A Neural Approach for Compensation of Effects of PAPR Causing BER Degradations in Hiperlan2

Shubhangi Rathkanthiwar, Chandrashekhar Dethe, and Kishore Kulat

Abstract— Emergent telecommunication systems use spectral efficient multilevel modulation formats together with multicarrier schemes such as Orthogonal Frequency division multiplexing (OFDM). OFDM transmission is an efficient way to deal with multipath. However one of its major drawbacks is its sensitivity to nonlinear distortions due to its greatly variable envelope and high peak to average power ratio (PAPR). Nonlinear distortions are mainly introduced by high power amplifiers (HPA), cause in band distortions. Misalignments in IQ modulators and demodulators causes imbalance, which results in loss of orthogonality and create intercarrier interference and spectral regrowth in an OFDM system. Nonlinear distortions also cause intermodulation effect. This degrades Bit error rate (BER) performance of the system. This paper introduces the self organization map(SOM) and parameterless self organization map(PLSOM) based and Hiperlan/2 receiver structure used for the compensation of nonlinear distortions. Simulation results presented in this paper clearly indicate the improved performance of the proposed system. Simulations are run for AWGN channel model and for two HPA models namely Travelling wave tube amplifier (TWTA) and Solid state power amplifier (SSPA), with and without SOM and PLSOM neural network blocks.

Index Terms— OFDM; HPA; TWTA; SSPA; BER; AWGN; SOM; PLSOM

I. INTRODUCTION

Wireless LAN standards such as Hiperlan/2 and 802.11a use OFDM as a multi-carrier modulation/multiplexing technique. OFDM transmission exhibits many benefits in wireless communications. An OFDM signal is the sum of sinusoids transmitted through multicarriers, so that peak power of the OFDM signal increases in proportion to the number of subcarriers. In OFDM systems, the combination of different signals with different phase and frequency gives a large dynamic range that is used to be characterized by a high PAPR, which results in severe clipping effects and nonlinear distortion if the composite time signal is amplified by a power amplifier which have nonlinear transfer function. This degrades the performance of an OFDM system [1-3]. As a result, multicarrier systems are more sensitive to presence of nonlinearities. Due to large dynamic range of the modulated

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signal, nonlinear distortion at the power amplifier causes interference both inside, resulting in intermodulation among the subcarriers as well as outside, which causes spectral spreading of OFDM signal. In band distortion may result in intermodulation, which is a mutual interference between signals spaced apart in frequency, after nonlinear amplification of signal by HPA. This causes degradation in Bit error rate (BER) performance of the system. Out of band components affect adjacent frequency band components [4]. A measure of the degradation can be very helpful in evaluating the performance of a given system, and in designing a signaling set that avoids degradation. This paper presents the performance of Hiperlan/2 with power amplifiers to study the effects of nonlinearities on the received signal. Back off strategies will then be used to minimize the effects of nonlinear distortions on the signal constellation of 16 QAM signal.

TWTA and SSPA models are most commonly used power amplifiers in wireless communication systems. To achieve maximum output power efficiency, HPA is usually operated in the saturation region, which is basically a nonlinear region. As OFDM signal is characterized by high PAPR and large dynamic variation of the signal amplitude, it is highly affected by nonlinear distortion [5].

Basic Hiperlan/2 model to be simulated is shown in Figure 1



Fig. 1. Hiperlan/2 Model

From fig. 1, first block is Bernauli binary generator block that provides the information source for the simulation. Convolutional code block creates convolutional code for the binary data. It encodes the sequence of binary input vectors to produce a sequence of binary output vectors. Puncture block carries out puncturing. It periodically removes bits from the encoded bit stream thereby increasing the code rate. Puncture pattern is specified by the puncture vector parameter in the mask. Matrix interleaver block permutes input symbols by filling a matrix by rows and emptying it by columns. General block interleaver block rearranges the elements of its input vector without repeating or omitting any elements. Rectangular QAM modulator base band block modulates using M ary QAM with a constellation on a rectangular

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lattice. Normalize block normalizes the rectangular QAM signal which is fed to the OFDM transmitter block. Discrete signal scatter plot scope is used to display a modulated signal constellation in its signal space by plotting the in phase component versus quadrature components. An OFDM symbol is a sum of N independent symbols mapped on N different sub-channels with 1/T frequency separation. T is the OFDM symbol period. Discrete time domain samples $b^i = (b_0^{i}, b_1^{i}, \dots, b_{N-1}^{i})$ to be transmitted are obtained via N point IFFT from complex 16 QAM symbols in this case. A block of QAM symbols is given by,

 $a^{i} = (a_{0}^{i}, a_{2}^{i}, \dots, a_{N-1}^{i}).$

Mathematically an OFDM symbol can be represented by equation (1)

$$b_n^i = \frac{1}{\sqrt{N}} \sum_{m=0}^{N-1} a_m^i e^{J 2\pi m n/N}$$
(1)

Where a_m^i is the QAM data symbol sent on mth subcarrier of ith OFDM symbol. For large number of subcarriers, time domain samples b_m^i have a zero mean Guassian distribution, as they are weighted sum of independent, identically distributed random variables. Some of these time domain samples, which lie at the tail of the distribution curve, gain high magnitudes and cause high PAPR of the system. Mathematically, PAPR of OFDM block of digital samples b=(b₀, b₁, ..., b_{N-1}) is given by equation (2) [6,7],

$$PAPR(b) = \frac{\max_{0 \le n \le N-1} |b_n^2|}{E\left\{ \|b_n^2\| \right\} / N}$$
(2)

It is well known that according to the central limit theory that the real and imaginary parts of the OFDM signal completely agree with the normal distribution and consequently its absolute agrees with the Rayleigh distribution with probability density function expressed by (3)

$$p(s) = \frac{x}{s} e^{-x^2/2s^2}$$
(3)

Where s is a parameter, mean is $\mu = s \sqrt{\frac{n}{2}}$ and variance is

given by (4)

$$\sigma^2 = ((4-n)/2)s^2.$$
 (4)

If base band equivalent of the signal at the input of HPA is,

$$x(t) = r(t)e^{j\mathcal{G}t}$$
(5)

then complex envelope of HPA output signal is given by (6),

$$\mathbf{y}(t) = \left[A(r(t))e^{j\phi(r(t))}\right]e^{j\theta(t)} = f(r(t))e^{j\theta(t)}$$
(6)

where x(t) represent Amplitude modulation/Amplitude modulation distortion and Amplitude modulation /Phase modulation distortion respectively which are introduced by HPA. A complex nonlinear distortion function f(), which

only depends on envelope of the input signal is given by equation (7),

$$f(r(t)) = A(r(t))e^{j\phi r(t)}$$
(7)

For an OFDM system x(t) is given by equation (1).

Saleh model is the popular TWTA model and Rapp's model is the SSPA model under consideration. These are the complex baseband models of amplifier with noise; basically used to model the nonlinearity Basic structure of nonlinear amplifier model is shown in figure 2.



Fig. 2. Nonlinear Amplifier model

First block multiplies the signal by a gain factor. Second block splits the complex signal into its magnitude and angle components. AM/AM conversion block applies an AM/AM conversion to the magnitude of the signal, according to the selected interpolation method, to produce the magnitude of the output signal. AM/PM conversion block applies an AM/PM conversion to the phase of the signal, according to the selected interpolation method, and the adder block add the result to the angle of the signal to produce the angle of the output signal. The next combiner block combines the new magnitude and angle components into a complex signal and multiplies the result by a gain factor, which is controlled by the linear gain parameter.

Figure 3 shows, for the Saleh method, plots of

- Output voltage against input voltage for the AM/AM conversion
- Output phase against input voltage for the AM/PM conversion



Fig. 3. Plots for AM/AM and AM/PM conversion (Saleh model)

For Saleh Model, the input scaling (dB) parameter scales the input signal before the nonlinearity is applied. The block multiplies the input signal by the parameter value, converted from decibels to linear units.

The AM/AM parameters, alpha and beta, are used to compute the amplitude gain for an input signal using the following function

$$F_{AM/AM(u)} = \frac{alpha * u}{1 + (beta * u^2)}$$
(8)

Where u is the magnitude of the scaled signal.

The AM/PM parameters, alpha and beta, are used to compute the phase change for an input signal using the following function (1.0)

$$F_{AM/PM(u)} = \frac{alpha * u^2}{1 + (beta * u^2)}$$
(9)

where u is the magnitude of the input signal. Note that the AM/AM and AM/PM parameters, although similarly named alpha and beta, are distinct. The Output scaling (dB) parameter scales the output signal similarly.For Rapp Model, the Smoothness factor and Output saturation level parameters are used to compute the amplitude gain for an input signal by the following function

$$F_{AM/AM(u)} = \frac{u}{\left(1 + \left(\frac{u}{O_{sat}}\right)^{2ds}\right)^{1/2s}}$$
(10)

where u is the magnitude of the scaled signal, S is the Smoothness factor and O_{sat} is the Output saturation level. The Rapp model does not apply a phase change to the input signal. Common operating parameters of HPA are shown in figure 4 [8].



Fig. 4. HPA operating parameters

Back off may be calculated from

1) Average signal power and saturated signal power at the output. This is Output back off (OBO).

$$OBO_{dB} = -10 \log_{10} \frac{E\left\{\left|V_{out}\right|^{2}\right\}}{P_{sat,OUT}} \qquad (11)$$

2) Average input signal power level and input power level corresponding to the saturation in the linearized model. This is input back off (IBO).

Input back off is the ratio of the signal power measured at the input to HPA to the input signal power that produces maximum signal power at the amplifier's output. It is expressed in dB, either as a positive or negative quantity.

$$IBO_{dB} = -10\log_{10}\frac{E\left\{\left|V_{IN}\right|^{2}\right\}}{P_{sat,IN}}$$
(12)

Neural networks are able to give solutions to complex problems in digital communications due to their nonlinear processing, parallel distributed architecture, self-organization, capacity of learning and generalization, as well as efficient hardware implementation [9]. Here the novel architecture is proposed for compensation of nonlinear distortions as shown in figure 5.



Fig. 5. Hiperlan/2 with neural model

Nonlinearity received is in time domain. Neural network is in frequency domain. Neural block is therefore placed after FFT block. Neural network architectures under consideration are SOM and PLSOM neural blocks.

SOM consists of a series of neurons that act upon a series of inputs. Each neuron is densely interconnected, which receives input signal, a great number of lateral interconnections from output of other units. The primary unit determines a winner node, which will have a certain cluster, and then following the input, the winner node with its surrounding neighborhood adapts to the input. This process continues for certain number of iterations until a certain degree of adaptations is reached.

To compensate for the nonlinearities, SOM algorithm is used after FFT block at the receiver side. Nonlinearity from HPA is in time domain, whereas SOM algorithm is in frequency domain. SOM algorithm is introduced in the following steps.

1) Initialize the values of nodes ω_i by using values of ideal 16-QAM signal constellations. We design SOM neurons as the same as the constellation of 16-QAM. The two dimensional weight coefficients of the neuron equal to in-phase and quadrature components of the point in 16-QAM constellations

2) Locate the winning node i for the input signal I by $\left\| \stackrel{\text{\tiny A}}{I}(k) - \omega_i \right\| = \min_i \left\{ \left\| I(k) \stackrel{\text{\tiny A}}{-} \omega_j \right\| \right\}$ (13)

After locating the winning node i, we use the Euclidean distance as neighborhood radius to define neighborhood of winning node i.

3) Modify the values of the winning node to the direction of the input data and modify the values of the neighbors of the winning node in the same way. The neighborhood function $h_{i,i}$ is defined by

$$h_{j,i} = \exp\left(-\frac{d_{j,i}^2}{2\sigma^2}\right) \tag{14}$$

where $d_{i,i}$ is the neighborhood radius and the parameter σ is the effective width of the topological neighborhood. To satisfy the requirement that the size of the topological neighborhood shrinks with time, we let the width σ of the topological neighborhood function $h_{i,i}$ decrease with time.

$$\sigma(n) = \sigma_0 \exp\left(-\frac{n}{\varphi_1}\right) \quad \text{For } n = 0, 1, 2 \quad (15)$$

 σ_0 is the value of σ at the initiation of SOM algorithm. φ_1 is a time constant. The topological neighborhood assumes a time varying form of its own and is given by

$$h_{j,i}(n) = \exp\left(-\frac{d_{j,i}^2}{2\sigma^2(n)}\right)$$
 (16)

Thus as the time/ number of iterations increases, width $\sigma(n)$ decreases at an exponential rate and the topological neighborhood shrinks in a corresponding manner.

For 16-QAM system, $\sigma = 2$ and $\varphi_1 = \frac{1000}{\log \sigma_0}$

For a network to be self-organizing, synaptic weight vector

 ω_j of neuron j in the network is required to vary in

relation to the input I(k). Increment of the weight vector of neuron j is

$$\Delta \omega_j = \eta h_{j,i} (\stackrel{\Lambda}{I} - \omega_i) \tag{17}$$

where η is a scalar valued adaptation gain and should be decreased with time.

$$\eta(n) = \eta_0 \exp\left(-\frac{n}{\varphi_2}\right) \tag{18}$$

Where φ_2 is another time constant of SOM algorithm. Even though the neighborhood function and learning rate parameter may not be optimal, they are usually adequate for the formation of feature map in a self organized manner.

4)For the input signal I(k) the output is defined by the modified weight $\omega_i(k+1)$ and reset the constellation by weight vector $\omega_i(k+1)$.

Unfortunately, this unsupervised learning is dependent on two annealing schemes, one for the learning rate and one for the neighborhood size. Parameterless self organizing map is a neural network, based on SOM that eliminates need for a learning rate and neighborhood size [10].

PLSOM algorithm:

Fundamental idea of PLSOM is that the amplitude and extent of weight updates are not dependent on iteration number, but how good the fit is, we calculate a scaling variable ε which is then used to scale the weight update, which can be defined through following equations (19) and (20).

$$\varepsilon(t) = \frac{\left\| x(t) - w_c(t) \right\|_2}{r(t)} \tag{19}$$

$$r(t) = \max(||x(t) - w_c(t)||, r(t-1))$$

$$r(0) = ||x(0) - w_c(t)||_2.$$
(20)

 $\mathcal{E}(t)$ is best understood as the normalized Euclidean distance from the input vector at time t to the closest weight vector. If this variable is large, network fits the input data poorly and needs a large adjustment. Conversely, if \mathcal{E} is small, the fit is likely to already be satisfactory for that input

and no large update is necessary. Algorithm for PLSOM uses a neighborhood size determined by ε thus replacing the equation governing the annealing of neighborhood with $\beta(t) = cons \tan t \forall t$.

 β is scaled by $\varepsilon(t)$, giving $\Theta(\varepsilon(t))$ the scaling variable for neighborhood function (21)

$$\Theta(\varepsilon(t)) = \beta(t)$$
 where
 $\Theta(\varepsilon(t)) \ge \theta_{\min}$ (21)

Second option for calculating $\Theta(\mathcal{E}(t))$ is given in eqn (22).

$$\Theta(\varepsilon(t) = (\beta - \theta_{\min})\varepsilon(t) + \theta_{\min} \quad (22)$$

Third alternative is equation (23).

$$\Theta(\varepsilon(t) = (\beta - \theta_{\min}) \ln(1 + \varepsilon(t))(e - 1) + \theta_{\min}$$
(23)

Here, ln() is the natural logarithm, e is the Euler number, θ_{\min} is some constant, whose value is taken as 1 for the equations (9) and (10), and 0 for the equation (11). Neighborhood function is given by,

$$h_{c,i}(t) = \frac{-d(i,c)^2}{e^{\Theta(\varepsilon(t))^2}}$$
(24)

d(i,c) is the distance measure along the grid in the output space from the winning node c to i, which is the node we are currently updating. This gives a value, that decreases further we get from c and the rate of decrease is determined by ε . Weight update functions are

$$w_i(t+1) = w_i(t) + \Delta w_i(t)$$
 (25)

$$\Delta w_i(t) = \mathcal{E}(t)h_{c,i}(t) \big[x(t) - w_i(t) \big].$$
(26)

Learning rate $\alpha(t)$ is now completely eliminated, replaced by $\mathcal{E}(t)$. The size of update is not dependent on the iteration number. The only variable, affecting the weight update which is carried over between the iterations is the scaling variable r(t).

SIMULATIONS:

Simulations are carried out using MATLAB SIMULINK model 16 QAM modulation schemes for ³/₄ code rate for AWGN channel. Hiperlan/2 Simulink model with TWTA (Saleh model) and SSPA (Rapp's model) has been simulated for four cases.

- 1) Hiperlan/2 without neural block with AWGN channel
- 2) Hiperlan/2 without neural block with Rayleigh fading channel
- 3) Hiperlan/2 with SOM block
- 4) Hiperlan/2 with PLSOM block

The function newsom creates a self organizing map. This returns a new SOM. For this paper, SOM is trained with 1000 epochs and the input vectors are plotted with the map that formed the SOM weights. SOM consists of a single layer with 'negdist' weight function, 'netsum' net input function and 'compet' transfer function. The layer has a weight from the input but no bias. The weight was initialized with 'midpoint'. Adaptation was done with the function 'trainr' and the weights were updated with the algorithm 'learnsom'. The distance function used is 'dist' which calculates the Euclidean distance from home neuron to any other neuron. All the neighborhoods for a S neuron layer map are represented by S X S matrix of distances. 'Gridtop' topology starts with the neuron in the rectangular grid. Weights of winning neurons are adjusted using Kohonen's rule. The rule allows the weights of neurons to learn an input vector. Thus the neuron, whose weight vector was closest to the input vector was updated to be even closer.

PLSOM completely eliminates selection of learning rate, the annealing rate and the annealing scheme of learning rate and the neighborhood size. It also decreases the number of iterations required to get a stable and ordered map. It has been proved that in 600 epochs we are getting the desired result.

Simulation setting for getting BER plot for Hiperlan/2 with Saleh model is given in table 1 and the BER plot is shown in figure 6.

TABLE 1: SIMULATION PARAMETERS FOR HIPERLAN/2 WITH SALEH MODEL

Parameter	Value/ Description
WLAN Model for	Hiperlan/2
simulation	-
Modulation scheme	16 QAM
Code rate	3/4
Puncture vector	
Number of sub carriers	52
FFT size	64
GI length	16
Channel model	AWGN/ Rayleigh
	fading
AM/AM parameter	2.1587
alpha	
AM/AM parameter	1.1517
beta	
AM/PM parameter	4.0033
alpha	
AM/PM parameter	9.1040
beta	



Fig. 6. BER plot for Hiperlan/2 with Saleh model

TABLE 2: SIMULATION PARAMETERS FOR HIPERLAN/2 WITH RAPP'S MODEL

Parameter	Value/ Description
WLAN Model for	Hiperlan/2
simulation	
Modulation scheme	16 QAM
Code rate	3/4
Puncture vector	
Number of sub carriers	52
FFT size	64
GI length	16
Channel model	AWGN/ Rayleigh
	fading
Smoothness factor	2

Simulation setting for getting BER plot for Hiperlan/2 with Rapp's model is given in table 2 and the BER plot is shown in fig. 7.



Fig. 7. BER plot for Hiperlan/2 with Rapp's model

II. CONCLUSION

This paper presents results of simulations run on neural network based Hiperlan/2 WLAN receiver structure in fading multipath environment. Hiperlan/2 uses OFDM as multiplexing scheme, which has a main drawback of having high peak to average power ratio. Most of the signal components are amplified in saturation region of the high power amplifiers used at the transmitter end causing nonlinear distortions. For this paper, simulations are run for Hiperlan/2 with HPA models like Saleh model (TWTA) and Rapp's model (SSPA). Modulation method is 16 OAM, and code rate is 3/4. Channel models are AWGN and Rayleigh fading. SOM and PLSOM blocks act as adaptive decision devices that not only compensate for nonlinear distortions but also follow up error signals. BER vs SNR plots clearly indicate the better performance of new neural based Hiperlan/2 WLAN receiver structure.

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