

Digital Predistortion

From basics to advanced topics

ICS902 – SMART (2022/2023)

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**SECURE CONNECTIONS
FOR A SMARTER WORLD**

C2S Team – Télécom Paris

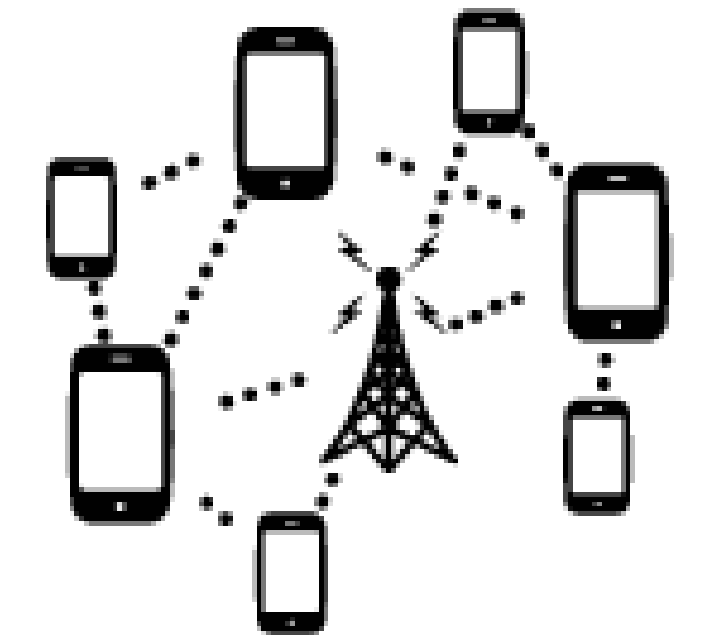


Data Converters

Radio Architectures

Networks and Comm. Systems

Smart Interface



Integrate algorithms in the AMS interface

C2S Research topics

- Cognitive Radio Network – Software defined radio
 - Algorithms & Architecture
 - Game theory based algorithms for security and reliability
- Architectures for communication systems
 - Rx architecture level : discrete-time receiver, $\Sigma\Delta$ receiver, CS
 - ADC architecture : $\Sigma\Delta$, Flash, Time-Interleaved
- Circuit-level design and algorithm implementation in CMOS
 - ADC: Flash, $\Sigma\Delta$, Time-Interleaved
 - Radio Receiver : $\Sigma\Delta$ receiver, analog discrete-time processing
 - Rx building blocks : filter, AGC, ADC, PLL, etc.
 - Digital algorithm : mismatch correction in time-interleaved architecture, digitally-assisted analog IC
- Machine learning
 - Hardware implementation
 - AI aided design

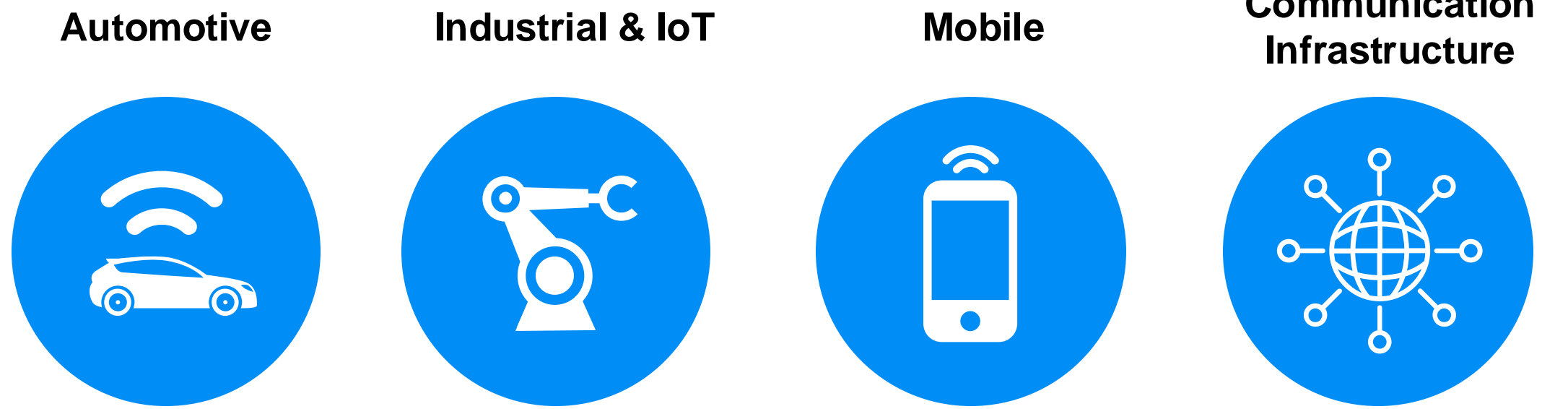
NXP SEMICONDUCTORS WORLDWIDE

Heritage from  and  semiconductors
MOTOROLA

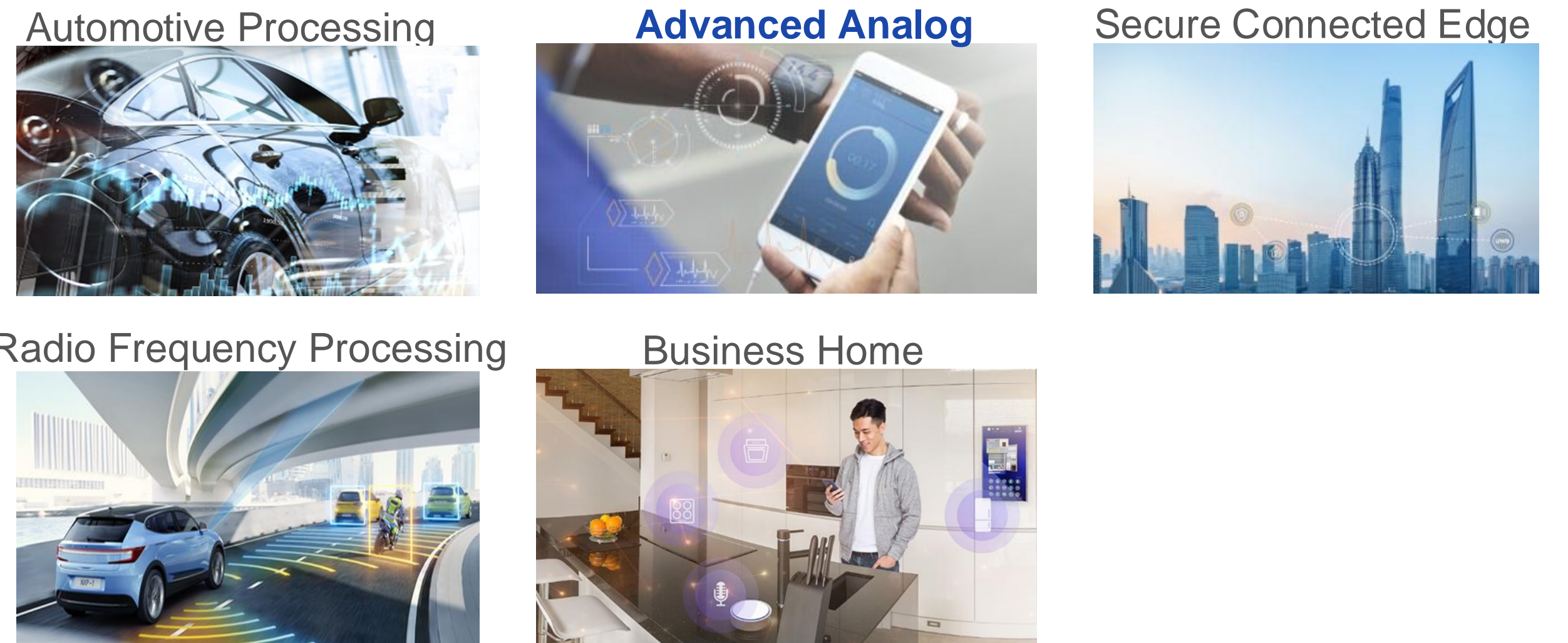


60 years of combined experience and expertise
Operations in more than 30 countries worldwide
Approximately 31,000 employees
Headquarters in The Netherlands – Eindhoven

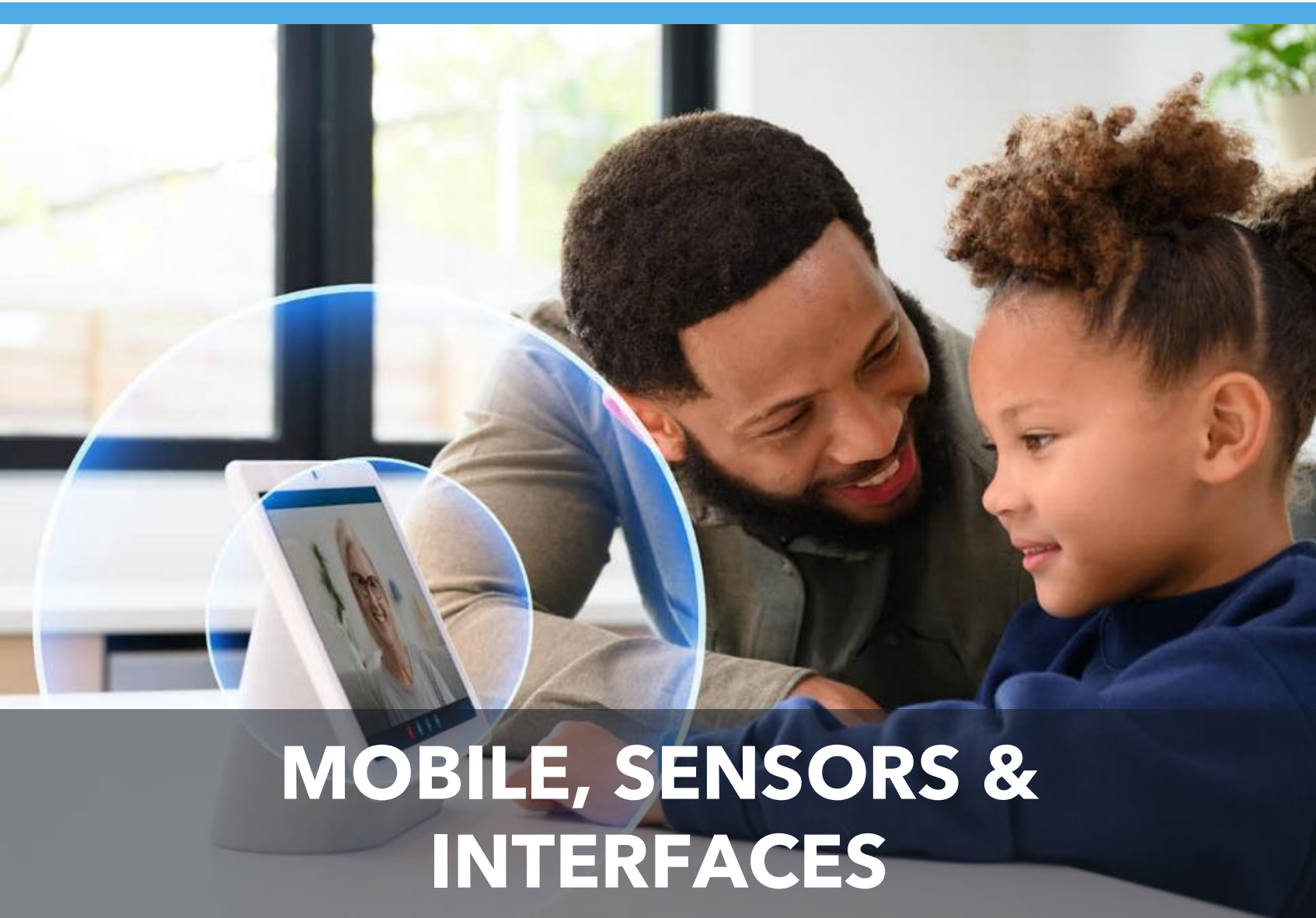
4 Focus Markets



Served by 5 business lines



ADVANCED ANALOG - FOCUSED PORTFOLIO



MOBILE, SENSORS & INTERFACES



POWER MANAGEMENT



ELECTRIFICATION



NETWORKING

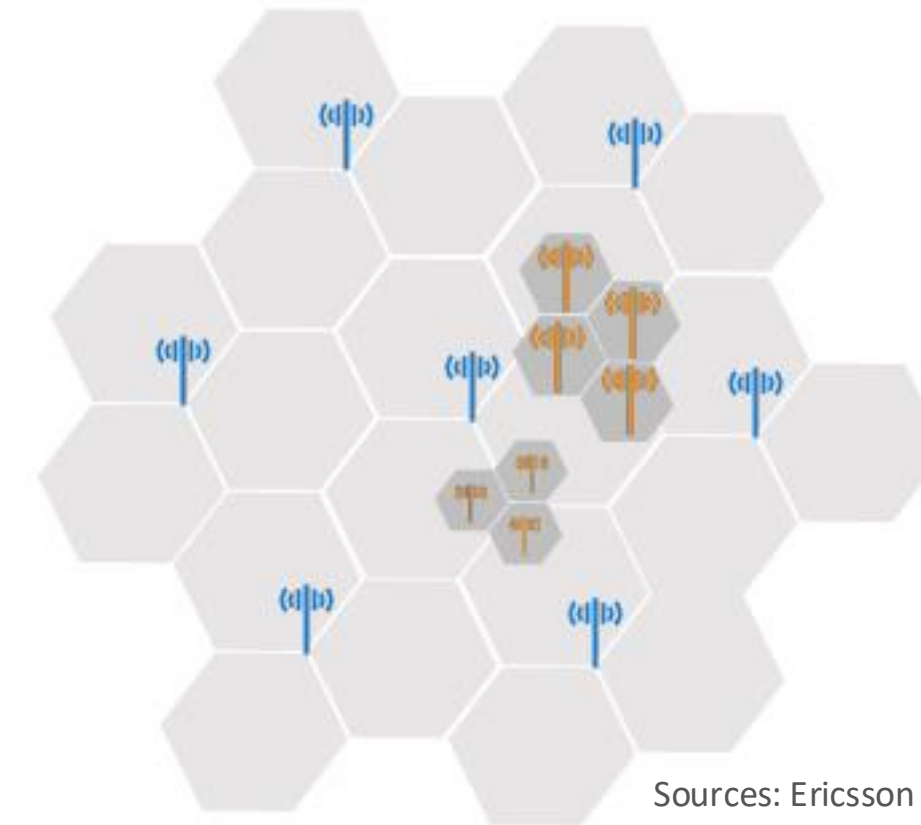
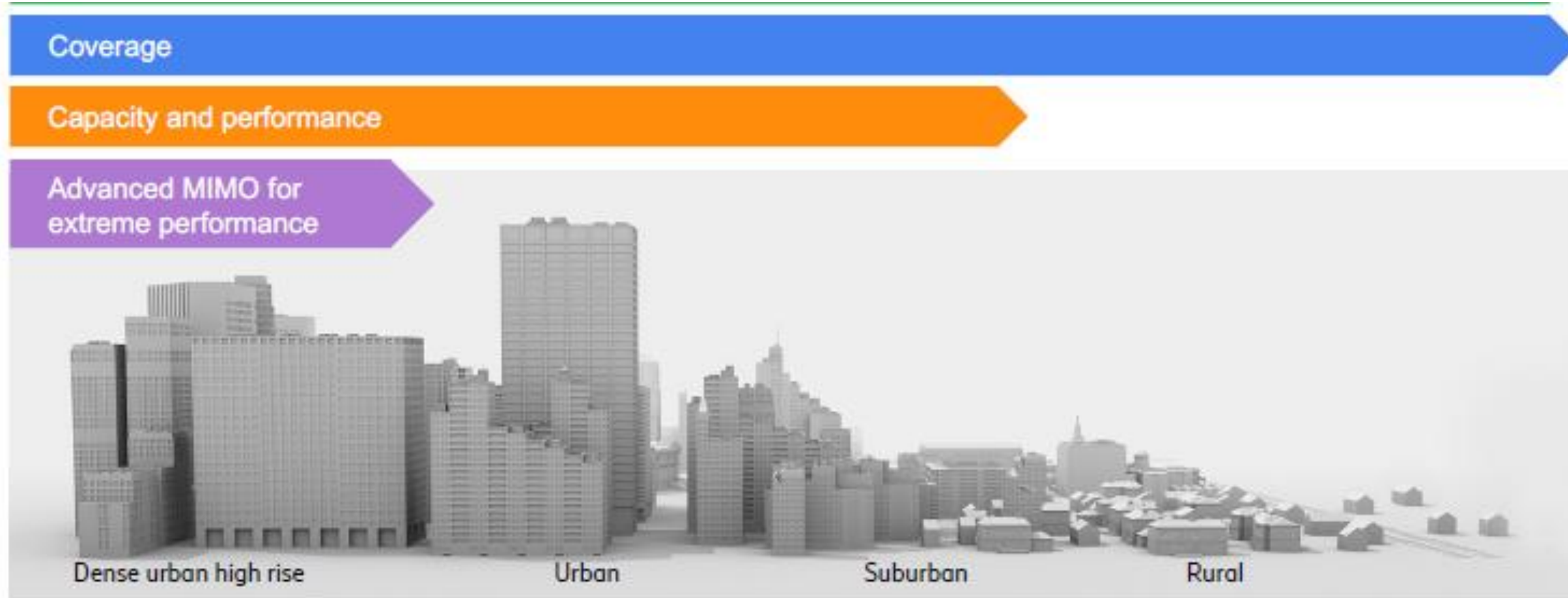


RADIO POWER





SECURE CAR ACCESS

RADIO POWER SOLUTIONS


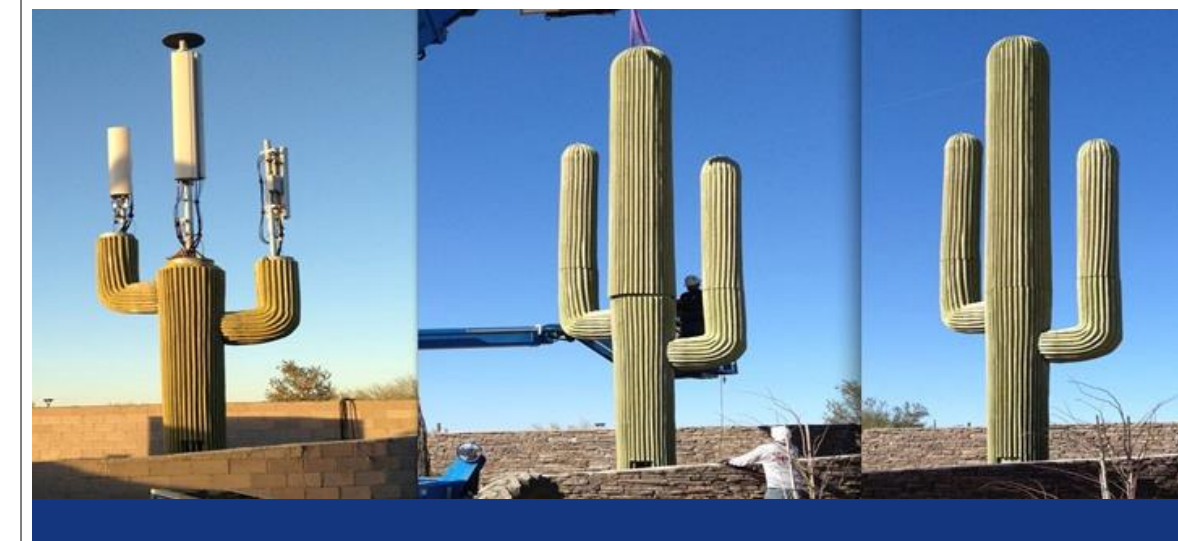


High Power Solutions
Product Line


RF Power – 4/5G 
Cellular Infra Transistors



RF Power
Cellular Infra ICs

Integrated Power Solutions
Product Line

5G mMIMO 
Cellular Infra Modules (std / hyb)



5G mMIMO
Cellular Infra Modules w/ controller



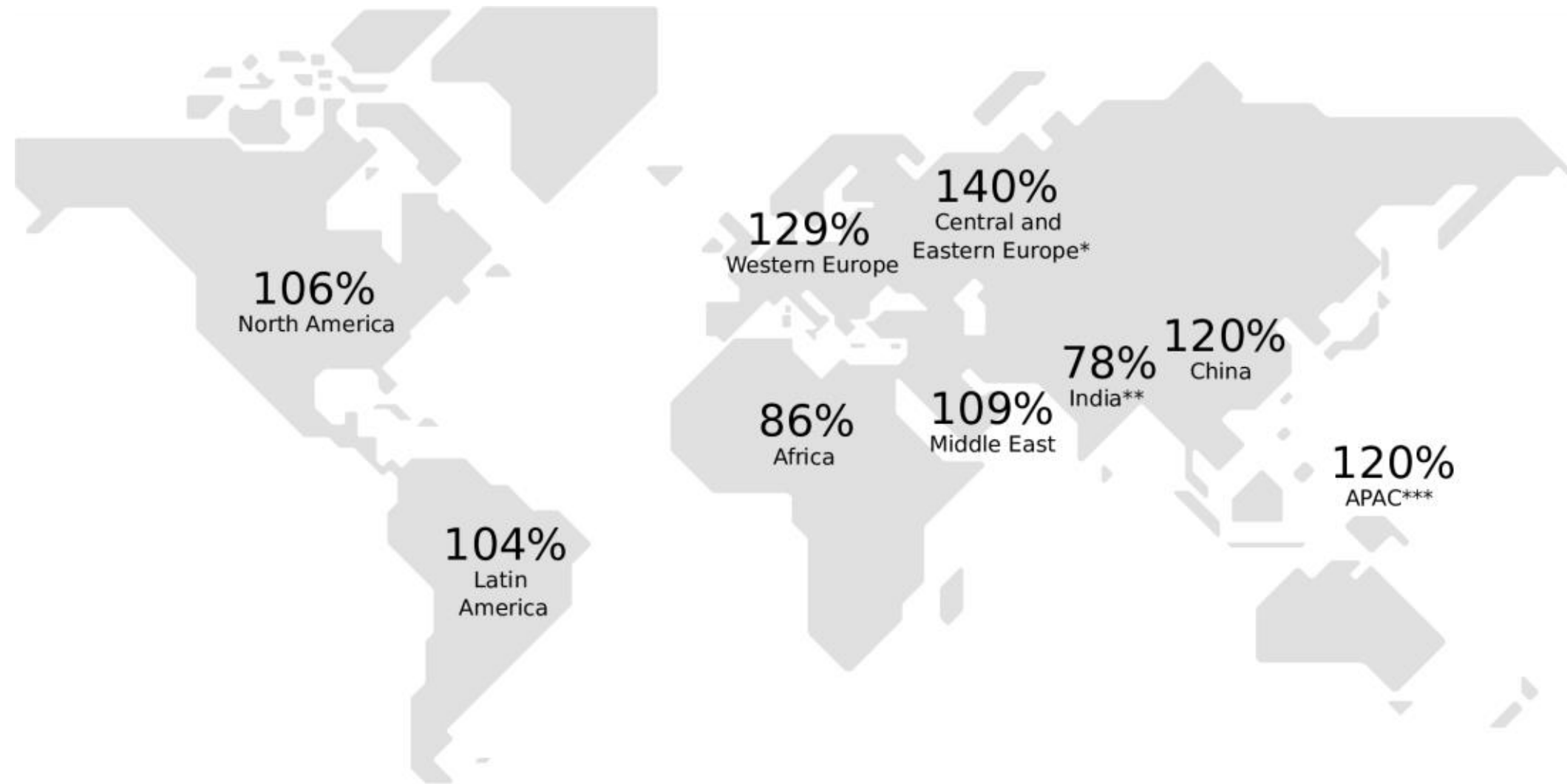
What Will You Learn Today?

- What is one of the main bottleneck for today wireless telecommunication systems (for higher data rates) ?
- What is one of the mostly used technique to improve the situation ?
- What needs to be known for making a proper linearization with the digital predistortion technique ?

Introduction

Why DPD ? 1/4

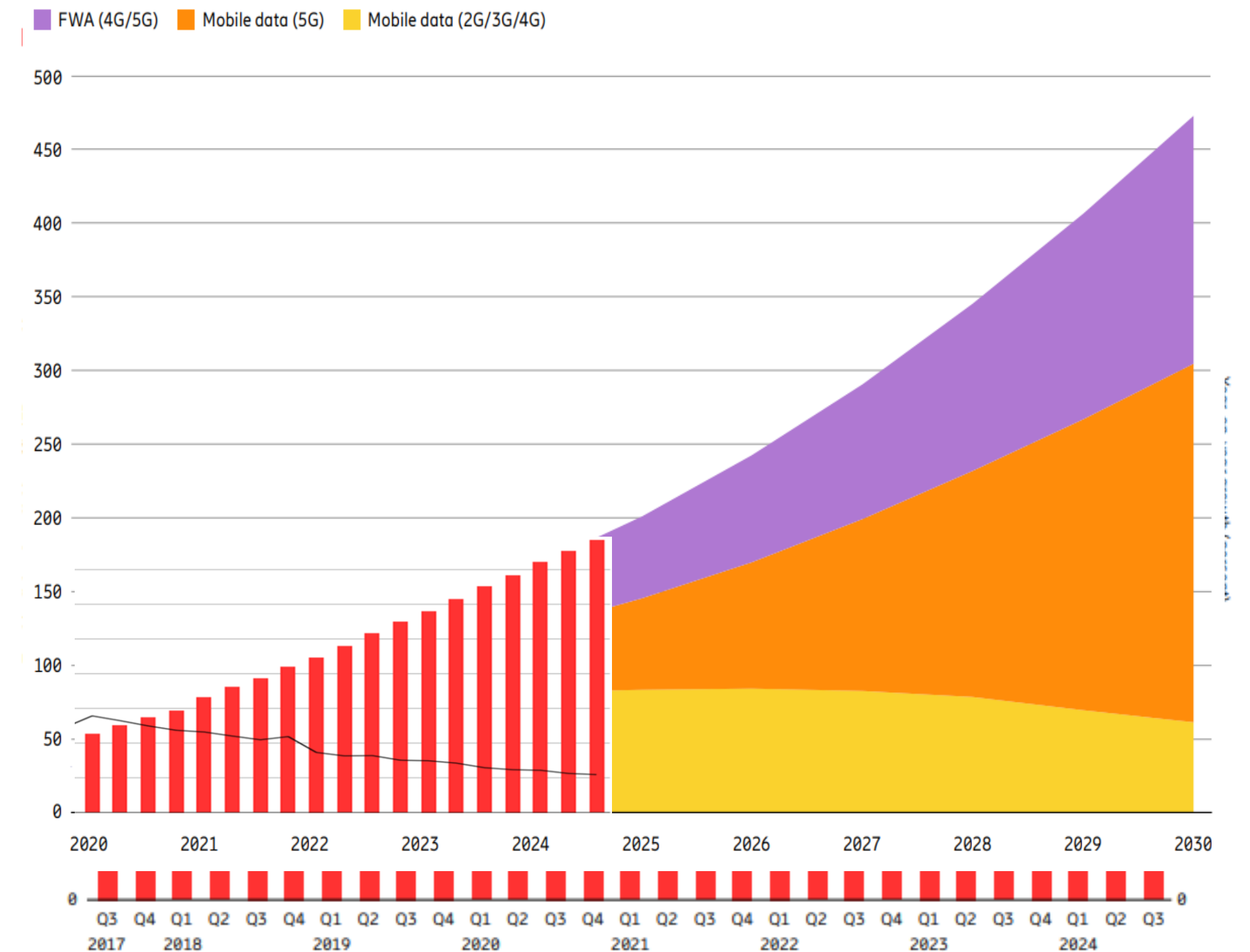
- **Because: ... wireless civilization ... in exponential demand for data services**



Subscription penetration (percent of population)

Source: Ericsson Mobility Report – 2022

Figure 5: Global mobile network data traffic (EB per month)



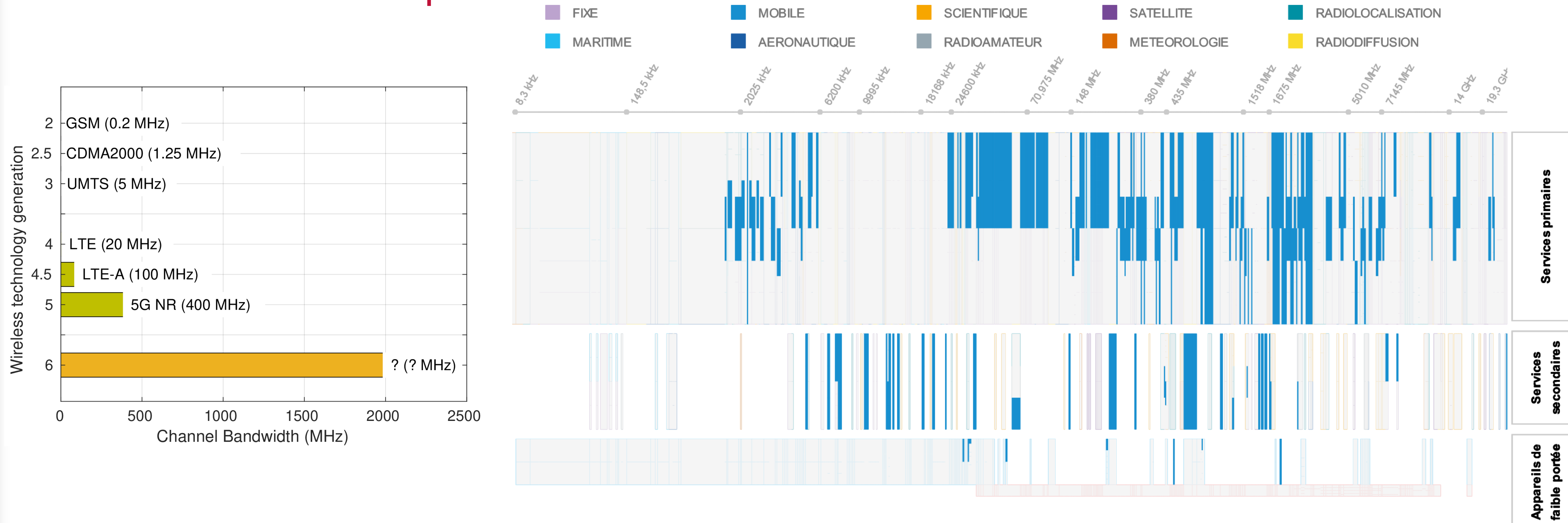
Note: Mobile network data traffic also includes traffic generated by Fixed Wireless Access services.

Global mobile network data traffic and year-on-year growth (EB per month)

Source: Ericsson Mobility Report – 2024

Why DPD ? 2/4

- **How to meet the demand ?**
 Increase the channel bandwidth ...
 but 8kHz -30GHz spectrum is crowded



- **Increase the network densification ...**
 - precise spectrum management and
 - high quality signals (at the receiver side)

Sources: ANFr

Why DPD ? 3/4

The energy consumption challenge

GSMA mobile operators vision

Mobile Operators consumed around 320 TWh of electricity in 2022, or around 1.3% of global electricity use.

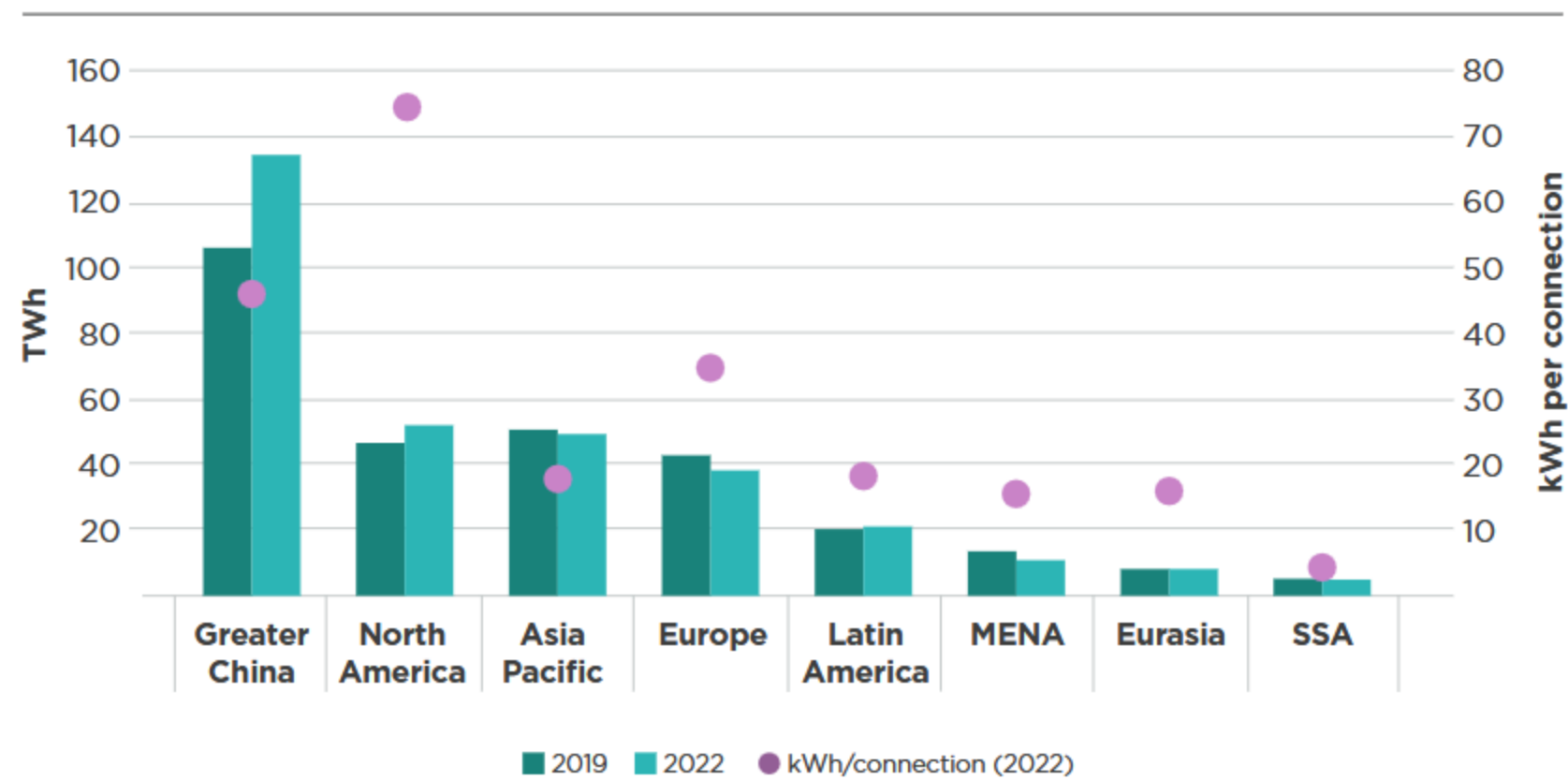
NXP Worldwide: ... Electricity consumption: ~1.7 TWh in 2022

My 3kWh solar panel production in 2022: ~3,7MWh

Source: <https://www.nxp.com/company/about-nxp/sustainability-and-esg/environment-health-and-safety/energy:ENERGY>

Source: <https://www.gsma.com/solutions-and-impact/connectivity-for-good/external-affairs/wp-content/uploads/2024/02/Mobile-Net-Zero-2024-State-of-the-Industry-on-Climate-Action.pdf>

Figure 7 | Electricity use by region

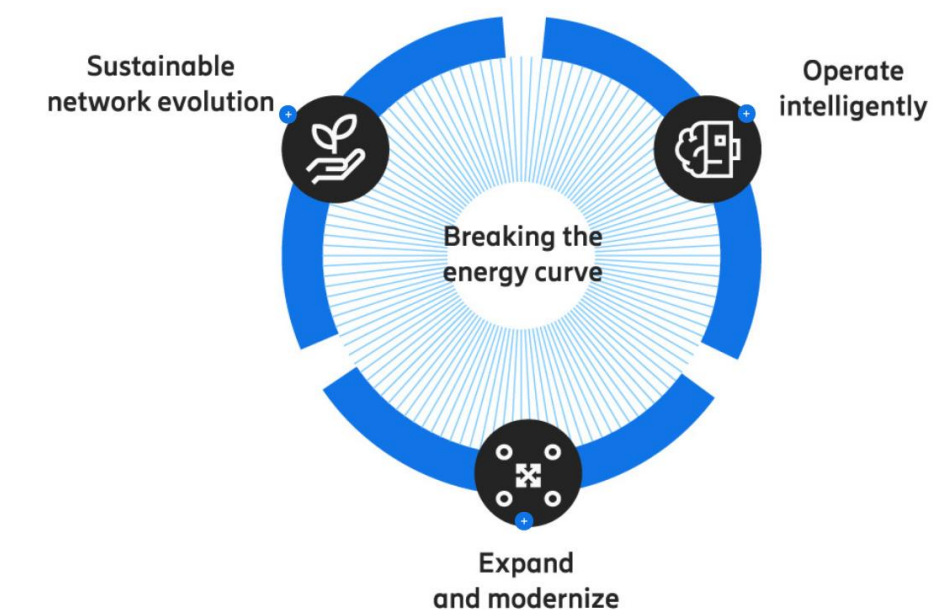
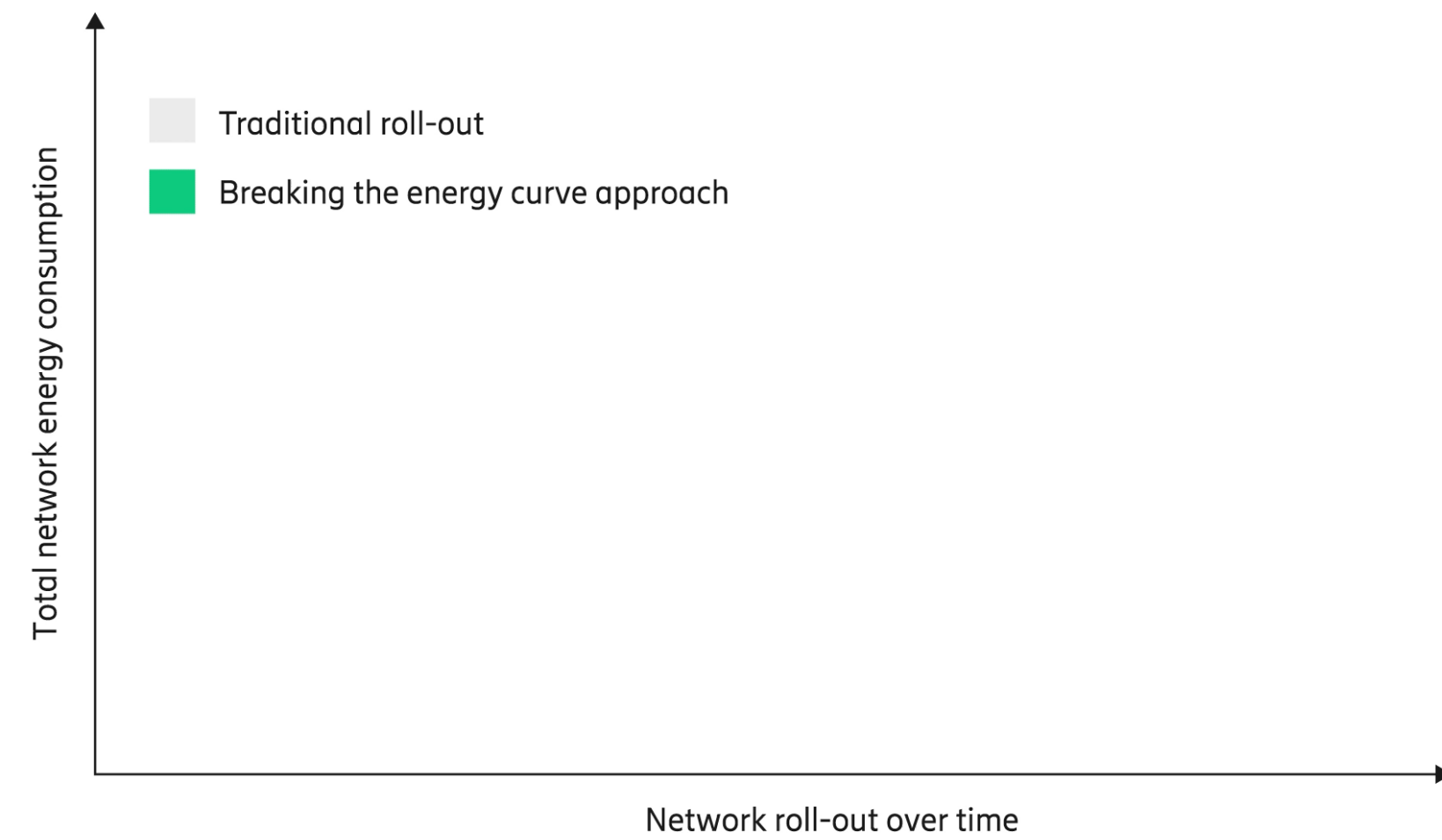


Note: Connections include mobile, fixed broadband and fixed voice.

Source: GSMA analysis based on CDP (2020; 2023) and corporate sustainability reports

Source: <https://www.gsma.com/solutions-and-impact/connectivity-for-good/external-affairs/wp-content/uploads/2024/02/Mobile-Net-Zero-2024-State-of-the-Industry-on-Climate-Action.pdf>

ERICSSON vision



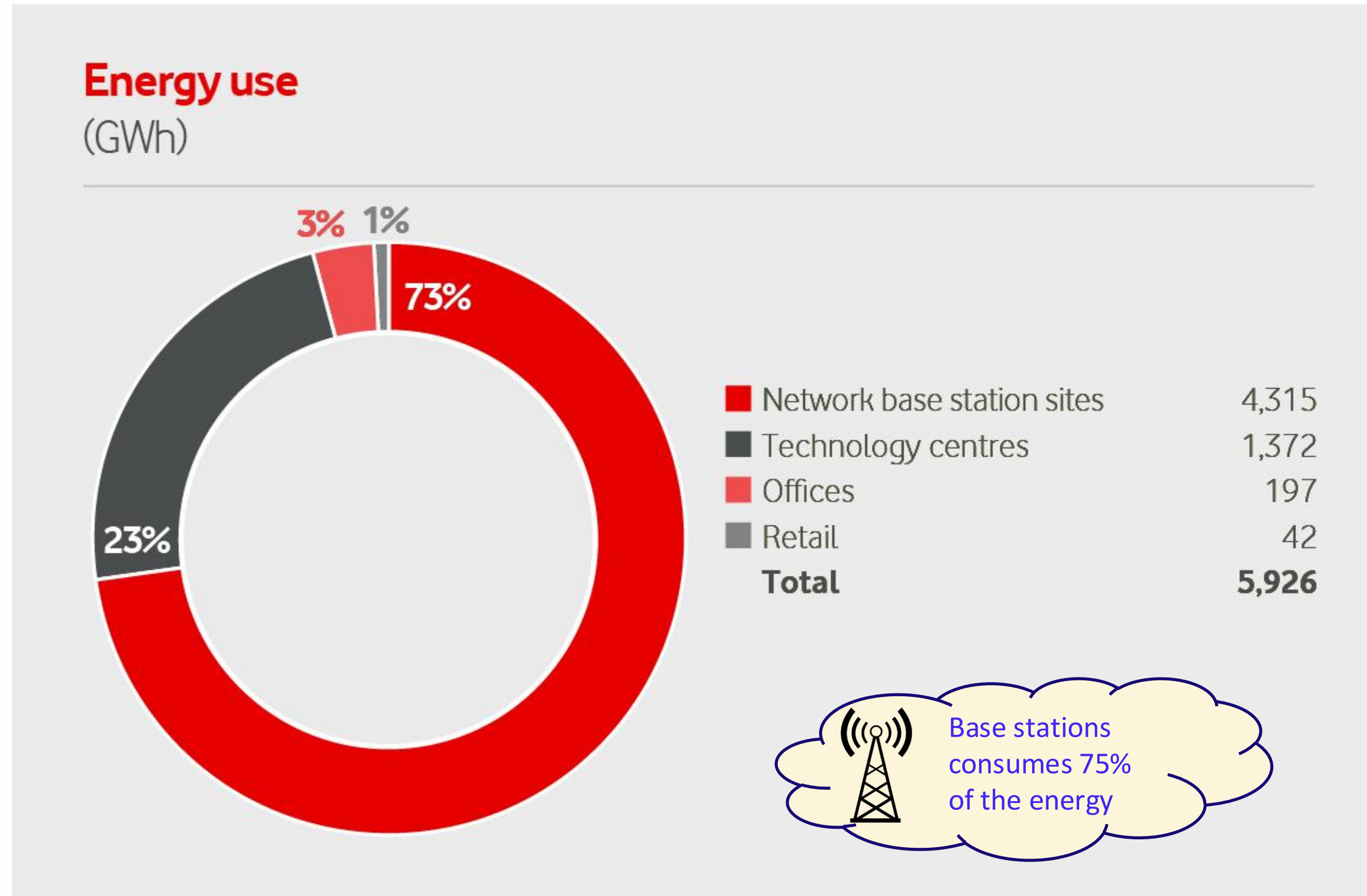
Source: Ericsson Mobility Report – 2024

<https://www.ericsson.com/en/about-us/sustainability-and-corporate-responsibility/environment/product-energy-performance>

Why DPD ? 3/3

- The Radio is energy hungry ...

Vodafone's example : Energy use (GWh)



GWh	2019	2020	2021	2022
Network base station sites	3 848	4 099	4 337	4 315
Technology centres	1 559	1 488	1 413	1 372
Offices	317	264	213	197
Retail	46	46	33	42
Total	5 770	5 897	5 997	5 926

- And inside base station**
- 1. Cooling system**
 - 2. PA**

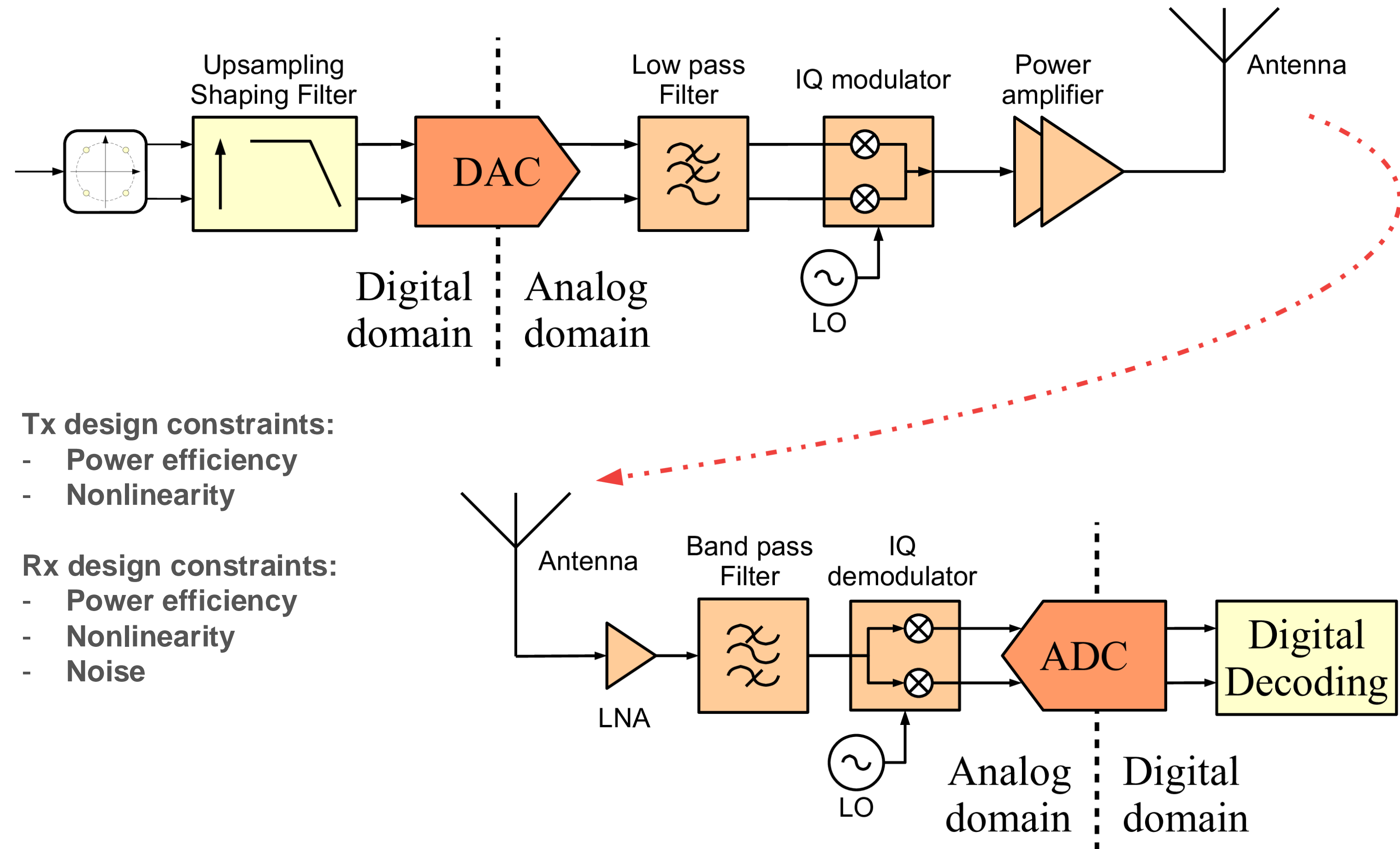
Source: Sustainable Business Report 2022 - Vodafone

We must watch out PA efficiency

Issues in Digital wireless communication systems

Issues in Digital wireless communication systems

- Hardware impairments



Tx design constraints:

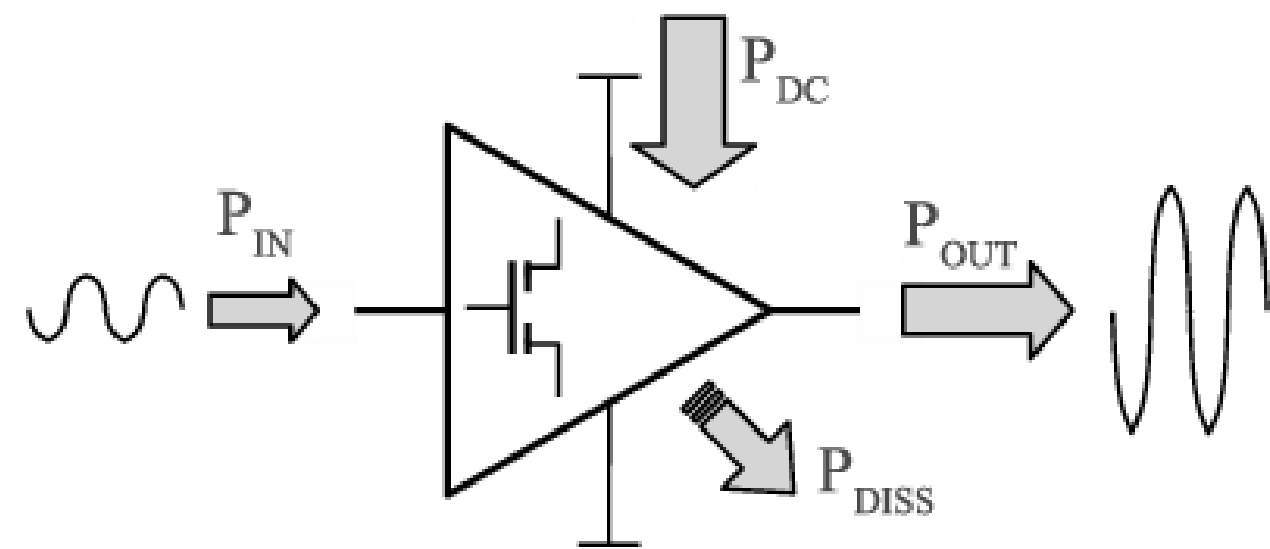
- Power efficiency
- Nonlinearity

Rx design constraints:

- Power efficiency
- Nonlinearity
- Noise

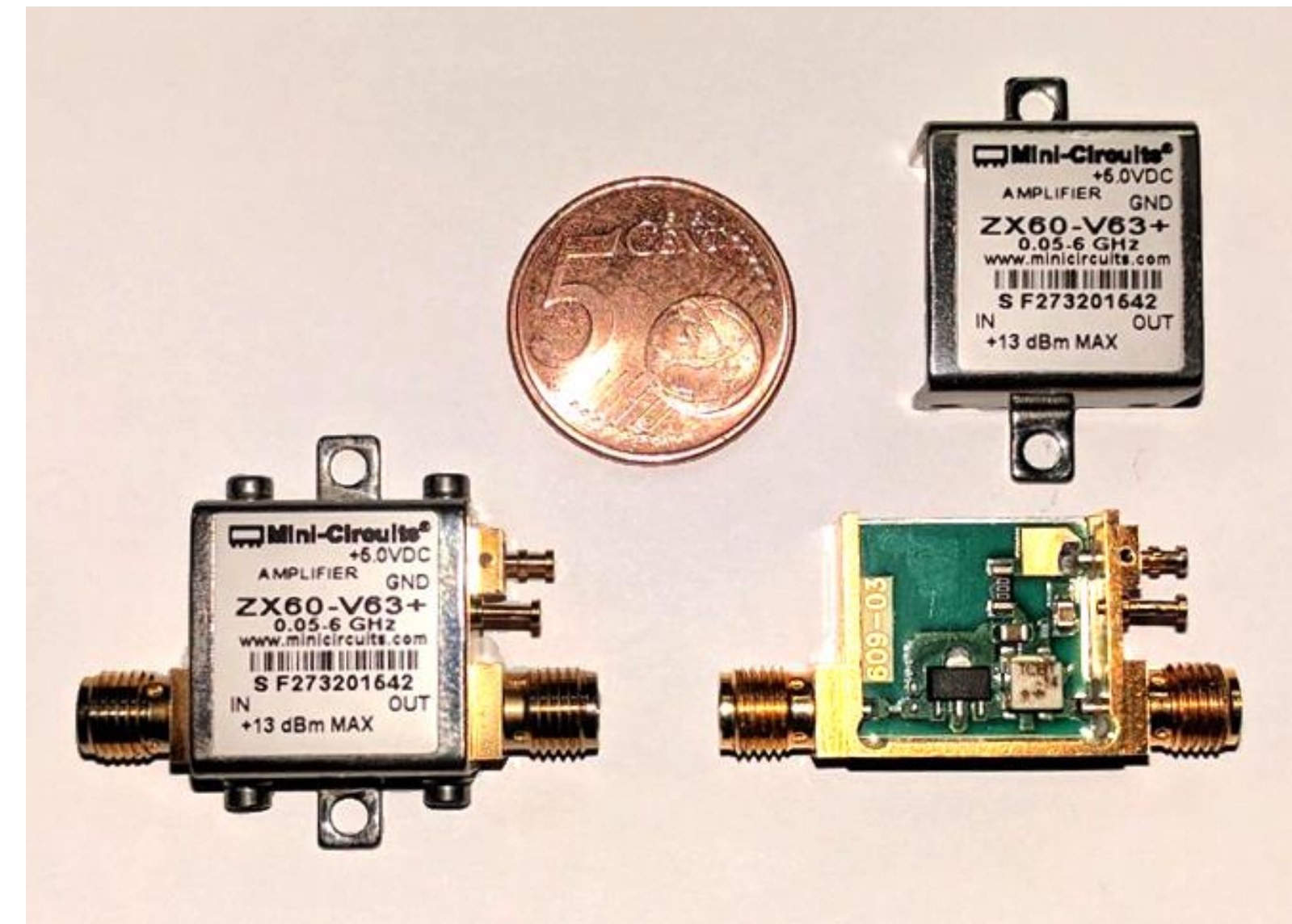
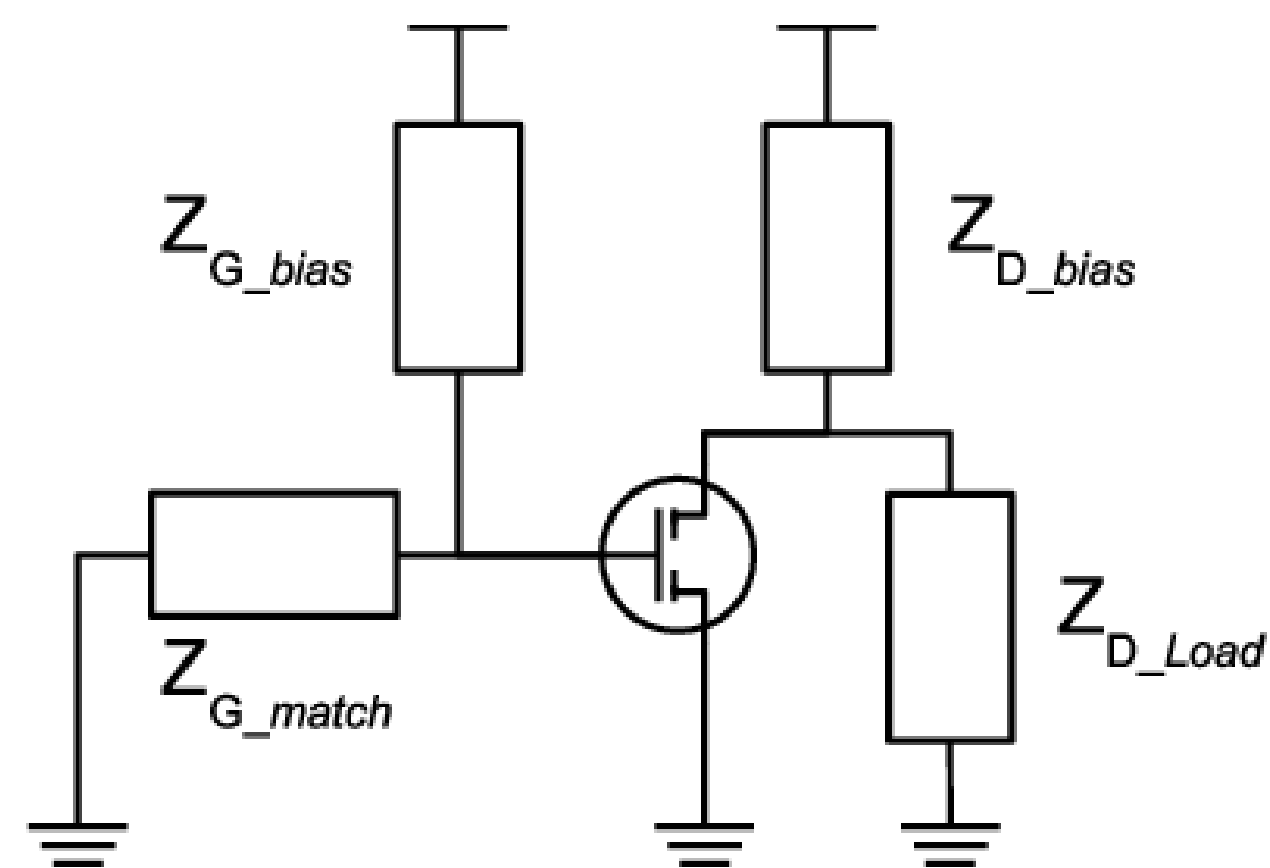
Power Amplifier ? What is it ?

- Abstract view

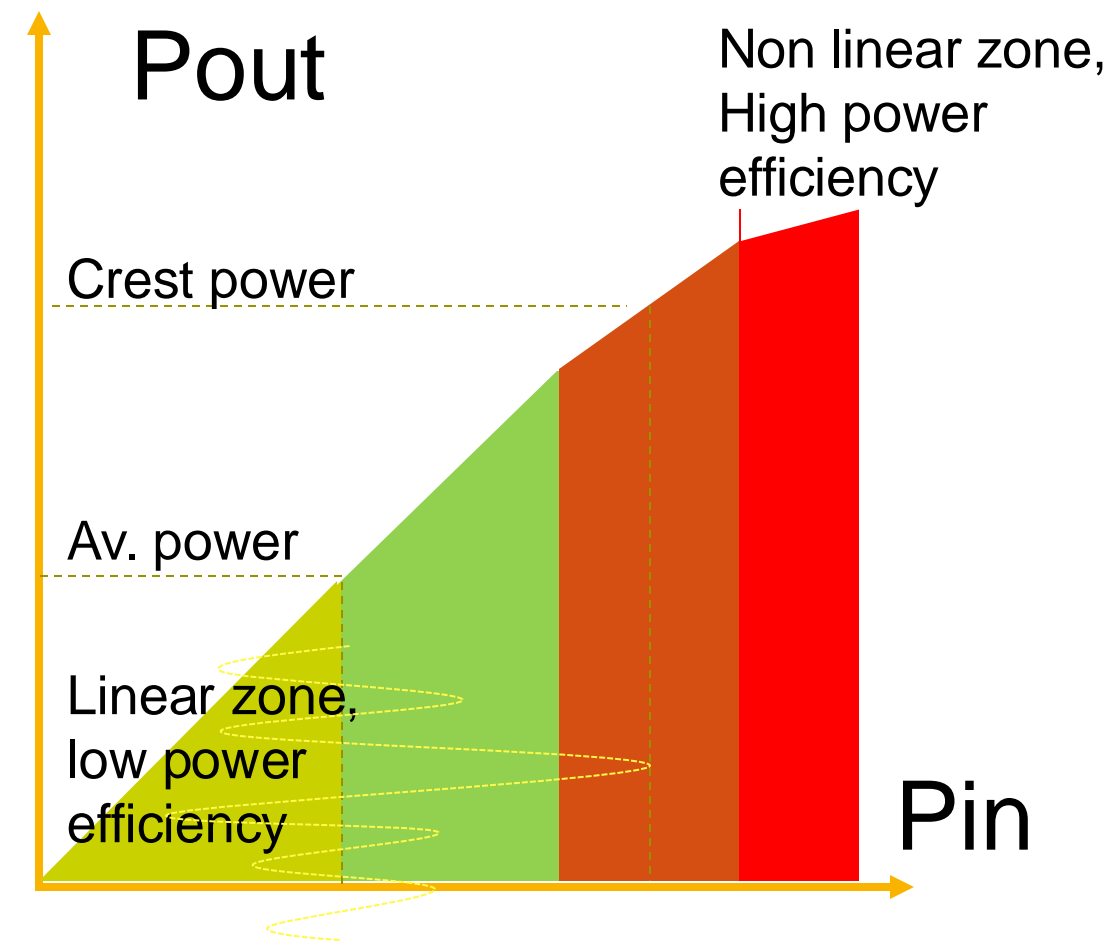


- Device example

- General circuit model



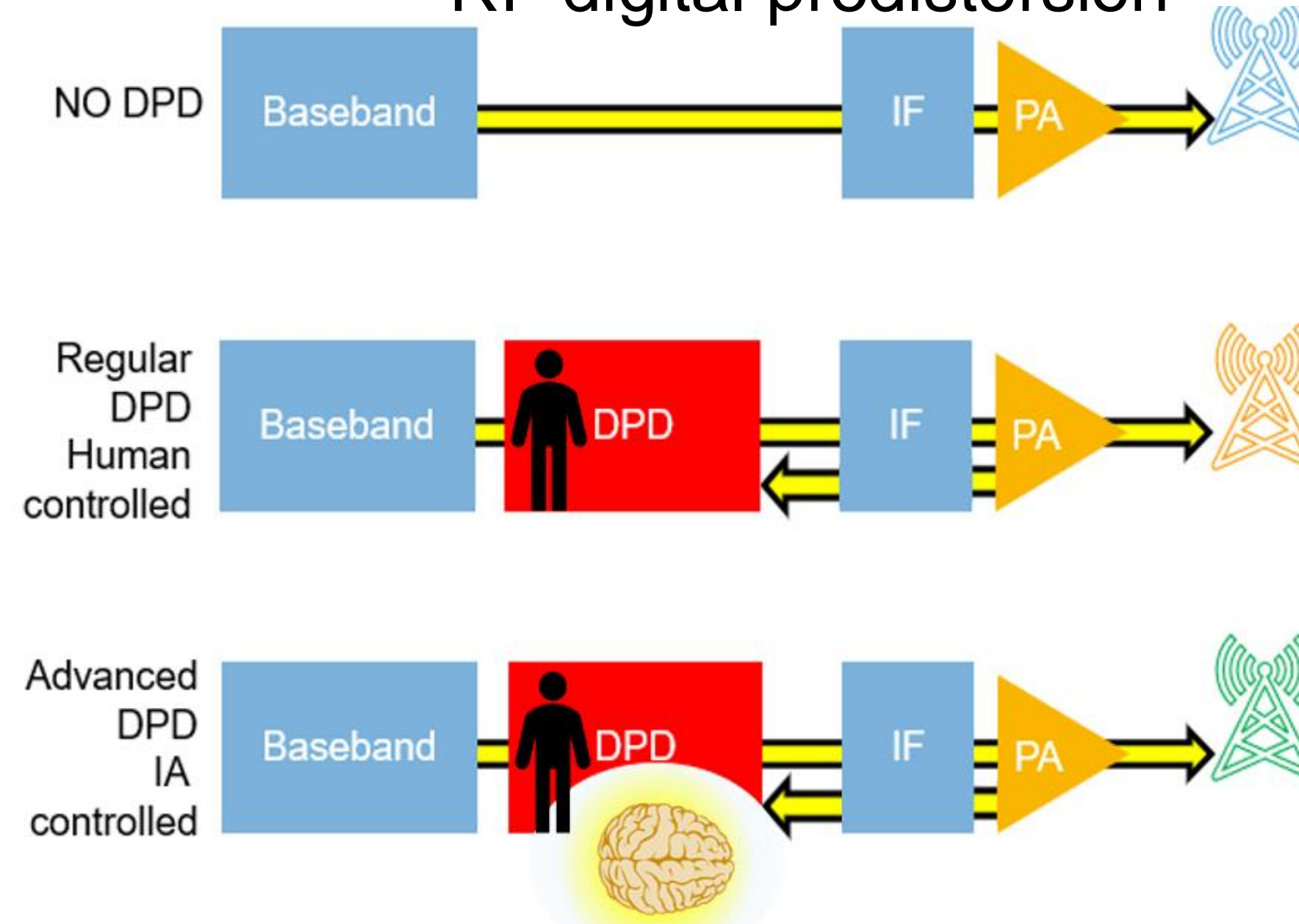
CONTEXT: RF Digital predistorsion (DPD)



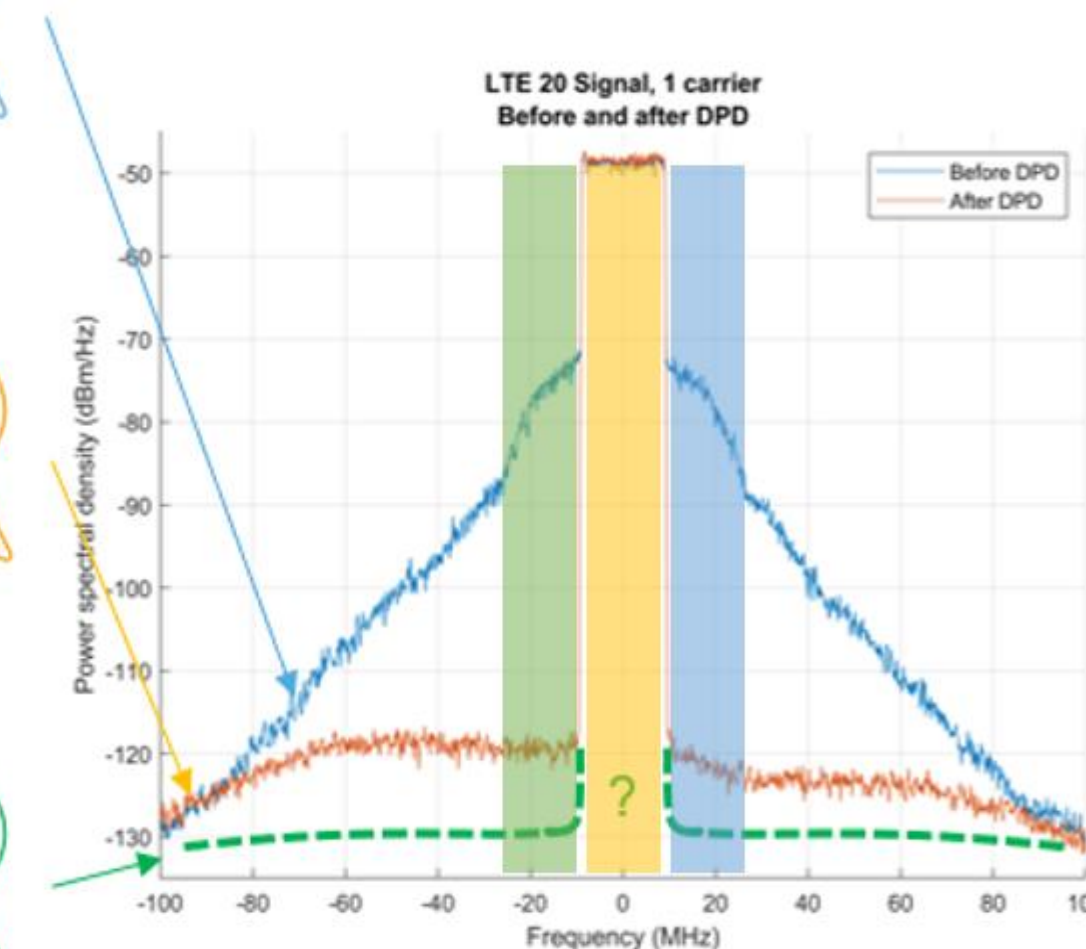
Power efficiency / linearity tradeoff
 DPD apply to baseband signal the inverse of PA transfer's function.

So that the signal sent to the antenna is as linear as possible

Application:
 RF digital predistorsion



Merit factor:
 Adjacent Channel Power ratio

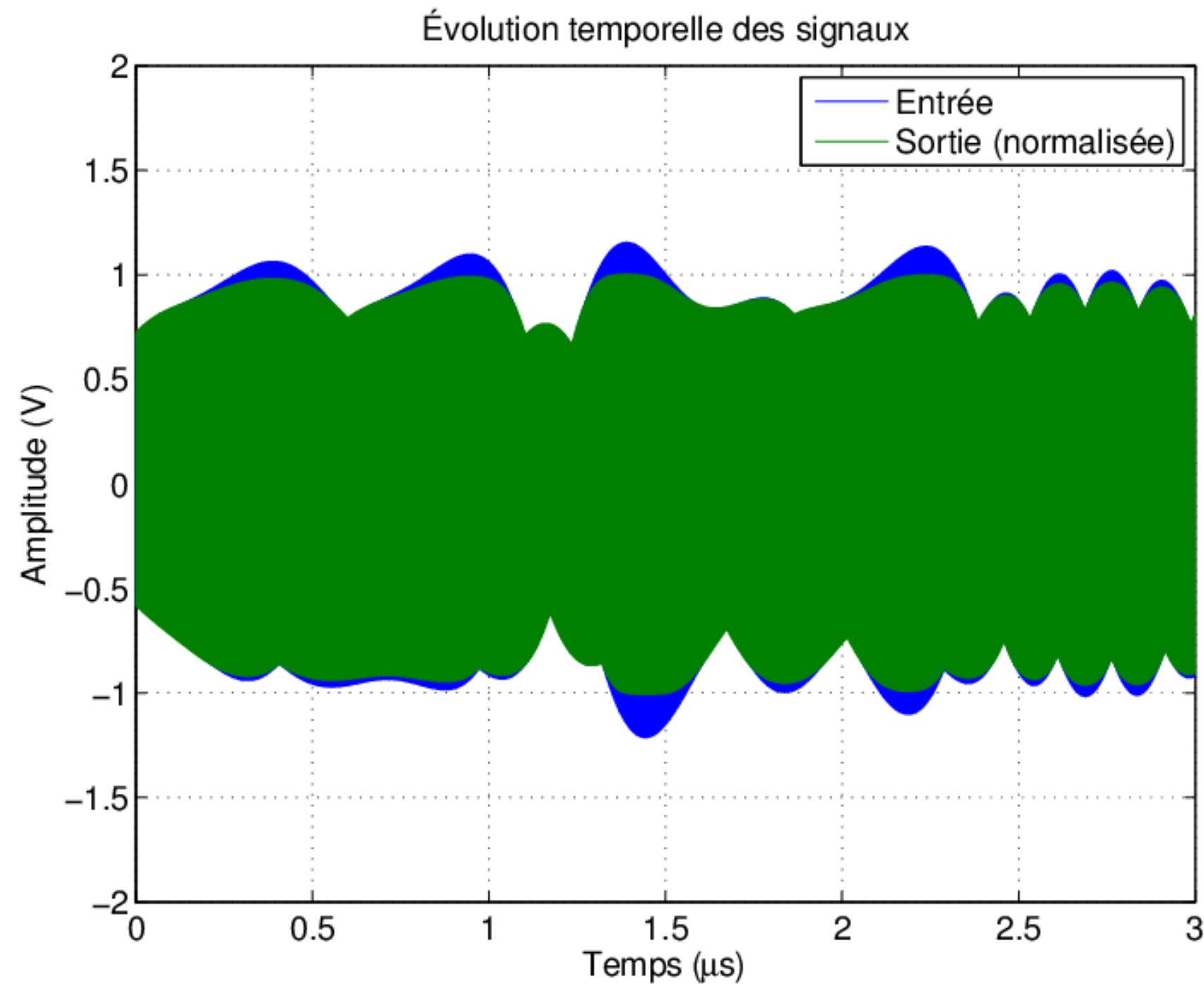


ACPL = $\frac{\text{Green}}{\text{Yellow}}$ ACPH = $\frac{\text{Blue}}{\text{Yellow}}$



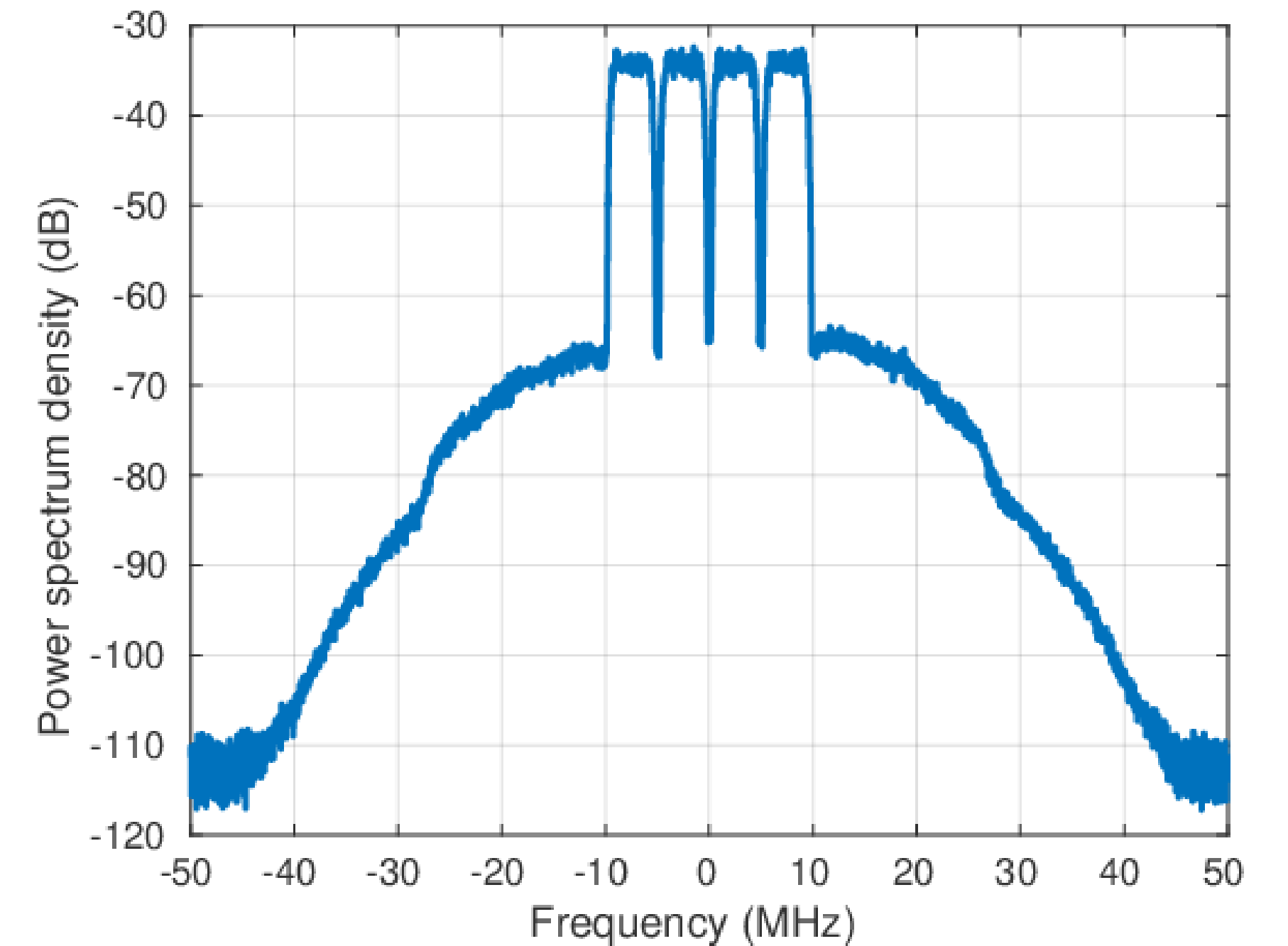
Impact of nonlinear distortions

- Time domain



- Signal quality degradation

- Frequency domain

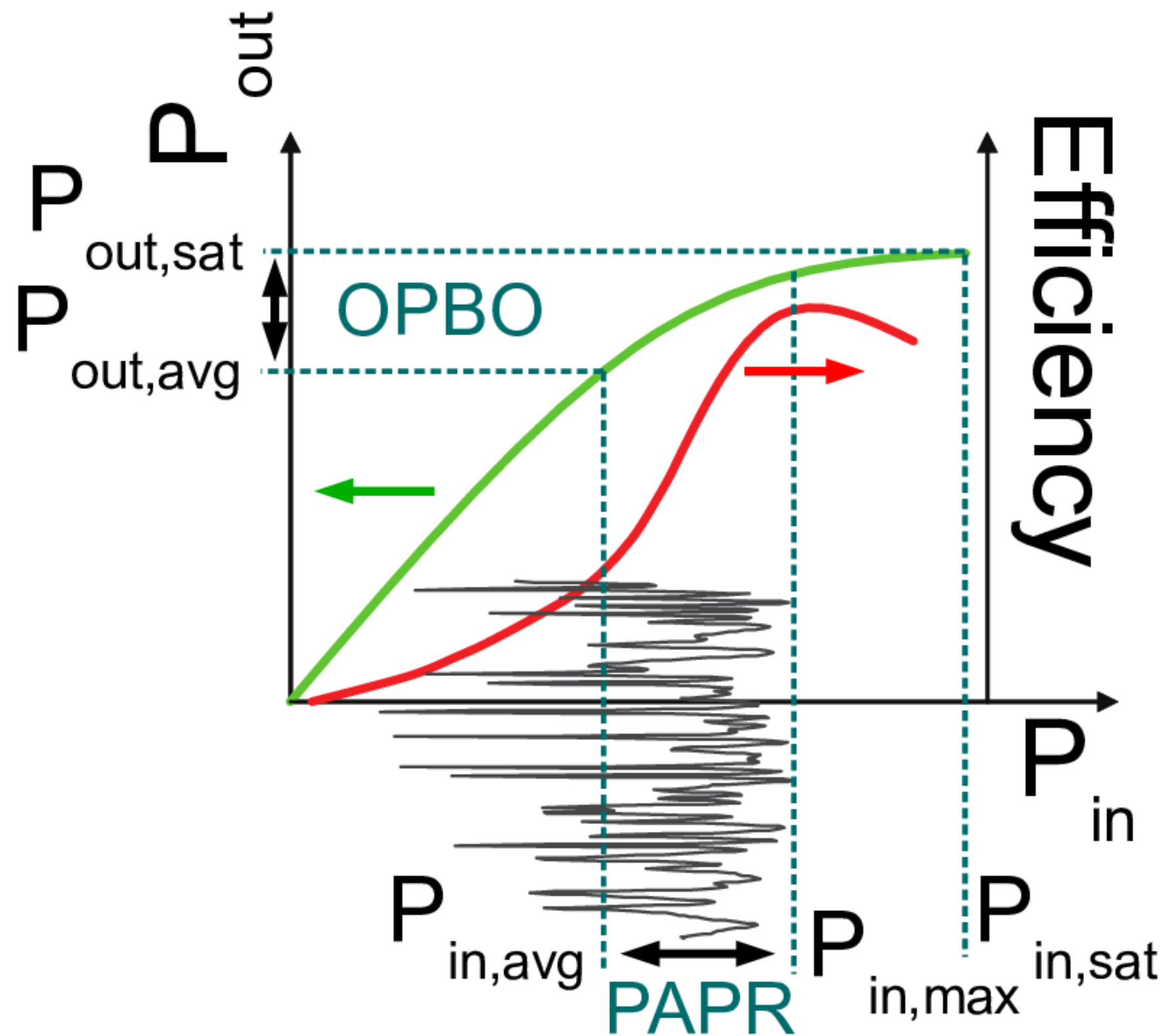


- Adjacent band interference

Fundamental metrics

Input/Output characteristics

- Quasi-static characteristic



- Gain

$$G = \frac{P_{RFout,avg}}{P_{RFin,avg}}$$

- Drain efficiency

$$\eta_D = \frac{P_{RFout,avg}}{P_{DC,avg}} = \frac{P_{RFout,avg}}{V_{DC,avg} \times I_{DC,avg}}$$

- Output power back-off (OPBO)

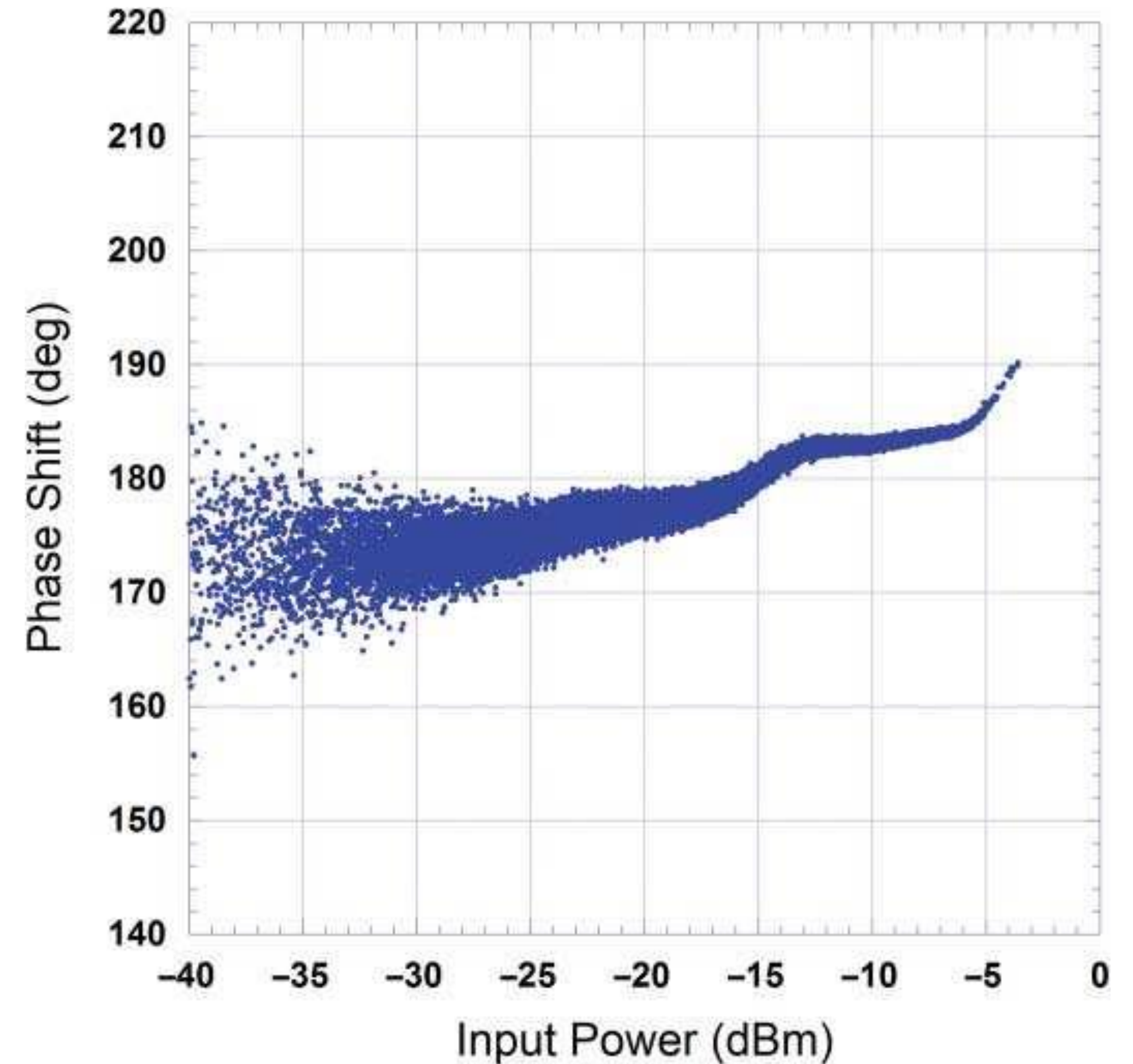
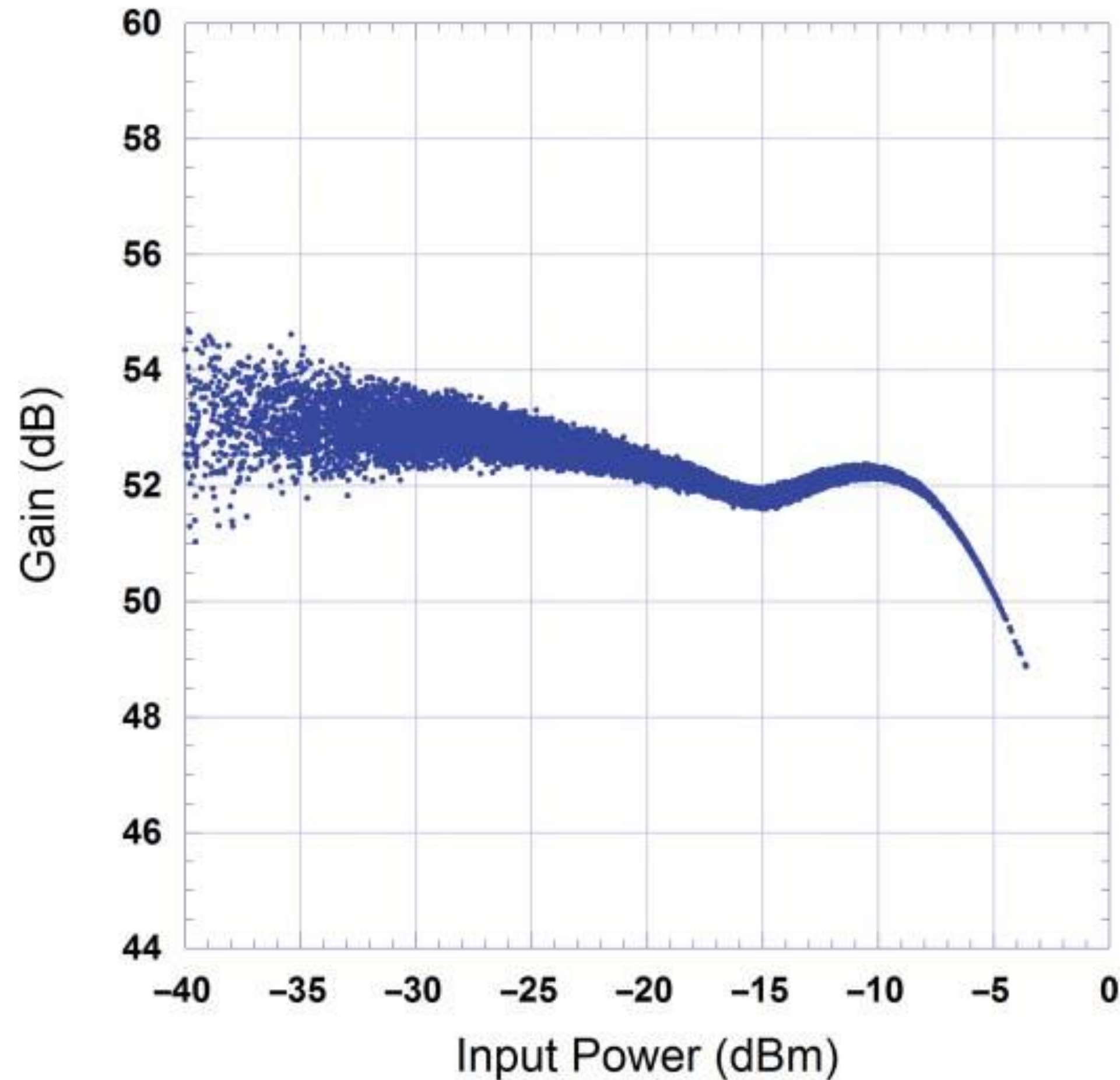
$$OPBO_{dB} = 10 \log_{10} \left(\frac{P_{RFoutavg}}{P_{RFoutsat}} \right)$$

- Signal property : **Peak-to-average power ratio (PAPR)**

$$PAPR_{dB} = 10 \log_{10} \left(\frac{P_{RFinmax}}{P_{RFinavg}} \right)$$

Input/Output characteristics – Visualization tools

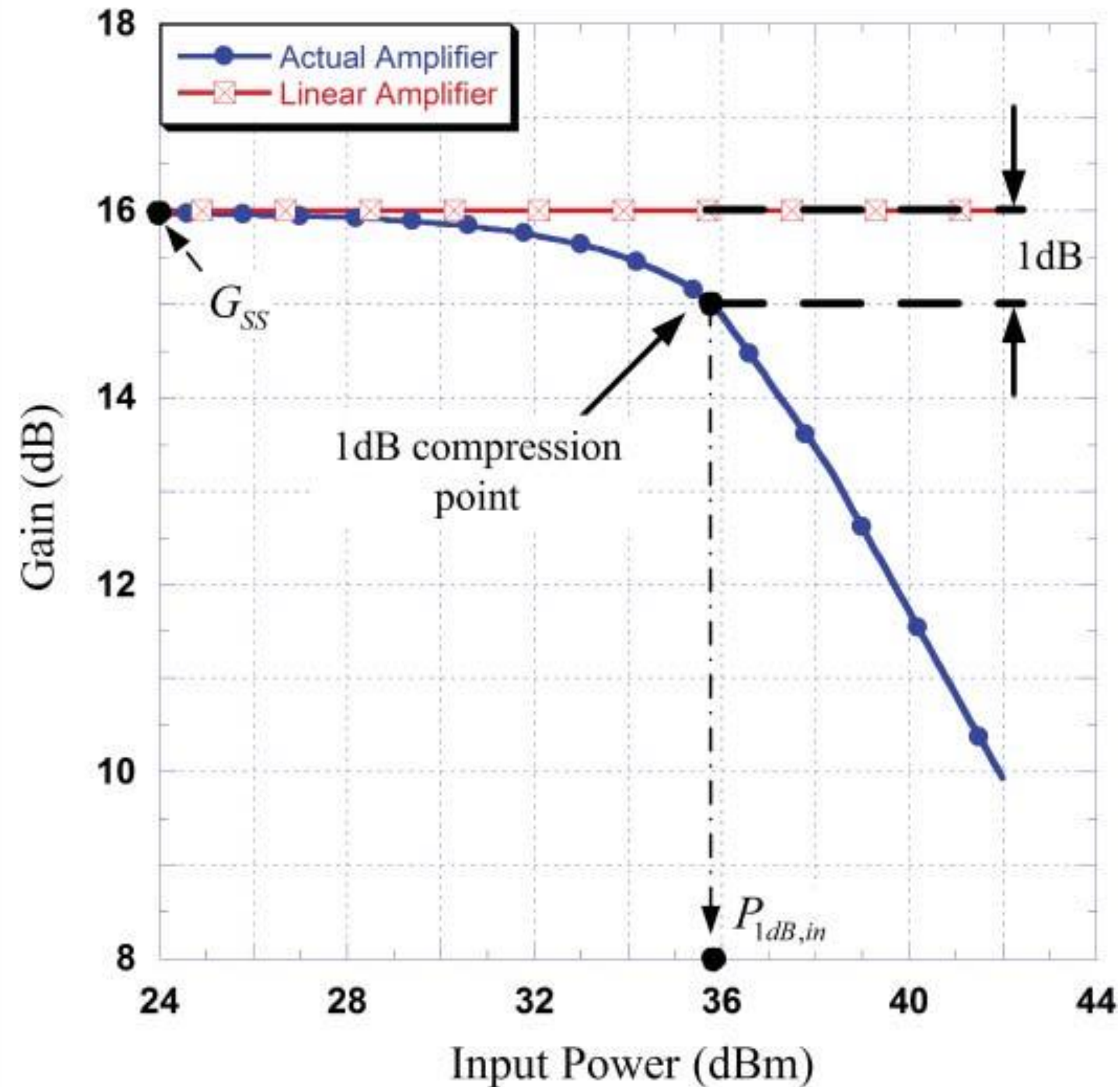
- AM/AM and AM/PM Plots



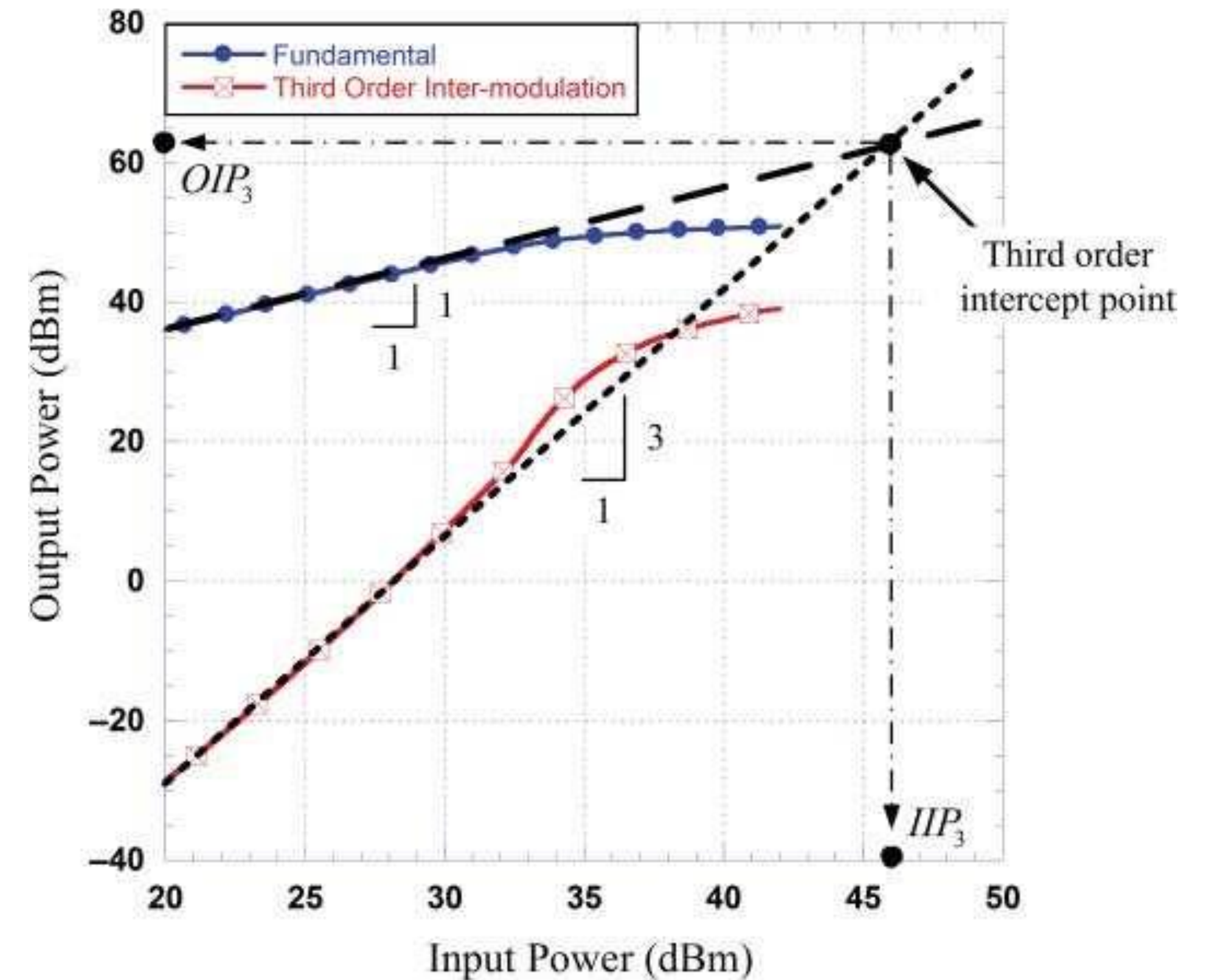
Sources: 2015 - Ghannouchi, Hammi, Helaoui - Behavioral Modeling and Predistortion of Wideband Wireless Transmitters

Input/Output characteristics

- 1 dB compression



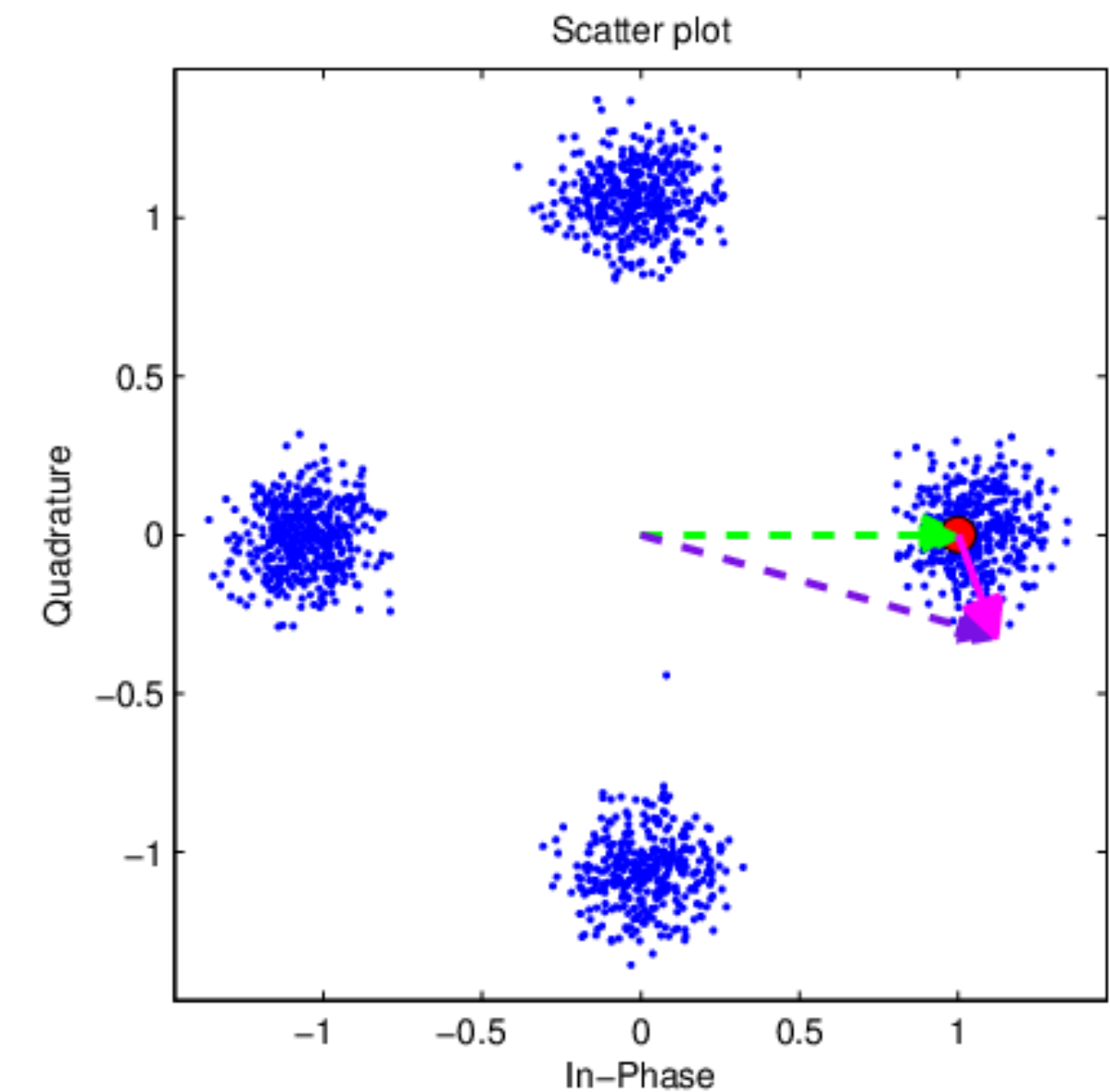
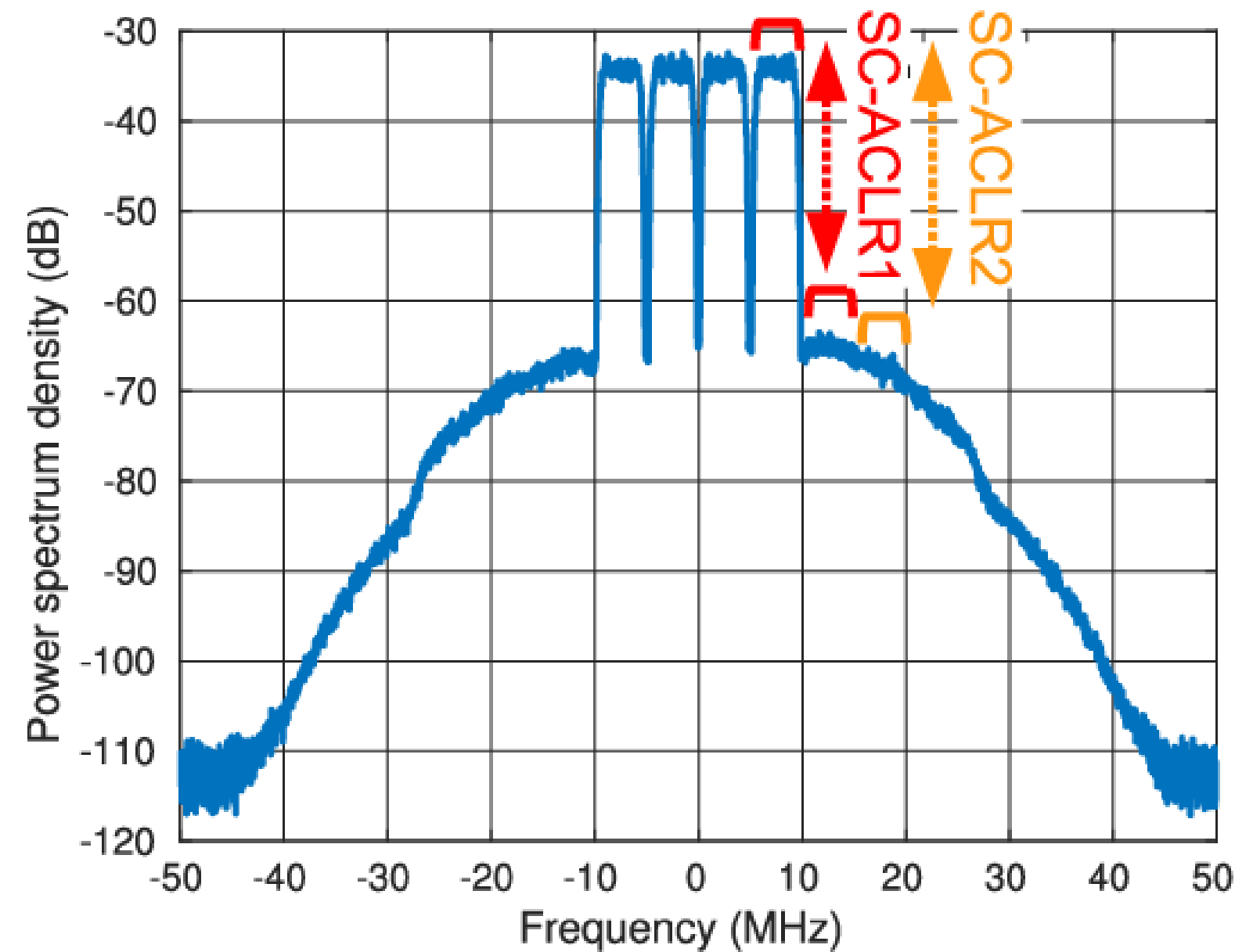
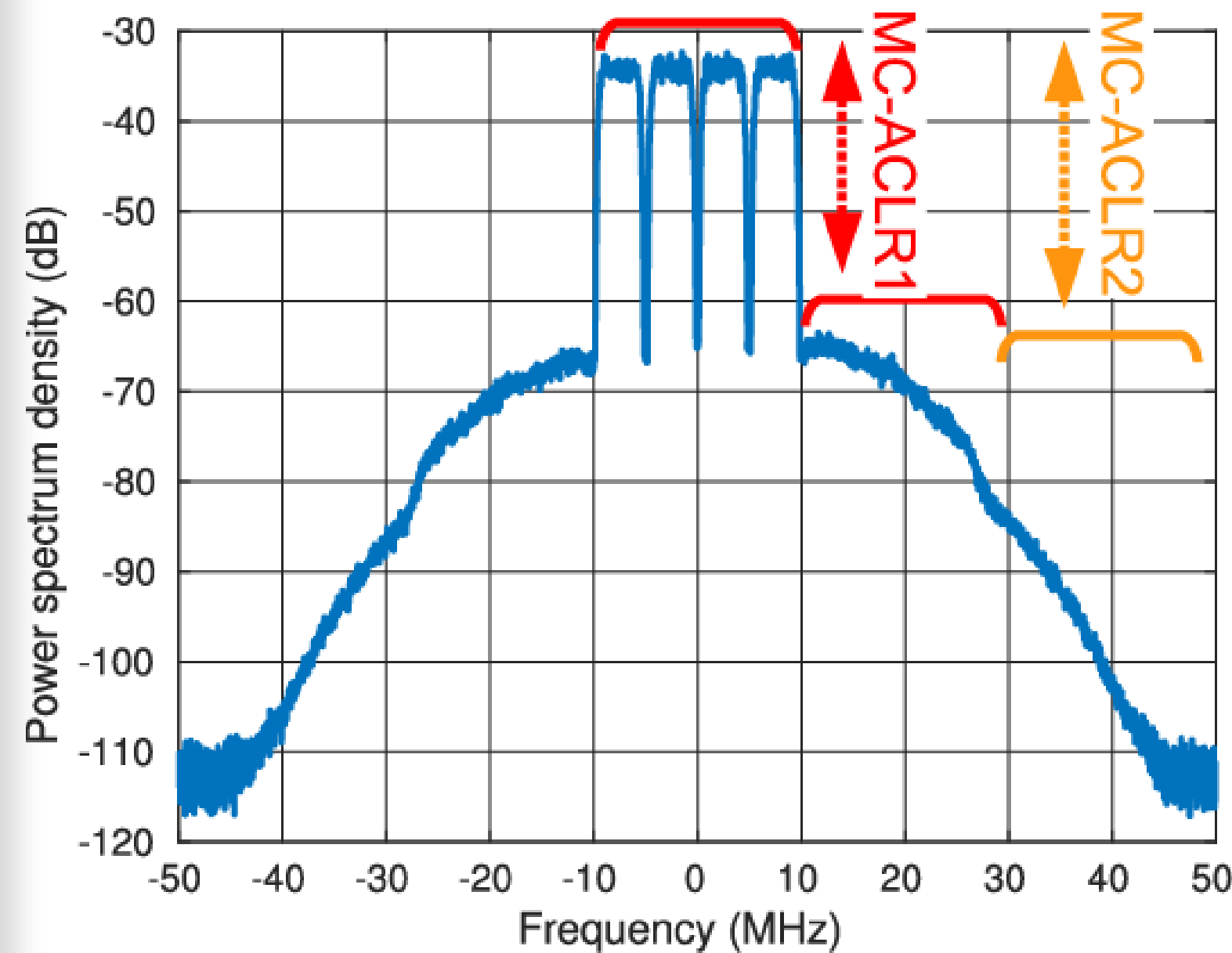
- Third order intercept point



Sources: 2015 - Ghannouchi, Hammi, Helaoui - Behavioral Modeling and Predistortion of Wideband Wireless Transmitters

Output characteristics – Mathematical expression

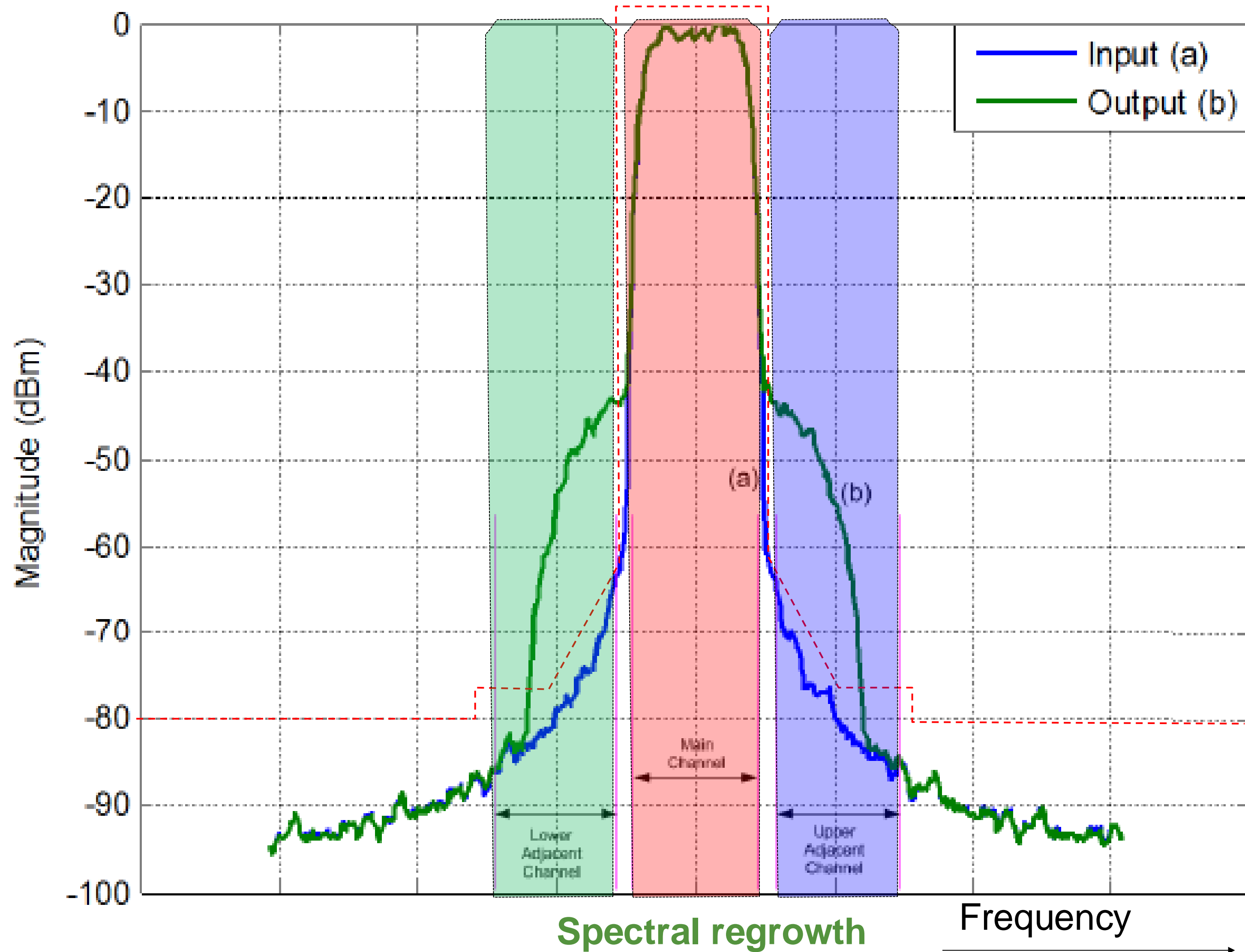
- Adjacent Channel Leakage (or Power) Ratio (ACLR/ACPR/ACP)
- Error Vector Magnitude (EVM)



$$ACPR_{dBc} = 10 \log_{10} \left(\frac{\int_{BW_c} P(f) df}{\int_{BW_{adj}} P(f) df} \right)$$

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

ACP / SEM CONSIDERATION



ACP: Adjacent Channel Power
 ACLR: Adjacent Channel Leakage
 power Ratio

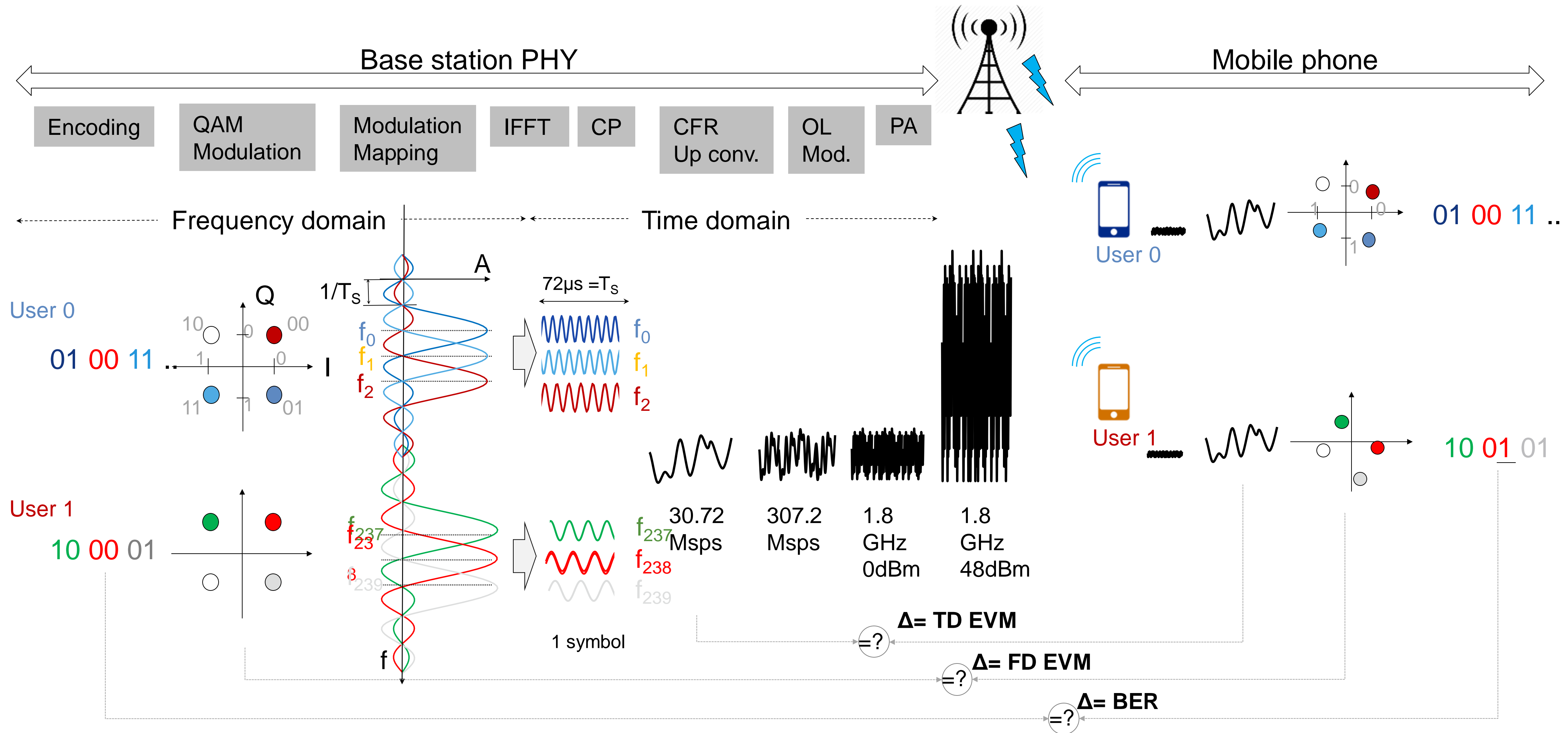
$$ACLR = \frac{\text{Power of adjacent channel}}{\text{Power of main channel}} \text{ (dBc)}$$

$$= \frac{\text{Green Box}}{\text{Red Box}} \text{ and } \frac{\text{Blue Box}}{\text{Red Box}}$$

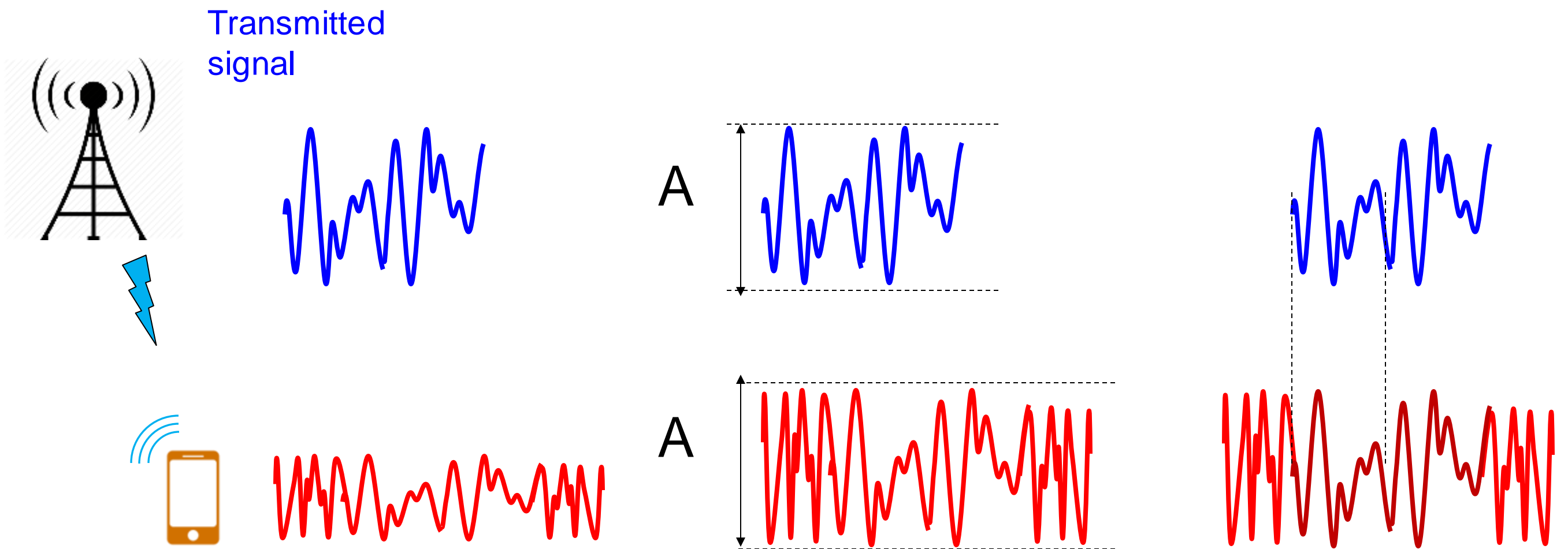
SEM: Spectral Emission Mask,
 3GPP defines ACLR targets &
 SEM targets

EVM CONCEPT

LTE signal processing chain (simplified)



TD EVM CONSIDERATION



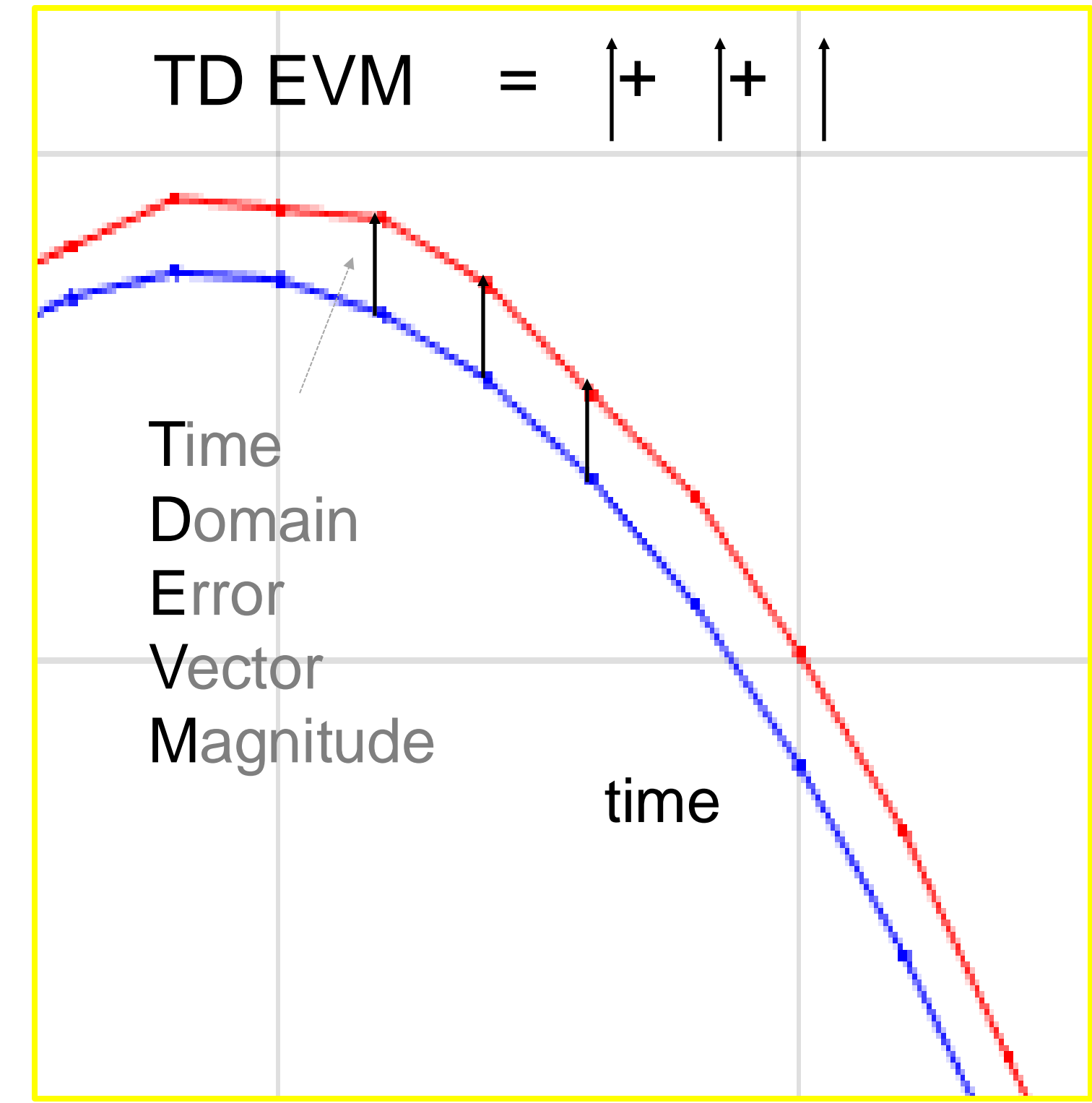
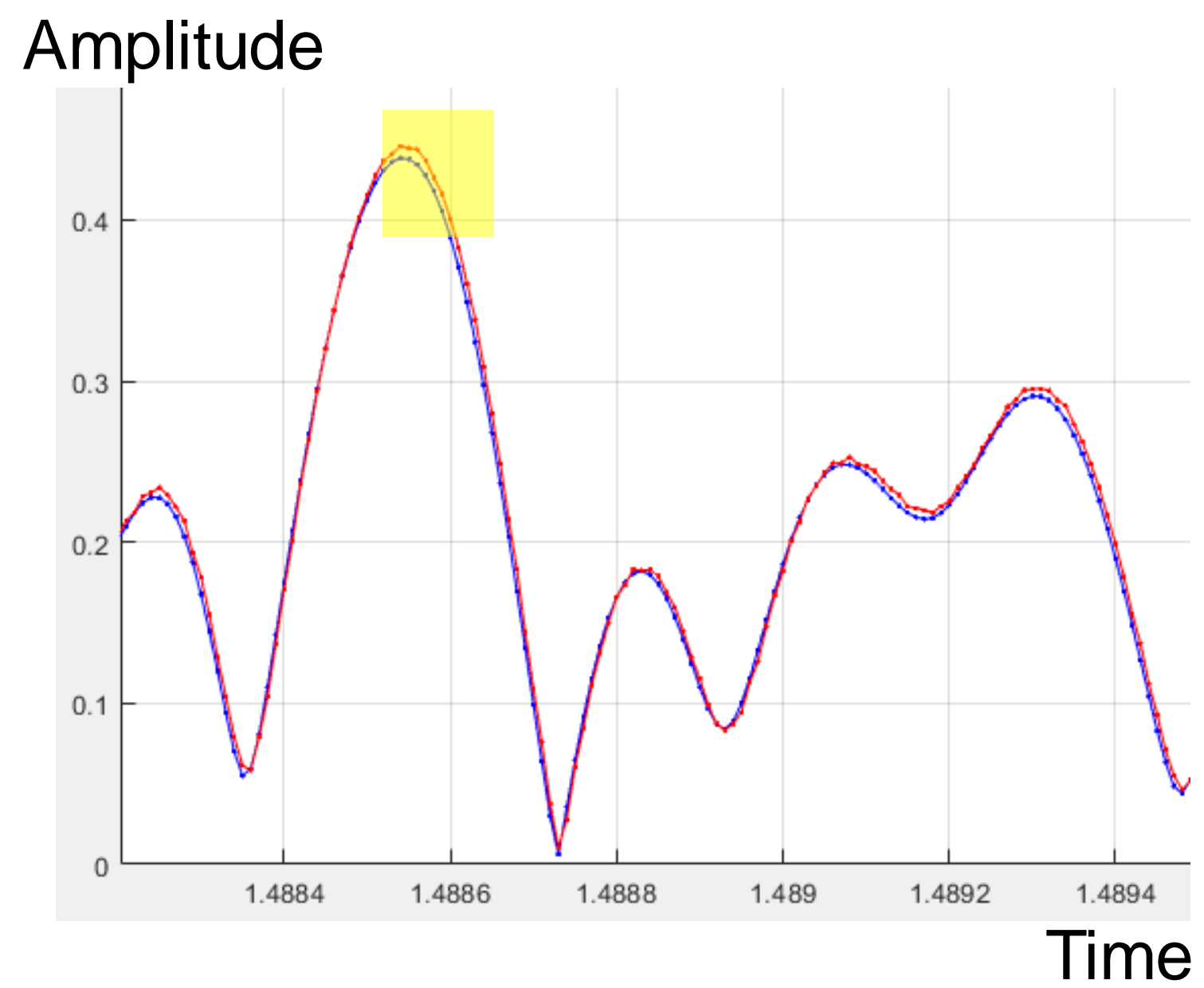
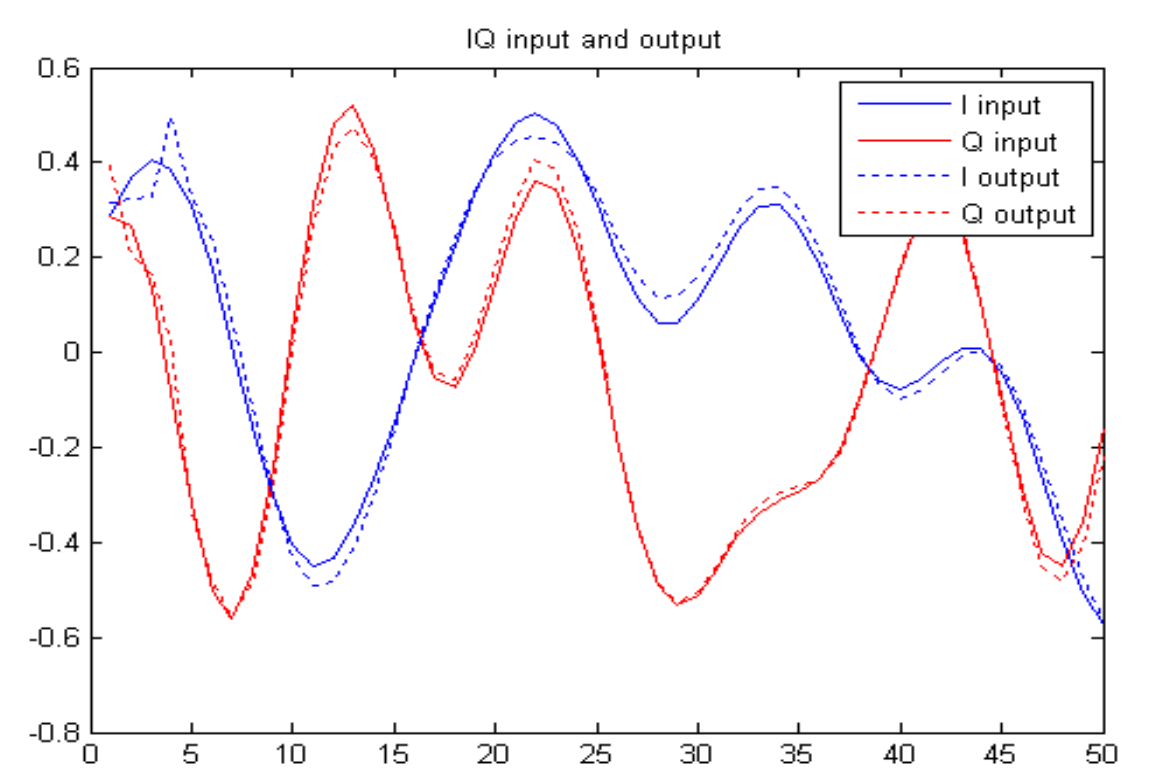
Received signal

Sampling at the same sampling rate 30.72Mps



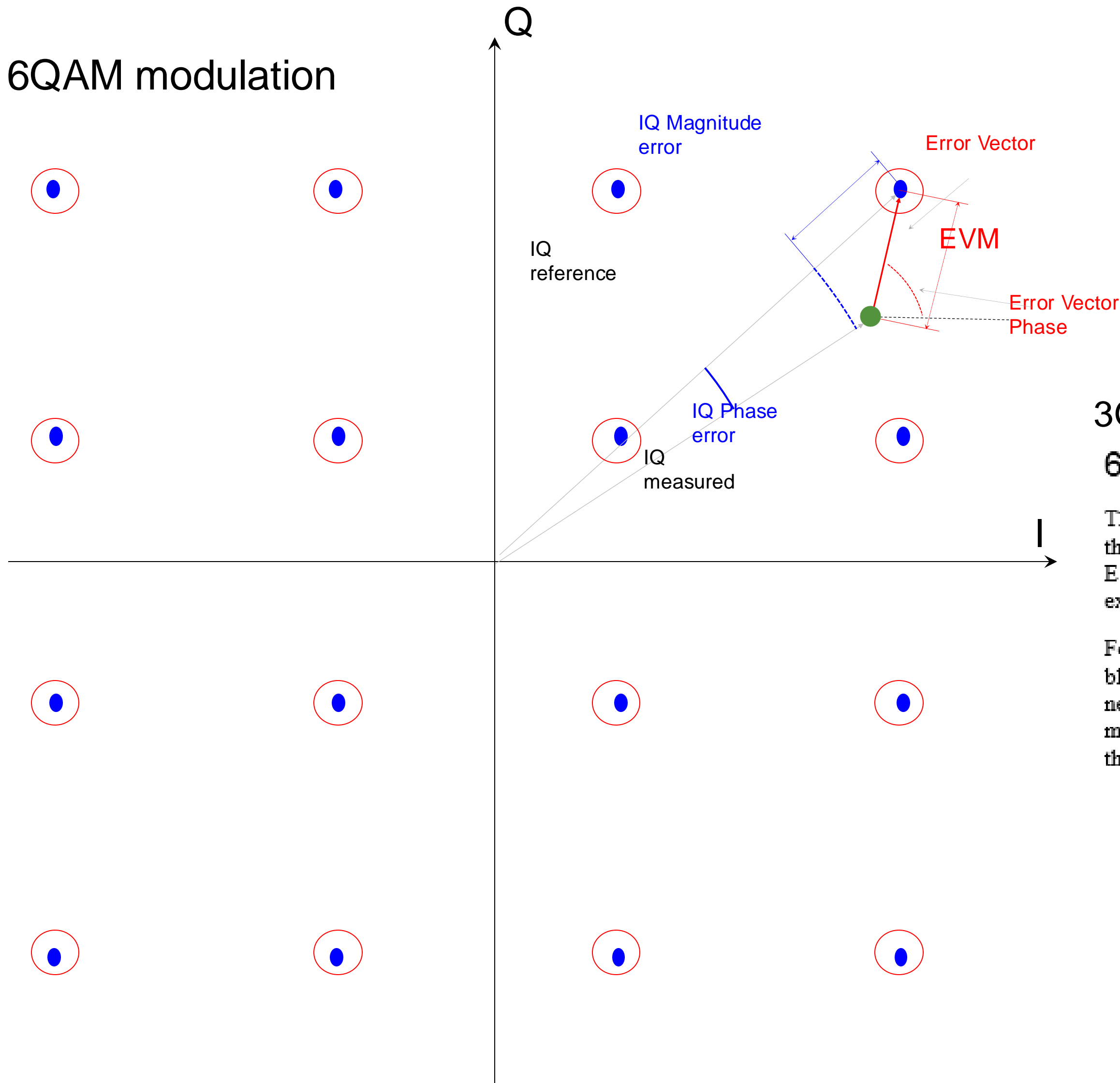
Amplitude rescaling

Time synchronization



FD EVM CONSIDERATION

16QAM modulation



$$EVM = \sqrt{\frac{\sum_{m=1}^M |S_{ideal,m} - S_{measured,m}|^2}{\sum_{m=1}^M |S_{ideal,m}|^2}}$$

FD EVM = distance between received signal vs expected signal

3GPP TS 36.104 V12.11.0 (2016-03)

6.5.2 Error Vector Magnitude

The Error Vector Magnitude is a measure of the difference between the ideal symbols and the measured symbols after the equalization. This difference is called the error vector. The equaliser parameters are estimated as defined in Annex E. The EVM result is defined as the square root of the ratio of the mean error vector power to the mean reference power expressed in percent.

For all bandwidths, the EVM measurement shall be performed for each E-UTRA carrier over all allocated resource blocks and downlink subframes within 10ms measurement periods. The boundaries of the EVM measurement periods need not be aligned with radio frame boundaries. The EVM value is then calculated as the mean square root of the measured values. The EVM of each E-UTRA carrier for different modulation schemes on PDSCH shall be better than the limits in table 6.5.2-1:

Table 6.5.2-1: EVM requirements

Modulation scheme for PDSCH	Required EVM [%]
QPSK	17.5 %
16QAM	12.5 %
64QAM	8 %
256QAM	3.5 %
NOTE: The EVM requirement for 256QAM applies to Home BS, Local Area BS, and Medium Range BS.	

Linearity requirements for 3G/4G/5G base stations

Standard	UMTS [37]	WiMAX [38]	LTE [39]	LTE-A [40]
Multiplexing Type	WCDMA	OFDMA	OFDMA	OFDMA
Single-channel bandwidth (MHz)	5	1.25, 5, 10, 20	1.4, 3, 5, 10, 15, 20	20
Maximum aggregated bandwidth (MHz)	60 (12-band)	20	20	100 (5-band)
In-band requirement EVM ^a (%)	<12.5	<6	<12.5	<12.5
Out-of-band requirement				
ACLR1 ^b (dBc)	<-45	<-45	<-45	<-45
ACLR2 ^c (dBc)	<-50	<-50	<-45	<-45
^a Based on the 16-QAM modulation scheme. ^b Refers to the first adjacent channel leakage power ratio. ^c Refers to the second adjacent channel leakage power ratio.				

Sources: 2014 - Guan, Zhu - Green Communications: Digital Predistortion for Wideband RF Power Amplifiers

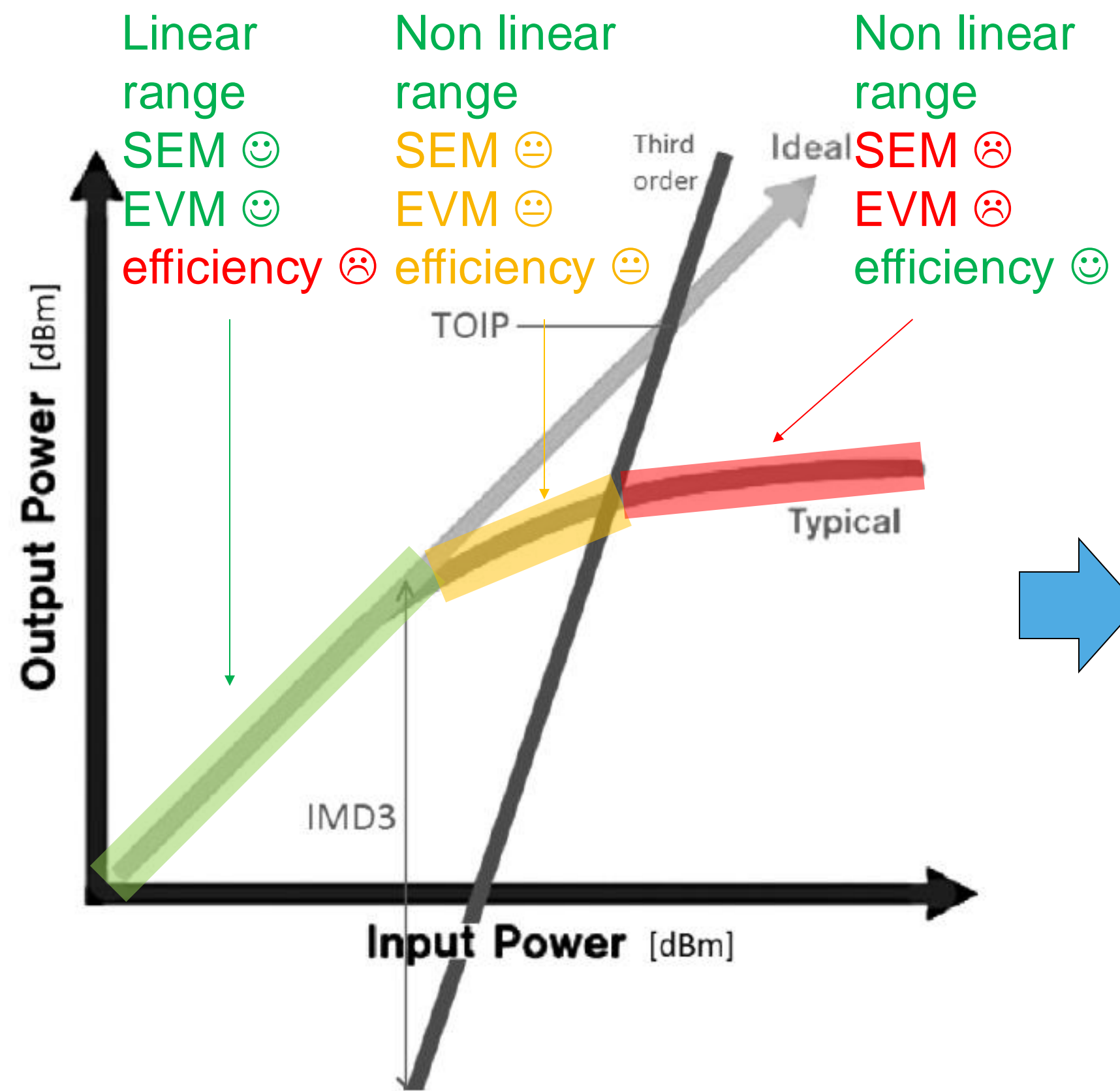


These requirements are challenging, solving them requires tons of engineering work
 Now way to solve them without help from digital ... Let's talk now about DPD concepts

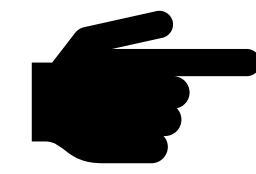
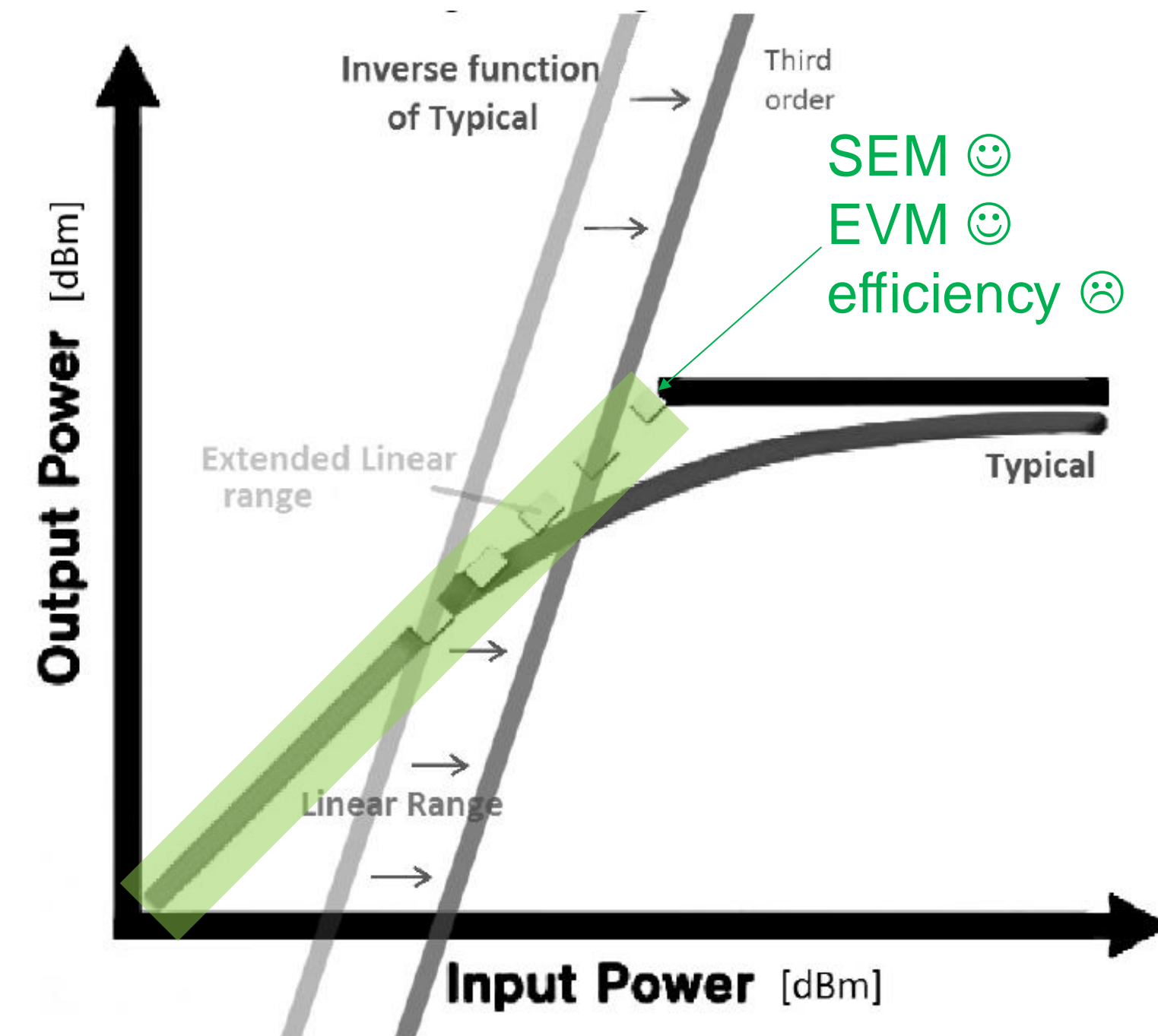
DPD concept

DPD PURPOSE

- The PA should operate at Pout level to ensure maximum efficiency to save power during BS operations. But, in order to meet LTE system requirements, the PA shouldn't degrade :
- ACP below a point to infringe spectrum emission mask (typically -45dBc)
 - EVM below a point where receiver cannot decode received message (typically 5% EVM (ETM3.1))



DPD
main
effect



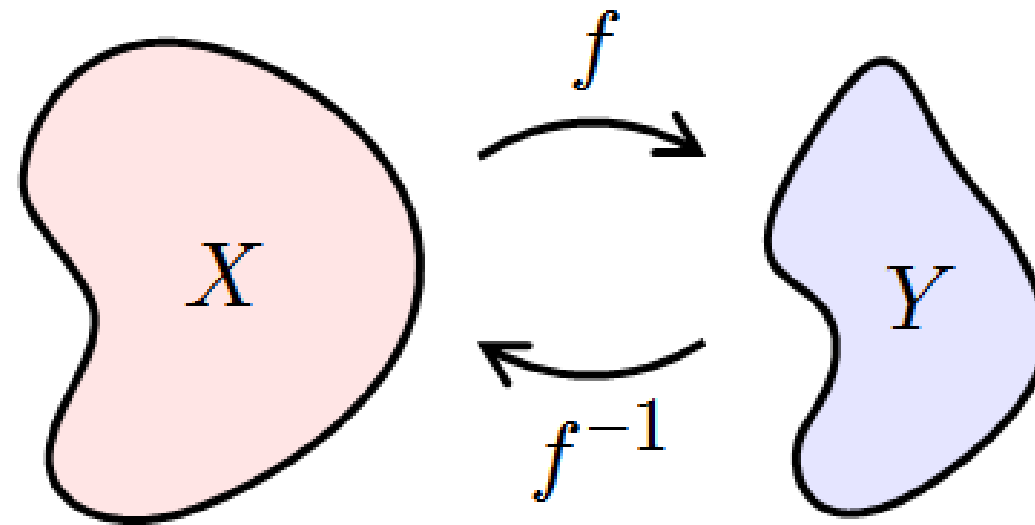
DPD system targets to extend the linear range of a PA to enable a better SEM/EVM/efficiency tradeoff

Concept of inverse

- **Inverse function... What is it !?**

- Definition

- $g(x)$ is the inverse of $f(x)$ when $g(f(x)) = x$
 - $g(x)$ is usually denoted $f^{-1}(x)$ by mathematicians

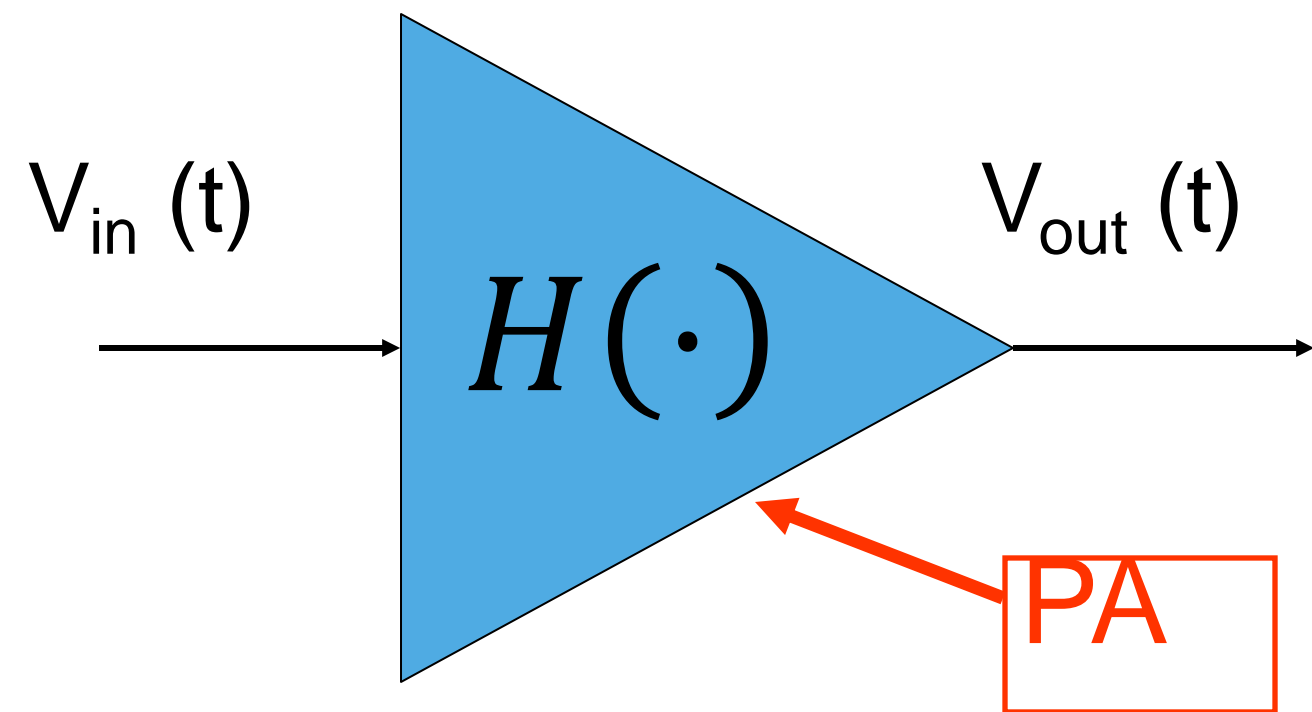


- $g(x)$ **does not always exist** ! Particularly true for nonlinear functions.
 - $g(x)$ is only possible for a limited range of x

- Example

- $f(x) = x^2$; $g(x) = \sqrt{x}$ only for $x \geq 0$
 - (Note the different "nature" of $f(\cdot)$ and $g(\cdot)$)

DPD PRINCIPLES

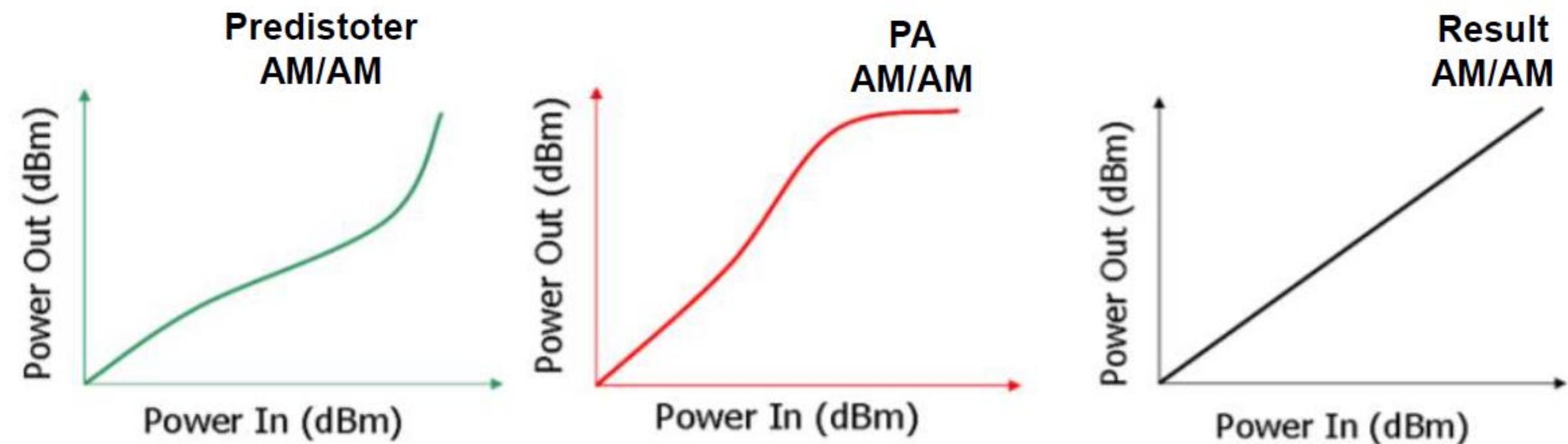
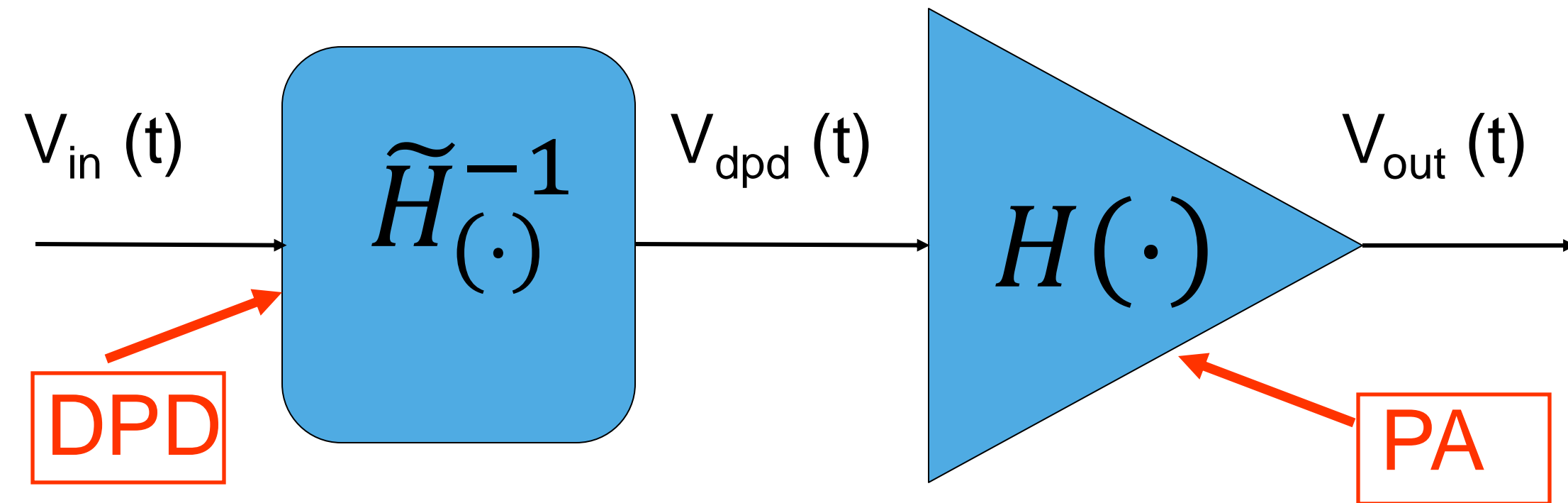


V_{in} and V_{out} have different values of Gain and Phase.

PAs are not ideal devices :
the AM/AM and AM/PM plots are not linear

To make the PA work more linearly,
create the **Digital Pre Distortion** block:
It adjusts the PA input to produce the desired output.

Need of a block that changes V_{in} to V_{dpd}
 V_{dpd} will be the corrected PA input.



The challenge is then to understand the PA non linearities and to model them

Or to model the “behavior” of the PA...

- $H(\cdot)$ = PA transfert function
- $\tilde{H}(\cdot)$ = PA transfert function estimate
- $\tilde{H}^{-1}(\cdot)$ = PA transfert function estimate inverted



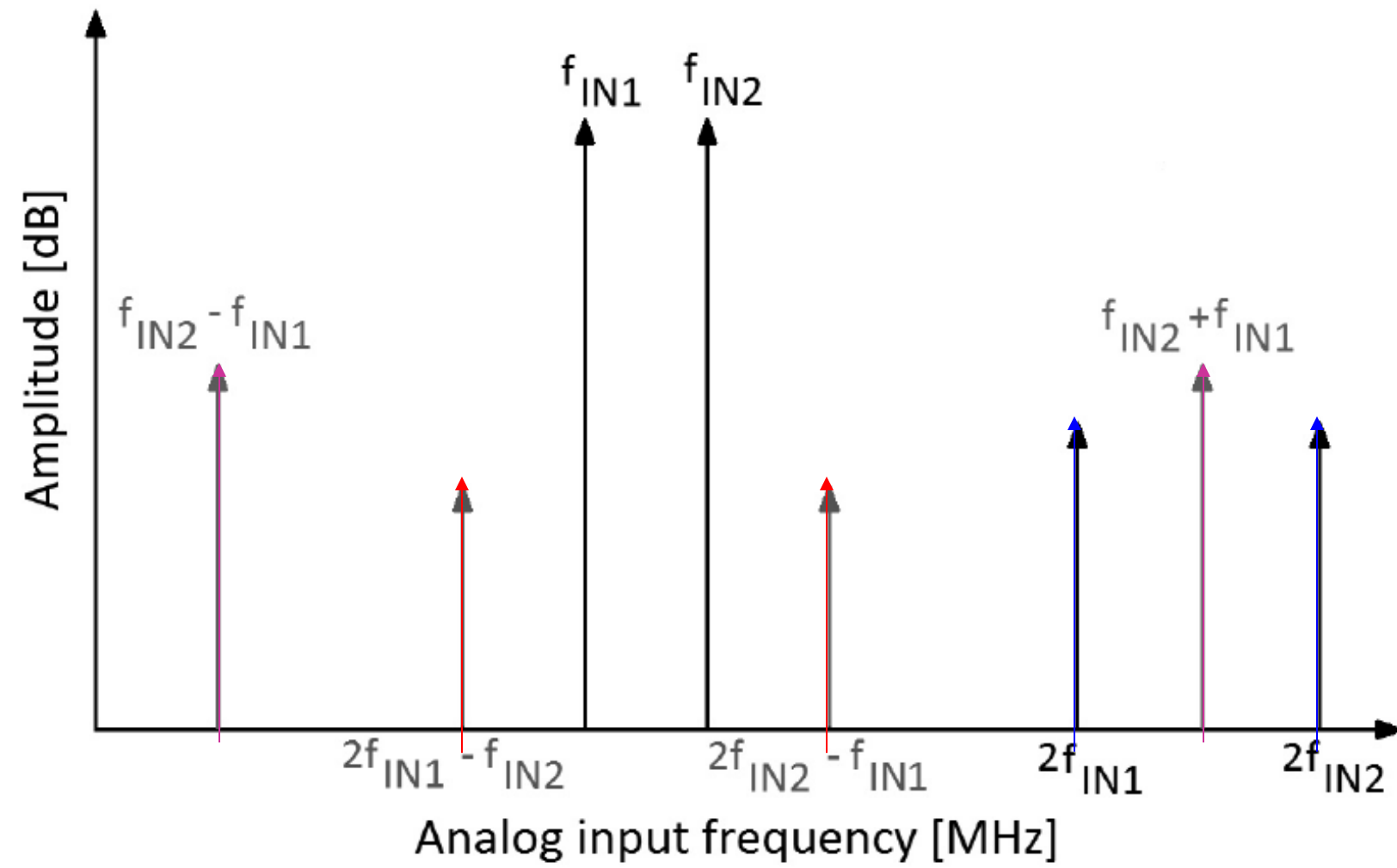
But what are those non linearities ?

Origins & impacts of non-linearities – Further details

ORIGINS AND IMPACTS OF THE NON LINEARITIES 1/5

Odd IMDs

- Memory effect
- Even order IMDs + BB resonance
- + H2
- Others

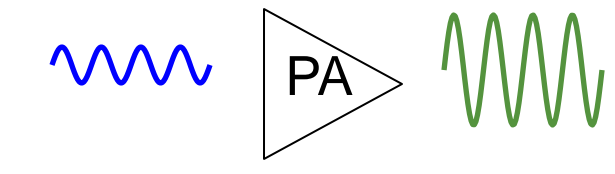


- f_{IN1}, f_{IN2} Fundamentals of the input tones
- $f_{IN1} \pm f_{IN2}$ 2nd order IMD products
- $f_{IN1} \pm 2f_{IN2}$ 3rd order IMD products
- $2f_{IN1}, 2f_{IN2}$ Second Harmonics

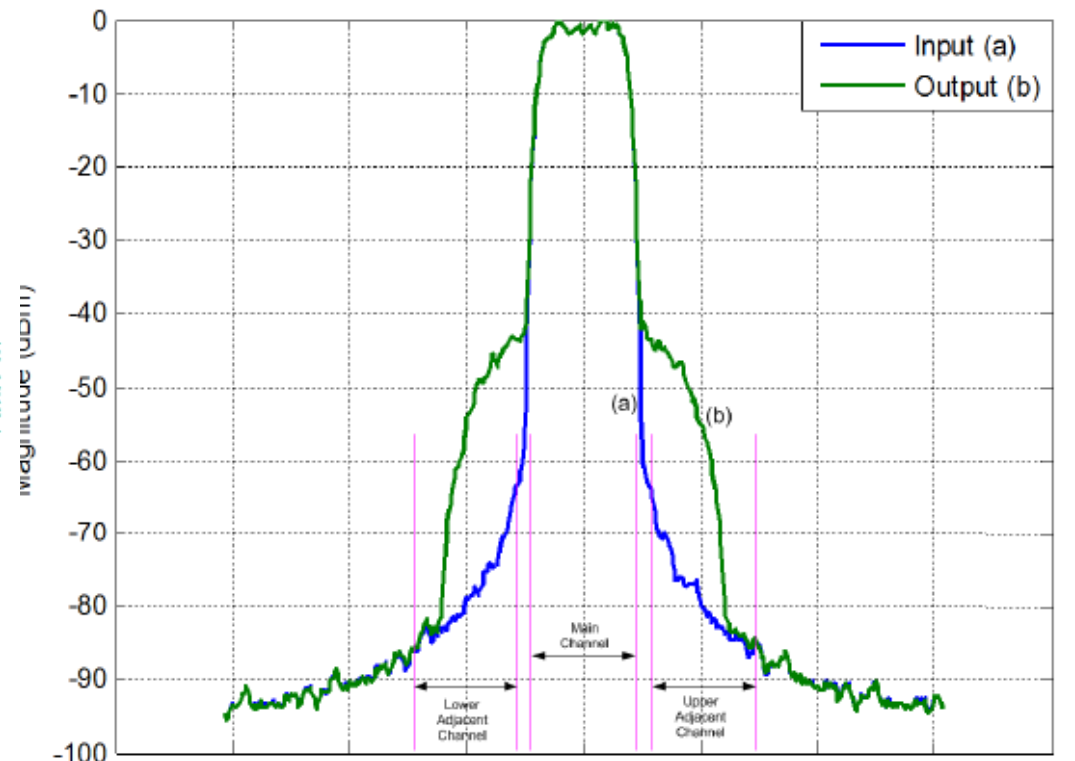
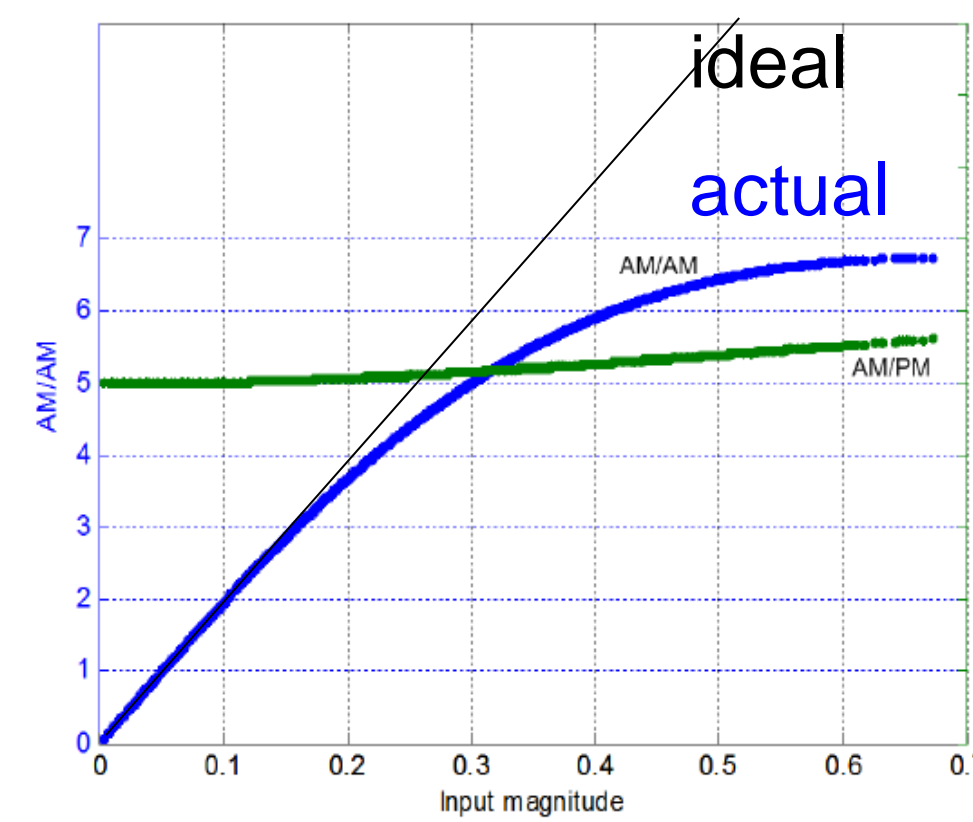
IMD3 are the more concerning

- IMD3 amplitude not negligible
- frequencies close to the useful signal

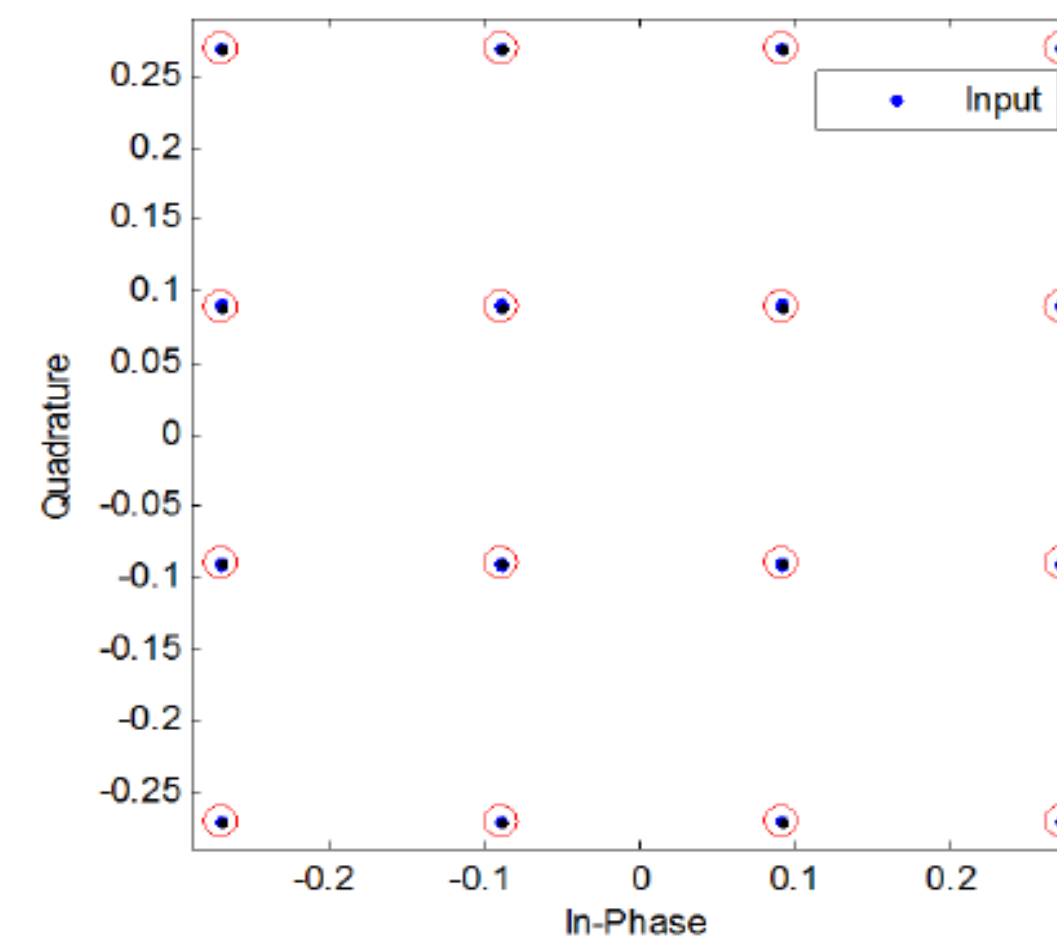
IMD even order are generally too far away to be a concern (NB) (at least in a first approach)



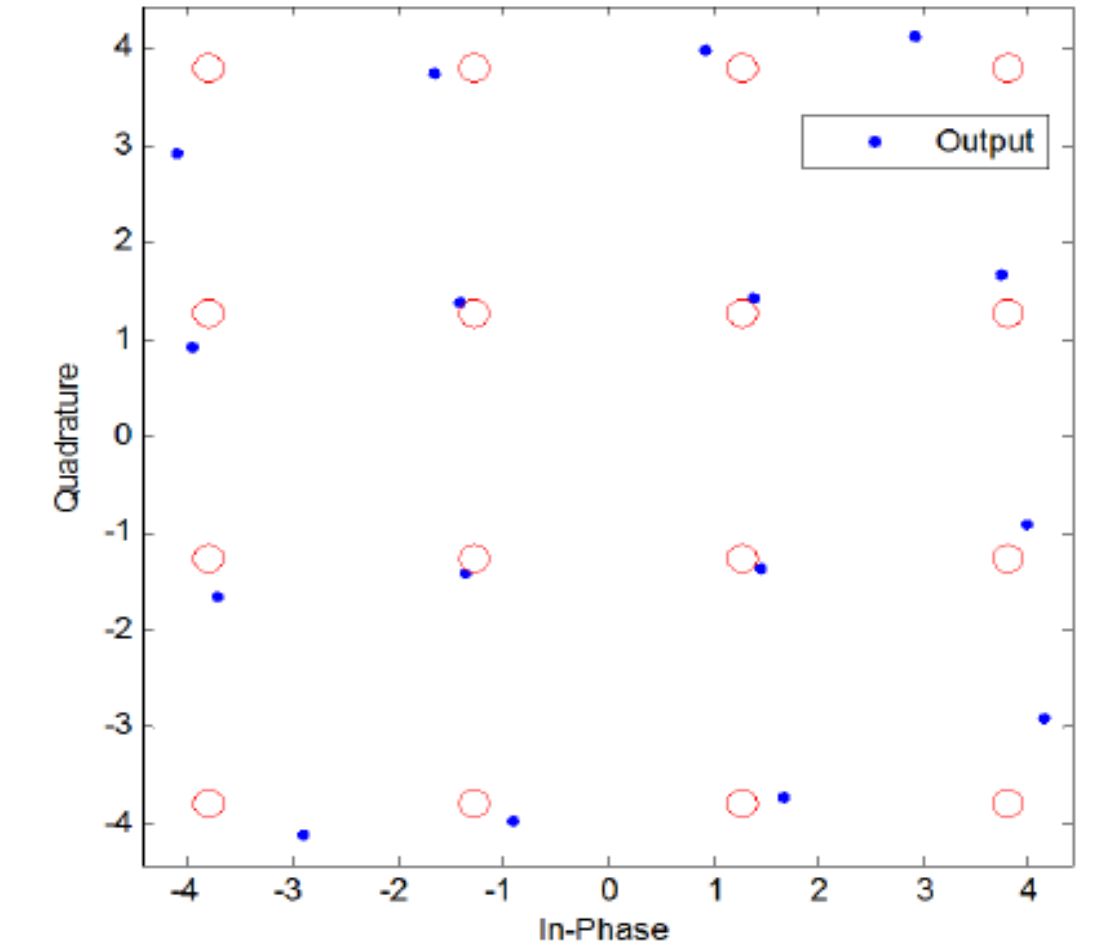
IMDs effects



IMDs causes spectrum regrow



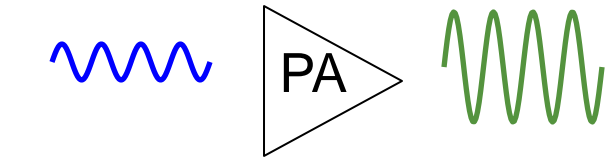
(a) Constellation of input



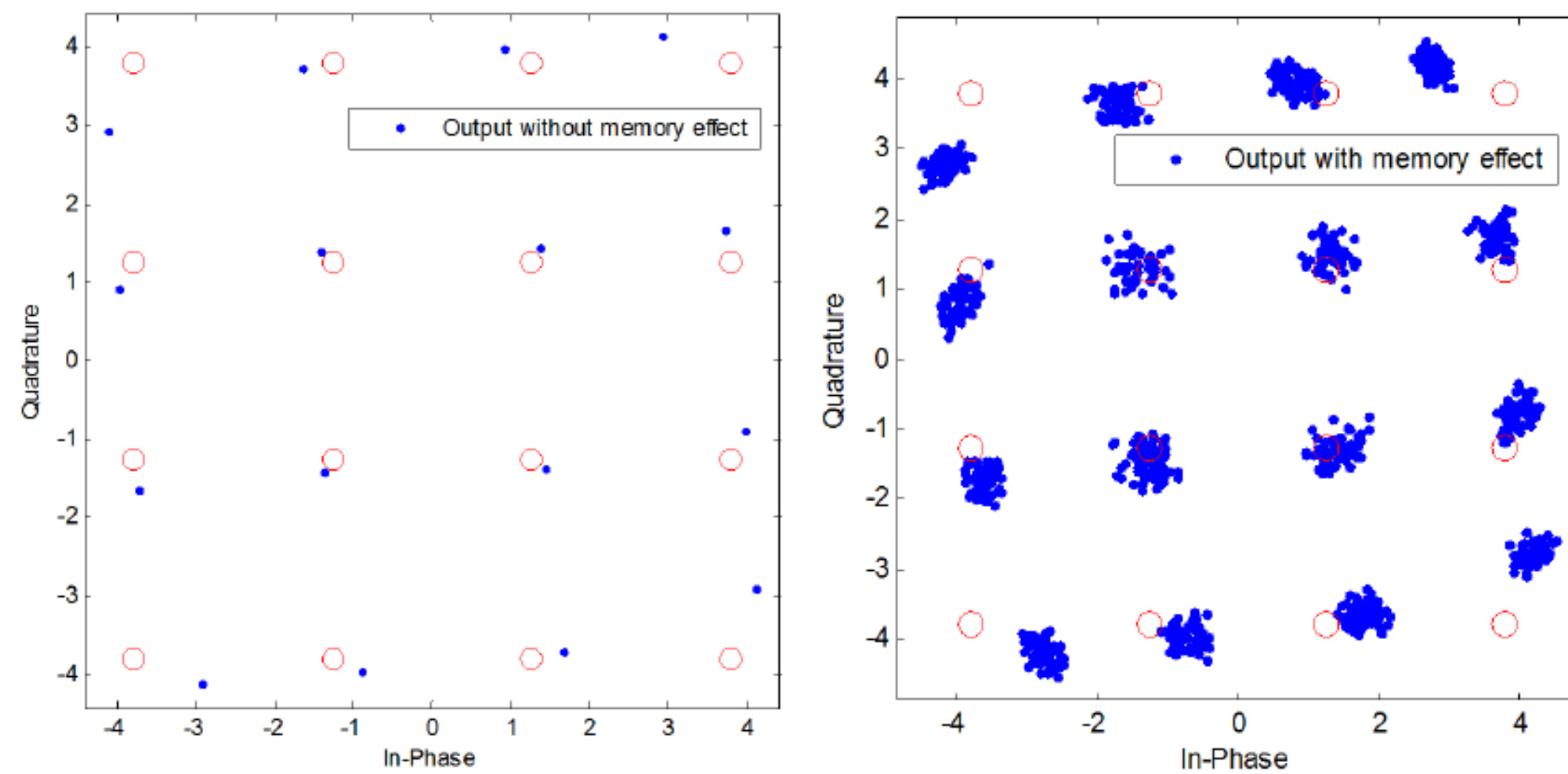
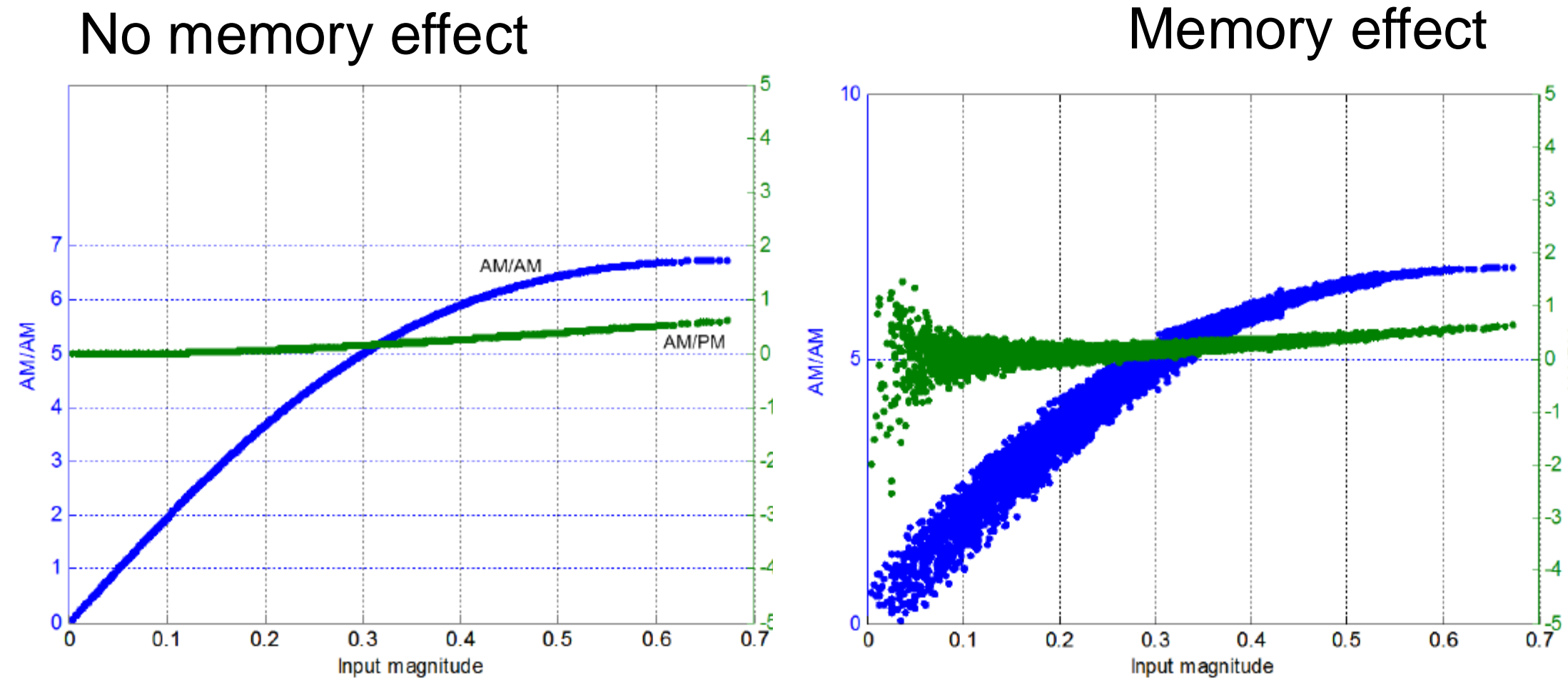
(b) Constellation of output

PA introduces constellation rotation and compression

ORIGINS AND IMPACTS OF THE NON LINEARITIES 2/5



- Odd IMDs
- Memory effect
- Even order IMDs
- + BB resonance
- + H2
- Others



(a) Output constellation without memory effect

(b) Output constellation with memory effect

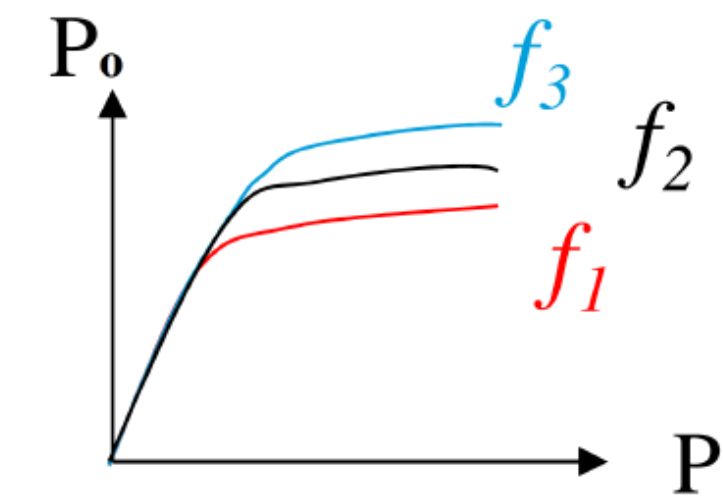
Memory effect

The PA output depends not only on the instantaneous input, but also on the previous inputs.

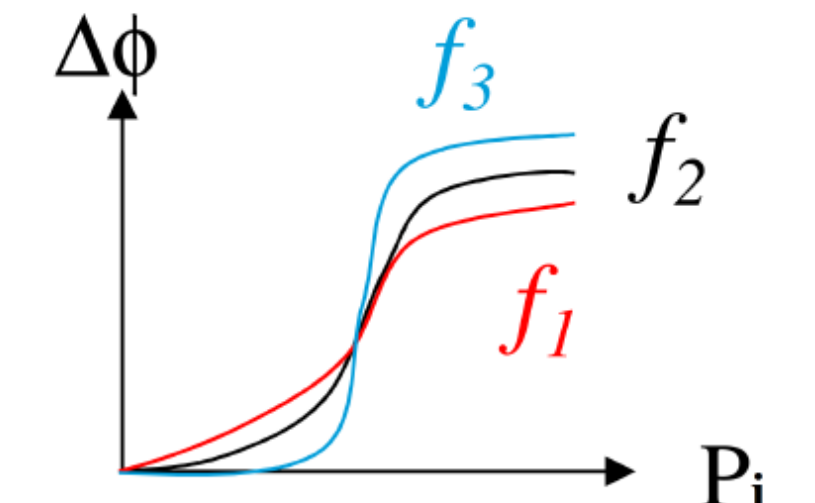
It means also that the characteristics of PA's behavior change with the frequency.

Origins:

- Thermic semiconductor effect
- Trapping effect
- Impedance matching delay
- Skin effect
- Wideband
- Others...



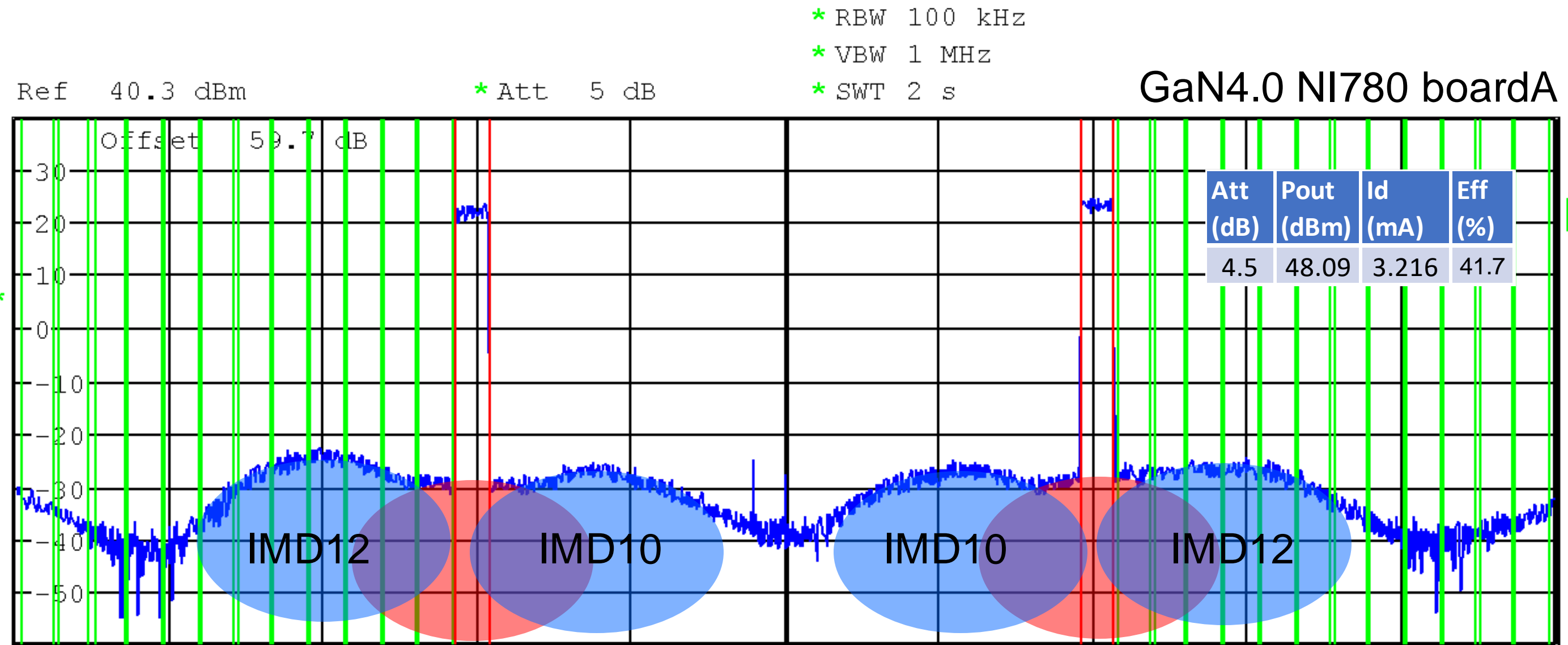
(a) AM/AM frequency dependent distortion



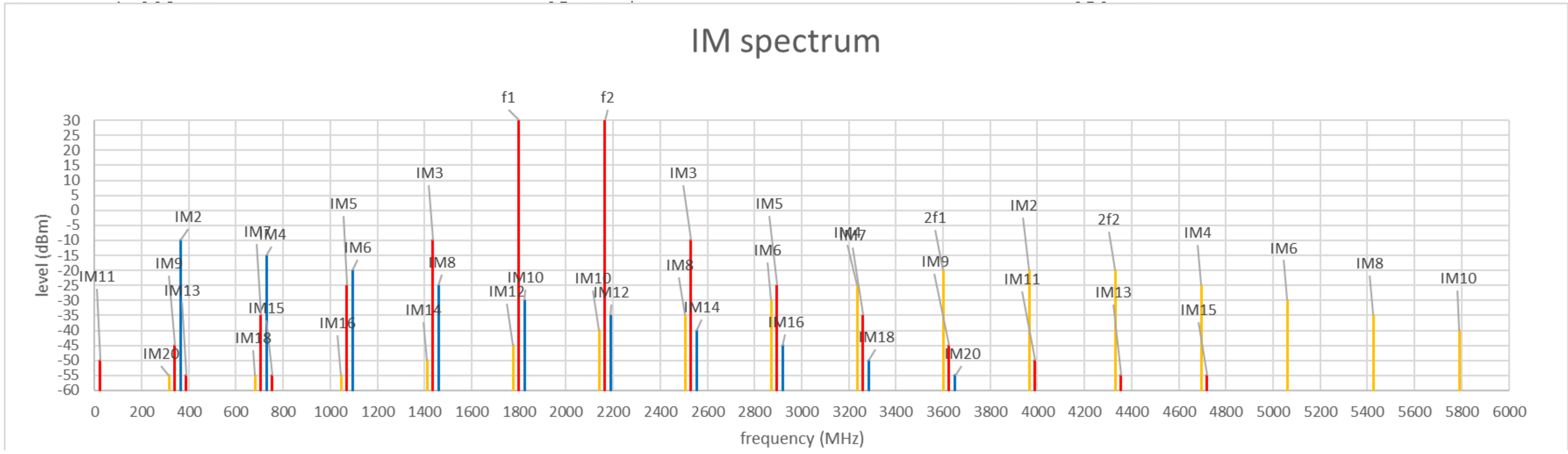
(b) AM/PM frequency dependent distortion

ORIGINS AND IMPACTS OF THE NON LINEARITIES 3/5

- Odd IMDs
- Memory effect
- Even order IMDs
- + BB resonance
- + H2
- Others



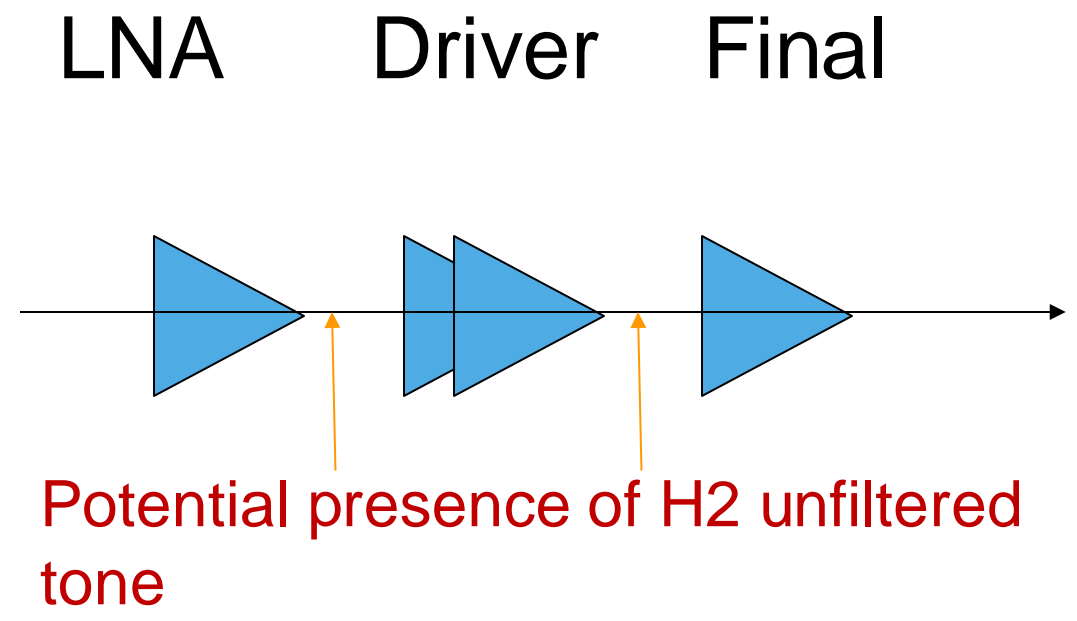
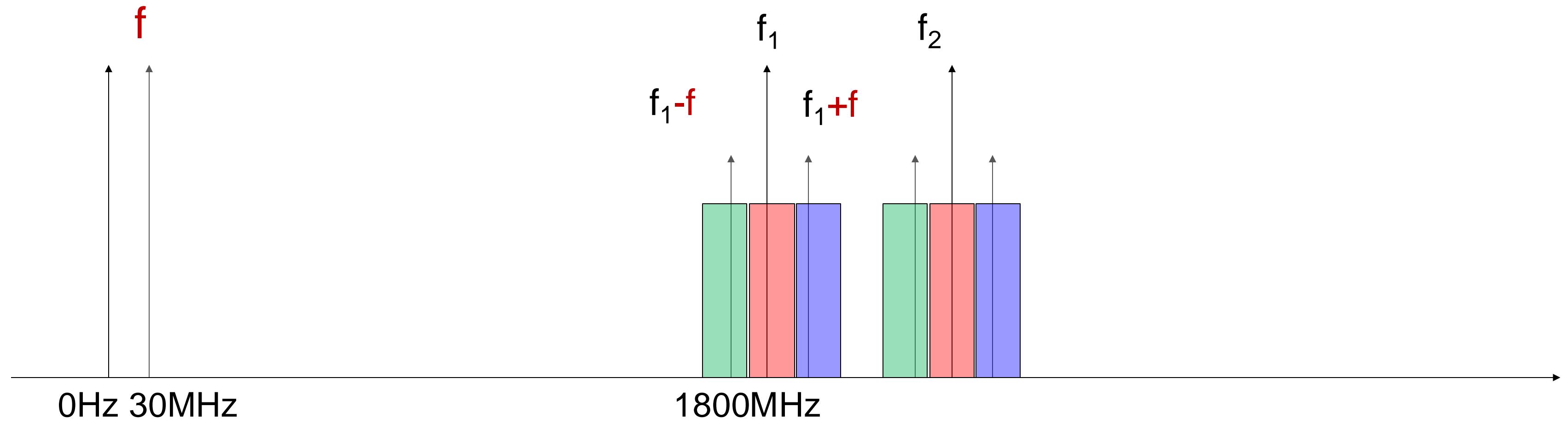
For 2xLTE20MHz
 365MHz IBW
 OL 1983MHz
 IMD10 & IMD12
 fall into the band
 And their levels
 aren't negligible
 for Gan 4.0 device



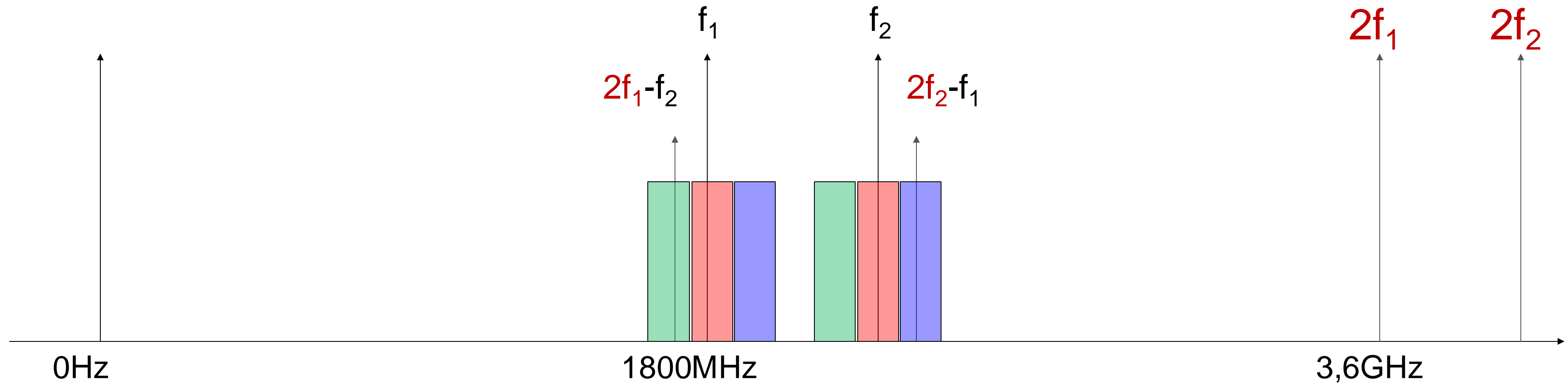
ORIGINS AND IMPACTS OF THE NON LINEARITIES 4/5

- Odd IMDs
- Memory effect
- Even order IMDs
- + BB resonance
- + H2
- Others

BB resonance



H2 products



ORIGINS AND IMPACTS OF THE NON LINEARITIES 5/5

Odd IMDs
Memory effect
Even order IMDs
+ BB resonance
+ H2
Others

Setups related (driver, passive)
Boards related
- BF decoupling,
- Power supply filtering
- shielding

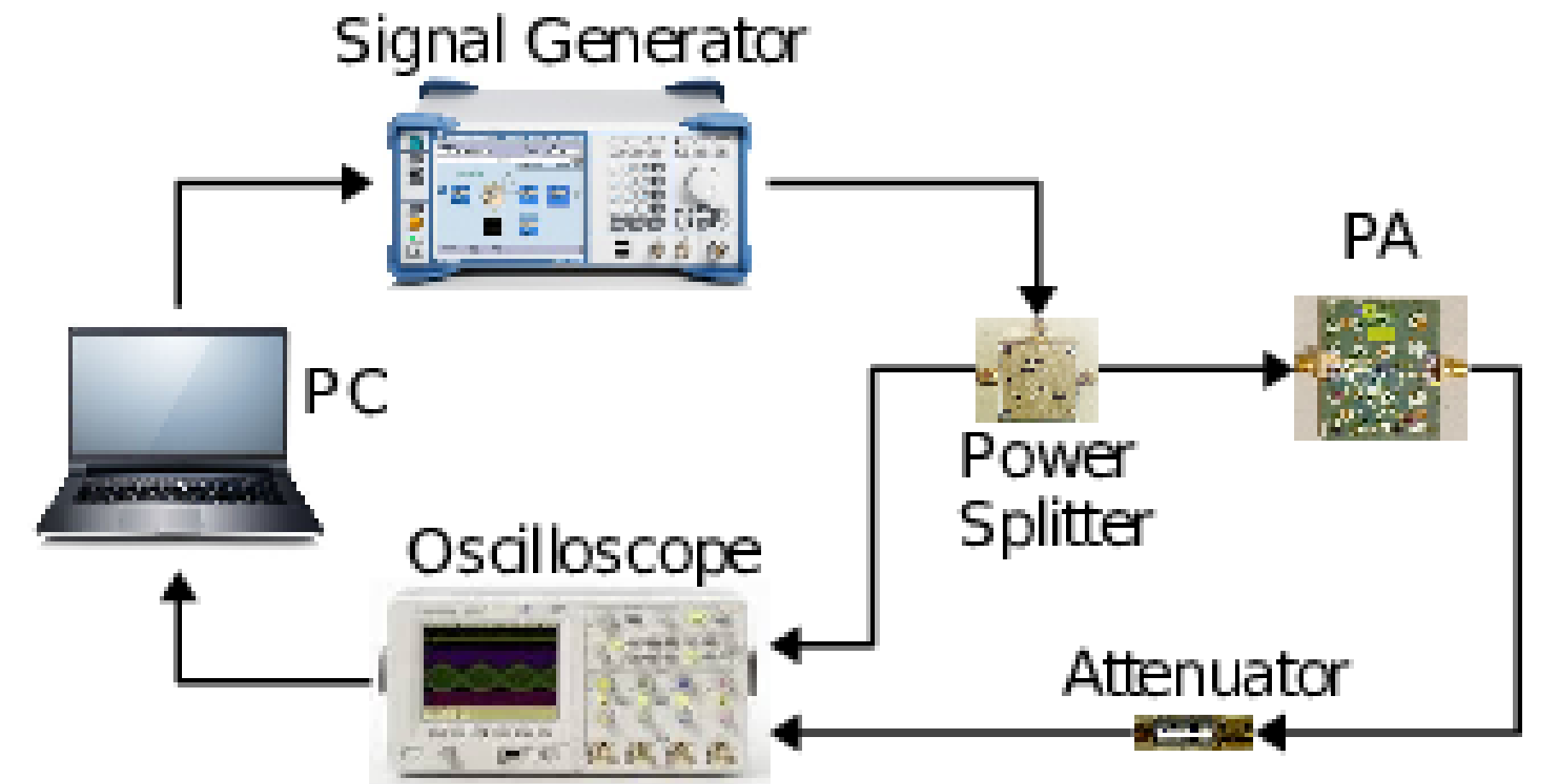
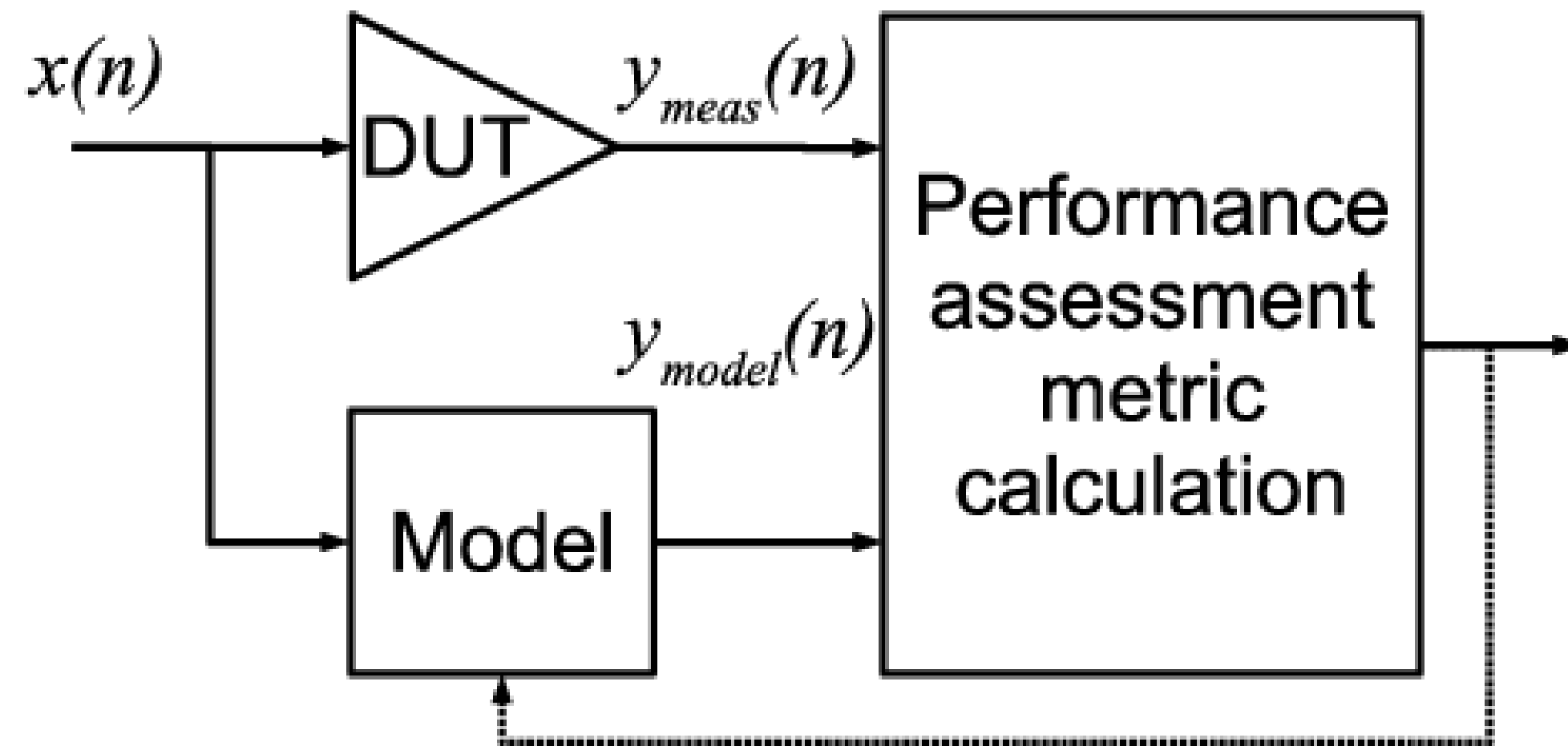
 Which PA behavioral model can be used to represent them accurately ?

Nonlinear Modeling : functions and fitting methodology

Preliminary questions

- What is a model ?
 - A mathematical function (for example a polynomial)
- What is a good model ?
 - A good model allows to accurately reproduce the behavior of a system. Ideally, the output of a model should be identical to the measurements.
 - Mathematical models must be practical and easy to manipulate
 - Complexity has to be taken into account

Modeling method and accuracy metrics



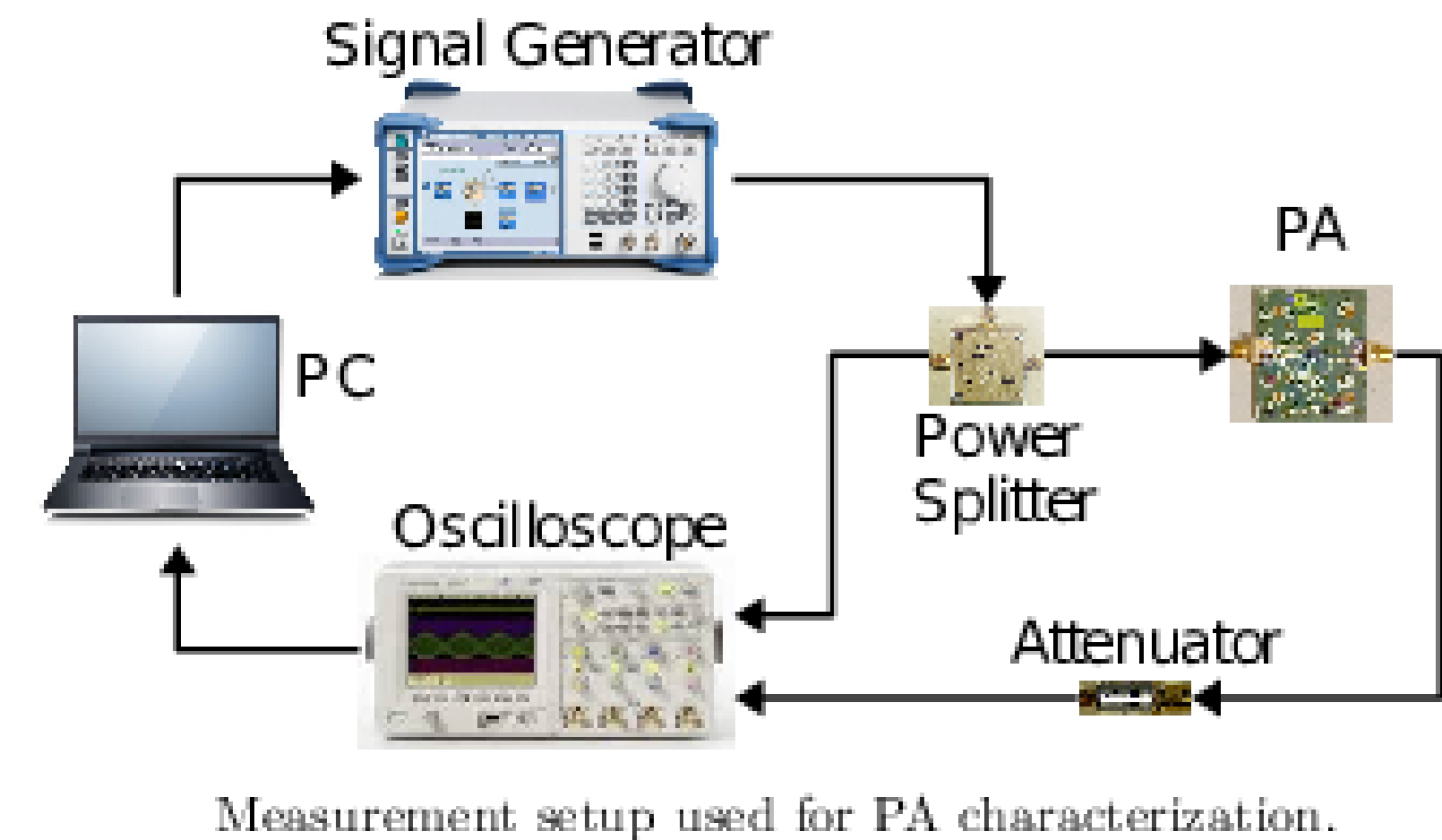
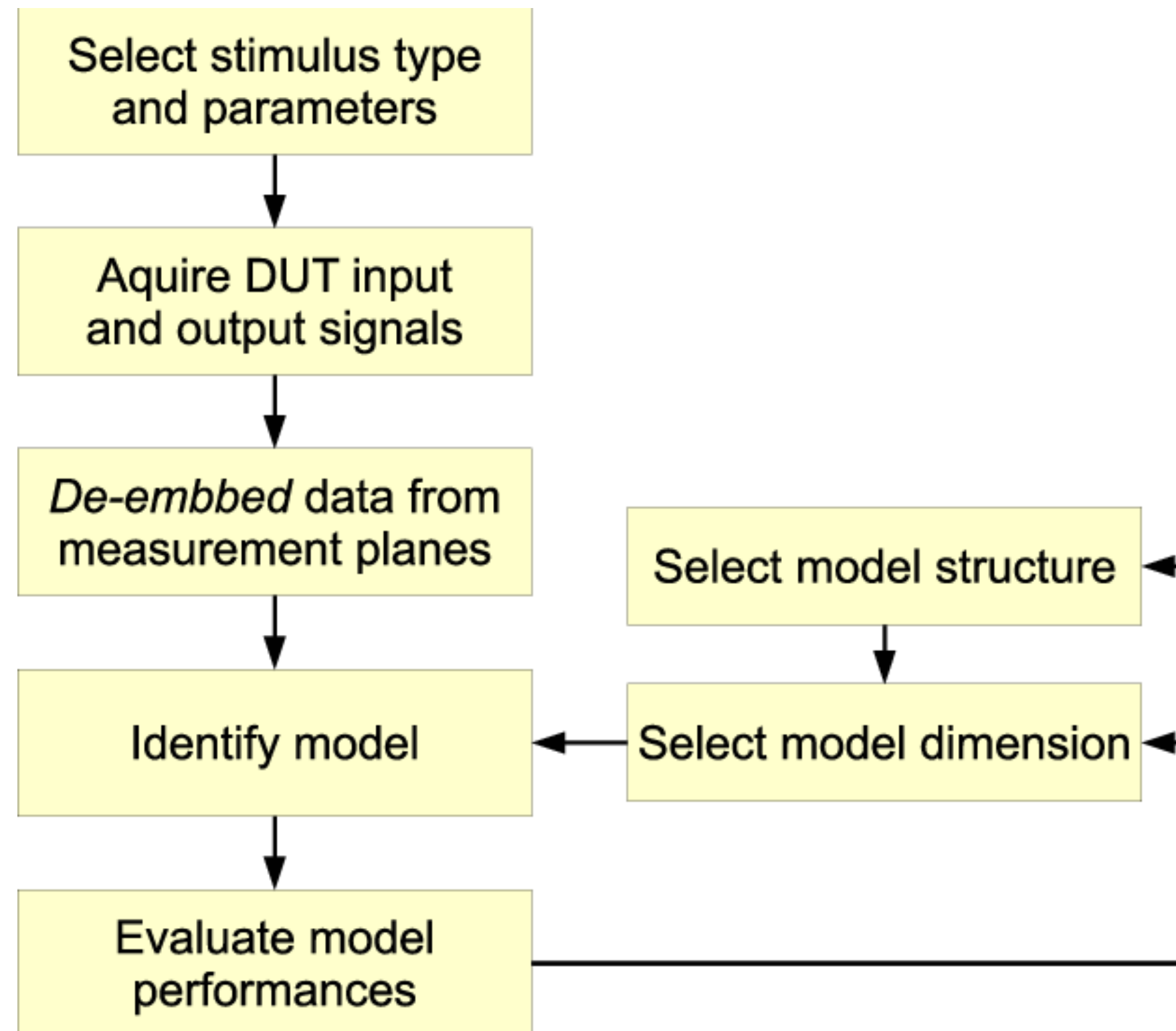
Measurement setup used for PA characterization.

- Time domain metric
 - Normalized Mean Square Error
- Frequency domain metric : frequency domain NMSE
 - Similar to time domain NMSE
 - Extra degree of freedom : inclusion/exclusion of specific components

$$NMSE = 10 \log_{10} \left(\frac{\sum_{l=1}^L |y_{model}(l) - y_{meas}(l)|^2}{\sum_{l=1}^L |y_{meas}(l)|^2} \right)$$

Characterization methods

- Behavioral modeling flow chart



Sources: 2015 - Ghannouchi, Hammi, Helaoui - Behavioral Modeling and Predistortion of Wideband Wireless Transmitters

Non-linear models

Nonlinear models – the most popular

- Baseband equivalent signal

$$x(t) = A(t)e^{j\theta(t)} \quad (A(t), \theta(t) \in \mathbb{R})$$

- Memoryless Systems

$$y(t) = x(t) \cdot G\{A(t)\} = A(t)G_A\{A(t)\}e^{j(\Phi_G\{A(t)\}+\theta(t))}$$

- Polar Saleh Model

$$G_A\{A(t)\} = \frac{\alpha_a}{1 + \beta_a A^2} \quad \Phi_G\{A(t)\} = \frac{\alpha_\phi}{1 + \beta_\phi A^2}$$

–Originally developed to mimic the behavior of TWTAs

- Polynomial

– Memoryless Systems

$$y(t) = \sum_{k=1}^N a_k |x(t)|^{k-1} x(t)$$

Nonlinear models – the most popular

- Memory polynomial based models

- Memory polynomial

$$y_{MP}(n) = \sum_{m=0}^M \sum_{k=1}^K a_{mk} x(n-m) |x(n-m)|^{k-1}$$

- Generalized memory polynomial

$$y_{GMP}(n) = \sum_{m=0}^{M_a} \sum_{k=1}^{K_a} a_{mk} x(n-m) |x(n-m)|^{k-1} \\ + \sum_{m=0}^{M_b} \sum_{k=2}^{K_b} \sum_{p=1}^P b_{mkp} x(n-m) |x(n-m-p)|^{k-1} \\ + \sum_{m=0}^{M_c} \sum_{k=2}^{K_c} \sum_{p=1}^P c_{mkp} x(n-m) |x(n-m+p)|^{k-1}$$

Memory polynomial variants

- Memory polynomial based models
 - Memory polynomial

$$y_{MP}(n) = \sum_{m=0}^M \sum_{k=1}^K a_{mk} x(n-m) |x(n-m)|^{k-1}$$

- Memory polynomials odd orders only

$$y_{MP}(n) = \sum_{m=0}^M \sum_{k=0}^K a_{mk} x(n-m) |x(n-m)|^{2k}$$

- Memory polynomials real-valued expression

$$y_{MP}(n) = \sum_{m=0}^M \sum_{k=0}^K a_{mk} x(n-m) x(n-m)^k$$

Nonlinear models – the most popular

- Volterra series models (real-valued)

$$y_{\text{volterra}}(n) = \sum_{k=1}^K \sum_{m_1=0}^M \cdots \sum_{m_k=0}^M h_k(m_1, \dots, m_k) \prod_{j=1}^k x(n - m_j)$$

VOLTERRA SERIES BASED DPD

Mathematical background

Need to find $f = \widetilde{H}^{-1}$, i.e. $input = f(output)$ or $y = f(x)$.

The output depends on the current and previous values.

$y(n) = f(x_0, x_1, \dots, x_\infty)$ with $x_k = x(n - k\Delta t)$ and $\Delta t \rightarrow 0$, ($\Delta t \approx 2\text{ns}$ for 491MSPS DPD)

$$y(n) = \sum_{k=0}^{+\infty} f_k(x_0, x_1, \dots, x_\infty)$$

$$y(n) = \sum_{(r,q) \in S} x(n-r) F_{r,q,k}(|x(n-q)|, a_{rqk})$$

r delay on the signal

q delay on the envelop

$F_{r,q}$ polynomial function with complex coefficient a_{rqk}

S = set of (r,q) delays combination

r = q = 0 static polynomial

r = q > 0 memory polynomial

r ≠ q cross term

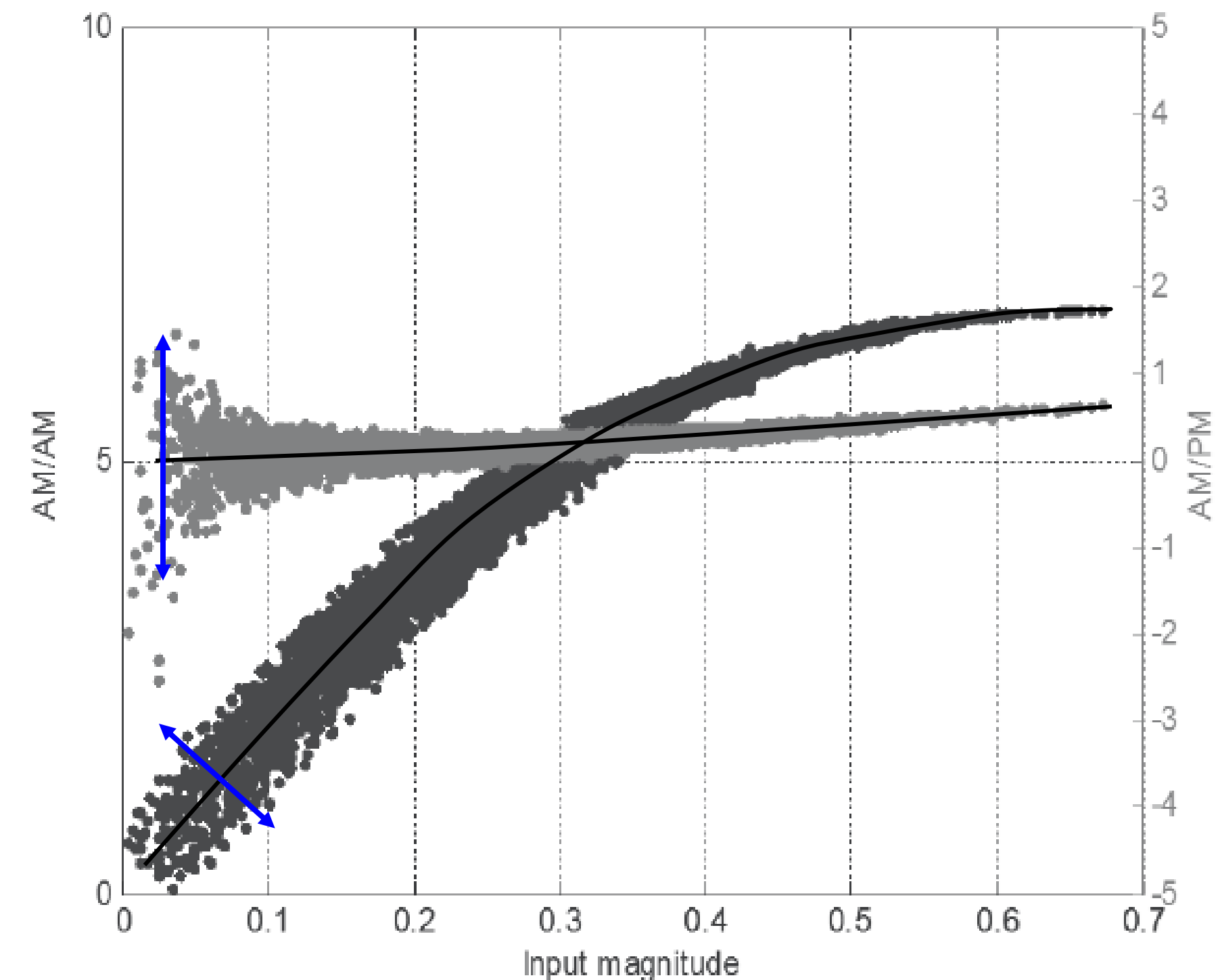
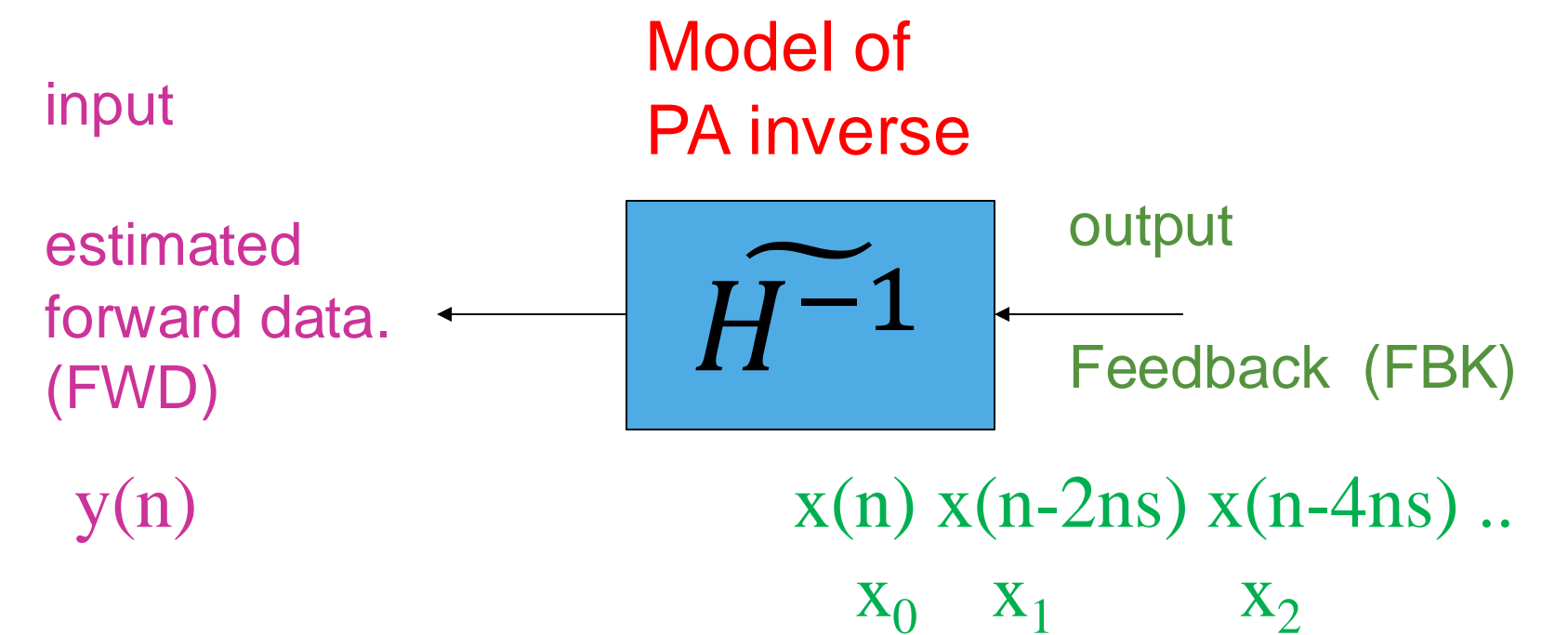
example

$$y(n) \approx a_{000}x_0 + a_{001}x_0^2 + a_{110}x_1 + a_{111}x_1^2 + a_{010}x_0x_1 + a_{100}x_1x_0$$

Static term

Memory term

Cross terms



MEMORY POLYNOMIAL

Static term	Memory term	Cross terms
$y(n) \approx a_{000}x_0 + a_{001}x_0^2$	$+ a_{110}x_1 + a_{111}x_1^2$	$+ a_{010}x_0x_1 + a_{100}x_1x_0$
$y(n) \approx a_{000}x_0 + a_{001}x_0^2$	$+ a_{110}x_1 + a_{111}x_1^2$	

Example case $r = 2$ $k = 2$

Generalized Memory Polynomial

Memory Polynomial

Memory polynomial

$$y(n) = \sum_{k=0}^{K-1} a_{0k,0} x_0^k + \sum_{k=1}^{K-1} a_{1k} x_1^k + \dots + \sum_{k=1}^{K-1} a_{rk} x_r^k + \epsilon$$

Memory Polynomial model is a simplification of Volterra

Still good in term of linearization performances

Models correctly the memory effect

Simpler to implement in real time system

VOLTERA SERIES COMPLEXITY - MP

		memory order									
K	R	1	2	3	4	5	6	7	8	9	10
Ord=1		1	2	3	4	5	6	7	8	9	10
Ord=2		2	5	9	14	20	27	35	44	54	65
Ord=3		3	9	19	34	55	83	119	164	219	285
Ord=4		4	14	34	69	125	209	329	494	714	1000
Ord=5		5	20	55	125	251	461	791	1286	2001	3002
Ord=6		6	27	83	209	461	923	1715	3002	5004	8007
Ord=7		7	35	119	329	791	1715	3431	6434	11439	19447
Ord=8		8	44	164	494	1286	3002	6434	12869	24309	43757
Ord=9		9	54	219	714	2001	5004	11439	24309	48619	92377
Ord=10		10	65	285	1000	3002	8007	19447	43757	92377	184755

development order

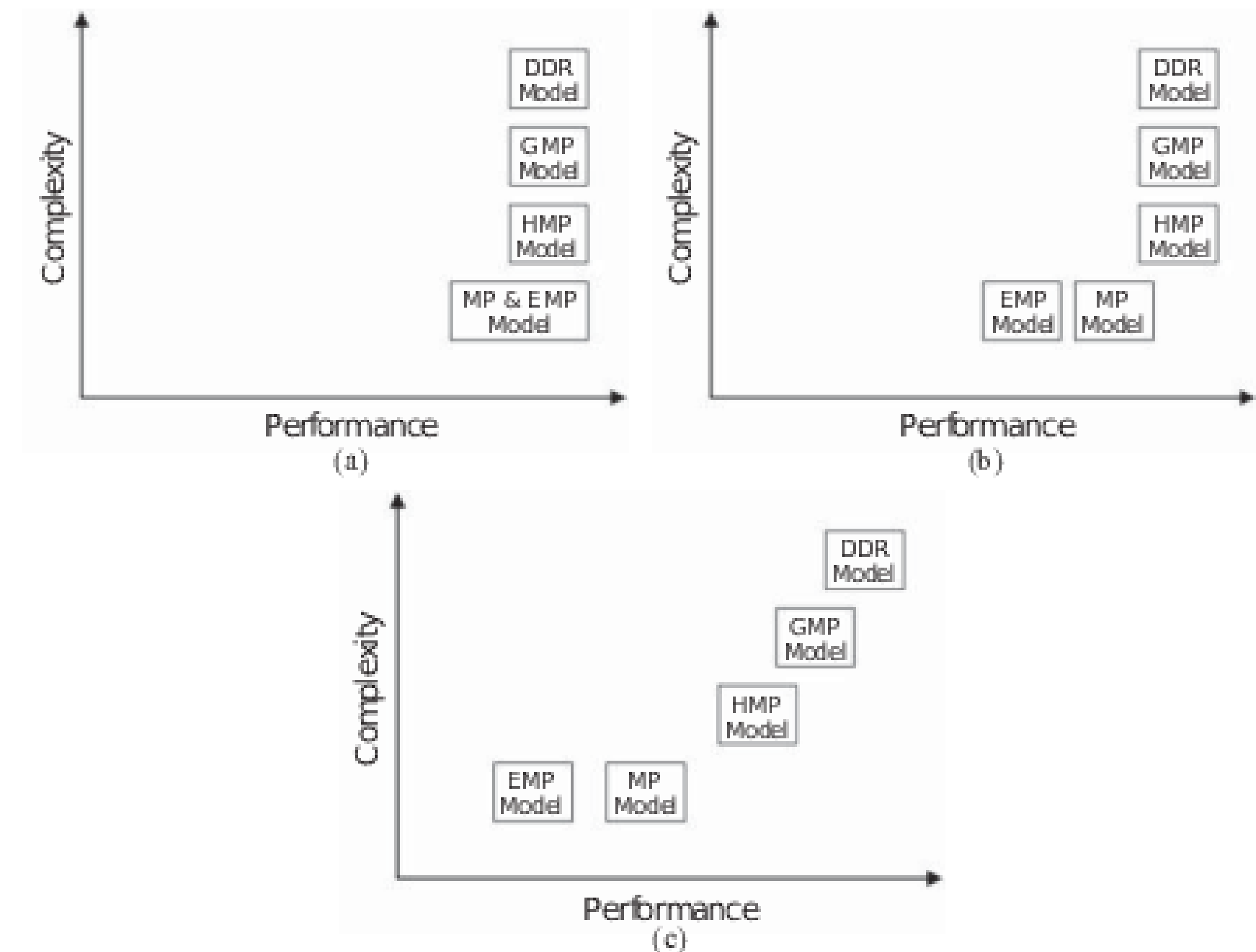
Number of coefficients to estimate depending on the development order and the memory order

1 DPD iteration ~ 10s 200s

 Need simplification

Nonlinear models – the most popular

- Many variations
 - Comparison between memory polynomial based models.
 - (a) Weakly nonlinear memory effects,
 - (b) mildly nonlinear memory effects,
 - (c) strongly nonlinear memory effects



Sources: 2015 - Ghannouchi, Hammi, Helaoui - Behavioral Modeling and Predistortion of Wideband Wireless Transmitters

Nonlinear models – the most popular

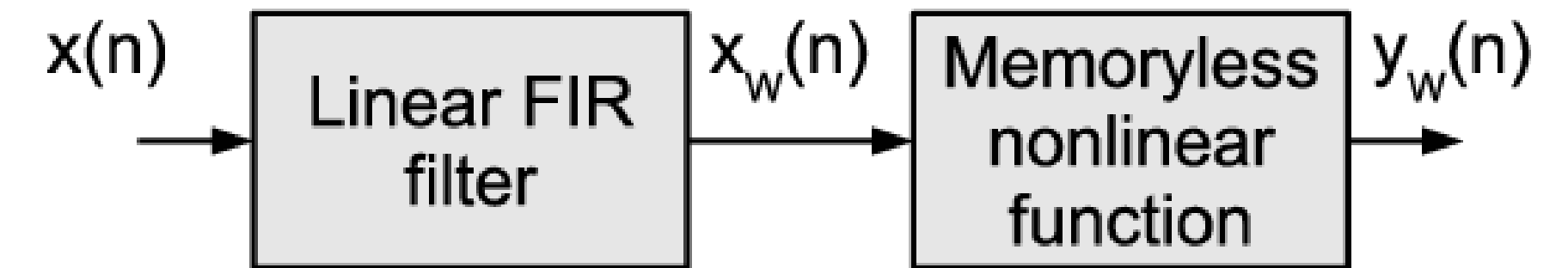
- **Box-Oriented models**

Stop here

- Wiener

$$y_W(n) = G_W\{|x_W(n)|\} \cdot x_W(n)$$

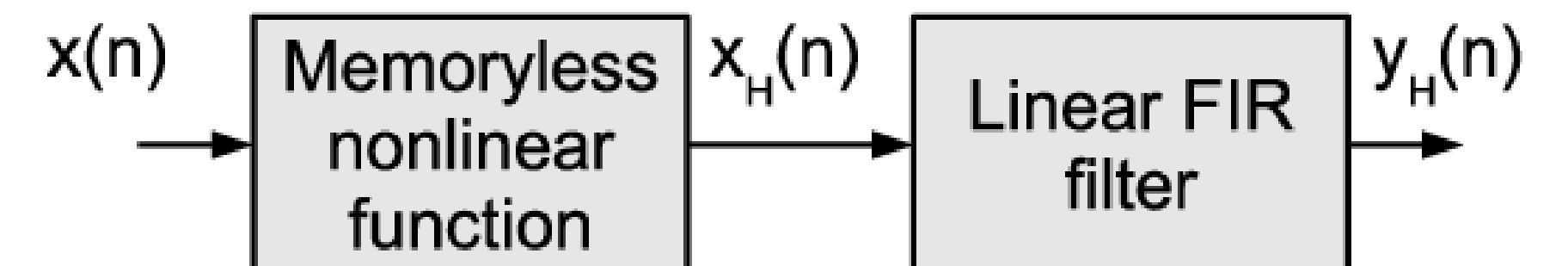
$$x_W(n) = \sum_{m=0}^M a_m x(n-m)$$



- Hammerstein

$$y_H(n) = \sum_{m=0}^M a_m x_H(n-m)$$

$$x_H(n) = G_H\{|x(n)|\} \cdot x(n)$$



Nonlinear models – the most popular

- Neural network based models
 - Example: Feedforward Neural Networks (multi-layer NN)

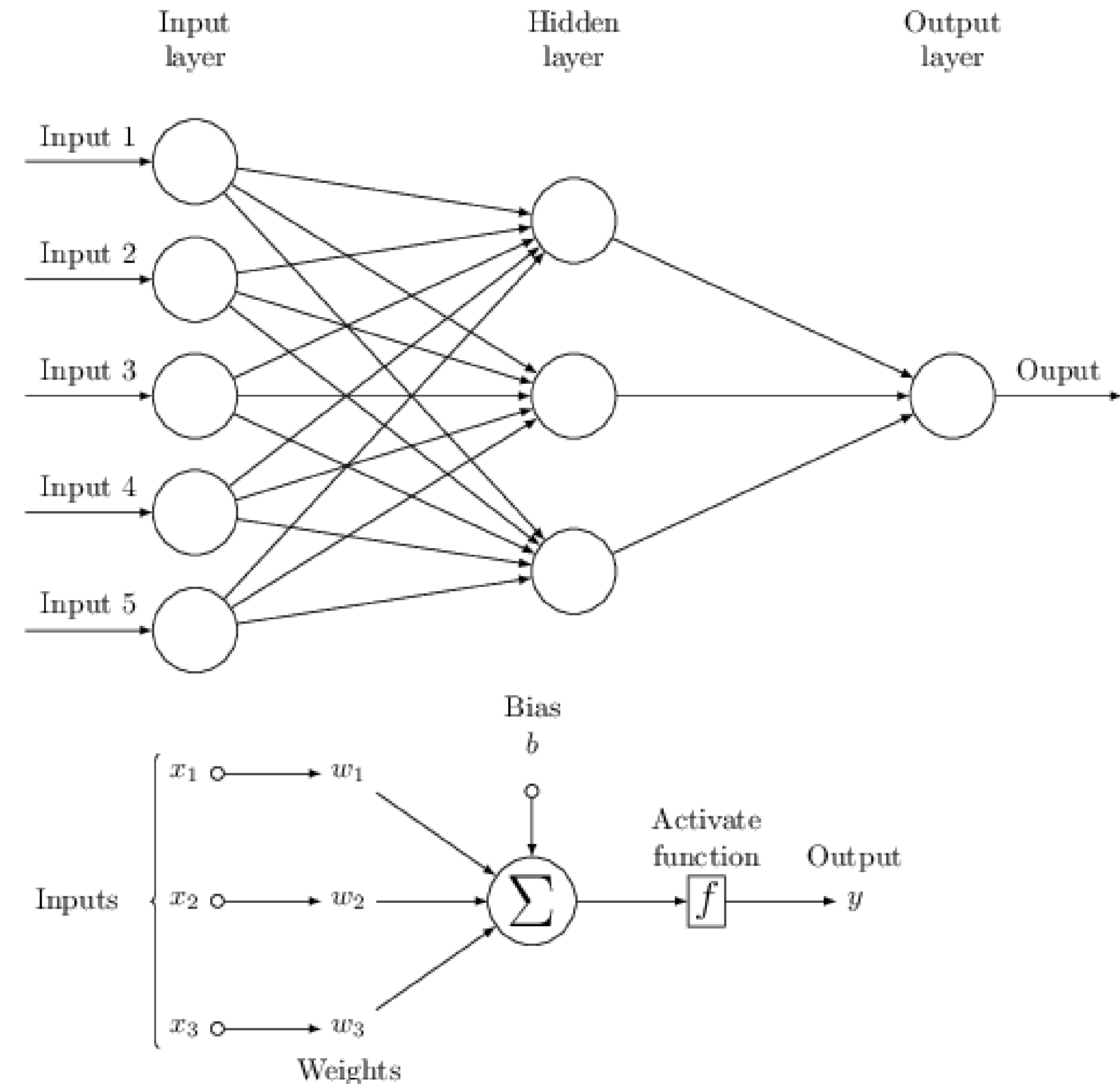
$$O_i^l(k) = f\{net_i^l(k)\}, \ell = 1, \dots, L - 1$$

$$net_i^1(k) = w_{i1}^1 \cdot x(k) + b_i^1$$

$$net_i^l(k) = \sum_{j=1}^N w_{ij}^l \cdot O_j^{l-1}(k) + b_i^l$$

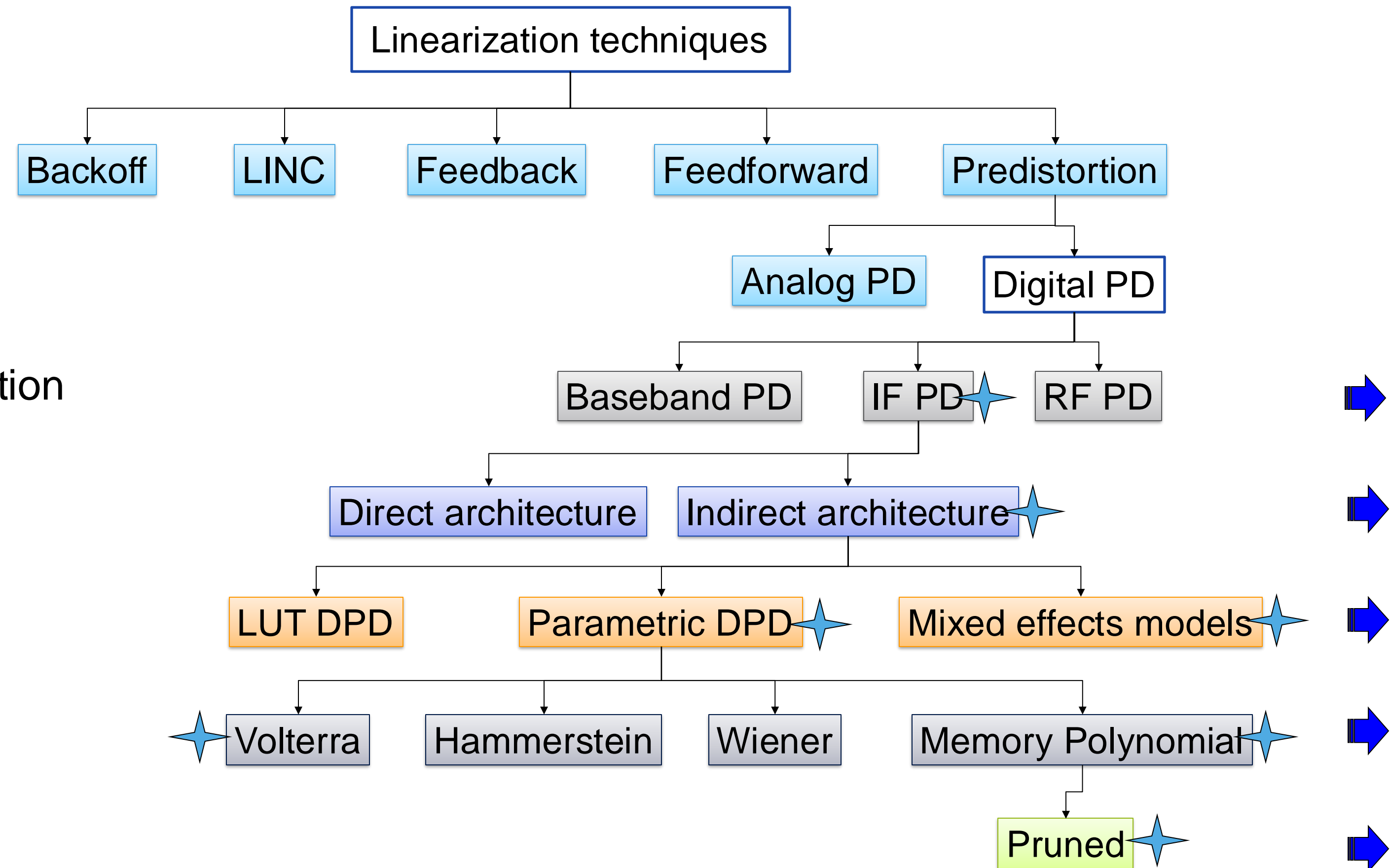
- Output of the FFNN:

$$y(k) = \sum_{j=1}^N w_{1j}^L \cdot O_j^{L-1}(k) + b_1^L$$



Sources: <http://tex.stackexchange.com/a/132471>

LINEARIZATION TECHNIQUES AND PA MODEL CHOICE



1990-2010's techniques

Chose IF DPD, tradeoff performance / implementation

Chose indirect architecture bc no inversion

Don't use LUT bc doesn't address memory effect, too memory costly & too slow to update

Volterra model too complex to implement

Hammerstein Wiener model sub-optimal for memory effect

Use memory polynomial, pruned version

NXP chosen models DPD

Fitting approaches (Identification methods)

Identification methods for linear-in-parameters models

- Memory polynomial example

$$y_{MP}(n) = \sum_{m=0}^M \sum_{k=1}^K a_{mk} x(n-m) |x(n-m)|^{k-1}$$

$$y(n) = \vec{\gamma}_x(n)^T \cdot \vec{A}$$

$$\vec{\gamma}_x(n) = [x(n)x(n-1) \cdots x(n-M)x(n) \cdot |x(n)|x(n-1) \cdot |x(n-1)| \cdots x(n-M) \cdot |x(n-M)|^{K-1}]^T$$

$$\vec{A} = [a_{01} a_{11} a_{21} \cdots a_{M1} a_{02} a_{12} \cdots a_{MK}]^T$$

Identification methods for linear-in-parameters models

- For a set of $N + 1$ samples: $\vec{y}(n) = \Gamma_x(n) \cdot \vec{A}$

$$\Gamma_x(n) = \begin{bmatrix} x(n) & x(n-1) & \dots & x(n)|x(n)| & x(n-1)|x(n-1)| \\ x(n-1) & x(n-2) & \dots & x(n-1)|x(n-1)| & x(n-2)|x(n-2)| \\ \vdots & \vdots & \dots & \vdots & \vdots \\ x(n-N) & x(n-1-N) & \dots & x(n-N)|x(n-N)| & x(n-1-N)|x(n-1-N)| \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & x(n-M)|x(n-M)|^{K-1} \\ \dots & \dots & \dots & \dots & x(n-M-1)|x(n-M-1)|^{K-1} \\ \dots & \dots & \dots & \dots & \vdots \\ \dots & \dots & \dots & \dots & x(n-M-N)|x(n-M-N)|^{K-1} \end{bmatrix}$$

Model identification \Leftrightarrow Compute \vec{A} ... but Γ_X is not invertible

Identification methods for linear-in-parameters models

- Exercise

- Write the matrix for

$$\vec{A} = [a_{01} a_{02} \cdots a_{0K} a_{11} \cdots a_{MK}]^T$$

- Exercise

- Write the matrix Γ_X in the case of the Generalized memory polynomial

Identification methods for linear-in-parameters models

- Approximate solutions

- Least-squares (LS):

$$\min_{\vec{A}} \left\| \vec{y}(n) - \Gamma_x(n) \cdot \vec{A} \right\|^2$$

- Common approaches: Moore–Penrose pseudo-inverse decomposition, SVD

$$A^+ = (A^H A)^{-1} A^H$$

- Significant computational complexity ($\mathcal{O}((M \times K)^3)$)

- Least-mean-squares (LMS):

$$\min_{\vec{A}} E \left[\left| y(n) - \vec{A}^H \cdot \vec{\gamma}_x(n) \right|^2 \right]$$

- Iterative approach:

$$e(n) = y(n) - \vec{A}^H(n) \cdot \vec{\gamma}_x(n)$$

- Reduced computational complexity ($\mathcal{O}(M \times K)$)

$$\vec{A}(n+1) = \vec{A}(n) + \mu e^*(n) \vec{\gamma}_x(n)$$

- Convergence issues (μ)

Identification methods for linear-in-parameters models

- Recursive (weighted) least-squares (RLS):

$$\min_{\vec{A}} \sum_{i=0}^k \lambda^{k-i} |y(i) - \vec{A}^H(i) \cdot \vec{\gamma}_x(k)|^2$$

- Iterative approach:

$$e(k) = y(k) - \vec{A}^H(k-1) \cdot \vec{\gamma}_x(k)$$

$$\vec{s}(k) = \mathbf{S}(k-1) \cdot \vec{\gamma}_x(k)$$

$$\vec{\kappa}(k) = \frac{\vec{s}(k)}{1 + \vec{\gamma}_x^H(k) \cdot \vec{s}(k)}$$

$$\mathbf{S}(k) = \frac{1}{\lambda} \left[\mathbf{S}(k-1) - \frac{\vec{\kappa}(k) \cdot \vec{\kappa}^H(k)}{\lambda + \vec{\gamma}_x^H(k) \cdot \vec{s}(k)} \right]$$

$$\vec{A}(k) = \vec{A}(k-1) + e^*(k) \cdot \vec{\kappa}(k)$$

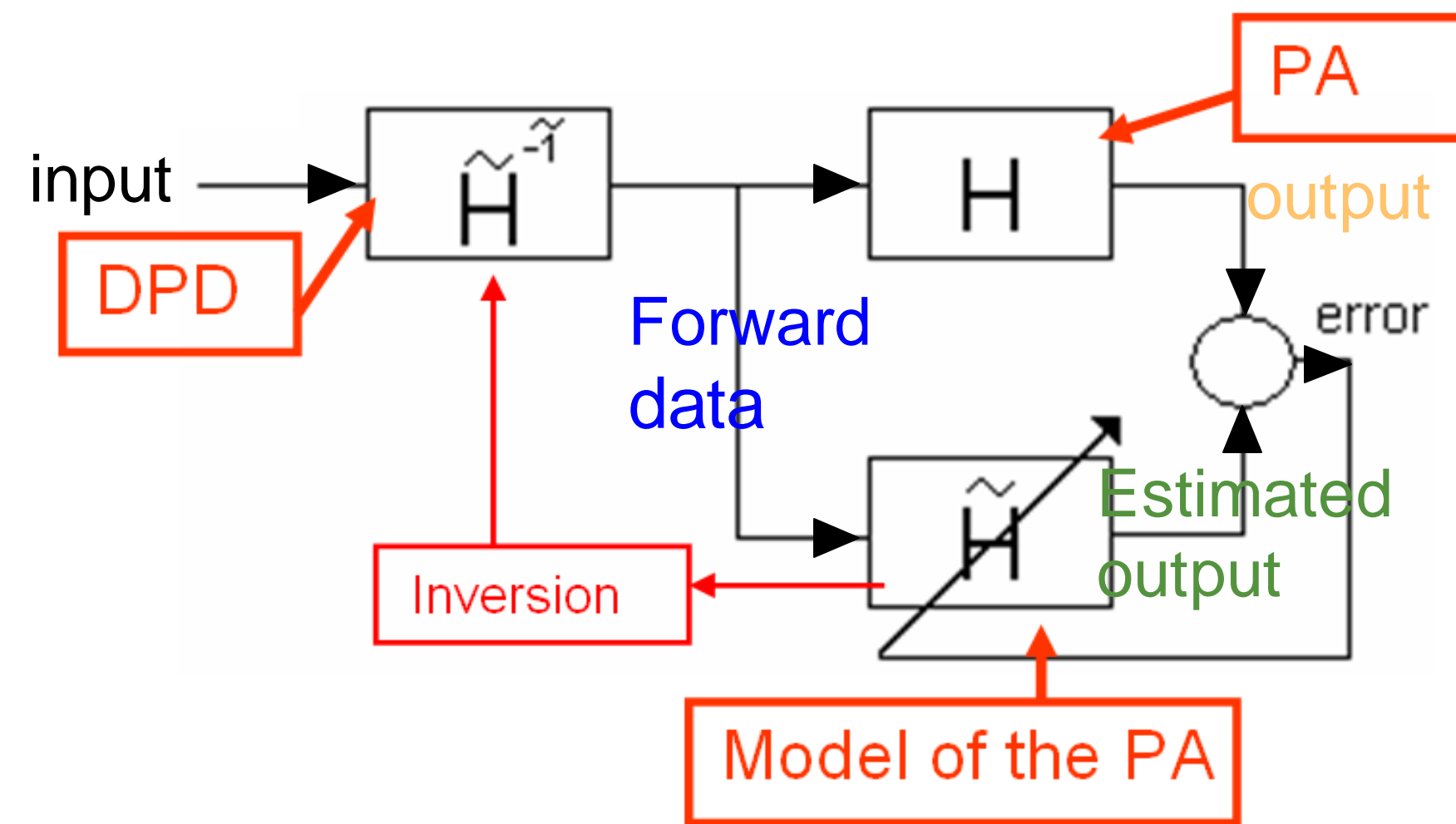
- Increased computational complexity ($\mathcal{O}((M \times K)^2)$)
- Robust convergence

Digital predistortion: Theory and implementation

Learning architectures

PA MODEL TOPOLOGY- DIRECT /INDIRECT LEARNING

Direct learning topology

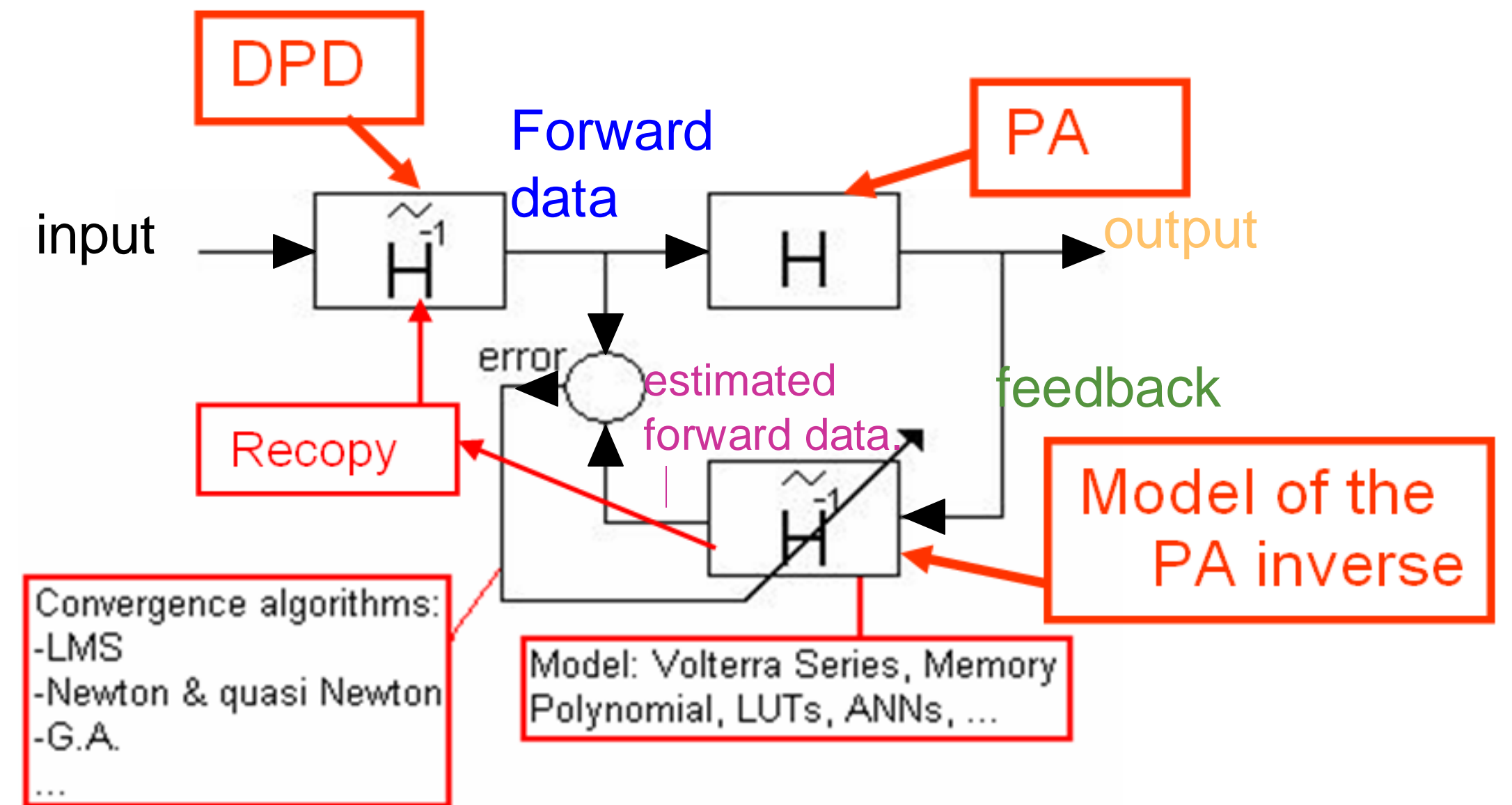


Minimize the delta bw **estimated output** and effective **output**
 The inverting of $H(\cdot)$ to \tilde{H}^{-1} is done numerically and hence implies additional approximations.

- more complex 😞
- error prone

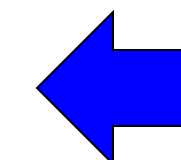
- $H(\cdot)$ = PA transfer function
- $\tilde{H}(\cdot)$ = PA transfer function estimate
- $\tilde{H}^{-1}(\cdot)$ = PA transfer function estimate inverted
- $\tilde{H}^{-1}(\cdot)$ = PA transfer function estimate inverted + error on inverse
- $\tilde{H}^{-1}(\cdot)$ = PA inverse transfer function estimate

Indirect learning topology

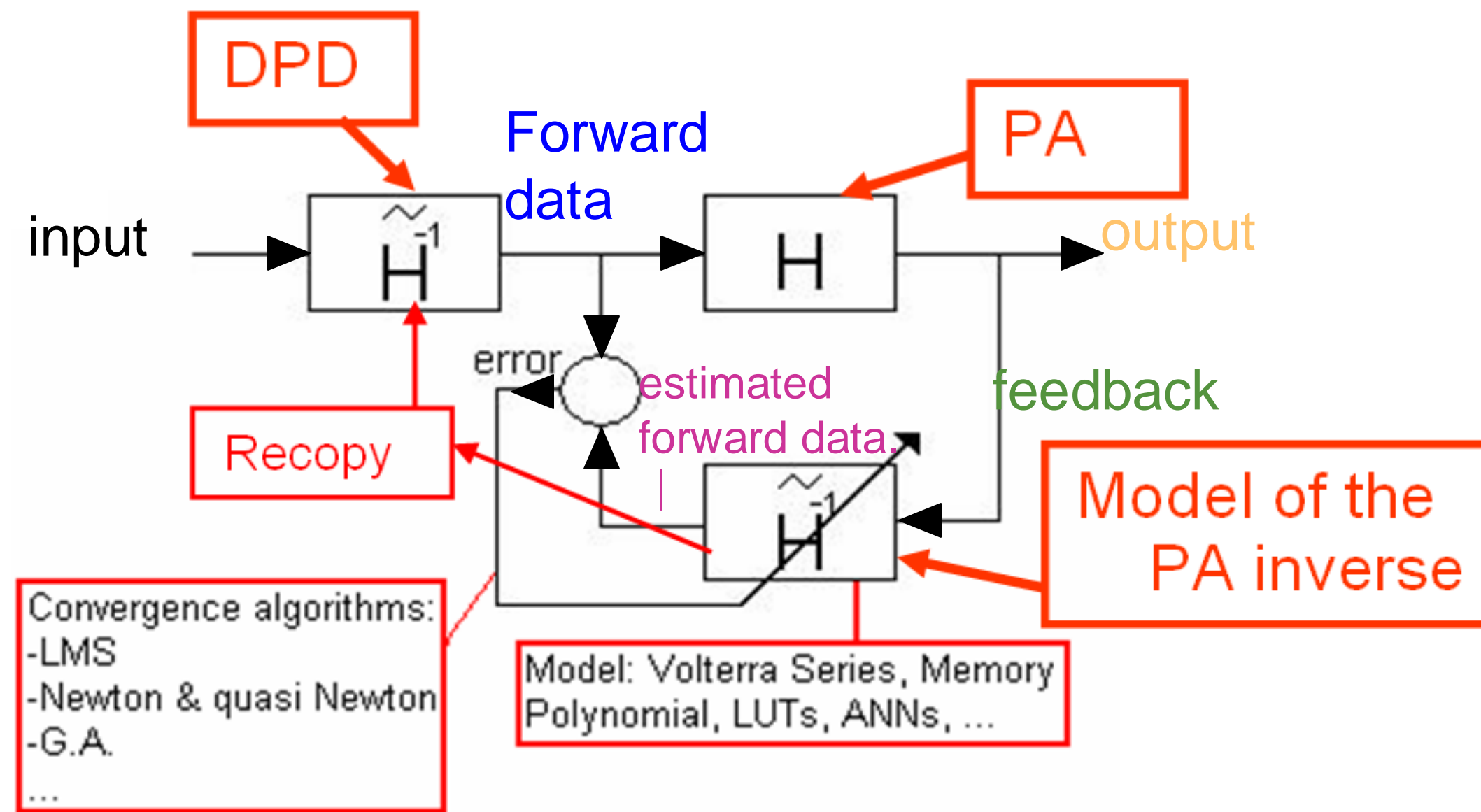


Minimize the delta bw **forward data** and **estimated forward data**.

- No more need to inverse a transfer function
- less complex
- less error prone 😊



LUT VS PARAMETRIC VS MIXED MODELS



LUT

DPD indirect learning LUT scheme consists to store into memory lookup tables static coefficients to transform **FBK** into **FWD data estimated**.

Requires learning PA phase

Introduces quantization as $f^\circ(\text{LUT size})$

Doesn't model memory effects



Parametric PA model

Volterra

Volterra model is based on Taylor series decomposition

Almost optimum in term of linearization performances

Models efficiently the memory effect

Very complex to implement in real time system

Searching for simplification



Memory Polynomial model

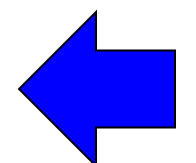
Memory Polynomial model is a simplification of Volterra

Still good in term of linearization performances

Models correctly the memory effect

Simpler to implement in real time system

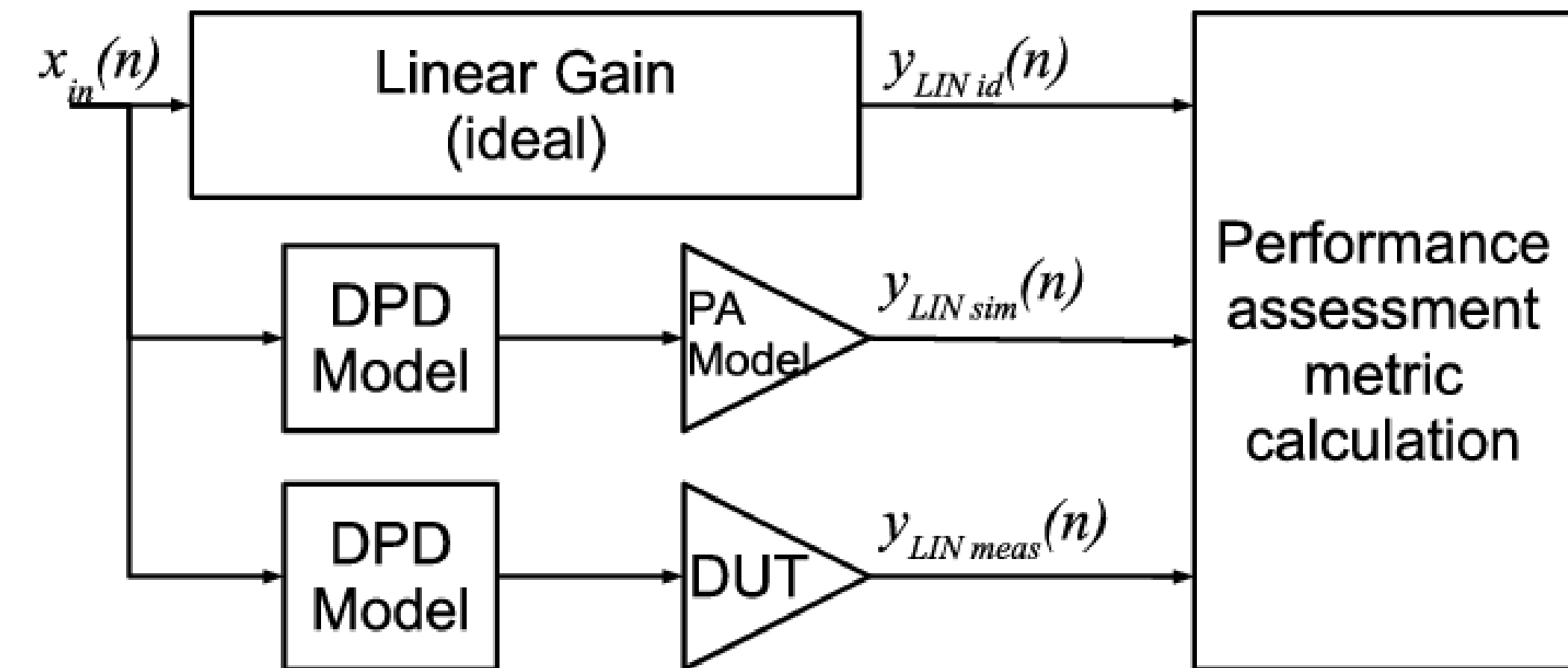
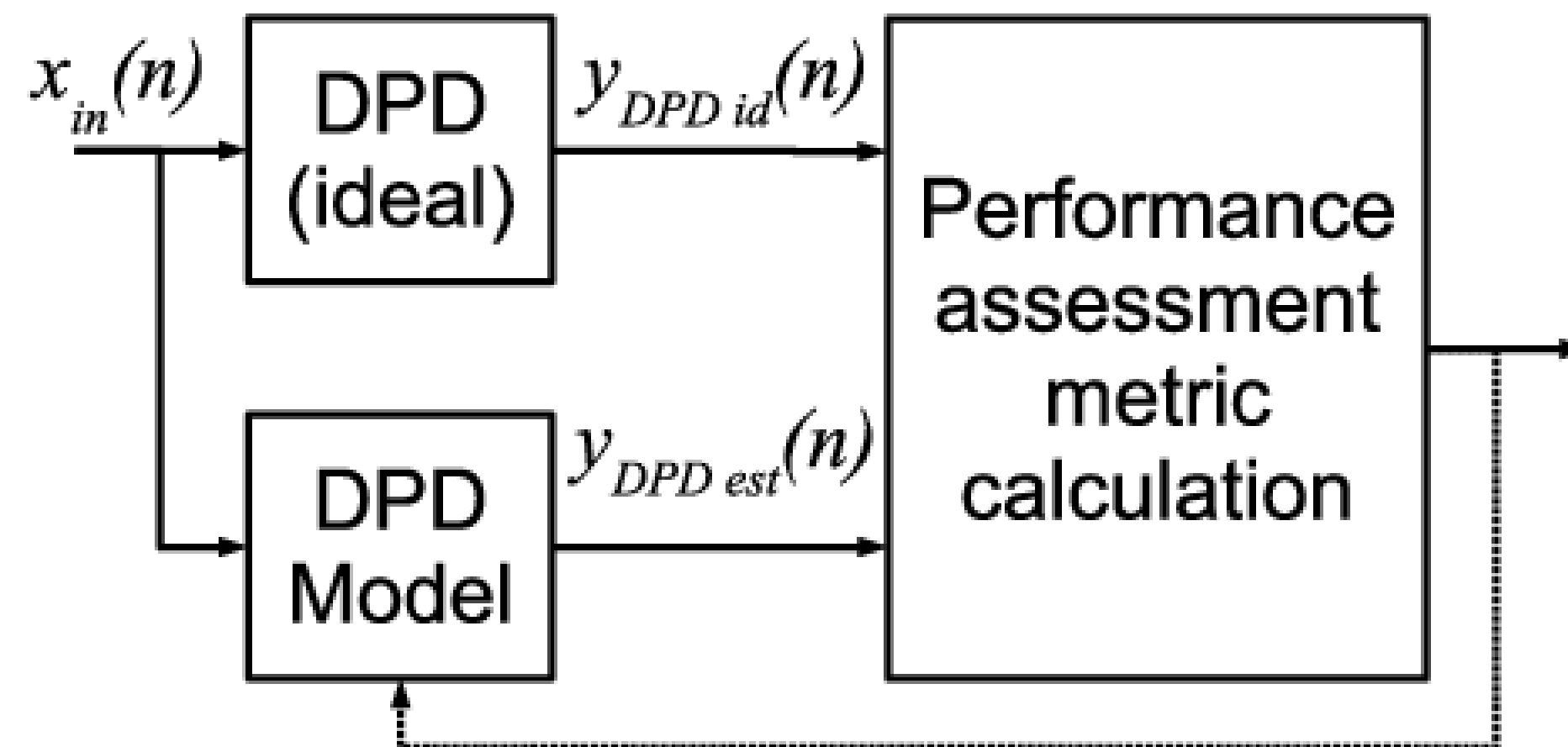
Searching for simplification



Identification of the DPD (=fitting of the inverse)

Mostly identical to PA Behavioural modeling

- Performance assessment



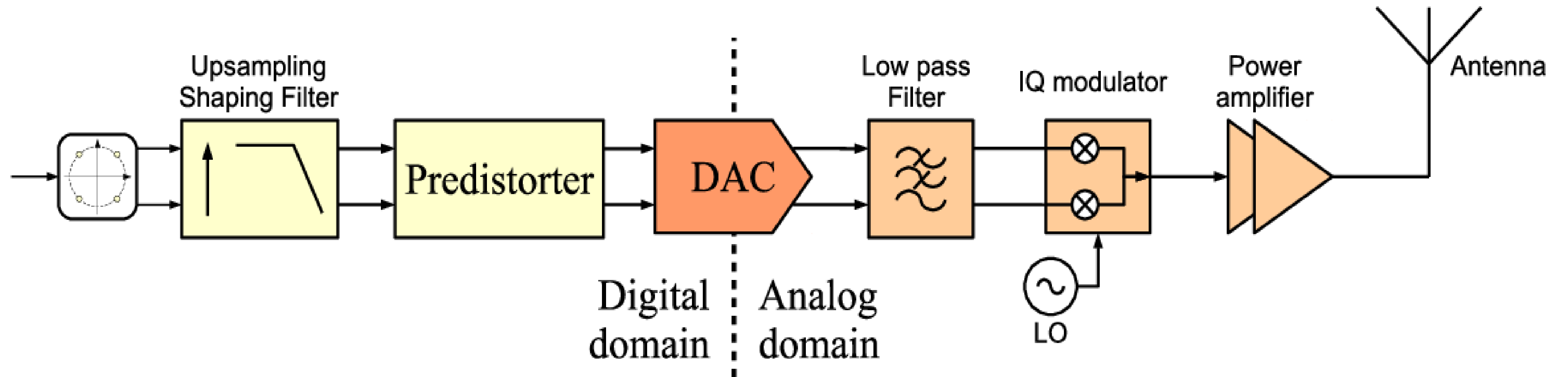
- Models
 - Memoryless
 - Memory-aware
 - Box oriented
 - Neural networks

- Computation methods
 - LS
 - LMS
 - RLS
 - (NN learning methods)

DPD Implementation

Concept

- Transmitter with DPD



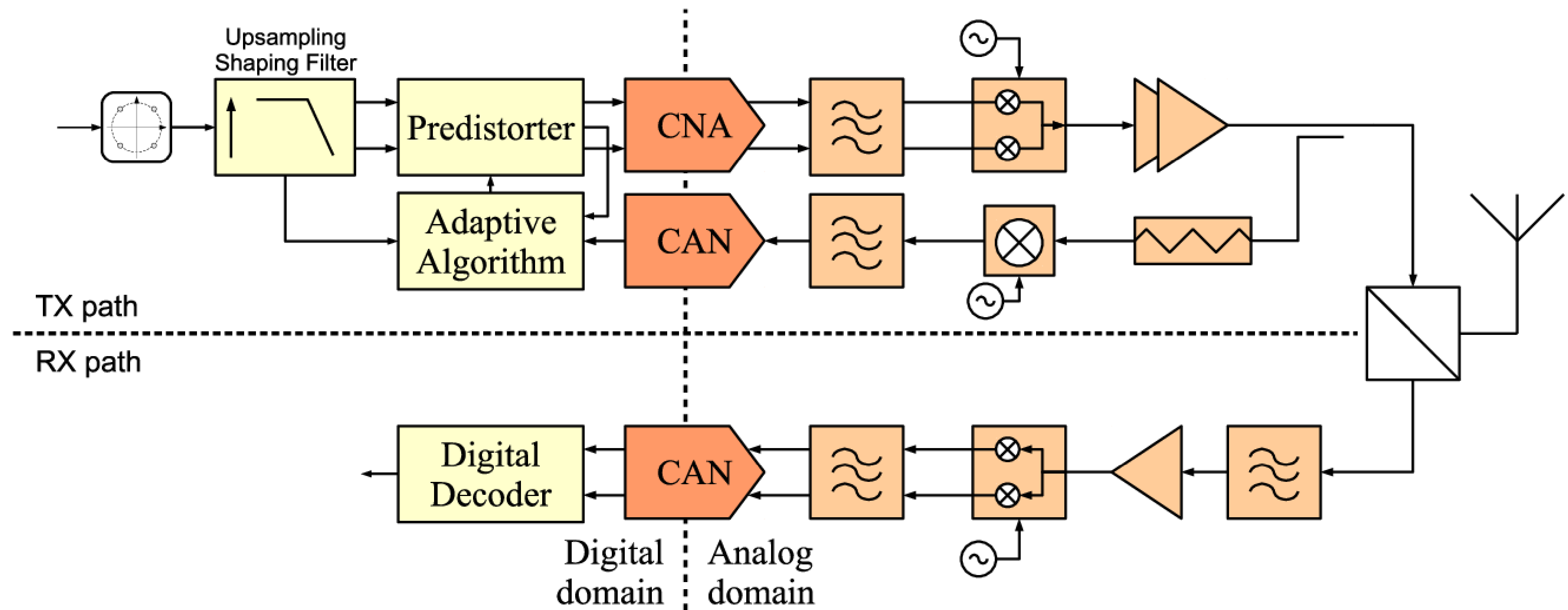
- Predistorter's nonlinear characteristics and the PA must match
- Nonlinearity of the PA varies with time due to changes in the drive signal, aging, or drifts
 - Update the predistortion function

Different types of DPD

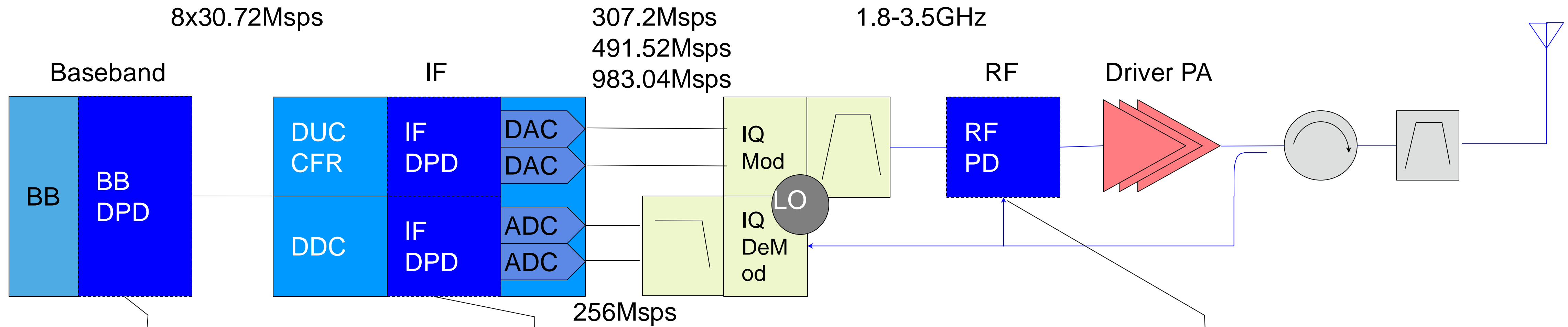
- High performance Lab DPD
 - Custom transceiver + custom DPD algorithm and models
 - On-the-shelf instrument (oscilloscope) + custom DPD algorithm and models
 - Automatic instrument based DPD
- Production sites : transceivers
 - BTS
 - Constrained hardware system
 - Mobile handset
 - Strongly constrained embedded system

Implementation for transceivers

- Regular base station implementation



BB-IF-RF CONSIDERATIONS FOR DPD



Option 1 BB DPD

- 😊 Works at a low sampling rate, Low complexity implementation
- 😞 Works before CFR, then low DPD efficiency

OR

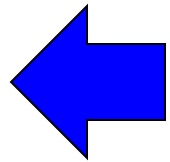
Option 2 IF DPD

- 😞 Works at a medium sampling rate, medium complexity implementation
- 😊 Works on composite signal after CFR, then good DPD efficiency

OR

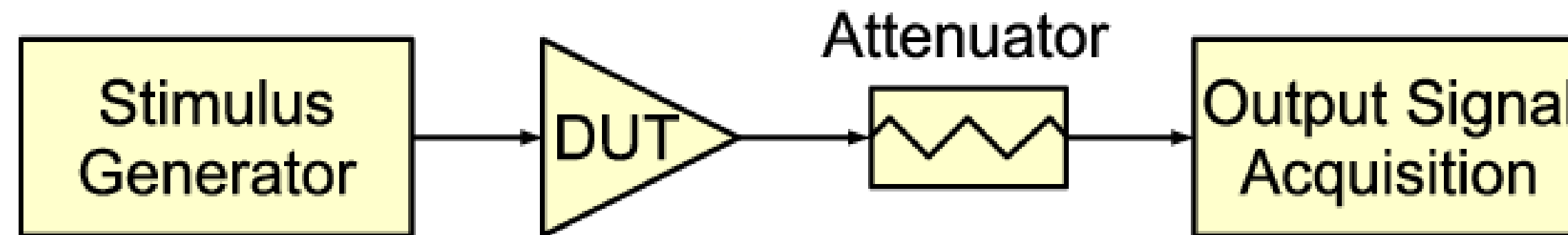
Option 3 RF PD

- 😞 Sampling rate too high, too complex implementation

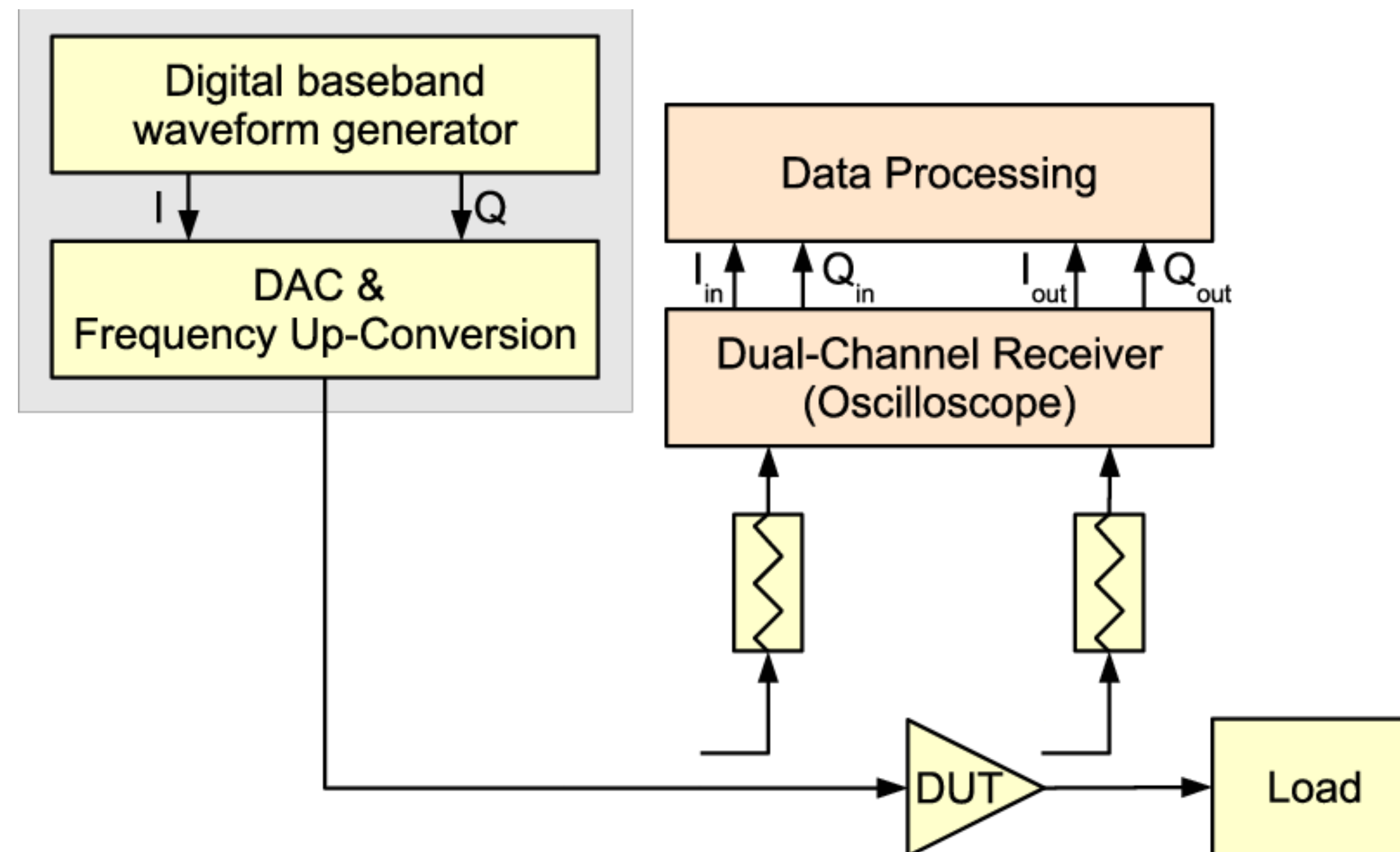


Implementation for Labs

- Tones signal (CW, dual, multitone) – Static Characterization

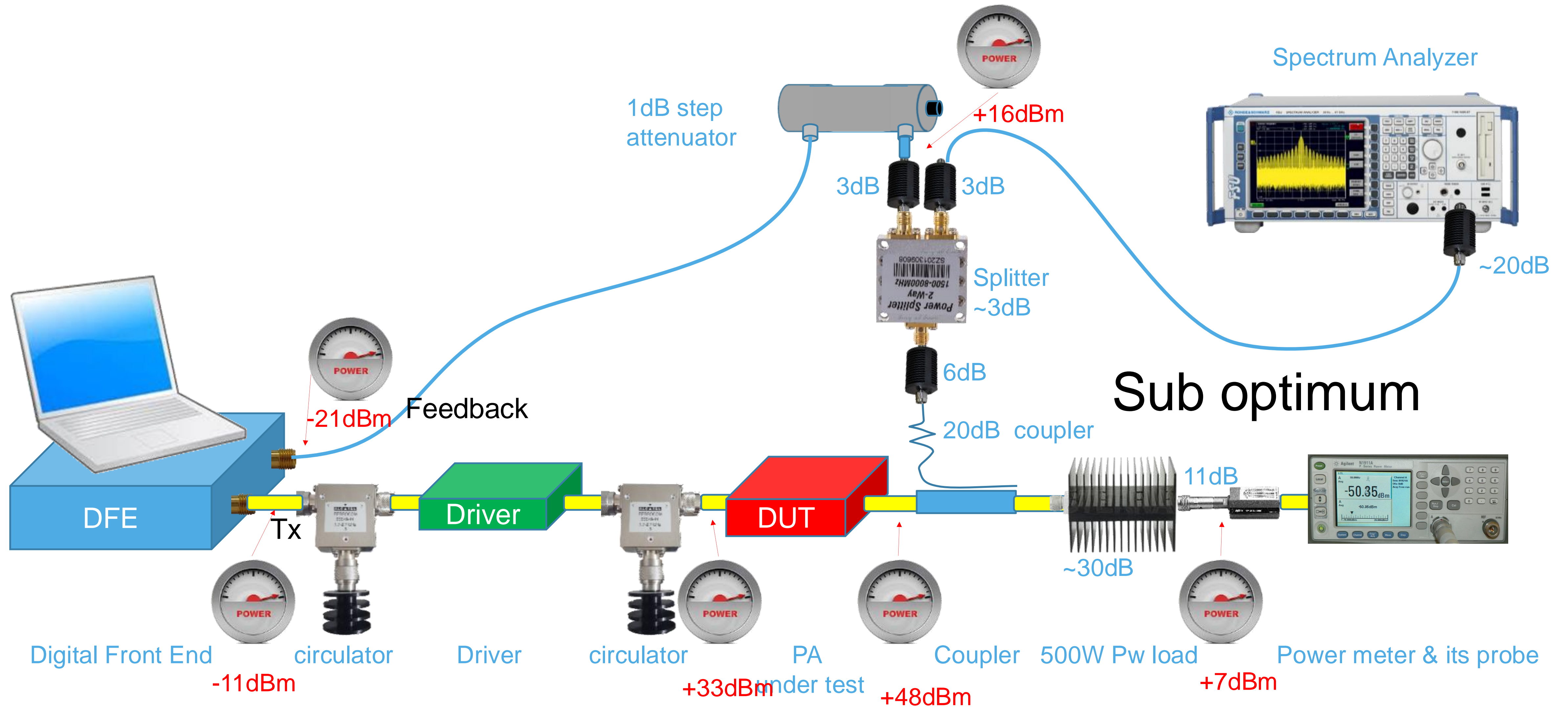


- Modulated signal

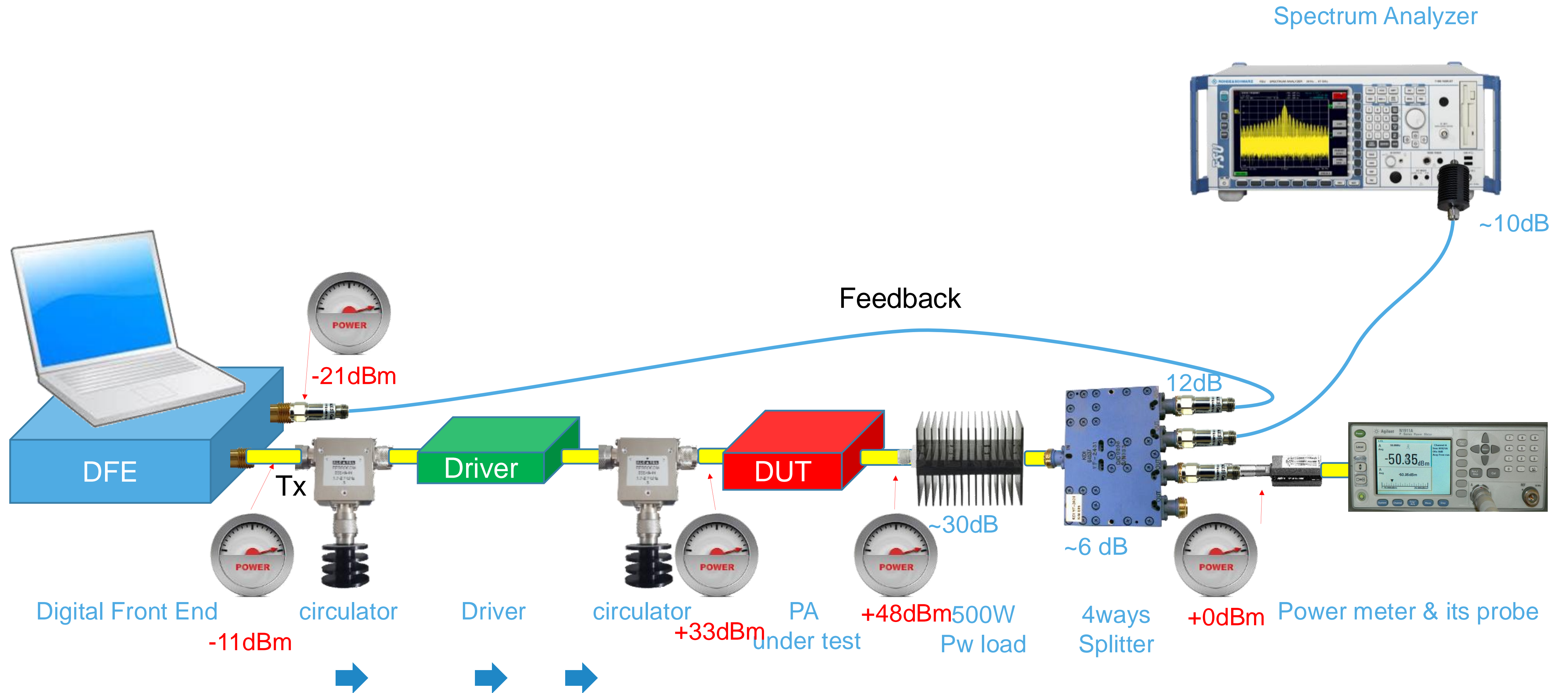


- Data De-Embedding is critical
 - power adjustment
 - time alignment

DFE SETUP – 0 – “INVERTED LOAD”



DFE SETUP – 1 – RECOMMENDED SETUP



DPD IMPLEMENTATION OTHER CONSIDERATIONS

- Real time vs non real time systems,
- Narrow band vs Wide band DPD
- Pout levels for NB & WB,
- DPD setup considerations (driver, circulator, load, SRX levels)
- Calibration

Conclusion

Conclusion

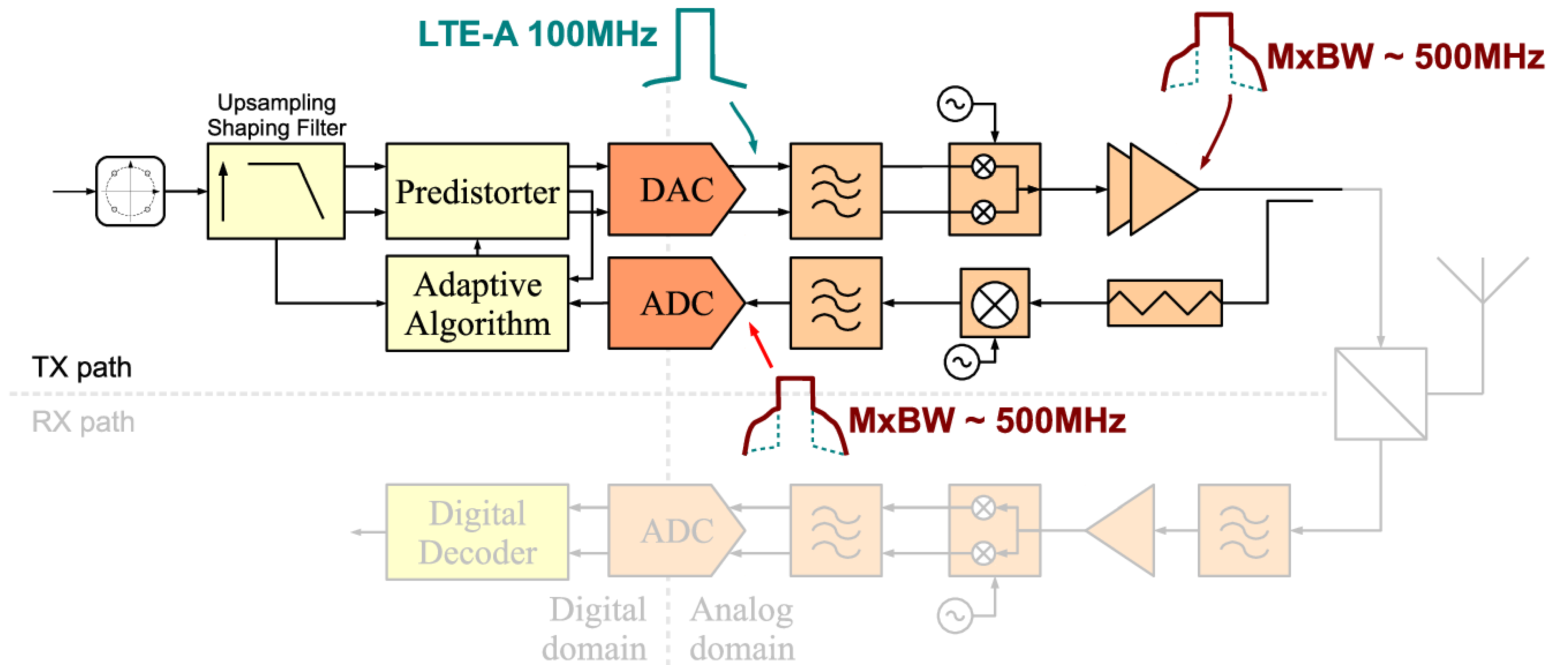
- Trans-disciplinary domain
 - theory and signal processing
 - digital communications
 - programming
 - circuit design
 - frontend baseband/RF
 - hardware
- Many design and system elements are interacting with each others
 - Multi-level approach is required
- New approaches are required for integration with key technologies for 5G
 - Massive MIMO
 - mmWave



Backup slides

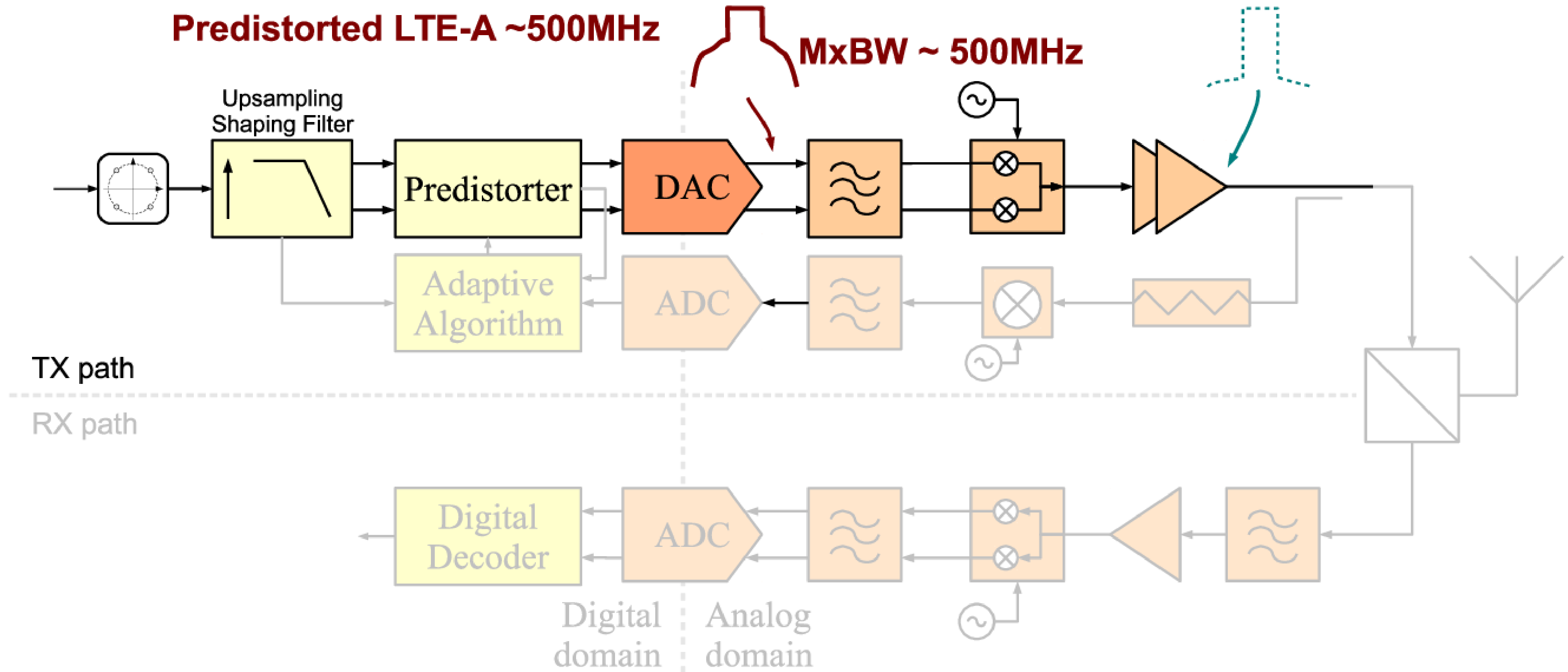
Wideband DPD in high power BTS

- ADC issue

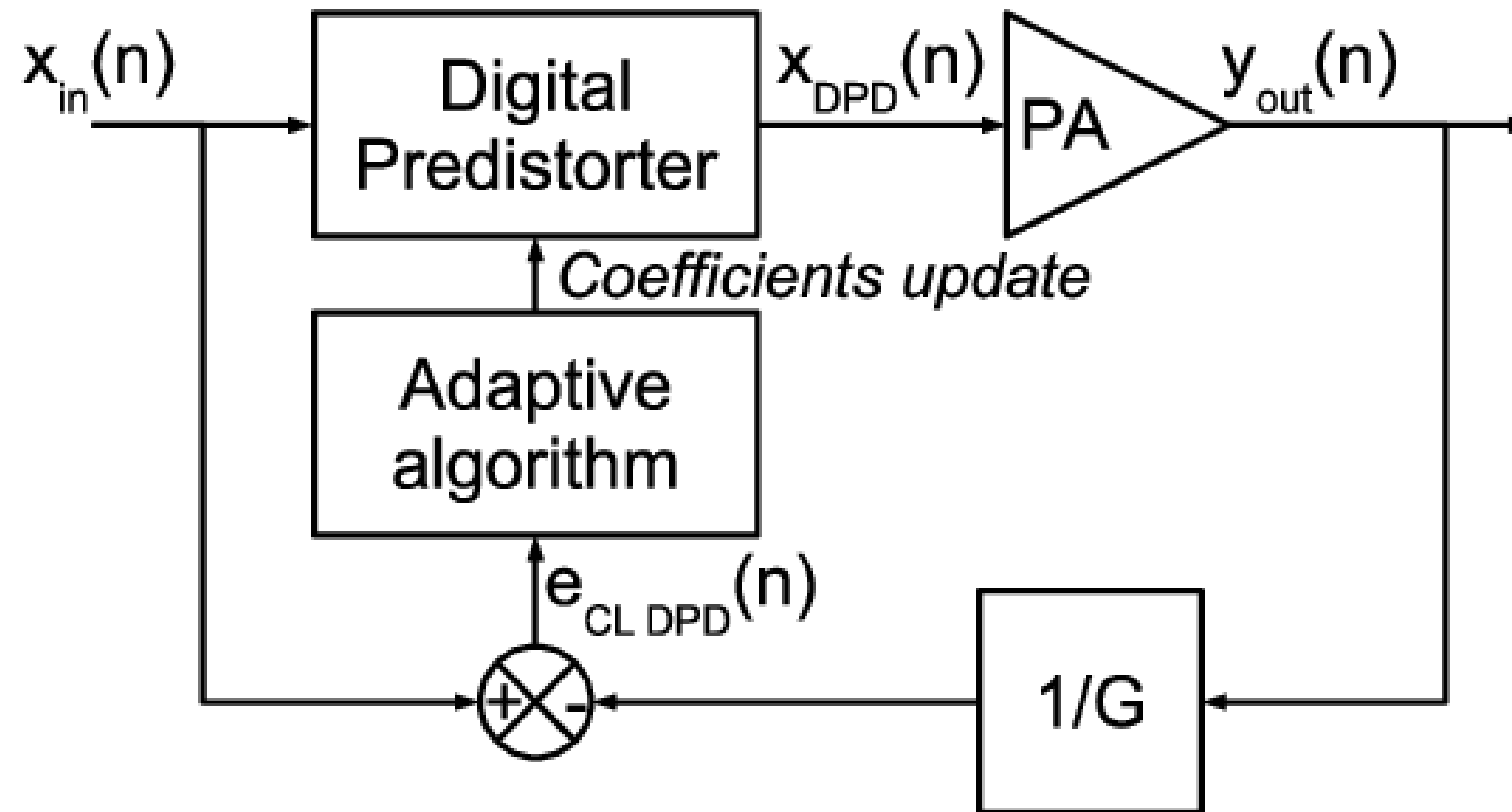


Wideband DPD in high power BTS

- DAC issue



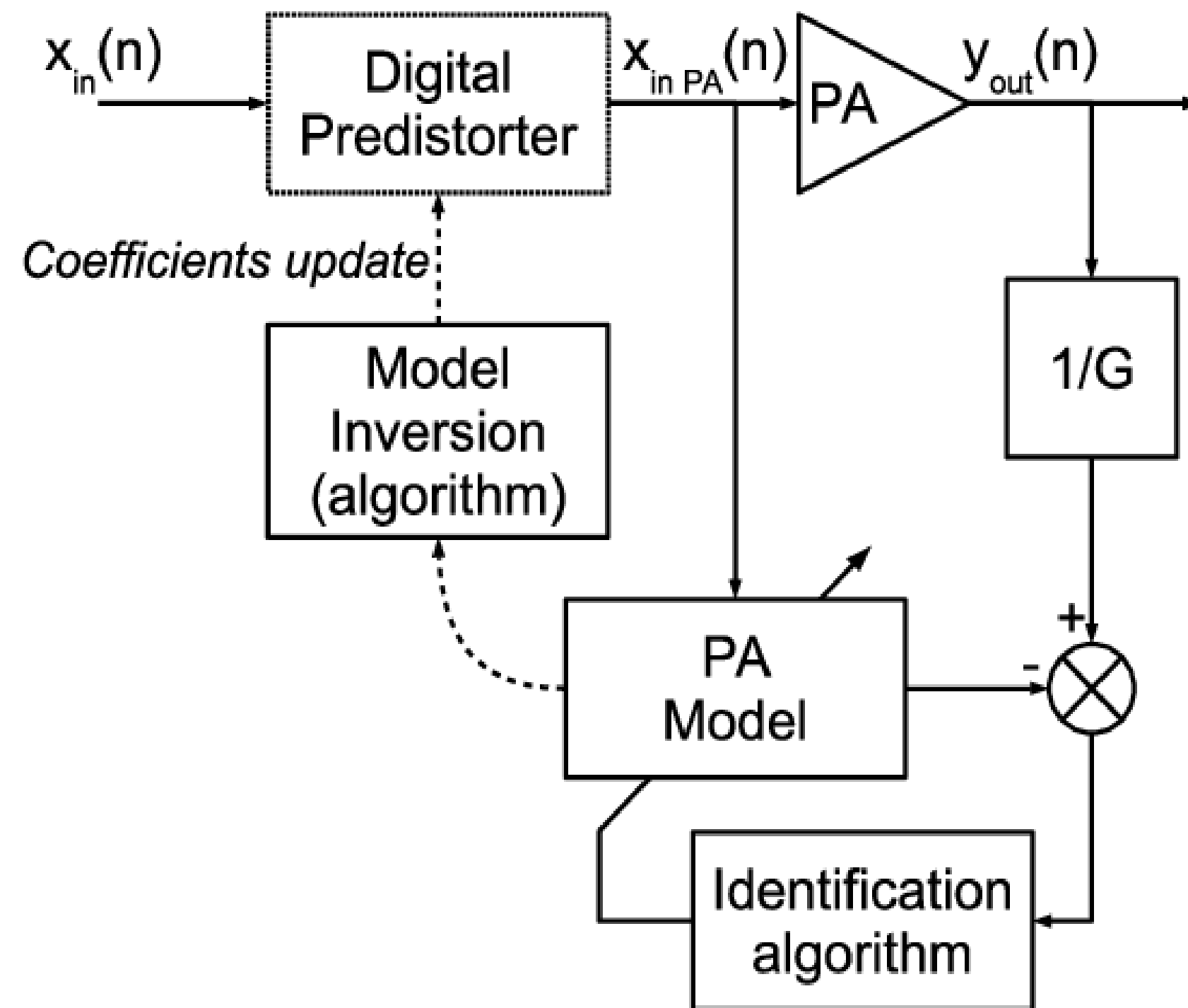
Closed loop Adaptive DPD



- Usually exhibit slow convergence and high computational complexity
 - No direct relation between the error signal and the predistorter's coefficients
- Prone to divergence if the PA is driven into saturation
- Direct learning technique to identify the predistorter's coefficients

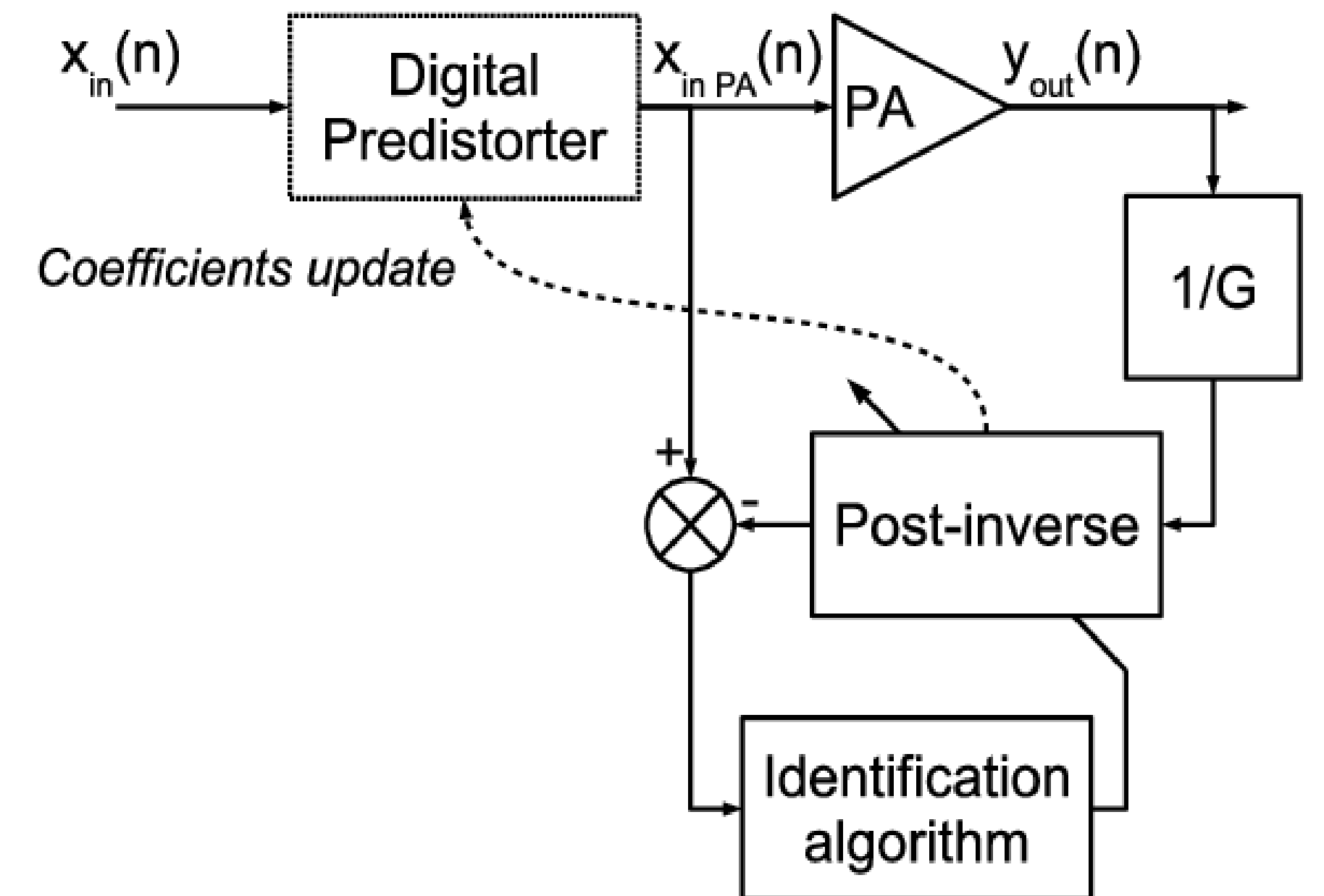
Open loop Adaptive DPD

- Direct learning architecture



- Amplifier's model is identified; then the DPD function is built by inverting the PA model
- Suitable for memoryless systems

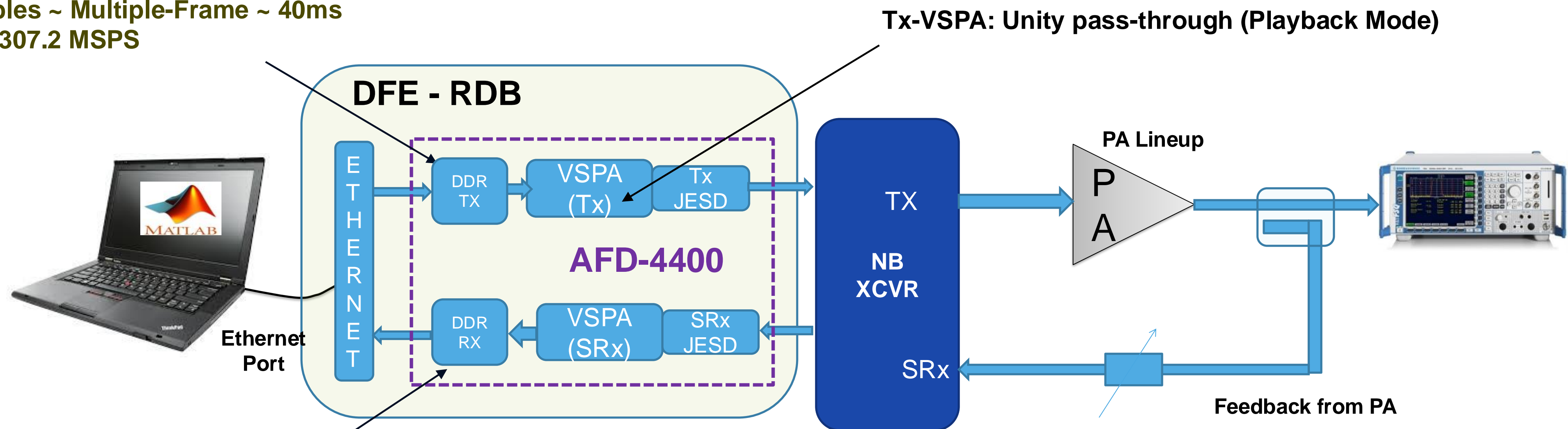
- Indirect learning architecture



- the predistortion function is directly derived by calculating the post-inverse of the amplifier
- Suitable for systems with memory

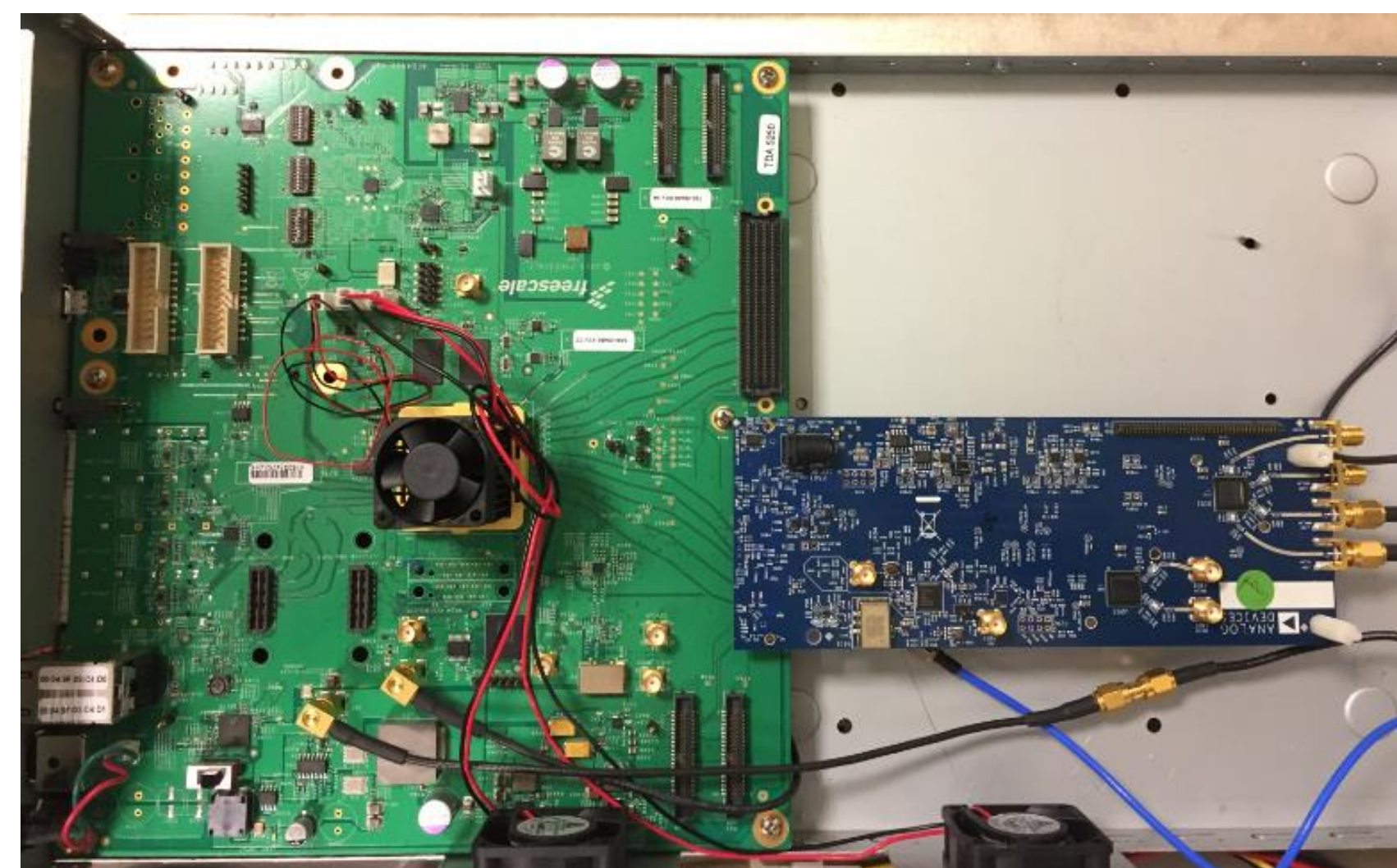
Narrowband Transceiver

Tx Buffer: loads waveform,
 number of samples ~ Multiple-Frame ~ 40ms
 Sampling rate= 307.2 MSPS
 1 sample ~ 3ns



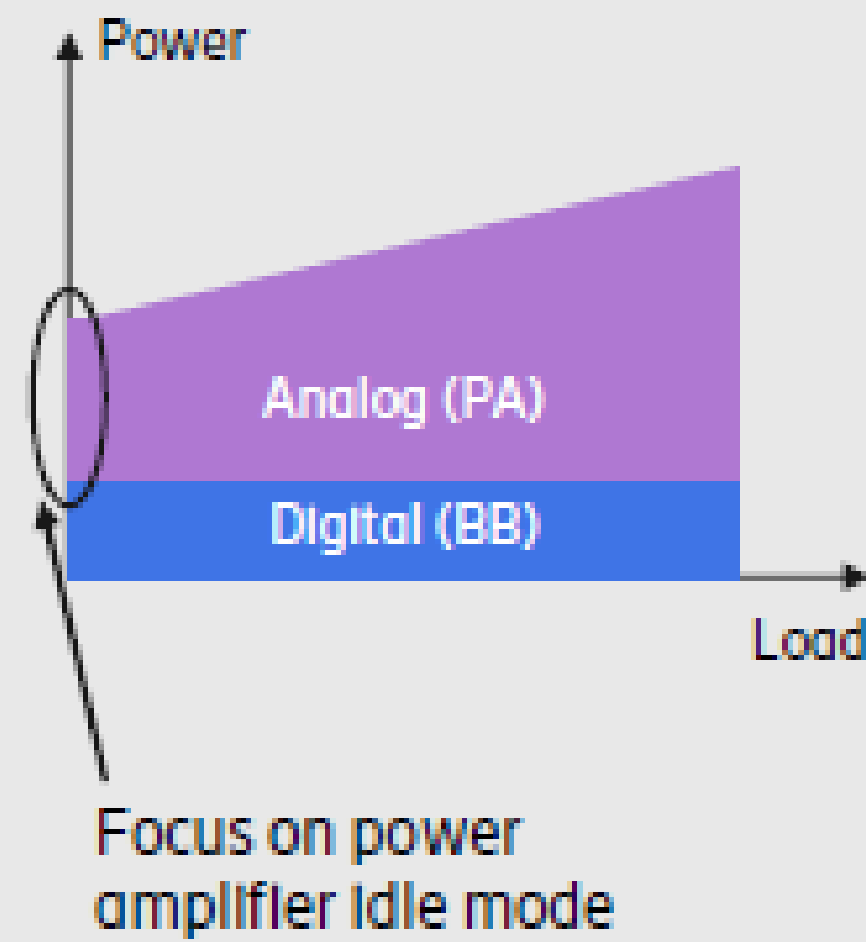
SRx Buffer: captures waveform,
 number of samples 2K~120K
 Sampling rate= 307.2 MSPS

Narrowband XCVR
 IQ Rate= 307.2 MSPS

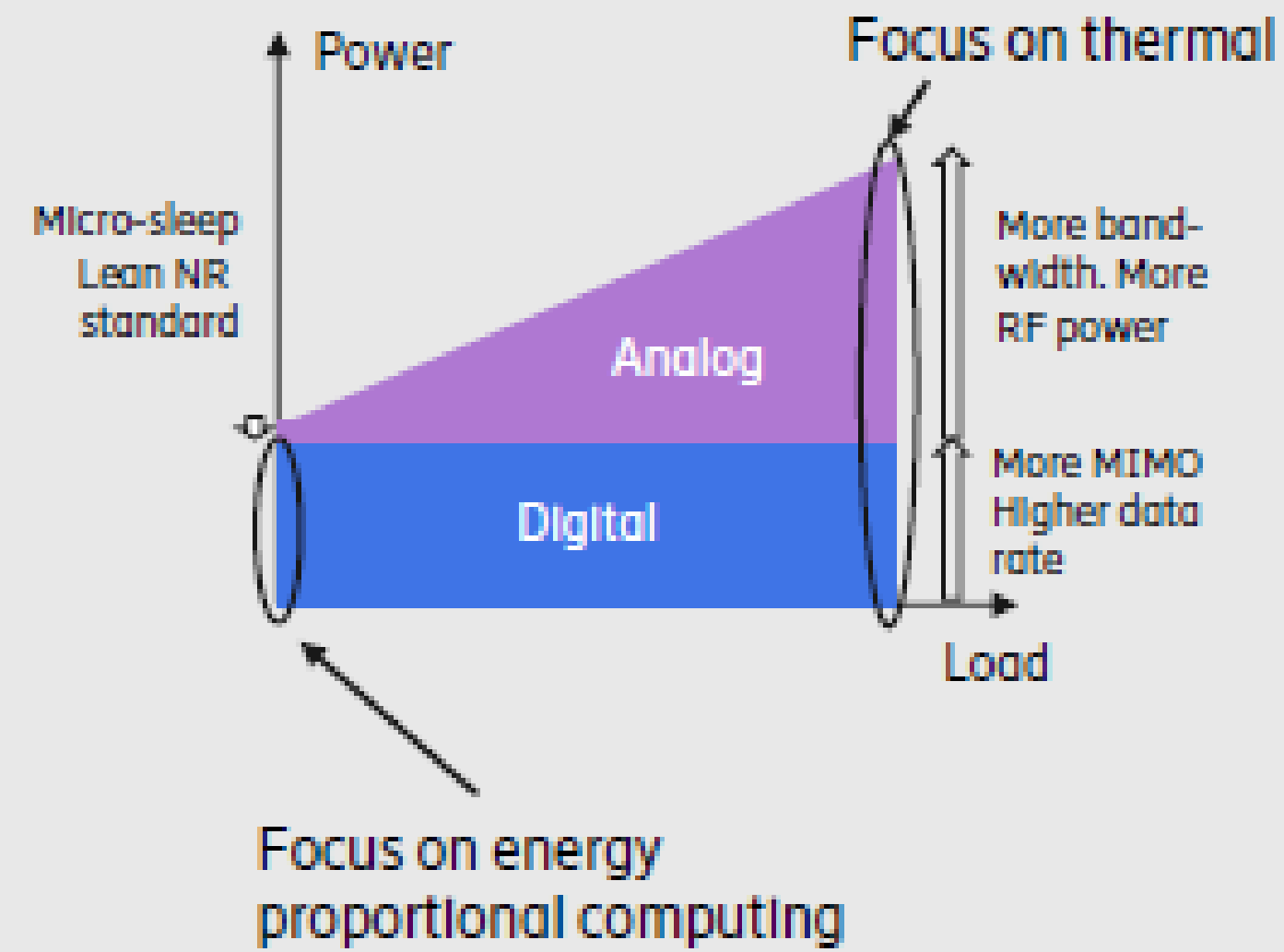


4G-5G-6G ENERGY PERFORMANCE JOURNEY

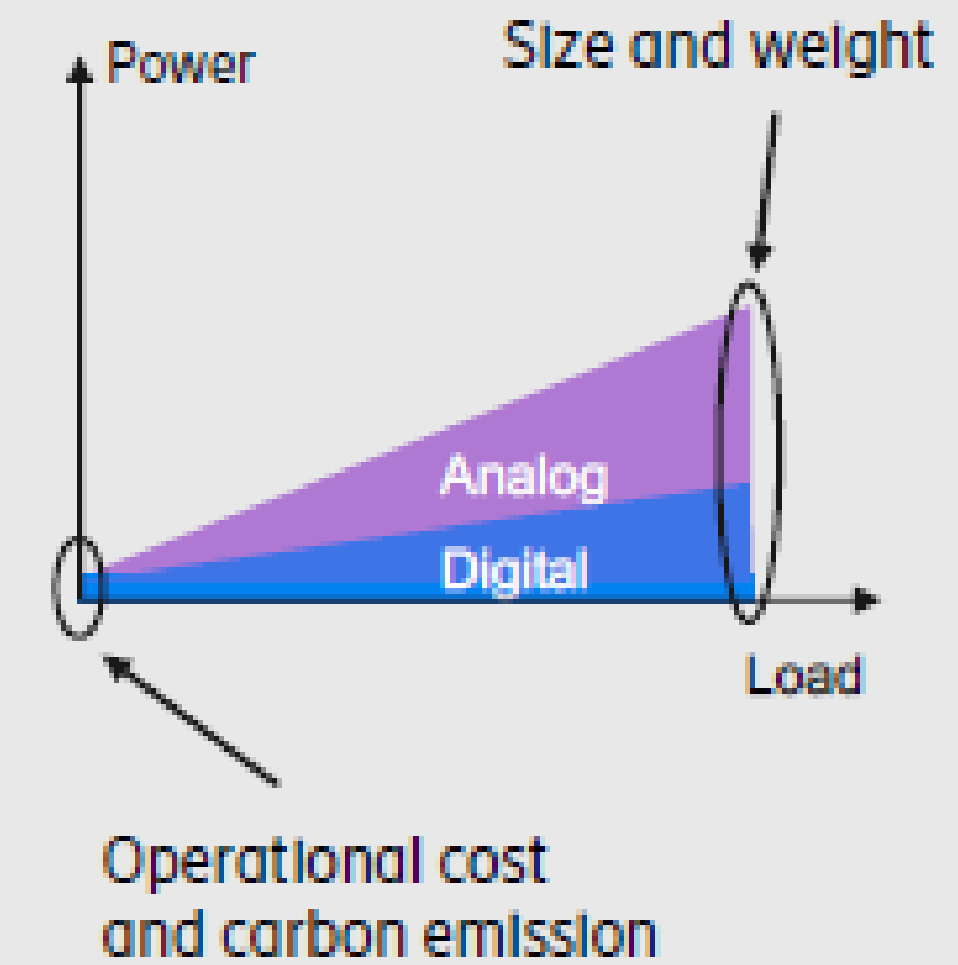
Early (LTE)



Today (NR)



Future

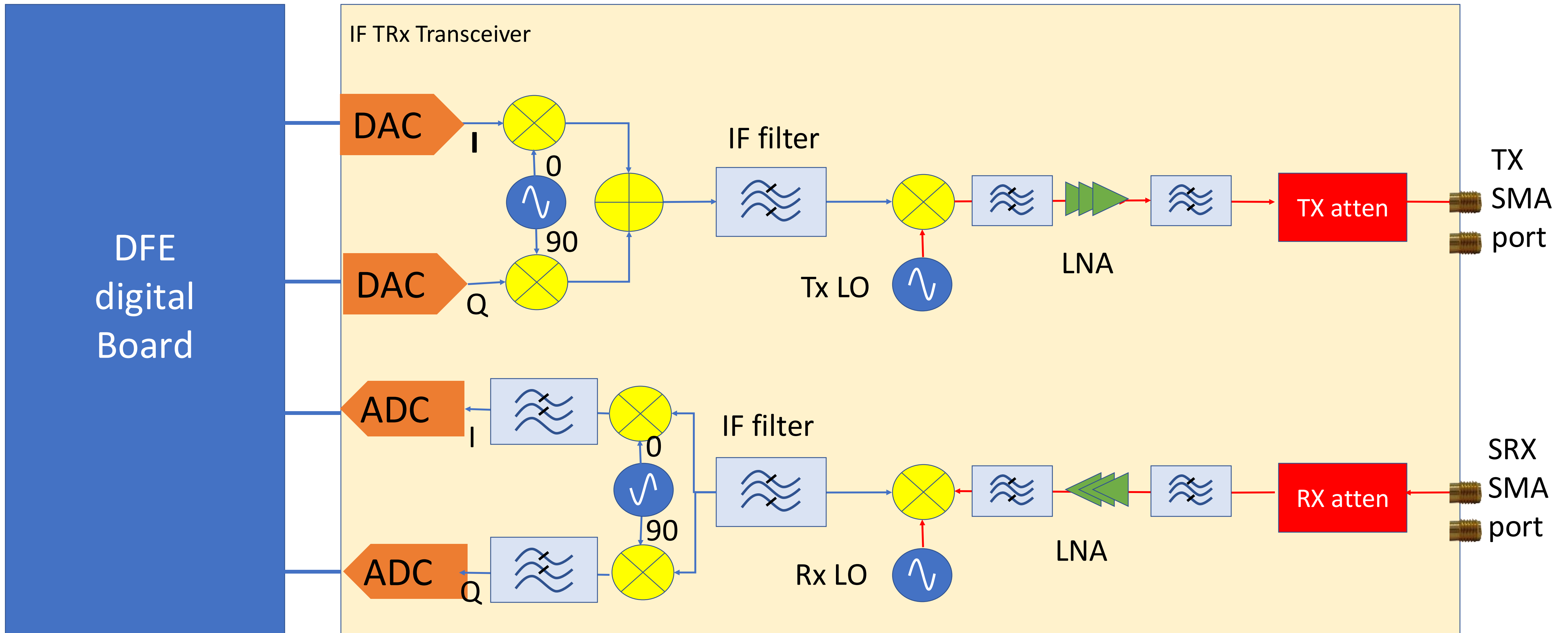


Sources: Ericsson massive-mimo-handbook- -2023

DPD SETUP CALIBRATION CONSIDERATIONS

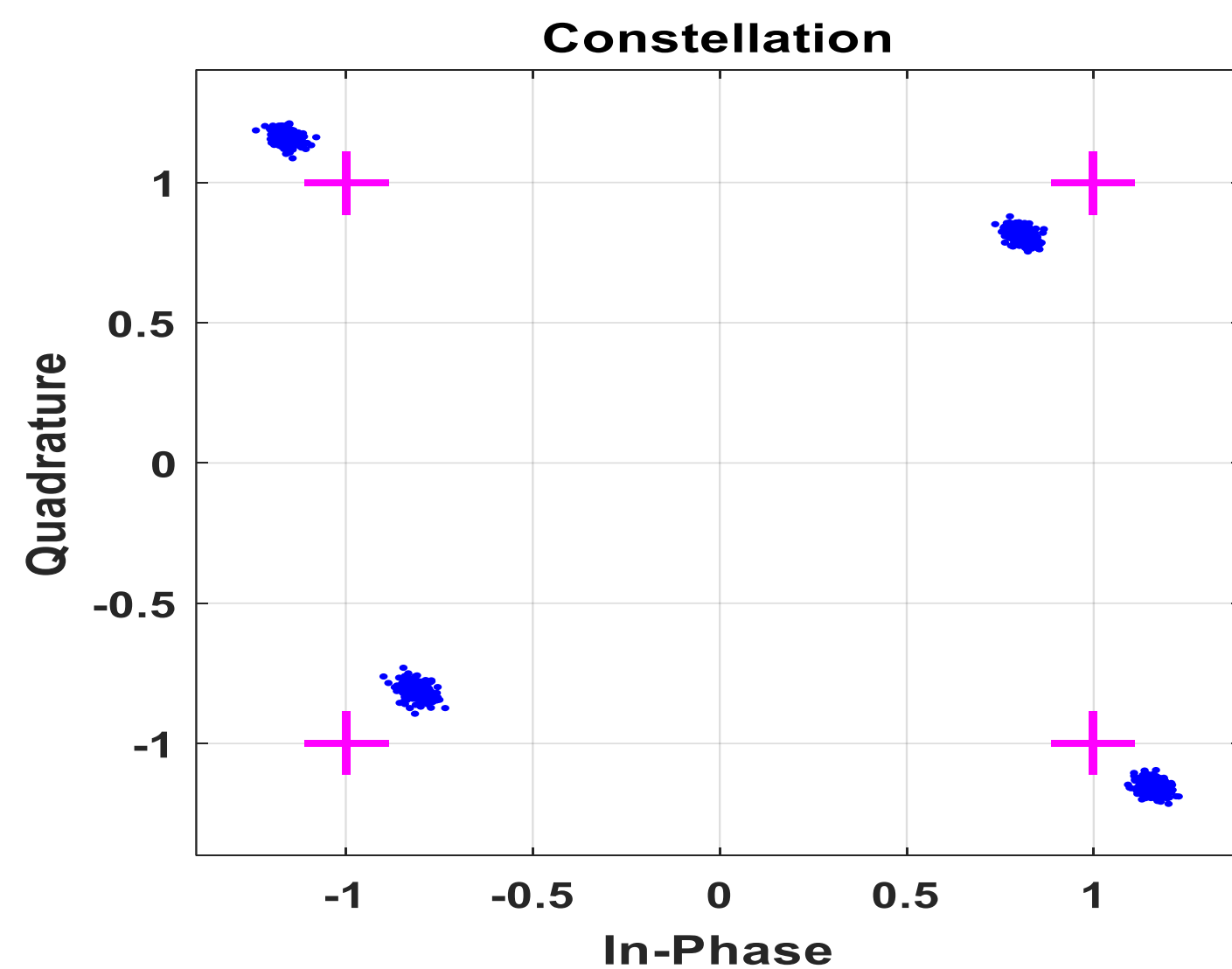
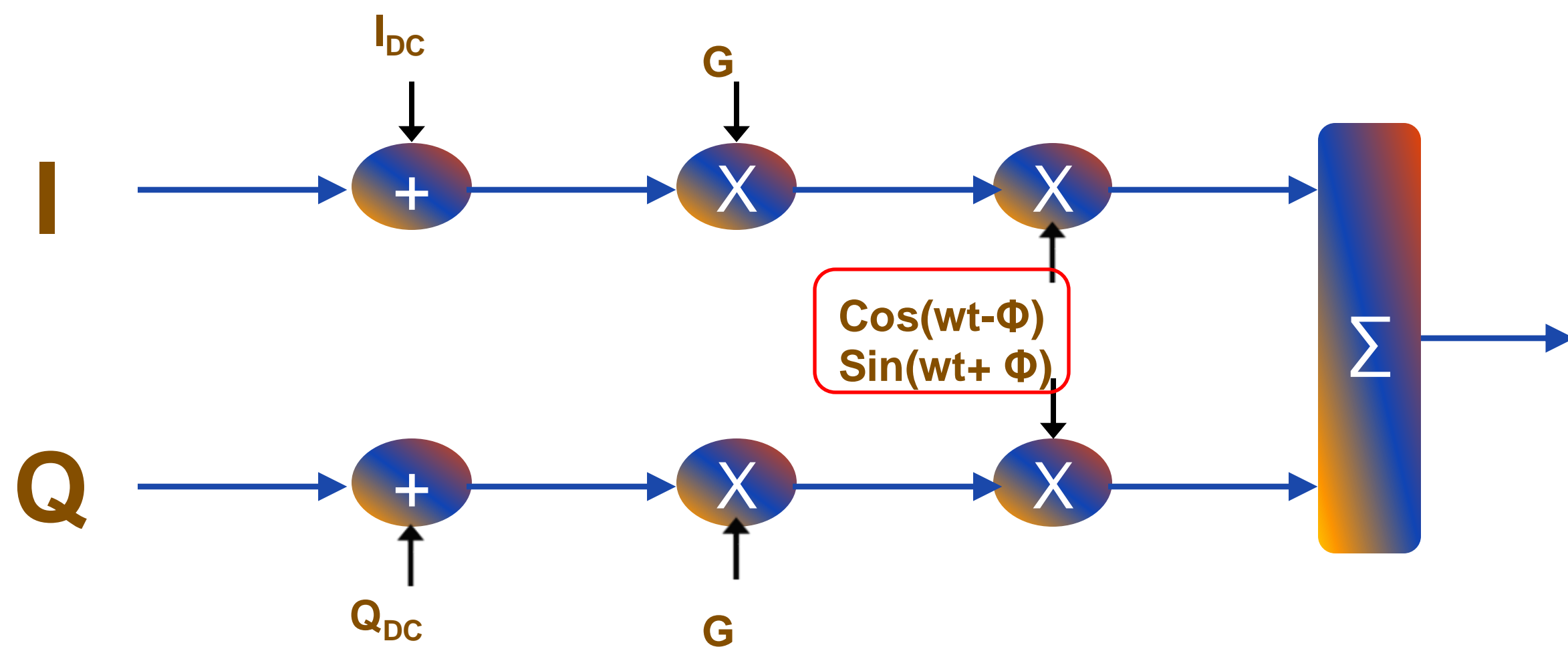
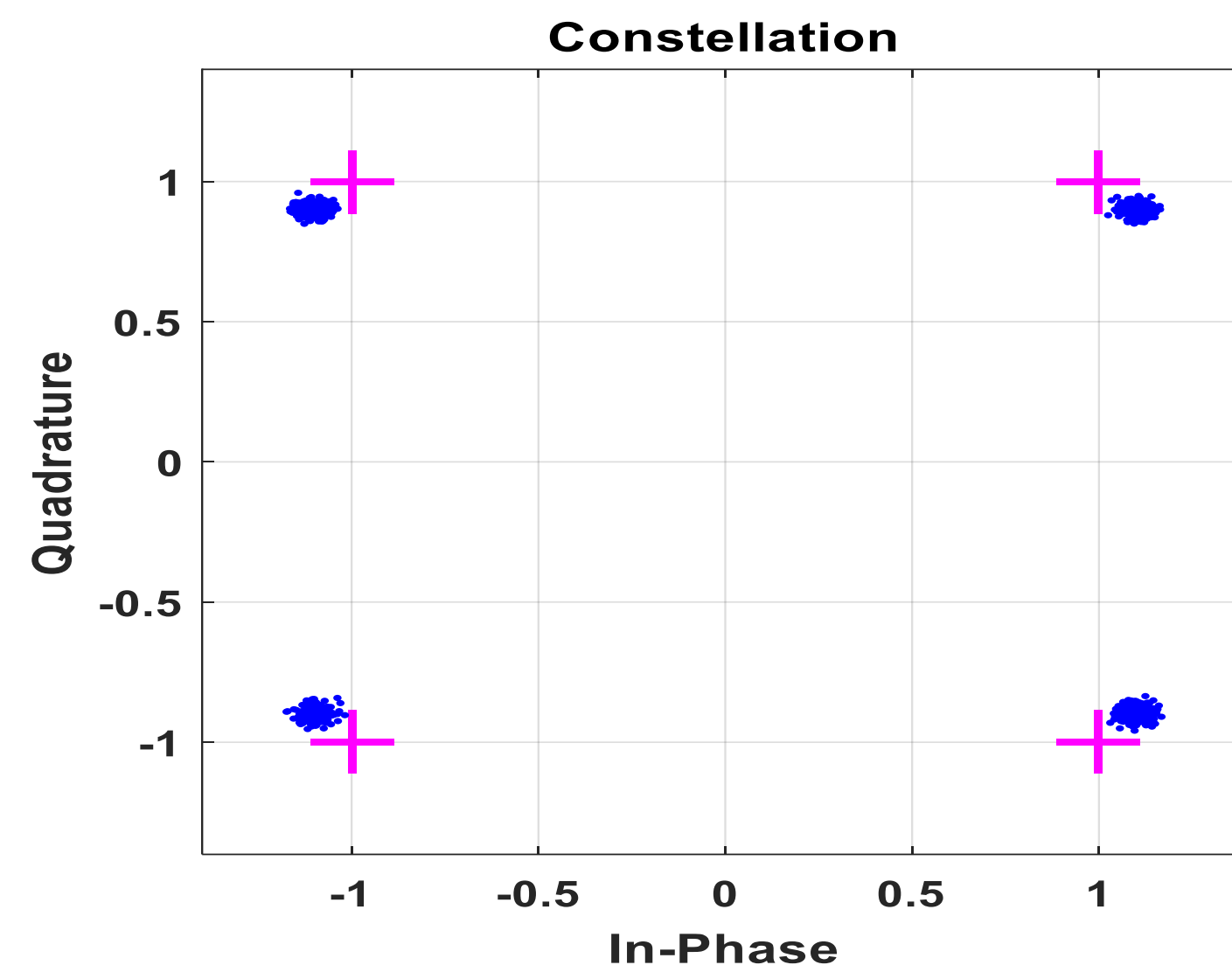
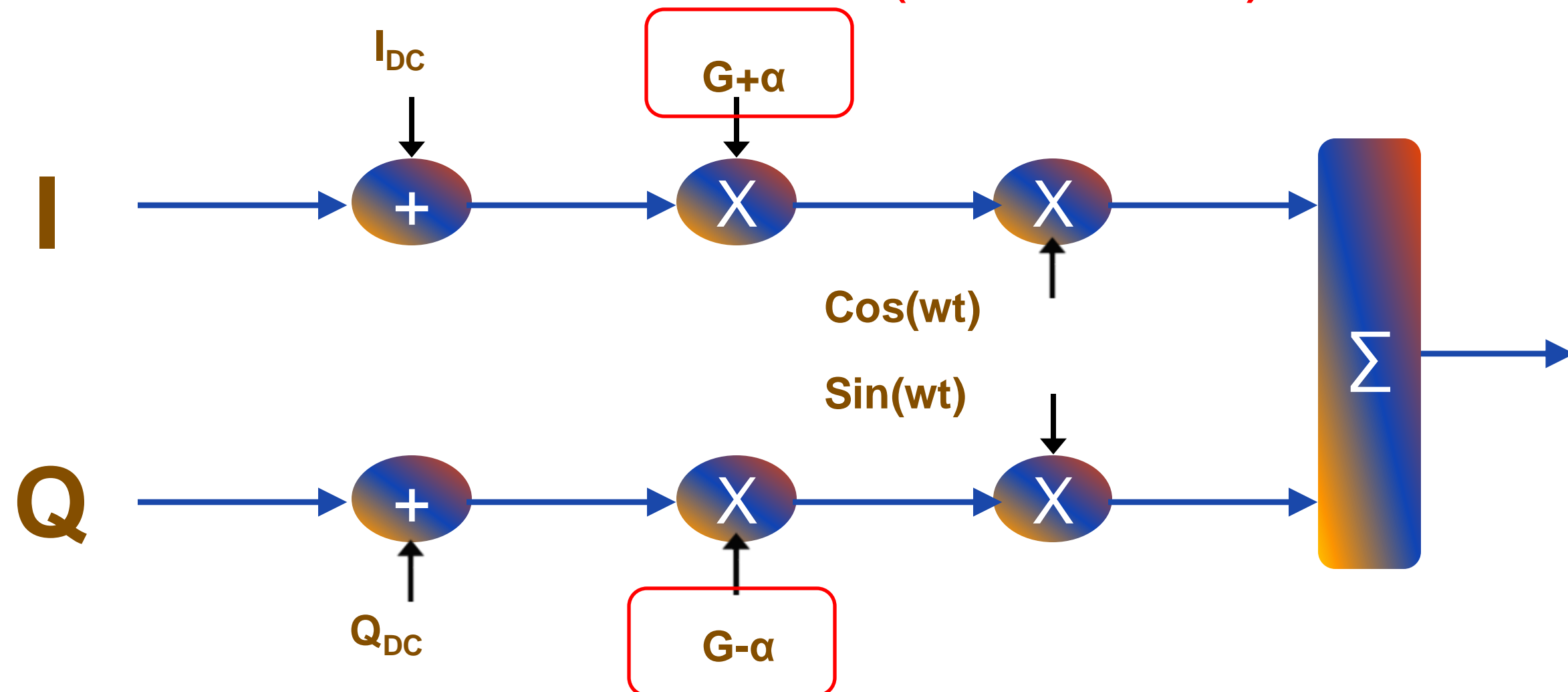


WB XCVR – BLOCK DIAGRAM



TRANSCIEVER IMPAIRMENTS – BASICS (III)

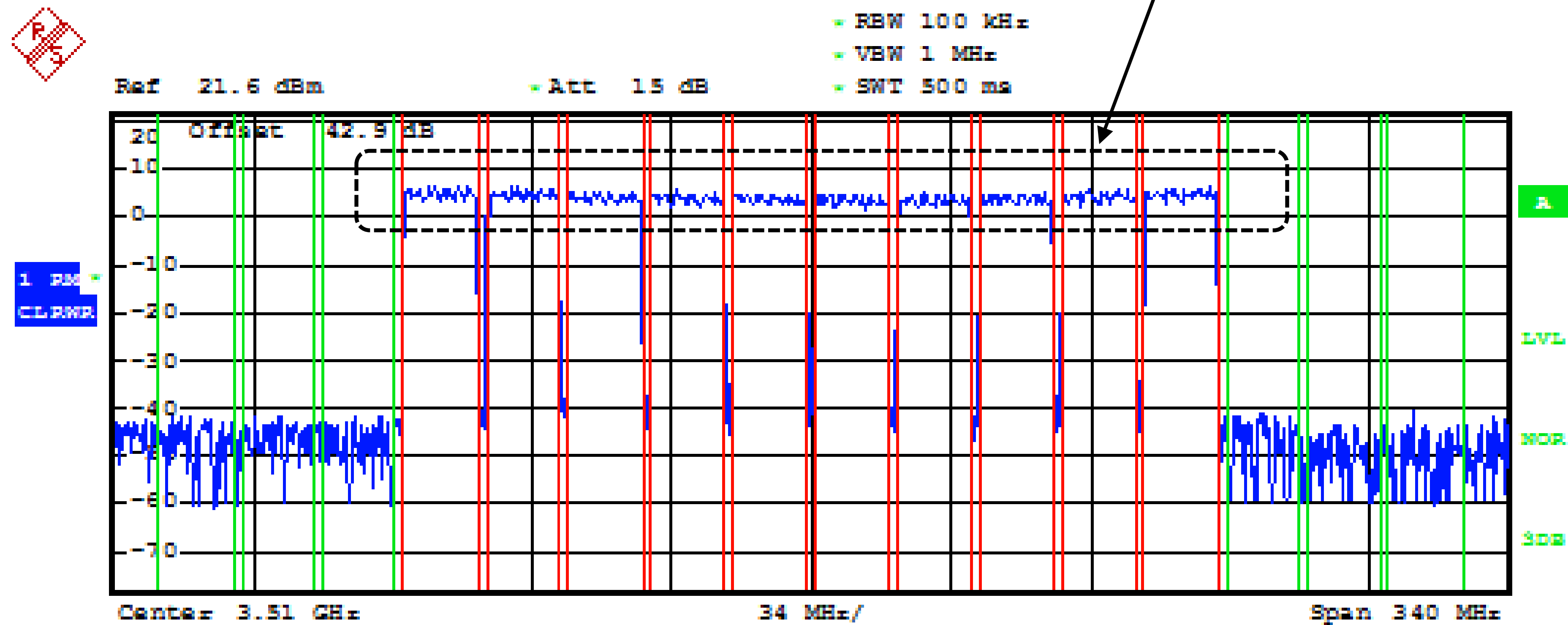
Gain Imbalance (Tx shown)



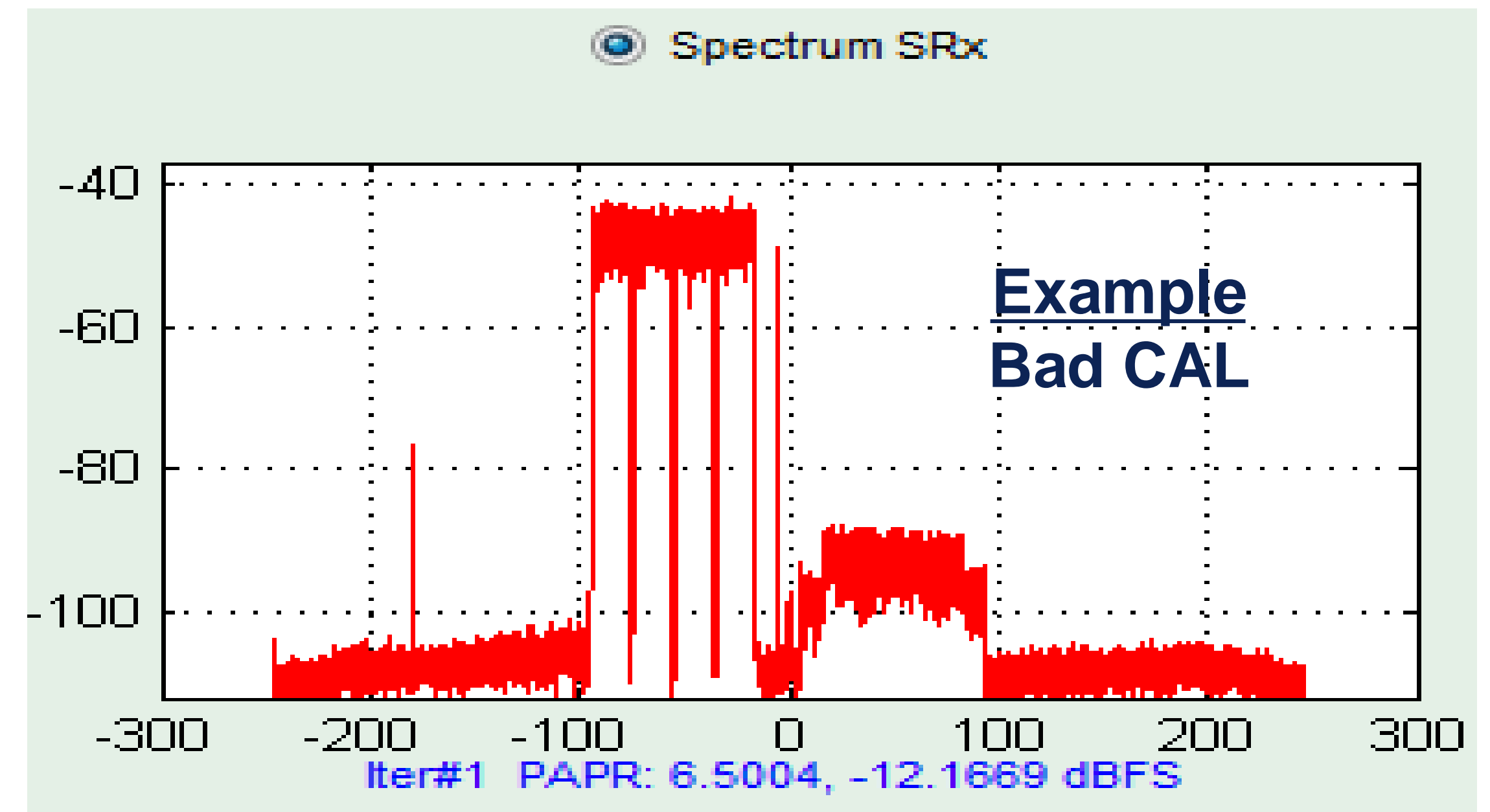
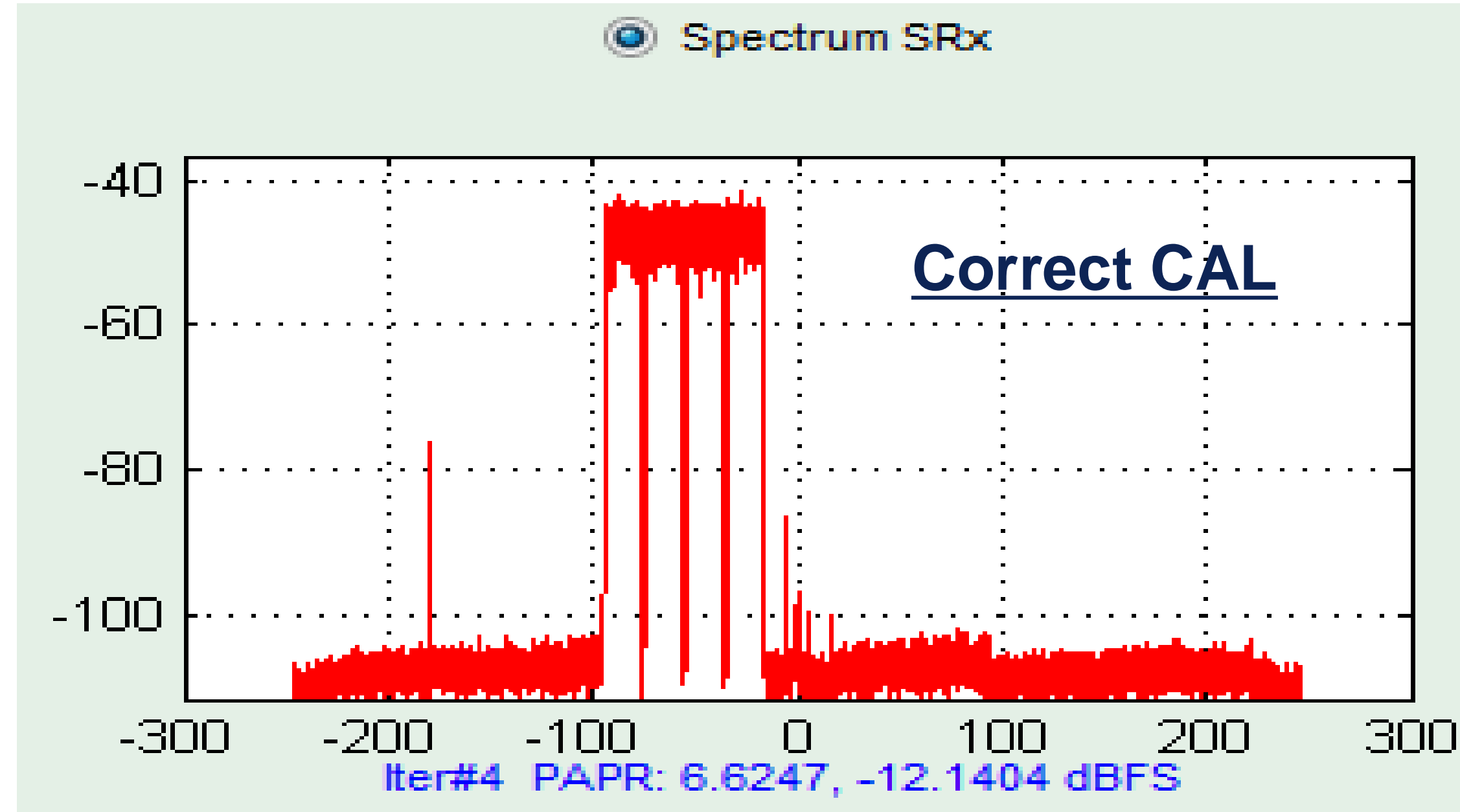
Phase Skew (Tx Shown)

Transceiver Impairments – Pass-band Ripple Performance (IV)

Ripple across band

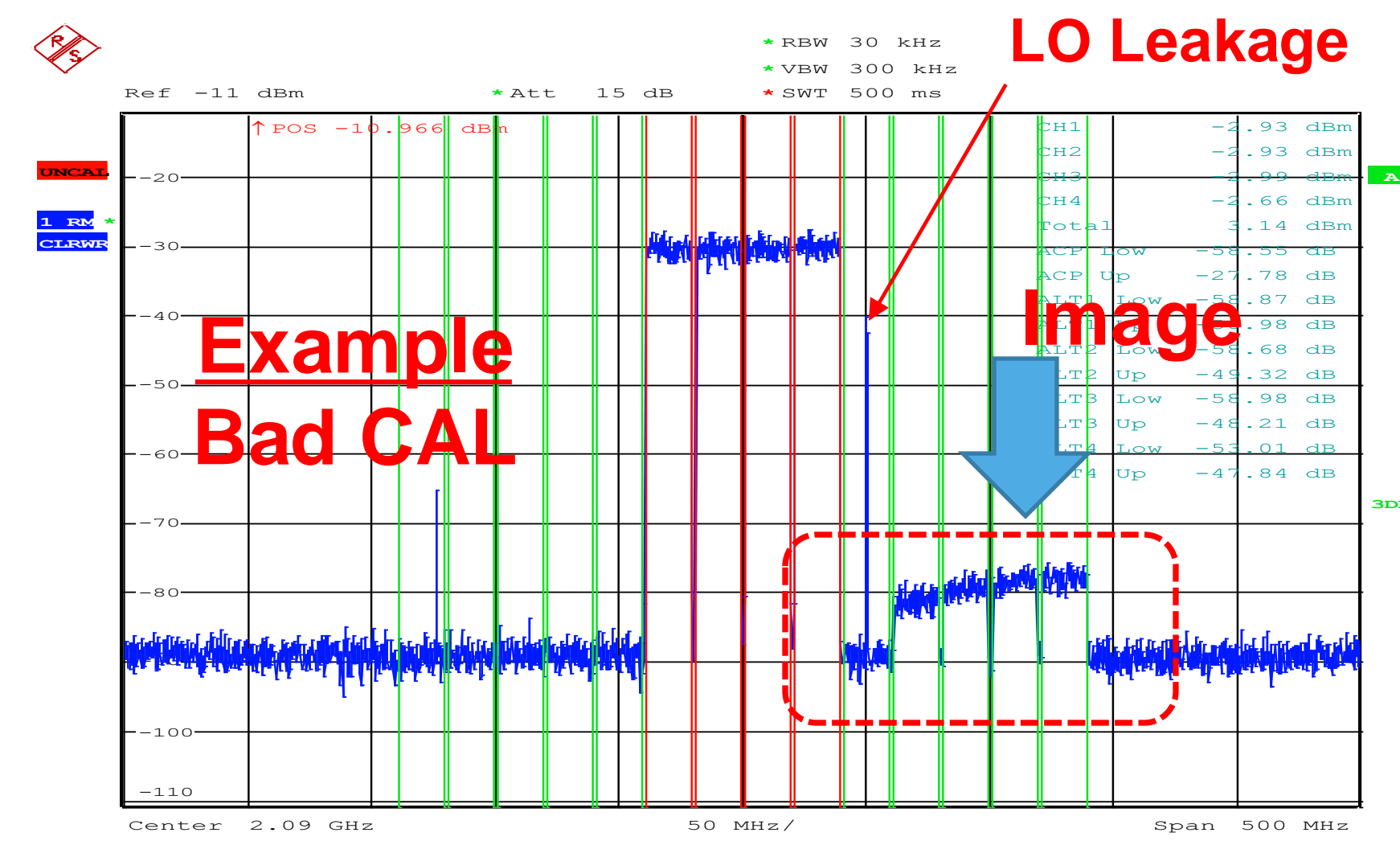
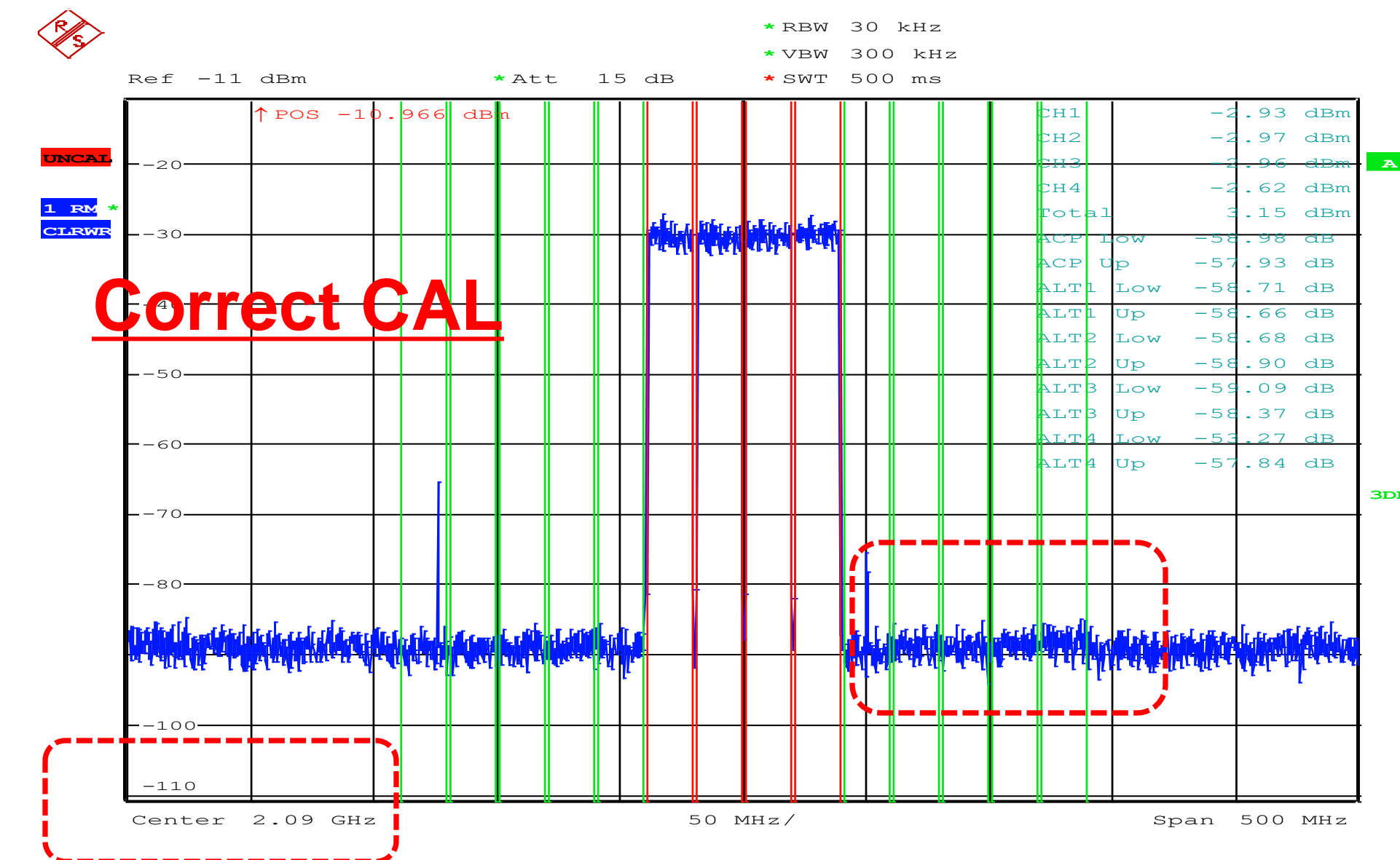
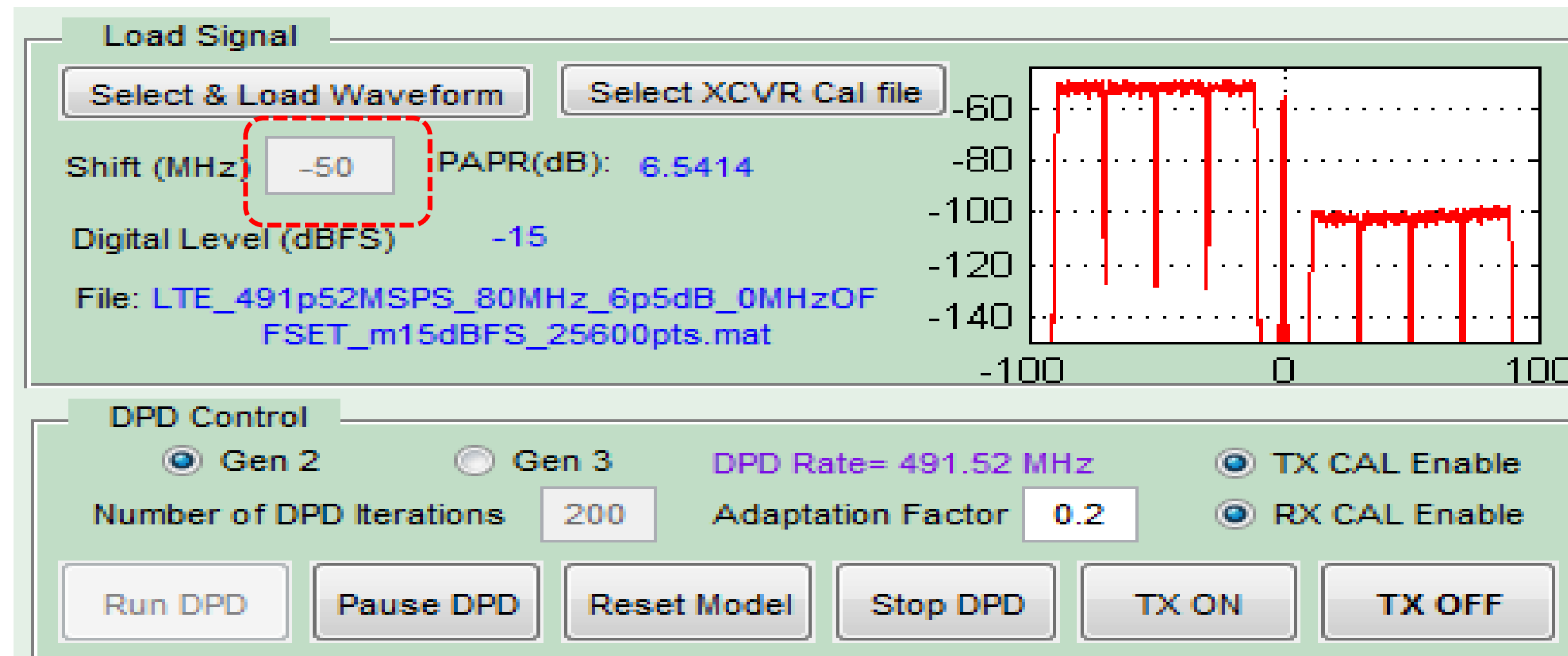


Transceiver Impairments – SRx CAL Quality (II)



- **With correct CAL parameters “images” are minimized on SRx captures (shown in GUI, Spectrum SRx)**

Transceiver Impairments – TX CAL Quality (I)



- Center Freq on SA = 2140- 50 (MHz)
- LO leakage shows at 2140 MHz. With correct CAL this should be minimum (won't be 0)
- Images should also be minimized

DPD PRACTICAL TIPS

- Average Power of PA : P_{3dB} – PAPR (PA should not be clipping)
- PA should be able to provide peak output power across the band of operation
- IMD Products
 - Symmetry: Should be symmetric upper/lower side (Within ~ 2 dB for best performance)
 - Two Tone Test with increasing BW: IMD variation should be limited ($< \sim 2$ dB)
- Group delay variation of Lineup (PA) across 125% of DPD bandwidth $<$ Clock period of Output TX rate
- DPD performs better if PA exhibits Monotonic AM-AM & AM/PM. Fewer coefficients may be needed (smaller Polynomial Order will be sufficient)
- PA should be properly shielded. This is especially critical with wider bandwidth use cases

