Thesis for the degree of Doctor of Philosophy

Behavioral modeling of wireless transmitters for distortion mitigation

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This thesis has been prepared using LaTeX.
Printed by Chalmers Reproservice,

To Haideh, Bahram,
and my beloved Sahar.

Abstract

As the demand for high speed and reliable wireless communication increases, the importance of having a linear transmitter has enhanced. Distortions created by the transmitter, such as power amplifier nonlinearity and I/Q imbalance, diminish the fidelity and limit the performance of wireless systems, if left undealt with. Among the techniques commonly used to mitigate these distortions, digital predistortion has established itself as a suitable candidate that minimizes the hardware overhead and only requires modest additional power in the transmitter architecture. An important pre-requisite for utilizing digital predistorters is developing accurate and low complex behavioral models, which is the main focus of this thesis.

After analyzing the importance of modeling and compensating for the distortion created by modulators and power amplifiers in the transmitter architecture, an overview of some commonly used models in the literature is presented. A novel behavioral modeling approach is proposed which is capable of modeling long term memory effects in power amplifiers, and a new dual–input modeling approach for I/Q imbalance compensation is presented that successfully compensates for distortion created by the modulator. Compared with conventional and recently proposed techniques, the approaches presented in this thesis show promising results in modeling transmitters accurately. The important issue of computational complexity in behavioral models is also discussed, and the accuracy/compexity tradeoff of some common behavioral models is analyzed. Once behavioral modeling techniques are established, they are used for digital predistortion of wireless transmitters. Issues such as identification of digital predistorters and adaptation of parameters due to changes in power amplifier behavior are discussed and a new measurement testbed to evaluate the performance in parameter adaptation algorithms is proposed.

The methods and techniques proposed in this work provide ways to both mitigate distortion in and evaluate performance of wireless transmitters in terms of accuracy and complexity, and can help contribute to a better service of quality in wireless communication systems.

Keywords: Behavioral modeling, computational complexity, digital predistortion, I/Q imbalance, nonlinear models, power amplifier, transmitter, Volterra series, wireless communications.

List of Publications

Appended papers

This thesis is based on the following publications:

Paper A
A. Soltani Tehrani, H. Cao, T. Eriksson, and C. Fager, “Black-box Modeling and Compensation of Long Term Memory Effects in RF Power Amplifiers", submitted to *IEEE Transactions on Microwave Theory and Techniques*, May. 2012.

Paper B
H. Cao, **A. Soltani Tehrani**, C. Fager, T. Eriksson, and H. Zirath, “I/Q imbalance compensation using a nonlinear modeling approach", *IEEE Transactions on Microwave Theory and Techniques*, 2009.

Paper C
A. Soltani Tehrani, H. Cao, S. Afsardoost, T. Eriksson, M. Isaksson, and C. Fager, “A comparative analysis of the complexity/accuracy tradeoff in power amplifier behavioral models", *IEEE Transactions on Microwave Theory and Techniques*, 2010.

Paper D
A. Soltani Tehrani, J. Chani, T. Eriksson, and C. Fager, “Investigation of parameter adaptation in RF power amplifier behavioral models”, to be submitted to *IEEE Transactions on Microwave Theory and Techniques*, Nov. 2012.

Other publications

The author has been involved in the following publications that are not appended to the thesis, either due to contents overlapping that of appended papers, or due to contents not related to the thesis.

(a) **A. Soltani Tehrani**, H. Cao, H. Nemati, C. Fager, T. Eriksson, and H. Zirath, “ Varactor-Based Dynamic Load Modulation of High Power Amplifiers”, in *arXiv:1210.3494*.

(b) H. Cao, H. Nemati, **A. Soltani Tehrani**, T. Eriksson, C. Fager, “ Digital Predistortion for High Efficiency Power Amplifier Architectures Using a Dual-input Modeling Approach” in *IEEE Transactions on Microwave Theory and Techniques*, volume 60, pp. 361-369, 2012.

(c) H. Cao, H. Nemati, **A. Soltani Tehrani**, T. Eriksson, J. Grahn, C. Fager, “ Linearization of Efficiency-Optimized Dynamic Load Modulation Transmitter Architectures”, in *IEEE Transactions on Microwave Theory and Techniques*, volume 58, pp. 873-881, 2010.

(d) **A. Soltani Tehrani**, “ Behavioral modeling of radio frequency transmitters”, Gothenburg: Chalmers University of Technology, ISSN 1403-266X, 2009.

(e) **A. Soltani Tehrani**, C. Fager, T. Eriksson, “ Modeling of Long Term Memory Effects in RF Power Amplifiers with Dynamic Parameters”, in *Proc. of IEEE International Microwave Symposium (IMS)*, Montreal, Canada, Jun. 2012.

(f) **A. Soltani Tehrani**, T. Eriksson, C. Fager, “ Measurement setup for digital predistortion adaptation”, in *RF Measurement Technology Conference*, Gavle, Sweden, 2011.

(g) H. Cao, C. Fager, T. Khan, **A. Soltani Tehrani**, T. Eriksson, “ Comparison of bandwidth reduction schemes in dynamic load modulation power amplifier architectures”, in *Proc. of IEEE Workshop on Integrated Nonlinear Microwave and Millimetre-Wave Circuits (INMMIC)*, Vienna, Austria, 2011.

(h) H. Nemati, B. Almgren, C. Andersson, H. Cao, T. Eriksson, C. Fager, U. Gustavsson, R. Jos, M. Ozen, **A. Soltani Tehrani**, H. Zirath, “Varactor-Based Dynamic Load Modulation of RF PAs”, in *Proc. of European Microwave Conference*, Manchester, UK, 2011.

(i) **A. Soltani Tehrani**, A. Behravan, H. Cao, C. Fager, T. Eriksson, “ Successive Cancellation of Power Amplifier Distortion for Multiuser Detection”, in *Proc. of IEEE Vehicular Technology Conference (VTC)*, Ottawa, Canada, Sep. 2010.

(j) **A. Soltani Tehrani**, H. Cao, C. Fager, T. Eriksson, " Complexity Analysis of Power Amplifier Behavioral Models", in *Proc. of IEEE Workshop on Integrated Nonlinear Microwave and Millimetre-Wave Circuits (INMMIC)*, Goteborg, Sweden, 2010.

(k) T. Eriksson, **A. Soltani Tehrani**, H. Cao, C. Fager, " Low-complexity volterra modeling of power amplifiers", in *Proc. of IEEE Workshop on Integrated Nonlinear Microwave and Millimetre-Wave Circuits (INMMIC)*, Goteborg, Sweden, 2010.

(l) T. Eriksson, **A. Soltani Tehrani**, C. Fager, " Model-Based Adaptation of RF Power Amplifiers", in *Proc. of GigaHertz Symposium*, 2010.

(m) C. Fager, H. Nemati, H. Cao, **A. Soltani Tehrani**, T. Eriksson, R. Jos, H. Zirath, "Highly Efficient Dynamic Load Modulation Transmitter", in *Proc. of GigaHertz Symposium*, 2010.

(n) C. Fager, H. Cao, T. Eriksson, R. Jos, H. Nemati, **A. Soltani Tehrani**, H. Zirath, "High Efficiency Transmitter Using Varactor Based Dynamic Load Modulation", in *Proc. of International Microwave Workshop Series on RF Front-ends for Software Defined and Cognitive Radio Solutions*, 2010.

(o) **A. Soltani Tehrani**, H. Nemati, H. Cao, T. Eriksson, C. Fager, "Dynamic Load Modulation of High Power Amplifiers with Varactor-Based Matching Netwokrs", in *Proc. of IEEE International Microwave Symposium (IMS)*, Boston, USA, 2009.

(p) H. Cao, **A. Soltani Tehrani**, H. Nemati, T. Eriksson, C. Fager, "Time Mismatch Effects in a Dynamic Load Modulation Transmitter Architecture", in *RF Measurement Technology for State of the Art Production and Design(RFMTC)*, 2009.

(q) H. Cao, **A. Soltani Tehrani**, H. Nemati, C. Fager, T. Eriksson, H. Zirath, "Time Alignment in a Dynamic Load Modulation Transmitter Architecture", in *Proc. of 39th European Microwave Conference (EuMC)*, Rome, Italy, 2009.

(r) H. Cao, **A. Soltani Tehrani**, C. Fager, T. Eriksson, H. Zirath, " Dual-Input Nonlinear Modeling for I/Q Modulator Distortion Compensation", in *Proc. of IEEE Radio and Wireless Symposium*, San Diego, USA, 2009.

(s) **A. Soltani Tehrani**, H. Cao, T. Eriksson, C. Fager, " Orthonormal-basis power amplifier model reduction", in *Proc. of IEEE Workshop on Integrated Nonlinear Microwave and Millimetre-Wave Circuits (INMMIC)*, Malaga, Spain, 2008.

(t) H. Cao, **A. Soltani Tehrani**, C. Fager, T. Eriksson, H. Zirath, " Compensation of Transmitter Distortion Using a Nonlinear Modeling Approach", in *Proc. of IEEE Workshop on Integrated Nonlinear Microwave and Millimetre-Wave Circuits (INMMIC)*, Malaga, Spain, 2008.

(u) **A. Soltani Tehrani**, H. Cao, T. Eriksson, C. Fager, "Comparative analysis of the complexity/accuracy tradeoff for power amplifier behavior models", in *Proc. of GigaHertz Symposium*, 2008.

(v) H. Cao, **A. Soltani Tehrani**, C. Fager, T. Eriksson, "Identification of Distortions in a RF Measurement System", in *Proc. of GigaHertz Symposium*, 2008.

(w) T. Eriksson, C. Fager, H. Cao, **A. Soltani Tehrani**, H. Nemati, H. Zirath, "Modeling of dual-input power amplifiers", in *Proc. of GigaHertz Symposium*, 2008.

(x) N. Seifi, **A. Soltani Tehrani**, M. Viberg, "Simulation of a wideband reconfigurable multi-antenna system with space-time coding", in *Nordic Matlab Users Conference*, Stockholm, Sweden, 2008.

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Contents

Acronyms

3GPP:	Third Generation Partnership Project
ACEPR:	Adjacent Channel Error Power Ratio
ACPR:	Adjacent Channel Power Ratio
ADC:	Analog to Digital Converter
AM:	Amplitude Modulation
ANN:	Artificial Neural Network
AR:	Autoregressive
ASIC:	Application-Specific Integrated Circuit
AWGN:	Additive White Gaussian Noise
BER:	Bit Error Rate
DAC:	Digital to Analog Converter
DC:	Direct Current
DDR:	Dynamic Deviation Reduction
DPD:	Digital Predistortion
DSO:	Digital Storage Oscilloscope
DSP:	Digital Signal Processing
DUT:	Device Under Test
E-UTRA:	Evolved Universal Terrestrial Radio Access
EVM:	Error Vector Magnitude
FIR:	Finite Impulse Response
FLOP:	Floating Point Operation
FPGA:	Field-Programmable Gate Array

GMP:	Generalized Memory Polynomial
GPIB:	General Purpose Interface Bus
I/Q:	Inphase / Quadrature phase
IIR:	Infinite Impulse Response
ILA:	Indirect Learning Architecture
KV:	Kautz–Volterra
LDMOS:	Laterally Diffused Metal Oxide Semiconductor
LO:	Local Oscillator
LS:	Least Squares
LSE:	Least Squares Estimate
LT-MP:	Long Term Memory Polynomial
LTE:	Long Term Evolution
LUT:	Look–Up Table
MER:	Memory Effect Ratio
MEMR:	Memory Effect Modeling Ratio
MIMO:	Multiple-Input Multiple-Output
MLP:	Multilayer Perceptron
MLS:	Modified Least Squares
MP:	Memory Polynomial
MSE:	Mean Squared Error
NARMA:	Nonlinear Autoregressive and Moving Average
NMSE:	Normalized Mean Squared Error
PA:	Power Amplifier
PC:	Personal Computer
PM:	Phase Modulation
QAM:	Quadrature Amplitude Modulation
RBFNN:	Radial-Basis Function Neural Networks
RF:	Radio Frequency

SC-FDMA: Single-Carrier Frequency Division Multiple Access

SER: Symbol Error Rate

SNR: Signal to Noise Ratio

TDNN: Time-Delayed Neural Networks

VSG: Vector Signal Generator

WCDMA: Wideband Code Division Multiple Access

WESPR: Weighted Error-to-Signal Power Ratio

Part I

Introduction

Chapter 1

Overview

1.1 Introduction

It has been more than a century since Nikola Tesla first introduced us to the idea and magic of wireless communication with his 1892 lecture "Experiments with Alternate Currents of High Potential and High Frequency" [1]. The prospect of being able to send messages without the need for wires excited many researchers and engineers and Guglielmo Marconi famously set out to construct the first technically correct and commercialized communication system a few years later. As always, these early systems were very unreliable, but they still worked remarkably well. A few more years had to pass until somebody came along and showed us how to transmit information in a channel reliably. "A Mathematical Theory in Communication" [2] (later appropriately renamed "*The* Mathematical Theory in Communication") was the landmark work by Claude Shannon paving the way for modern, reliable communication.

None of these progresses made by researchers and engineers would have been possible without the earlier works of Michael Faraday, James Maxwell, and Heinrich Hertz who, among others, tried to find mathematical representations of our physical world and construct the first "models" for wireless propagation. Since then modeling physical phenomena has been an ever important part of understanding the world and how to deal with the challenges it throws at us, and has been an important tool for researchers and engineers alike.

Nowadays transmitting data is just an everyday part of our lives. While the struggle in the beginning of wireless communication era was on finding applications and ways to commercialize such systems, today the tables have turned and it is people pushing researchers and engineers for better and faster systems. We have gone from requiring wireless communication systems to transmit clicks of the Morse code over short distances, to demanding 3D movies, webpages, and even images from Mars. This demand has led to increased requirements on the speed, reliability, availability and mobility of wireless systems, which coupled with the limited energy and radio frequency (RF) resources, has put a huge burden on modern wireless data communication systems. Such systems are nowadays required to be highly linear and low power consuming, which in itself is normally a tradeoff.

Practical wireless transmitters, like all physical systems, are not ideal and have hardware impairments which will introduce distortions in the communication signals we would like to transmit. Any distortion created from these hardware impairments have to be dealt with, and in order to compensate for such effects it is first necessary to represent them with suitable models. Modeling the transmitter in a wireless systems and compensating for the distortion created by the imperfect hardware with the help of digital predistortion is thus, the focus of this thesis.

1.2 Thesis outline

The thesis is organized as follows. In Chapter 2, the different types of distortion created in the modulator and power amplifier due to the non-ideality of the hardware is presented, and then effect this distortion has on communication system aspects such such symbol to error ratio and spectral regrowth is discussed. Metrics to evaluate the linearity of modern transmitters is also presented.

In Chapter 3, behavioral modeling of transmitters is discussed. A theoretical background for behavioral modeling in transmitters is established. Considerations on the requirements of power amplifier behavioral model structure, as an important part of wireless transmitters, is explained. Some commonly-used power amplifier behavioral models are categorized, allowing for a better understanding of the differences between models and two new behavioral modeling techniques are presented, one for modulators and one for power amplifiers. Evaluating the complexity and the accuracy/complexity tradeoff is also discussed in this section.

In Chapter 4 the basics of digital predistortion as a method to mitigate errors is presented, and after presenting techniques for identifying digital predistorters, mitigating distortion is shown with two examples, one for a modulator and another for a power amplifier. Finally parameter adaptation in modern transmitters is discussed, and a new measurement setup paradigm that is capable of emulating parameter adaptation in behavioral–model based predistorters with real–time circuitry is presented. Finally in Chapter 5, conclusions are drawn from the research done, the contributions of the appended papers is presented and future work in this field is discussed.

Chapter 2

Requirement for linearity in RF transmitters

As wireless systems become more widespread in our everyday lives, the demand and requirements on transmitters, such as linearity and power efficiency, has increased. This chapter deals with linearity in RF transmitters as one of the important demands that enables reliable wireless communication. First a short background on the distortion created by the transmitter is presented and then the effect of distortion on the communication system is analyzed. Performance metrics that are commonly used to evaluate how well transmitters operate are proposed, and finally different techniques to mitigate distortion in the literature are presented.

2.1 Distortion created by imperfect hardware

Transmitters have an important role in wireless systems and are tasked with modulating a bit stream into a waveform suitable for propagation in the RF channel [2]. A block diagram of such transmitters can be shown in Fig. 2.1. From this figure it can be noticed that the modulator is associated with the analog circuitry that produces a real-valued passband modulated signal from the complex-valued baseband signal. The output of the modulator is then fed to the power amplifier (PA), to amplify the signal to a suitable level to transmit in the channel, and given to the antenna for wireless propagation.

The transmitter architecture shown in Figure 2.1 has two main sources of distortion: the power amplifier and the modulator. In the rest of this thesis, the modulator and PA will be referred to as simply the transmitter. A simple block diagram of a modulator is shown in Figure 2.2. The real and imaginary part of the complex baseband input signal are fed to two orthogonal paths, commonly called the *Inphase* (I) and *Quadrature phase*

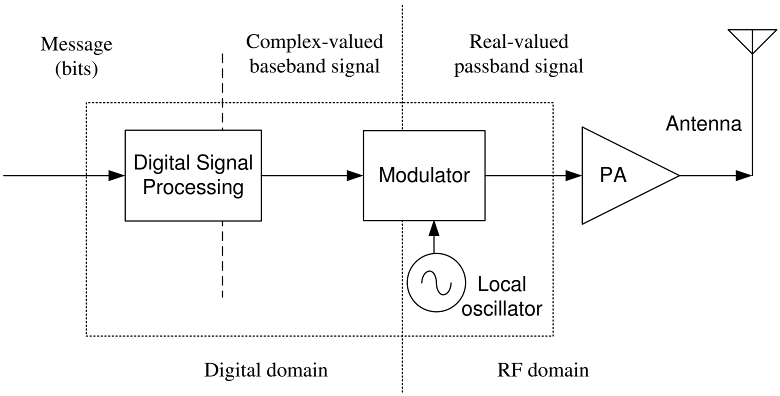


Figure 2.1: Block diagram of a simplified modern transmitter architecture.

(Q) paths. Digital to analog converters (DACs) transform the digital signal into an analog one. These devices commonly introduce *nonlinear distortion* in the process, which may show up as a discrete current (DC) offset. The analog signal is fed through a reconstruction filter, which may introduce time delays and phase shifts. These phenomena show themselves in the form of *memory effects*, i.e., the output sample depends on not only the sample at time t, but also on samples that have passed before this time.

The output of the reconstruction filter is fed to an upconverter that takes the baseband signal into the passband domain. This process is prone to imperfections as well, for example there may be imbalance between the gain for the two branches, which is commonly called I/Q imbalance [3]. It is also common that a portion of the local oscillator (LO) signal undesirably passes through. This phenomena is called called LO leakage. The oscillator may also introduce a skewness due to phase shifts in the hardware. This may reduce the orthogonality between the two branches and will severely impact the communication signal.

Figure 2.3 shows an ideal and imbalanced I/Q modulator (with a center frequency of f_{LO}) with a single sinusoid ($Ae^{j2\pi ft+\phi}$) as the input. The received signal for this input generally looks like [1]:

$$r(t) = \frac{G_I + G_Q}{2} Ae^{j2\pi ft+\phi} + \frac{G_I - G_Q}{2} Ae^{-(j2\pi ft+\phi)} + \mathrm{LO}, \qquad (2.1)$$

where G_I and G_Q are the complex gains of the different paths and LO is the leakage from the oscillator that passes through to the output. When

[1] using considerations for representing passband signals with complex baseband ones from Section 3.1

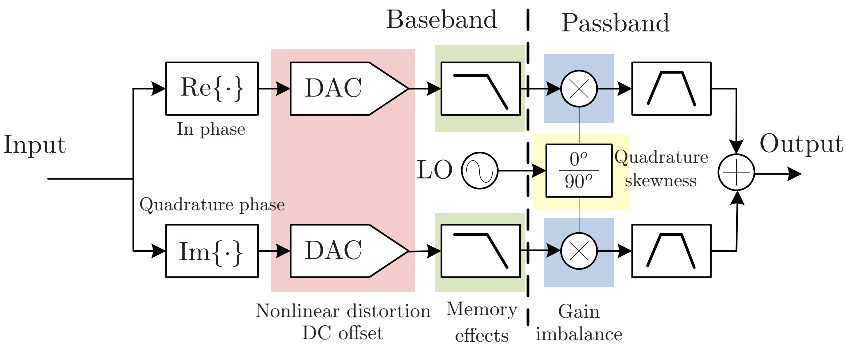


Figure 2.2: Block diagram of a simplified power amplifier architecture.

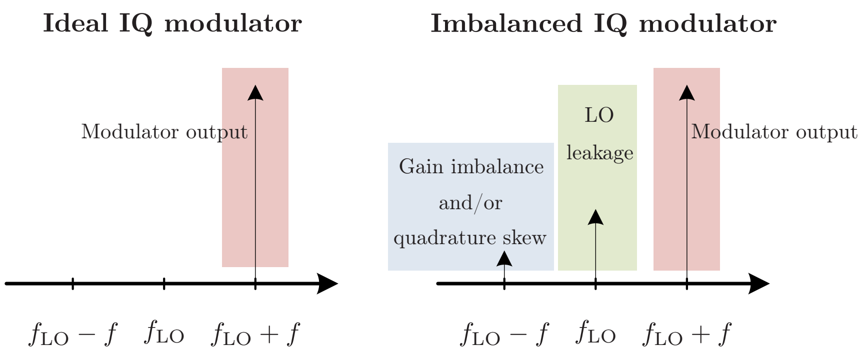


Figure 2.3: Block diagram of a simplified power amplifier architecture.

$G_I \neq G_Q$, i.e. the complex gain in the two paths are different, IQ imbalance occurs.

It can be noticed that instead of the single tone at frequency $f_{\mathrm{LO}} + f$ as expected, multiple tones appear that are due to the LO leakage – LO from (2.1), and I/Q imbalance and skewness – when $(G_I - G_Q)/2 \neq 0$ from (2.1). These distortions will affect the communication signal and further induce more distortions when connected to the PA afterwards.

Power amplifiers are tasked with linearly amplifying the communication signal to the required output power level to overcome channel losses. In practice, these devices tend to have a nonlinear behavior, especially when driven close to saturation. A block diagram of a simple PA architecture is shown in Figure 2.4. From this figure different types of distortion created by the PA can be noticed. These distortions can be classified into:

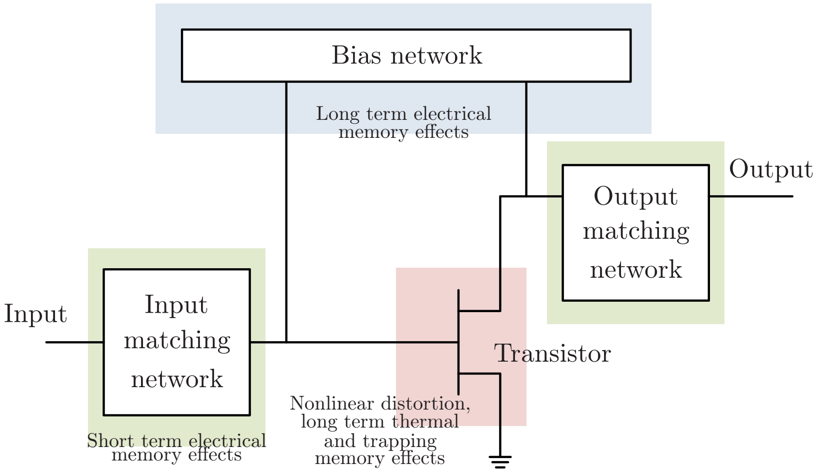


Figure 2.4: Block diagram of a simplified power amplifier architecture.

- Nonlinear distortion, mainly from the device nonlinear dc characteristics.

- Short–term memory effects, which are normally attributed to time delays, or phase shifts, in the matching networks and the device and circuit elements used.

- Long–term memory effects, which may be caused by non-ideal bias networks, trapping effects, temperature dependence and other sources.

A typical input-output amplitude characteristic for a power amplifier is shown in Figure 2.5. It can be noticed from this figure that the input/output no longer has a linear relationship, and a practical PA output differs from the ideal PA response, i.e., as the output becomes saturated the PA gain diminishes. This distortion severely effects communication signals with varying amplitude as the gain is non-uniform.

Another power amplifier distortion that is visible from Figure 2.5 is the power amplifier memory effect. Since the input-output relationship is no longer a one-to-one function, the same input sample may result in a range of output samples depending on the signal history. This shows itself in the figure as the blurring when the amplitude increases.

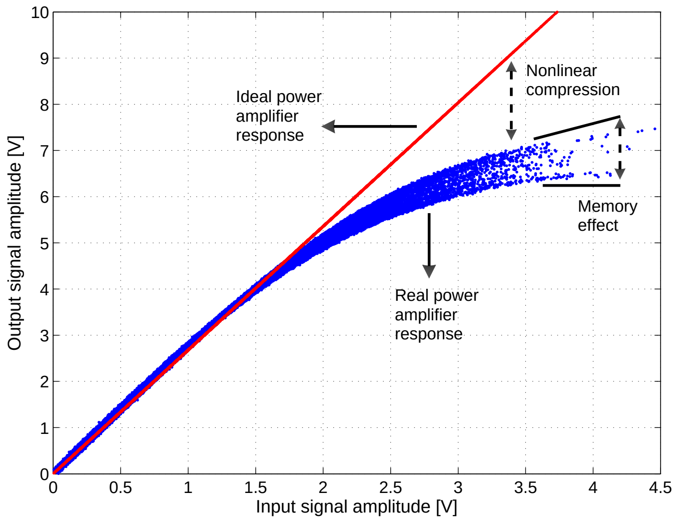


Figure 2.5: Input-output characteristics of an ideal and a practical power amplifier.

2.2 Effects of transmitter distortion on communication system

After analyzing the different types of distortions created by the modulator and PA, it is important to understand how these imperfections affect the communication system. In this section, some of the more important effects of distortion on system performance is analyzed.

2.2.1 Distortion effects on the constellation diagram

The effect of I/Q imbalance and skewness is shown in Figure 2.6. In order to construct this figure, a 75% gain mismatch between the I and Q branches (the gain in the I branch is 0.75 times the gain in the Q branch) and a 8 degree skewness is introduced. From the figure it can be noticed that the constellation points no longer are in the ideal positions and the I and Q branches are not orthogonal. Further it can be noticed that the distance between constellation points has changed, which will result in a loss of performance of the system.

The effect of PA nonlinear distortion on the constellation diagram at the receiver after matched filtering of a 16 quadrature amplitude modula-

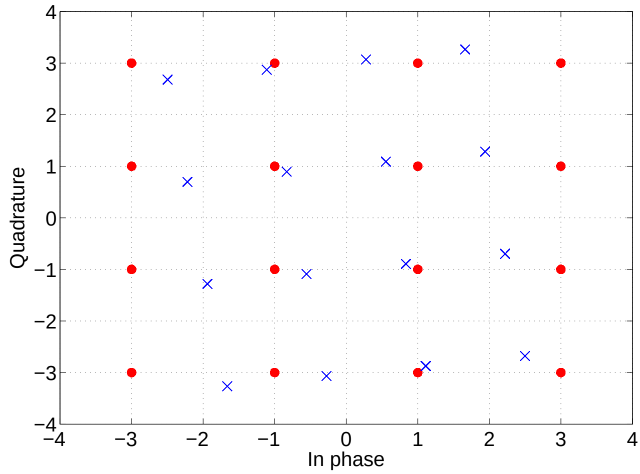


Figure 2.6: Adverse effects of I/Q imbalance and skewness on the constellation of the input signal. The ideal 16 QAM is shown with the red dots, and the distortion created by the modulator with blue.

tion (QAM) signal with a single-carrier frequency–division multiple access (SC–FDMA) modulation format is shown in Fig. 2.7, in the presence of an ideal channel. It can be noticed that even though there is no channel noise added to the system, the PA nonlinearity creates clouded constellation points instead of the ideal 16 QAM, and these points are compressed compared to the ideal case. Adding channel noise on top of this distortion would further diminish the communication system performance, and therefore it is necessary to compensate for such effects appropriately.

2.2.2 Distortive effects of the on the SER

The distortion created by the non–ideality of the transmitter results in a loss of information in the communication signal. This in itself increases the symbol–error–rate (SER) or bit–error–rate (BER) in the overall communication system. The effect of the distortion created by the PA in the SC–FDMA setup (combined with the effect of the distortion of adjacent users) on the SER performance is shown in Fig. 2.8 for an additive white gaussian noise (AWGN) channel. It can be noticed that not only does the SER performance deviate from the ideal performance, it also suffers from a performance floor where increasing the transmitting power will not improve the performance, due to the saturating factor in the transmitter and inter-

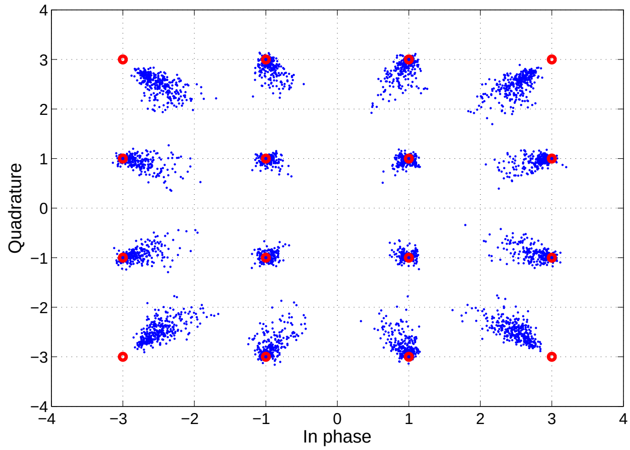


Figure 2.7: Adverse effects of power amplifier distortion on the constellation of the input signal. The ideal 16 QAM is shown with the red dots, and the distortion created by the PA after the matched filter in the receiver is shown with blue crosses.

ference. If not dealt with, this will limit the performance achievable from wireless systems.

2.2.3 Spectral regrowth distortion

The distortions created by the transmitter also have an impact in the frequency response of the communication system, resulting in what is known as *spectral regrowth*. This corresponds to the spectral leakage of power into adjacent channels of the frequency spectrum. Spectral regrowth is a product of the nonlinearity in the transmitter, i.e., linear components do not result in spectral regrowth. Figure 2.9 shows the effects of the distortion of a power amplifier in the frequency domain. It can be observed that spectral regrowth results in out-of-band leakage that may not satisfy the requirements set by frequency regularization organizations [4]. For example in this figure, the out-of-band distortion is so strong that it partially masks an adjacent user and distorts its communication.

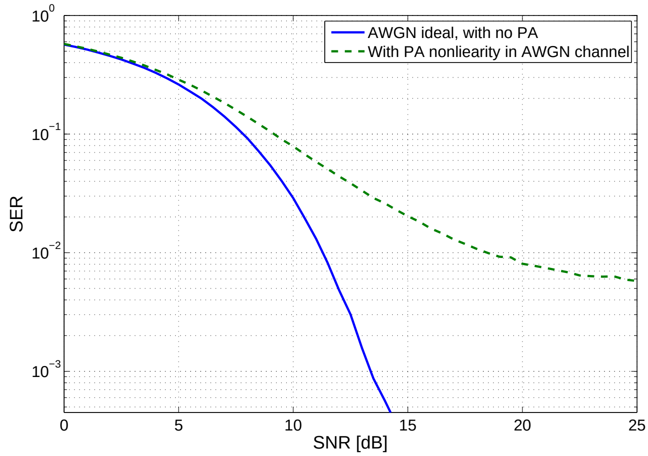


Figure 2.8: Adverse effects of power amplifier distortion on symbol–error–rate performance (from the setup in contribution i).

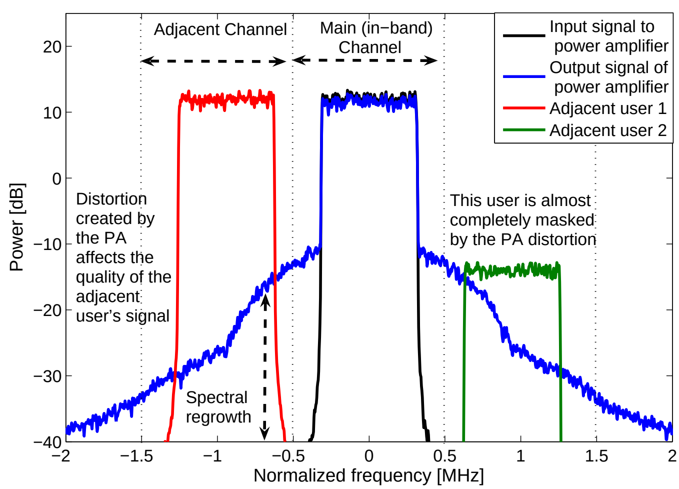


Figure 2.9: Adverse effects of power amplifier distortion on adjacent users.

2.3 Evaluating performance of an RF transmitter

In order to be able to evaluate the amount of distortion created by the imperfect hardware, it is necessary to develop metrics that represent how well the transmitter operates. These metrics are often specified by communication standard regulations to not only maintain suitable performance of the system, but also as requirements that must be fulfilled to ensure that the communication system does not interfere with other systems using the wireless resource. This section presents some of the main metrics used to evaluate how well the transmitter operates.

2.3.1 Performance evaluation of transmitters

In wireless transmitters, the ultimate goal is to minimize the difference between the output signal of the system, and the desired output signal we would have liked to have been fed to the antenna. This difference can be written as

$$e[n] = y_{\text{measured}}[n] - y_{\text{desired}}[n] \tag{2.2}$$

where $e[n]$ is the error signal, $y_{\text{measured}}[n]$ is the sampled measured output of the system and $y_{\text{desired}}[n]$ is the sampled desired output that should be fed to the antenna. The simplest metric to measure how well the transmitter performs with the given data set in terms of accuracy is to use (2.2) to find the mean–squared–error (MSE). The MSE can be written as

$$\text{MSE} = \sum_n |y_{\text{measured}}[n] - y_{\text{desired}}[n]|^2. \tag{2.3}$$

Use of this metric may not be suitable for comparing systems with different power levels, and commonly in the literature the normalized MSE (NMSE) is used for these cases. The NMSE can be defined as [5]

$$\text{NMSE} = \frac{\sum_n |y_{\text{measured}}[n] - y_{\text{desired}}[n]|^2}{\sum_n |y_{\text{measured}}[n]|^2}, \tag{2.4}$$

Since NMSE is a power measure, and the bulk of the transmitter power is normally in–band (from Fig. 2.9), NMSE is commonly considered an in–band measure for the transmitter performance. In applications were the out–of–band is important, the adjacent channel power ratio (ACPR) is used to measure the amount of power leaked from the transmitter into adjacent channels (from Fig. 2.9) of the wireless system, and can be defined as

$$\text{ACPR} = \max_{m=1,2} \left[\frac{\int\limits_{(\text{adj})_m} |Y_{\text{measured}}(f)|^2}{\int\limits_{\text{ch}} |Y_{\text{measured}}(f)|^2} \right], \tag{2.5}$$

where the integration in the numerator is over the main channel and in the denominator over adjacent channels of the wireless system. This measure can effectively represent the amount of distortion created in the adjacent channels of a communication system, which is very important in many applications.

2.4 Mitigating transmitter distortion in literature

In order to achieve the required performance of wireless transmitters set by the communication standards, researchers have developed different techniques to mitigate the unwanted distortion created by these devices. The commonly used methods in the literature to combat this distortion can be categorized into analog and digital techniques.

Analog techniques can be grouped into *feedforward*, *feedback* and *predistortion* techniques. Analog feedforward linearization is a technique to mitigate distortion by adding a phase–reversed version of the error to the output of the PA [6]. In analog feedback a portion of the output signal is taken, amplified and phase shifted, and injected to the input of the PA to cancel distortion [7, 8]. In analog predistortion, the inverse of the transmitter is applied to the input signal, rendering the overall system linear. These techniques generally have the benefit of being able to cope with high input signal bandwidth, however they are normally frequency–sensitive, cumbersome and expensive to implement [9–11]. Other analog techniques, such as *outphasing*, which originally was suggested as a technique to improve power efficiency [12, 13] but can be seen as a linearization method [14], and *envelope tracking* [15] and *envelope elimination and restoration* [16] have also been viewed as techniques for improving the linearization/power efficiency tradeoff.

The main digital technique for compensating distortion in transmitters, and specifically for distortion created by the PA, is *digital predistortion* (DPD). In this technique the signal is passed through an inverse filter of the transmitter in the digital domain. This technique has been shown to reduce the size and cost for distortion mitigation compared to other linearization methods [17], and has the added benefit of being independent of the operating frequency. Due to the widespread use of digital predistortion in the literature [18–27] and ease of implementation, the thesis focuses on mitigating distortion by using DPD. In order to construct the inverse of the transmitter, it is vital to develop accurate models of the transmitter first. Classifying and developing models for both the modulator and PA considering the different types of distortion mentioned, is the focus of Chapter 3.

Chapter 3

Behavioral modeling of RF transmitters

As discussed in the previous chapter, in order to compensate for distortions created by the imperfect hardware using DPD, finding accurate models of the transmitter is an important pre-requisite. Different approaches have been taken to model the transmitter, from detailed models constructed from physical laws to input/output models utilized in system level simulations. Depending on the type of data needed for identification, models can generally be divided into two main groups: physical/circuit models, and empirical models [28, 29]. Physical models give an accurate description of a device based on fundamental physical laws [30]. In circuit models, electrical circuit elements and circuit theory are used to model the system. Such techniques have high precision limited only by the quality of the device models. This precision has a high price in simulation time, limiting the practical use of these type of models for modeling complete wireless systems. Further, it is unclear how to create an inverse circuit model, to compensate for the nonideal effects.

Empirical models attempt to model the system with little or no *a priori* knowledge of the internal circuitry of the devices. They are commonly called *behavioral models*, or *black-box models*, and are constructed from the sampled measured input and output signals. Due to the ease of implementation and fast simulation/processing time of these type of models, they are commonly used for DPD [31]. In [17], [19] and [28] it was shown that developing accurate models can lead to suitable DPD performance, and therefore the focus of this type of modeling.

In order to understand how behavioral models work and their limitations, in this thesis models are classified based on the type of distortion they describe. As there are many models in the literature, it is a tedious task to list all such models. Therefore, in this work, some which are representative of most models are chosen and analyzed. An important issue in PA modeling and later for DPD, namely the computational complexity of behavioral modeling, is also presented in this section. Finally, parameter identification in behavioral models is discussed.

3.1 Baseband representation of passband signals

Power amplifiers used in wireless transmission are *passband* devices, and modeling the PAs with passband signals has been suggested in the literature [32]. However, by assuming that the input signal to the power amplifier is band-limited, computationally efficient techniques can be constructed to represent the power amplifier with discrete baseband models [33]. This greatly reduces the computational complexity, as instead of using passband samples (at high sample rates), baseband samples (at lower sample rates) can be used.

In [34] and [35], it was shown that a narrowband passband signal $\tilde{x}(t)$ centered around frequency f_0 can be represented by its baseband equivalent where

$$\tilde{x}(t) = x_{\mathrm{I}}(t)\cos(2\pi f_0 t) - x_{\mathrm{Q}}(t)\sin(2\pi f_0 t), \tag{3.1}$$

where

$$x_{\mathrm{I}}(t) \stackrel{\text{def}}{=} \Re[x(t)] = \tilde{x}(t)\cos(2\pi f_0 t) + \hat{x}(t)\sin(2\pi f_0 t), \tag{3.2}$$

and

$$x_{\mathrm{Q}} \stackrel{\text{def}}{=} \Im[x(t)] = \hat{x}(t)\cos(2\pi f_0 t) - \tilde{x}(t)\sin(2\pi f_0 t), \tag{3.3}$$

where $\hat{x}(t)$ is the Hilbert transform of $\tilde{x}(t)$, $x_{\mathrm{I}}(t)$ is commonly called the in-phase component of $x(t)$ and $x_{\mathrm{Q}}(t)$ the quadrature. Alternatively this formulation can be written as [36]

$$\tilde{x}(t) = \frac{e^{j2\pi f_0 t}x(t) + e^{-j2\pi f_0 t}x^*(t)}{2}, \tag{3.4}$$

where $x^*(t)$ is the complex conjugate of $x(t)$. This complex baseband representation for passband signals is used in the rest of this thesis.

3.1.1 Baseband model structures

In the previous section the baseband representation for passband signals was presented. However, when dealing with behavioral models, it is possible to find certain characteristics in the baseband model structure that further simplifies the model structure needed for such devices.

In the passband frequency range, a memoryless power amplifier can be thought of as a mapping of a real-valued input signal to a real-valued output signal [37]. Approximating this nonlinearity by a power series – under a range of general conditions for the power amplifier like stability, continuity, fading memory, etc. [28] – the output can be written as

$$\tilde{y}(t) = \sum_{k=1}^{K} \tilde{b}_k \tilde{x}^k(t), \tag{3.5}$$

where $\tilde{x}(t)$ is the passband power amplifier input, $\tilde{b}_k$ are real-valued coefficients, and $\tilde{y}(t)$ is the passband output. From [19], since the output of a power amplifier is normally passed through a bandpass filter centered at $\pm f_0$, only terms that are centered around this frequency will contribute to the output signal and the terms that fall out of this range will be filtered out. Therefore, (3.5) can be constructed in baseband form as [34],[p.69]

$$y(t) = \sum_{k=1}^{K} b_k x(t) \left| x(t) \right|^{2(k-1)}, \tag{3.6}$$

where

$$b_k = \frac{1}{2^{k-1}} \binom{k}{\frac{k-1}{2}} \tilde{b}_k. \tag{3.7}$$

Two important observations can be made from these equations. First, in (3.6), only even order power terms of $|x(t)|$ exist . Secondly, that in (3.7), since $\tilde{b}_k$ is real-valued, b_k are also real-valued. Therefore, only amplitude-amplitude distortions (AM/AM) are generated by a memoryless power amplifier. By allowing the $\tilde{b}_k$ to be complex-valued, quasi-memoryless models can be constructed, which can also account for amplitude-phase distortions (AM/PM). These kinds of complex baseband power series form the basis for most of the power amplifier models presented in subsequent sections.

While this simple power series representation simplified the model structure for power amplifiers, it raised an important issue in the literature regarding the so called *odd* and *even* order power terms. Authors in [38] first noted that using not only odd–order power for the model and including even–order powers improved the modeling performance and rewrote the power series as

$$y(t) = \sum_{k=1}^{K} b_k x(t) \left| x(t) \right|^{k-1}. \tag{3.8}$$

It can be noticed that all powers of $|x(t)|$ exist in this formulation, but the resulting function remains an odd function making it valid for passband modeling. In this thesis both even and odd order power terms are used for polynomial–based models.

By considering the baseband representation, it can be seen that behavioral models can be considerably simplified. Therefore, all models presented in this thesis will be in baseband form and the reductions discussed in this section are applied. In general such simplifications may not be applicable for modulators as they are no longer only passband devices but also operate in baseband.

3.2 PA behavioral models background

A simple categorization is used to help distinguish the models based on the type of distortion they represent, using the classifications mentioned in Section 2.1. Single-input single-output power amplifier nonlinear behavioral models can thus be categorized in four main categories: memoryless models and models with linear memory, and models with short and long term nonlinear memory effects.

3.2.1 Memoryless and Models with linear memory

As described in the previous section, a complex power series can be used for power amplifier modeling. As the input-output relationship only depends on the instantaneous sample, this type of model is commonly called a *static* or *memoryless* model. In this section, first an overview of these type of models is presented, then some models that considered linear memory effects are presented.

Memoryless models

Some popular static memoryless models that have been proposed and used in the literature are the Saleh models [39], both the original and the modified version, the Rapp model [40], the Fourier series models [41], Bessel-Fourier models [41], and Hetrakul and Taylor models [41].

Models with linear memory

As communication signal bandwidth increased in wireless systems, memory effects has become more apparent. The models presented in this section were the first models that attempted to address these effects, by using linear memory.

In the simplest case, authors have suggested that the memory effects and the nonlinearities can be separated. This has resulted in a class of commonly called two-box models. In this class, a nonlinearity is followed by a linear filter – known as the Hammerstein model [42] – or a filter is followed by a nonlinear function – the Wiener model [42] as depicted in Figure 3.1.

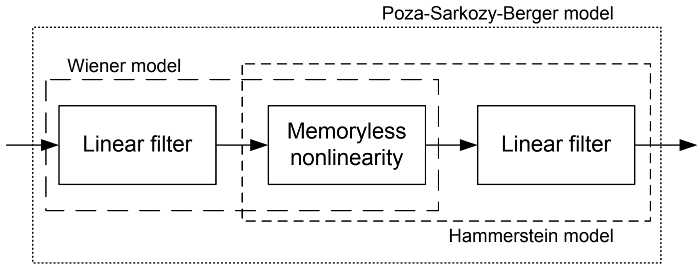


Figure 3.1: The block diagram of the two-box and three-box models.

It should be noted that the Hammerstein model is linear in the parameters, while the Wiener model is not. This will later prove important when parameter identification is discussed in Section. 3.6.1.

In order to better represent linear memory, a three-box model has also been used in the literature. These models tend to have a linear filter - memoryless nonlinearity - linear filter model structure, and are also called three–box Wiener–Hammerstein models. Examples of such models are the frequency dependent Saleh model [39], and the Poza-Sarkozy-Berger model [43]. A simple block diagram of the three classes of models explained is shown in Figure 3.1.

Another class of models are parallel-cascade models that describe nonlinear system with linear memory effects by constructing severely branches connected in parallel. Two of the important models in this class are the polyspectral model [44–46] and the Abuelma'aati model [47].

3.3 PA Behavioral models accounting for nonlinear memory effects

As communication signals become more wideband in modern wireless communication systems, the need for advanced models that can describe nonlinear memory effects becomes evident. Many mathematical tools have been suggested for such modeling purposes, such as polynomial-based functions and neural networks. The focus of this thesis is mainly on polynomial based models, due to interesting properties in identification and ease of use.

3.3.1 Volterra series model

The Volterra series is a widely used mathematical tool for modeling any nonlinear function including memory. The Volterra series and the Volterra theory was developed by Vito Volterra in the late 19$^{\text{th}}$ century [48]. It has been commonly described as a generalized Taylor series with memory, the discrete baseband representation of the Volterra series can be formulated as [5, 49],

$$
\begin{aligned}
y_{\text{Volterra}}[n] = & \sum_{\substack{p=1 \\ p \text{ odd}}}^{P} \sum_{m_1=0}^{M} \sum_{m_2=m_1}^{M} \cdots \sum_{m_{(p+1)/2}=m_{(p-1)/2}}^{M} \\
& \times \sum_{m_{(p+3)/2}=0}^{M} \cdots \sum_{m_p=m_{p-1}}^{M} \theta_{p,m_1,m_2,\cdots,m_p} \\
& \times \prod_{i=1}^{(p+1)/2} x[n-m_i] \prod_{k=(p+3)/2}^{p} x^*[n-m_k]. \qquad (3.9)
\end{aligned}
$$

where P is the nonlinear order and M is the memory depth of the model.

The series can be re-written in matrix form as

$$
\mathbf{y}_{\text{Volterra}} = \mathbf{H_x}\theta, \qquad (3.10)
$$

where $\boldsymbol{\theta}$ is a vector containing all the coefficients $\theta_{p,m_1,m_2,\cdots,m_p}$, $\mathbf{H_x}$ is the generating matrix containing all the permutations of $x[n]$ from (3.9):

$$
\mathbf{H_x}(n,j) = \prod_{i=1}^{(p+1)/2} x[n-m_i] \prod_{k=(p+3)/2}^{p} x^*[n-m_k], \qquad (3.11)
$$

where $\mathbf{H_x}(n,j)$ is the n^{th} row and j^{th} column entry, where j represents different settings for $p, m_1, m_2, \cdots, m_p$. It is common to call (3.11) the *kernels* of the Volterra series.

It has been shown that a wide class of nonlinearities can be represented at good precision with a Volterra filter [50, 51]. It is also interesting to note that while the Volterra series is a nonlinear model, it is linear in the parameters which greatly simplifies the identification process.

It can be noticed further from (3.9), that as the nonlinear order P or memory depth M increases, the number of parameters grows rapidly. This has rendered the Volterra series useful for only mildly nonlinear systems [28], and much research has been focused on finding ways to reduce the number of parameters and terms in the Volterra model. The following is representative of the many models in the literature for PA modeling.

3.3.2 Reduced Volterra series-based models

A popular technique to obtain behavioral models from the Volterra series is to identify and construct a model based on the most important terms in the series. Therefore in practice, these models are often named reduced Volterra series models or pruned–Volterra series models. An overview of some of the most widely-used models are presented in this section.

Polynomial-based models

An important and widely used model is the *memory polynomial* (MP) model [21, 52]. This model can be described as both an extension of the normal polynomial model to include memory, or as a reduction of the Volterra model to only include diagonal terms. A similar model has been constructed in the literature by connecting parallel Hammerstein models [5], and separating the nonlinear and memory terms. In fact, as shown in [23], the memory polynomial model is equivalent to the parallel Hammerstein model but with better compromise between generality and ease of parameter estimation and implementation. The model can be written as

$$y_{\mathrm{MP}}[n] = \sum_{p=1}^{P} \sum_{m=0}^{M} \theta_{p,m} x[n-m] \left| x[n-m] \right|^{p-1} . \tag{3.12}$$

It can be noticed that the memory polynomial model is also linear in the parameters.

Similar to the parallelization of the Hammerstein model in MP, the Wiener model can be parallelized as well. This model, known as the *parallel-cascade Wiener* model [53], can also model nonlinear memory effects in a power amplifier. However, it suffers from the same complex identification as the Wiener model, as it is no longer linear in the parameters.

In [19] a new model is proposed that generalized the memory polynomial model by including leading and lagging terms. This model is called the *generalized memory polynomial* (GMP) model. Compared to the memory polynomial model, there is an extra degree of freedom in terms of choosing the leading or lagging delay.

The authors in [54] derive a *base-band Volterra* series for power amplifier modeling. By rewriting the Volterra series terms with amplitude and phase as inputs, they generalize the memory polynomial model. The model structure is somewhat similar to the GMP structure, derived in a more theoretical manner.

Dynamic Volterra Series

In order to find ways to rewrite the Volterra series, in [55] a new mathematical model for power amplifiers is presented based on modeling the static and dynamic parts separately. This work was constructed into the behavioral model format in [56] and [57]. Further work was done in [58] and [59]. This model, known as the *Volterra model with dynamic deviation reduction* (Volterra DDR), or the dynamic Volterra series representation, reformulates the Volterra series based on the number of dynamics involved. In this way, the number of parameters in the Volterra series may be reduced by choosing a lower number of maximum dynamics.

A similar modeling approach was proposed in [60], where the Volterra series was modified by considering the Fourier integral in place of the convolution, and the *sliding kernels dynamic Volterra series* model was constructed.

3.3.3 Generalized Volterra series based models

Another track of Volterra based behavioral modeling has been to find ways to generalize the Volterra series. This can help reduce the amount of memory depth needed for modeling. However, these models tend to no longer be linear in the parameters, which complicates the identification process.

IIR–based models

The Volterra series is a natural expansion from a linear finite impulse response (FIR) model [61]. In this format, it is assumed that the output signal can be modeled with the input signal only. This assumption may not be generally valid as there is an inherent feedback in the power amplifier circuit. One proposal was the use of infinite impulse response filters (IIRs) in [62], but due to the recursive nature, stability was a major problem.

In order to avoid these stability issues, authors have proposed the use of orthonormal basis functions instead. In [63], the use of *Laguerre functions* as the basis for the Volterra expansion is proposed, replacing the Dirac impulses of the Volterra FIR filter with a fixed-pole orthonormal Laguerre function. This function decays exponentially to zero at a controlled rate, and has a similar structure to an IIR filter with a pre-decided pole to alleviate the stability issues.

In [64], the *Kautz function* was suggested as an orthonormal basis. This model is similar to the Laguerre-based model, except that in the Laguerre-based model the orthonormal-basis poles are chosen to be real, while in the Kautz-based model the poles are allowed to be complex as well. A similar model is constructed in contribution [s] but instead of using a full Volterra, an MP–based model is constructed to reduce complexity.

3.3.4 Models considering long term memory effects

In the models proposed in the previous section, in order to capture memory effects a memory depth parameter is defined that specifies the maximum number of memory taps used in the behavioral model. For the models in Sect. 3.3.2 and Sect. 3.3.3, as the memory depth is increased, the number of parameters of these models increase dramatically, and the complexity of such models deems them practically unusable for capturing memory effects longer than a few samples.

Models that are capable of modeling long term memory effects which, as mentioned in Chap. 2, are becoming more important for bursty data signals have been the focus of research recently. In [65] sparse delay taps were suggested for capturing long term effects. In [66] gray–box knowledge of the thermal filter of the PA is utilized to develop a model that includes long–term memory effects. A lower complex version is proposed in [67] that seperates the model into static and dynamic terms, similar to the dynamic Volterra series. In [68] continuous time models are proposed for capturing long term memory effects, and identification with numerical techniques for this model is presented in [69].

Long–term memory effects with dynamic parameters

In Paper [A] and in contribution [e], a new behavioral modeling technique is proposed that enables capturing long–term memory effects in the parameters of the model instead of constructing complicated model structures. The model is written as

$$y_{\text{model}}[n] = \mathbf{H}_{x[n]} \left(\boldsymbol{\theta}^{(0)} + s[n]\boldsymbol{\theta}^{(1)} \right), \tag{3.13}$$

where $\mathbf{H}_{x[n]}$ can be the generating matrix of any of the previously mentioned models in Sect. 3.3.2, $s[n]$ is a state parameter that tracks slowly–varying long term memory effects (in this work by linear filtering of $|x[n]|^2$), $\boldsymbol{\theta}^{(0)}$ are the parameters of the behavioral model independent of the state parameter $s[n]$, and $\boldsymbol{\theta}^{(1)}$ are the dynamic parameters dependent on state $s[n]$. In Paper [A], the MP and GMP models are used to construct the behavioral model. The block diagram of the proposed modeling technique is shown Fig. 3.2. A simple version of the proposed behavioral model is presented in contribution [70] and a more detailed version and model generalization in Paper [A].

3.3.5 Other models

Some other important models which either could not be easily classified into the groups above or were not the main focus of the thesis are discussed in this section.

Look-up tables (LUT)

A widely used technique to model and predistort power amplifiers, are lookup tables. In this technique, typically the AM/AM and AM/PM characteristics of a PA are used to construct tables for modeling and inverting the PA. In [71], multiple lookup tables for different power levels are used to model and predistort the power amplifier, enabling a faster response to

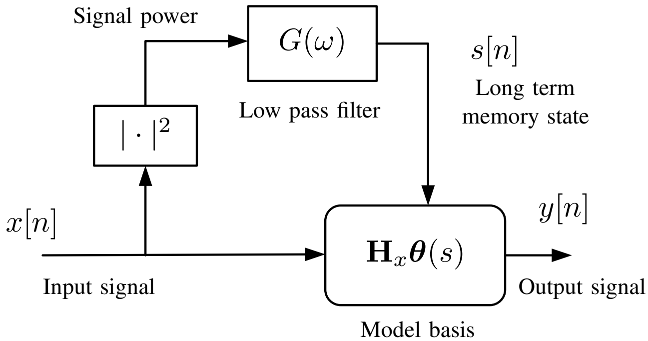


Figure 3.2: Block diagram of a novel modeling technique capable of capturing long term memory effects. $G(\omega)$ is a low–pass filter.

changes in the PA characteristics. In [72] multi–dimension LUTs are constructed to enhance PA linearization.

Switching models

Models which partition the input signal into regions and find different models for these regions have also been analyzed in the literature. *Piecewise Volterra filters* were derived in [73], and it is shown that parameter estimation remains a linear problem when the regions are partitioned. In [74], a *piecewise Hammerstein structure* is used to construct the piecewise model. In [75], *spline functions* are used to switch between different regions. In [76], a model is proposed for envelope tracking applications based on *vector threshold decomposition*. Normally for these types of models, each output sample is constructed by summing the output of many models. Therefore, computational complexity becomes a limiting factor in these type of model structures. In [77] a new switching behavioral model is proposed where the output is only involved with a single model at a time to aleviate this issue. Vector switching is utilized for DPD with good results.

Artificial neural networks

Artificial neural networks (ANNs) have also gained recognition in recent years [78] for PA modeling. It has been shown that the single-hidden-layer multilayer perceptron (MLP) ANN have universal approximation capabilities [79, 80]. Two main approaches have been taken in ANN design for behavioral modeling, MLP and time-delayed neural networks (TDNN) [81–85], and radial-basis function neural networks (RBFNNs) [86, 87]. For TDNNs, it was shown in [28], that the network is similar to the memory polynomial model in structure, with a different nonlinear function. Different approaches have been taken to model the power amplifier using TDNNs, the common approach has been to use two real-valued TDNNs for the I and Q signals and then combine the output. Another approach has been the use of a complex valued neural network [88]. In [81], one real-valued neural network is used with both I and Q as the input. RBFNNs consist of three layers, an input layer, a hidden layer, and an output layer. The input layer to the hidden layer space has a nonlinear transformation using Green's function [89], while the hidden layer to output layer has a linear transformation.

NARMA models

The nonlinear autoregressive moving-average (NARMA) model has been used to model power amplifiers [41, 90]. These models could also be treated as models with nonlinear memory. In this model, a nonlinear feedback path is added to enable the modeling of IIR terms. However NARMA models generally suffer from the same stability issues as in [62]. Some studies on the stability and the stability criterion for this model can be found in [91].

State-space models

Another type of behavioral model that has been used are state-space models [31]. These models may include linear memory terms, or nonlinear terms, based on the formulation. The main advantage with these models is the ability to model the power amplifier behavior as a full two port device, and not as a single-input single output system, which may be beneficial as they can represent both voltage and current changes in systems. Such a model is proposed in [92], where power amplifiers are modeled as nonlinear two-port RF networks. In [93], a dual-input Volterra series model is proposed that takes both RF input and supply power as inputs, to remove voltage ripple of the power supply.

Gray-box models

All models discussed in this thesis were black-box models. However, it is important to also mention *gray-box* models. In these type of models, some knowledge of the internal circuitry is used to find good behavioral models. Identification of such models is discussed in [94], and in [32], the circuit structure is used to find the relationship between parameter terms and physical phenomenon. Authors in [9] and [95] have proposed a low–complex MP model based on the model from [32] that shows better modeling performance in low parameter regions.

3.4 Commonly–used models for modulator modeling

While when modeling power amplifiers some model simplifications – due to the passband nature of the PA – could be made (as specified in 3.1), these conditions no longer hold for modulators. The modulator upconverts the baseband I/Q signal to modulated RF signals to be fed to the PA, and therefore include both passband and baseband nonlinearities (which can be different in the I and Q branch while at RF I and Q are identical). Hence the model structures for modulators may not use the simplifications from Sect. 3.1.1 and general forms are used [96].

In an RF modulator, I/Q imbalance is considered to be the most important distortion [97], and has been categorized in different ways. It has been categorized based on the physical location of the modeling and compensation; either at the transmitter and receiver separately [98–100] or jointly for both transmitter and receiver imbalance at the receiver [101–103], the type of data needed for modeling and compensation; data–aided techniques that utilize pilot symbols [104–106] and blind statistical techniques that use properties like correlation between the I and Q branch for modeling [107–109], whether they are frequency–dependent [110, 111] or independent [112, 113], and finally whether they can model and compensate for linear [108] or both linear and nonlinear effects [114]. In this thesis, keeping with the categorization used for PA modeling, I/Q imbalance modeling is categorized into linear and nonlinear I/Q imbalance sections, with focus on modeling the imbalance in transmitters and for frequency dependent I/Q imbalance as the dominant effect [115]. Some representative models are presented in this section.

3.4.1 Linear I/Q imbalance

Gain and phase

In traditional frequency–independent I/Q imbalance models, only gain and phase mismatch are represented. In [108] and [116] blind estimation techniques are proposed. These techniques, while suitable for narrowband signals, cannot effectively model for memory effects exhibited by the transmitter, and hence may not be useful for modern wideband communication signals.

FIR filters

In [117] it was shown that the performance of frequency–independent I/Q imbalance models is limited by the quadrature down-conversion and the mismatch in complex filtering. In [118] and [119] finite impulse response

(FIR) filters are used represent these type of distortions. In [99] and [100] asymmetrical widely linear filters are used where filtering is done on the conjugate of the signal for compensation. While the experimental results from these works show improvement in representing I/Q imbalance, they are only capable of modeling linear I/Q imbalance and nonlinear effects in the I and Q branches are not modeled.

3.4.2 Nonlinear I/Q imbalance

Nonlinear equalization

In [120] the effect of nonlinearity in the baseband I and Q channels was investigated and shown to considerably affect the performance. Nonlinear equalizers are used in [114] to compensate for static nonlinearities generated by the clipping in the DACs. The results show an improvement in compensating for I/Q imbalance, however no nonlinear memory effects (which occur due to slew–rate limits of operational–amplifiers used to implement reconstruction filters [114]) are modeled and compensated for.

Dual–input I/Q imbalance model

In Paper [B], a new dual–input nonlinear behavioral model is proposed to model for both frequency–dependent and frequency–independent I/Q imbalance. In this formulation, the I and Q branches are separately used to construct two dual–input real–valued DPDs for the I and Q branch, as shown in Fig. 3.3. This modeling enables representing both static and dynamic nonlinearities. Details of this model and the measurement setup used for evaluation is presented in Paper [B]. The model can be further simplified by MP, DDR or GMP (Sect. 3.3.2) models instead of the Volterra series, as shown in contribution [r]. The same modeling approach is also successfully used to jointly compensate I/Q imbalance and PA distortion in contribution [t]. A similar modeling approach using an extended parallel Hammerstein structure for joint mitigation of I/Q and PA distortion is also done in [24], where statistically orthogonal polynomials are used for the nonlinear distortion.

3.5 Comparative analysis of behavioral models

A common issue that is noticed in behavioral model literature, is how to compare the model performance [5, 121]. Obviously, by disregarding model order, the Volterra series will theoretically yield the best performance, since it can model any mildly nonlinear function accurately. In practice however, as the number of parameters grow, the performance is restricted by the uncertainties in parameter identification and computational complexity. Thus,

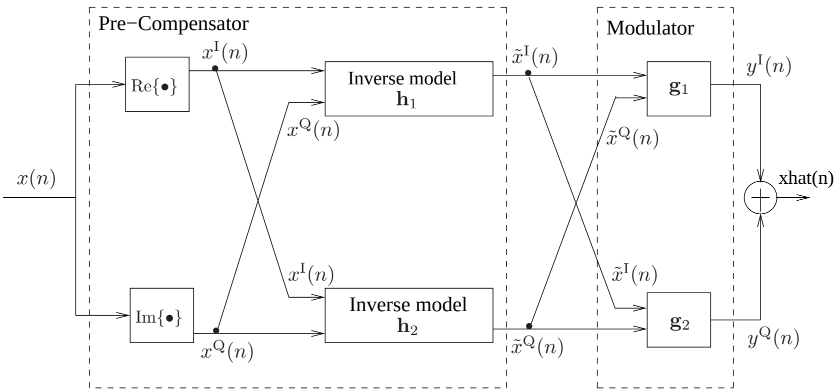


Figure 3.3: Cascade of I/Q imbalance pre-compensator and modulator.

for these reasons, the Volterra series and other Volterra–based models have to be truncated.

Different models are truncated differently, making fair comparisons between them difficult. For example, it is often seen that the performance of a Volterra with nonlinear order 3 and memory depth of 2 is compared with a memory polynomial model with nonlinear order 5 and memory depth 4. Such a comparison may not be comprehendible or fair.

3.5.1 Metrics used for computational complexity

In order to establish a common fair basis for which behavioral models can be compared, computational complexity – how much computational effort is needed to obtain a certain performance – is proposed as an important metric in Paper [C].

In literature, complexity has been notated by different measures [122]. Often it is measured in orders denoted by the Landau symbol $O(\cdot)$, which represents the algorithm complexity. Unfortunately, for behavioral model analysis, this representation is not precise enough for practical considerations [123].

In the area of behavioral modeling, it is common to compare models based on the number of parameters. This can determine the memory size needed for a behavioral model. However, this representation may not always be an appropriate measure. For example, the number of parameters for a neural network may not correctly represent the computational complexity of this model, as the main source of complexity stems from the operations needed per sample, and not necessarily the number of parameters.

The number of floating point operations or FLOPs is another widely used measure for complexity. In most DSP hardware, the computational effort is mainly spent on additions, subtractions and multiplications, which is precisely what FLOPs count.

3.5.2 Different types of computational complexity

Another important issue in behavioral model complexity is where the complexity originates from. They can be classified as:

Identification complexity

The identification procedure differs for behavioral models, as discussed in section 3.6.1. Since the identification of the behavioral model is typically done once and offline, this complexity can normally be considered a relatively minor issue for comparing behavioral models.

Adaptation complexity

In practical systems, due to slight changes in the power amplifier such as temperature change or different mismatching effects, behavioral models might need to be updated at time intervals. These time intervals can normally be much larger than the symbol period. The adaptation of the behavioral model to these changes is considered adaptation complexity.

Running complexity

Running complexity is the number of calculations that is done on each sample when the model is utilized. This complexity severely limits the system due to the fact that it is a real-time problem. Depending on the application, the maximum acceptable complexity varies. The comparisons and focus of the work in this thesis is on this type of complexity.

For this type of complexity, in Paper [C], efficient algorithms for some different PA behavioral models are derived. A general algorithm for implementing Volterra based models from [33] can be simplified in two steps:

Step i) Construct *basis functions* – matrix $\mathbf{H}_{\mathbf{x}}$ from (3.9).

Step ii) Filter the basis with *kernels* ($\mathbf{H}_{\mathbf{x}}\boldsymbol{\theta}$).

The computational complexity of the second step is directly related to the number of kernels, since each kernel will be multiplied by the according basis function and then summed with the remaining results. Thus, the complexity is solely dependent on the number of coefficients. Behavioral

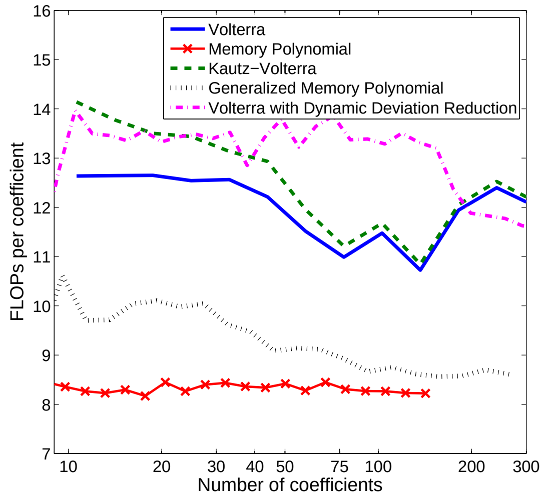


Figure 3.4: Number of FLOPs per coefficient vs number of coefficients for different models.

models will, however, differ in the construction of the basis functions. The complexity C can be written as the sum of the complexity of each part, or

$$C = C_{\text{basis}} + C_{\text{filter}}, \tag{3.14}$$

where C represents the total complexity, C_{basis} represents the basis construction complexity from Step i, and C_{filter} represents the filtering complexity from Step ii. Details on computational complexity is presented in Paper [B].

From Fig. 3.4 (derived from contribution [j]), it can be seen that for different behavioral models, a different number of FLOPs per coefficient is needed, meaning that not all models have the same amount of computational complexity for C_{basis}. Therefore, any comparative analysis of the performance of behavioral models with respect to complexity should include this complexity.

3.5.3 Accuracy/complexity tradeoff

In order to compare different behavioral model performance, the accuracy/complexity tradeoff is developed in Paper [C]. To compare different behavioral models appropriately, all different parameter combinations have to be swept, and scatter plots such as Fig. 3.5 are constructed. By using

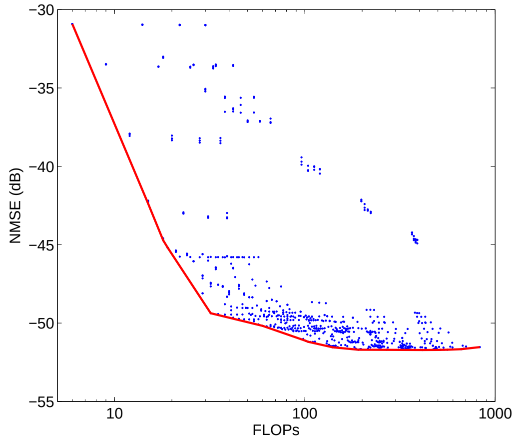


Figure 3.5: Scatter plot of the performance of a behavioral model vs the number of FLOPs. The dots represent the different configurations of parameters. The solid red line shows the convex hull of the configurations that resulted in best performance.

the convex hull of the all possible configurations the accuracy/complexity tradeoff for different behavioral models can be compared. It should be noted that all FLOP-NMSE pairs on the convex hull are not necessarily realizable, but they represent the approximate performance of the model.

The result of comparing different behavioral models with respect to their accuracy/complexity tradeoff is shown in Fig. 3.6. It can be noticed that GMP model performs best and shows the most promise in terms of accuracy vs. complexity. More comparisons and details are analyzed in Paper [B]. Recently in [9] more models have also been compared in this regard with number of parameters as the complexity measure, where a newly proposed model performs better in the low parameter regions.

3.6 Model parameter identification

An important issue in behavioral modeling is parameter identification. It has been noted that black-box models may suffer from uncertainty in modeling [28], and hence, the parameter estimation process needs to be analyzed carefully.

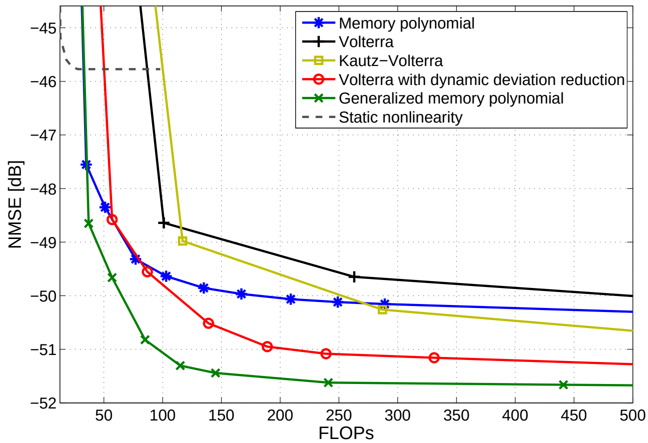


Figure 3.6: NMSE vs FLOPs.

3.6.1 Identification algorithms

Different models will have different parameter identification strategies. All models that are linear in parameters for example, may be identified by the least-squares estimate (LSE) algorithm. This is an important advantage for such models, as the least-squares algorithm guarantees global convergence [124]. The LSE solution by using a training set data with input signal $\mathbf{x}$ and output $\mathbf{y}$ can generally be written as [124]

$$\hat{\boldsymbol{\theta}} = \left(\mathbf{H_x}^H \mathbf{H_x}\right)^{-1} \mathbf{H_x}^H \mathbf{y}, \tag{3.15}$$

where $\mathbf{H_x}$ is a matrix containing all permutations of the input signal of a model structure (for example from 3.9–3.10), and $\hat{\boldsymbol{\theta}}$ is the estimated parameters. In practice, for efficient implementation in computers, (3.15) can be calculated using Moore-Penrose pseudoinverse or QR-decomposition techniques [124, 125].

For models that are not linear in parameters, iterative procedures are typically used for parameter identification. There is no guarantee for global convergence for these models, and in some cases local minima may hinder the identification process. In this work, for the models discussed in Section 3.3.3 a full search of poles for each nonlinear order is used [64]. With this technique, after finding the optimum poles, the problem becomes a normal least squares estimation.

3.6.2 Bias and variance in parameter identification

When identifying a power amplifier behavioral model, it is important to be aware of the two types of errors in parameter estimation; bias and variance. In general, the expected value of the quadratic error in parameter estimation can be approximated as [126],[p500-504]

$$E\left[\left|y(Z^N) - y_{\text{model}}(\hat{\theta}_k, Z^N)\right|^2\right] \approx \underbrace{V_N(\hat{\theta}_k, Z^N)}_{\text{Bias}} + \underbrace{2\lambda\frac{k}{N}}_{\text{Variance}} , \tag{3.16}$$

where V_N is the sum of the squared errors, $\hat{\boldsymbol{\theta}}_k$ are the estimated k parameters, Z^N is the two–by-N input and output data vector, λ is a scaling for the expectation of the square of error, and N is the size of the data set. As the number of parameters grow, the first term, the bias, becomes smaller since more parameters can reduce the quadratic error, but due to the uncertainty in parameter estimation, the second term, the variance, grows.

The implications of this fact is that in order to be able to identify the parameters properly, the data set size has to be large enough to avoid *overfitting*. Overfitting occurs when the number of parameters becomes too large compared to the data set size. This phenomenon can be observed in the two tests in Figure 3.7. In the first test, labeled closed test, memory polynomial models (3.12) with different number of parameters are identified, and the same data set that was used for identification is also used for validation. In the second experiment, labeled open test, the model is identified with one set of data, and another independent set of similarly generated data is used for validation. In these experiments the data length size is kept fixed.

It can be seen that as the number of parameters increase, in the closed test, the model performance consistently improves. However, this is misleading, since in the open test the performance diminishes as the number of parameters increase. This is because the uncertainty in the parameter estimation grows as $\frac{k}{N}$ grows, and overfitting occurs. The overfitting effect can be reduced by using different, but statistically similar, data sets for identification and validation. All model evaluation results presented in this thesis use different data sets for the model identification and validation, respectively.

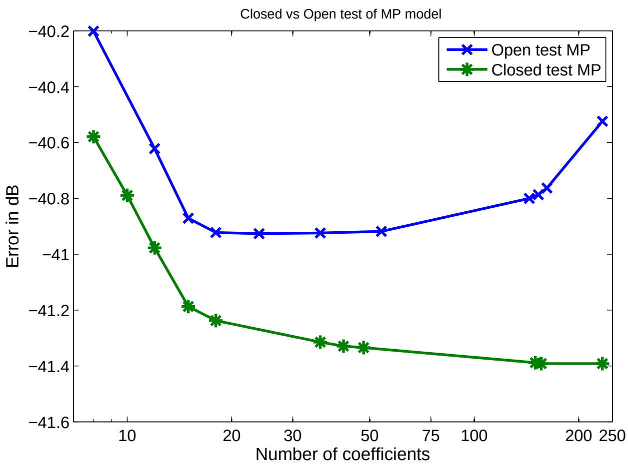


Figure 3.7: Overfitting in power amplifier behavioral modeling identification. The complete data vector is 2500 samples.

Chapter 4

Digital predistortion of RF transmitters

As indicated in Chap. 2, the main challenge in wireless transmitters is the need for high linearity while spending as little power as possible. In this chapter, first a short background is given to explain the basic principles and identification methods for digital predistortion. Some results showing DPD for PAs and modulators is shown. Finally parameter adaptation in digital predistorters is discussed and investigated.

4.1 Identifying digital predistorters

In predistortion, the input signal is fed to the inverse function of the transmitter. If the inverse of the transmitter is constructed perfectly, the overall response of the system of the combined DPD and transmitter will be linear. This is shown intuitively in Fig. 4.1. In practice however, not all nonlinear systems are invertible. This section presents techniques for identifying DPD parameters for Volterra–series and reduced Volterra series based models, with focus on DPD for power amplifiers as the main contributor to distortion in the transmitter.

4.1.1 P^{th} order inverse

In [48, 127] an important theory was developed that states that the inverse of a Volterra system is itself a Volterra system . In [128], it was shown that the P^{th} order *pre-inverse* of a system is identical to its P^{th} order *post inverse*, effectively meaning that it is possible to utilize the easily obtained post inverse of a Volterra system and just copy it as a pre-inverse (correct up to the P^{th} order for linearization). This technique has the drawbacks

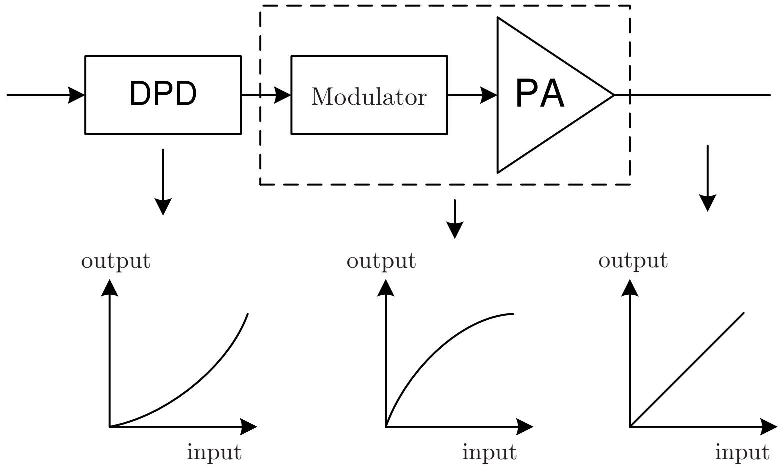


Figure 4.1: Basic principle of digital predistortion.

of being computationally heavy [27], terms of higher nonlinear order than P are not considered, and only stable if and only if the linear part of the system is stable and casual.

4.1.2 Direct learning architecture

In the literature, a different method compared to the Volterra system method utilized in the P$^{\text{th}}$ order inverse has been developed which is based on the self-tuning controller [129], called the *direct learning architecture*. This technique is done by first constructing a direct model of the transmitter and then inverting this model. A block diagram of this method is shown in Fig. 4.2. It should be noticed that inverse of the power amplifier behavioral model is used directly to construct the DPD. This architecture commonly utilizes iterative optimization procedures for the parameter of the DPD to minimize the error [9].

4.1.3 Indirect learning architecture

In practice, the nonlinear function of the transmitter is generally unknown and needs to be estimated from the data, which can be prone to fitting errors [130], and inverting a model constructed by noisy data may not be optimal. A different technique has been developed in the literature by placing the inverter function after the PA at the output. This post–compensator models the output into the desired input, and using Schetzen's theorem, can be used

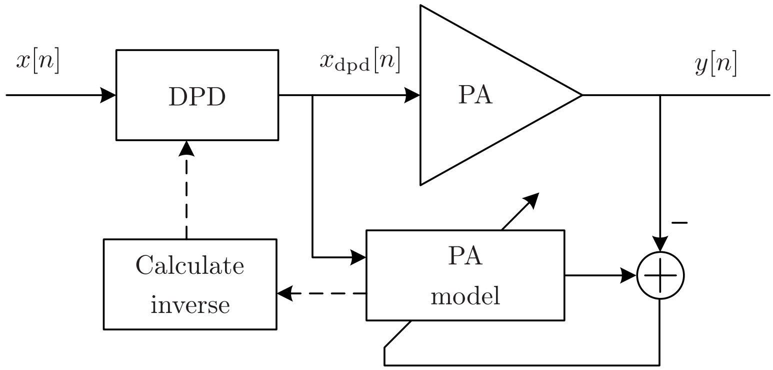


Figure 4.2: Direct learning architecture. The PA model parameters sent to the inverting block, where DPD parameters are calculated from and sent to the predistorter.

as a pre–inverting model for the DPD [96]. This technique is referred to as the *indirect learning architecture* in the literature. This technique is also a special case of the self tuning controller, and is in fact the same as the self-tuning control with inverse modeling. A block diagram of this setup is shown in Fig. 4.3. This method was proposed by [27] and will be used in this work for parameter identification. The parameter identification is similar to that in Sect. 3.6 with the output signal used as the input of the model and the desired output (which is the original input signal before predistortion) as the output of the model.

Using the indirect learning method (ILA), it has generally been shown that when a good behavioral model is obtained, a good inverse model can also be obtained [131]. It was shown in [132], based on the theory from [48] and for Volterra systems, that the model structures that are useful for modeling PAs are also suitable for pre–inverses. This observation is generally applied for non–Volterra based systems successfully as well. For this reason, the focus on this thesis was mostly on behavioral modeling, and once suitable models are constructed the are used for DPD of traditional and non–traditional PA architectures.

Examples of DPD using ILA

In this section two examples of using the ILA for DPD of a power amplifier and a transmitter is presented.

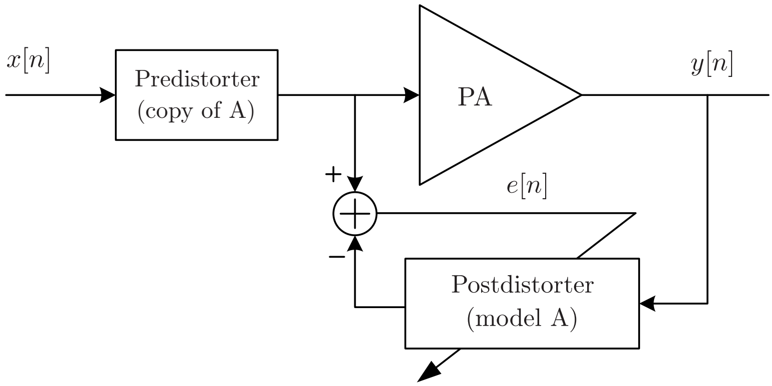


Figure 4.3: Indirect learning architecture. The parameters identified by the postdistorter are copied to the DPD.

PA predistortion

Figure 4.4 shows DPD performance using ILA for a PA with a bursty signal and the setup proposed in Paper [A]. This figures shows the instantaneous NMSE computed over blocks of 4000 samples after predistortion for different models. It can be noticed that the model proposed in Paper [A] with an MP basis (called LT-MP in the figure) successfully improves the linearity of the system by around 3-4 dB in the high power segment. This effect is specifically noticeable in the switching of the bursts where the performance improvement is around 4 dB.

I/Q imbalance compensation

ILA can be used to compensate for distortions created by transmitters as well. Figure 4.5 shows the power spectrum of the errors between the received signal $y(n)$ after pre-compensation using ILA technique for different models and the original input signal $x(n)$, using the setup from Paper [B]. Two cases are analyzed, case A with artificially introduced distortion and case B with no artificially introduced distortion. From the two figures it can be seen that the proposed dual–input nonlinear model has better performance compared to the other compensation techniques.

4.2 Parameter adaptation in DPD

In practical scenarios, to compensate for varying conditions in the transmitter such as PA aging, bias network variations, temperature shifts, and etc., parameter adaptation has been used [135, 136]. As communication systems

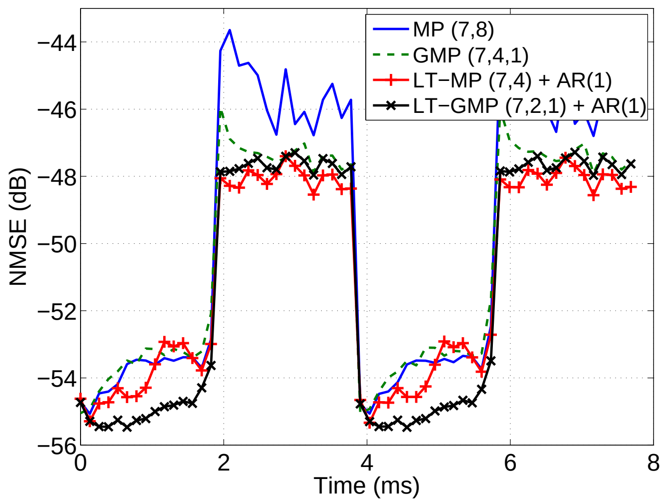
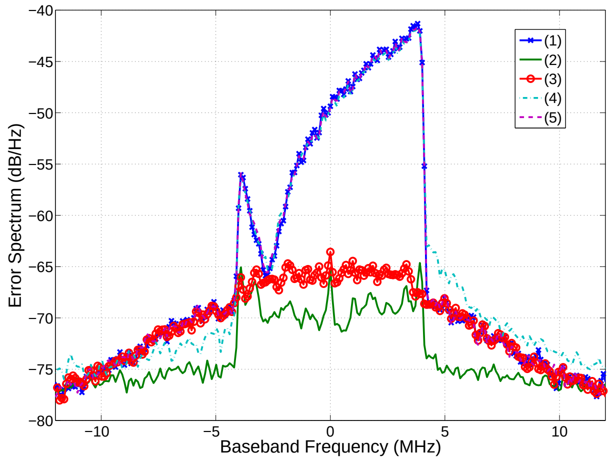
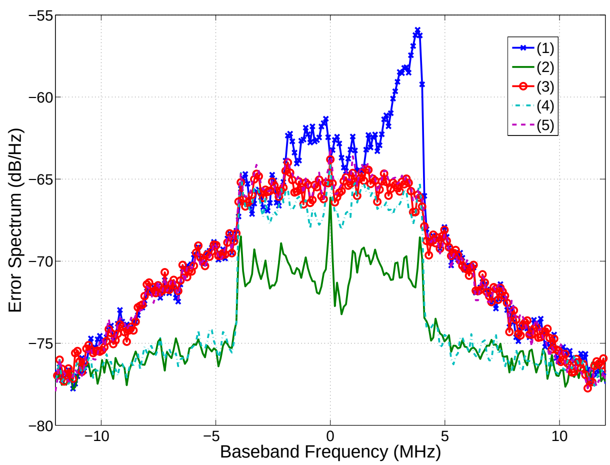


Figure 4.4: Instantaneous NMSE after predistortion for the different models. MP(7,8) represents the MP model with nonlinear order 7 and memory depth 6. GMP(7,4,1) represents the GMP model with nonlinear order 7, memory depth of 4 and maximum lagging terms of depth 1. LT-MP represents the model presented in Paper [A] with an MP basis and LT-GMP with GMP basis.



(a) Case A



(b) Case B

Figure 4.5: Power spectrum of errors after pre-compensation: (1) Without compensation. (2) Proposed dual-input nonlinear model from Paper [C] with nonlinear order 3 and memory depth 4. (3) The linear FIR filters in [133] with 20 taps. (4) Nonlinear equalizer in [114] with nonlinear order 3 and memory depth 4. (5) Linear equalizer [134] with 20 taps.

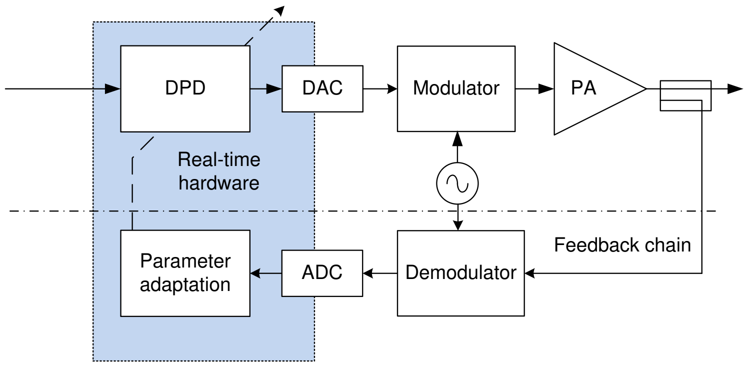


Figure 4.6: Block diagram of adaptive DPD in transmitters.

move towards packet–based systems, and communication networks utilize techniques such as switching PAs off to conserve energy, rapid changes in PA input signal power and temperature drifts require more advanced adaptation systems. This has resulted in the need for complete feedback chains to construct a closed loop for adaptation in the transmitter. Such feedback chains however, greatly increase the hardware complexity in the transmitter and it is important to develop efficient, fast converging and as low-hardware-demanding as possible algorithms. A simplified block diagram of a transmitter with adaptive DPD is shown in Figure 4.6. It can be noticed that in order to analyze and develop adaptation algorithms, real–time hardware like field-programmable gate arrays (FPGAs) and application-specific integrated circuits (ASICs) are needed.

As shown in this figure, parameter adaptation of DPDs is commonly implemented with real–time hardware, which has high development costs both in terms of time and hardware. Further, commonly once these systems are designed, their settings are fixed and changing configurations and structures to analyze performance is highly time–consuming and expensive. From Fig. 4.6 it can be noticed that the performance of adaptive DPD systems is heavily dependent on both the adaptation algorithms used to update the parameters, and the quality of the signal in the feedback path. Issues such as bandwidth and quantization noise in the feedback loop, inphase and out of phase imbalance in the direct and feedback path, timing, convergence speed etc. are important issues that need to be analyzed and investigated, which requires a flexible measurement setup.

In the literature, in order to implement and analyze adaptation algorithms, due to the high cost in equipment and time required for designing a complete closed loop system, two approaches have been taken, using LUTs instead of Volterra series based behavioral models, and iterative identification and adaptation using block-based techniques.

4.2.1 LUT–based techniques

LUT–based DPDs implementation has been well–studied in the literature. In [137] an adaptive predistorter is proposed and used to construct one and two dimensional lookup tables. In [138] Cartesian feedback is used to train a Cartesian look-up table which resulted in a reduced amount of digital signal processing (DSP) circuitry. A $\Delta\Sigma$ modulator is utilized in [139] by placing a LUT in the feedback path which enables the $\Delta\Sigma$ to invert the PA nonlinearity and perform interpolation between LUT entries. A new technique is developed in [136] and analyzed further in [140] that combines analog feedback predistortion by adding a look-up table in the feedback path and combining it with the forward path LUT, which shows faster convergence compared to previous techniques. Multiple LUTs are used in [141] for adaptation, which are also implemented on an FPGA board and tested on prototyping scenarios. NARMA–based LUTs are used in [72] and are implemented both in real–time with FPGAs and with an external adaptation scheme with a DSP. These approaches generally suffer from a huge increase in size of LUTs needed to compensate for the different drifts in PA behavior.

4.2.2 Block–based techniques

Another approach has been to use neural networks and Volterra–series based structures and utilize iterative block–based updates [81, 142–144]. In these techniques a block of data is uploaded and captured from the setup (this block can either be the entire data set [81,144] or shorter blocks for faster updates [143]), an adaptation technique, such as ILA or modified least squares (MLS), is used to update the parameters, then the next block of data (or the entire signal again) is passed through the adapted DPD and fed to the setup. Although the block based technique represents parameter adaptation, it is not able to accurately describe the closed loop adaptation that happens in practice where the PA is constantly run and not turned off for parameter updates. For example in traditional measurement setups, after the data is captured from the PA and fed to the PC, the PA receives no data while the new data is fed to the DPD and uploaded to the system, which means the the PA will face temperature drifts and the state of the PA is not consistent with the closed loop performance in real–time. In order to be able to mimic the real–time performance of adaptation systems, a measurement testbed needs to be constructed that addresses these issues.

4.2.3 Measurement setup for parameter adaptation in behavioral model–based DPDs

In order to accurately represent the closed loop adaptation transmitter in Fig. 4.6 with an open–loop structure, it is vital to ensure that the PA is in a consistent state with respect to the closed loop architecture. Developing a flexible measurement setup that enables analysis of parameter adaptation is a focus of Paper [D]. This is achieved by utilizing multiple measurements with overlapping blocks, where the final portion of the block is used at each step to update the DPD. By using enough of an overlap from the previous block we can ensure that the PA is in a correct state. The block diagram of the proposed open–loop adaptation testbed is shown in Fig. 4.7.

In order to maintain a known state at the beginning of the process, an initialization block is added before the original data. The only requirement on this data is for it to be known, so the start of the data under analysis is not random. In the initialization step, after capturing the data from the output of the PA and sending it to the PC, we can add artificial hardware impairments in the digital domain, such as quantization noise, bandwidth limitations, etc, as we see fit to investigate robustness of the different adaptation algorithms. This is shown in the figure with the feedback impairments block. It should be noticed that only the final portion of the data is used for analysis, shown with a gray box, to ensure that the PA is in a correct state.

After adding artificial impairments to the signal, the captured PA output is used to update the parameters of the DPD using an adaptation technique. The next block of data is fed to the DPD with the updated parameters, and the output of the DPD is placed at the end of the block of data to be uploaded instead of the original block of data. This is shown for Adaptation step 1 with the red data used instead of the data labeled Block 2 and for step 3 with the green data.

The measurement setup is utilized to investigate the performance of different parameter adaptation techniques. Fig. 4.8 shows the NMSE vs time for the different adaptation techniques and setup as specified in Paper [D]. When the input data amplitude increases, it can be noticed that the models show a loss in performance. However, as the parameters are updated to reflect on the changing behavior of the PA, the performance is improved. This is consistent with what is expected in a real–time adaptation setup, but adds the flexibility to change configurations and settings for a more thorough analysis on issues such as convergence speed, the effect of quantization noise in the feedback loop and etc.

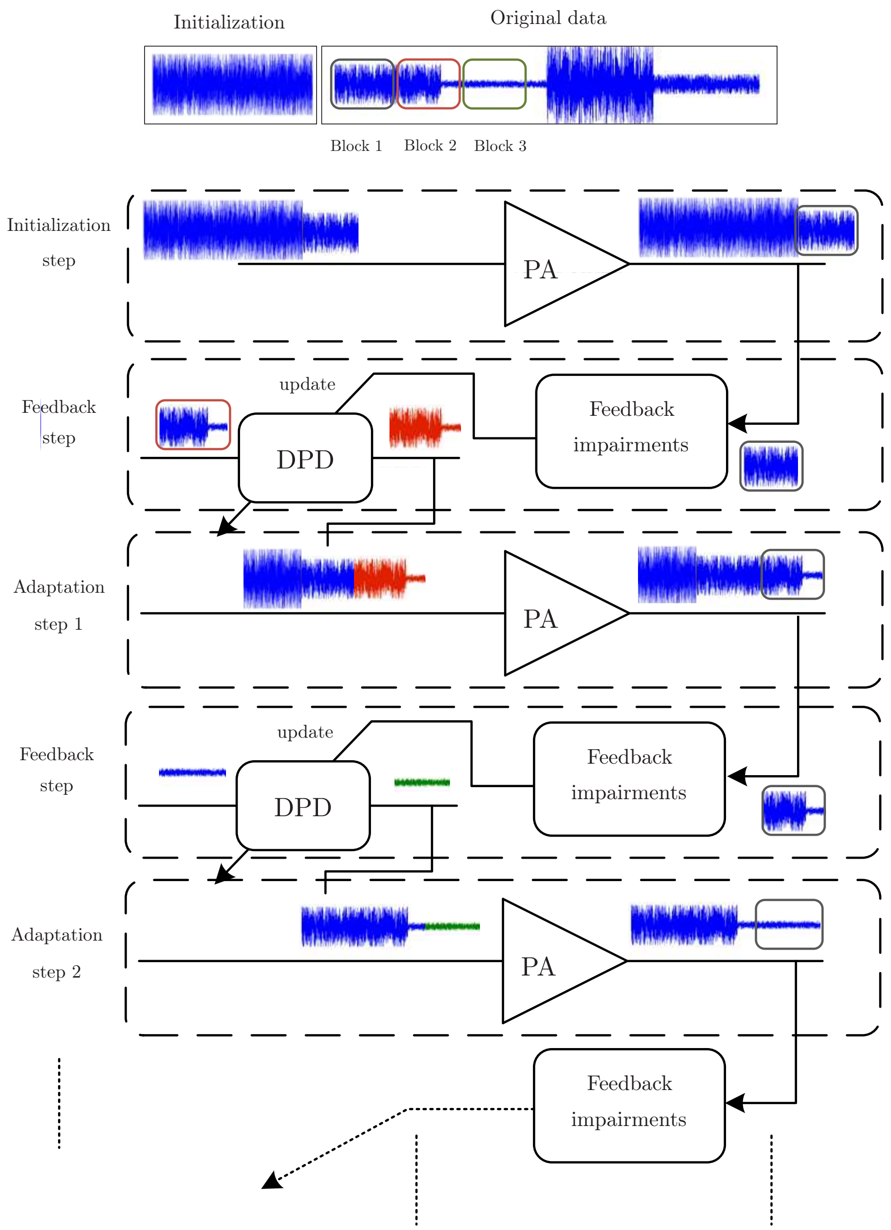


Figure 4.7: Proposed open–loop testbed to mimic the closed loop adaptation DPD from Fig. 4.6 without real–time hardware.

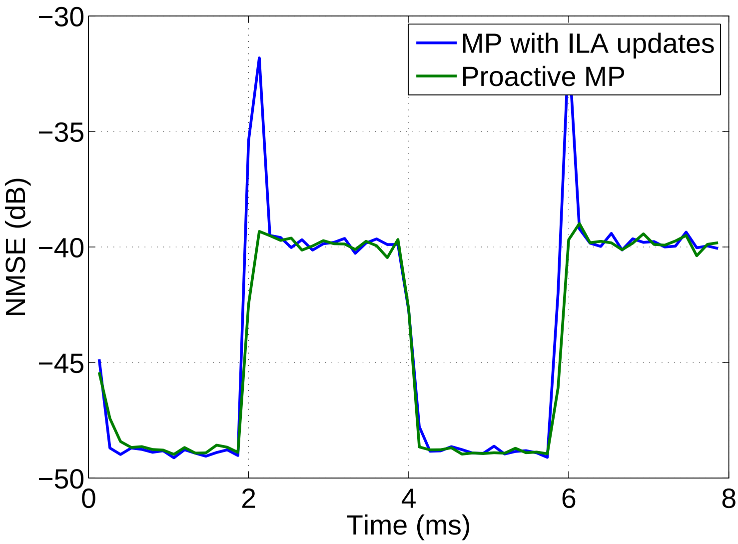


Figure 4.8: NMSE vs time for the different models. The models and adaptation algorithms are specified in Paper [D].

4.3 Summary

In this chapter identification and parameter adaptation in DPDs was presented and discussed. The indirect learning architecture was used to successfully linearize distortion created by power amplifiers and also to compensate I/Q imbalance using a newly proposed model. Finally the issue of parameter adaptation in RF transmitters was addressed, and a measurement setup that emulates a practical adaptive DPD based on utilizing repeated measurements is developed. This setup alleviates the need for real–time hardware and allows the flexibility to investigate parameter adaptation in behavioral model based DPDs.

Chapter 5

Conclusions, Contribution, and Future work

5.1 Conclusions

This thesis addresses the issues of modeling and distortion compensation in modern wireless transmitters. Issues such as modeling accuracy, transmitter linearity and computational complexity have been addressed, and modeling and linearity of PAs with bursty data signals have been successfully done.

Important issues in power amplifier model structure design has been addressed, and some representative power amplifier behavioral models in the literature were presented and organized depending on how they address memory effects in PAs. A new behavioral model is proposed that is capable of tracking changes in PA behavior due to bursty input data, which is a general trend in modern packet–based communication signals. The complexity of behavioral modeling is addressed as an important issue and the tradeoff between complexity and accuracy for some behavioral models was presented. It was shown that accuracy by itself can not completely represent behavioral model performance, but that computational complexity must be considered as well.

A dual–input model for IQ modulator compensation was introduced, that enables modeling and compensation of both linear and nonlinear and memory effect distortion created by modulators. The proposed technique is also capable of jointly compensating for PA and I/Q imbalance distortions. Finally parameter adaptation in behavioral model–based DPDs is discussed, and a measurement setup framework capable of mimicking parameter adaptation without real–time hardware is developed. The setup is used to investigate convergence speed and the effect of quantization noise in some parameter adaptation algorithms.

5.2 Contribution

A short description of the contribution of the author in each paper is presented in this section.

Paper A - Black-box Modeling and Compensation of Long Term Memory Effects in RF Power Amplifiers

This paper presents a novel approach to model and compensate for long–term memory effects in RF power amplifiers due to bursty input signals. The proposed modeling technique extends commonly used behavioral models by placing a long term memory effect in the parameter of the model. Identification and performance of this model is also presented.

My contributions are: Design, analysis, identification, and evaluation of the behavioral model. Laboratory measurements. Authoring the paper.

Paper B - I/Q imbalance compensation using a nonlinear modeling approach

This paper constructs a new model that can represent all kinds of distortion created by an I/Q modulator. In this model, we separate the input signal into the real and imaginary parts and construct a dual–input model to compensate for the distortions. Results show that the model successfully compensates linear and nonlinear distortions in I/Q modulators.

My contributions are in: Identifying the problem, model structure construction, proof–reading and coauthoring paper.

Paper C - A comparative analysis of the complexity/accuracy tradeoff in power amplifier behavioral models

In this paper, complexity of power amplifier behavioral modeling is discussed and FLOPs are suggested as a suitable measure to compare behavioral models. Computational complexity for some behavioral models is calculated, and experiments are done to analyze the accuracy/complexity tradeoff for these models. For the models tested, it was shown that the generalized memory polynomial model showed the best accuracy/complexity tradeoff.

My contributions are: Constructing models in Matlab, finding the complexity for different models. Laboratory measurements. Authoring the paper.

Paper D - Investigation of Parameter Adaptation in RF Power Amplifier Behavioral Models

In this paper, a new measurement framework is developed to mimic real–time adaptation systems while maintaining flexibility in the design process.

This setup is used to investigate different properties such as convergence speed and the effect of quantization noise in some adaptation algorithms.

My contributions are: Design and construction of the setup framework, laboratory measurements, analysis of adaptation algorithms and authoring the paper.

5.3 Future Work

The work presented in this thesis provides solutions to some of the practical problems in PA and transmitter modeling and linearization and can be extended in any of the following ways.

Addressing the issue of linearity without considering power efficiency in transmitter architectures is not complete. As higher power efficiency architectures are developed, the need for behavioral models that are better representative of such systems is becoming more apparent. These models should be able to capture and compensate distortive effects in such architectures with acceptable complexity. Some interesting architectures are envelope tracking and dynamic supply modulation architectures, dynamic load modulation architectures, and outphasing architectures.

In modern wireless systems, it is becoming common to include many standards on the same device, and this has led to needing multiple RF chains. It would desirable to be able to reduce the number of RF chains in for example cellphones to reduce power consumption in these devices. This provides both hardware and software challenges. For example one common solution is by carrier aggregation, sending two signals with different center frequency through the same PA. Modeling and compensating for the distortive effects of the PA on the two different signals will be vital for use of such techniques. Such a modeling approach can also be taken for compensating for distortion in MIMO systems.

Another interesting topic is to identify and compensate distortion at the receiver instead of the transmitter. This will enable the operation of the transmitter in a more nonlinear, and thus more power efficient, state. This can be done with or without the knowledge of the PA behavioral model, either by sending the model information as overhead or estimating it directly from the data.

Finally parameter adaptation for behavioral model–based DPD systems can be analyzed further. This is an important area that has been lacking mainly due to complicated design process involved in real–time systems, and by utilizing the flexible technique proposed in this work more detailed analysis can be done.

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