WIDECOM 2025

International Conference on Wireless Intelligent, and Distributed Environment for Communication

Network Digital Twins for AI-Native 6G: Case Studies in Transport and Radio Access

Aldebaro Klautau

Joint work with several colleagues and students, sponsored by Ericsson and others

Telecommunications, Automation and Electronics Research and Development Center (LASSE)

UFPA - Federal University of Pará

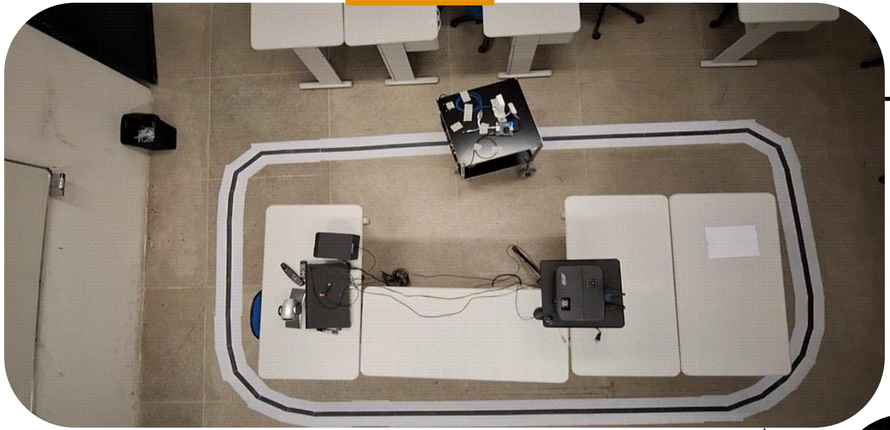
Guamá Science and Technology Park (PCT)

Belém, Pará, Brazil

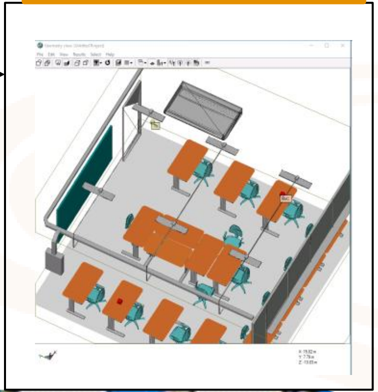
October 30, 2025

6G Radio access network (RAN): Beam management using network digital twin (NDT)

PTwin

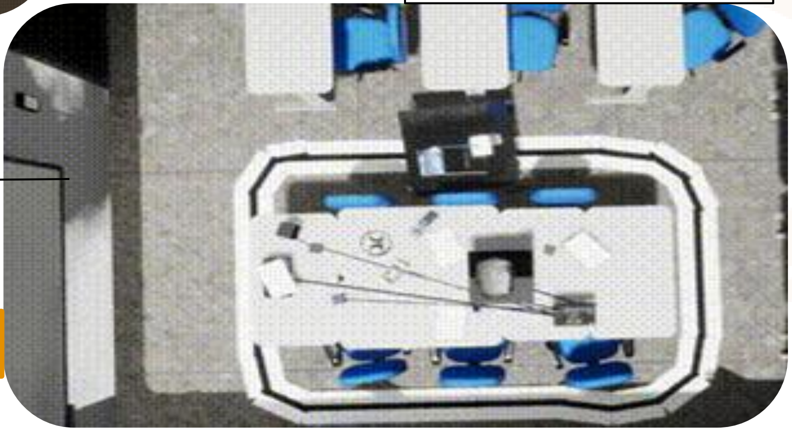


Blender 3D model



1) The physical twin (PTwin) shares the receiver (Rx) position in real-time

2) The virtual twin (VTwin) uses a 3D model of the room and ray tracing to estimate the channel and the best beam



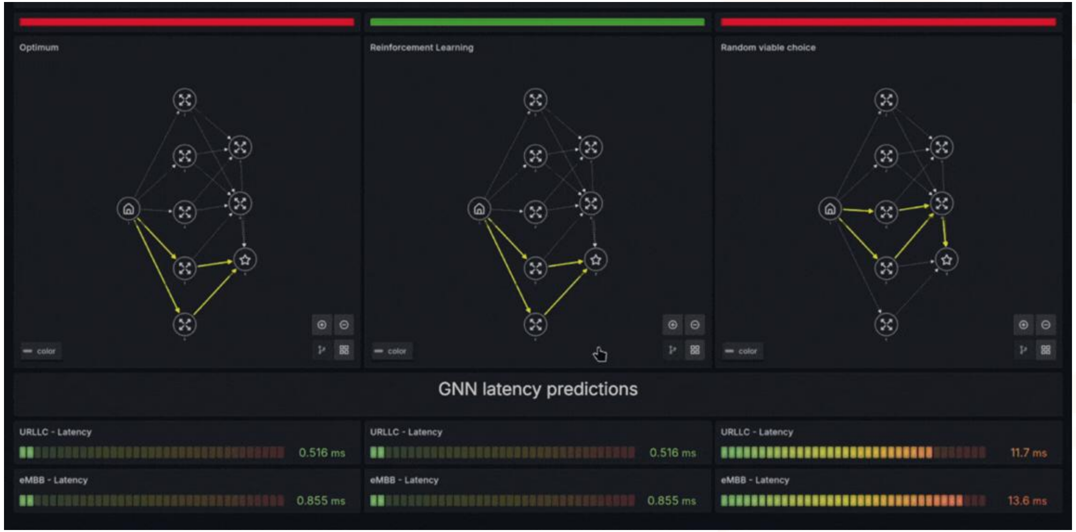
3) Instead of sending probing signals to find the best beam, the PTwin simply uses the suggestion by the VTwin, reducing the communication overhead and improving goodput

VTwin

6G transport network: NDT-based what-if analysis in case of link failure

Slice metrics monitoring

What-if analysis



Definition of NDT (by ETSI):

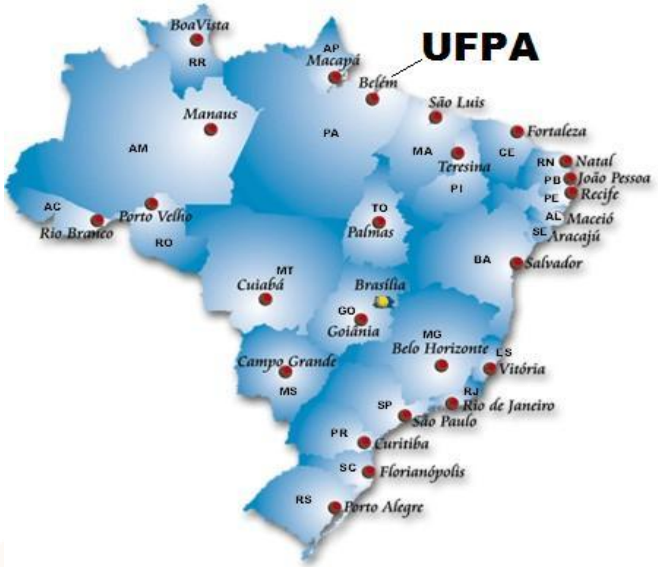
1) "Network Digital Twin (NDT) is a virtual replica of a communications network or part of one"
2) Data must flow
   a) "to the NDT, to support accurate modelling of the physical network and its use; and"
   b) "from the NDT to other components of operations systems."

In both previous examples, we used artificial intelligence (AI) together with NDTs

https://www.etsi.org/deliver/etsi_gs/ZSM/001_099/018/01.01.01_60/gs_ZSM018v010101p.pdf

Agenda

- UFPA and our group LASSE
- NDTs in 5G, 5G Advanced and 6G
- Use case 1: NDT for RAN
    - Experimental platform KA6G
    - Simulation: Raymobtime and CAVIAR
- Use case 2: NDT for transport network



Federal University of Pará (UFPA): Largest research institution in the Amazon

Established in 1957. 12 campi in the state of Pará. 50k students

UFPA promotes sustainable development in the Amazon via science and technology

Pará area: 1.2 million km^2, larger than any country in Europe, but Russia

Science and Technology Park Guamá

- First technological park in northern Brazil, located on the banks of the **Guamá River**
- It promotes applied research, sustainable entrepreneurship, and innovation
- It houses over 30 resident companies, more than 40 associate members, 12 R&D laboratories, and a technical school.

https://pctguama.org.br/sobre/

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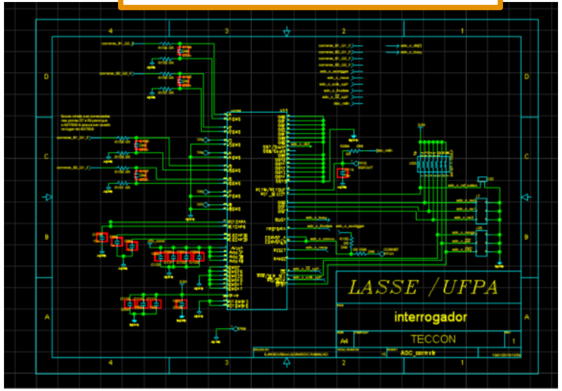
LASSE @ PCT Guamá, UFPA:
Human resources are main asset

5 faculty members, 21 graduate students, 31 undergrad

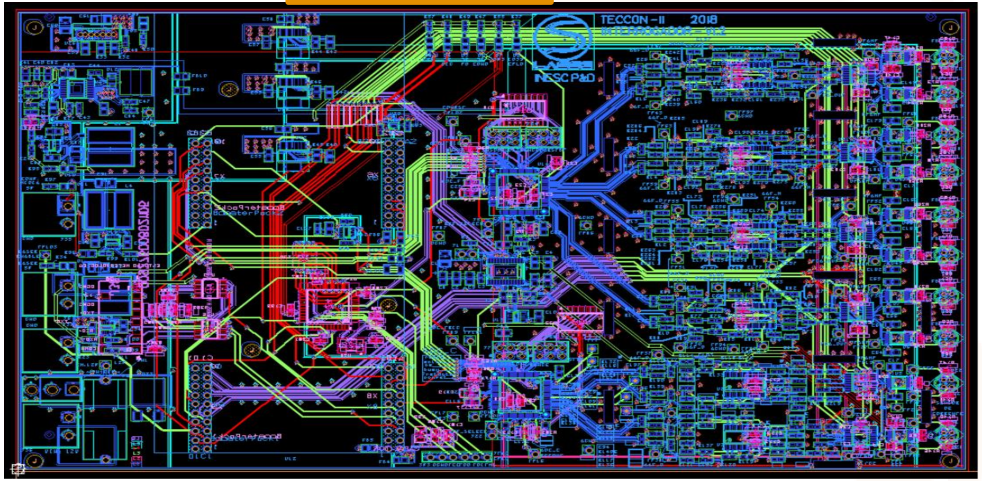
Rooms totaling 400 m^2. Approximately U$ 1.9M in equipment (PCB prototyping, SMD rework stations, spectrum / network analyzers, oscilloscopes, etc.)

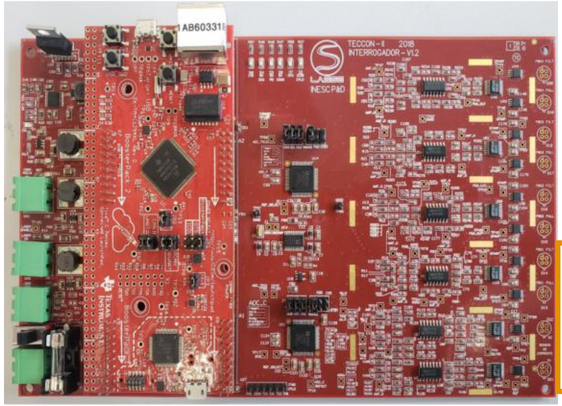
We like to build things

1) Schematics



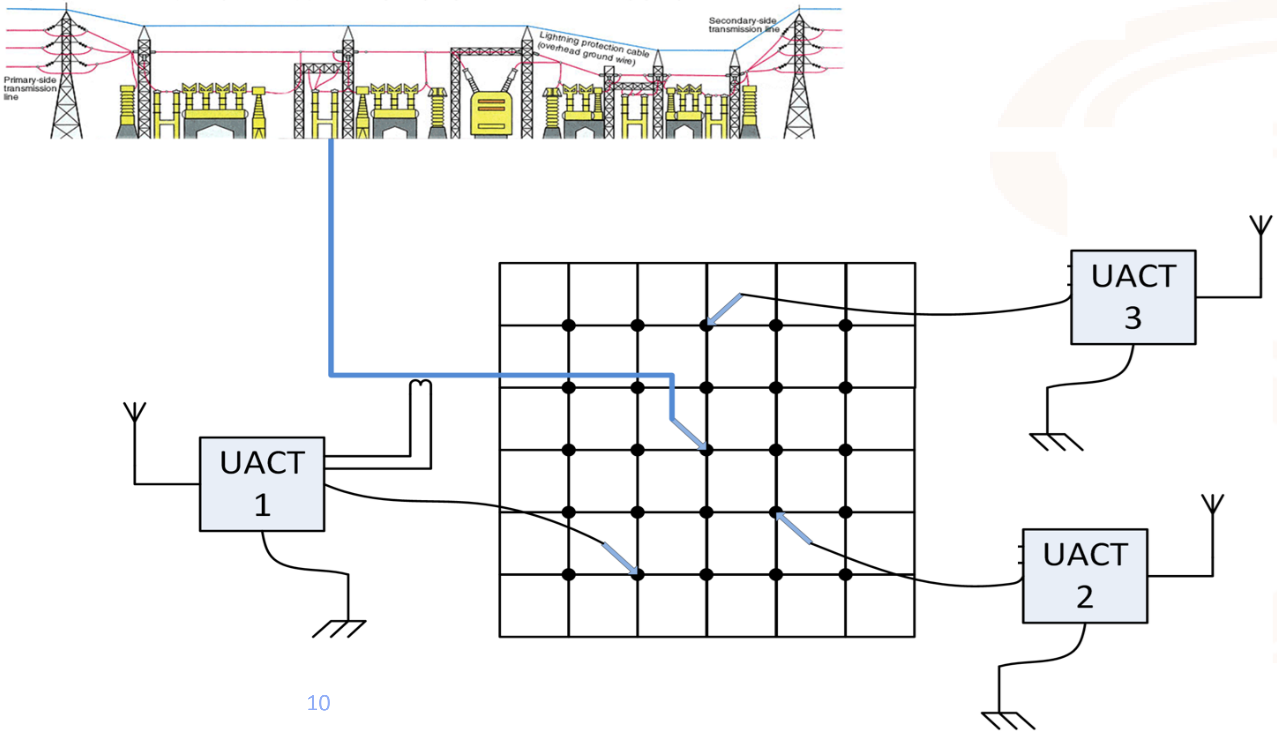
2) Layout





3) Assembly of components on the printed circuit board (PCB)

Wireless sensors (UACT) for measuring leakage current in the grounding grid of electrical substations



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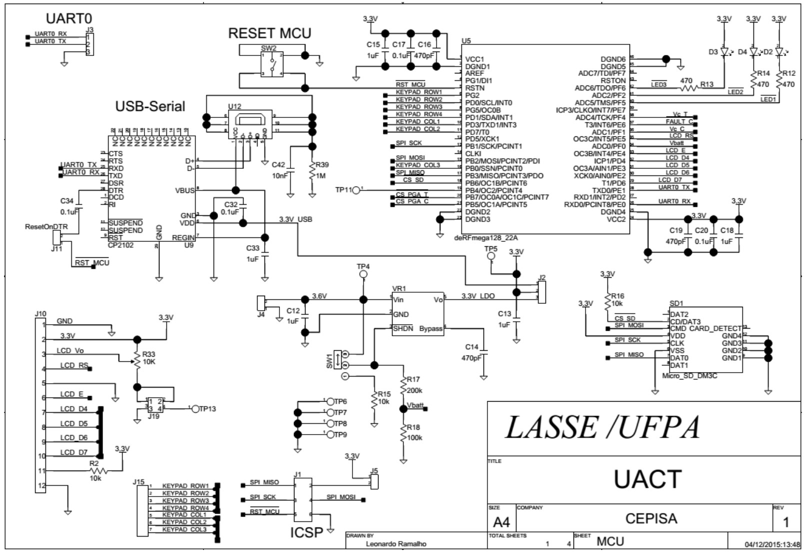
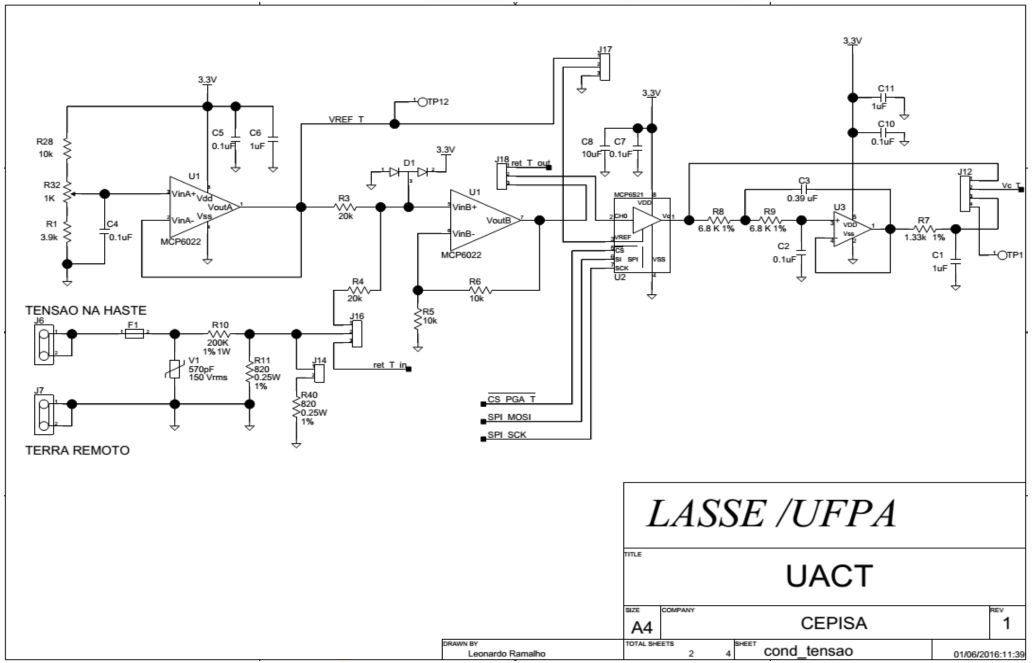
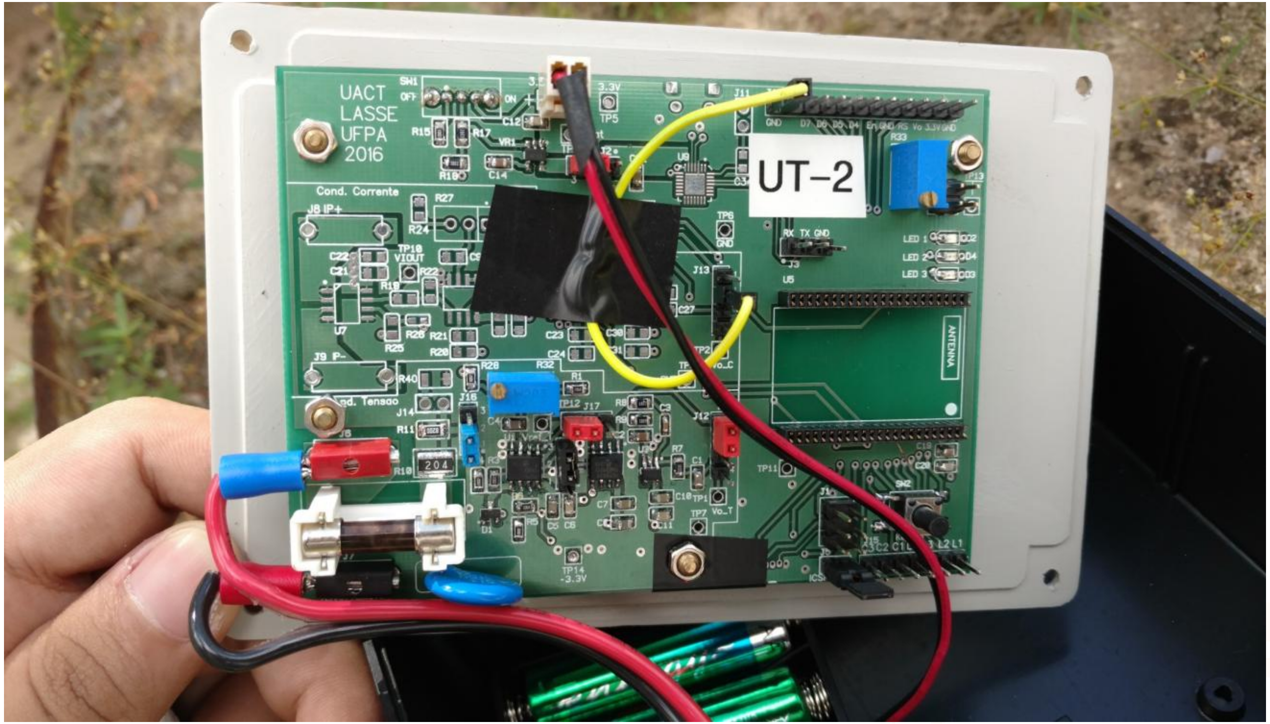
Schematics of digital and analog electronic subsystems





Assembled board



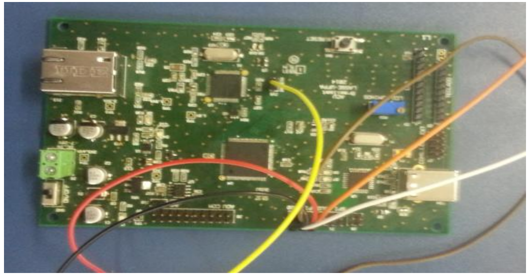
Deployment and tests

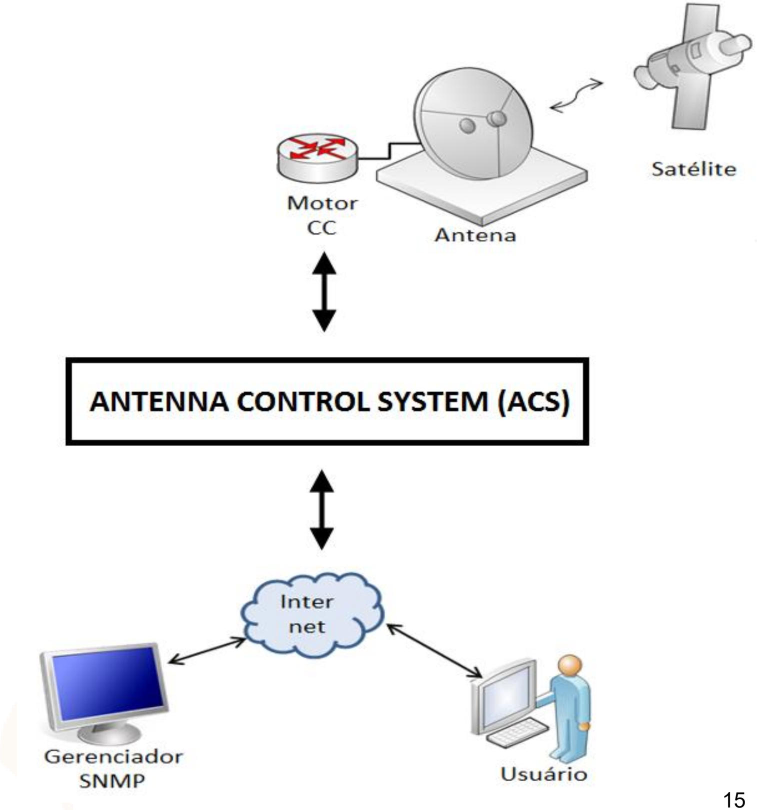
Polymeric insulator instrumented with optical fiber, sensors, and intelligent signal processing

TECCON II: the emergence of more efficient and intelligent energy systems.

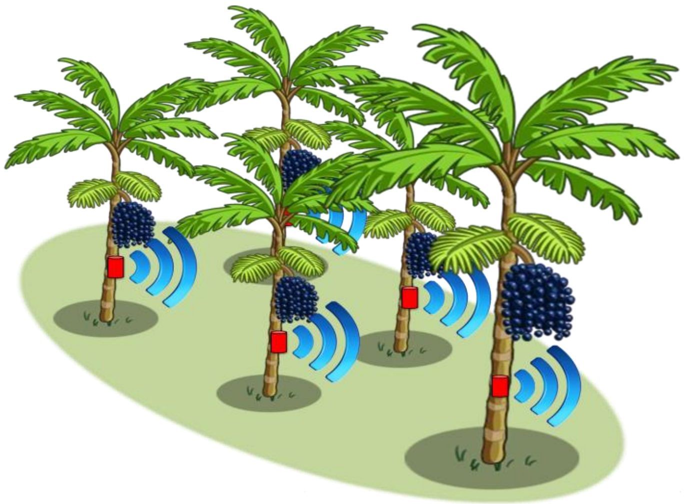
https://www.youtube.com/watch?v=FzTxstaZV1A

Satellite antennas control

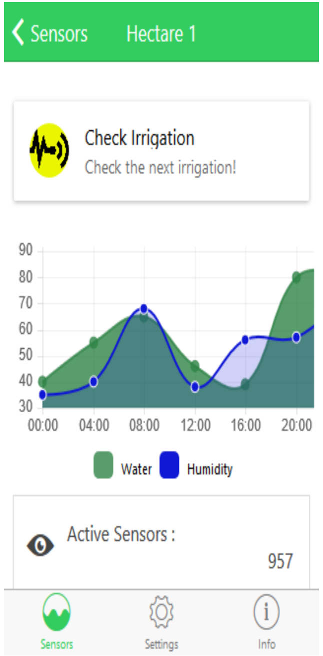




IoT System for precise irrigation of Açaí palms



Sensors



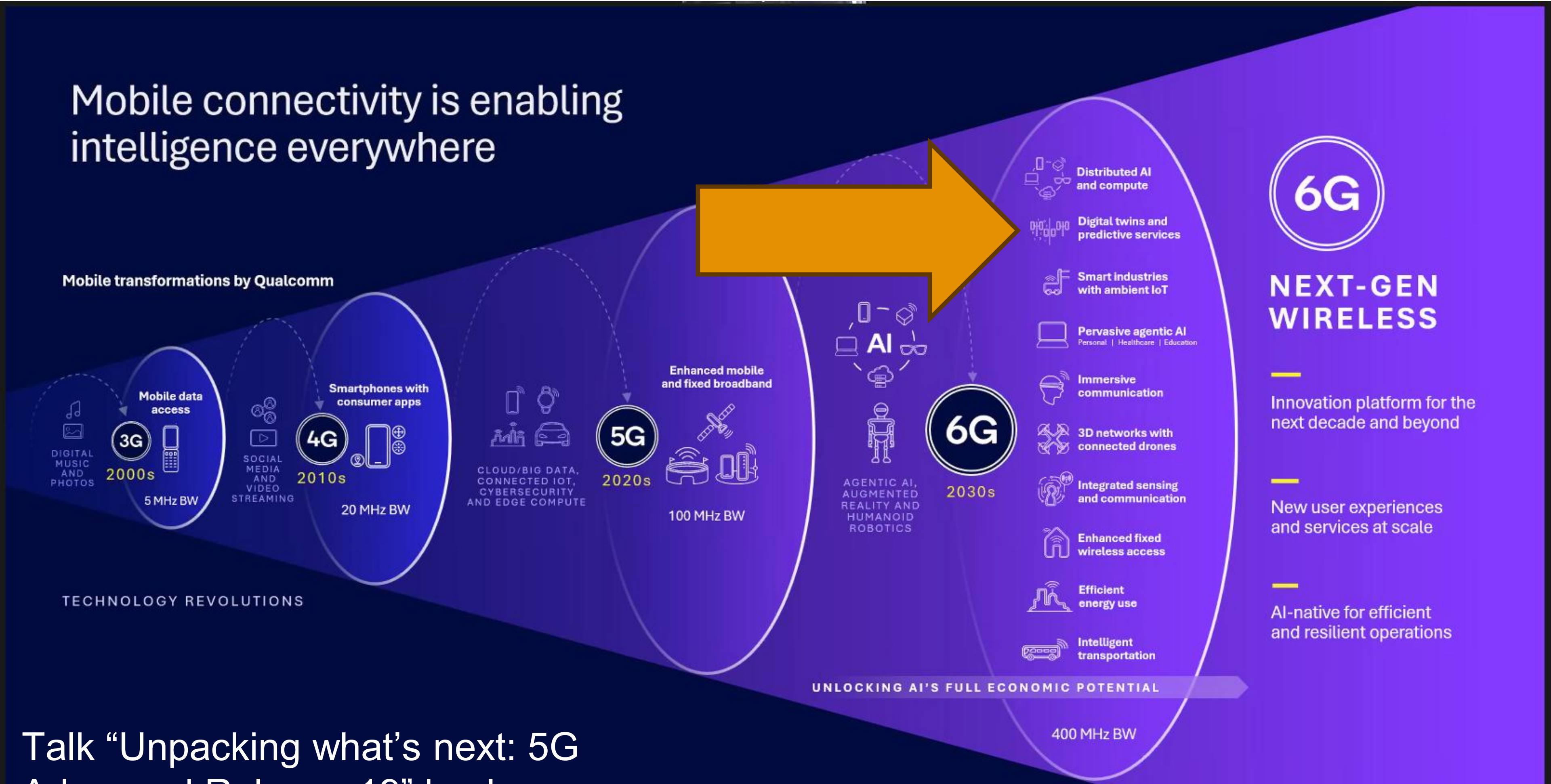
Software

Students @ field

Essential info about açaí (acai)

Foto: Marcela Maria Martins

NDTs in the context of 5G, 5G Advanced and 6G



Talk “Unpacking what’s next: 5G Advanced Release 19” by Juan Montojo, Qualcomm (yesterday)

Talk by Juan Montojo

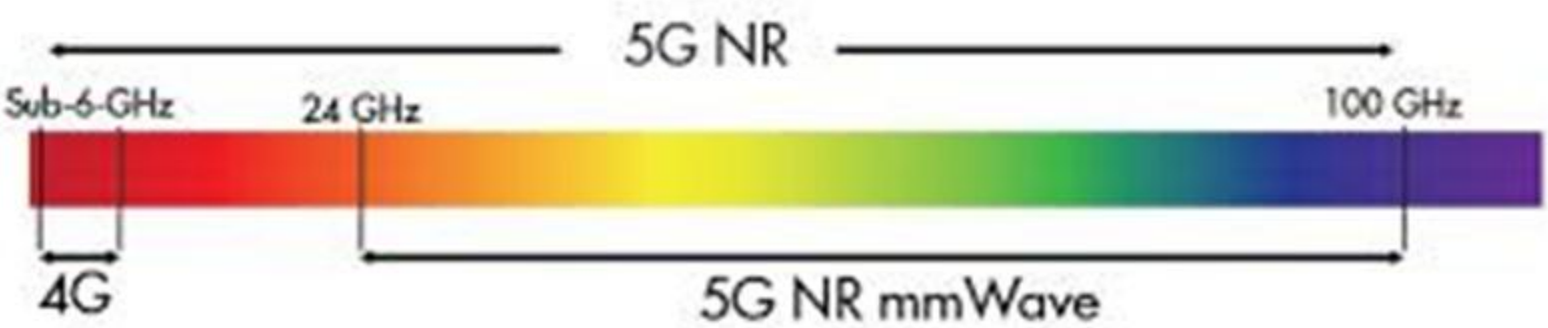
On the path to 6G… from 5G and 5G Advanced

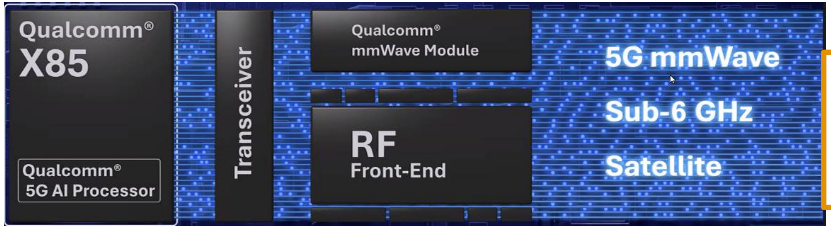
Use Case 1:
NDT applied to the 6G RAN

Based on a Low-Cost Experimental Platform for AI-Based Beam Management Using WiFi Radios

From B=5 MHz (3G) to 400 MHz (6G): Increased bandwidth → increased bit rate

Capacity equation (for AWGN channels): $$C = B \log_2 \left(1 + \frac{S}{N}\right)$$





X85 5G Modem-RF
Downlink: 12.5 Gbps
Uplink: 3.7 Gbps

https://www.qualcomm.com/modems/products/qualcomm-x85-5g-modem-rf

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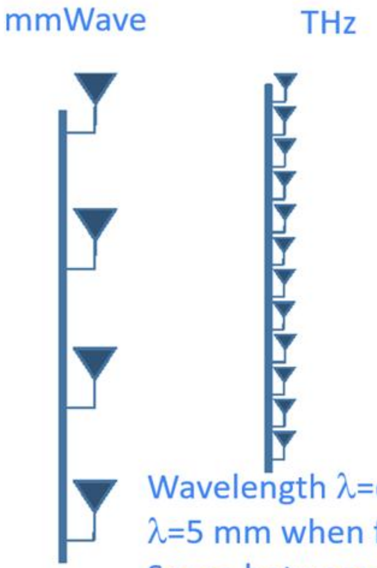
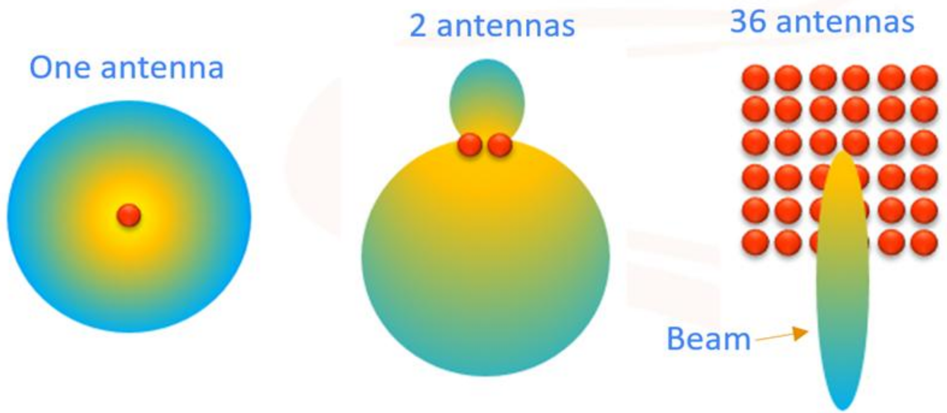
Improving communications with antenna arrays

Array form factor decreases when frequency increases (mmWave in 5G / THz in 6G)

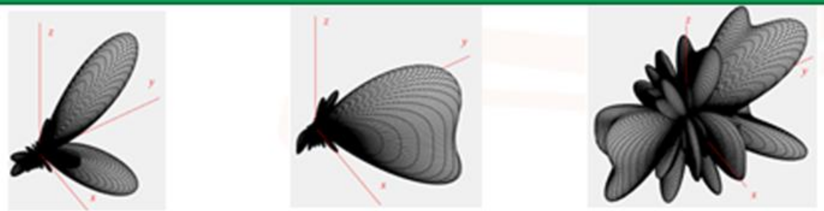


Wavelength $\lambda = c/f$
$\lambda = 5$ mm when $f = 60$ GHz
Space between antenna elements = $\lambda/2$

Illustrative radiation patterns of an array:

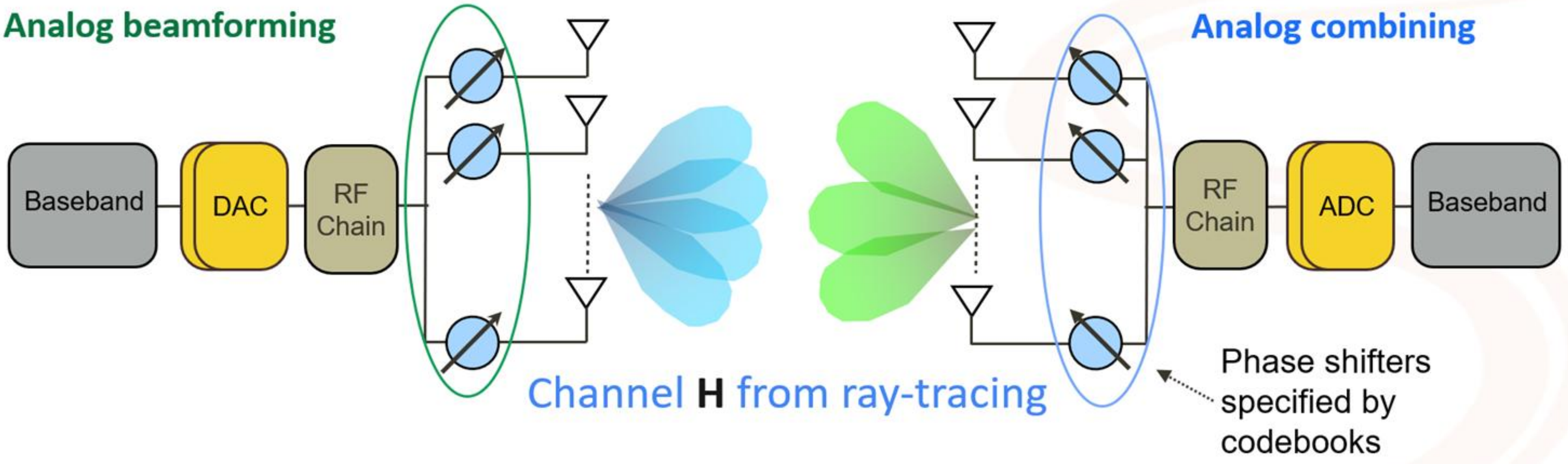


Given a phased antenna array, we choose a "beamvector" to impose a radiation pattern



Beam training (selection) in millimeter wave

Related to initial access in 5G mmWave



Brute force: try all possible pairs of beams (e.g. $N_{tx}\ N_{rx}$)

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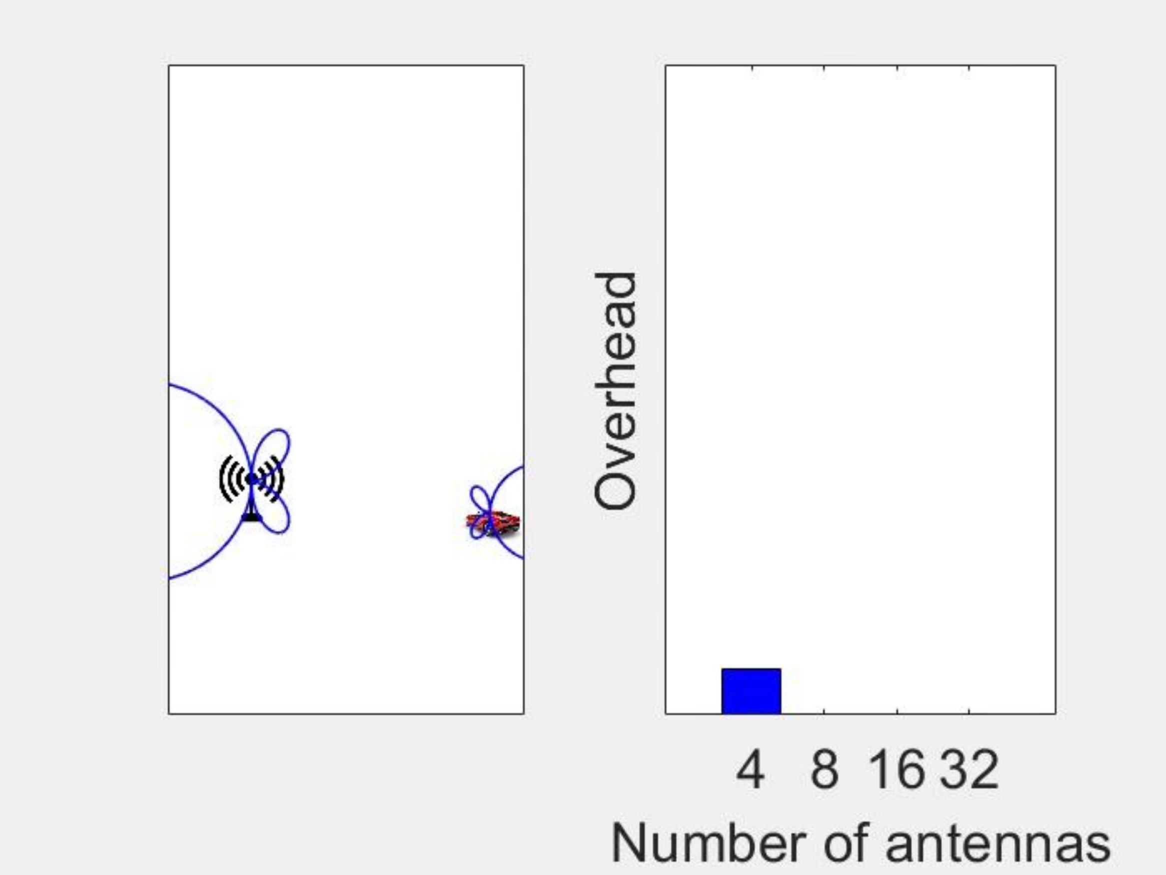
Beam selection in vehicular networks (V2I)

High mobility but predictable trajectories

Communication overhead increases with number of antennas

Machine learning can decrease overhead by choosing subset of candidates



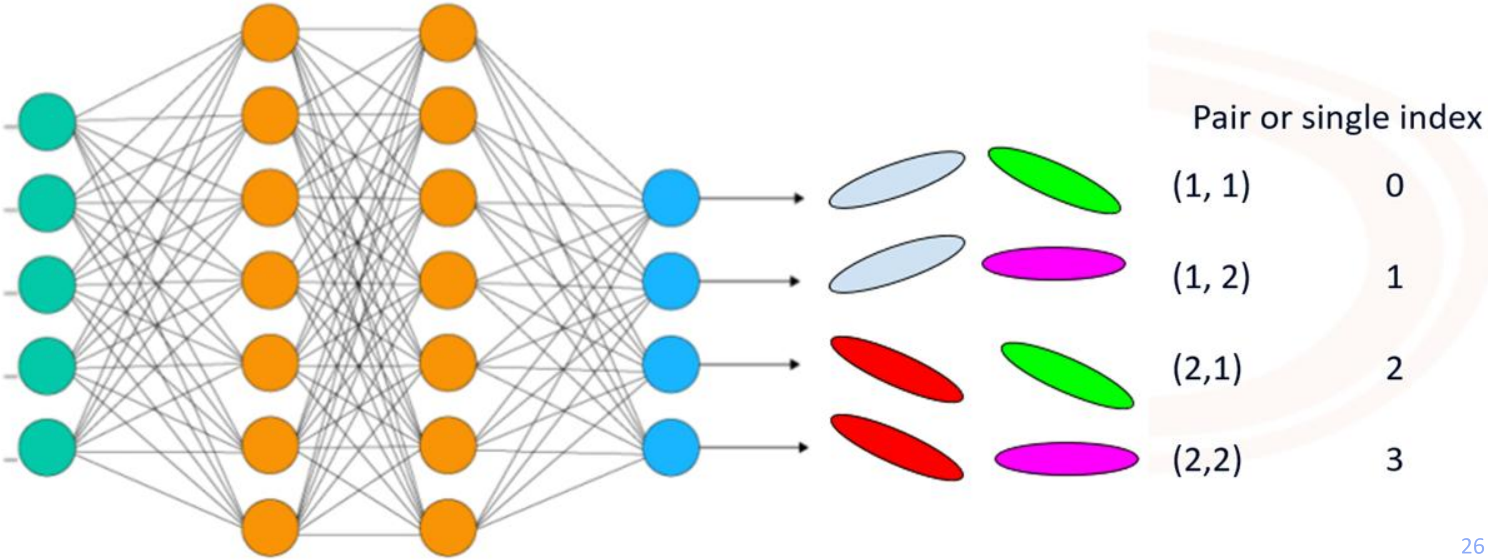
Y. Wang, A. Klautau, M. Narasimha, and R. W. Heath Jr., "MmWave beam selection with situational awareness", 2019

AI-based beam management in 5G/6G mmWave

Example with two beamvectors per codebook

Typically posed as a classification problem

Inputs from communication system and also from sensors such as cameras, LIDARs and GPS



Context regarding mmWave beam management experiments

- mmWave is essential for delivering the multi-gigabit speeds that will redefine mobile connectivity

- 3GPP has been investigating AI/ML for Beam Management in 5G-Advanced - TR 38.843 [1]

- **Building an experimental mmWave platform may be very expensive ⇒ we need low cost and flexible solutions**

https://www.5g-networks.net/5g-coverage-using-fr2-mmwave-frequencies/

[1] https://portal.3gpp.org/desktopmodules/Specifications/SpecificationDetails.aspx?specificationId=3983

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Budget for mmWave platform

Company	Product	Unit value	Units	Total
UCSD	M-Cube with 4 RF chains	$4,500.00	1	**$35,550.00**
	SDR USRP N310 Ettus	$10,350.00	3	
Company 1	Innovator Kit	$56,250.00	2	**$112,500.00**
Company 2	SDR platform	$12,000.00	2	**$130,000.00**
	MmWave module	$26,500.00	4	
Company 3	Frequency converter	$30,000.00	2	**$135,000.00**
	Beamforming Development Tool	$37,500.00	2	

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Motivation

We identified three requirements for a low-cost experimental mmWave platform:

- Compatibility with low-cost, widely available transceivers;
- Automated data collection for repeatability in mobility/blockage scenarios;
- Tight synchronization between wireless metrics and environmental context (e.g., vision sensors).

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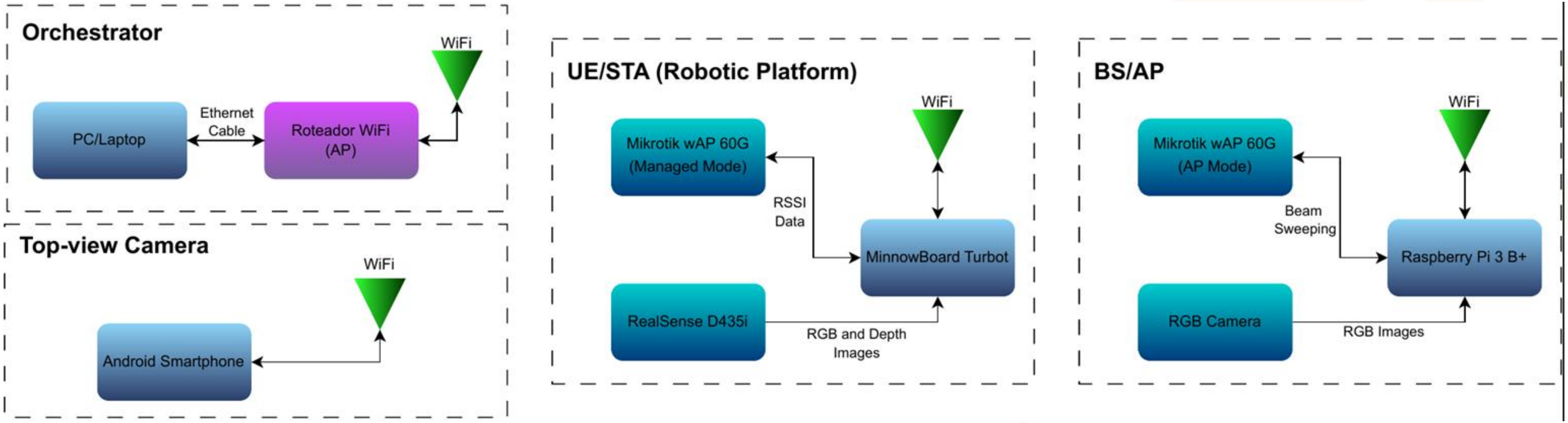
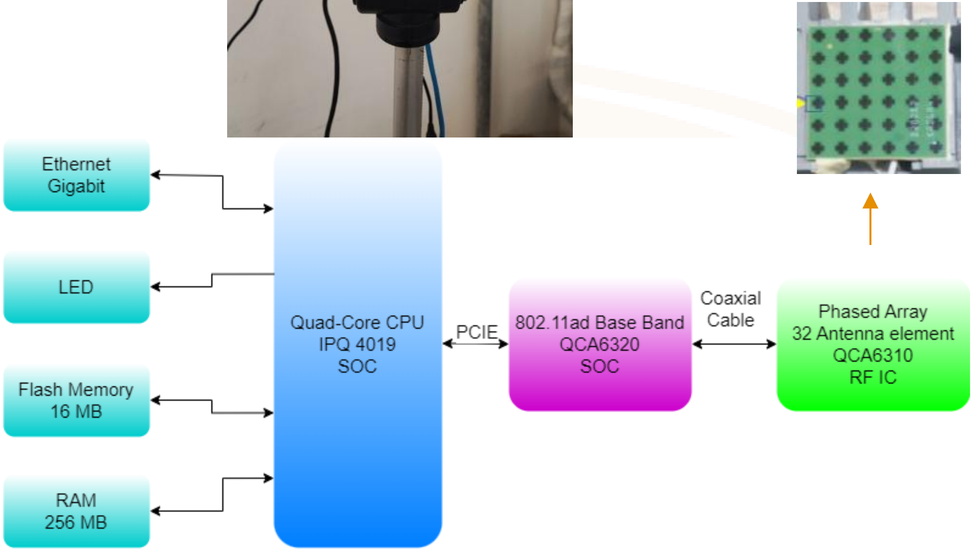
Proposed low-cost mmWave experimental platform

- Contribution: design and validation of a synchronized client-server architecture that is low-cost and enables mmWave beamforming experiments
- Built upon modified 802.11ad radios: fine-grained control of beamforming and access to low-level radio metrics. We utilize a network time protocol (NTP) server for synchronization.



Low-cost COTS radio

- MicroTik wAP 60G that operates according to the IEEE 802.11ad standard at 60 GHz
- It costs about USD 200 in Brazil
- The radio is equipped with a 6×6 Uniform Planar Array (UPA)
- It utilizes the RouterOS, which we replace by a modified OpenWRT



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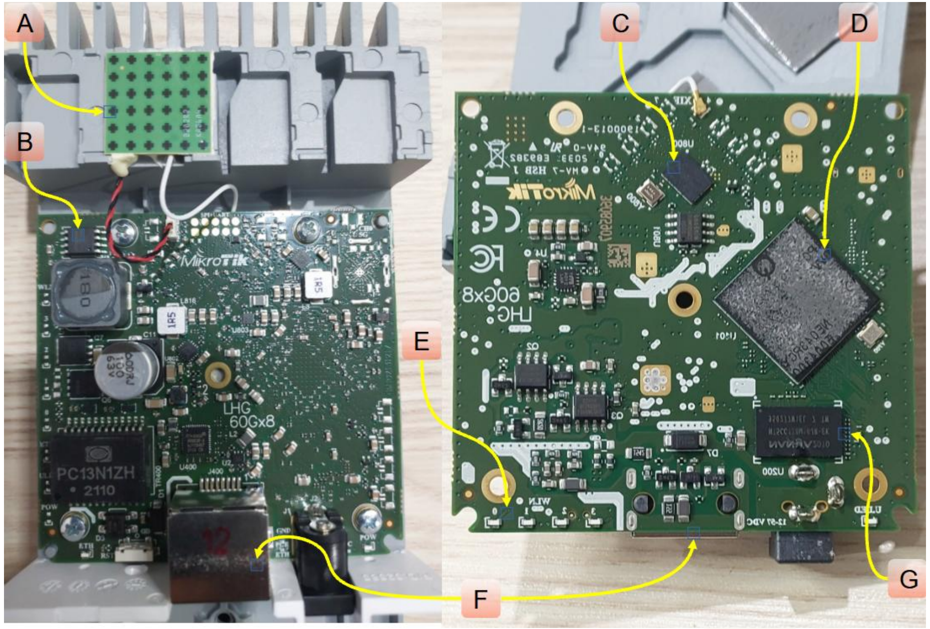
Hacking the MicroTik radio

We installed the customized OpenWRT OS and modified the firmware of the baseband module to access RSSI, Angle of Departure, Angle of Arrival and time of flight. The Nexmon framework [1] was utilized to modify the mmWave module and redirect the desired information to a memory section available for developers.

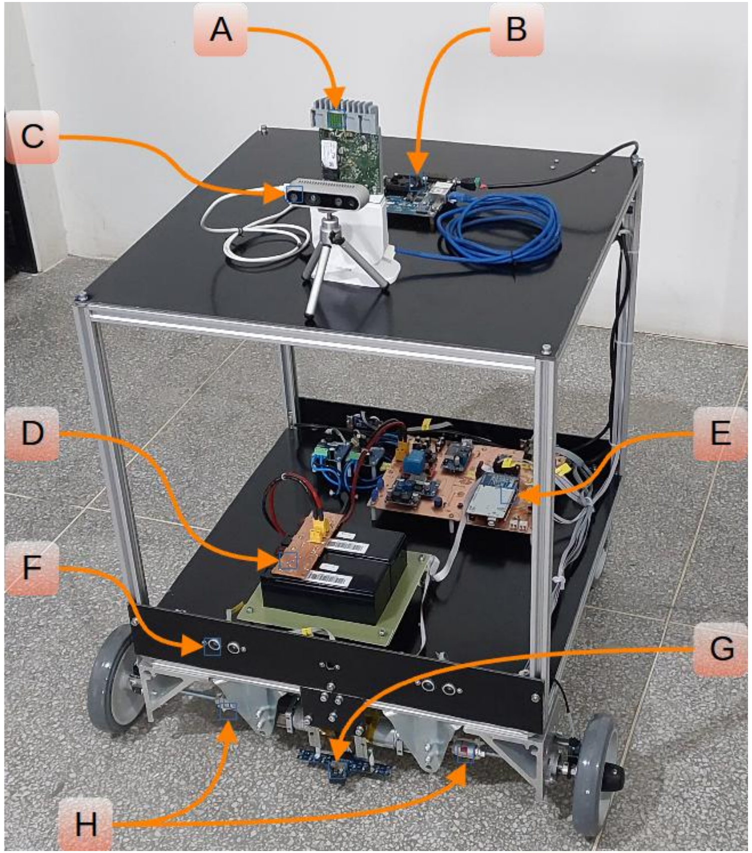


(A) mmWave antenna (B) Flash memory (C) 802.11ad Base Band chip (D) CPU ARM Cortex-A7 (E) LEDs (F) Ethernet port (G) RAM.

[1] https://github.com/seemoo-lab/nexmon/tree/master

ACAI (açaí) robotic platform

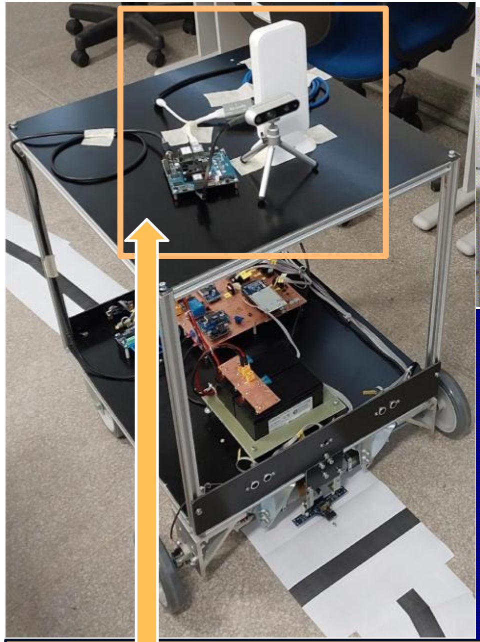
We designed a robotic platform named Acquisition Control Systems Automatic Implementation (ACAI). This platform was developed in-house and mechanically structured to carry all the necessary components for data collection, including the radio and a single-board computer.

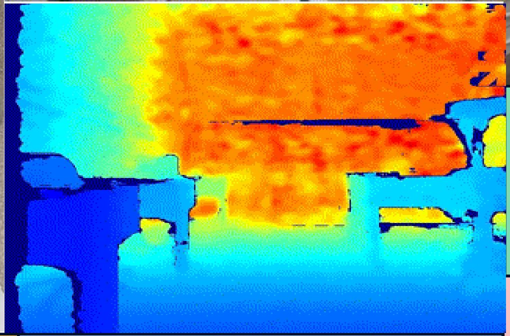


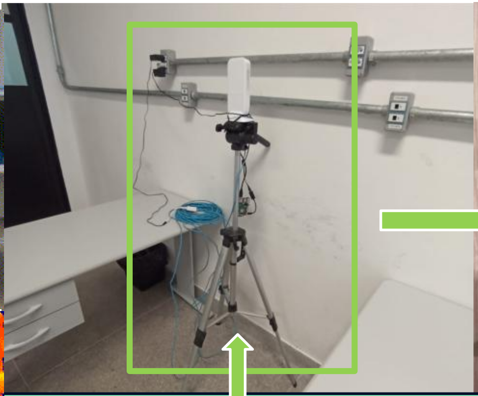
A) mmWave radio. B) Single-board computer. C) RGB camera with depth sensor. D) Battery pack.E) Robot controller board. F) Distance sensors. G) Follow line sensor. H) Electric motors.

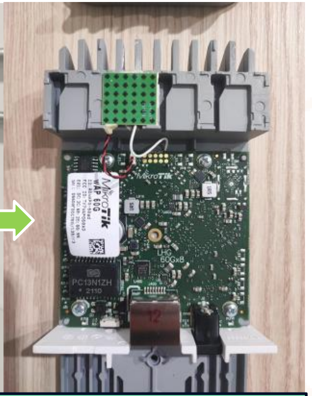
Our multimodal beam selection PTwin setup

It gives us RGB and depth images from the rx's POV ("point of view") and also RGB top view, along with RSSI ("received signal strength indicator") readings









Radios
Tx and Rx are modified MikroTik WiFi radios that monitor RSSI via beam sweeping

Receiver
with RGB + depth camera
(Intel RealSense D435i)

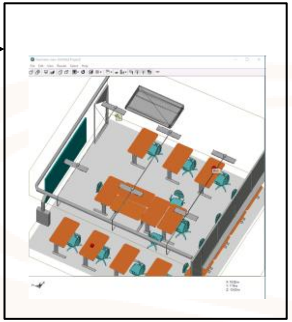
Receiver images from RGB and depth camera

Operate in 60 GHz with
6x6 uniform planar array (UPA)

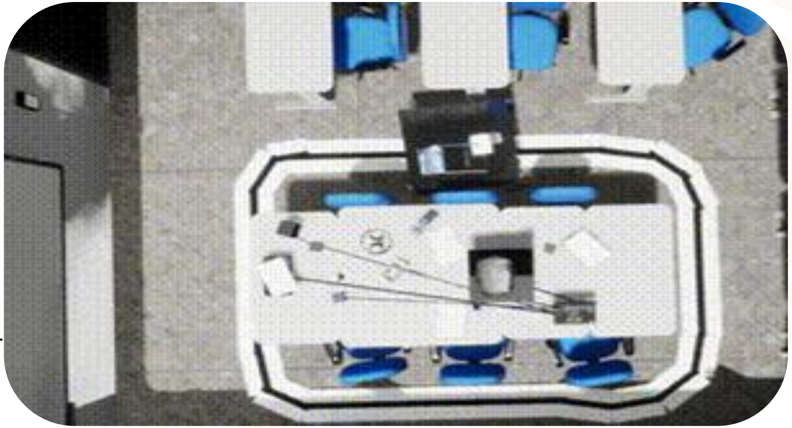
Complete RAN NDT PoC

NDT-enabled site-specific beam selection optimization

The PTwin shares the rx position in real-time via a top view camera and reference points



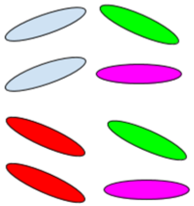
With this, the rx can be accurately placed within a virtual model of the room, which can then be used for ray tracing-based channel modeling



The same model can also be used with textures, for synthetic multimodal data generation

A number "K" of best performant beams (the "top-K") is determined and their indices are sent back to the PTwin to optimize the beam search procedure by reducing the search options

Using the simulated channel info, beam selection is executed in the VTwin. This can be done via beam sweeping or via an intelligent beam selector (AI/ML beam management)



Results

Using the customized OS and firmware, we can read and write the desired amplitude and phase for each antenna element of the 6x6 UPA, and we can update them in real time

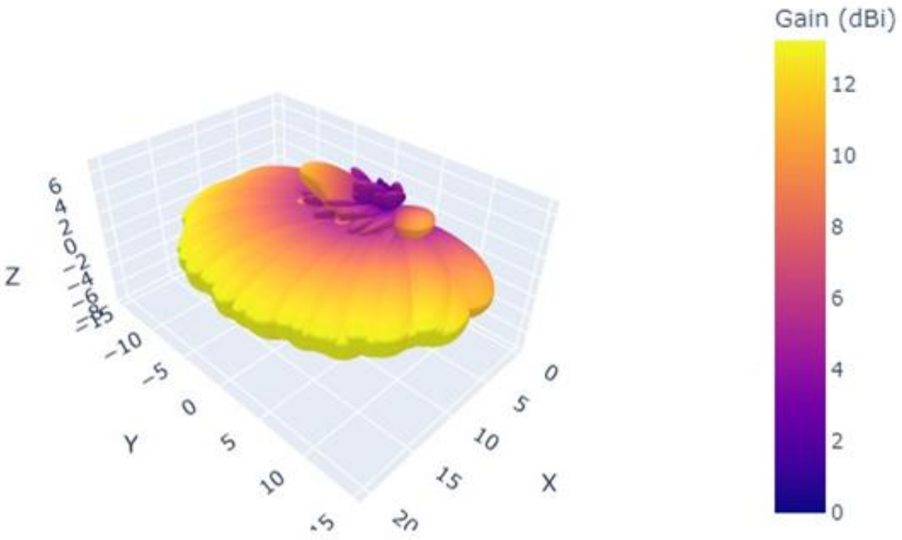
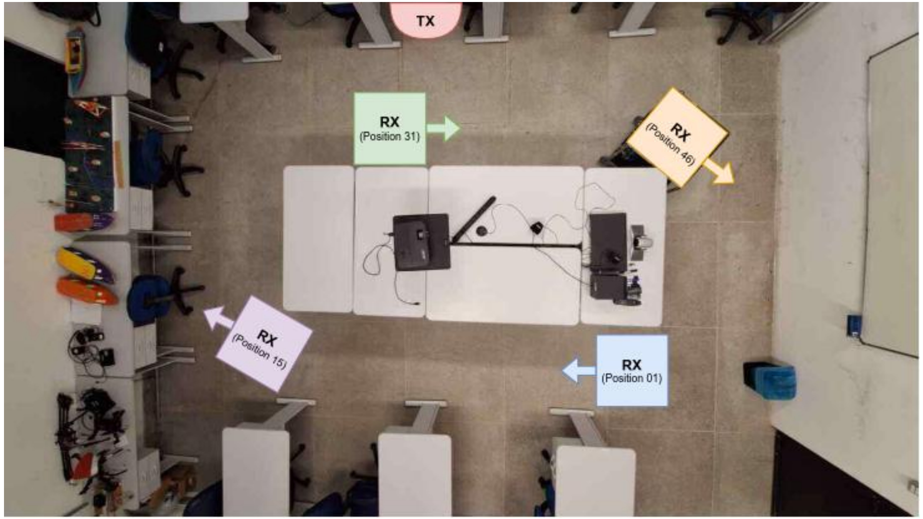
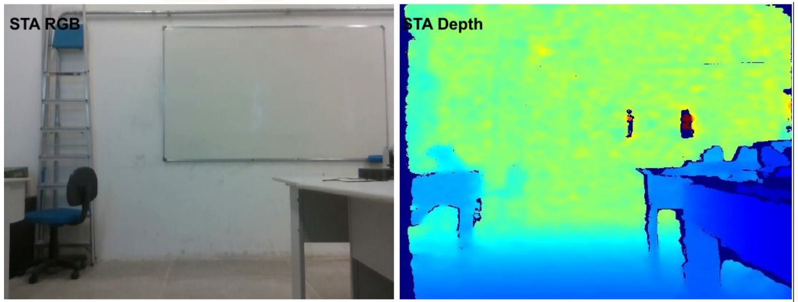


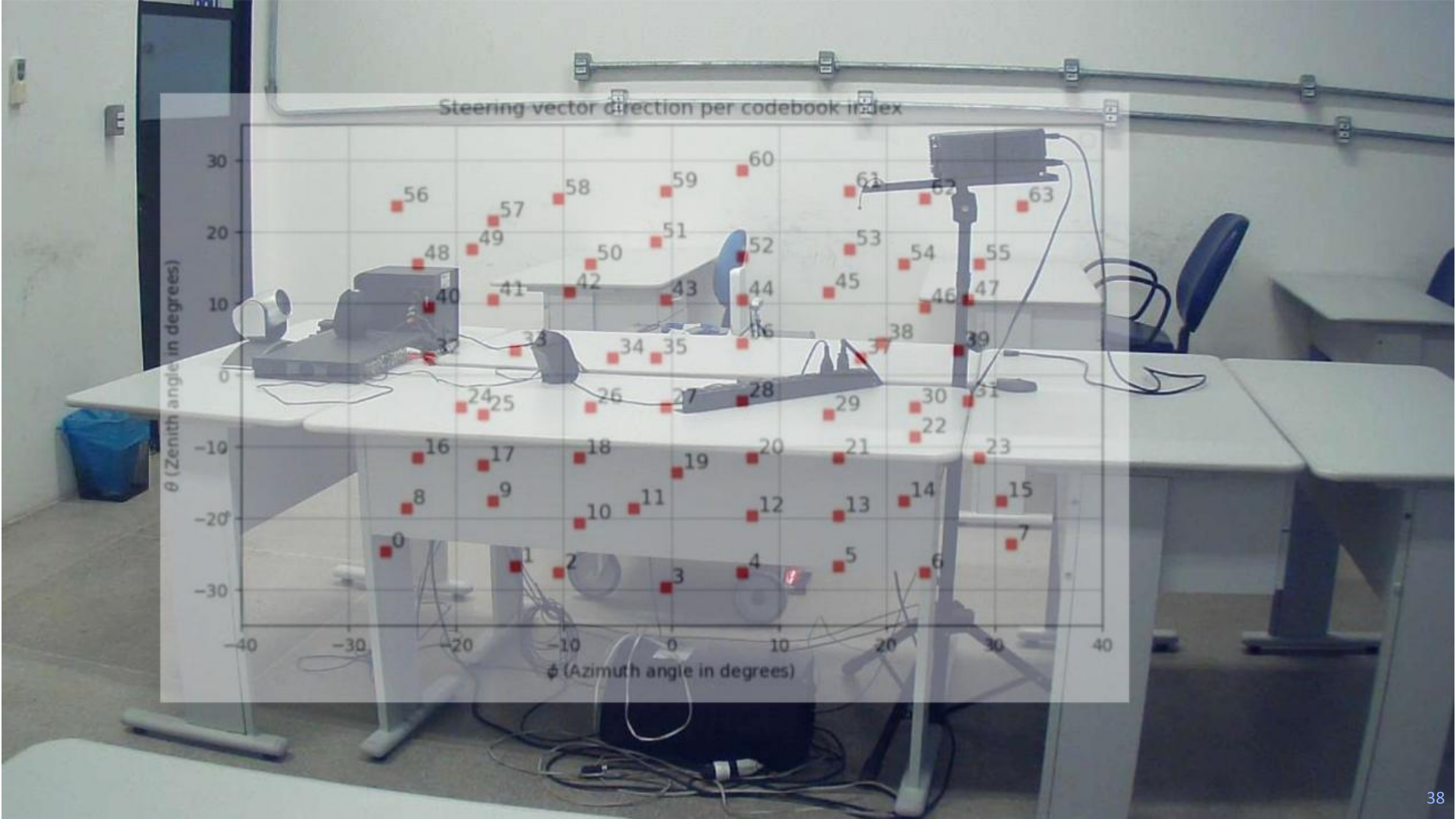
Illustration of the Azimuth sweeping codebook irradiation pattern

Results - Data capture

Measurements campaigns using the developed system were conducted within an indoor environment with an area of approximately 6.5×6 m^2, including multiple workbenches, chairs, and other obstacles for the beamforming.







Steering vector direction per codebook index
θ (Zenith angle in degrees)
ϕ (Azimuth angle in degrees)
30
20
10
0
−10
−20
−30
−40
−30
−20
−10
0
10
20
30
40

Important result:

We were able <u>to match results from real-life in the virtual replica</u>

Key research question: how to improve the *"mimic accuracy"* of the VTwin with respect to the PTwin?

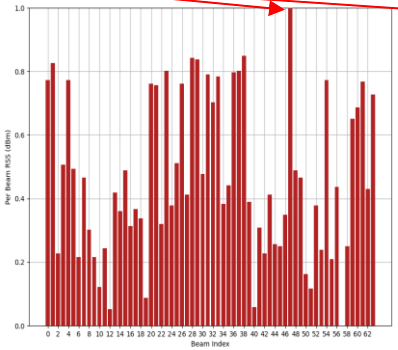
Best beam

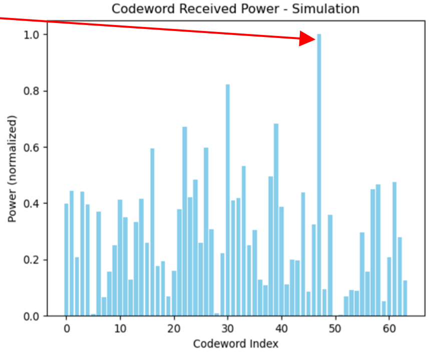
Best beam

From PTwin

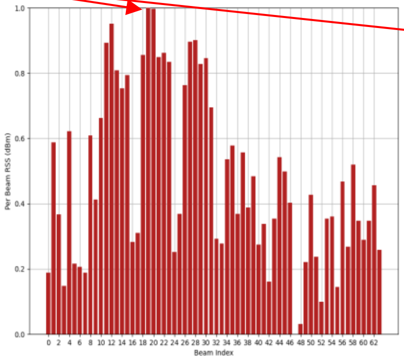
From VTwin

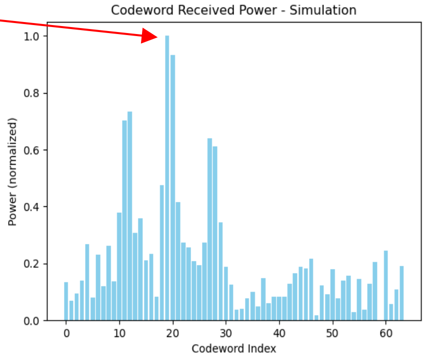
Instant t_1:





Instant t_2:



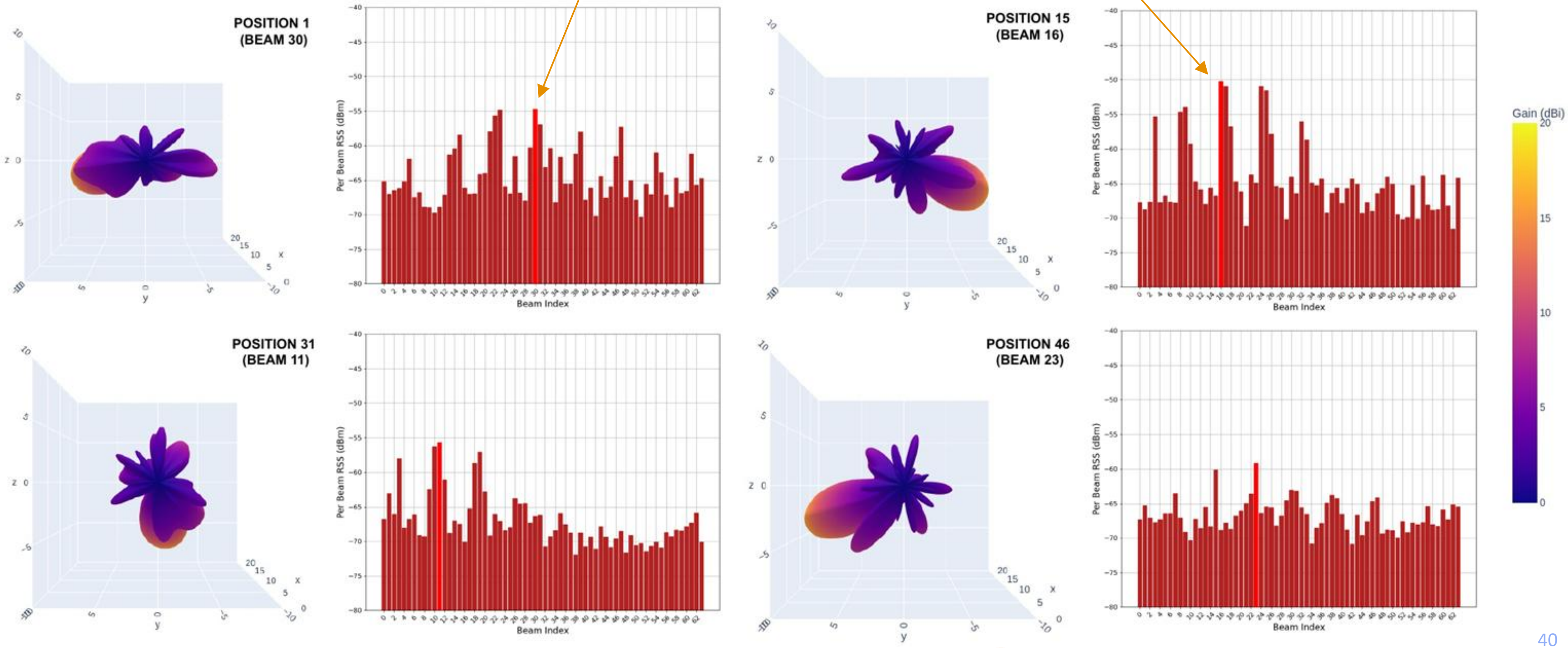


At the left we have the <u>normalized received powers in dB</u> for each of the 64 possible beam indexes

Although not every beam is equally matched between real and virtual, <u>the best beams are</u> (in t_1 it's **47** and in t_2 it's **19**)

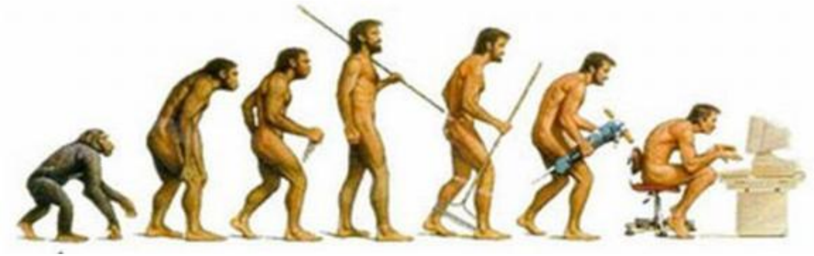
Results - Data capture

Marked with light red: VTwin choice. Others: PTwin result



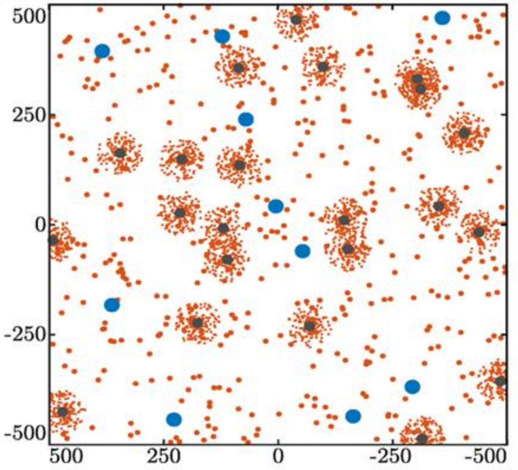
With new 5G / 6G experimental platforms, do we still need to model and simulate NDTs?

6G R&D tools



Past

- **Divide and conquer**: link level versus system level simulations
- **Drop-based** simulations

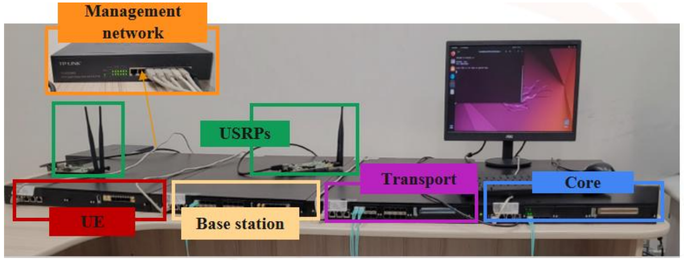


Today

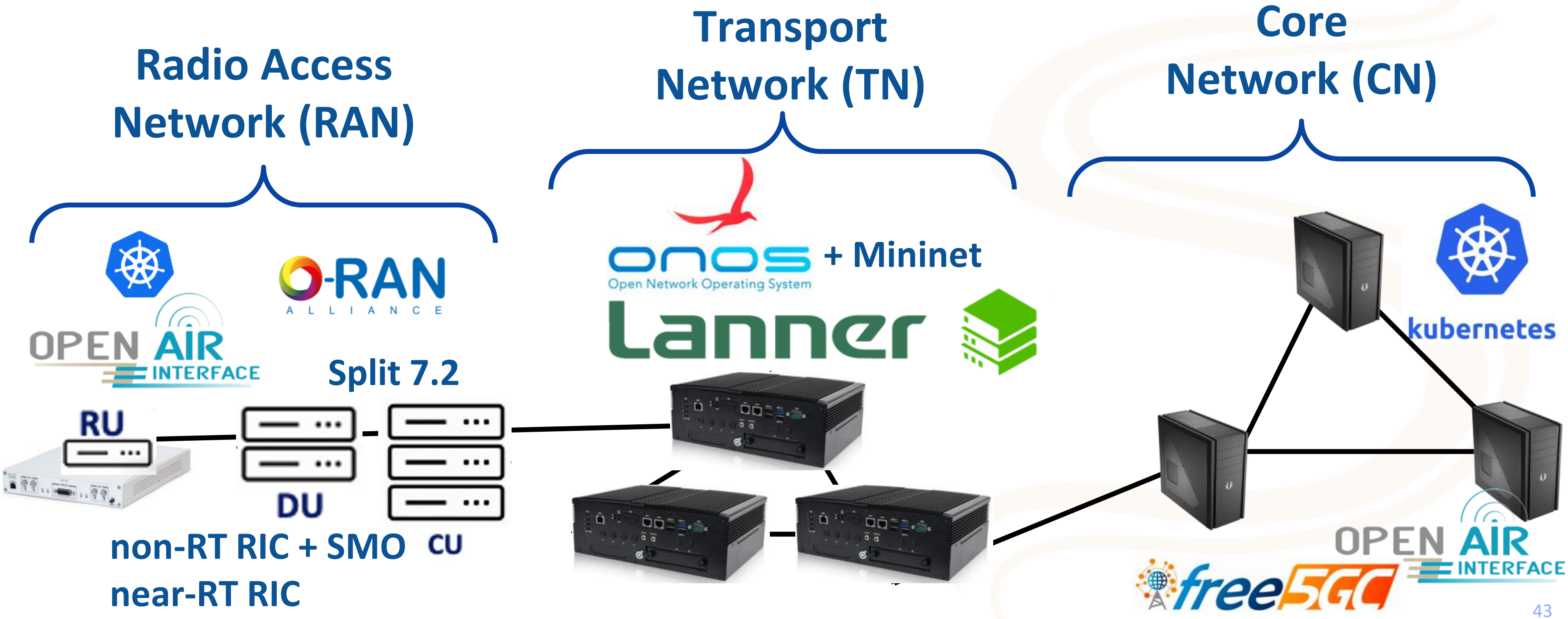
Advanced (site-specific) simulators, GenAI models, open-source full stack implementations, chipset SDKs, etc.

We developed at UFPA:

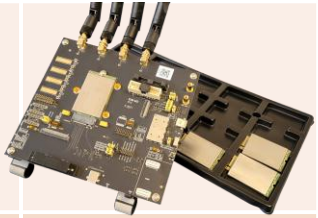
The "**Full-StacK Experimental PlAtform for 6G**" (**KA6G**)



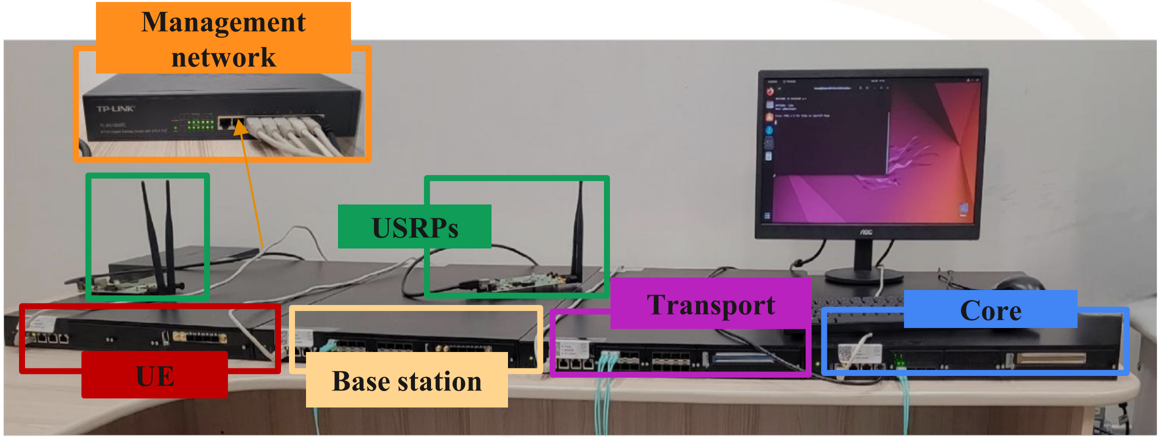
KA6G experimental platform at UFPA



KA6G hardware components

Types of UEs	Models	
Smartphone	Samsung M52 and A54	
Fibocom (Qualcomm chipsets)	4 modules	
5G Fixed Wireless Access (FWA) Router	Intelbras GX 3000	
UE Emulated with USRP	B210 and X310	

Machine	CPU	RAM	Core/ Threads
UE	Intel(R) Xeon(R) Gold 5418N	62 GB	48 / 2
BaseStation	Intel(R) Xeon(R) Gold 6430	62 GB	64 / 2
Transport	Intel(R) Xeon(R) Gold 6430	62 GB	64 / 2
Core (+RICs, SMO, NDTs)	Intel Xeon Platinum 8470N	503 GB	104 / 2



KA6G UEs connected over the air

These experiments used as base station a B210 USRP running OAI with BW= 40 MHz @ 3.6 GHz. More robust results can be obtained with X310 USRP and new daughterboards supporting BW = 100 MHz

Fibocom / Qualcomm

Type of UEs (Individual Test)	Downlink throughput (Mbps) - Average
Emulated UE (USRP)	22.0
Smartphone via WiFi to 5G FWA router	41.8
Smartphone	54.4
Fibocom (Qualcomm)	93.5
Fibocom (Qualcomm) using MIMO	139.5

Smartphones

5G FWA Router

OAI-emulated UE via USRP

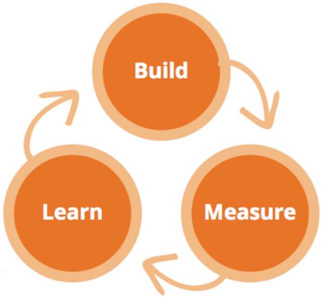
To simulate or not to simulate?

Platforms (testbeds, emulators, etc.) are valuable for obtaining realistic KPIs. They support the full protocol stack and leverage ASICs or FPGAs for complex computations, such as channel coding. Nevertheless, the limited diversity of wireless channels may restrict their applicability in certain scenarios

Analogy with other domains:

Domain	Nature provides
Speech recognition	Spoken language
Computer vision	3D world
Communication systems	Channel

Channel,
The Almighty



$$$

Given the high cost of measurement campaigns (especially in mmWave and THz), simulations (especially using ray-tracing) will be increasingly useful to generate channels in scale and feed simulations **and emulators**, also providing multimodal “paired” data for artificial intelligence (AI), integrated sensing and communication (ISAC), etc.

Hybrid Co-Simulation of 5G/6G Systems with CAVIAR

CAVIAR Framework: Communication Networks, Artificial Intelligence and Computer Vision with 3D Imagery

Virtual 3D world
Realistic 3D scenarios provided by Unreal Engine, Cesium, OpenStreetMap, etc.

Mobility
Pedestrians, connected cars and drones with mobility imposed e.g. by SUMO

Communications
MIMO channel generation with ray tracing (Wireless InSite), ns-3 and 5G-LENA

AI integration
AI algorithms can interact in real-time with the simulations using Tensorflow, Pytorch, etc.

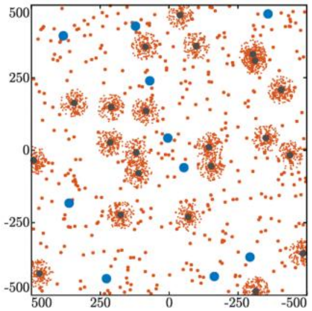
Three examples:
- Beam selection
- Precision agriculture
- Search & rescue w/ UAV

Publications about CAVIAR: https://ieeexplore.ieee.org/document/10571791 and https://www.itu.int/pub/S-JNL-VOL2.ISSUE4-2021-A10

Strategies to simulate mobile communication systems

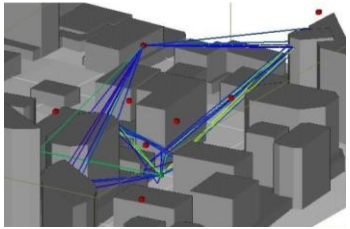
Two extreme examples:

1) Drop-based



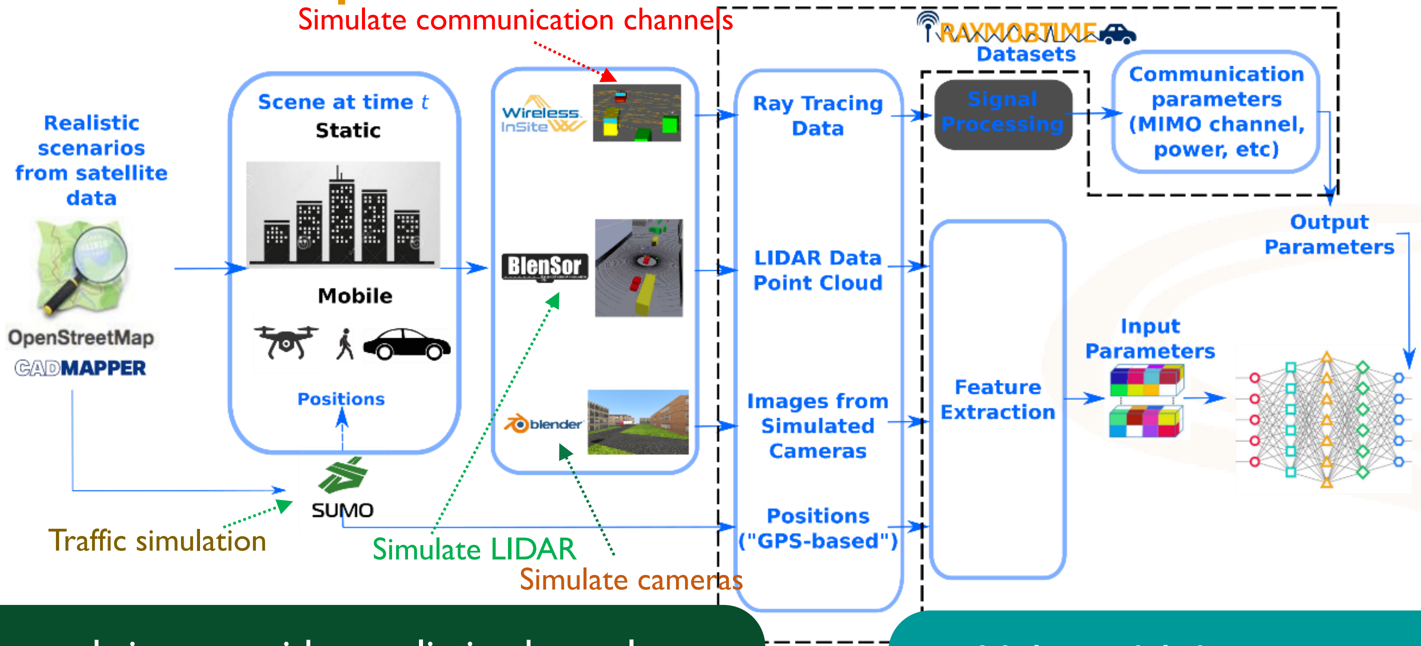
Fast: Site-independent, drop-based, statistical channel model, SNR (based on distance) ➔ capacity equation ➔ rate

2) Ray tracing



Accurate: Site-specific, ray tracing channel generation, waveform ➔ convolution ➔ full PHY stack ➔ rate

Raymobtime methodology for pre-computed channels dataset with multimodal paired information about the environment



Example of rays obtained in a traffic jam simulation [1]

Raymobtime provides realistic channels obtained with ray-tracing, taking in account the mobility of transceivers and scatterers and their evolution over time

Multimodal datasets motivated by the increasing interest on designing integrated sensing and communication systems are also available

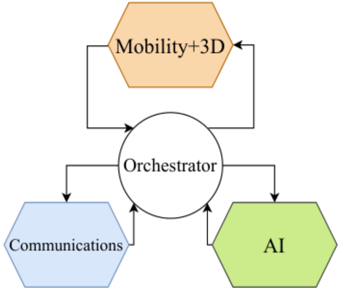
[1] A. Klautau, P. Batista, N. González-Prelcic, Y. Wang and R. W. Heath, "5G MIMO Data for Machine Learning: Application to Beam-Selection Using Deep Learning," in Proc. of the Information Theory and Applications Workshop (ITA), San Diego, CA, 2018, pp. 1-9.

[2] A. Klautau and N. González-Prelcic, "Realistic simulations in Raymobtime to design the physical layer of AI-based wireless systems," ITU News Magazine, No. 5, 2020

CAVIAR synchronizes all modules via a global simulation clock

Example: ns-3 + ray tracing for channel simulation + 3D engine rendering + AI, with sampling interval T_s

(a) At time t.　(b) Time $t + T_s$.　(c) Time $t + 18T_s$.

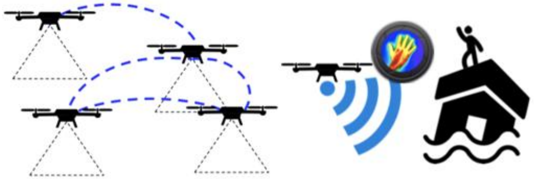


Module	Example of compatible simulators/tools
Mobility+3D	Unreal Engine, Unity3D
Communications	NVIDIA Sionna, Wireless InSite®, ns-3
AI	TensorFlow, PyTorch, scikit-learn
Message passing	NATS, 0MQ

Borges et al (2024). CAVIAR: Co-simulation of 6G Communications, 3D Scenarios and AI for Digital Twins. https://ieeexplore.ieee.org/document/10571791

CAVIAR: enabling interaction among the AI agent and the simulation (mobility, etc.)

- Suppose the simulation of a search and rescue mission that evaluates AI models to define the trajectories of UAVs that are equipped with 6G radios. Because the trajectories depend on actions taken "on-the-fly", it is not possible to pre-compute the wireless channels.



CAVIAR enables **"in-loop"** mode [1], which supports AI decisions inside the simulation loop (e.g., changing UAV trajectories)

Data for 6G apps can be pre-computed according to the **Raymobtime** methodology or generated on-the-fly with **CAVIAR** simulation tools

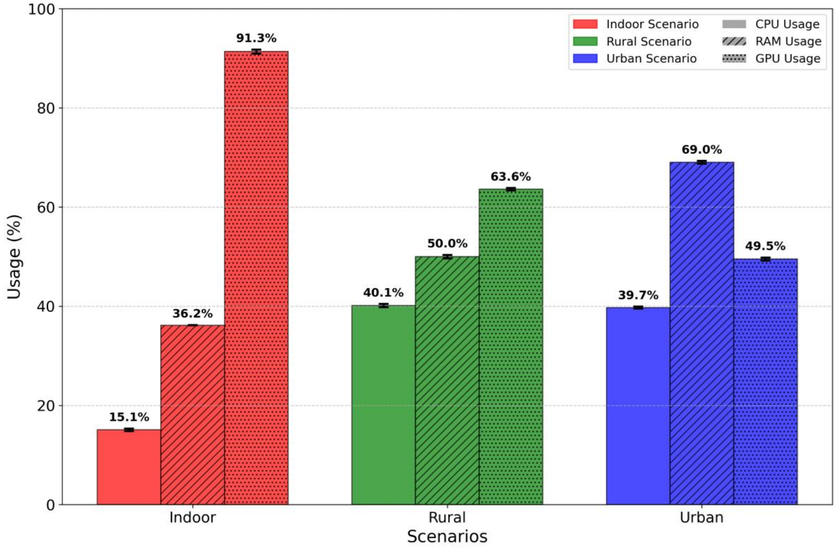
[1] CAVIAR: Co-Simulation of 6G Communications, 3-D Scenarios, and AI for Digital Twins, https://ieeexplore.ieee.org/document/10571791

General CAVIAR results

Table 10 – Simulation hardware specifications.

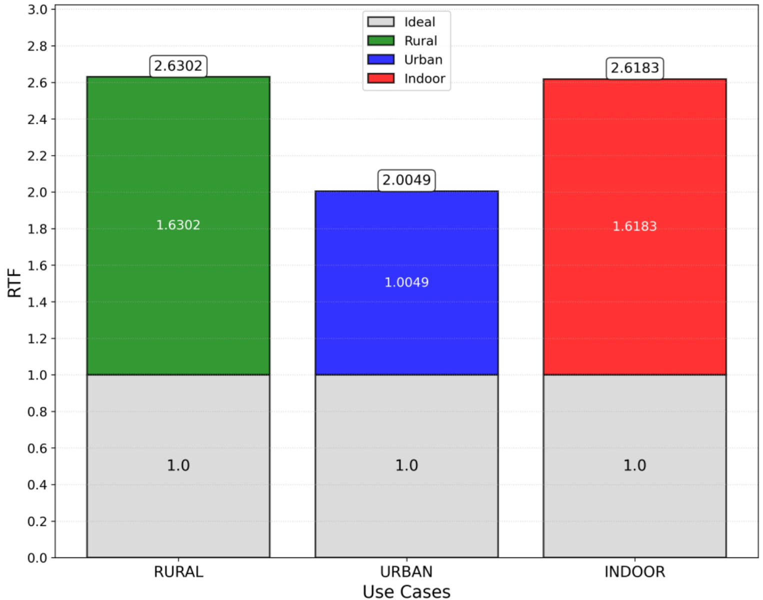
CPU	13th Gen Intel® Core™ i7-13700HX × 24
RAM	32 GiB
GPU	NVIDIA GeForce RTX 4060

Figure 32 – Average CPU, GPU, and RAM usage among all use cases.



real-time factor (RTF) = wall-clock / simulated

Figure 33 – The overall RTF for all use cases.



Several tradeoffs when modeling the real-world. A key aspect to decrease computational cost: use adequate abstractions

CAVIAR

Divide and conquer

Hybrid simulation

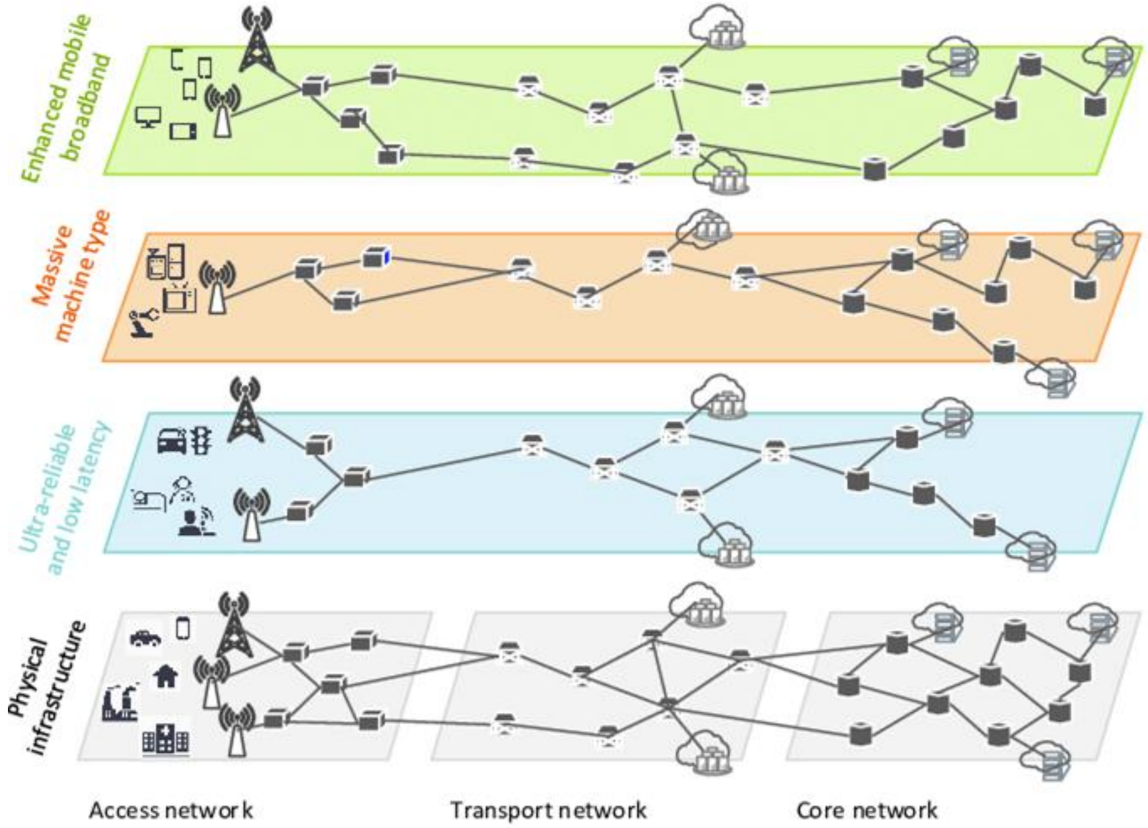
Modern hybrid simulators

Trend towards more sophisticated simulators, but the best option depends on the use case

Use Case 2:
NDTs for 6G transport networks

What-if analysis using graph neural networks (GNNs) and reinforcement learning (RL)

Network slicing



"Flow" and "link" data:

Features	Feature Role	Unit
Average bandwidth	Flow	Mbits/s
Average packet size	Flow	Bytes
Average packet rate	Flow	pps
Propagation delay	Flow	ms
Link capacity	Link	Mbits/s
Link load	Link	ratio

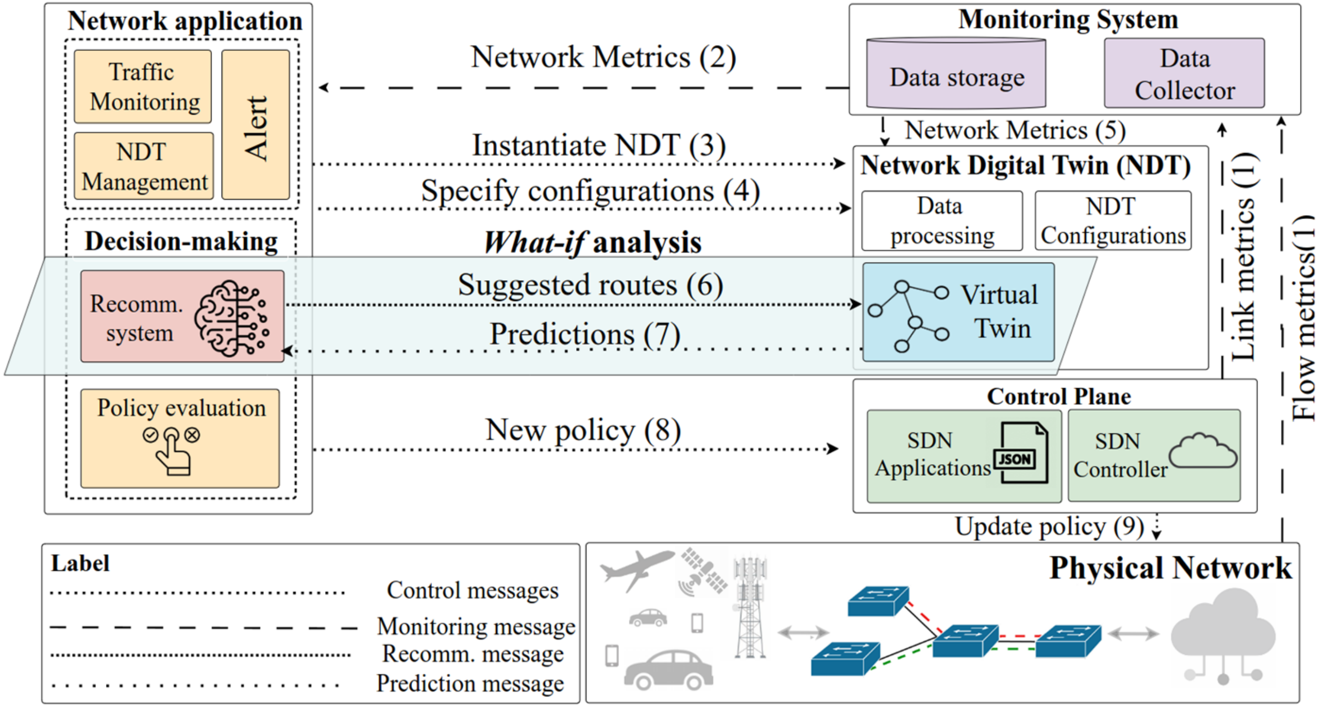
S. Zhang, "An overview of network slicing for 5G," IEEE Wireless Communications, vol. 26, no. 3, pp. 111–117, 2019.

NDT for transport network

What-if analysis in routing optimization use case

How accurate is the network performance prediction made by the Virtual Twin compared to the actual performance after implementing the action on the Physical network?

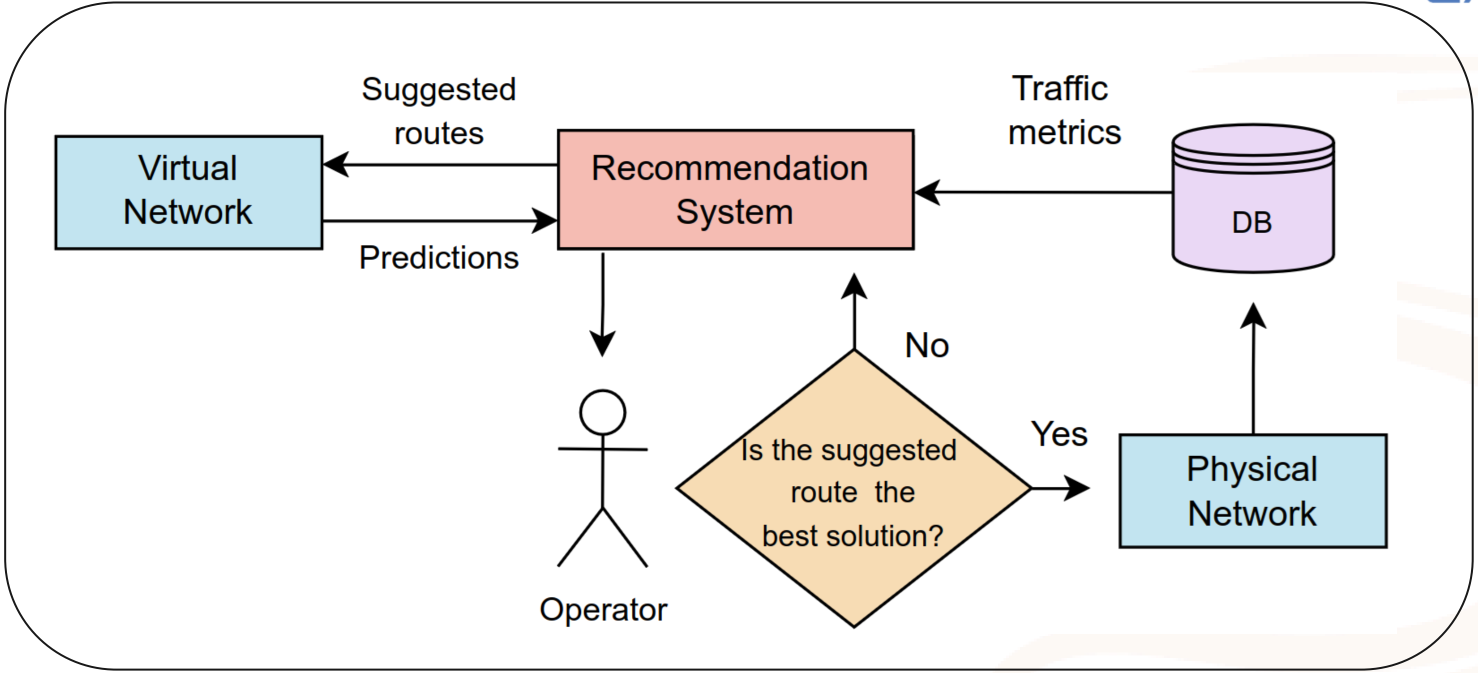
How does NDT performance vary as network size increases?



*The figure's colors are distributed as follows: green for the Control Plane, blue for the virtual twin, purple for the Monitoring System, pink for the recommendation system, and yellow for the Control Functions of the Network Application layer.

NDT for transport network

What-if analysis in routing optimization use case



*The representation of decision-making with the network operator options (accept or reject the solution) highlighted in yellow

Prototype

Summary on how each layer of our NDT was implemented in our prototype

A. Physical Network

B. Control Plane

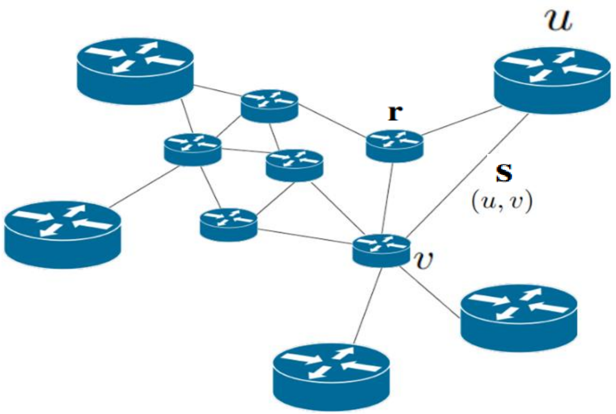
C. Monitoring System

D. Network Virtual Twin

E. Network Applications

Prototype

A. Physical Network



Parameter	Value	
Operating System	Ubuntu 20.04.4 LTS	
Software	ONOS 2.7-latest, Mininet[19] 2.3.0, Python 3.8.19	
Protocols	OpenVSwitch 2.13.8	
Packet size	125 bytes	
Bandwidth	eMBB	URLLC
	10 Mbps	1 Mbps
Max Latency	10 ms	1 ms

Table I - Technical configuration details

- Directed graph
- One source, one destination
- Follows a pairwise manner defined by a 4-tuple graph $\mathcal{J}$

$$\mathcal{J} = (\mathcal{V}, \mathcal{E}, \mathbf{r}, \mathbf{s})$$

Set of nodes

$$\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$$

Node features

edge features

As all links can handle both slices without congestion, the focus shifts to the total *path delay*

Slices

Ultra-reliable Low-Latency (URLLC)

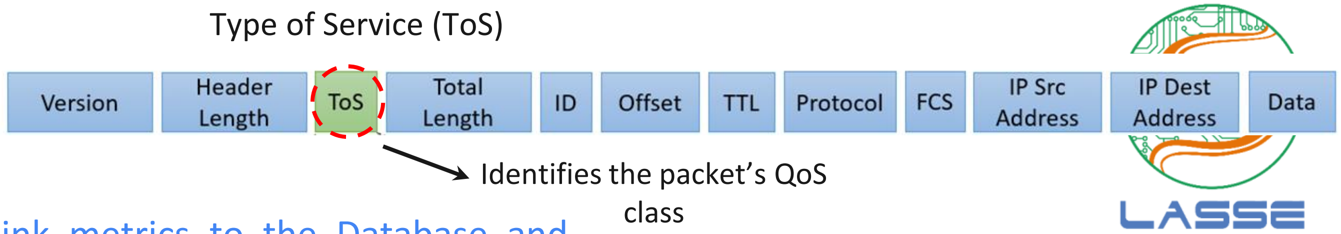
Strict requirements for reliability, availability, and ultra-low latency

enhanced Mobile Broadband (eMBB)

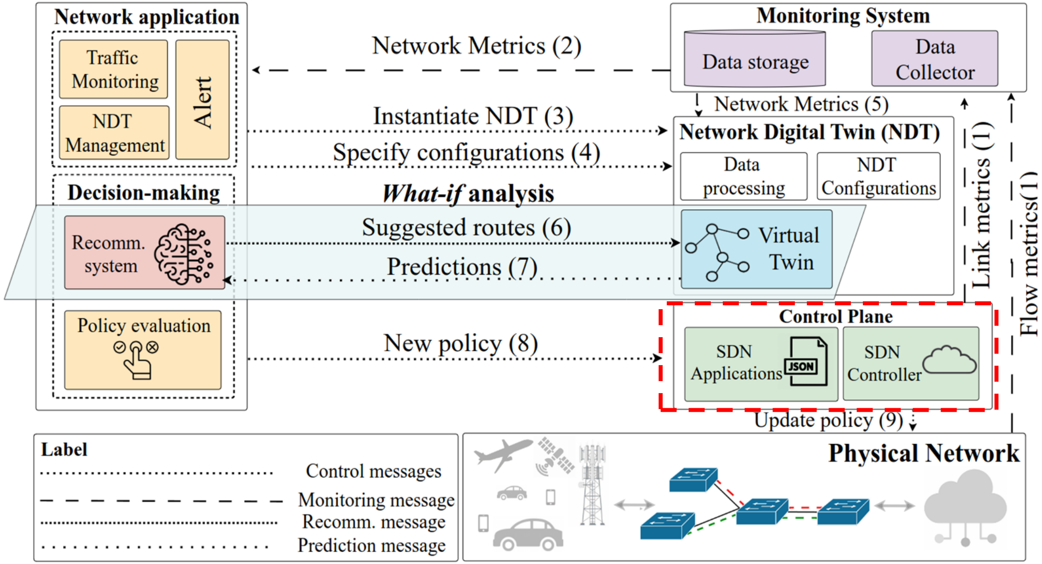
High throughput and low latency

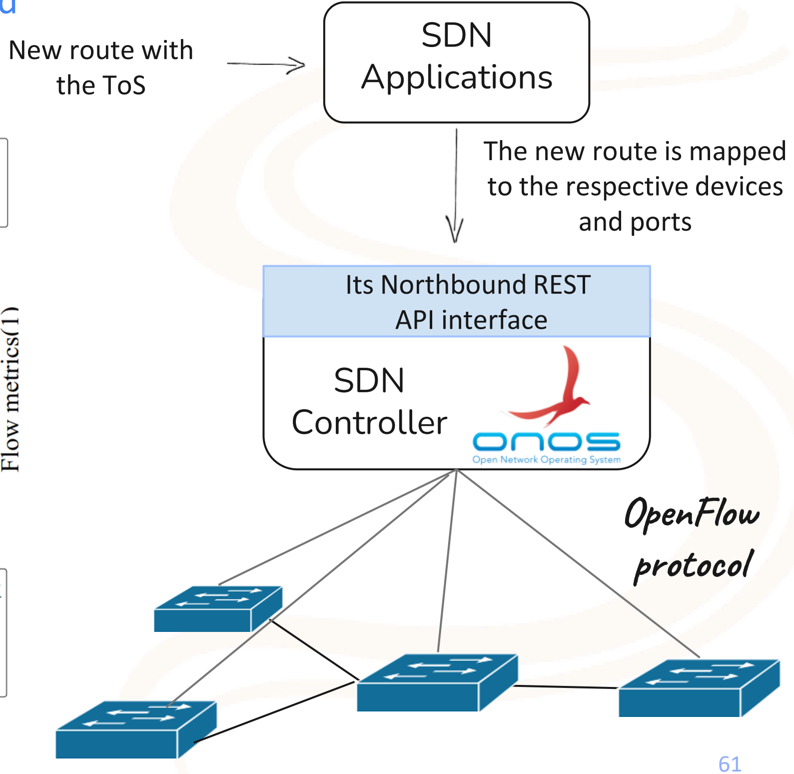
Prototype

B. Control Plane



Responsible for sending link metrics to the Database and implementing decisions in the physical network.

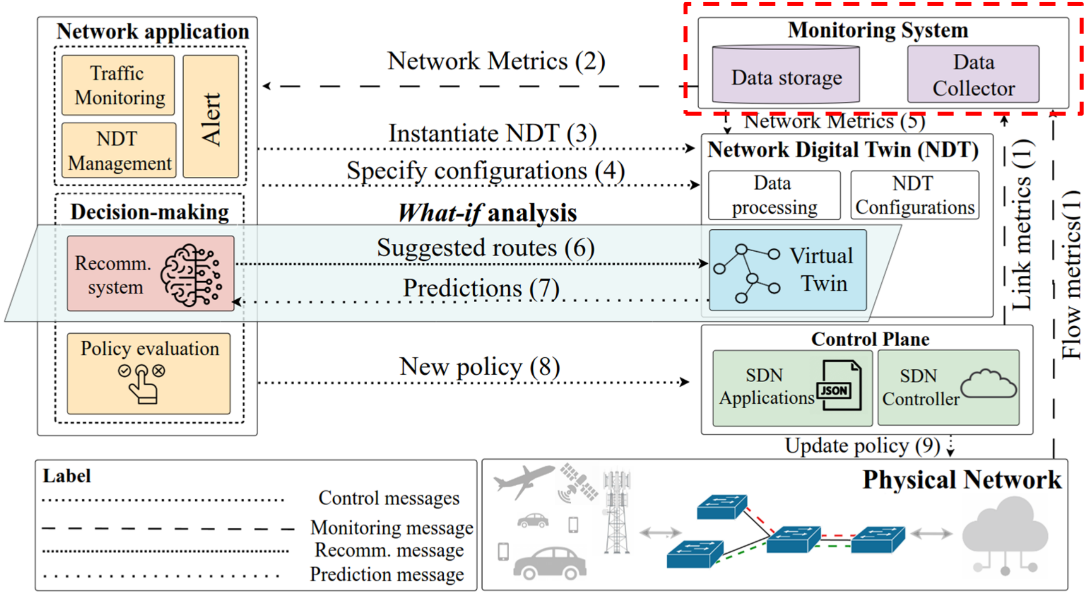


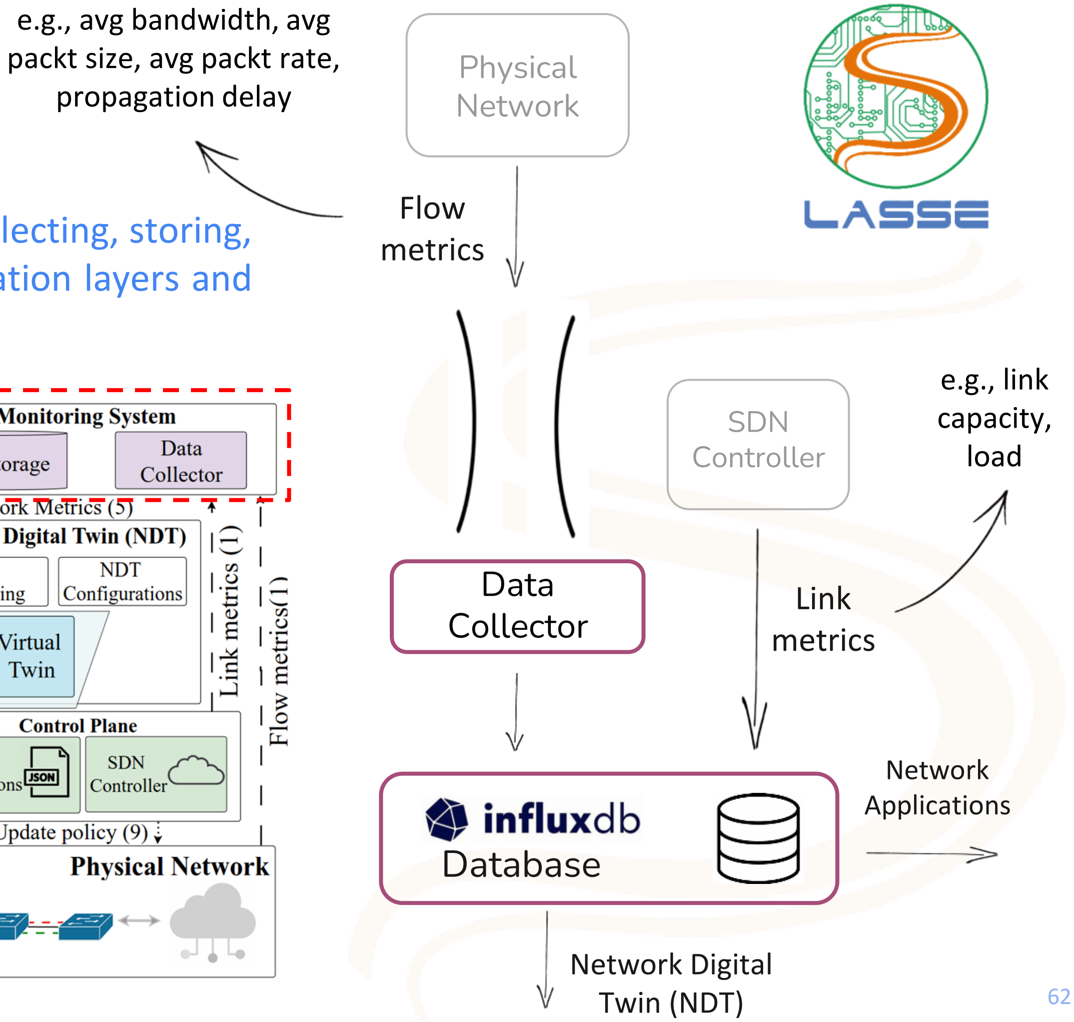


Prototype

C. Monitoring system

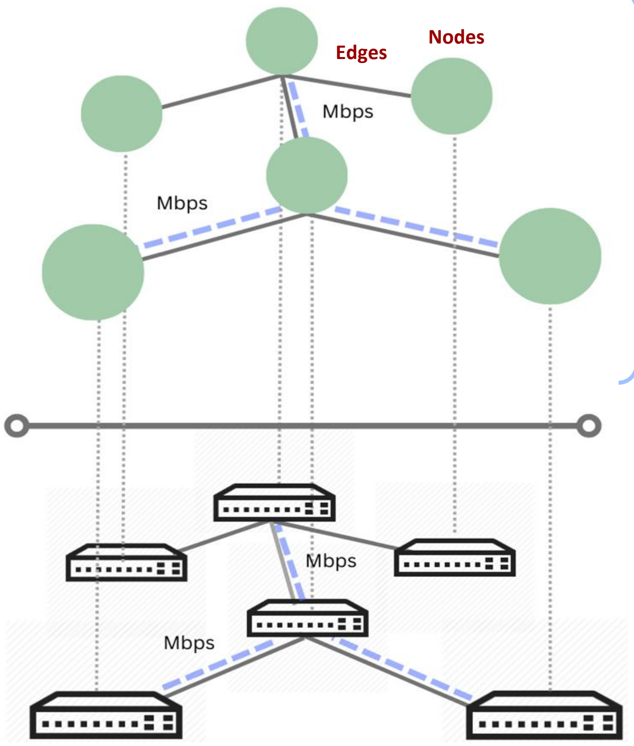
The Monitoring System plays a vital role in collecting, storing, and transmitting traffic metrics to the Application layers and the NDT when instantiated.





Prototype

D. Network virtual twin



Virtual Twin represented by
Graph Neural Network (GNN)

GNN addresses the limitations of conventional approaches at tackling complex tasks by efficiently processing large-scale data and generalizing across unseen topologies, **overcoming the limitations of conventional approaches.** [16]

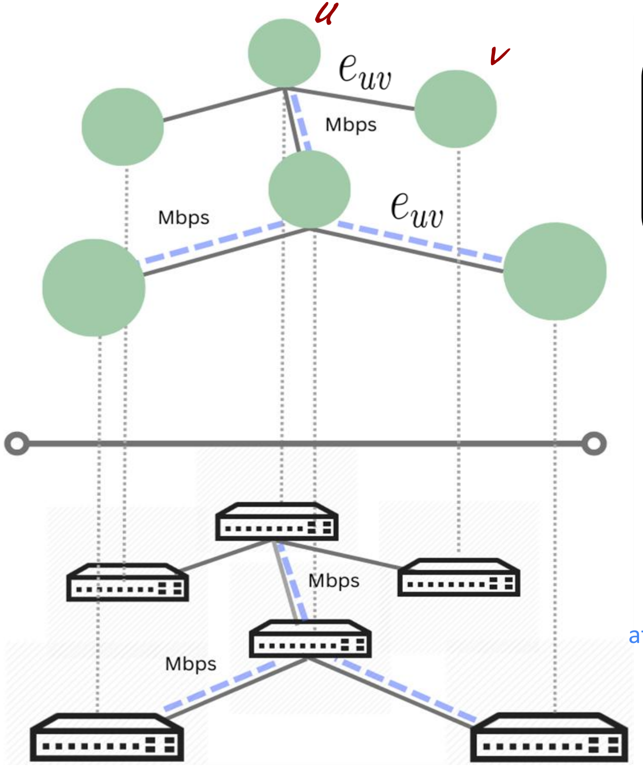
Message-Passing Neural Networks

Nodes communicate with neighbors to update their features, learning structured embeddings that reflect the graph's topology and interactions

[16] M. Ferriol-Galmés, J. Paillisse, J. Suarez-Varela, K. Rusek, S. Xiao, and e. a. Shi, "Routenet-fermi: Network modeling with graph neural networks," IEEE/ACM Transactions on Networking, 2023

Prototype

D. Network virtual twin



Message-Passing ⊇ Attention

Attention mechanism

Another layer that provides a kind of fine-tuning to dynamically adjust the importance of the features

Update function

Attention Coefficient

$$e_{uv} = a^T \mathrm{LeakyReLU}(\mathbf{W}[h_u || h_v])$$

Normalization

$$\alpha_{uv} = \mathrm{softmax}(e_{uv})$$

Learnable weight vector

Learnable weight matrix

Normalized attention coefficient

$$\alpha_{uv} = \frac{\exp(\mathbf{a}^T \mathrm{LeakyReLU}(\mathbf{W}[\mathbf{h}_u || \mathbf{h}_v]))}{\sum_{k \in \mathcal{N}_u} \exp(\mathbf{a}^T \mathrm{LeakyReLU}(\mathbf{W}[\mathbf{h}_u || \mathbf{h}_k]))}$$

The neighborhood of interest node u

Concatenation operation

[17] C. Modesto, R. Aben-Athar, A. Silva, S. Lins, G. Goncalves, and A. Klautau, "Delay Estimation Based on Multiple stage Message Passing with Attention Mechanism using a Real Network communication Dataset," ITU Journal on Future and Evolving Technologies, vol. 5, pp. 465–477, 2024.

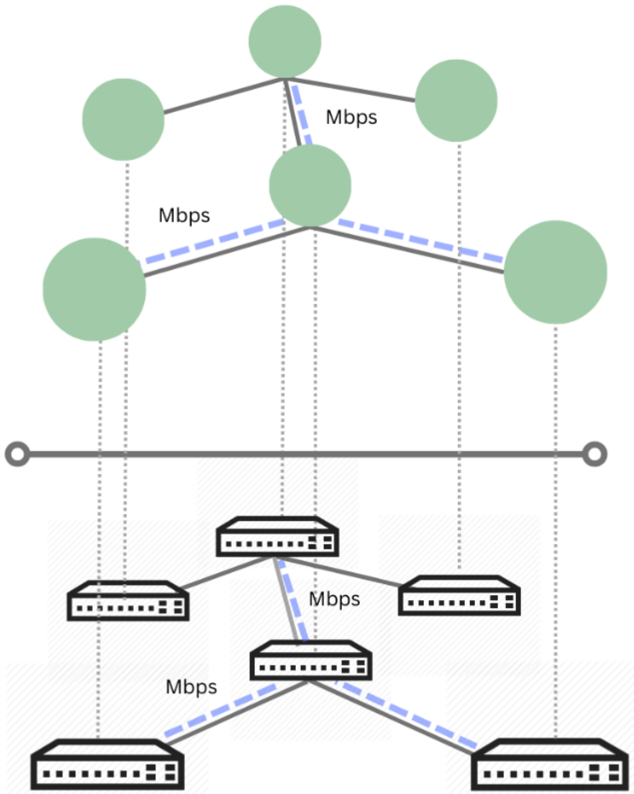
[18] S. Brody, U. Alon, and E. Yahav, "How attentive are graph attention networks?" 2022. [Online]. Available: https://arxiv.org/abs/2105.14491

[19] M. Ferriol-Galmés, J. Paillasse, J. Suárez-Varela, K. Rusek, S. Xiao, and e. a. Shi, "Routenet-fermi: Network modeling with graph neural networks," IEEE/ACM Transactions on Networking, 2023.

Prototype

D. Network virtual twin

The virtual twin was pre-trained on a dataset[20] using a topology ranging from 5 to 8 nodes and tested on various topologies with different node counts.



The Virtual Twin input include:

1) **The flow metrics**: $\mathbf{r} \in \mathbb{R}^n$ where n is the number of flow features, represented as the set $\mathcal{M} = \{R_1, R_2, \ldots, R_n\}$, with each R_i denoting a distinct feature.

2) **The link metrics**: defined as $\mathbf{s} \in \mathbb{R}^2$ with the number 2 representing the number of link features.

3) **The suggested route from the recommendation system**: A subset of $\mathcal{J}$ represented by $\mathcal{P}$ where $\mathcal{P} = (\mathcal{V}_p, \mathcal{E}_p, \mathbf{r}_p, \mathbf{s}_p)$, where $\mathcal{V}_p \subseteq \mathcal{V}$ and $\mathcal{E}_p \subseteq \mathcal{E}$ correspond, respectively, to the subset of nodes and links that form the selected route.

Features	Feature Role	Unit
Average bandwidth	Flow	Mbits/s
Average packet size	Flow	Bytes
Average packet rate	Flow	pps
Propagation delay	Flow	ms
Link capacity	Link	Mbits/s
Link load	Link	ratio

Table II - Features used as input for Virtual Twin

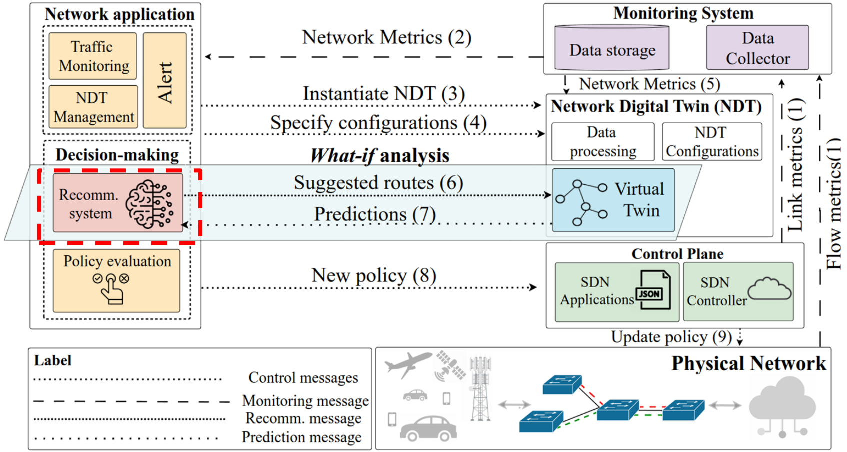
[20] https://bnn.upc.edu/challenge/gnnet2023/dataset/

Prototype

E. Network Applications

The virtual counterpart and the different routing algorithms in the recommendation system form the ***what-if* analysis**

The recommendation system is activated when an Service Level Agreement (SLA) violation is detected in the network, and it starts suggesting alternative routes.



Algorithms for route recommendations

Random

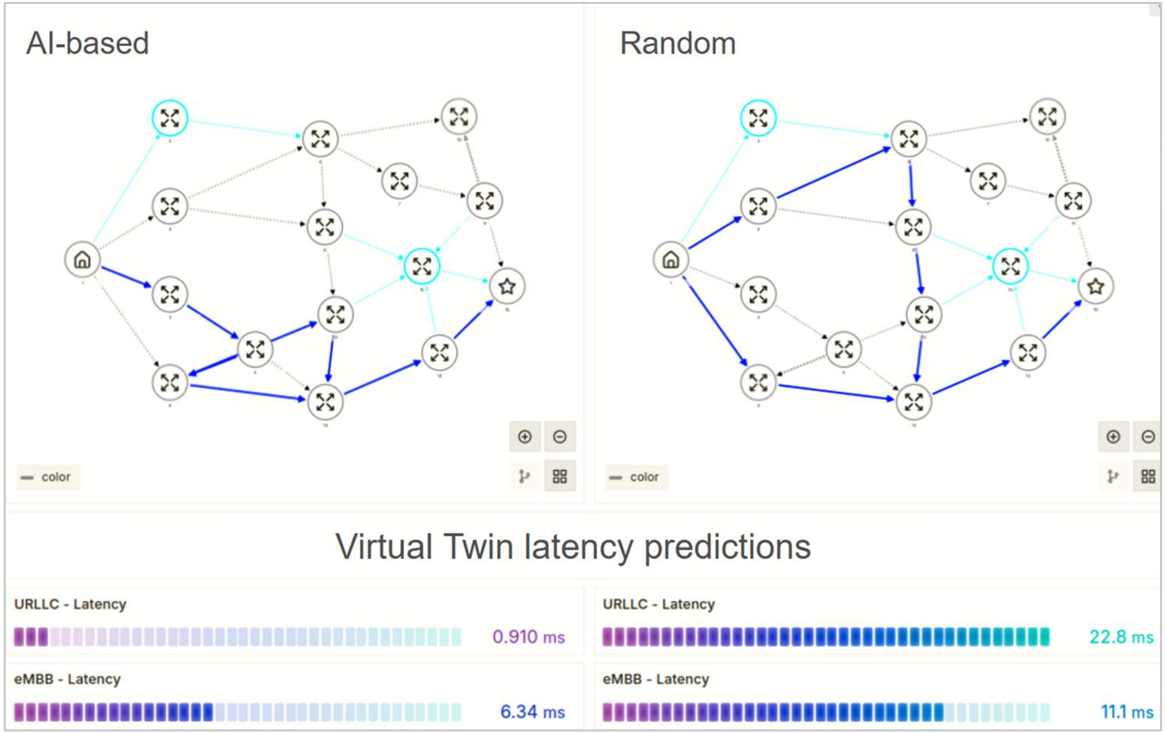
Randomly selects a route among all available routes

AI-based

- Reinforcement Learning with the Proximal Policy Optimization (PPO).
- Identify the paths that best meet the requirements of each service in terms of latency.

Performance Evaluation

The suggested routes by the recommendation system and the GNN latency predictions for each solution, composing the ***what-if* analysis**, for the 16-node topology.



We used three synthetically generated network datasets:

- 8-node topology with 15 links;
- 16-node topology with 27 links;
- 30-node topology with 75 links.

Legend

Source node

Destination node

Unavailable route

Suggested route

Predicted latency by virtual twin for each slice

Performance Evaluation

To evaluate the performance of our NDT, we compared the **latency predictions generated by the virtual twin** with the actual latencies measured on the physical network for each slice for each suggestion solution, in each different node count topologies.

		Routing Algorithm	
Topology	**Slice**	**Random**	**AI-based**
8 nodes	URLLC	1.73%	1.89%
	eMBB	1.84%	1.82%
16 nodes	URLLC	1.92%	1.67%
	eMBB	1.95%	1.81%
30 nodes	URLLC	2.12%	2.28%
	eMBB	2.10%	2.15%

Table III - Mean Absolute Percentage Error (MAPE) of the predicted End-To-End (E2E) latency for each slice compared to the true latency across 8-,16-, and 30-node network topologies

Using the predicted and the actual delay measured on the physical network after the implementation

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \right|$$

Thanks to professors Glaucio Carvalho and Isaac Woungang for the opportunity!

Thank you for your attention!

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