

MULTIPLICATIVE NEURAL NETWORK WITH SWARM INTELLIGENCE FOR MULTICARRIER TRANSMITTER

Nibaldo Rodriguez, Claudio Cubillos

School Informatic, Pontifical Catholic University of Valparaiso, Av. Brasil 2241, Chile

Orlando Duran

School Mechanic, Pontifical Catholic University of Valparaiso, Av. Brasil 2241, Chile

Keywords: Neural Networks, Swarm intelligence, Multicarrier Communications.

Abstract: In this paper, we propose a novel effective distortion compensation scheme suitably developed to reduce nonlinearities of the traveling wave tube amplifier (TWTA) in orthogonal frequency division multiplexing (OFDM) systems at the multicarrier transmitter side. This compensator is developed in order to combine in the most effective way the capability of the quantum particle swarm optimization technique and multiplicative neural networks. The compensator effectiveness has been tested through computer simulations. The improvements in the reduction of constellation warping and enhanced performance in terms of the bit error rate (BER) are offered for the TWTA with an input back-off level of 0 dB.

1 INTRODUCTION

Multicarrier Transmitter based on orthogonal frequency division multiplexing (OFDM) appears to be an attractive transmission scheme in order to overcome the impairments of wireless broadband channels. Due to this fact, various standards for wireless communications using OFDM signals. However, the main drawback of OFDM signal is the large envelope fluctuations, making the system sensitive to the nonlinearities introduced by the traveling wave tube amplifier (TWTA) (A.M., 1981), which cause spectral regrowth in adjacent channels and deformation of the signal constellation. To reduce nonlinear distortions, it is necessary to operate the TWTA with a large power back-off level. However, such amplification schemes possess a low power efficiency since the maximum power efficiency is only attained when the TWTA is operated near its saturation point. Hence, TWTA compensation techniques are often necessary to achieve a trade-off between the linear amplification and high power efficiency. Many compensation schemes based on artificial neural network (Abdulkaader F., 2002), (Rodriguez N. and R., 2003) to reduce nonlinearities and their effects have been proposed in the recent literature.

In most existing techniques, complex models'

input-output measured signals are initially converted to either a polar or rectangular representation and then two separate and uncoupled real-valued models are used to estimate the amplitude and phase output as a function of the input power amplitude. The real parameters of the two models were obtained during a training procedure based on back-propagation algorithm and gradient descent method, but the main disadvantage of these compensation schemes is their slow convergence speed and elevated requirements of computing resources. Particle Swarm Optimization (PSO) was originally proposed by J. Kennedy as a simulation of social behavior of bird flock, and was initially introduced as a heuristic optimization method in 1995 (Kennedy, 1995). Recently Sun et al. (Sun J. and W., 2004) proposed a global convergence-guaranteed search technique called quantum-behaved particle swarm optimization algorithm (QPSO), whose performance is superior to the standard PSO. The proposed QPSO algorithm, kept to the philosophy of PSO, is based on Delta potential well and depicted only with the position vector without velocity vector, which is a simpler algorithm. The results show that QPSO performs better than standard PSO on several benchmark test functions and is a promising algorithm due to its global convergence guaranteed characteristic. In this

paper, we explore the effectiveness of the QPSO technique with a multiplicative neural networks (QPSO-MNN) to maximize linearity and power efficient of an OFDM multicarrier transmitter. The MNN has only one hidden layer consists of product units, while the output layer has additive units. Moreover, both layers use linear activation function and QPSO is applied for determining the MNN's parameters.

The remainder of this paper is organized as follows: The compensation scheme of the TWTA and an parameter identification algorithm are presented in Section 2 and 3; respectively. The performance curves of the constellation warping effect and bit error rate (BER) of 16QAM-OFDM signals with 256-subcarrier are discussed in Section 4. Finally, the conclusions are drawn in the last section.

2 COMPENSATION SCHEME

A baseband block model for a compensation scheme with TWTA is shown in Fig. 1. The output of the compensator is given as

$$y(n) = M(|x(n)|) \exp\{j[\theta_x + N(|x(n)|)]\} \quad (1)$$

where the functions $M(\cdot)$ and $N(\cdot)$ are used to invert the nonlinearities introduced by the TWTA.

The combination of a TWTA and the corresponding compensator will result in

$$z(n) = A[M(|x(n)|)] \exp\{j[\theta_n + N(|x(n)|) + P[M(|x(n)|)]]\} \quad (2)$$

where $A(\cdot)$ and $P(\cdot)$ are the nonlinear amplitude (AM/AM) and nonlinear phase (AM/PM) conversion of the TWTA; respectively. The AM/AM and AM/PM conversion of a TWTA can be approximated as (?)

$$A(|y(n)|) = \frac{\alpha_A |y(n)|}{1 + \beta_A |y(n)|^2} \quad (3)$$

$$P(|y(n)|) = \frac{\alpha_P |y(n)|^2}{1 + \beta_P |y(n)|^2} \quad (4)$$

with $\alpha_A = 2, \beta_A = 1, \alpha_P = \pi/3$ and $\beta_P = 1$

The nonlinear distortion of a high power amplifier depends on the back-off. The input back-off (IBO) is defined as the ratio of the input power saturation, where the output power begins to saturate, to the average input power.

$$IBO(dB) = 10 \log_{10} \left(\frac{P_{i,sat}}{P_{i,avg}} \right) \quad (5)$$

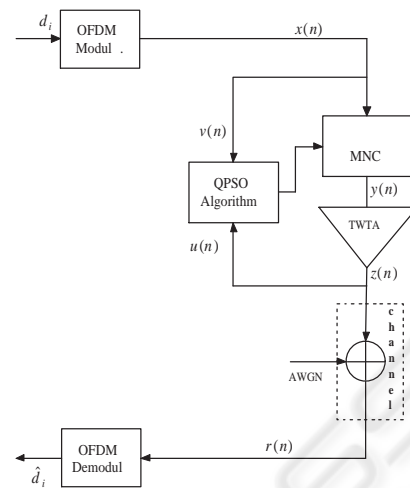


Figure 1: Baseband OFDM transmission system.

where $P_{i,sat}$ is the input power saturation and $P_{i,avg}$ is the average power at the input of the TWTA.

In order to achieve the ideal linearizing function, the signal $z(n)$ will be equivalent to the input OFDM signal $x(n)$. That is:

$$A[M(|x(n)|)] = \alpha |x(n)| \quad (6a)$$

$$N(|x(n)|) = -P[M(|x(n)|)] \quad (6b)$$

where $\alpha |x(n)|$ is the desired linear model. In this paper, the desired linear gain was set to $\alpha = 1$, so that saturation power was reached at 0 dB. We therefore write the ideal linearizing function as

where $A^{-1}[\cdot]$ represents the inverse AM-AM function of the TWTA.

Finally, in order to achieve (6), it is necessary only to find the real-valued function $A^{-1}[\cdot]$, which can be approximated by using a multiplicative Neural Network and a finite number of samples of the (AM/AM) function.

2.1 QPSO-MNN based Compensator

In quantum-behaved particle swarm optimization, the particles move according to the following iterative equations (Sun J. and W., 2004):

$$p = \phi \cdot P_{ij} + (1 - \phi) \cdot P_{gj} \quad \phi \sim U(0, 1) \quad (7)$$

$$X_{ij} = p \pm \alpha \cdot |mbest_j - X_{ij}| \cdot \ln(1/u) \quad u \sim U(0, 1) \quad (8)$$

where X_{ij} is an infinitesimal particle in the D -dimensional space with $i = 1, 2, \dots, M$ and $j =$

$1, 2, \dots, D$. The vector P_{ij} is the best previous position of particle i , vector P_{gj} is the position of the best particle among all the particles and known as the global best position. The parameter α is called contraction-expansion coefficient and the global point $mbest_d$ is the mean best position among the particles. The global point is defined as

$$mbest_j = \sqrt{\sum_{i=1}^M (P_{ij} - \bar{P})^2} \quad j = 1, 2, \dots, D \quad (9)$$

where

$$\bar{P} = \frac{1}{M} \sum_{i=1}^M P_{ij} \quad (10)$$

The compensator's output signal $y(t)$ is approximated using a multiplicative neural network, which is given as:

$$\hat{y}(u) = \sum_{j=1}^m a_j \cdot h_j(u) \quad (11a)$$

$$h_j(u) = \prod_{i=1}^D u^{b_{ji}} \quad (11b)$$

where a_j are the linear parameters, b_{ji} are nonlinear weights, m is the number of hidden nodes, u is the input value.

For a three-layered MNN, b_{ji} and a_j represent the connection weight matrix between the input layer and the hidden layer, and that between the hidden layer and the output layer; respectively. During training of the MNN, the k -particle is denoted by $X_k = (a_j^k, b_{ji}^k)$. In order to determine the fitness of the k -particle is used the mean square error of the MNN, which is defined as

$$E(X_k) = \frac{1}{N_s} \sum_{i=1}^{N_s} (u_i - \hat{y}(u_i))^2 \quad (12)$$

where N_s is the number of training set samples. The desired output v_i and input data u_i are obtained as

$$v_i = \frac{|x(n)|}{\max\{|x(n)|\}} IBO \quad (13a)$$

$$u_i = |z(n)| \quad (13b)$$

3 INTRODUCTION

The numerical results presented in this section are based on the following setup: In the transmitter, an OFDM signal with $N = 256$ subcarrier is generated and all subcarriers are 16-Quadrature Amplitude

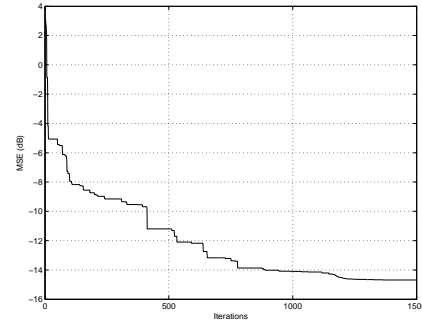


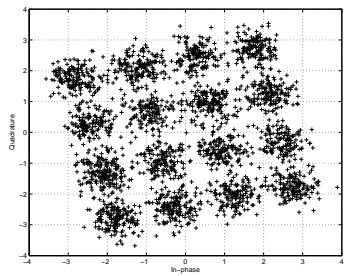
Figure 2: Best MSE history of neural network training.

modulated (16-QAM). The TWT amplifier is operated at $IBO = 0$ dB and the channel model under consideration is an AWGN (Additive White Gaussian Noise) channel. The parameters of the multiplicative neural compensator (MNC) were estimated during the training process using $N_s = 100$ subcarrier 16-QAM-OFDM and the TWTA was operated at $IBO = 0$ dB. The MNC was configured with one input node, one linear output node, three hidden nodes and one bias units. In the training process the particles swarm were initialized by a Gaussian random process with a normal distribution $U(0, 1)$. The population size was set to $M = 20$ and dimension space was set to $D = 3 + 3 + 1 = 7$. The contraction-expansion coefficient varies linearly from 1.0 to 0.5 over the iterations. Training was only one run with 1500 iterations and the normalized mean square error after convergence was approximately equal to -15 dB. In decision-direct mode, the MNC is simply a copy of the multiplicative neural network obtained during the QPSO-training process.

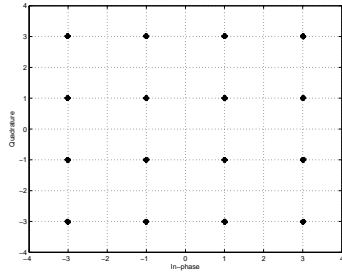
Fig.2 demonstrate the training and the performance of the MNC using conventional QPSO scheme. From Fig.2, it is easy to see MNC trained with QPSO algorithm converges quickly and can generate mean square error value about of -15 dB.

To demonstrate the performance of the proposed QPSO-MNC scheme, we evaluated the constellation warping effect and the BER versus signal to noise rate (E_b/N_0) using 50 Monte Carlo runs for an input data stream of length equal to 10,000 bits and the input back-off level was set at $IBO = 0$ dB for TWTA combined with MNC (MNC+TWTA). Moreover, we also show the performance for the system without MNC and the system with ideal (AWGN) channel. The BER of the OFDM symbols without TWTA in the AWGN channel is very similar to the corresponding 16-QAM system and is used here for benchmarking the performance of the 16QAM-OFDM system.

The effects of the TWTA on the 16QAM-OFDM received constellations in the absence of the AWGN



(a) TWTA operated at IBO = -9 dB without MNC



(b) TWTA operated at IBO = 0 dB with MNC

Figure 3: Received 16QAM-OFDM Constellation in absence AWGN channel.

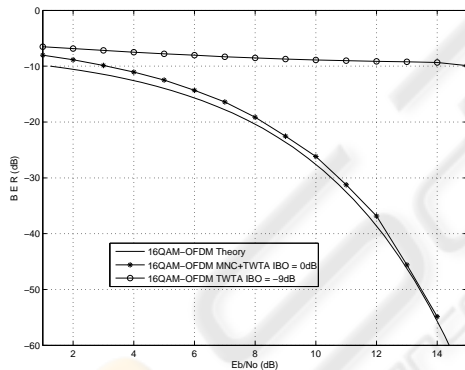


Figure 4: BER performance of 16QAM-OFDM over a non-linear AWGN channel.

channel are shown in Fig. 3(a) and 3(b), which correspond to the TWTA without and with MNC operated at an input back-off level of -9 dB and 0 dB; respectively. According to Fig. 3(a) and 3(b), it is observed that square 16QAM constellation is severely distorted by the nonlinear AM/AM and AM/PM characteristics of the TWTA without MNC. This distortion is interpreted as in-band noise, and it is called constellation warping effect. From Fig. 3(a) and 3(b) it can be seen that the proposed multiplicative neural compensator scheme significantly reduces the constellation warping effect on the received 16QAM-OFDM symbols.

Fig. 4 shows the BER performance for 16QAM-

OFDM with and without MNC in presence of a TWTA. From Fig. 4 it can be seen that at $E_b/N_o = 14$ dB is achieved a $BER = -10$ dB when the TWTA without MNC is operated at $IBO = -9$ dB. Thus, the BER performance is very poor due to nonlinearities of the TWTA. In addition, also the MNC achieves a $BER = -55.6$ dB at $E_b/N_o = 14$ dB, which is favorably compared to the BER corresponding to the linear amplification ideal case.

4 CONCLUSIONS

In this paper, we have presented the performance of a TWTA without and with compensation scheme using the QPSO technique with a multiplicative neural network. We have also demonstrated the performance enhancement achieved using QPSO-MNN compensator with a simple and efficient algorithm for estimating the weights of the multiplicative neural network.

Simulation results have shown that the proposed QPSO-MNN compensation offers a significant constellation warping effect and BER reduction. Moreover, the QPSO-MNN compensator achieves a BER very close to the one corresponding to the ideal case of linear amplification.

ACKNOWLEDGEMENTS

This work has been partially supported by the Vice-rectoria of the Catholic University of Valparaiso.

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