upon both the roles of the gNB transmitter and the UE receiver. The PROPSIM channel emulator connects the TX ports of the MTRX (which correspond to the gNB transmit antenna ports) with its RX ports (which correspond to the receive antenna ports at the UE), and takes the role of emulating the DL channel between gNB and UE.

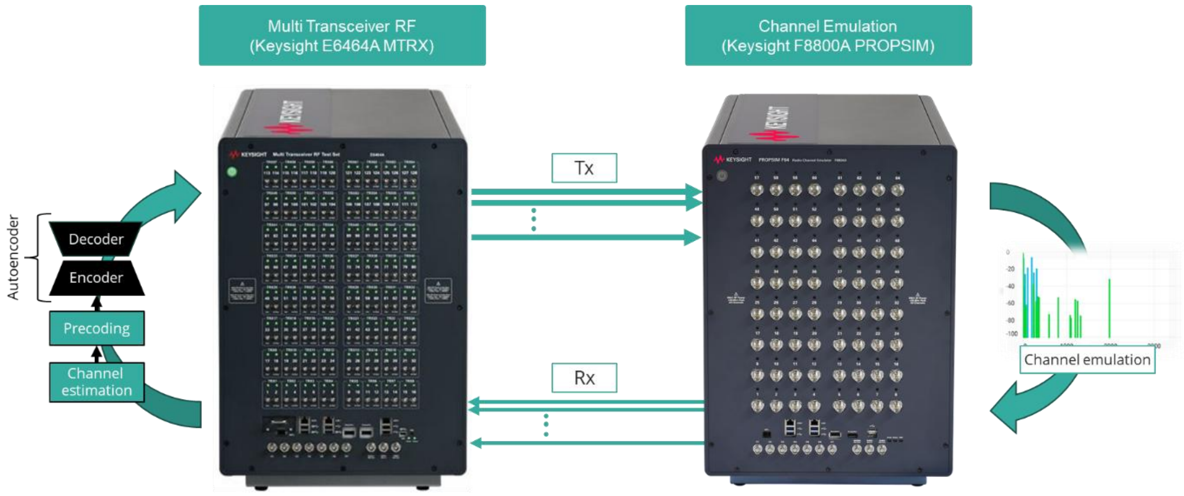

Figure 32: Illustration of the hardware setup used for PoC4

On the left-hand side of the MTRX platform in Figure 32, as simplified representation of the signal processing performed between consecutive transmissions is depicted. This part is represented in higher detail in the diagram of Figure 33. We will use it to illustrate the workflow of the PoC, which is described next:

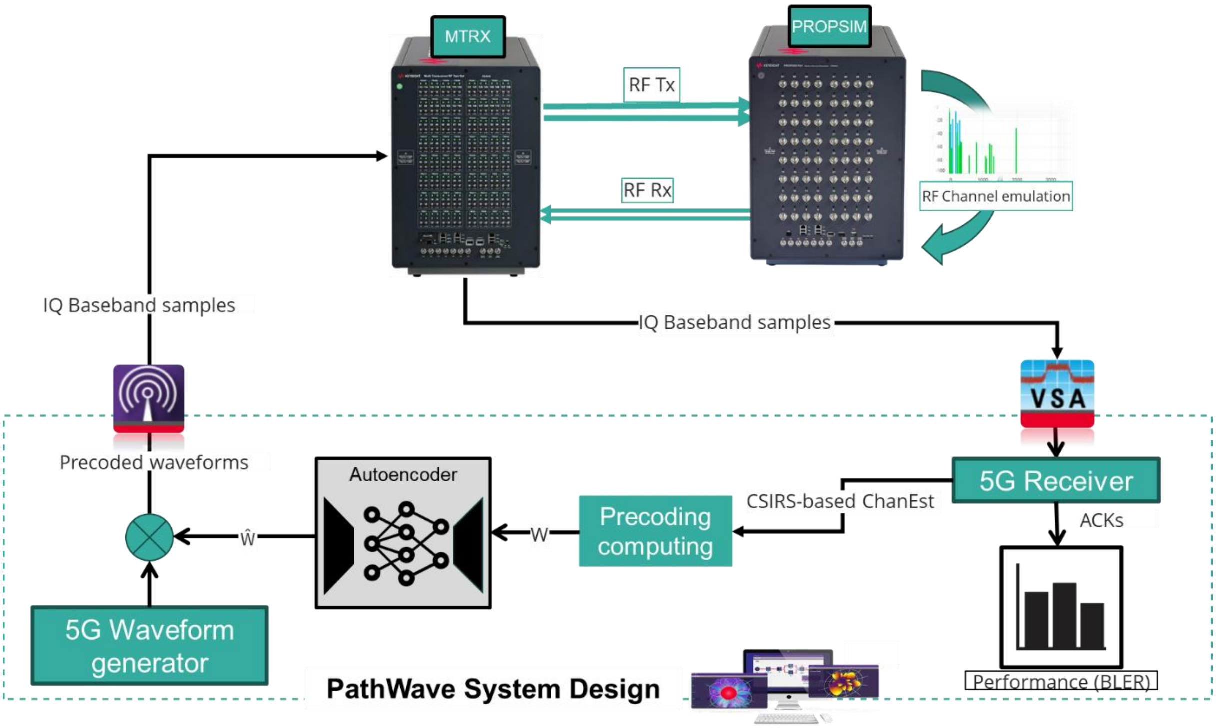

Figure 33: Illustration of the hardware and software setup used for PoC4

1. In an initial step, an RF 5G NR DL transmission is performed by MTRX, containing among others a set of CSI-RS signals. The signal is configured using Keysight's PathWave Signal Generation software [9]. This initial transmission is not precoded and, after emulation of the channel convolution at the PROPSIM platform, the resulting RF signal is fed back to MTRX, representing the signal received by a UE. PROPSIM is set to emulate channel responses obtained from standard 3GPP channel models.
2. The IQ baseband samples received after the transmission in Step 1 are then, through VSA software [8], fed to the PathWave System Design software [10]. There, via the use of 5G receiver models available in the platform, an estimate of the channel is obtained based on the received CSI-RS signals.
3. After potentially some preprocessing, the CSI estimates are fed to the NNs performing CSI compression and CSI reconstruction, which are integrated in PathWave System Design. Note that the UL transmission in which the UE feeds the compressed CSI to the gNB is assumed ideal and is, therefore, not emulated in the testbed. That is, it is assumed that the CSI compressed by the UE is received without error at the gNB.
4. Using the CSI obtained after the processing by the AI models under test, a computation of the precoder to be used in the next transmission is performed in PathWave System Design. Using the computed precoders, PathWave Signal Generation is used again to create a new DL 5G NR signal which is now precoded.
5. The transmission of this DL precoded signal is then emulated again in MTRX and PROPSIM, following a procedure analogous to that described in Steps 1 and 2.
6. The IQ samples obtained after the reception of the precoded DL transmission are then fed again to PathWave System Design, where some postprocessing of them is done in order to extract KPIs such as the Received SNR or the BLER.

The baseband processing models used in PathWave System Design for the processing described in Steps 3, 4 and 6 are depicted in Figure 34. Particularly interesting is the CSI feedback block, in which the integration of the NN model under test is performed. There, we can observe that, between some MATLAB-based preprocessing and postprocessing blocks, the AI model under test is embedded in the form of an Open Neural Network Exchange (ONNX) model. This solution provides an easy way to integrate diverse NN models, potentially belonging to different vendors, into the testbed.

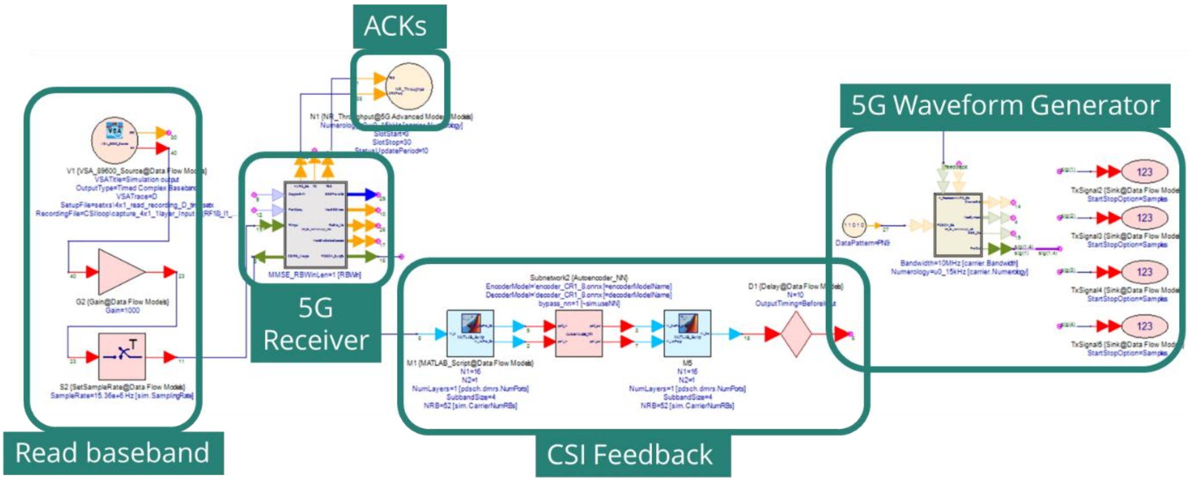

Figure 34: Illustration of the baseband processing blocks for PoC4 performed using PathWave System Design

The AI model used in this PoC is a low complexity transformer-based AI model for CSI compression developed by Nokia in the context of WP3 work. The approach introduces a lightweight transformer-based neural network with an autoencoder architecture that achieves state-of-the-art performance with significantly fewer parameters within the transformer-based architecture. As widely accepted in 3GPP, the system distributes processing by implementing the encoder on the UE side and the decoder on the gNB, enabling compression and accurate reconstruction of CSI across spatial, frequency, and temporal domains. This architecture not only improves reconstruction accuracy while reducing CSI feedback overhead bits but also enables predictive capabilities when temporal correlations are incorporated. The model employs domain-specific optimization metrics—Normalized Mean Squared Error (NMSE) for explicit (raw) CSI and Squared Generalized Cosine Similarity (SGCS) for implicit CSI such as precoding matrices—ensuring optimal performance across different CSI types is guaranteed. The models are trained based on synthetic data from 3GPP standard models.

3.4.2 Assessed KPIs and Results

The PoC is currently still in the last stages of the development at the time of writing of this report. Hence, no final results are yet available, and only preliminary, intermediate results have been obtained. We describe next, nonetheless, the KPIs and baselines that we aim to obtain with the described setup. In terms of KPIs, the testbed will produce:

- Receive SNR of the precoded DL transmissions: this will be evaluated based on the IQ samples obtained when the DL transmission is precoded based on the CSI compressed and reconstructed using the AI model under test. From this KPI, other related KPIs, such as achievable rates, can be derived.
- BLER: this will be obtained again from the same receive IQ samples, after processing by an assumed UE baseband receiver model.
- UL overhead: this KPI is a direct result of the architecture of the tested CSI compression model, as it is fully determined by the dimensionality of the latent space representation of the autoencoder. Nonetheless, this is an important KPI, as different models should be compared in fair conditions, that is, under the same constraints of the maximum allowed UL overhead.

In addition, the tested AI model will be compared against two main benchmarks:

- Uncompressed CSI: in this baseline, the CSI estimated at the UE is readily available for precoding at the BS without following any compression and reconstruction process.
- Type II compression: as another non-AI based baseline, the performance of the tested AI models will be compared to that of current 3GPP standard compression using Type II codebooks.

As illustration of the intermediate results obtained in the testbed, we show in Figure 35 snapshots of the real and imaginary parts of a 4X1 DL MIMO channel across physical resource blocks. On the left hand side, we observe the CSI estimates obtained by the UE from the initial DL transmission. On the right hand side, we observe the reconstructed counterparts after the CSI compression and reconstruction using Nokia's AI model. As it can be seen, in spite of the introduction of a small amount of compression noise, the reconstructed CSI faithfully follows the uncompressed CSI behaviour.

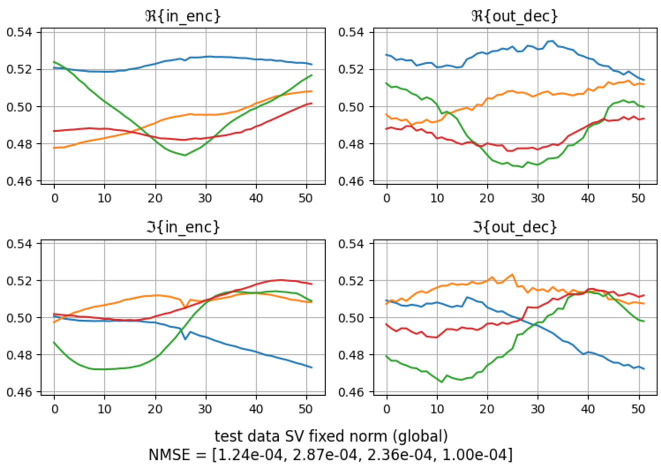

Figure 35: Snapshots of the original CSI (left) and reconstructed CSI (right) observed in the testbed of PoC4

3.4.3 Dissemination

PoC4 will be showcased in the upcoming EuCNC conference to be celebrated in Poznan, Poland, at the beginning of June 2025. There, CENTRIC will have a booth used to showcase the final results of the project, which concludes at the end of June 2025. In addition to this, a joint journal article between Nokia and Keysight is currently being written, which will combine the simulation results obtained by Nokia in the assessment of their proposed CSI compression model with the experimental validation results obtained via PoC4.

While there will be no more time for additional dissemination actions within the time-frame of the CENTRIC project, the use of PoC4 in other dissemination activities after the conclusion of CENTRIC is not discarded, and opportunities for this will be sought in agreement between Keysight and Nokia.

4 Conclusions

4.1 Conclusions

This deliverable has documented the work carried out in WP5 of CENTRIC to enable PoC demonstrators of a selection of CENTRIC's AI technologies for the air interface. Three different testbed setups have been developed, which have enabled demonstration of 4 CENTRIC technological enablers: a NN-based channel estimator, and an NN-based multi-user MIMO receiver structure, and NN-based model for sensing based on 5G NR SRS, and a NN model for CSI compression and reconstruction in Massive MIMO systems.

The results obtained from the testbeds and PoCs serve as confirmation that the technologies research in CENTRIC can show significant gains also outside the simulation realm when real RF hardware is utilized. Overall, they represent an important step forward to validate that AI-based techniques for the air interface have significant potential in real-word scenarios and commercial systems.

In addition to the technical insights obtained by elevating the degree of realism of the evaluation of CENTRIC techniques in the testbeds, the PoCs are also an invaluable tool for dissemination and communication of CENTRIC results to the academic community, the industry, and the public at large.

4.2 Next Steps

In the remaining 2 months of work in CENTRIC, WP5 work will focus on the following actions:

- Finalizing the last stages of PoC4, which include postprocessing and presentation of the KPIs evaluated via the PoC.
- Last dissemination actions connected to the project PoCs:
    - PoC2 and PoC3 will be showcased at the Demo Exhibition of the IEEE ICMLCN in Barcelona, Spain, at the end of May 2025.
    - PoC4 will be showcased in the CENTRIC booth at EuCNC 2025 in Poznan, Poland, at the beginning of May 2025.
    - A journal article using the results of PoC4 is currently being written.
- Leveraging the testbeds and PoCs reported in this deliverable to generate the datasets that will be the main output of *D5.5 – Dataset of Measurement Results*, due at the end of June 2025.

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