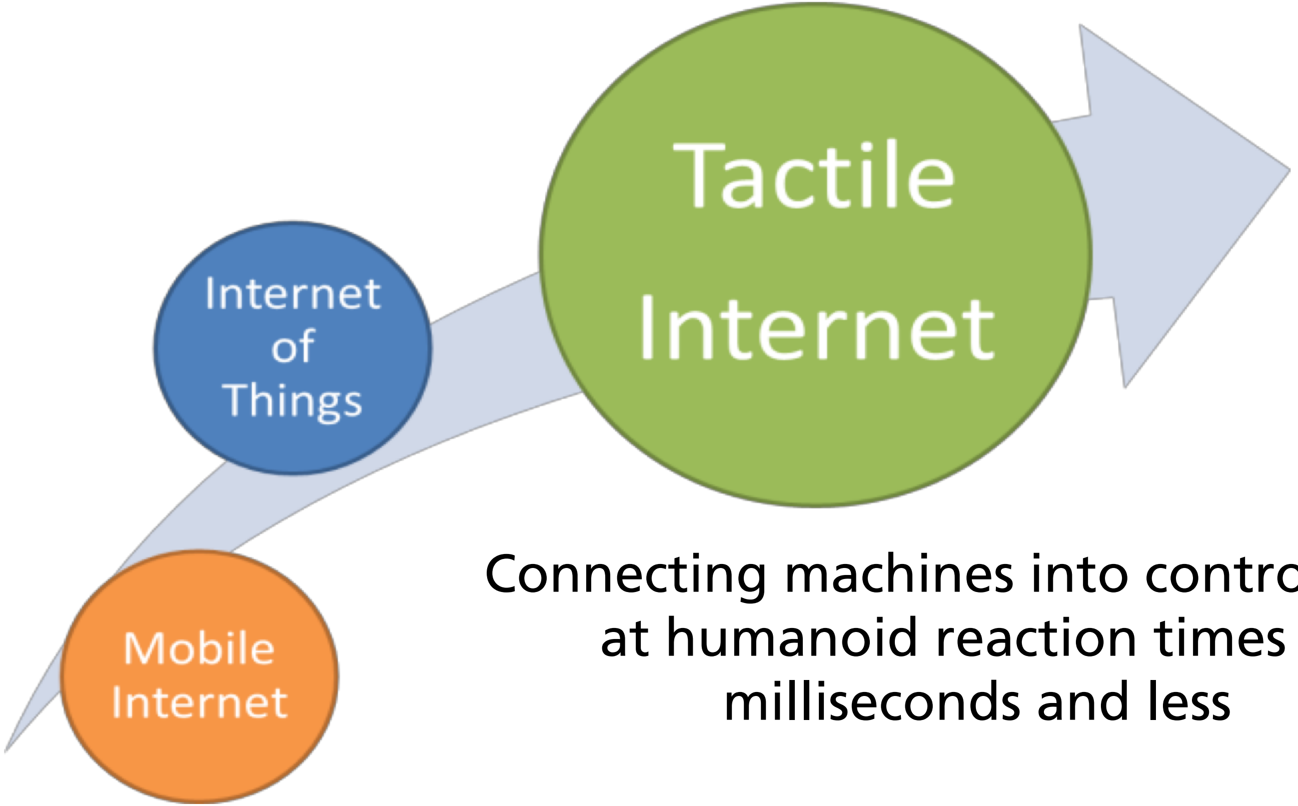
Softwareization of Mobile Radio Networks

Slawomir Stanczak and Alexander Keller

Joint work with Daniyal Amir Awan, Renato Cavalcante, Jochen Dommel, Martin Kurras, Matthias Mehlhose, Zoran Utkovski

Fraunhofer HHI

Revolutionary Leap of Tactile Internet

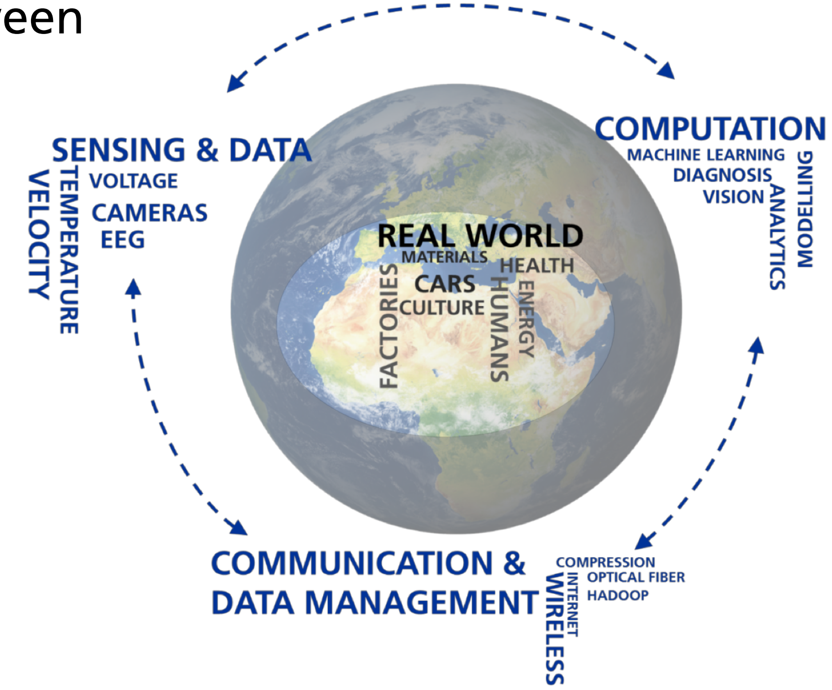


Connecting machines into control loops at humanoid reaction times of milliseconds and less

Source: ITU TechWatch Report: The Tactile Internet

Challenges

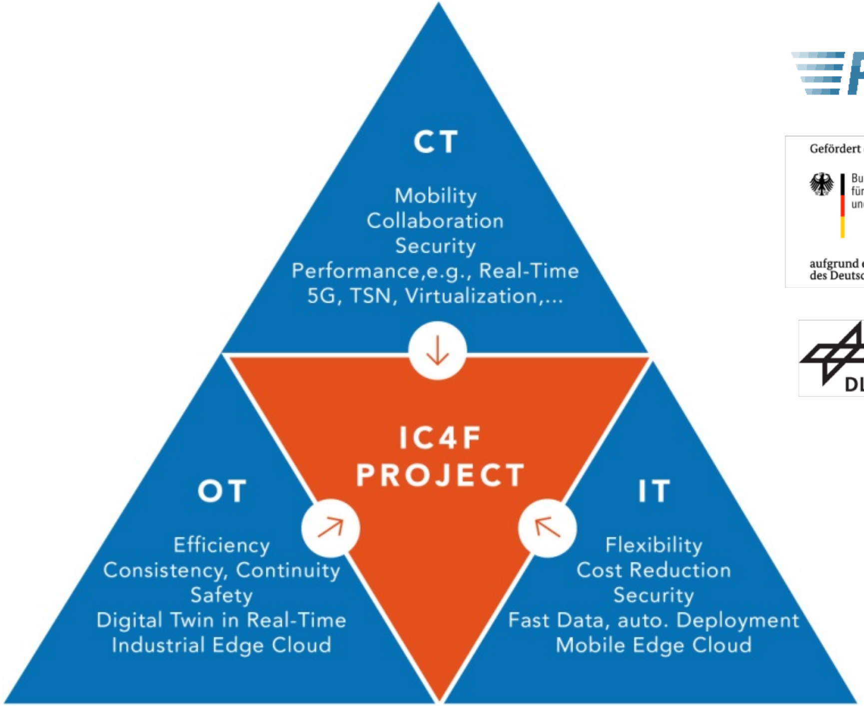
- Optimal functional split & interplay between
  - sensing
  - computation
  - communication
- Future networks need to provide
  - higher data rates and
  - higher reliability at lower latencies



Tactile Internet for Production and Logistics

5G for Industry 4.0

- Reliable remote machine operation
- Augmented worker/workspace
- Predictive maintenance
- Machine and process monitoring
- High precision positioning
- Industrial edge cloud
- Truck-to-X communication
- Secure remote access

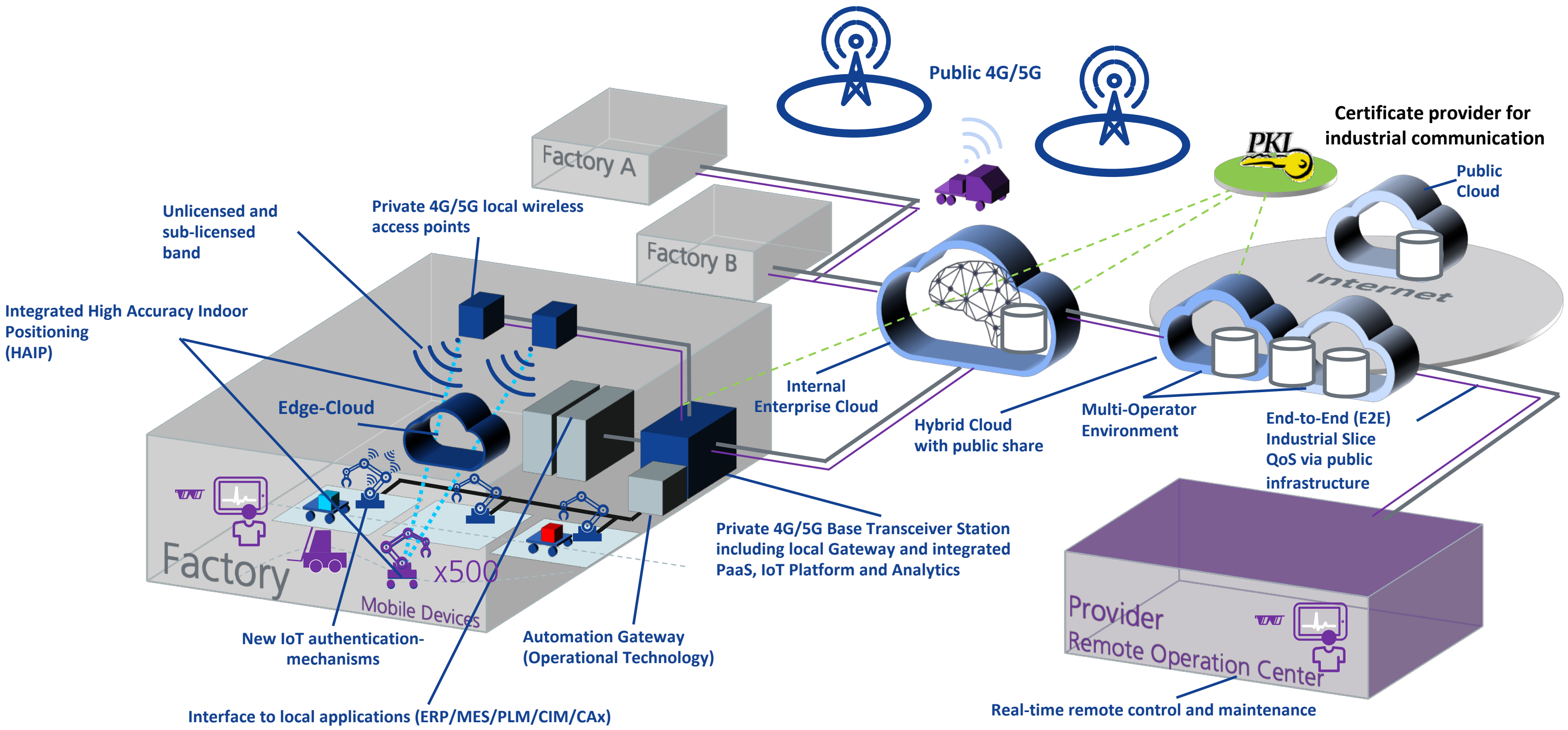


Gefördert durch:
Bundesministerium für Wirtschaft und Energie
aufgrund eines Beschlusses des Deutschen Bundestages

DLR Projektträger

Fraunhofer HHI

Future Architecture for Industrial Communications



Martin Kurras

Fraunhofer HHI

IC4F

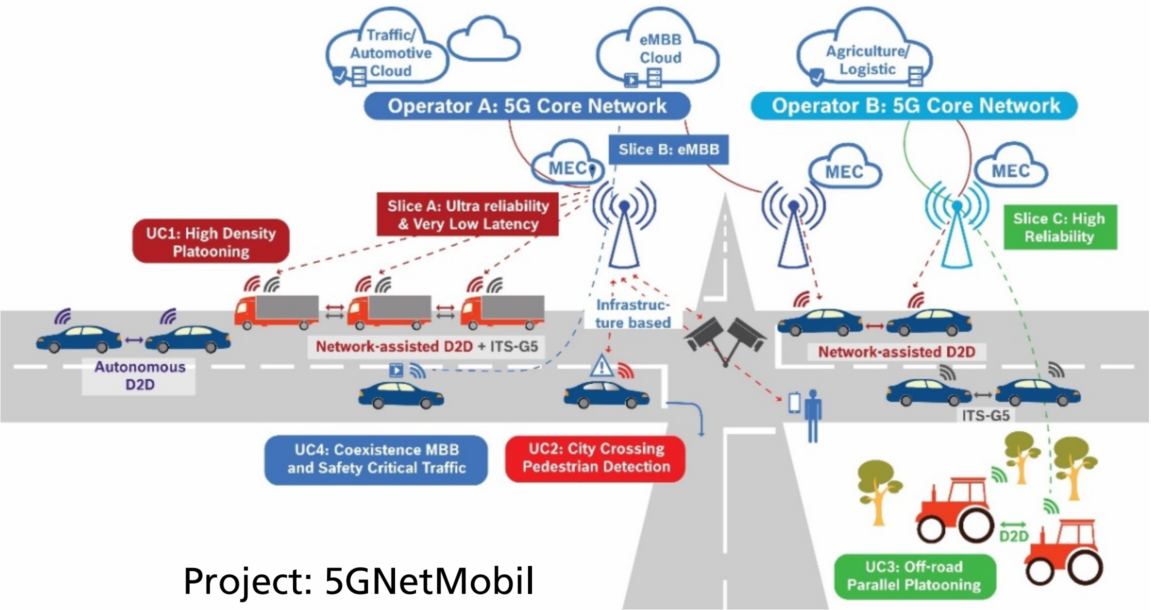
INDUSTRIAL
COMMUNICATION
FOR FACTORIES

Tactile Networked Mobility

GEFÖRDERT VOM
Bundesministerium für Bildung und Forschung

5G in Networked Driving

- Platooning
- Crossing traffic
- Collaborative driving
- Remote driving
- AR-based driver assistance
- Complete street perception
- Analysis of vehicle & driver conditions

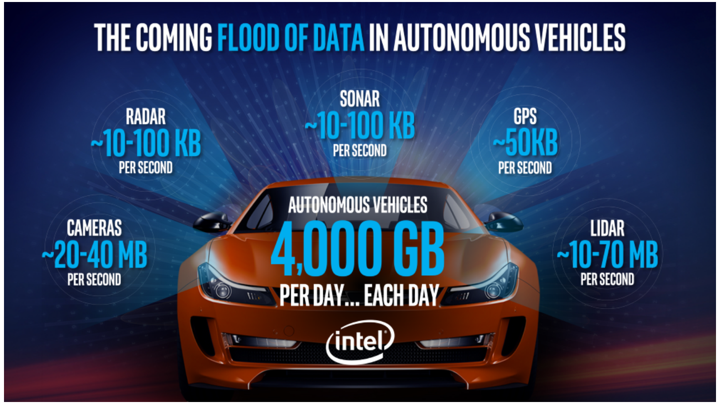


Project: 5GNetMobil

Fraunhofer HHI

To Shift or Not to Shift (the Burden to the Network)?

- Main drawbacks of **in-vehicle processing**
  - No coordination of decisions in scenarios with multiple cars
  - Range reduction of e-cars due to high power consumption (storage, cooling...)
  - Integration of sensors



© Intel

- Network-side sensing and processing may be infeasible in current networks

Fraunhofer HHI

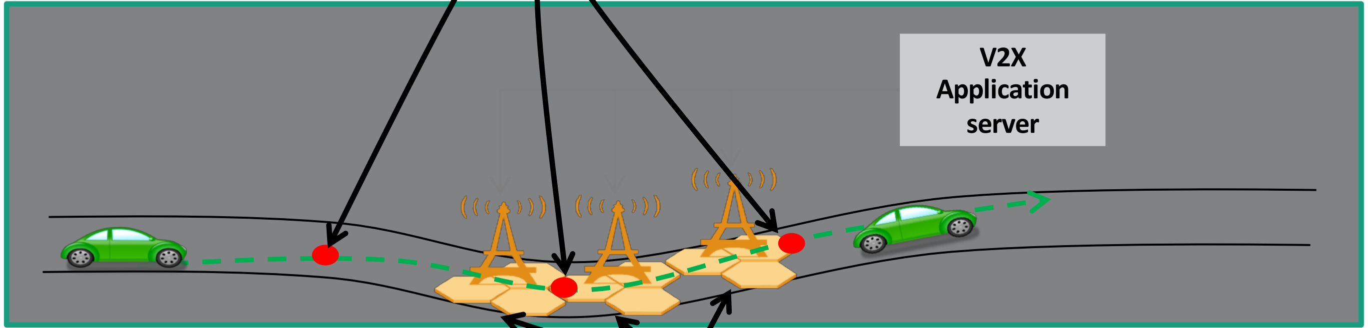
Key Enabler: End to End (E2E) Quality of Service (QoS) Prediction

- V2X communication must provide **guaranteed QoS** for a certain amount of time
  - For example, 10 Mbps with 1ms delay for the next 20 seconds, and
  - **Predict changes** in the radio link quality to **pro-actively perform adaptation**.

Softwareization: Machine Learning in the Base Stations

By ***predicting future radio conditions*** the BS provides to the UE:
1) Scheduling and channel allocation
2) Predicted link quality, network capacity

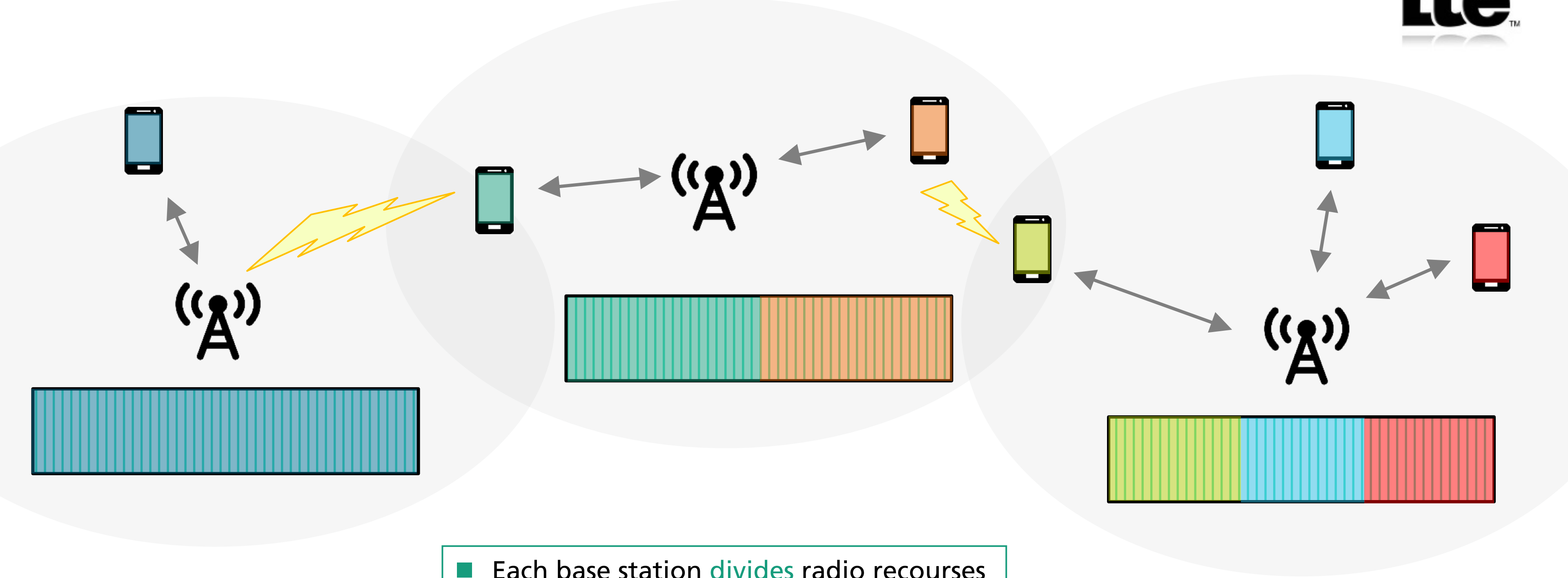
E.g. coverage holes or out of coverage areas and link quality (considering network environment e.g., obstacles) may be predicted



Base Stations use ***Machine Learning*** for prediction and look-ahead scheduling based on collected data from UEs and V2X application servers

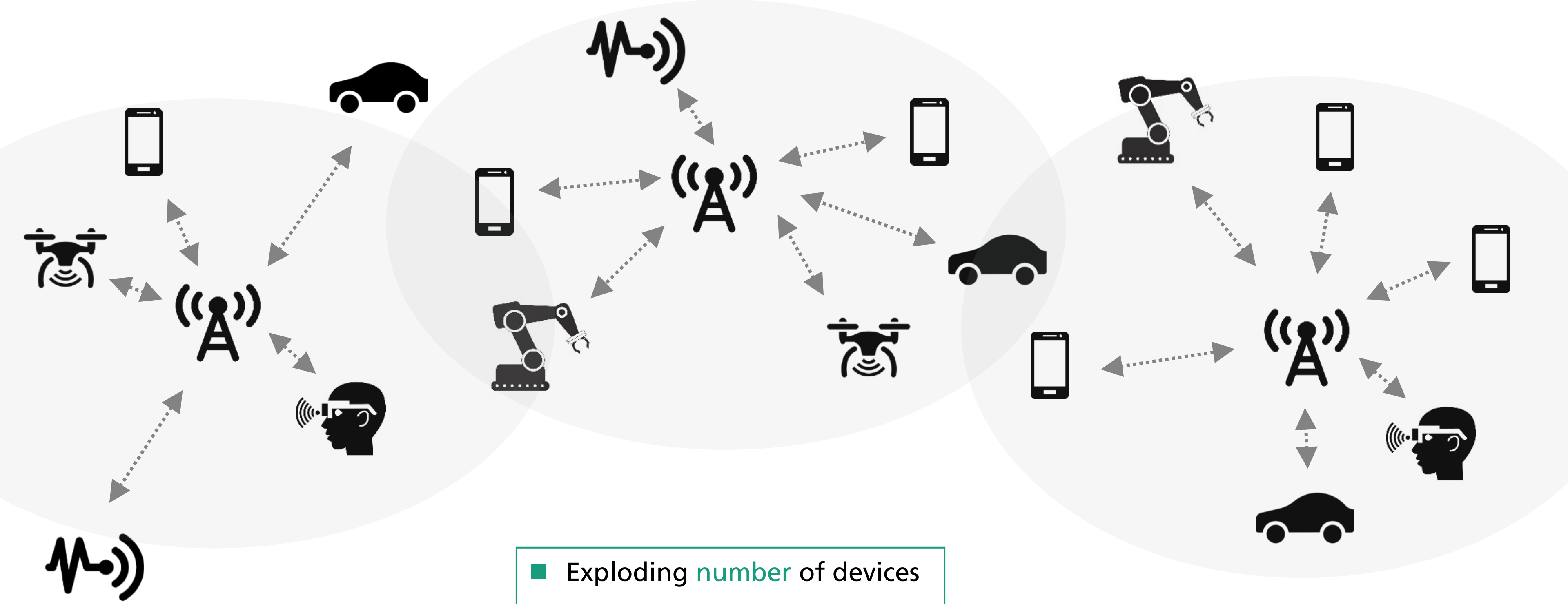
Fraunhofer HHI

Wireless Communication Networks – Today



- Each base station divides radio recourses
- Interference between cells

Wireless Communication Networks – Tomorrow



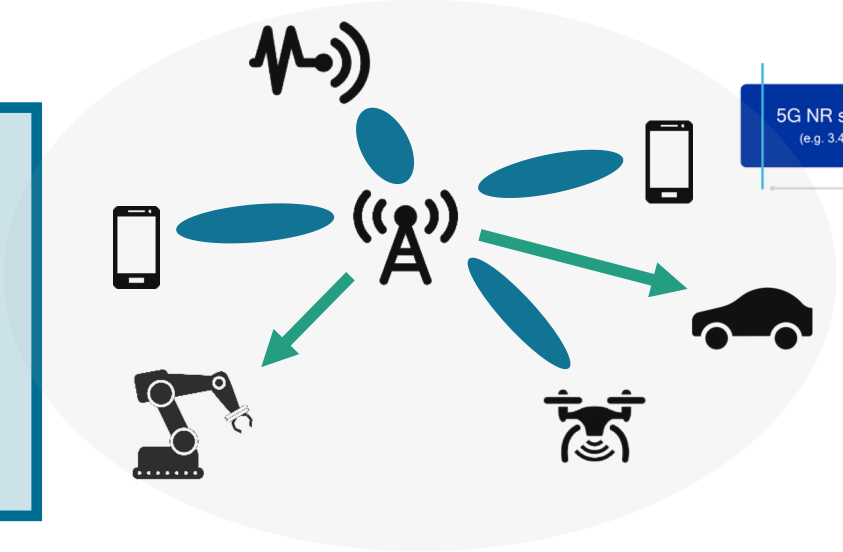
- Exploding number of devices
- Different new service classes

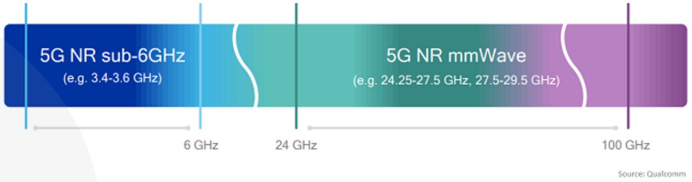
Fraunhofer HHI

Wireless Communication Networks – Tomorrow

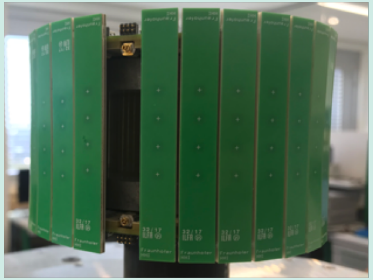
Massive MIMO

More antennas





mmWave



More resources

- High spectral efficiency → Massive MIMO
- Additional bandwidth → mmWave

Fraunhofer HHI

mmW und THz Radio for Industrial Communication

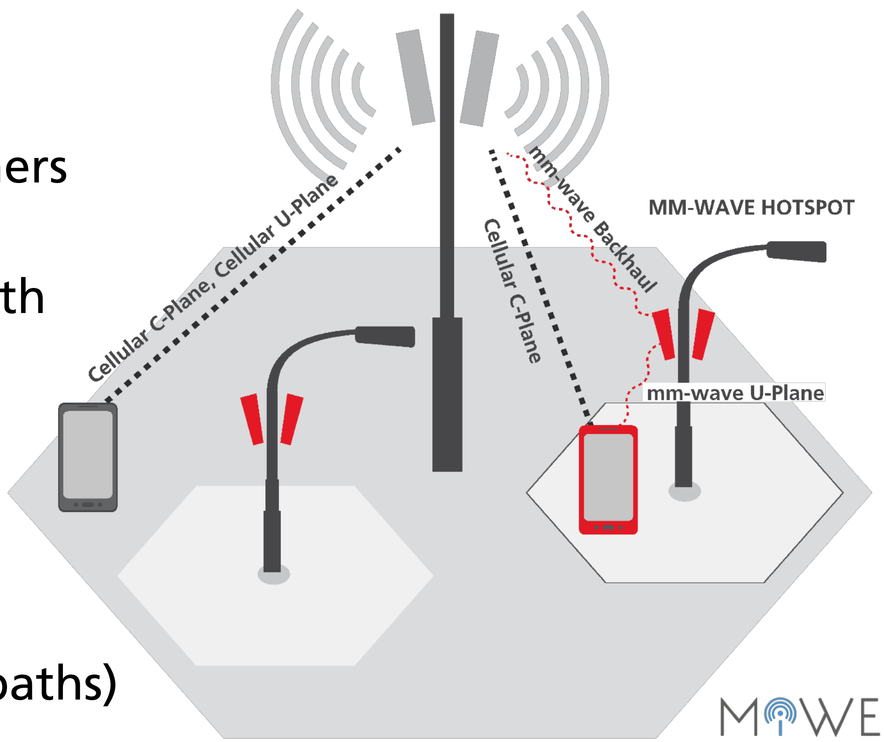
© Bosch

- Potential solution for production cells or distributed industrial plants
- Point to multi-point networking with directional transmission
- large bandwidth, low latency
- low interference to neighboring systems
- **Higher immunity to jamming and eavesdropping**

Fraunhofer HHI

Operating Networks in the mmWave Band

- **Hardware**
  - 28,39,60 und 70/80 GHz
  - hybrid analog-digital beamformers
  - low-rate ADCs
  - large number of antennas at both transmitters and receivers
  - high directivity
- **Characteristics**
  - High attenuation
  - High penetration loss
  - Sparse channels (few clustered paths)
  - Mobile massive MIMO



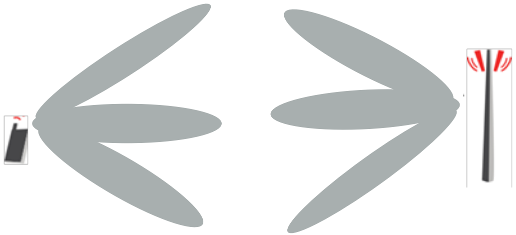
Fraunhofer HHI

Operating Networks in the mmWave Band: Challenges

- Interference is reduced compared to cmWave networks. But:
  - Interference management problems are typically combinatorial (selection of beam directions, beam widths, etc.)
- Initial access, handover, and mobility management are challenging tasks
- Requirement for relays: cooperation and multi-connectivity techniques

Beam Alignment

- **mmWave with hybrid beamforming**
  - Find suitable beams for communication at the receiver and the transmitter
  - Naive approach: probe all possible beams (inefficient)

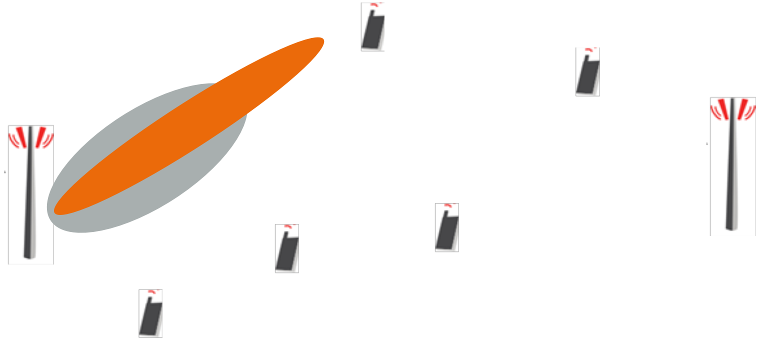


  - Proposals (also present in standards): Start with wide beams and refine them in a multi-step approach

Fraunhofer HHI

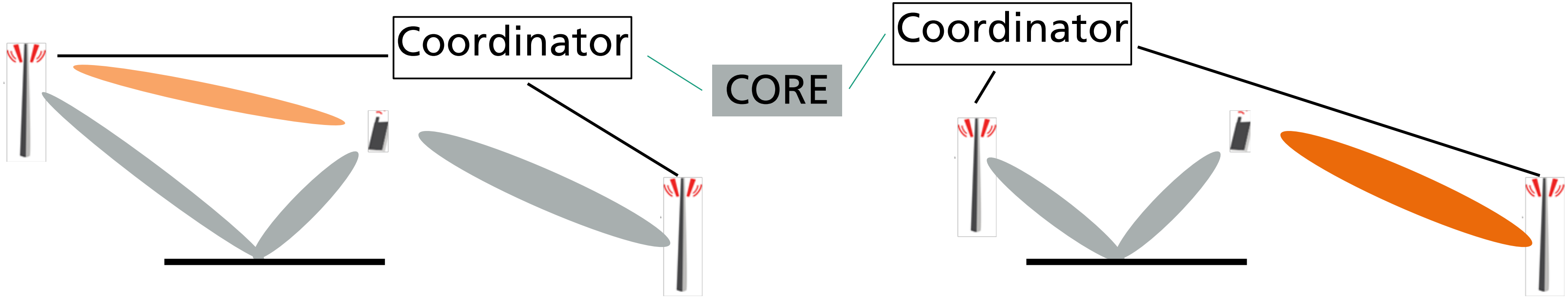
Beam Alignment: Networking Challenges

- Coordinate UEs and BSs to keep track of the individual beams in the network
- Significant overhead in uplink-downlink communication, especially in dense networks with moving UEs and traditional handover mechanisms
- Efficient probing schemes have to be devised



Mobility Management

- **Idea**: UEs communicate with a main beam and keep locking into backup beams
  - Backup beams can be reflections of different beams of the serving BS or other BSs
  - The communication is transparent for the UE; no formal handover procedure
- **Challenge**: Coordinate the beams of multiple BSs and multiple UEs



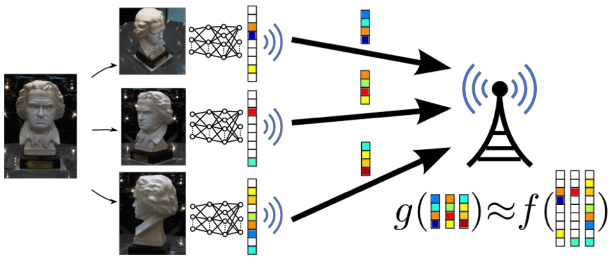
Fraunhofer HHI

Potential Benefits of Machine Learning and GPU-based Processing

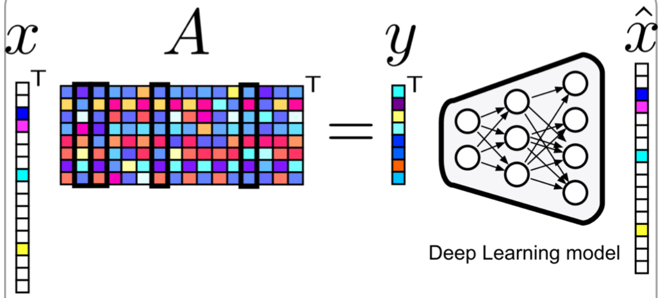
- To enable us to cope with a massively increased complexity
  → diminish mismatch between model and reality
- to reduce the number of measurements and facilitate robust decisions
  → enabling massive connectivity, MIMO, and mmWave
- To provide ultra-high speed processing (through massive parallelization)
  → meeting strict latency constraint in highly dynamic environments
- to facilitate self-organizing mmWave networks
  → cognitive network management
- to provide robust predictions
  → QoS prediction, anticipatory networking

Fraunhofer
HHI

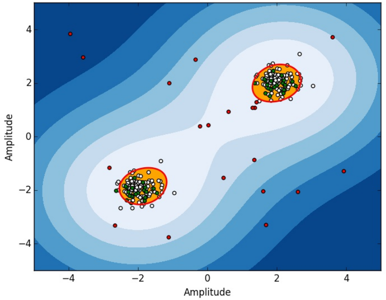
Machine Learning for 5G and Beyond: Examples



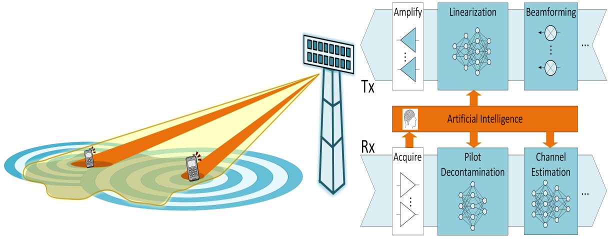
Cooperative Deep Learning



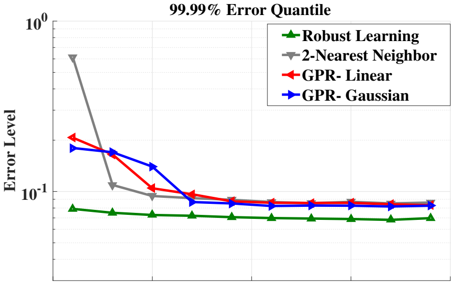
Neural Architecture for Bayesian CS



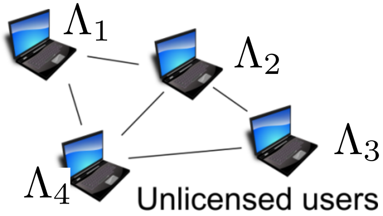
Learning with Kernels



GPU-Accelerated & ML-based RAN Functions



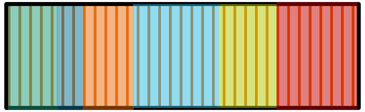
Hybrid-driven Methods for Small Data Sets



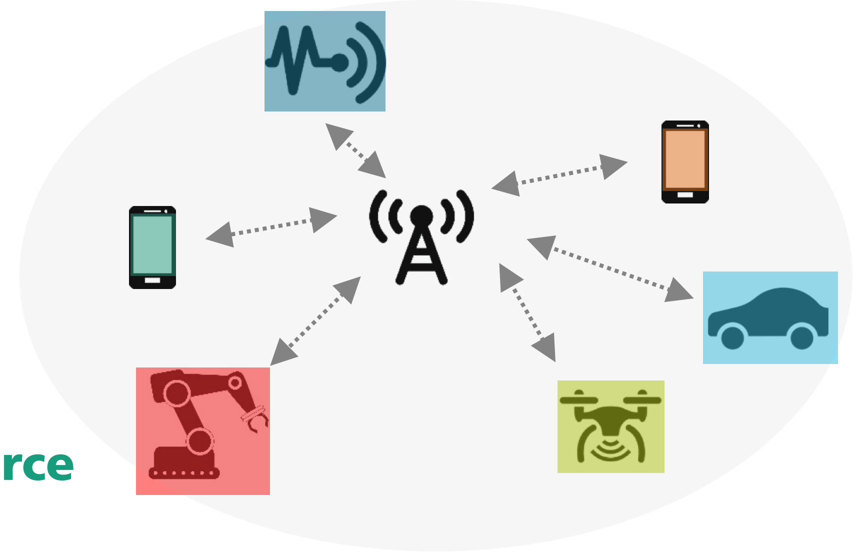
Distributed Learning

Wireless Communication Networks – The Future

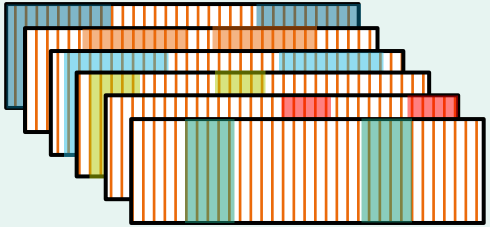
LTE / 5G



„Exclusive“ resource allocation



5G NOMA



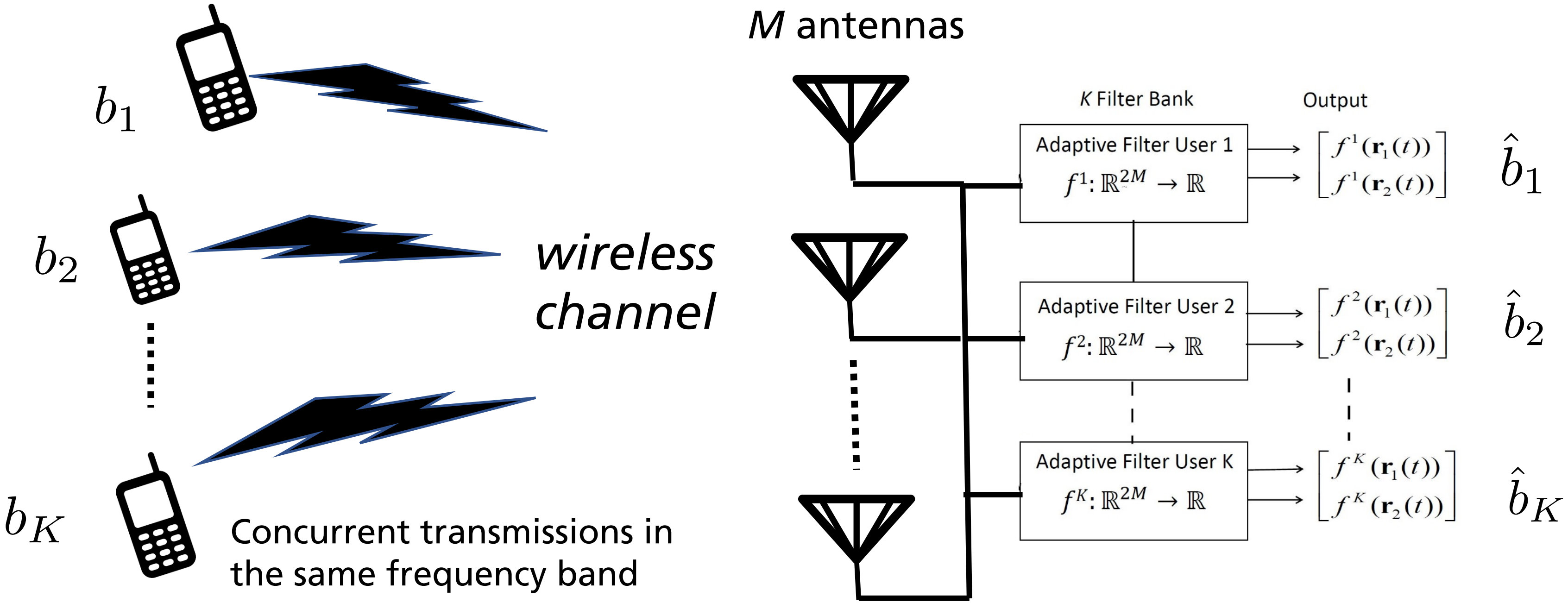
More devices than resources!

- Non-exclusive resource sharing between devices
- Complex receivers to cope with interference

Fraunhofer HHI

5G NOMA Example: Multiple User Uplink

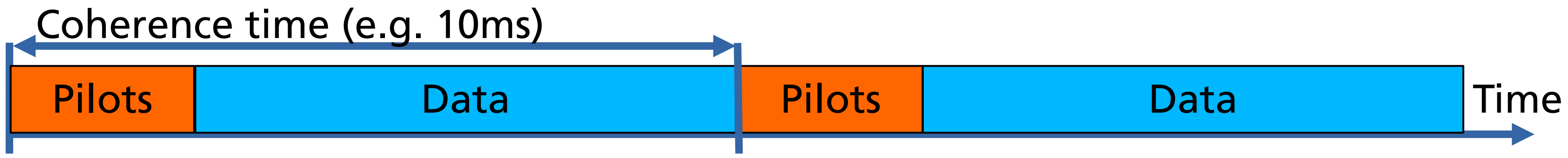
- **Objective**: For each user learn a filter f to minimize the probability of error



Machine Learning for 5G NOMA

- Many unknowns: fast-time varying channels, varying number of users, inter- and intra-cell interference, changing modulation and power, etc.
- Consequences

1. Training samples are highly limited (hundreds). Deep neural networks often require hundreds of thousands or more samples
2. Training and detection have to be performed within the coherence time, or ML tools have to learn (or be given) time-invariant features

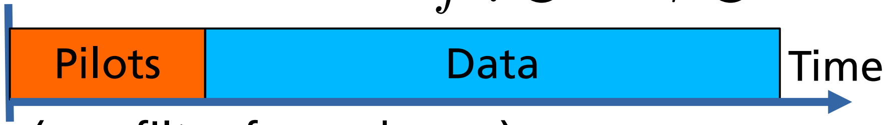


Machine Learning for 5G NOMA

Conventional approach:

1. Send pilots
2. Estimate channels and other system parameters
3. Construct, for example, a linear filter (receiver)
4. Detect the symbols with the filter in step (3)

$$f : \mathbb{C}^M \to \mathbb{C}$$



(one filter for each user)

Our machine-learning (ML) approach:

1. Send pilots
2. ~~Estimate channels and other system parameters~~
3. Use pilots for ML tool training
4. Detect the symbols with the ML tool

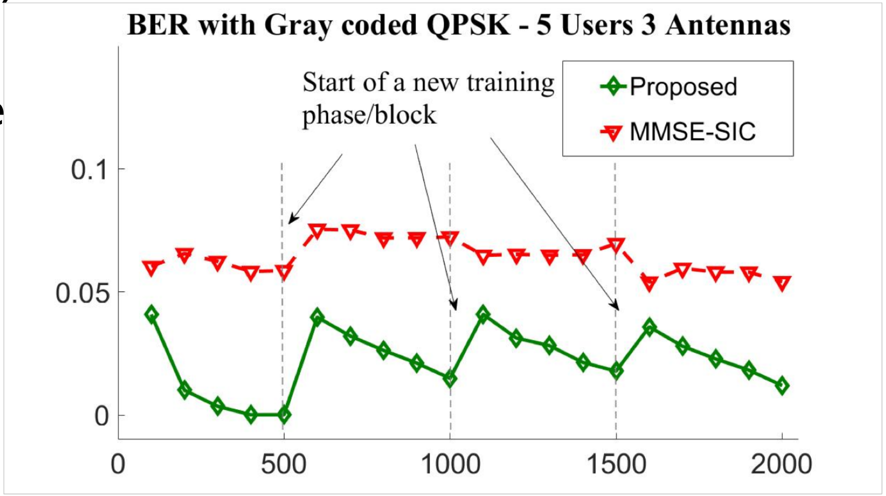
$$f_{\mathrm{ML}} : \mathbb{C}^M \to \mathbb{C}$$

(one nonlinear filter for each user)

Fraunhofer HHI

Machine Learning for 5G NOMA

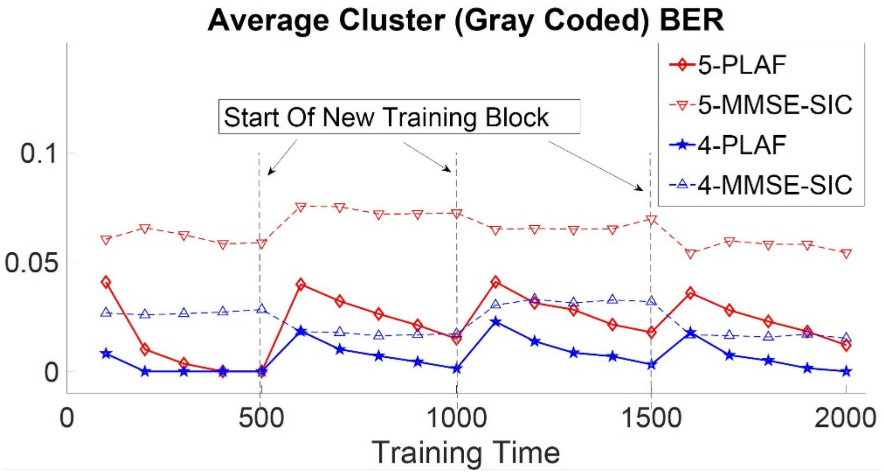
- **Goal**: Use pilots to learn the receiver (filter) structure directly
- **Approach**: Online adaptive learning in the sum space of linear and Gaussian RKHS
  - Initial fast convergence and low complexity
  - Easy to exploit side information and convergence guarantees



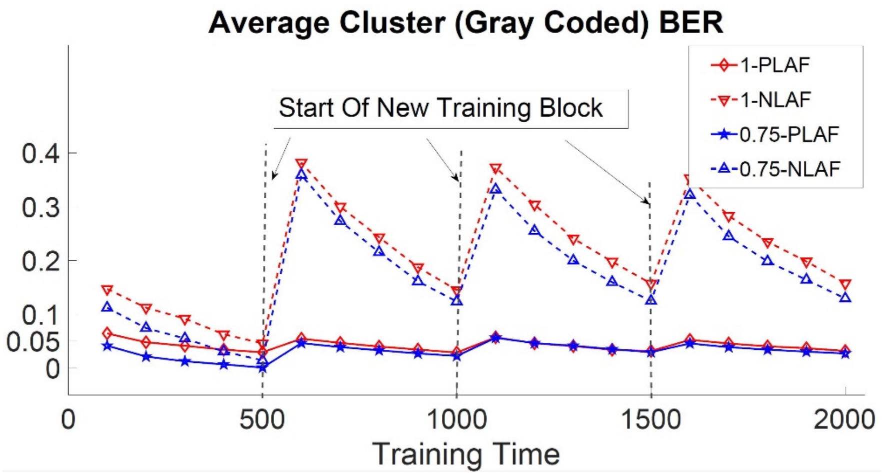
D. A. Awan, R. L. G. Cavalcante, M. Yukawa, and S. Stańczak, "Detection for 5G-NOMA: An Online Adaptive Machine Learning Approach," in Proc. IEEE International Conference on Communications (ICC), May 2018

Fraunhofer HHI

Simulation Results



Partially linear filtering (PLAF) vs. MMSE-SIC

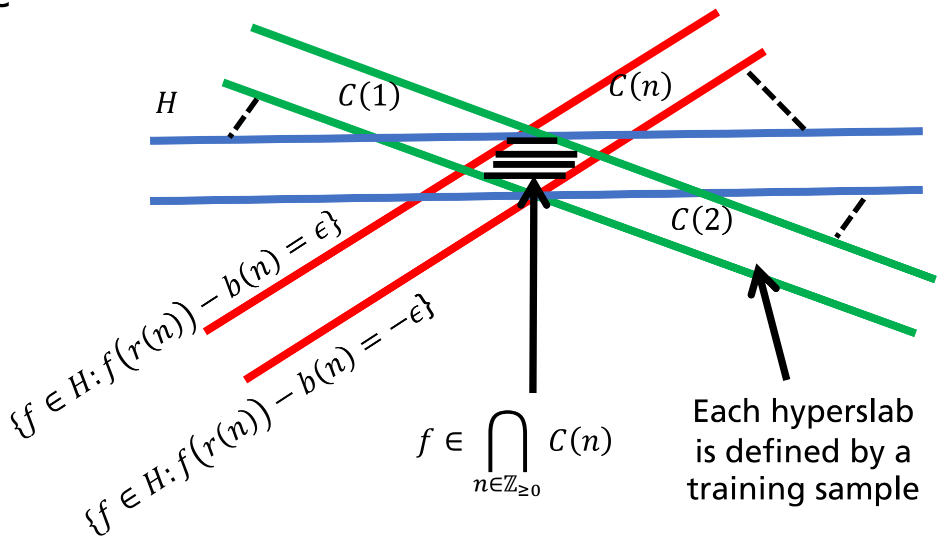


PLAF vs. Nonlinear filtering (NLAF)

Fraunhofer HHI

Online Adaptive Learning in Reproducing Kernel Hilbert Spaces

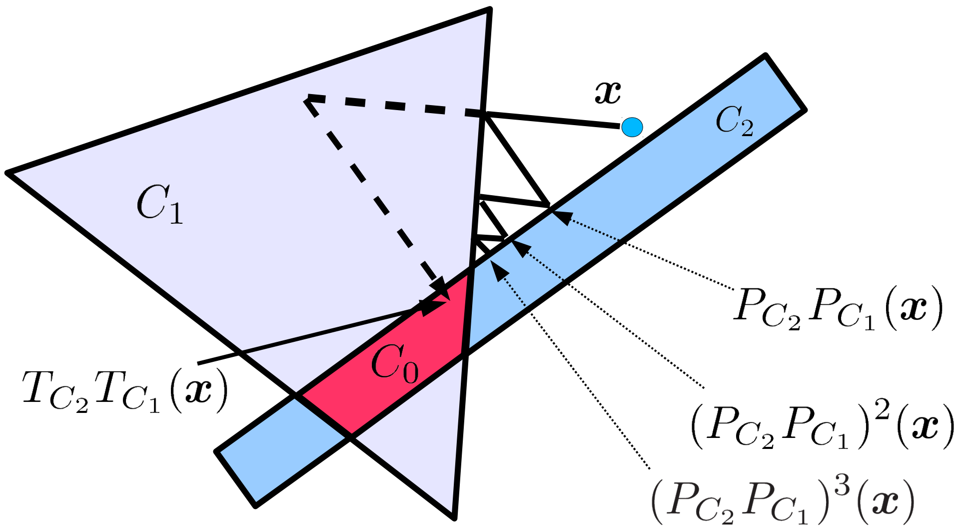
- Train the receiver f such that it is in the intersection of all the sets:
  - $C(n) := \{f \in H: |f(r(n)) - b(n)| \leq \epsilon\}$
  - n is time index
  - $\epsilon > 0$ accounts for noise
- **Challenge**: Find a point in the intersection within latency constraints
  ➔ Convex feasibility problem (CFP)
  ➔ Massive parallelization across symbols and users



Fraunhofer HHI

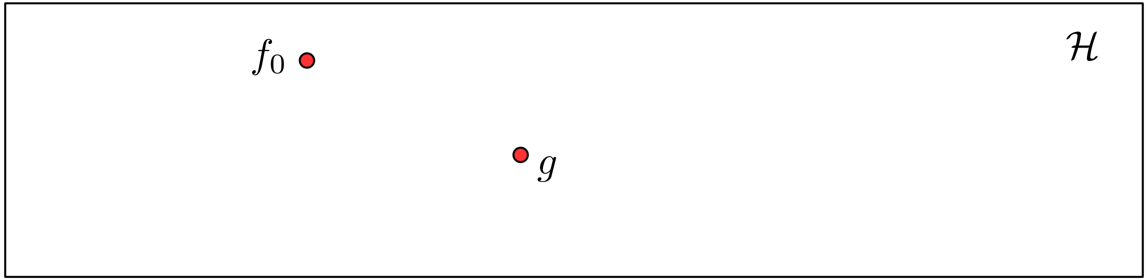
Basic Methodology

- Many ML algorithms are designed for convex feasibility problems
- Projection methods are a natural candidate for solving such problems



Projection-Based Methods for CFP: Main Idea

1. Assume that the sought function $g : \mathbb{C}^N \to \mathbb{C}$ belongs to an appropriate Hilbert space $\mathcal{H}$ (e.g., a reproducing kernel Hilbert space), and let $f_0 : \mathbb{C}^N \to \mathbb{C}$ be its initial estimate

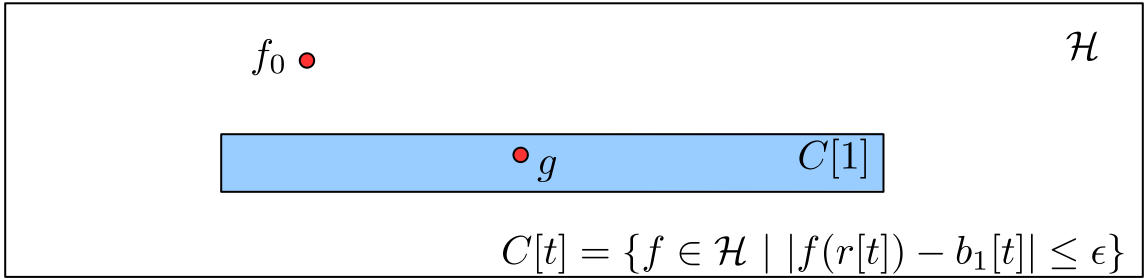


Fraunhofer HHI

Projection-Based Methods for CFP: Main Idea

1. Assume that the sought function $g : \mathbb{C}^N \to \mathbb{C}$ belongs to an appropriate Hilbert space $\mathcal{H}$ (e.g., a reproducing kernel Hilbert space), and let $f_0 : \mathbb{C}^N \to \mathbb{C}$ be its initial estimate

2. For each pilot $b_1[t]$, construct a closed convex set $C_1[t]$ that is likely to contain the function *g*



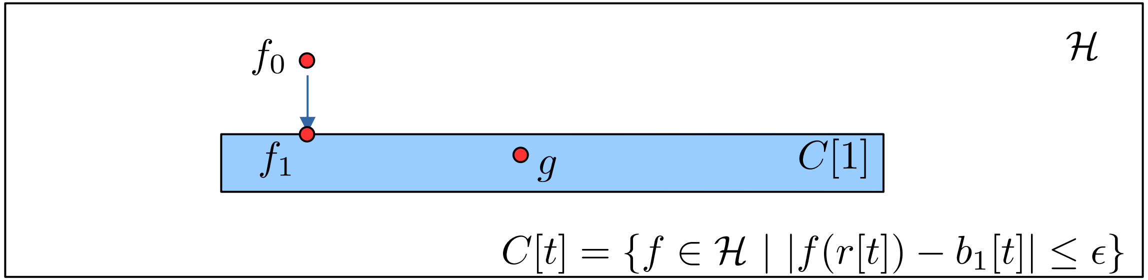
Fraunhofer HHI

Projection-Based Methods for CFP: Main Idea

1. Assume that the sought function $g : \mathbb{C}^N \to \mathbb{C}$ belongs to an appropriate Hilbert space $\mathcal{H}$ (e.g., a reproducing kernel Hilbert space), and let $f_0 : \mathbb{C}^N \to \mathbb{C}$ be its initial estimate

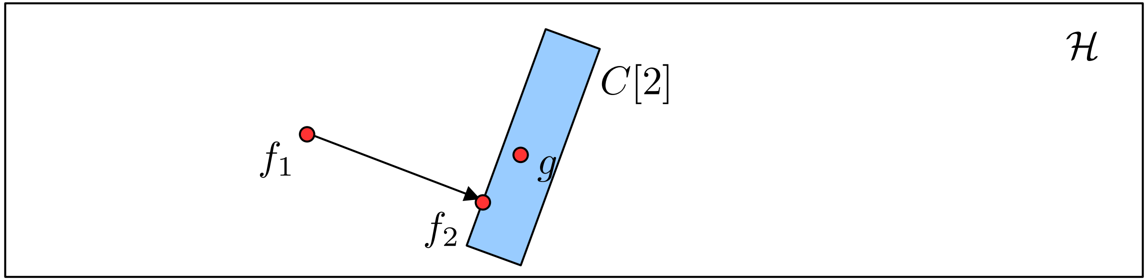
2. For each pilot $b_1[t]$, construct a closed convex set $C_1[t]$ that is likely to contain the function *g*

3. Update the current estimate by projecting on the convex set



Projection-Based Methods for CFP: Main Idea

1. Assume that the sought function $g : \mathbb{C}^N \to \mathbb{C}$ belongs to an appropriate Hilbert space $\mathcal{H}$ (e.g., a reproducing kernel Hilbert space), and let $f_0 : \mathbb{C}^N \to \mathbb{C}$ be its initial estimate
2. For each pilot $b_1[t]$, construct a closed convex set $C_1[t]$ that is likely to contain the function *g*
3. Update the current estimate by projecting on the convex set
4. Repeat the (2)-(3) for each pilot symbol

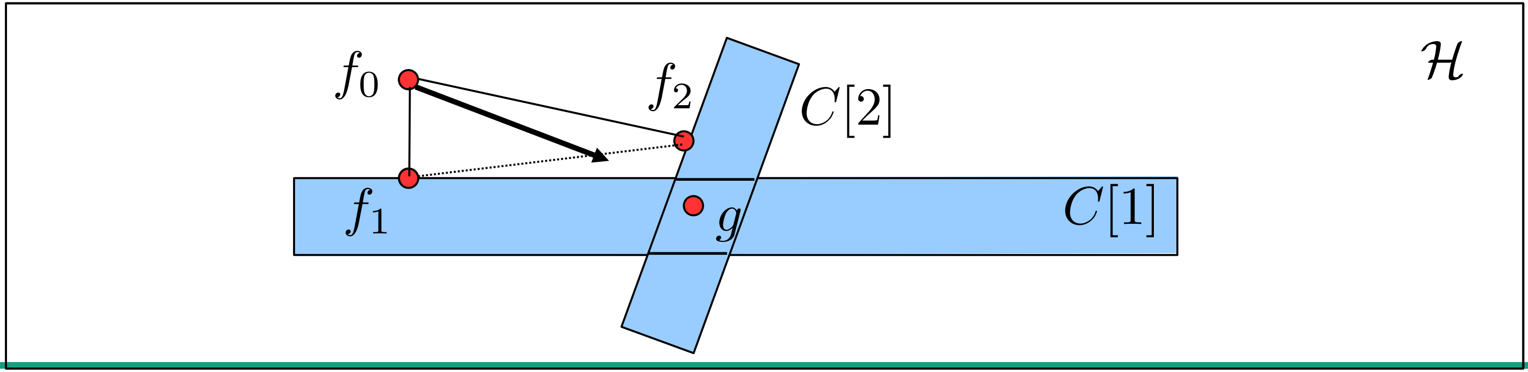


Fraunhofer HHI

Adaptive Projected Subgradient Methods (APSM)

- Sequential methods are too slow for many applications

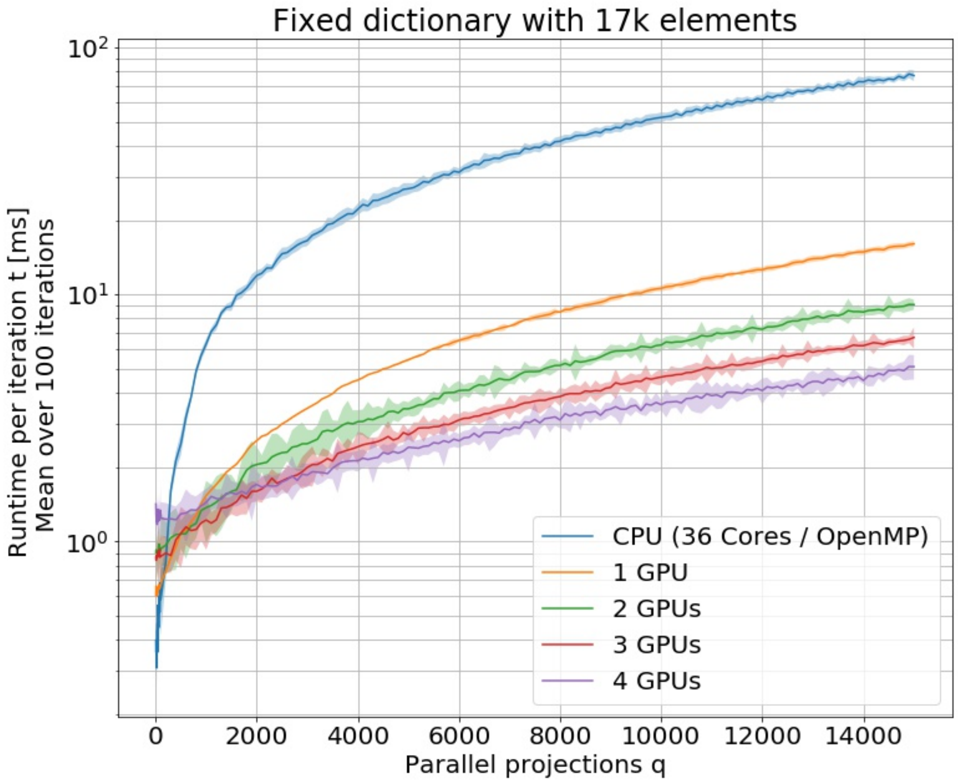
→ Massive parallelization via APSM-based approaches



Fraunhofer HHI

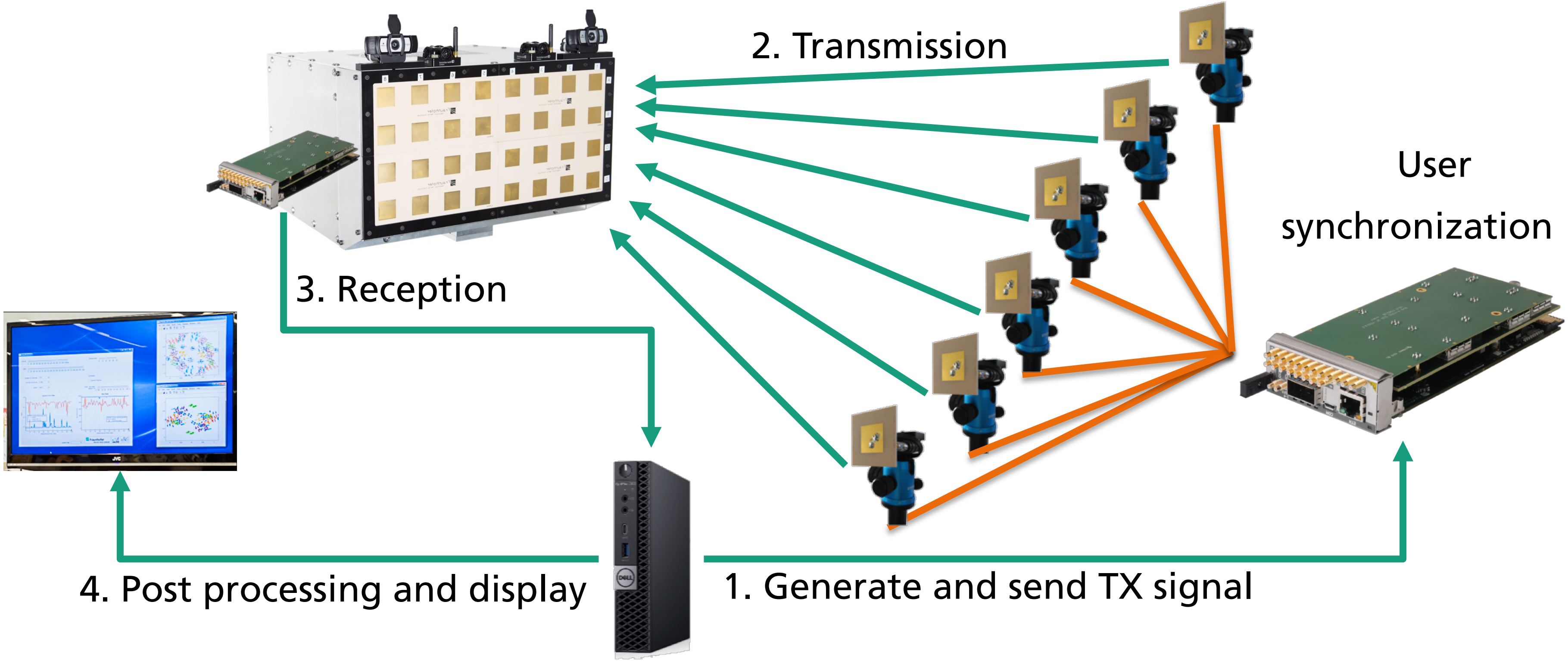
Adaptive Projected Subgradient Methods (APSM)

- CPU vs. GPU

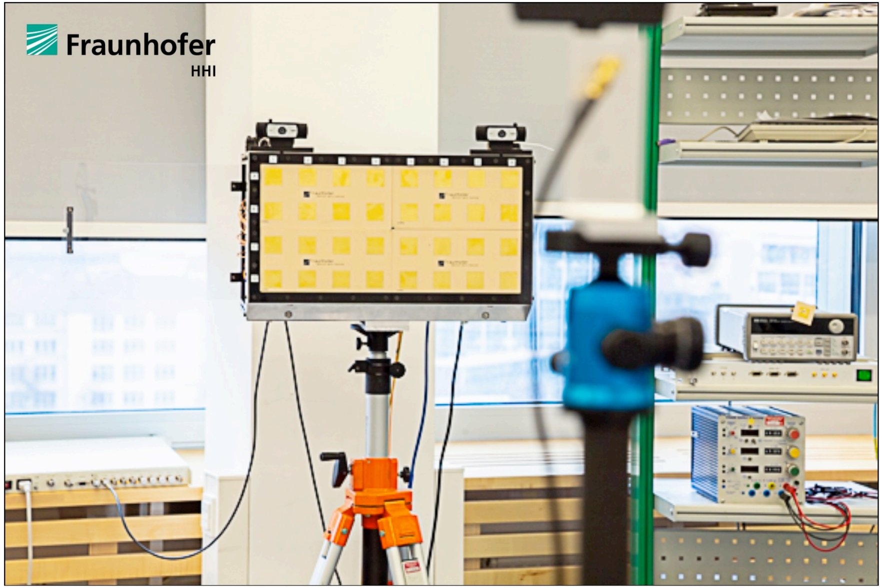


Fraunhofer HHI

Proof of Concept: Hardware in the Loop Setup



Proof of Concept: Lab Pictures



User view on base station

Base station view on 4 out of 6 users

Fraunhofer
HHI

Proof of Concept: Lab Pictures

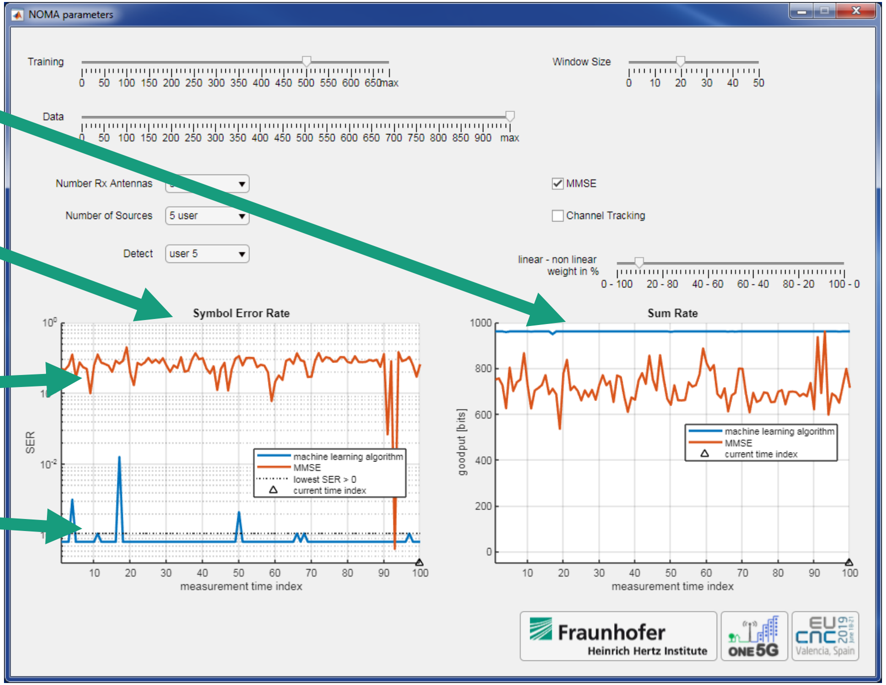
- Users, display, processing, base station
- GUI, TX and RX constellations

GUI – graphical user interface, RX – receive, TX – transmit

Fraunhofer
HHI

Proof of Concept: Evaluation

- Measured key performance indicators
  - Sum rate (goodput) as successful received bits of all users
  - Symbol error rate (SER) of a single user (worst user)
- Comparison
  - MMSE
  - ML-approach



Fraunhofer
HHI

Proof of Concept: Findings

- Carrier frequency offset (CFO) between local oscillators at users and BS
- CFO drifts (prominent for longer data-sequences)

Initial claim: ML can learn and “counteract” hardware impairments

- No explicit channel estimation
- Good channel tracking capabilities
  - Straight forward implementation
  - Very efficient in terms of symbol error rate (SER) for longer data-sequences

Softwareization of Mobile Radio Networks

- Challenges of 5G are opportunities for machine learning (ML)
- Addressed by massively parallel algorithms on GPUs
- Example: APSM for NOMA