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A Strategy of Signal Detection for Performance Improvement in Clipping Based OFDM System

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Abstract: In this paper, the supervised Deep Neural Network (DNN) based signal detection is analyzed for combating with nonlinear distortions efficiently and improving error performances in clipping based Orthogonal Frequency Division Multiplexing (OFDM) ssystem. One of the main disadvantages for the OFDM is the high Peak to Average Power Ratio (PAPR). The clipping is a simple method for the PAPR reduction. However, an effect of the clipping is nonlinear distortion, and estimations for transmitting symbols are difficult despite a Maximum Likelihood (ML) detection at the receiver. The DNN based online signal detection uses the offline learning model where all weights and biases at fully-connected layers are set to overcome nonlinear distortions by using training data sets. Thus, this paper introduces the required processes for the online signal detection and offline learning, and compares error performances with the ML detection in the clipping-based OFDM systems. In simulation results, the DNN based signal detection has better error performance than the conventional ML detection in multi-path fading wireless channel. The performance improvement is large as the complexity of system is increased such as huge Multiple Input Multiple Output (MIMO) system and high clipping rate.

Keywords: Clipping, DNN, ML, nonlinear distortion, OFDM.

1 Introduction

An Orthogonal Frequency Division Multiplexing (OFDM) is one of the most popular broadband transmission system used in various wireless communication systems such as 3GPP, Long-Term Evolution (LTE) and IEEE 802.11 Wireless Fidelity (Wi-Fi). The OFDM decomposes a frequency selective broadband channel into several narrowband channels. Each narrowband channel undergoes frequency flat channel since the OFDM uses Cyclic Prefix (CP) which makes an effect of wireless channel as simple multiplications at the receiver. Due to robustness in frequency selective channel, the

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OFDM is jointly used with Multiple Input Multiple Output (MIMO) [Wolniansky, Foschin, Golden et al. (1999); Li, Gao, Li et al. (2019)], i.e., MIMO-OFDM. The MIMO-OFDM increases spectral efficiency tremendously without an additional bandwidth [Chang, Ueng, Shen et al. (2019)]. However, one of the main disadvantages for the OFDM is the high Peak to Average Power Ratio (PAPR) since multi-carriers are used. The high PAPR reduces power efficiency and battery life. For the PAPR reduction, several methods have been developed such as clipping and Partial Transmit Sequence (PTS) methods [Kang, Park, You et al. (2018)]. The clipping method simply limits the peak power for each subcarrier, and it does not require side information. However, the received signals are nonlinearly distorted and system performances are seriously degraded. At the MIMO-OFDM receiver, signal detection is applied for separation of each independent transmission stream. Among several signal detections, a Maximum Likelihood (ML) and a low-complexity ML detection such as a QR Decomposition-*M* Algorithm (QRD-*M*) have optimal error performance when an effect of distortion is linear [Ro, Kim, You et al. (2017); Ro, Yu, You et al. (2020); Choi, Shim, You et al. (2019)]. The system performance is seriously degraded as the clipping rate is large and the error performance for the ML detection is no longer optimal.

Recently, an application of the Deep Neural Network (DNN) is one of popular research areas in wireless communication systems such as wireless channel estimation, signal detection, and joint or end-to-end optimizations for multivariable cost functions and difficult mathematical models [Mu and Zeng (2019); Ha, You and Song (2018); Qin, Ye, Li et al. (2019), Samuel, Diskin and Wiesel (2017); Baek, Kwak, Jung et al. (2019); Poudel, Oshima, Kobayashi et al. (2019)]. The DNN model updates all weights and biases at fully-connected layers by using training data sets and calculating loss functions. The weights and biases are adjusted to minimize the output value of loss function. Thus, transmit symbols are detected well in nonlinear distortions when the DNN based signal detection is used. Also, the DNN model is simply learned by using only training data sets and it does not require complex mechanism to handle distortions.

In this paper, the supervised DNN based signal detection is analyzed in the clipping based OFDM transmission system for better performances in the nonlinear distortions. The complexity of the learning is very high when the used hyper parameters are heavy and the DNN model has high complexity. However, huge complexity is not required during the online signal detection when the coherence time of the wireless channel is long enough compared to the required time for the learning since the learning is performed in the offline in advance and the online operation is based on simple weighted-sum operations. The used weights and biases for the online signal detection were already calculated in the offline learning.

2 System model

This paper considers the clipping based MIMO-OFDM with the DNN based signal detection. Fig. 1 shows the clipping based $N_t \times N_r$ MIMO-OFDM system model where the receiver uses the DNN model for the signal detection which is driven from the offline learning. The transmitter generates complex baseband output values of the Inverse Fast

Fourier Transform (IFFT) and it is denoted as $\mathbf{x}=\left[x_1(n) \quad x_2(n) \quad \cdots \quad x_{N_t}(n)\right]^T$ where $x_j(n)$ is transmit symbol at the j-th transmit antenna in discrete time index n. For the PAPR reduction, the clipping based OFDM symbol $x_{c,j}(n)$ is as follows:

$$x_{c,j}(n)=\begin{cases} x_j(n), & \left|x_j[n]\right| \le A, \\ Ae^{\arg(x_j(n))}, & \text{otherwise}, \end{cases} \tag{1}$$

where A is the clipping amplitude and the maximum absolute value is confined to A.

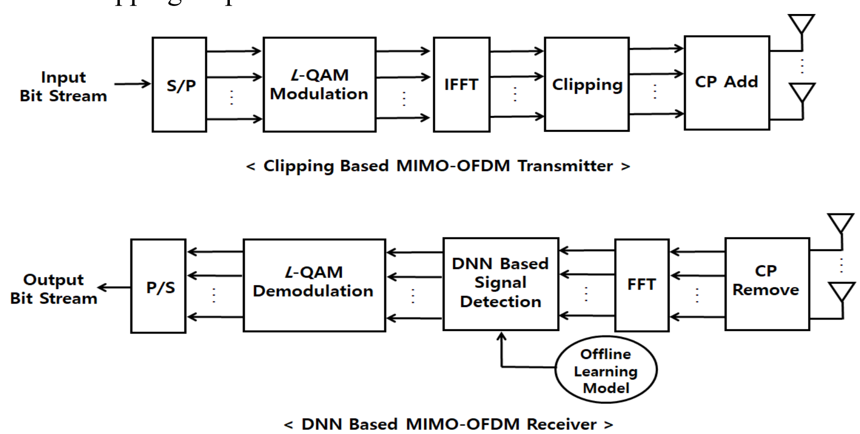

Figure 1: The clipping based MIMO-OFDM system model with online DNN receiver

The complex received symbols vector $\mathbf{Y}=\left[y_1 \quad y_2 \quad \cdots \quad y_{N_r}\right]^T$ after the Fast Fourier Transform (FFT) where an index of subcarrier is ignored for simple notation is as follows:

$$\begin{aligned}\mathbf{Y} &= \sqrt{P}\mathbf{H}\mathbf{X}_c+\mathbf{N} \\ &= \sqrt{P}\underbrace{\begin{bmatrix} H_{11} & H_{12} & \cdots & H_{1N_t} \\ H_{21} & H_{22} & \cdots & H_{2N_t} \\ \vdots & \vdots & \ddots & \vdots \\ H_{N_r1} & H_{N_r2} & \cdots & H_{N_rN_t}\end{bmatrix}}_{\mathbf{H}}\underbrace{\begin{bmatrix} X_{c,1} \\ X_{c,2} \\ \vdots \\ X_{c,N_t}\end{bmatrix}}_{\mathbf{X}_c}+\underbrace{\begin{bmatrix} N_1 \\ N_2 \\ \vdots \\ N_{N_r}\end{bmatrix}}_{\mathbf{N}},\end{aligned} \tag{2}$$

where P is transmit power, H_{ij}, i.e., $i=1,2,\cdots,N_r$, $j=1,2,\cdots,N_t$ is independent and identically distributed complex baseband Rayleigh fading coefficient with zero-mean and unit variance from the j-th transmit antenna to the i-th receive antenna, $X_{c,j}$ is clipped transmit symbol at the j-th transmit antenna in frequency domain, and finally, N_i is complex baseband Additive White Gaussian Noise (AWGN) with zero-mean and unit variance at the i-th receive antenna.

3 Conventional signal detection

This paper deals with the ML detection as a conventional scheme which has optimal error performance in linear distortions. The ML detection calculates L^{N_t} Euclidean distances in

L-Quadrature Amplitude Modulation (QAM) system and its complexity is extremely high in huge MIMO-OFDM systems where the number of transmit antennas and L are large. However, the low-complexity ML detection which has the same error performance as ML is not considered since the main interest of this paper is only improvement of the error performance compared to the ML detection in nonlinear distortions. Also, various schemes for estimating clipped symbols have been researched [Felix, Guerreiro and Dinis (2019); Guerreiro, Dinis, Montezuma et al. (2019)]. However, this paper does not use these schemes as a conventional scheme since the basic results for the performance improvement by using the DNN in the clipping system are not clearly revealed before. Thus, the ML detection is one of the reasonable conventional scheme to show clear break point of the optimal scheme in nonlinear distortions when the total complexity is not main issue. The ML detection estimates transmit symbols by calculating minimum Euclidean distance as follows:

$$\hat{\mathbf{X}} = \underset{\mathbf{X}\in L^{N_t}}{\arg\min} \left\| \mathbf{Y} - \mathbf{HS} \right\|^2, \tag{3}$$

where $\mathbf{S}$ is one of set of all reference symbols and the number of possible sets for $\mathbf{S}$ is L^{N_t}.

4 DNN based signal detection

For performance improvement in the clipping systems, this paper uses the supervised DNN signal detection. For the online signal detection, the offline learning is performed in advance with training data sets which include complex received symbols, channel coefficients, and real labels for transmit symbols. The required processes for the offline learning are mining for training data sets, separations of complex numbered training data sets into real and imaginary numbers, generation of output values at fully-connected layers, and classifications for transmit symbols at output layer. The training data sets are generally complex number. Thus, it has to be separated into real and imaginary numbers for easy operations since all weights and biases in the network are real values. At fully-connected layer, output values are generated from separated training data sets with weighted-sum operations between all neurons of adjacent layer, and activation functions such as sigmoid or Rectified Linear Unit (ReLU) functions. At output layer, transmit symbols are classified by using softmax function which is popular activation function. For the DNN based signal detection, the complete training data matrix $\mathbf{G} = \begin{bmatrix} \mathbf{g}_1^T & \mathbf{g}_2^T & \cdots & \mathbf{g}_R^T \end{bmatrix}^T$ is required where R is the number of total training data sets and $\mathbf{g}_m = \begin{bmatrix} \underbrace{\mathbf{Y}_m^p}_{1\times N_r} & \underbrace{\mathbf{H}_m^p}_{1\times N_r N_t} & \underbrace{x_m^p}_{1\times 1} \end{bmatrix}$ is the m-th training data vector. The superscript p is an expression for highlighting training data sets. The m-th training data vector $\mathbf{g}_m$ is composed of the m-th training data for received symbols vector $\mathbf{Y}_m^p = \begin{bmatrix} y_{m,1}^p & y_{m,2}^p & \cdots & y_{m,N_r}^p \end{bmatrix}$, channel vector $\mathbf{H}_m^p = \begin{bmatrix} \mathbf{h}_{m,1}^p & \mathbf{h}_{m,2}^p & \cdots & \mathbf{h}_{m,N_r}^p \end{bmatrix}$ where $\mathbf{h}_{m,i}^p = \begin{bmatrix} h_{m,i1}^p & h_{m,i2}^p & \cdots & h_{m,iN_t}^p \end{bmatrix}$ is channel coefficients vector from all transmit antennas to the i-th receive antenna, and x_m^p is label data which is required for classifications at output layer. The elements of $\mathbf{G}$ are generally complex number except for final column. Tab. 1 shows detailed examples for separations of complex numbered training data sets into real and imaginary numbers in Single Input Single Output (SISO) with 16-QAM and 2×2

MIMO with Quadrature Phase Shift Keying (QPSK) systems.

Table 1: Examples of separated training data. (a) SISO with 16-QAM, (b): 2×2 MIMO with QPSK

	$y_{m,1}^{p}$ (Real part)	$y_{m,1}^{p}$ (Imaginary part)	$h_{m,11}^{p}$ (Real part)	$h_{m,11}^{p}$ (Imaginary part)	x_{m}^{p} (Label)
$m=1$	$\mathrm{Re}\{y_{1,1}^{p}\}$	$\mathrm{Im}\{y_{1,1}^{p}\}$	$\mathrm{Re}\{h_{1,11}^{p}\}$	$\mathrm{Im}\{h_{1,11}^{p}\}$	5
$m=2$	$\mathrm{Re}\{y_{2,1}^{p}\}$	$\mathrm{Im}\{y_{2,1}^{p}\}$	$\mathrm{Re}\{h_{2,11}^{p}\}$	$\mathrm{Im}\{h_{2,11}^{p}\}$	13
$m=3$	$\mathrm{Re}\{y_{3,1}^{p}\}$	$\mathrm{Im}\{y_{3,1}^{p}\}$	$\mathrm{Re}\{h_{3,11}^{p}\}$	$\mathrm{Im}\{h_{3,11}^{p}\}$	2
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$m=R$	$\mathrm{Re}\{y_{R,1}^{p}\}$	$\mathrm{Im}\{y_{R,1}^{p}\}$	$\mathrm{Re}\{h_{R,11}^{p}\}$	$\mathrm{Im}\{h_{R,11}^{p}\}$	10

(a)

	$y_{m,1}^{p}$ (Real part)	$y_{m,1}^{p}$ (Imaginary part)	$y_{m,2}^{p}$ (Real part)	$y_{m,2}^{p}$ (Imaginary part)	$h_{m,11}^{p}$ (Real part)	$h_{m,11}^{p}$ (Imaginary part)	$\cdots$	$h_{m,22}^{p}$ (Real part)	$h_{m,22}^{p}$ (Imaginary part)	x_{m}^{p} (Label)
$m=1$	$\mathrm{Re}\{y_{1,1}^{p}\}$	$\mathrm{Im}\{y_{1,1}^{p}\}$	$\mathrm{Re}\{y_{1,2}^{p}\}$	$\mathrm{Im}\{y_{1,2}^{p}\}$	$\mathrm{Re}\{h_{1,11}^{p}\}$	$\mathrm{Im}\{h_{1,11}^{p}\}$	$\cdots$	$\mathrm{Re}\{h_{1,22}^{p}\}$	$\mathrm{Im}\{h_{1,22}^{p}\}$	9
$m=2$	$\mathrm{Re}\{y_{2,1}^{p}\}$	$\mathrm{Im}\{y_{2,1}^{p}\}$	$\mathrm{Re}\{y_{2,2}^{p}\}$	$\mathrm{Im}\{y_{2,2}^{p}\}$	$\mathrm{Re}\{h_{2,11}^{p}\}$	$\mathrm{Im}\{h_{2,11}^{p}\}$	$\cdots$	$\mathrm{Re}\{h_{2,22}^{p}\}$	$\mathrm{Im}\{h_{2,22}^{p}\}$	15
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\vdots$	$\vdots$
$m=R$	$\mathrm{Re}\{y_{R,1}^{p}\}$	$\mathrm{Im}\{y_{R,1}^{p}\}$	$\mathrm{Re}\{y_{R,2}^{p}\}$	$\mathrm{Im}\{y_{R,2}^{p}\}$	$\mathrm{Re}\{h_{R,11}^{p}\}$	$\mathrm{Im}\{h_{R,11}^{p}\}$	$\cdots$	$\mathrm{Re}\{h_{R,22}^{p}\}$	$\mathrm{Im}\{h_{R,22}^{p}\}$	4

(b)

The labels are set to 0 to 15 since the number of total possible combinations for transmit symbols is L^{N_t} where both cases are 16. All labels are one-hot encoded for classifications of transmit symbols where only one bit is encoded to 1 and other bits are encoded to 0. Tab. 2 shows detailed examples for the one-hot encoding in SISO with 16-QAM and 2×2 MIMO with QPSK systems. As the number of total possible combinations for transmit symbols is 16, the length of one-hot encoded streams is also 16. The one-hot encoded streams go through the DNN model for learning training data sets. The DNN model for the signal detection is composed of fully-connected layer and classification layer. The fully-connected layer is composed of dense layer based several neurons and activation functions. After the calculations of output values at fully-connected layer, activation functions at the classification layer is operated such as softmax function by comparing output values of activation function with one-hot encoded streams since output values of softmax function are analyzed as probability. The weights and biases are updated by minimizing output values of loss function such as cross entropy function. The training data sets are learned again per batch size with updated weights and biases during one epoch, and learning process is completely finished in final epoch where the batch size and epoch are hyper parameters, and these parameters are variously set according to system design.

Table 2: Examples of one-hot encoded stream. (a) SISO with 16-QAM, (b) 2×2 MIMO with QPSK

(a)

Label	Bits	One-hot encoded stream
0	0000	0000000000000001
1	0001	0000000000000010
2	0010	0000000000000100
3	0011	0000000000001000
4	0100	0000000000010000
5	0101	0000000000100000
6	0110	0000000001000000
7	0111	0000000010000000
8	1000	0000000100000000
9	1001	0000001000000000
10	1010	0000010000000000
11	1011	0000100000000000
12	1100	0001000000000000
13	1101	0010000000000000
14	1110	0100000000000000
15	1111	1000000000000000

(b)

Label	Bits (T×1)	Bits (T×2)	One-hot encoded stream
0	00	00	0000000000000001
1	00	01	0000000000000010
2	00	10	0000000000000100
3	00	11	0000000000001000
4	01	00	0000000000010000
5	01	01	0000000000100000
6	01	10	0000000001000000
7	01	11	0000000010000000
8	10	00	0000000100000000
9	10	01	0000001000000000
10	10	10	0000010000000000
11	10	11	0000100000000000
12	11	00	0001000000000000
13	11	01	0010000000000000
14	11	10	0100000000000000
15	11	11	1000000000000000

The learning process is performed during several epochs, and all weights and biases are updated to cope with nonlinear distortions. After the offline learning, the online signal detection is performed by using already learned DNN structure. Learning weights and biases have very low accuracy when the coherence time of wireless channel is shorter than the required time for the offline learning since the property of the wireless channel are varied. Again, however, these problems are not considered in this paper since the main interest is only performance improvement in nonlinear distortions by using the DNN model. Fig. 2 shows the MIMO-OFDM system model based on the DNN receiver with the offline learning.

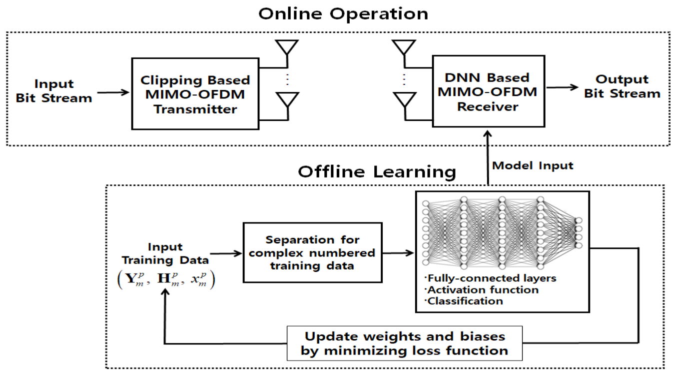

Figure 2: The MIMO-OFDM system model based on DNN receiver with offline learning

5 Simulation results

For performance evaluations, Bit Error Rate (BER) performances for the conventional ML and the DNN based signal detection are measured in the clipping based OFDM systems. For performance evaluations of the DNN based signal detection, the complex numbered training data is generated by MATLAB software and the offline learning is performed by Keras library. For the offline learning, ReLU functions are used as an activation function at fully-connected layer, and softmax functions are used as an activation function at output layer. Also, the cross-entropy function is used as a loss function. Tab. 3 represents the used system parameters.

Table 3: The used system parameters

Parameters	Value or scheme
FFT length	128
CP length	32
Multi-path	7
Antenna structure	SISO, 2×2 MIMO
Digital modulation	QPSK, 16-QAM
Clipping rate	24% $(A=1.2)$, 30% $(A=1.1)$ *24% and 30% are not fixed values with respect to A. These values are generally varied according to system parameters although the value of A is perfectly same.
Channel model	Zero mean and unit variance multi-path Rayleigh fading (Multi-path:7)
Noise	Zero mean and unit variance AWGN

From Figs. 3 to 5, BER performances are shown for the conventional ML and the DNN based signal detection in the SISO-OFDM system with the QPSK and 16-QAM modulations, and the MIMO-OFDM system with the QPSK modulation respectively. In each case, the BER performance for the conventional ML detection without the clipping is also shown for comparison. Additionally, the BER performance for the QRD-*M* detection is shown in Fig. 5 where it has the same BER performance as ML detection. For various performance evaluations, clipping rates are set to 24% and 30% in all simulations. The used hyper parameters and learning accuracy for the DNN based signal detection in each case are represented in Tab. 4. The used hyper parameters and DNN model are heavy in the MIMO or 16-QAM system compared to the SISO or QPSK system, i.e., more data sets, smaller batch size, larger learning rate and epochs, complex network model. The optimization for these parameters is one of key issues for the DNN model since low-latency is very critical issue in wireless communication systems. However, these subjects are not handled in this paper. Also, the accuracy of the DNN model is improved by using training data sets with proper noisy received symbols. However, the used training data sets for the received symbols are noiseless in all simulations for clear visualization of the performance improvement without the learning process of decision boundary in constellation. Finally, perfect estimations for the wireless channel and clipping amplitude at the receiver, and enough coherence time compared to required time for the offline learning are assumed.

Table 4: The used hyper parameters and learning accuracy for DNN based signal detection in each case

	SISO and QPSK (Fig. 3)	SISO and 16-QAM (Fig. 4)	2×2 MIMO and QPSK (Fig. 5)
The number of training data sets	500,000	2,000,000	2,000,000
Batch size	100	50	50
Learning rate	0.0001	0.00001	0.00001
Epochs	30	80	80
The number of total layers	3	5	5
The number of total neurons at each layer	256 (4 for output layer)	512 (16 for output layer)	512 (16 for output layer)
Learning accuracy for 24% clipping in final epoch	100%	95%	97%
Learning accuracy for 30% clipping in final epoch		94%	96%

In Fig. 3, the DNN based signal detection has the same BER performance as ML detection regardless of the clipping rate since the QPSK is only phase-rotated modulation and the number of total possible combinations for transmit symbols is only 4. Thus, effects of clippings are approximated to linear distortions in the SISO-OFDM system with the QPSK modulation, and it results in no performance gains for the DNN based signal detection compared to the ML detection. Also, the linearly approximated distortions are resulted in slight loss of error performance compared to the non-clipping system. However, in Fig. 4, BER performances for clipping systems are nonlinearly degraded compared to the non-clipping system regardless of the clipping rate since the 16-QAM is amplitude and phase modulation, and the number of total possible combinations for transmit symbols is 16. Unlike the results in Fig. 3, the DNN based signal detection has better BER performance than the ML detection regardless of the clipping rate since all weights and biases in the DNN model are adjusted for equalizations of nonlinear distortions where it is very remarkable merit compared to the conventional ML detection.

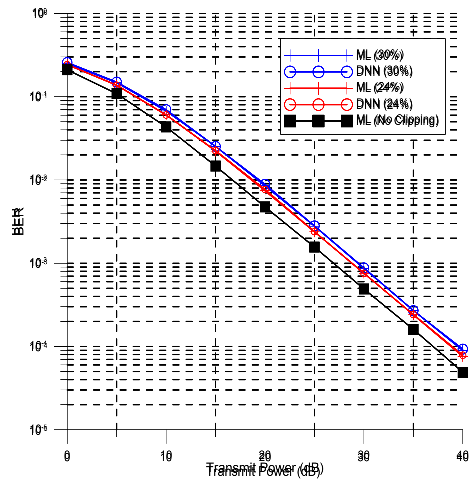

Figure 3: The BER performances for conventional ML and DNN based signal detection in SISO-OFDM system with QPSK modulation

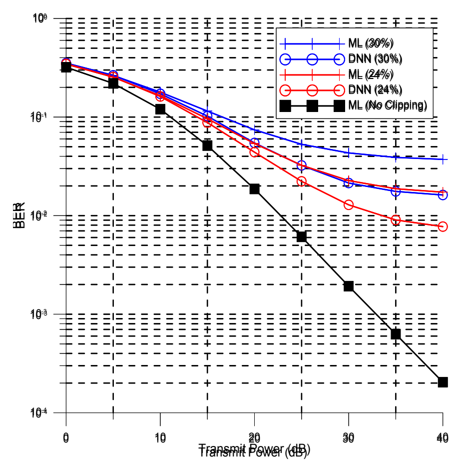

Figure 4: The BER performances for conventional ML and DNN based signal detection in SISO-OFDM system with 16-QAM modulation

However, the DNN based signal detection also suffers from irreducible error rate since the learning accuracy is low. In Fig. 5, the DNN based signal detection has better BER performance than the ML detection and suffers from irreducible error rate as results in Fig. 4. However, the gap of BER performance between the conventional ML and the DNN based signal detection is decreased remarkably compared to results in Fig. 4 since the used modulation is QPSK although the number of total possible combinations for transmit symbols is same as 16.

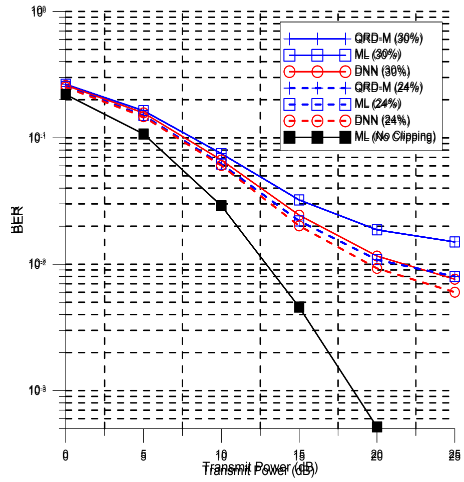

Figure 5: The BER performances for conventional ML and DNN based signal detection in 2×2 MIMO-OFDM system with QPSK modulation

5 Conclusion

In this paper, the DNN based signal detection is used in the clipping based OFDM system to combat with nonlinear distortions efficiently. For online operations, the DNN model is generated in the offline learning. In simulation results, the DNN based signal detection has better BER performance than the conventional ML detection. Also, it is shown that the performance improvement for the DNN based signal detection is remarkable in complex systems where the used modulation and the number of transmit antennas are large. The DNN based signal detection is very attractive in the clipping system since it operates based on only data sets and the conventional ML detection cannot overcome nonlinear distortions. However, BER performances are seriously degraded compared to the non-clipping system. Thus, our future researches are performance improvement by performing optimizations for model parameters, mixture of preprocessing structures, and robust data mining.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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