EQUALIZATION OF SATELLITE UMTS CHANNELS USING NEURAL NETWORK DEVICES

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Abstract— **The presence of non-linear devices in several communication channels, such as satellite channels, causes distortions of the transmitted signal. These distortions are more severe for non-constant envelope modulations such as 16-QAM. Over the last years Neural Networks (NN) have emerged as competitive tools for linear and non-linear channel equalization. However, their main drawback is often slow convergence speed which results in poor tracking capabilities. The present paper combines simple NN structures with conventional equalizers. The NN techniques are shown to efficiently approximate the optimal decision boundaries which results in good symbol error rate (SER) performance. The paper gives simulation examples (in the context of satellite mobile channels) and compares neural network approaches to classical equalization techniques.**

I. Introduction

The worldwide growth of wireless mobile telecommunications services requires the transmission of more and more data at high rates over long distances. This involves the use of non-linear amplifiers to improve the transmission channel efficiency. For instance, Satellite Universal Mobile Telecommunication Systems (S-UMTS) links employ Travelling Wave Tube Amplifiers (TWTA) and Solid State Power Amplifiers (SSPA). Such devices cause severe distortions for the transmitted signal. Therefore efficient equalizers are needed in order to overcome these distortions.

Over the last decade Neural Network (NN) equalizers have raised much interests (See [9] for an overview). Their non-linear structures and good learning properties make them good candidates to solve the equalization of linear as well as non-linear channels problem. Multilayer Perceptron (MLP) [6], [12] and Radial Basis Function networks (RBF) [7], [8] were shown to be optimal symbol-by-symbol equalizers with regard to Bayes theory. Nevertheless their slow convergence speed does not allow them to efficiently track time-varying channels such as UMTS channels. Alternative approaches were proposed in [2], [11], and [14]. Simple NN-based structures were combined to conventional Linear Transversal Equalizers (LTE) or Decision Feedback Equalizers (DFE) to form hybrid equalizers. In [2] a particular MLP called LF-NLN (Linear Filter - Nonlinear Network) was successfully applied to the equalization of a 4-QAM S-UMTS channel. [14] proposed RBF networks as decision devices for non-linear channels. Kohonen Self-Organizing Maps (SOM) were also combined with DFE equalizers in [11] and [4].

The present paper proposes several NN structures and compares their performance when applied to the equalization of a 16-QAM S-UMTS channel.

The paper is organized as follows: Section II describes non-linear channels. In Section III several hybrid NN-based equalizers are presented. Section IV applies these equalizers to 16-QAM Satellite-UMTS channels.

II. Problem Statement

A. Satellite Channel Model

Figure 1 gives a discrete equivalent model for a non-linear transmission channel. The transmitted signal $s(n)$ is filtered by the uplink linear filter $H_u(z)$. Colored gaussian noise $u(n)$ is then added. The signal passes then through a memoryless non-linear function $f(.)$ (which represents the nonlinear amplifier transfer function). The downlink is composed of a linear filter $H_d(z)$. The equalizer performs a non-linear function $g(.)$ of the delayed received sample $X(n) = [x(n), x(n-1), ..., x(n-L+1)]$. The purpose of the equalizer is to provide an estimation of the transmitted signal.

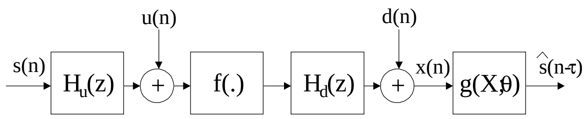

Figure 1 : Discrete equivalent model for non-linear channel equalization.

The memoryless non-linear amplifier is modelled by a complex gain $G(r) = A(r).e^{j\Phi(r)}$ depending only on the input signal instantaneous power r^2. We have used the Saleh's analytical model for the amplifier non-linearity [13]:

$$\begin{cases} A(r) = \frac{2}{1+r^2} \\ \Phi(r) = \frac{4.0033r^2}{1+9.104r^2} \end{cases} \tag{1}$$

Two kinds of distortions result from the use of non-linear amplifiers : phase wrapping and amplitude distortion. Let us consider the channel described in Figure 1 with $H_u(z) = H_d(z) = 1$ and $f(.)$ represented by Saleh's model. The optimal decision boundaries for 4-QAM and 16-QAM signals are derived from the estimation of the probability density function of each transmitted symbol (Figure 2). The downlink noise tends to mask the effect of the non-linearity on the decision boundary for 4-QAM signals. Indeed, Figure 2-b shows that 15dB downlink noise makes results in an optimal decision boundary which is linear (intersection of hyperplanes). This decision boundary can be achieved by a simple sign operator. However, non-constant modulus modulations such as 16-QAM are more severely distorted by the non-linearity. Figure 2-d shows that even in presence of downlink noise, the optimal decision boundary cannot be achieved by a threshold operator. Thus, more sophisticated non-linear deviced are required.

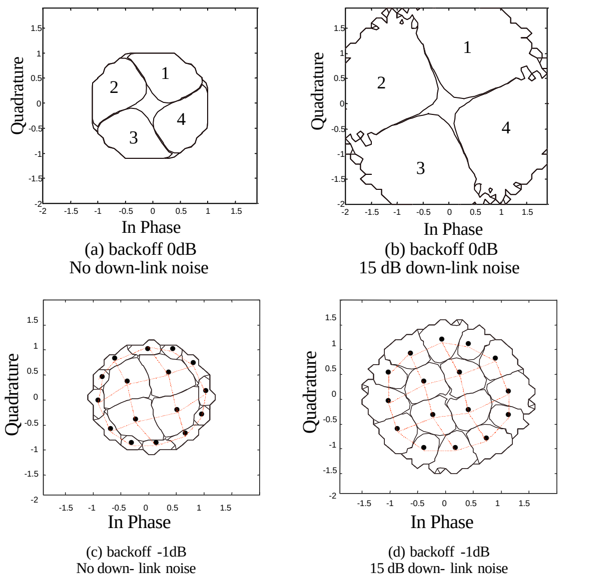

Figure 2 : Optimal decision boundaries: (a) (b) 4-QAM, (c) (d) 16-QAM.

B. Satellite-UMTS Channel Model

The S-UMTS channel model used in our simulations is described in Figure 3. The emission filter F_1 is an IIR square-root raised cosine filter. Its bandwidth is limited to the symbol rate $\frac{1}{T_s}$. This filter introduces intersymbol interference (ISI). In order to add white noise in the signal bandwidth only in the uplink and downlink, white gaussian noise is first filtered by an elliptic low-pass filter F_e with a very abrupt transition. The SNR parameters of the channel correspond to the effective SNR in the signal bandwidth. The signal is scaled by a gain factor before entering the amplifier. It enables to adjust the backoff of the signal power compared to the saturation point of the amplifier. $0dB$ backoff was used for 4-QAM signals and $-5dB$ for 16-QAM. The TWTA uses Saleh's model (equation 1).

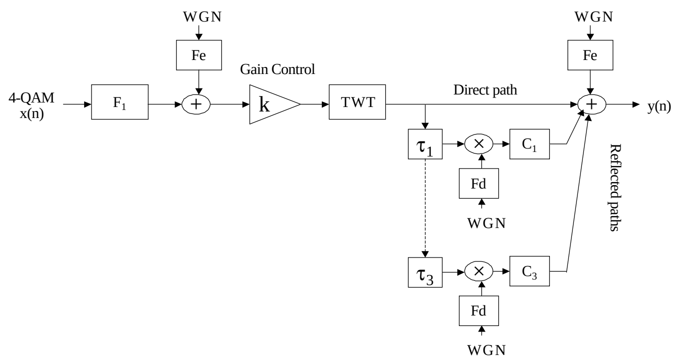

Figure 3 : Satellite mobile communication channel model.

Line Of Sight (LOS) (i.e. with a direct path) communications are considered. In the case of multipath mobile communications, the receiver gets time delayed replicas of the direct path. These replicas are attenuated and multiplied by a Doppler noise. The Doppler noise is obtained by filtering a complex gaussian noise by a low-pass Doppler filter F_d. The transfer function of F_d is given in 2.

$$F_d(p) = \frac{1}{\frac{p^2}{\omega_0^2} + \frac{2\xi p}{\omega_0} + 1} \tag{2}$$

where $\xi = 0.1$ and $\omega_0 = 2\pi f_d$. $f_d = f_c \frac{v_{mob}}{c}$ is the Doppler frequency, f_c is the carrier frequency (2.2GHz), v_{mob} is the mobile speed (up to 300km/h) and c is the light speed (3.10^8m/s). Once multiplied by the Doppler noise, each reflected path k is filtered by a low-pass filter C_k. C_k models the time spread caused by refractions on obstacles. The impulse response of C_k decays exponentially : $C_k(n) = e^{-n\frac{T_e}{T_s}}$, where T_e is the sample duration and T_s is the delay spread (10^{-9}s). In the following simulations only one reflected path (which is delayed by $0.1s$ and attenuated by $10dB$) was considered. According to [5] this corresponds to a suburban area transmission at low elevation angle (around 15^o).

III. Neural Networks as Adaptive Decision Devices

The decision device in LTE and DFE equalizers is usually a hard limiter with two or more levels (depending on the modulation). In this section we show how neural networks can improve the decision process.

A. The LF-NLN

In [2] a particular MLP called LF-NLN was introduced. The structure of the LF-NLN is given in Figure 4. An input linear filter is followed by a memoryless non-linearity. The memoryless non-linearity consists of a hidden layer with sigmoidal neurons. The linear filter of the LF-NLN is supposed to deal with the linear ISI and the memoryless non-linear network cancels the remaining non-linear distortions. This NN structure was successfully applied to satellite channel identification [10]. In [2] the LF-NLN was shown to give very low MSE when applied to a 4-QAM satellite channel. Its simple structure enables to track time varying channels. This results in BER improvement in non-stationary environment.

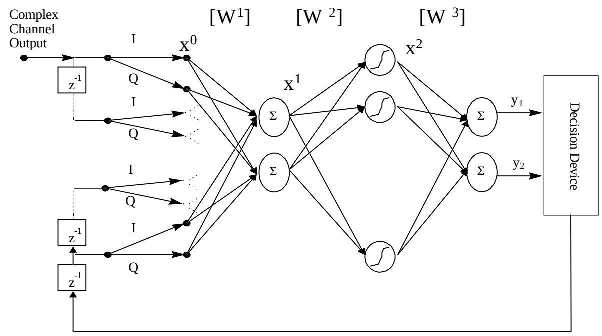

Figure 4 : Linear Filter - Non-Linear Network equalizer.

The linear filter and non-linear network weights are adapted by the real backpropagation algorithm. The complex version of the LF-NLN and the generalization of the complex backpropagation algorithm to the LF-NLN are detailed in [2]. The real valued algorithm is given below :

- *Forward Phase:*

$$\begin{cases} x_1^1(n) = \sum_{k=1}^{N_0} w_{1k}^1(n).x_k^0(n) \\ x_2^1(n) = \sum_{k=1}^{N_0} w_{2k}^1(n).x_k^0(n) \end{cases}$$

$$x_k^2(n) = f(\textstyle\sum_{j=1}^{2} w_{kj}^2(n).x_j^1(n)) \quad , \forall k \in \{1, .., N_h\}$$

$$\begin{cases} y_1(n) = \sum_{k=1}^{N_h} w_{1k}^3(n).x_k^2(n) \\ y_2(n) = \sum_{k=1}^{N_h} w_{2k}^3(n).x_k^2(n) \end{cases}$$

- *Backpropagation:*

3rd layer : $d(n) = \begin{pmatrix} d_1(n) \\ d_2(n) \end{pmatrix}$ is the desired output,

$$\begin{aligned} \varepsilon^3(n) &= \begin{pmatrix} \varepsilon_1^3(n) \\ \varepsilon_2^3(n) \end{pmatrix} = \begin{pmatrix} d_1(n) - y_1(n) \\ d_2(n) - y_2(n) \end{pmatrix} \\ \delta^3(n) &= \varepsilon^3(n) \end{aligned}$$

$$\begin{cases} w_{1k}^3(n+1) = w_{1k}^3(n) + \mu(n).\delta_1^3(n).x_k^2(n) \\ w_{2k}^3(n+1) = w_{2k}^3(n) + \mu(n).\delta_2^3(n).x_k^2(n) \end{cases}$$

$$, \forall k \in \{1, .., N_h\}$$

2nd layer : $\forall k \in \{1, .., N_h\}$,

$$\begin{aligned} \varepsilon_k^2(n) &= \sum_{j=1}^{2} w_{jk}^3(n).\varepsilon_j^3(n) \\ \delta_k^2(n) &= \varepsilon_k^2(n).f'(x_k^2) \end{aligned}$$

$$\begin{cases} w_{k1}^2(n+1) = w_{k1}^2(n) + \mu_{LFNLN}(n).\delta_k^2(n).x_1^1(n) \\ w_{k2}^2(n+1) = w_{k2}^2(n) + \mu_{LFNLN}(n).\delta_k^2(n).x_2^1(n) \end{cases}$$

1st layer :

$$\begin{aligned} \varepsilon_j^1(n) &= \sum_{l=1}^{N_h} w_{lj}^2(n).\varepsilon_l^2(n) \quad , \forall j \in \{1, 2\} \\ \delta^1(n) &= \varepsilon^1(n) \end{aligned}$$

$$\begin{cases} w_{1k}^1(n+1) = w_{1k}^1(n) + \mu_{LFNLN}(n).\delta_1^1(n).x_k^0(n) \\ w_{2k}^1(n+1) = w_{2k}^1(n) + \mu_{LFNLN}(n).\delta_2^1(n).x_k^0(n) \end{cases}$$

$$, \forall k \in \{1, .., N_h\}$$

For non-constant modulus modulation schemes like 16-QAM, [1] suggested to use the following activation function $F(.)$ for an MLP, taking advantage of *a priori* information about the transmitted signal:

$$F(x) = \frac{1}{3}\left[f(\frac{x - x_0}{\sigma}) + f(\frac{x}{\sigma}) + f(\frac{x + x_0}{\sigma})\right]$$

where x_0 is a threshold parameter, σ is a slope steepness tuning parameter and $f(.)$ is the tanh function. The parameters used in our simulations are $x_0 = 0.62$ and $\sigma = 0.05$. In the following simulations the LF-NLN was used with $F(.)$ to equalize 16-QAM signals. The algorithm is the same as described above with $f(.)$ and $f'(.)$ respectively replaced by $F(.)$ and $F'(.)$.

B. The LTE-RBF

In [14] an RBF network with memory was used to improve the decision device of a DFE in the case of non-linear channels. In the case of satellite channel equalization it is difficult to get precise channel state estimates because of non-linear distortions as well as up-link noise and IIR filtering. Assuming that a conventional linear or non-linear equalizer deals with the linear ISI and cancels the effect of the memory, the RBF networks needs to fight the memoryless non-linear distortion. For 4-QAM signals the best fitted RBF has 4 neurons (as shown in Figure 5-a) and has 16 neurons for 16-QAM signals. More neurons may help getting better boundaries approximations but would result in poor tracking capabilities.

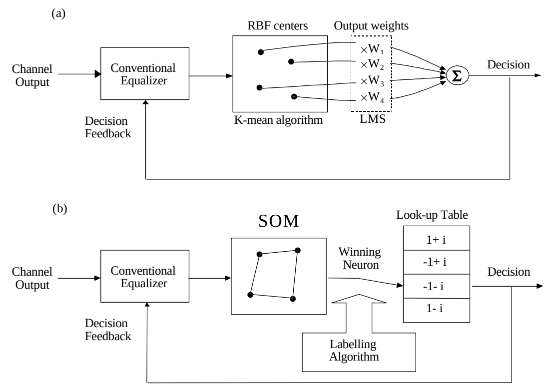

Figure 5 : (a) LTE-RBF equalizer for 4-qam signals, (b) LTE-SOM equalizer for 4-qam signals.

The LMS algorithm was used to adapt the LTE and RBF weights. The RBF neurons are adapted with the k-mean clustering algorithm :

$$\widetilde{k} = \arg(\min_k \|X(n) - C_k(n)\|)$$

$$\begin{cases} C_{\widetilde{k}}(n+1) = C_{\widetilde{k}}(n) + \mu_{RBF}(n)\left[X(n) - C_{\widetilde{k}}(n)\right] \\ C_i(n+1) = C_i(n) \qquad , \forall i \neq \widetilde{k} \end{cases}$$

It is usefull to update the centers with the Kohonen learning rule (described below) as suggested in [3]. It prevents the neurons centers from getting trapped in local minima.

C. The LTE-SOM

The decision device can be improved by using Kohonen Self Organizing Maps (SOM). In [11] SOM were shown to compensate for both corner collapse and lattice collapse non-linear effects. As shown in Figure 5-b, the SOM performs a "winner-takes-all" decision on the conventional equalizer (LTE or DFE) output. Each neuron of the SOM is associated with a transmitted symbol through a look-up table. For 4-QAM signals the SOM has a 2-by-2 square topology. For 16-QAM signals it has a 4-by-4 square topology.

The neurons of the SOM are adapted with the Kohonen learning rule:

$$\widetilde{k} = \arg(\min_k \|X(n) - C_k(n)\|)$$

$$C_i(n+1) = C_i(n) + h_{\widetilde{k}i}(n)\left[X(n) - C_i(n)\right] , \forall i \in \{1, ..., N\}$$

where $C_{\widetilde{k}}$ is the winning neuron, and $h_{ij}(n)$ is the neighborhood kernel. The neighborhood function was chosen as an exponentially decaying function. Not only the winning neuron is moved towards the input vector, but also its neighbors. This helps the SOM neurons fit the received signal constellation correctly. For instance, it prevents one neuron from covering two or more clusters by attracting the neighbors of this neuron in its region. It ensures a better distribution of the neurons over the received signal constellation. This is particularly useful when the topology of the transmitted signal constellation is complicated (like M-QAM with $M > 4$).

IV. Application to S-UMTS channels

A. Decision Boundaries

The decision boundaries performed by the described NN for 16-QAM signals are given in Figure 6 (for $20dB$ uplink and $25dB$ downlink conditions). The SOM seems to give the best approximation to the optimal decision boundaries (which were described in Figure 2-c-d).

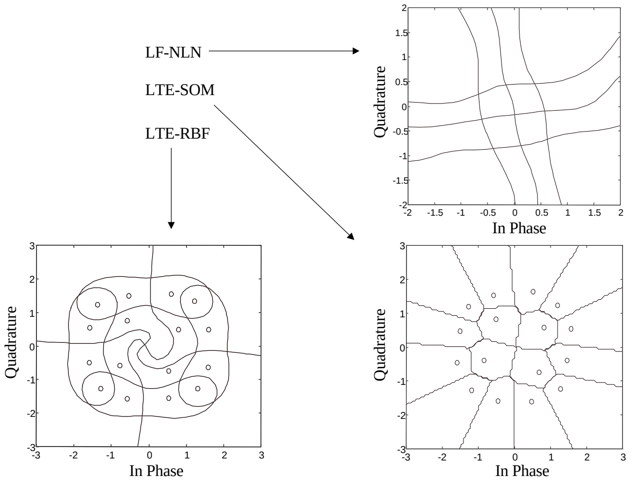

Figure 6 : Decision boundaries performed by NN-based memoryless decision devices: LF-NLN, LTE-RBF and LTE-SOM.

B. Performance Comparison

The performance of NN equalizers applied to 4-QAM modulations was studied in [2], [3], [11], [8]. In this paper we focus on 16-QAM modulations.

For each equalizer, a preliminary study enabled to find out the parameters (i. e. the number of neurons and the learning rates) the give the best trade off between computational complexity and SER performance. Figure 7 gives the Symbol Error Rates (SER) performance of the equalizers when applied to the stationary S-UMTS link (i.e. time-invariant channel). The LTE-SOM outperforms all equalizers. The LF-NLN gives an SER performance which is very close to the LTE-SOM for high downlink SNR. The LTE-RBF suffers from the bad shape of the decision boundaries in the constellation center.

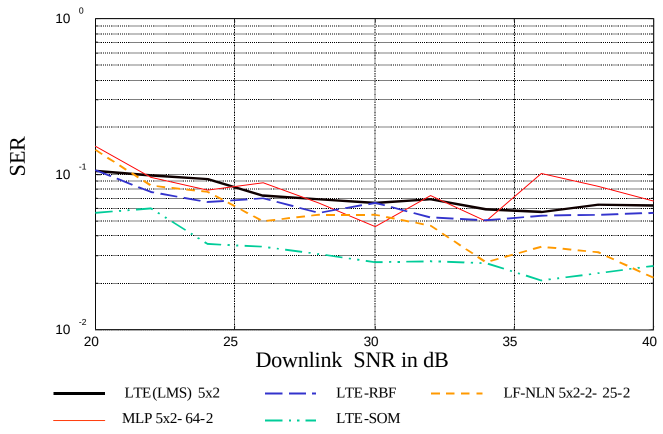

Figure 7 : SER vs. downlink SNR with 20dB uplink SNR and stationary channel.

Figure 8 gives the SER vs. downlink SNR performances for the mobile satellite link ($V_{mob} = 150 km/h$). The LTE-SOM manages to track the channel variations and reaches 10 times lower SER than the other equalizers. The LF-NLN is too slow to confirm its good performance for the stationary channel.

V. Conclusion

The paper presented several neural network (NN) based structures for satellite UMTS channel equalization. Among all tested NN-based equalizers, the LTE-SOM was shown to track the channel variations and give the best approximation to the optimal decision boundary. This makes it a very attractive device to non-constant modulus signal equalization combining both simplicity and efficiency.

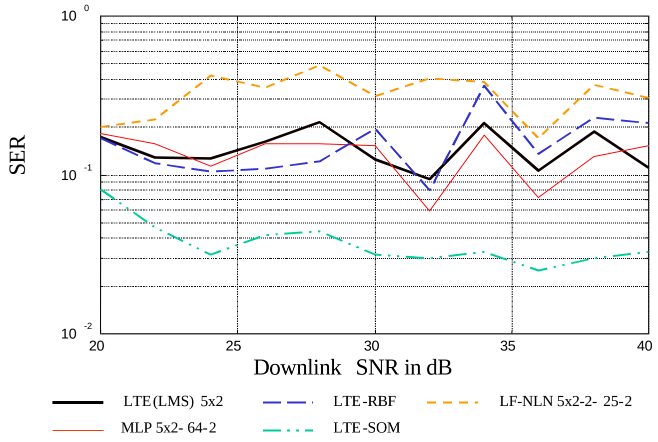

Figure 8 : SER vs. downlink SNR with 20dB uplink SNR and 150km/h mobile speed.

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