OPTIMIZING 5G NETWORK PERFORMANCE BY COMBINING NEURAL NETWORK BASED PREDISTORTION WITH LDPC CODING

RAKOTONIRINA Hariniony Bienvenu[1], RANDRIAMITANTSOA Paul Auguste[2]
[1] *PhD student, TASI, ED-STII, Antananarivo, Madagascar*
[2] *Thesis director, TASI, ED-STII, Antananarivo, Madagascar*

ABSTRACT

In this article, we have proposed a new power amplifier linearization technique based on the combination of neural network predistortion with Low Density Parity Check (LDPC) coding. We evaluated the performance of this new technique by applying it in the 5G network. The results of the simulation reveal that the combination of neural network predistortion with LDPC coding allows the 5G telecommunications network to offer both high communication reliability (low error rate) and low energy consumption of the access network.

Keyword: *5G, Predistortion, Neural network, LDPC, Power amplifier, non-linearity*

---

1. INTRODUCTION

Current and future telecommunication networks will use multicarrier modulations but no longer single-carrier modulations in order to increase throughput and to reduce transmission errors. As proof, 4G is based on OFDM (Orthogonal Frequency Division Multiplexing) modulation and four multicarrier modulations are proposed for 5G: F-OFDM, UFMC, FBMC and GFDM. Despite the advantages offered by these modulations, their main drawback is the high Peak-to-Average Power Ratio (PAPR) of the modulated signal which cause non-linearity problem of the power amplifier. This problem results in a degradation of the Binary Error Rate (BER) and in the increase of energy consumption of the power amplifier. All of this increases network operating and maintaining cost for operators and decreases cell phones autonomy for subscribers. In order to solve this problem, we proposed a new linearization technique witch combine neural network based predistortion with LDPC coding. In this article, we will see the performance of this new amplifier linearization technique by applying it in the 5G telecommunication network.

2. 5G telecommunication network

Mobile and wireless traffic has grown exponentially since the deployment of 2G, 3G and 4G networks. It is expected that mobile data traffic will multiply by a factor of 1000 between 2010 and 2020. This sharp increase in traffic is due to the increase in the number of subscribers and the number of connected things (IoT or Internet Of Things). The use of mobile networks is therefore no longer limited to telephony, short messages and browsing the Web. In addition, new services such as e-banking, e-health, e-learning, artificial intelligence, online games and augmented reality have born. All of these services increase traffic volume and require high data transfer rates and low latency. To achieve this goal, the 5G network was born.

2.1 5G network architecture

The overall architecture of the 5G telecommunications network consists of an access network called NG-RAN (Next Generation Radio Access Network) and a core network called 5G Core (5GC) [1] [2]. Figure 1 illustrates this architecture

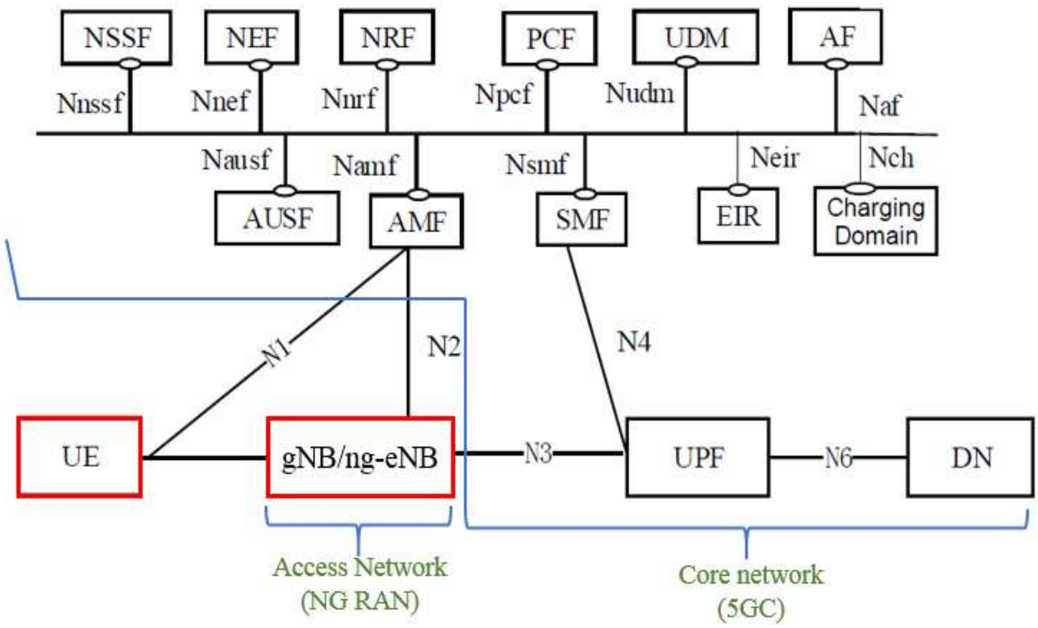

Fig -1: 5G network architecture

User equipment (UE) communicates with base stations: either by a 5G radio link, or by a 4G radio link. If the communication is in 5G, the base station is called next Generation Node Base Station (gNB), if the communication is in 4G, the base station is an advanced eNB station which allows interconnection with the 5G core network. This base station is called Next Generation - eNb (ng-eNb) or eLTE-eNB.
The new amplifier linearization technique that we are developing is deployed at the level of the red blocks (NG-RAN and UE) of the 5G architecture shown in figure 01. In the following paragraph, we will see the NG-RAN architecture.

2.2 NG-RAN architecture

The 5G access network is made up of the gNB and ng-eNB stations. The gNB station is divided into three parts [3] [4]. There is :

- Central Unit (CU)
- Distributed Unit (DU)
- Remote Unit (RU)

This new architecture facilitates the access network virtualization and brings more flexibility to the network. Figure 02 shows us a comparison between e-UTRAN (4G) and NG-RAN (5G). The link between the CU and the 5G core network is called backhaul. It is typically implemented using very high speed optical transport technologies. It is expected that speeds of up to 400 Gbps will be possible over distances of up to 200 km.
The link between the CU and the DU is called midhaul and carries data from the F1 interface. It is an IP / Ethernet link that must support speeds of up to 100 Gbps over distances of 0 to 40 km.
Finally, the link between DU and RU is called fronthaul. For this link, 3GPP continues to study different options. For example, here are some technologies proposed for the fronthaul:

- **CPRI (Pulic Common Radio Interface) :** It is the transport of the digital RF signal on an optical medium. It is used by 4G.
- **eCPRI (enhanced CPRI) :** It is an improvement of the CPRI technology to allow transmission over the Ethernet network.
- **ARoF (Analog Radio over Fiber):** allows the transport of the analog RF signal over an optical fiber.

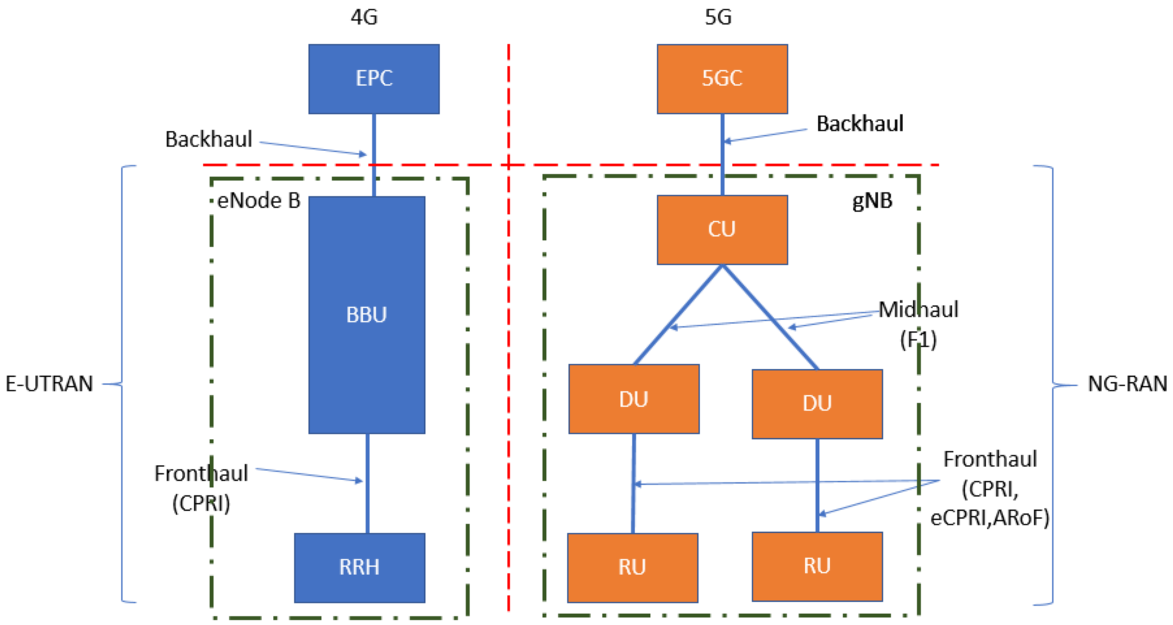

Fig -2: Comparison between e-UTRAN (4G) and NG-RAN (5G)

Our research is deployed on the 5G NG-RAN more specifically at the RU entity. In the next paragraph, we will talk about RU architecture.

2.3 RU architecture

The RU fulfills physical layer role. Figure 03 shows us the architecture of this entity.

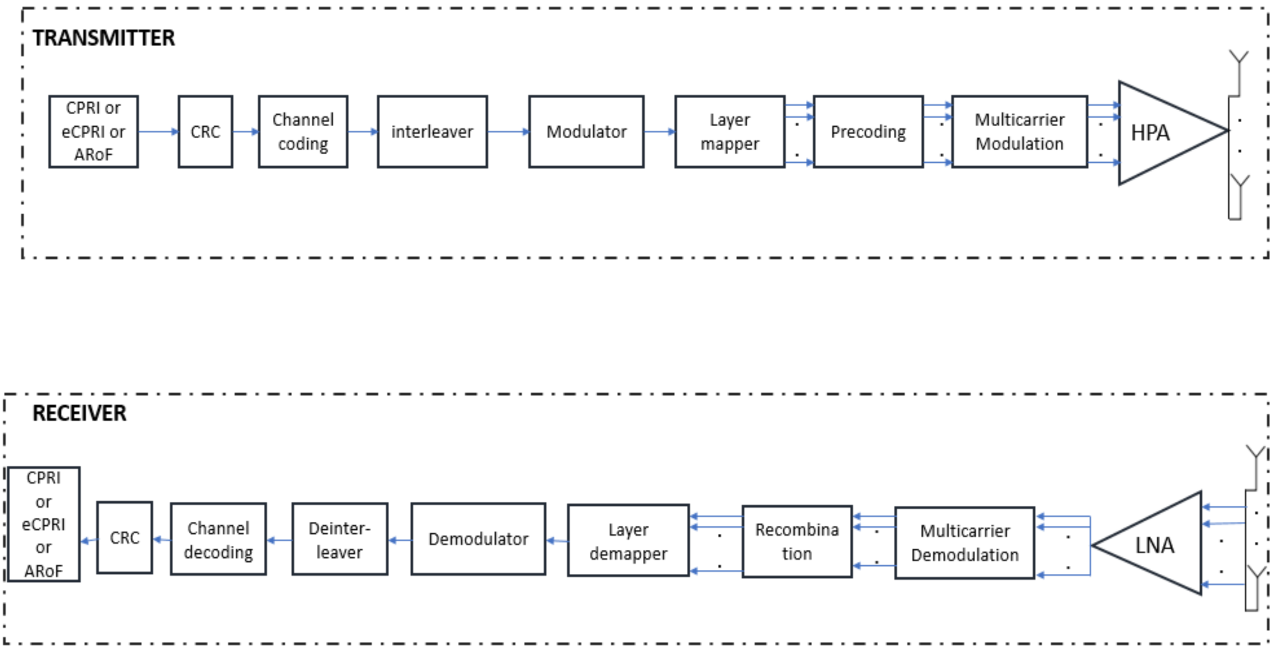

Fig -3: RU architecture

- **CPRI, eCPRI et ARoF :** These are technologies that can be used for fronthaul link that is to say the link between RU and DU.
- **CRC (Cyclic Redundancy Check) :** This block adds a CRC at the end of each frame to verify the integrity of the information received at the receiver.

- **Channel coding:** This block adds redundancies at the information in order to protect it against noises that reign in the transmission channel. These are error detection and correction codes.
- **Interleaver:** This block will swap the bits that form the information to make it more robust against noises.
- **Modulator:** This block will group together the binary information found at its input in bit packets called digital symbols. The number of bits constituting a digital symbol depends on the modulation used. For example, if we use the BPSK, there will be 1 bit per symbol, for the case of QPSK, there will be 2bits per symbol and for 16-QAM there will be 4bits per symbol.
- **Layer Mapper:** This block will make the correspondence between the digital symbols coming from the modulator and N_{TX} transmission channels. Indeed, this block will send the symbols through N_{TX} transmitting antennas.
- **Precoding:** It is a technique applied to transmitter to optimize transmission system performance.
- **Multicarrier modulation:** The precoded information will be modulated using multicarrier modulation. For the case of 5G, there are several candidates for this modulation. But in our research, we will be using FBMC / OQAM modulation.
- **HPA:** It is the power amplifier that will amplify the signal before transmission.
- **LNA (Low Noise Amplifier):** Block for amplifying noisy signals from an antenna.
- **Multicarrier demodulation:** Performs the inverse operation of the multicarrier modulation block.
- **Recombination:** It is a technique used at receiver in MIMO systems to recombine the different versions of the transmitted signal.
- **Layer demapper:** Performs the inverse operation of the layer mapper block.
- **Demodulator:** Performs the inverse operation of modulator block.
- **Deinterleaver:** Performs the inverse operation of interleaver block.
- **Channel decoding:** Detects and corrects transmission errors.

3. Performance of neural network-based predistortion combined with LDPC coding applied to the 5G telecommunication network

We will apply neural network-based predistortion combined with LDPC coding in the 5G network in order to linearize the power amplifier and optimize the performance of this network in terms of BER and energy consumption. This new technique is deployed at the RU entity located at the gNB. Figure 04 shows the block diagram of the modified RU entity.

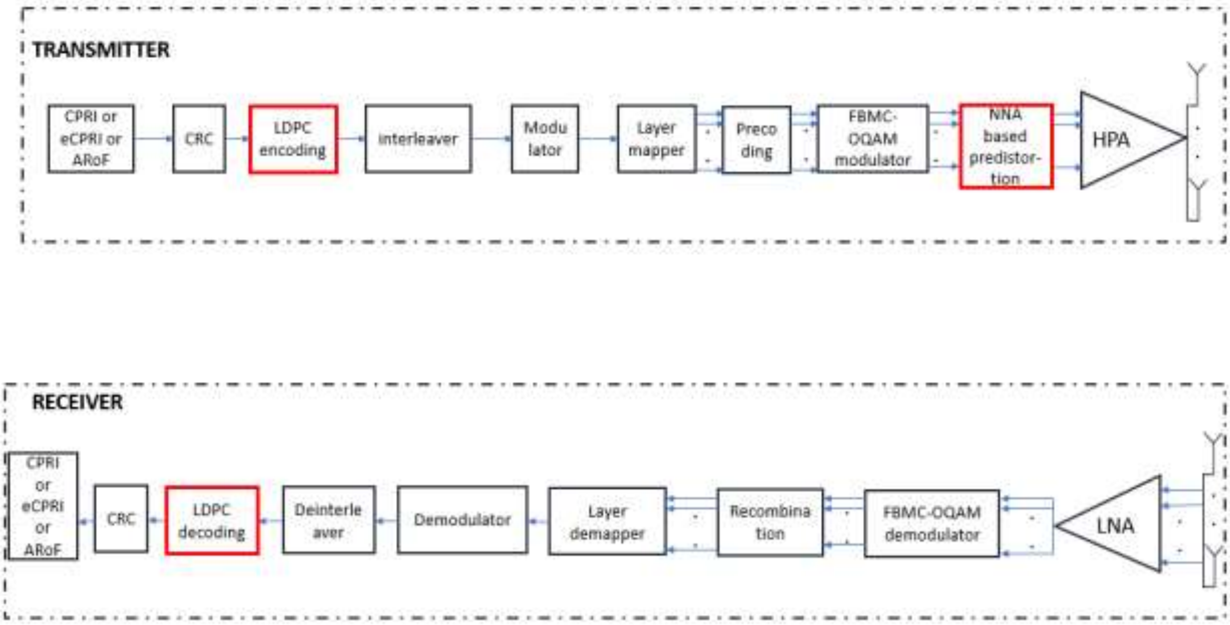

Fig -4: RU architecture with new amplifier linearization technique

Unlike figure 03, we can see in figure 04:

- A neural network-based predistortion block before the power amplifier
- LDPC is also used to perform channel encoding and decoding

In the following paragraph, we will talk about the principle of these two technologies.

3.1 Predistortion technique

Definition 1:

The predistortion consists in compensating for the non-linearity of the amplifier by adding to its input a block presenting an inverse non-linearity, so that the juxtaposition of the two non-linear blocks gives a linear transfer function (see figure 05).

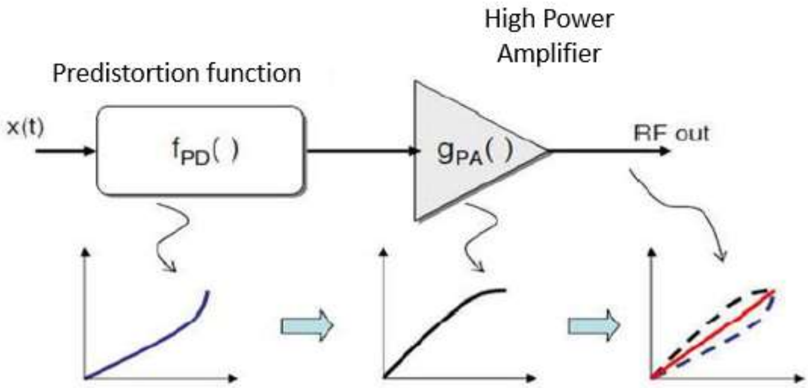

Fig -5: Principle of predistortion technique

Digital predistortion can be divided into two categories [5]:

- LUT (Look-up table) predistortion
- Predistortion by mathematical models

In this article, we will focus on predistortion by mathematical model. This technique is based on the mathematical modeling of the system (predistortion block) used to determine the inverse transfer characteristic of the amplifier. In this approach, the predistortion function is implemented using mathematical models.

3.1.1 Predistortion by polynomial model or classic predistortion

The polynomial model appeared to be a fairly efficient approach to linearize amplifiers. We must first identify the coefficients of this model. To do this, we must identify a « postdistortion» function $\boldsymbol{f_{POST}}$ from the input and output signals of the amplifier (figure 06). We find the function $\boldsymbol{f_{POST}}$ by minimizing the mean error $\|x - y_{post}\|^2$ where x is the signal at the input of the amplifier and y_{post} the signal at the output of the post-distortion function (see figure 06). As soon as the minimization criterion is fulfilled, the estimated post-distortion function is copied into the predistortion module, that is to say f_{PD}=f_{POST}. Here are the steps to follow for the realization of the predistortion by polynomial model:

Step 1: Normalization of the power amplifier output by the linear gain G of this device to obtain the samples $y_{norm}(n)$ of expression:

$$y_{norm}(n) = \frac{1}{G}.y(n) \tag{1}$$

Step 2: Finding the post-distortion polynomial defined as follows:

$$y_{post}(n) = f_{POST}(y_{norm}(n)) \tag{2}$$

This f_{POST} function will be mathematically modeled using a polynomial model according to relation 03.

$$y_{post}(n) = \sum_{k=1}^{K} a_k y_{norm}(n)|y_{norm}(n)|^{k-1} \tag{3}$$

Where a_k: the polynomial's coefficients, note that we must look for them
K: is the non-linearity order of the predistortion function

In matrix form, equation 03 becomes:

$$y_{post} = H.a \tag{4}$$

Where

$y_{post} = \left[y_{post}(0)\ y_{post}(1) \dots\ y_{post}(N-1)\right]^T$ with N the number of symbols.

$a = [a_1\ a_2 \dots\ a_K]^T$ the vector of the coefficients of the post-distortion polynomial

$H = [H_1\ \ H_2 \dots\ H_{\boldsymbol{K}}]^T$ with H_k=$[h_k(0)\ \ h_k(1) \dots\ h_k(N-1)]^T$ and $h_k(n) = \frac{y(n)}{G}.\left|\frac{y(n)}{G}\right|^{k-1}$

Looking at Figure 6, the expression for the predistortion error is given by equation 05.

$$e = x - y_{post} \tag{5}$$

Using equations 04 and 05, we can find the expression for the average predistortion error given by equation 06.

$$\left\|x - y_{post}\right\|^2 = \|x - H.a\|^2 \tag{6}$$

$$\left\|x - y_{post}\right\|^2 = (x\ - Ha)^T(x\ - Ha) \tag{7}$$

$$\left\|x - y_{post}\right\|^2 = x^T x\ -\ a^T H^T x\ -\ x^T Ha + a^T H^T Ha \tag{8}$$

Our objective is to find the coefficients a_k of the post-distortion polynomial which minimize the average error defined by the relation 08 (average predistortion error), for that it is necessary that its derivative compared to a be zero, we have then equation 11:

$$\frac{d}{da}||x - Ha||^2 = 0\ -\ H^T x\ -\ Hx^T + 2H^T Ha \tag{9}$$

$$\frac{d}{da}||x - Ha||^2 = -2H^T x + 2H^T Ha \tag{10}$$

$$\frac{d}{da}||x - Ha||^2 = 0 \leftrightarrow -2H^T x + 2H^T Ha = 0 \tag{11}$$

Hence

$$2H^T Ha = 2H^T x \tag{12}$$

$$a = (H^T H)^{-1} H^T x \tag{13}$$

As the samples y are complex numbers, H is a complex matrix so the transpose becomes Hermitian hence:

$$a = (H^H H)^{-1} H^H x \tag{14}$$

Step 3: Step 2 gives us the expression of the post-distortion polynomial f_{POST} (equation 04 where a is defined by equation 14). The last step is to copy f_{POST} into the predistortion block ie f_{PD}=f_{POST}. Figure 6 summarizes the principle of predistortion by polynomial model.

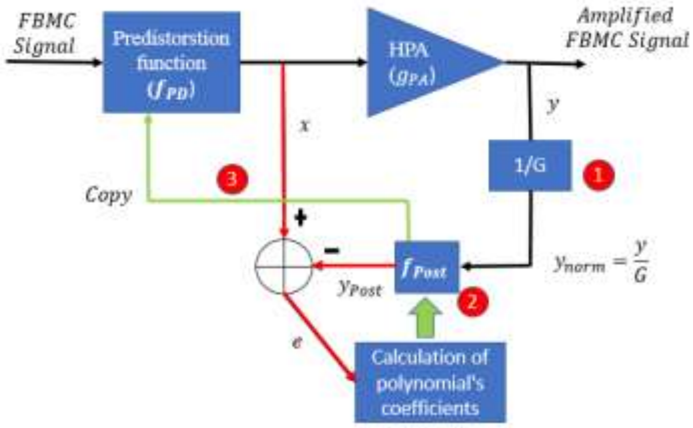

Fig -6: Principle of Predistortion by polynomial model or classic predistortion

3.1.2 Neural network based predistortion

3.1.2.1 Universal approximation property of neural networks

This property is stated as follows: « for any function, there exists at least one non-looped neural network, having a layer of hidden neurons and a linear output neuron, which performs an approximation of this function and of its successive derivatives » [6]. So unlooped neural networks may be quite suitable for modeling the desired predistortion function in order to linearize the amplifier. Among the various architectures of unlooped networks, we will use a feedforward neural network.

3.1.2.2 Principle of neural network-based predistortion

From the «universal approximation» property of neural networks, it can be deduced that the predistortion function f_{PD} used to inverse the transfer characteristic of the amplifier can be approximated using a non-looped neural network of type feedforward. To achieve this goal, we must train this network. We will therefore use a supervised learning algorithm called the back-propagation algorithm. Here are the steps to follow for the realization of the neural network-based predistortion (see figure 07).

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

Step 2: Introduction of a training data. Indeed, the network will receive at its input the output data of the power amplifier.

Step 3: The neural network will estimate the output data that corresponds to the input data (the output data of the amplifier)

Step 4: Comparison between the outputs estimated by the neural network and the desired outputs which are the input data of the 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.

$$e = y_{des} - y_{est} \tag{15}$$

Where

y_{des} **:** the desired outputs

y_{est} **:** the outputs estimated by the neural network

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

Step 5: Updating the synaptic weights of the neural network using equation 17.

$$W_{nouvelle} = W_{ancienne} - \Delta W \tag{17}$$

Where:

$\boldsymbol{W_{ancienne}}$ **:** old synaptic weight value

$\boldsymbol{W_{nouvelle}}$ **:** new value of synaptic weight

$\boldsymbol{\Delta W}$ **:** Correction value that depends on the optimization algorithm used to minimize the cost function J.

Step 6: We copy the network trained in the pre-distortion block.
Figure 07 summarizes the principle of the neural network-based predistortion technique.

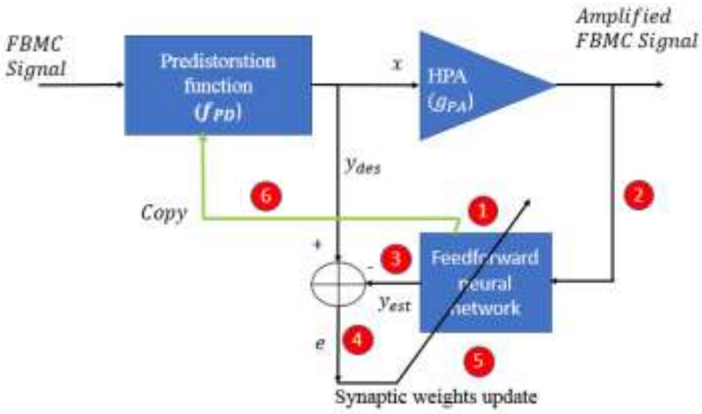

Fig -7: Principle of neural network-based predistortion

3.2 LDPC code

Definition 2 :
LDPC (Low Density Parity Check) codes were invented by Gallager in 1962. They are binary codes characterized by a parity matrix H at low density ie the number of 1 in this matrix is low. LDPC codes are linear block codes [7] [8].
To build the parity matrix H of an LDPC code, there are several techniques such as:

- The Gallager's construction
- The algebraic construction
- Random construction

3.2.1 LDPC encoding

3.2.1.1 Encoding using the generator matrix

As the LDPC code is a linear block code, the encoding of a message m is done by multiplying the latter by the generator matrix G of this code. So we have to find the expression of this generator matrix from the parity matrix H. Its expression is:

$$G = (H_2 H_1^{-1} : I_k) \tag{18}$$

Where
I_k is an identity matrix with k the length of the message to be encoded.
H_1 is a square matrix of dimension $(n-k) \times (n-k)$ where n is the length of the code word
H_2 is a rectangular matrix of dimension $k \times (n-k)$

And the parity matrix H is defined as follows $H^T = \begin{bmatrix} H_1 \\ \cdots \\ H_2 \end{bmatrix}$.

3.2.1.2 Encoding using the H parity matrix

The principle of this method is to modify the parity matrix H to have the form given in figure 08.

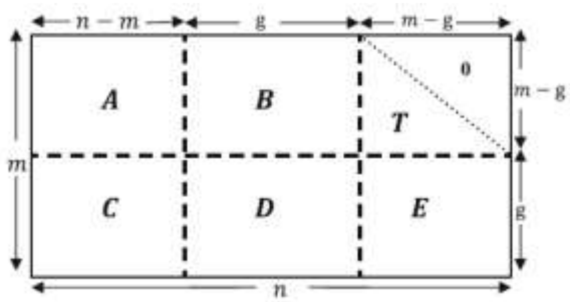

Fig -8: New form of the parity matrix H with a triangular matrix (T)

Where g is a real that we try to minimize
And the expression of the code word C is given by equation 19

$$C = [m : p_1 : p_2] \quad (19)$$

Where
m is a vector containing the message and
$p_1^T = -\emptyset^{-1}(-ET^{-1}A + C)m^T$ avec $\emptyset = -ET^{-1}B + D$
$p_2^T = -T^{-1}(Am^T + Bp_1^T)$

3.2.2 LDPC decoding

For the decoding operation, there are two techniques that can be used:

- Belief propagation Decoding
- Bit flipping decoding

3.3 Simulations, results and interpretations

3.3.1 Simulation parameters

Here are the parameters used in the simulation:

- **Multicarrier modulation:** FBMC-OQAM
- **Number of carriers:** 64
- **Constellation OQAM:** Deduced from the 16 QAM
- **Overlapping factor:** K = 4
- **Prototype filter:** PHYDYAS filter for K = 4
- **Power amplifier model:** Rapp model (See Figure 09)
- **Knee factor :** $p = 3$
- **Amplifier gain is equal to 4**
- **Saturation amplitude is equal to 4 volts**

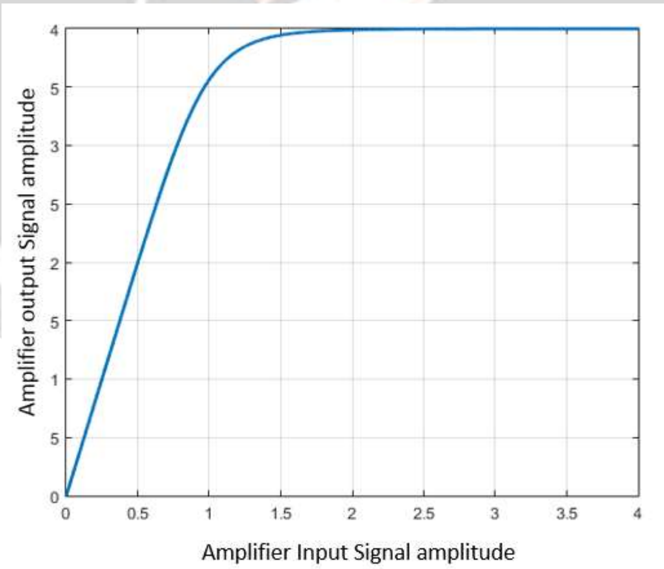

Fig -9: Rapp model

- **Neural network architecture:** feedforward type neural network with three layers: an input layer consisting of a single neuron, a hidden layer of 10 neurons with a hyperbolic tangent activation function and an output layer consisting of a single neuron whose activation function is linear (see figure 10). The learning algorithm used is the backpropagation algorithm associated with the Levenberg Marquardt optimization method
- Code rate of LDPC code: $R = \frac{4}{5}, R = \frac{1}{2}, R = \frac{1}{3}$

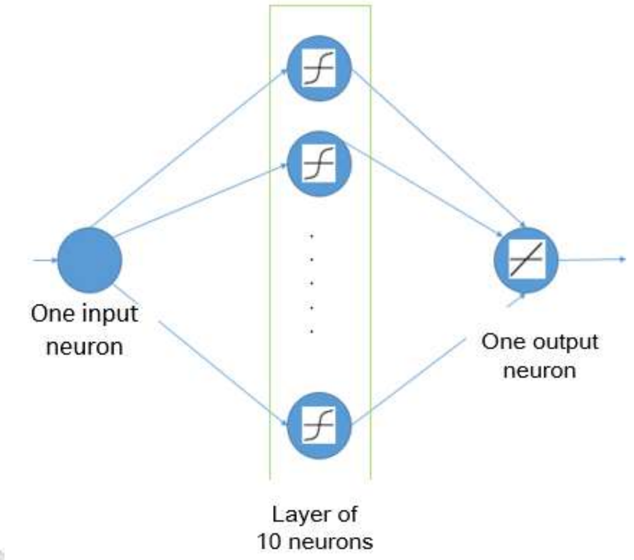

Fig -10: Feedforward neural network used

3.3.2 Predistortion function precision

Definition 3:

The inverse transfer characteristic of the power amplifier is called the predistortion function. It is placed before the amplifier to linearize this device.

We will compare the predistortion function modeled from the neural network with that modeled from the polynomial model which is a standard predistortion technique. Figure 11 illustrates this comparison.

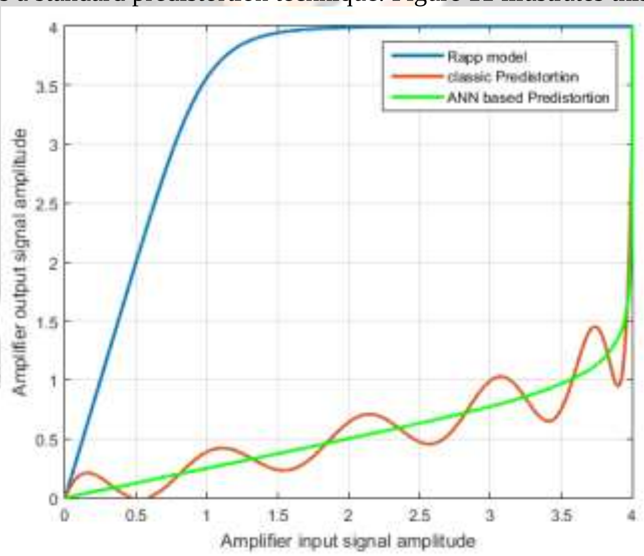

Fig -11: Comparison of the shape of the predistortion function obtained from the neural network-based predistortion with that obtained using the classical predistortion

We deduce from Figure 11 that the predistortion function obtained from the neural network is more precise compared to that obtained by the polynomial model (classical predistortion). Indeed, the neural network is a universal approximator so it is obvious that it gives a more precise result compared to the polynomial model

Figure 12 shows us the transfer characteristic of the power amplifier after the neural network-based predistortion (the curve in green) and that obtained after the classical predistortion (the curve in orange). We deduce that the neural network-based predistortion is more efficient to linearize the power amplifier and the transfer characteristic of the amplifier obtained after the application of this technique coincides with the ideal transfer characteristic (circles in yellow).

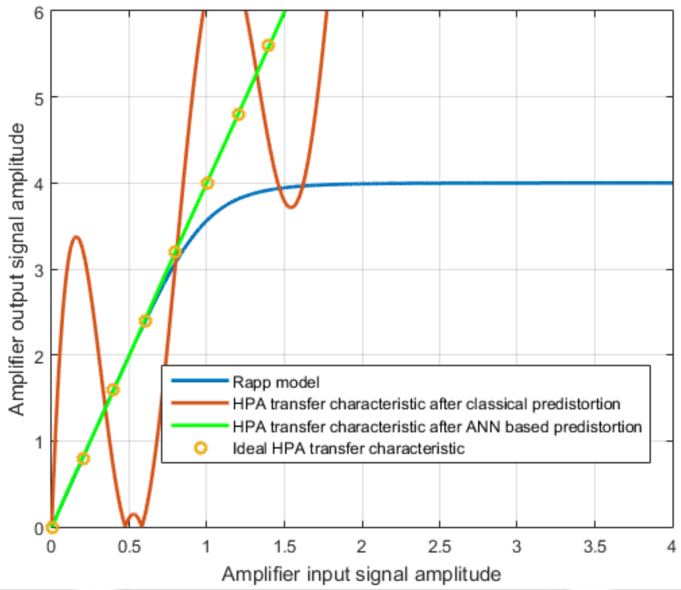

Fig -12: Comparison of the amplifier transfer characteristic obtained from the neural network-based predistortion with that obtained using the classical predistortion

3.3.3 Power Spectral Density of FBMC-OQAM signal after digital predistortion

In our research, we decided to use FBMC-OQAM modulation and in this part, we will compare the Power Spectral Density of an FBMC-OQAM signal obtained after neural network-based predistortion with that obtained after classic digital predistortion (see figure 13).

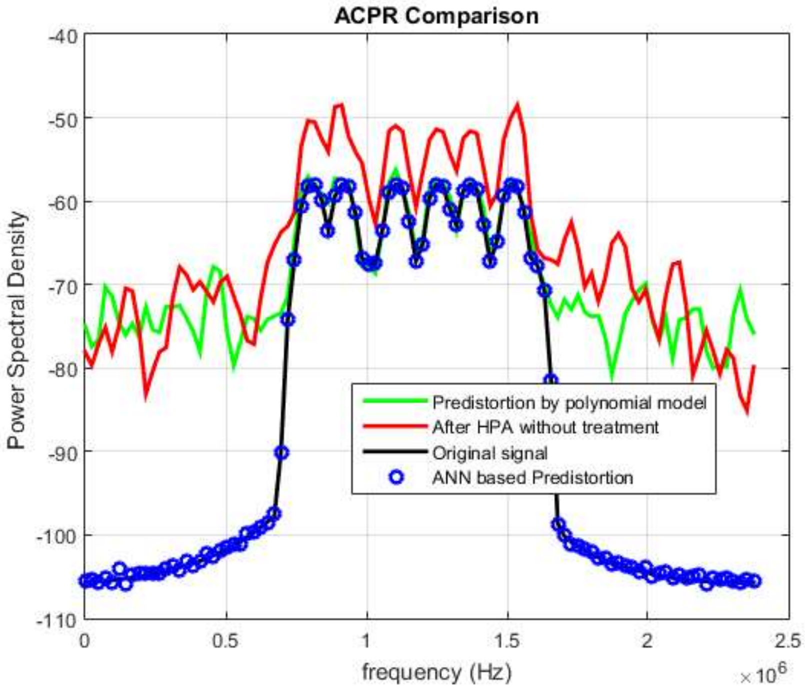

Fig -13: Spectrum of the FBMC-OQAM signal obtained from digital predistortion techniques

It can be seen from Figure 13 that digital predistortion techniques allow to reduce the spectral regrowth caused by the non-linearity of the power amplifier.

It can also be deduced from this that the spectral regrowth reduction resulting from the neural network-based predistortion is greater compared to that obtained after the classical predistortion. The latter can therefore cause interference with adjacent channels.

It is also noted that the spectrum of the FBMC-OQAM signal obtained after neural network-based predistortion is superimposed with that of the original signal without distortion. This performance is due to the precision of the predistortion function obtained from the neural network.

3.3.4 BER of the FBMC-OQAM signal after digital predistortion

Now let's compare the Binary Error Rate (BER) after applying three different digital predistortion techniques in the RU entity. Here are the three techniques used:

- Digital predistortion based on a polynomial model or classical predistortion
- Neural Network Based Digital Predistortion
- Neural network based digital predistortion combined with LDPC coding. The code rate of the code takes the values 4/5, 1/2, and 1/3.

The performance of these techniques is evaluated using two types of transmission channel:

- The AWGN channel which is a standard channel for doing a simulation
- And the Rayleigh channel which really reflects reality because in this channel there is no line of sight between the transmitter and the receiver and there is the existence of multipaths.

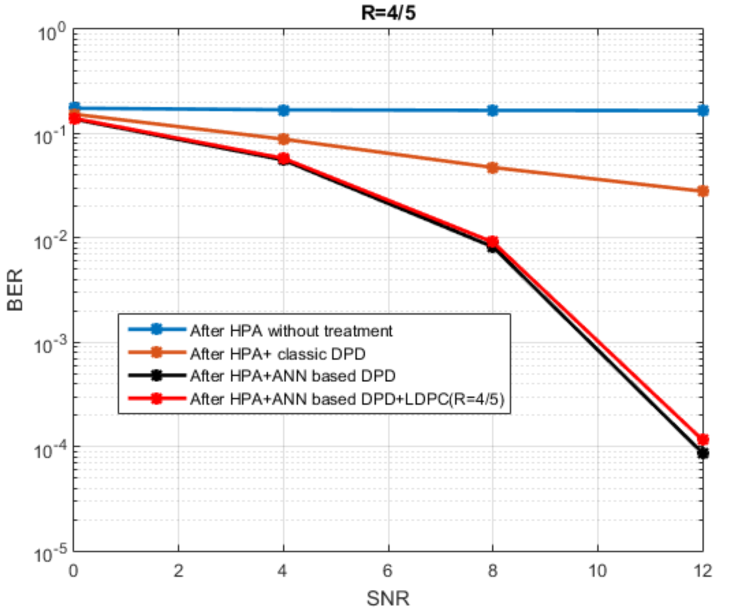

Fig -14: BER after digital predistortion through an AWGN channel for an LDPC code rate equal to 4/5

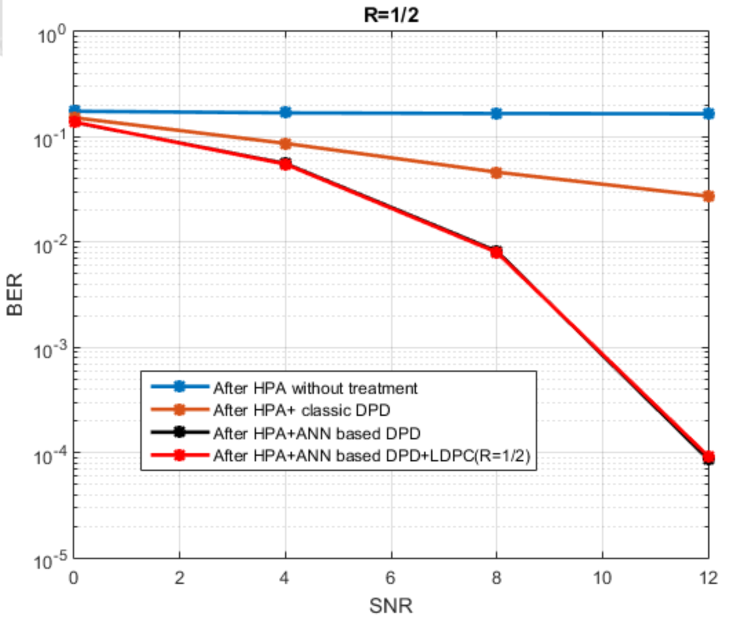

Fig -15: BER after digital predistortion through an AWGN channel for an LDPC code rate equal to 1/2

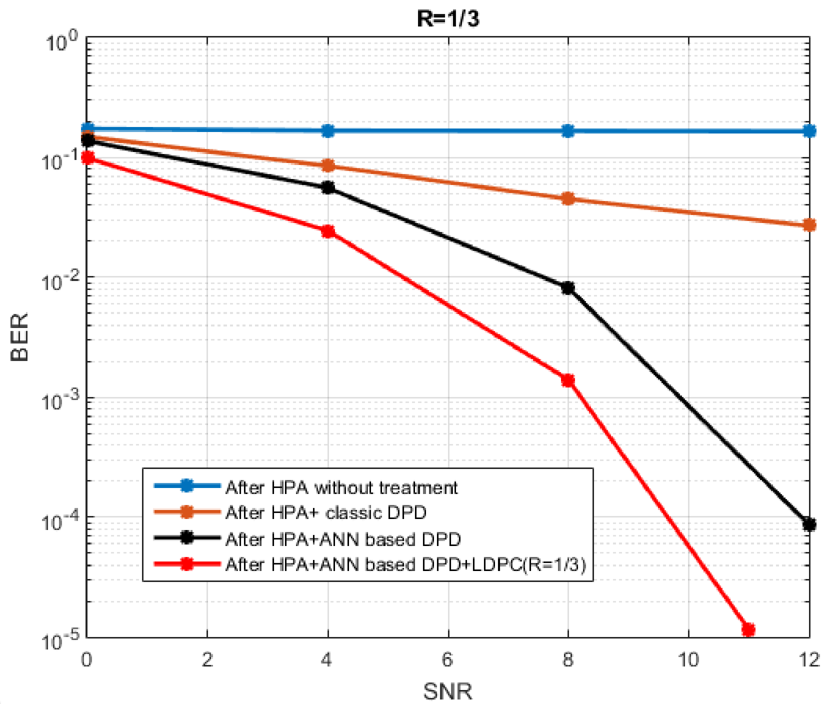

Fig -16: BER after digital predistortion through an AWGN channel for an LDPC code rate equal to 1/3

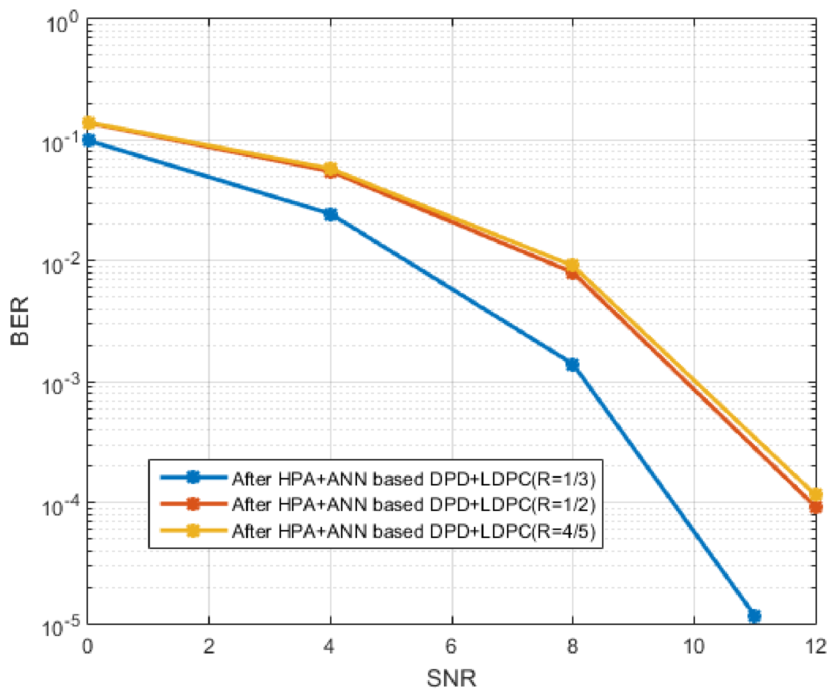

Fig -17: BER after neural network based predistortion combined with LDPC coding for code rate equal to 1/3, 1/2 and 4/5 and across the AWGN channel

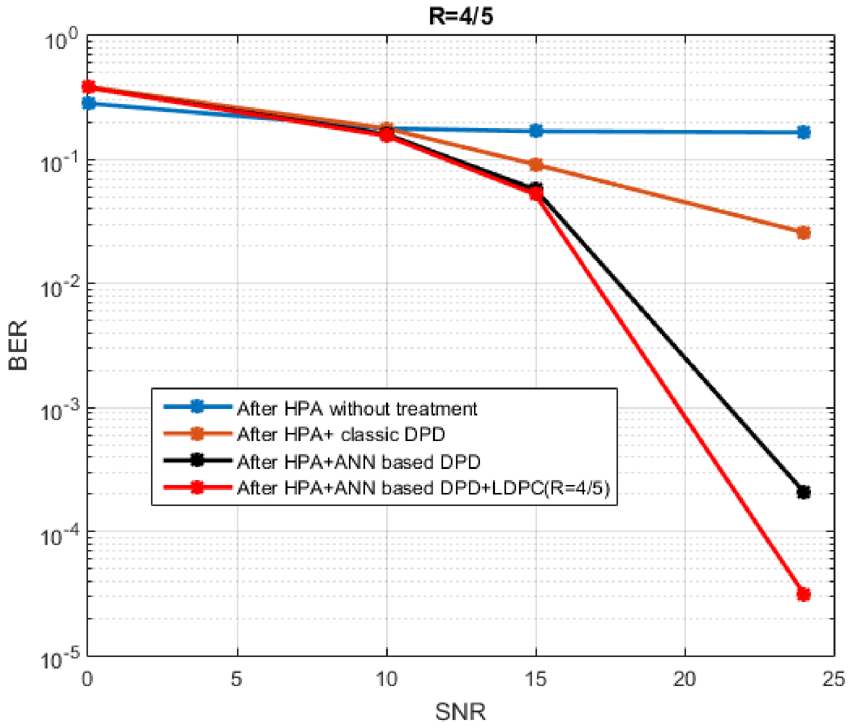

Fig -18: BER after digital predistortion through an Rayleigh channel for an LDPC code rate equal to 4/5

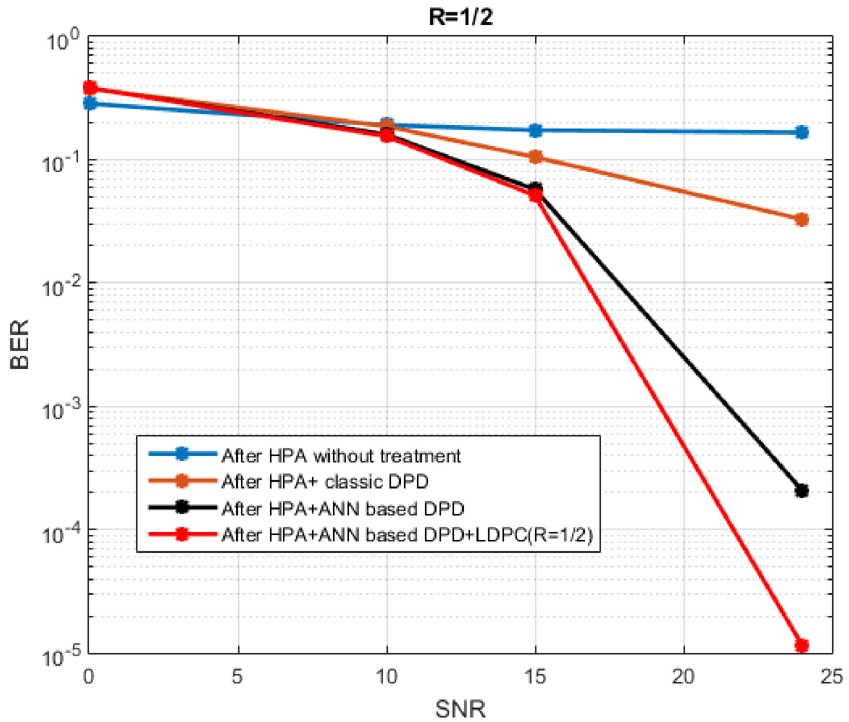

Fig -19: BER after digital predistortion through an Rayleigh channel for an LDPC code rate equal to 1/2

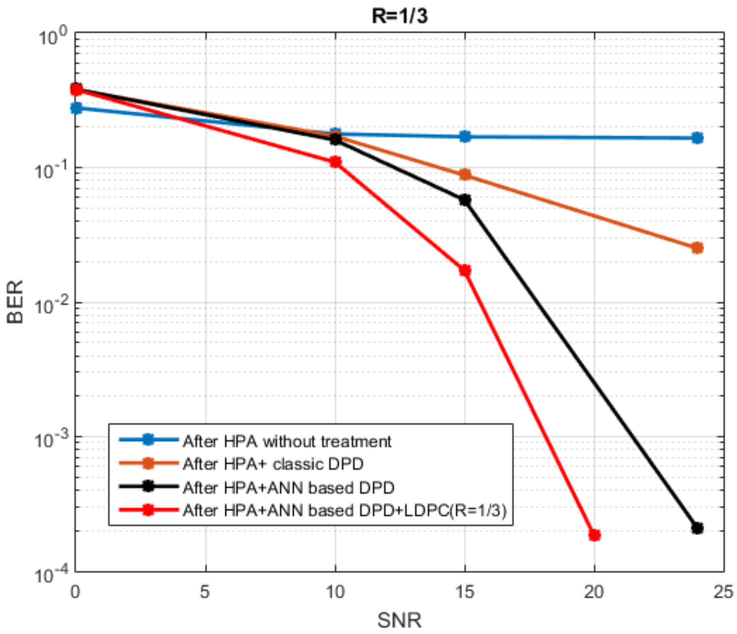

Fig -20: BER after digital predistortion through an Rayleigh channel for an LDPC code rate equal to 1/3

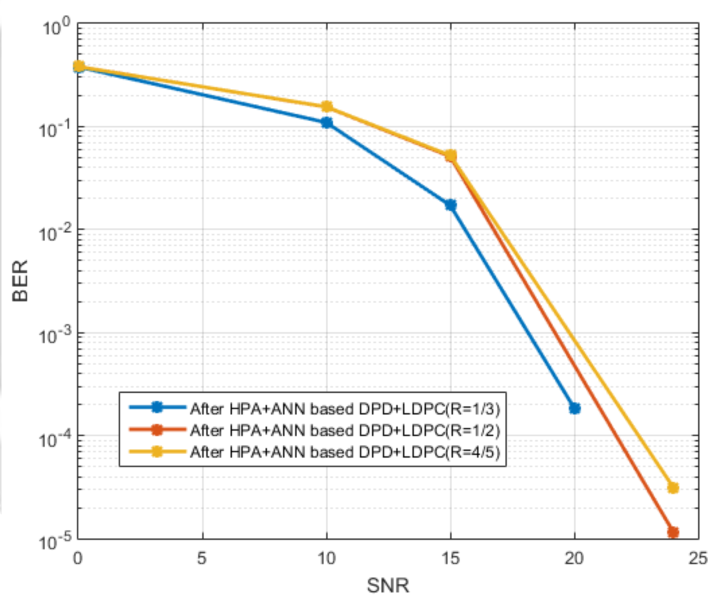

Fig -21: BER after neural network based predistortion combined with LDPC coding for code rate equal to 1/3, 1/2 and 4/5 and across the Rayleigh channel

- Figures 14, 15 and 16 show us the BERs obtained through an AWGN channel after the application of three different digital predistortion techniques at the RU entity. It is deduced from this that it is the neural network-based predistortion techniques which offer a low BER. In addition, for a code rate of the LDPC code equal to 4/5 and 1/2, the performance of techniques based on neural networks are very similar and even identical. When the code rate of the LDPC code is 1/3, the combination of the neural network based predistortion with the LDPC coding provides a lower BER compared to the simple neural network based predistortion.

- Figure 17 illustrates BERs obtained through an AWGN channel after neural network based predistortion combined with LDPC coding. A low BER is obtained when the code rate of the LDPC code is equal to 1/3. This is because a code rate equal to 1/3 offers a higher information protection compared to code rate with a value of 4/5 or 1/2.

- For the case of the Rayleigh channel, Figures 18, 19 and 20 show us the BERs obtained after the application of the three predistortion techniques at the RU entity of the base station. It can be seen that techniques based on neural networks offer a low BER. It can also be deduced that for different values of the code rate of the LDPC code, it is the combination of the neural network-based predistortion with this code that offers a low BER. We can therefore conclude that for the case of the Rayleigh channel, LDPC coding improves the performance of neural network-based predistortion.

- Figure 21 shows the BERs obtained after combining the neural network-based predistortion with the LDPC coding for different values of the code rate. Note that the channel used is that of Rayleigh. We deduce that a low BER is obtained if the code rate of the LDPC code is 1/3. This result further proves that a code rate equal to 1/3 offers a high level of information protection compared to code rate with a value of 1/2 or 4/5.

In short, the combination of neural network-based predistortion with LDPC coding is more efficient compared to other predistortion techniques. Further, the lowest BER is obtained when the code rate of the LDPC code is 1/3. In the rest of this paragraph, we will use this value.

To further demonstrate the performance of neural network based predistortion combined with LDPC coding, we will use the image shown in figure 22 as information and send it through the network. We will use different SNR (Signal to Noise Ratio) values and calculate BER, PSNR (Peak Signal to Noise Ratio) and SSIM (Structural SIMilarity) between the original image and the received image.

Fig -22: Original image to send to the network

Definition 4:
The PSNR or Peak Signal to Noise Ratio is a measurement of distortion used in digital imaging. An infinite value of the PNSR corresponds to an image identical to the original image, and it decreases with the distortion.

Definition 5:
Structural SIMilarity or SSIM is a measure of similarity between two digital images. It was developed to measure the visual quality of an image compared to the original image. The idea of SSIM is to measure the structural similarity between the two images, rather than a pixel-to-pixel difference like the PSNR. The assumption is that the human eye is more sensitive to changes in the structure of the image. It is essential to specify that two images are identical when the SSIM is equal to 1 and it is equal to 0 otherwise.

- **Case SNR=6dB**

Fig -23: Received image if no amplifier linearization technique is used (SNR = 6dB)

Fig -24: Received image after classic predistortion (SNR = 6dB)

Fig -25: Received image after neural network-based predistortion (SNR = 6dB)

Fig -26: Received image after neural network-based predistortion combined with LDPC coding (R = 1/3, SNR = 6dB)

- Figures 23, 24, 25 and 26 show us the images received for a signal to noise ratio equal to 6 dB. We considered four scenarios:
  - Scenario 1: Presence of power amplifier (HPA) at RU entity but no linearization technique is used
  - Scenario 2: Presence of the power amplifier in the RU and the classical predistortion technique is used as a linearization technique
  - Scenario 3: Presence of the power amplifier in the RU entity and the linearization technique used is neural network-based predistortion
  - Scenario 4: Presence of power amplifier at RU entity and combination of neural network based predistortion with LDPC coding is used as linearization technique.

For each of these scenarios, we calculated the BER, PSNR and SSIM between the original image and the received image. Table 01 shows us the results.

Table -1: Quality of the received image for an SNR = 6dB

Scenario	Description	BER	PSNR	SSIM
1	After HPA without treatment	0.3125	10.6894	0.1355
2	After HPA+ classic DPD	0.2822	10.6514	0.1344
3	After HPA+ ANN based DPD	0.0230	25.2033	0.3350
4	After HPA+ ANN based DPD+LDPC	10^{-4}	39.3094	0.9655

For scenarios 1 and 2, the PSNRs are low and the SSIMs are close to 0. It is therefore evident that the images received for these scenarios are deteriorated (figures 23 and 24). For the case of scenario 3 which uses neural network-based predistortion, the values of PSNR and SSIM are higher compared to the first two scenarios. Figure 25 shows an improvement in the visual quality of the image, however, the noise is not completely eliminated. For scenario 4 which uses the combination of neural network-based predistortion with LDPC coding, a great improvement in visual image quality was seen (Figure 26). The values of the PSNR and the SSIM prove this assertion. Indeed, the PSNR is high and the SSIM is close to 1. The received image is therefore almost identical to the original image.

- **Case SNR=8dB**

Fig -27: Received image if no amplifier linearization technique is used (SNR = 8dB)

Fig -28: Received image after classic predistortion (SNR = 8dB)

Fig -29: Received image after neural network-based predistortion neurones (SNR=8dB)

Fig -30: Received image after neural network-based predistortion combined with LDPC coding (R = 1/3, SNR = 8dB)

Figures 27, 28, 29 and 30 show us the received image for a signal to noise ratio equal to 8 dB. We still consider the four previous scenarios. Table 02 shows us the values of BER, PSNR and SSIM.

Table -2: Quality of the received image for an SNR = 8dB

Scenario	Description	BER	PSNR	SSIM
1	After HPA without treatment	0.3119	10.7214	0.1360
2	After HPA+ classic DPD	0.2748	10.7416	0.1387
3	After HPA+ ANN based DPD	0.0075	29.9730	0.5725
4	After HPA+ ANN based DPD+LDPC	0	Infinity	1

For Scenarios 1 and 2, the PSNR and SSIM are low. The quality of the received image is therefore deteriorated (Figure 27 and 28). For scenario 3, the PSNR is quite high 29.9730 and the SSIM greater than 1/2. Unlike the two previous scenarios, the visual quality of the image is more improved (Figure 29) despite the existence of noise. For the last scenario which uses the combination of neural network based predistortion with LDPC coding, the PSNR is equal to infinity and the SSIM is equal to 1, so the received image (Figure 30) is identical to the original image (Figure 22).

The different scenarios using different values of the signal-to-noise ratio (SNR) prove that among the predistortion techniques, it is the combination of neural network-based predistortion with LDPC coding that is the best.

3.3.5 Energy saving performance of the new amplifier linearization technique

First of all, we will compare the PAPR of the FBMC-OQAM signal before and after applying LDPC encoding. To evaluate the PAPR, we use the Complementary Cumulative Distribution Function called CCDF.

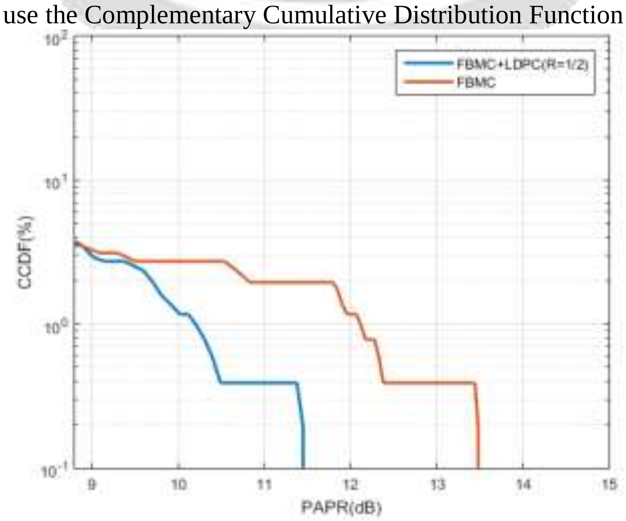

Fig -31: PAPR of FBMC-OQAM signal before and after LDPC encoding

From Figure 31 it can be deduced that the PAPR of the FBMC-OQAM signal after the application of the LDPC coding is lower compared to that of the original signal. This allows the power amplifier to work close to the saturation zone for high efficiency and low energy consumption.

Next, we will compare the BER at receiver for two scenarios:

- Scenario 1: Presence of the power amplifier (HPA) at RU entity but no linearization technique is used. The amplifier's Input Back Off (IBO) is fixed at 6dB, that is, the amplifier works in the linear zone away from the saturation zone.
- Scenario 2: Presence of the power amplifier at RU entity and the combination of neural network based predistortion with LDPC coding is used as a linearization technique. The amplifier's Input Back Off (IBO) is set at 0dB, that is, the amplifier work in the saturation zone.

Figure 32 shows us the BERs obtained

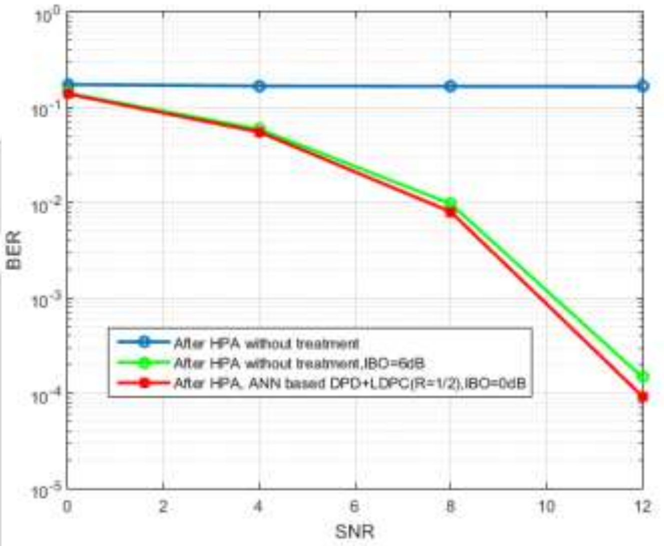

Fig -32: Gain in IBO using neural network based DPD combined with LDPC coding

We deduce from figure 32 that the BERs obtained are very close for scenarios 1 and 2. So the use of digital predistortion based on neural networks combined with LDPC coding gives us a gain of 6 dB on the IBO. This gain results in an increase in the efficiency of the amplifier. As proof, let us consider figure 33 which shows us the variation of the efficiency of the power amplifier according to the IBO. It can be deduced from this figure that the more the IBO increases, that is to say the closer the amplifier works to the linear zone, more the efficiency of this device will decrease. We also note that for an IBO = 6dB, the efficiency of the amplifier is equal to 16.59% while for an IBO = 0 dB, this efficiency is equal to 66.05%.

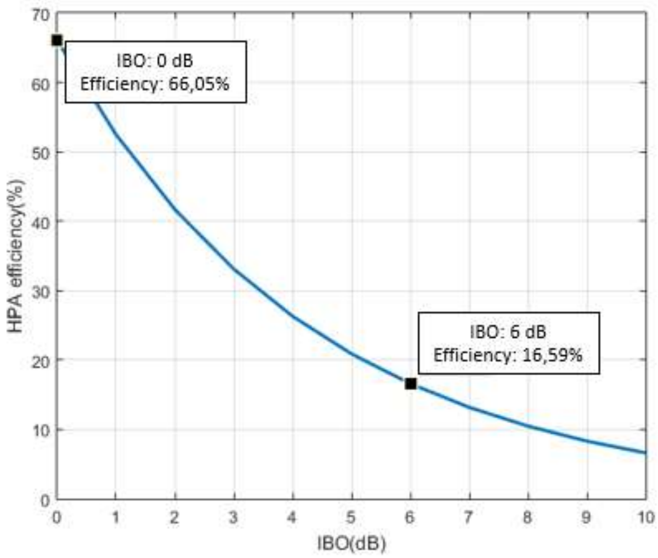

Fig -33: Variation of amplifier efficiency as a function of the IBO

Let's continue the reasoning, equation 20 gives us the efficiency of the amplifier.

$$\eta_{DC} = \frac{P_s}{P_{dc}} \tag{20}$$

We deduce from equation 20 the DC input power (power supply) $\boldsymbol{P_{dc}}$ of this device:

$$P_{dc} = \frac{P_s}{\eta_{DC}} \tag{21}$$

Where $\boldsymbol{P_s}$ the output power and $\boldsymbol{\eta_{DC}}$ the efficiency of the amplifier.
Let's vary the output power and look at the DC input power for the two scenarios considered. Figure 34 shows us the result.

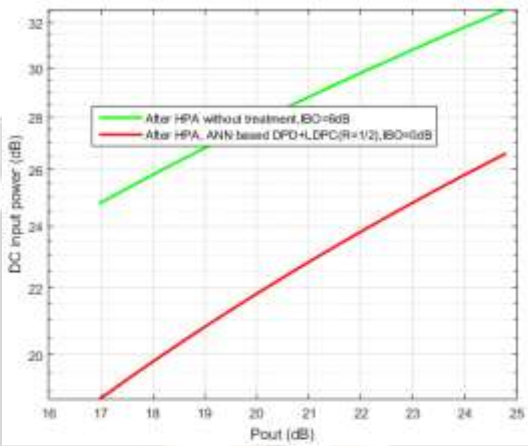

Fig -34: Variation of the DC input power according to the output power

We deduce from figure 34 that to have the same output power of the amplifier, scenario 1 which does not use any linearization technique needs much more energy (power supply) compared to scenario 2 which uses the combination of neural network based predistortion with LDPC coding.
To conclude, the combination of neural network-based predistortion with LDPC coding reduces the energy consumption of the power amplifier. Therefore, for the case of mobile phones, there will be an increase in battery life and for base stations, there will be a decrease in energy consumption hence the decrease in the operating cost of the 5G access network.

4. CONCLUSION

The new amplifier linearization technique that has been proposed is implemented at the 5G access network, more specifically within the RU (Remote Unit). Indeed, a neural network-based predistortion block is placed in front of the power amplifier to linearize the transfer characteristic of this device and thus reduce distortions in the amplified signal. This allows us to have a low bit error rate. We combined with this predistortion technique the LDPC coding which is error detection and correction code and which allows the amplifier to work close to the saturation zone in order to have high efficiency and low energy consumption. We have demonstrated in this article that this new power amplifier linearization technique enables 5G to provide reliable communication with low energy consumption. Hence the reduction in operating and maintaining cost this network.

5. REFERENCES

[1]. Y. Wu, H. Huang, C. Wang, Y. Pan, *« 5G Enabled Internet Of Thing »*, CRC Press,2019
[2]. E. Dahlman, S. Parvall, J. Sköld, *« 5G NR : The Next Generation Wireless Access»*, Academic Press, 2018
[3]. 5G PPP Architecture Working Group, *«View on 5G Architecture»*, Version 3.0, juin 2019
[4]. S. Ahmadi, *«5G NR Architecture, Technology, Implementation, and Operation of 3GPP New Radio Standards»*, ACADEMIC PRESS, 2019
[5]. M. Ghannouchi, O. Hammi et M. Helaoui, *«Behavioral modeling and predistortion of wideband wireless transmitters »*, Wiley, 2015
[6]. S. Shanmuganathan, S. Samarasinghe, *« Artificial Neural Network Modelling »*, Springer, 2016
[7]. K. D. Rao, *«Channel Coding Techniques for wireless communications»*, Springer, 2015.

[8]. V. Guruswami, *« Iterative decoding of Low Density Parity Check Code »*, Department of Computer Science and Engineering of Washington, September 2006.