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

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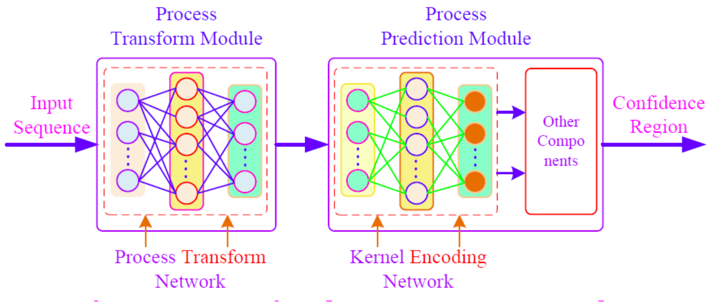
Opportunities for DL in PHY Comms

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



LeanCom Overview



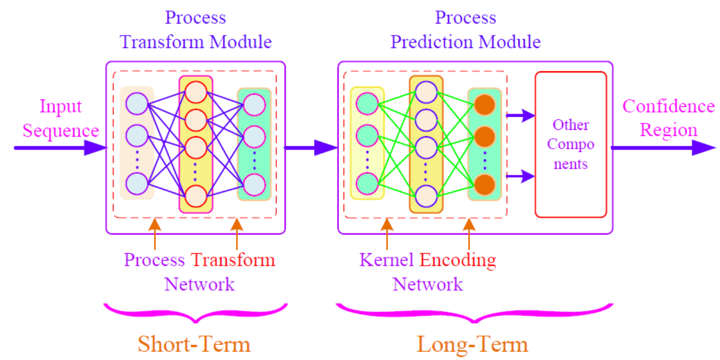

LeanCom Objectives

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.

EPSRC
Engineering and Physical Sciences Research Council

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

Neural-Network (NN) Based Transceivers



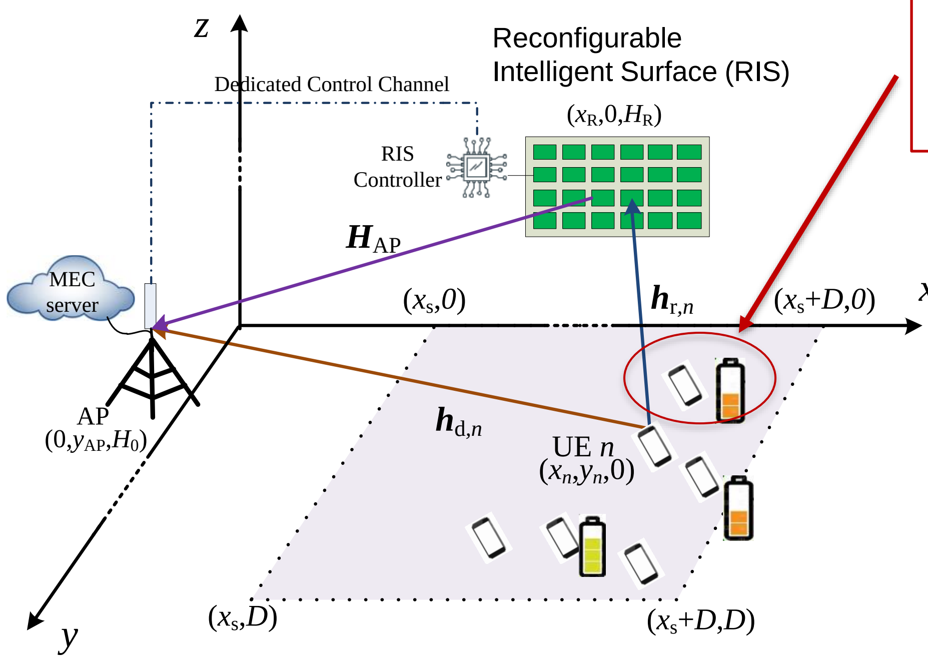
Outline

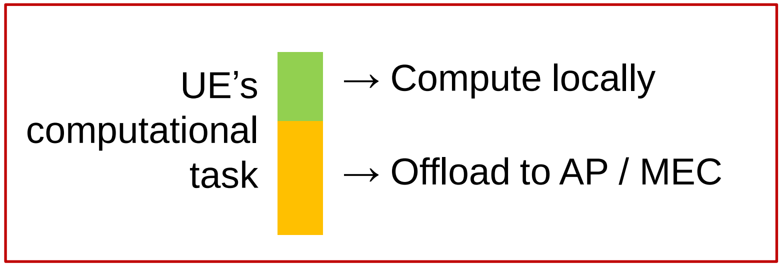
- Technical Highlights - Application examples
  - Deep Learning for CSI relaxation
  - DL-Comms with Hardware-Friendly Neural Networks
  - DL for Radar-Assisted Vehicular Networks
  - DL for Fixed Wireless Access
  - Joint Precoding and CSI sparsification
- Further Opportunities for DL in Communications
  - Net-Zero Energy Communications
  - Integrated Sensing and Communications

Technical Highlights

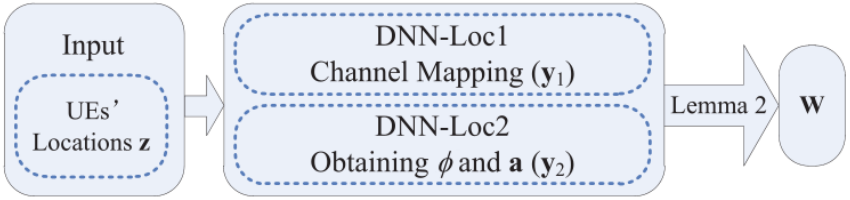
From CSI based to Location based Data-Driven Transmission

RIS aided MEC: Channel-Information based → location based



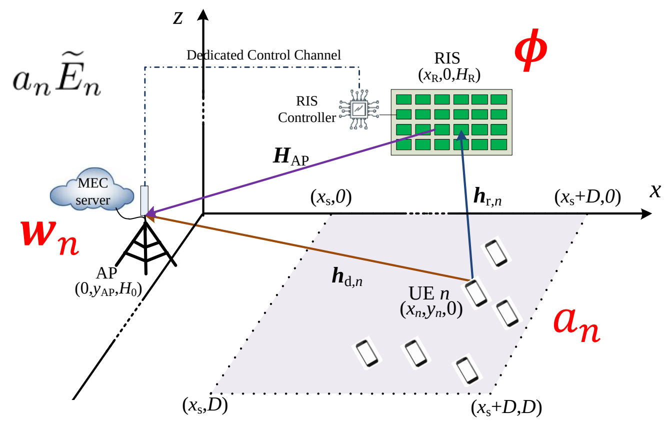


- Learning of: UE Energy Allocation + RIS precoding + AP combining
- Close to optimization-based solution **with only UE location information**, dispensing of channel estimation



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, *vol. 69, no. 6, pp. 3709-3725, June 2021*

- Total energy available at the *n* -th UE: E_n
- Energy for computation offloading: $a_n E_n$ J $\Rightarrow$ $p_n = \dfrac{a_n E_n}{T} \triangleq a_n \widetilde{E}_n$
- RIS coefficient matrix: $\boldsymbol{\Phi} = \mathrm{diag}\{\boldsymbol{\phi}\}$
  - $\boldsymbol{\phi} = [\phi_1, \ldots, \phi_K]^{\mathrm{T}}$ with phase shifts $\phi_k = e^{j\theta_k}$



- Estimated signal: $\widehat{s}_n = \mathbf{w}_n^{\mathrm{H}} \mathbf{y} = \mathbf{w}_n^{\mathrm{H}} \sum_{n=1}^{N} (\mathbf{H}_{\mathrm{AP}} \boldsymbol{\Phi} \mathbf{h}_{\mathrm{r},n} + \mathbf{h}_{\mathrm{d},n}) \sqrt{p_n} s_n + \mathbf{w}_n^{\mathrm{H}} \mathbf{n}, \ \forall n \in \mathcal{N}$
- Completed task bits (CTB) with offloading:

$$\boxed{R_n^{\mathrm{off}}(\mathbf{a}, \mathbf{w}_n, \boldsymbol{\phi})} = BT \log_2(1 + \gamma_n(\mathbf{a}, \mathbf{w}_n, \boldsymbol{\phi})), \ \forall n \in \mathcal{N} \text{ with } \gamma_n(\mathbf{a}, \mathbf{w}_n, \boldsymbol{\phi}) = \frac{a_n \widetilde{E}_n |\mathbf{w}_n^{\mathrm{H}} (\mathbf{H}_{\mathrm{AP}} \boldsymbol{\Phi} \mathbf{h}_{\mathrm{r},n} + \mathbf{h}_{\mathrm{d},n})|^2}{\sum_{i=1, i \neq n}^{N} a_i \widetilde{E}_i |\mathbf{w}_n^{\mathrm{H}} (\mathbf{H}_{\mathrm{AP}} \boldsymbol{\Phi} \mathbf{h}_{\mathrm{r},i} + \mathbf{h}_{\mathrm{d},i})|^2 + \sigma^2 \|\mathbf{w}_n^{\mathrm{H}}\|^2}$$

- Energy for local computing: $(1 - a_n) E_n$ J $\Rightarrow$ $(1 - a_n) E_n = T \kappa_n f_n^3$
- CTB with local computing: $\boxed{R_n^{\mathrm{loc}}(a_n)} = \dfrac{f_n T}{C_n} = \dfrac{T}{C_n} \sqrt[3]{\dfrac{(1 - a_n) \widetilde{E}_n}{\kappa_n}}, \ \forall n \in \mathcal{N}$

κ_n: Effective capacitance coefficient

C_n: Required CPU cycles/bit

Optimization Based Approach

Total CTB maximization problem

$$\text{(P0)} \; \max_{\mathbf{a},\mathbf{W},\boldsymbol{\phi}} \sum_{n=1}^{N} \left(R_n^{\text{off}}(\mathbf{a},\mathbf{w}_n,\boldsymbol{\phi}) + R_n^{\text{loc}}(a_n)\right)$$
$$\text{s.t.} \quad a_n \in [0,1], \; \forall n \in \mathcal{N},$$
$$|\phi_n| = 1, \; \forall n \in \mathcal{N},$$

- Non-convex optimization problem
- Block coordinate descending (BCD)
  - RIS reflecting coefficients design $\boldsymbol{\Phi}$
  - Receive beamforming design $\mathbf{W}$
  - Energy partition optimization $\mathbf{a}$

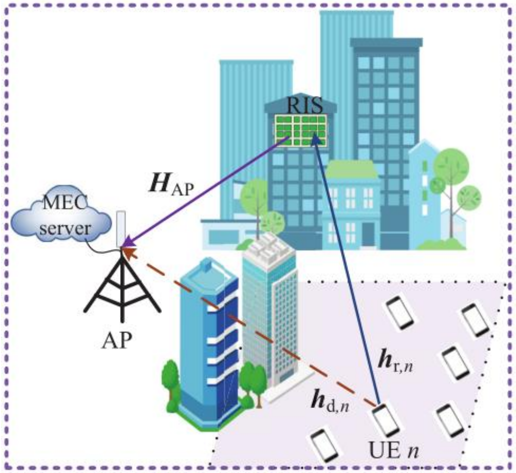
- Sloved by breaking into sub-problems for the optimization of $\boldsymbol{a}, \boldsymbol{W}, \boldsymbol{\phi}$
- $\boldsymbol{W}$ can be obtained in closed form for given $\boldsymbol{a}, \boldsymbol{\phi}$
- Solved with Alternating Optimization and Block Coordinate Descend (BCD)

- BCD optimization algorithm → Effective solution with guaranteed convergence.
- High computational complexity: $O(L(L_1K^6 + L_3N^{3.5}))$ N users, K RIS elements
- Online implementations → Reduce the computational complexity ?

→ Learning with DNNs!

- Offline Training: Emulating the BCD algorithm!
- Online Inference: With significantly reduced complexity!

Using full CSI



without LoS direct links between UEs and AP.

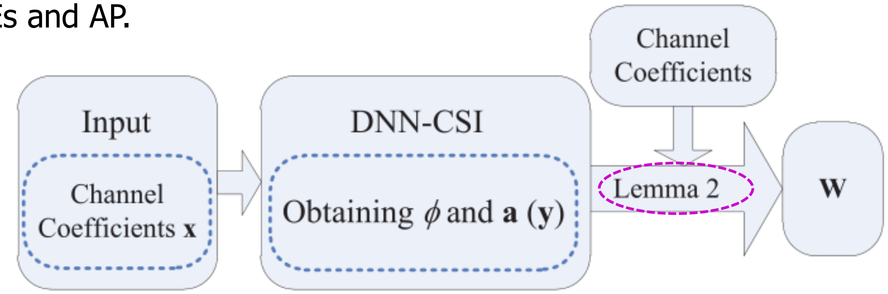
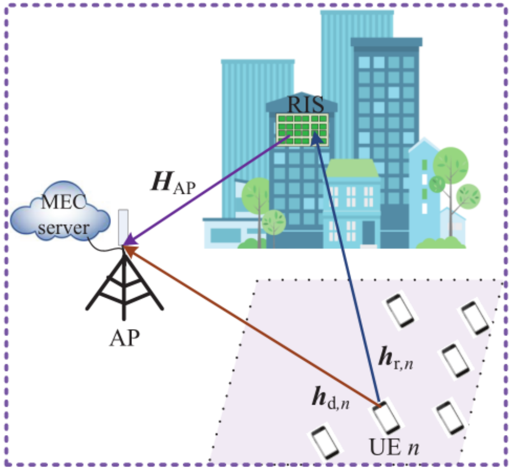


Fig. 5: The architecture for obtaining the solutions of {ϕ,a,W} with the CSI-based DNN-CSI.

Using Location-only



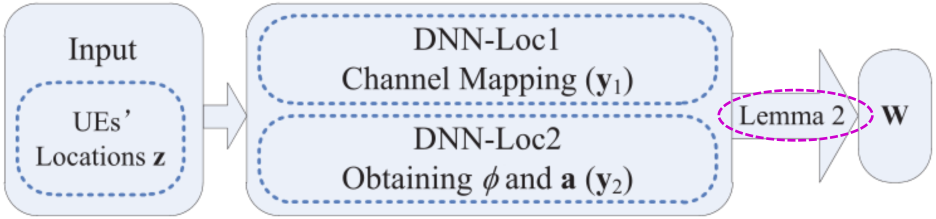


Fig. 7: The architecture for obtaining the solutions of {ϕ,a,W} with the location-only DNN-Loc1 and DNN-Loc2.

- Removing pilot channel estimation and feedback
- Easier to implement with further reduced complexity

with strong LoS direct links between UEs and AP.

Robustness and Complexity Reduction

- Practical cases with input feature uncertainty
  - CSI-based DNN: $\hat{\mathbf{x}} = \mathbf{x} + \triangle\mathbf{x}$, where $\triangle\mathbf{x} \sim \mathcal{N}(0, \sigma^2_{\triangle\mathbf{x}})$
  - Location-only DNNs: $\hat{\mathbf{z}} = \mathbf{z} + \triangle\mathbf{z}$, where $\triangle\mathbf{z} \sim \mathcal{N}(0, \sigma^2_{\triangle\mathbf{z}})$

How much complexity can be reduced through deep learning methods?

TABLE V
PROCESSING TIME OF THE PROPOSED ALGORITHMS

	Parameter	DNN-CSI	DNN-Loc1	DNN-Loc2
	Trainable parameters	1,632,288	702,208	186,304
Perfect CSI	Training samples	$(\mathbf{x}, \mathbf{y})$	$(\mathbf{z}, \mathbf{y}_1)$	$(\mathbf{z}, \mathbf{y}_2)$
Perfect CSI	Training time	5.7426 h	3.3504 h	1.3979 h
Perfect CSI	Testing time	0.3883 s	0.2418 s	0.1025 s
Perfect CSI	Average inference time	38.83 μs	24.18 μs	10.25 μs
Imperfect CSI	Training samples	$(\hat{\mathbf{x}}, \mathbf{y})$	$(\hat{\mathbf{z}}, \mathbf{y}_1)$	$(\hat{\mathbf{z}}, \mathbf{y}_2)$
Imperfect CSI	Training time	6.0345 h	3.5123 h	1.4862 h
Imperfect CSI	Testing time	0.4015 s	0.2568 s	0.1156s
Imperfect CSI	Average inference time	40.15 μs	25.68 μs	11.56 μs
	Average BCD Running Time	28.7 s		

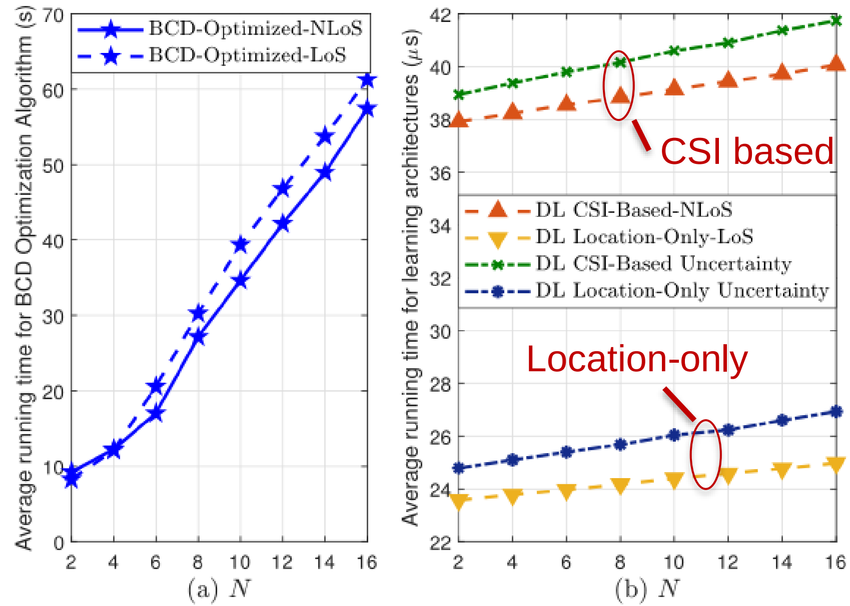
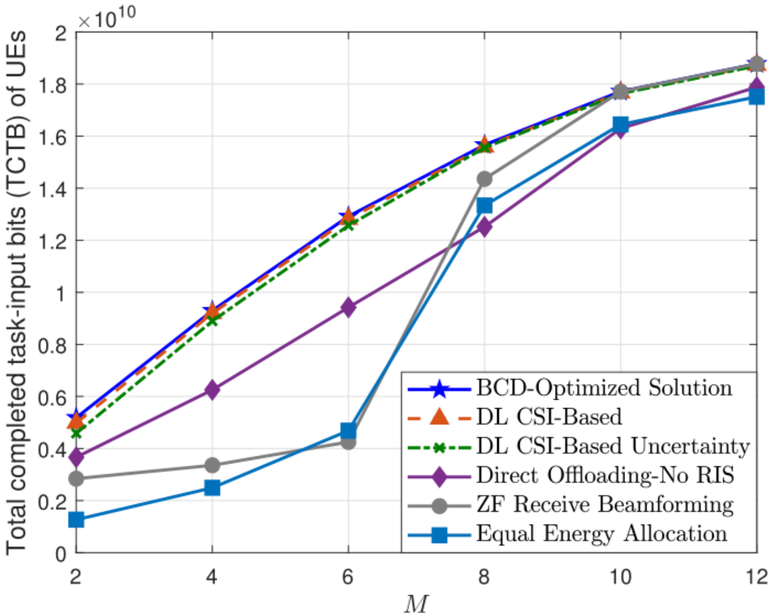


Fig. 8. The average running time per realization vs the number of UEs (N).

- Running time reduced to 1/10^6 of BCD;
- Location-only DL is more lightweight;
- Uncertainty increases complexity;

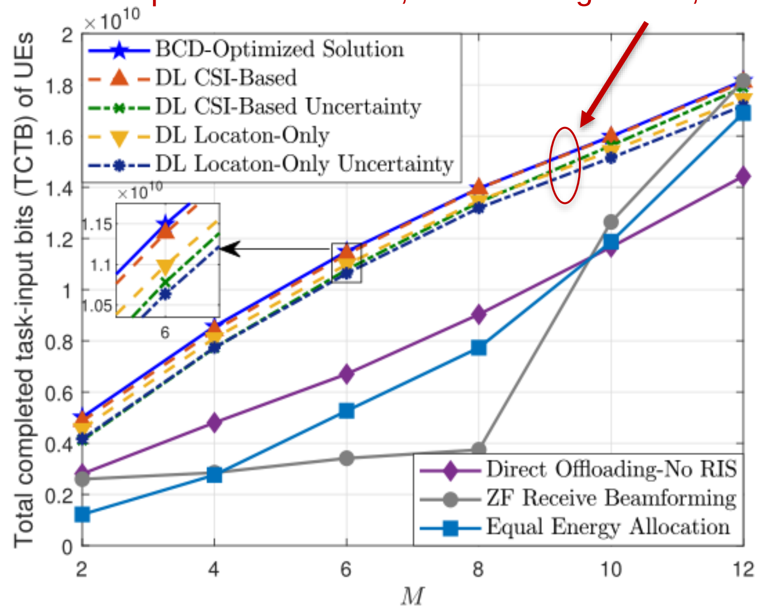
Simulation Results

Scenario (a) without LoS direct links



Scenario (b) with strong LoS direct links

Optimization based, CSI learning-based, location based



The TCTB of UEs versus the number of AP's antennas *M* with *N* = 8.

- Significant performance improvement of BCD vs benchmarks;
- A close match between the BCD algorithm and the CSI-based learning method;
- Location-only learning method can achieve excellent performance when strong LoS direct links are available;
- High robustness and generalizability;

Technical Highlights

Hardware Friendly NNs for MIMO

1. Deep Learning for Multi-antenna detection

Classical Approach

Transmitter

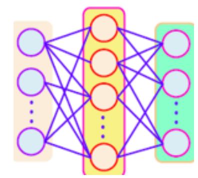
Receiver

s → Channel → Detection → $\hat{s}$

- Maximum likelihood
- Sphere detector
- SIC
- Linear (ZF, MMSE)
- …

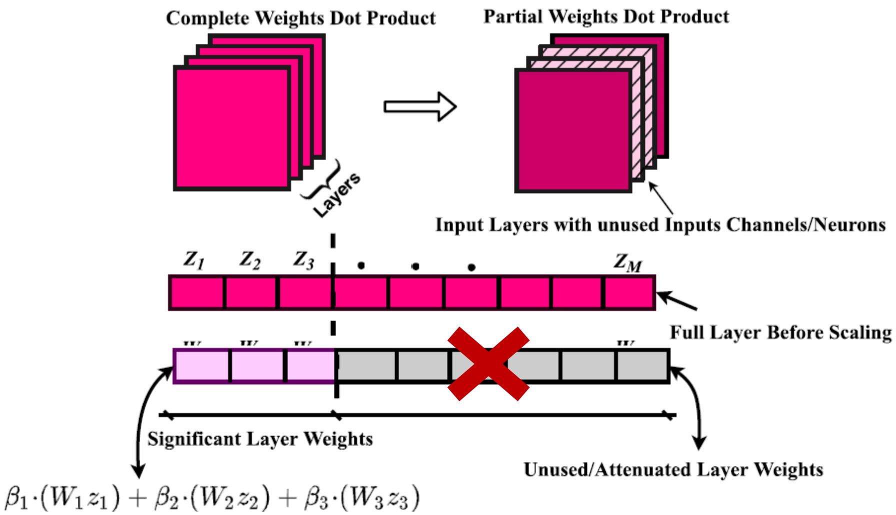
DL-based Approach

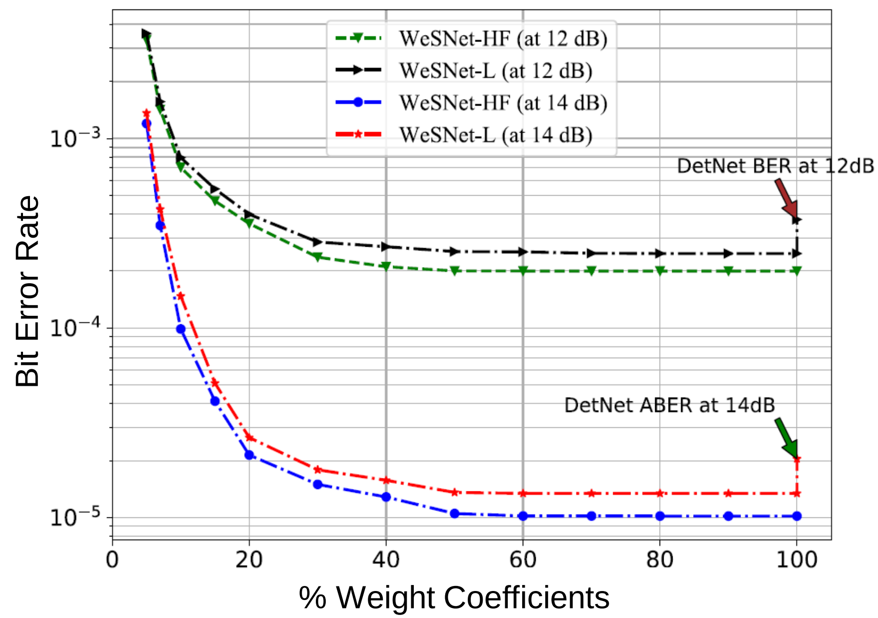
Receiver



$\hat{s}$

Complexity-scalable NNs for Multi-antenna detection





- Scaling of ‘non-significant’ weights to **reduce dimension/complexity of NNs**
- Close to optimal performance with less than 50% of weights

Memory consumption

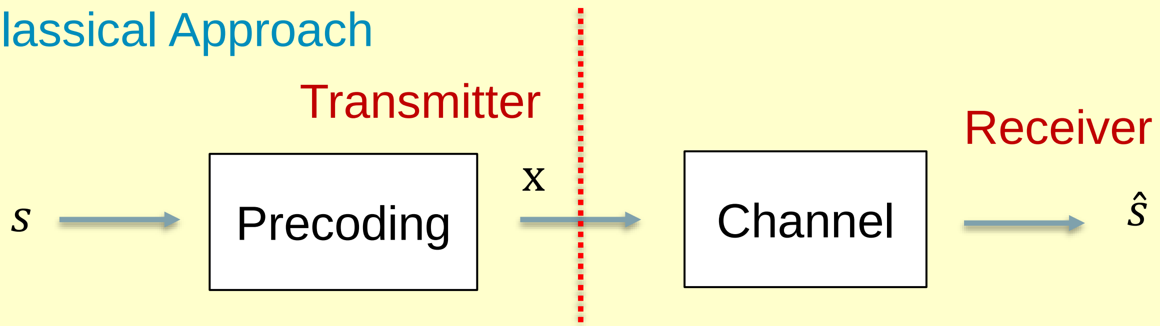
Complexity

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

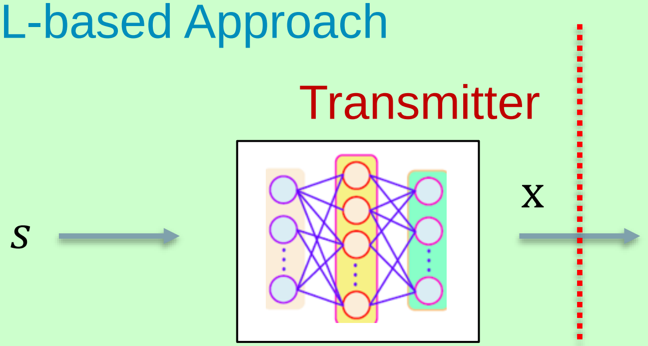
2. Deep Learning for Multi-antenna precoding

Classical Approach



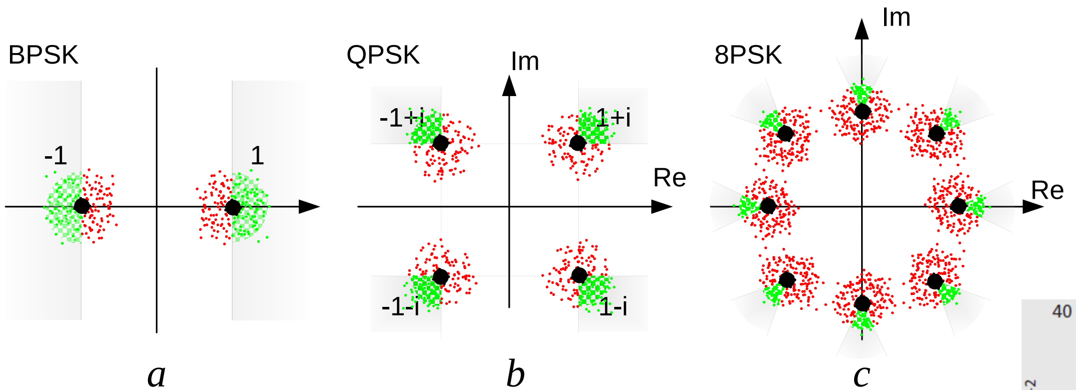
- Optimization based
- Sphere encoding
- THP
- Linear (ZF, MMSE)
- …

DL-based Approach

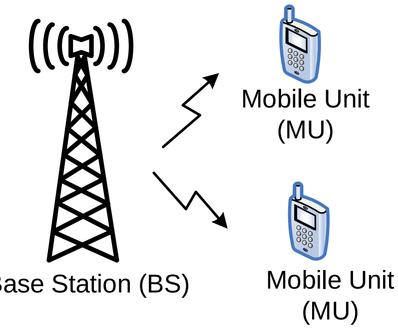


Symbol Level Precoding (SLP)

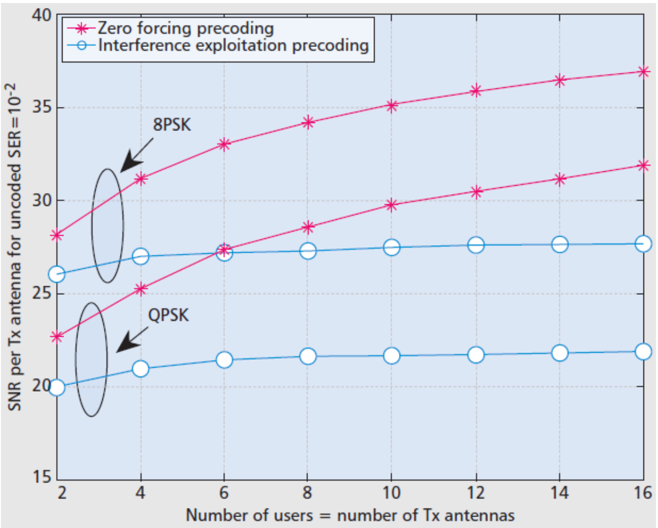
Key Concept: Exploitation of green interference power



PSK constellations and constructive – destructive interference sectors



Up to 10x Power Reduction



SLP Power Minimization

$$\min_{w} \|\mathbf{w}\|^2$$

$$s.t.\ \left|Im\left(\mathbf{h}_i^T \mathbf{w} e^{j(-\phi_i)}\right)\right| \leq \left(Re\left(\mathbf{h}_i^T \mathbf{w} e^{j(-\phi_i)}\right) - \sqrt{\Gamma_i \omega_0}\right) \tan\phi$$

C. Masouros, M. Sellathurai, T. Ratnarajah, "**Vector Perturbation Based on Symbol Scaling for Limited Feedback MIMO Downlinks**", IEEE Trans. Sig. Proc., vol. 62, no. 3, pp. 562-571, Feb.1, 2014

C. Masouros and G. Zheng, "**Exploiting Known Interference as Green Signal Power for Downlink Beamforming Optimization**", IEEE Trans. Sig. Proc., vol.63, no.14, pp.3668-3680, July, 2015

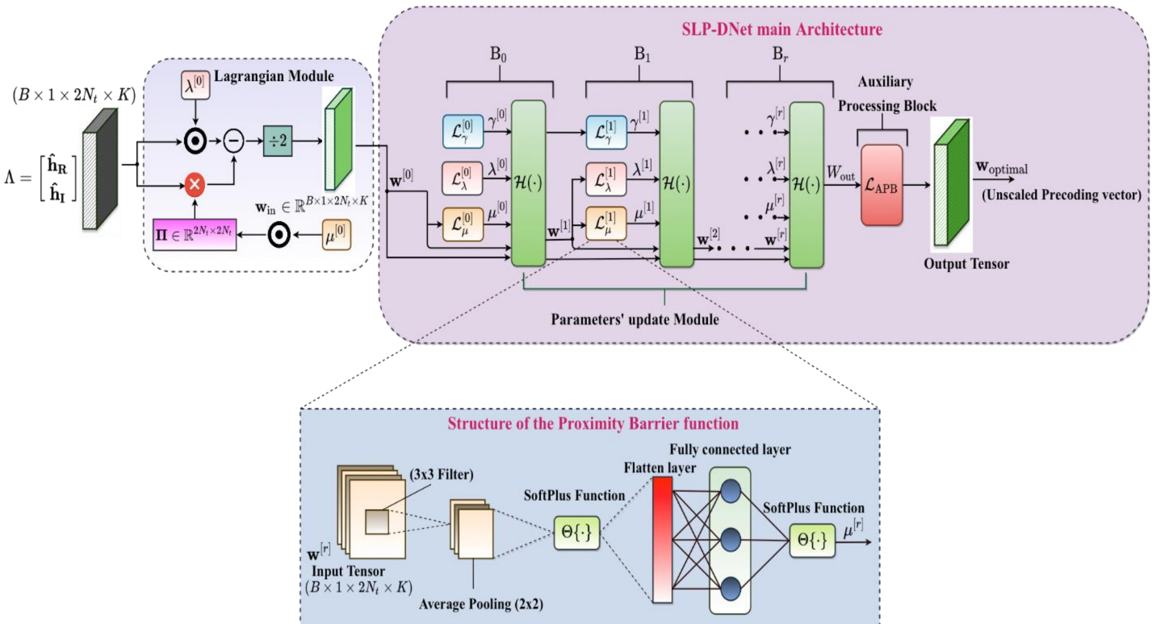
Data-Driven Based SLP (SLP-DNet)

Power Minimization

$$\min_{w} \|\mathbf{w}\|^2$$
$$s.t.\ \left|Im\left(\mathbf{h}_i^T \mathbf{w} e^{j(-\phi_i)}\right)\right| \leq \left(Re\left(\mathbf{h}_i^T \mathbf{w} e^{j(-\phi_i)}\right) - \sqrt{\Gamma_i \omega_0}\right) \tan\phi$$

$$\min_{\{\mathbf{w}_1\}} \quad \|\mathbf{w}_1\|_2^2$$
$$\text{s.t.} \quad \left|\mathbf{\Lambda}_i^T \mathbf{\Pi} \mathbf{w}_1\right| \leq \left(\mathbf{\Lambda}_i^T \mathbf{\Pi} \mathbf{w}_1 - \sqrt{\Gamma_i w_0}\right) \tan\phi\ ,\ \forall i$$

$$\mathbf{\Lambda} = \left[\hat{\mathbf{h}}_{Ri}\ ;\ \hat{\mathbf{h}}_{Ii}\right] \quad \mathbf{w}_1 = \left[\mathbf{w}_R \quad -\mathbf{w}_I\right]^T$$
$$\mathbf{\Pi} = \begin{bmatrix} \mathbf{O}_{N_t} & -\mathbf{I}_{N_t} \\ \mathbf{I}_{N_t} & \mathbf{O}_{N_t} \end{bmatrix}$$



Unfolding using the Lagrangian → regularised loss function:

$$\mathcal{L}_{\mathrm{rl}}(\mathbf{w}_1, \mu_1,\ \mu_2) = \frac{1}{N}\sum_{i=1}^{N} \|\mathbf{w}_1\|_2^2$$
$$+ \frac{1}{N}\sum_{i=1}^{N}\left(\mu_1\left(\mathbf{\Lambda}_i^T \mathbf{\Pi} \mathbf{w}_1 - \mathbf{\Lambda}_i^T \mathbf{w}_1 \tan\phi + \sqrt{\Gamma_i w_0}\right)\right)$$
$$- \frac{1}{N}\sum_{i=1}^{N}\left(\mu_2\left(\mathbf{\Lambda}_i^T \mathbf{\Pi} \mathbf{w}_1 + \mathbf{\Lambda}_i^T \mathbf{w}_1 \tan\phi - \sqrt{\Gamma_i w_0}\right)\right)$$
$$+ \frac{\vartheta}{NL}\sum_{i=1}^{N}\sum_{i=1}^{L} \|\boldsymbol{\theta}_i\|_2^2,$$

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

Data-Driven Based CI – NN Quantization

Quantized NN weights

Binary (SLP-DBNet):

$$\mathbf{B}_w = sign(\mathbf{W}) = \begin{cases} +1 & \text{if } \mathbf{W} \geq 0 \\ -1 & \text{otherwise,} \end{cases}$$

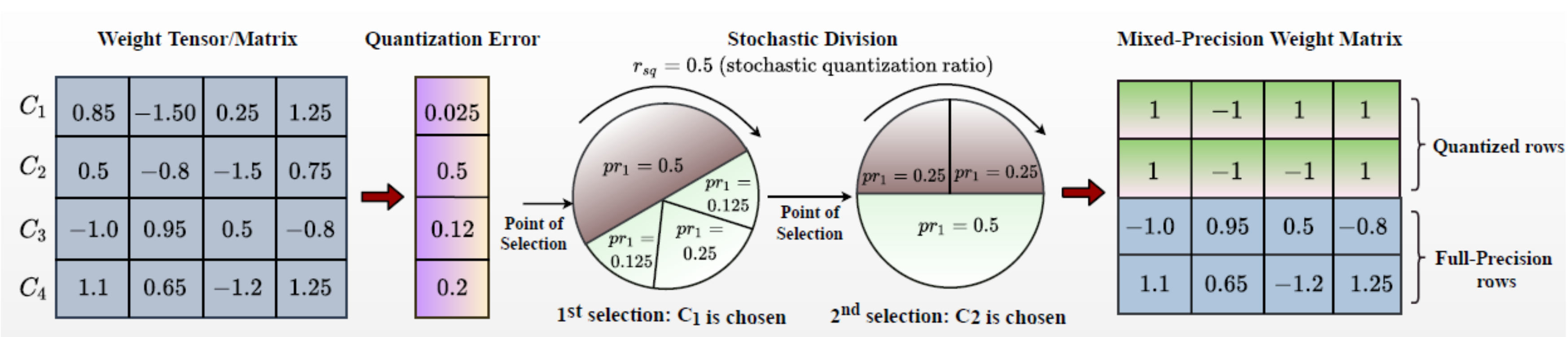
Ternary (SLP-DQNet):

$$\mathbf{B}_{\mathrm{w}}^{*} = \begin{cases} +1 & , \text{ if } \mathbf{W} > \delta \\ 0 & , \text{ if } |\mathbf{W}| \leq \delta \\ -1 & , \text{ if } \mathbf{W} < -\delta, \end{cases}$$

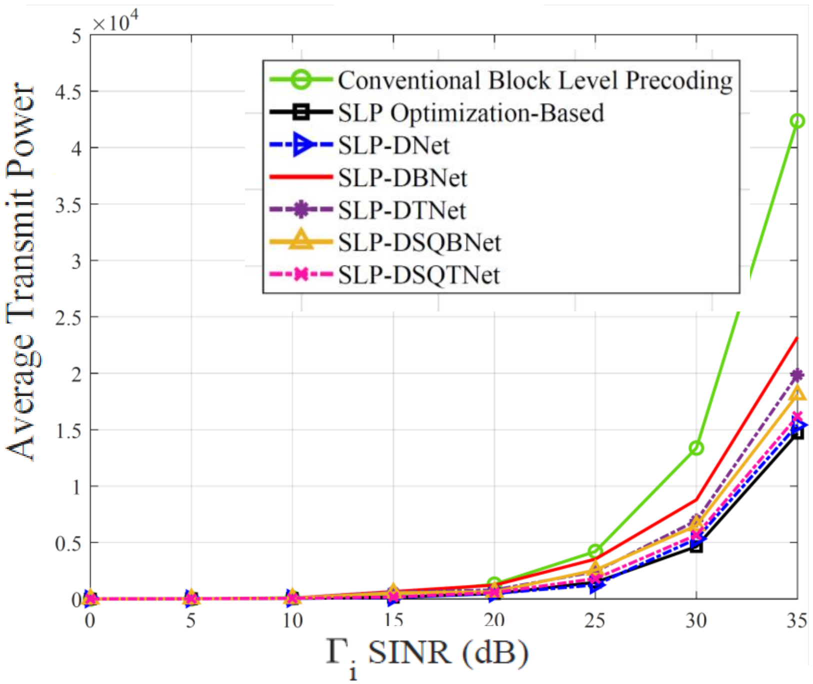
Stochastic quantization (SLP-DQNet):

$$\mathbf{B}_w = \begin{cases} +1 & \text{with probability } p = \rho(\mathbf{W}) \\ -1 & \text{with probability } 1 - p, \end{cases}$$

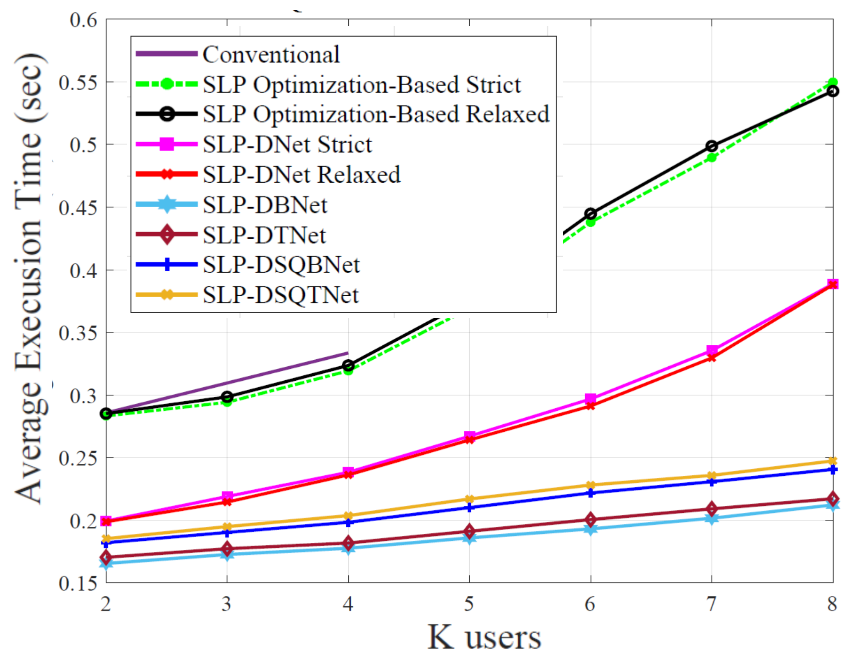
- Memory consumption
- Complexity
- Hardware Friendly



Numerical Results – PSK, Quantization Ratio: 50% of NN weights



BER v.s. SNR, QPSK, $K = N_t = 4$



Complexity vs K, QPSK, $N_t = 4$

- Data-driven (SLP-DNet) performance very close to optimal SLP.
- Some losses with Quantization, less so with Stochastic Quantization.
- Reduction down to 40% complexity per optimization.

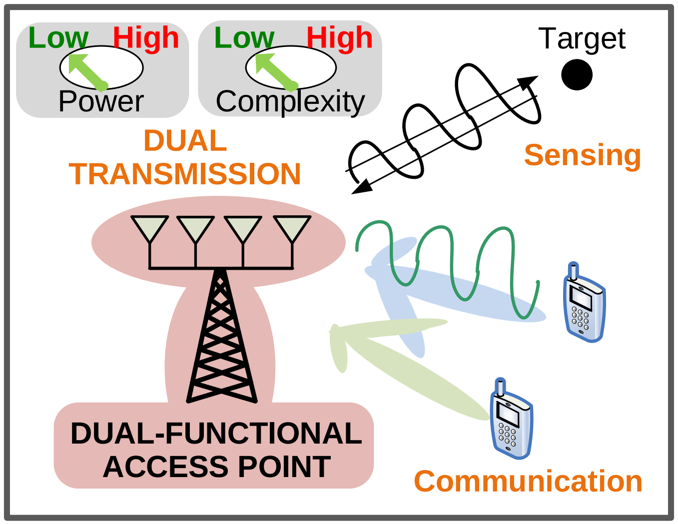
Technical Highlights

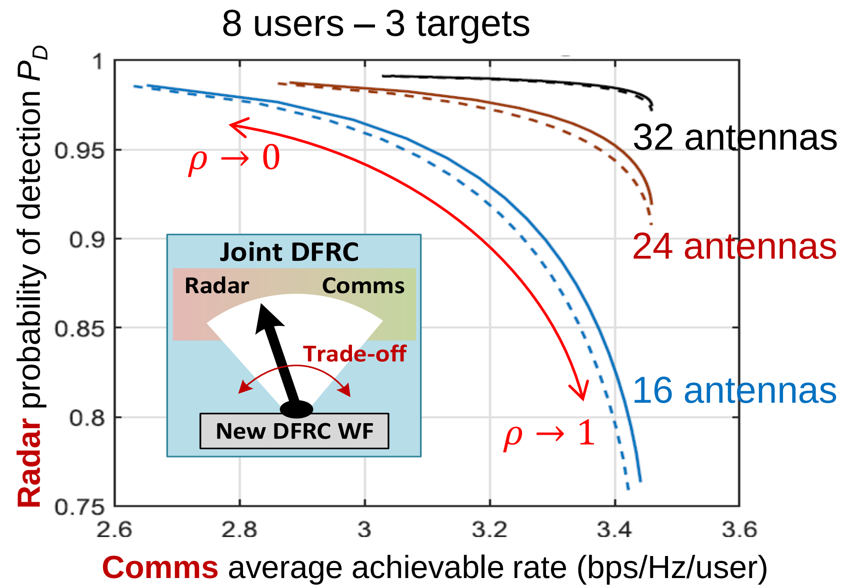
Radar-assisted Vehicular Network

Efficient use of spectrum
Integrated Sensing and Communications (ISAC)

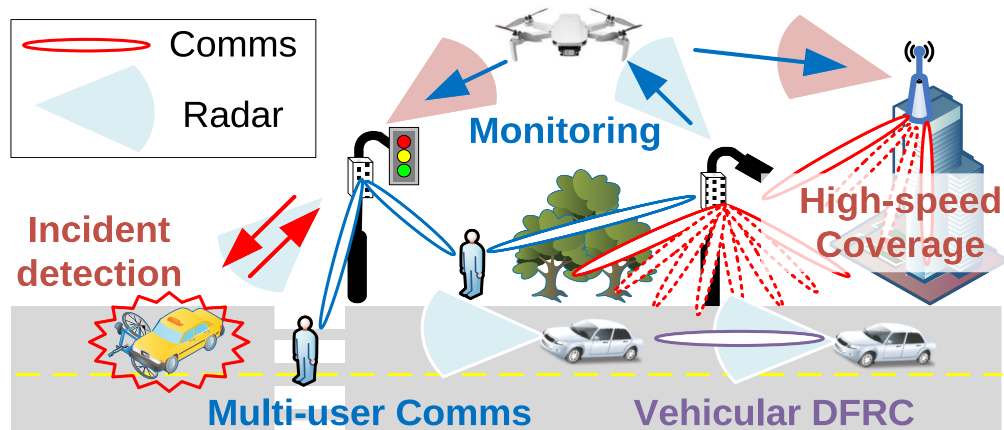
UCL

Spectrum Sharing → Dual Transmission





Smart-cities sensing through 5G dense cellular infrastructure



UDRC

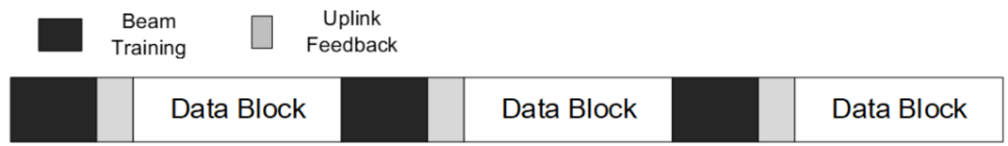
Part of UDRC Project
Mar 2019 – Dec 2021 (£1m)

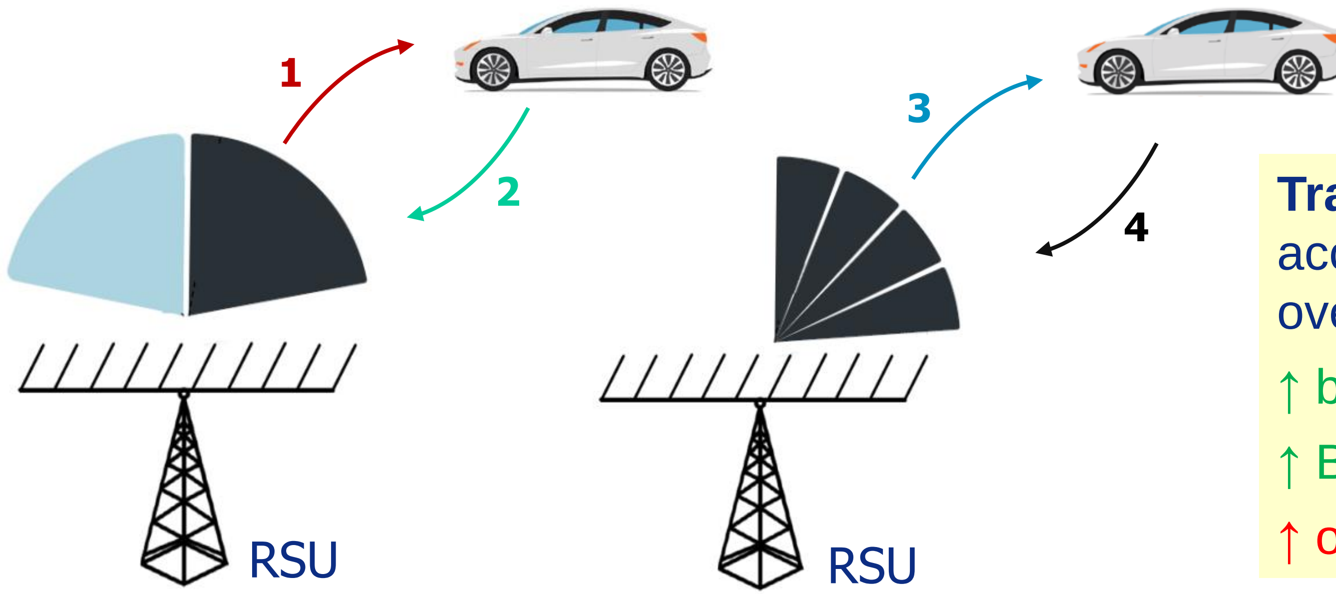
Marie Curie Fellowship
Nov 2018 – Oct 2020 (£160k)

IEEE ComSoc IEEE Communications Society ISAC

Integrated Sensing and Communication Emerging Technology Initiative

Comms-based Beam Training





Tradeoff: estimation accuracy vs signalling overhead: ↑ pilots

↑ beam accuracy

↑ BF gain and SNR

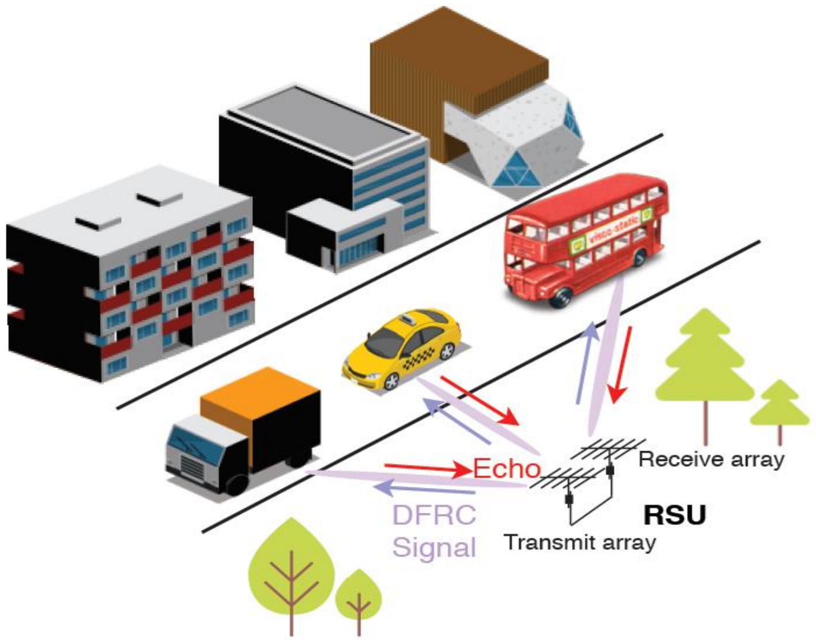
↑ overhead and latency

1. RSU transmits with different AoA, to scan the angular interval of interest
2. User 1) measures signal strength and 2) feeds back the SNR / beam index
3. RSU identifies a narrower angular interval and scans with narrow beams
4. User 1) measures signal strength and 2) feeds back the SNR / beam index

A. Alkhateeb, O. El Ayach, G. Leus, and R. W. Heath, "Channel estimation and hybrid precoding for millimeter wave cellular systems," IEEE J. Sel. Topics Signal Process., vol. 8, no. 5, pp. 831–846, 2014

Radar-assisted Vehicular Network:

Comms served by Sensing: Radar tracking or Comms beam-steering

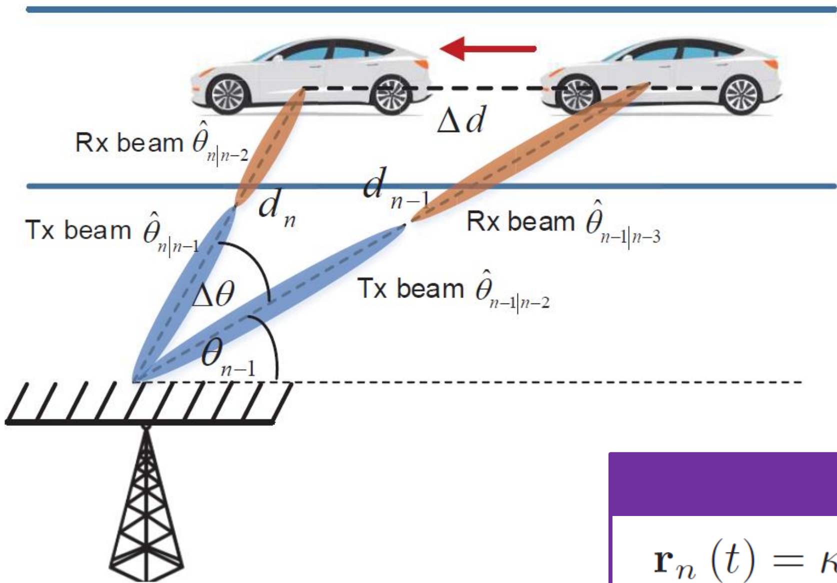


Advantages of DFRC Signalling:

- No dedicated downlink pilots are needed;
- No uplink feedback is needed;
  - No feedback overhead/errors
  - No quantization errors
- The whole downlink frame can be used for tracking
- Significant matched-filtering gain over conventional beam tracking

- **Assumptions**: LoS channel, straight road, parallel mMIMO antenna arrays **- AoA equals to AoD**
- Separate Rx array, inc RF isolator

System Model - Signal Model



State transition model

$$\mathbf{x}_n = \mathbf{g}\left(\mathbf{x}_{n-1}\right) + \boldsymbol{\omega}_n$$

$$= \begin{cases} \theta_n = \theta_{n-1} + d_{n-1}^{-1} v_{n-1} \Delta T \sin\theta_{n-1} + \omega_{\theta,n}, \\ d_n = d_{n-1} - v_{n-1} \Delta T \cos\theta_{n-1} + \omega_{d.n}, \\ v_n = v_{n-1} + \omega_{v,n}, \\ \beta_n = \beta_{n-1}\left(1 + d_{n-1}^{-1} v_{n-1} \Delta T \cos\theta_{n-1}\right) + \omega_{\beta,n}, \end{cases}$$

Radar measurement model

$$\mathbf{r}_n(t) = \kappa\sqrt{p_n}\beta_n e^{j2\pi\mu_n t}\mathbf{b}\left(\theta_n\right)\mathbf{a}^H\left(\theta_n\right)\mathbf{f}_n s_n\left(t-\tau_n\right) + \mathbf{z}_n(t)$$

matched filtering

$$\mathbf{y}_n = \mathbf{h}\left(\mathbf{x}_n\right) + \tilde{\mathbf{z}}_n$$

$$= \begin{cases} \tilde{\mathbf{r}}_n = \beta_n\sqrt{Gp}\kappa\mathbf{b}\left(\theta_n\right)\mathbf{a}^H\left(\theta_n\right)\mathbf{f}_n + \mathbf{z}_{\theta,n} \\ \hat{\tau}_n = \dfrac{2d_n}{c} + z_{\tau,n} & \text{Round-trip delay} \\ \hat{f}_{D,n} = \dfrac{2v_n\cos\theta_n f_c}{c} + z_{f,n} & \text{Doppler offset} \end{cases}$$

Communication model

$$c_n(t) = \tilde{\kappa}\sqrt{p_n}\alpha_n\mathbf{w}_n^H\mathbf{u}\left(\theta_n\right)\mathbf{a}^H\left(\theta_n\right)\mathbf{f}_n s_n(t) + z_c(t),$$

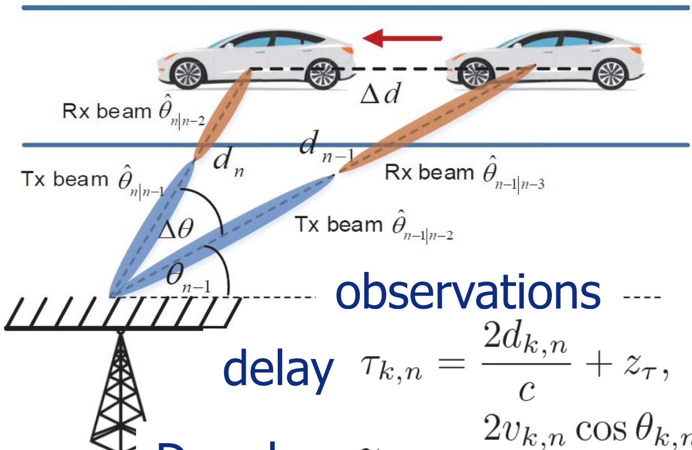
Predictive Beamformers

Tx: $\mathbf{f}_n = \mathbf{a}\left(\hat{\theta}_{n|n-1}\right)$ Rx: $\mathbf{w}_n = \mathbf{u}\left(\hat{\theta}_{n|n-2}\right)$

F. Liu, W. Yuan, C. Masouros and J. Yuan, "Radar-Assisted Predictive Beamforming for Vehicular Links: Communication Served by Sensing", IEEE Trans. Wireless Commun., vol. 19, no 11, pp. 7704-7719, Nov. 2020

Prediction Approach - Model-Based Bayesian Learning

Beyond EKF



observations

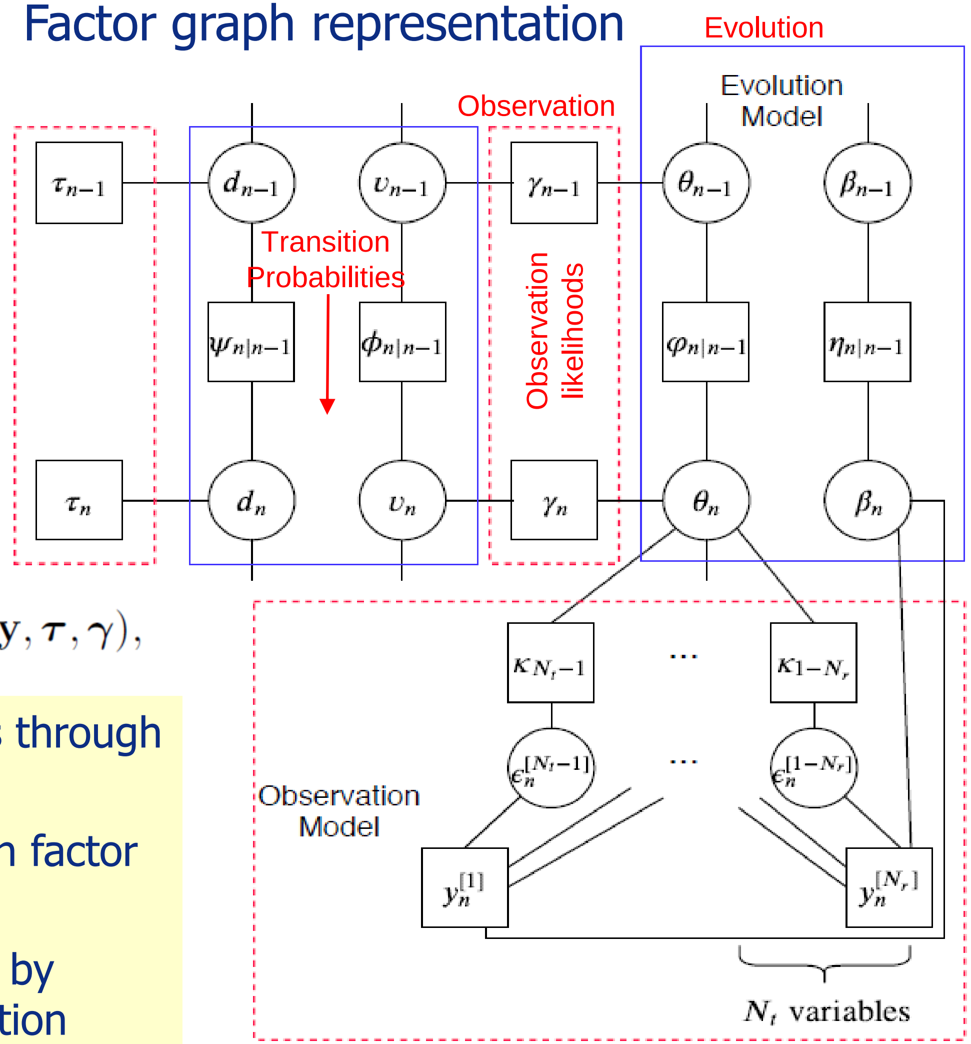
delay $\tau_{k,n} = \frac{2d_{k,n}}{c} + z_\tau,$ and

Doppler $\gamma_{k,n} = \frac{2v_{k,n}\cos\theta_{k,n} f_c}{c} + z_\gamma,$

$$\{\hat{\mathbf{d}}, \hat{\boldsymbol{\theta}}, \hat{\mathbf{v}}, \hat{\boldsymbol{\beta}}\} = \arg\max_{\mathbf{d},\boldsymbol{\theta},\mathbf{v},\boldsymbol{\beta}} p(\mathbf{d}, \boldsymbol{\theta}, \mathbf{v}, \boldsymbol{\beta} | \mathbf{y}, \boldsymbol{\tau}, \boldsymbol{\gamma}),$$

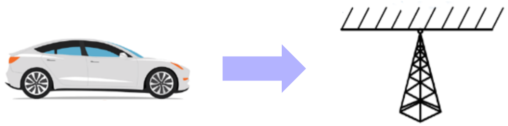
- Predict the motion parameters of vehicles through maximum a posteriori (MAP) estimator
- Represent a posteriori distribution through factor graph framework and message passing
- Higher estimation accuracy is guaranteed by exploiting second-order Taylor approximation

Factor graph representation

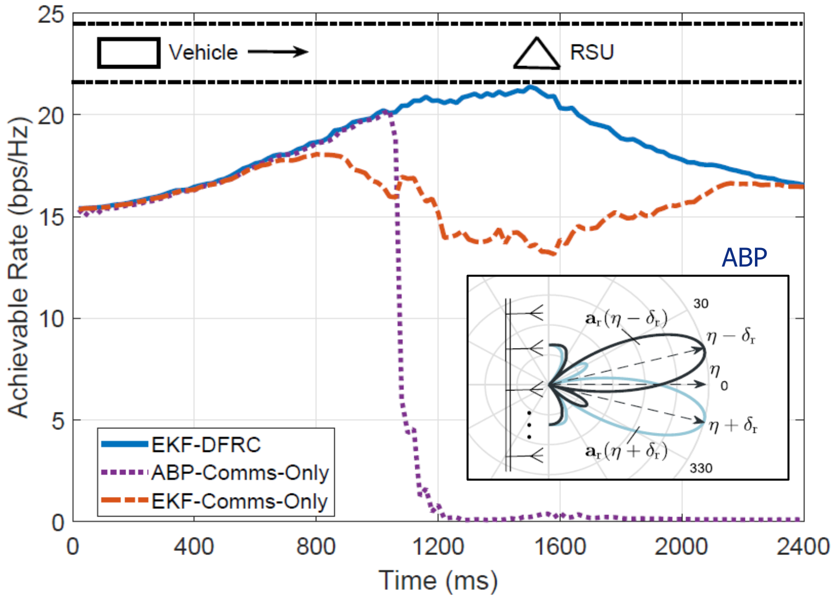


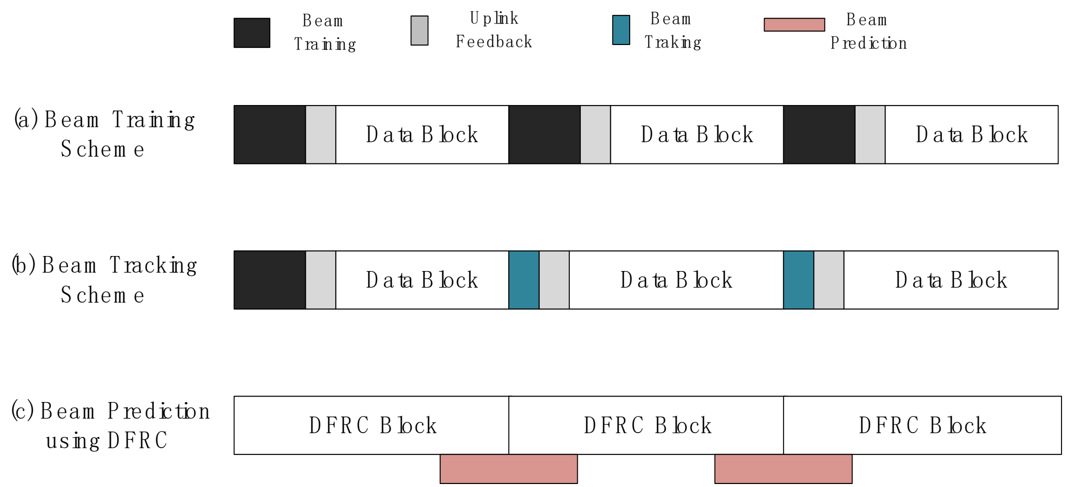
W. Yuan, F. Liu, C. Masouros, J. Yuan, D. W. K. Ng, N. Prelcic, “Bayesian Predictive Beamforming for Vehicular Networks: A Low-Overhead Joint Radar-Communication Approach”, IEEE Trans. Wireless Comms., *vol. 20, no. 3, pp. 1442-1456, March 2021*

Numerical Results - DFRC vs Comms only



N = 64, v_0 = 18m/s





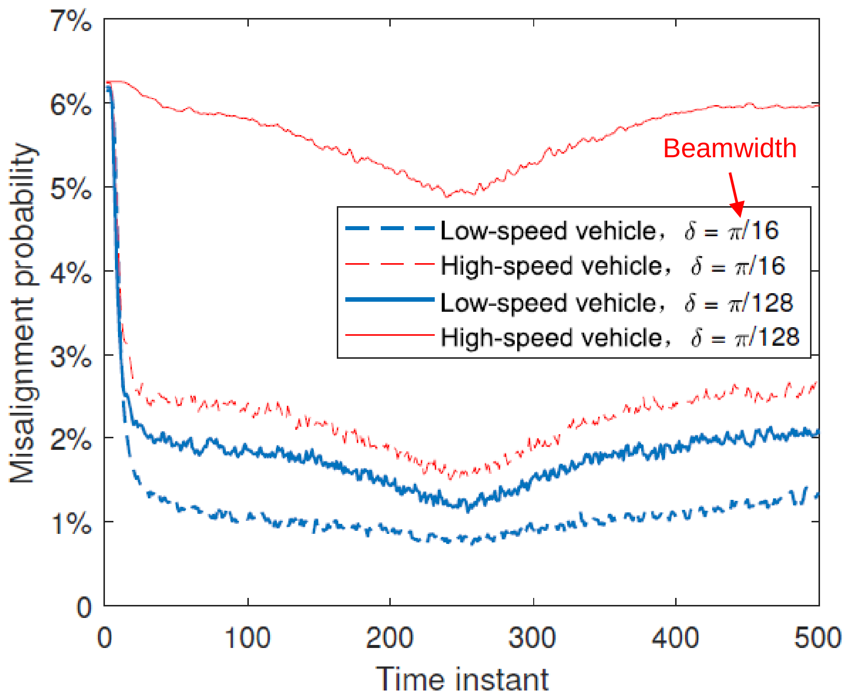
- EKF-Comms-only: poor angle estimation at RSU crossing point – suffering data rate
- Auxiliary Beam Pair (ABP) tracking: at RSU crossing point the correct beam will unlikely fall into angle search interval – beam goes beyond the search space and is not recovered
- EKF-DFRC: Minimal disruption in the rate

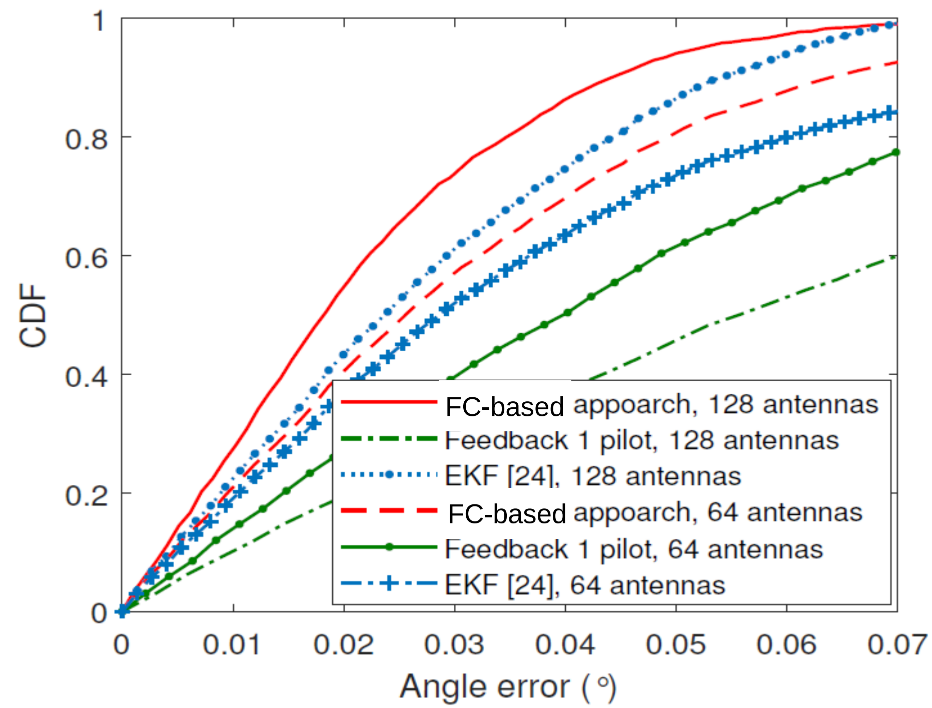
F. Liu, W. Yuan, C. Masouros and J. Yuan, "Radar-Assisted Predictive Beamforming for Vehicular Links: Communication Served by Sensing", IEEE Trans. Wireless Commun., vol. 19, no 11, pp. 7704-7719, Nov. 2020

F. Liu and C. Masouros, "A Tutorial on Joint Radar and Communication Transmission for Vehicular Networks - Part II: State of the Art and Challenges Ahead", IEEE Commun. Lett., vol. 25, no. 2, pp. 332-336, Feb. 2021 - EiC Invited Paper

Numerical Results

Single vehicle tracking - Factor graph vs. EKF





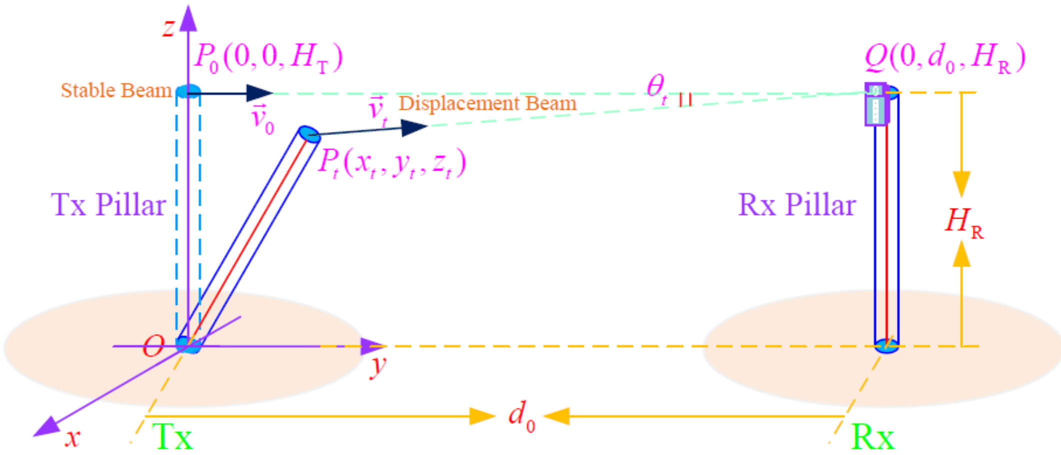
- Better misalignment probability and angle tracking for smaller BW
- The factor graph (FC) based approach outperforms the EKF, and the comms-only feedback based techniques in angle and velocity tracking.

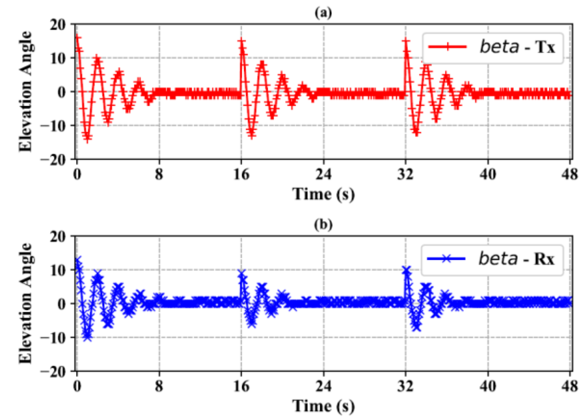
W. Yuan, F. Liu, C. Masouros, J. Yuan, D. W. K. Ng, N. Prelcic, "Bayesian Predictive Beamforming for Vehicular Networks: A Low-Overhead Joint Radar-Communication Approach", IEEE Trans. Wireless Comms., *vol. 20, no. 3, pp. 1442-1456, March 2021*

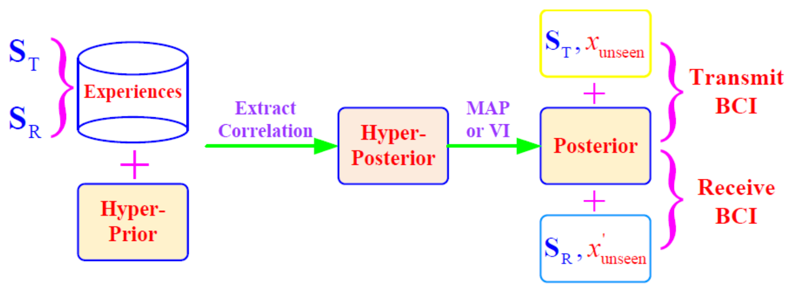
Technical Highlights

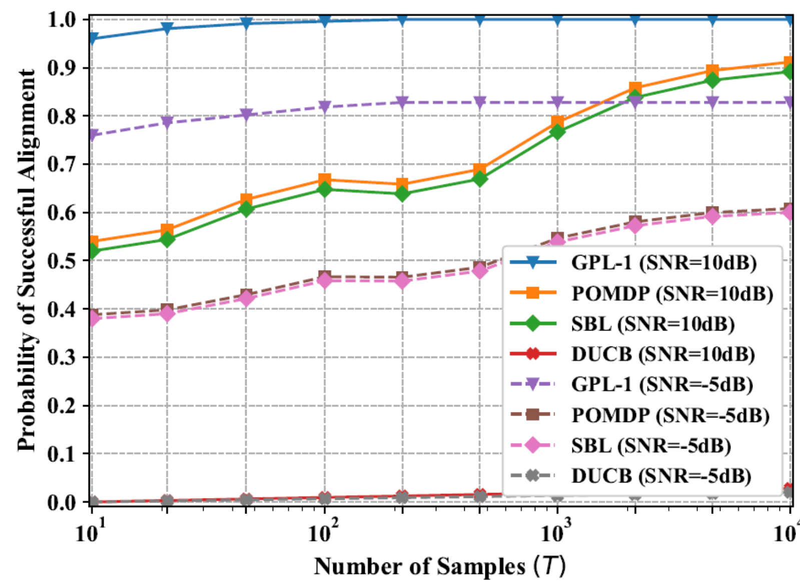
Beam prediction for Fixed Wireless Access Links

Beam prediction for Fixed Wireless Access Links









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

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*

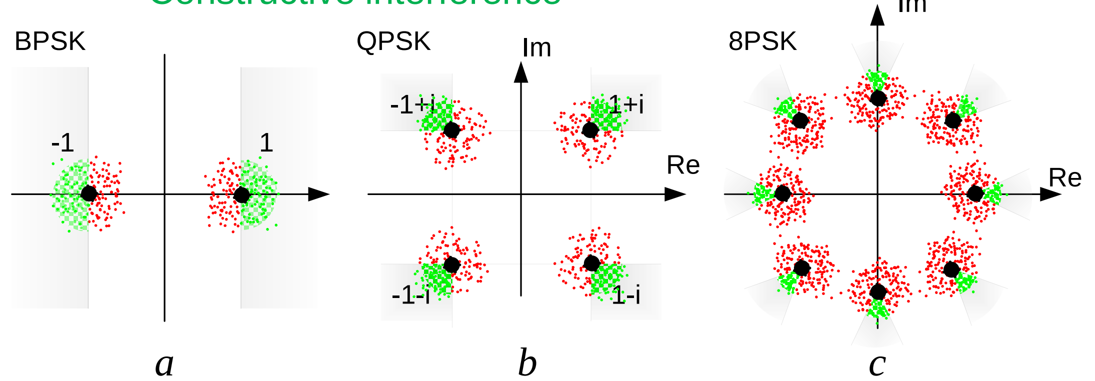
Technical Highlights

Joint Precoding and Channel Sparsification

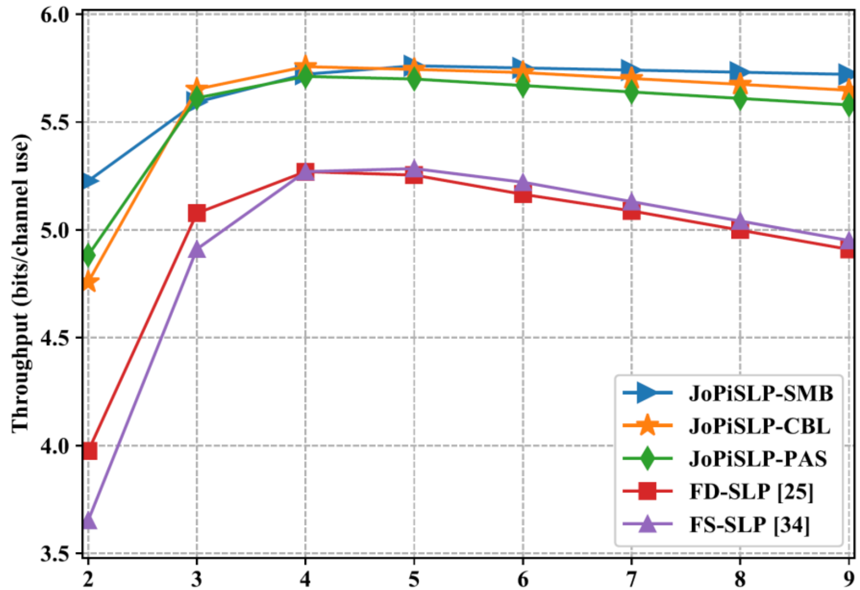
Joint Precoding and Channel Sparsification

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

Constructive interference



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



J. Zhang, C. Masouros, “**A Unified Framework for Precoding and Pilot Design for FDD Symbol-Level Precoding**”, IEEE Trans Comms., *under review*

Further Research Directions

- Complex problems with inaccurate modelling
- Problems with complex modelling, difficult to solve analytically

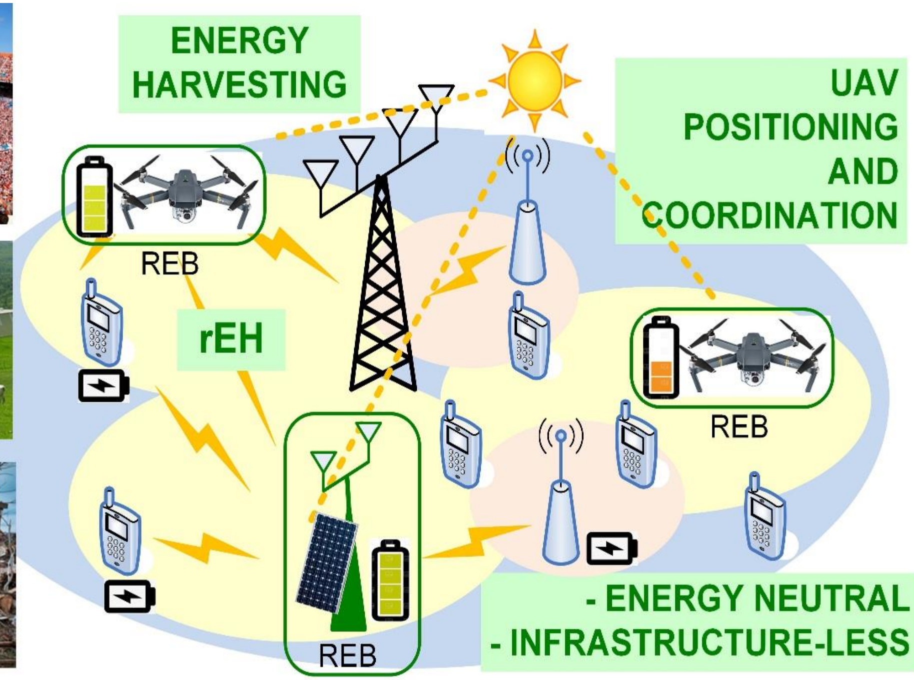
Net-Zero Energy Communications
Energy-autonomous Portable Access-Points

UCL

- CO^2 emissions and OPEX
- Power grid infrastructure

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

UCL
NOKIA Bell Labs
The American College of Greece — Pierce Deree Alba 1875
University of Cyprus
LYRA ELECTRONICS
MANCHESTER 1824 — The University of Manchester
cnrs
AALBORG UNIVERSITY DENMARK
RIO SYSTEMS



HORIZON 2020

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

http://painless-itn.com/

Painless ITN

@PainlessITN

Net-Zero Energy Communications
Energy-autonomous Portable Access-Points

Learning based Solutions:

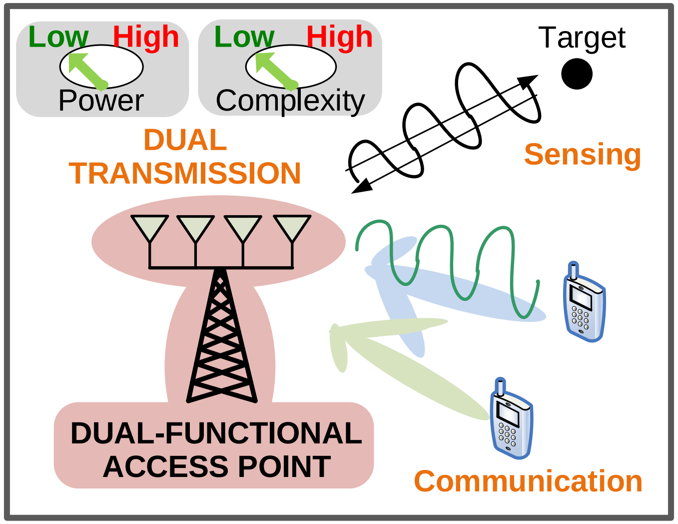
- For complex optimization problems in balancing energy harvesting vs storage vs consumption
  - To address complex modelling of batteries / photovoltaics / … / …
- UAV trajectory optimization
  - Online trajectory adaptation based on comms / energy / navigation /… /… metrics
  - Reinforcement learning approaches seem promising

Efficient use of spectrum

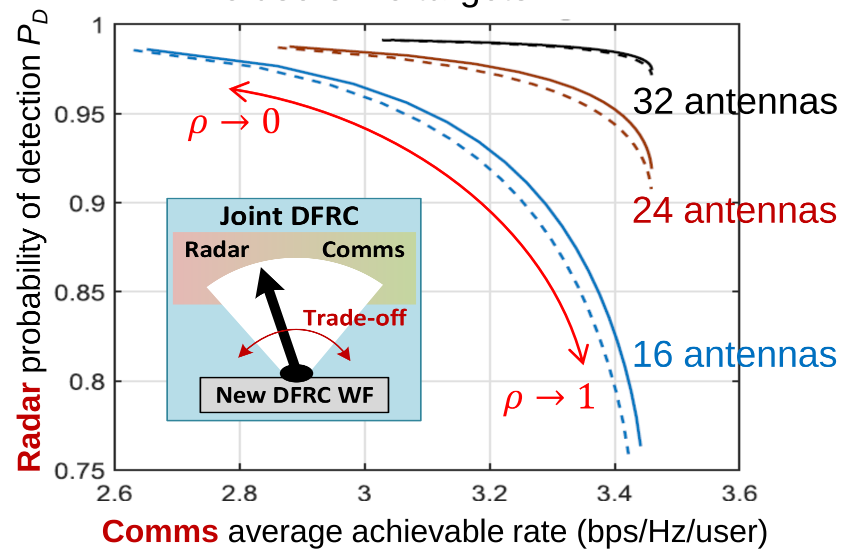
Integrated Sensing and Communications (ISAC)

UCL

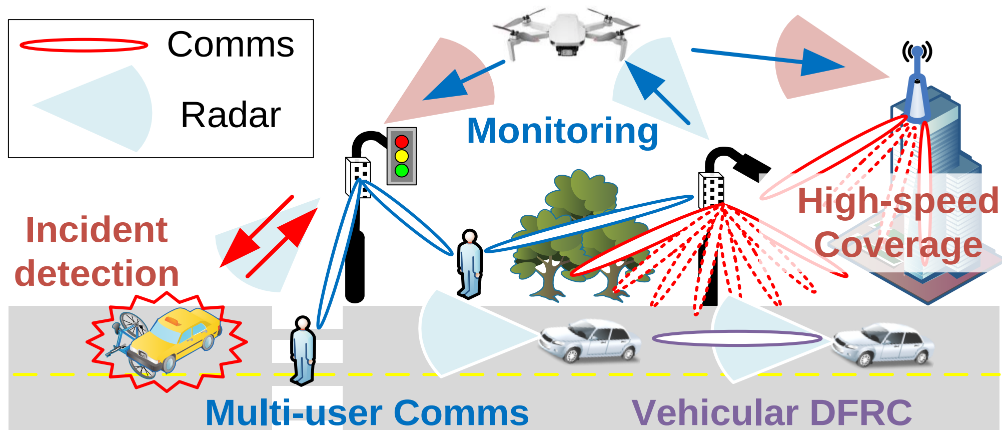
Spectrum Sharing → Dual Transmission



8 users – 3 targets



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)

IEEE ComSoc ISAC **Integrated Sensing and Communication Emerging Technology Initiative**

Efficient use of spectrum
Integrated Sensing and Communications (ISAC)

Learning based Solutions:

- For complex optimization problems in joint waveform design
  - To address complex joint comms – radar metrics
  - Complex target / user scenarios

- Receive processing for ISAC signals
  - Joint target detection and data detection – DL for complex environments

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- 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*
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- 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
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ISAC

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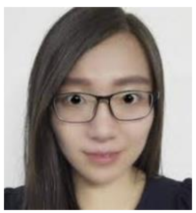
- F. Liu, L. Zhou, C. Masouros, A. Li, W. Luo, A. Petropulu "**Toward Dual-functional Radar-Communication Systems: Optimal Waveform Design**", IEEE Trans. Sig. Proc., vol. 66, no. 16, pp. 4264-4279, Aug.15, 15 2018

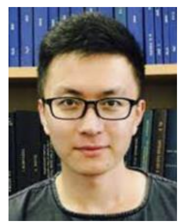
Big thanks!



Xiaoyan

Jianjun

Abdullahi



Tongyang

Iman

Xiaoye

Abdel

Thank you

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