Wireless Cellular Systems Performance Improvement Based on Neural Network

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***Abstract*—**In this paper, a neural network (NN) part has been imposed to overcome a previously mitigated drawback that is found in Orthogonal Frequency Division Multiplex technology (OFDM) systems. In the learning process we make use of the results obtained from the previously published work to reduce the Peak to Average Power Ratio (PAPR) problem based on different linear coding techniques.

The proposed technique shows that an improvement in the OFDM technology performance has been achieved based on reducing the system's complexity. Moreover, the reduction percentage of the PAPR compared to the previously published one; which combats the PAPR based on Low Density Parity Check (LDPC), turbo coding and convolutional coding has been attained exactly. Our simulation results show that 15% reduction in PAPR over current values in the literature can be achieved depending on the system's type. This is in addition to that the use of NN reduces the overall OFDM system's complexity. This is because that in the proposed technique the system does not need to send extra data to recombine the processed OFDM symbols at the receiver side. Thus, the performance improvement could be attained.

***Keywords*—**Multiple Input Multiple Output, Orthogonal Frequency Division Multiplexing, Neural Network, Linear codes.

I. Introduction

THE main challenge of the new generation of wireless cellular systems is the reliability of providing data rate of around 100 Mbps and 30 Mbps for the downlink and uplink physical layer transmission, respectively. Therefore, researchers have turned their attentions toward the combination of two powerful techniques, namely Orthogonal Frequency Division Multiplex (OFDM) and Multiple-Input Multiple-Output (MIMO) technology to achieve these rates [1,2].

Due to this fact, OFDM has been adopted in various wireless communications standards in recent years [3,4] such as wireless networking (IEEE 802.11), digital terrestrial television broadcasting and Broadband Radio Access Network (BRAN). However, the main drawback of OFDM is the large envelope fluctuations, also known by Peak-to-Average Power ratio (PAPR), making the system sensitive to the nonlinearities introduced by the travelling wave tube amplifier. Thus a spectral regrowth in adjacent channels and deformation of the signal constellation could happen [5]. Consequently, average signal power must be kept low in order to prevent the limiting action of the transmitter amplifier and other circuitry. Minimising the PAPR allows a higher average power to be transmitted for a fixed peak power, improving the overall signal to noise ratio at the receiver. In the literature there are many solutions to reduce the effect of PAPR in the OFDM signal [5-10]. One of reduction solutions is to operate the Travelling Wave Tube Amplifier (TWTA) with a large power back-off level [6]. In this way there is a limitation in attaining the maximum power efficiency, which is only at the saturation point of the TWTA. Therefore, there is a chance to utilize the neural network (NN) and the neuro-fuzzy systems to achieve a trade-off between the linear amplification and high power efficiency [5,6,8,9]. The other solutions in the literature are presented in [7,10-14] as Selective mapping, Golay sequences, Cyclic coding, clipping and filtering; and multiple signal representation techniques.

MIMO technology also has a number of powerful advantages including the ability to increase the system capacity and improving the communication reliability via the diversity gain. The capacity of MIMO channels scale linearly with respect to the minimum available transmitter and receiver antennas.

Unlike the work in the literature, when imposing the neural networks in this work we in particular focus on presenting a scheme based on NN to achieve the goal of maximum amplification [15]. The proposed NN will be trained based on the previously published work [16] and then it will be imposed after the IFFT stage in the MIMO-OFDM systems. Then in an intelligent manner, it will choose the best form to replace the effected OFDM symbol before the transmission through the MIMO arrangement. In this work, the MIMO technology is used either to increase the overall system capacity or to enhance the system's robustness. While in previous published works, it has been used to send the rest of the processed affected OFDM symbol simultaneously with the OFDM signal. The achieved results from imposing the NN will be compared with the previously published results in combating the PAPR [16]. In [16] the authors have used linear coding techniques to mitigate the PAPR problem, which improves the performance of the MIMO-OFDM system.

This paper is organized as follow; the MIMO-OFDM system description is given in section II. Validation of the simulation results of the PD-NN and the previously proposed work are given in section III, followed by conclusion in section IV.

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II. System Description of Combating PAPR of MIMO-OFDM

In this work, the turbo encoder of 2/3 coding ratio is used for the coding stage. Two different modulation techniques are used; BPSK and 64QAM, together with a Vertical Bell Laboratories Layered Space-Time (V-BLAST) MIMO encoder. V-BLAST is used for increasing the overall throughput expressed in terms of bits/symbol, while applying the IFFT to generate the OFDM symbols. After the IFFT stage and due to the coherent addition of the independently modulated subcarriers to produce OFDM symbol, a large PAPR ratio could appear.

Thus we try to reduce the effect of these peaks by apply the NN and then compare it to the achieved results from the previously published work by using linear coding techniques [16]. Subsection *A* describes the MIMO-OFDM-based NN PART systems, while Subsection *B* gives briefly an overview of the previously published work to combat the PAPR problem. In this configuration, the transmitted OFDM signal consists of a sum of subcarriers that are modulated using the M-ary PSK, QAM or any multi-level modulation technique. These subcarriers could be expressed as in [5]:

$$s(t)=\sum_{i=\frac{-N_s}{2}}^{\frac{N_s}{2}}\left[d_{\left(i+\frac{N_s}{2}\right)}e^{\left(j2\pi\left(f_c-\frac{i+0.5}{T}\right)(t-t_s)\right)}\right],\ t_s\le t\le t_s+T \quad (1)$$

where, d_i is a complex input symbol after the modulation stage, f_c is the carrier frequency of the *i-th* subcarrier, *T* is the OFDM symbol duration and the starting time of one OFDM symbol is $t=t_s$.

A. PAPR combating-based NN

The use of N-points Inverse FFT (IFFT) in the OFDM transmitter causes the PAPR problem. This arises when N signals are added with the same phase in IFFT stage to produce OFDM symbol. A high peak power equals to N times the average power occasionally appears as a result of this addition process. Thus, the PAPR definition can be written as:

$$\text{PAPR} = 10\log_{10}\left\{\frac{P_{peak}}{P_{avg}}\right\} \text{--------(2)}$$

where, Ppeak is the maximum power of an OFDM symbol, and Pavg is the average power. The PAPR can be reformulated as:

$$\text{PAPR}=\frac{|s(t)|^2}{\frac{1}{NT}\int_0^{NT}|s(t)|^2dt} \text{--------(3)}$$

where x(t) is the OFDM symbol at time, t, Moreover, the average power of the OFDM symbol in (3) can be written as:

$$P_{avg}=\sum\left\{|s_i(t)|^2\right\}=\frac{1}{T}\int_0^T|s(t)|^2dt \text{--------(4)}$$

$$P_{avg}=\frac{1}{T}\int_0^T\left|\sum_{v=0}^{N-1}c_v e^{j2\pi\frac{v}{NT}t_v}\right|^2 dt \text{-----(5)}$$

$$=\frac{1}{T}\int_0^T\left(\sum_{v=0}^{N-1}c_v\cos\left(2\pi\frac{v}{NT}t_v\right)\right)^2+\left(\sum_{v=0}^{N-1}c_v\sin\left(2\pi\frac{v}{NT}t_v\right)\right)^2dt$$

$$P_{avg}=\frac{1}{T}\int_0^T\left(\sum_{v=0}^{N-1}c_v^2\right)dt \text{-----(6)}$$

where c_v is the magnitude of the modulated data. For simplicity, if BPSK modulation is used without any channel coding techniques, then $|c_v|=1$, when t $\in[0, T]$. This can be substituted in (6). The result from this substitution leads to a direct relationship between the average power and the total number of the IFFT points, N, which can be taken directly from

$$P_{avg}=\frac{N}{T}\int_0^T c_v^2dt = \text{N ------(7)}$$

From (7), the average power is equal to the number of the BPSK-modulated orthogonal subcarriers. As already mentioned, the maximum peak amplitude is N, therefore, the maximum power of the OFDM symbol is N2. As a result, from (2), the PAPR of uncoded BPSK will be $10\times\log_{10}(P_{avg})$ dB. Therefore, the PAPR will decrease if the average power of the OFDM symbol is decreased. This mathematical derivation was the basis of our previously published work to combat the effect of the PAPR drawback on the MIMO-OFDM systems [16].

One of the affected components by the nonlinearity problem in MIMO-OFDM systems is the Radio Frequency Power Amplifier (RFPA). Imposing the NN can improve MIMO-OFDM systems performance; as it is the simplest way of linearization for RFPA. This is due to the NN ability of simultaneous BW linearization [9]. Figure 1, shows the modified MIMO-OFDM transmitter to cover the imposition of NN.

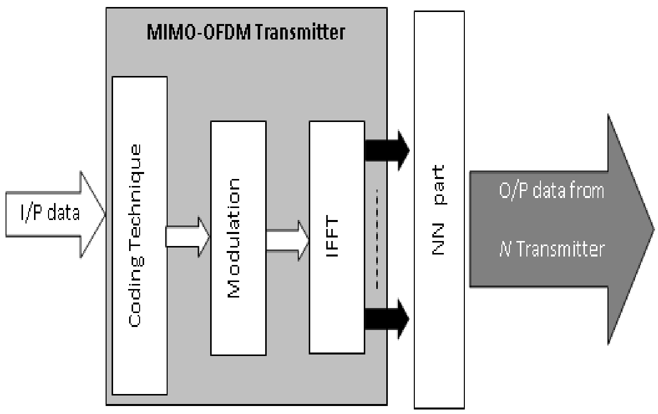

Figure 1. AN MIMO-OFDM-Based NN Transmitter

Intelligent controllers are generally self-organizing or adaptive and are naturally able to cope with the significant changes in the plant and its environment. As processes increase in complexity, they become less amenable to direct mathematical modeling based on physical laws, since they may be, distributed, stochastic, nonlinear and time-varying.

Research into intelligent systems integrates concepts and methodologies from a range of disciplines including neurophysiology, artificial intelligence, optimization and approximation theory, control theory and mathematics. This integration of research fields has led to an emergent discipline, frequently referred to as connectionism or neuron science that inherently incorporates distributed processing concepts organized in an intelligent manner. Connectionist or neurons systems, unlike conventional techniques and self-programming, appear to be stochastic or fuzzy, heuristic and associative. An approximation to the desired mapping is constructed in intelligent or learning systems [17].

ANNs or simply NNs go by many names such as connectionist models, parallel distributed processing models, and neuromorphic systems, Whatever the name, all these models attempt to achieve good performance via dense interconnection of simple computational elements. Computational elements or nodes used in neural net models are nonlinear and typically analog. The simplest node sums N weighted inputs and passes the results through a nonlinear function.

A special type of nonrecurrent NNs is feed-forward neural net, or FFNN, which consists of layers of neurons with weighted links connecting the outputs of neurons in one layer to the inputs of neurons in the next layer.

A neural network has the power and ability to learn and therefore generalize which make it possible to solve complex (large-scale) problems that are currently intractable. The use of NN offers the following main useful properties [18]

1- Parallelism: An NN derives its computing power through its massively parallel distributed structure.

2- Nonlinearity: A neuron is basically a nonlinear device which is a highly important property, particularly if the underlying physical mechanism responsible for the generation of an input signal (e.g. speech signal) is inherently nonlinear

3- Generalization: This refers to the producing of reasonable outputs for inputs not encountered during training.

4- Adaptivity: NNs have a built-in capability to adapt their synaptic weights to changes in the surrounding environment.

5- Fault tolerance: An NN, implemented in hardware form, has the potential to be inherently fault tolerant. For example, if a neuron or its connecting links are damaged, recall of a stored pattern is impaired in quality. Owing to the distributed nature of information in the networks, the damage has to be extensive before the overall response of the network is degraded seriously. Thus, in principle, the NN exhibits a graceful degradation in performance rather than catastrophic failure.

6- VLSI implementation: The particular virtue of VLSI is that it provides a means for capturing truly complex behavior in a highly hierarchical fashion, which makes it possible to use an NN with the massively parallel nature as a tool for real-time applications involving pattern recognition, signal processing, and control.

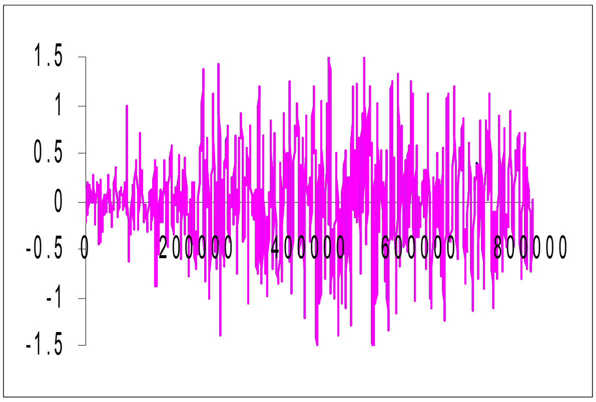

Figure 2.a

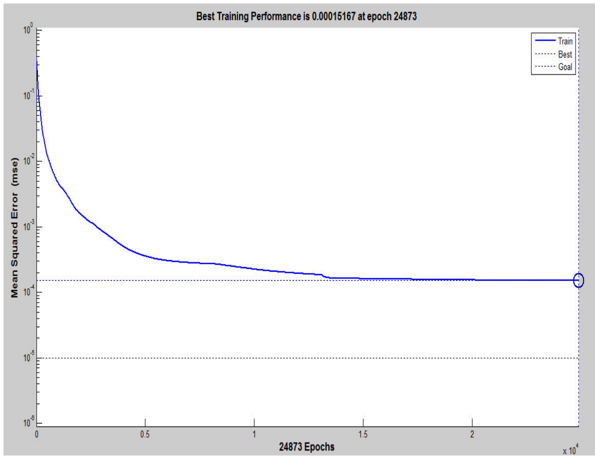

Figure 2.b

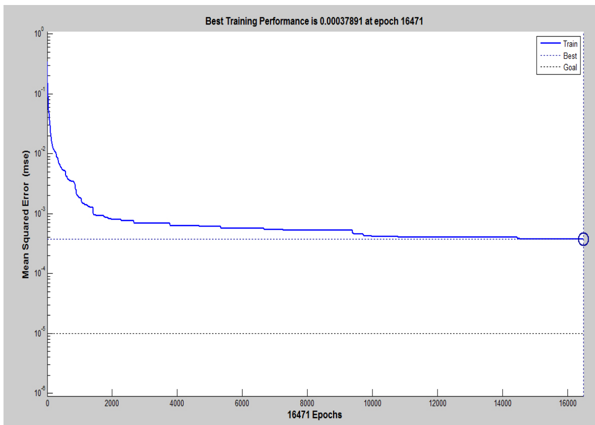

Figure 2.c

Figure 2: (a) Errors, Sample of Learning Pattern for both the real part (b), and Imaginary one (c)

FFNN is extensively used in applications, with some limitations as listed below: -

1- Choosing the network size: It is not known what (finite) size of networks is best for a given problem. If the network is too small, it will not be capable of forming a good model of the problem. On the other hand, if the network is too big then poor approximation to actual problem will take place.

Hence one would like a network whose size best captures the structure of the data.

2- Complexity of learning: Even if one is able to determine the optimal network size, it turns out that finding the correct weights for a network is an inherently difficult problem. The problem of finding a set of weights for a fixed-size network which performs the desired mapping exactly for some training set is known as the loading problem.

Figure of errors and a sample of learning pattern are illustrated as below in Figure 2.

B. PAPR combating-based linear coding techniques

Based on the mathematical derivation in (1-7), a proposed model to reduce the appearance of large power peaks in the OFDM symbols was presented in [16]. Figure 3 is a flowchart to describe the main stages of the proposed technique.

In the first stage, the proposed technique starts with a check on the OFDM symbol to see if it is suffering from high PAPR values or not (this depends on the application itself; in our case the threshold is settled to be 10 dB based on mobile communication systems [16]. If the PAPR is within a set tolerance, "*I*" coded symbols generated through a Space Time Block Coder (STBC) will be transmitted through "*I*" number of antennae. If the PAPR, however, exceeds a predetermined acceptable threshold, the symbol will pass through linear coding block having first removed the guard interval.

In [16], different linear coding techniques have been used to accomplish this aim, such as convolutional encoding, LDPC codes and turbo coding. The period of the affected symbol will be spread according to the chosen spreading rate, to be "*I* " times the original one, where "*I* " is the spreading rate. The second stage of the proposed technique deals with the new symbol and choosing the data with the lowest PAPR value. The spread symbol will be mapped to "*I*" parallel blocks, each of which has the same duration as the conventional symbol duration. The number of iterations that is needed to calculate the PAPR of each block, and choosing the lowest value is given by $[((I-1)N)+1]$. Thus, the proposed technique will add a first order complexity in according to the variable *N*. Due to the achieved spreading by using linear coding; these blocks will have a PAPR value less than the threshold value. This will be the starting point in our work.

We have got the affected OFDM symbols and the desired ones that were achieved from the previously proposed work; these are the needed data to train the NN in this work. This will simplify the previously published work since we usually use a complicated receiver [20] to ensure the transmission of the processed OFDM symbol simultaneously with the OFDM signal from *I* antennas.

In [16], an LDPC code design has been proposed based on back-substitution once the parity check matrix has been changed into an upper matrix. Despite the parity check matrix is an approximate upper matrix the back-substitution operation is highly reused. This drawback mitigated in [21] (where the back-substitution operation is replaced by a few matrix-vector multiplications).

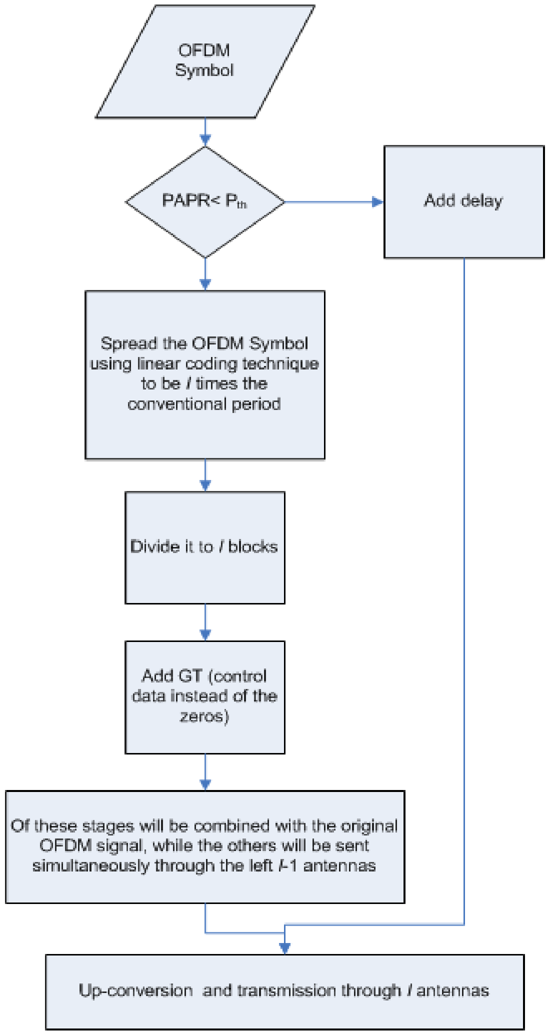

Figure 3 The flowchart of the proposed algorithm

To fulfill this replacement, the approximate upper triangular parity check matrix has the form shown in Figure 4, where $\mathbf{I}_1$ and $\mathbf{I}_2$ are identity matrices, Z is a zero matrix and g is the gap of the approximate triangulation and is used to change the matrix into an upper triangular matrix.

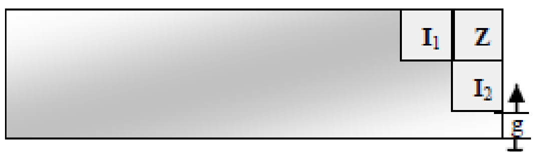

Figure 4 The encoder-aware parity check matrix structure

According to the weight distribution of the matrix columns and rows, two different sets of weight distributions have been generated:

$$\{a_1, a_2, \ldots\ldots a_n\}, \text{ where } \begin{array}{ll} a_j = w_{c_j}, & 1 \le j \le (n-m+\gamma) \\ w_{c_j} - 1, & (n-m+\gamma \le j \le n) \end{array} \quad (9)$$

$\{b_1, b_2, \ldots\ldots b_m\}$, where $b_i = \begin{cases} w_{r_i} - 1, & 1 \le i \le (m-\gamma) \\ w_{r_i}, & (m-\gamma+1 \le i \le m) \end{cases}$ (10)

Starting with j=1, the a_j null blocks on the j-th block column will be replaced by a_j right cyclic shifted identity matrix. This is attained by :

1. Replacing $\mathbf{H}_{i,j}$ with a right cyclic shift of bxb identity matrix with a randomly generated shift value (i is randomly picked from the set of $\{1,2,\ldots m\}$and b_i>0).
2. If the minimum cycle degree is less than the initial cycle degree, the replacement will be rejected and step 1 will be repeated (bearing in mind that for all variable nodes on a cycle, the sum of degrees[1] is defined as the cycle degree of this cycle. It is, therefore, intuitively desirable to make the cycle degree as large as possible for those unavoidable small cycles).
3. Let $b_i = b_i$-1
4. If $d < d_{\min}$, terminate and restart the procedure where d and d_{min} are the calculated node degree distribution and the minimum node distribution threshold.
5. The remaining null blocks should then be replaced with zero matrices, resulting in the output matrix; a flowchart of the encoding procedure is shown in Figure 7.
6. The back-substitution makes the presented work in [16] preferable over the one by Richardson [22]. The encoder design is accomplished by exploiting the structural property of the code parity check matrix.
7.
8. The parity check matrix could be written according to Figure 6 as an upper triangular matrix and a combination of some other sparse matrices (each of them consist of at most $O(p_2)$ elements) as follows

$$\mathbf{H} = \begin{bmatrix} \mathbf{A} & \mathbf{B} & \mathbf{C} \\ \mathbf{D} & \mathbf{E} & \mathbf{F} \end{bmatrix} \text{ ------------------------------- } (11)$$

where , $\boldsymbol{A}$ is $(p_1$-$g)$x$(p_2$- $p_1)$, $\boldsymbol{B}$ is $(p_1$-$g)$x(g), $\boldsymbol{C}$ is an upper triangular matrix (where $\boldsymbol{C}$=$\boldsymbol{C}^{-1}$) in the size of $(p_1$-$g)$x $(p_1$-$g)$, $\boldsymbol{D}$ is (g)x$(p_2$- $p_1)$, $\boldsymbol{E}$ is (g)x(g) and $\boldsymbol{F}$ is (g)x$(p_1$-$g)$.

According to (9), let the information vector, $\mathbf{S_1}$, in length of $(p_2$- $p_1)$ decomposed with the redundant parity check vectors, $\mathbf{R_1}$ and $\mathbf{R_2}$ in the length of (g) and $(p_1$-$g)$, respectively, to form $[\mathbf{S_1}, \mathbf{R_1}, \mathbf{R_2},]$ codeword . Here, $\mathbf{R_1}$ and $\mathbf{R_2}$ could be defined from $\mathbf{S_1}$ by $[-\mathbf{FCB}+\mathbf{E}\left[\mathbf{FCAS_1^T}+\mathbf{DS_1^T}\right]$ and $\left[\mathbf{C}(\mathbf{AS_1^T}+\mathbf{BR_1^T}\right]$, respectively.

From the previous description, the overall computational complexity is much less than that of the encoding based on generator matrix. This is because all multiplications are performed between sparse matrices and vectors (as an example, to determine the complexity of $\mathbf{R_1}$, first $\mathbf{AS_1^T}$ has complexity of $O(p_2)$ since $\mathbf{A}$ is sparse, next multiply the result by $\mathbf{C}^{-1}$). Since $\mathbf{C}^{-1}\,\mathbf{AS_1^T}$ = y^T is equivalent to $\mathbf{AS_1^T}$ =$\mathbf{C}y^T$ this also can be accomplished in $O(p_2)$ by back-substitution, since $\mathbf{C}$ is sparse and lower triangular.

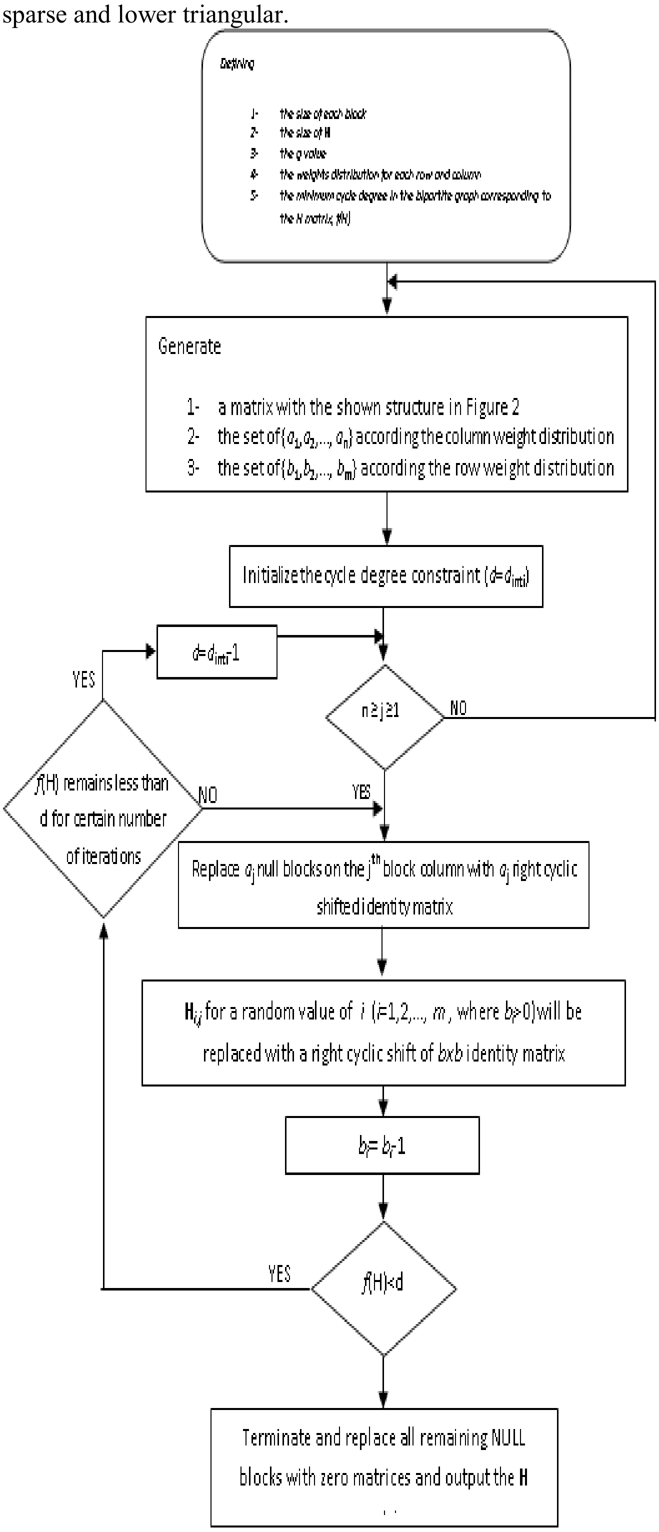

Figure 5 The flowchart of generating the **H** matrix

[1] The node degree distribution is equivalent to the parity check matrix row and column weight distribution [22]

Follow this procedure to reach the complexity of $O(p_2+g^2)$, while the complexity of calculating $\mathbf{R}_2$ is $O(p_2)$). For example let the **H** matrix is given as

$$\mathbf{H}(3,6)=\begin{bmatrix} 1&1&1&0&0&1&1&0&1&0&0&0\\ 1&1&1&1&0&0&0&1&0&1&0&0\\ 0&0&0&0&1&1&1&0&1&1&1&0\\ 1&0&0&1&1&0&0&0&0&1&1&1\\ 0&1&0&1&0&0&1&1&0&0&1&1\\ 0&0&1&0&1&1&0&1&1&0&0&1 \end{bmatrix},$$

with g = 2 and the information vector equals (1, 0, 1, 0,1, 0), therefore the codeword is equal to [$\mathbf{S}_1$, $\mathbf{R}_1$, $\mathbf{R}_2$,] = [1, 0,1, 0,1, 0, 0, 1, 1, 0, 1, 0].

III. Simulation Results and Discussion

Numerical experiments have been carried out to evaluate the MIMO-OFDM system performance after imposing NN PART. As shown in Figure 1, the NN PART is just used to classify the affected MIMO-OFDM symbol by high PAPR. After this classification process and based on the number of transmitting antennas, the NN PART will send the specified target that is accompanied with the input signals. Experimentally, the structure of the NN PART which gives the best performance is tabulated in Table 1.

Table 1 NN part main parameters

Functions	Description
Network Type	Feed-Forward Backpropagation
Number of Layers	Three Layers: Input, hidden, and output
Number of Neurons (based on Spreading rate)	512 input, 30 hidden, and 512 output
Activation Function	bipolar-sigmoid
Training Function	Error Back propagation
Performance Function and Number of epochs (Real, Imaginary)	10^{-3} and (24873,16470)

In this table, it is clearly shown that application of linear coding for spreading purposes has decreased the PAPR compared to the case of no compensation. In terms of applying linear coding techniques; there are three different linear codes have been used. It is clearly shown that the use of simple linear code such as the convolutional coding has reduced the maximum power peaks around 64% as an average reduction when using the BPSK.

Using a heavier modulation technique gives a better result to reach a 66% as an average reduction ratio. Moreover, using these ratios has been modified when using the turbo coding technique. Thus, an extra 9% has been attained when using the BPSK and around 3% extra reduction when using the 64QAM. Using the LDPC coding has further reduced the PAPR over the turbo coding approach by up to 3.14% and 4.1% for spreading rate of 2 and 3 respectively depending on the modulation method and the coding rate.

Table 2 The simulation results of the proposed technique based on different linear coding techniques

Modulation Technique	Channel Coding Rate	Spreading using Linear coding techniques (I=3)			
		PAPR(dB) No Coding	PAPR (dB) after using Convolutional coding	PAPR (dB) after using Turbo coding	PAPR (dB) after using LDPC coding
BPSK	1/2	12.6	4.3	3.3	1.8
	1/3	10.9	4.1	2.5	1.2
64QAM	1/2	9.7	3.2	2.03	1.4
	1/3	8.3	2.9	1.76	0.97

Figure 6 shows the CCDF plot of imposing the linear coding techniques to overcome the PAPR problem in the MIMO-OFDM system. The CCDF plots for the reduction performance with BPSK and 64QAM modulation technique are depicted in Figures 8.a and 8.b respectively. These figures compare the threshold value against the probability that the PAPR will exceed the threshold value. From these figures the reduction improvements are clearly shown over what have been achieved in our previous published work in [16].

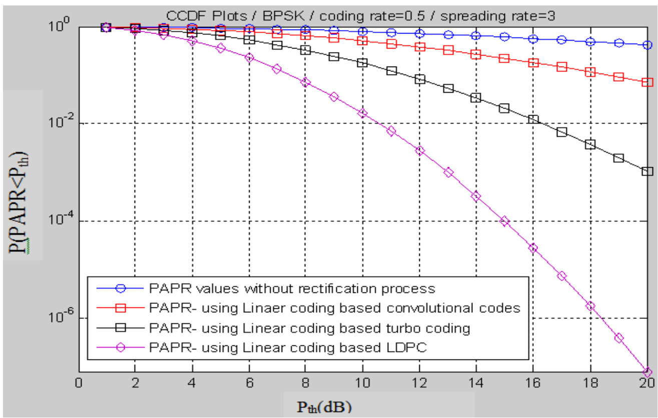

Figure 6.a

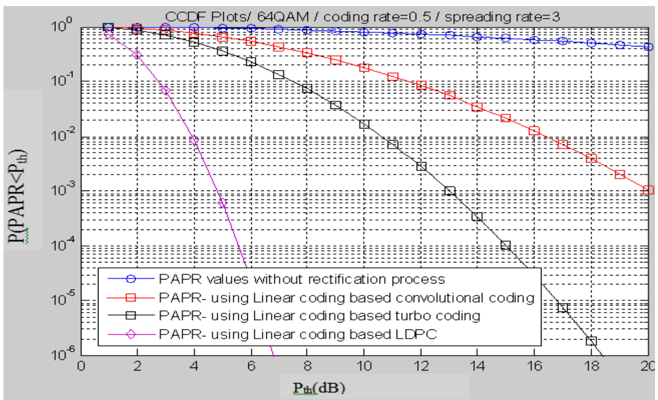

Figure 6.b

Figure 6 Comparison between the probabilities of PAPR values that exceed a certain threshold for applying linear coding techniques (coding rate equals to 1/2, and two different spreading 3 for BPSK and 64QAM modulation process, in figure 6.a and 6.b, respectively).

After the PAPR reduction is complete based on different linear coding techniques, both of the affected OFDM symbol and the chosen one after applying the spreading techniques have been used in the learning process of the NN PART. The overall MIMO-OFDM system based NN PART has been modeled through a multipath fading channel. Table 3 shows the achieved results of the training procedure.

Table 3 Powell-Beale conjugate gradient back-propagation

Learning parameter η	MSE	Number of trained OFDM symbols
0.1	6.254×10^{-5}	100
0.01	8.157×10^{-5}	100

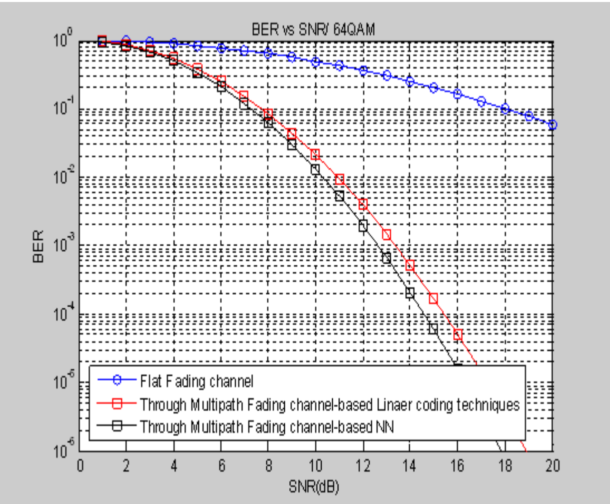

Figure 7 BER vs. SNR comparison between the achieved results of using linear coding techniques and the ones of NN PART through a multipath fading channel.

From Figure 6.a, it can be seen that at a PAPR threshold of 6 dB, the probability of the PAPR values that exceed this threshold is reduced from 0.89×10^{-1} to 0.9×10^{-2} using LDPC codes which is the best results achieved over the use of both of turbo coding and convolutional encoding, while Figure 6.b shows clearly the situation that using 64QAM instead BPSK enhances the PAPR reduction ratios. From Figure 7, using the NN slightly enhances the BER vs. SNR plots. As an example at 10 dB SNR the BER has been enhanced from 2.5×10^{-2} to 1.1×10^{-2}.

IV. Conclusion

In this paper, a work based on neural networks has been introduced to enhance the OFDM systems performance. Basically, the learning process of the proposed NN is based on the previously published work.

The simulation results demonstrate the reduction of PAPR based on different linear coding techniques, and show that the use of LDPC gives the best result of reduction. Also, increasing the weight of modulation techniques improves the achieved results. Moreover, and comparing the results of imposing NN instead of the previously published work gives a slight enhancing in the PAPR reduction process.

In this work, using the NN reduces the added complexity at the receiver side since there is no need to send a control data that has been sent in the previously published work. The use of MIMO technology here just either for improving the system capacity or enhancing the systems performance.

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