Digital Pre-Distortion Using Deep Learning

A Project Report

submitted by

POTTIGARI SACHIN MOHAN (EE19M024)

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CERTIFICATE

This is to undertake that the Thesis titled **DIGITAL PRE-DISTORTION USING DEEP LEARNING**, submitted by **POTTIGARI SACHIN MOHAN (EE19M024)**, to the Indian Institute of Technology Madras, for the award of **MASTER OF TECHNOLOGY**, is a bona fide record of the research work done by me under the supervision of Professor Devendra Jalihal. The contents of this Thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

Dr Devendra Jalihal
Project Guide,
Professor,
Dept. of Electrical Engineering,
IIT Madras, 600 036

Place : Chennai
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ABSTRACT

The aim of the project is to use deep learning to implement digital pre-distortion. Non-linearities are introduced when a power amplifier is operated close to its peak power. The term "digital pre-distortion" refers to a technique for distorting a signal before it enters the PA so that the output will remain linear even when the amplifier is operated at near peak power. The effect of predistortion can be viewed through AM-AM, AM-PM plots and also in spectral plots as pre-distortion results in the suppression of the side bands of the output spectrum that arises due to the nonlinearity of power amplifier. Due to inability to access a physical power amplifier, a power amplifier was modelled using RF Blockset library in Simulink where the amplifier can be modelled as nonlinear, memory polynomial using a Memory Polynomial Model which is derived from the Volterra series that is commonly used to represent any form of non-linearity with M-tap memory. Prior to applying neural networks approach for DPD, a primitive algorithm which is based on inverse characteristics approach was employed. The effectiveness of neural networks over this primitive algorithm comes to forefront when the neural networks approach could compensate even for the memory effect of the power amplifier. Quantitative analysis in terms of band powers and suppression in the sidebands due to compensation by DPD has been done as part of the project.

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CHAPTER 1

INTRODUCTION

The power amplifier is a critical part of a wireless communication transmitter (PA). The PA should be operated at or close to its peak power for maximum efficiency. However, this could cause the device to operate in a non-linear manner. Non-linearity introduces spectral re-growth outside of the allocated bandwidth. In addition, in-band distortion caused by the PA's non-linear behaviour causes higher error vector magnitude (EVM) at the transmitted output in the case of linear modulations. Linearisation techniques are used to achieve both linearity and efficiency at the same time. The non-linearity exhibits memory effects for wideband waveforms with symbol durations comparable to the device memory, making compensation challenging.PA linearization can be carried out in either the analogue or digital domains. Due to the freedom of design as well as the diversity and repeatability of implementation, the latter is frequently chosen.

Digital Pre-Distortion (DPD) is a popular linearisation approach that pre-distorts the envelope using baseband digital signal processing so that the distortion generated by the PA may be recovered. The idea is driven by the fact that baseband equivalent discrete-time models may be used to predict the behaviour of the PA and thus its inverse (the pre-distorter).Deep Neural Networks (DNNs) have recently gotten a lot of attention in the signal processing field, especially in the areas of image and speech processing. The application of DNNs to solve communication challenges is a relatively new technique. Two techniques or approaches to employ DPD for a power amplifier are discussed in the thesis. The first is an Inverse Characteristics Approach, which is a primitive algorithm to apply DPD.The second technique is using DNNs to employ DPD to achieve linearization. The effectiveness of using DNNs for DPD comes to the forefront when this approach could compensate even for the memory effects.

1.1 Memory effect on a Power Amplifier

The time difference between excitation (input) and response (output) is characterised as memory. Only when the system to which stimulation is applied could slow down can this happen. Those means are components capable of storing electromagnetic energy, e.g., inductors and capacitors. Nonlinearity in an amplifier manifests itself as a change in gain (compression or expansion) and the development of intermodulation products. It is intuitively clear why additional products are generated because the total power of the signal in the time domain is represented by spectral components in the frequency domain, so the sum of all components must be constant and equal to the value of total power. Thus, if one of those components' power is reduced due to compression, there will be increase in power in other components, which is confirmed by Parseval's theorem. Fig. 1.1 illustrates the effect of memory observed in an AM-AM plot, which is a plot of variation of output power versus variation in input power.

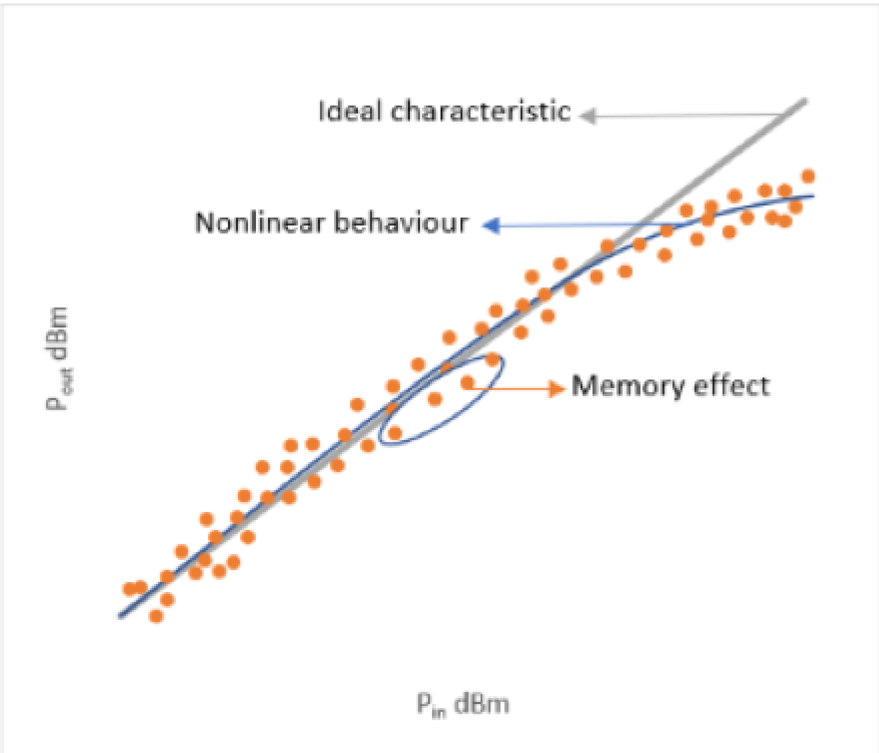

Fig. 1.1: Generalized AM-AM plot

1.2 Flow of Thesis

- In the first chapter, basic introduction to the project was discussed.
- In the second chapter, the Inverse Characteristics Approach of Digital Predistrotion for linearizing a PA will be discussed.
- In the third chapter, modelling a PA in simulink usinf RF Blockset will be discussed.
- In the fourth chapter, quantitative analysis of the Neural Networks Approach will be discussed.

CHAPTER 2

Inverse Characteristics Approach

The idea behind this technique is to subject the input signal to the inverse AM/AM and inverse AM/PM characteristics, and then pass the predistorted signal through the PA, which would result in an improvement in linearity. The figure below gives a pictorial representation of this approach.In the figure, PD stands for predistorter, PA stands for power amplifier. AM/AM curve is the plot of power at output of PA vs power at input of PA. AM/PM curve is the plot of phase difference between synchronized input and output symbols vs power at input of PA. Ideally, the AM/AM plot for a PA should be a y=x line when input and output samples are normalized, and AM/PM curve should be along the x axis i.e. zero over the entire range of input power levels.

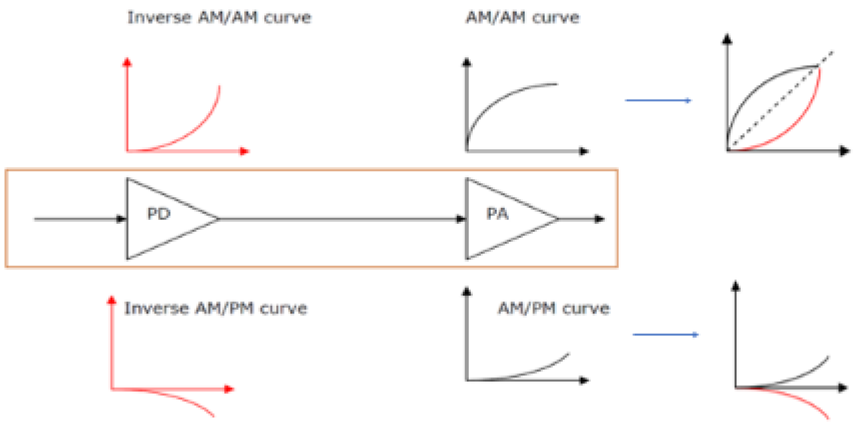

Fig. 2.1: Inverse Characteristics Approach

In the Fig. 2.1, PD stands for predistorter, PA stands for power amplifier. AM/AM curve is the plot of power at output of PA vs power at input of PA. AM/PM curve is the plot of phase difference between synchronized input and output symbols vs power at input of PA. Ideally, the AM/AM plot for a PA should be a y=x line when input and output samples are normalized, and AM/PM curve should be along the x axis, i.e. zero over the entire input power levels. The graphical representation of the algorithm for this approach is shown in the figure below.

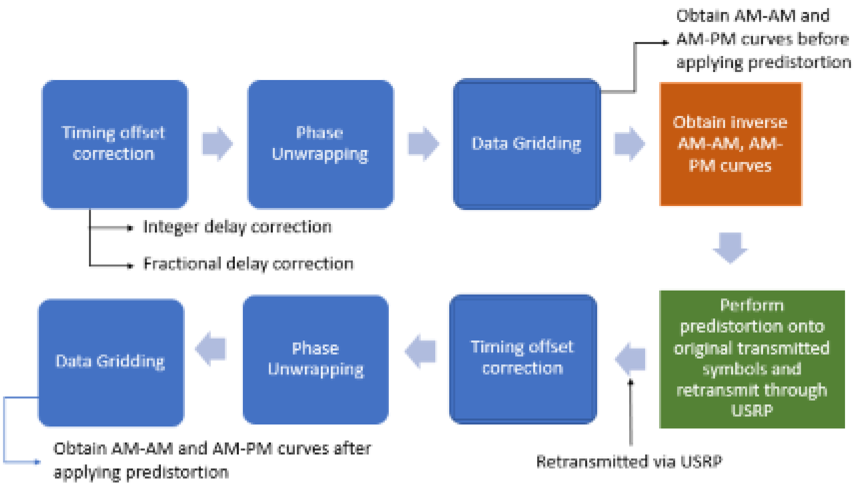

Fig. 2.2: Graphical Representation of Inverse Characteristics Algorithm

Timing offset correction, phase unwrapping and data gridding are applied to obtain the plots before applying any predistortion. The purpose of data gridding is to obtain averaged characteristic curves and it also eliminates any outliers in the data if present. Once the curves are obtained, we can obtain the inverse AM-AM and AM-PM curves, then using the polynomial coefficients that characterize the inverse AM-AM and AM-PM curves, predistortion is applied onto the original transmitted symbols. On transmitting these symbols through the PA and follow the steps as explained above to obtain the new AM-AM and AM-PM characteristic curves. To establish the correctness of the algorithm, before applying this algorithm onto a real-world dataset, it was applied on simulated datasets.The first dataset is of the uniformly distributed constellation in the square with vertices [+0.7, +0.7], i.e. the maximum magnitude over all these transmitted symbols does not exceed one. The received symbols are a delayed and non-linearity induced version of the transmitted symbols. An arbitrary delay(in samples) has been forced upon the transmitted samples. The plots obtained are for the following scenarios:
1) Fifth order non-linearity with real coefficients, i.e. $x - 0.1x(|x|)^2 + 0.005x(|x|)^4$ is introduced.
2) Fifth order non-linearity with complex coefficients :
$x - 0.1x|x|^2 + (0.005x|x|^4)\, e^{j\pi/4}$

To observe the spectral suppression in the sidebands, instead of using samples corresponding to the arbitrary constellation as in the previous case, QPSK symbols(with max amplitude of 1), at a sampling rate of 2M samples/sec and 16 samples per symbols, accounting to 125K syms/sec with a rolloff rate of 0.2, are used. The power spectra are plotted for the original transmitted symbols, received symbols before applying predistortion and received symbols obtained after applying predistortion. Welch averaged periodogram method with 50% overlap is used for plotting the power spectrums.

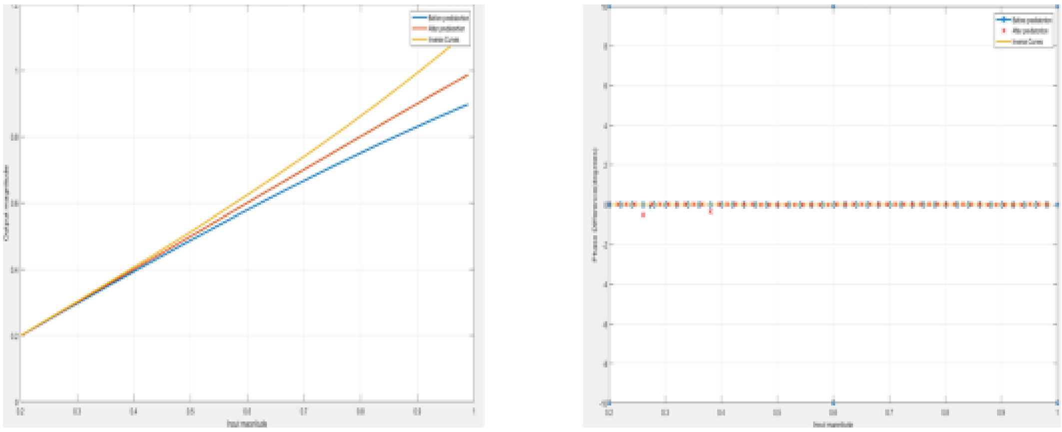

Fig. 2.3: AM-AM and AM-PM plot for real coefficients scenario

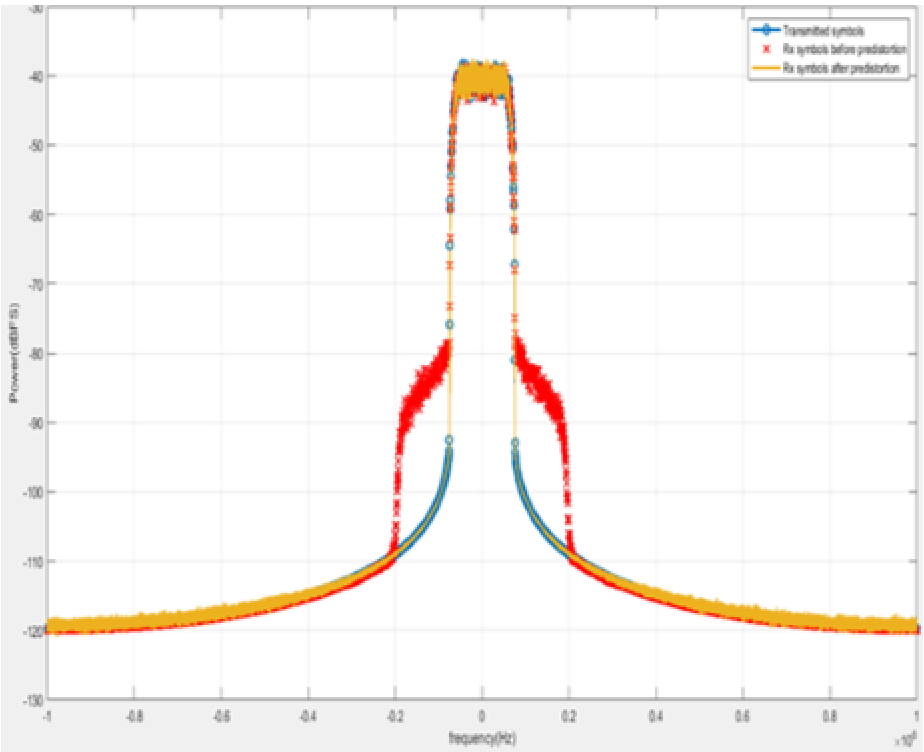

Fig. 2.4: Power Spectra for real coefficients scenario

From Fig. 2.4 and Fig. 2.6, we can infer that the algorithm is able to suppress the side bands arising in the spectrum of received symbols due to the nonlinearity.

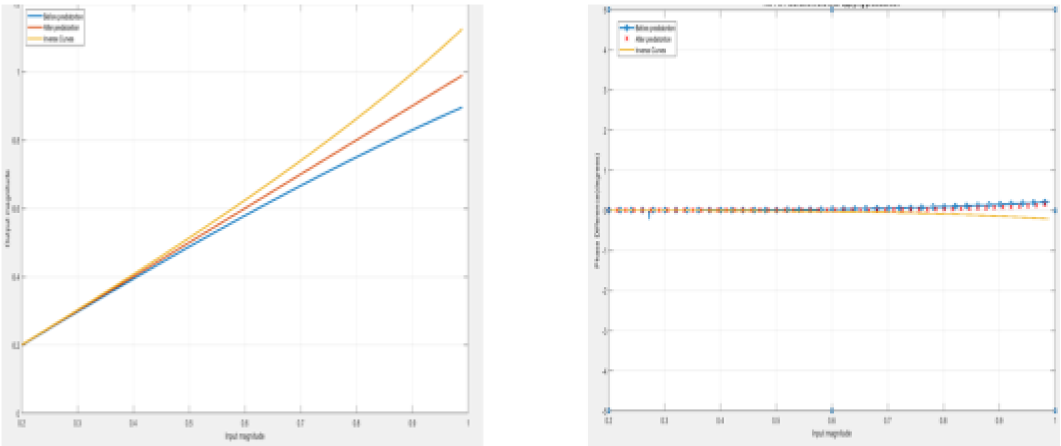

Fig. 2.5: AM-AM and AM-PM plot for imaginary coefficients scenario

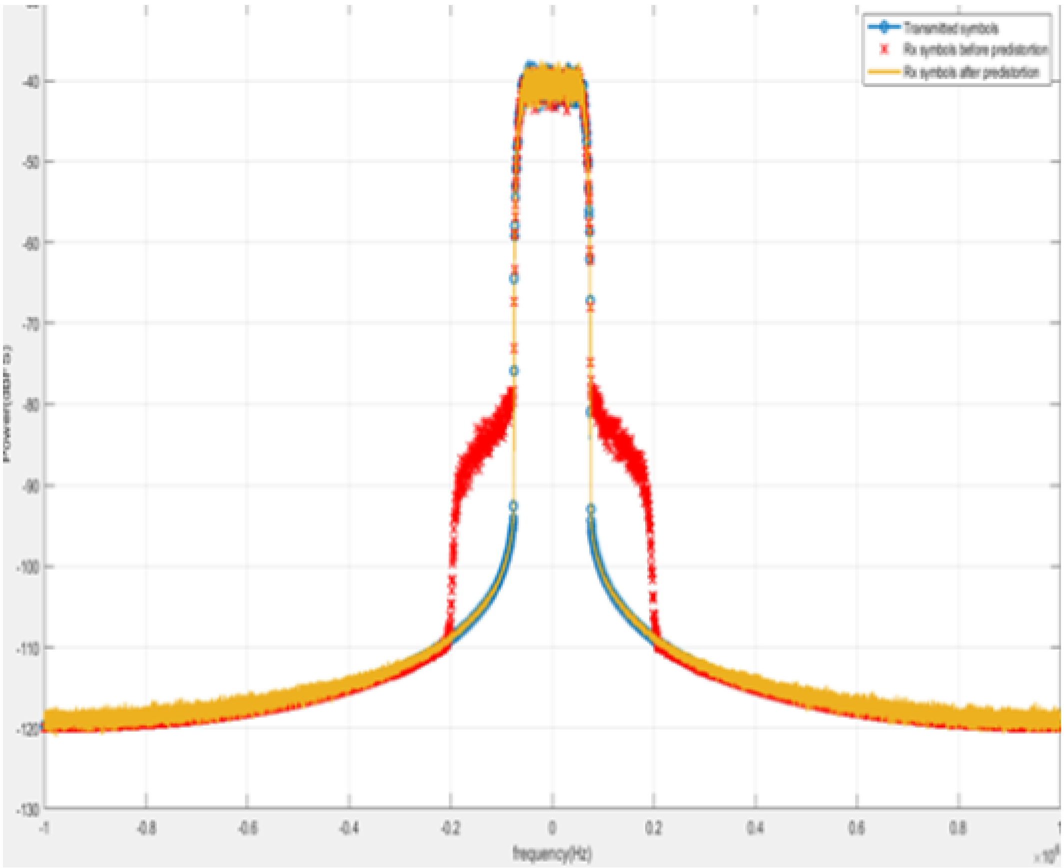

Fig. 2.6: Power Spectra for imaginary coefficients scenario

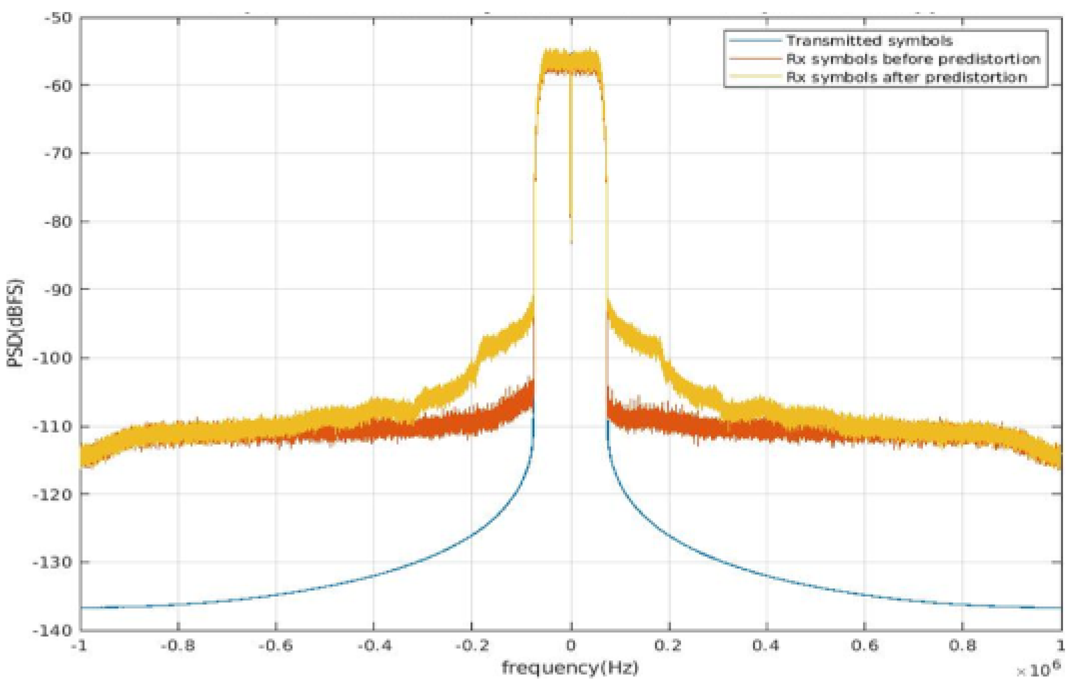

Fig. 2.7: Power Spectra for real world dataset

It is also clear that this algorithm works well with memoryless PA models with real or complex coefficients. When this algorithm is employed on a real world dataset, it fails to linearize the PA. Infact it further increases the power in the side bands after compensation as shown in Fig. 2.7.

CHAPTER 3

Modelling a PA using RF Blockset

RF Blockset provides a Simulink model library that allows us to simulate RF transceivers and front ends. We can model nonlinear RF amplifiers to estimate gain, noise, even-order and odd-order intermodulation distortion, including memory effects. In case of absence of access to a physical power amplifier, this RF Blockset library could be used to model a PA. The way to model is, we have to provide input and output samples from a real power amplifier setup and the polynomial coefficients that caharacterize the PA are derived as a least square estimation of the 'Memory Polynomial' model as in the equation:

$$y_{MP}(n) = \sum_{k=0}^{K-1} \sum_{m=0}^{M-1} a_{km} x(n-m)|x(n-m)|^k \tag{3.1}$$

This equation is derived from the Volterra series, which is generally used to represent any form of nonlinearity with M-tap memory. In 3.1, m represents memory length and k represents order of nonlinearity. Suppose we want to fit a polymial to the input and output data that we have and let us say we want a memory length of 3 and order of nonlinearity of 3, then the coefficients a_{km} are elements of a 3x3 matrix comprising of complex numbers, which are obtained using least squares estimation.

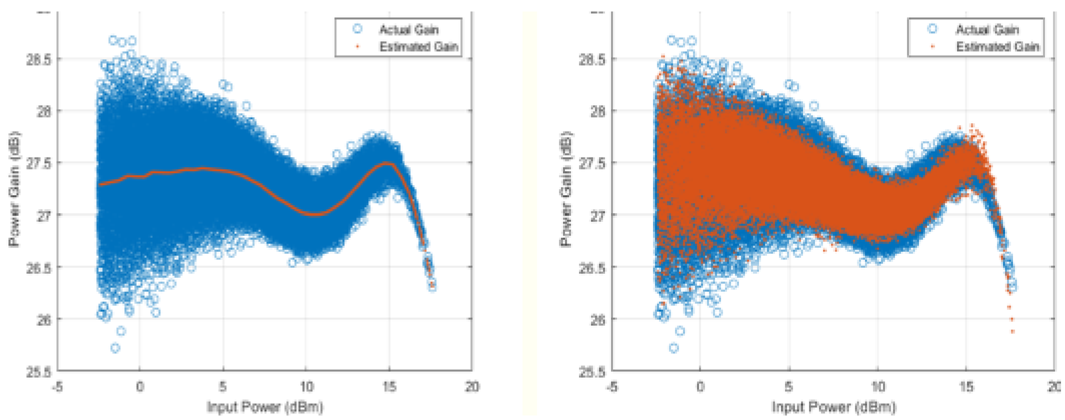

Fig. 3.1: Memoryless vs Memory Model Fitting

Real world data obtained for an NXP Airfast PA by passing a 100MHz OFDM waveform with 64-QAM modulation at a sampling rate of 860.12 MHz is used to model the PA in Simulink for the thesis. Fig 3.1 depicts the comparison of actual gain vs estimated gain of the PA when the amplifier is modelled as memoryless non-linear model with 5th order nonlinearity. To validate the fitting, percentage RMS error of the fitted signal with the actual output signal could be computed.

Memory length	Degree of Non-linearity	RMS error(%)
1	3	12.1884
2	3	8.7763
3	3	7.0758
4	3	6.68
5	3	6.2159
1	5	9.0412
2	5	8.5599
3	5	6.9641
4	5	6.4847
5	5	6.1056
6	5	6.073
7	5	6.018

The table above indicates the RMS error in percentage when varying the memory length and degree of nonlinearity for fitting the input and output data to model the PA. The RMS error is about 12% when the PA is modelled as memoryless and when modelled with memory length of 5 or above, it comes down to 6%. Since the RMS error does not dip by a considerable amount for memory lengths greater than 5, henceforth for the thesis, the PA was modelled as 5^{th} order nonlinear, memory length.

CHAPTER 4

Neural Networks Approach

A quantitative analysis to the already established algorithm was done as part of the project. In this approach, a neural network is trained as a predistorter and symbols are first passed through this network and then through the memory polynomial function that represents the power amplifier. The neural network that is trained as a predistorter has 2 hidden layers. The pictorial representation of the algorithm is as follows.

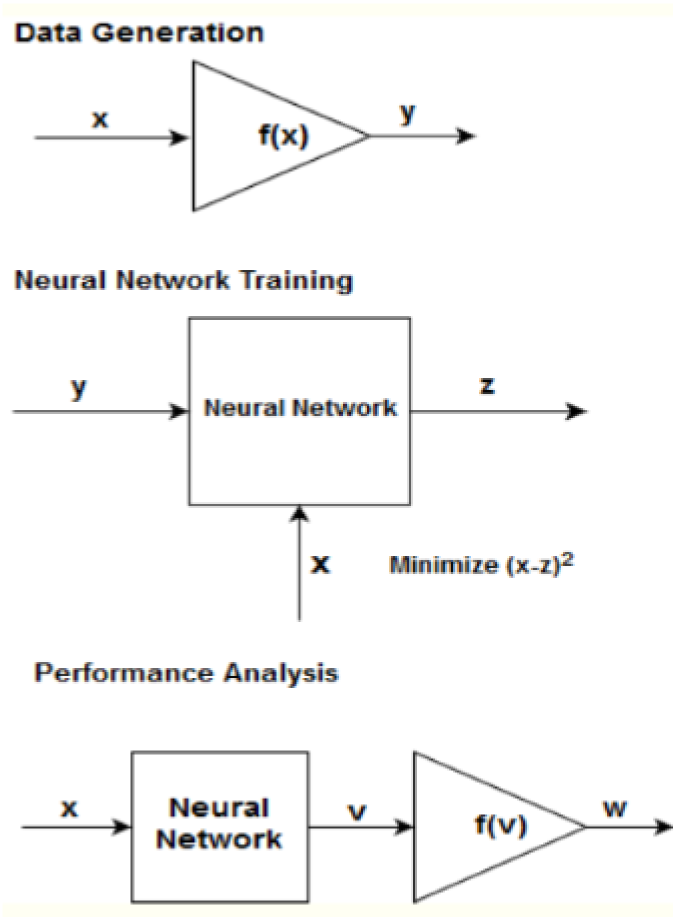

Fig. 4.1: Neural Networks Algorithm

In fig. 4.1, the f(x) function represents the PA characteristic polynomial defined by the Memory Polynomial Model.The PA that is represented here is an NXP Airfast

PA which has an operating frequency range from 3.6GHz-3.8GHz. It gives a typical gain of 28.2dB when operated at 3.7GHz. Calculating the band powers including the main band and the side bands of the power spectrum for the received symbols before predistortion and received symbols after applying predistortion gives us the amount of suppression in the sidebands in dB. This process is done at different operating points of the power amplifier and doing this gives us an idea of where this algorithm is going to fail. Operating points considered are for example 0.5dB compression point, 1 dB compression point, etc. The input and output power levels corresponding to these operating points are given in the table below.

Operating point	Input power(dBm)	Output Power(dBm)
In Linear Region	13.0103	40.5261
0.5dB compression point	17.1052	43.75
1dB compression point	17.5846	43.9107
1.5dB compression point	18.1346	43.9107
Beyond 1.5dB compression point	18.5846	43.9107

As stated earlier that band powers have been calculated for transmitted symbols, received symbols before and after compensation for different scenarios. The tables below are the observations recorded when QPSK modulated waveform with 8 samples per symbol at a sampling rate of 8MHz and a roll-off factor of 0.2 is used as test signal. So the bandwidth of the main band of the QPSK signal being transmitted accounts to 1.2 MHz.

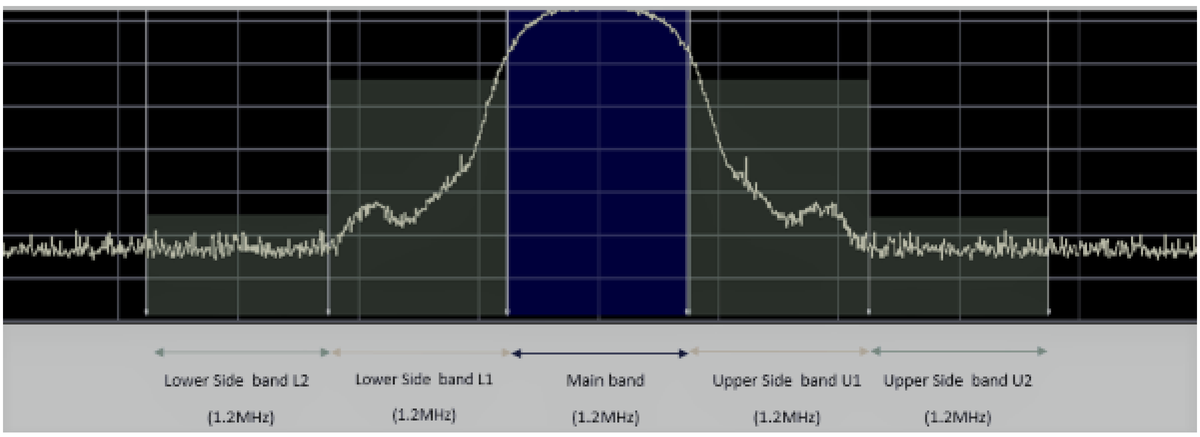

Fig. 4.2: Band powers representation

The tables below will give a picture of how much suppression of sidebands is the algorithm able to produce under different scenarios.

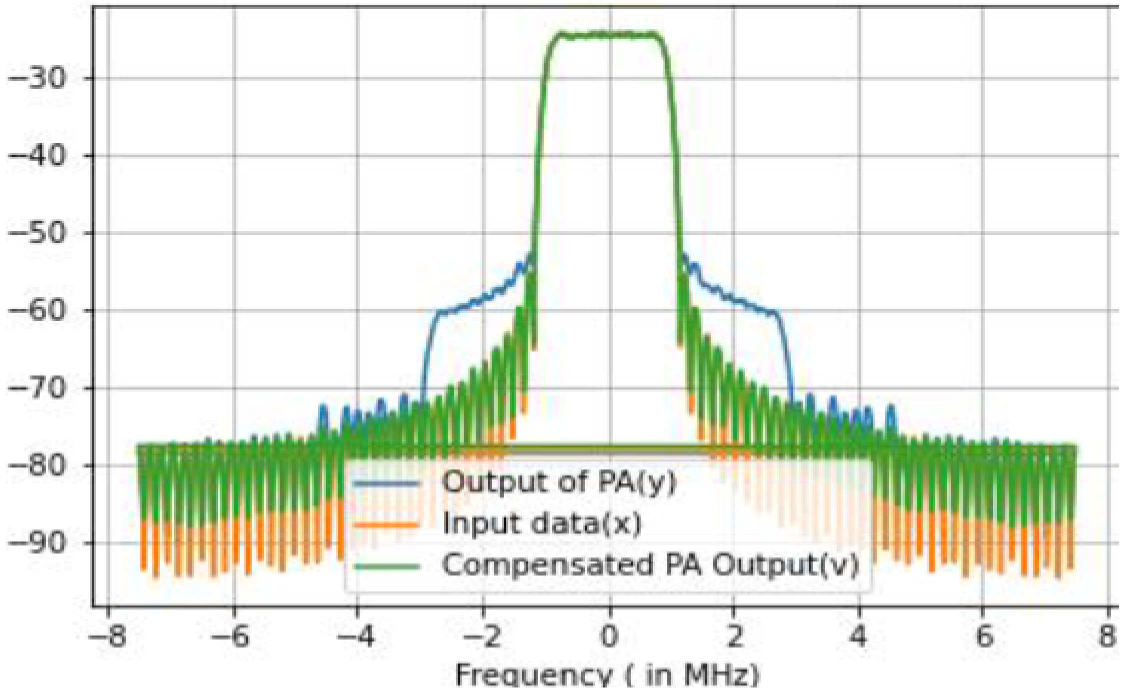

Fig. 4.3: Spectral Analysis - Operating point in Linear Region

Table 4.1: Band powers - Operating point in Linear Region

Band	Transmitted Symbols Power(dBm)	Received Symbols Power before Compensation(dBm)	Received Symbols Power after Compensation(dBm)	Suppression due to compensation(dB)
Main Band	5.6978	5.7019	5.7837	
L1 band	-35.5292	-26.7628	-34.7168	7.9558
U1 band	-35.6057	-26.422	-34.758	8.3058
L2 band	-46.7072	-33.653	-44.0532	10.879
U2 band	-46.703	-34.3682	-44.0947	9.4002

So, for the case where PA is operated in the linear region, the suppression of sidebands that is happening because of predistortion in L1 and U1 sidebands is about 8dB and about 10dB in case of L2 and U2 sidebands.

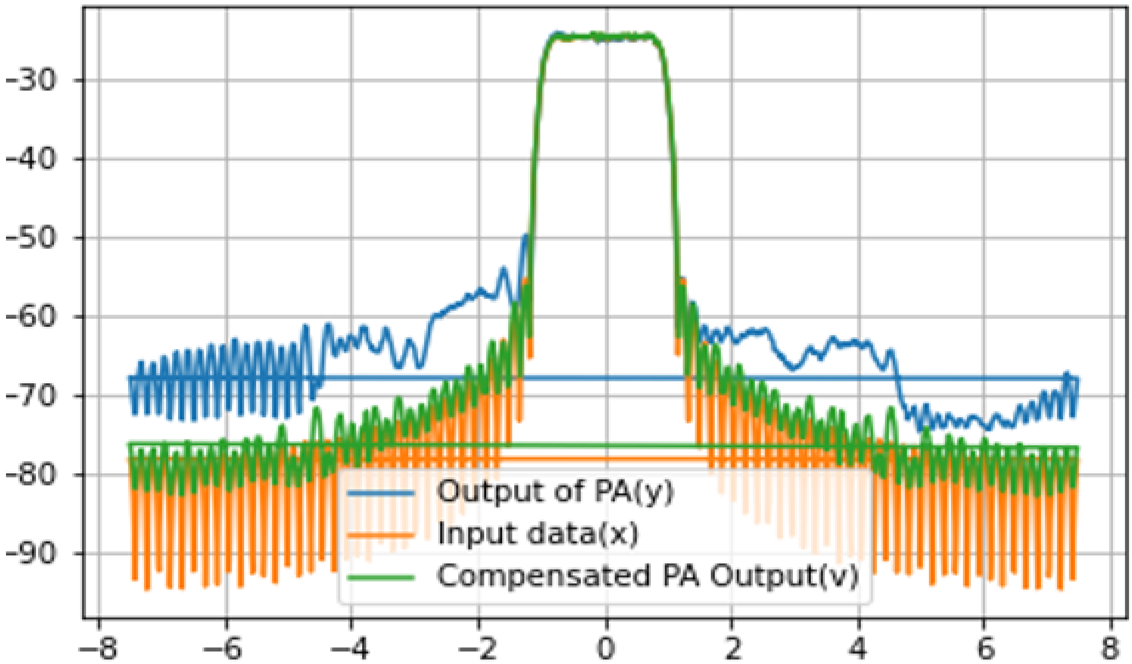

Fig. 4.4: Spectral Analysis - Operating point at 0.5dB compression point

Table 4.2: Band powers - Operating point at 0.5dB compression point

Band	Transmitted Symbols Power(dBm)	Received Symbols Power before Compensation(dBm)	Received Symbols Power after Compensation(dBm)	Suppression due to compensation(dB)
Main Band	5.6546	5.6221	5.5653	
L1 band	-35.5646	-27.6831	-35.4831	7.994
U1 band	-35.6373	-27.3635	-35.5262	8.1627
L2 band	-46.7762	-41.9498	-45.5877	3.6379
U2 band	-46.771	-40.6592	-45.5967	4.9375

For the case where the PA is operated at 0.5dB compression point, the suppression is about 8dB in L1 and U1 sidebands and about 4-5dB in L2 and U2 sidebands.

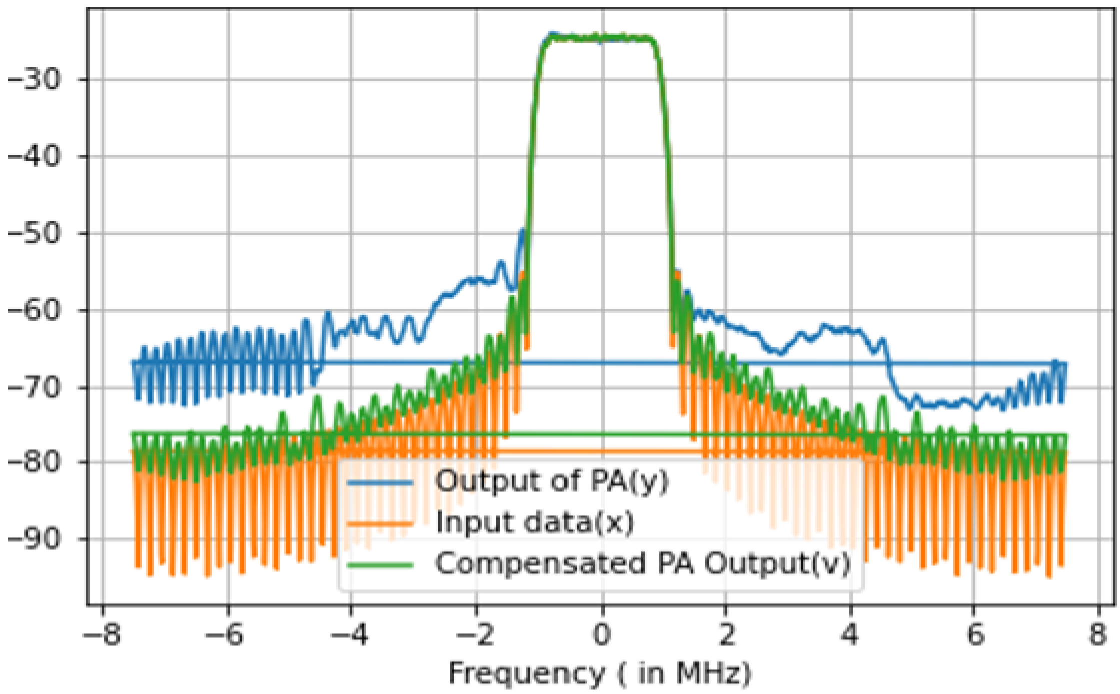

Fig. 4.5: Spectral Analysis - Operating point at 1dB compression point

Table 4.3: Band powers - Operating point at 1dB compression point

Band	Transmitted Symbols Power(dBm)	Received Symbols Power before Compensation(dBm)	Received Symbols Power after Compensation(dBm)	Suppression due to compensation(dB)
Main Band	5.6354	5.6393	5.6602	
L1 band	-35.6575	-26.1178	-36.6453	8.5275
U1 band	-35.566	-31.0773	-34.5551	3.4778
L2 band	-46.7818	-32.6693	-43.3351	10.6658
U2 band	-46.842	-33.5959	-43.3947	9.7988

In the case of PA bening operated at 1dB compression point there is about 8dB compression in L1 sideband and 3.5dB compression inU1 sidebands. The difference in suppressions in L1 and U1 sidebands is more in this case due to the unsymmetrical power spectrum on both sides of dc.

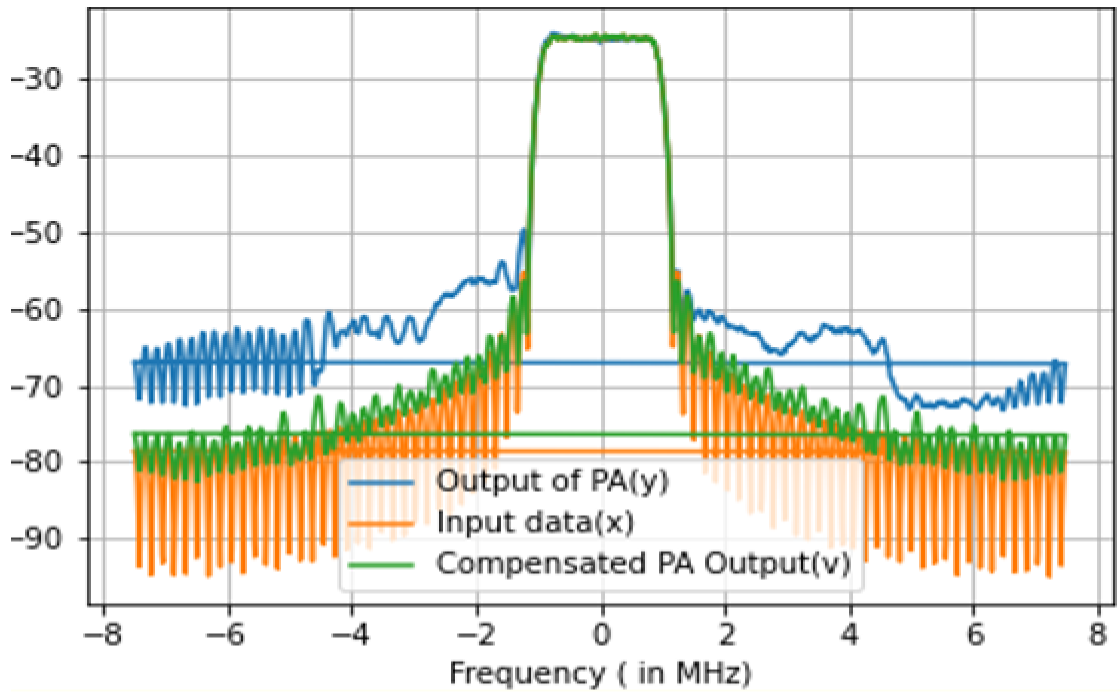

Fig. 4.6: Spectral Analysis - Operating point at 1.5dB compression point

Table 4.4: Band powers - Operating point at 1.5dB compression point

Band	Transmitted Symbols Power(dBm)	Received Symbols Power before Compensation(dBm)	Received Symbols Power after Compensation(dBm)	Suppression due to compensation(dB)
Main Band	5.6546	5.6502	5.5803	
L1 band	-35.5645	-24.3858	-29.4359	5.0501
U1 band	-35.6373	-28.349	-29.4087	1.0597
L2 band	-46.7762	-31.2451	-36.1545	4.9094
U2 band	-46.771	-32.3148	-36.1263	3.8115

When PA is operated at 1.5dB compression point, the amount of suppression starts decreasing. There is 5dB and 1dB suppression in L1 and U1 bands respectively.

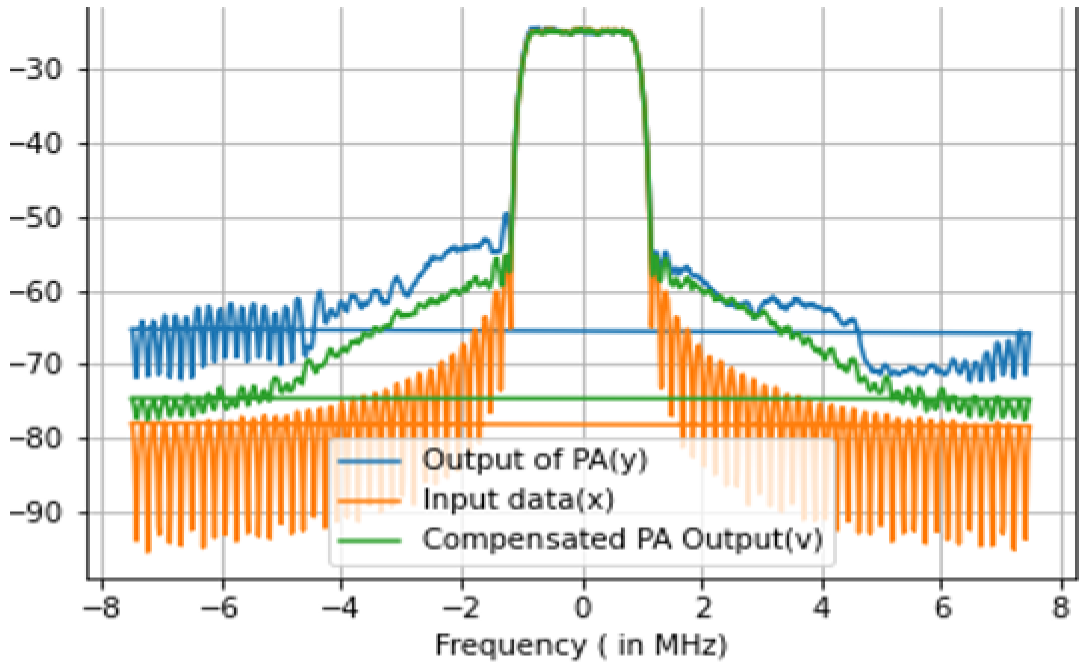

Fig. 4.7: Spectral Analysis - Operating point beyond 1.5dB compression point

Table 4.5: Band powers - Operating point beyond 1.5dB compression point

Band	Transmitted Symbols Power(dBm)	Received Symbols Power before Compensation(dBm)	Received Symbols Power after Compensation(dBm)
Main Band	5.6416	5.6109	5.5252
L1 band	-35.5899	-21.2074	-20.6825
U1 band	-35.607	-23.7813	-20.6772
L2 band	-46.7818	-28.1895	-27.3169
U2 band	-46.7902	-30.293	-27.3353

This algorithm breaks down when PA is operated beyond 1.5dB compression point for the power amplifier model in consideration. Here, the power in the sidebands for received symbols after applying predistortion is higher then for received symbols before applying predistortion as depicted in the fig. 4.7.

CHAPTER 5

CONCLUSION

In the absence of access to a real power amplifier, RF Blockset comes in very handy to model the power amplifier and thus helps in maintaining the continuity of a project. With the Neural Networks approach, until the power amplifier was operated at 1.5 dB compression point, the algorithm is successfully able to suppress the sideband power by a minimum of 5dB in the immediate sidebands. The third and foremost important point is the dataset that was used to model the PA had input power corresponding to 1.5dB compression point only. Thus beyond 1.5dB compression point, the PA model in Simulink does not paint the true characteristics of the real world PA. While using RF Blockset in Simulink, the data available to model the PA using Memory Polynomial must include the entire range of input power that the PA can handle ($P_{in} < P_{maxinput}$) to get a more accurate model of the amplifier over the entire range.