



CENTRIC

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

EuCNC & 6G Summit – The 6G Series Workshop by Hexa-X-II

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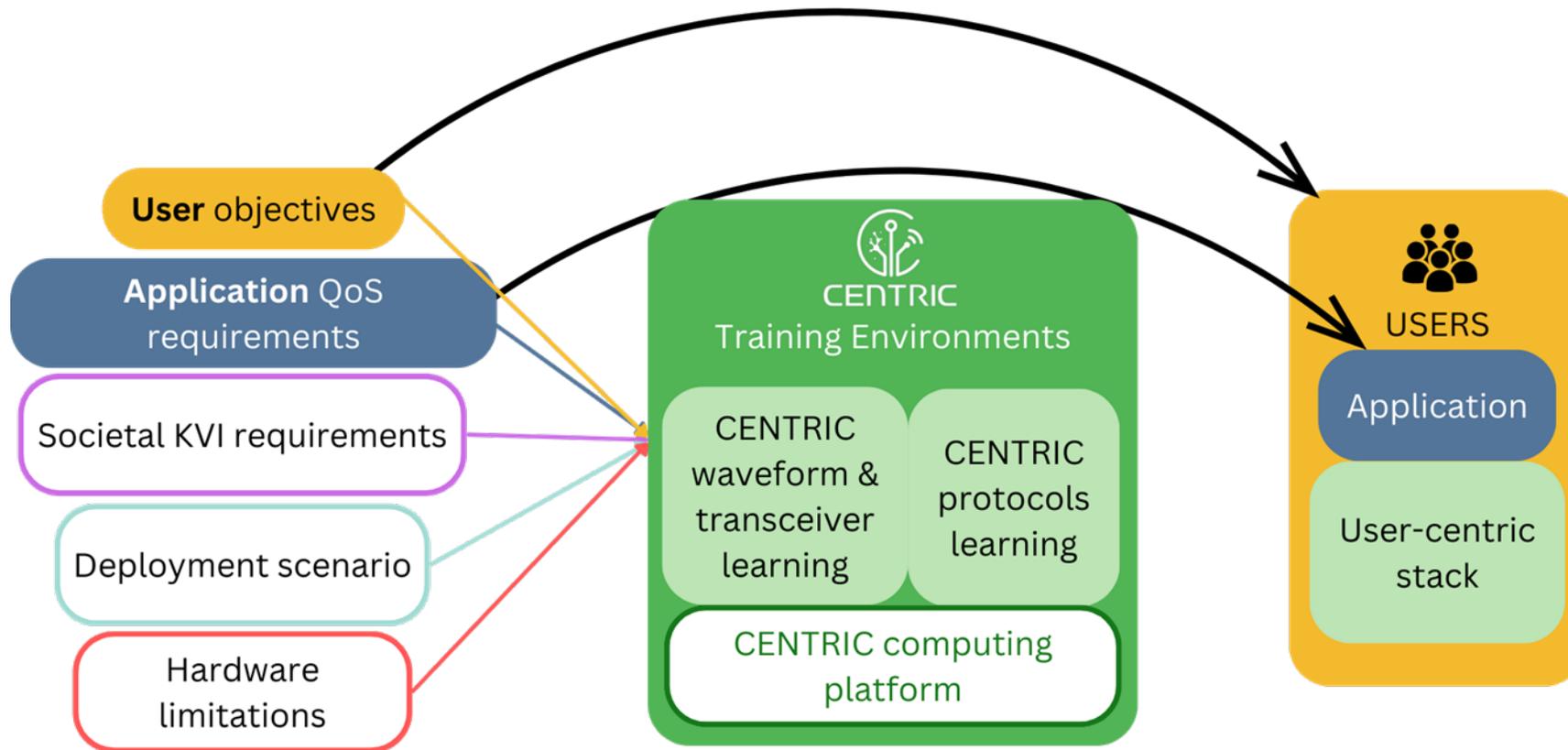
Key Facts

- CENTRIC is an SNS-JU phase 1 STREAM-B-01-02 – “Wireless Communication Technologies and Signal Processing” project
- Project Period: January 2023 – June 2025
- Budget: € 6,840,005.94 of budget (EU Contribution of €4,215,999.00)
- Consortium Partners:
 - Coordinator: Eurescom (DE).
 - Academic: Aalborg University (DK) (Technical Coordinator), CNIT (IT), CNR (IT), King’s College London (UK), University Oulu (FI).
 - Industry: Nokia Networks France (FR), NVIDIA (DE), Sequans Communications (FR), Keysight Technologies (ES), Interdigital Europe (UK), Nokia Solutions and Networks (DE)
 - SME: Synthara AG (CH)



Vision & Goal

“The goal of project CENTRIC is to enable sustainable, user-centric 6G networks through an AI-native Air Interface (AI-AI).”



Objectives

To develop AI methods for the discovery of **novel and efficient waveforms**

To develop AI methods for the discovery of **novel and efficient transceivers**

To develop AI methods for the discovery of **customized lightweight communication protocols**

To introduce novel **end-to-end hardware co-design solutions for energy-efficient AI-native transceivers**

To develop **training and monitoring environments** as enablers for AI-AI deployments

To **validate user-centric AI-AI solutions** in a lab setting

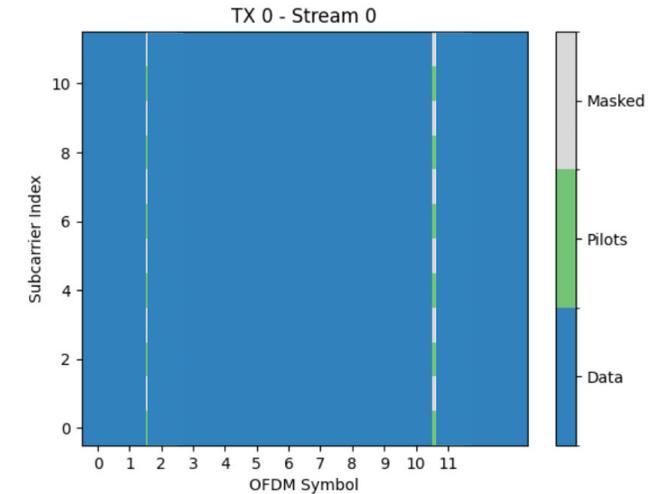
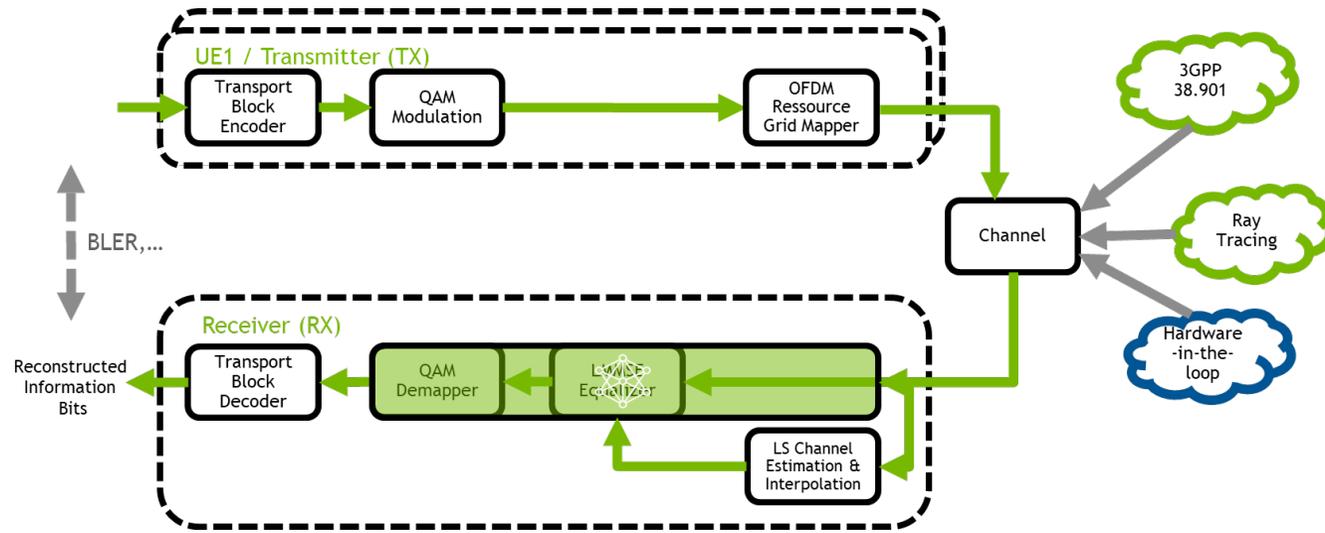
To **demonstrate and disseminate AI-AI concepts**



Selected AI-AI Concepts

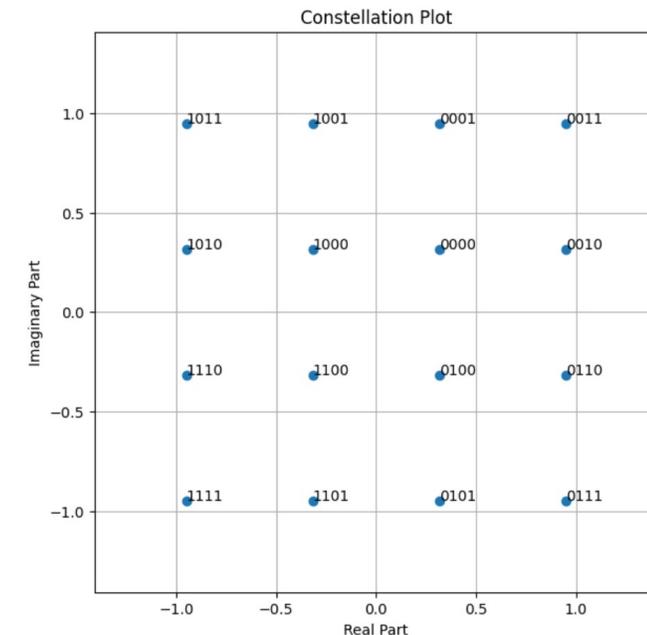
Physical Layer Methods

Pilotless communications enabled by Neural Receivers



- Core idea: remove any DMRS [1] from PUSCH slots
- Trainable custom constellations replace *classical* QAM
- Neural receiver learns implicit channel estimation and equalization

Only additional 32 real-valued trainable weights required



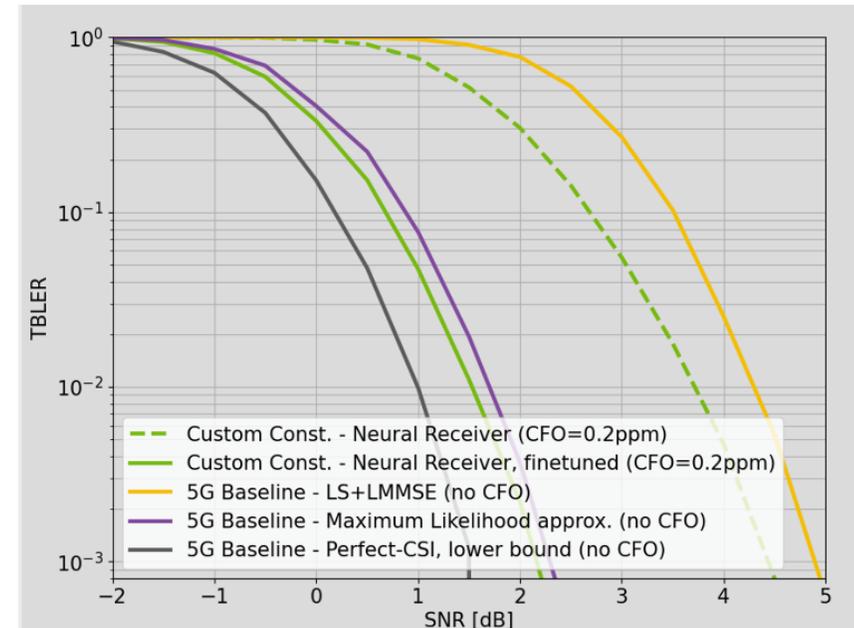
Trained in Simulations – Verified in the Lab

Mobile World Congress 2024 Demonstrator



Hardware-in-the-loop experiment

- 2x4 MIMO configuration
- 273 PRBs/100 MHz bandwidth @ 2.14 GHz
- Post-FFT signal processing by a neural network trained with data generated by NVIDIA Sionna
- Trained to compensate residual CFO up to 0.3 ppm



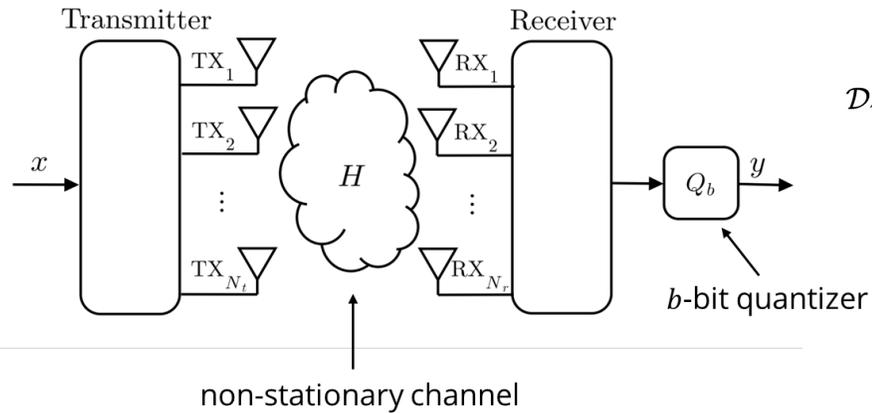
Verified by Rohde & Schwarz test equipment

- Modified 5G NR PUSCH signal
- Custom constellations from NVIDIA Sionna
- *DMRs-free* slots
- 428 Hz residual CFO (=0.2ppm)
- Fading profiles following the 3GPP conformance tests
- TDL-B 100ns/400Hz

In-Context Learning for Adaptable Wireless AI

- Motivation:

- Application of AI to wireless hinges on its adaptability in the face of changes in the environment conditions.
- For example, AI receivers must adapt to non-stationary environments based on a few limited pilots.

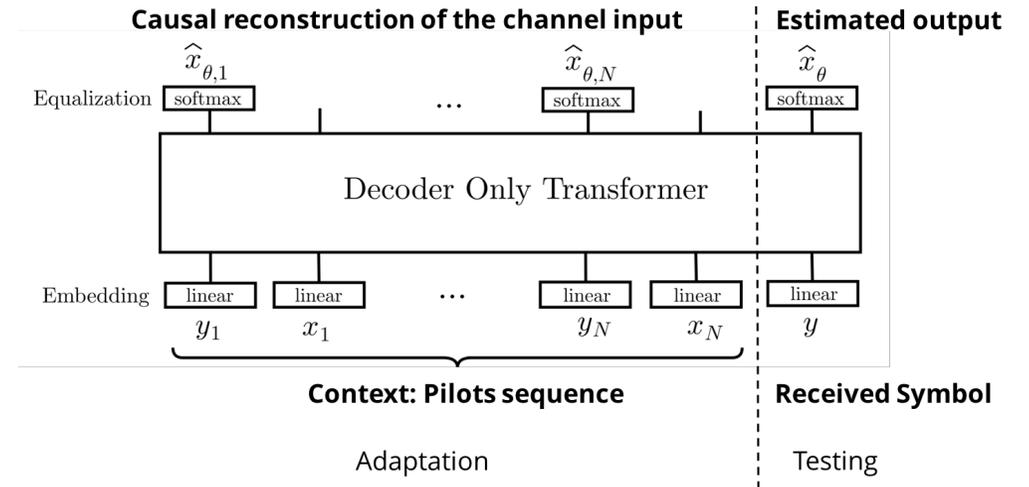


Pilots

$$\mathcal{D}_\tau = \{(x_i, y_i)\}_{i=1}^N \sim P_{y,x|\tau}^{\otimes N}$$

Equalizer

$$\hat{x} = \hat{x}_\theta(\mathcal{D}_\tau, y)$$



- ICL-Based Equalization:

- Transformer models can be trained to perform in-context learning (ICL).
- Adaptation is based on the pilot sequence, without model parameter updates.

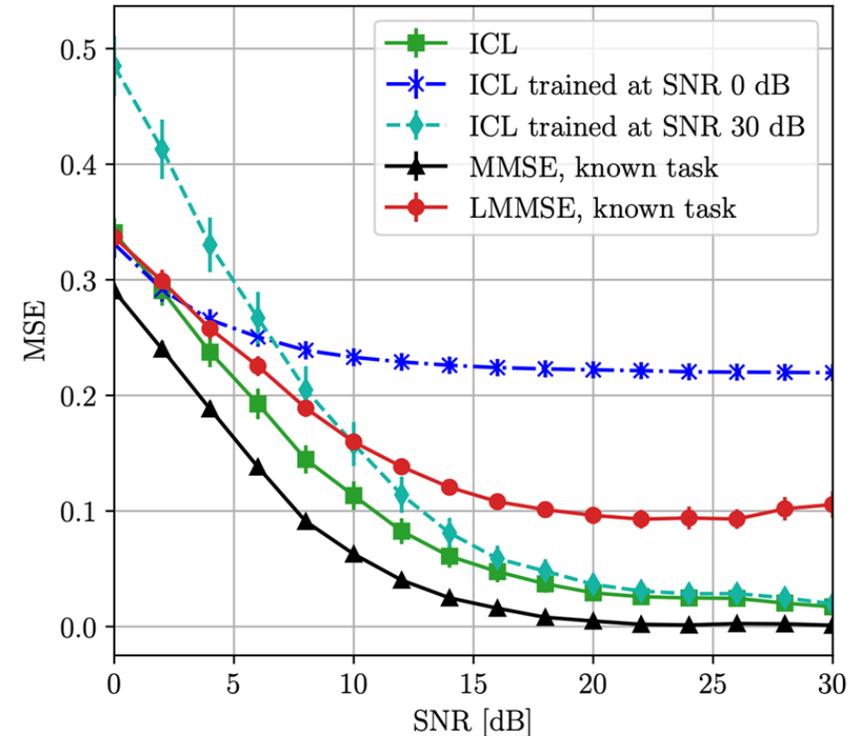
In-context Learning for MIMO Equalization

Channel-aware receivers:

- MMSE with channel knowledge (optimal)
- **Linear MMSE** with channel knowledge

Channel-oblivious receivers (10 pilots):

- ICL trained at 0dB SNR
- ICL trained at 30dB SNR
- ICL trained on diverse SNR tasks.
- ICL outperforms the **Linear MMSE** receiver.
- Task diversity improves the generalization of the model.



ICL can be used to produce highly adaptable equalizers!



Selected AI-AI Concepts

Learned Communication Protocols

Emerging multiple-access protocols for specialized services

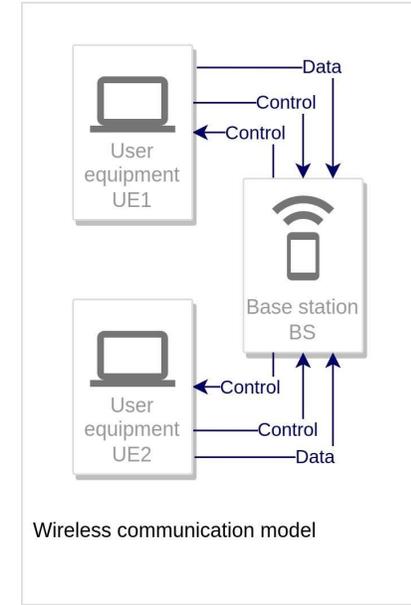
Protocol definition: Logic and signaling necessary for distributed nodes to organize.

Problem:

- **General-purpose RAN protocols** do not leverage the properties of the scenarios they serve.

Q: Can we train scenario-tailored protocols as ML models?

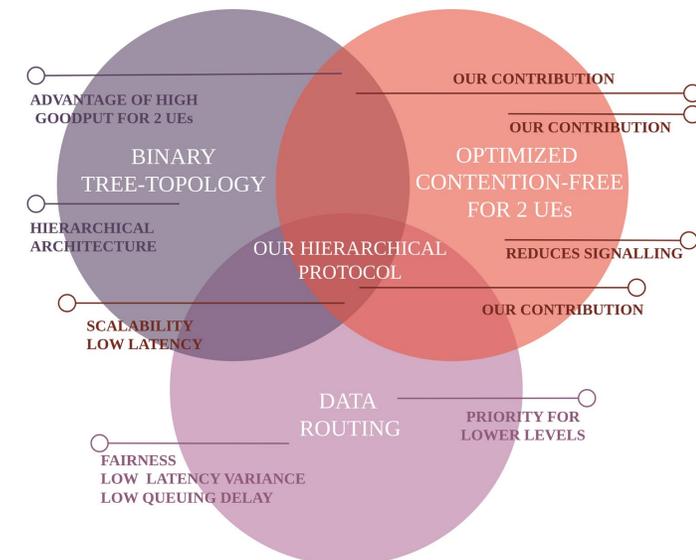
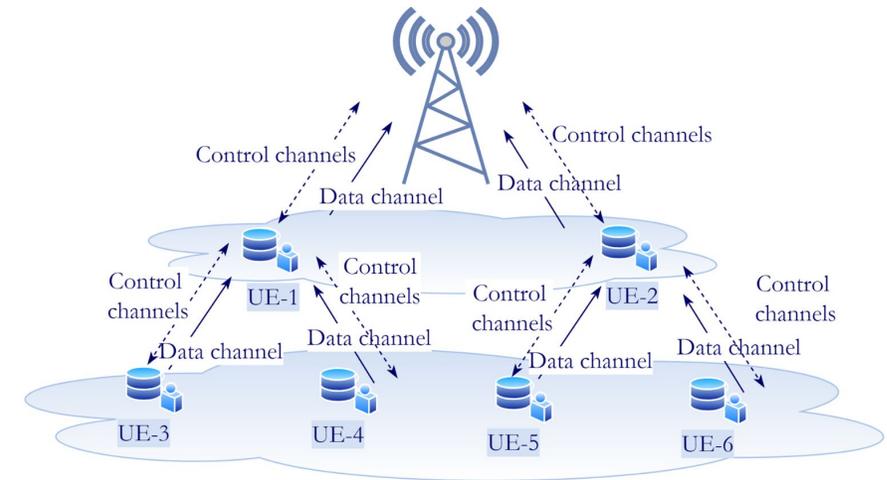
- Short answer: “Yes, but...”
- It only works in very small scenarios
 - A handful of User Equipments
 - A handful of signaling messages
- Ambitious KPIs (latency, throughput, massive connectivity) are also required in 6G



Emerging multiple-access protocols for specialized services

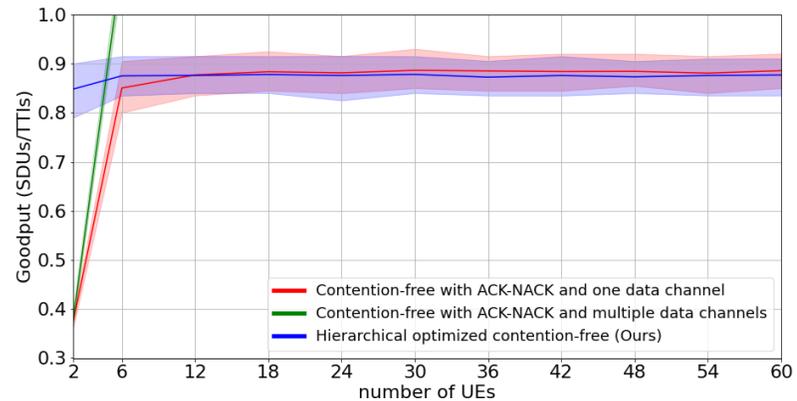
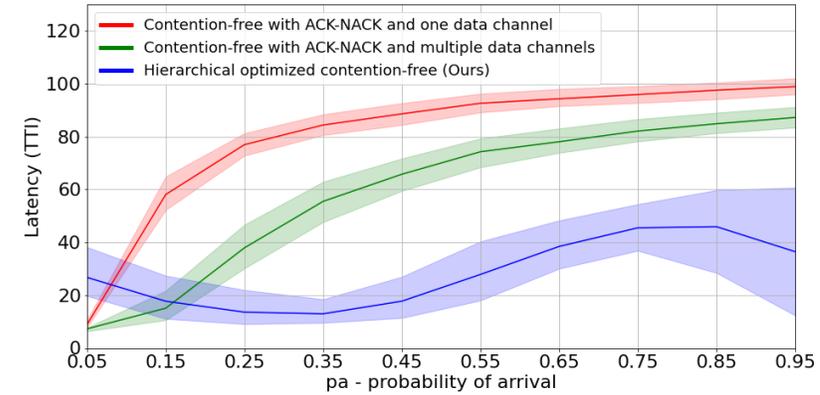
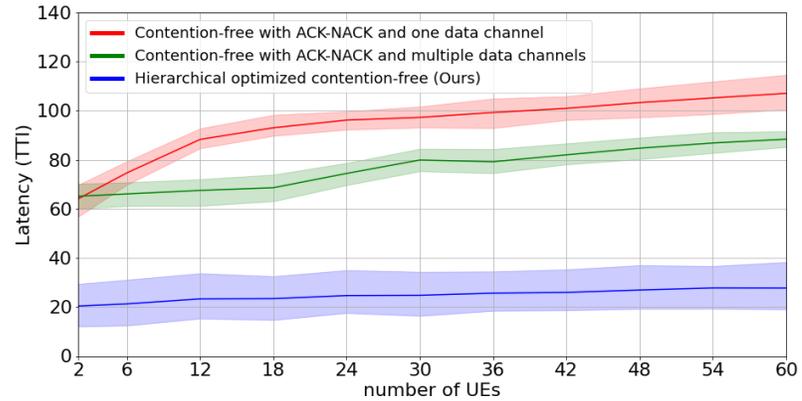
Proposed solution:

- Goal is to optimize contention-free access protocol with random scheduling
- New signaling messages for data transmission synchronization
- **Hierarchical architecture** based on a binary tree-topology that scales well to any number of UEs
- Hierarchical topology designed for a fair trade-off between latency and goodput

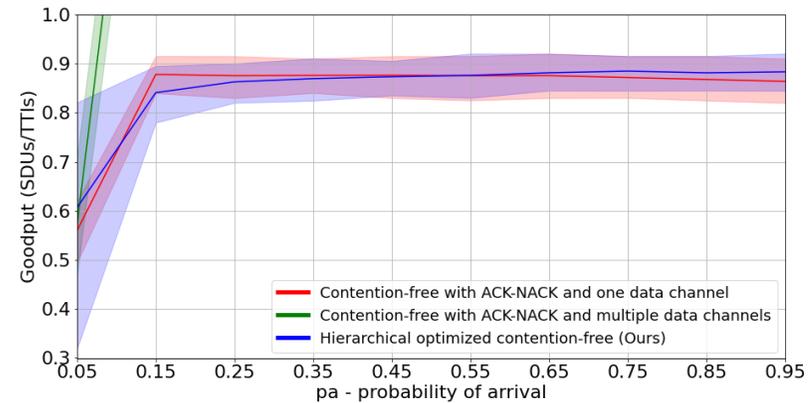


Emerging multiple-access protocols for specialized services

Results:



Scaling to user density



Scaling to traffic density

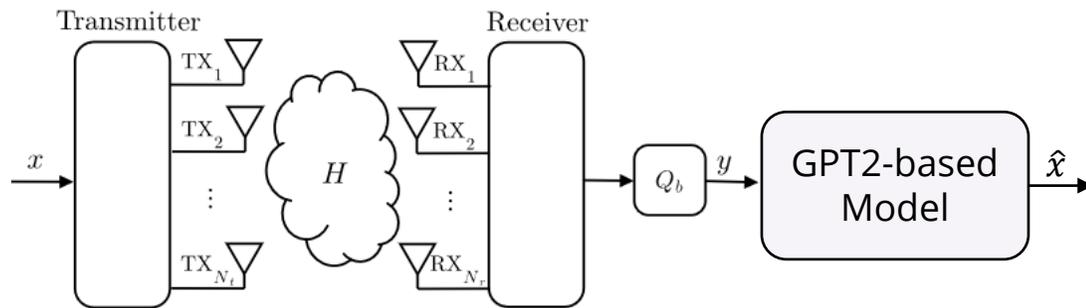


Selected AI-AI Concepts

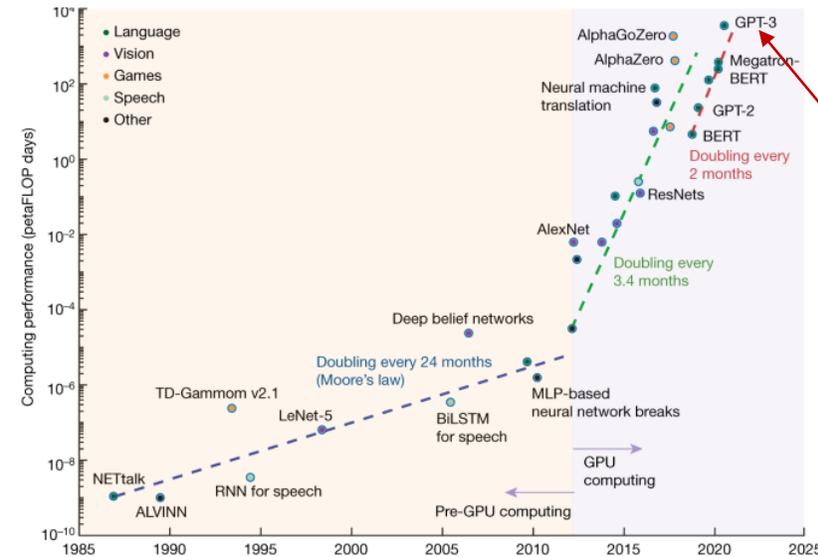
Hardware Enablers for AI-AI

Neuromorphic Hardware Implementation

- Transformer models have in-context learning capabilities that can be leveraged to quickly adapt AI modules to changing conditions.
- However, the transformer's high power consumption limits its applicability for telecom.



Transformer for MIMO equalization

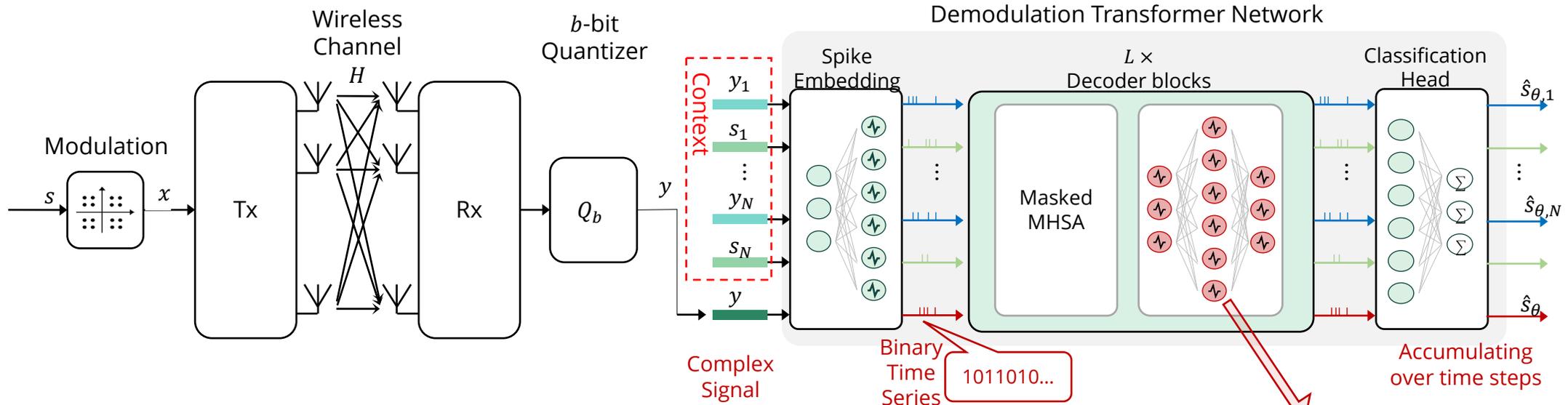


GPT-3
175 billion parameters
113kW
1,300 MWh
502 tons CO₂

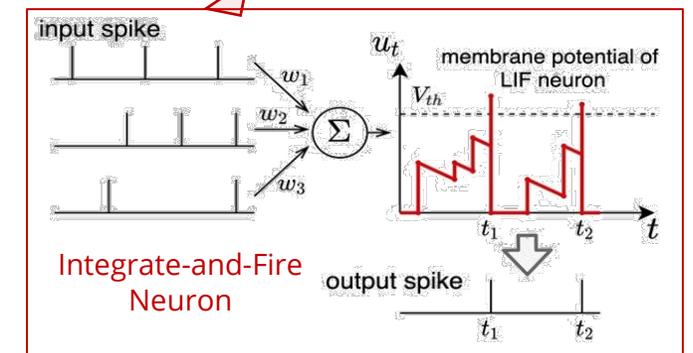
Computing power demands

- **Goal:** Introduce low-power computing paradigm for Transformer models in AI receivers

Neuromorphic Hardware Implementation

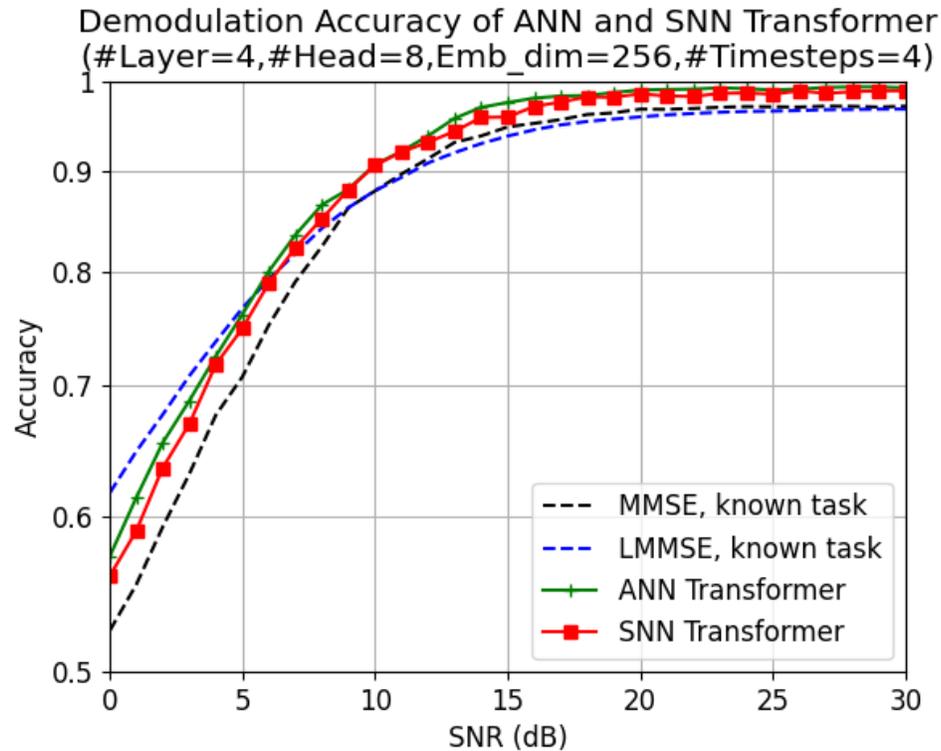


- SNNs replace multiplication with additions, significantly reducing power consumption.

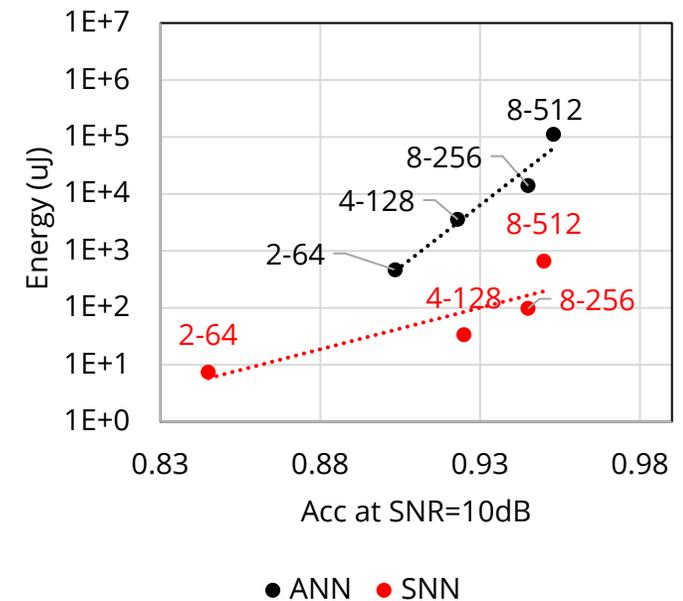


Neuromorphic Hardware Implementation

- Energy Evaluation: based on basic energy metrics for 45 nm CMOS technology
- Energy Efficiency: The SNN architecture (with hardware acceleration), achieves up to an order of magnitude higher energy efficiency compared to ANN.



Computing Energy VS Accuracy of ANN&SNN with Different Sizes



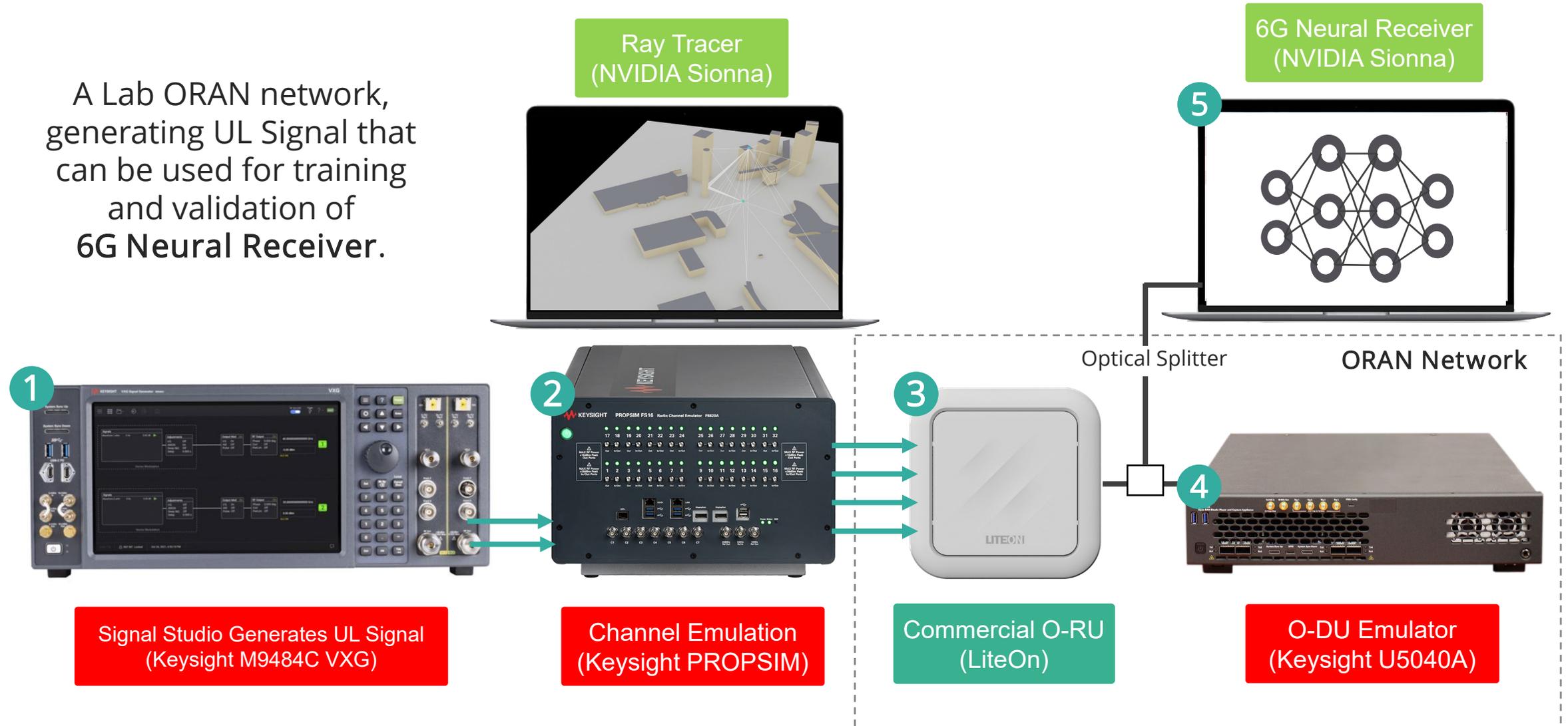


Selected AI-AI Concepts

AI-AI Validation and Testing

PoC: 6G AI MU-MIMO Neural Receiver

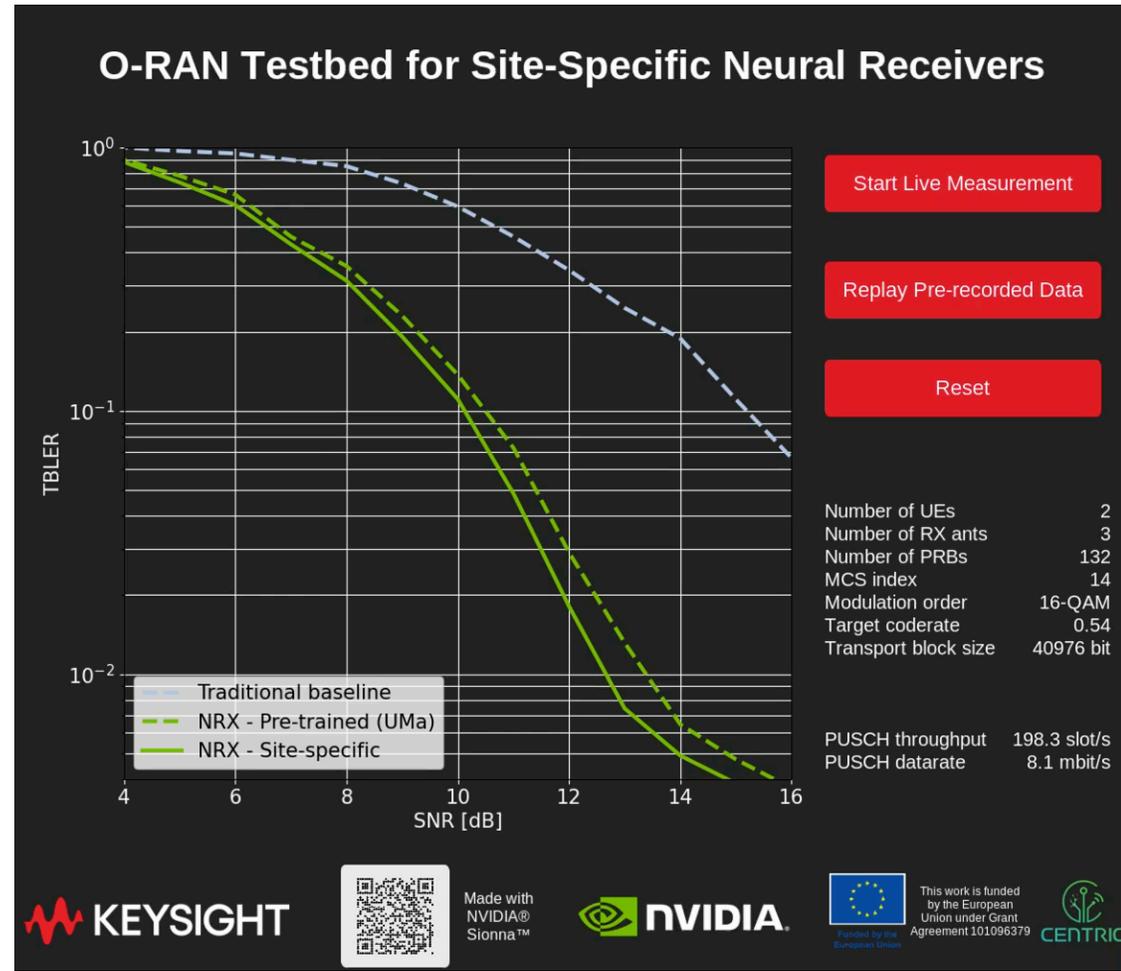
A Lab ORAN network, generating UL Signal that can be used for training and validation of 6G Neural Receiver.



PoC: 6G AI Neural Receiver Design

NVIDIA Neural Receiver

- Neural Receiver receives live data from ORAN Testbed.
- We can see live results converged to the precomputed curves.
- Clear gains between NRX and the baseline.
- Site-specific training improves performance.
- It works!



Conclusion and Outlook

- CENTRIC has made significant contributions towards actualizing its AI-AI vision.
- Other than those shown in this presentation, CENTRIC is developing:
 - Methods for waveform and modulation learning for sub-THz communication and short packet transmissions.
 - Application- and scenario-specific RRM methods with controlled user EMF exposure.
 - AI-based sensing aided beam management in mmWave ISAC scenarios.
 - Real-time implementation of AI receivers.
 - ... and many more!
- CENTRIC has just had a successful mid-term review, you can expect more interesting results in the second half. Stay tuned!

Many thanks for your attention!



Consiglio Nazionale delle Ricerche



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<https://centric-sns.eu/>



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