ANALYSIS OF PERFORMANCE FOR MEMORYLESS PREDISTORTION LINEARIZERS CONSIDERING POWER AMPLIFIER MEMORY EFFECTS

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Acknowledgements

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Outline

- **Introduction**
- New nonlinear PA model
- Model verification for real PA
- Pre-D improvement vs. Memory Effects
- Conclusions

Memory Effects in PA

- Memory Effects: The output depends on the past and current input signal

Reasons

- RF frequency response in main signal path
- Non-constant impedance in DC bias circuits
- Self heating effects at the device level

Phenomena

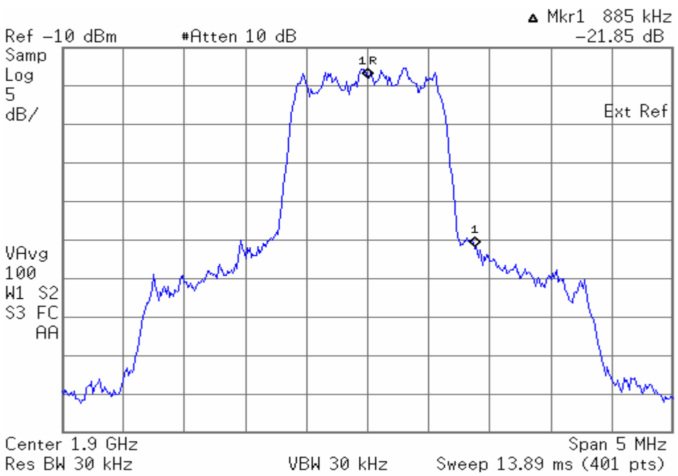
- Input & Output domain:
  - Dynamic AM/AM and AM/PM
- Frequency domain:
  - The asymmetric IMD and spectral regrowth

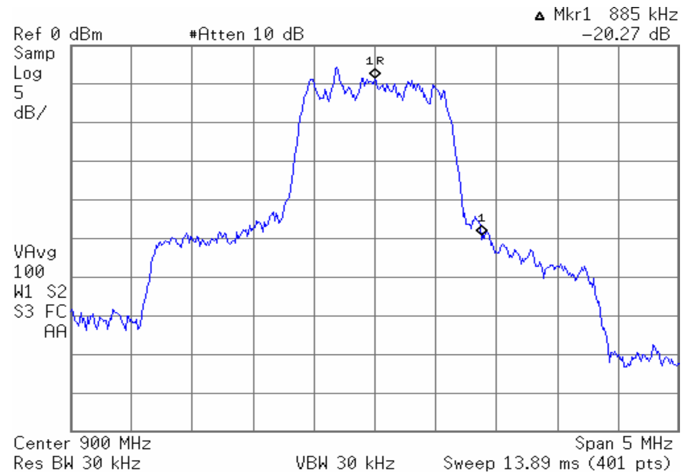
Memory Effects in Pre-D

Memoryless PA (Sirenza 0.5W LPA)

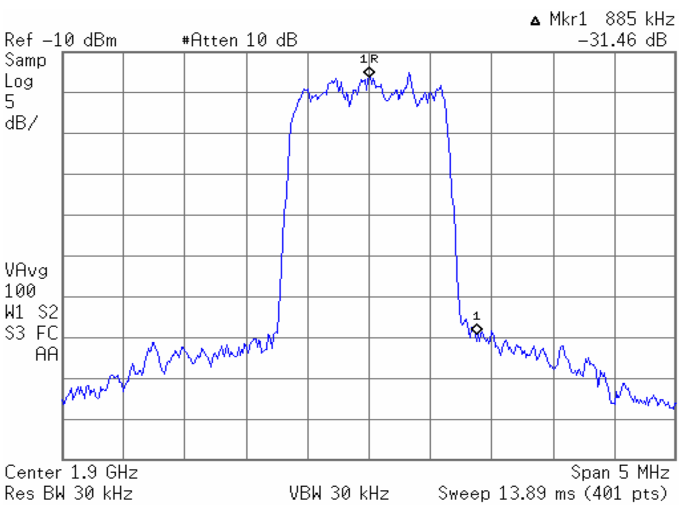
PA with Memory (Ericsson 45W HPA)

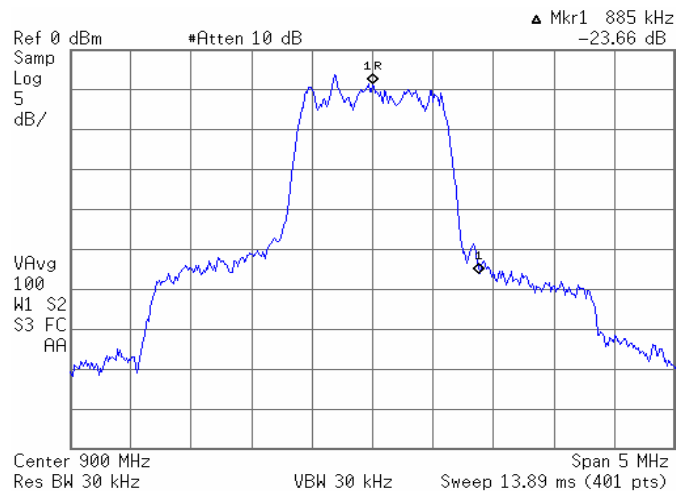
Without Pre-D





With Pre-D





*** Result from J. S. Kenney, W. Woo, L. Ding, R. Raich, H. Ku, and G. T. Zhou, "The impact of memory effects on predistortion linearization of RF power amplifiers,"** ***Proc. of the 8th Int. Symp. on Microwave and Optical Techn.*****, Montreal, Canada, June 19-23 2001, pp. 189–193.**

Research Issues

- How can we model a PA with memory effects accurately and efficiently?
- How can we quantify the memory effects in PA?
- What is the relationship between degradation of Pre-D and PA memory effects?

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- **New nonlinear PA model**
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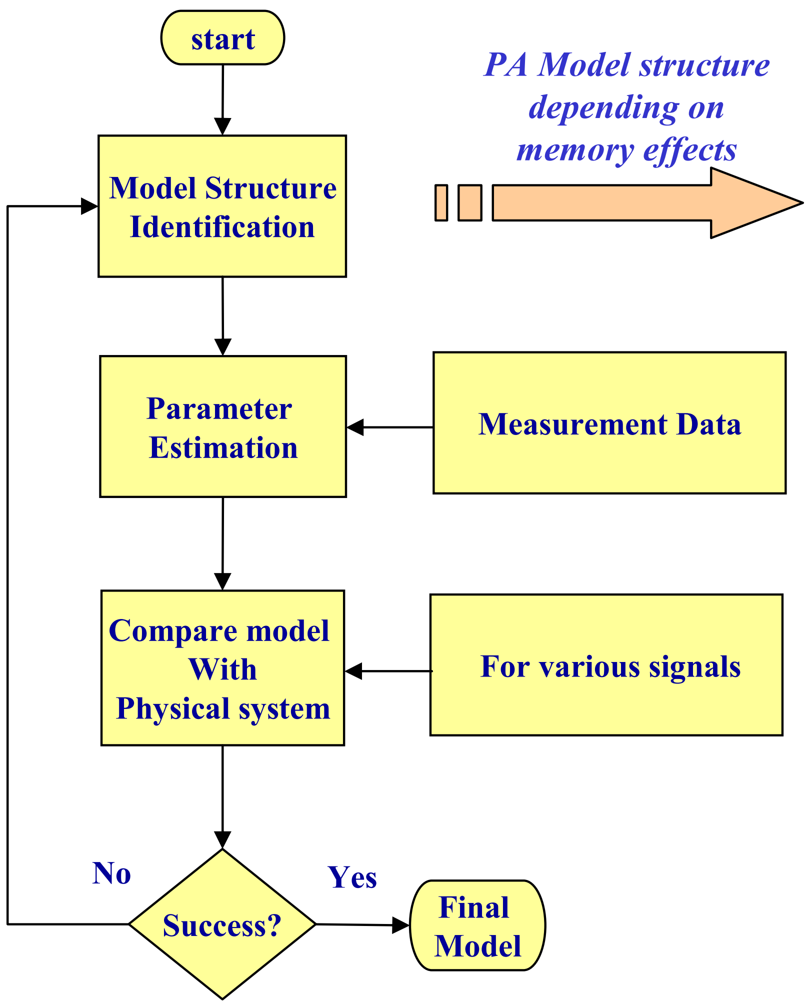
PA Behavioral Modeling



	PA characteristic	Modeling Method	Comment
Memoryless System	AM/AM	Taylor series (real polynomial)	No phase distortion
Quasi-memoryless system	AM/AM, AM/PM	Complex polynomial or Quadrature AM/AM model for each I & Q	Circuit time constant are much smaller than the $1/f_m$
Systems with memory	Dynamic AM/AM, AM/PM / Asymmetric IMD	Volterra /Wiener Approach	Including Long-term memory effect

PA with Memory Effects Model I

- Volterra Model

$$y(t) = h_0 + \int_{-\infty}^{+\infty} h_1(\tau_1)x(t-\tau_1)d\tau_1 + \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} h_2(\tau_1,\tau_2)x(t-\tau_1)x(t-\tau_2)d\tau_1 d\tau_2$$
$$+\cdots+\int_{-\infty}^{+\infty}\cdots\int_{-\infty}^{+\infty} h_p(\tau_1,\tau_2,\cdots,\tau_p)x(t-\tau_1)x(t-\tau_2)\cdots x(t-\tau_p)d\tau_1 d\tau_2\cdots d\tau_p + \cdots$$

- Volterra Model Drawback

- **Complexity: The complexity of the model increases immensely with the length of the system memory and the order of the nonlinearity**
- **Difficulty in measuring the Volterra kernels: Volterra kernels is not orthogonal, thus each kernels distributions cannot be separated from the total system response**

Example: Kernel complexity

Kernel order	N^p (when N =7)
1	7
2	49
3	343
4	2401
…	…
10	282475249

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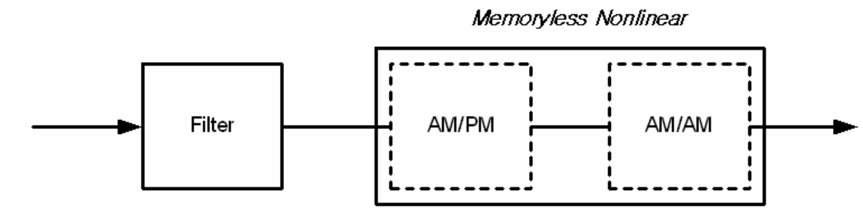
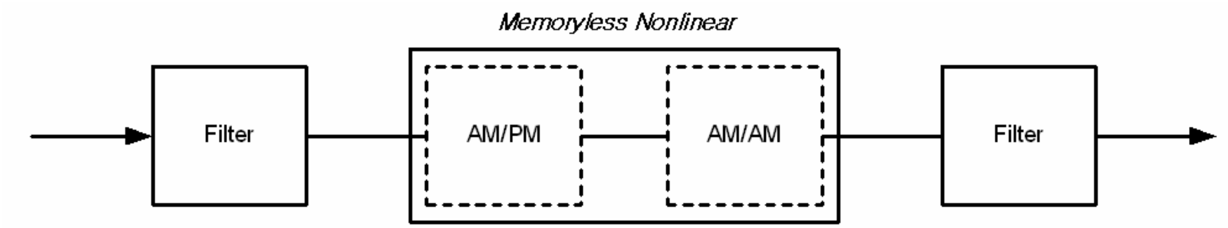
PA with Memory Effects Model II

Two Box Models: One Filter + Memoryless Nonlinear (Wiener Model)



Three Box Models: One Filter + Memoryless Nonlinear + One Filter

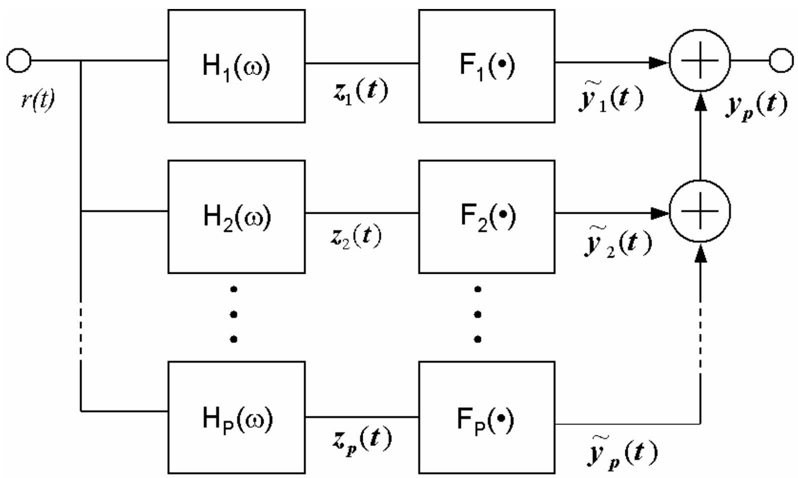


- These models have been usually used to capture memory effects in PA modeling (H. B. Poza, A. A. Saleh, T. Vuong, M. S. Muha, and *et al.*)
- Drawbacks*
  - These models cannot describe the change of shape in AM/AM and AM/PM function depending on tone spacing.
  - These models cannot describe the interaction between the instantaneous tone

C. J. Clark, et al., "Power Amplifier Characterization Using a Two-Tone Measurement Technique," IEEE Trans. Microwave Theory Tech., vol. 50, no. 6, pp. 1590-1602, June, 2002

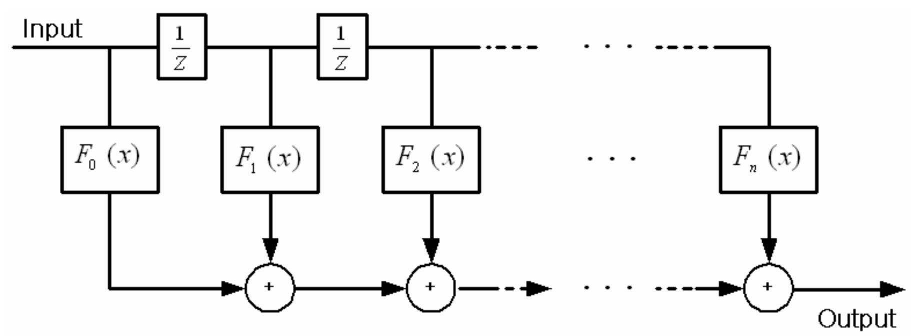
PA with Memory Effects Model III

Parallel Wiener model



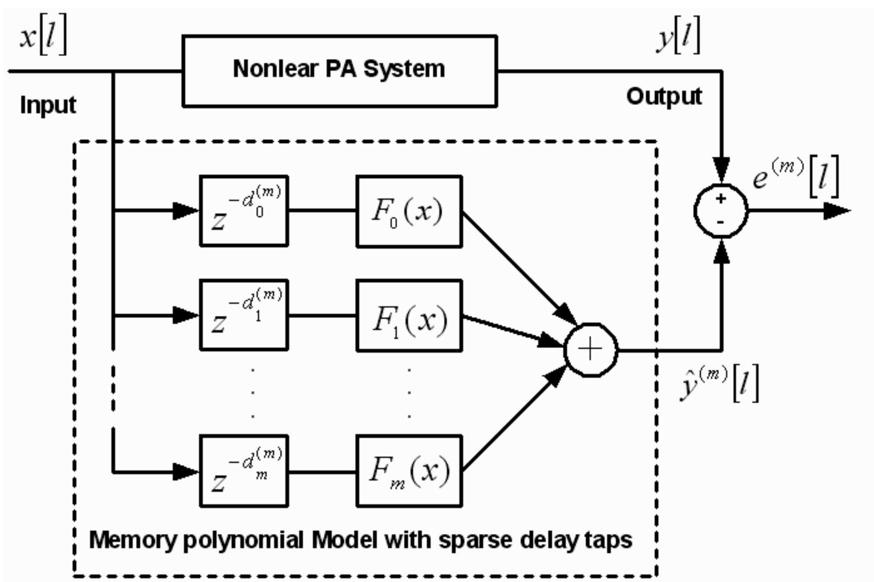
Memory polynomial Model (MPM)

$$y(k) = \sum_{i=0}^{n} F_i[x(k-i)]$$



- These models are simple compared to general Volterra series and complex compared to two or three box model.
- These models compensate the drawbacks for Volterra models and two or three box models
- These models can quantify the memory effects in power amplifier and can apply to linearizer design

MPM with Sparse Delay Tap (MPMSD)

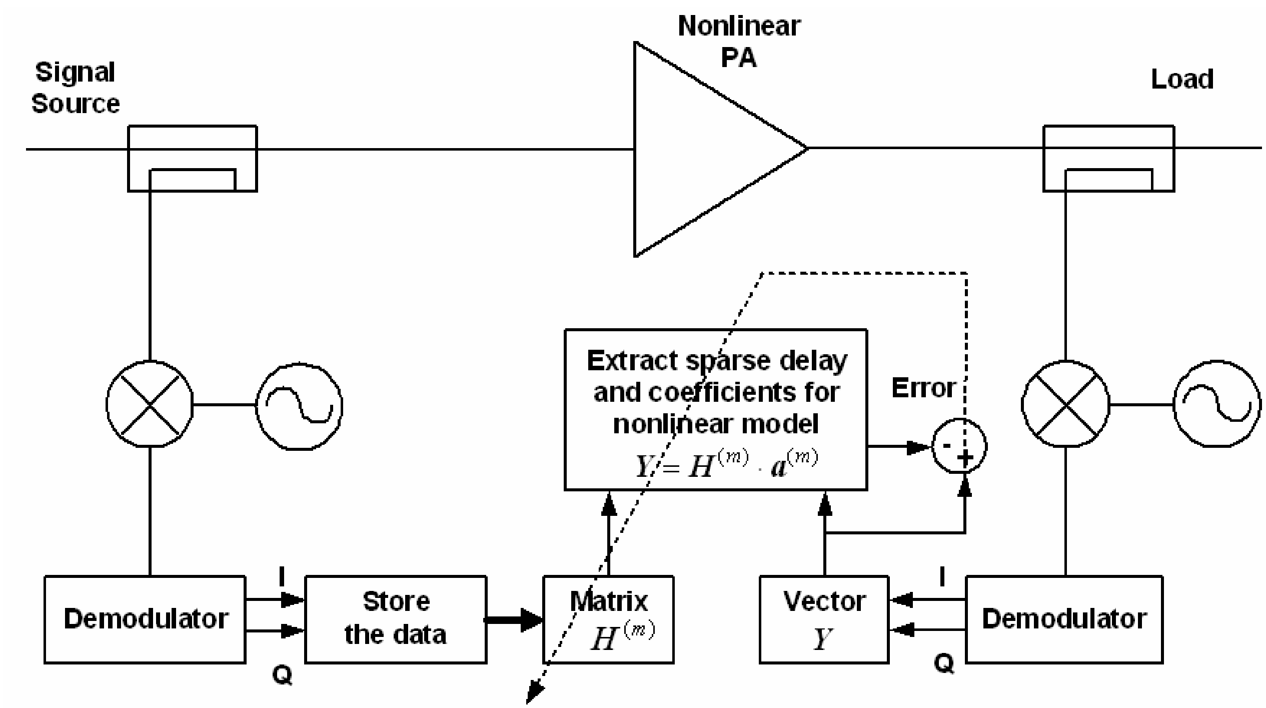


$$y[l] = \sum_{q=0}^{m} \sum_{k=1}^{n} a_{2k-1,q} \left| x\left[l - d_q^{(m)}\right] \right|^{2(k-1)} \cdot x\left[l - d_q^{(m)}\right]$$

- A unit delay tap delay in MPM is replaced with sparse delay taps
- Longer time constant memory effects may be modeled in parallel with short time constant effects using fewer parameters
- MPMSD can improve convergence rate of error compared to MPM

* H. Ku and J. S. Kenney, "Behavioral modeling of power amplifiers considering IMD and spectral regrowth asymmetries," in *IMS 2003,* Philadelphia, PA, 2003.

Application to PA Modeling

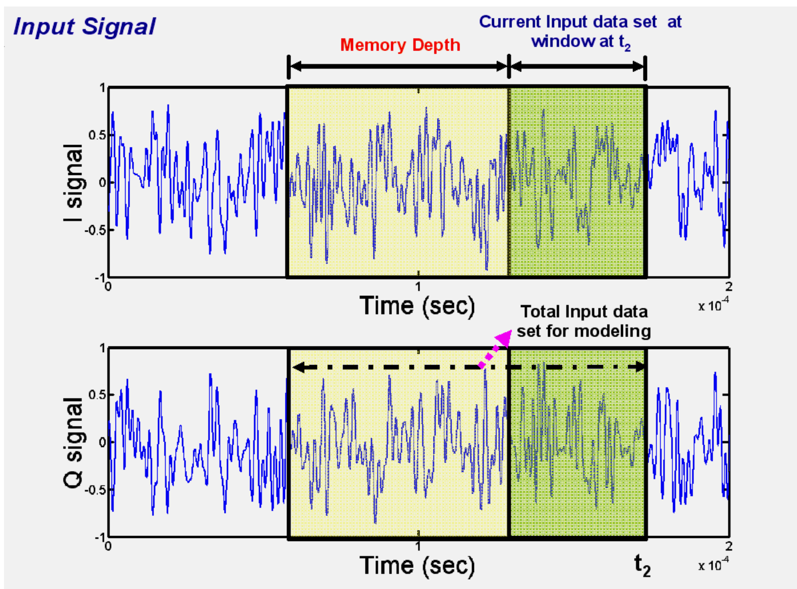


- Easy implementation using linear matrix equation
- Adaptive modeling by sliding window
- Iterative modeling by adding the branch using output data and error

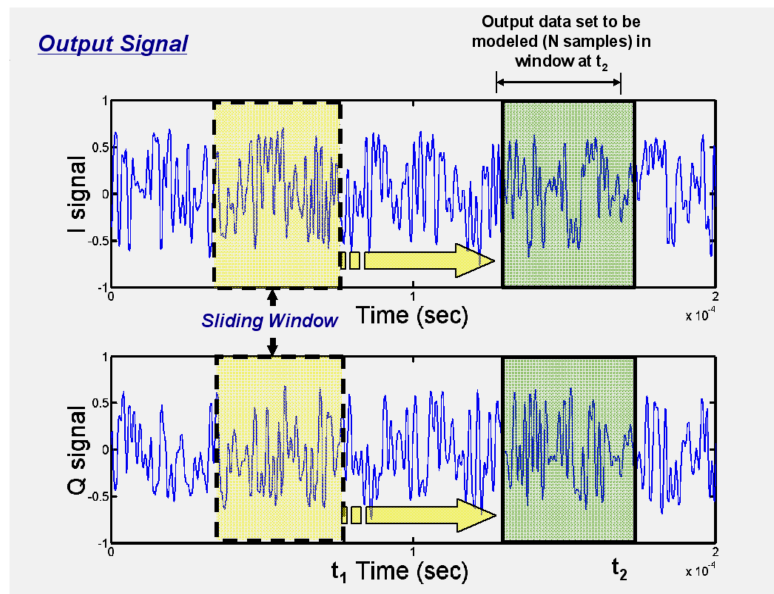
Coefficients Extraction for MPMSD

- **Coefficients Extraction:** $\hat{a}^{(m)} = H^{(m)-1} \cdot Y$

Input complex envelope *x*



Output complex envelope *y*



- $H^{(m)}$: A matrix from PA input time data

$$H^{(m)} = \left[H_0^{(m)} \quad \cdots \quad H_q^{(m)} \quad \cdots \quad H_m^{(m)} \right]$$

***M+1:* The number of branches**

***Nx(m+1)* matrix**

- *Y*: Vector from PA output time data

$$Y = \left[y[l] \quad y[l+1] \quad \cdots \quad y[l+N-1] \right]^T$$

N*: length of sliding window *Y

***Nx1* vector**

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Delay Tap Extraction for MPMSD

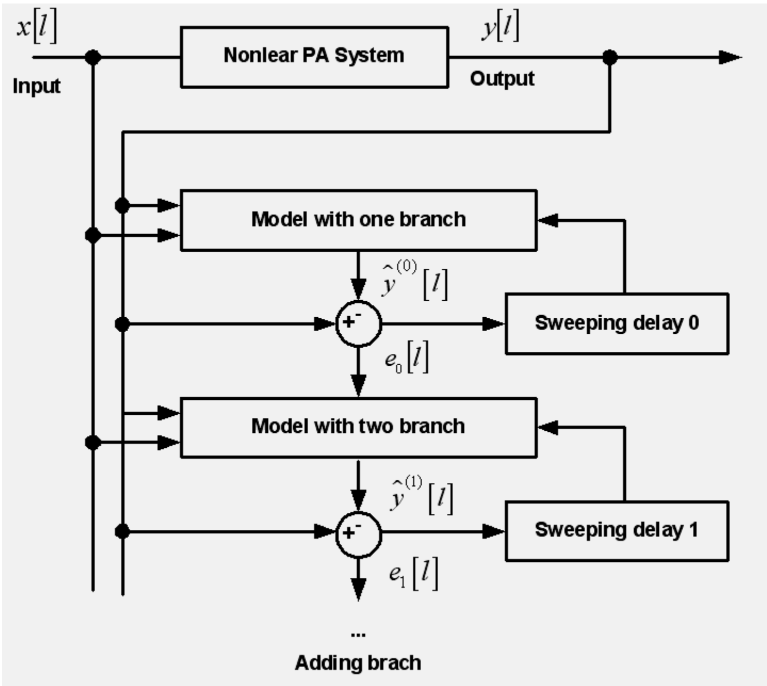
Objective: To acquire delay tap set which minimize rms error

$$\boldsymbol{d}_{opt}^{(m)} = \left\{ \boldsymbol{d}^{(m)} \mid \min_{\boldsymbol{d}^{(m)}} \left(\left\| \boldsymbol{E}^{(m)} \right\|_2^2 \right),\ \boldsymbol{d}^{(m)} = \left\{ d_0^{(m)} \cdots d_m^{(m)} \right\} \right\}$$

where

$$\left\| \boldsymbol{E}^{(m)} \right\|_2^2 = \boldsymbol{Y}^* \boldsymbol{Y} + \hat{\boldsymbol{a}}^{(m)*} \boldsymbol{H}^{(m)*} \boldsymbol{H}^{(m)} \hat{\boldsymbol{a}}^{(m)} - 2\,\mathrm{Re}\left\{ \boldsymbol{Y}^* \boldsymbol{H}^{(m)} \hat{\boldsymbol{a}}^{(m)} \right\}$$

- **It is difficult to derive optimal sparse delay taps analytically**
- **In this case, sequential identification can give simple method to derive delay tap function**



New Memory Effect Figures of Merit

- **Memory effect ratio (MER)** $\text{MER} = \left\| \boldsymbol{E}^{(0)} \right\|_2 / \left\| \boldsymbol{Y} \right\|_2$
  - Quantify the magnitude of memory effects
  - The value is 0 if memoryless case, and increases with increasing memory effects
- **Memory effect modeling ratio (MEMR)** $\text{MEMR}_m = 1 - \left\| \boldsymbol{E}^{(m)} \right\|_2 / \left\| \boldsymbol{E}^{(0)} \right\|_2$
  - Quantify the improvement in modeling memory effects in the suggested model.
  - This value is 0 when no memory effects are included, and is 1 when all of the memory effects are included.

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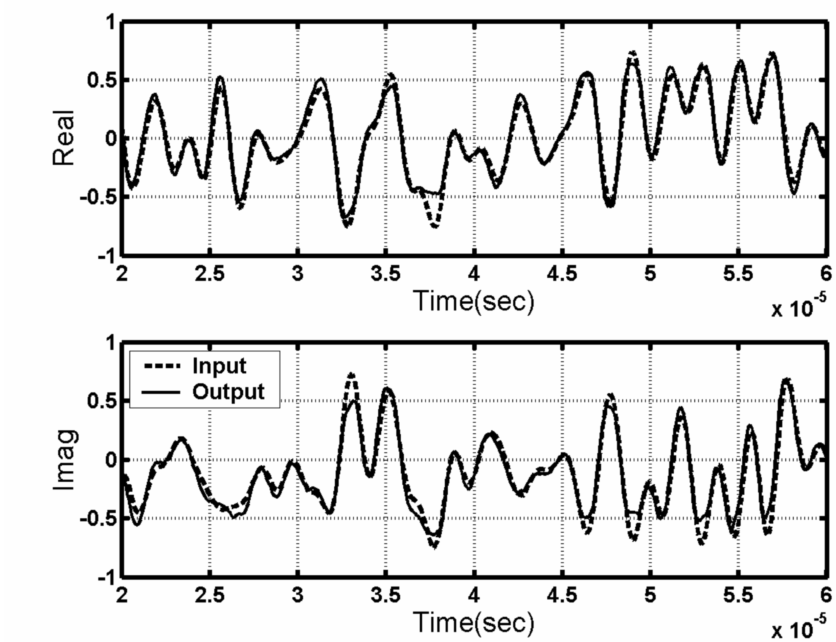
Power Amplifier Measurement

- Agilent VSA 89410 was used to capture time domain data
- Measured CDMA IS-95B time-domain input and output envelope signals for in-phase and quadrature

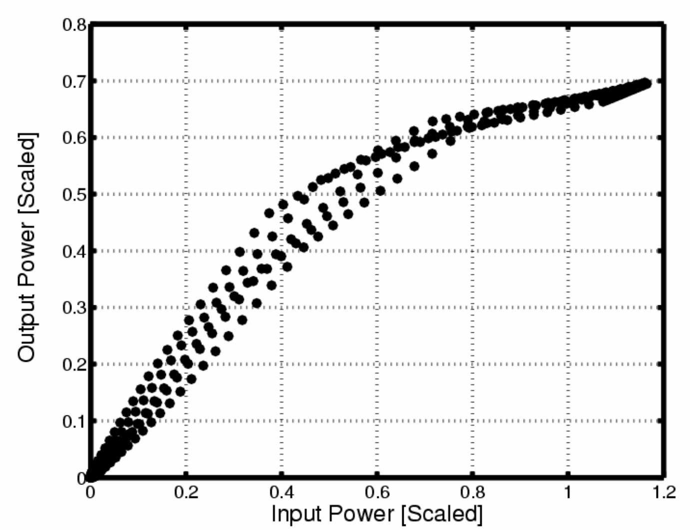
- DUT: One LDMOS PA (MRF9180) section of an Danam 880 MHz 50W HPA system
- Test signal: CDMA IS-95B Signal

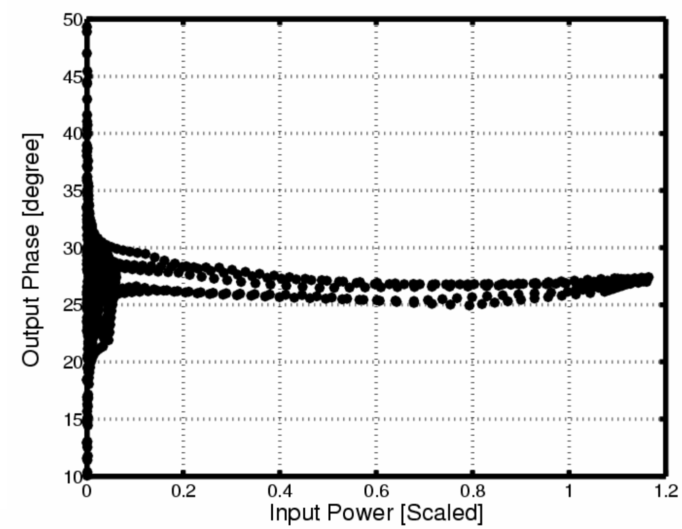


Measurement Result

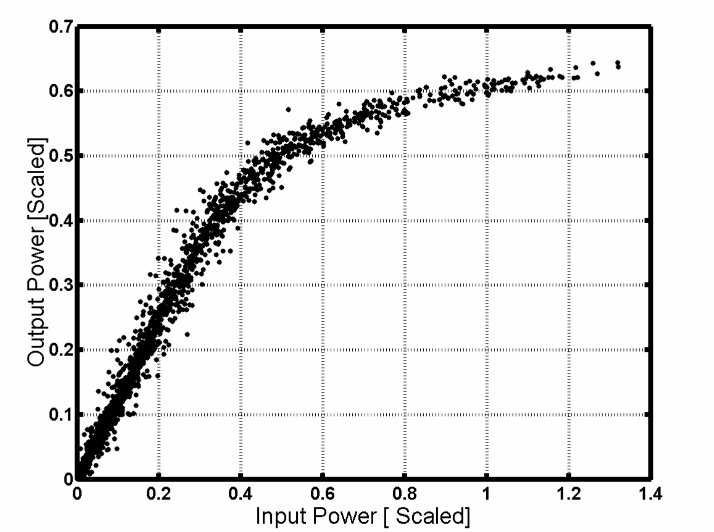
AM/AM response | **AM/PM response**

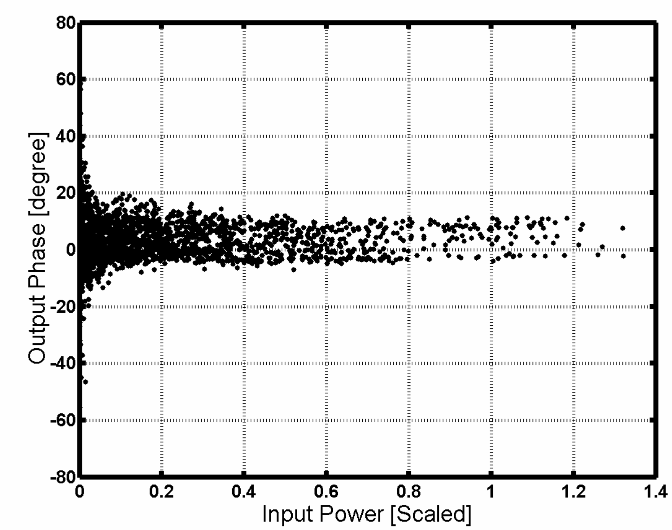
Eight-tone





IS-95B





Extracted Parameters & Results

Memoryless Model → row 0

MPMSD Model With 4-additional branches → row 4

	Branch	Delay	Coefficients 1st order	Coefficients 3rd order	MEMR
0	0	0	1.1636+0.1841i	-0.3807-0.0795i	0
1	0	0	1.6660+0.2151i	-0.5600-0.1098i	0.55
	1	1	-0.5144-0.0331i	0.1896+0.0458i	
2	0	0	1.9702+0.1931i	-0.5934-0.1174i	0.59
	1	1	-0.9606+0.0036i	0.2300+0.0560i	
	2	3	0.1591-0.0132i	-0.0112-0.0094i	
3	0	0	1.9480+0.2380i	-0.5963-0.1253i	0.62
	1	1	-0.9309-0.0597i	0.2347+0.0648i	
	2	3	0.1485+0.0082i	-0.0117-0.0108i	
	3	37	-0.0075+0.0043i	0.0198+0.0111i	
4	0	0	1.9832 + 0.2129i	-0.6169 - 0.1214i	0.64
	1	1	-0.9748 - 0.0244i	0.2553 + 0.0614i	
	2	3	0.1630 - 0.0045i	-0.0211 - 0.0089i	
	3	37	-0.0106 - 0.0022i	0.0244 + 0.0142i	
	4	98	0.0065 - 0.0014i	0.0038 + 0.0144i	

- Nonlinearity order : third order (odd order only)
- Number of branches : 5
- Sampling time: 101.73 nsec
- The number of samples for input and output measured data:2229 (0~0.2266msec)
- The number of samples for modeling: 200 (0.20345 usec~0.40588 usec)
- MER= 8.89%

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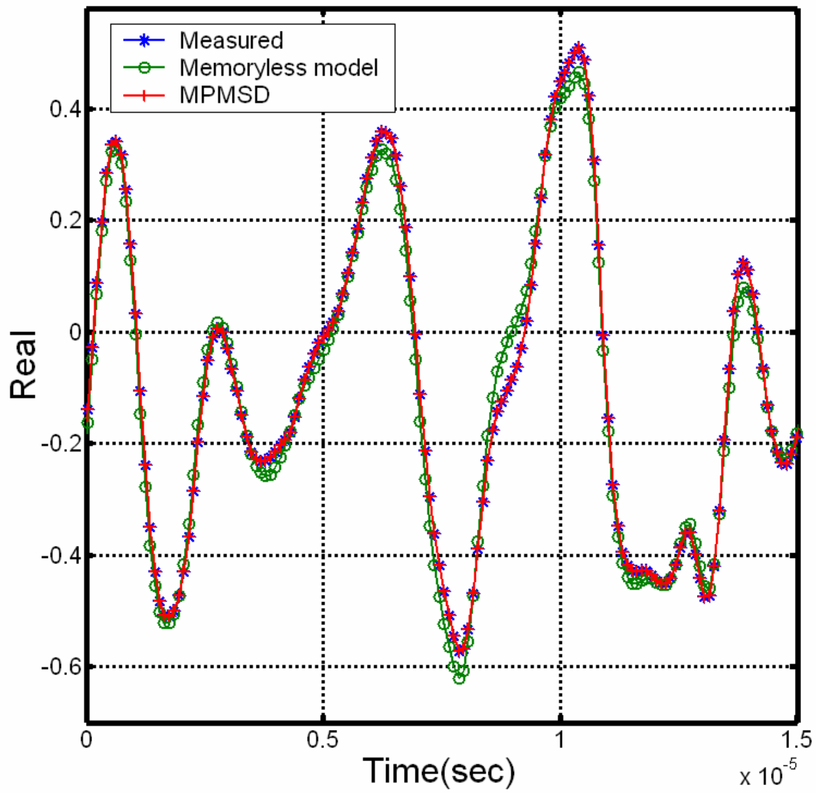
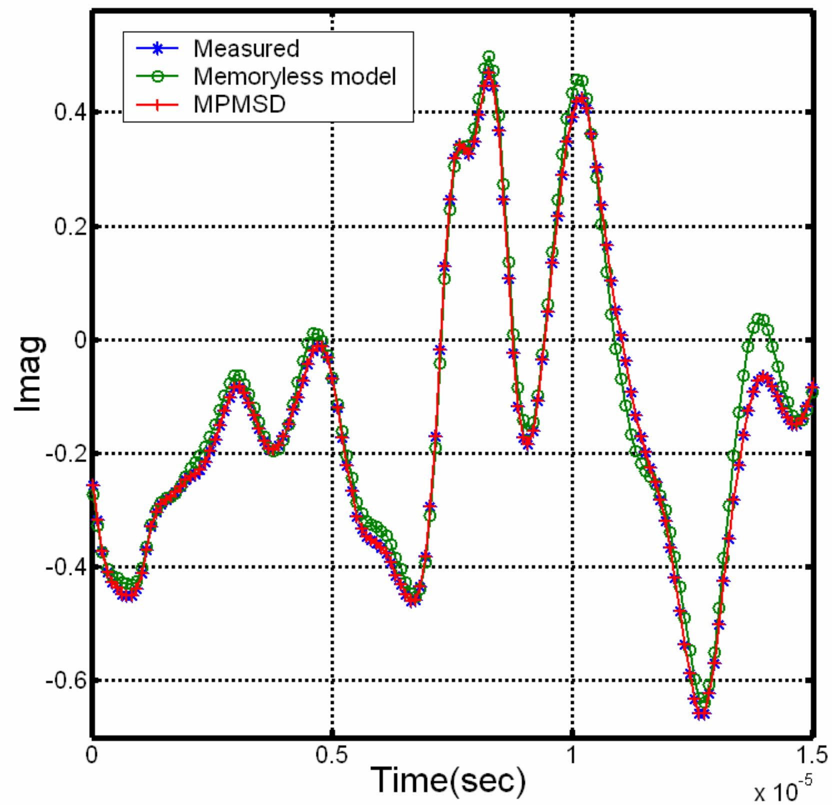
Time Domain Results





	ML Model	MPMSD Model
RMS Error	0.041	0.016

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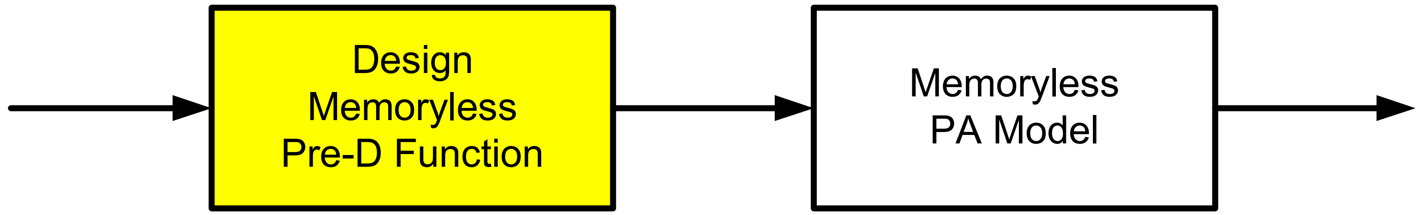
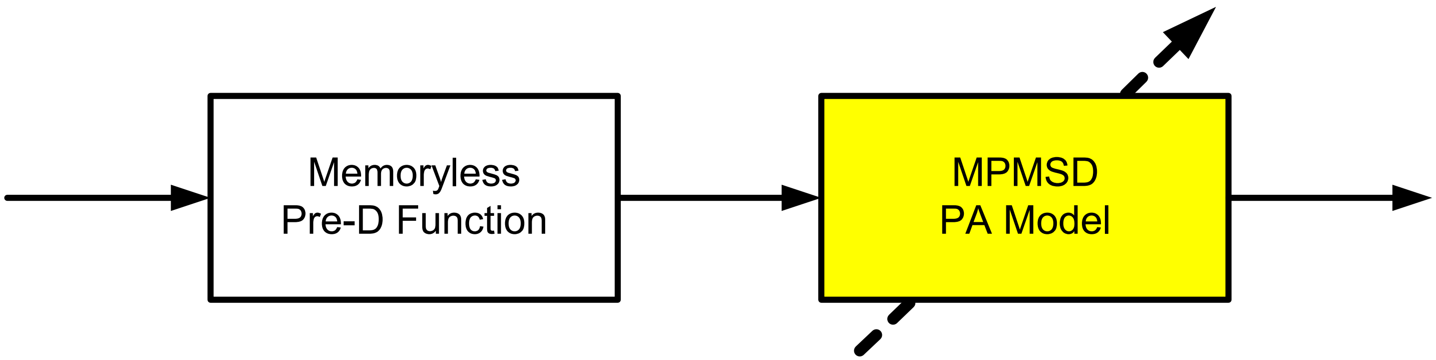
Pre-D Test Procedure

1. Design memoryless Pre-D based on memoryless model

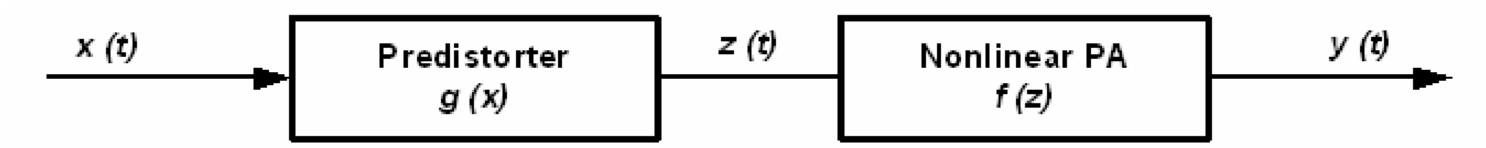


2. Apply the extracted memoryless Pre-D to PA model with memory



3. The Performance of Pre-D is analyzed by sweeping MER in the MPMSD model

Pre-D Design I (p-th order inverse)



$$g(x) = \sum_{k=1}^{p} b_{2k-1} |x|^{2(k-1)} \cdot x \qquad f(x) = \sum_{k=1}^{n} a_{2k-1} |x|^{2(k-1)} \cdot x$$

Output: $$y = f(z) = \sum_{c=1}^{n} \sum_{d=1}^{p} a_{2c-1} \cdot b_{2d-1} \cdot \left(\sum_{l=1}^{p} \sum_{m=1}^{p} b_{2l-1}{}^{*} b_{2m-1} |x|^{2(l+m-1)} \right)^{c-1} |x|^{2(d-1)} \cdot x$$

Expected output: $$y = x + e = x + \sum_{k=p+1}^{\infty} \tilde{a}_{2k-1} |x|^{2(k-1)} \cdot x$$

Compare & Extract coefficients of Pre-D

- **Using Pre-D based on Polynomial Equation (p-th order inverse)**

$$P_3(x) = (0.8384 - 0.1327i) \cdot x + (0.2007 - 0.0218i) \cdot |x|^2 \cdot x$$

$$P_5(x) = (0.8384 - 0.1327i) \cdot x + (0.2007 - 0.0218i) \cdot |x|^2 \cdot x$$
$$+ (0.1433 - 0.0132i) \cdot |x|^4 \cdot x$$

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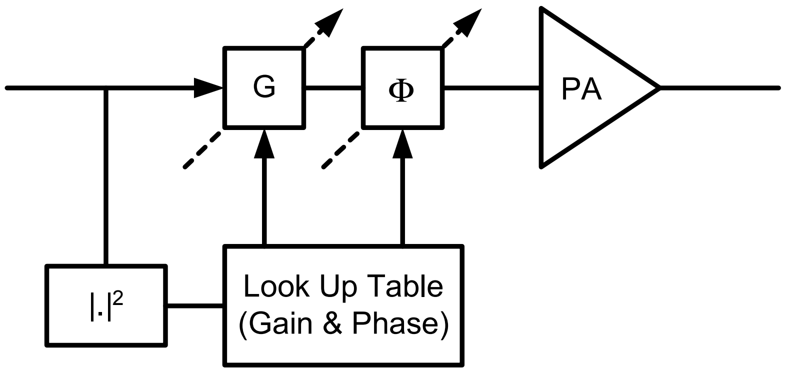
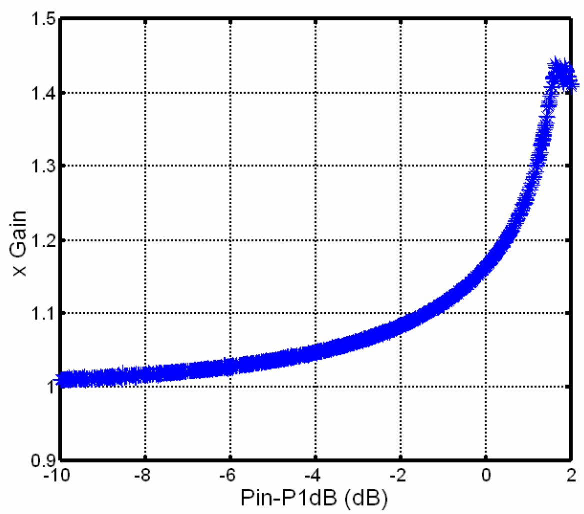
Pre-D design II (LUT)



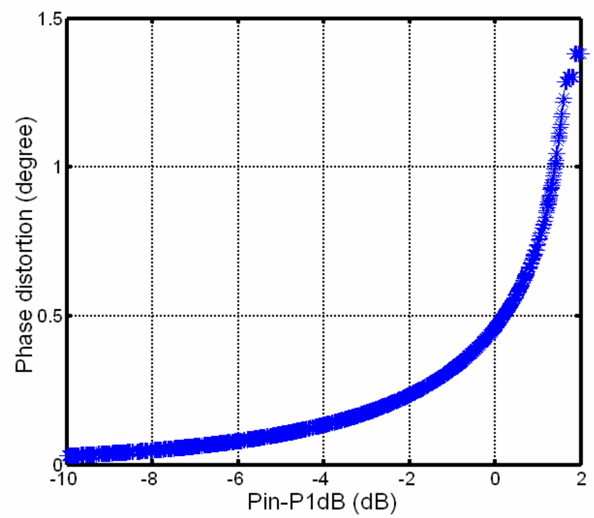
- **Using Pre-D based on LUT**

$$P_{LT}(x) = \left[Gain_{LT}(P_{in}) \cdot \exp(j(Phase_{LT}(P_{in}))\right] \cdot x$$

- **Gain LUT**

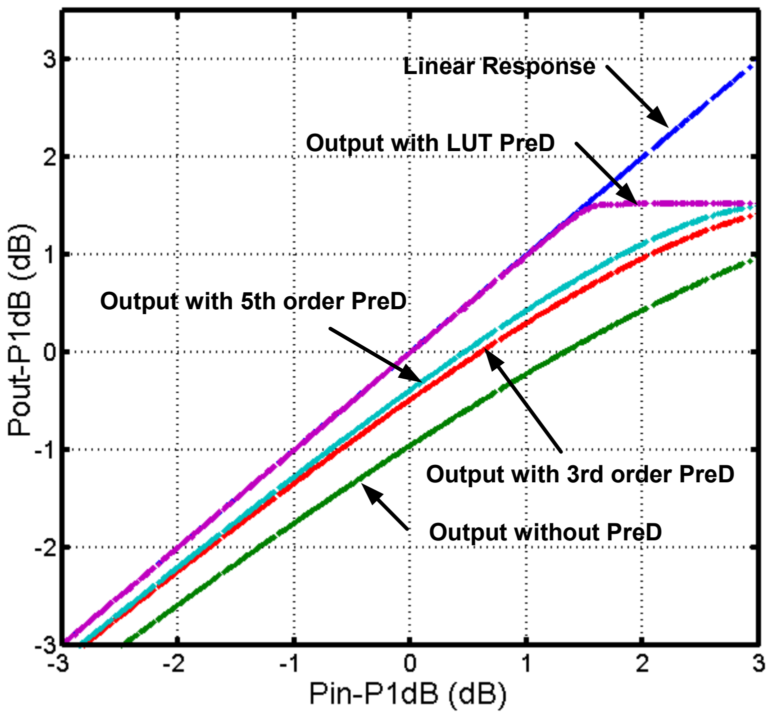


- **Phase LUT**

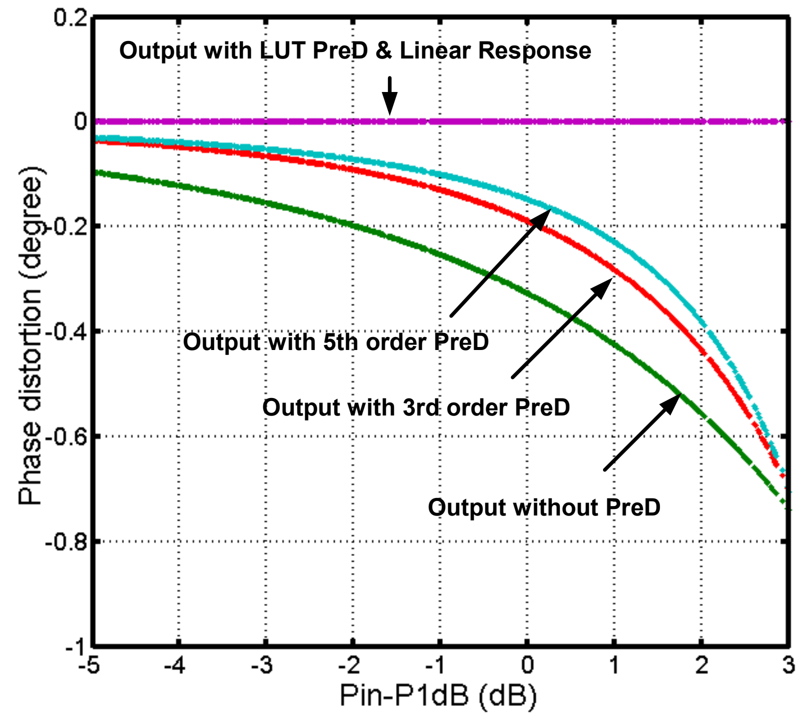


Response for PA with Pre-D

- **AM/AM Response**



- **AM/PM Response**



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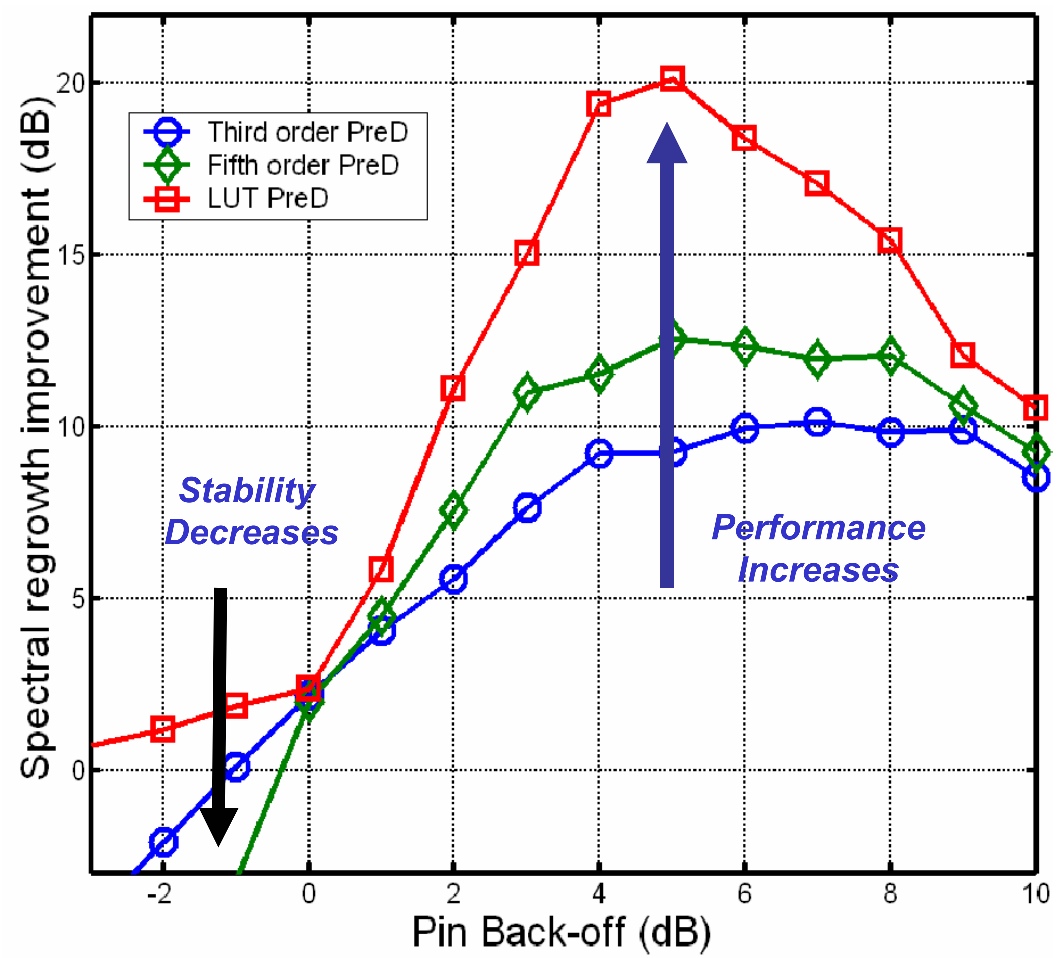
ACPR Improvement



- For p-th order predistorter, the performance increase as order increases. But stability decrease as order increases
- PreD using LUT gives best performance: 20dB improvement in ACPR (IBO=5 dB)

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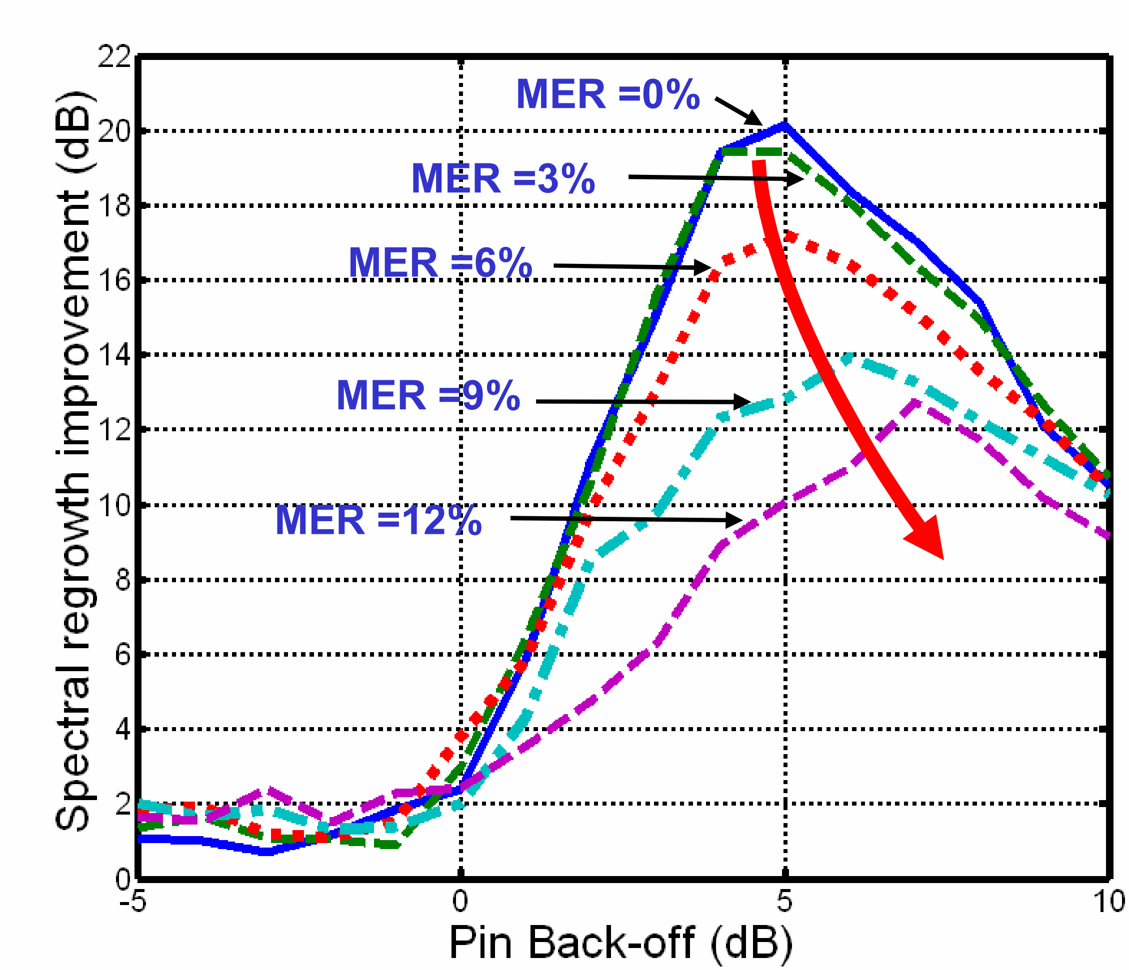
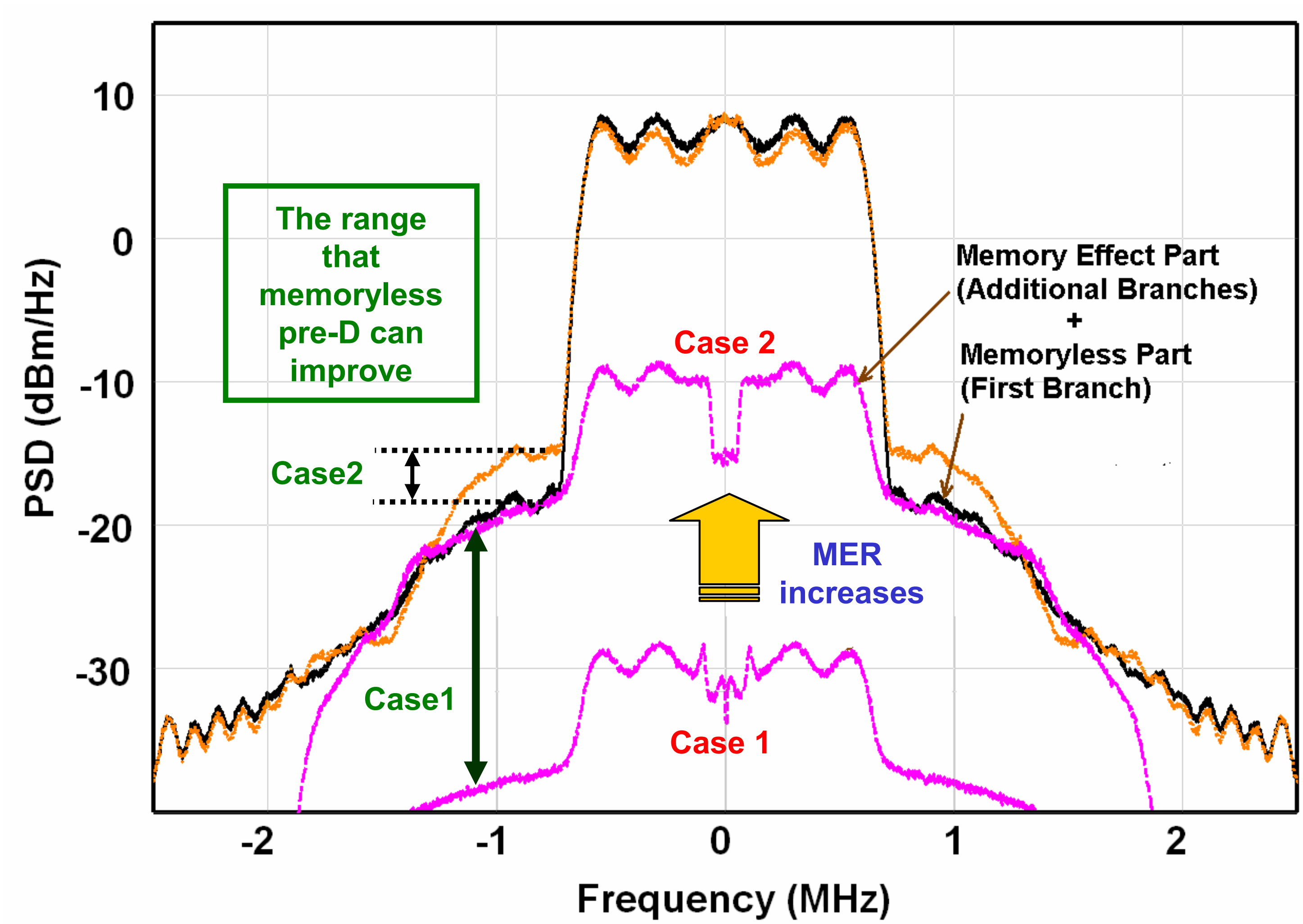
ACPR Improvement Degradation



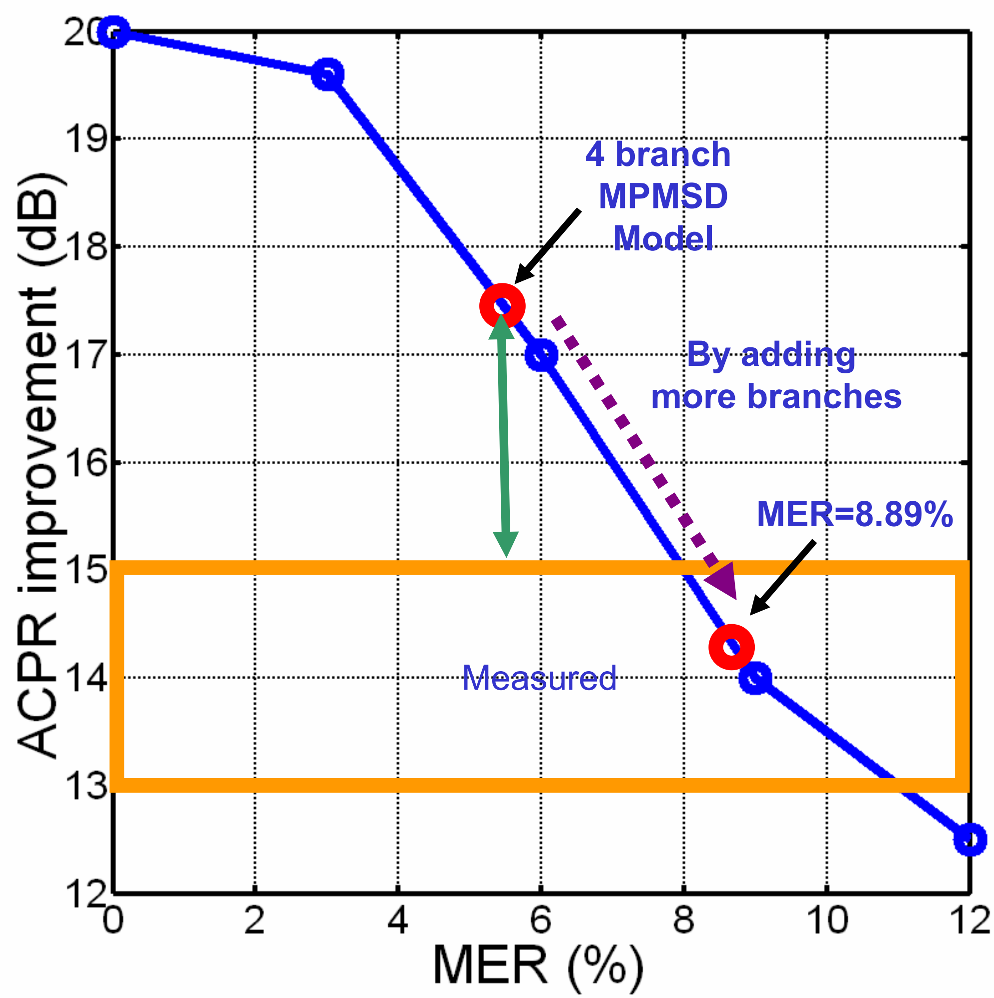
- By changing MER value (@ 5dB IBO) in model (increasing weighting factor for the additional branches) , compare the ACPR improvements

Analysis in Frequency Domain



* H. Ku, M. McKinley, and J. S. Kenney, "Quantifying Memory Effects in Power Amplifiers," *IEEE Trans. on Microwave Theory and Tech.* vol. 50, no. 12, Dec, 2002.

MER vs. Pre-D Improvement



- As MER increases, the improvement decrease : (20dB @ MER= 0%, **14dB@ MER = 9%** 12.5dB @ MER=12%)
  : Accurate Prediction for Pre-D improvement

- Discrepancy between measured result and simulated result from MPMSD Model=> Because 64% of memory effects are captured in the model (36% are not captured)

Conclusions

- Memory polynomial model with sparsely delayed taps (MPMSD) is suggested to model PAs with memory effects such as asymmetric IMD and spectral regrowth: Simple method to implement
- Figure of merits introduced to quantify the amount of memory effects (MER) and quantify the modeling improvement of the suggested model (MEMR).
- Model was extracted for high power LDMOS PA and verified against measurements
- PreD degradation vs. MER is analyzed and simulated

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