AN ADAPTIVE NEURAL NETWORK PRE-DISTORTER FOR NON STATIONARY HPA IN OFDM SYSTEMS

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ABSTRACT

It is well known that HPAs (High Power Amplifiers) are inherently nonlinear devices. Hence, many researches have focused on the pre-distortion of memoryless stationary HPAs.

However HPAs can no longer be considered as stationary in a real satellite system. In fact, if the amplifier exhibit nonlinear characteristics constant in time, which is a reasonable assumption in many low power cases, a fixed pre-distorter is enough to achieve a good linear performance. However, power amplifiers operating under more stringent conditions may undergo slow but significant changes in their AM/AM and AM/PM characteristics basically due to factors like temperature, age of components, power level, biasing variations, frequency changes and so on.

In this paper, we present an adaptive pre-distortion technique based on a feed-forward neural network that makes it possible to compensate the nonlinearities of an HPA with taken into consideration the time variations of HPA characteristics. We use an indirect approach that calculates a post-distortion system applied as a pre-distortion. The performance of the proposed scheme is examined through computer simulations for 16-QAM OFDM signals.

1. INTRODUCTION

Orthogonal frequency division multiplexing (OFDM) was initially presented in 1966 [1]. A transmission channel is divided into a great number of parallel, low-rate subchannels. In this way every subchannel has relatively flat channel response, which is conventionally called nondispersive channel. With the increasing demand of multimedia services, various emerging telecommunication systems make use of this technique capable of providing a broadband access to such services. Hence, OFDM potentially plays a considerably vital pole in the future communication.

Power amplifiers are indispensable components in a communication system and are inherently nonlinear. To reduce the nonlinearity, the power amplifier can be backed off to operate within the linear portion of its operating curve. However, newer transmission formats, such as wideband code division multiple access (WCDMA) and orthogonal frequency division multiplexing (OFDM), have high peak to average power ratios, i.e., large fluctuations in their signal envelopes. This means that the power amplifier needs to be backed off far from its saturation point, which results in very low efficiencies, typically less than 10% [8]; i.e., more than 90% of the dc power is lost and turns into heat.

Among all linearization techniques, digital pre-distortion is one of the most cost effective. It adds a digital pre-distorter in the baseband to create an expanding nonlinearity that is complementary to the compressing characteristic of the power amplifier. Ideally, the cascade of the pre-distorter and the power amplifier becomes linear and the original input is amplified by a constant gain. With the pre-distorter, the power amplifier can be utilized up to its saturation point while still maintaining a good linearity, thereby significantly increasing its efficiency. In reality, the power amplifier characteristics may change over time because of temperature drift, component aging, etc. Therefore, the pre-distorter should also have the ability to adapt to these changes.

In this paper, we present a preliminary implementation of a data pre-distortion system using a multilayer perceptron neural network which forms an adaptive nonlinear device whose response approximates the inverse function of the HPA nonlinearity. We attempt to design a pre-distorter which is adaptive, robust, and requires only a moderate amount of storage and computational resources by taking advantage of a neural network's ability to estimate a nonlinear function. In fact, we have developed an adaptive and iterative algorithm which the main advantage is its fast initialization characteristic. Secondly, an adaptive estimation post-distortion for HPA time-varying properties is proposed that is applied as a pre-distortion.

The organization of the paper is as follows. Section II describes the modeling of an HPA. Section III describes the adaptive pre-distortion scheme and the initialization and adaptation algorithms. In Section IV, the proposed scheme is then evaluated using computer simulations and Section V presents some final conclusions.

2. SYSTEM DESCRIPTION

Figure 1 shows a simplified block diagram for compensation of the HPA nonlinearity for an OFDM system presented in [2].

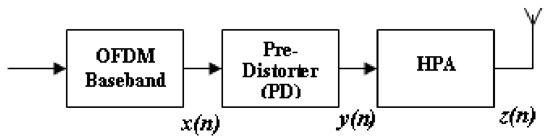

Figure 1 –Simplified OFDM transmitter with PD and HPA

The pre-distorter (PD) of figure 1 is a nonlinear zero memory device that precomputes and cancels the nonlinear distortion present in the zero memory HPA which follows the PD.

2.1 TWTA Model

For the HPA model, we have chosen Saleh's well-established TWTA model [3]. In this model, AM/AM (amplitude modulation to amplitude modulation) and AM/PM (amplitude modulation to phase modulation) conversion of the TWTA can be represented as

$$A(r)=\frac{\alpha_a\cdot r}{1+\beta_a r^2} \quad \text{and} \quad P(r)=\frac{\alpha_p\cdot r^2}{1+\beta_p r^2} \qquad (1)$$

where r is the input modulus of the TWTA and α_a, β_a , α_p, β_p are four adjustable parameters. The behavior of (1) is illustrated in Figure 2. In this figure, we use $\alpha_a=2$, $\beta_a=1$, $\alpha_p=4$ and $\beta_p=9$ as a typical TWT model used in satellite communications [4,8]. The output of the TWTA without the PD can be represented as

$$z(t) = A(r)\exp\left(j\cdot(w_c t+\phi(t)+P(r))\right) \qquad (2)$$

Where $\varphi(t)$ is the phase of the input signal.

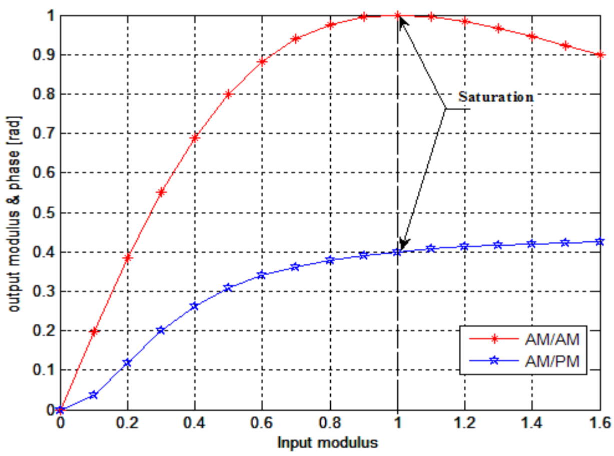

Figure 2 –Nonlinear amplitude and phase transfer function of Saleh's TWTA model

3. ADAPTIVE PREDISTORTER FOR TWTA

3.1 Time-invariant case

The basic idea proposed is to identify the TWT inverse transfer function with a feed-forward neural network. Therefore, by using this structure, we aim at obtaining direct estimation of the amplitude and phase nonlinearities.

3.1.1 Training and generalization

Figure 3 shows the detailed scheme of pre-distortion system.

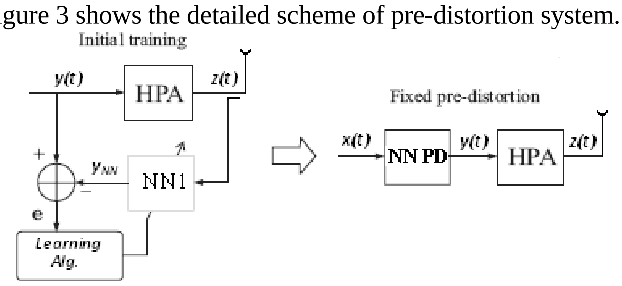

Figure 3 –Block diagram for training of the PD with TWTA

Training: where NN1 aims to identify the TWTA inverse transfer function, the error sent to "learning algorithm" bloc that reacts on coefficients of NN1.

Generalization: coefficients of the NN1 are recopied on the NNPD that achieves the pre-distortion.

3.1.2 Neural networks structure

The multi-layer [5] feed forward neural network (MLNN), called also multi-layer perceptron (MLP), is one of the most popular neural network architectures used in digital communications. Its basic unit, the neuron (Fig. 4), is composed of a linear combiner followed by an activation function. The neuron receives inputs from other processors. The linear combiner output is the weighted sum of the inputs plus a bias term. The activation function gives then the neuron output:

$$z = g(d) \quad \text{where} \quad d = \sum_{j=1}^{N} w_j z_j + b \qquad (3)$$

where z_j is the j^{th} input value of the neuron, w_j the corresponding synaptic weight, and b the bias term. $\{w_j\}$ and $\{b\}$ form the free parameters of the neuron.

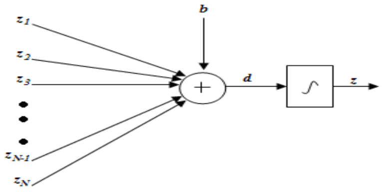

Figure 4 –Basic architecture of one neuron

A multi-layer neural net (see Fig. 5) is composed of neurons connected to each other.

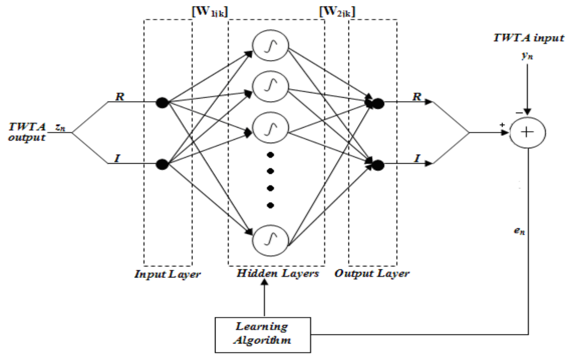

Figure 5 –A multi-layer neural network: The network has two layers, two input signals, one hidden Layers, 2 neurons in the output layer, and 2 output signals. (Indexes R and I refer to the real and imaginary parts, respectively)

The layer index is denoted by i. z_{li} is the output of neuron i of layer l. w_{lji} is the weight that links the output z_{i-lj} to neuron i of layer l. $N(l)$ is the number of neurons in layer l. With these notations, the output z_{li} of neuron (l,i) is given by:

$$z_{li} = g(d_{li}) \qquad (4)$$

where

$$d_{li} = \sum_{j=1}^{N(l-1)} w_{lji} z_{l-1j} + b_{li} \qquad (5)$$

3.1.3 Learning algorithm

The neural network is used to identify the TWTA inverse transfer function using supervised learning. At each iteration, a pair of TWTA input - TWTA output signals is presented to the neural network.

Gradient-based training algorithms, like back-propagation, are most commonly used by researchers. They are not efficient due to the fact that the gradient vanishes at the solution. Hessian-based algorithms used as reported in [6], allow the network to learn more subtle features of a complicated mapping. The training process converges quickly as the solution is approached, because the Hessian does not vanish at the solution. To benefit from the advantages of Hessian based training, we focused on the Levenberg-Marquardt Algorithm reported in [6,7]. The LM algorithm is basically a Hessian-based algorithm for nonlinear least squares optimization.

In the LM method, the change (Δ) in the weights (w) is obtained by solving

$$\alpha\Delta = -\frac{1}{2}\nabla E \qquad (6)$$

where E is the mean-squared network error

$$E = \frac{1}{Na}\sum_{k=1}^{Na}\left[y(z_k) - y_k\right]^2 \qquad (7)$$

N_a is the number of samples, $y(z_k)$ is the network output corresponding to the sample z_k and y_k is the desired output for that example.

The elements of the α matrix are given by

$$\alpha_{ij} = \left(1+\lambda\delta_{ij}\right)\sum_{r=1}^{Ns}\sum_{k=1}^{N_a}\left[\frac{\partial y_r(z_k)}{\partial w_i}\frac{\partial y_r(z_k)}{\partial w_j}\right] \qquad (8)$$

where N_s is the number of outputs of the network and δ_{ij} is the learning rate.

Starting from initial random weights, both α and ∇E are evaluated, and solving (6), a correction for the values of the weights is obtained $\left(w(k+1) = w(k) + \Delta\right)$. This is known as an LM learning cycle. Each iteration of this cycle reduces the error until the desired goal is achieved or a minimum is found. The λ variable in (8) is a parameter that is adjusted at each cycle, according to the error evolution. If it is very small the α matrix becomes an approximation of the Hessian, and the method is the inverse-Hessian method. If $\lambda \gg 1$, the method becomes analogous to steepest descent.

3.2 Time-varying adaptive case

We now extend this solution to the time-varying case as follows. As a time varying model, we assume that the four parameters α_a, β_a, α_p, β_p are changing with time.

Previously, we took into account the convenience of performing the estimation of the inverse HPA characteristics in a post-distortion stage rather than in a simple pre-distortion one. According to this, the pre-distortion architectures presented here are basically derived from a post-distortion adaptive structure which may employ two general alternatives for its operation. These alternatives are:

1st Alt: Loading the pre-distorter with completely trained coefficients after a complete learning stage. (Fig. 3)

2nd Alt: Simultaneous updating of the pre-distorter during the adaptation at the post-distortion loop. (Fig. 6)

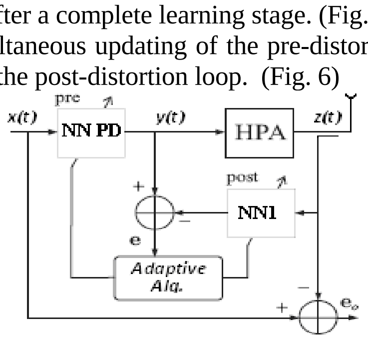

Figure 6 – Simultaneous PD updating

Fig. 6 shows the detailed scheme of an adaptive pre-distortion system based on feedforward neural network. Where $x(t)$ denotes the input signal to the pre-distorter, $y(t)$ denotes the signal coming out from the pre-distorter and sent as input to the TWTA and $z(t)$ denotes the TWTA output signal.

The weights of the neural network pre-distorter (NN PD) are determined by the fixed pre-distortion presented previously and are adjusted using an adaptive algorithm based on Levenberg -Marquardt method. A summary of this algorithm is given bellow:

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% Initialize the algorithm by setting

x(0)=[w_1(i,j) w_2(j,k) b_j] ;

net : neural network, X : Network weight and biases values vector

w_1(i,j): is the weight that links the output z_{i-1j} to neuron i of layer 1

w_2(j,k): is the weight that links the output z_{j-2k} to neuron j of layer2

For each sampling time : 0,1,2,….,n

Determination of the performance of the MLP at sampling time n

$y_{NN}(n) = w_2(n)\left[g(w_1(n)z(n))\right]$;

$Perf(n) = \left[y_{NN}(z_n) - y_n\right]^2$;

dw = - $[J^TJ + \mu I]^{-1} J^Te$;

J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, e is a vector of network errors and I is the identity matrix.

x(n+1) = x(n) + dx;

New estimated values of the weights for each layer of the network.

net2 =net(x(n+1));

Determination of the performance of net at sampling time n+1

$y_{NN}(n+1) = w_2(n+1)\left[g(w_1(n+1)z(n+1))\right]$;

$Perf(n+1) = \left[y_{NN}(z_{n+1}) - y_{n+1}\right]^2$;

if (Perf(n+1)<Perf(n))

net=net2; The new parameters of the MLP calculated previously are accepted.

end

end

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4. SIMULATION RESULTS AND DISCUSSION

In this section, the validity of the proposed pre-distortion technique for compensation of the HPA nonlinear distortion is demonstrated with computer simulations followed by a discussion of the results. The Additive white Gaussian noise (AWGN) channels were assumed to clearly observe the effect of nonlinearity and performance improvement by the proposed PD. An OFDM system with 64 subcarrier and 16 QAM is considered. In the operation of the HPA, a relative level of power back-off is needed to reduce distortion. However, this power back-off is not so desirable because it reduces the power efficiency.

In our work, a compensation solution always exists in the range r < A_0, where A_0 is the maximum output amplitude. So, if the input average power is the same as A_0^2, we get maximum power efficiency, but it is highly nonlinear.

Thus, we need a criterion to show how much power back-off is needed for optimum power efficiency. In the simulations, we define the input back-off (IBO) as

$$IBO = 10\log_{10}\left(\frac{A_0^2}{p_{in}}\right) \qquad (9)$$

where P_{in} is the input average power .

4.1 Fixed pre-distortion

We now present OFDM simulation results with the assumption that parameters α_a, β_a, α_p, β_p are time-invariant with the suitable neural network pre-distorter presented in [2] which allows the linearization of the power amplifier presented previously.

The neural pre-distorter consists of two inputs and two outputs (R and I), one hidden layer of 9 neurones. Activation functions of hidden layer are hyperbolic tangent, while output layer is linear.

In the training phase using a Levenberg Marquardt algorithm, only 200 training iterations and the MSE was lower than $1{,}5.10^{-5}$, resulting an accurate estimation of the coefficients for the neural pre-distorter.

The symbol error rate (SER) performance curve, in Figure 7, shows that the PD can significantly reduce nonlinear distortion in an OFDM system.

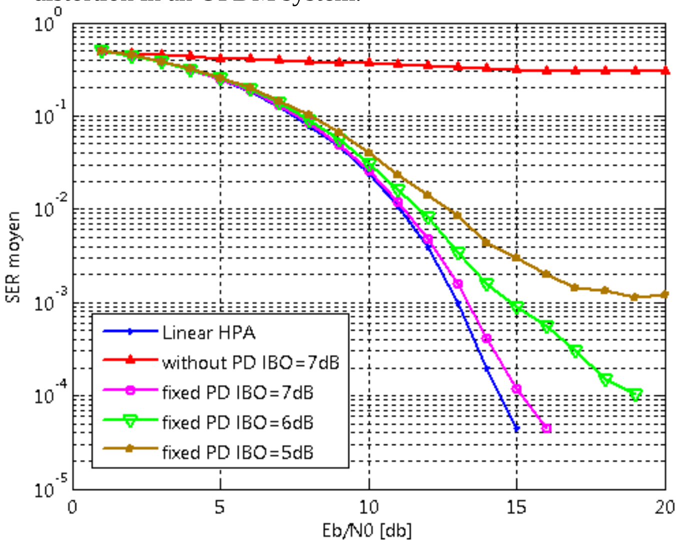


Figure 7 –SER performance of PD in OFDM, with time-invariant TWTA.

4.2 Adaptive pre-distortion

As we mentioned previously, the HPA can be a time-varying system. In this subsection, we assume that the four parameters α_a, β_a, α_p, β_p are time varying; thus, the pre-distorter must track variations of α_a, β_a, α_p and β_p. We assume that these four parameters change linearly with time according to the following conditions.

- four parameters change in the following ranges:

$$1.01 \le \alpha_a \le 2 \quad (10)$$
$$0.01 \le \beta_a \le 1 \quad (10)$$
$$2.5 \le \alpha_p \le 4 \quad (12)$$
$$7.5 \le \beta_p \le 9 \quad (13)$$

- Input and output normalization condition, $\beta_a = \alpha_a - 1$.
- Saturation condition, signal is clipped above 1.

The reason why we have chosen these conditions on the amplitude and phase is to maintain normalization constraints in both input and output and the saturation condition in the above range ($r > A_0$), even if the amplitude is changed.

In this paper we use the following function to define the temporal variation for each parameter while respecting the conditions shown previously.

$$f(t) = A * t + C \quad (14)$$

where A is the constant that defines the speed of the temporal variation and C is the constant that defines the initial value.

The following figure presents the temporal variation of α_a and β_a with various speeds.

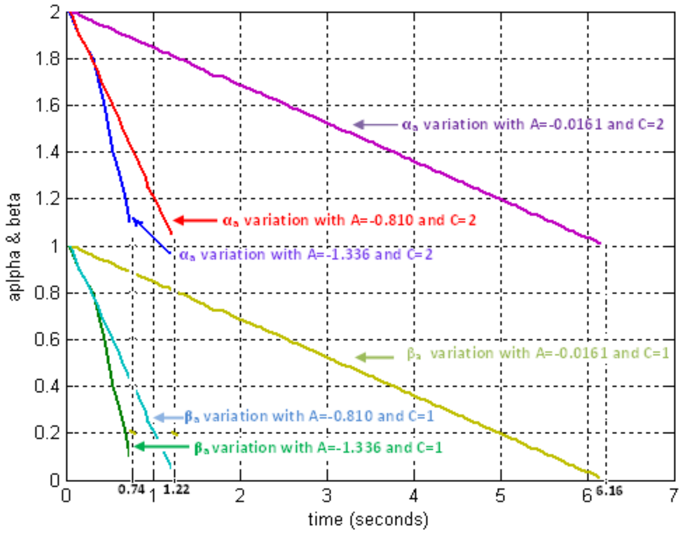


Figure 8 –Variation of α_a and β_a versus time with various speeds

The following figure represents the variation of AM/AM and AM/PM in order to show the extent variations of HPA used in this work.

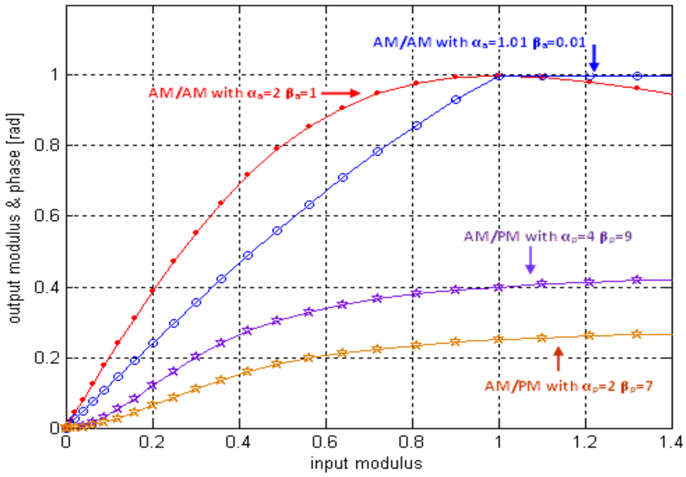


Figure 9 –Modulus and phase variation

The following figure shows the curve of the performance of neural network used as an adaptive pre-distorter. We note that the adaptive neural network converges still better towards the good solution and the MSE is decreased to less than 3.10^{-6} after 50 iterations, resulting to an accurate estimation of the coefficients for the neural pre-distorter. It can also be noticed that after the 5th iteration, the MSE does not decrease almost any more.

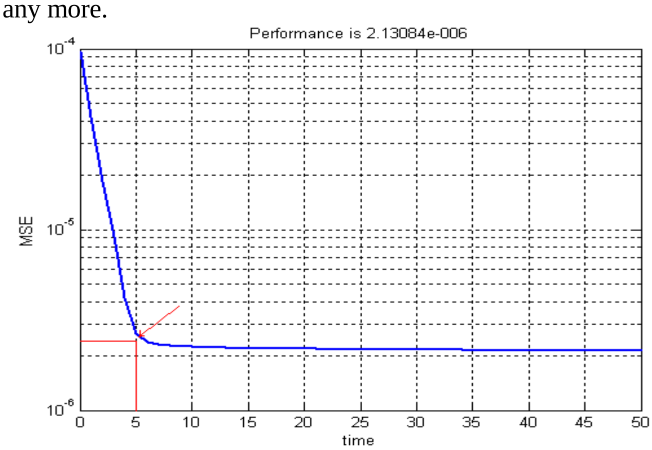


Figure 10: MSE vs Iterations number with adaptive training

The SER performance of the adaptive pre-distortion structure in OFDM system is compared to the fixed pre-distortion which has determined the inverse transfer function of the initial HPA with (α_a=2, β_a=1, α_p=4, β_p=9).

The following figures show the SER performance of the proposed adaptive pre-distortion compared to the one of the fixed pre-distortion with a varying time HPA where (α_a=1.5, β_a=0.5, α_p=2.5, β_p=7.5).

We note from Figure 11, that if the variation of the HPA is not tracked, the performance is much worse than when it is tracked with the adaptive PD. The simulation results thus show that this ability to use an adaptive pre-distortion adds value to the system performance.

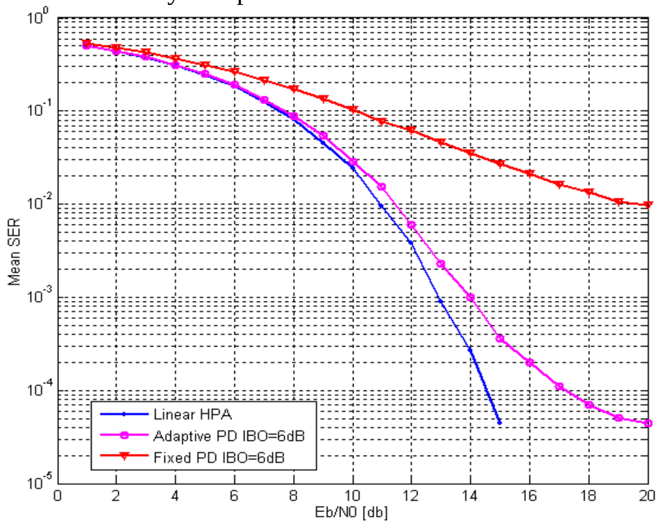
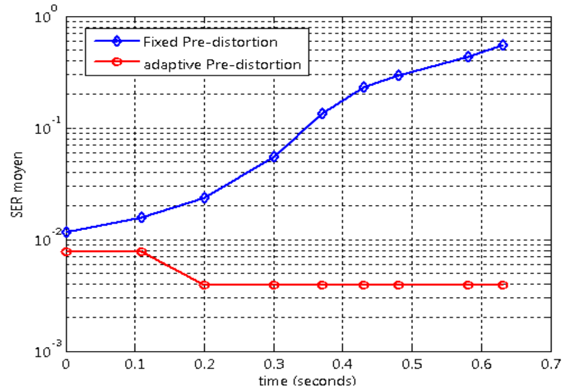
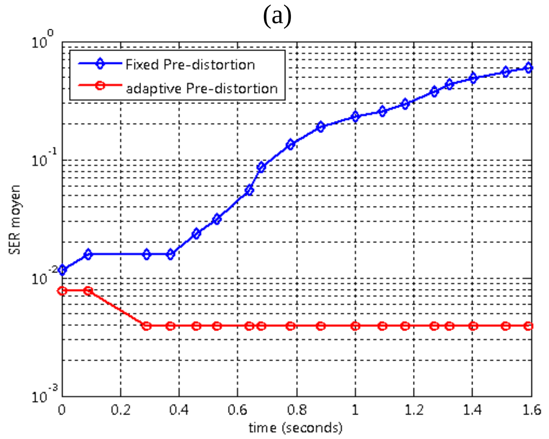


Figure 11 –SER performance of PD in OFDM, with time-varying TWTA, IBO = 7 dB.

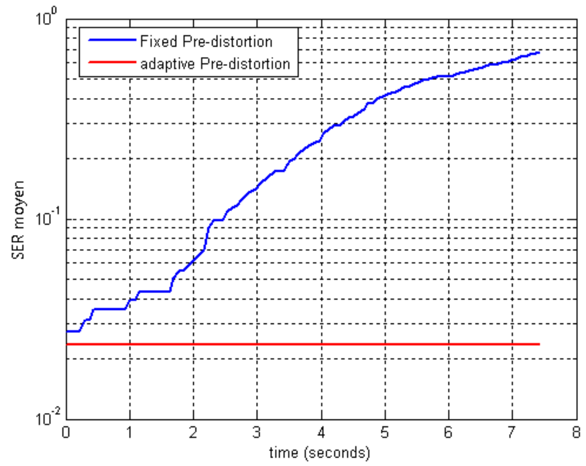
In this section we study the variation of SER versus time with an adaptive and fixed pre-distortion with various speeds of the variation of the HPA characteristics.



(a)



(b)



(c)

Figure 12 –SER of PD in OFDM versus time in seconds, with time-varying TWTA, IBO = 7 dB, SNR = 15dB.
(a) A = 1.33 (b) A=0.81 (c) A=0.016

Looking at figure 12, we can see that the SER for the adaptive pre-distortion remains almost constant when varying the characteristics of the amplifier, on the contrary with the fixed pre-distortion the SER increase.

5. CONCLUSION

We have proposed a new adaptive baseband pre-distortion based on a feed forward neural network for eliminating or mitigating nonlinear distortion in time-varying HPAs used in OFDM-based wireless communications. We have proposed an adaptive and iterative algorithm to estimate the weights of the proposed adaptive pre-distortion. The preliminary results presented here indicate that neural networks have potential use in the pre-distortion of nonlinear HPAs. Their nonparametric approach, combined with the fact that the algorithm performs as a universal approximator should allow its successful use in a variety of conditions and amplifier designs.

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