Digital Predistortion: principles, techniques and trends

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Data and mobile growth predictions

100x
By 2022, global mobile data traffic will be over 100 times the volume in 2012.

+25 billion
IoT connections will reach over 25 billion by 2025, up from 9 billion in 2018.

20%
By 2022, global mobile data traffic will account for 20% of global total IP (fixed and mobile data) traffic, up from 9% in 2017.

3x
By 2022, the number of devices connected to IP networks will be more than three times the global population.

Worldwide all connected user-related devices and equipment energy consumption is increasing by around 25% per year.

Energy efficient equipments are required to reduce their environmental footprint.

Vodafone Sustainable Business Report 2019

Estimated energy consumption for main Telecom Network sectors

Vodafone energy use (GWh)

- **Our base station sites**
  - 2017: 3.651 GWh
  - 2018: 3.657 GWh
  - 2019: 3.684 GWh
  - **66% in BSs**

- **Our technology centres**
  - 1,510 GWh
  - 1,569 GWh
  - 1,571 GWh
  - **28%**

- **Our offices**
  - 350 GWh
  - 308 GWh
  - 282 GWh
  - **5%**

- **Our retail stores**
  - 51 GWh
  - 55 GWh
  - 45 GWh
  - **1%**

- **Total**
  - 5.561 GWh
  - 5.569 GWh
  - 5.582 GWh

Energy consumption of the various components of the base stations

- **Power Amplifier incl. Feeder**
  - 50-80% (65%)

- **Air Condition**
  - 10-25% (17.5%)

- **Signal Processing (Analogue + Digital)**
  - 5-15% (10%)

- **Power Supply**
  - 5-10% (7.5%)

*[Vodafone Sustainable Business Report 2019]*

*Alberto Conte, Alcatel-Lucent Bell Labs France 2012*
Efficient Base Station Transceiver?

- Technology enablers
  - energy-efficient single radio access network equipment
  - energy-saving software features
    - optimize radio resources and energy consumption
  - active antennas

PA → Most power-hungry!!

[Birafane et al. 2010]
Predistortion and Challenges in 5G

- **Predistortion challenges in 5G small-cell BSs**
  - High signal bandwidths (>100 MHz) → Memory Effects $\uparrow$
  - Complex modulation formats → PAPR $\uparrow$
  - Low-power and low-cost → Cheaper PA with Nonlinearity $\uparrow$
NONLINEAR MODELS AND CLASSICAL ARCHITECTURES
Non Linearity characterization

- Adjacent Channel Leakage (or Power) Ratio (ACLR/ACPR)

\[
ACPR_{\text{dB}} = 10 \log_{10} \left( \frac{\int_{B_W_{\text{main}}} P(f) \, df}{\int_{B_{\text{adj}}} P(f) \, df} \right)
\]

- Error Vector Magnitude (EVM)

\[
EVM(\%) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} |S_{\text{actual},i} - S_{\text{ideal},i}|^2}
\]

Example: 5G specifications
- ACLR > 45 dBc
- EVM < 12.5% for LTE-A for 16-QAM
Adaptive DPD system

Transmission Path (aka TX path)

Observation Path (aka TX Feedback path)

- Predistorter's nonlinear characteristics and the PA must match
- Nonlinearity of the PA varies with time due to changes in the drive signal, aging, or drifts
  - Track variations and update predistortion function
The predistorter implementation

- **Objectives**: model the non-linear behavior, estimate the model coefficients, compensate (suppress) the non-linearities
- **Main implementations**:
  - **LUT**: numeric table of the inverse of the PA’s complex gain indexed by input signal power
    - In its simplest form, unable to accommodate memory effects
  - **Non Linear model**: an inverse model of the PA’s transmission characteristics
    - Usually polynomial or Volterra basis functions → able to accommodate memory effects
Discrete Volterra series

• NL PA with memory effects: \( y[n] = f[x(n), x(n-1), \ldots, x(n-Q)] \)

• Usual NL model with non-linear memory is the Volterra series which is able to model all mildly and weakly nonlinear systems.

• In the digital signal processing: “truncated”
  – polynomial order of \( K \)
  – memory depth of \( Q \)

\[
y[n] = \sum_{k=1}^{K} \sum_{q_1=0}^{Q} \sum_{q_2=0}^{Q} \ldots \sum_{q_d=0}^{Q} h_k(q_1, q_2, \ldots, q_d) \prod_{i=1}^{k} x[n - q_i]
\]

\( K=2 \quad Q=1 \)
\[
y[n] = h_1(0)x[n] + h_1(1)x[n-1] + h_2(0,0)x^2[n] + h_2(0,1)x[n]x[n-1] + \ldots
\]
\[
+ h_2(1,0)x[n-1]x[n] + h_2(1,0)x^2[n-1]
\]

• Coefficients number of a Volterra series: \( N = \sum_{k=1}^{K} \frac{(Q + k)!}{Q! k!} \)
Conventional MP DPD model

- **Memory polynomial (MP) DPD**: Moderate complexity & good performance

\[
z_{PD,MP}[n] = \sum_{k=0}^{K-1} \sum_{q=0}^{Q} a_{kq} x[n-q] |x[n-q]|^k
\]

- Other methods for “pruning” the Volterra series:
  - dynamic deviation reduction (DDR), generalized MP (GMP)
  - Singular value decomposition (SVD) eigenvalue identification methods

- Even so, the number of unique basis functions in the model can still be of the order of 50-100, requiring this number of coefficients to be identified.

- DPD signal bandwidth of several hundred MHz
  \(\rightarrow\) digital clock at several GHz
  \(\rightarrow\) DSP predistorter at GHz rates
  \(\rightarrow\) requires advanced CMOS technology nodes, power-hungry
Lookup Table Predistorter

- LUTs: viable, low-cost, fast-adapting predistorter technique
- PAs with memory effects: Multiple LUT

- DSP predistorter at GHz rates using nonlinear basis functions → challenging hardware

- Return of the LUT to reduce the number of calculations → Multiple LUTs, one for each memory delay

- It reduces the number of complex calculations that need to be carried out in the predistorter at each sample

L. Guan and A. Zhu, “Low-cost FPGA implementation of Volterra series-based digital predistorter for RF power amplifiers,” 2010
DPD architectures – Open loop

• “2 steps” learning technique

**Advantages**
- PA model is identified
- A theoretical inverse model can be computed as the p-th order inverse
- For memoryless systems, this is fairly straightforward

**Drawbacks**
- more difficult for PA systems with memory
- Inaccuracies in the inversion degrade the DPD performance
DPD architectures – Open loop

• «1 step» learning technique: *indirect* learning architecture

![Diagram showing DPD architectures]

**Advantages**
- The PD function is directly derived by calculating the post-inverse of the PA
- Suitable for weakly nonlinear systems with memory
- Easy to code in MATLAB and generally gives good results

**Drawbacks**
- Convergence using least-squares methods
  \[ x_{inPA} = Y \hat{a} \]
- Noisy source data results in multiplicative and additive biases on the estimate for the DPD coefficients \( \hat{a} \)
DPD architectures – Closed loop

• *Direct* learning architecture

![Diagram](image)

- **Advantages**
  - Well suited to memory correction
  - As the optimization converges, the bandwidth of $y_{out}[n]$ approaches that of the input signal → the observation receiver bandwidth could be reduced

- **Drawbacks**
  - works best when the distortion is quite small
  - Usually exhibit slow convergence and high computational complexity
Estimation and Adaptation

• Observation receiver ADC
  – acquire 2k to 32k samples in FIFO memory

• Time-alignment with the input data stream
  – using the information signal itself, making use of fixed preambles, codes, training sequences
  – using a test calibration code

• Estimation of the model coefficients: algorithmic approaches to coefficient estimation for nonlinear basis function modeling.

Estimation and Adaptation

- The polynomial or Volterra based models are **linear in the coefficients**, with the nonlinearity described by the basis functions.

- **Least-mean-squares (LMS):** \( \min_A E[|y(n) - \vec{A}^H \cdot \vec{y}_x(n)|^2] \)
  
  - Iterative approach: \( e(n) = y(n) - \vec{A}^H(n) \cdot \vec{y}_x(n) \)
  
  \( A(n+1) = A(n) + \mu e^*(n)\vec{y}_x(n) \)

  - Reduced computational complexity \( (O(M \times K)) \)
  - Convergence issues (\( \mu \))

- **Least-squares (LS):** \( \min_A ||\vec{y}(n) - \Gamma_x(n) \cdot \vec{A}||^2 \)
  
  - Common approaches: Moore–Penrose pseudo-inverse \( A^+ = (A^H A)^{-1} A^H \), QR decomposition, SVD
  - Significant computational complexity \( (O((M \times K)^3)) \)

Slow convergence

Mostly used
Part 2

DPD TRENDS
DPD challenges

- Modulation schemes:
  - Bandwidth
  - Concurrent bands
  - MIMO

- PA architectures:
  - Doherty
  - Outphasing
  - LMBA
  - SMPA
  - ...

- Frequency domains:
  - Sub-6GHz
  - mmWave
    - 28GHz
    - 100GHz
DPD main research topics

Signal Processing
- PA/Inverse models
- Fitting algorithms

Hardware design
- Analog & digital interfaces

System & architecture optimization
DPD main topics and solutions

• Bandwidth/Sampling rate:
  – Bandwidth limited, subband and ADC architectures
  – Concurrent bands
  – Hybrid systems

• Modeling:
  – Physically inspired models
  – Machine learning models

• Transmitters and PA architectures:
  – MIMO
  – Multibranch PAs
  – Switch Mode PAs
PA and DPD Bandwidth expansion

• PA bandwidth expansion
  – Observation (TX feedback) path
    • Learning phase

• DPD bandwidth expansion
  – Transmission (TX) path
    • Inference phase
Bandwidth limited DPDs

- Filtered TX [Yu, 2012]
- Constrained feedback [Liu, 2015]
New Algo & ADCs for DPD: spectrum sensing

- Low rate identification [Hammler, 2019]

**Features**
- (Analogue) Discrete Fourier Transform for non-periodic signals
- Improved conditioning of the system of equations
- Identify the PA first
- 30x reduction bandwidth and sample rate
New Algo & ADCs for DPD: parallel subbands ADC

• FFT-based Subband DPD [Pham, 2018]
New Algo & ADCs for DPD: parallel subbands ADC

• Mitigating subband edge effects

Exclusion of subband edges

\[ \tilde{Z}_{lin} = \Gamma_V h^{pd} = \tilde{X} \]

\[ \Gamma_V \sim \left( \text{ift} \left( \tilde{z} \right), \text{ift} \left( \tilde{z}^2 \right), \text{ift} \left( \tilde{z}^4 \right), \ldots \right) \]

13% lossless reduction
Concurrent bands

- nD-DPD [Younes, 2013; Chen, 2016]

- Cross-band terms
  - Example:

\[
y[n] = \sum_{m=0}^{M-1} \sum_{k=0}^{K-1} \sum_{j=0}^{k} \sum_{i=0}^{j} c_{k,j,i} \left[ m \right] \\
\times x_1[n-m] |x_1[n-m]|^{k-j} \\
\times |x_2[n-m]|^{j-i} |x_3[n-m]|^i
\]
A/RF/PDs

• Analog Predistortion (APD)

• Analog RF Predistortion (ARFPD)

<table>
<thead>
<tr>
<th>Feature</th>
<th>DPD</th>
<th>ARFPD</th>
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<tbody>
<tr>
<td>Transmit chain BW requirement</td>
<td>❌</td>
<td>✔</td>
</tr>
<tr>
<td>Robust to PVT</td>
<td>✔</td>
<td>❌</td>
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<tr>
<td>Predistorter Power consumption</td>
<td>✔</td>
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<tr>
<td>Overall Power consumption</td>
<td>❌</td>
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<td>ACLR correction Performance</td>
<td>✔</td>
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<tr>
<td>Design challenges</td>
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**Hybrid Mixed-Signal Predistorter**

- **Mixed Signal PD [Manyam, 2018]**
  
  - Linear memory distortion modeled effectively
    - Relax memory (delay) requirements for APD
    - High BW signals linearizable
  
  - Improved correction performance (ACLR) compared to MP
DPD main topics and solutions

• Bandwidth/Sampling rate:
  – Bandwidth limited, subband and ADC architectures
  – Concurrent bands
  – Hybrid systems

• Modeling:
  – Physically inspired models
  – Machine learning models

• Transmitters and PA architectures:
  – MIMO
  – Multibranch PAs
  – Switch Mode PAs
Machine learning models

- Feedforward Neural networks
  - MLP, ConvNets...

- Recurrent NN
  - Long Short-Term Memory

[Wang, 2019][Ghannouchi, 2015]

[Li, 2020]
Machine learning models & methods

• Features
  – Generalization capabilities
  – Memory effects
  – More complex nonlinear systems
  – ML frameworks maturity

• Challenges for DPD
  – Computation resources of BTS / small cells / mobile unit
    • Training complexity
    • Inference complexity

• Key enablers
  – DPD testing and development
    • Efficient model sizing strategies
    • Autonomous algorithm and device testing
  – DPD deployment
    • Efficient model training

• Promising training strategies
  – Genetic algorithms [citations]
  – Reinforcement learning [citations]
Conclusion

• Trans-disciplinary domain
  – Analog/RF
  – Data converters
  – Digital

• Many design elements are interacting
  – Multi-level approach is required

• Challenges and opportunities for 5G/6G
  – PA architectures
  – Massive MIMO
  – mmWave
  – Machine learning
    • replace or complement existing DPD algorithms
References


