5G Technology Workshop during Mobile World Congress in Barcelona

# Dimensionality Reduction Techniques for Digital Predistortion Linearization of NR-5G Amplification Architectures

Pere L. Gilabert, Gabriel Montoro, David López, Thi Quynh Anh Pham

Department of Signal Theory and Communications

plgilabert@tsc.upc.edu

# Outline

- Introduction
- Linearity vs. Efficiency Trade-off
- High Efficient Amplification Architectures
- Digital Predistortion (DPD) Linearization
- Dimensionality Reduction Techniques
- Conclusion

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# Introduction

Source: https://www.thegigcartel.com/News/mobile-phones-banned-at-two-london-eventim-apollo-gigs.htm

- Increasing demand of data traffic ⇨
  - ⇨ Spectrally efficient modulation schemes required + CA + MIMO
  - ⇨ Wide bandwidths and high PAPRs signals

# Introduction

- In 5G-NR the same network infrastructure will be able to efficiently serve different types of traffic with a very wide range of requirements:
  - huge number of users for the Internet of Things,
  - ultra-low latency and high reliability for mission critical systems,
  - or enhanced transmission rates for broadband mobile communications.

- 5G-NR intends to provide very high data rates everywhere:
  - Bandwidths up to GHz will be allocated at mm-wave.
  - Aggregated bandwidths of hundreds of MHz will be required at sub-6 GHz.

# Introduction

For the design of radio transceivers, some of the demanding challenges that needs to be faced are related to:

- ensuring the linearity of signals having bandwidths of several hundreds of MHz and peak factors exceeding 10 dB,
- improving energy and computational efficiency, as more dense deployments of base stations is expected to scale down the need for transmitted power,
- transmitting architectures with multiple antennas (massive MIMO in mm-wave bands) and multiple power amplifiers to apply beamforming techniques that allow increasing the capacity and decreasing the radiated power,
- simultaneous transmission and reception (full-duplex FDD in sub 6 GHz bands, TDD in mm-wave bands).

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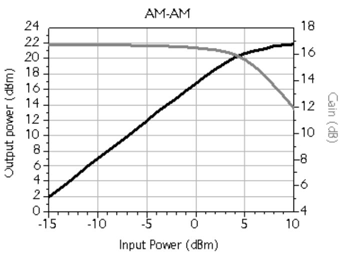
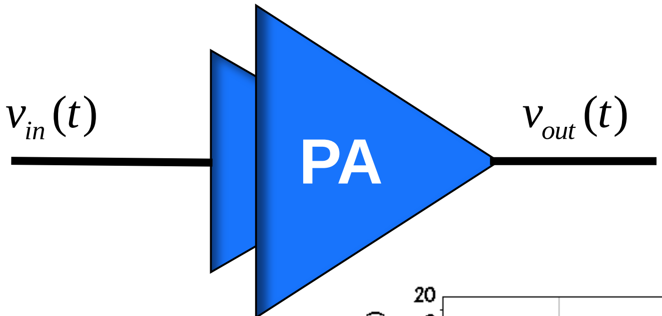
# Linearity vs. Efficiency

The Power Amplifier is a power hungry device...

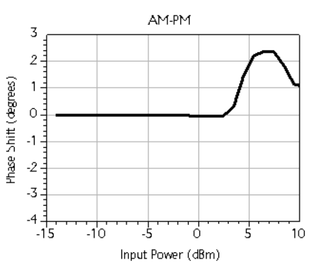
AM-AM

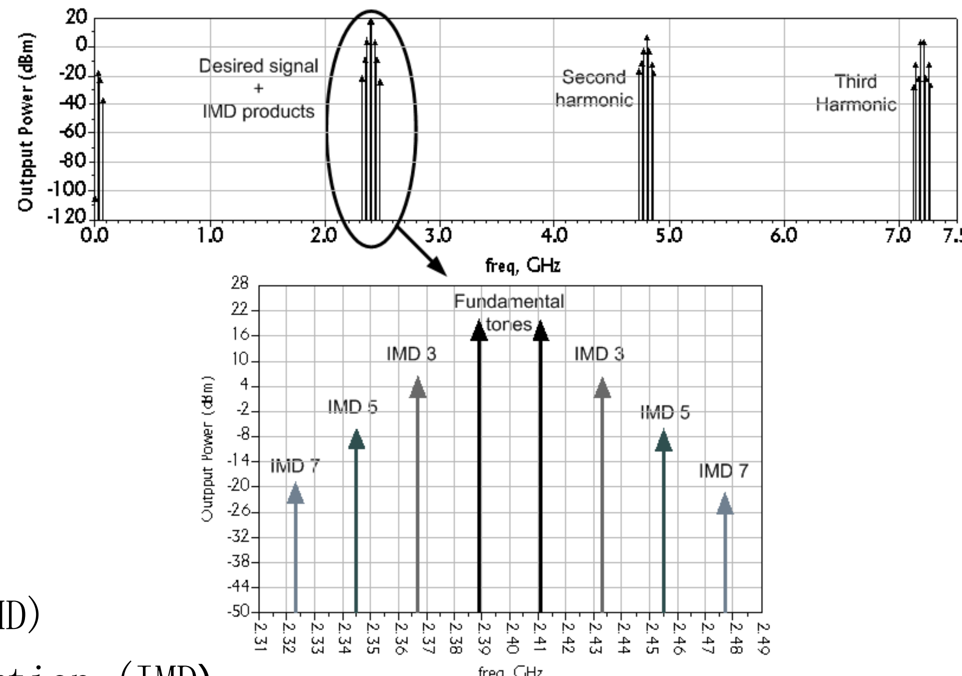



$$v_{out}(t) \approx \sum_{k=1}^{\infty} g_k v_{in}^k(t)$$

AM-PM




## In-Band Distortion

- Compression
- Capture

## Out-of-Band Distortion

- Harmonic Distortion (HD)
- Intermodulation Distortion (IMD)

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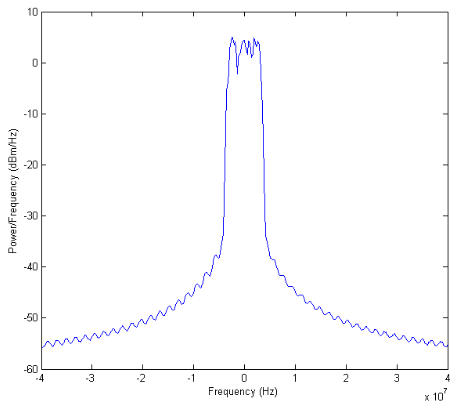
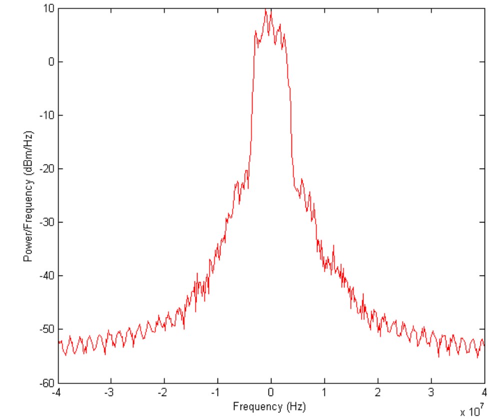
# Linearity vs. Efficiency

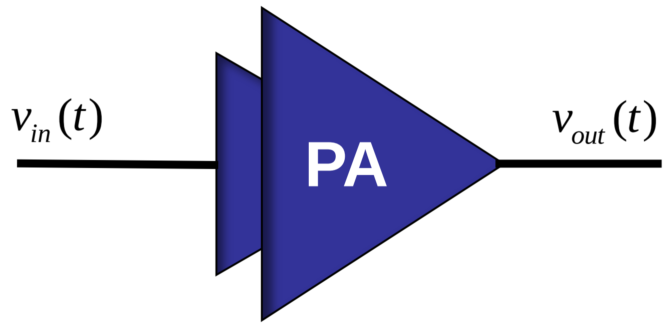
...that introduces unwanted nonlinear distortion...

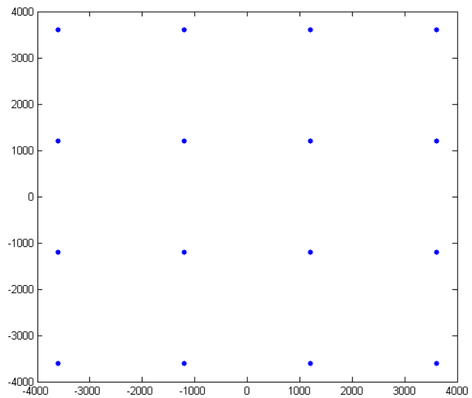



## Out-of-band Distortion

$$ACPR = \frac{\int_B P_{out}(f)\cdot df}{\int_{LS} P_{out}(f)\cdot df + \int_{US} P_{out}(f)\cdot df} \quad [dBr]$$

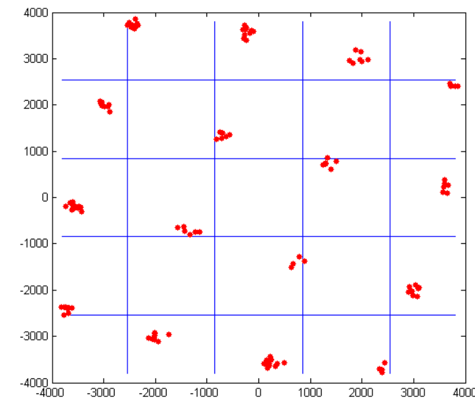


## In-band Distortion

$$EVM = \sqrt{\frac{\frac{1}{N}\sum_{1}^{N}\left(\Delta I^2 + \Delta Q^2\right)}{S_{max}^2}} \quad [\%]$$



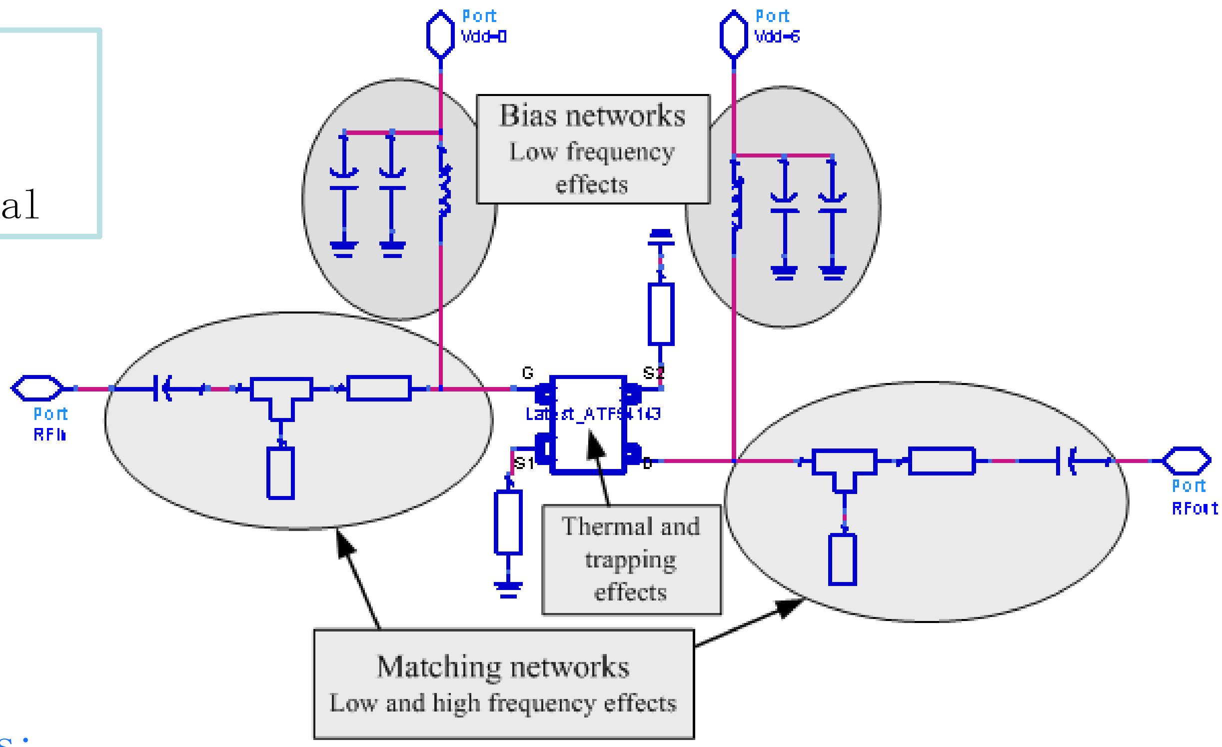
# Linearity vs. Efficiency

...and linear distortion (memory effects)...

Main sources of memory effects in PAs

Main types:

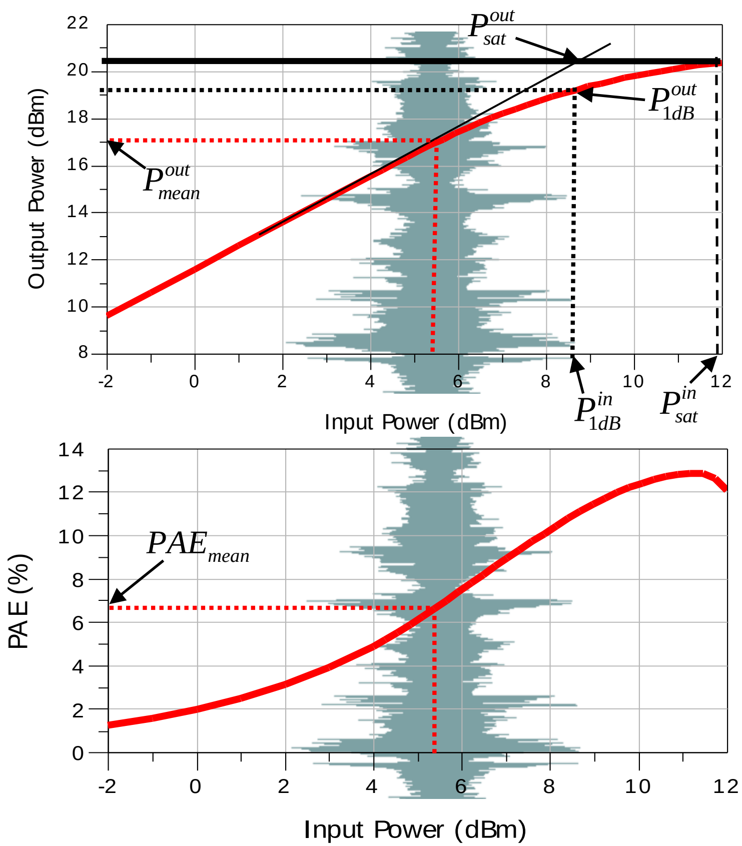
- Electrical
- Electrothermal




- They appear as:
  - Asymmetries in the IMD products (frequency domain)
  - Dispersion in the decision points of the constellation (time domain)

# Linearity vs. Efficiency

Back-off operation results power inefficient (class A, class AB below 20% with PAPR up to 9dB). The more efficient is the PA class of operation the more nonlinear it results.




- 2G → GMSK → PAPR=0dB. With constant envelope modulated signals → class-C PAs → drain efficiency around 65%.
- 3G/4G/5G → non-constant envelope modulated signals:
  - WCDMA → PAPR=10.6 dB;
  - OFDM-based → PAPR~12 dB;

Modulations designed to maximize spectral efficiency, not power efficiency!

# Linearity vs. Efficiency

PAPR or Crest Factor Reduction (CFR) techniques for multicarrier signals

| | Distortionless | Power increase | Data rate loss | Requires processing at transmitter (Tx) and receiver (Rx) |
|---|---|---|---|---|
| Clipping and filtering | No | No | No | Tx: Amplitude clipping, filtering<br>Rx: None |
| Coding | Yes | No | Yes | Tx: Encoding or table search<br>Rx: Decoding or table search |
| PTS | Yes | No | Yes | Tx: $M$ IDFTs, $W^{M-1}$ complex vector sums<br>Rx: Side information extraction, inverse PTS |
| SLM | Yes | No | Yes | Tx: $U$ IDFTs<br>Rx: Side information extraction, inverse SLM |
| Interleaving | Yes | No | Yes | Tx: $K$ IDFTs, $(K - 1)$ interleavings<br>Rx: Side information extraction, inverse interleaving |
| TR | Yes | Yes | Yes | Tx: IDFTs, find value of PRCs<br>Rx: Ignore non-data-bearing subcarriers |
| TI | Yes | Yes | No | Tx: IDFTs, search for maximum point in time, tones to be modified, value of $p$ and $q$<br>Rx: Modulo-$D$ operation |
| ACE | Yes | Yes | No | Tx: IDFTs, projection onto "shaded area"<br>Rx: None |

Seung Hee Han and Jae Hong Lee, "An overview of peak-to-average power ratio reduction techniques for multicarrier transmission," in *IEEE Wireless Communications*, vol. 12, no. 2, pp. 56-65, April 2005.

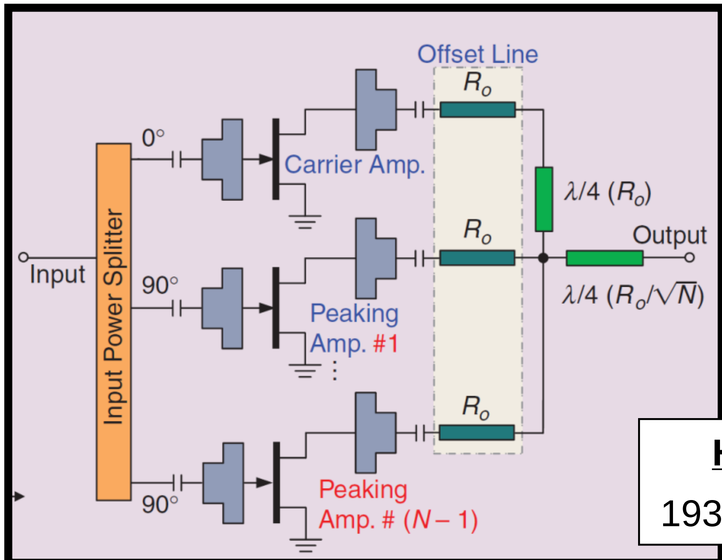
# Outline

# High Efficient PAs

- Alternative amplification architectures/topologies to the conventional Cartesian Tx with linear class AB PA to achieve high power efficiency with the high PAPR waveforms.
  - Dynamic Load Modulation (Doherty PAs, Outphasing techniques)
  - Dynamic Supply Techniques (ET/ Class G PAs)
  - All-digital Tx
- Crest Factor Reduction (CFR) techniques to control PAPR.
- High efficient topologies demand linearization techniques to guarantee the linearity levels (i.e., ACLR, NMSE, EVM).

# High Efficient PAs

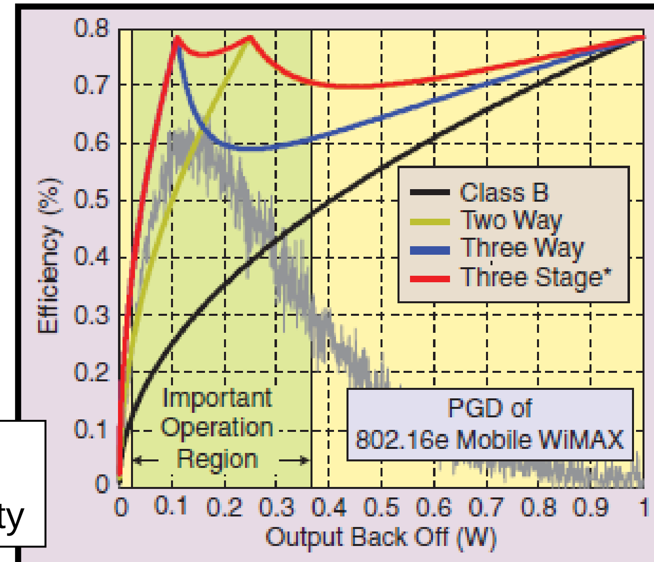
## Doherty Power Amplifier




N-way Doherty PA

**HISTORY:**

1936 W. Doherty

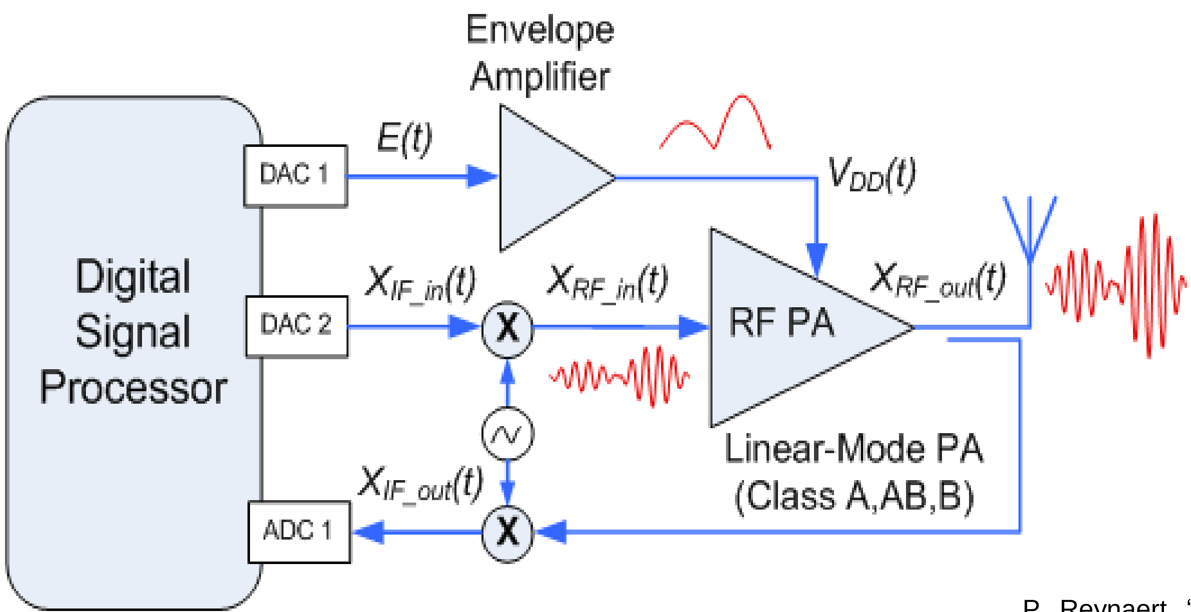


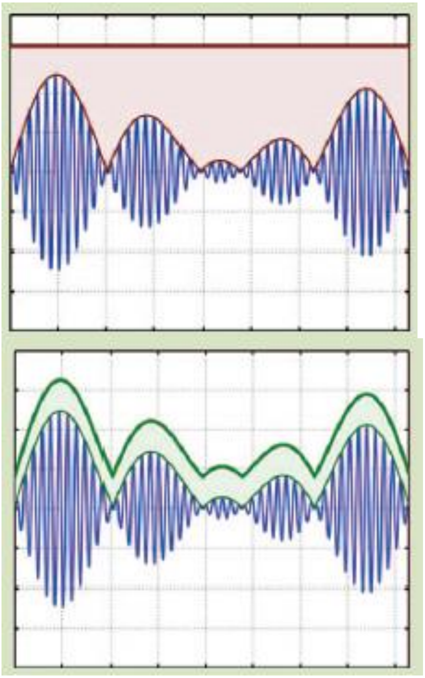

Efficiency of different Doherty and class B PAs

The Doherty configuration uses separate carrier and peaking PAs. Only the carrier PA is turned on during low-power operation, while the two PAs are turned on at high power → high efficiency at backed-off output power level as well as at the peak power.

# High Efficient PAs

## Envelope Tracking



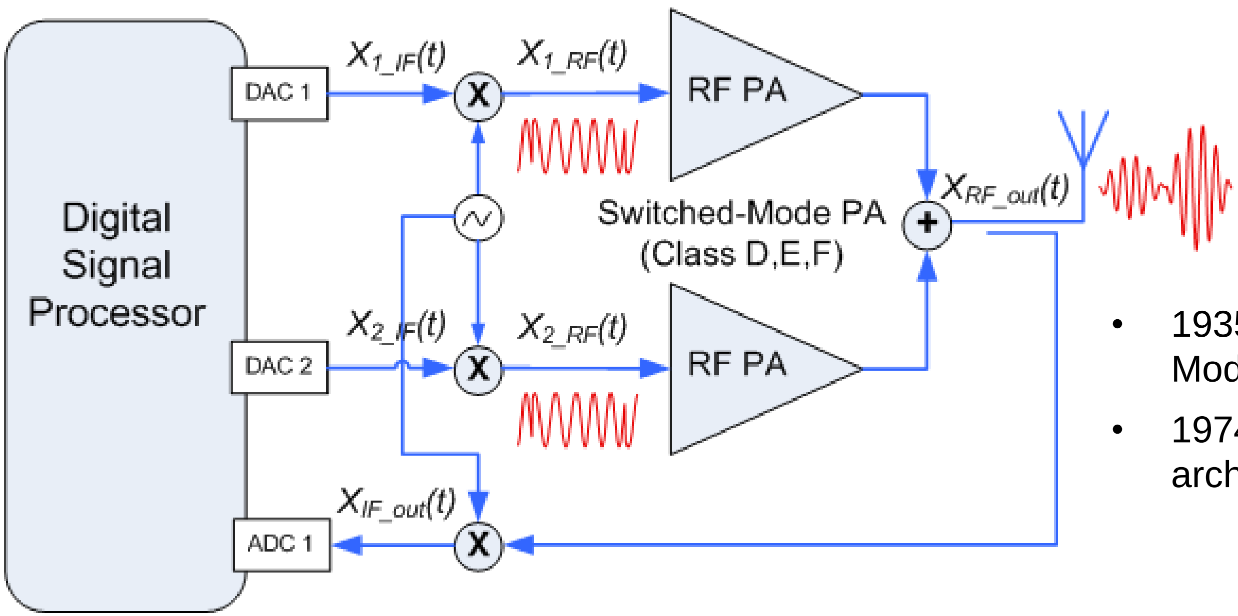



P. Reynaert, "Polar Modulation," *IEEE Microwave Magazine,* vol. 12, pp. 46-51, Feb. 2011.

The supply voltage of the RF PA is adjusted according to the envelope of the RF carrier. Thanks to the dynamic supply the RF PA is always operating close to saturation which increases the power efficiency at power back-off.

# High Efficient PAs

## LINC or Outphasing PAs



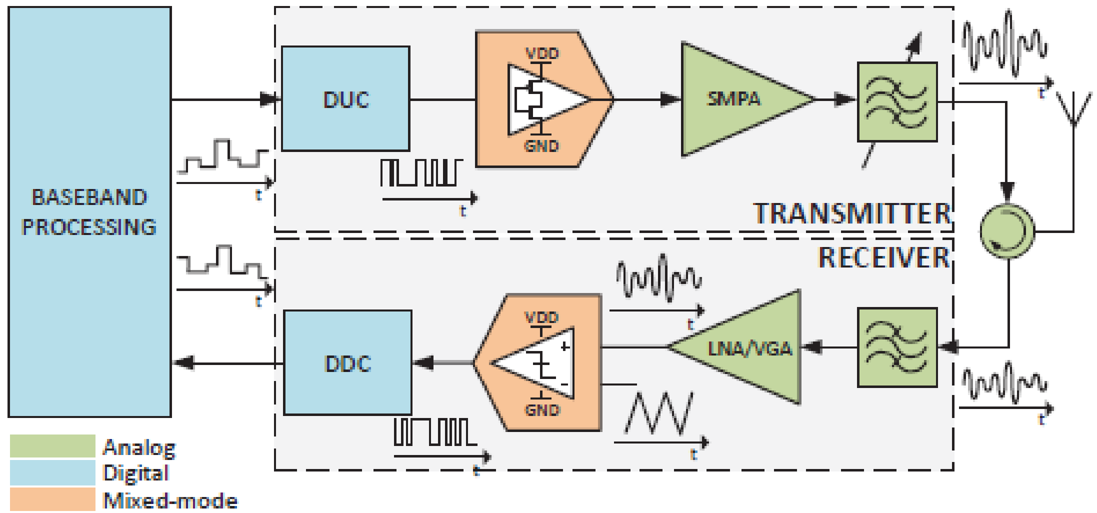

**HISTORY**

- 1935, H. Chireix - Outphasing Mod. Arrangement
- 1974, D.C. Cox - LINC architecture

The input signal is converted into two constant envelope signals. These two signals are amplified independently by two high-efficient switched-mode PAs in parallel branches. At the PA outputs, both signals are added in a two-to-one combiner obtaining a linear amplified replica of the input.

# High Efficient PAs

## All-digital Transmitters




A. Prata, R. F. Cordeiro, D. C. Dinis, S. R. Oliveira, J. Vieria and N. B. Carvalho, “All-Digital Transceivers – Recent Advances and Trends,” in Proc IEEE International Conf. on Electronics, Circuits and Integrated Systems - ICECS, Monte Carlo, Monaco, Vol., pp. - , December, 2016.

In all-digital Tx. architectures, pulse width or delta-sigma modulators convert the signal from multi-level to 2-level. The pulsed digital RF signal is converted to the analog domain with a high-speed digital buffer and a 2-level Switched-Mode PA. The analog output reconstruction filter removes the quantization noise.

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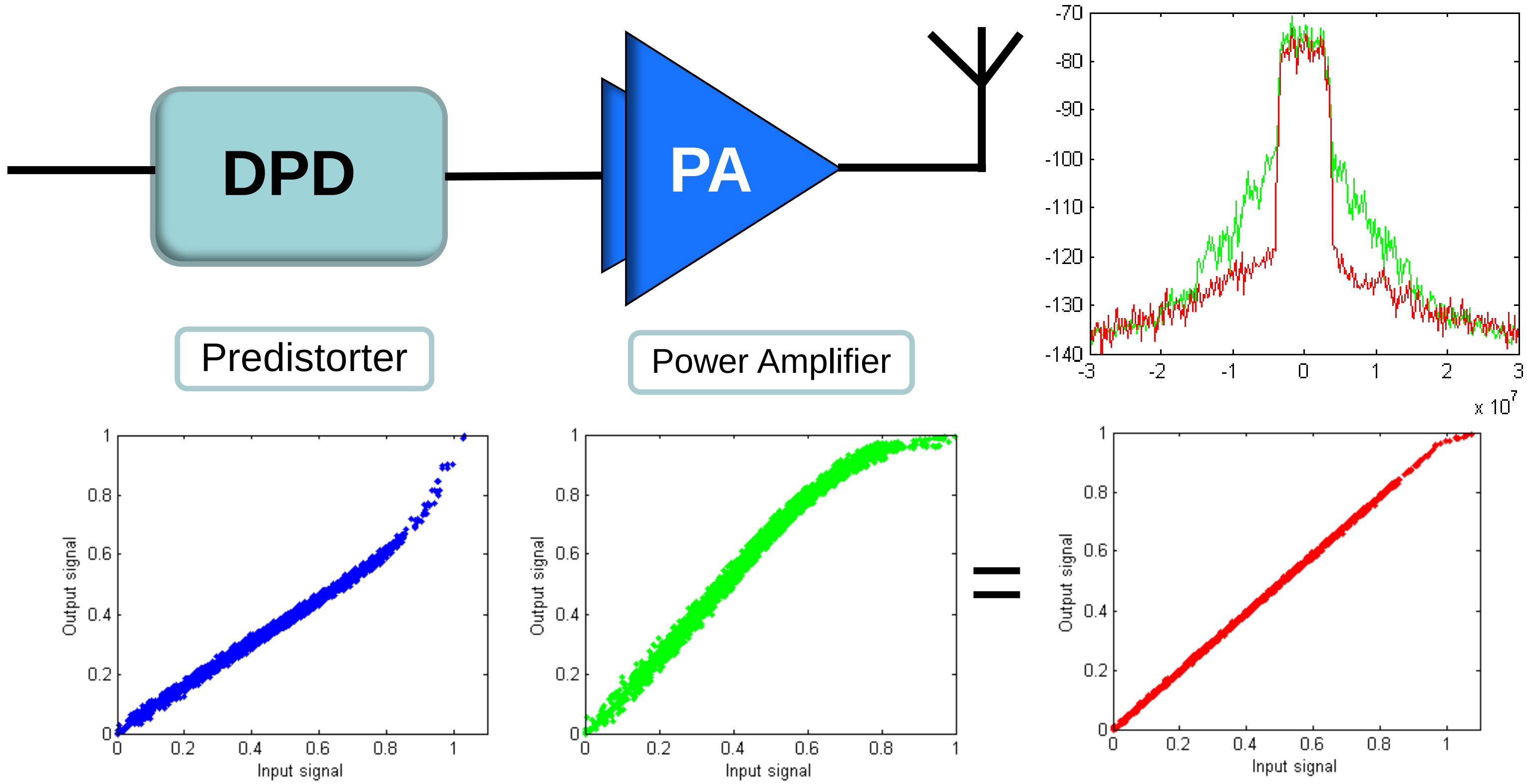
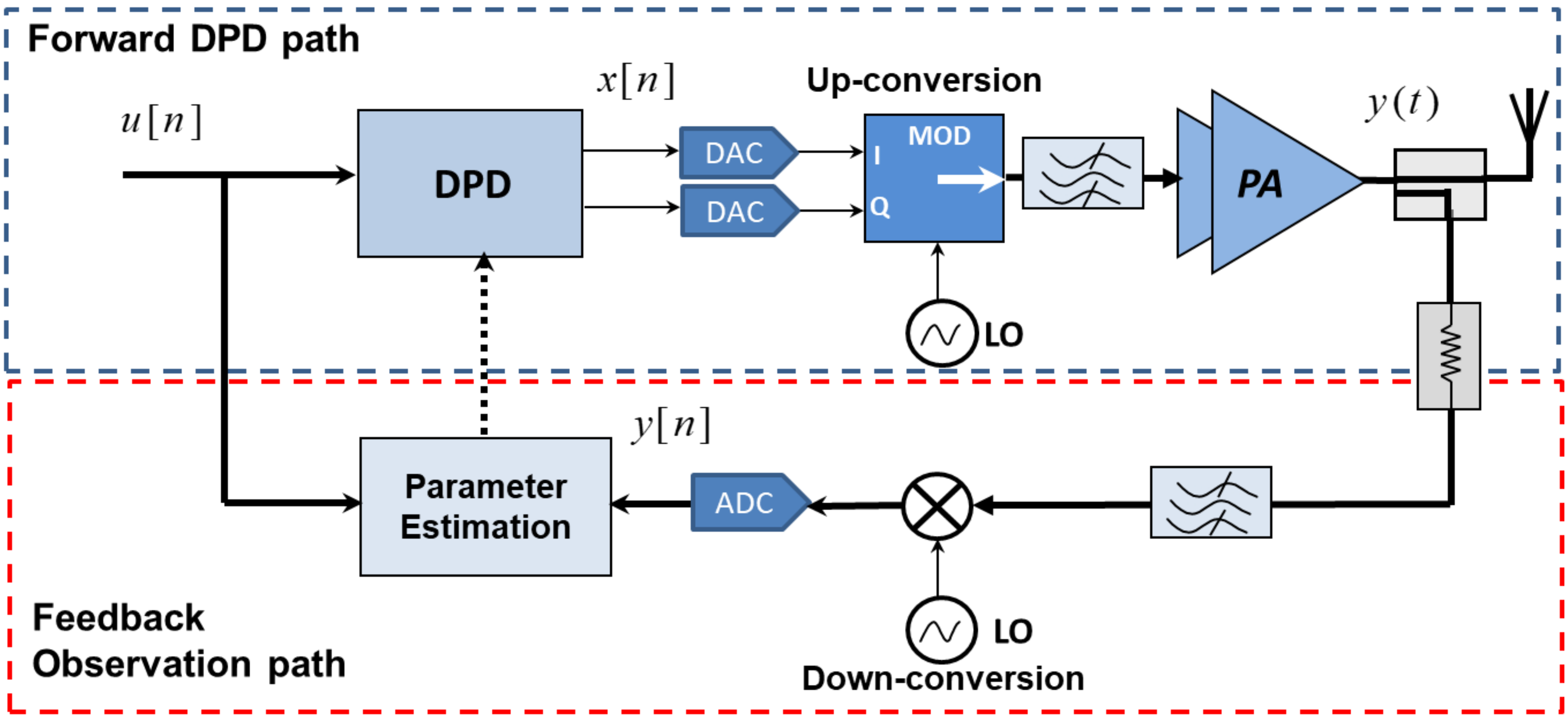
# DPD Linearization



# DPD Linearization



## SISO DPD

### Memory Polynomial

$$\hat{y}[n]=\sum_{i=0}^{N}\sum_{p=0}^{P}\gamma_{pi}\cdot x[n-\tau_i]\cdot\left|x[n-\tau_i]\right|^{p}$$

J. Kim, K. Konstantinou, "Digital predistortion of wideband signals based on power amplifier model with memory", Electronics Letters, vol. 37, n. 23, pp: 1417-1418, Nov. 2001

### Nonlinear Auto-Regressive Moving Average (NARMA)

$$\hat{y}[n]=\sum_{i=0}^{N}\sum_{p=0}^{P}\alpha_{pi}\cdot x[n-\tau_i^N]\cdot\left|x[n-\tau_i^N]\right|^{p}-\sum_{j=1}^{D}\sum_{q=0}^{Q}\beta_{qj}\cdot\hat{y}[n-\tau_j^D]\cdot\left|\hat{y}[n-\tau_j^D]\right|^{q}$$

G. Montoro et al.A New Digital Predictive Predistorter for Behavioral Power Amplifier Linearization," IEEE Microwave and Wireless Components Letters, vol. 17, pp. 448-450, June 2007.

### Generalized Memory Polynomial

$$\hat{y}[n]=\sum_{l=0}^{L_A}\sum_{p=0}^{P_A}a_{pl}\cdot x[n-\tau_l^A]\cdot\left|x[n-\tau_l^A]\right|^{p}+\sum_{l=1}^{L_B}\sum_{m=1}^{M_B}\sum_{p=0}^{P_B}b_{pml}\cdot x[n-\tau_l^B]\cdot\left|x[n-\tau_l^B-\tau_m^B]\right|^{p}$$

$$+\sum_{l=1}^{L_C}\sum_{m=1}^{M_C}\sum_{p=0}^{P_C}c_{pml}\cdot x[n-\tau_l^C]\cdot\left|x[n-\tau_l^C+\tau_m^C]\right|^{p}$$

D. R. Morgan, Z. Ma, J. Kim, M. G. Zierdt, and J. Pastalan, "A Generalized Memory Polynomial Model for Digital Predistortion of RF Power Amplifiers," IEEE Trans. on Signal Proc., vol 54, pp. 3852-3860, Oct. 2006.

## SISO DPD

**Volterra Series**

$$\hat{y}[n]=\sum_{k=1}^{R}\sum_{q_k=0}^{Q_k-1}\cdots\sum_{q_1=0}^{Q_1-1}h_k(q_1,\cdots,q_k)\prod_{i=1}^{k}x[n-\tau_{q_i}]$$

**Variations of Volterra series:**

- **Dynamic Deviation Reduction Volterra Series**

A. Zhu, J. Pedro and T. Brazil, "Dynamic Deviation Reduction-Based Volterra Behavioral Modeling of RF Power Amplifiers," IEEE Transactions on Microwave Theory and Techniques, vol. 54, no. 12, pp. 4323-4332, December 2006.

- **Volterra Behavioral Model for Wideband PAs (VBW)**

C. Crespo-Cadenas, J. Reina-Tosina and M. J. Madero-Ayora, "Volterra behavioral model for wideband RF amplifiers," IEEE Transactions on Microwave Theory and Technology, vol. 55, no. 3, p. 449–457, 2007.

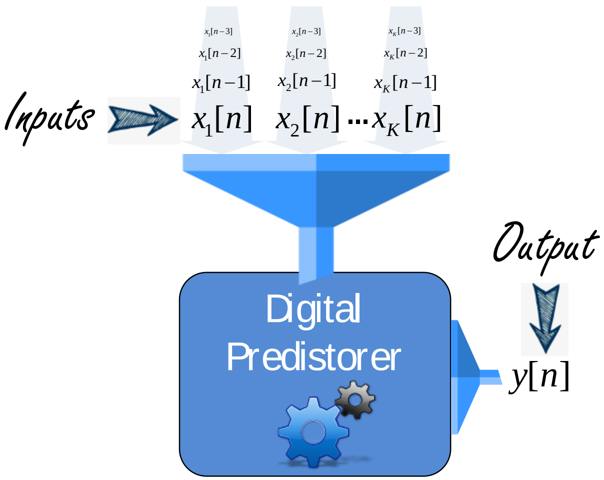
- **Multi-band Volterra series**

M. Younes, A. Kwan, M. Rawat and F. M. Ghannouchi, "Linearization of Concurrent Tri-Band Transmitters Using 3-D Phase-Aligned Pruned Volterra Model," in IEEE Transactions on Microwave Theory and Techniques, vol. 61, no. 12, pp. 4569-4578, Dec. 2013.

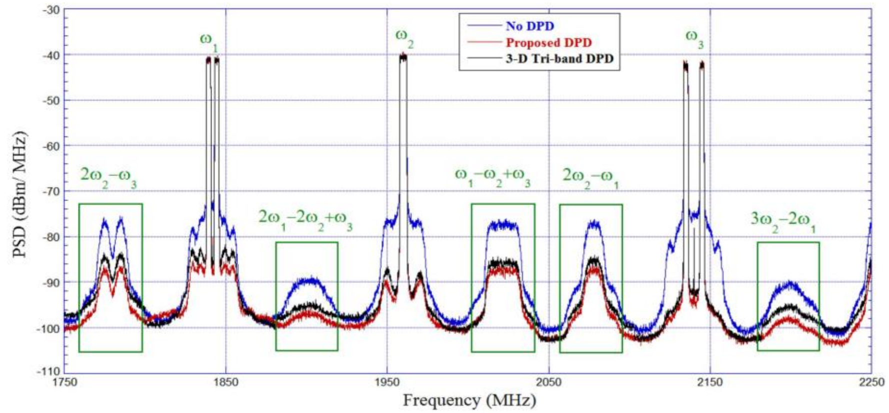
J. Kim, P. Roblin, D. Chaillot, and X. Zhijian, “A generalized architecture for the frequency-selective digital predistortion linearization technique,” IEEE Transactions on Microwave Theory and Techniques, vol. 61, no. 1, pp. 596-605, 2013.

# DPD Linearization

## MISO DPD

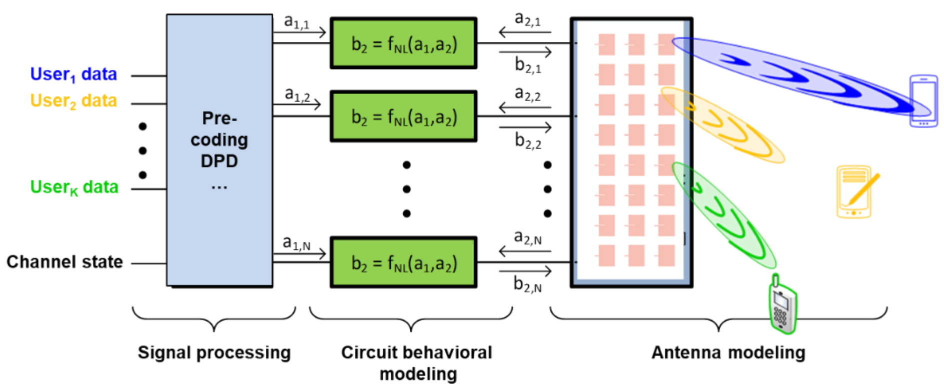


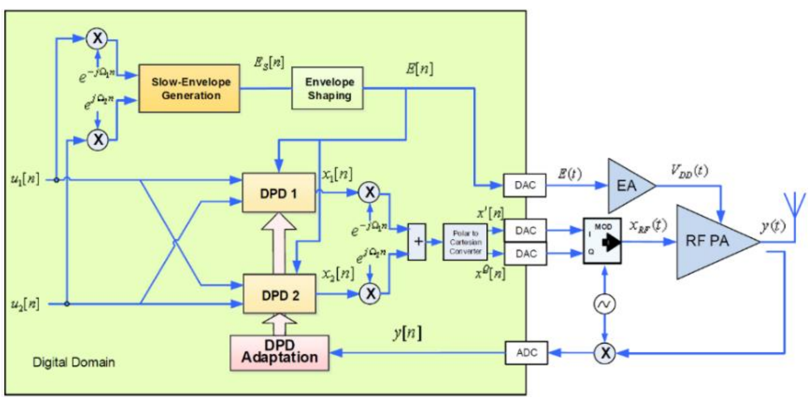

- For Concurrent Multi-Band TX.



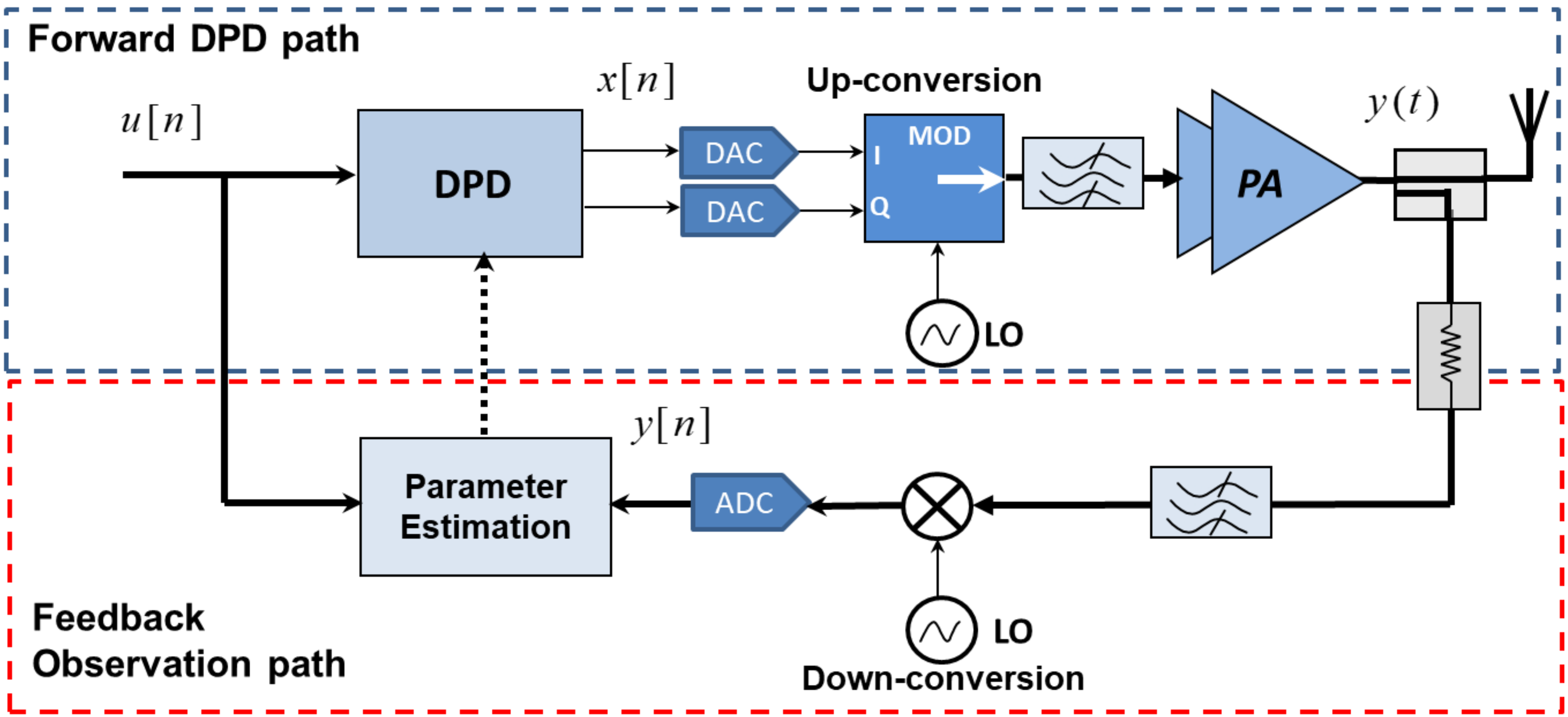

- For Envelope Tracking/Outphasing PAs

- For MIMO TXs



# DPD Linearization



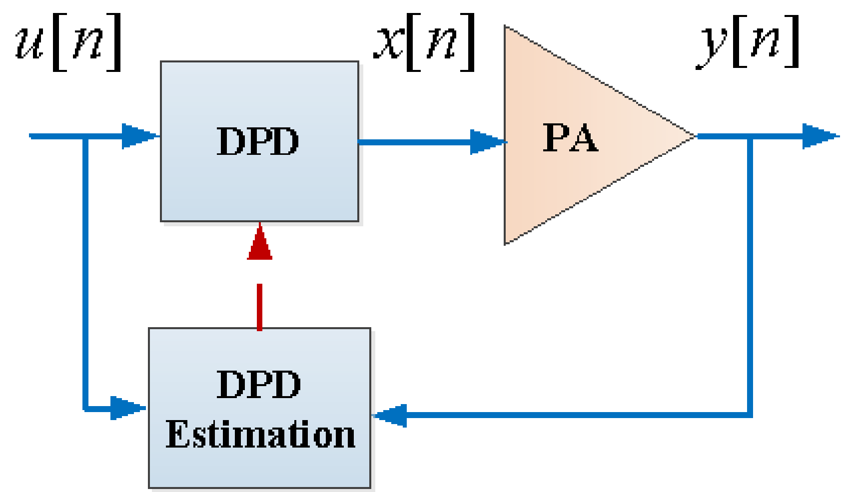
# DPD Linearization

## Direct Learning DPD

$$x[n] = u[n] - \boldsymbol{\varphi}_n \mathbf{w}$$

$$\mathbf{w}^{i+1} = \mathbf{w}^{i} + \mu\left(\mathbf{U}^{\mathbf{H}}\mathbf{U}\right)^{-1}\mathbf{U}^{\mathbf{H}}\mathbf{e}$$

$$e[n] = y[n]/G_0 - u[n]$$




$$\mathbf{U} = \left(\boldsymbol{\varphi}_0, \boldsymbol{\varphi}_1, \ldots, \boldsymbol{\varphi}_{L-1}\right)^T$$ *LxM* data matrix (n=0, 1,··· L-1)

$$\boldsymbol{\varphi}_n = \left(\varphi_0[n], \varphi_1[n], \ldots, \varphi_{M-1}[n]\right)$$ *1xM* data vector containing the basis functions

$$\mathbf{w} = \left(w_0, w_1, \ldots, w_{M-1}\right)^T$$ *Mx1* vector of coefficients

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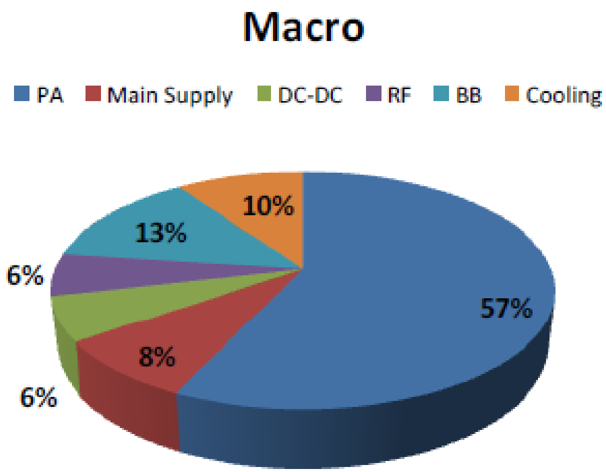
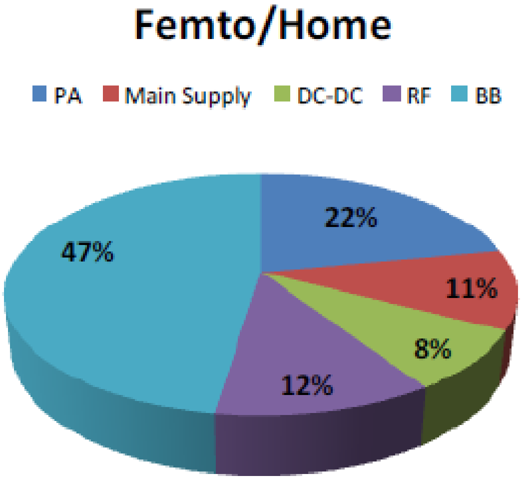
# Dimens. Reduction for DPD

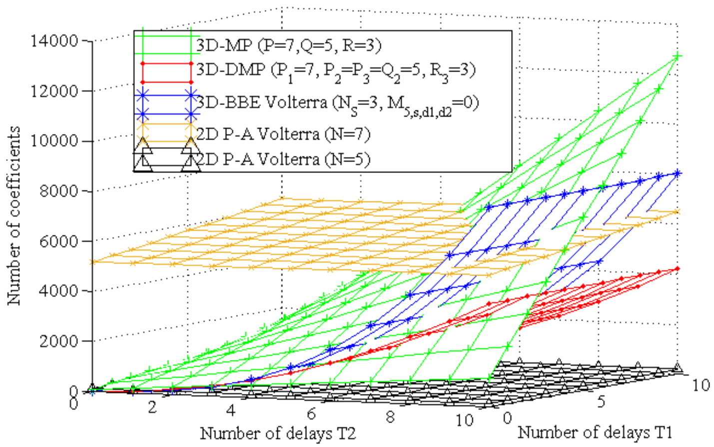
- In macro BSs it is mainly the PA that dominates the total power consumption
- While in smaller BSs it is the baseband part that dominates the overall power consumption



# Dimens. Reduction for DPD

Considering wide bandwidth signals, carrier aggregation, concurrent multi-band transmissions, MIMO TXs → the number of required DPD coefficients grow significantly.



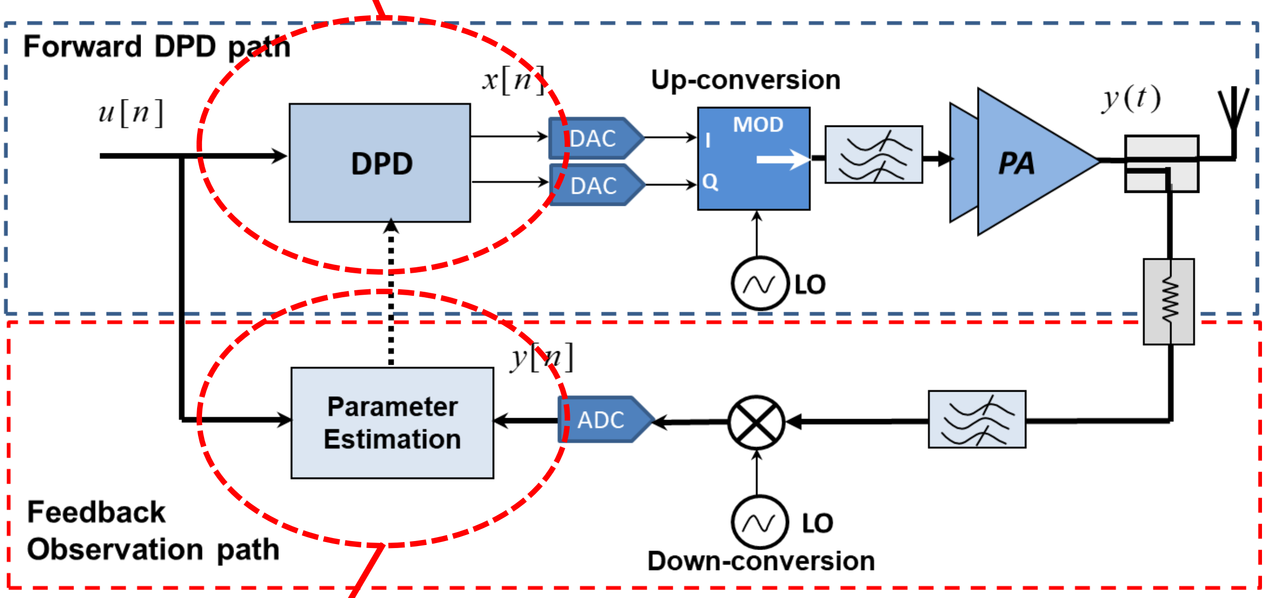

Model order reduction techniques can be applied to:

- reduce the computational complexity → reduce baseband processing power consumption.
- improve the conditioning of the data matrices in the identification procedure (critical with high number of parameters/basis functions).

# Dimens. Reduction for DPD

Feature Selection Techniques:

- LASSO (l1-norm regularization)
- Ridge Regression (l2-norm regularization)
- Sparse Bayesian learning (SBL) alg.
- **Orthogonal Matching Pursuit (OMP) alg.**
- etc.




Feature Extraction Techniques:

- **Principal Component Analysis (PCA)**
- **Partial Least Squares (PLS)**
- Canonical Correlation Analysis (CCA)
- etc.

# Dimens. Reduction for DPD

The sparsity of the behavioral model basis functions can be exploited to obtain an ordered sequence of the most significant components.

$$\min_{\mathbf{w}} \quad \|\mathbf{w}\|_0$$
$$\textit{subject to} \quad \|\mathbf{y} - \mathbf{U}\mathbf{w}\|_2^2 \leq \varepsilon$$

non-deterministic polynomial-time hard (NP-hard) problem

The solution is obtained by minimizing the number of active components (l0-norm) subject to a constraint on the l2-norm squared of the identification error.

# Dimens. Reduction for DPD

## Feature Selection: Orthogonal Matching Pursuit (OMP)

1. Initialization

$$\mathbf{e}^{(0)} = \mathbf{y} - \hat{\mathbf{y}}^{(0)}; \quad \hat{\mathbf{y}}^{(0)} = 0;$$

$S^{(0)} = \{\ \}; \quad S^{(n)} \equiv$ support set containing the indices of the active coefficients of the model

2. for n=1:1:$n_{max}$

2.1 $$i^{(n)} = \arg\min_{i} \left\{ \min_{\mathbf{w}_i} \left\| \mathbf{e}^{(n-1)} - \mathbf{U}_{\{i\}} w_i \right\|_2^2 \right\} \approx \arg\max_{i} \left\{ \left| \mathbf{U}_{\{i\}}^{H} \mathbf{e}^{(n-1)} \right| \right\}$$

2.2 $$S^{(n)} = S^{(n-1)} \cup i^{(n)}$$

2.3 $$\mathbf{w}^{(n)} = \left( \mathbf{U}_{S^{(n)}}^{\mathbf{H}} \mathbf{U}_{S^{(n)}} \right)^{-1} \mathbf{U}_{S^{(n)}}^{\mathbf{H}} \mathbf{y}$$

2.4 $$\hat{\mathbf{y}}^{(n)} = \mathbf{U}_{S^{(n)}} \mathbf{w}^{(n)}$$

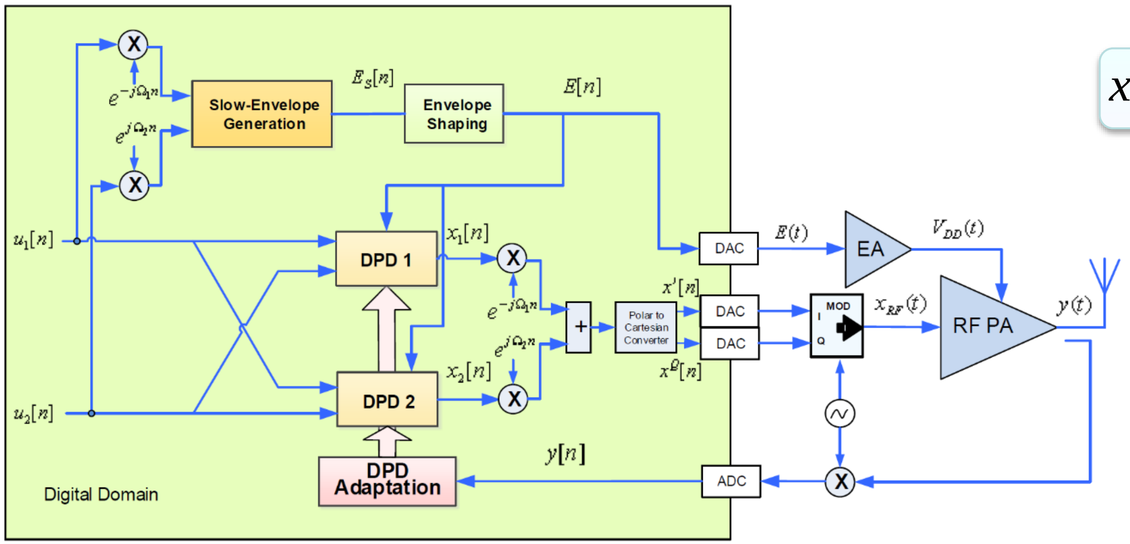
2.5 $$\mathbf{e}^{(n)} = \mathbf{y} - \hat{\mathbf{y}}^{(n)}$$

end

J. Reina-Tosina, M. Allegue-Martinez, et al.,"Behavioral Modeling and Predistortion of Power Amplifiers Under Sparsity Hypothesis," in IEEE Trans. on Microw. Theory and Tech.,vol.63, nº.2, pp.745-753, Feb. 2015

# Dimens. Reduction for DPD

## 3D-DPD for Concurrent Dual-Band Envelope Tracking PAs




$$x[n] = f_{DPD}\left(u_1[n], u_2[n], E_s[n]\right)$$

Q. A. Pham, D. Lopez-Bueno, T. Wang, G. Montoro and P. L. Gilabert, "Multi-dimensional LUT-based digital predistorter for concurrent dual-band envelope tracking power amplifier linearization," 2018 IEEE Topical Conference on RF/Microwave Power Amplifiers for Radio and Wireless Applications (PAWR), Anaheim, CA, 2018, pp. 47-50.

$$x_1[n] = \sum_{i=0}^{N_1-1} u_1[n-\tau_i^{u_1}]\, f_{\overline{\Phi}_{1,i}}\left(\left|u_1[n-\tau_i^{u_1}]\right|\right) +$$

the linear combination of basis functions of linear interpolation/extrapolation, 1-D LUT.

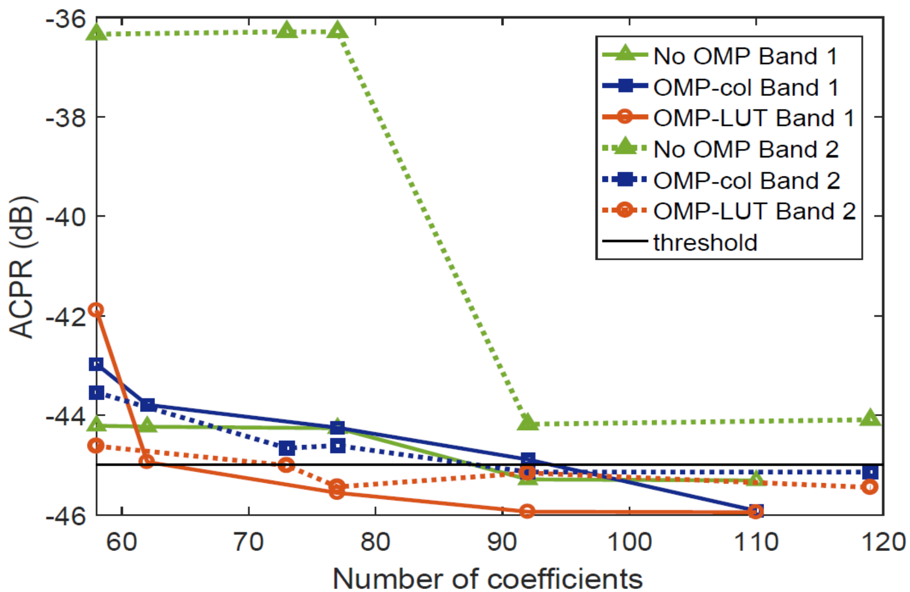
$$\sum_{i=1}^{N_2-1}\sum_{j=1}^{M_2-1} u_1[n]\, f_{\overline{\Phi}_{1,i,j}}\left(\left|u_1[n-\tau_i^{u_1}]\right|, \left|u_2[n-\tau_j^{u_2}]\right|\right) +$$

$$\sum_{i=1}^{N_3-1}\sum_{k=1}^{K_3-1} u_1[n]\, f_{\overline{\Phi}_{1,i,k}}\left(\left|u_1[n-\tau_i^{u_1}]\right|, E[n-\tau_k^{e}]\right)$$

the linear combination of basis functions of bilinear interpolation/extrapolation, 2-D LUT.

# Dimens. Reduction for DPD

## OMP for 3D-DPD for Concurrent DB ET PAs



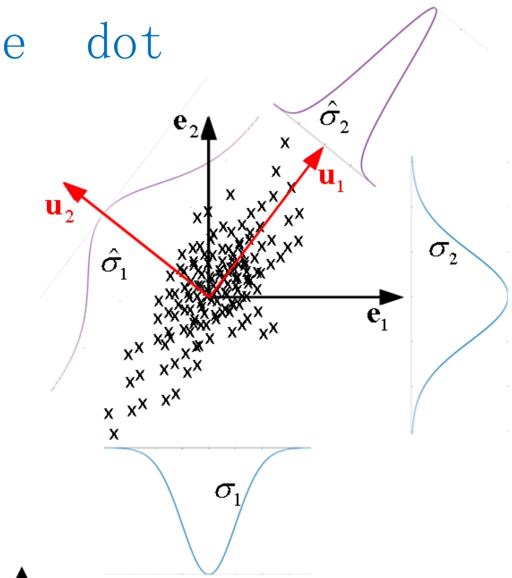

| Method | Pout (dBm) | $\eta$ (%) | NMSE (dB) | ACPR (dB) | Num. coeff. |
|---|---|---|---|---|---|
| *(a)* No OMP | 23,1 | 18,97 | B1: -36,51<br>B2: -37,67 | B1: -45,59<br>B2: -46,02 | B1: 85<br>B2: 153 |
| *(b)* OMP-col | 22,8 | 18,21 | B1: -36,30<br>B2: -37,48 | B1: -45,14<br>B2: -45,33 | B1: 92<br>B2: 92 |
| *(c)* OMP-LUT | 23,0 | 18,67 | B1: -36,50<br>B2: -37,14 | B1: -45,05<br>B2: -45,25 | B1: 62<br>B2: 73 |

With OMP the most relevant basis functions (or LUT coefficients) are selected → trade-off between the number of coefficients used and the amount of non-linearity compensation.

# Dimens. Reduction for DPD

## Feature Extraction: PCA and PLS

In PCA and PLS, thanks to the orthogonality of the resulting transformed matrix, the DPD coefficients' extraction can be carried out with simple dot products (avoiding matrix inversions).

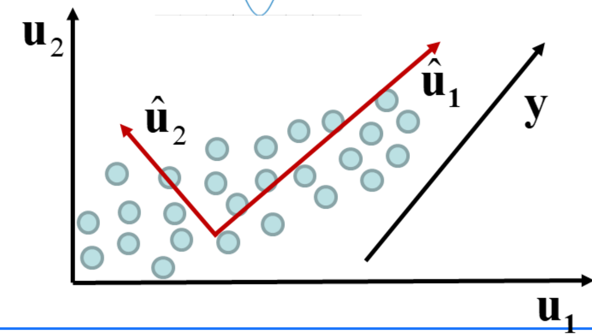



$$\hat{\mathbf{U}}_{PCA} = \mathbf{UV}$$

The principal components are linear combinations of the original variables oriented to capture the maximum variance in the data contained in $\mathbf{U}$.

$$\hat{\mathbf{U}}_{PLS} = \mathbf{UT}$$

PLS generates components that capture most of the information in $\mathbf{U}$, that are useful for predicting $\mathbf{y}$.



# Dimens. Reduction for DPD

## Feature Extraction: PCA and PLS

$$\boxed{\hat{\mathbf{U}}_{PCA} = \mathbf{UV}} \Rightarrow \left(\hat{\mathbf{U}}^{\mathbf{H}}\hat{\mathbf{U}}\right)^{-1} = diag\left(\lambda_1^{-1}\ \lambda_2^{-1}\ \mathrm{L}\ \ \lambda_N^{-1}\right)$$

$\lambda_i$ are the eigenvalues of $U^H U$ (with i=1, 2, …N)

$$\hat{\mathbf{w}}_{n+1} = \hat{\mathbf{w}}_n + \mu\Delta\hat{\mathbf{w}}_n \rightarrow \begin{bmatrix} \hat{w}_1(\mathrm{n+1}) \\ \hat{w}_2(\mathrm{n+1}) \\ \mathrm{M} \\ \hat{w}_N(\mathrm{n+1}) \end{bmatrix} = \begin{bmatrix} \hat{w}_1(\mathrm{n}) \\ \hat{w}_2(\mathrm{n}) \\ \mathrm{M} \\ \hat{w}_N(\mathrm{n}) \end{bmatrix} + \mu \begin{bmatrix} \lambda_1^{-1}\gamma_1(\mathrm{n}) \\ \lambda_2^{-1}\gamma_2(\mathrm{n}) \\ \mathrm{M} \\ \lambda_N^{-1}\gamma_N(\mathrm{n}) \end{bmatrix} e(\mathrm{n}) \Rightarrow \boxed{\mathbf{w} = \mathbf{V}\hat{\mathbf{w}}}$$

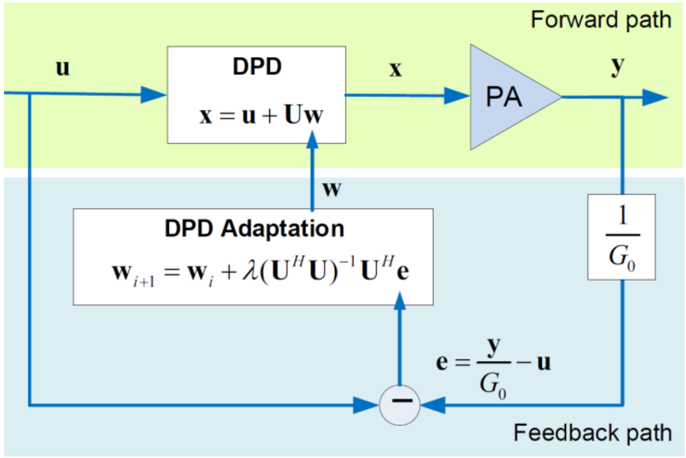
$$\boxed{\hat{\mathbf{U}}_{PLS} = \mathbf{UT}} \Rightarrow \left(\hat{\mathbf{U}}^{\mathbf{H}}\hat{\mathbf{U}}\right)^{-1} = I$$

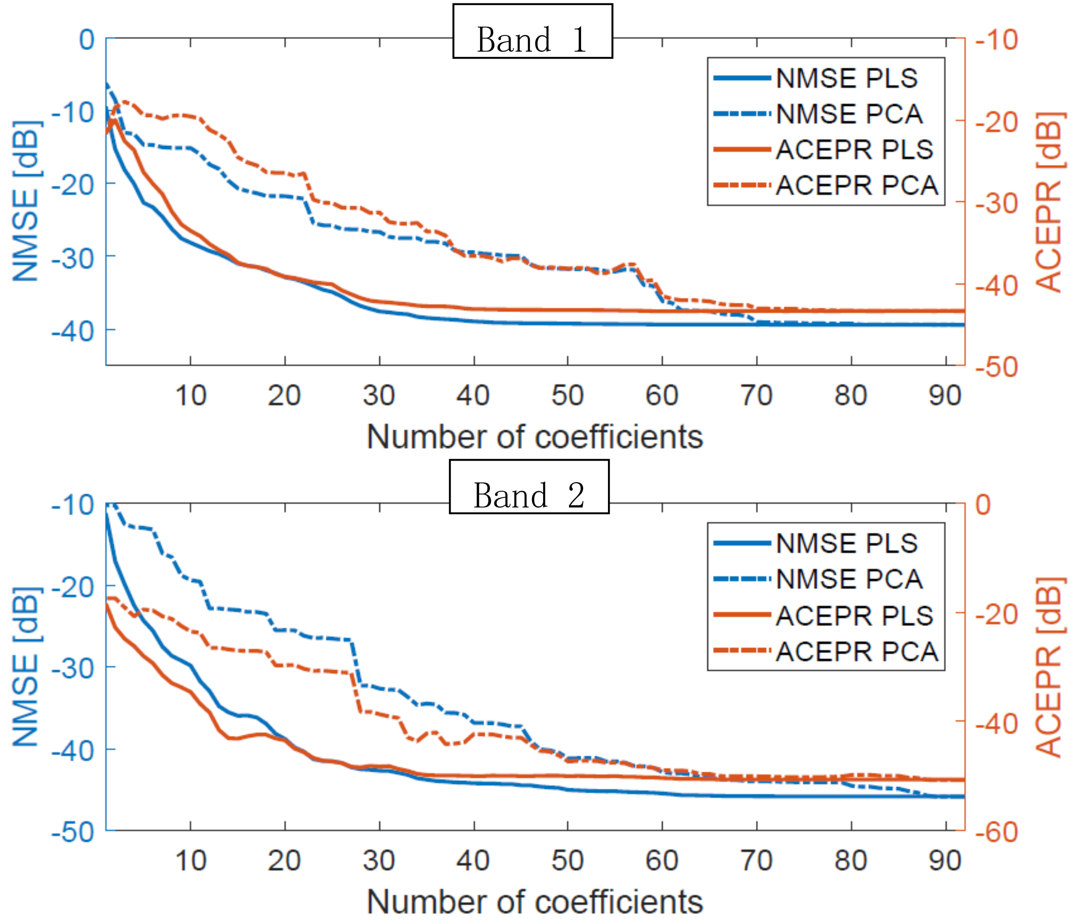
$$\hat{\mathbf{w}}_{n+1} = \hat{\mathbf{w}}_n + \mu\Delta\hat{\mathbf{w}}_n \rightarrow \begin{bmatrix} \hat{w}_1(\mathrm{n+1}) \\ \hat{w}_2(\mathrm{n+1}) \\ \mathrm{M} \\ \hat{w}_N(\mathrm{n+1}) \end{bmatrix} = \begin{bmatrix} \hat{w}_1(\mathrm{n}) \\ \hat{w}_2(\mathrm{n}) \\ \mathrm{M} \\ \hat{w}_N(\mathrm{n}) \end{bmatrix} + \mu \begin{bmatrix} \gamma_1(\mathrm{n}) \\ \gamma_2(\mathrm{n}) \\ \mathrm{M} \\ \gamma_N(\mathrm{n}) \end{bmatrix} e(\mathrm{n}) \Rightarrow \boxed{\mathbf{w} = \mathbf{T}\hat{\mathbf{w}}}$$

# Dimens. Reduction for DPD

## Performance Comparison between PCA and PLS

- Forward path: OMP-col
- Feedback path: PLS/PCA

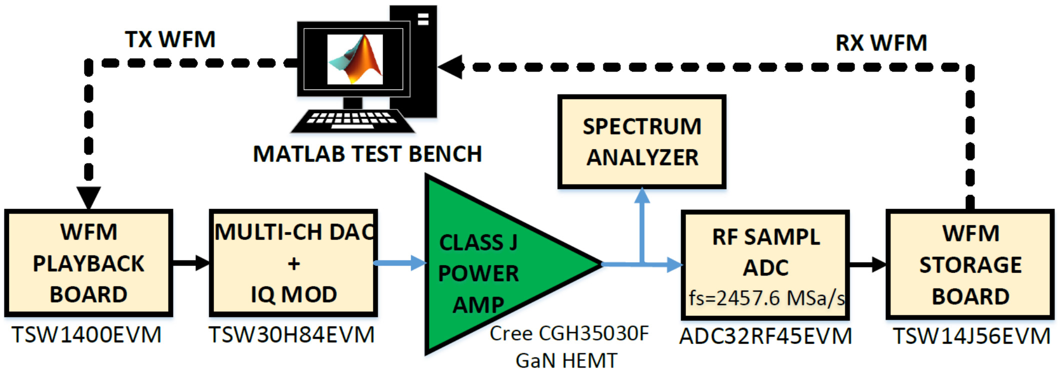


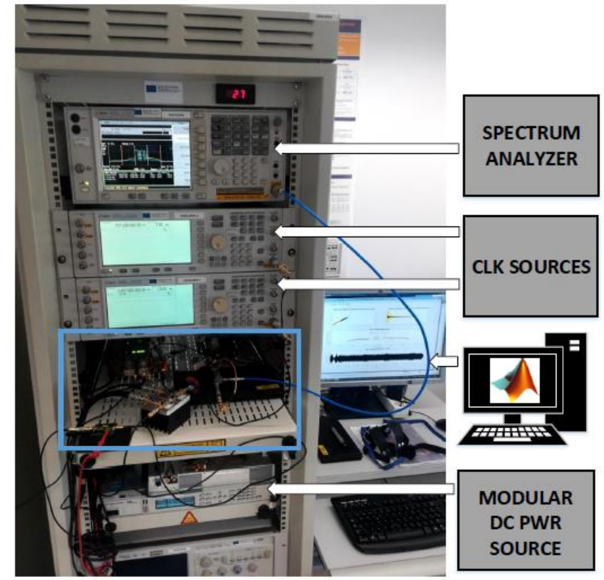




Q. A. Pham, D. Lopez-Bueno, T. Wang, G. Montoro and P. L. Gilabert, "Partial Least Squares Identification of Multi Look-up Table Digital Predistorters for Concurrent Dual-Band Envelope Tracking Power Amplifiers" submitted to T-MTT.

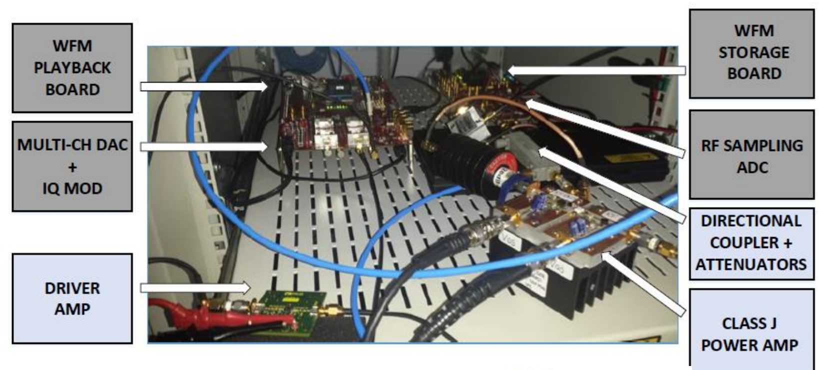
# Dimens. Reduction for DPD

Matlab-controlled digital linearization test bench.




- Test signal: filter bank multi-carrier signal with 80 MHz bandwidth and 13 dB of PAPR.
- Mean output power: 28 dBm
- Targeted ACPR levels <-45 dB
- GMP-based DPD
- DUT: Broadband high efficiency continuous mode class-J GaN power amplifier at 875 MHz.

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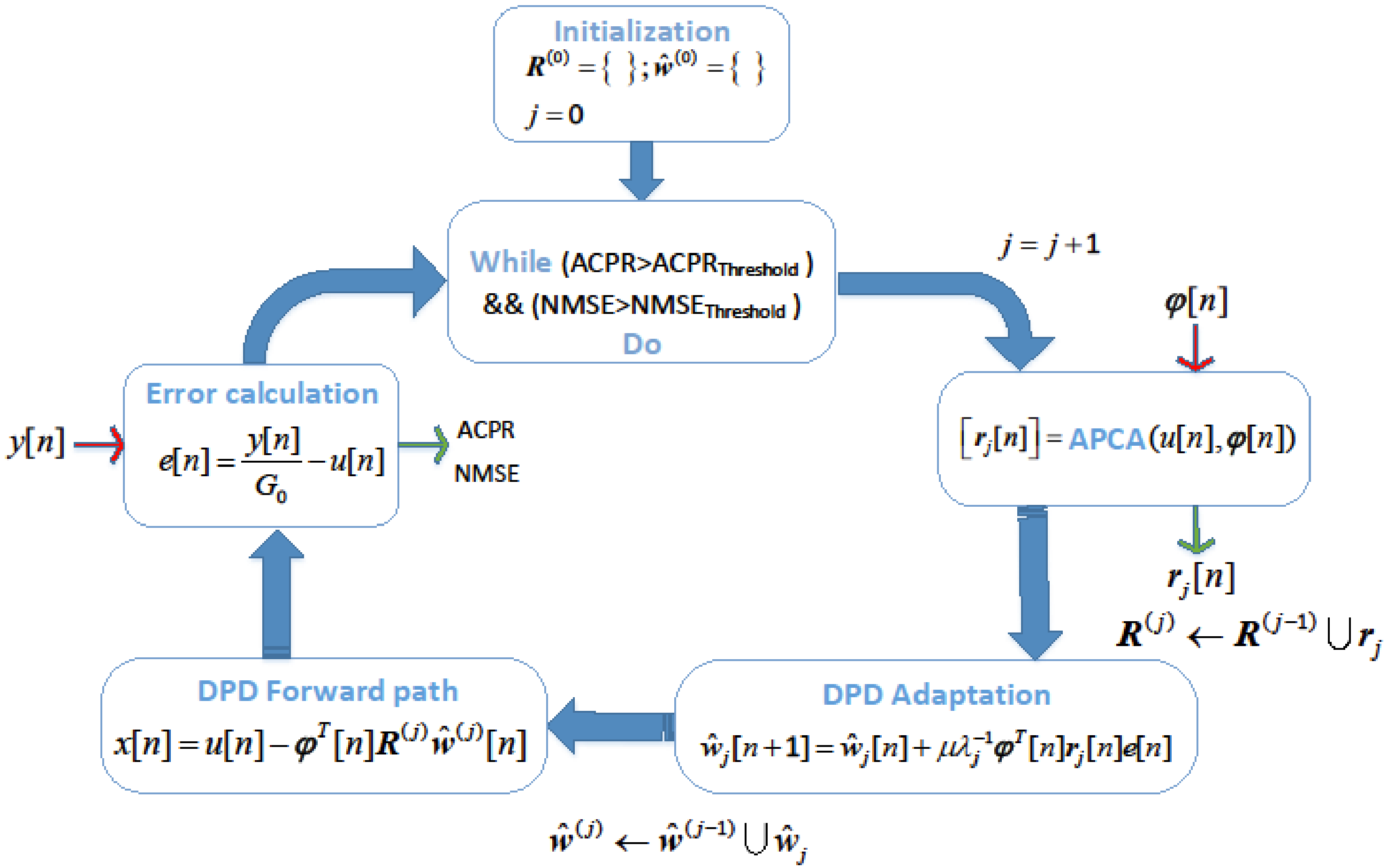
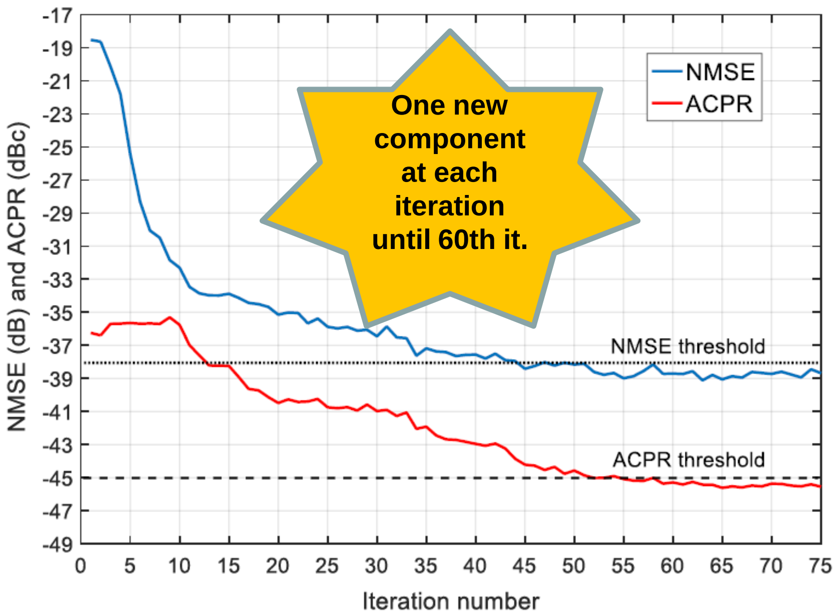
## Independent DPD Adaptation using Adaptive PCA



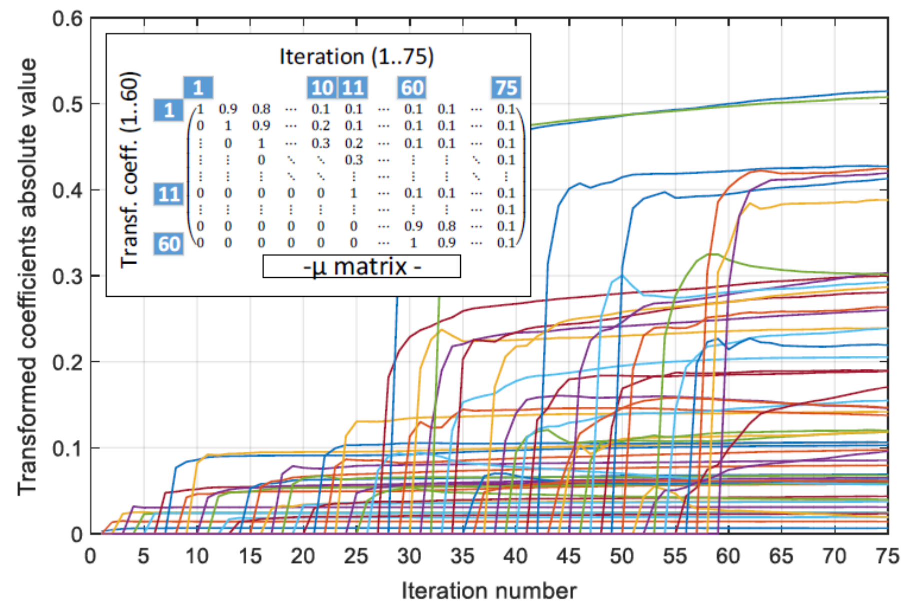

D. Lopez, Q. A. Pham, G. Montoro, P. L. Gilabert, "Independent Digital Predistortion Parameters Estimation Using Adaptive Principal Component Analysis", *IEEE Transactions on Microwave Theory and Techniques.*

# Dimens. Reduction for DPD

## Independent DPD Adaptation using Adaptive PCA




Evolution of the NMSE and the ACPR considering 60 components and 75 iterations.




Evolution of the absolute value of the 60 DPD coefficients.

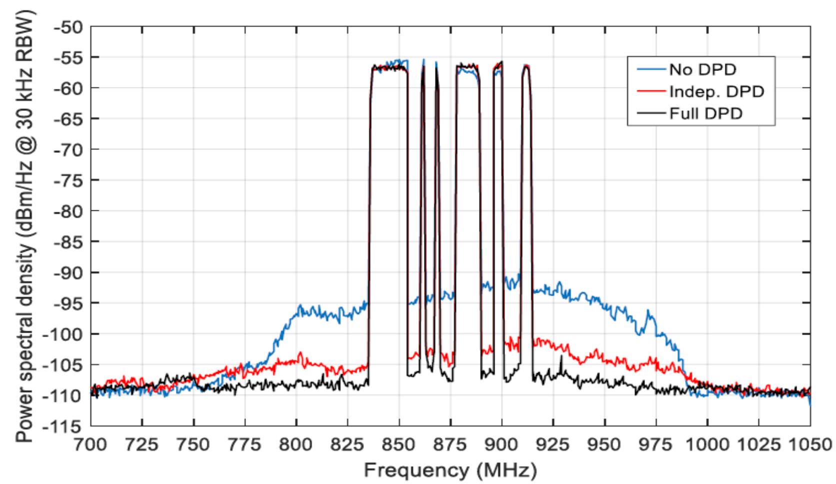
D. Lopez, Q. A. Pham, G. Montoro, P. L. Gilabert, "Independent Digital Predistortion Parameters Estimation Using Adaptive Principal Component Analysis", *IEEE Transactions on Microwave Theory and Techniques,* vol. 66, no. 12, pp. 5771-5779, Dec. 2018.

# Dimens. Reduction for DPD

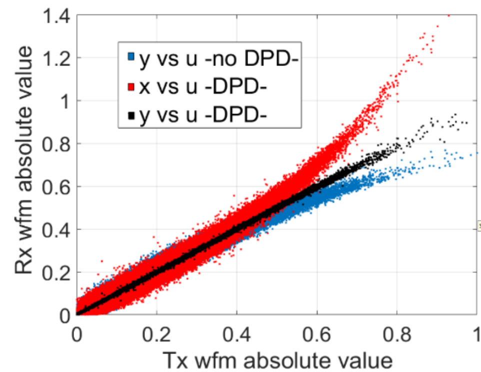
## Independent DPD Adaptation using Adaptive PCA

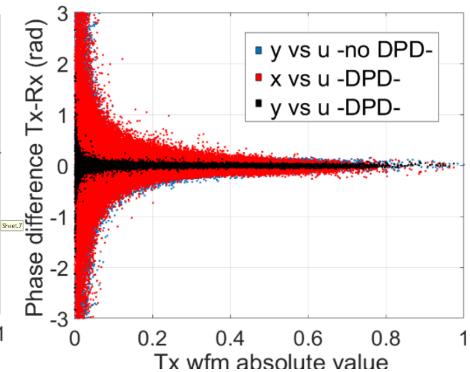
DPD linearization results

| Configuration 80 MHz FC-FBMC | Coeff. No. | NMSE [dB] | *ACPR* [dBc] | *EVM* [%] |
|---|---|---|---|---|
| No DPD | - | -18.5 | -36.25 | 5.75 |
| Full DPD w/ Matlab's '\' | 322 | -41.1 | -50.7 | 1.05 |
| Indep. DPD w/ APCA | 60 | -38.7 | -45.3 | 1.35 |




With APCA, to meet the targeted linearity specifications (ACPR ≤ -45 dBc, NMSE ≤ -38 dB), only 60 coeff. (= 19% of Full DPD) are required.

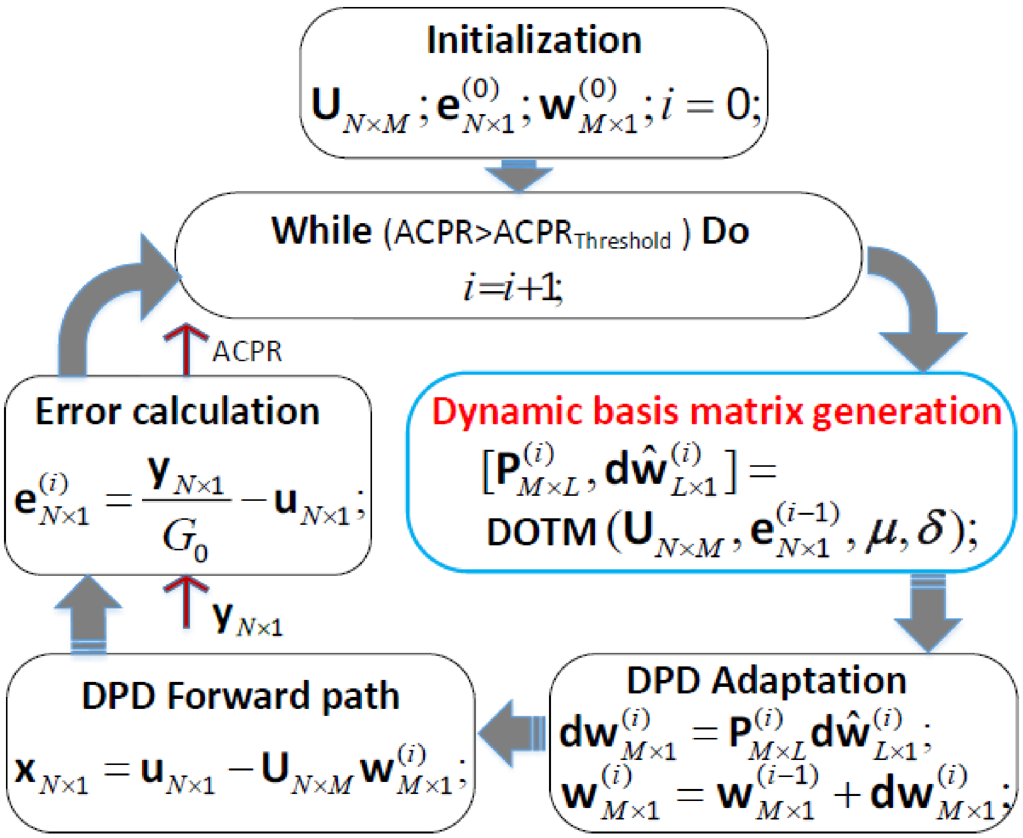



D. Lopez, Q. A. Pham, G. Montoro, P. L. Gilabert, "Independent Digital Predistortion Parameters Estimation Using Adaptive Principal Component Analysis", *IEEE Transactions on Microwave Theory and Techniques,* vol. 66, no. 12, pp. 5771-5779, Dec. 2018.

# Dimens. Reduction for DPD

## Dynamic basis selection for DPD adaptation using PLS

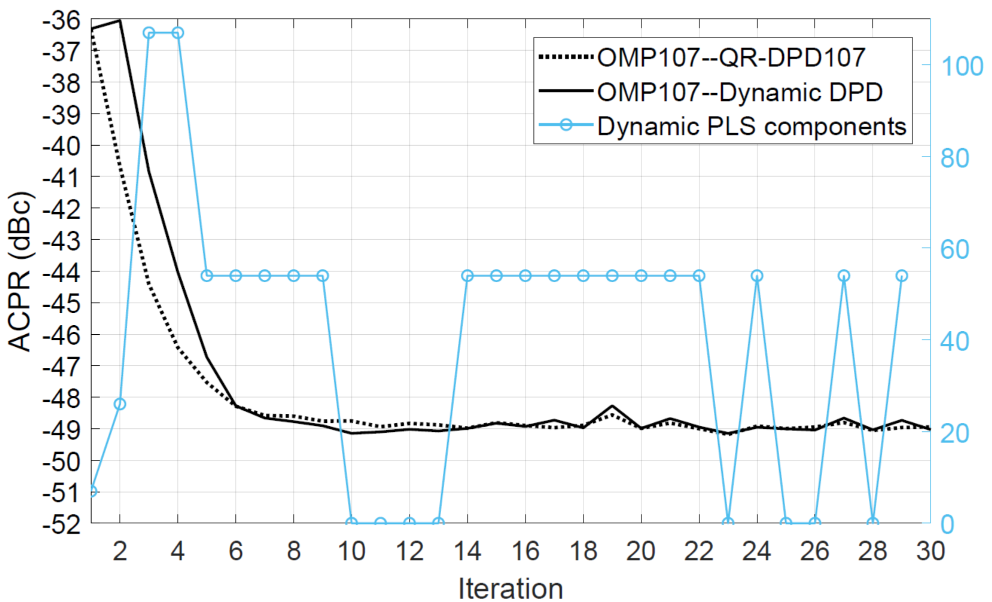



Dynamic Orthonormal Transformation Matrix (DOTM) alg. is a modification of the SIMPLS alg.

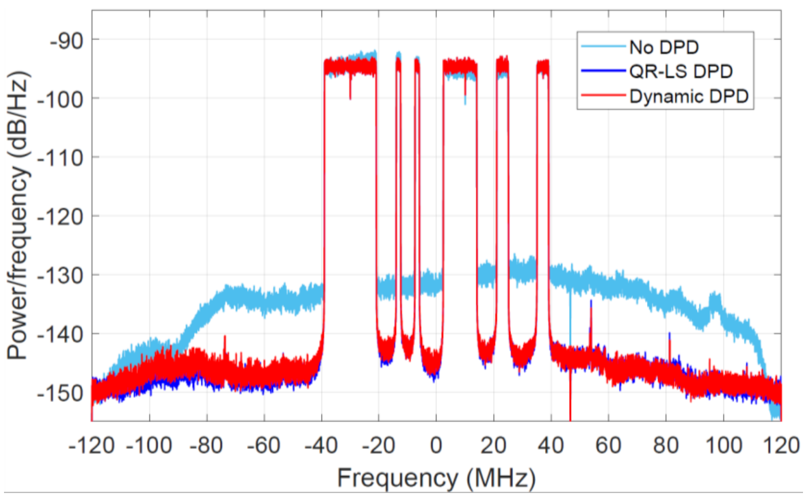
Q. A. Pham, D. López-Bueno, G. Montoro, and P. L. Gilabert, "Dynamic selection and update of digital predistorter coefficients for power amplifier linearization," in *Proc. 2019 IEEE Topical Conf. on RF/Microw. Power Amplifiers for Radio and Wireless Appl. (PAWR)*, Jan. 2019, pp. 1–4.

# Dimens. Reduction for DPD

## Dynamic basis selection for DPD adaptation using PLS




The DPD estimation/adaptation with DOTM vs. with QR decomposition.




- Original basis functions: 322 coeff.
- Forward path, after OMP: 107 coeff.

- Both DPD adaptations converge after 10 iterations with same ACPR level.
- DPD with QR-LS (using Givens rotations alg.) requires 107 coeff. at every iteration.
- DPD with DOTM need less coeff. (53, 21, 5 or 1 coeff.) to achieve same ACPR.

# Outline

- Introduction
- Linearity vs. Efficiency Trade-off
- High Efficient Amplification Architectures
- Digital Predistortion (DPD) Linearization
- Dimensionality Reduction Techniques
- **Conclusion**

# Conclusion

- In the field of DPD linearization, dimensionality reduction techniques are used with a double objective:
  - Ensure a proper, well-conditioned parameter identification.
  - Reduce the number of coefficients to be estimated and thus relaxing the computational complexity and memory requirements of a hardware implementation.
- As an alternative to QR-RLS to solve the LS regression problem and targeting a reliable estimation we can combine:
  - an a priori off-line search (e.g. OMP) to reduce the number of basis functions of the DPD in the forward path
  - with PLS/PCA identification in the adaptation path → regularization and reduction of the number of estimated coeficients.

# Conclusion

- In PCA and PLS, thanks to the orthogonality of the resulting transformed matrix, the DPD coefficients' extraction can be carried out with simple dot products (avoiding matrix inversions).
- PLS shows better performance than PCA (at the expenses of increasing the computational time) because takes into account the output data vector to compute the transformation matrix.
- Future work: Combining PCA+PLS → obtaining a performance equivalent to CCA.

5G Technology Workshop during Mobile World Congress in Barcelona

# Dimensionality Reduction Techniques for Digital Predistortion Linearization of NR-5G Amplification Architectures

Pere L. Gilabert, Gabriel Montoro, David López, Thi Quynh Anh
Department of Signal Theory and Communications
plgilabert@tsc.upc.edu