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# BER Analysis and CS-Based Channel Estimation and HPA Nonlinearities Compensation Technique for Massive MIMO System

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**ABSTRACT** Massive Multiple Input Multiple Output (MIMO) system has gathered lately a huge interest from researchers and it has been known as a backbone technology for the 5th generation because it can greatly improve the capacity of wireless communication and it can potentially provide energy efficiency and security. Before ensuring the full advantages, massive MIMO system has to overcome many challenges. One of them is to accurate an exact estimation of the Channel Impulse response (CIR) between each transmit-receive antenna pair. The other problem arises when implementing such a system in presence of High Power Amplifiers (HPA) which imposes a nonlinear distortion on the transmitted signals. This paper proposes contributions in three key areas. Firstly, we investigate the nonlinear effects of memoryless HPA, which is modeled using Saleh model, by deriving its Bit Error Rate expression (BER) in massive MIMO Orthogonal Frequency Division Multiplexing (OFDM) system. Secondly, we highlight the necessity of providing the accurate channel characteristics by estimating it using Compressive Sensing (CS) techniques. Moreover, we propose also a CS compensation algorithm based on Orthogonal Matching Pursuit (OMP) to mitigate the nonlinear distortion in the receiver. The proposed CS-based compensation technique has been compared to the Neural Network (NN) pre and post compensation technique and it has shown a good performance not only in terms of BER but also in terms of complexity.

**INDEX TERMS** Channel estimation, compressive sensing, power amplifier, nonlinear distortion, linearization, OMP, BER, NN, pre-compensation, post-compensation.

## I. INTRODUCTION

Over the past decade, the wireless network has known a huge evolution to respond to the increasing demand of user terminals. Massive MIMO which is a huge antenna array with a few hundreds of element antennas in the Base Station (BS) serving one or multiple User Equipments (UE) at the same time, has been emerged as a key method for ultra high speed data service, spectral and power efficiency [1].

To take advantage of the complete benefits of a massive MIMO system, the perfect knowledge of the CIR of each transmit-receive antenna pair has to be ensured. The channel estimation is a very challenging task in massive MIMO system especially in Frequency Division Duplexing (FDD) mode where the CIR is estimated after the pilot signal has been transmitted from the BS on the downlink frequency and then send it back to the user on a different uplink frequency which means that a huge amount of resources will be dedicated only to the pilot sequence [2], [3]. Whereas, with the Time Division Duplexing (TDD) mode and thanks to the channel reciprocity, the Channel State Information (CSI) can be obtained using only uplink pilot sequence [4]. However, many channel estimation approaches have been proposed in the literature beginning with the conventional one such as training based techniques [5] arriving to CS techniques which assume that wireless channels tend to be sparse due to the few number of paths containing the magnitude of the received signal.

On the other hand, to enforce even more the power efficiency of the massive MIMO system, the use of HPAs at the transmitter is crucial since they are the responsible elements for increasing the power of the transmitted signal to reach its destination with a good quality [6].

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Unfortunately, these passive elements present a major problem by generating nonlinear distortion due to their saturation characteristic [7], [8]. That's why, next generation wireless communication must make an adequate tradeoff between efficiency and linearity in the power of HPA to ensure a better quality of the transmission. This tradeoff has pushed the researchers not only, to study intensively the impact of the nonlinear distortion on the performance of massive MIMO system but also to find a compensation technique to restrain the nonlinear effect.

To overcome the HPA imperfections, several compensation techniques [8] have been proposed which can be divided into two categories: compensation at the transmitter such as peak-to-average power ratio (PAPR) reduction technique [9], power back-off and linearization techniques [10], [11] including the feedback method, the feedforward method and predistortion. The second category is the compensation at the receiver for example postdistortion which is mainly used in the uplink scenario to compensate the HPA's nonlinearity. However, NN which has known a great interest as compensation technique for MIMO-OFDM system and so for massive MIMO-OFDM system, can be studied either at the transmitter or the receiver side [12].

Many other studies have been concentrated on using CS as an alternative solution for the compensation technique. Therefore, CS techniques have been used not only as a channel estimation approach but also as a compensation method.

Generally, the HPA models can be classed into two kinds of models: memoryless nonlinear models and nonlinear models with memory. Memoryless nonlinear models include Soft Envelop Limiter (SEL), Solid State Power Amplifiers (SSPA) [13] and Saleh model [14] which are characterized by their amplitude-to-amplitude (AM/AM) and amplitude-to-phase (AM/PM) conversions whereas the nonlinear models with memory such as memory polynomial model, Volterra and Hammerstein depend on AM/AM and AM/PM of the previous input levels [15], [16].

In this paper, we will begin with presenting our system model of TDD uplink massive MIMO-OFDM system where we will focus on three main blocks which are the passive and essential elements such as HPA block, the CS-estimation block and the compensation block. For the HPA block, in order to emphasize their importance in each transmission system, a classification of HPA models will be presented and then an analytical expression of BER in presence of HPA will be demonstrated. For the estimation block, our earlier proposed algorithm B-OMP will be presented and we will study its performance in presence of not only a HPA elements but also a compensation block. For the compensation block, a two compensation methods will be introduced: we will begin with the well-known NN as a compensator then we will propose a CS-based scheme and algorithm to compensate the nonlinear effect of HPA elements. Finally, these two methods will be compared in terms of computational complexity and BER performance.

The reminder of this paper is organised as follows: Section 2 covers Related work. The considered system model is presented in section 3. In section 4, a theoretical analysis of BER for the massive MIMO in linear and nonlinear mode is introduced. The NN compensator and the proposed CS-based compensation technique are presented in section 5. Section 6 presents the simulations and results of the proposed nonlinear compensation technique on the performance of massive MIMO system in terms of BER. conclusions are summarized in section 7.

**Notation:** Throughout this paper, lower-case and upper-case boldface letters denotes vectors and matrices, respectively; $(.)^T$ denotes the transpose of a matrix, $\mathbf{A_s}$ denotes the sub-matrix consisted of columns of $\mathbf{A}$ according to the index set $S$. $\|.\|_p$ is the $l_p - norm$. We use diag($\mathbf{x}$) to transform a vector $\mathbf{x}$ into a diagonal matrix with the entries of $\mathbf{x}$ spread along the diagonal. The discrete Fourier transform (DFT) is represented by $\mathbf{F}$.

## II. RELATED WORK

Certainly, the use of massive MIMO system increases significantly the capacity of the wireless channel.

On the other hand, OFDM which is wideband multicarrier modulation [17] transmission technique, converts frequency selective channels into several independent flat fading subchannels thereby it greatly attenuates the effect of multipath. Thus, it improves the spectrum efficiency due to its strong anti-inter symbol interference and anti-multipath fading.

Therefore, the combination of massive MIMO with OFDM has been remained as the most capable method and promising technique for high-speed data rates to achieve enhanced reliability, high capacity and high robustness in broadband wireless communications.

Furthermore, considering the combined massive MIMO-OFDM system, several researchers have focused on the channel estimation issue to better know the CIR before data transmission and then ensure a better signal reliability. Among the different contributions concerning channel estimation; Least Square (LS) [5] and minimum mean square error (MMSE) [18] have always been used to estimate the CSI but these conventional techniques can not be used in massive MIMO system because they suffer from huge complexity due to the inversion of very large channel estimation matrix. Because of that, many researchers have been attracted to use CS technique as a promising alternative technique for recovering CIR while assuming that the channel signal is sparse [19]–[23]. This field has motivated us previously to propose two channel estimation algorithms based on CS technique in particularly OMP, Adaptive OMP (AOMP) [24] and Block OMP (B-OMP) [25] which have been introduced for the uplink TDD massive MIMO system.

Meanwhile, to guarantee a better signal propagation with relatively good signal to noise ratio, HPA is needed as indispensable component to provide enough power for the signal transmission through the wireless channel. Unfortunately, these components degrade the performance of the masive

MIMO-OFDM system in terms of BER due to its nonlinear distortion when operating near to its saturation zone.

In this context, the theoretical analysis of nonlinear distortion effects in an OFDM signals has been done by Dardari *et al.* in [26], Conti *et al.* in [27], Gregorio *et al.* in [28], and Bohara and Ting in [29].

Considering this point, the issue of HPA nonlinearity has been studied not only in OFDM system, MIMO system but also lately in massive MIMO system. Obviously, the nonlinear issue becomes more complicated in massive MIMO system comparing to MIMO and Single Input Single Output (SISO) systems due to the high M-array modulation. Therefore, a big variety of research efforts have investigated the effect of the HPA nonlinear distortion in massive MU-MIMO downlink [30], [31]. Many other approaches have considered the nonlinear distortion issue in the parallel HPA units as a relatively simple additive noise model [32], [33] dissenting from the Bussgang theorem [34]. Some other researchers have focused on studying the impact of the nonlinear distortion of HPA on the energy-efficient design of massive MIMO system [35]. In [36], the spatial characteristic of the nonlinear distortion which radiates from antenna arrays has been demonstrated. Moreover, several studies have been focused on the effect of nonlinear distortion on BER and PAPR investigations of OFDM system [30], [37], [38]. However, OFDM system suffers from PAPR due to its high envelope fluctuations which causes signal distortion and consequently, leading to performance degradation [39].

Aiming the uncertainty of the signal quality in presence of HPA, linearity becomes a rigours requirement so that many effective mitigation schemes and compensation methods have been proposed. Among these methods, the decision-assisted recognition technique [40] which has been proposed to reduce the harmful effects of nonlinear distortion. Other traditional solutions including recording clipping data and sender coding [41], [42] have also been proposed to compensate the nonlinear distortion. However, all of these methods need supplementary data to be transferred which affect the system effectiveness. Thus, the choice of compensation technique is a challenging task for researchers.

Recently, NN has known a big attention and it has been proposed as a good tool for nonlinearity compensation in communication systems. For instance, in [43] an adaptive predistortion technique based on a feed-forward NN has been proposed as a compensation technique at the transmitter to linearize the transmitted signal from HPAs. This efficient technique has been extended in [44] to MIMO-OFDM system. In [45] a compensation technique at the receiver was proposed to compensate the joint effects of HPA's nonlinearity. The authors in [46] have extended NN to be applied also as a Beam-Oriented Digital Predistortion (BO-DPD) technique for HPAs in hybrid beamforming massive MIMO. In our case, we will focus on both the predistortion and the postdistortion structure in frequency domain.

On the other side, since the nonlinear distortion can be modeled as a sparse signal, CS technique is applied as a solution for recovering the linear signal at the receiver. For instance, the authors in [47] have used CS to reduce the PAPR of the optical OFDM signal. In [48], CS is applied to recover the original signal after the clipping issue by using $l_1$-norm optimization which has a high computational complexity. However, the OMP is often used as a CS algorithm to reconstruct the linear signal due to its simplicity and less complexity than Basis Pursuit (BP) algorithms [49]–[51].

## III. SYSTEM MODEL

We consider a massive MIMO-OFDM uplink system which consists of a Base Station (BS) with $N_t$ element antennas equipped with $N_t$ HPA serving $U$ ($U \leq N_t$) single antenna User Terminals (UT) as it is shown in Fig 1. As a training technique for the channel estimation, we have opted for the pilot sequence which is transmitted along with a block of transmit symbols.

### A. TRANSMITTER

#### 1) LINEAR MASSIVE MIMO-OFDM SYSTEM

At the transmitter, the OFDM modulation transmission technique is presented with $N_c$ subcarriers which employed to cope with multipath interference including $N_p$ pilot subcarriers which are uniformly allocated with the corresponding indices $p = [p_1, p_2, \cdots, p_{N_p}]$. So that the training sequence per user is denoted as $\mathbf{x} = [\mathbf{x}(p_1), \mathbf{x}(p_2), \cdots, \mathbf{x}(p_{N_p})]^T$. Passing through the fast inverse Fourier Transform (IDFT) module, the input signal is converted to the time domain $\mathbf{x}$ which is given as:

$$\mathbf{x(n)} = \frac{\mathbf{1}}{\mathbf{N_c}} \sum_{\mathbf{i=0}}^{\mathbf{N_c-1}} \mathbf{X(i)e^{j2\pi ni/N}}, n = 0, 1, \ldots, N_c - 1 \quad (1)$$

where $\mathbf{X}(i)$ is the complex symbol on the $i^{th}$ subcarrier.

This equation can be written also as:

$$\mathbf{x} = \mathbf{F^H X} \quad (2)$$

#### 2) NONLINEAR MASIVE MIMO-OFDM SYSTEM

After the OFDM modulator, a mandatory use of HPA is expected before transmitting the signal into the channel as shown in Fig.1. However, these HPAs generate nonlinearity effects. For nonlinear HPA, we consider a memoryless model, in particular Saleh's model. Generally, the HPA operates at a given Input Back-Off (IBO) which is defined as:

$$IBO = 10 \log_{10}(\frac{I_0^2}{P_0}) \quad (3)$$

where $I_0$ is the input power at the saturation point and $P_0$ is the average power of the input signal.

The complex envelope of the input signal of HPA per user at each branch can be presented as:

$$\mathbf{x_u} = \rho_\mathbf{u} \mathbf{e}^{\mathbf{j}\theta_\mathbf{u}} \quad (4)$$

where $\rho_u$ and $\theta_u$ denotes, respectively, the amplitude and the phase of $\mathbf{x}_u$. The general formulation of the complex envelope

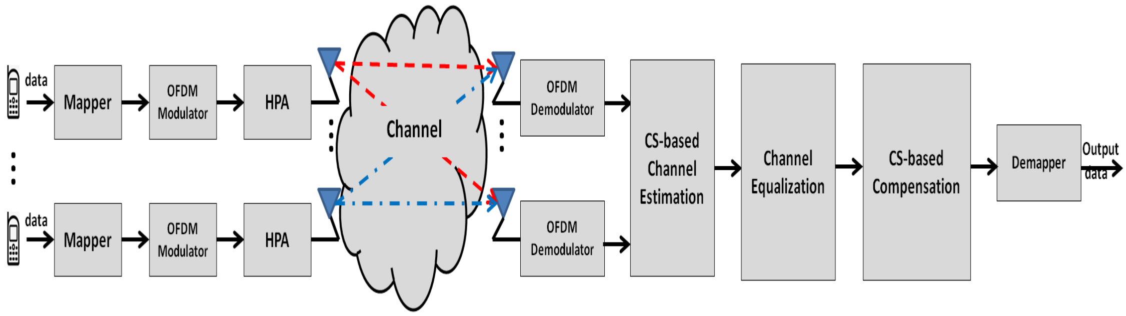


**FIGURE 1.** CS-based channel estimation and compensation model for massive MIMO-OFDM system.

of a memoryless HPA output $\mathbf{z}_u$ is given as follows:

$$\mathbf{z_u} = \mathbf{g(x_u)} = \mathbf{B}(\rho_\mathbf{u})\mathbf{e}^{(\mathbf{j}\theta_\mathbf{u}+\phi(\rho_\mathbf{u}))} = \mathbf{S}(\rho_\mathbf{u})\mathbf{e}^{\mathbf{j}\theta_\mathbf{u}} \tag{5}$$

where $g[.]$ is the HPA transfer function, $B(.)$ and $\phi(.)$ denotes the AM/AM and AM/PM characteristics of HPA, respectively.

For the Saleh's model, the AM/AM and AM/PM characteristics can be represented as follows:

$$\mathbf{B}(\rho_\mathbf{u}) = (\frac{\alpha_\mathbf{a}\rho_\mathbf{u}}{\mathbf{1}+\beta_\mathbf{a}\rho_\mathbf{u}^2})\ \phi(\rho_\mathbf{u}) = (\frac{\alpha_\mathbf{p}\rho_\mathbf{u}^2}{\mathbf{1}+\beta_\mathbf{p}\rho_\mathbf{u}^2}) \tag{6}$$

where $\alpha_a$ and $\beta_a$ are the parameters that decide the nonlinear level, and $\alpha_p$ and $\beta_p$ are phase displacements.

Therefore, the multi carrier signal after passing the nonlinear HPA is expressed as:

$$\mathbf{z_u(n)} = \mathbf{g(x_u(n))} = \mathbf{U_0}x_u(n) + c_u(n) \tag{7}$$

where $\mathbf{x_u(n)}$ is the input signal vector in time domain of Eq.1, $U_0$ is the gain of the linear part and $\mathbf{c_u(n)}$ is the nonlinear distortion term uncorrelated with the input signal.

This Eq.7 can be expressed in frequency domain as:

$$\mathbf{Z_u} = \mathbf{U_0}X_u + C_u \tag{8}$$

### 3) CHANNEL MODELING

The transmitted signal presented in the previous section is running over Rayleigh fading channel. In fact, in wireless communication, the transmitted signal is transferred to the receiver through multiple reflective paths and since that the number of scatters in propagation environment is insufficient, it has been proven that the massive MIMO CIRs are sparse so that the number of non-zero taps of the channel, denoted as $K$, is much smaller than the total number of CIR taps $L$ ($K \ll N_p \ll L$). Moreover, the non-zero elements locations in each vector on the measured channel matrix change slightly during an OFDM symbol. So, we assume that each channel $H^{nt}$ is independent from the other and each uplink CIR is assumed to have its unique support of non-zero elements positions as well as the measurement vectors which are considered independent.

## B. RECEIVER

### 1) LINEAR RECEIVED SIGNAL

The received signal $\mathbf{Y} \in \mathbb{C}^{N_p\times N_t}$ in subset $\mathbf{p}$ at all the receive antennas after cyclic prefix removal and DFT operation, can be expressed as

$$\mathbf{Y} = \sum_{u=1}^{U}\mathbf{X_u F_{Np,L} H_u} + \mathbf{W} \tag{9}$$

where $\mathbf{X_u} = diag(\mathbf{x_u})$ is a diagonal matrix with the entries of $x_u$ as diagonal elements, $\mathbf{F_{Np,L}}$ contains the $N_p$ rows according to $\mathbf{p}$ and the first $L$ columns of $\mathbf{F_{Nc}}$,

$\mathbf{H_u} = [\mathbf{h^1}_\mathbf{u}, \mathbf{h^2}_\mathbf{u}, \cdots, \mathbf{h^{Nt}}_\mathbf{u}] \in \mathbb{C}^{L\times N_t}$ represents the CIRs from the $u^{th}UT$ to the BS and $\mathbf{W}$ is the white Gaussian noise with zero mean and variance $\sigma^2$ $\mathbf{I}$.

### 2) NONLINEAR RECEIVED SIGNAL

According to Eq.7 the nonlinear transmitted signal is composed from two terms the input signal $\mathbf{x_u}$ and the nonlinear distortion $\mathbf{c_u}$. Therefore, to express the nonlinear received signal, we have just to replace Eq.7 in Eq.9 as follows:

$$\mathbf{Y} = \sum_{u=1}^{U}\mathbf{Z_u F_{Np,L} H_u} + \mathbf{W} \tag{10}$$

where $\mathbf{Z_u} = diag(\mathbf{z_u})$ is a diagonal matrix with the entries of $\mathbf{z_u}$ as diagonal elements. We define the measurement matrix $\mathbf{A} \triangleq [\mathbf{Z_1F_{Np,L}}, \mathbf{Z_2F_{Np,L}}, \cdots, \mathbf{Z_UF_{Np,L}}] \in \mathbb{C}^{N_p\times UL}$ and $\mathbf{H} = [\mathbf{H}_1^T, \mathbf{H}_2^T, \cdots, \mathbf{H}_u^T]^T \in \mathbb{C}^{UL\times N_t}$ then Eq.10 is rewritten as:

$$\mathbf{Y} = \mathbf{AH} + \mathbf{W} \tag{11}$$

In CS concept, the number of rows $Np$ of the measurement matrix $\mathbf{A}$ must be very small comparing to the number of its columns $UL$ so we have $Np \ll UL$.

### 3) CS CHANNEL ESTIMATION

Since the CIRs in massive MIMO system are sparse, we have proposed in our previous work, two CS channel estimation algorithms based on OMP which are AOMP and B-OMP. We proved in our latest work [52] that B-OMP has shown more resistance to the nonlinear distortion of memoryless HPA including Saleh model comparing to AOMP. Therefore, in this paper, we will focus on using B-OMP as channel estimation algorithm. Following, a briefing presentation for B-OMP algorithm:

It is a novel high dimensional sparse signal recovery algorithm based on CS technique which aims to reduce the total number of needed iteration for the matrix recovery, the MMV model presented in Eq.11 is transformed to a block SMV model as follows:

$$\mathbf{y} = \mathbf{Dh} + \mathbf{w} \tag{12}$$

where $\mathbf{y} = vect(\mathbf{Y^T}) \in \mathbb{C}^{N_pN_t \times 1}$ is the vectorization of the matrix $\mathbf{Y}$ formed by stacking its columns into a single column vector and it represents the observation signal in the proposed block SMV model, $\mathbf{D} = A \bigotimes \mathbf{I_{Nt}} \in \mathbb{C}^{N_pN_t \times LN_t}$ represents the new measurement matrix for the proposed block SMV model and it is the result of the Kronecker product of the two matrices $\mathbf{A} \in \mathbb{C}^{N_p \times L}$ which represents the measurement matrix in MMV model presented in equation (2) and the identity matrix $\mathbf{I} \in \mathbb{C}^{N_t \times N_t}$, $\mathbf{h} = vect(\mathbf{H^T}) \in \mathbb{C}^{LN_t \times 1}$ represents the new channel vector and it is the vectorization of the channel matrix $\mathbf{H}$ and finally $\mathbf{w} = vect(\mathbf{W^T}) \in \mathbb{C}^{N_pN_t \times 1}$ is the vectorization of the noise matrix $\mathbf{W}$.

Each iteration of the B-OMP algorithm consists of the following stages:

1. **Identification:** we identify $N_t$ atoms from the measurement matrix $\mathbf{D}$ with largest inner product and store its indexes in the set $\mathbf{T}_j$.

2.**Update support set:** we add the $\mathbf{T}_j$ to the support set $\Omega_j$.

3.**Signal estimation by least square:** The solution to this minimization problem is: $\mathbf{h}_{\Omega j} = (\mathbf{D}^{\mathbf{H}}_{\Omega j}\mathbf{D}_{\Omega j})^{-1}\mathbf{D}^{\mathbf{H}}_{\Omega j}y$.

4.**Update residual:** we update the residual using the new solution of vector estimation.

After determination of the channel estimation vector $\tilde{\mathbf{h}}$, we come back to the expression of Eq.11 and we have $\tilde{\mathbf{H}} \in \mathbb{C}^{L \times N_t}$. matrix form by using reshape command so we obtain an estimated channel matrix $\tilde{\mathbf{H}} \in \mathbb{C}^{L \times N_t}$.

#### 4) CHANNEL EQUALIZATION

Once the channel matrix has been estimated $\tilde{\mathbf{H}}$, then the next step is to determine the equalized signal.

Referring to Eq.11 and replacing the matrix $\mathbf{A}$ with its expression, we obtain:

$$\mathbf{Y} = \mathbf{ZFH} + \mathbf{W} \tag{13}$$

Let denote $\mathbf{F}\tilde{\mathbf{H}} = \tilde{\mathbf{H}}_{\mathbf{freq}}$ then the equalized signal can be written as:

$$\mathbf{Y}\tilde{\mathbf{H}}^{-1}_{\mathbf{freq}} = \mathbf{ZI} + \mathbf{W}\tilde{\mathbf{H}}_{\mathbf{freq}} \tag{14}$$

where $\mathbf{Z}$ is multiplied by the identity matrix $\mathbf{I_{N_pN_t}}$, then $\mathbf{Z} \in \mathbb{C}^{N_p \times N_t}$

Combining Eq.8 and Eq.14 give the following equation:

$$\mathbf{Y}\tilde{\mathbf{H}}^{-1}_{\mathbf{freq}} = (\mathbf{U}_0\mathbf{X} + \mathbf{C}) + \mathbf{W}\tilde{\mathbf{H}}^{-1}_{\mathbf{freq}} \tag{15}$$

## IV. BIT ERROR RATE EXPRESSION

In this section, a mathematical approach is presented to evaluated the impact of HPA's nonlinear distortion on achievable uplink approximated BER for massive MIMO-OFDM system. The proposed approach is applicable for any arbitrary $U$ antenna users number and $N_t$ antenna numbers. Therefore, this section will be divided into two subsections linear and nonlinear BER. Based on the analytical expression of the obtained BER results in linear form, we will discuss the impact of the nonlinear distortion and determine its BER expression.

### A. LINEAR BER

We begin with the linear massive MIMO-OFDM system. In general, the overall narrowband fading channel per user is represented by:

$$\mathbf{h(t)} = \alpha\mathbf{(t)}\mathbf{e}^{\mathbf{j}\phi} \tag{16}$$

where $\alpha$ is the Rayleigh fading envelope with a Probability Density Function (PDF):

$$f_\alpha(\alpha) = \frac{\alpha}{\alpha_0^2}e^{-\frac{\alpha^2}{2\alpha_0^2}}, \quad \alpha \geq 0 \tag{17}$$

Since that Re[h] and Im[h] are Independent and Identically Distributed (i.i.d) Gaussian with variance $\alpha_0^2$, $E[\alpha] = \sqrt{\frac{\pi}{2}}\alpha_0$ and $E[\alpha^2] = 2\alpha_0^2$.

and $\phi$ is the channel phase uniformly distributed in $[-\pi, \pi[$ with PDF

$$f_\phi(\phi) = \begin{cases} \frac{1}{2\pi}, & -\pi \leq \phi \leq \pi \\ 0, & \text{otherwise.} \end{cases} \tag{18}$$

For the SISO case, the PDF of the instantaneous SNR per bit can be obtained from Eq.17 by simple changing from $\alpha$ to $\gamma$:

$$f_\gamma(\gamma) = \frac{1}{\overline{\gamma}}exp(-\frac{\gamma}{\overline{\gamma}}), E[\gamma] = \overline{\gamma}, \quad \gamma \geq 0 \tag{19}$$

where $\gamma = \alpha^2(E_b/N_0)$ with an average value equals to $\overline{\gamma} = E[\alpha^2](E_b/N_0)$.

By analogy to Eq.19, the PDF of SNR for the massive MIMO system can be given as [53]:

$$f_\gamma(\gamma) = \frac{1}{(N_t-1)!}\frac{\gamma^{N_t-1}}{\overline{\gamma}^{N_t}}exp(-\frac{\gamma}{\overline{\gamma}}) \tag{20}$$

assuming that the SNR of each user is following the same PDF such as $\overline{\gamma} = \overline{\gamma}_1, = \ldots = \overline{\gamma}_U$.

Therefore, the average BER for the linear massive MIMO system under i.i.d Rayleigh fading channel is expressed as follows:

$$\overline{P_b}(\overline{\gamma}) = \int_0^\infty f_\gamma(\gamma)P_e(\gamma)d\gamma \tag{21}$$

After substitution of Eq.20 in Eq.21 we obtain:

$$\overline{P_b}(\overline{\gamma}) = \frac{1}{(N_t-1)!\overline{\gamma}^{N_t}} \int_0^\infty \gamma^{N_t-1} exp(-\frac{\gamma}{\overline{\gamma}}) P_e(\gamma) d\gamma \quad (22)$$

On the other hand, considering the Eq.9 of the linear received signal, we have already mentioned that $\mathbf{W}$ is white Gaussian noise with zero mean and variance $\sigma^2$ $\mathbf{I}$. then:

$$P_e(\gamma) = \int_0^\infty \frac{1}{\sqrt{2\pi\sigma^2}} exp(-\frac{\gamma^2}{2\sigma^2}) d\gamma \quad (23)$$

### B. NONLINEAR BER

Referring to the Eq.10 of the received signal with HPA, the received signal for the $U^{th}$ user can be expressed as:

$$\mathbf{Y}_u = \underbrace{U_0 X_u F_{Np,L} H_u}_{useful\ signal} + \underbrace{C_u F_{Np,L} H_u}_{nonlinear\ distortion} + \underbrace{\mathbf{W}_u}_{noise} \quad (24)$$

To provide the theoretical expression of BER in nonlinear massive MIMO system, the nonlinear distortion term is needed to be approximate as an independent Gaussian random variable $\mathbf{G}$ with average $\mu_G$ and variance $\sigma_G$.

Thus, the Eq.24 becomes:

$$\mathbf{Y}_u = \underbrace{U_0 X_u F_{Np,L} H_u}_{useful\ signal} + \underbrace{G_u}_{nonlinear\ distortion} + \underbrace{\mathbf{W}_u}_{noise} \quad (25)$$

The PDF of random variable $\mathbf{G_u}$ can be expressed as:

$$P(\mathbf{G_u}) = \frac{1}{\sqrt{2\pi\sigma_G^2}} exp(-\frac{(\mathbf{G}-\mu_G)^2}{2\sigma_G^2}) \quad (26)$$

Similarly to the Eq.22, the average BER for the nonlinear massive MIMO system under i.i.d Rayleigh fading channel can be given as:

$$\overline{P_b}(\overline{\gamma}) = \frac{1}{(N_t-1)!\overline{\gamma}^{N_t}} \int_0^\infty \gamma^{N_t-1} exp(-\frac{\gamma}{\overline{\gamma}}) P_e(\gamma, \mu_G, \sigma_G) d\gamma \quad (27)$$

With:

$$P_e(\gamma, \mu_G, \sigma_G) = \int_0^\infty \frac{1}{\sqrt{2\pi(\sigma^2+\sigma_G^2)}} exp(-\frac{(\gamma-\mu_G)^2}{2(\sigma^2+\sigma_G^2)}) d\gamma \quad (28)$$

## V. OUTAGE CAPACITY

Foschini and Gans in [54], proved that in order to achieve a large capacity, the deployment of multiple antennas at both transmitter and receiver is required. In [55] and [56], they have considered that the channel propagation parameters have an effect on the capacity of the studied system. In [57], the authors have studied the outage capacity of space diversity systems in presence of a discrete multipath fading channel. In consequence, they focused on the performance of the CSI feedback respect to the Rayleigh model in presence of MIMO system and they found that the diversity gain is affected by the number of multipath component $L$ rather than the size of the array system $Nt$. They proved that the capacity of MIMO system approach to Rayleigh channel performance only when $L$ is twice equal to the number of transmitter and receiver antennas. It is theoretically known that the massive MIMO system offers a greater data rate than a conventional MIMO system. Therefore, we will present here the expression of the capacity of massive MIMO system and then in the simulation part, we will show the effect of the multipath component on the capacity performance.

$$C = log_2[1+\gamma] \quad (29)$$

## VI. NONLINEARITIES COMPENSATION

In this section, we present first of all the NN compensator and then we will present our proposed CS compensation technique.

### A. NN COMPENSATOR

The NN compensator can be implemented at the transmitter as well as at the receiver and in this paper, we will study its performance at both the transmitter and the receiver.

#### 1) ARCHITECTURE OF THE APPLIED NN

In communication networks, the most popular NN's architecture used is the Multi Layer Perceptron (MLP) [58] which consists of many neurons connecting to each other from the input layer passing through the hidden layers to reach finally the output layer as it is shown in Fig.2. Thanks to its simple network structure and fast training process, only a fewer hidden layers are needed to formulate the output of HPA. For instance, in Fig.2 the network has only 2 hidden layers with 4 neurons in the first layer and 3 neurons in the second layer, it has also 1 input layer and 2 neurons in the output layer. The input layer is connected to all neurons of the hidden layers which are also connected to the output layer. Each neuron is characterized by a linear combiner and an activation function giving the output neuron as:

$$\hat{\mathbf{X}}_{\mathbf{ij,n_t}} = \mathbf{f}(\sum_{\mathbf{n_l}=0}^{\mathbf{N_l}-1} \mathbf{W}_{\mathbf{n_l,m}} \tilde{\mathbf{X}}_{\mathbf{ij,n_t}} + \mathbf{B}_{\mathbf{n_l,m}}) \quad (30)$$

with $\tilde{\mathbb{X}}_{ij,n_t}$ is the input signal into the neuron from the $j^{th}$ component of the $i^{th}$ vector of the $n_t$ receive antenna, $\mathbb{W}_{n_l,m}$ is the weight matrix connecting $m$ neurons in layer $n_l$ and $\mathbb{B}_{n_l,m}$ is the biais term.

#### 2) TRAINING AND GENERALIZATION

We aim to identify the inverse transfer function of TWT with a feed-forward neural network by obtaining a direct estimation of the amplitude and phase nonlinearities.

##### a: TRAINING

As it is shown in Fig.3, NN1 aims to identify the HPA's inverse transfer function, the complex envelope signals are differentiated and the error sent to the learning algorithm bloc that reacts on coefficients of NN1.

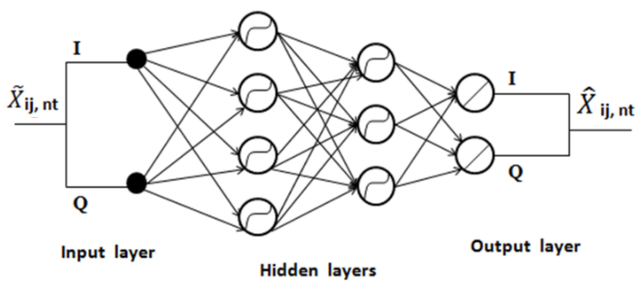


**FIGURE 2.** Multilayer NN architecture.

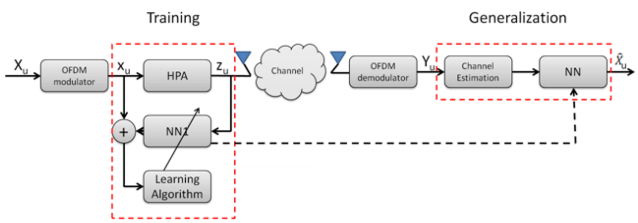


**FIGURE 3.** Training and generalization block diagram of the NN compensation in frequency domain.

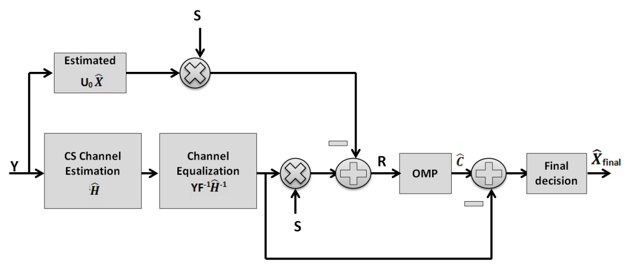


**FIGURE 4.** CS-based compensation scheme for massive MIMO-OFDM system.

### b: GENERALIZATION

The NN1's coefficients are recopied on NN that achieves the equalization.

## B. PROPOSED CS COMPENSATION TECHNIQUE

In this section, we will present our proposed CS compensation technique therefore we will describe the CS compensation scheme which is shown in Fig.4 then we will present the proposed iterative CS compensation algorithm relative to the proposed scheme.

### 1) PROPOSED ITERATIVE CS COMPENSATION SCHEME

As the channel matrix $\tilde{\mathbf{H}}$ is now accurate, the Eq.15 is needed to be multiplied by a selection matrix $\mathbf{S}$ which is generated by selecting the $N_p$ columns of the identity matrix $\mathbf{I}_{N_cN_p}$ to apply the CS algorithm and determine the nonlinear distortion $\mathbf{C}$ so $\mathbf{S} \in \mathbb{C}^{N_c \times N_p}$.

$$\mathbf{SY\tilde{H}_{freq}^{-1}} = \mathbf{S(U_0X + C) + SW\tilde{H}_{freq}^{-1}} \quad (31)$$

Let denote $\mathbf{Q} = \mathbf{Y\tilde{H}_{freq}^{-1}}$ then:

$$\mathbf{SQ = SC + U_0SX + SWH}_{freq}^{\tilde{-1}} \quad (32)$$

Next, we subtract the estimated value $\mathbf{U_0S\tilde{X}}$ from the above equation and we get:

$$\mathbf{SQ - U_0S\tilde{X}} = SFC + \underbrace{U_0S(X - \tilde{X}) + SW\tilde{H}_{freq}^{-1}}_{noise} \quad (33)$$

with $\mathbf{C} = \mathbf{diag(c)}$ is the time domain matrix of nonlinear distortion. Let denote $\phi = \mathbf{SF} \in \mathbb{C}^{N_c \times N_p}$ is the measurement matrix,

$\eta = \mathbf{U_0S(X - \tilde{X}) + SWF^{-1}\tilde{H}}^{-1}$ is the noise matrix and $\mathbf{R} = \mathbf{SQ - U_0S\tilde{X}}$

$$\mathbf{R} = \phi\mathbf{C} + \eta \quad (34)$$

From the above equation, the CS algorithm can be applied to reconstruct the nonlinear distortion $\tilde{\mathbf{C}}$. Finally, the linear signal can be determined as follows:

$$\mathbf{X}_{final}\hat{} = Q - \tilde{\mathbf{C}} \quad (35)$$

### 2) PROPOSED ITERATIVE CS COMPENSATION ALGORITHM

According to the iterative compensation scheme presented in Fig.4, after obtaining the estimated value of the distortion $\tilde{\mathbf{C}}$, it is subtracted from the equalized signal and then a second decision is required to get a more accurate value $\mathbf{X}_{n+1}^{\tilde{}}$ of $\mathbf{X}$ by using the maximum likelihood estimator.

$$\mathbf{X}_{n+1}^{\hat{}} = \mathbf{argmin}\left|\mathbf{Q} - \tilde{\mathbf{C}}_\mathbf{n} - \mathbf{P_r}\right| \quad (36)$$

where $\mathbf{P_r} \in \chi$ is the preset constellation points set.

The first decision value can be determined when $\tilde{\mathbf{C}}_0$ is a zero matrix as follows:

$$\hat{\mathbf{X}}_0 = \mathbf{argmin}\,|\mathbf{Q} - \mathbf{P_r}| \quad (37)$$

From the above equations Eq.36 and Eq.37 and including the iterative CS compensation scheme presented in Fig.4, The proposed approach is more detailed in algorithm 1.

By mixing the CS-based compensation scheme and the proposed iterative CS compensation algorithm, we obtain a summary of our proposed compensation method as follows:

1. Get the initial estimation of $\mathbf{U_0\tilde{X}}$ from equalized signal $\mathbf{Q}$;
2. Define the selection matrix $\mathbf{S}$;
3. Determine the observation matrix $\mathbf{R}$ according to Eq.34;
4. Reconstruct the nonlinear distortion $\tilde{\mathbf{C}}_{\mathbf{n+1}}$ using the first iteration of algorithm 1;
5. Update the decision value $\hat{\mathbf{X}}_{\mathbf{n+1}}$ according to Eq.36;
6. Update the residual using the new solution of estimated nonlinear distortion matrix $\tilde{\mathbf{C}}_{\mathbf{n+1}}$;
7. Return to step 4 until the iteration terminates and calculate the final decision $\hat{\mathbf{X}}_{\mathbf{final}}$.

**Algorithm 1:** Iterative Recovery of Nonlinear Distortion Based on OMP

**Input:**

A $N_c \times N_p$ measurement matrix $\phi$

A $N_c \times N_t$ matrix $\mathbf{R}$

The sparsity level $K$

**Output:**

An $N_p \times N_t$ estimated matrix $\hat{\mathbf{X}}_{\mathbf{final}}$

**Initialization:**

$\phi_{\mathbf{0}}$ is an empty matrix

$\tilde{\mathbf{C}}_0$ is a zero matrix

$\mathbf{Res} = \mathbf{R}$ the residual

$\Omega = \theta$ the index set

and $j = 1$ the iteration counter.

**Procedure :**

1) Calculate $(\mathbf{Q} - \mathbf{C_0})$ to get estimated $U_0\ \tilde{\mathbf{X}}_0$

**while** $j < K$ **do**

a) Find a column of matrix $\phi$ the most correlated with a the current residual

$$\lambda_j = argmax_{n=1,2,\ldots,N_p} |\mathbf{Res_{j-1}}, \phi_{\mathbf{n}}|$$

b) Add the most correlated column into the set of selected columns

$$\Omega_j = \Omega_{j-1} \cup \{\lambda_j\}$$

and the matrix of the chosen atoms

$$\phi_{\mathbf{0}j} = \phi_{\Omega_j}$$

c) Solve the least-squares problem to obtain a new signal estimate.

$$C_j = argmin_C ||\phi_{\mathbf{0}j}\mathbf{C} - \mathbf{R}||_2$$

d) Update residual

$$\mathbf{Res} = \mathbf{R} - \phi_{\mathbf{0}j}\mathbf{C}_j$$

e) Increment $j$ $j = j + 1$

**end**

2) Get the final accurate value of $(\mathbf{Q} - \mathbf{C_0})$ using the maximum likelihood estimator.

$$\hat{\mathbf{X}}_{\mathbf{final}} = \mathbf{argmin} \left| \mathbf{Q} - \tilde{\mathbf{C}} \right|$$

### C. COMPLEXITY ANALYSIS

It has been shown in [59] that the computational complexity of OMP algorithm is equal to $O(KN_cN_p)$ including the inner product operation and the least square operation whereas the computational complexity of our proposed CS-based compensation scheme equals to $O(KN_cN_pN_t)$. Considering that $K$ is too negligible comparing to $N_c$, $N_p$, $N_t$ and assuming that $N_c = N_p = N_t = n$ then the overall complexity is equal to $O(n^3)$.

**TABLE 1. Complexity values.**

| OMP compensator | NN compensator |
|---|---|
| $O(KN_cN_pN_t) \approx O(n^3)$ | $O(n_t(n^3)) \approx O(n^4)$ |

For the feedforward NN, the computational complexity depends on the number of inputs $n$, the total number of layers $N_l$ and the number of neurons $m_{n_l}$ in each layer.

On the other side, the overall computational complexity depends on the complexity of the activation function and the $n_t$ training examples.

Each neuron is characterized by an activation function which will be applied $N_l - 1$ times. The activation function as it is presented in Eq.30 includes a multiplication of two matrix $\mathbf{W_{n_l,m}}\tilde{\mathbf{X}}_{\mathbf{ij,n_t}}$. Generally, it has been proven that the complexity of multiplication of two matrix is around of $O(n^3)$. Considering the $n_t$ training examples then the total complexity is equal to $O(n_t(n^3))$. Assuming that $n_t = n$ then the total complexity becomes $O(n^4)$.

In terms of complexity, it has been demonstrated above that the proposed CS-based compensation gives a reduced complexity comparing to NN.

## VII. SIMULATION AND RESULTS

For the simulation, we have opt for the 3GPP channel model which is characterized by $k = 6$ significant multipath taps and the maximum delay spread is set to be $L = 60$. The proposed massive MIMO system with $N_t = 100$ BS antennas serving $U = 10$ UT. The total OFDM subcarriers $N_c = 1024$ and the pilot subcarriers $N_p = 128$. As a performance metric, we will based on BER to analyze simulation results.

First, we consider a comparison of the spectral behaviour of transmitted OFDM signal in massive MIMO system in presence of Saleh's HPA model with the linear signal. In fact, Fig.5 shows the HPA's nonlinearities effect on the spectrum of OFDM signal. It can be observed that there is a regrowth in the amplitude of the nonlinear OFDM signal comparing to the linear signal. When the IBO value increases, the amplitude of the nonlinear OFDM signal increases accordingly. On the other hand, it can be seen also that the nonlinear OFDM signal presents a large lobes comparing to the linear signal.

In Fig.6, the impact of the propagation parameters especially the multipath taps on the performance of the capacity of the massive system according to the Rayleigh model is presented. From this Fig, it can be seen that more the environment is rich in the number of scatters (which is known as the multipath taps or also the sparsity level ), more the capacity is enhanced. Therefore, the capacity depends on the number of the multipath component.

Then, to highlight the impact of the Saleh's HPA nonlinearities on the B-OMP performance, a comparison in terms of

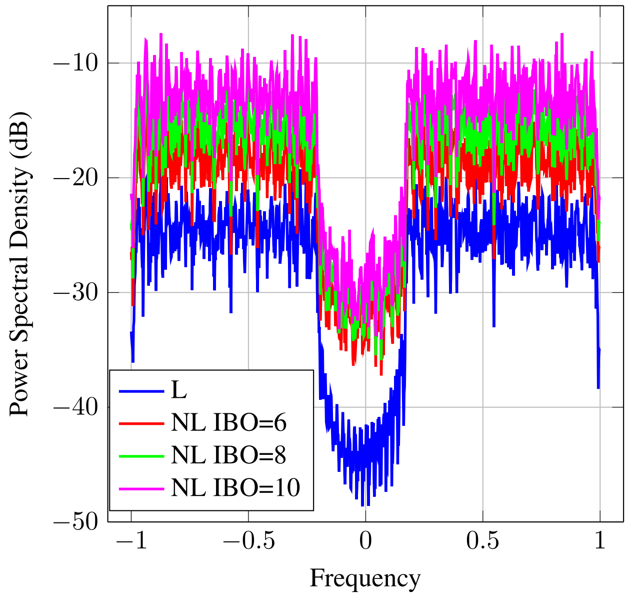


**FIGURE 5.** Power density spectral for OFDM with and without the effect of HPA for different IBO values.

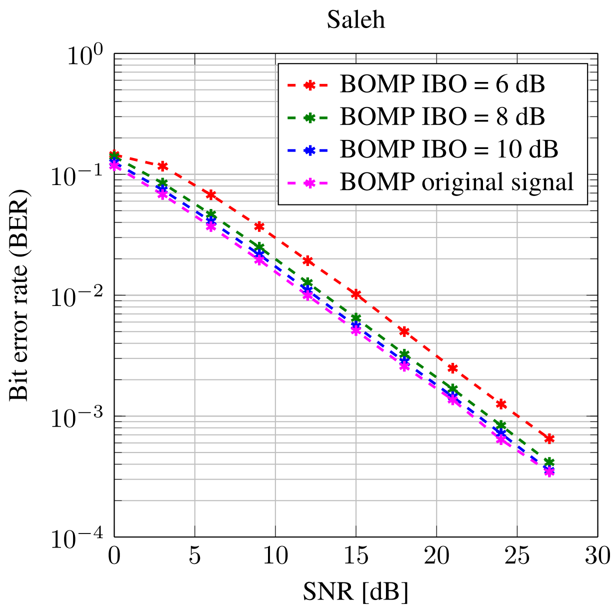


**FIGURE 7.** Impact of Saleh model on B-OMP algorithms with different values of IBO.

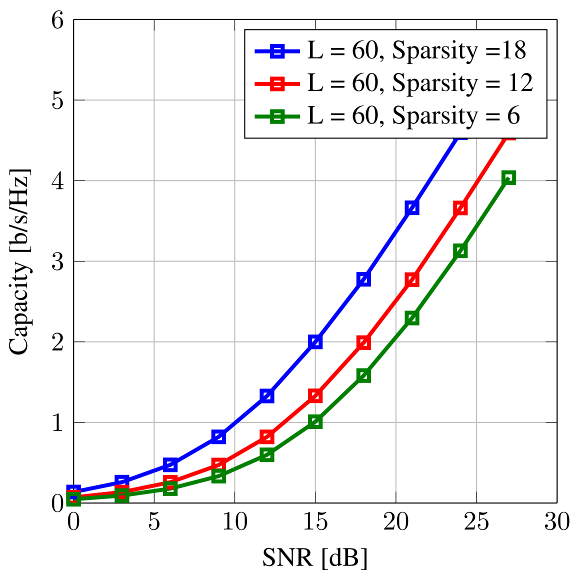


**FIGURE 6.** Capacity evaluation in massive MIMO system in rich multipath environment.

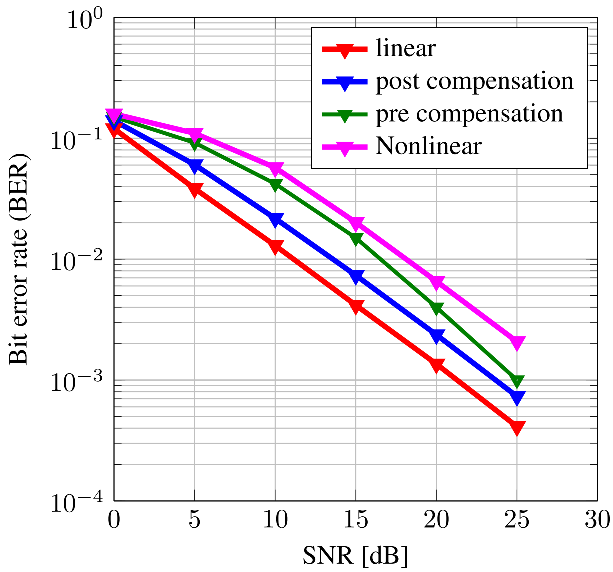


**FIGURE 8.** Impact of NN pre and post compensation on massive MIMO system.

BER with different IBO values is shown in Fig.7. It is obvious that more IBO value increases, the less BER result we get.

For example, for IBO = 6 **dB** and with SNR equals to **15dB**, B-OMP presents a BER of $\mathbf{1 \times 10^{-2}}$ while with IBO = 8 **dB**, B-OMP presents a BER equals to $\mathbf{6.2 \times 10^{-3}}$ Finally, with IBO = **10 dB**, and always with SNR equals to **15dB**, a BER of $\mathbf{6 \times 10^{-3}}$ is realised by B-OMP.

To evaluate the performance of the proposed CS-based compensation technique, we will compare it to the NN pre and post compensation technique.

Fig.8 shows the effects of NN pre-compensation and NN post-compensation on massive MIMO system. These compensation techniques are compared to the original linear signal before adding any HPA and the nonlinear signal after adding saleh model. In this figure, it is clear that the NN post-compensation outperforms the NN pre-compensation technique where it makes a gain of about **2dB**. For instance, with SNR equals to **10dB**, the post-compensation represents a BER of $\mathbf{2 \times 10^{-2}}$ while the pre-compensation represents a BER of $\mathbf{4 \times 10^{-2}}$.

On the other side, the NN pre-compensation technique presents a gain equals to **1dB** over the nonlinear signal. For example, comparing with the same SNR of **10dB**, the NN pre-compensation technique offers a BER equals to

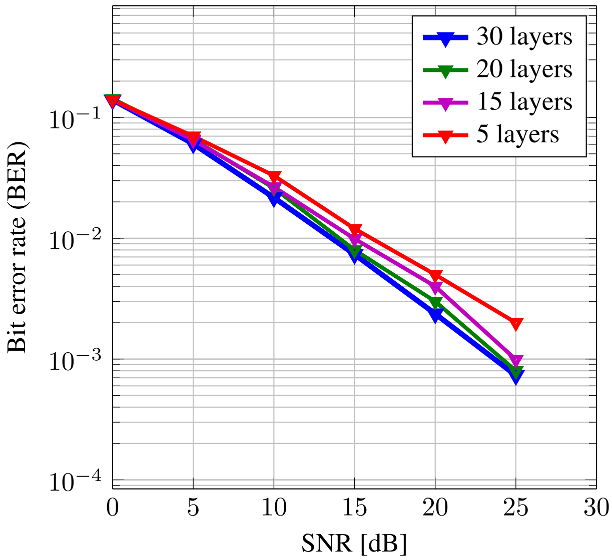


**FIGURE 9.** Variation in number of layers for the NN post-compensation technique.

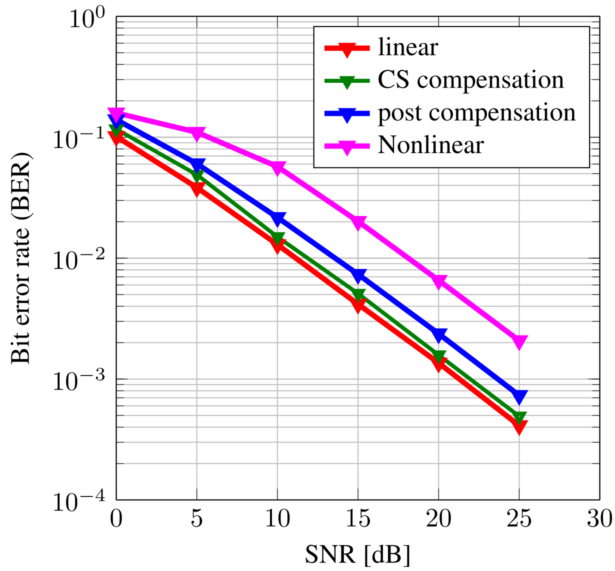


**FIGURE 10.** CS-based compensation technique Vs NN post-compensation technique.

$\mathbf{4 \times 10^{-2}}$ whereas the nonlinear signal presents a BER equals to $\mathbf{5 \times 10^{-2}}$.

From these two comparison, it can be concluded that the NN post-compensation technique presents a reduction in a BER of about **3dB** over the nonlinear signal.

Despite of this achieved gain **3dB** over the nonlinear signal, the NN post-compensation technique succeed only to approach to the original linear signal by **1dB**. Considering always the same value of SNR **10dB**, as it has been mentioned above the NN post-compensation technique presents a BER of $\mathbf{2 \times 10^{-2}}$ whereas the original linear signal presents a BER of $\mathbf{1 \times 10^{-2}}$. Therefore, for the next simulations, and as a comparison to our proposed CS based compensation technique, we will use only the NN post-compensation technique.

Fig.9 shows the effects of increasing the number of layers of the NN post-compensation technique. It is obvious from this figure that when the number of layers increases, the BER decreases and the NN post-compensation technique gives a better performance. For instance, for an SNR equals to **10dB**, the NN post-compensation technique with **30** layers offers a BER of $\mathbf{2 \times 10^{-2}}$ whereas the curve with only **5** layers presents a BER of $\mathbf{3 \times 10^{-2}}$. The gain between these two curves is about **1dB**. It should be mentioned that even with a high number of layers like **30**, the compensation has been ameliorated slightly. Nevertheless, increasing the number of layers generates a high computational complexity.

In Fig.10, a comparison between the proposed CS-based compensation technique and the NN post-compensation technique has been presented which are compared both to the original linear signal and the nonlinear signal that must to be compensated. From this figure, it can be seen that the CS-based compensation curve outperforms not only the NN post-compensation technique but also it succeed to be too close to the original linear signal. For instance, with SNR equals to **10dB**, a BER of $\mathbf{2 \times 10^{-2}}$, $\mathbf{1.5 \times 10^{-2}}$ and $\mathbf{1.3 \times 10^{-2}}$ are represented by the NN post-compensation curve, the CS-based compensation curve and the original linear signal curve, respectively. It can be noticed also that more the SNR increases, closer the curve of the CS-based compensation is to the original linear curve which means that the proposed CS-based compensation technique can give a better performance even with high values of SNR. For example, with SNR equals to **25dB**, the CS-based compensation technique offers a BER of $\mathbf{4.5 \times 10^{-4}}$ which is slightly worse than the original linear with a BER of $\mathbf{4 \times 10^{-4}}$ while the NN post-compensation technique provides a BER of $\mathbf{7 \times 10^{-4}}$. As it has been mentioned previously, the nonlinear curve presents a BER of $\mathbf{5 \times 10^{-2}}$ for an SNR equals to **10dB** so the proposed CS-based compensation technique presents a BER reduction about a **4dB**.

After showing the efficiency of the proposed CS-based compensation technique over the NN pre and post-compensation technique, the Fig.11 shows the effect of varying the sparsity level on the performance of CS-based compensation technique. From this figure, it is clear that increasing the sparsity level generates an amelioration in the performance of the CS-based compensation technique. It means that when the sparsity increases the BER reduces as well. For example, with an SNR equals to **15dB**, a BER of $\mathbf{3 \times 10^{-2}}$ and $\mathbf{5 \times 10^{-3}}$ are achieved by the CS-based compensation technique with the sparsity level of **6** and **30**, respectively.

However, we should highlight that the sparsity level has to be a small number to confirm that the signal is well sparsed and we can apply the CS technique.

The Fig.12 represents different CS algorithms which have been used in our previous work to determine the channel estimation, are now implemented as CS-based compensation

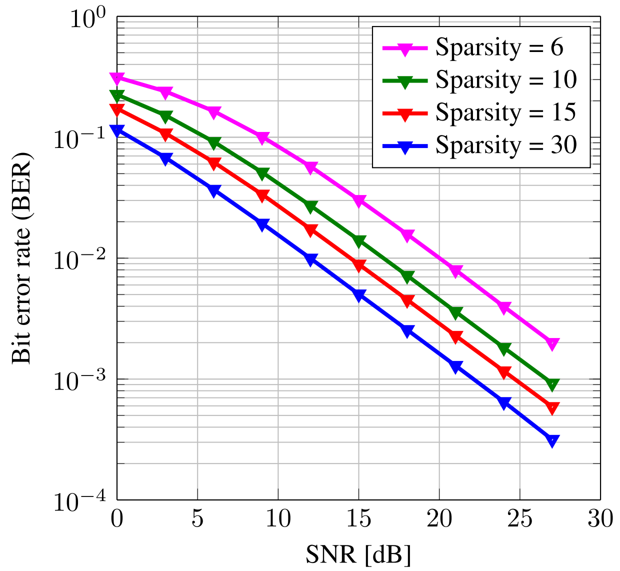


**FIGURE 11. The impact of the variation of the sparsity level on the CS-based compensation algorithm.**

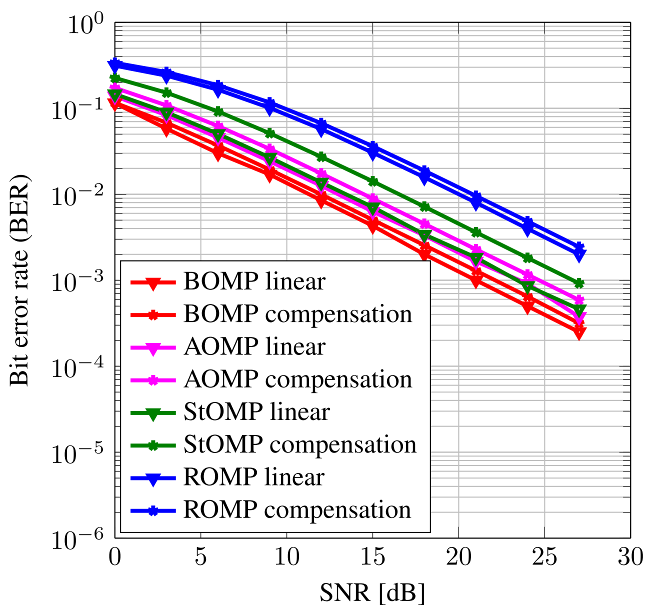


**FIGURE 12. Comparison between compensation algorithms based on OMP.**

algorithms in order to compare them and decide which algorithm gives the best performance for channel estimation as well as HPA nonlinearities compensation.

It is shown in this figure, for the linear curves as well as compensation curves, the B-OMP algorithm outperforms Regularized Orthogonal Matching Pursuit (ROMP), Stagewise Orthogonal Matching Pursuit (StOMP) and AOMP algorithms. Let's concentrate on linear curves, as it has been shown in our previous work, the best performance for channel estimation is given by B-OMP while AOMP and StOMP give a very close results and ROMP represents the worst performance. For example, with SNR equals to **15dB**, a BER of $\mathbf{4} \times \mathbf{10^{-3}}$ is achieved with B-OMP algorithm while a BER of $\mathbf{7} \times \mathbf{10^{-3}}$ is achieved by both StOMP and AOMP and a BER of $\mathbf{3} \times \mathbf{10^{-2}}$ is represented by ROMP algorithm. However, when they are implemented as CS-based compensation algorithms, it can be seen that the same performance is realised for the B-OMP and ROMP but AOMP represents a remarkable amelioration over StOMP. For instance, taking always the same SNR, a BER of $\mathbf{6} \times \mathbf{10^{-3}}$ and $\mathbf{3.6} \times \mathbf{10^{-2}}$ are achieved by B-OMP and ROMP respectively, whereas, a BER of $\mathbf{8.9} \times \mathbf{10^{-3}}$ and $\mathbf{1.4} \times \mathbf{10^{-2}}$ are achieved by AOMP and StOMP respectively. It is clear from the numerical results represented above that B-OMP has succeeded to give a compensation result that is so close to the linear mode.

## VIII. CONCLUSION AND FUTURE DIRECTIONS

This paper dealt mainly with two axes; the first axe is studying the impact of the passive elements such as the HPA nonlinearities on the performance of channel estimation of Uplink TDD massive MIMO-OFDM system. The second axe is how to compensate these nonlinear effects to get a better performance for the channel estimation. To achieve the first axe, we have started by introducing the different HPA models then presenting an analytical expression of BER in presence of HPA nonlinearities and finally showing the behaviour of our CS-based channel estimation algorithm B-OMP in presence of Saleh model with different IBO values. To tackle the second axe, we have presented first of all the feedforward NN which has known a huge success as a compensation technique for HPA nonlinearities. This NN has been used as pre and post-compensation technique to compare our proposed scheme and algorithm which is based also on CS technique. The results have proven that the proposed CS algorithm outperformed the NN technique not only in terms of BER but also in terms of complexity. To more emphasize the performance of our proposed compensation algorithm, it was compared to other CS algorithms such as AOMP,StOMP and ROMP and it has always given best results in terms of BER. Besides, a comparison between linear and nonlinear curves have been dressed for the NN compensation technique as well as the proposed CS-based compensation technique and it has shown that our proposed CS-based scheme and algorithm succeed to get close to the linear mode. In our future work, we will implement the coding and decoding blocks and see how they can enhance the performance of massive MIMO system.

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