

Research Article

Exploitation of Feedforward Neural Networks to Improve HPA Predistortion Performance and Application to OTFS Signals

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Abstract

6G (Next-generation mobile telephony) communication systems require modulation schemes robust against channel fading, and Orthogonal Time Frequency Space (OTFS) has emerged as a key technology to achieve this goal. However, OTFS exhibits high amplitude variations (high PAPR), making it particularly susceptible to High Power Amplifier (HPA) nonlinearities, which degrade spectral purity (ACPR or Adjacent Channel Power Ratio) and increase the Bit Error Rate (BER). Digital predistortion (DPD) is the most effective method for HPA linearization, but classical polynomial models struggle to capture complex nonlinearities especially when applied to demanding signals like OTFS. In this paper, we propose and evaluate an innovative DPD approach based on a feedforward neural network. A multi-criteria analysis demonstrates that this method significantly outperforms polynomial predistortion: it achieves precise predistortion function approximation with a Mean Squared Error (MSE) of 7.38×10^{-6} , improves ACPR by 22 dB (from -15 dB to -36 dB), and attains a BER nearly identical to that of a linear amplifier even in a Rayleigh fading channel. Moreover, it enables the HPA to operate in saturation (low IBO or Input Back-off, ~70% efficiency) while preserving optimal transmission quality, thereby breaking the traditional trade-off between energy efficiency and linearity. Our approach is simple, robust, and computationally lightweight, paving the way for highly efficient 6G transmission chains tailored for mobile environments.

Keywords

HPA, OTFS, PAPR, Predistortion, ANN, Nonlinearity

1. Introduction

Next-generation mobile communication networks, particularly 6G, aim to meet increasingly stringent requirements in terms of data rate, ultra-low latency, extreme mobility, and spectral efficiency. In this context, Orthogonal Time Frequency Space (OTFS) modulation has emerged as a key technology promising robust transmission even in highly fading environments. Unlike traditional modulations such as

OFDM, OTFS encodes data in the Delay–Doppler domain, thereby offering superior resilience to time and frequency-selective channels [2, 3]. However, like all multicarrier modulations, OTFS is characterized by high amplitude variations, measured by the Peak-to-Average Power Ratio (PAPR). This high PAPR renders the signal particularly sensitive to nonlinearities in power amplifiers (HPA), which are critical

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components in transmission chains. Indeed, when a HPA operates near its saturation region where its energy efficiency is maximized, it introduces amplitude (AM/AM) and phase (AM/PM) distortions, degrading the signal through spectral regrowth, inter-channel interference, and increased bit error rate (BER) [7, 8]. To mitigate these effects, Digital Predistortion (DPD) is widely employed. This technique applies an inverse nonlinearity to the input signal, such that the combined response of the predistorter and amplifier yields an overall linear behavior. Traditionally, the predistortion function is modeled using polynomials. However, this approach faces limitations when dealing with the complex and dynamic nonlinearities of modern HPA. To address these challenges, artificial neural networks, and in particular feedforward networks, offer a promising alternative due to their universal approximation property. In this paper, we propose and evaluate a feedforward neural network-based predistortion solution to enhance power amplifier linearity in an OTFS system. Our contribution lies in applying this technique to OTFS signals and conducting a multi-criteria evaluation that incorporates not only spectral quality and BER performance, but also the impact on the amplifier's energy efficiency. The originality of

this work lies in the multicriteria demonstration that a simple feedforward neural network non-recurrent is sufficient to significantly outperform classical polynomial predistortion methods. Unlike many studies limited to conventional modulation schemes (such as OFDM or FBMC), our research specifically targets OTFS modulation, which has been identified as a foundational waveform for 6G.

2. Power Amplifier and OTFS Signals

2.1. OTFS Signals

Multicarrier modulation aims to mitigate the effects of frequency selectivity of the channel, thereby achieving a locally flat channel response at the level of each subcarrier. OTFS (Orthogonal Time Frequency Space) is widely regarded as one of the key technologies for 6G networks, particularly to meet extreme requirements in terms of mobility, reliability, ultra-low latency, and spectral efficiency [1-5]. Figure 1 illustrates the principle of OTFS modulation.

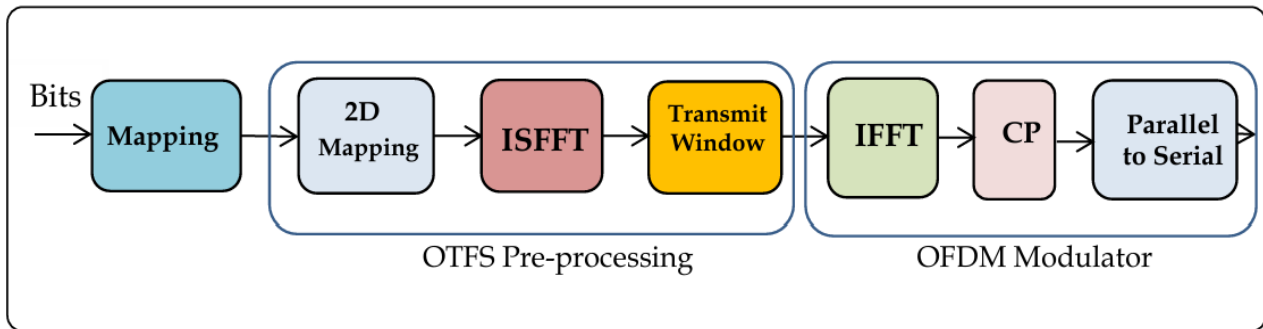


Figure 1. OTFS modulation.

Step 1: Mapping

Conversion of bits into complex symbols using single-carrier modulation QPSK, 16-QAM,

Step 2: 2D Mapping in the Delay-Doppler Domain

The complex symbols are placed on a 2D grid:

- 1) Horizontal axis: delay index l (temporal delay)
- 2) Vertical axis: Doppler index k (frequency shift)

Data is organized in the delay-Doppler domain, not in the time or frequency domain.

Step 3: ISFFT (Inverse Symplectic Finite Fourier Transform)

This transformation converts the symbols $x[k, l]$ from the delay-Doppler domain into the time-frequency domain $X[n, m]$. [1-5].

$$X[n, m] = \frac{1}{\sqrt{MN}} \sum_{l=0}^{M-1} \sum_{k=0}^{N-1} x[k, l] e^{j2\pi(\frac{nk}{N} - \frac{ml}{M})} \quad (1)$$

l : Delay index

k : Doppler index

n : Time index

m : Frequency index

Step 4: Transmit Window

Filter the signal to reduce sidelobes and inter-symbol interference (ISI).

Step 5: IFFT (Inverse Fast Fourier Transform)

OFDM modulation

Step 6: CP (Cyclic Prefix)

Append a copy of the beginning of the symbol to its end. This is a standard technique in an OFDM system, which prevents inter-symbol interference.

Step 7: Parallel to Serial

The time-domain samples are serialized to form a continuous time signal.

Figure 2 illustrates the principle of OTFS demodulation.

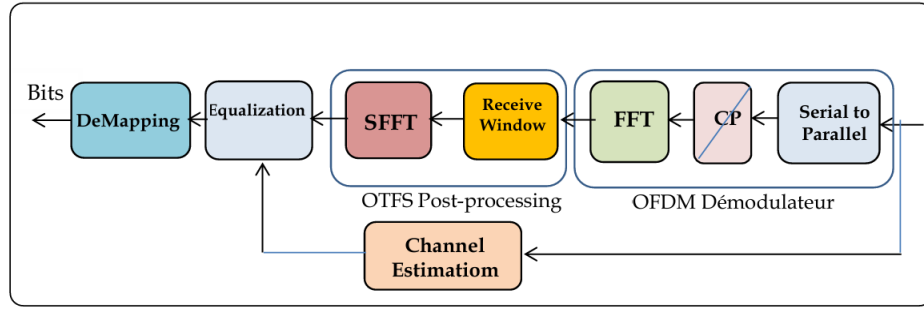


Figure 2. OTFS demodulation.

Step 1: Serial to Parallel

Conversion of the serial stream into parallel.

Step 2: Removal of the Cyclic Prefix

The cyclic prefix, which was added at transmission to avoid inter-symbol interference, is removed here.

Step 3: FFT (Fast Fourier Transform)

Converts the time-domain signal into the frequency domain.

Step 4: Receive Window

Filtering to reduce spectral leakage and smooth transitions between symbols.

Step 5: SFFT (Symplectic Finite Fourier Transform)

Converts the data from the time-frequency domain $Y[n, m]$ into the delay-Doppler domain $y[k, l]$.

Step 6: Channel Estimation

Channel estimation is performed using pilot symbols inserted at transmitter. A pilot symbol is a symbol known in advance by both the transmitter and the receiver. By comparing the transmitted and received symbols, the channel state can be estimated.

Step 7: Equalization

Using the channel estimate obtained in the previous step,

the effects of the channel on the received symbols can be compensated.

Step 8: DeMapping

Conversion of the estimated complex symbols into binary bits using QPSK, QAM,... demodulation.

Multi-carrier signals, such as OTFS signals, are characterized by high amplitude variations. To measure the amplitude variation of the signal, the PAPR (Peak to Average Power Ratio) is used. Indeed, when the PAPR is high, the signal exhibits large amplitude variations. Equation (2) provides the general expression for the PAPR. This parameter is defined as the ratio between the peak power (P_{max}) and the average power (P_{moy}) of the signal $S(t)$ over a time interval T :

$$PAPR = \frac{P_{max}}{P_{moy}} = \frac{\max_{t \in [0, T]} |S(t)|^2}{\frac{1}{T} \int_0^T |S(t)|^2 dt} \quad (2)$$

To evaluate the PAPR, the CCDF is used. This function gives the probability that the PAPR exceeds a threshold value ψ , and is expressed by Equation (3).

$$CCDF(\psi) = \Pr[PAPR \geq \psi] \quad (3)$$

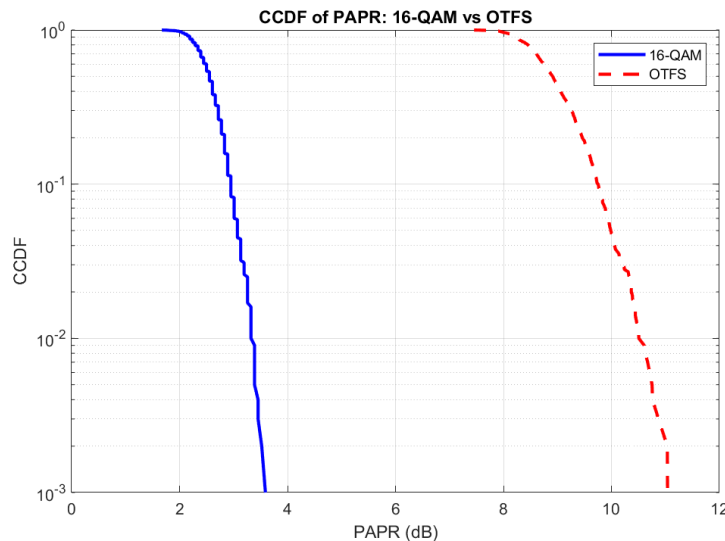


Figure 3. CCDF of PAPR: 16-QAM vs OTFS.

The slower the CCDF decreases, the higher the probability that the signal has a high PAPR. From Figure 3, we deduce that the OTFS signal (multi-carrier) has a higher probability

of exhibiting a high PAPR than the 16-QAM signal (single-carrier).

2.2. Amplification of OTFS Signal

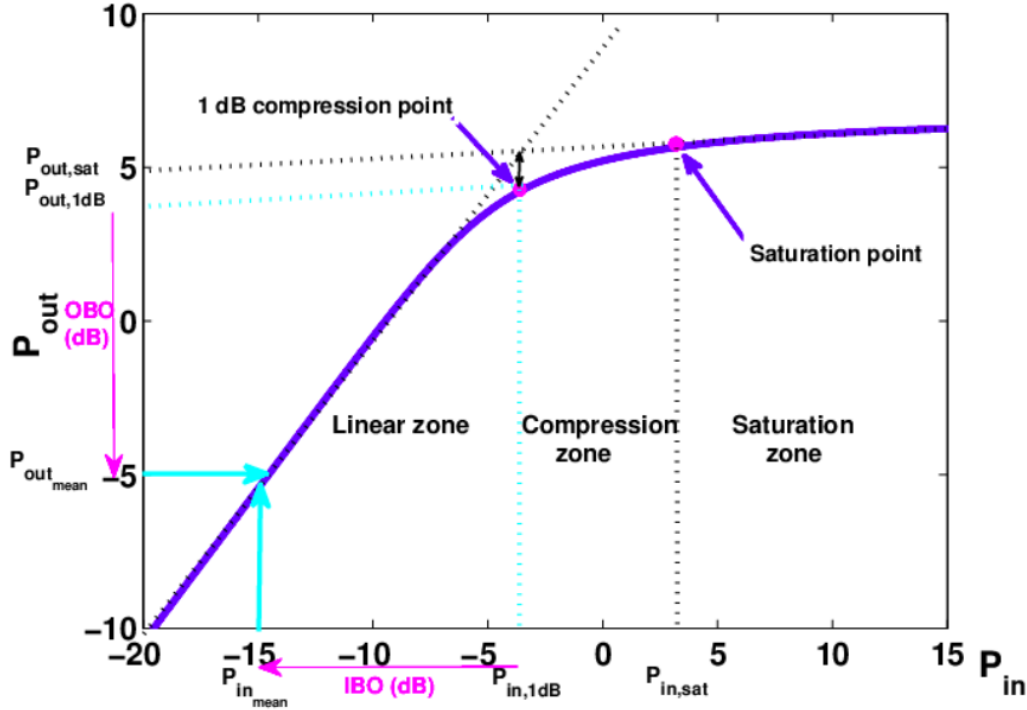


Figure 4. AM/AM characteristics.

The curve showing the variation of output power as a function of input power of a power amplifier is also referred to as the AM/AM characteristic. It exhibits a typical shape for all amplifiers (see Figure 4).

The AM/AM characteristic of a power amplifier is divided into three regions [6-15]:

Linear zone: In this region, the amplifier exhibits linear behavior. The output power is proportional to the input power, with the proportionality factor known as the amplifier gain. Input power levels are low. In this region, distortions caused by nonlinearity are nonexistent. When operating with sufficient back-off to avoid distortions, the amplifier functions within this linear region.

Compression zone: In this region, output power is no longer proportional to input power. The curve begins to bend, marking the onset of nonlinear behavior. Signal distortions appear and become increasingly significant as input power rises. The amplifier gain decreases for high input power levels, which is why this region is referred to as the gain compression region. The 1-dB gain compression point lies within this

region; it is defined as the point where the difference between the actual gain curve and the ideal linear gain equals 1 dB. This point is a key characteristic of the power amplifier.

Saturation zone: In this region, the output power remains nearly constant regardless of further increases in input power. This constant output power level is referred to as the saturation power, which is another fundamental characteristic of the power amplifier.

The curve showing phase shift as a function of input amplitude is called the AM/PM transfer characteristic. It has no standard shape; it varies depending on the amplifier's design technique and operating conditions.

In short, amplification is a nonlinear operation characterized by amplitude compression (AM/AM) and phase shift at the output (AM/PM).

The nonlinearity of a power amplifier causes distortion of the amplified signal, especially when the signal exhibits large amplitude variations. Indeed, these distortions result in transmission errors (Figures 5-6) and spectral regrowth, which can cause interference (Figure 7).

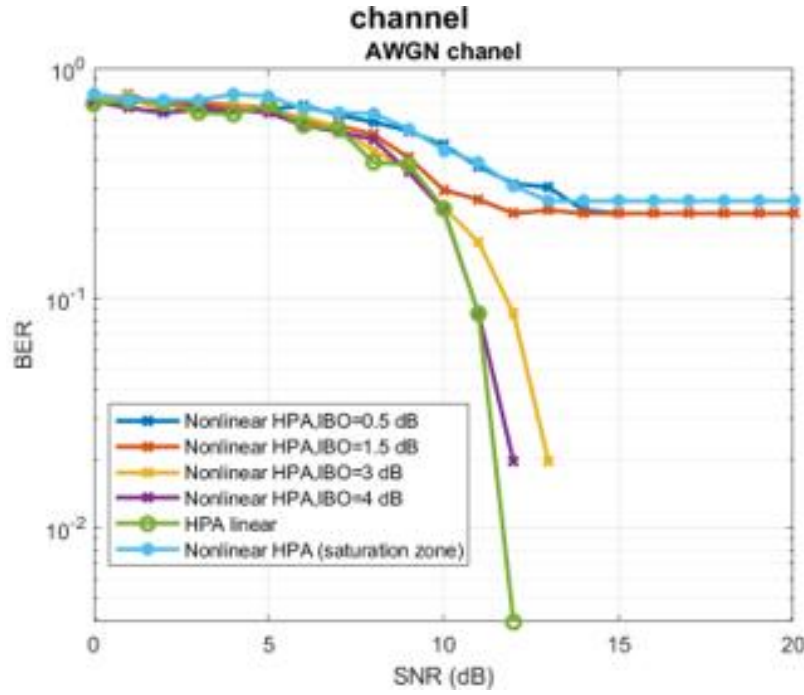


Figure 5. BER over AWGN Channel.

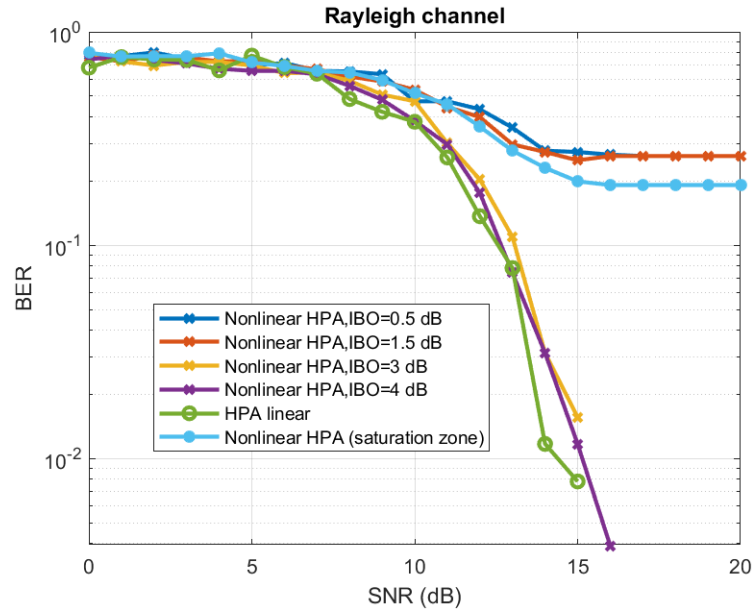


Figure 6. BER over Rayleigh Channel.

All curves exhibit a high BER at low SNR, followed by a rapid decrease as the SNR increases.

The BER after linear amplification (green curve) is the lowest, as it represents an ideal amplifier without nonlinear distortion.

The BER after nonlinear amplification (light blue curve) remains very high even at high SNR. Nonlinear amplification thus saturates the signal and causes significant information loss.

We also observe that a higher IBO (Input Back Off) significantly improves the BER: the higher the IBO, the closer

the amplifier operates to its linear region. To avoid or at least mitigate the detrimental effects caused by amplifier nonlinearity, the amplifier is often oversized i.e., operated with a certain amount of back-off to ensure operation within or near the linear region. This back-off is typically referenced either to the 1-dB compression point or to the saturation power level. Input Back-Off (IBO), typically expressed in dB, is the ratio between the input-referred saturation power $P_{in,sat}$ and the actual input signal power P_{in} , or alternatively, the ratio between the input power at the 1-dB compression point $P_{in,1dB}$

and the actual input signal power P_{in} .

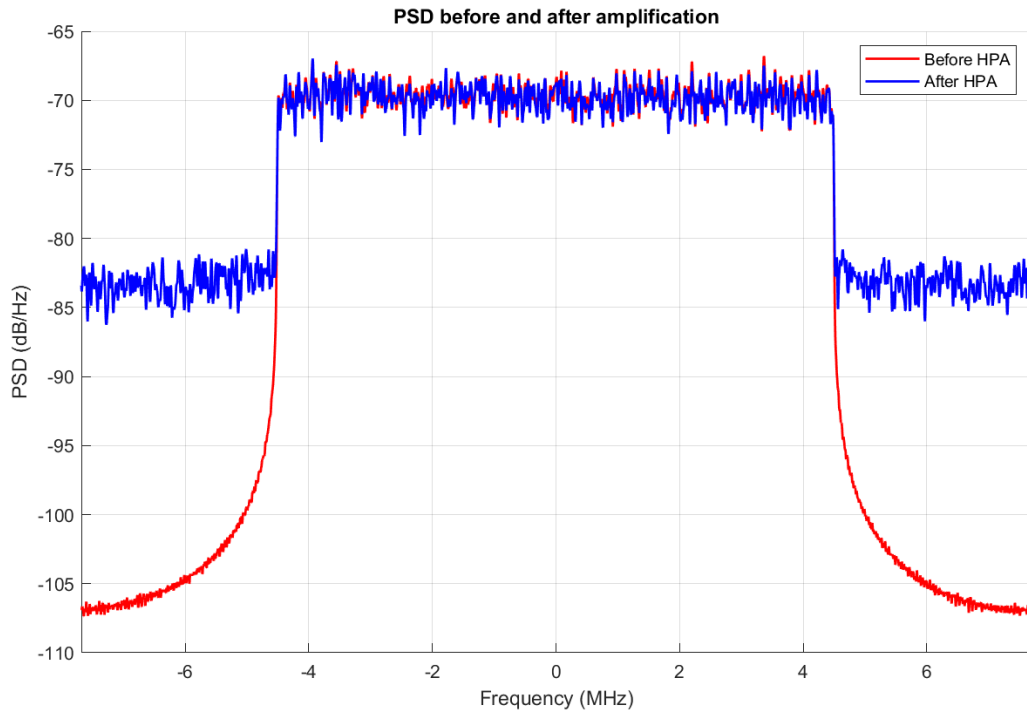


Figure 7. PSD before and after amplification.

Table 1. ACRP before and after amplification.

ACPR before HPA	ACPR after HPA
-37 dB	-15 dB

From these results, we deduce that the signal spectrum before amplification is well confined within the useful bandwidth (approximately ± 4 MHz). The side lobes decay rapidly. Indeed, the ACRP before amplification is -37 dB. We conclude that, prior to amplification, the signal spectrum is very clean, with minimal interference in adjacent channels.

After amplification, a significant increase in spectral noise is observed in the adjacent bands. Moreover, the shape of the spectrum within the main band is slightly distorted. The ACRP after amplification is -15 dB, meaning that the power in the adjacent channel has increased by 22 dB hence, the risk of interference with neighboring channels increases significantly.

3. Classification of Techniques for Compensating Power Amplifier Nonlinearity

Techniques for compensating power amplifier nonlinearity are located either at the transmitter side, the receiver side, or

distributed between both. In this article, we focus on techniques implemented at the transmitter. These are divided into two main categories:

- 1) The first technique involves processing the signals at the input of the amplifier to mitigate the effects of its non-linearity. This processing aims to reduce the signal's Peak-to-Average Power Ratio (PAPR).
- 2) The second technique directly aims to invert the amplifier's transfer characteristic in order to linearize it. These are known as "linearization techniques."

In the following, we focus on linearization techniques. Several varieties of linearization techniques exist, but the most effective among them is Digital Predistortion (DPD). It consists of compensating the amplifier's nonlinearity by adding an input block with an inverse nonlinearity, such that the combination of the two nonlinear blocks results in a linear transfer function [6-15] (see Figure 8).

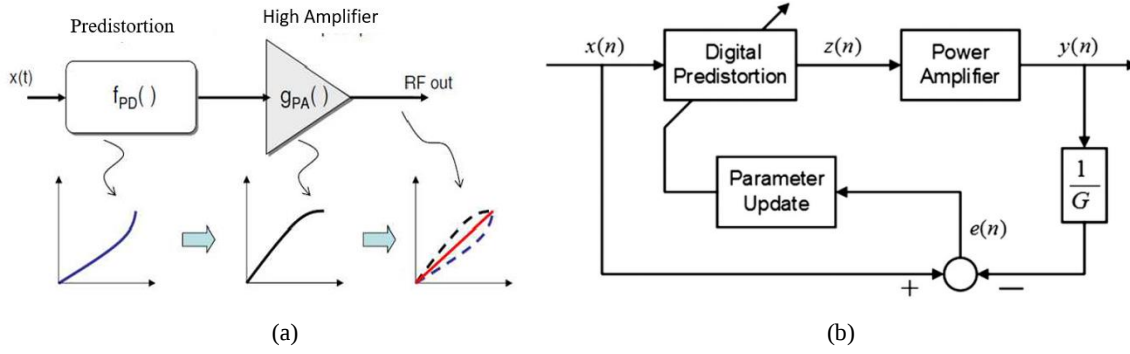


Figure 8. (a). Principle of the predistortion technique; (b). Direct Method.

4. Mathematical Model-based Predistortion

This technique relies on the mathematical modeling of the system (the predistortion block) used to determine the inverse transfer characteristic of the amplifier. In this approach, the predistortion function $f_{PD}()$ is implemented using mathematical models. The predistortion function can be determined in two ways:

1) Direct Method

The principle of this technique is to minimize the error between the input data of the predistortion block and the output data of the amplifier. Once the minimization criterion is satisfied, the predistortion function is updated directly as illustrated in Figure 9.

2) Indirect Method

In this new architecture, the idea is no longer to close the loop between the input of the predistortion block and the output of the amplifier, but rather between the input and the output of the amplifier, as illustrated in Figure 9.

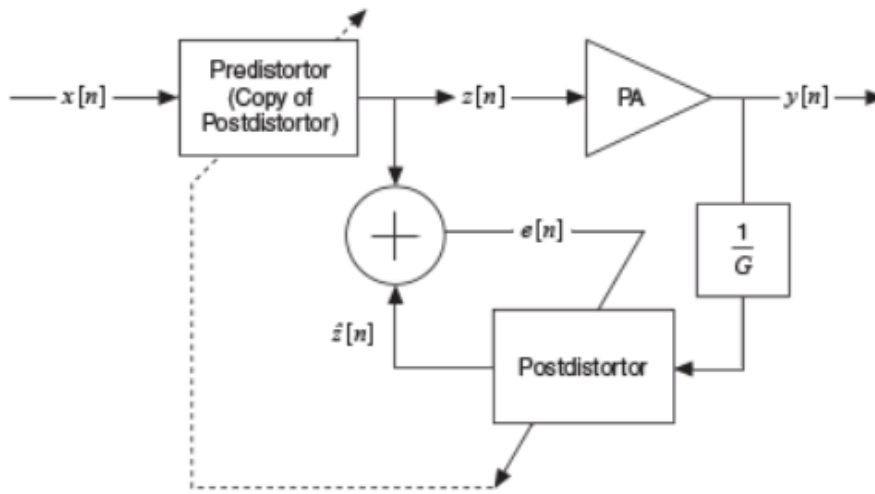


Figure 9. Indirect Method.

It is called indirect method because the predistortion function is no longer updated directly, instead, a postdistortion function, is computed, which is equivalent to the predistortion function when the error e (Figure 9) is very small.

4.1. Polynomial Model Predistortion

The polynomial model has emerged as an approach to linearize amplifiers. First, the coefficients of this model must be identified. To this end, the indirect learning identification method will be implemented. Figure 10 summarizes the principle of this polynomial model predistortion technique.

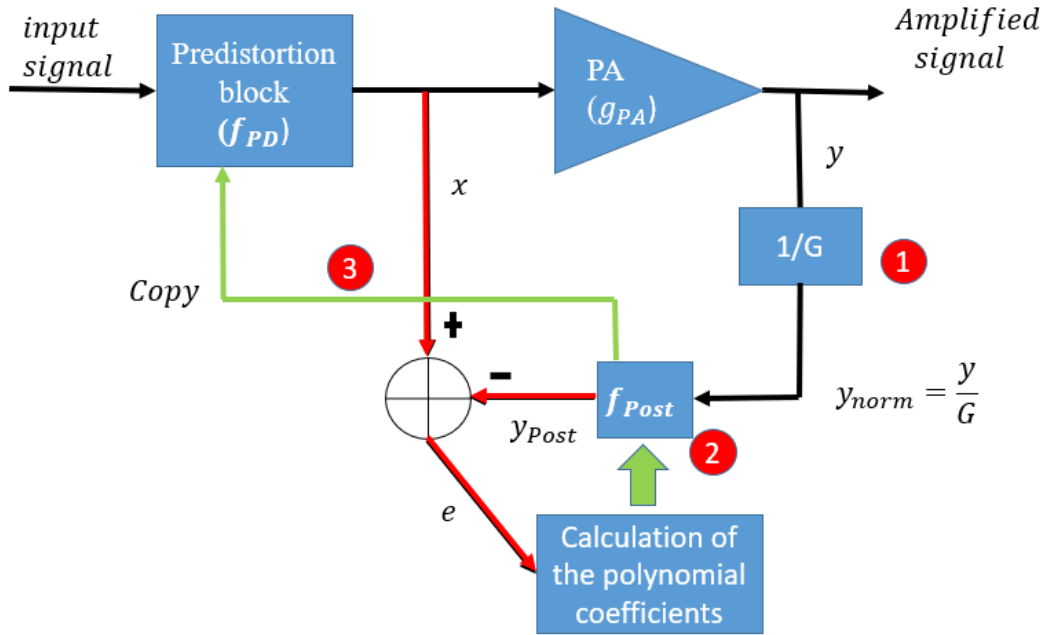


Figure 10. Polynomial model predistortion technique.

Step 1: Normalize the output of the power amplifier by the linear gain G of the device to obtain the normalized samples $y_{norm}(n)$, given by:

$$y_{norm}(n) = \frac{1}{G} \cdot y(n) \quad (4)$$

$$y_{post} = H \cdot a \quad (5)$$

Where:

$a = [a_1 \ a_2 \ \dots \ a_K]^T$: vector of polynomial coefficients and K the nonlinearity order of predistortion function.

Step 2: Determine the post-distortion polynomial function, defined as follows:

$y_{post} = [y_{post}(0) \ y_{post}(1) \ \dots \ y_{post}(N-1)]^T$ the output of postdistortion function and N Number of symbols.

$$H = [H_1 \ H_2 \ \dots \ H_K]^T$$

$$H_k = [h_k(0) \ h_k(1) \ \dots \ h_k(N-1)]^T \text{ and } h_k(n) = \frac{y(n)}{G} \cdot \left| \frac{y(n)}{G} \right|^{k-1}$$

The expression for the post-distortion error is given by equation (6).

$$e = x - y_{post} \quad (6)$$

Where x the input of the power amplifier.

By combining equations (5) and (6), the expression for the average postdistortion error (equation (7) can be obtained:

$$\|x - y_{post}\|^2 = \|x - H \cdot a\|^2 = x^T x - a^T H^T x - x^T H a + a^T H^T H a \quad (7)$$

Our goal is to find the coefficients a_k that minimize this error, for this, the derivative of the error with respect to a must be zero:

$$\frac{d}{da} \|x - H a\|^2 = 0 \leftrightarrow -2H^T x + 2H^T H a = 0 \quad (8)$$

Hence

$$a = (H^T H)^{-1} H^T x \quad (9)$$

Since the samples are complex numbers, H is a complex matrix, so the transpose becomes Hermitian, yielding:

$$a = (H^H H)^{-1} H^H x \quad (10)$$

Step 3: Step 2 provides the expression of the post-distortion polynomial f_{POST} (a are vector of polynomial coefficients). The final step consists of copying this function into the predistortion block, i.e., $f_{PD} = f_{POST}$.

4.2. Artificial Neural Network-based Predistortion

4.2.1. Artificial Neural

The artificial neural is a mathematical model of the operating principles of the biological neural. It receives input variables from other neurons. Each input is associated with a weight w_i , which represents the strength of the connection. The information thus gathered is processed by an activation function to produce the neural's output.

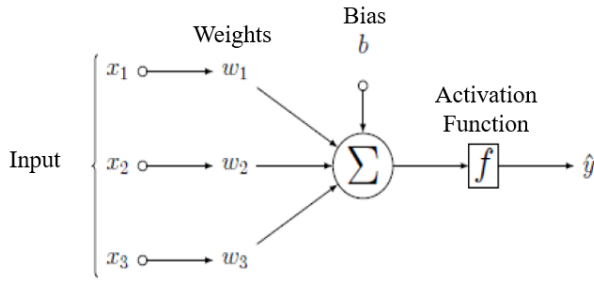


Figure 11. Artificial neural.

The inputs of the neural are represented by the column matrix $\mathbf{x}$, defined by Equation (11).

$$\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \quad (11)$$

The matrix $\mathbf{W}$ represents the corresponding weights.

$$\mathbf{W} = \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix} \quad (12)$$

The output of the summation unit, denoted as $s(\mathbf{x})$, is given by the expression:

$$s(\mathbf{x}) = \sum_{i=1}^n w_i x_i + b = \mathbf{W}^T \mathbf{x} + b \quad (13)$$

Therefore, the output of the neuron, denoted as y , is given by the expression:

$$y(\mathbf{x}) = f(s(\mathbf{x})) = f(\sum_{i=1}^n w_i x_i + b) \quad (14)$$

Where f is the activation function of the neuron and b is the bias (a synaptic weight corresponding to an input equal to +1).

Without an activation function a neural network would reduce to a simple linear transformation equivalent to a single

neuron. The nonlinearity introduced by the activation function is therefore essential for the network to model complex, nonlinear phenomena. In the context of our paper, the activation function enables the neural model to approximate the nonlinear inverse characteristic of the power amplifier.

4.2.2. Feedforward Neural Network

An artificial neural network is the interconnection of multiple formal neurons. A feedforward network is a network in which all neurons in one layer are connected to all neurons in the next layer. It is the simplest type of artificial neural network, where information travels in only one direction from the input layer, through any hidden layers, to the output layer without any feedback loops. This structure is ideal for tasks like pattern recognition, image classification, and function approximation.

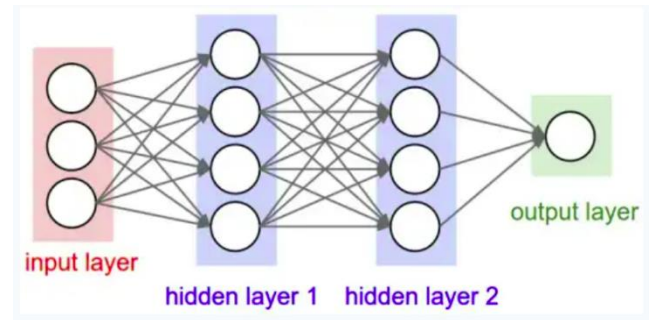


Figure 12. Feedforward Neural Network.

4.3.3. Universal Approximation Property of Neural Networks

This property is stated as follows: "for any function, there exists at least one feedforward neural network, possessing one hidden layer and a linear output neuron, that achieves an approximation of this function and its successive derivatives" [16-27]. Therefore, feedforward neural networks can be entirely suitable for modeling the desired predistortion function in order to linearize the amplifier.

4.3.4. Principle of Artificial Neural Network (ANN)-based Predistortion

The universal approximation property of neural networks implies that the predistortion function f_{PD} used to invert the amplifier's transfer characteristic, can be approximated using a non-recurrent feedforward neural network. To achieve this, the network must be trained. Therefore, a supervised learning algorithm known as the backpropagation algorithm will be employed. The following steps outline the implementation of neural network-based predistortion (see also Figure 13).

Step 1: Initialization of the synaptic weights of the feedforward network.

Step 2: Introduction of a training dataset. Specifically, the

network receives at its input the output data from the power amplifier.

Step 3: The neural network estimates the output data corresponding to the input data (i.e., the power amplifier's output data).

Step 4: Comparison between the outputs estimated by the neural network and the desired outputs, which are the input data of the power amplifier. The error between these values is defined by Equation (15). Often, this error is associated with a cost function J given by Equation (16).

$$e = y_{des} - y_{est} \quad (15)$$

With

y_{des} : desired outputs

y_{est} : outputs estimated by the neural network

$$J = \frac{1}{2} \sum (e)^2 \quad (16)$$

Step 5: Updating the synaptic weights of the neural network using Equation (17).

$$W_{nouvelle} = W_{ancienne} - \Delta W \quad (17)$$

With

$W_{ancienne}$: previous synaptic weight value

$W_{nouvelle}$: updated synaptic weight value

ΔW : correction term, which depends on the optimization algorithm used to minimize the cost function J :

If the optimization method used to minimize the cost func-

tion J is Gradient Descent, then [16-27].

$$\Delta W = \lambda \frac{\partial J}{\partial W} \quad (18)$$

Where $\frac{\partial J}{\partial W}$ is the gradient of the cost function with respect to the synaptic weights of the neural network, and λ is the learning rate.

If the optimization method used to minimize the cost function J is Gauss-Newton, then [16-27].

$$\Delta W = \lambda [J''(W)]^{-1} J'(W) \quad (19)$$

Where $J'(W) = \frac{\partial J}{\partial W}$ is the gradient of the cost function with respect to the synaptic weights of the neural network, $J''(W) = \left(\frac{\partial^2 J}{\partial W^2} \right)$ is the Hessian matrix of the cost function with respect to the synaptic weights, and λ is the learning rate.

If the optimization method used to minimize the cost function J is Levenberg-Marquardt, then [16-27].

$$\Delta W = [J''(W) + \lambda I]^{-1} J'(W) \quad (20)$$

Step 6: The trained network is copied into the predistortion block.

Figure 12 summarizes the principle of neural network-based predistortion.

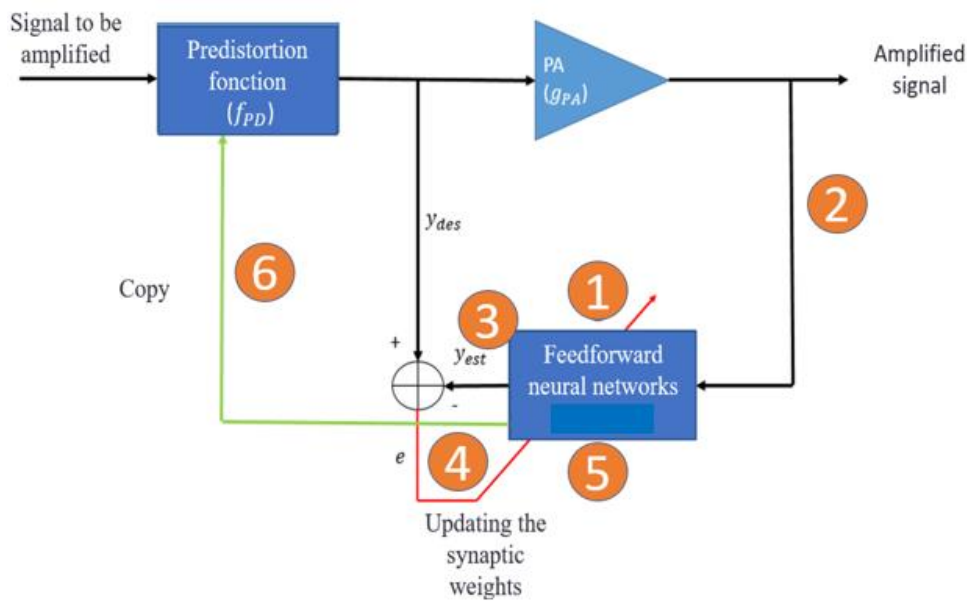


Figure 13. Principle of neural network-based predistortion.

5. Performance Analysis of Neural Network-based Predistortion for OTFS Signals

5.1. Simulation Parameters

Here are the parameters used in the simulation:

- 1) Modulation: OTFS
- 2) Mapping: 16-QAM
- 3) Number of subcarriers in frequency domain (N): 16
- 4) Number of subcarriers in time domain (M): 16
- 5) SNR (Signal-to-Noise Ratio): 0 dB – 20dB
- 6) IBO: 0.5dB, 1.5dB, 3dB, 4dB
- 7) Amplifier model: Rapp model because we are in a terrestrial radio transmission context
- 8) AM/AM characteristics of a power amplifier:

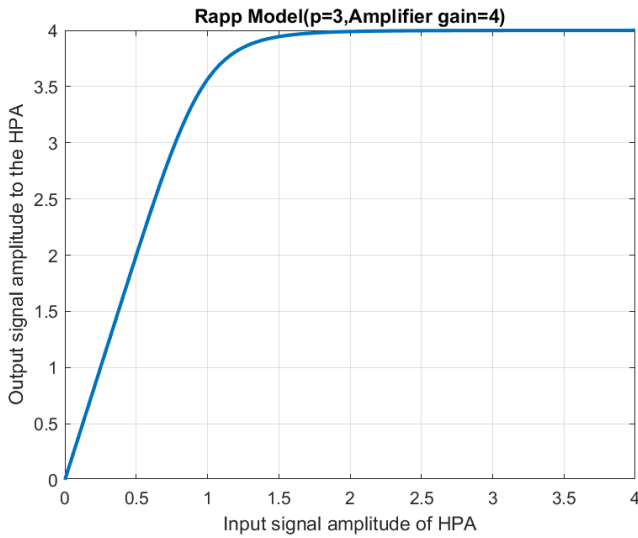


Figure 14. AM/AM characteristics of a power amplifier.

- 1) Programming environment: MATLAB 2023
Hardware specifications: CPU: Intel (R) Core i7-9750H, GPU: NVIDIA GeForce RTX 2060, RAM: 16Go
- 2) Architecture of the neural network used:

An input layer comprising a single neuron. Indeed, since the neural network has only one input, a single neuron in the input layer is appropriate. A hidden layer with ten neurons using the hyperbolic tangent activation function. This activation function allows us to randomly initialize the synaptic weights during training, thereby accelerating the convergence of the learning algorithm. An output layer consisting of a single neuron with a linear activation function. In this study, we employed Levenberg-Marquardt learning algorithms.

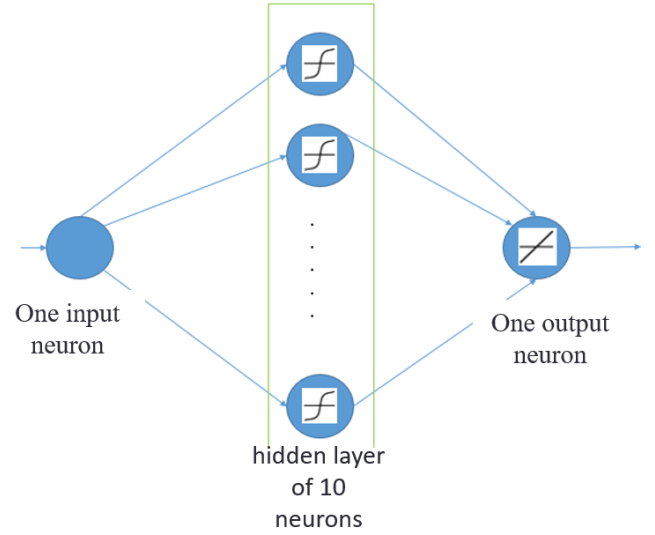


Figure 15. Architecture of the neural network used.

- 1) Predistortion polynomial coefficients for $K = 15$ (the nonlinearity order of predistortion function):
 $a = [3.04 \ -13.24 \ 15.29 \ 0 \ 0 \ -10.88 \ 0 \ 14.54 \ -10.03 \ 0 \ 2.8 \ -1.44 \ 0.34 \ -0.04 \ 0.0020]$
- 2) We evaluated predistortion technique over two channels: AWGN (Additive White Gaussian Noise): This is an ideal noise model, additive and uniformly distributed across the entire frequency band. It serves as a reference for evaluating the performance of communication systems, particularly in terms of Bit Error Rate.

Rayleigh: This is a channel model in which there is no direct line-of-sight (NLOS) between the transmitter and receiver. In this channel, multiple propagation paths exist, each undergoing independent fading. It represents a realistic scenario for wireless communication environments.

5.2. Performance Metrics of Predistortion

BER (Bit Error Rate):

It is a key performance metric in digital communication systems that measures the number of erroneous bits received divided by the total number of bits transmitted.

ACPR (Adjacent Channel Power Ratio):

It is the ratio of the power that a communication system transmits into the adjacent frequency channels to the power that it transmits into the main frequency channel.

$$ACPR = \frac{\text{Power in adjacent channel}}{\text{Power in main channel}} \quad (21)$$

ACPR is an important parameter that is used to ensure that a communication system does not interfere with the other systems operating in the nearby frequency bands. If the ACPR is low, the risk of interference with adjacent channels is low.

Amplifier efficiency

Power efficiency expresses the ratio between the output power and the power supplied by the power source. This

parameter provides information about the amplifier's power consumption.

MSE (Mean Squared Error)

To evaluate the performance of predistortion function, we used the Mean Squared Error (MSE). In our case, it represents the arithmetic mean of the squared differences between the ideal transfer characteristic of a linear amplifier and the transfer characteristic obtained after predistortion technique.

$$MSE = \frac{1}{N} \sum_{k=1}^N (y_i[k] - y_{est}[k])^2 \quad (22)$$

y_i : ideal transfer characteristic of a linear amplifier

y_{est} : transfer characteristic obtained after linearizing nonlinear amplifier using predistortion technique

5.3. Results

1) Predistortion function shape

Figures 16 and 17 show the shape of the predistortion function and amplifier transfer characteristic after predistortion, using a polynomial model (Figure 16) and a neural network model (Figure 17).

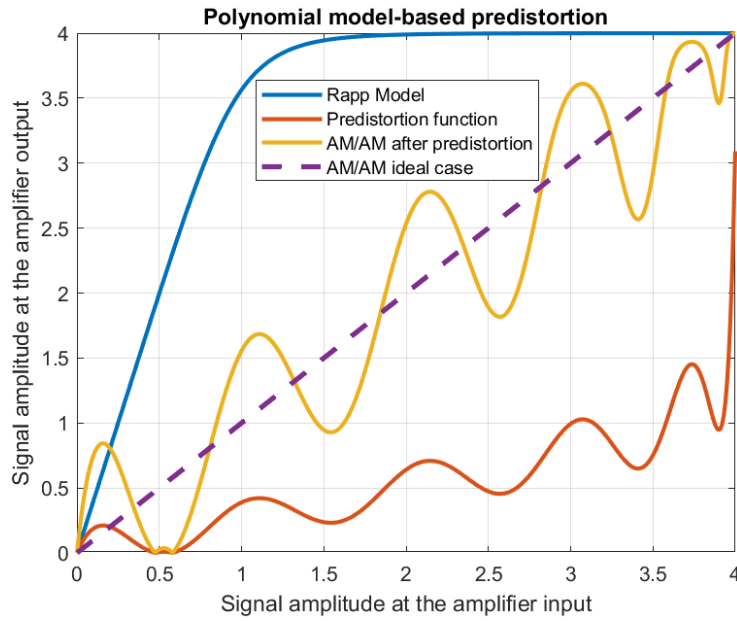


Figure 16. Predistortion function and amplifier transfer characteristic after polynomial model based predistortion.

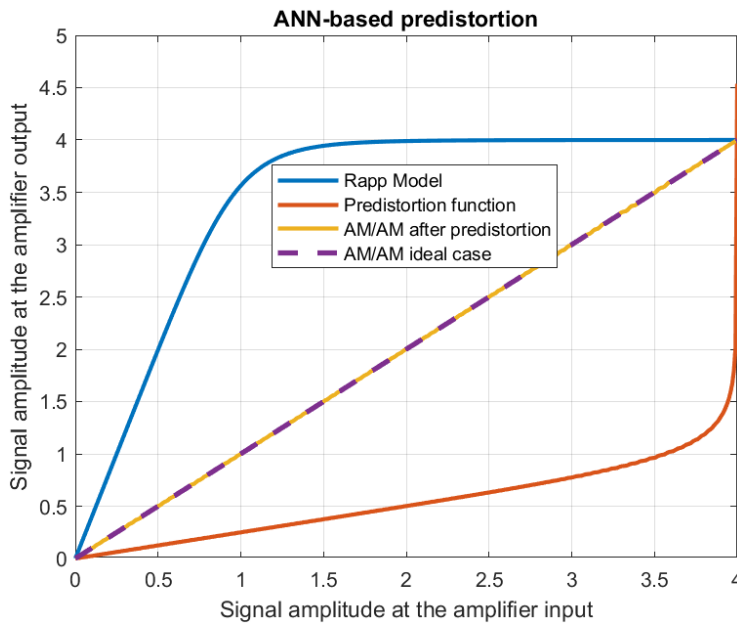


Figure 17. Predistortion function and amplifier transfer characteristic after ANN based predistortion.

Table 2 shows the MSE between the ideal transfer characteristic of a linear amplifier (AM/AM ideal case) and the transfer characteristic obtained after predistortion technique (AM/AM after predistortion).

Table 2. MSE after predistortion.

MSE Polynomial based predistortion	MSE ANN based predistortion
0.2017	7.3858×10^{-6}

The two graphs illustrate how a predistortion function is applied to a nonlinear amplifier (Rapp model) to correct its nonlinearity and bring its response closer to the ideal (linear) characteristic.

The curves shown are:

- 1) Rapp Model (blue): The nonlinear response of the amplifier before correction.
- 2) Predistortion function (orange): The predistortion function applied upstream of the amplifier.
- 3) AM/AM after predistortion (yellow): The overall response of the amplifier after applying predistortion.
- 4) AM/AM ideal case (purple dashed): The ideal linear response (output = input).

response (output = input).

For polynomial-based predistortion, the shape of the predistortion function is not precise. The AM/AM curve after predistortion (yellow) follows the amplifier's ideal transfer characteristic (purple dashed) reasonably well, but exhibits significant oscillations and noticeable deviations. Moreover, the MSE value of 0.2017 confirms this observation. While polynomial predistortion significantly improves linearity, it is not perfect it introduces artifacts (oscillations) and fails to fully correct the amplifier's nonlinearity.

For ANN-based predistortion, the predistortion function (orange) is significantly more accurate and smoother than in the polynomial case, exhibiting no oscillations reflecting the neural network's ability to approximate complex functions. The AM/AM curve after predistortion (yellow) closely follows the amplifier's ideal transfer characteristic. Moreover, the MSE is extremely low at 7.3858×10^{-6} . Neural network-based predistortion is markedly more effective, nearly perfectly correcting the amplifier's nonlinearity and delivering a quasi-linear response.

2) Spectrum shape after predistortion

In this section, we compare the Power Spectral Density (PSD) of OTFS signal after neural network-based digital predistortion with that obtained after polynomial-based digital predistortion.

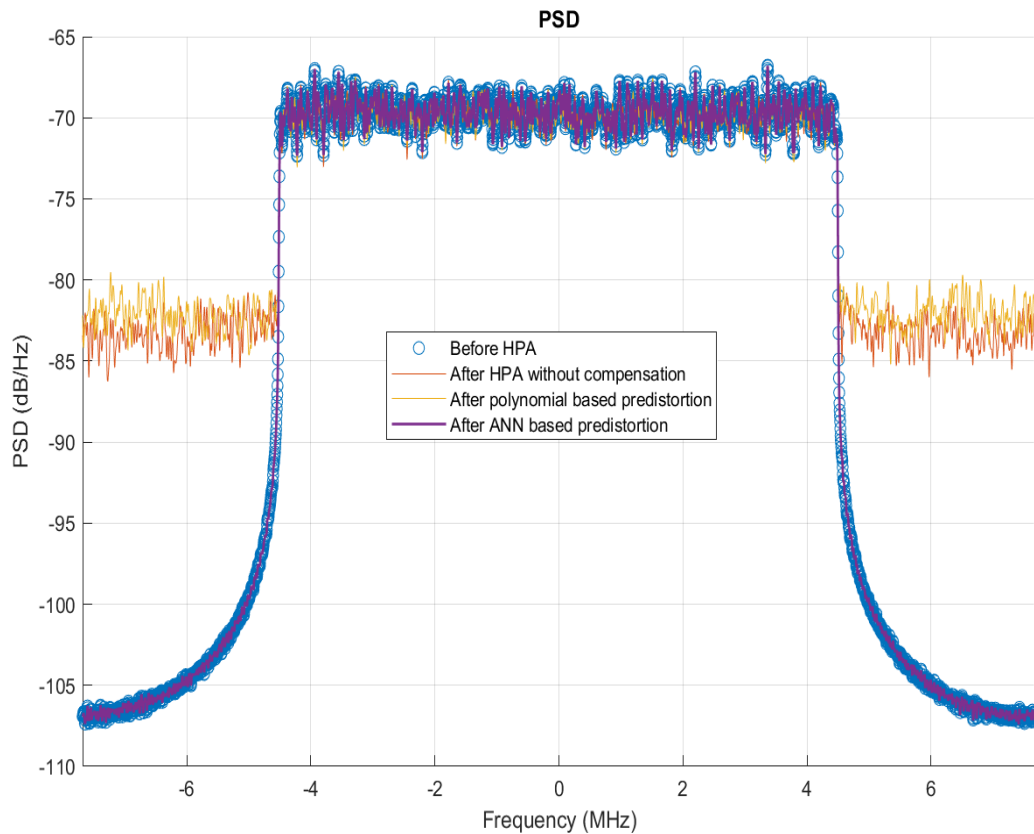


Figure 18. Spectrum shape after predistortion.

From the PSD, we obtain the ACPR values given in Table 3.

Table 3. ACPR after predistortion.

ACPR before HPA	ACPR after ANN based predistortion	ACPR after polynomial based predistortion	ACPR after HPA
-37 dB	-36 dB	-14 dB	-15 dB

Figure 18 shows the power spectral density (PSD) for four different cases:

- 1) Before HPA (blue circles): The signal prior to passing through the high-power amplifier (HPA).
- 2) After HPA without compensation (orange line): The signal after HPA, with no compensation applied.
- 3) After polynomial-based predistortion (yellow line): The signal after HPA with polynomial predistortion.
- 4) After ANN-based predistortion (purple line): The signal after HPA with neural network (ANN)-based predistortion.

Before amplification, the ACPR is -37 dB, indicating a clean spectrum with minimal noise in the adjacent bands.

After amplification without compensation, the ACPR is -15 dB, clearly revealing spectral distortion. The signal spreads beyond the useful bandwidth, resulting in a significant in-

crease in spectral power in the adjacent bands (an increase of 22 dB), which can cause interference with other channels.

After polynomial-based predistortion, the ACPR is -14 dB. Spectral distortion is partially reduced but remains significant. Spectral regrowth in the adjacent bands is still visible, although less pronounced than without any correction.

After ANN-based predistortion, the ACPR is -36 dB, and the spectrum is nearly identical to the original signal before amplification. The power within the useful band is uniform, and out-of-band emissions are very low. This indicates that ANN-based predistortion has almost entirely eliminated the spectral distortion introduced by the HPA.

3) BER after predistortion

Figures 19 and 20 show the BER of OTFS signal after predistortion.

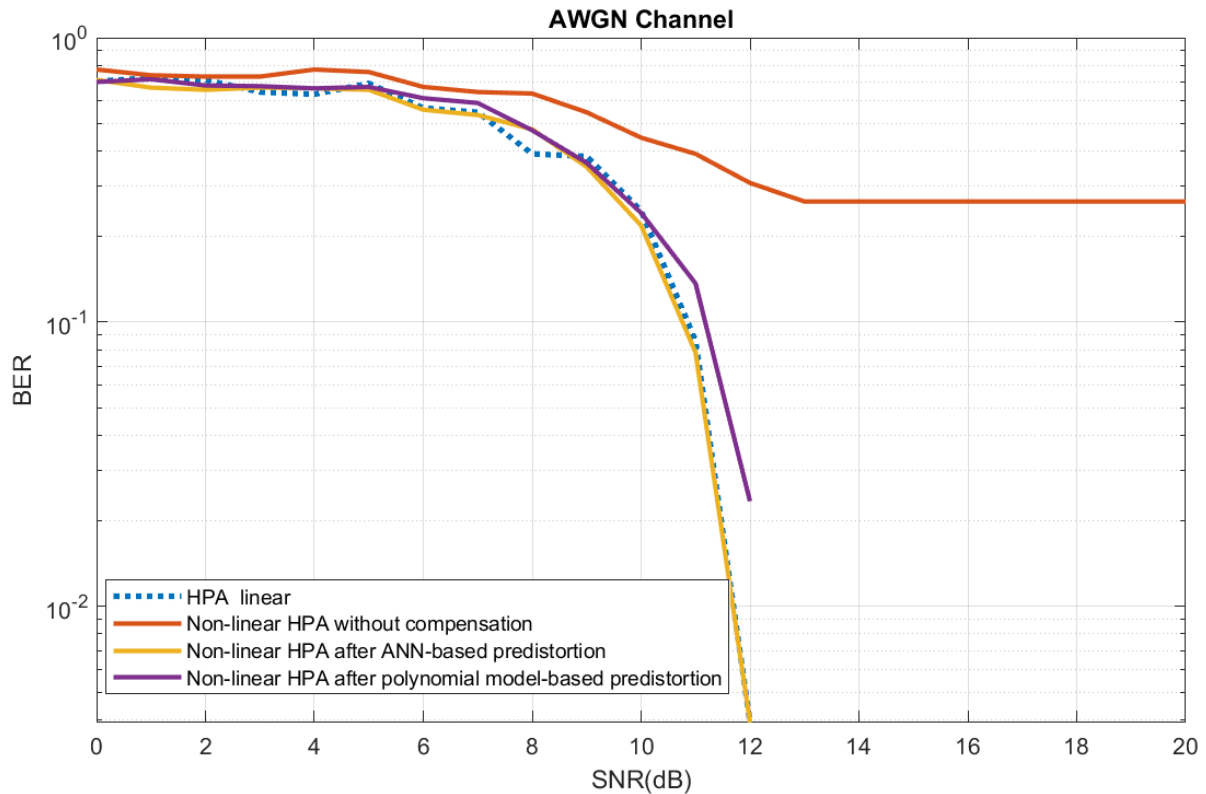


Figure 19. BER after predistortion (AWGN Channel).

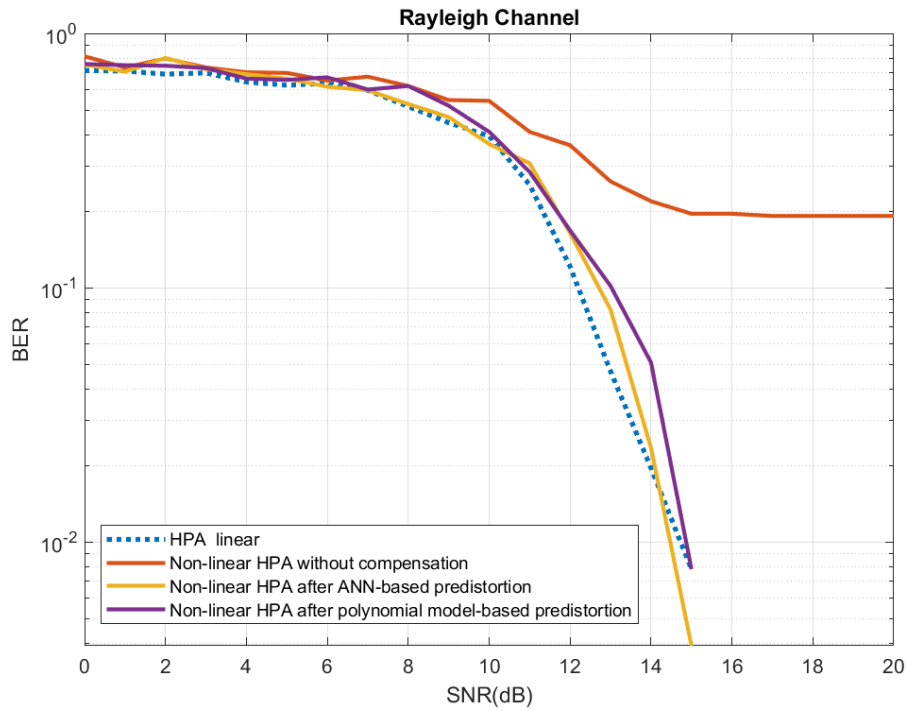


Figure 20. BER after predistortion (Rayleigh Channel).

The BER after linear amplification serves as the reference, as it represents the ideal case.

The BER after nonlinear amplification without compensation remains high even at high SNR values, demonstrating that the HPA's nonlinearity severely degrades performance.

After polynomial-based predistortion, an improvement is observed compared to the uncompensated case, but the BER curve does not decrease as rapidly as the linear reference.

After ANN-based predistortion, the BER is nearly identical to that of the linear HPA, indicating that ANN-based

predistortion effectively compensates for the nonlinearity.

Power amplifiers exhibit complex nonlinearities. A polynomial model cannot capture all these nuances. A neural network with a hidden layer can approximate any continuous function. This means that the ANN can faithfully model the inverse nonlinearity of the HPA, even if it is highly complex.

4) Amplifier efficiency after predistortion

Figure 21 shows the evolution of amplifier efficiency as a function of IBO.

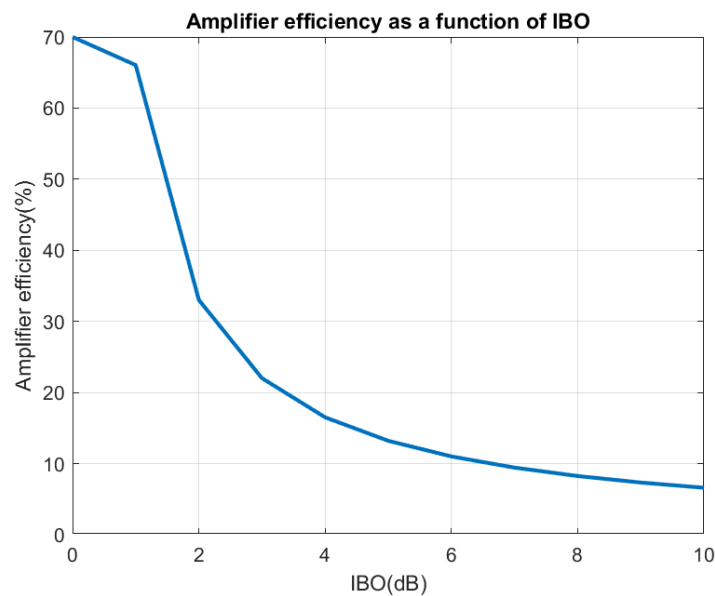


Figure 21. Amplifier efficiency as a function of IBO.

From this figure, we deduce that as the IBO increases, the amplifier efficiency decreases.

Between IBO = 0 dB and IBO = 2 dB, efficiency drops rapidly from 70% to 33%. This corresponds to the region where the amplifier begins to exit saturation, reducing distortion but at the cost of a significant loss in efficiency.

Between IBO = 2 dB and IBO = 6 dB, the amplifier efficiency continues to decrease, but more gradually. We typically

force the amplifier to operate in this range to achieve a good compromise between signal quality (low distortion) and acceptable efficiency (15–30%).

In summary, to ensure sufficient linearity and avoid distortion, it is necessary to reduce the input power (increase the IBO), but this significantly degrades energy efficiency.

Figure 22 also shows the BER after ANN-based predistortion and for different values of IBO.

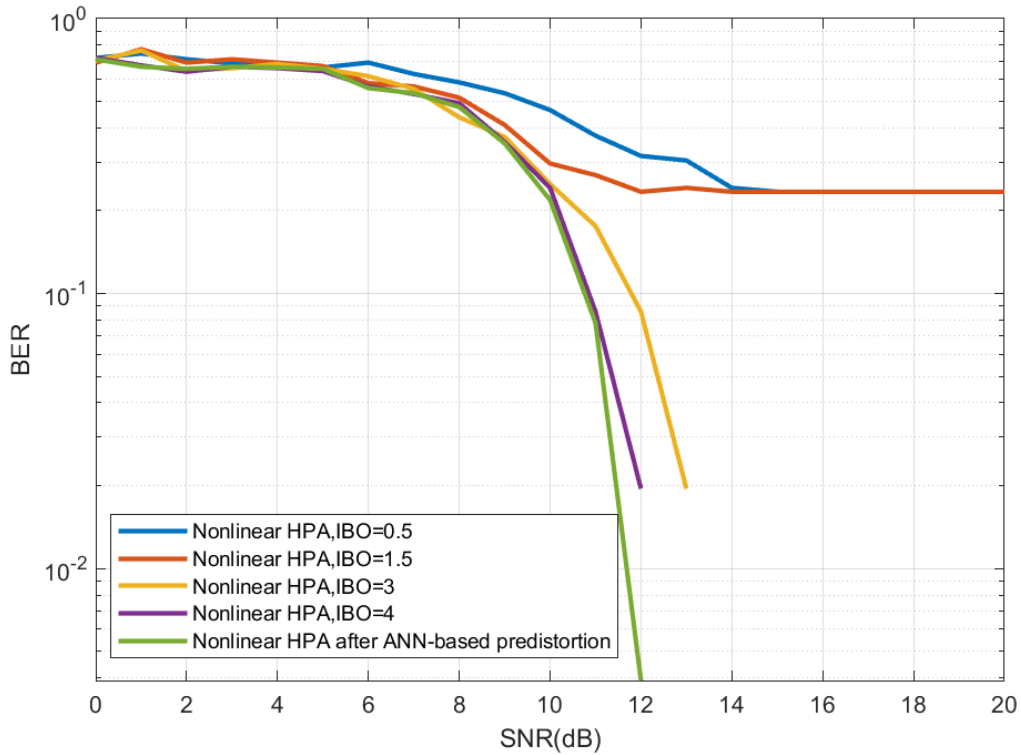


Figure 22. BER after ANN-based predistortion and for different values of IBO.

From this figure, we deduce that after neural network-based predistortion, the BER performance is nearly identical to that achieved with an IBO of 4 dB. This means that, thanks to this predistortion technique, the HPA can operate in the saturation region to achieve high efficiency without introducing distortions into the amplified signal.

ANN-based predistortion breaks the traditional trade-off between amplifier efficiency and BER. It enables excellent signal quality (low BER) while maintaining high efficiency.

6. Originality and Our Contribution to the Research

The originality lies in the systematic, consistent, and multi-criteria demonstration that a simple feedforward neural network-based predistortion (non-recurrent, not deeply layered) is sufficient to significantly outperform the classical polynomial predistortion method even under realistic oper-

ating conditions. Unlike many studies that limit their evaluation to conventional modulations such as OFDM or FBMC, this research was conducted on OTFS modulation, a revolutionary waveform recognized as one of the key enabling technologies for 6G. The personal contributions of this work are as follows:

- 1) Multi-criteria evaluation: This study assesses the performance of neural network-based predistortion on an OTFS system by simultaneously considering linearity, spectral purity (ACPR), transmission quality (BER), and power amplifier efficiency.
- 2) Breakthrough of the efficiency-linearity trade-off in a 6G context: The work demonstrates that ANN-based predistortion enables the HPA to operate in saturation (low IBO) while maintaining a BER close to the ideal performance even for high-PAPR signals like OTFS. This revolutionizes 6G base station design, where energy efficiency is critical and channels often experience very high mobility.

- 3) Realistic scenario validation: By evaluating performance in a Rayleigh fading channel, this study proves that the proposed solution is not merely theoretical but practically applicable to future mobile networks.
- 4) Simplicity and efficiency of the proposed technique: By employing a simple feed forward neural network without complex architectures (e.g., LSTM (Long Short-Term Memory), CNN (Convolutional Neural Networks)), high performance is achieved without prohibitive computational cost making it viable for integration into real-world network equipment such as base stations and user terminals.

7. Conclusion

In this paper, we propose and evaluate a digital predistortion technique based on a feedforward neural network to enhance power amplifiers linearization in communication systems employing OTFS modulation, a key technology identified for 6G networks. Unlike conventional approaches relying on polynomial models, our solution leverages the universal approximation property of neural networks to accurately learn the inverse non-linearity of the amplifier, even under demanding operational conditions. A multi-criteria evaluation was conducted, assessing linearization quality (MSE), spectral purity (ACPR), transmission performance (BER) in both AWGN and Rayleigh fading channels, and the impact on the amplifier's energy efficiency. Results demonstrate that neural network-based predistortion significantly outperforms the polynomial method:

- 1) It achieves precise approximation of the predistortion function with an MSE of 7.38×10^{-6} .
- 2) It nearly restores the signal spectrum, with ACPR improving from -15 dB without compensation to -36 dB with ANN predistortion, compared to only -14 dB with the polynomial model.
- 3) It achieves a bit error rate (BER) nearly identical to that of an ideal linear amplifier, even in a realistic Rayleigh fading channel.
- 4) Crucially, it breaks the traditional trade-off between energy efficiency and linearity: the HPA can operate near saturation (low IBO), achieving high efficiency (~70%), while maintaining excellent transmission quality.

In summary, this study demonstrates that neural network-based predistortion enables optimal performance in future communication systems such as 6G. The results presented here are obtained through simulation. The next step is to implement and test the solution on a hardware prototype (e.g., FPGA or SDR – Software Defined Radio) to validate its robustness against real-world imperfections: clock jitter, signal quantization, processing latency, and thermal drifts.

Abbreviations

6G Sixth Generation of Mobile Communications

ACPR	Adjacent Channel Power Ratio
AM	Amplitude
ANN	Artificial Neural Network
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
CCDF	Complementary Cumulative Distribution Function
CNN	Convolutional Neural Networks
CP	Cyclic Prefix
FFT	Fast Fourier Transform
HPA	High Power Amplifier
IBO	Input Back-Off
IFFT	Inverse Fast Fourier Transform
ISFFT	Inverse Symplectic Finite Fourier Transform
LSTM	Long Short-Term Memory
OBO	Output Back-Off
OFDM	Orthogonal Frequency Division Multiplexing
OTFS	Orthogonal Time Frequency Space
PAPR	Peak-to-Average Power Ratio
PM	Phase
QAM	Quadrature Amplitude Modulation
SFFT	Symplectic Finite Fourier Transform
SNR	Signal-to-Noise Ratio

Author Contributions

Hariniony Bienvenu Rakotonirina: Conceptualization, Formal Analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Writing – original draft, Writing – review & editing

Marie Emile Randrianandrasana: Supervision, Validation

Data Availability Statement

The datasets and code used for reconstruction are available upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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Research Field

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