Learned Pulse Shaping Design for PAPR Reduction in DFT-s-OFDM

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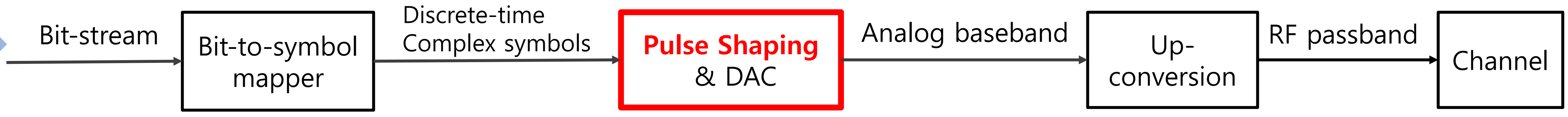
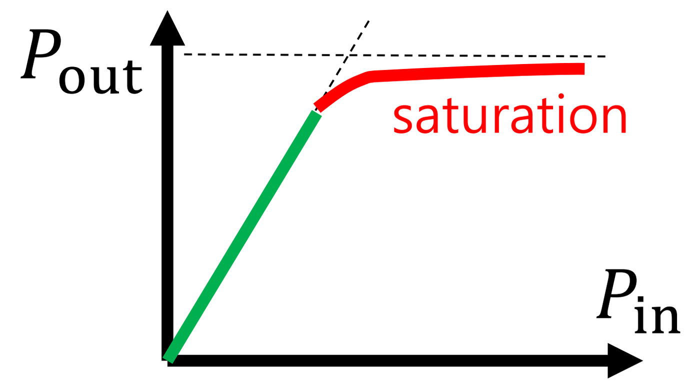
Introduction



Motivation: Peak-to-Average Power Ratio (PAPR) reduction

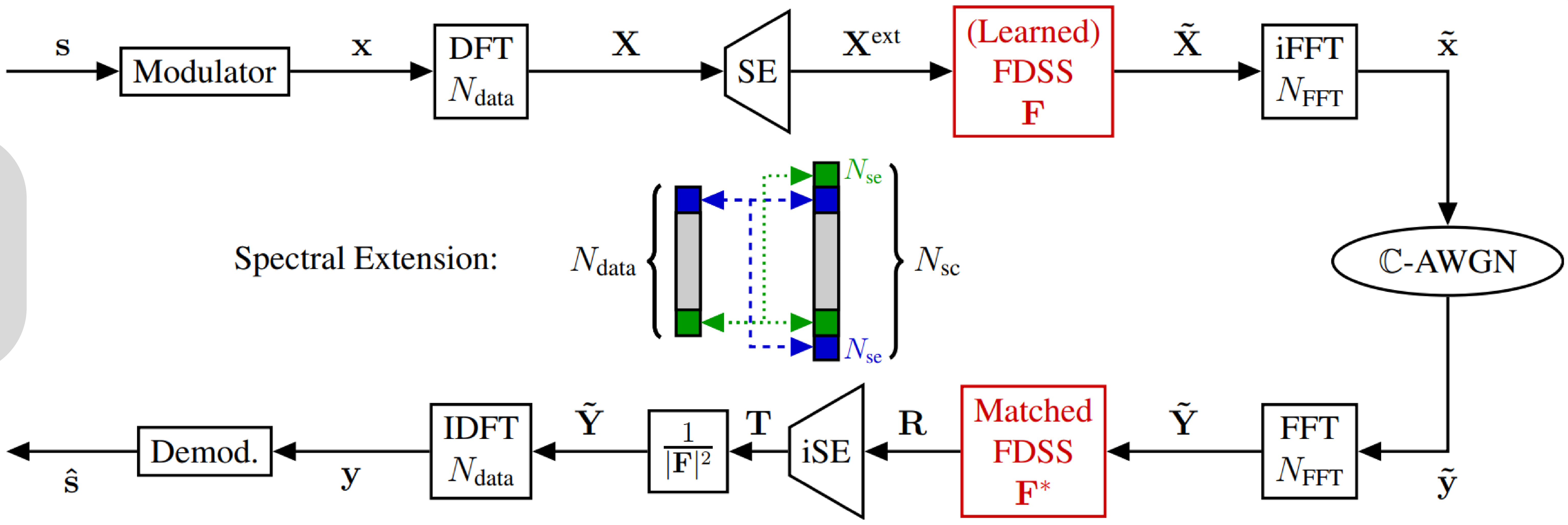
- High PAPR → input power back off to **avoid PA saturation** → **reduced SNR / coverage!**
- **Impact of low-PAPR waveforms**: increased uplink coverage; allow use of cheaper PA on mobile device



Objective: design pulse shaping filter with the following requirements

- **(almost) zero-ISI** and **(almost) flat impulse** response in the passband
- **PAPR reduction** with **limited SNR degradation**

System Model: DFT-s-OFDM with FDSS

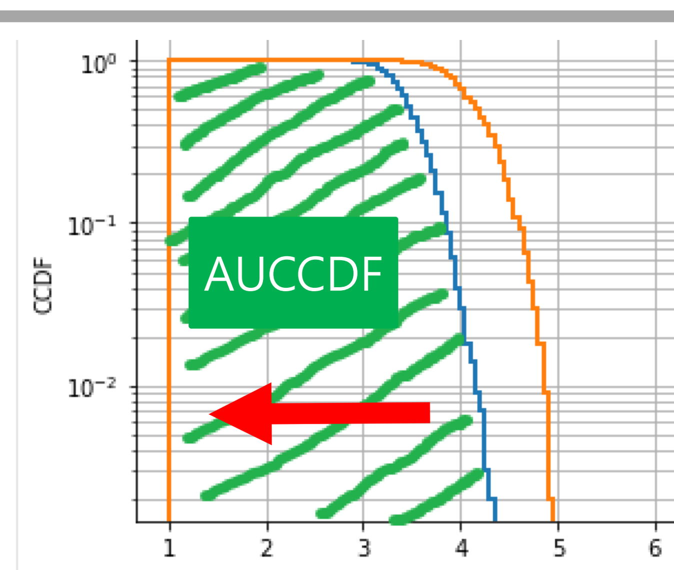


Proposed solution for PAPR reduction

Learn filter taps: $F_1, F_2, \dots, F_{N_{sc}}$

Loss function: $\mathcal{L} = \mathcal{E} + \lambda\mathcal{P} + \gamma\mathcal{S}$

- **SER component** $\mathcal{E}$: MSE between $(\mathbf{x}, \mathbf{y})$
- **PAPR component** $\mathcal{P}$:
  - Instantaneous PAPR $= 10\log_{10}\frac{\max|\tilde{x}_t|^2}{\sum|\tilde{x}_t|^2/N_{\text{FFT}}}$
  - Area under CCDF (AUCCDF)
- **FDSS shape component** $\mathcal{S}$: Spectral flatness $= 10\log_{10}\frac{(\prod F_i)^{1/N}}{\sum F_i/N}$

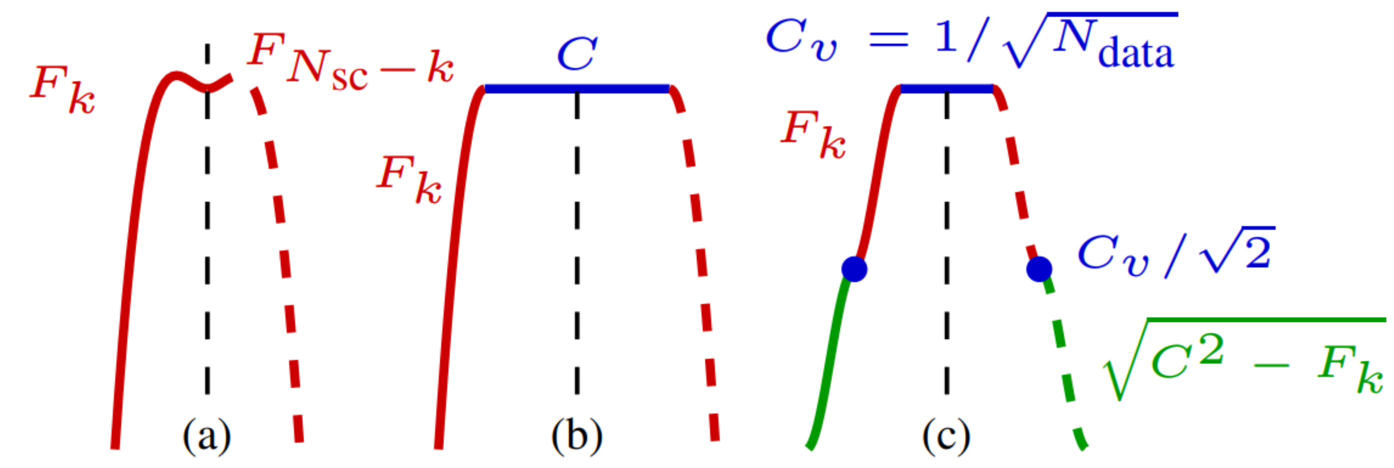


Constrained FDSS design: Polynomial approx

Parameters: $D+1$ polynomial coefficients $\{a_i\}_0^D$

Define filter taps: $F_k = \sum_{d=0,\dots,D} a_d\,[s(k)]^d$,

k: subcarrier index, $s(k)$: support value



Results

Limiting cases

- **When only SER is important** ($\lambda \to 0$ and $\gamma \to 0$) → any zero-ISI pulse works (i.e., flat passband and vestigial symmetry on the sideband)
- **When only PAPR is important** ($\lambda \to \infty$) → "bell-shaped" pulse

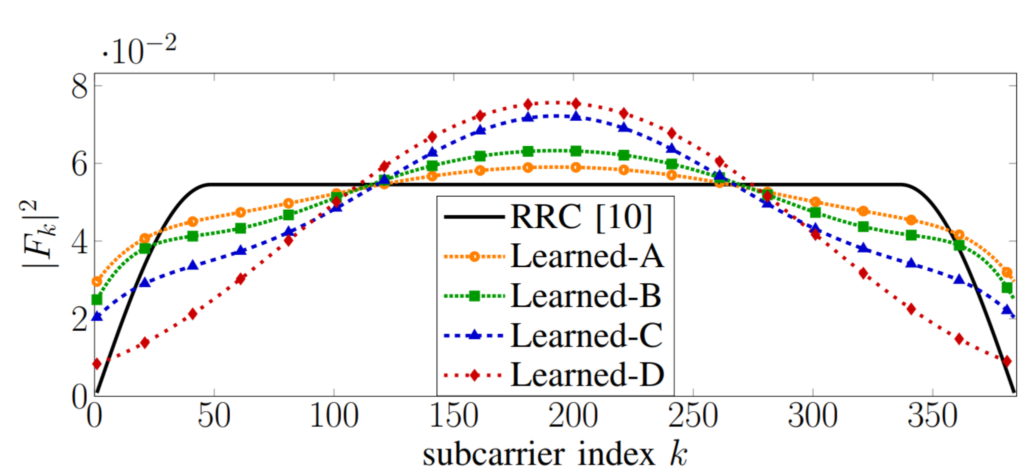


Fig. 3: Learned FDSS filters for limiting cases when EBW = 14.2%. Resulting performance w.r.t. RRC FDSS:

Baseline: RRC [10]	SNR loss at SER=10^{-2}	PAPR gain at CCDF=10^{-3}
Learned-A	0.10 dB	1.15 dB
Learned-B	0.25 dB	1.4 dB
Learned-C	1 dB	1.8 dB
Learned-D	3 dB	2.3 dB

Almost flat and flat filters

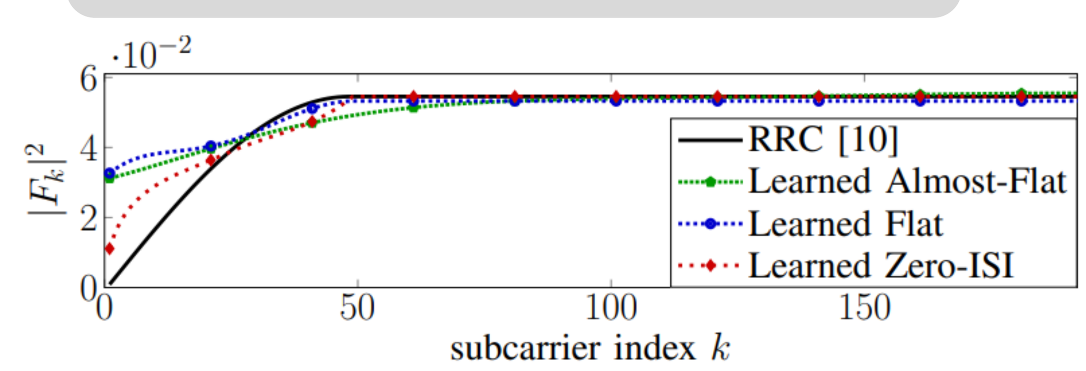
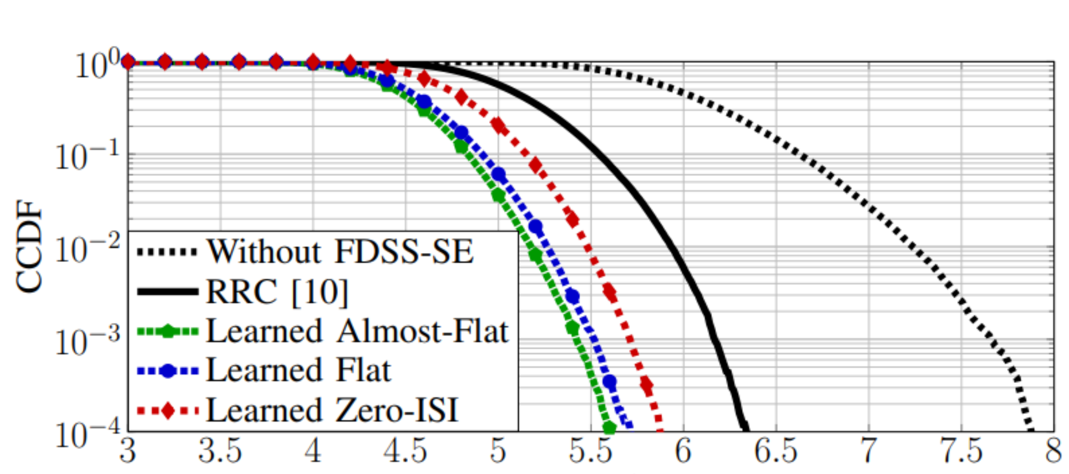


Fig. 4: Learned FDSS filters with different constraints when EBW = 14.2%. Only the first half of the subcarriers is shown in this plot. Resulting performance w.r.t. RRC FDSS:

Baseline: RRC [10]	SNR loss at SER=10^{-2}	PAPR gain at CCDF=10^{-3}
Learned Almost Flat	0.05 dB	0.8 dB
Learned Flat	0.05 dB	0.65 dB
Learned Zero-ISI	0 dB	0.5 dB



Resampled vs retrained filters

- Learn a filter for a specific configuration of N_{SC} and EBW
- *Resample* a filter learned for a different configuration

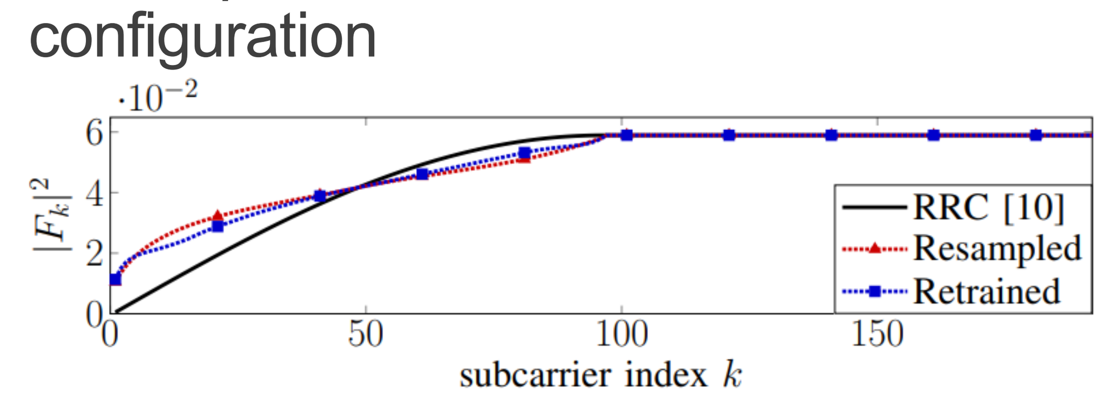


Fig. 6: Learned FDSS filters with zero-ISI design when EBW = 33.3%. The resampled filter is the same (learned zero-ISI for EBW = 14.2%) as Fig. 4, but with the sideband has been sampled more finely. Performance w.r.t. RRC FDSS:

Baseline: RRC [10]	PAPR gain at CCDF=10^{-3}
Resampled Zero-ISI (Fig. 4)	0.3 dB
Retrained Zero-ISI	0.4 dB

Conclusion

✓ End-to-end ML-based FDSS design

✓ Flexible loss function and constraints

✓ Outperform conventional baselines

✓ Good benchmark for achievable PAPR

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