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# AI-Native Air Interface: Learning Receivers and Waveforms

Dani Korpi

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With contributions by:
Mikko Honkala
Janne Huttunen
Esha Wang
Harish Viswanathan
Mikko Uusitalo
Faycal Ait Aoudia
Jakob Hoydis

# DeepRx: Fully learned MIMO receiver

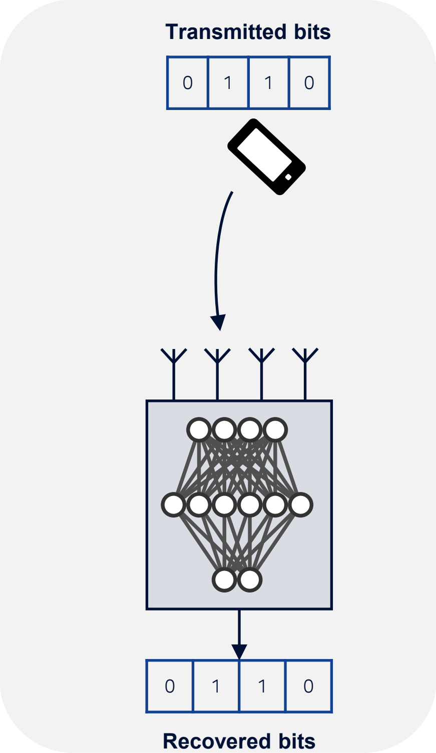
# Introduction

**Starting point**

- What is the best way to take advantage of ML in the physical layer?
    - Higher performance
    - Higher flexibility
    - Reduced algorithm design effort

**Our approach:**

- *Learn the whole receiver*

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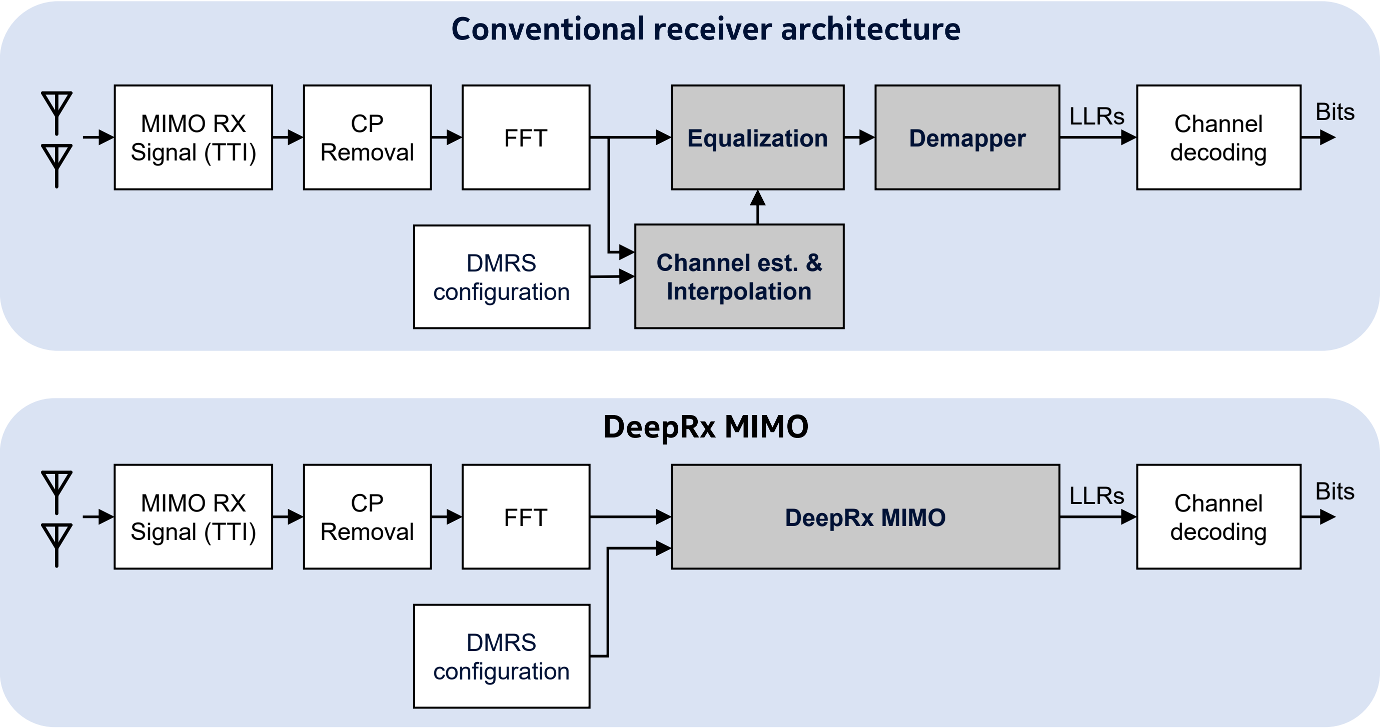
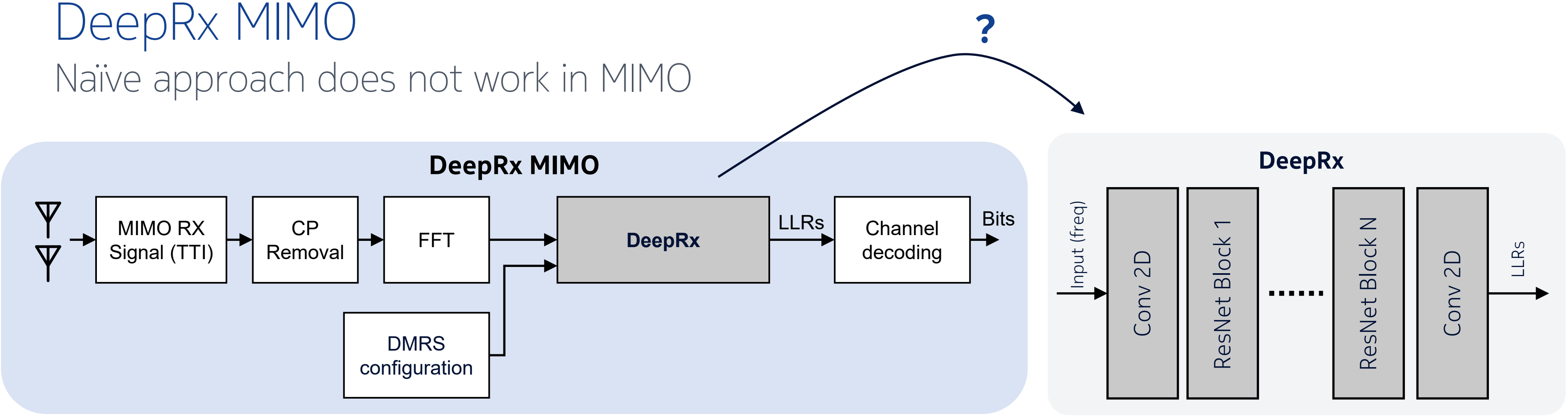
# System Model



# DeepRx MIMO

## Naïve approach does not work in MIMO

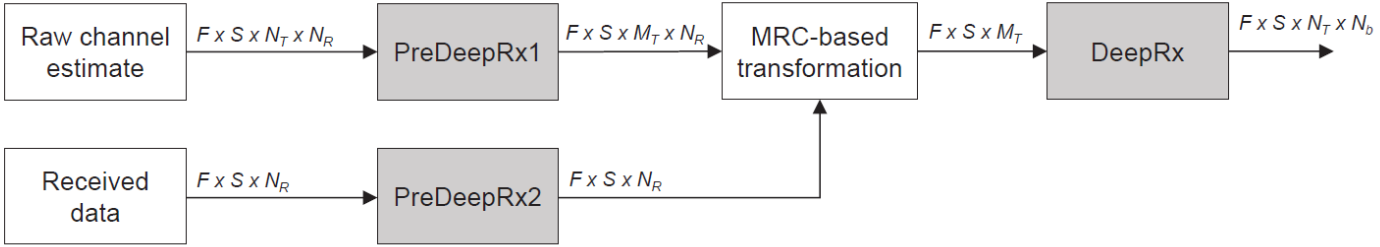



- In SIMO cases without spatial multiplexing, good performance was achieved by simply applying a large ResNet-type CNN[1]
- However, such a pure CNN architecture is not sufficient for MIMO detection
- Learning efficient MIMO detection requires some expert knowledge!

[1] M. Honkala, D. Korpi, and J. Huttunen, “DeepRx: Fully convolutional deep learning receiver,” IEEE Transactions on Wireless Communications, 2021.

# DeepRx MIMO

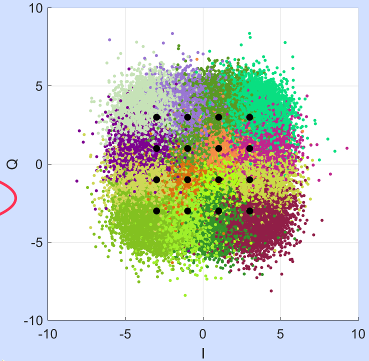
## Version 1: MRC-based transformation




- In order to help the learning task, we can utilize maximum ratio combining (MRC) as a preprocessing layer
- It performs *very* coarse equalization
- Performance can be increased by utilizing so-called virtual layers

**Maximum Ratio Combining (MRC)**

- For subcarrier *i* at OFDM symbol *j*:
  - Channel estimate: $\hat{\mathbf{H}}_{ij} \in \mathbb{C}^{N_R \times N_T}$ (interpolated with nearest neighbor method)
  - Received sample: $\mathbf{y}_{ij} \in \mathbb{C}^{N_R \times 1}$
  - MRC transformation: $\mathbf{y}_{ij,MRC} = \mathbf{S}\hat{\mathbf{H}}_{ij}^{H}\mathbf{y}_{ij} \in \mathbb{C}^{N_T \times 1}$
  - Where $\mathbf{S}$ is a $N_T \times N_T$ diagonal matrix for scaling the channel gains, and $\hat{\mathbf{h}}_{ij,k}$ denotes the *k*th column of $\hat{\mathbf{H}}_{ij}$



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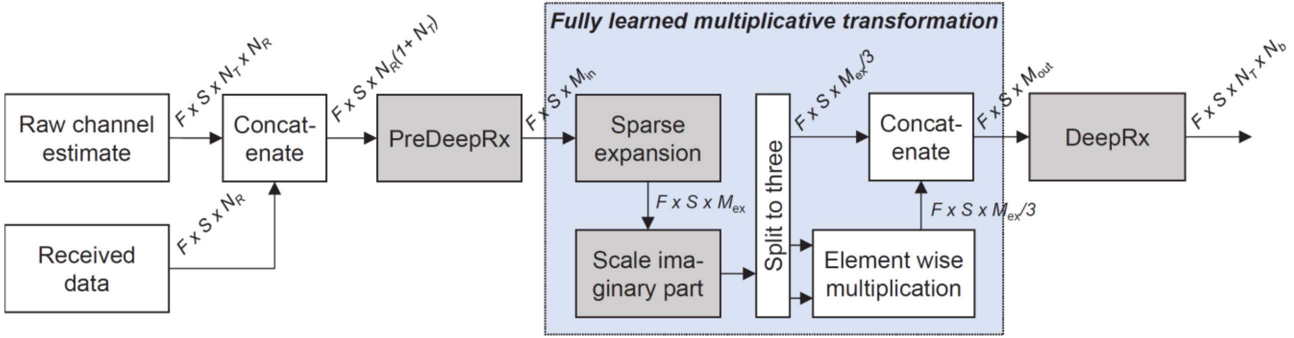
# DeepRx MIMO

## Version 2: Fully learned multiplicative transformation




- Inspired by the MRC-based processing, we then developed a fully learned multiplicative transformation
  - It contains expert knowledge via facilitating multiplication between inputs
- It consists of:
  1. Sparse selection of inputs for multiplication (multiplication of the input channels with matrix $\mathbf{W}_1$, regularized to be sparse)
  2. Learned scaling of the imaginary component (element wise multiplication of the imaginary part with vector $\mathbf{w}_2$)
  3. Element wise multiplication between inputs
- Main principle of operation: learn to select the proper inputs to multiply and complex conjugate

# DeepRx MIMO

## Training procedure

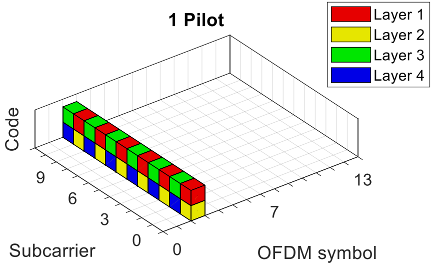
- Training is based on weighted cross entropy loss:
  - $L_q(\boldsymbol{\theta}) = \log_2\left(1 + snr_q\right) CE_q(\boldsymbol{\theta})$
- This ensures that samples with low SNR do not dominate the loss term
- When using the fully learned multiplicative transformation, the regularization term $\alpha \|\mathbf{W}_1\|_{L_1}$ is added to $L_q(\boldsymbol{\theta})$ to ensure that $\mathbf{W}_1$ is sparse
- Training is done with a total batch size of 96, using LAMB optimizer with a base learning rate of $3.5 \cdot 10^{-3}$

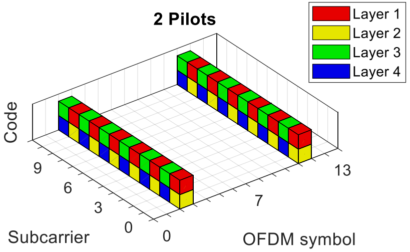
<table>
<tr><th>Layer</th><th colspan="2">MRC-based</th><th>Fully learned</th></tr>
<tr><td>Input 1</td><td colspan="3">RX signal: $\mathbf{Y} \in \mathbb{C}$</td></tr>
<tr><td>Input 2</td><td colspan="3">Raw interpolated channel estimate: $\widehat{\mathbf{H}} \in \mathbb{C}$</td></tr>
<tr><td rowspan="4">PreDeepRx</td><td>PreDeepRx1</td><td>PreDeepRx2</td><td>PreDeepRx</td></tr>
<tr><td colspan="3">3 Resnet blocks, 3x3 convs ($\mathbb{C}$), 64–384 channels</td></tr>
<tr><td>1x1 conv ($\mathbb{C}$), 16 channels</td><td rowspan="2">Output: 384 channels represented as $24 \times 16$ array</td><td rowspan="2">Output: 128 channels</td></tr>
<tr><td>Output: 16 channels</td></tr>
<tr><td>Transformation</td><td colspan="2">MRC, output has 24 channels</td><td>Fully learned, $M_{\mathrm{in}} = 128$, $M_{\mathrm{ex}} = 240$, output has 160 channels</td></tr>
<tr><td>DeepRx</td><td colspan="3">CNN consisting of 11 ResNet blocks and depthwise-separable 2D convolutional layers ($\mathbb{R}$), following the same architecture as in [1] but with quadruple channel count (although limiting the maximum number of channels to 512).</td></tr>
</table>

# Simulation Results

## Data

- Data is generated using a PUSCH link simulator, implemented with Matlab 5G Toolbox
- In total, 500 000 TTIs are generated, 60% of which is used for training
- Two different DMRS configurations are present in the data

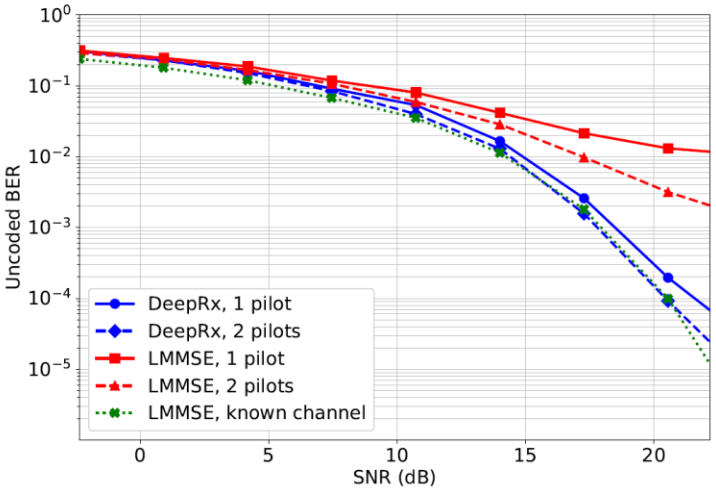


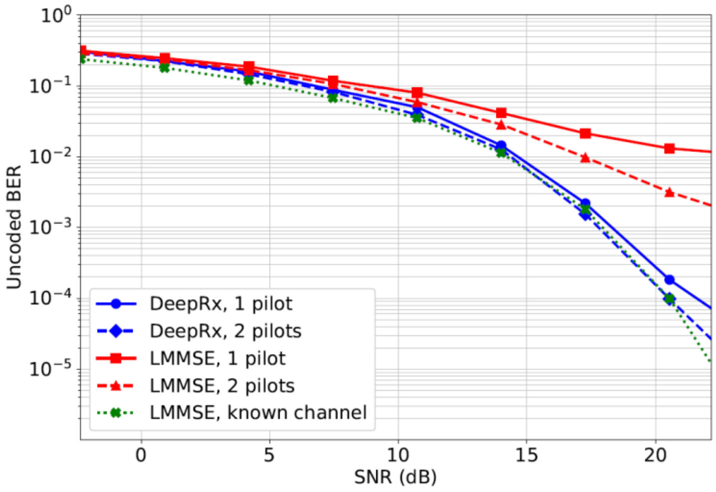

| Parameter | Training | Validation | Randomization |
|---|---|---|---|
| Carrier frequency | 2.6 GHz | | None |
| Channel model | TDL-B, TDL-C, TDL-D | TDL-A, TDL-E | Uniform |
| Spatial correlation | Low | | Uniform |
| RMS delay spread | 10 ns – 300 ns | | Uniform |
| Maximum Doppler shift | 0 Hz – 325 Hz | | None |
| SNR | -4 dB – 32 dB | | None |
| Number of PRBs | 26 | | None |
| Subcarrier spacing | 30 kHz | | None |
| OFDM symbol duration | 35.7 μs | | None |
| TTI length | 14 OFDM symbols | | None |
| Modulation scheme | 16-QAM | | None |
| Code rate | 658/1024 | | None |
| No. of RX antennas | 16 | | None |
| No. of TX antennas | 4 | | None |
| No. of MIMO layers | 4 | | None |
| DMRS configuration | 1 or 2 pilots with FD-CDM2 | | Uniform |

# Simulation Results

**MRC-based transformation**




**Fully learned transformation**




- Both architecture variants achieve excellent performance
- On par with LMMSE having perfect channel knowledge



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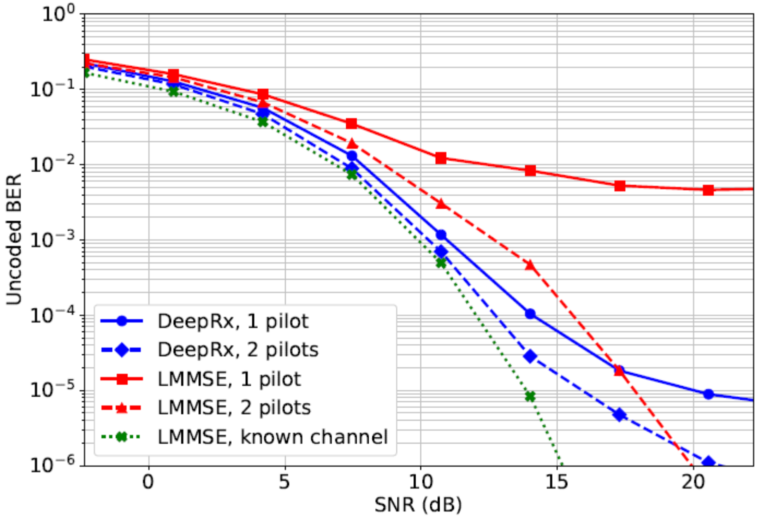
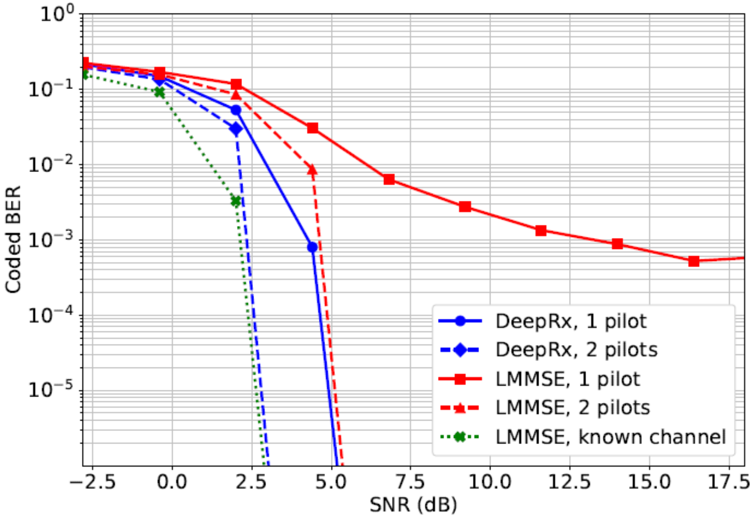
# Simulation Results

## Fully learned transformation: TDL-A (NLOS)




- Under NLOS channel conditions, DeepRx MIMO achieves high performance with most SNRs
- When SNR approaches 20 dB, it seems to encounter an error floor
- The gains translate to coded BER, indicating that also the magnitudes of the LLR estimates are accurate

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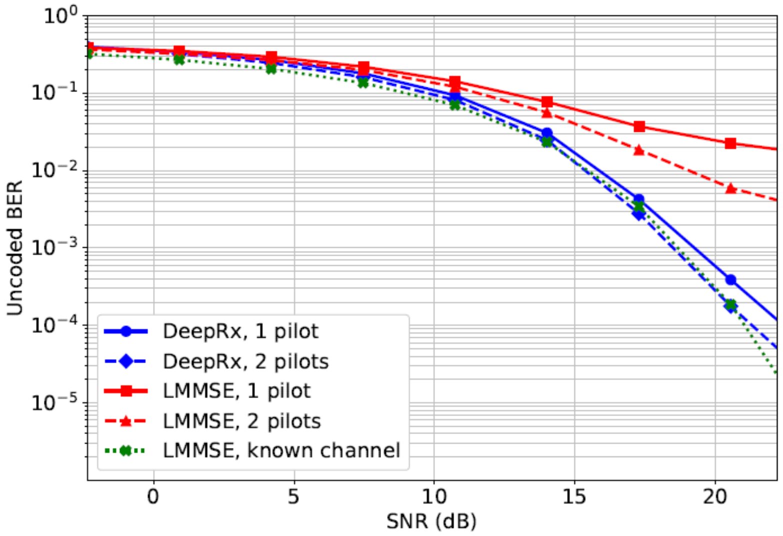
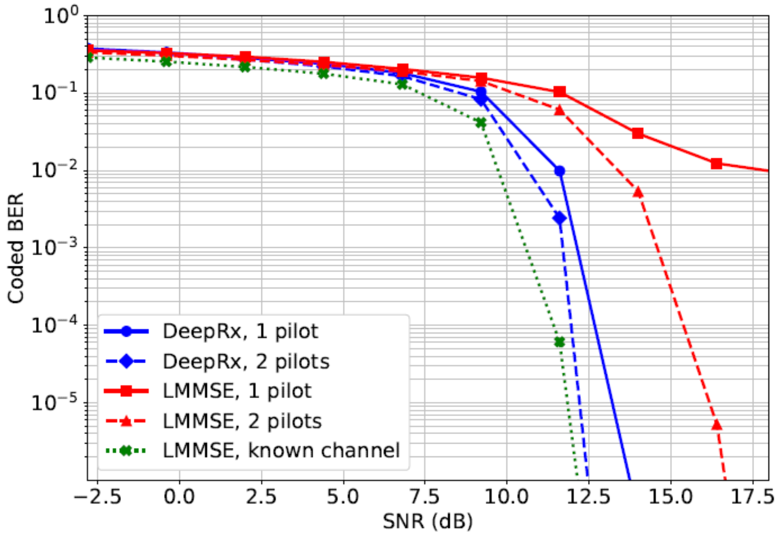
# Simulation Results

## Fully learned transformation: TDL-E (LOS)




- No error floor is encountered under LOS conditions, where the BERs are higher
- Again, the performance gains are visible also after LDPC decoding

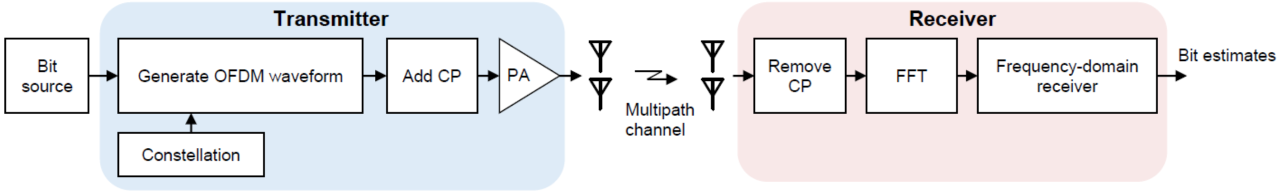
# Related Publications


- M. Honkala, D. Korpi, and J. M. J. Huttunen, “DeepRx: Fully convolutional deep learning receiver,” *IEEE Transactions on Wireless Communications*, vol. 20, no. 6, pp. 3925–3940, Jun. 2021.
- D. Korpi, M. Honkala, J. M. J. Huttunen, and V. Starck, “DeepRx MIMO: Convolutional MIMO detection with learned multiplicative transformations,” in *Proc. IEEE International Conference on Communications (ICC)*, Jun. 2021.
- J. Pihlajasalo, D. Korpi, M. Honkala, J. M. J. Huttunen, T. Riihonen, J. Talvitie, M. A. Uusitalo, and M. Valkama, “Deep learning based OFDM physical-layer receiver for extreme mobility,” in *Proc. Asilomar Conference on Signals, Systems, and Computers (ASILOMAR)*, Nov. 2021.
- J. Pihlajasalo, D. Korpi, M. Honkala, J. M. J. Huttunen, T. Riihonen, J. Talvitie, A. Brihuega, M. A. Uusitalo, and M. Valkama, “HybridDeepRx: Deep learning receiver for high-EVM signals,” in *Proc. IEEE 32nd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, Sep. 2021.

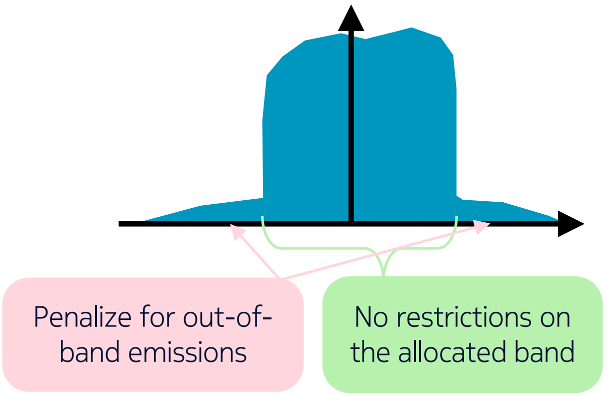
# Waveform learning for minimizing out-of-band emissions

# Background & Idea




- Is it possible to learn a TX waveform that
  1. Is more resistant to PA-induced distortion?
  2. Results in lower out-of-band emissions?

- Training procedure is the key:
  - Reward for low reception error rate
  - Penalize for emissions



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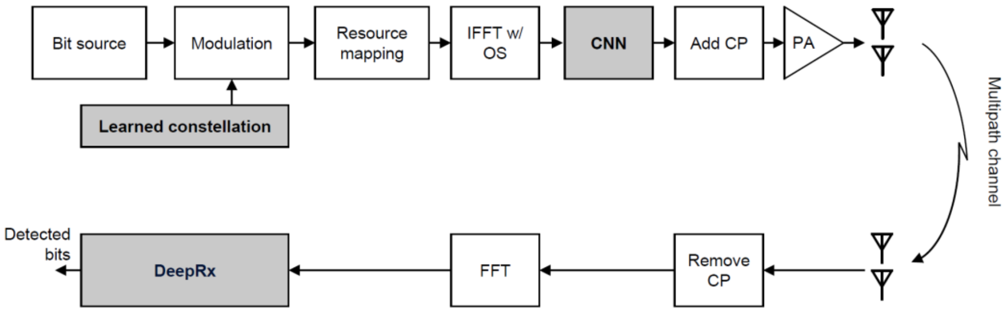
# System Model

- Supervised end-to-end training
  - All blocks are differentiable
- Loss has two components:
  - Cross-entropy between TX and RX bits
  - Energy emitted outside the designated band



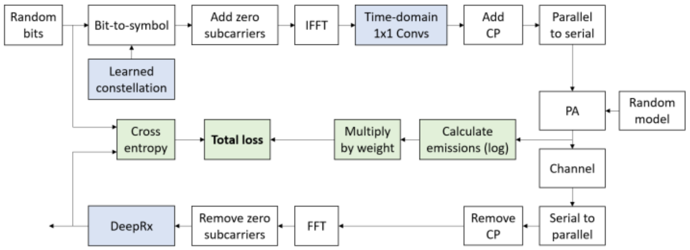

 

# Training

- Loss consists of cross entropy and emissions
  - $L(\boldsymbol{\theta}) = \sum_{q=1}^{Q} \log_2\left(1 + snr_q\right) CE_q(\boldsymbol{\theta}) + W_E \ln\left(\sum_{q=1}^{Q} E_q(\boldsymbol{\theta})\right)$

Binary cross entropy

Emission power at PA output




- Supervised learning task
  - End-to-end training
- Randomized PA response to prevent fitting to a single PA model
- Adam optimizer with a specific learning rate schedule
  - Warm-up period and reducing learning rate to zero at the end



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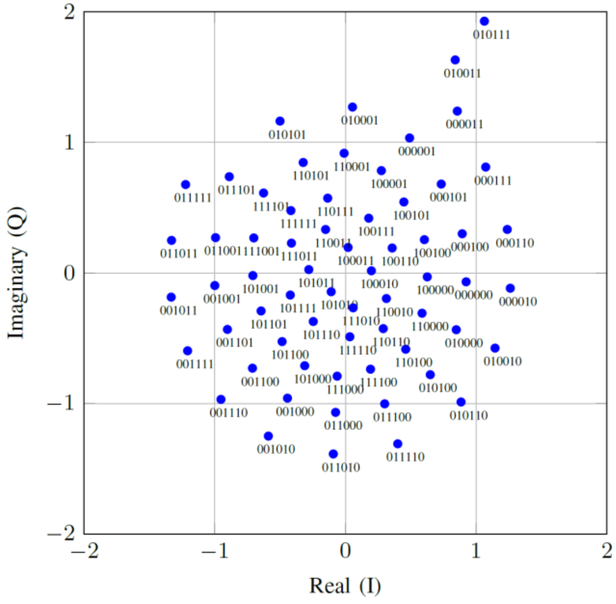
# Simulation Results

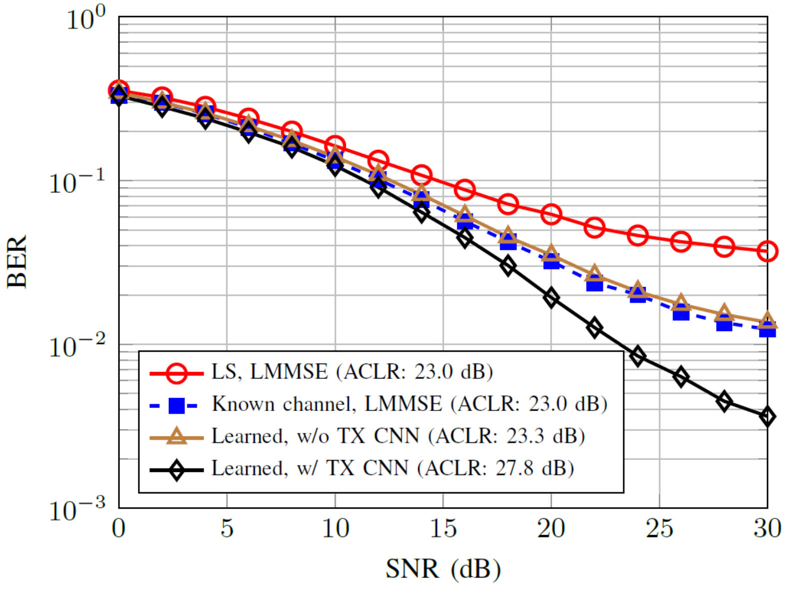
- Simulator implemented in TensorFlow
- Relying on Quadriga channel models
- Fully differentiable from end-to-end

| **Parameter** | **Value** | **Randomization** |
|---|---|---|
| Carrier frequency | 3.5 GHz | None |
| Channel model | UMi LOS, UMi NLOS | Uniform |
| PA model | Polynomial, $P = 17$ | Dithered coefficients |
| UE velocity | 0 m/s – 25 m/s | Uniform |
| SNR | 0 dB – 30 dB | Uniform |
| Number of subcarriers ($N_f$) | 144 | None |
| TX oversampling factor | 2 | None |
| Subcarrier spacing | 30 kHz | None |
| OFDM symbol duration | 35.7 $\mu$s | None |
| CP duration | 2.7 $\mu$s | None |
| TTI length ($N_s$) | 14 OFDM symbols | None |
| Bits per symbol ($Q_m$) | 6 | None |

# Simulation Results

## Snapshot



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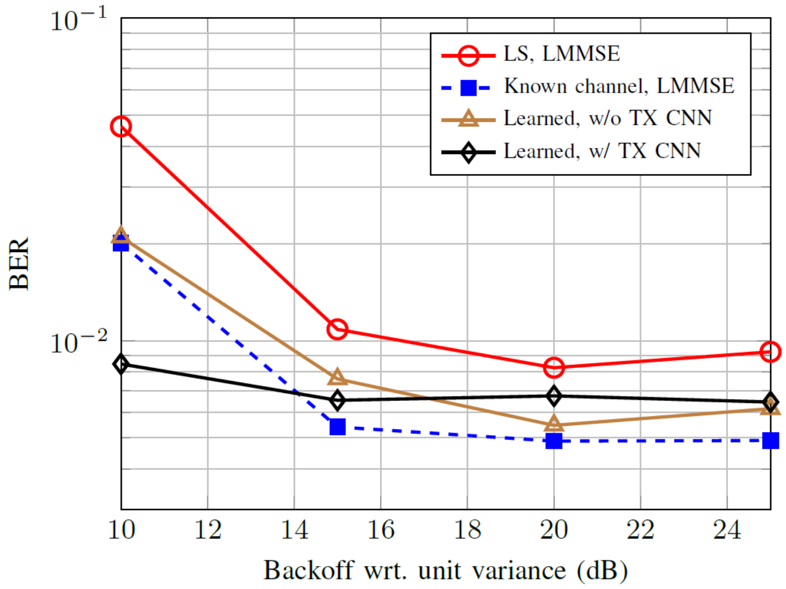
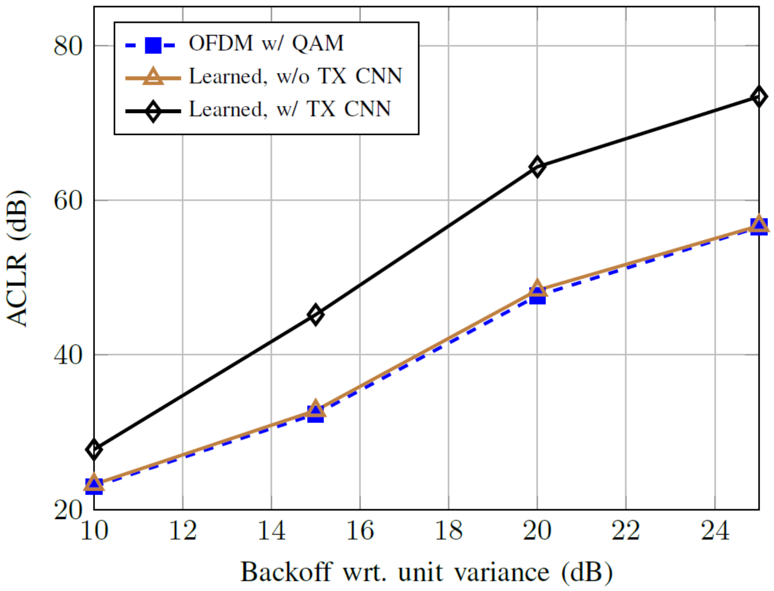
# Simulation Results

## SNR fixed at 24 dB

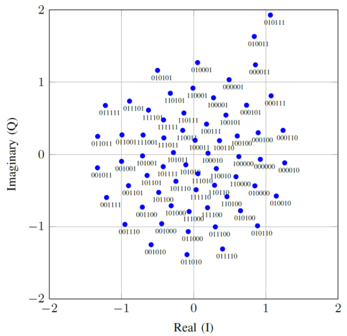


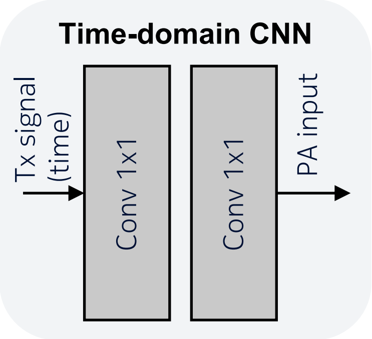




More linear PA

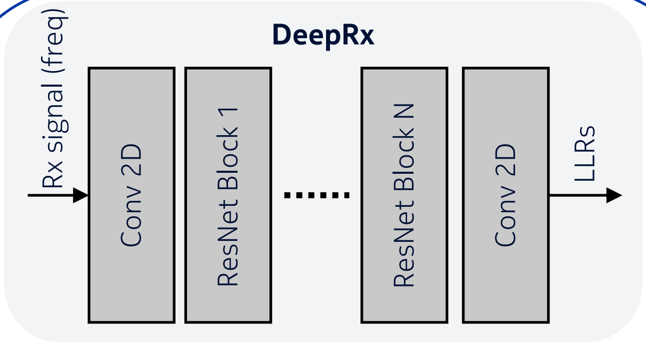
# Conclusions

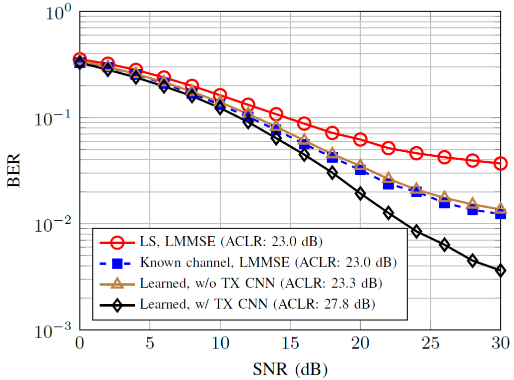
**Transmitter**




**Receiver**




- The proposed approach can limit emissions while improving link performance
- Facilitates either higher TX powers or more efficient PA modules

# Related Publications


- Dani Korpi, Mikko Honkala, Janne Huttunen, Faycal Ait Aoudia, Jakob Hoydis, “Waveform Learning for Reduced Out-of-Band Emissions Under a Nonlinear Power Amplifier,” submitted to *EUCNC 2022*.
- Mathieu Goutay, Fayçal Ait Aoudia, Jakob Hoydis, Jean-Marie Gorce, “Learning OFDM Waveforms with PAPR and ACLR Constraints,” submitted to *IEEE Transactions on Wireless Communications*, 2021.
- F. A. Aoudia and J. Hoydis, "Trimming the Fat from OFDM: Pilot- and CP-less Communication with End-to-end Learning," in *Proc. IEEE International Conference on Communications Workshops (ICC Workshops)*, Jun. 2021.

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