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High Power Amplifier Predistorter Based on Fuzzy Wavelet Neural Networks for WiMAX Signals

Radouane Iqdour

Regional Center for Education Careers and Training, Marrakesh, Morocco

Younes Jabrane

OSCARS Laboratory
National School of Applied Sciences
Cadi Ayyad University, Marrakesh, Morocco

Abstract

In this paper, we present a novel predistortion method based on Fuzzy Wavelet Neural Networks (FWNN) to linearize the High Power Amplifier (HPA) for WiMAX (Worldwide interoperability for Microwave Access). To analyze and evaluate the proposal, we are considered the model of Traveling Wave Tube Amplifiers (TWTA), both memoryless and with memory. The simulation results show that the proposed scheme provide a satisfactory performances in term of Bit Error Rate (BER) and EVM criteria.

Keywords: HPA, Predistorter, FWNN, WiMAX

1 Introduction

During the last two decades, the wireless communication systems experienced a great evolution to meet demand for broadband by many services such as videoconferencing, IP telephony (VoIP) and many others. Among these wireless communication networks, there is WiMAX. The goal of WiMAX is to provide broadband access to areas where wireline service is not available. This technology theoretically achieves 70 Mbit/s rates to a range of 50 km, however in reality this rate will not exceed 20 Mbit/s with the presence of obstacles [1-2]. Given its proprieties, such as high bandwidth efficiency, robustness to the selective fading problem, use of small guard interval, and the ability to combat the inter-symbol interference problem, the IEEE 802.16d, fixed WiMAX standard, adopted the Orthogonal Frequency Division Multiplexing (OFDM) as its physical layer (PHY) [3]. Unfortunately, the OFDM presents some drawbacks such as high PAPR (Peak to Average Power Ratio). Consequently, WiMAX hardware equipments, especially the HPA (High Power Amplifier), are exposed to non-linearity caused by the high PAPR in OFDM signals.

Two strategies have been used to remove the nonlinear effect of HPA for OFDM systems. The first one includes techniques that directly address the OFDM signal to reduce the PAPR before transmitting it [4]. These techniques often do so at the expense of the increased system complexity and/or the increase in average power, the degradation of the bit error rate (BER) and/or the raising of the secondary lobes and / or the decrease in throughput [5-10]. The second one is the Digital Pre-Distortion (DPD). The idea of DPD techniques is predistortion of the signal before the HPA in such a way that the output signal, after passing through the HPA, will be similar to the originally transmitted (HPA linearization). In literature, the solutions that have been proposed aim at estimating and linearizing the AM/AM (Amplitude Modulation / Amplitude Modulation) and the AM/PM (Amplitude Modulation / Phase Modulation) characteristics of the memoryless HPA, usually done by large Look Up Tables (LUT). In the case of the HPA with memory, techniques such as 2D LUT are also applied for the linearization [11]. Other methods based on polynomial approaches, derived from the Volterra model, are also used to overcome this problem [12-13]. Numerical results show the effectiveness of these methods to linearize HPA in the two scenarios with memory and memoryless.

Due to their properties, as universal approximator, Neural Networks (NNs) and Fuzzy Inference Systems (FIS) have been used to model HPA and design predistorters [14-15]. The principle of these methods is to make the learning process on how to distort the input signal in order to approximate the inverse function of the HPA. The researchers are focused on the use of Multi-Layers Perceptron (MLP), which is the most popular and simplified neural network architecture, and Adaptive Neural Fuzzy Inference Systems (ANFIS). The simulation results show that these methods have potential use in the pre-distortion of nonlinear HPA.

The FWNN (Fuzzy Wavelets Neural Networks) system is a combination of wavelet network and fuzzy set theory that have the advantages of high approximation accuracy of nonlinear systems which are characterized by uncertainty and also allow to develop systems that have fast training convergence. The motivation to use the FWNN in the pre-distorting problem is due to its successful application to the problems of function approximation, system identification and control among others [16-17].

The organization of this paper is as follows. After introducing briefly the FWNN theory in the second section, we present a predistorter scheme based on FWNN to linearize the HPA for WiMAX signals based on IEEE 802.16d standard in the third one. The FWNN pre-distorter scheme here proposed is then evaluated using computer simulations in section four. Finally, we present some final conclusions.

2 Fuzzy Wavelet Neural Networks

The FWNN is the result of combination of wavelet theory, fuzzy logic and Neural Networks. In general, the structure of the FWNN is practically similar to the ANFIS. In this paper, FWNN architecture (Fig.1) of seven layers is used [16].

Layer 1: Called the input layer is composed from a number of nodes equal to the number of input signals, which are used for transmitting the input signals.
Layer 2: Each node in this layer has a Gaussian membership function. The output of this layer is given by:

$$\eta_j(x_i) = e^{-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}} \qquad i = 1, \dots, k \text{ and } j = 1, \dots, n \tag{1}$$

Where k is the number of input signals, n is the number of fuzzy rules, c_{ij} and σ_{ij} are the center and the width of the Gaussian membership functions of the jth term of ith input variable, respectively, and $\eta_j(x_i)$ is the membership function of the ith input variable for the jth term.
Layer 3: The number of nodes in this layer corresponds to the number of rulesR_1, R_2, . . . , R_n. Each node represents one fuzzy rule. The output of the layer is given by:

$$\mu_j(x) = \prod_i \eta_j(x_i) \ , i = 1, \dots, k \text{ and } j = 1, \dots, n \tag{2}$$

$\prod$ represents the “Min” operation.
Layer 4: Called WNNs layer. Each node in this layer is a wavelet function. The output of the lth wavelet is calculated as:

$$u_l = w_l \psi_l(z), \psi_l(z) = \sum_{i=1}^{k} |d_{il}|^{-\frac{1}{2}} \left(1 - z_{il}^2\right) e^{\frac{z_{il}^2}{2}} \tag{3}$$

Here $z_{il} = (x_{il} - m_{il})/d_{il}$ with m_{il} and d_{il} are respectively the translation and dilatation parameters of the WF between the ith $(i = 1, \dots, n)$ input and the lth output of $(l = 1, \dots, n)$ the wavelet.
Layer 5: In this layer the output signals of the third layer $\mu_j(x)$ are multiplied by the output signals of the WNNs layer u_l.
Layers 6 and 7: The defuzzification function is applied to obtain the output of the system. In these layers, the contribution of each wavelet to the output of the FWNN is determined:

$$y = \sum_{l=1}^{n} \mu_l(x)\, u_l / \sum_{l=1}^{n} \mu_l(x) \tag{4}$$

With u_l are the outputs of the WNNs.

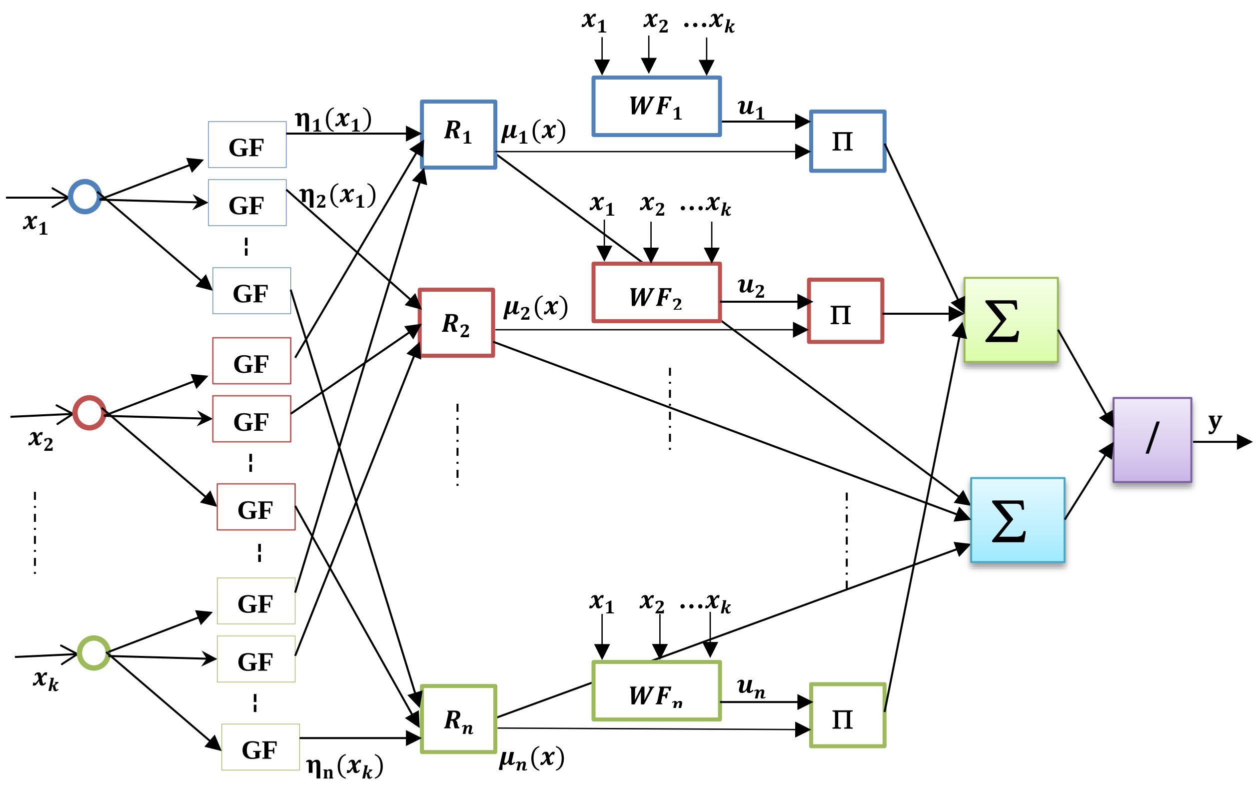

Fig.1: The adopted FWNN architecture

3 Digital Predistortion schemes

In this section, we present a FWNN based predistortion model that is valid for memory and memoryless HPA. The architecture of this model is shown in Figure.2. The aim of the FWNN pre-distorter model is to provide the amplitude and phase of the WiMAX input signals.

3.1 Training stage

The proposed predistorter model is composed of two FWNN sub-models. The first FWNN1 is used to approximate the pre-distorter AM/AM function $\mathrm{PF}(|\mathrm{x(t)}|) = \mathrm{F}^{-1}(|\mathrm{x(t)}|)$, and identified by applying the HPA output amplitude $|\mathrm{y(t)}|$ as the training input of the FWNN scheme, while the input amplitude of HPA $|\mathrm{x(t)}|$is provided as the output training data.
After the training stage, the FWNN1 output will be very close to the inverse of the AM/AM HPA function. The second FWNN2 uses the input amplitude signal of the HPA as training input data, while the output is the phase differences between the input and output signals of the HPA. When this FWNN model converges, it approximates the AM/PM HPA function $\mathrm{P\varphi}(|\mathrm{x(t)}|) = -\varphi[\mathrm{PF}(|\mathrm{x(t)}|)] = \varphi[\mathrm{F}^{-1}(|\mathrm{x(t)}|)]$.

For an optimized initialization of the wavelet parameters, we use a method based on the input domains defined by the examples of the training sample for the translation and dilation parameters [9]. While the Gaussian membership parameters (the center $\mathbf{c_{ij}}$ and the width $\boldsymbol{\sigma_{ij}}$) and the weights $\mathbf{w_j}$ are initialized in small random values between 0 and 1.

After the initialization phase, the FWNN is further trained using the Levenberg–Marquardt algorithm in order to approximate the AM/AM and AM/PM functions of the HPA.

3.2 Generalization

Once the FWNN1 and FWNN2 models are identified, in the real-time running operation, the amplitude and the phase of the modulated signal is computed. The amplitude of the WiMAX signal is introduced into the FWNN1 and its output is fed to the FWNN2 and to the output amplitude of the signal. Next, the output of FWNN2 is subtracted from the original WiMAX signal phase and this signal feeds the output phase block. This modulo-phase block will generate the final pre-distorted signal to be amplified by the HPA.

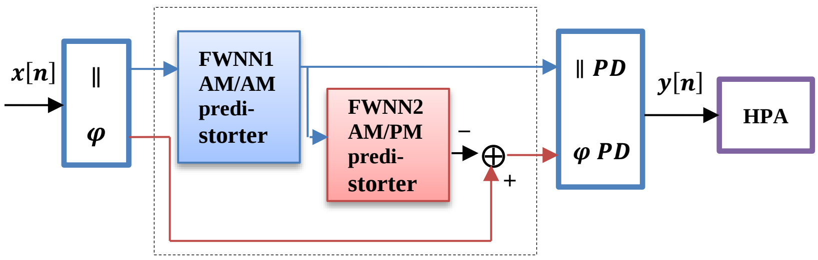

Fig.2. FWNN based pre-distortion architecture in real-time running operation.

4 Simulation results and discussion

In this section, the proposed FWNN predistorter scheme is evaluated for a typical Saleh's TWTA model [18], both with and without memory, used in broadcasting systems [15] and an IBO of 5dB. The parameters of this model are $\alpha_A = 2$, $\beta_A = 1$, $\alpha_\varphi = 4$, $\beta_\varphi = 9$. The simulation results are obtained for a WirelessMan–OFDM PHY-layer based on IEEE802.16d which stipulates the use of a total of 256 subcarriers, such as 192 data carriers (64QAM signal mapping), 8 pilots, 56 null subcarriers and guard intervals (1/8) as shown in Table.1.

Table.1: WiMAX IEEE802.16d parameters

Parameters	Values
Channel Bandwidth	10 MHz
Modulation scheme	64 QAM
FFT Size	256
Number of data subcarriers	192
Cyclic prefix or guard time	1/8
Pilots subcarriers	8
Null subcarriers	56

Figures 3 and 4 illustrate the power spectral density of the signal respectively with and without using our proposal. These figures show that more spectral re-growth suppression about 30 dB and 20 dB is acquired for memoryless and HPA with memory respectively. On the other hand, compared to the original spectrum, the spectral re-growth after our predistorter remains negligible is about 1dB in the case of memoryless HPA, less than 3dB for the memory one. These numerical results are valid for fulfilling the strict spectral mask in broadcasting systems, fixed WiMAX in this case.

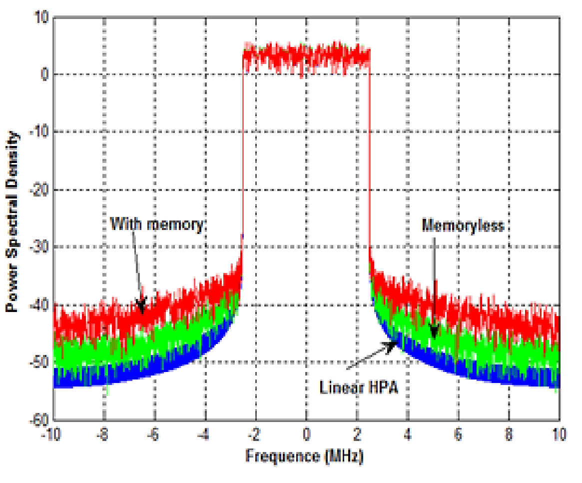

Fig.3: Power spectral density after memory and memoryless HPA with the FWNN

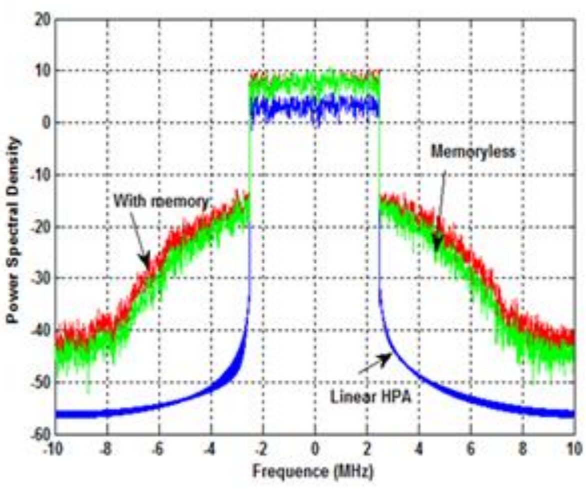

Fig.4: Power spectral density without the FWNN predistorter.

To evaluate the performance of our proposed scheme, we have traced in Figure.5 the BER performance after HPA with and without memory. From this figure, we cannot observe any performance degradation for memoryless HPA. However, for HPA with memory, we notice a slight degradation not exceeding 0.1 dB for high SNR.

In order to better appreciate the quality of the proposed FWNN based predistorter, we use the EVM (Error Vector Magnitude) criteria. The EVM is a common figure of merit for assessing the quality of digitally modulated signals. It accounts for the difference between the expected complex voltage value of a demodulated symbol and the value of the current received symbol. It is very useful for microwave engineers because it contains information about amplitude and phase errors in the signal [19]. The average EVM is defined as:

$$\mathrm{EVM} = \frac{1}{N_s}\frac{1}{N}\sqrt{\frac{\frac{1}{M}\sum_{r=1}^{M}\left|S_{ideal}^{r}-S_{measured}^{r}\right|^2}{\frac{1}{M}\sum_{r=1}^{M}\left|S_{ideal}^{r}\right|^2}} \qquad (5)$$

Where $S_{ideal}^{r} \in \mathbb{C}$ and $S_{measured}^{r}$ are respectively the rth point out of M for ideal constellation in a M-QAM modulation and the measured rth point after the pre-distorter and the HPA, N_s is the number of symbol.
The EVM obtained by using our proposed pre-distorter scheme is very low. Thus, in the case of memoryless HPA the EVM is $8.01.10^{-6}$ and for the memory HPA the EVM is $3.56.10^{-5}$.

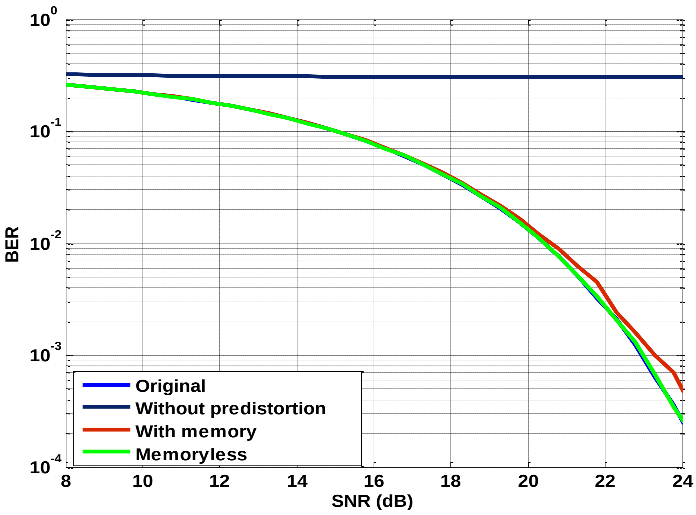

Fig.5: BER performance after memory and memoryless HPA with the FWNN predistorters.

5 Conclusion

In this paper, we have presented and studied a novel HPA predistorter based on FWNN with application to WiMAX IEEE 802.16d signals. The Levenberg–Marquardt algorithm is employed for the identification of the system parameters. The proposed method, which does not need any further requirement, once it has been trained, performs successful results in terms of BER and EVM criteria, both for memory and memoryless HPA. Thus, we can conclude that our proposal can be used as an alternative predistortion method for broadcasting systems.

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