

Learning to Communicate: Deep Learning based solutions for the Physical Layer of Communications [LeanCom]

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LeanCom Overview



Duration: Oct 2019 – Sep 2022, Value: £860k

Why Deep Learning for comms:

- Address mathematically non-tractable problems
- Learning-based approaches to reduce complexity of known signal processing solutions

Comms particular challenges:

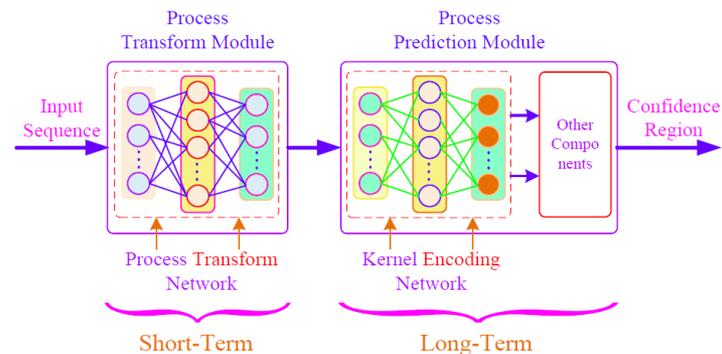
- Need new comms-oriented NN loss-functions / architectures
- Limited online training
- NN complexity – need lightweight and hardware-friendly NNs

Opportunities in the Comms domain:

- Good model-based solutions exist – good starting points
- Develop hybrid model-based + data-driven approaches



Neural-Network (NN) Based Transceivers



EPSRC

Engineering and Physical Sciences
Research Council

LeanCom Overview



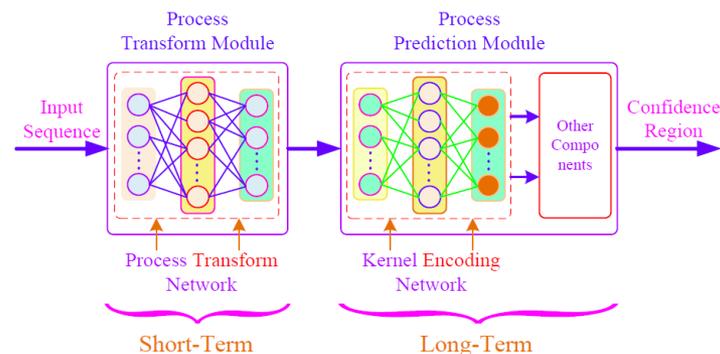
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LeanCom Objectives

1. Establish a **DL framework specifically tailored for wireless communications**,
2. **PHY layer transceiver designs based on NN training and optimisation - mathematically complex communication scenarios**,
3. Address low-cost, low-specification devices by **hardware-efficient DL-based transceivers**,
4. **Demonstrate DL-inspired communications** by proof of concept experiments.



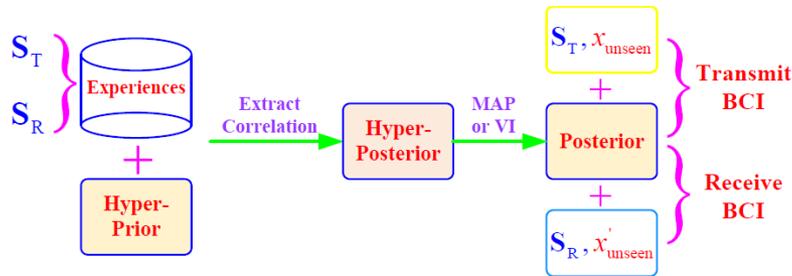
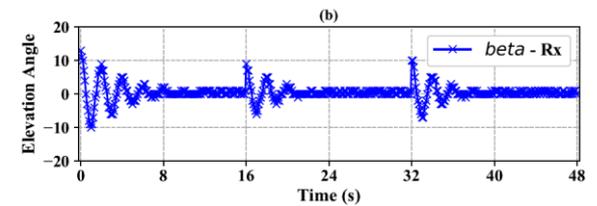
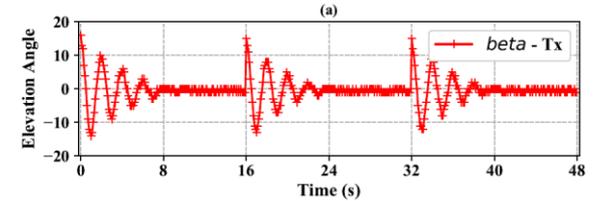
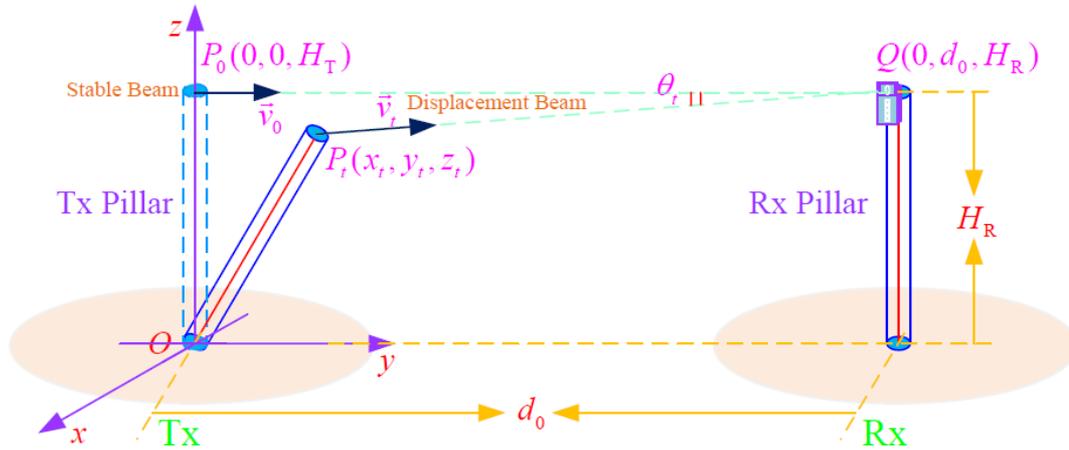
Neural-Network (NN) Based Transceivers



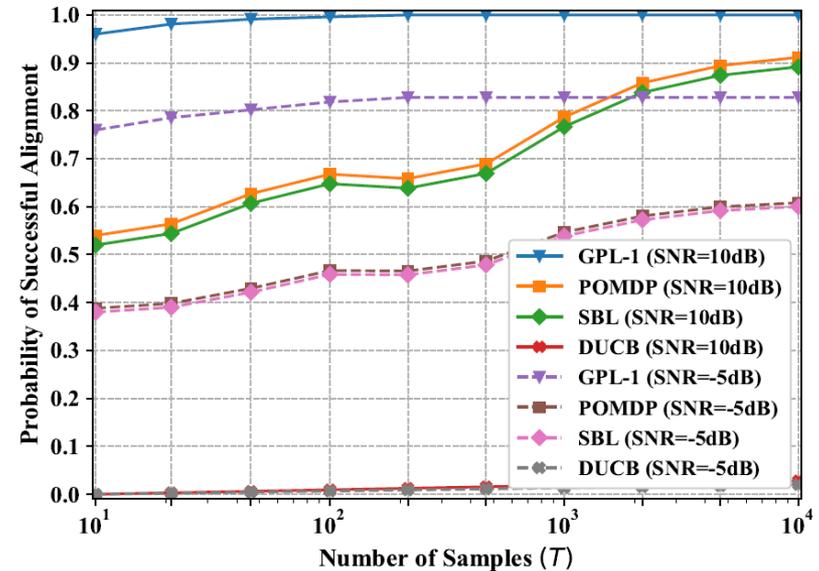
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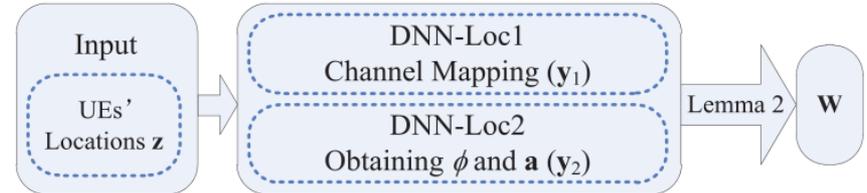
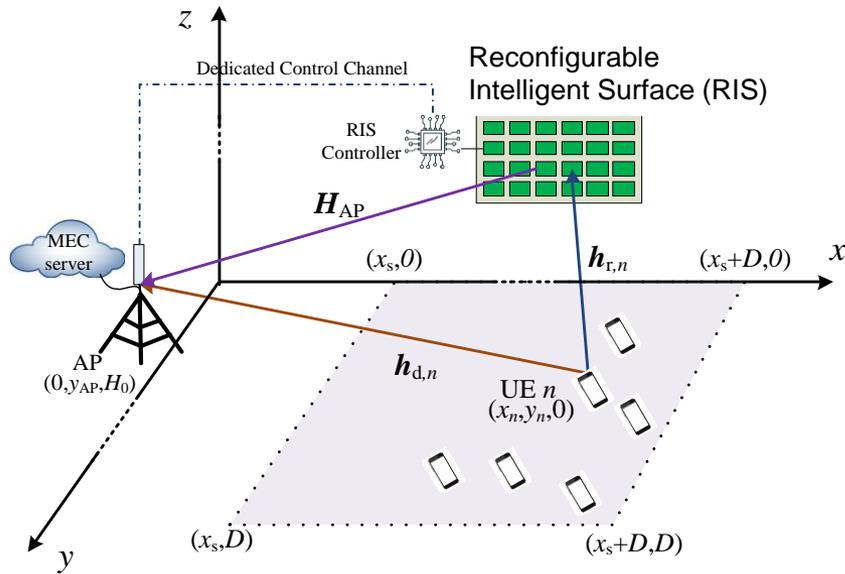
Beam prediction for Fixed Wireless Access Links



- Beam angle prediction based on geometric models
- Beam alignment with relatively **small #training samples**

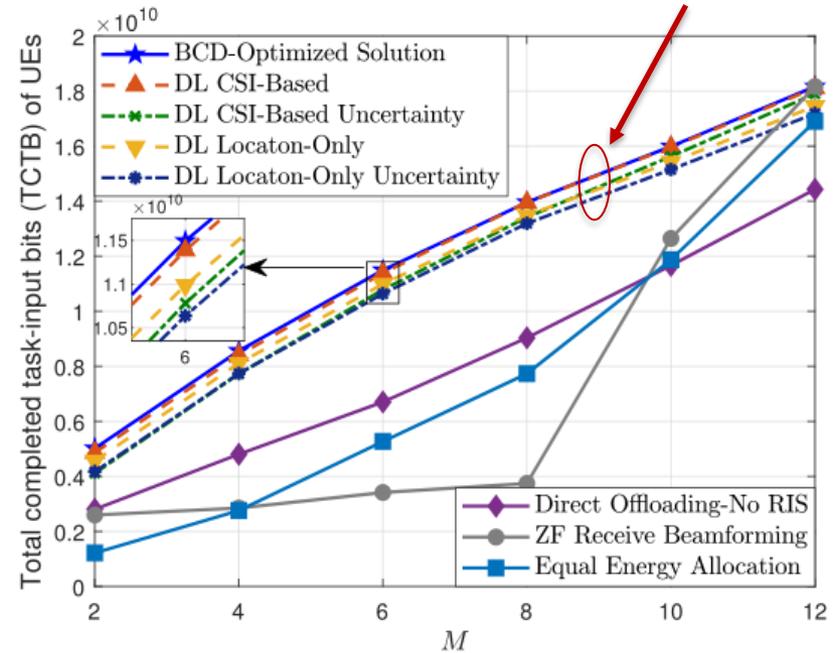


RIS aided MEC: Channel-Information based → location based

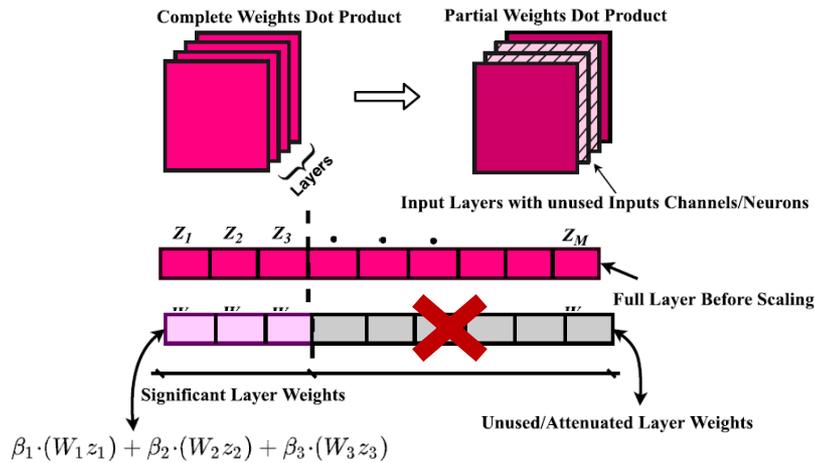


- Learning of: UE precoding + RIS precoding + AP combining
- Close to optimization-based solution **with only UE location information**, dispensing of channel estimation

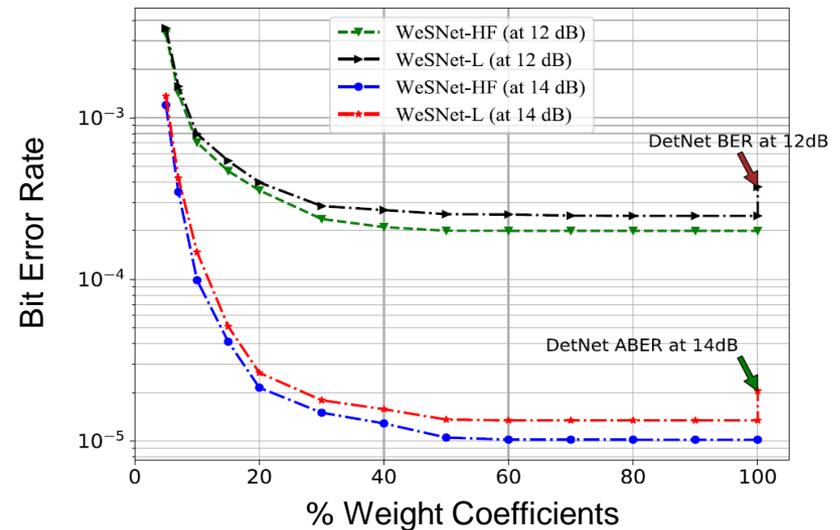
Optimization based, CSI learning-based, location based



Complexity-scalable NNs for Multi-antenna detection



	Weight Tensor/Matrix				Mixed-Precision Weight Matrix				
C_1	0.85	-1.50	0.25	1.25	1	-1	1	1	Quantized rows
C_2	0.5	-0.8	-1.5	0.75	1	-1	-1	1	
C_3	-1.0	0.95	0.5	-0.8	-1.0	0.95	0.5	-0.8	Full-Precision rows
C_4	1.1	0.65	-1.2	1.25	1.1	0.65	-1.2	1.25	



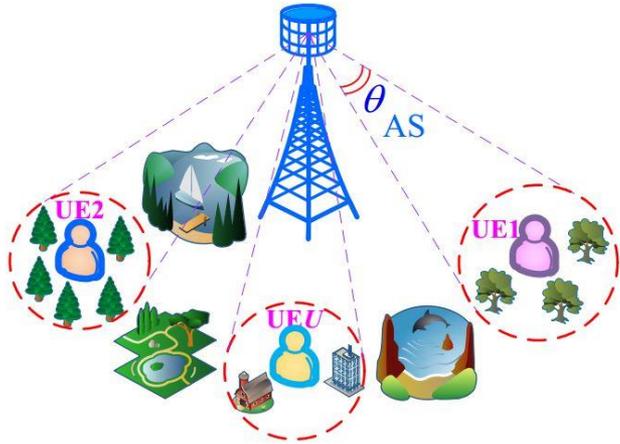
- Scaling of 'non-significant' weights to **reduce dimension/complexity of NNs**
- **Finite-resolution (few-bit) NNs**
- Close to optimal performance with less than 50% of weights

Memory consumption
 Complexity Hardware Friendly

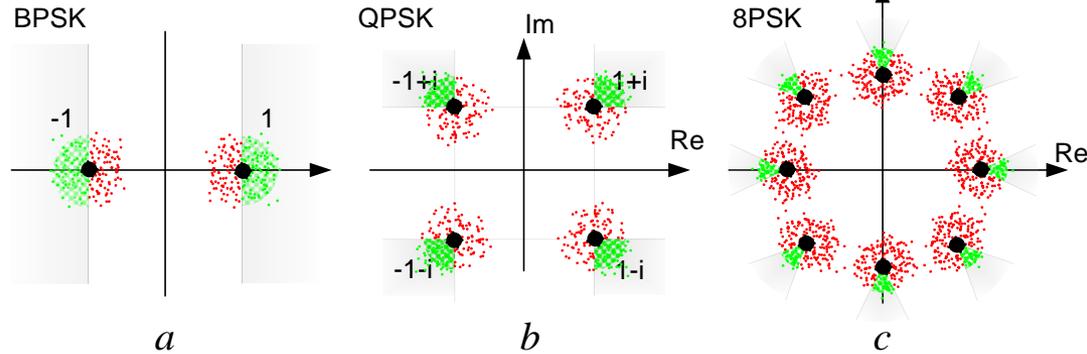
A. Mohammad, C. Masouros, I. Andreopoulos, "Complexity-Scalable Neural Network Based MIMO Detection With Learnable Weight Scaling", IEEE Trans. Comms., vol. 68, no. 10, pp. 6101-6113, Oct. 2020

A. Mohammad, C. Masouros, I. Andreopoulos, "A Memory-Efficient Learning Framework for Symbol Level Precoding with Quantized NN Weights", IEEE Trans. Comms., *under review*

Joint Precoding and Channel Sparsification

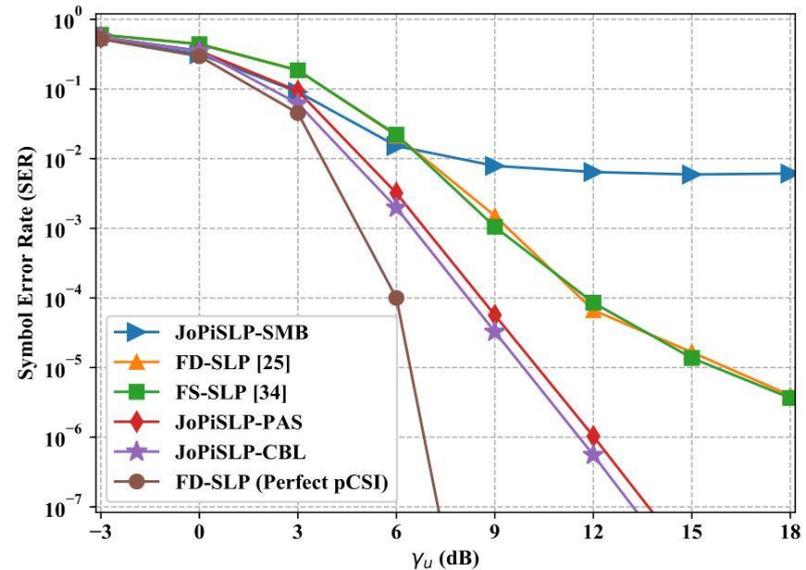


Constructive interference



$$\begin{aligned} \min_{\mathbf{d}} \quad & \|\mathbf{F}\mathbf{d}\|_2^2 + \rho\|\mathbf{d}\|_1 \\ \text{s.t.} \quad & |\text{Im}(\bar{\mathbf{h}}_u^H \mathbf{F}\mathbf{d}e^{-j\xi_u})| \leq \left(\text{Re}(\bar{\mathbf{h}}_u^H \mathbf{F}\mathbf{d}e^{-j\xi_u}) - \gamma_u \right) \cdot \tan(\pi/K_u), (\forall u \in \mathcal{U}). \end{aligned}$$

- **Two things at once:** a) channel sparsification, b) Precoding for interference exploitation
- Reduced CSI approach, close to full CSI based precoding



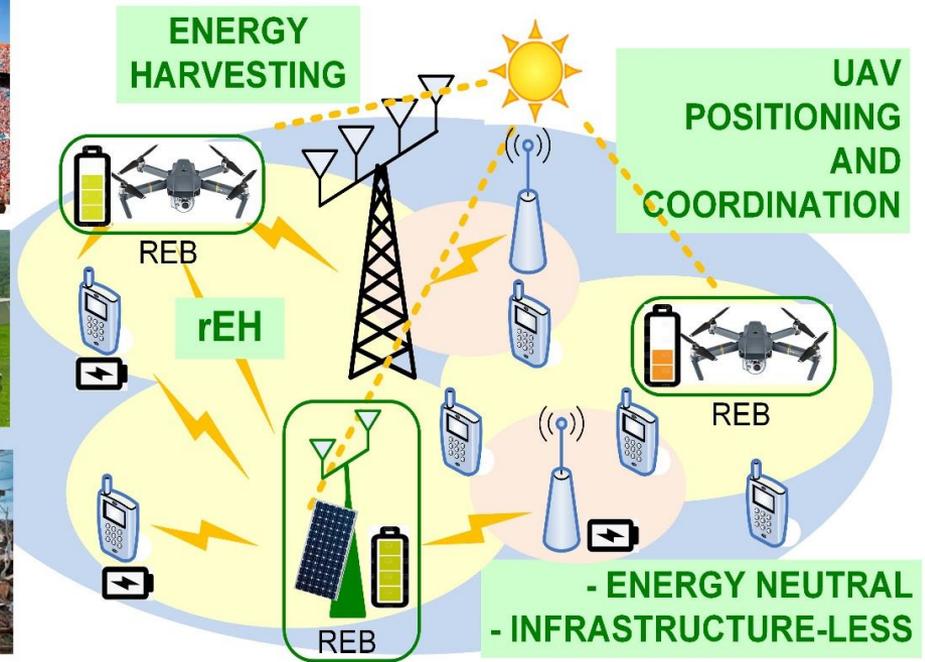
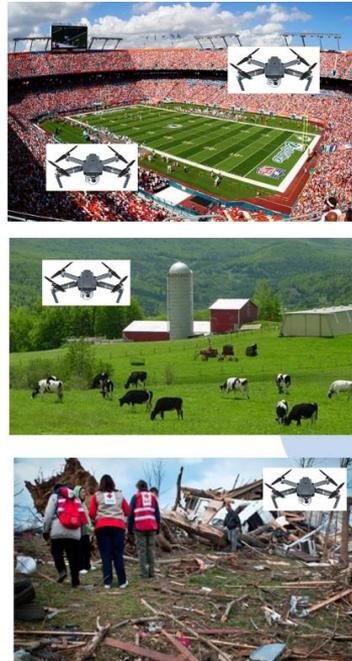
Net-Zero Energy Communications

Energy-autonomous Portable Access-Points



- ↓ CO² emissions and OPEX
- ✗ Power grid infrastructure

- Renewable Sources + Energy Harvesting
- Portable Base Stations
- UAVs



HORIZON 2020

Innovative Training Network
Oct 2018 – Sep 2022 (€4.2m)

<http://painless-itn.com/>



Painless ITN



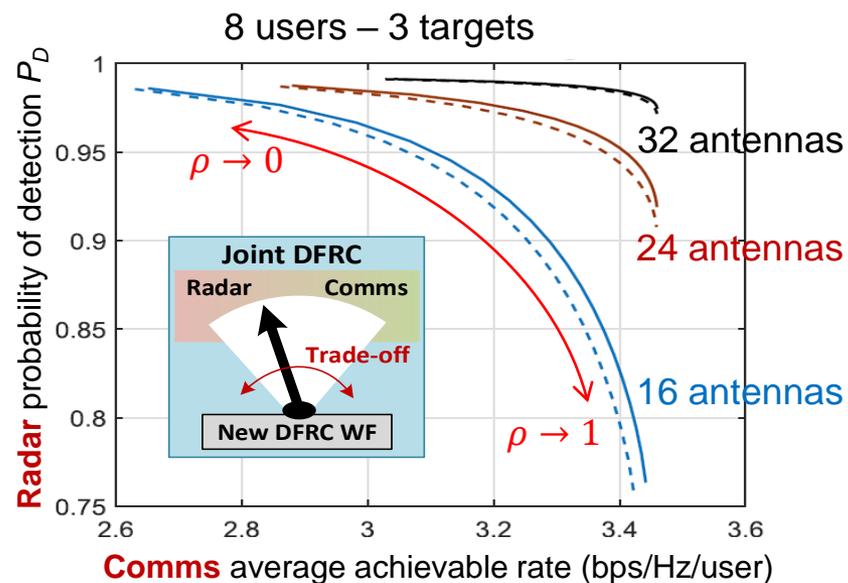
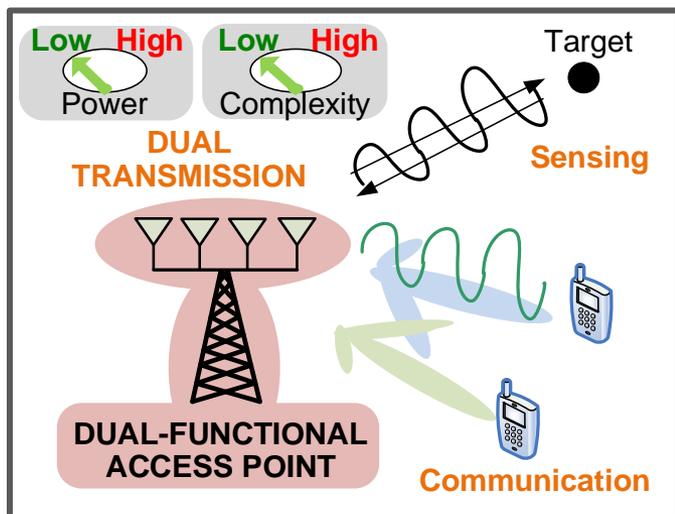
@PainlessITN

Efficient use of spectrum

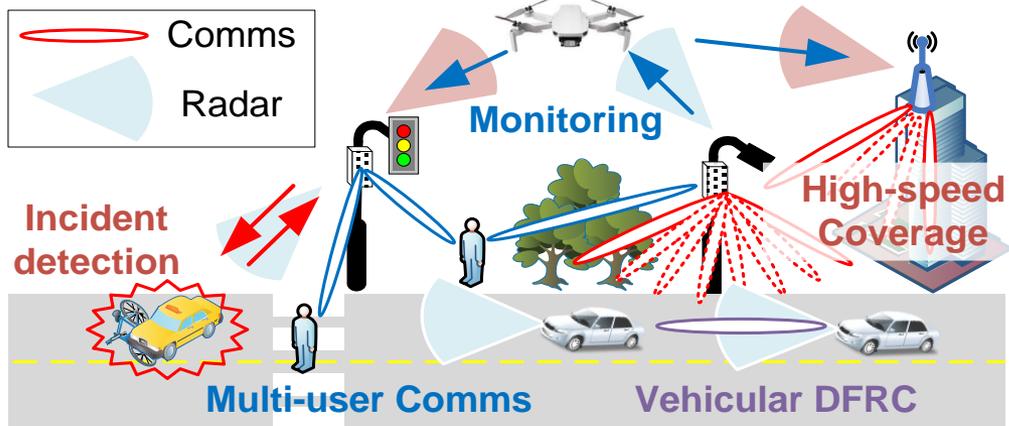
Integrated Sensing and Communications (ISAC)



Spectrum Sharing → Dual Transmission



Smart-cities sensing through 5G dense cellular infrastructure



Part of UDRC Project
Mar 2019 – Dec 2021 (£1m)



Marie Curie Fellowship
Nov 2018 – Oct 2020 (£160k)

ML-Comms

- J. Zhang, C. Masouros, “**Learning-Based Predictive Transmitter-Receiver Beam Alignment in Millimeter Wave Fixed Wireless Access Links**”, IEEE Trans Sig. Proc., *early access on IEEExplore*
- X. Hu, C. Masouros, K. K. Wong, “**Reconfigurable Intelligent Surface Aided Mobile Edge Computing: From Optimization-Based to Location-Only Learning-Based Solutions**”, IEEE Trans Comms, *early access on IEEExplore*
- A. Mohammad, C. Masouros, I. Andreopoulos, “**Complexity-Scalable Neural Network Based MIMO Detection With Learnable Weight Scaling**”, IEEE Trans. Comms., vol. 68, no. 10, pp. 6101-6113, Oct. 2020
- J. Zhang, C. Masouros, “**A Unified Framework for Precoding and Pilot Design for FDD Symbol-Level Precoding**”, IEEE Trans Comms., *under review*

Net-Zero Energy Comms

- I. Valiulahi, A. Salem, C. Masouros, “**Power Allocation Policies for Battery Constrained Energy Harvesting Communication Systems with Co-Channel Interference**”, IEEE Trans Comms., *under review*
- X. Jing, J. Sun, C. Masouros, “**Energy Aware Trajectory Optimization for Aerial Base Stations**”, IEEE Trans. Comms, vol. 69, no. 5, pp. 3352-3366, May 2021

ISAC

- F. Liu, C. Masouros, H. Griffiths, A. Petropulu, L. Hanzo “**Joint Radar and Communication Design: Applications, State-of-the-art, and the Road Ahead**”, IEEE Trans Comms, *EiC invited paper* vol. 68, no. 6, June 2020
- F. Liu, L. Zhou, C. Masouros, A. Li, W. Luo, A. Petropulu “**Toward Dual-functional Radar-Communication Systems: Optimal Waveform Design**”, IEEE Trans. Sig. Proc., vol. 66, no. 16, pp. 4264-4279, Aug.15, 15 2018

Thank you

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