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Recent Advances in Digital Predistortion Methods

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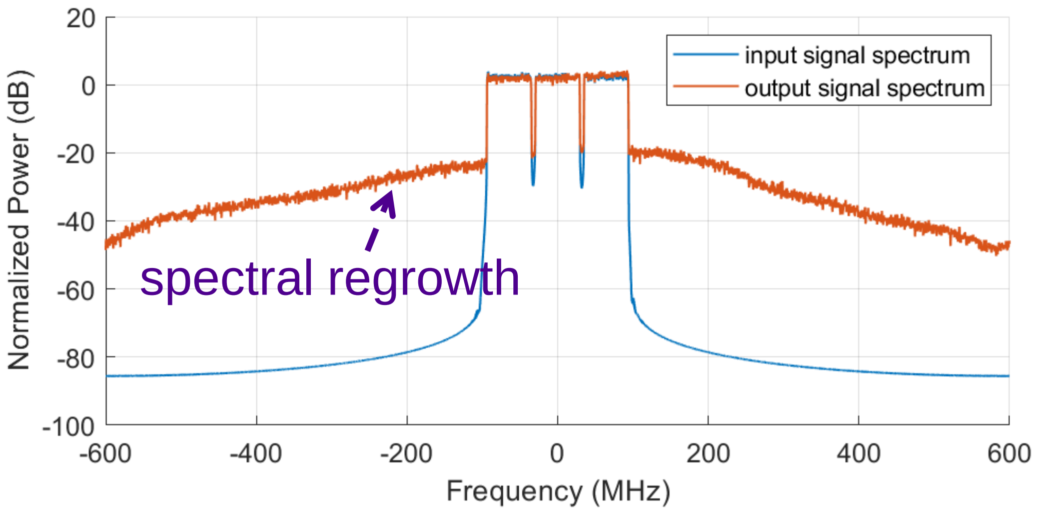
Outline

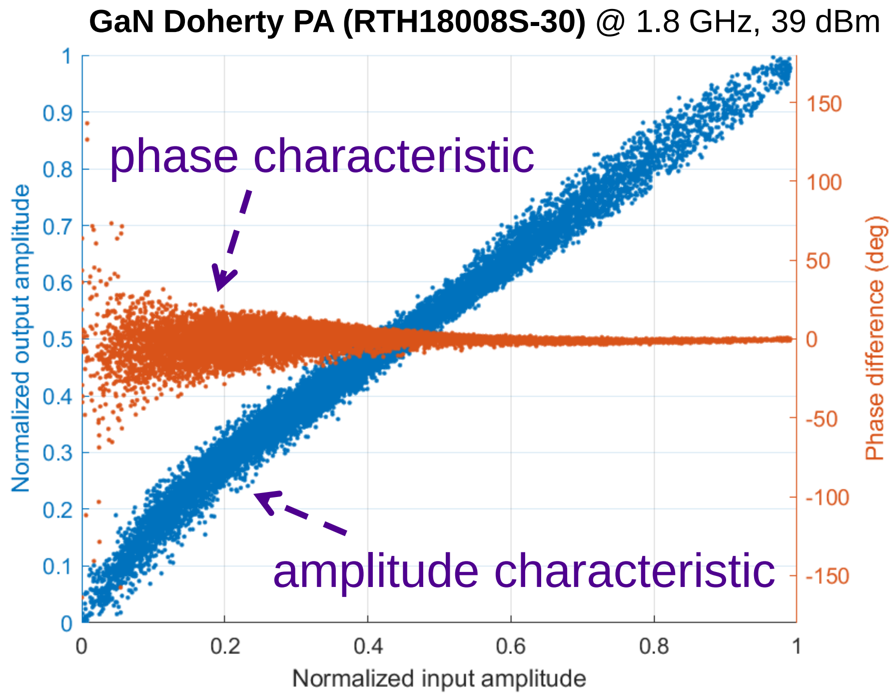
- Power amplifier nonlinearity and DPD – Quick recap
- **Neural networks for PA linearization**
- **Phase-normalized NNs**
- **Multi-antenna DPD**
- Summary and Future work
- References

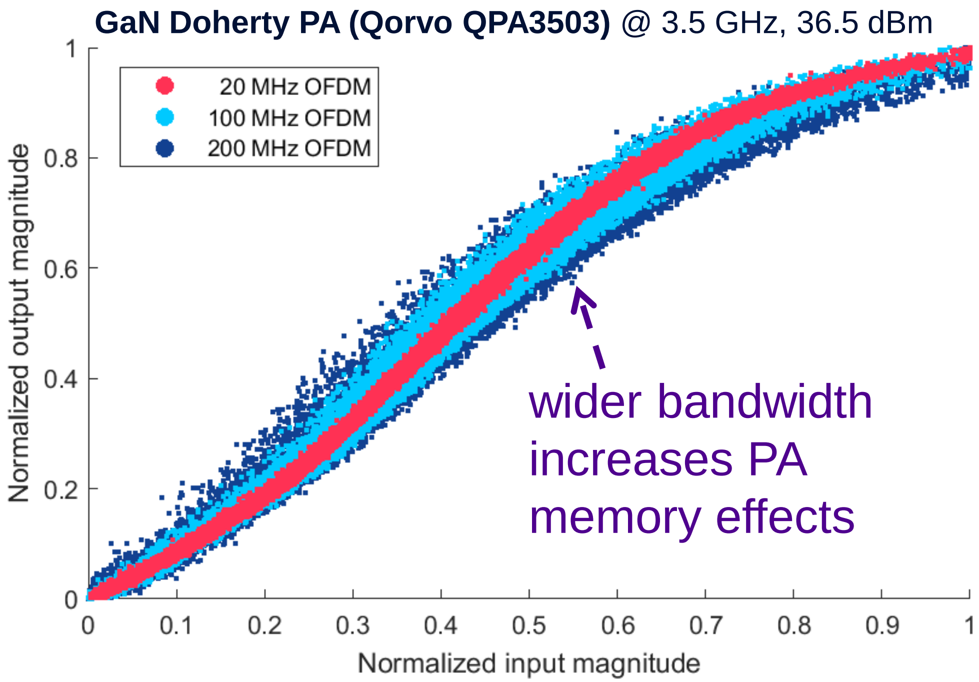
PA distortion
Problem

Complex valued envelope/baseband signals

- **nonlinear distortion**
- **dynamic distortion (“memory”)**
- *time-variant distortion -> solved by adaptation*



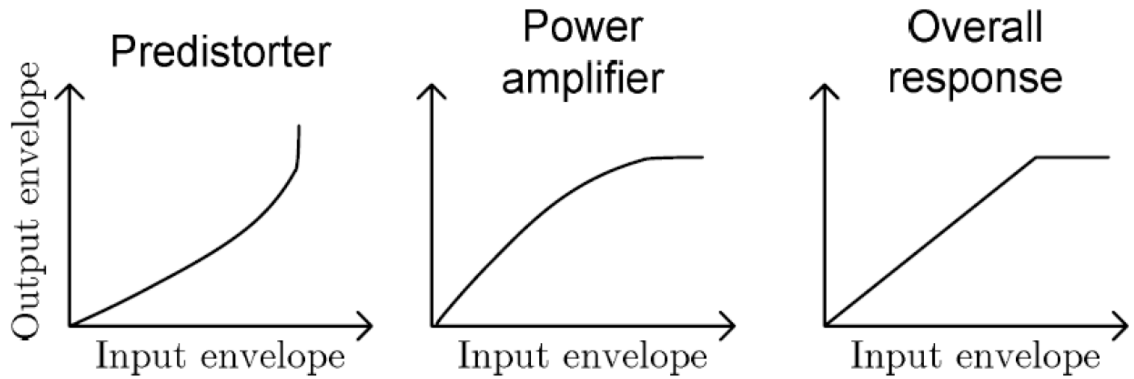


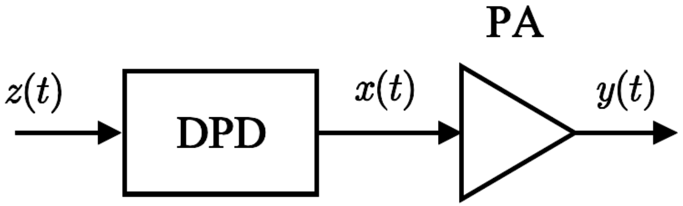


Digital predistortion (DPD)

DPD means preprocessing the digital transmit signal such that when put through a nonlinear PA, the overall response is more linear

- Thus, naturally, nonlinear preprocessing is needed
- The DPD models are based on PA behavioral models





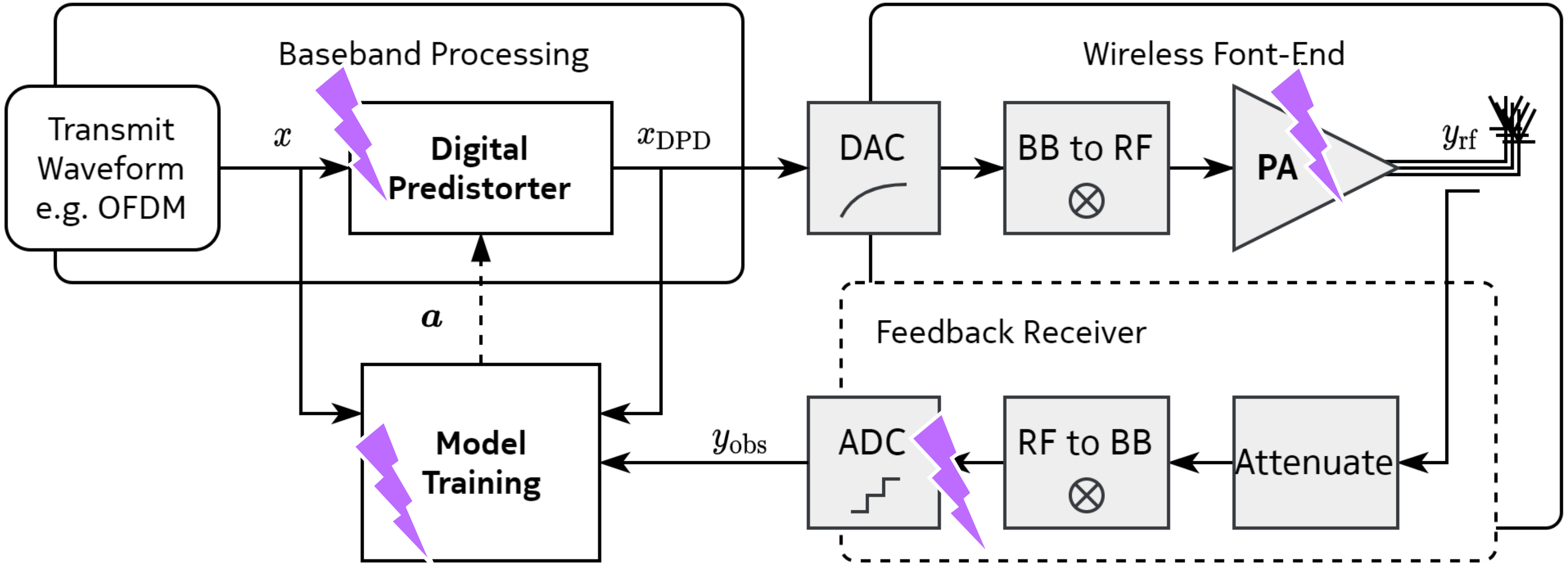
DPD targets

- Improve EVM
- Improve ACLR
- Reduce spurious emissions
- Improve transmitter power efficiency with given emission constraints

DPD Challenges

- *capable models required to compensate distortion*
- low-complexity requirement for efficient inference

- wide-band signals stimulate strong dynamic distortion
- new PA technologies (GaN, HEMT, etc.)
- *antenna coupling, load modulation → beam-dependent DPD*



- model identification complexity
- real-time adaptation to signal changes
- beam adaptation

- high linearity and bandwidth requirement
- sampling rate is driving ADC energy / cost
- Observation architecture in multi-antenna systems?

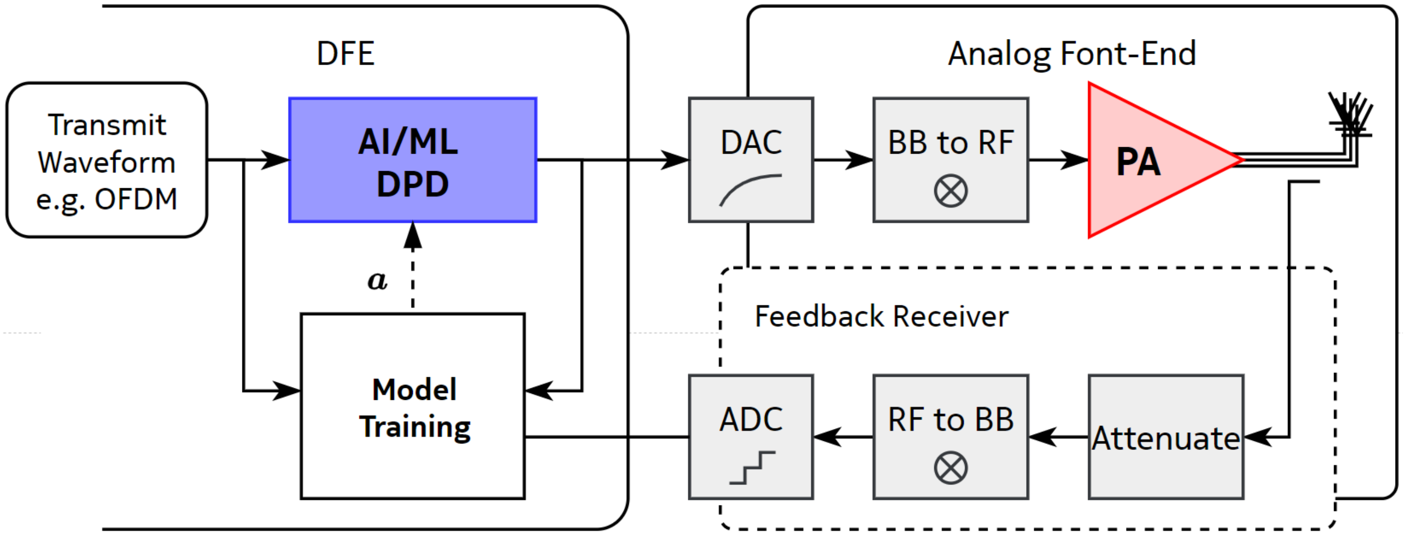
Neural Network DPD

Why AI/ML?

Motivation

6G DPD requirements

- low area and energy footprint
- excellent linearization (wideband, FCC)
- high flexibility



AI/ML offer

- NN offer high modeling capacity with good generality
- fully data-driven approach, low manual tuning effort

Q: Can AI/ML DPD deliver superior linearity with competitive complexity/cost?

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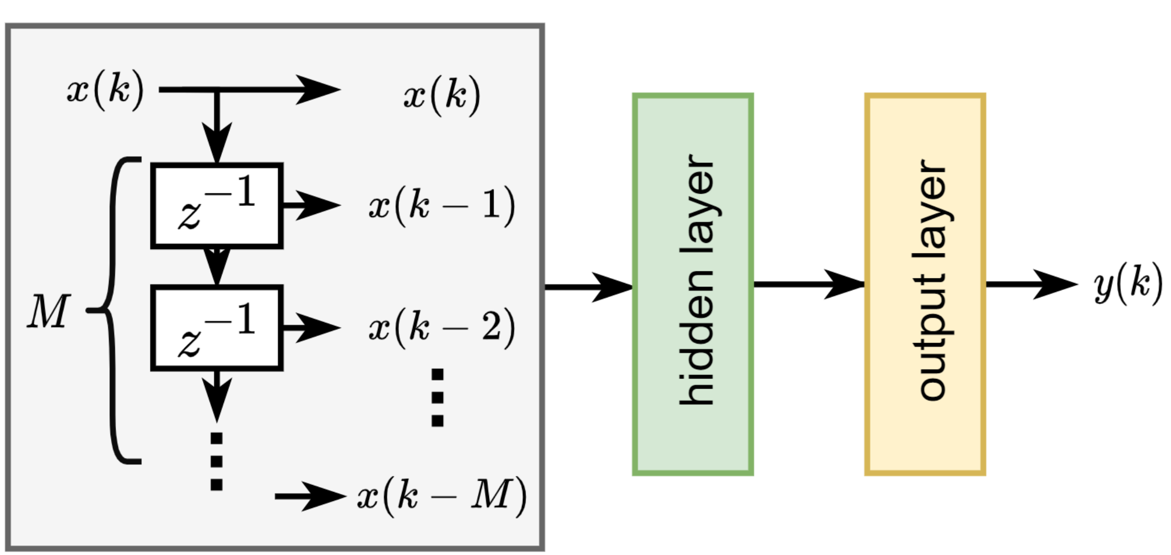
Modeling dynamic distortion with NNs

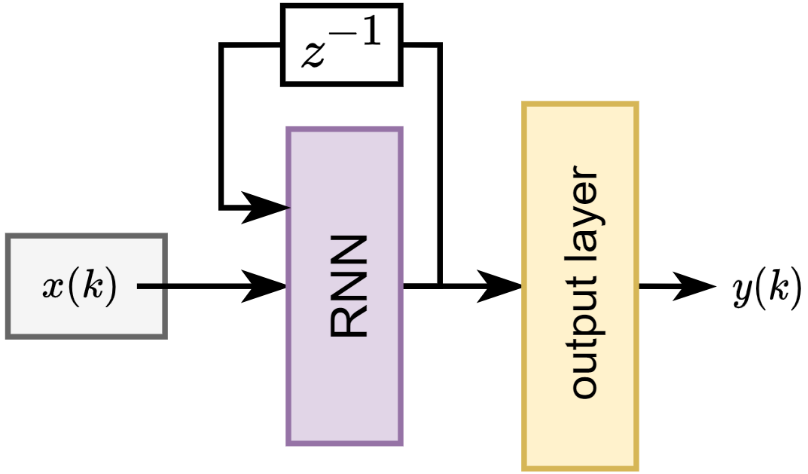
NN architectures

Time-delay Neural Network



- “simpler” architecture
- limited memory depth

Recurrent Neural Network

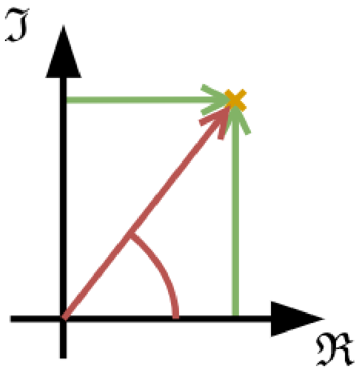


- more complex training and structure
- infinite memory depth (in theory)
- closer to PA physics

Complex-valued baseband signals

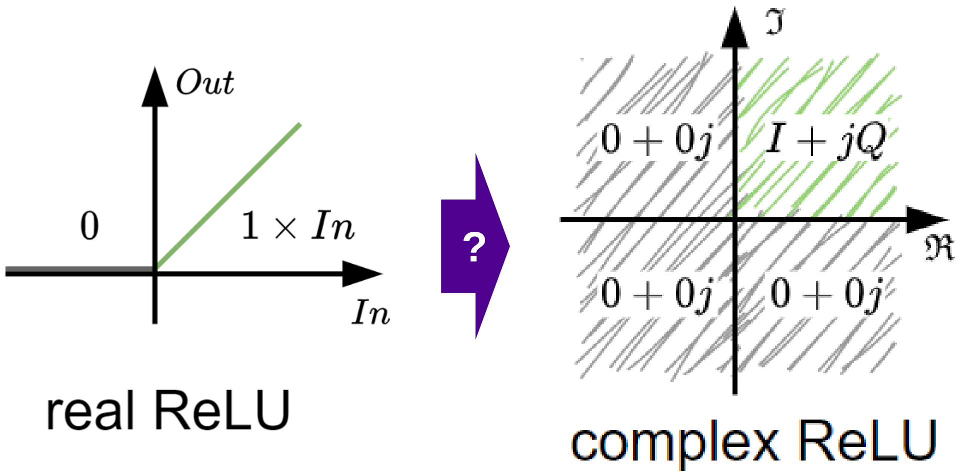
…with real-valued NN structures

- decompose cartesian: real & imaginary
  - *joint or separate processing ?*
  - *support for complex-valued arithmetic?*



- decompose polar: magnitude & angle
  - *significance of phase depends on magnitude ?*
  - *support for $\pm\pi$ periodicity ?*

- complex-valued neural network
  - *non-obvious choice of activation function ?*
  - *complication with back-propagation ?*
  - <u>*theory and tools not fully developed*</u>



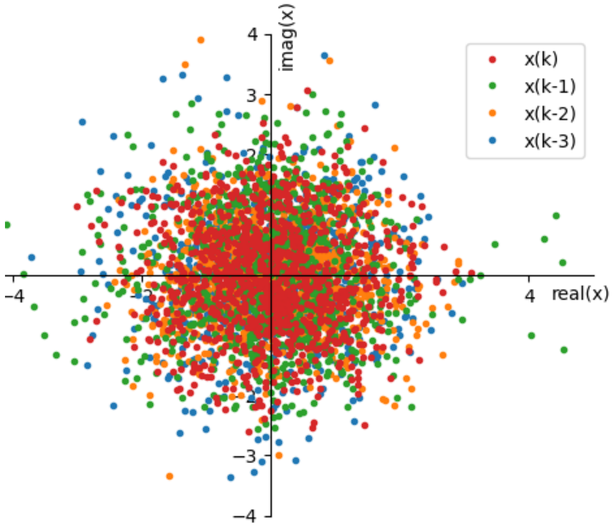
Phase-Normalized NN

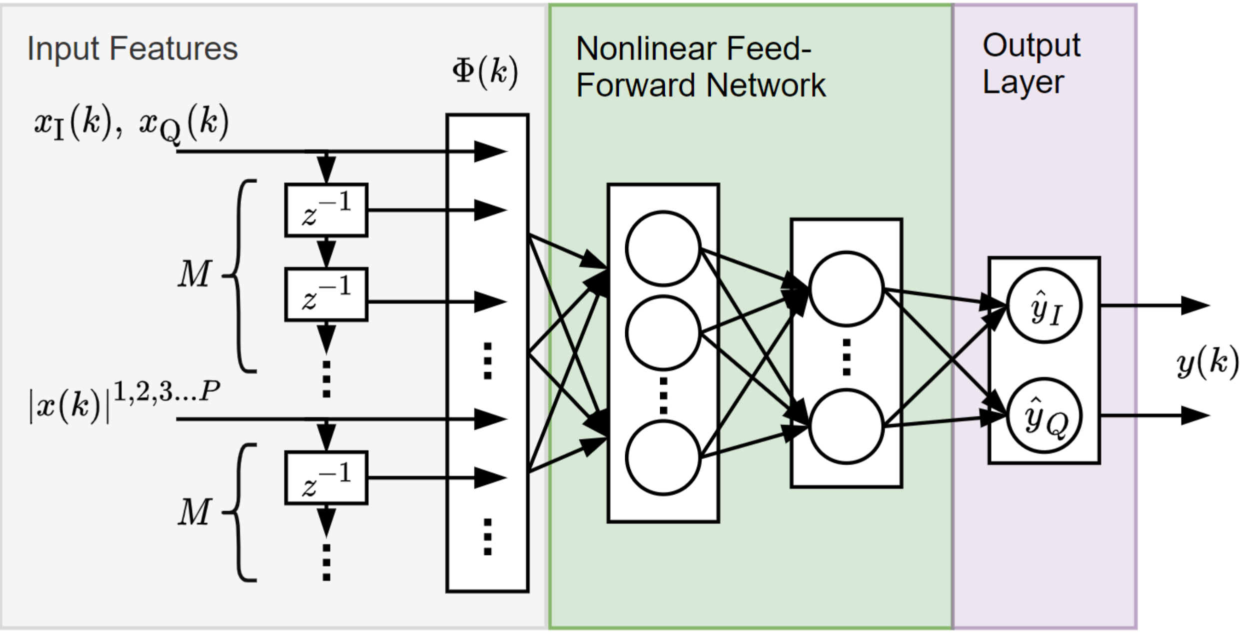
Augmented real-valued TDNN

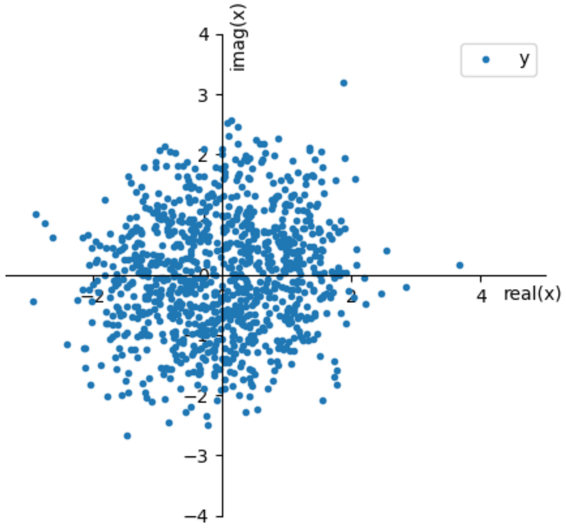
Decompose real & imaginary

separation of real/imaginary part (I/Q)
$\rightarrow$ real-valued processing

additional absolute/envelope inputs $|x(k)|$
$\rightarrow$ nonlinear effects depend on envelope







Issues: 1) can also express non-physical RF effects
2) inefficient at processing of complex data

Distortion-phase dependency

Baseband	↔	**RF passband**
PA/DPD model		nonlinear PA
complex-valued I/Q signal	↔	I/Q-modulated RF carrier
signal magnitude	↔	envelope modulation
phase derivative	↔	frequency modulation

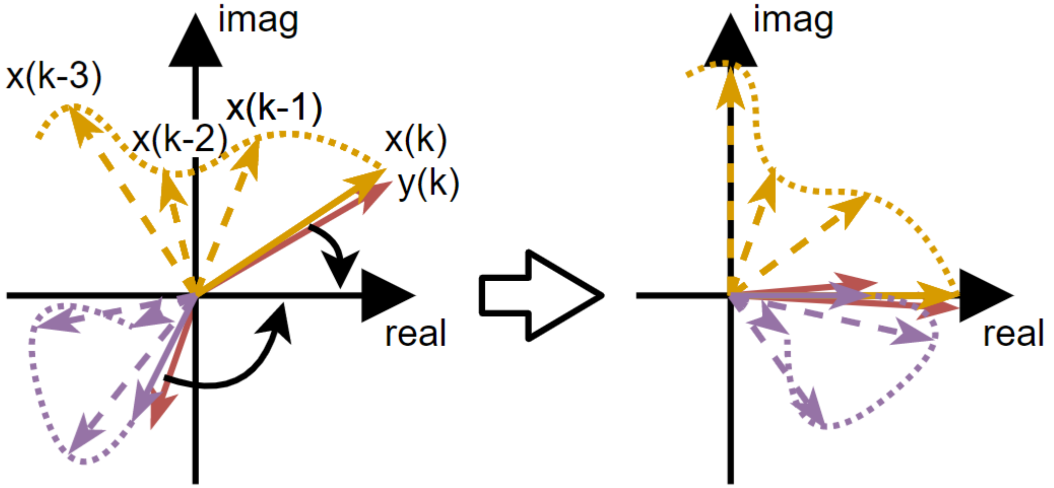
- Instantaneous baseband signal phase is meaningless in the RF domain
- Only *phase derivative* contributes to PA distortion

Phase normalization

Proposed solution

process only magnitude and phase trajectory instead of I/Q decomposed signal

- rotating the input vectors with angle of current input



Normalization factor: $r(k) = x^*(k)/|x(k)|$

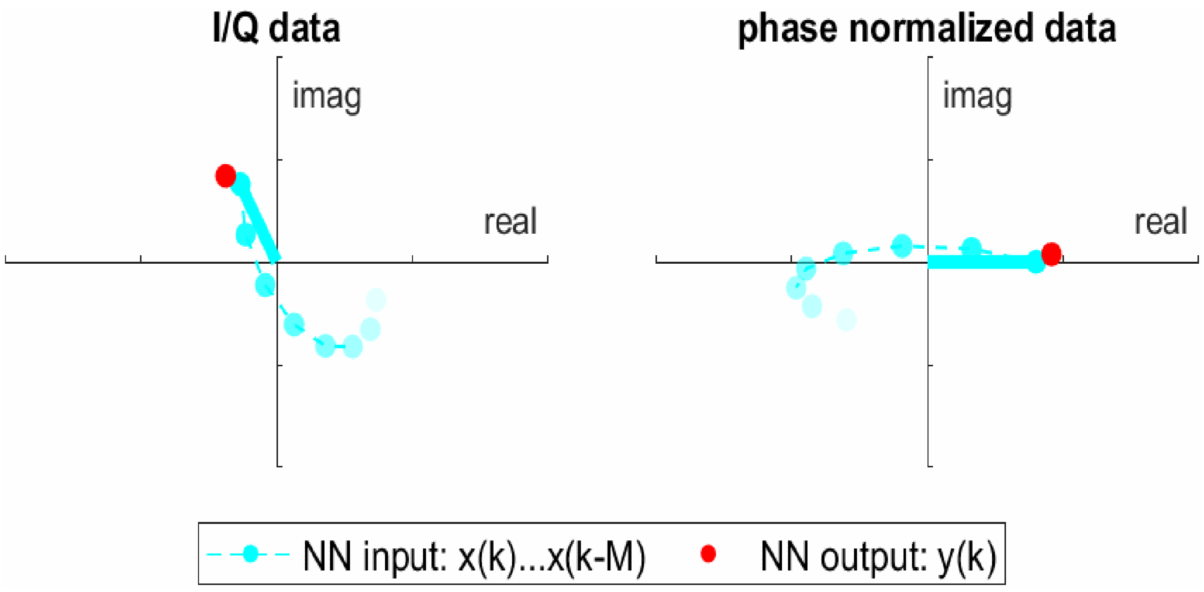
Phase normalized NN inputs:

$$\boldsymbol{X}(k) = r(k)[x(k), x(k-1), x(k-2), \dots, x(k-M)]$$

$$= [\,|x(k)|, r(k)x(k-1), \dots, r(k)x(k-M)]$$

NN output phase recovery:

$$y(k) = r^*(k)\, f_{\mathrm{NN}}(\,\boldsymbol{X}(k)\,)$$



A. Fischer-Bühner, L. Anttila, M. D. Gomony and M. Valkama, "Phase-Normalized Neural Network for Linearization of RF Power Amplifiers," in *IEEE Microwave and Wireless Technology Letters*, Sept. 2023, doi: 10.1109/LMWT.2023.3290980

Phase normalized time-delay NN

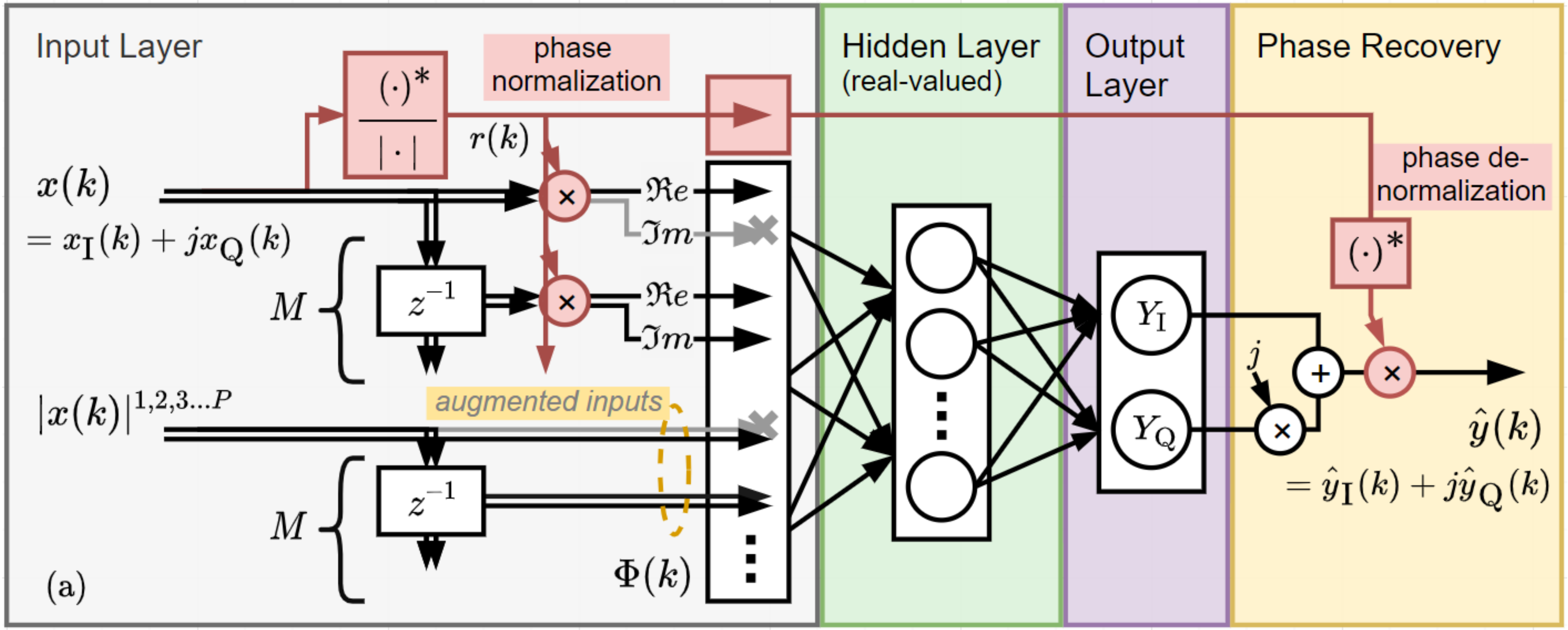
PNTDNN

real-valued NN

baseband processing

passband nonlinearity

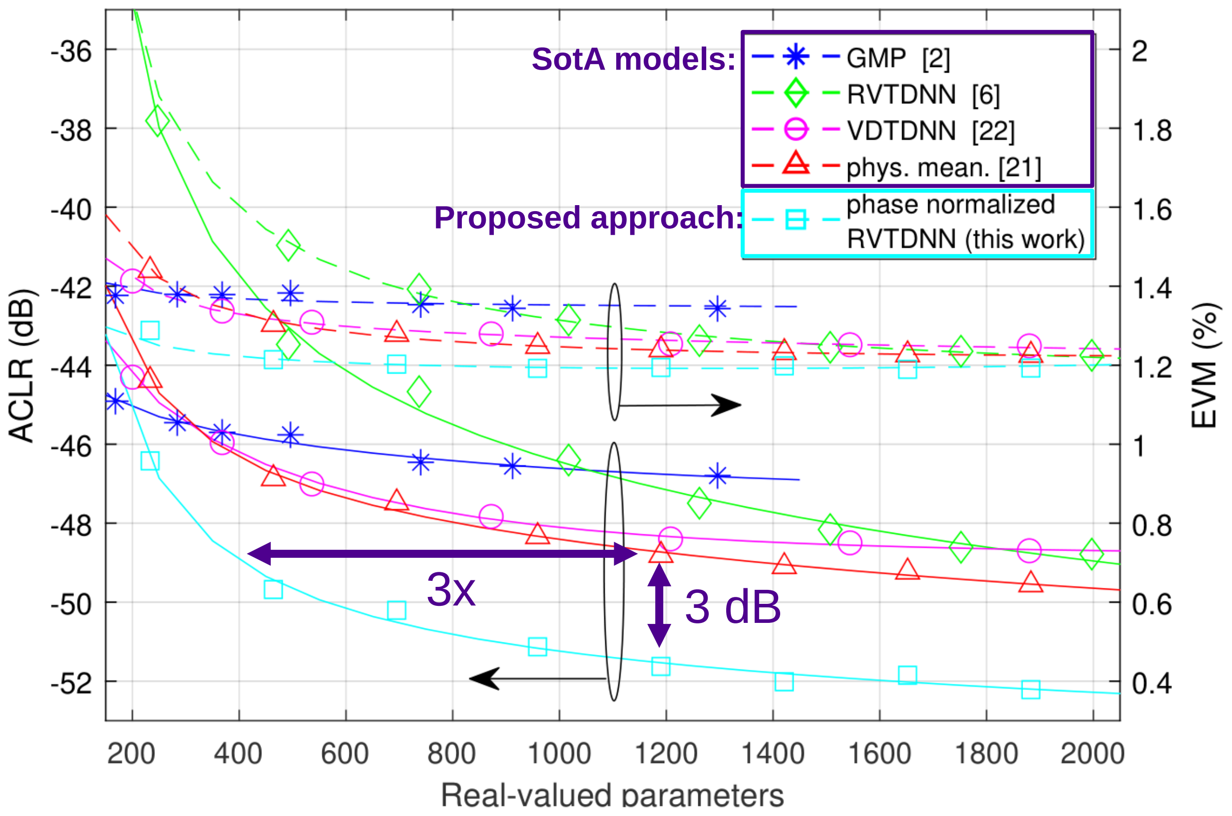
Embedded into augmented real-valued time-delay NN (ARVTDNN)

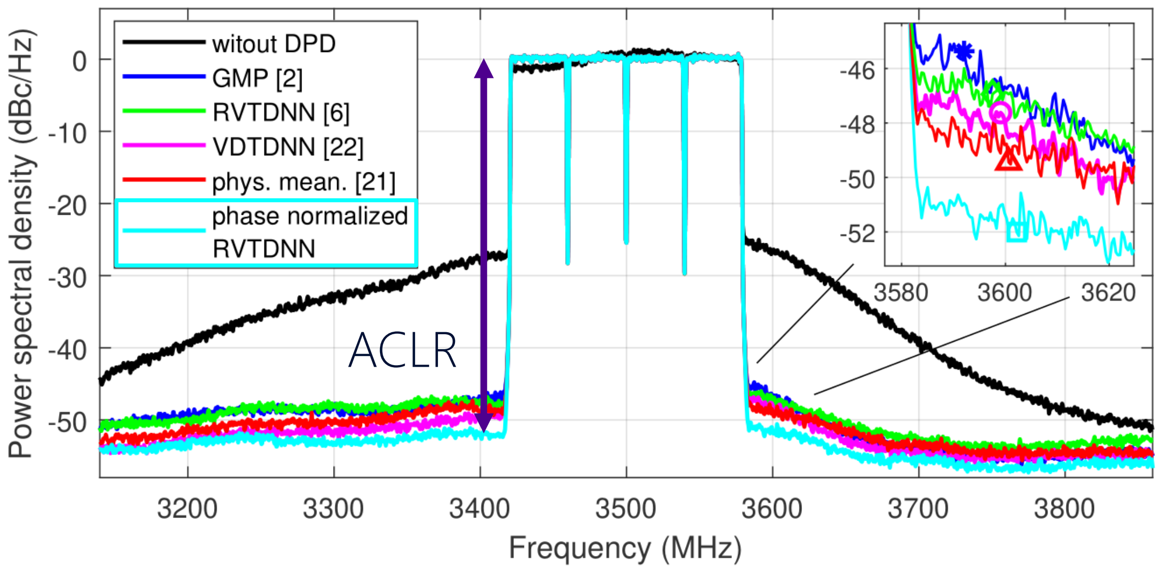


DPD linearization results

DUT: QPA3503, 3.5 GHz, 160 MHz, 8.5 dB PAPR

Generalized memory polynomial (GMP)
Real-valued time delay NN (*RVTDNN*)
Vector decomposed time-delay NN (*VDTDNN*)
"Physically Meaningful" DPD model (*Phys. Mean.*)





- ➢ **3 dB lower/better ACLR**
  (compared with best published SotA NN)
- ➢ **1/3 model complexity**
  (similar performance)

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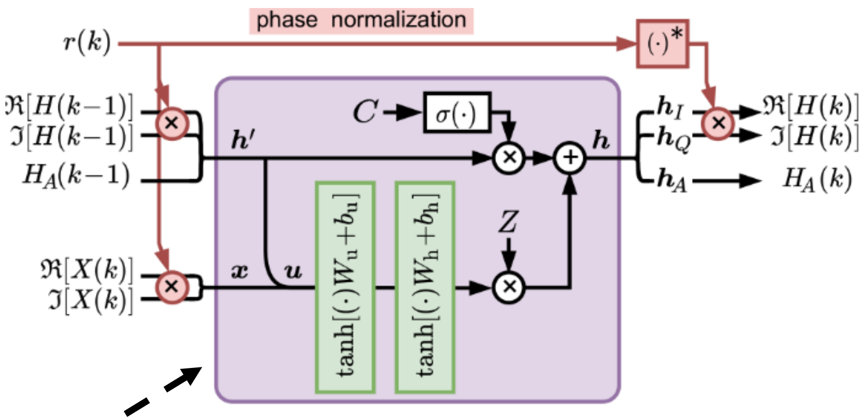
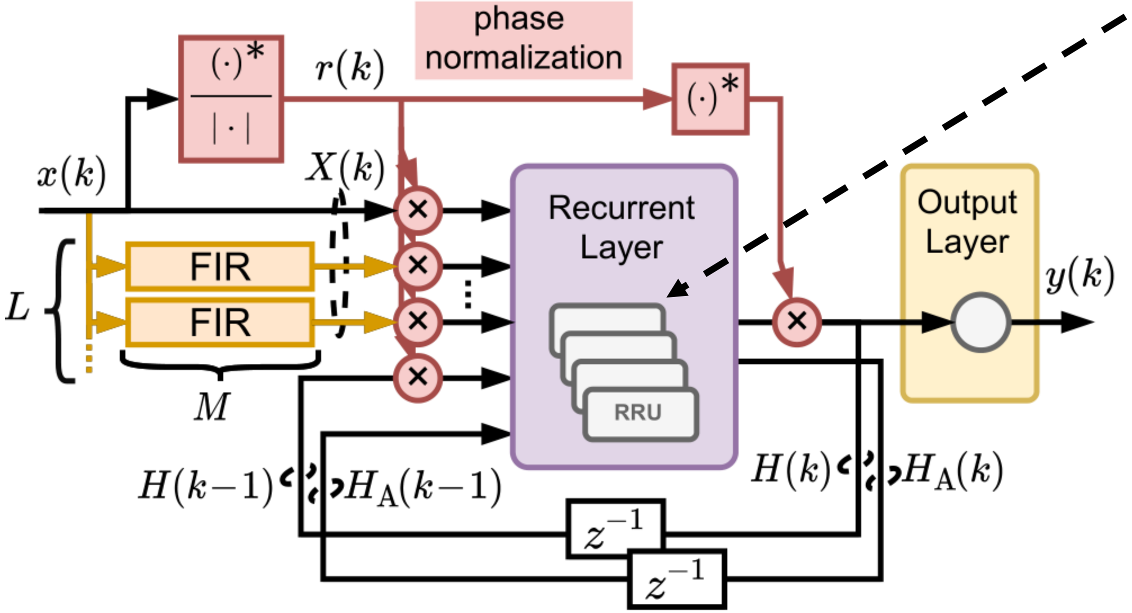
Augmented phase-normalized RRU (APNRRU)

- incorporated phase-norm to RNNs with complex-valued RNN internal state representation
- added learnable input-side FIR filters
- utilized the Residual Recurrent Unit (RRU)

Residual recurrent unit (RRU)





A. Fischer-Bühner et al., "Augmented Phase-Normalized Recurrent Neural Network for Modeling for RF Power Amplifier Linearization," in *IEEE Transactions on Microwave Theory and Techniques, 2024*

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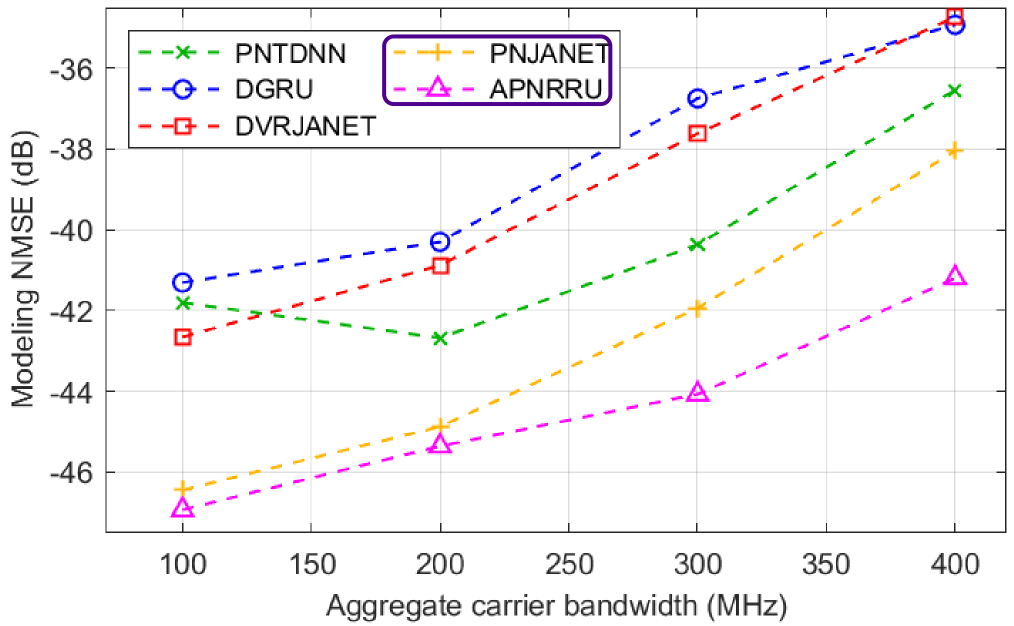
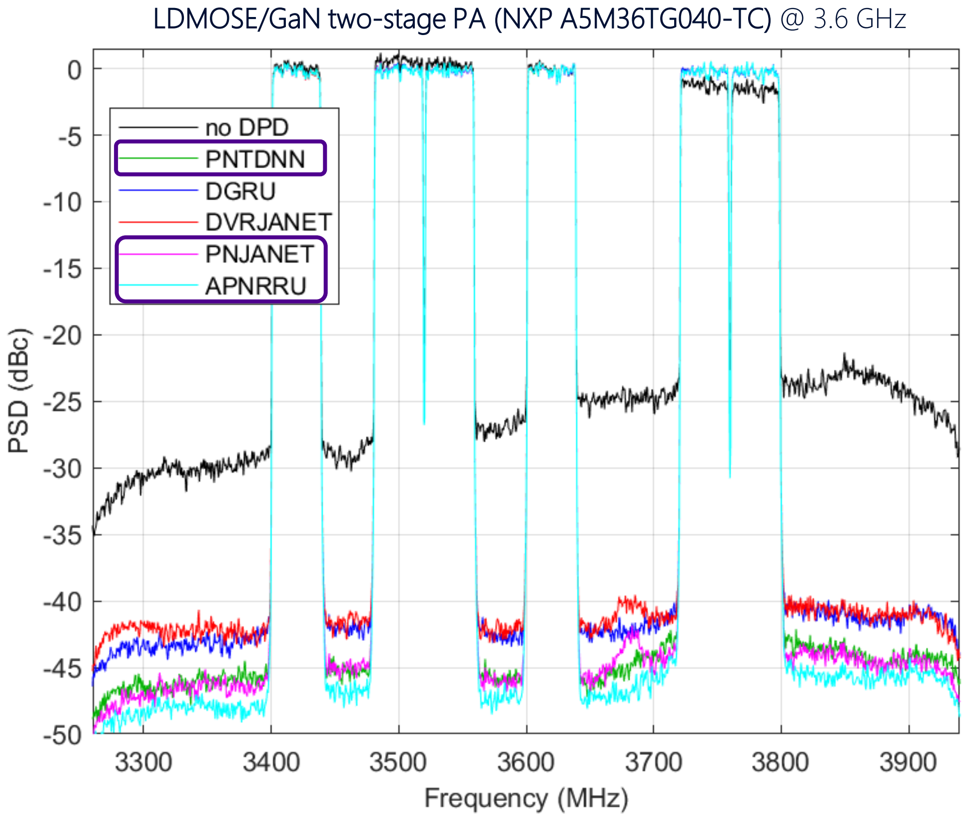
APNRRU – Wideband Modeling and DPD results





Dense GRU (DGRU)
Decomposed Vector Rotation JANet (DVR-JANet)
Phase normalized time-delay NN (PNTDNN)

Name	Parameters	NMSE (dB)	ACLR (dB)	EVM (%)
without DPD	–	-17.60	-23.52	6.16
PNTDNN	1110	-33.38	-43.18	1.80
DGRU	1045	-32.18	-40.42	1.71
DVRJANET	1098	-32.36	-40.19	1.56
PNJANET	1026	-34.63	-43.80	1.48
APNRRU	1041	-35.93	-45.24	1.24

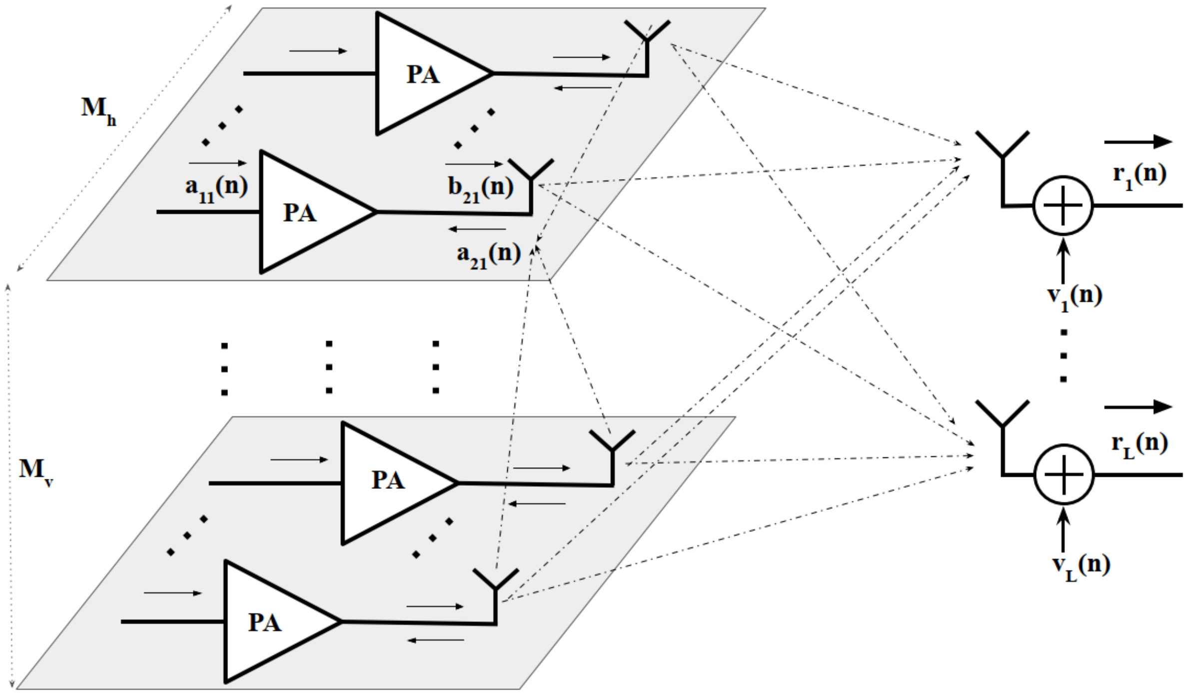
Multi-antenna DPD

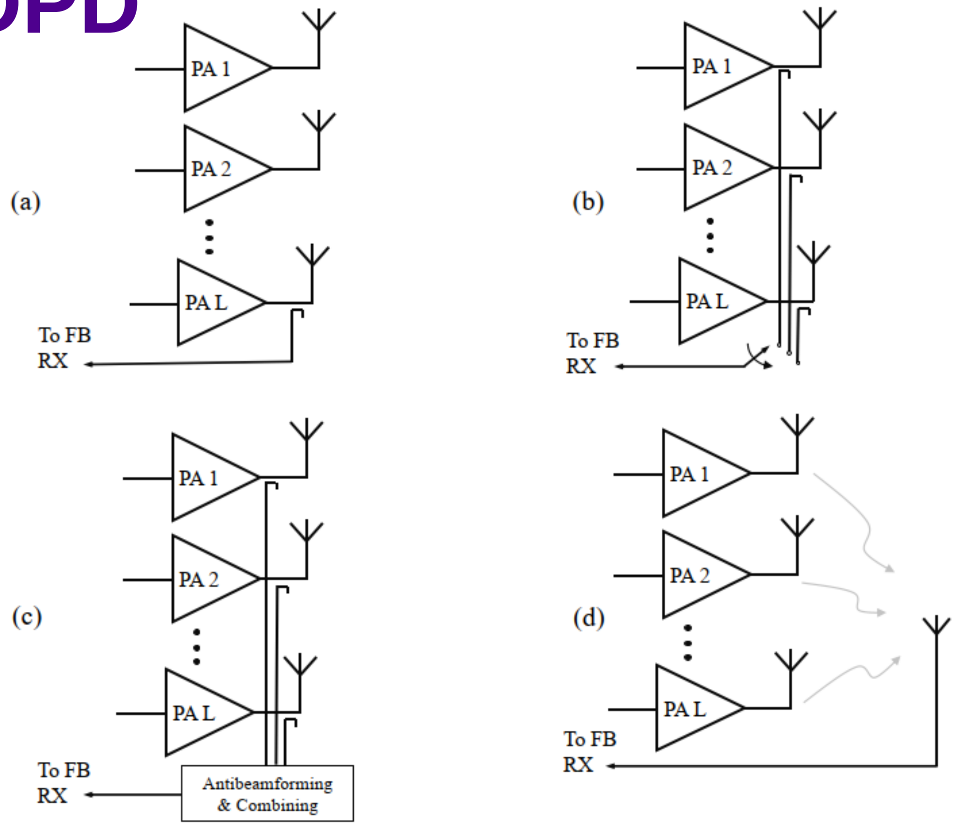
Some Challenges in Multi-Antenna DPD

Antenna coupling and **PA load modulation**

→ **Cross-modulation** between antenna signals

→ **Beam-dependent nonlinear distortion**





How to arrange feedback for DPD learning?

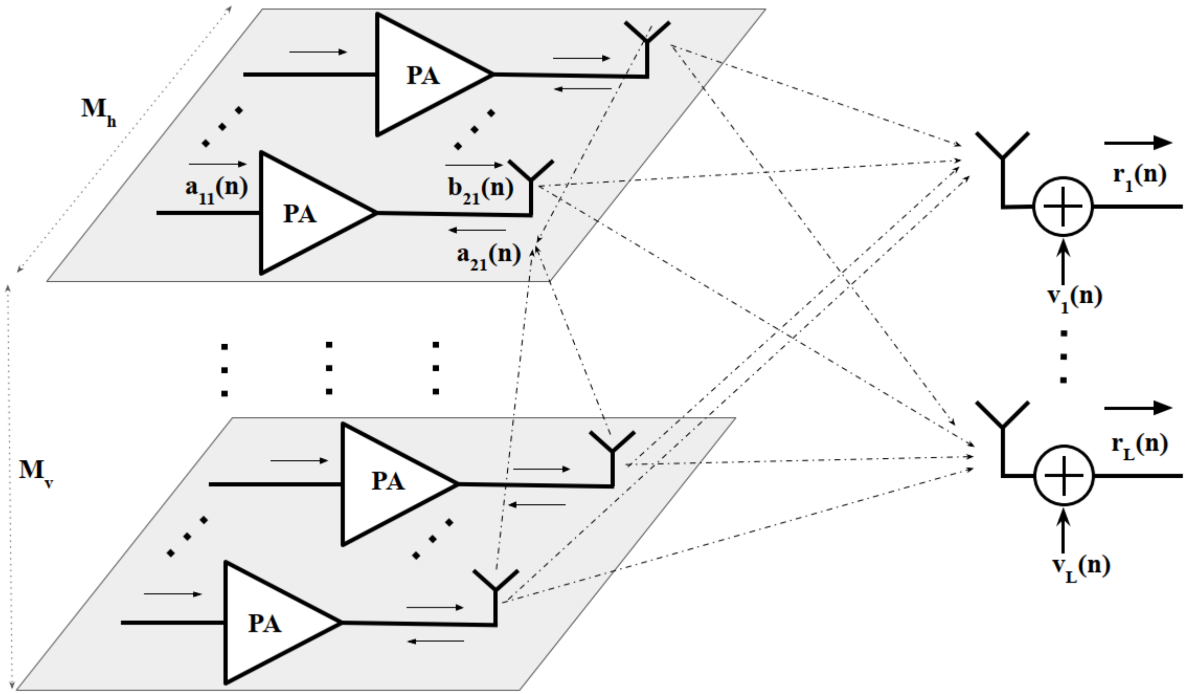
a) Single feedback
b) Shared feedback
c) Combined-feedback
d) Over-the-air (OTA) feedback
e) Dedicated feedback (not shown)

Modeling Multi-Antenna TX under Load Modulation

Problem: PA forward model estimation from <u>OTA observations</u>

We recently developed an iterative algorithm, under the following assumptions:

- Minimum two observation antennas/RXs required
- <u>Dual-input memory polynomial models</u> for modeling the nonlinear PAs under load modulation
- Beam-sweeping observations over ≥K directions
- Coupling coefficients (S-parameters) between antennas are known



- The estimated PA models are used in a subsequent step for DPD learning

$$b_{2k} = \sum_{p=0}^{(P-1)/2} \alpha_{kp} a_{1k}^{(p+1)} {a_{1k}^{*}}^{p} + \sum_{p=0}^{(P-1)/2} \beta_{kp} a_{1k}^{p} {a_{1k}^{*}}^{p} a_{2k} + \sum_{p=1}^{(P-1)/2} \gamma_{kp} a_{1k}^{(p+1)} {a_{1k}^{*}}^{(p-1)} a_{2k}^{*}$$

$$a_{2k} = \sum_{i=1, i\neq k}^{K} \lambda_{ki} b_{2i}$$

J. Fernandez et al., "Over-the-Air Linearization of Phased Array Transmitters Affected by Load Modulation," *IEEE Transactions on Circuits and Systems I: Regular Papers*, doi: 10.1109/TCSI.2025.3527701. (Early Access)

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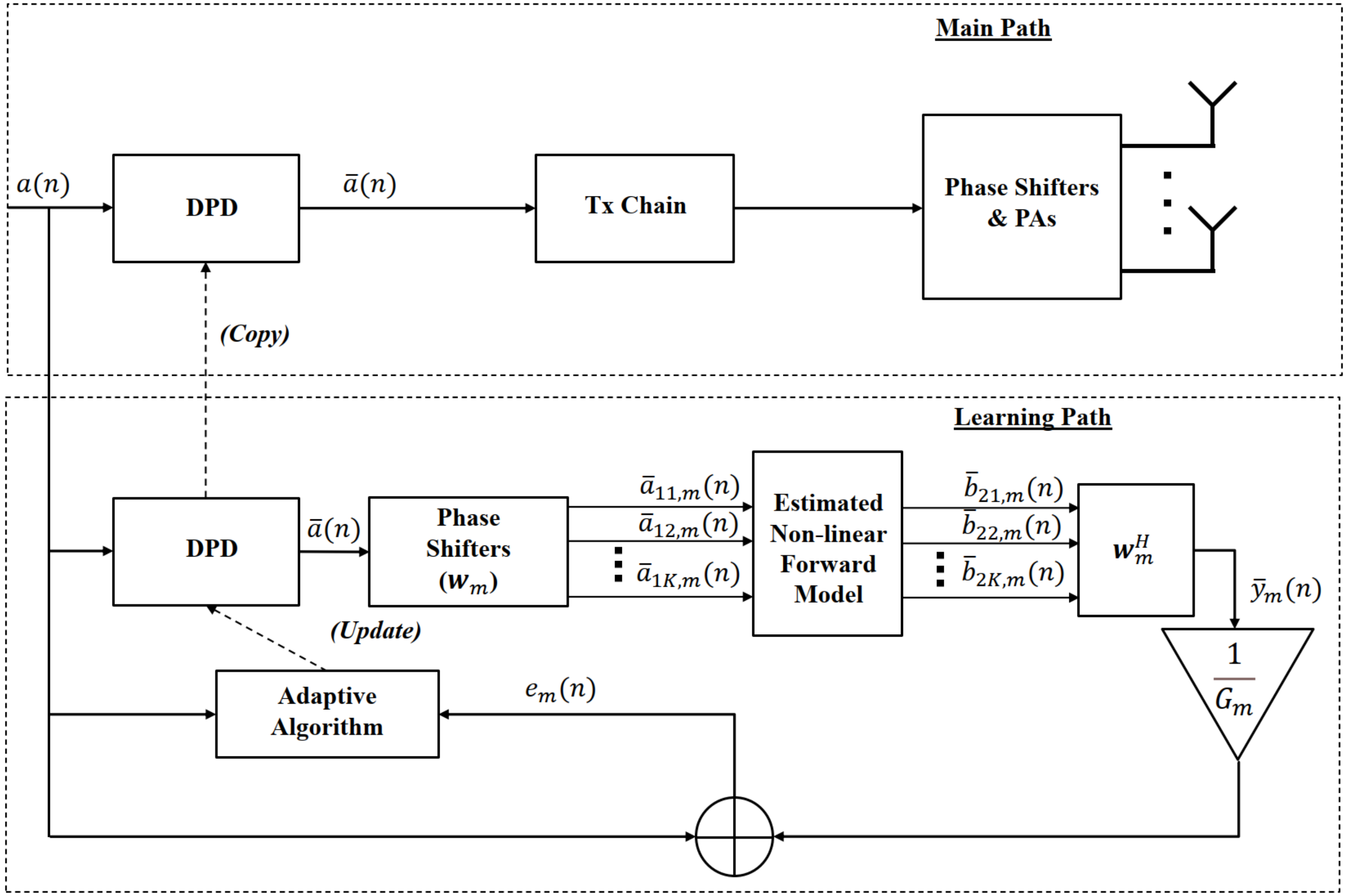
DPD Architecture for Phased Array

Utilizing the estimated nonlinear forward model, we developed a DPD solution, which

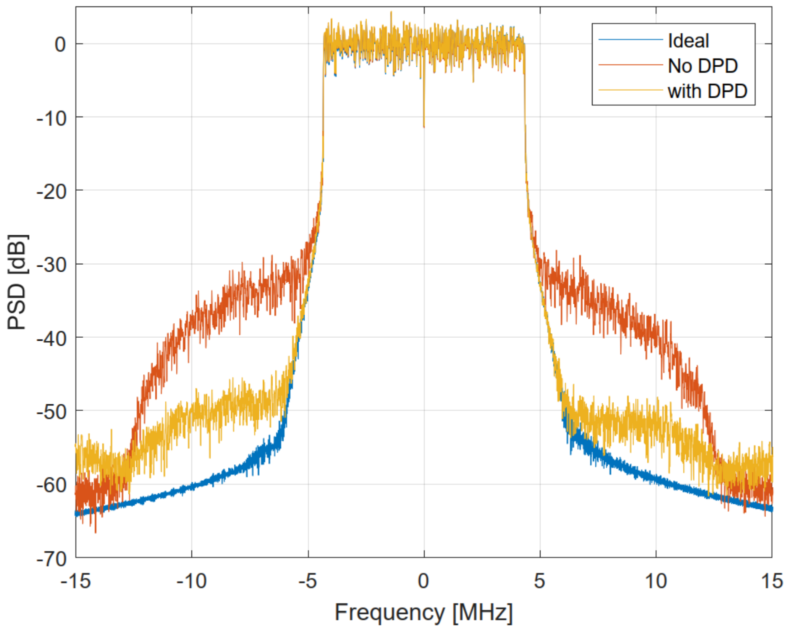
- Accounts for PA load modulation caused by antenna coupling.
- Enables on-line adaptation while steering the beam.
- Has low computational complexity.
- Addresses beam-dependency of nonlinear distortions, greatly improving transmitter linearity.

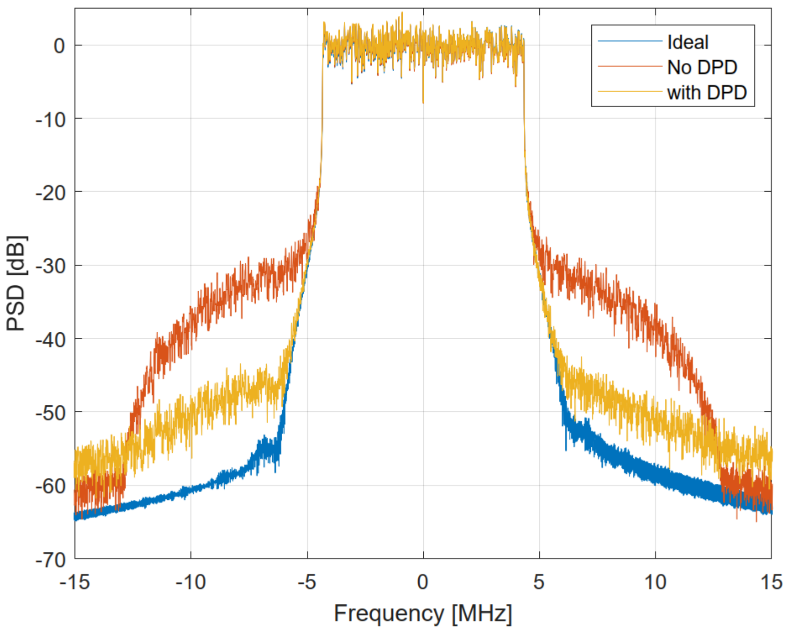


Proof-of-Concept Measurement Results

- Measured PA signals with load modulation, utilizing a coupling emulation technique
- 4x1 array coupling model
- Successful linearization over different beamforming angles

- First OTA DPD technique that can handle load modulation!





Beamforming angle (in degrees)	Simulation with a measured PA model				Measurement with an actual PA array			
	EVM (w/o DPD)	EVM (with DPD)	ACPR (w/o DPD)	ACPR (with DPD)	EVM (w/o DPD)	EVM (with DPD)	ACPR (w/o DPD)	ACPR (with DPD)
-60°	5.207%	3.049%	−35.82	−52.29	5.427%	3.001%	−35.37	−50.07
-30°	4.571%	2.418%	−36.00	−53.28	5.066%	2.738%	−35.29	−50.36
0°	5.038%	3.006%	−35.63	−50.01	5.154%	2.793%	−35.50	−46.90
30°	4.591%	2.605%	−36.55	−51.25	5.183%	2.781%	−35.51	−49.60
60°	4.964%	2.846%	−36.57	−51.15	5.910%	3.504%	−35.14	−49.65

Summary and Future Work

- Phase-normalized NN for DPD
  - Time-delay and recurrent variants developed
  - State-of-the-art performance at given complexity

- Multi-antenna DPD under load modulation
  - Developed OTA based learning solution for phased-array TX – First solution
  - Developed NN model for forward modeling and DPD in digital MIMO TX – SoTA perf

- On-going and Future work
  - Merging these two study lines
  - Further research on OTA-based multi-antenna DPD
  - Developing the ML/NN-based solutions further:
    - complexity reductions, learning architecture research, MIMO measurement studies, design exploration towards implementation

Literature

[1] A. Fischer-Bühner, L. Anttila, M. Dev Gomony and M. Valkama, "Phase-Normalized Neural Network for Linearization of RF Power Amplifiers," in *IEEE Microwave and Wireless Technology Letters*, Sept. 2023, doi: 10.1109/LMWT.2023.3290980.

[2] A. Fischer-Bühner, L. Anttila, M. Turunen, M. Dev Gomony and M. Valkama, "Augmented Phase-Normalized Recurrent Neural Network for RF Power Amplifier Linearization," in IEEE Transactions on Microwave Theory and Techniques, vol. 73, no. 1, pp. 412-422, Jan. 2025, doi: 10.1109/TMTT.2024.3484581.

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[7] P. Jaraut, M. Rawat, and F. M. Ghannouchi, “Composite neural network digital predistortion model for joint mitigation of crosstalk, I/Q imbalance, nonlinearity in MIMO transmitters,” *IEEE Transactions on Microwave Theory and Techniques*, vol. 66, no. 11, pp. 5011–5020, 2018.