IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2020.Doi Number

Sparse Index OFDM Modulation for IoT Communications

Hany S. Hussein[1,2](Senior Member, IEEE), Ahmed S. Mubarak[3](Member, IEEE), Osama A. Omer[2], Usama S. Mohamed[4] (Member, IEEE), and Mostafa Salah[3]

[1]Electrical Engineering Department, Faculty of Engineering, King Khalid University, PO Box 394, Abha 61411, Saudi Arabia
[2]Electrical Engineering Dept., Faculty of Engineering, Aswan University, Aswan 81542, Egypt
[3]Electrical Engineering Dept., Faculty of Engineering, Sohag University, Sohag, Egypt
[4]Electrical Engineering Dept, Faculty of Engineering, Assiut University, Assiut, Egypt

Corresponding author: Hany S. Hussein (hany.hussein@aswu.edu.eg).

The authors extend their appreciation to the Deanship of Scientific Research at King Khalid University for funding this work through research groups program under grant number (R.G.P.I /202/41).

ABSTRACT One of the greatest challenges facing the physical layer design of the internet of things (IoT) resides in the imposed constraint of very low power consumption. Recently, new modulation scheme termed OFDM with sparse index modulation (OFDM-SIM) has been introduced as an energy efficient multicarrier scheme (MCS). Although of its high energy efficiency (EE) and spectral efficiency (SE), OFDM-SIM cannot fulfill the IoT energy requirements owing to its high PAPR. In this regard, an enhanced OFDM-SIM is proposed in this paper as an energy efficient MCS for IoT communications. In particular, a novel clipping-compressive sensing (CS) based PAPR reduction technique for OFDM-SIM is proposed. In the transmitter (TX) side, considering the complexity constraints for IoT devices, the simple and low complex clipping method is exploited to deal with the PAPR issue. On the receiver (RX) side, a robust CS signal recovery scheme is proposed to deal with tough resulting clipping noise. Unlike high complex conventional CS-based schemes, the proposed scheme exploits the inherent sparsity of the received enhanced OFDM-SIM signal rather than clipping noise sparsity to achieve a low complex CS signal detection. Moreover, in this paper, the information-theoretic limits on sparsity recovery are exploited to derive an upper bound measure of the bit error rate (BER). The simulation results demonstrate the superiority of the proposed scheme, as it significantly enhances the overall system performance in terms of EE and PAPR reduction compared to the conventional clipped coded-OFDM.

INDEX TERMS IoT; OFDM-Sparse index modulation (OFDM-SIM); PAPR; Clipping; Compressive sensing (CS).

I. INTRODUCTION

Internet of things (IoT) assumes very low-power consumption through various strategies on different layers [1]. However, the power saving in physical layer for radio transmission and data acquisition has high impact on the overall energy efficiency (EE) of the system [2]. Single carrier or constant envelop modulation schemes with ideal high peak-to-average power ratio (PAPR) seems to as a natural choice for IoT. However, the most leading partners in wireless communication standardization 3GPP and IEEE have agreed on extending the orthogonal frequency division multiplexing (OFDM) scheme on the physical layer of IoT [3]. PAPR represents the main drawback of OFDM system that leads to a large power lose for preserving signal linearity. Traditionally, PAPR reducing without bit-error-rate (BER) performance degradation usually implies a corresponding complexity/overhead increase that may not be recognized in low cost and simple realization. In literature, OFDM with index modulation (OFDM-IM) has drawn intriguing attention owing to its superior performance enhancement in terms of energy efficiency (EE) and spectral efficiency (SE) [4-6]. In OFDM-IM is subset of space modulation (SM) techniques [7-9], whereas the information is conveyed through both the combinatorial pattern of activated subcarriers and the conventional M-ary amplitude-phase modulation. Thus, OFDM-IM can provide higher EE, noise immunity and lower complexity than the conventional OFDM. Motivated by its advantages, a special emphasize on the energy saving introduced by OFDM-IM in the context of IoT and wireless sensor network (WSN) [10-12]. Although of its appealing advantages, there are some challenges such as PAPR problem still need to be overcome in OFDM-IM.

Unfortunately, PAPR problem introduces a non-linear distortion that degrades the overall OFDM/OFDM-IM performance and limits its usage for IoT. In fact, even though it usually only activates the half number of subcarriers, both OFDM-IM and conventional OFDM have nearly the same high PAPR levels as reported in [5]. This is due to the fact that, PAPR is not significantly affected by the number of activated subcarriers [13]. Lately, sparse index modulation with OFDM (OFDM-SIM) [14-16] has been introduced as an elegant low power subclass of index modulation. In OFDM-SIM, the data is only conveyed by the indices of a very few active subcarriers without subcarrier grouping nor QAM modulation. This sparse activation in frequency domain is intended to maximize the EE of the OFDM system with comparable SE. Actually, the sparsity nature OFDM-SIM can be exploited to reduce PAPR without any PAPR reduction technique [15]. However, PAPR performance of OFDM-SIM is still needed to be further improved to meet the low power requirements for IoT systems.

Literately, many approaches have been introduced to reduce PAPR, which can be broadly classified into three groups: clipping, coding and probabilistic approaches [17]. With clipping method, a significant PAPR reduction can be obtained by simply cut the peak signal exceeds a specific threshold. Coding-based method give a good performance, but at the cost of spectral efficiency (SE) degradation. Finally, the probabilistic approaches associated with high computational complexity. Among these approaches, the low complex clipping method has been selected in most of the practical OFDM systems for PAPR issue mitigation.

Generally, the transmitted data of OFDM/OFDM-IM signal resides in its frequency domain. Hence, the detection process can be regarded as a spectral estimation problem. Conventionally, fast Fourier transform (FFT) is used at the OFDM/OFDM-IM receiver (RX) side, as a spectral detection algorithm. However, FFT belongs to non-parametric spectral estimation family, in which there is no prior information about the received signal is considered. Therefore, any distortion (i.e., clipping noise), will lead to spectral leakage and/or inter-carrier interference (ICI) and results in a sever bit-error-rate (BER) degradation. Many works have been proposed in literature to mitigate clipping noise at the RX to improve the BER performance. For example, channel coding rate is adapted in [18, 19] to cope with the rough clipping noise, but this solution associated with low SE and high system hardware complexity.

Furthermore, compressive sensing (CS)-based solutions [20] has been proposed in literature to mitigate clipping noise during signal detection, which will be explained in details in the related wok Section. The work in [21], is based on sparsity of the clipping distortion to enable the estimation of the clipping distortion effect before symbol detection. However, according to [21], the clipping level should be relatively high to ensure this sparsity, which in turns limits the achievable PAPR reduction levels.

In this paper, an enhanced OFDM-SIM scheme is introduced as an energy efficient multicarrier scheme for IoT networks. Specifically, the PAPR issue of the OFDM-SIM is investigated and a novel clipping-CS based PAPR reduction technique is proposed. In line with the requirements of IoT systems, the proposed scheme utilizes the simple and low complex clipping technique in the transmitter (TX) side to reduce the PAPR to the desired levels. On the RX side, CS is adapted to alleviate clipping noise and to support the signal detection process. Mainly, the proposed scheme is supported by high degree of embedded sparsity in frequency domain of the OFDM-SIM signal and the prior-knowledge of the amplitudes of the activated/inactivated subcarriers. Specifically, the inherent sparsity is exploited to resolve the RX signal under severe noise/distortion contamination. On the other hand, the activated/inactivated subcarriers prior information enable the proposed scheme to perform the detection utilizing the sparsity of RX signal rather than the estimation clipping noise. Thus, low clipping levels can be used in the proposed scheme to achieve significant PAPR reduction without any overhead /BER degradation in the TX/RX. Although the proposed CS-based clipping technique is based on sparsity in the time domain, it can be easily extended by embedding essential sparsity in any domain. Thus, there are many opportunities for applying the proposed PAPR reduction scheme on many OFDM systems as long as the sparsity in any domain is guaranteed.

The paper contribution can be summarized as follow:

- OFDM-SIM is introduced and investigated as a promising candidate solution for IoT systems.
- Exploring how the PAPR reduction meets sparse data detection in the OFDM-SIM.
- Enhanced OFDM-SIM scheme is proposed as an energy efficient / extremely low PAPR multicarrier scheme for IoT uplink transmission.
- Clipping-CS based PAPR reduction technique is proposed. The clipped signal is formulated into proper CS-based spectral estimation. Unlike conventional CS-based PAPR reduction approaches, a completely new formulation for CS-based PAPR reduction is introduced. Whereas the signal intrinsic sparsity is exploited instead of relying on the limited/ uncontrollable sparsity of the clipping interference. Thus, the limitations on clipping ratios are relaxed, which improves the proposed system flexibility in choosing between a wide range of PAPR reduction levels to fulfill the IoT low power requirements. In other words, the proposed approach guarantees extremely low PAPR (under low clipping level) without increasing the detection complexity nor BER degradation.
- BER performance is verified through driving the upper bound of average probability of error by the aid of information-theoretic limits of CS.
- Monte Carlo simulations for BER performance over additive white Gaussian noise (AWGN) and Rayleigh

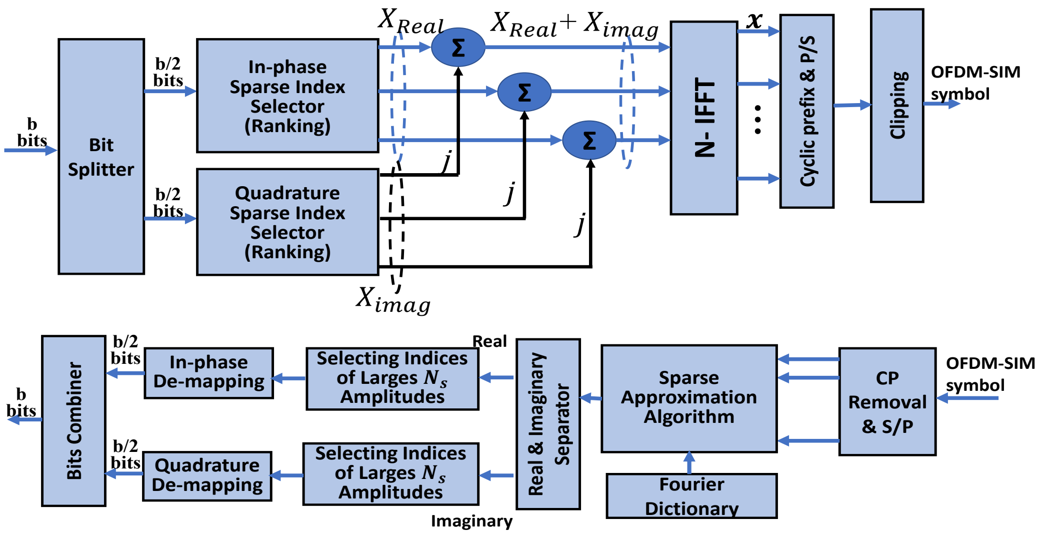

FIGURE 1. The Block diagram of the Enhanced OFDM-SIM system.

fading channels are performed and compered with the theoretical ones.

The rest of the paper is organized as follows: Section II discusses the related work. Section III presents the modeling of both the proposed scheme and the clipping distortion. The proposed scheme is presented in Section IV along analytical analysis of the error probability upper bound of the perfect support detection. Section VI presents simulation results and discussion. Finally, the paper is concluded in Section VII.

II. RELATED WORK

As mentioned previously, there are many challenges such as PAPR problem still need to be overwhelmed in OFDM-SIM scheme to be applicable for IoT applications. It is notable that PAPR results in nonlinear distortion which substantially decrease system performance.

In literature, many PAPR reduction technique have been proposed for OFDM systems [15-18, 22]. Among these techniques, clipping is implemented in OFDM practical systems to combat high PAPR because it is a very simple and effective. However, clipping could cause a significant increase in BER of the decoded signal at the RX. To address this problem, authors in [18, 19] introduced a channel coding-based technique to mitigate the rough clipping noise. However, this solution reduces the system SE and increases the system hardware complexity. In general, alleviating the clipping distortion impact comes at the expense of increased complexity, bandwidth expansion or data rate reduction.

Among the above works, CS-based solutions based on exploiting the sparse modeling of the clipping distortion have been proposed in literature to alleviate the clipping impact. However, most of CS-based schemes are associated with poor BER performance due to the vulnerability of CS scheme to the channel noise. In [23, 24], exploiting the sparsity of the clipping noise, the clipping noise estimation techniques have been introduced as a pre-processing step to compensate the clipping distortion effect before symbol detection at RX. However, according to [21], the clipping level should be relatively high to ensure this sparsity, which in turns limits the achievable PAPR reduction levels.

Works in [20, 21], are based the exploiting the amplitude feature of the clipped signal. Specifically, the samples with high amplitudes have higher probability to be clipped than those with smaller amplitudes. Hence, in [20, 21], samples with higher amplitudes were classified as unreliable samples and excluded while the detection process, and only the reliable ones with smaller amplitudes were considered.

Regarding the PAPR reduction for OFDM-IM systems, the conventional techniques for the plain OFDM can be reused, but with regarding of the special features of OFDM-IM signals. In [25], the conventional active constellation extension (ACE) technique have been extended to the OFDM-IM systems. Particularly, an optimized dither signal in idle subcarriers through the convex programming solution have been introduced to mitigate the PAPR issue [25]. However, this solution associated with very high computational cost regarding mobile TX. Hence, the multicarrier transmission remains a problematic choice for uplink transmission even under index modulation OFDM as well as in the plain OFDM.

Authors in [26] introduced an iterative search algorithm instead of convex optimization while extending ACE to OFDM-IM systems, which significantly enhanced the system performance.

In this paper, a novel clipping-CS based PAPR reduction technique for OFDM-SIM is proposed. In the proposed scheme, clipping technique is applied to combat high PAPR because it is a very simple and effective, but with regarding of the unique features of the OFDM-SIM signals.

Particularly, the unique frequency domain embedded sparsity feature of OFDM-SIM signals is considered, which in turns allow hard and low-level clipping implementation without overhead or BER degradation.

Accordingly, higher levels of PAPR reduction can be reached with the proposed scheme than clipping noise estimation-based techniques such as in [26, 27]. Besides sparsity feature exploitation, prior-knowledge of the amplitudes of the activated/inactivated subcarriers are exploited by the proposed scheme to perform a low complex CS-based detection at RX. Unlike [18, 19], due to robustness and reliability of the proposed scheme, there is no need for channel coding for mitigating the clipping distortion and the channel noise As will be indicated in the simulation Section, EE and humble hardware complexity of the proposed OFDM-SIM scheme make it a promising candidate for IoT systems.

III. SIGNAL MODEL

In this Section, the system model of the OFDM-SIM is introduced. In this model, the detection process of is interpreted and formulated as a spectral estimation problem regarding the information resides in the frequency domain. Moreover, the modeling of the clipping process is introduced in this Section.

A. OFDM-SIM SYSTEM MODEL

The transceiver structure of the OFDM-SIM system is depicted in Fig. 1. Considering N_s sparse active subcarriers out of a total available N_T orthogonal subcarriers. Therefore, there are $N_C = \binom{N_T}{N_S}$ different pattern combinations, where $\binom{\cdot}{\cdot}$ is the binomial operator. Any combination pattern C_j of subcarriers can be written as a set of indices as follows:

$$C_j = \{i_{N_s}, i_{N_s-1}, \dots\dots, i_k, \dots\dots, i_2, i_1\}, \qquad i_k \in [1, N_T] \quad (1)$$

Accordingly, the combinatorial coded bits which could be selected can be expressed as $b_{SIM} = 2\left\lfloor log_2 \binom{N_T}{N_S} \right\rfloor$ bits, where $\lfloor . \rfloor$ denotes to the floor to the nearest integer operator.

Moreover, the double indexing on real/imaginary spaces is employed. The bit combinations are assumed to be sorted in a predefined order such as lexicographic order avoiding the exhaustive listing for all combinations such introduced in [27]. For each possible combination, the corresponding index can be simply expressed as follows [15, 16]:

$$I = \binom{i_{N_s}}{N_s} + \dots\dots + \binom{i_2}{2} + \binom{i_1}{1}. \quad (2)$$

As shown in Fig. 1, in TX side, the incoming block of b bits to be transmitted at any specific time is divided into two distinct sets for both indexing the real and the imaginary spaces independently. Therefore, the generated $N_T \times 1$ frequency domain signal is $X = X_R + J\, X_I$, where X_R and X_I represent the real and the imaginary of X and can be represented as:

$$X_{R/I} = \begin{cases} \pm 1 & \forall\, i \in C_j \\ 0 & otherwise \end{cases} \quad (3)$$

Both X_R and X_I consist of $(N_T - N_S)$ null subcarriers and $N_S << N_T$ active subcarriers which are selected based on incoming bit stream. Then, X is converted into $N_T \times 1$ time domain signal, $\boldsymbol{x}$, by applying the IFFT as follows:

$$x(n) = \frac{1}{N_T} \sum_{k=0}^{N_T-1} X(k) e^{j\frac{2\pi}{N_T}kn} \; for\; 0 \le n \le N_T - 1 \quad (4)$$

Or equivalently in matrix form as:

$$x = F^H X, \quad (5)$$

where, F^H denotes the $N_T \times N_T$ Hermitian transpose of the discrete Fourier transform (DFT) matrix.

Each column of the DFT matrix represents a complex sinusoidal (subcarrier). Hence, the resulting time domain vector $\boldsymbol{x}$ becomes a sparse in frequency domain as a sparse linear combination of subcarriers.

Actually, the main differences between OFDM-IM [28] and OFDM-SIM [15, 16] reside in: 1) OFDM-SIM is supported by inherit sparsity feature enabling CS-based detection. 2) OFDM-SIM characterized by a high noise immunity because it does not employ QAM for the activated subcarriers (i.e., it hardly depends on the amplitude information). 3) OFDM-SIM has a larger combinatorial space than OFDM-IM, this due to the fact that in OFDM-SIM combinatorial indexing is performed on the overall frequency space by selecting small number of active subcarriers from a whole space. On the other hand, in OFDM-IM grouping is utilized and half number of subcarriers from each group is activated. 4) unlike OFDM-IM, channel coding is not no longer needed for OFDM-SIM due to it inherits robustness against noise. 5)The same sparse detection algorithm can be applied for sparsity detection of data in frequency domain and the channel sparsity in frequency domain [14].

B. PAPR MODEL

The PAPR of the time domain signal can be given as:

$$PAPR \triangleq \frac{P_{max}}{P_{avg}} = \frac{\underset{0 \le n \le N_T-1}{max}\{|x(n)|^2\}}{\frac{1}{N_T}\sum_{n=0}^{N_T-1}|x(n)|^2}, \quad (6)$$

where P_{max} and P_{avg} are the maximum and average power of the transmitted OFDM-SIM symbol, respectively.

Peak amplitudes of the generated OFDM-SIM symbol can be clipped according to the following criterion:

$$x_c(n) = \begin{cases} x(n), & for\; |x(n)| \le \gamma \\ \gamma e^{j \arg[x(n)]}, & for\; |x(n)| > \gamma \end{cases}. \quad (7)$$

where γ is the clipping threshold.

It is better to express the degree of clipping in-terms-of the well-known clipping ratio (CR), where $CR = \frac{\gamma}{\sqrt{P_{avg}}}$.

C. CLIPPING DISTORTION MODEL

Mainly, modeling the clipping distortion depends on the clipping threshold γ, which in turns affect the achievable PAPR reduction PAPR level [29]. Consequently, the most common clipping distribution schemes have been reported in literature can be classified in the two following categories

1) ADDITIVE SPARSE (IMPULSIVE) MODEL

In this model, the clipping range may be limited to high clipping ratios ($CR \geq 1.5$). Hence, the clipping event happens in few (sparse) times during one symbol interval.

$$x_c(n) = x(n) + c(n), \tag{8}$$

where $c(n)$ represents a sparse impulsive noise (distortion).

However, for maintaining clipping noise sparsity in time domain, high clipping levels are applied. Which in turns limits the achievable PAPR reduction levels [20-24, 30].

2) AWGN MODEL

In this model, hard clipping is applied through lower clipping ratio ($CR < 1.5$), which results in sparsity degree reduction for the clipped samples. This modeled can be mathematically expressed as attenuated signal pulse AWGN component as follow [31]:

$$x_c(n) = \alpha x(n) + d(n), \tag{9}$$

where d represents AWGN component. α is the attenuation factor and can be expressed as follows:

$$\alpha = 1 - e^{-CR} + \frac{\sqrt{\pi}\ \ CR}{2}\, erfc\,(CR), \tag{10}$$

Obviously, according to the AWGN model the overall distortion is modeled also as severe Gaussian noise enabling to deal with the clipping effect just as signal to noise ratio (SNR) loss [31].

In the proposed scheme, the AWGN clipping model will be exploited where a hard clipping is used to achieve higher PAPR reduction levels.

IV. PROPOSED CLIPPING AND CS-BASED PAPR REDUCTION SCHEME

In this Section, the proposed clipping-CS based PAPR reduction technique for OFDM-SIM will be discussed. Whereas a simple and low-cost clipping technique with lower clipping levels is applied in the proposed scheme TX to reduce the PAPR. In the RX side, exploiting the sparsity feature, a CS-based approach is applied for signal detection and clipping noise mitigation.

A. CLIPPING SCHEME AT TX

As shown in Fig. 1, the signal is generated though a simple IFFT operation. Then, a hard clipping with low threshold applied to address the PAPR issue in the TX side. Sensibly, the achievable PAPR reduction levels will be depending on the clipping degree, i.e., lower clipping threshold results in high PAPR reduction value and vice versa.

On the other hand, hard clipping at the TX results in more distortion at the RX, which in turns complicates the detection process at the RX. As, the clipping distortion should be evaluated before deciding the optimal parameters that fitting the operating spectral estimator at RX. From this perspective, the relation between the clipping distortion and the achievable PAPR levels should be investigated to bound the performance limits of the proposed scheme.

By decreasing clipping ratio (through lowering clipping threshold), the percentage of clipped samples increases. Hence, the spectral estimation process is performed based on a lower number of unaffected samples. In this paper, the signal clipping distortion is represented as percentage of clipped samples to the total number samples per symbol.

Mathematically, the percentage of clipped samples during one symbol interval may be approximated according to the level-crossing rate approximation as [13]:

$$P(r > \gamma) \approx \frac{\gamma\, e^{-\gamma^2}}{\bar{r}\, e^{-\bar{r}^2}} \tag{11}$$

where $r = |x|$ represents the envelop of a Rayleigh distribution with the probability density function (pdf) of:

$$f(r) = 2\, r\, e^{-r^2} \tag{12}$$

Also, $\bar{r}$ represents certain threshold less than clipping threshold γ.

B. PROPOSED CS-BASED SCHEME AT RX

In this paper, to overcome the degradation of FFT performance under clipping distortion, CS-based super-resolution spectral estimation is utilized to perform the signal detection task at RX.

Specifically, the high sparsity feature of OFDM-SIM is exploited to perform a robust CS-based sparsity detection to handle the tough clipping distortion at RX.

In this Section the problem formulation for the proposed CS-based detection scheme is introduced along with the supported theoretical bases from CS theory.

Aiming to formulate the proposed CS problem, we propose two directions for considering the intercepted clipping signal distortion at the RX side. Specifically, the received clipped signal is interpreted as *highly noisy* signal or as a *signal with missing samples*.

According to the first direction, the clipping noise is regarded as an additional source of additive white Gaussian noise which results in the overall system SNR degradation. Accordingly, the CS problem is reformulated as a compressive spectral estimation under sever noise conditions. Particularly, the sparsity constraint on OFDM-SIM signal introduces a higher order of noise immunity for sparse vector estimation under heavy noise contaminated measurements [32, 33].

IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

On the other hand, the second direction is based on dropping out the severely clipped samples from the detection process. Hence, the problem is modeled as compressive sampling problem where the high dimensional sparse signal can be extracted from the lower dimensional measurements (under sampled). According to the second direction, the received signal is considered as irregularly sampled signal or a signal with randomly missing samples. The missing/unequally sampled signal corresponds to an underdetermined linear system that has not a unique solution, however, the sparsity constraint enables finding unique solution according to CS theory [30, 33]. The CS problem formulation according to the previously mentioned directions can be mathematically formulated as following:

1) HIGHLY NOISY RECEIVED SIGNAL

In general, Eq. (7) can be rewritten in the summation form as follows where the transmitting channel is assumed as AWGN for simplicity:

$$y_{rec}\ (n) = \ \alpha\, x(n) + \underbrace{d(n) + \nu(n)}_{e_T}, \qquad (13)$$

where $d(n)$ is the clipping distortion and it can be formed as,

$$d(n) = \begin{cases} 0, & |x(n)|\ \le \gamma \\ (\gamma - |x(n)|)e^{j\arg[x(n)]}, & |x(n)|\ > \gamma \end{cases}$$

Under low clipping ratio, the effect of the clipping distortion can be modeled as AWGN noise, $d{\sim}(\mu_{clip}, \sigma_{clip})$. The transmitted signal incurs the clipping distortion besides to the channel additive noise $\nu(n)\ {\sim}(\mu_n\ , \sigma_n)$, so, the received signal $y_r(n)$ can be rewritten as**:**

$$y_{rec}(n) \approx \ \alpha\, x(n) + e_T \qquad (14)$$

where $e_T = \ \nu(n) + d(n)$, combines all sources of errors (even equalization error that may be neglected under full channel knowledge).

By regarding the fact that, the total distortion e_T is as a summation of two independent random variables with normal distributions, the total distortion follows the same normal distribution with $e_T{\sim}(\mu_{clip} + \mu_n\ , \ \sigma_{clip} + \sigma_n)$. At this end, the receiver detection problem can be reformulated as the sparsity-based spectral estimation problem as follows:

$$y_{rec} = DX + e_T\ . \qquad (15)$$

2) CLIPPED SAMPLES DROPPING OUT

Here the clipping problem is formulated as a CS problem with underdetermined linear system. Whereas, during the signal estimation process, the system is classified the samples of the received signal. In which, the samples with the highly likelihood that they were clipped in the TX side, are dropped from the received signal. Thus, a short length version of the received signal is generated based on the process. Hence, the generated signal y_M has $M < N$ samples, where N is the number of samples of the original received signal. Hence, the samples of the new signal y_M are seemed to be randomly selected from the original received signal. Consequently, the problem can be mathematically formulated as the well-known compressive sensing model [10]:

$$y_l\ = \ \Phi\Psi\ \mathrm{X} + e, \qquad y_M \overset{\text{def}}{=} \forall\, y_l \neq 0 \qquad (16)$$

where y_M has $M < N$ random samples of the original measurement signal y_{rec} that has N_S sparse representation in a given orthogonal dictionary Ψ, and Φ represents the measurement matrix that randomly selects the samples.

The orthogonal matrix Ψ is $N \times N$ full rank Fourier dictionary, whose columns are complex sinusoids of orthogonal frequencies. While the measurement matrix Φ in our case is look like $N \times N$ semi-identity matrix $\mathbb{I}$ with rank equal to $M < N$. We mean by semi-identity matrix that, Φ with zero off diagonal elements and its diagonal is given by $diag(\Phi(l,l)) \in [0,1]$ where $diag(.)$ gives the matrix diagonal and $diag(\Phi)$ has M ones elements and $N - M$ random zero elements. Thus, the measurement matrix Φ is working as spike (randomly) basis selection over orthogonal dictionary Ψ. Fortunately, the spike matrix Φ and the Fourier Dictionary are maximally incoherent (minimum coherence, $\mu = 1$), as it was reported in [10], which improves the performances of proposed system.

Here, Φ is constructed randomly and independently in each OFDM symbol detection process. Specifically, the received time domain samples with the highest absolute value are most likely clipped samples, thus they are dropped i.e., their corresponding elements/locations in $diag(\Phi)$ are set to zero. Therefore, Φ will contains $M < N$ rows, and each row contains one nonzero element in different locations while the other $N - M$ rows contain only zeros in their elements. Thus, when the zero rows in Φ are eliminated its size will be reduced to $M\ \times N$, The result of $\Phi\Psi$ is then will be $\Phi\Psi \equiv D$ and $D\ is\ M\ \times N$.

One example of a sampling pattern that used for constructing the measurement matrix is provided in Fig. 6. Moreover, in the proposed scheme, the DFT matrix is exploited as orthogonal dictionary.

By take a deep look in the proposed system Eq. (15) and Eq. (16), we will find that the two system are nearly apply the same concept. We can say that $\Phi\Psi \equiv D$, where Φ in Eq. (15) is $N \times N$ identity matrix I, thus D becomes over-complete dictionary. While in Eq. (16) , $\Phi\ is\ N \times N$ semi-identity matrix $\mathbb{I}$ with rank equal to M or the sparse signal is sampled in lower rate than traditional Nyquist rate where, the measurement matrix excludes samples with the highly likelihood that they were clipped. And since the samples are naturally clipped random, thus we can confirm that Φ in Eq. (16) is a random measurement matrix.

In terms-of the sparsity detection, the sparseness of the solution for the problems in Eq. (15) and Eq. (16) can be imposed explicitly (with ℓ_0-norm) while minimizing the error as follow:

$$\min\|X\|_0\ \ S.t\ \ \|y - \mathrm{D}\,\mathrm{X}\,\|_2^2\ \ < \varepsilon. \qquad (17)$$

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3024157, IEEE Access

Algorithm 1: Pseudo Code for the Proposed Algorithm

1- **Inputs**: y_p, No. of iterations: i, sparsity order: Ns/NT.
2- **Initialize estimator**: covariance matrix $R \leftarrow I$.
3- Processing the equalized received signal y_{eq} as follow: -
4- **For** $j = 1{:}\ i$
- **For** k=0: N_T-1

$$X(k) = \frac{a^H(w_k)R^{-1}\, y_p}{a^H(w_k)R^{-1}\, a(w_k)}.$$

- **End for**

$$R = \sum_{k=0}^{N_T-1} |X(k)|^2\ a(w_k)\ a^H(w_k)$$

5- **End for**
6- Return estimated spectra vector X.
7- Applying energy detection on X in the real/imaginary spaces to detect the high energy Ns indices.

$$Ind_R = \max_{N_S}(|real\ (X(k))|)$$
$$Ind_I = \max_{N_S}(|img\ (X(k))|)$$

8- **Output:** $Index \rightarrow Bits$ // combinatorial conversion.

where $\|\ \|_0$ denotes ℓ_0-norm, that always be replaced by another measures of sparsity for its computational unfeasibility.

Many sparsity-based estimators can be addressed for solving the problem in Eq. (17). For instance, the standardized Least Absolute Shrinkage and Selection Operator (LASSO) optimization problem [34] can be applied, through implicitly enforcing the sparsity constraint on the parameter vector by including ℓ_1-norm in a convex optimization problem while minimizing the noise through including ℓ_2-norm on the noisy term:

$$\hat{X} = \arg\min_{\mathrm{X}} \left(\frac{1}{2}\|\mathrm{y} - \mathrm{D\,X}\|_2 \ + \ \mu\|\mathrm{X}\|_1\right) \quad (18)$$

The main solving approaches [12] for the formulated problem in Eq. (18) go around either convex optimization [34, 35] or iterative greedy algorithms [36, 37]. However, iterative greedy algorithms have lower computational complexities, thus it will be recommended.

Several iterative approaches [34] can be addressed for solving the sparse linear regression formulated in LASSO problem Eq. (18). Without loss of generality, in this paper the iterative adaptive approach (IAA) and missing data IAA (MIAA) [38] will be exploited here to validating the two CS-based proposed systems in Eq.(15) and Eq.(16), respectively.

However, the IAA/MIAA is adapted to cope with the tough clipping distortion problem in the proposed scheme. Moreover, the adopted IAA and MIAA are applied on two different version of preprocess input single y_p. Whereas the y_p for IAA is just the channel equalized received signal. With the assumption that the channel state information (CSI) is known at the RX, it is easily to equalize the received signal.

The pseudo-code of the adapted IAA for estimating the sparse vector support is summarized in Algorithm 1.

As shown in Algorithm 1, the spectral estimation at any frequency ω_k from the orthogonal frequency grid ($k = 0,1, \ldots\ldots, N_T - 1$), is found iteratively by estimating $X(k)$ and the covariance matrix R (initialized by identity matrix I) until convergence.

$X(k)$ and R can be expressed as follows:

$$X(k) = \frac{a^H(\omega_k)R^{-1}\,\mathrm{y}}{a^H(k\omega_k)R^{-1}\, a(\omega_k)} \quad (19)$$

$$R = \sum_{k=0}^{N_T-1} |X(\mathrm{k})|^2\ a(\omega_k)\ a^H(\omega_k) \quad (20)$$

where $a(\omega_k)$ denotes the complex exponential subcarrier in time domain which represents the k-th column vector in the dictionary matrix D.

Under IAA approach, the introduced CS-based solution just tries to enhance the noise immunity of the sparse estimation process. The receiver is interested in estimating the sparse frequency activation represented in X over Fourier dictionary $D \equiv F^H$ in the presence of the combined channel and clipping noise e_T. In other words, the clipping noise is simply regarded as a naturally added noise as in Eq. (13). Thus, the sparsity estimation problem Eq. (15) can be thought as an estimation of the subspace (subcarriers) in the D domain where, the received signal y_{rce} is approximately defined in that domain under sparse mapping constraint.

While, to solve Eq. (16) the MIAA approach is exploited. However, Algorithm 1 is also used to implement the MIAA, but with a different y_p. To find y_p for the MIAA approach more preprocessing steps are applied received signal y_{rec} before apply Algorithm 1. After applying the channel equalization process on the received signal and with knowledge of the clipping ratio ($i.e., CR$), the indices of the samples that they most likely were clipped are estimated then excluded from the received equalized vector as well as its corresponding rows in the dictionary, D.

$$y_M = \Phi_{M\,\mathrm{N}}\ y_{rec} \equiv \Phi\Psi\ \mathrm{X} + e \ \equiv \theta\, X + e\,, \quad (21)$$

and $\quad a_M(\omega) = \Phi_{M,N_T}\ a(\omega)\,,$

where, Φ denotes a $M \times N_T$ measurements matrix, that excludes N_{miss} time samples corresponding to the estimated clipped samples and $\theta \equiv \Phi\Psi$ is called the sensing matrix. After obtaining y_M and $a_M(\omega)$, Algorithm 1 is used with $y_p = y_M$ and $a(\omega) = a_M(\omega)$ to solve Eq.(16).

However, by excluding excessively clipped samples from the spectral estimation operation, the impact of clipping noise is relaxed to some extent. Moreover, this approach has lower computational complexity arising from involving lower number of samples in the estimation process. The overall performance of the system will be discussed in the simulation analysis Section.

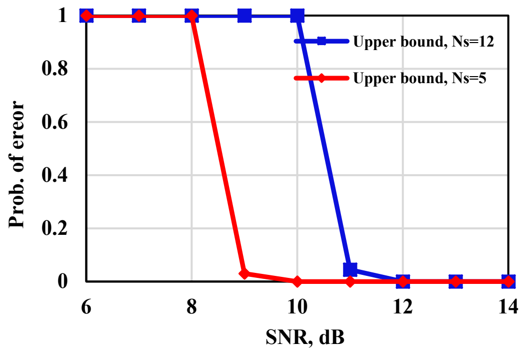

Figure 2: **Upper Bound of the Error Prob. for exact Support Recovery-based on 60% of signal samples ($CR = 1$).**

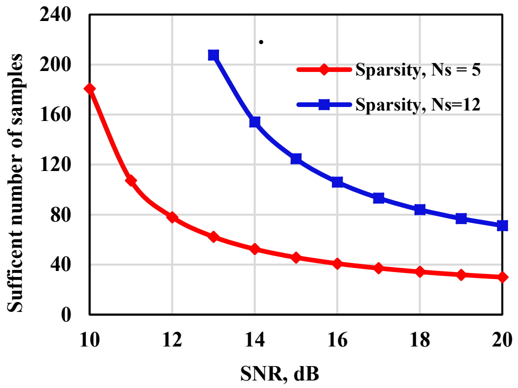

Figure 3: **Sufficient number of samples for exact support recovery corresponding to different SNRs levels, with $N = 256$ samples**

From another side, the selection of measurement/sensing matrix has high impact on the performance of the CS estimation. The CS imposes two essential conditions (i.e., restricted isometry property and basis incoherence) on the employed sensing matrix to ensure a comprisable representation of a higher dimension signal in-terms-of lower dimensional measurements [12].

$$\mu(\Phi,\Psi) = \sqrt{N} \max_{1\le k,j\le N} \left|\langle \varphi_k , \psi_j \rangle\right| \qquad (22)$$

The basis coherence (correlation) $\mu(\Phi,\Psi)$ between measurement matrix and the representing dictionary should be kept as minimum as possible where $\mu(\Phi,\Psi) \in [1, \sqrt{N}]$. Minimizing coherence factor leads to minimum number of needed measurements [12]. Roughly, the number of measurements M should obey the following rule for extracting the correct sparse support with overwhelming probability.

$$M \ge C\mu^2(\Phi;\Psi)\, N_S \log N_T, \qquad (23)$$

where C is a small constant, it may be assumed $C = 2$ [12].

Since the Φ is a spik matrix, and Ψ is an orthogonal Fourier matrix, hence the minimal coherence or maximal incoherence will be attained i.e., $\mu(\Phi,\Psi) = 1$ as it was reported in [10], and $M \ge 2\, N_S \log N_T$.

V. THEORITICAL ANALYSIS OF ERROR

From the communication point-of-view, it is common to drive the analytic expressions of the BER performance (in a closed-form) that often agrees with the exact performance arising from Monte Carlo simulation. However, under compressive sensing solutions, it is convenient to have only an upper-bound error probability where the derivation of the exact error expression is too exhaustive [39].

The sparsity recovery of X means the recapture of the non-zero values N_S. The estimated vector $\hat{X}$ appears as approximate sparse vector where the supposed null elements may have finite non-zero values due to additive noise. Hence, after applying the CS-based estimating algorithm, the energy detection is applied for largest N_S supporting bases. So, the estimated support regards only the N_s-largest elements of the estimated vector $\hat{X}$ as $\hat{S} = \left\{ i\colon \hat{X}_{i_1} \ge \hat{X}_{i_2} \ge \cdots . \ge \hat{X}_{i_{N_S}} \right\}$ indices of the activated (the most salient in energy) subcarriers, i.e., identifying the exact set of indices among $\binom{N_T}{N_S}$ possible different sets. However, this problem is defined as the exact (perfect) support recovery of sparsity pattern. Whereas element (index) missing/mismatch leads to erroneous sparsity recovery because each combination maps to a different bit stream.

Generally, the error probability of exact support recovery can be analyzed in-terms-of a maximum likelihood (ML) decoder by assuming that all $\binom{N_T}{N_S}$ possible subsets within N_S elements are equiprobable [11, 40]. However, the error event happens when the estimated support does not coincide with the true support, $P_e = \Pr(S \neq \hat{S})$. Hence, the average error probability of exact support recovery is defined as:

$$P(E) = \frac{1}{\binom{N_T}{N_S}} \sum_i \mathrm{P_r}\left(\hat{S} \neq S_i \mid S_i\right) \qquad (24)$$

Then the average error probability can be stated as [40]:

$$P(E) \le \sum_{i=1}^{K\equiv N_S} 2^{-M\, f(\rho)}, \qquad (25)$$

and

$$f(\rho) = \frac{1}{2}\log\left(1 + (1-\rho)\frac{2i\,\sigma^2\, SNR}{M} \right) - \frac{1}{4M}\log 4 - \frac{\log\left(\binom{N-N_S}{i}\binom{N_S}{i}\right)}{M} \qquad (26)$$

where M represents number of measurements, N total number of samples, $\rho \in [\frac{1}{\sqrt{N}}, 1]$ denotes the correlation coefficient (related to coherence) between columns of the sensing matrix and the coefficient of the support and it may be assumed fixed and equal (for the non-zero elements only) $\sigma = |X_i|$, hence, $\sigma^2 = \frac{SNR}{N_S}$. It is worth to that, $\rho = \sqrt{M}$, where the sensing matric is resulting from the multiplication of spike matrix and Fourier matrix.

TABLE I. SIMULATION SETUP PARAMETERS

Parameters	Coded- clipped OFDM, [19]	Proposed clipped OFDM-SIM
Total No. of subcarriers (N)	256	256
Subcarrier spacing	15 kHz	15 kHz
Total No. of active subcarriers (N_{active})	256 (100%)	$N_s \in (5,12)$
Modulation scheme	BPSK/QPSK	On/OFF
Channel Model	AWGN & Slowly fading	
Channel length	10	10
CP length (L)	16	16
Channel coding	1/4 CC	Not employed
Clipping ratio	1 $(0dB)$	

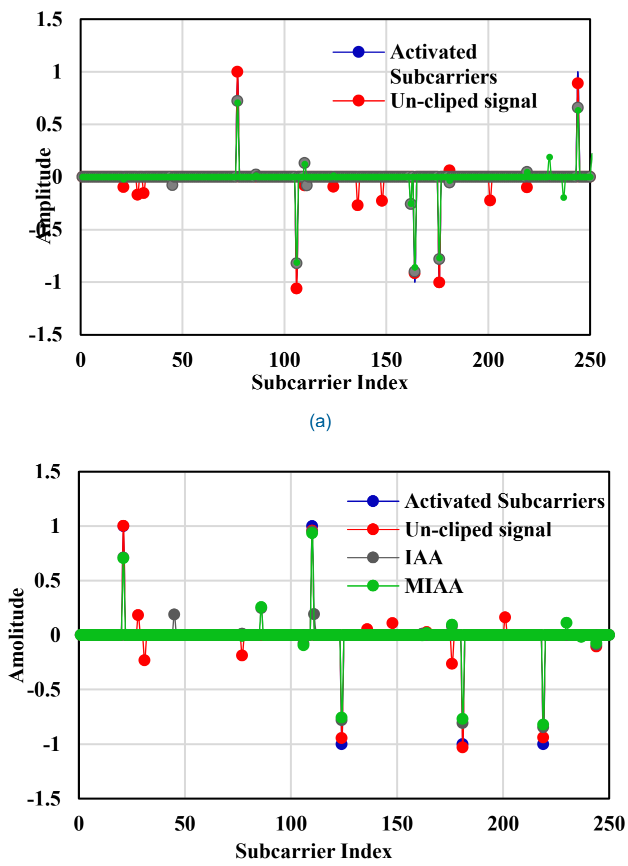

Figure 4: **Sparsity detection ($Ns/Nt = 5/256$) through IAA/MIAA under $SNR = 4\ dB\ and\ CR = 1$ (a) Estimated subcarriers for real indexing space (b) Estimated subcarriers for Imaginary indexing space.**

The upper bound of error probability can be demonstrates as shown in Fig. 2, where the clipping ratio is fixed at CR=1 that corresponds to clipping/missing about 40 % of the signal samples, for the two sparsity levels, $N_s \in [5,12]$. Whereas the sparsity level corresponds to the amount of data conveyed by the signal. Thus, this figure reflects the impact of the signal sparsity on the probability of error. Signal with high sparsity (less activation) enjoys more noise immunity than less sparse signals. It is worth to note the abrupt dropping of probability of error at certain critical SNRs points may be defined as critical points. For SNRs lower than critical points, almost there is low probability for detecting the correct signal support. It may be called as SNR cutoff.

From design point of view, the conditions of guaranteed exact support recovery may appear more helpful through introducing bounds for minimum SNR and the minimum number of measurements (M) at certain sparsity level ($S = \frac{N_S}{N_T}$) as follows.

$$SNR_{min} = \Omega\left(\log_2(N_T)\right) \qquad (27)$$

$$M = \Omega\left(\frac{N_S \log_2\left(\frac{N}{N_S}\right)}{\log_2\left(1+\left(1-\frac{1}{\sqrt{N}}\right)\frac{SNR}{N_S}\right)}\right) \qquad (28)$$

By preserving the minimum required SNR, the number of measurements (M) remains a function of sparsity level and the operating SNR. Clear representation of that relation can be found in [39] as

$$M > \left(\frac{4\log\left(\exp(1)\sqrt{\alpha-1}\right)}{\log\left(\frac{SNR^2}{2N_s\exp(1)}\right)}+1\right)N_S \qquad (29)$$

where $\alpha \equiv \frac{N_T}{N_S}$.

Fig. 3 demonstrates the dependence of the required lower bound of the number of samples on the operating SNR for guaranteed support recovery. For too little measurements (samples), the correct support recovery fails with high probability. Similar to SNR cutoff, there is a measurement cutoff for number of measurements lower than critical measurements, M.

VI. SIMULATION RESULTS

In this section, the superiority of the proposed clipped sparse index modulation (OFDM-SIM) is examined in terms of BER enhancement against the conventional coded and clipped OFDM scheme (with BPSK/QPSK) under the same effective SE and clipping ratio (similar PAPR levels) for fair comparison.

A. SIMULATION SETUP

Our simulation parameters are similar to that used in [19]. The simulation is running on $N_T = 256$ under AWGN and slow Rayleigh fading channels. To reduce the clipping effect, the coded OFDM in [19] relies on two stages of convolutional channel coding with rate 1/2, that correspond to a net channel coding rate of 1/4. Both BPSK and QPSK are applied on subcarrier modulation. On the other hand, the proposed scheme relies on a sparse subcarrier activation with orders of N_s/N_T = 5/256 and 12/256 subcarriers per real/imaginary spaces for providing almost the same effective SE of the conventional OFDM [19]. Proposed scheme does not employ QAM modulation nor channel coding. The sparsity adaptation, $N_s \in [5,12]$, corresponds to the conventional concept of adaptive modulation. Moreover, the key simulation parameters are shown in Table I.

The modified IAA/MIAA (Algorithm 1) is applied for a detection algorithm with 50 iterations as upper bound condition for convergence.

B. RESULTS AND DISCUSSION

Figure. 4 shows an example for indexing recovery from real/ imaginary subcarrier spaces under $SNR = 4\,dB$ and $CR = 1$. The activated subcarriers estimated amplitudes may vary slightly from actual amplitudes due to the channel noise and clipping distortion. However, the activated subcarriers still can be distinguished from null subcarriers clearly.

The relationship between the percentage of clipped samples and the average PAPR at different CR values via Monte Carlo simulation is indicated in Fig.5. For example, under $CR = 1$, $PAPR = 2dB, \gamma \approx 4.89$, and $\bar{r} = 4.8$, the resulting clipping percentage is nearly 40% of total samples.

As indicated in Fig. 5 that; due to the inverse proportion relation it is a matter of trading off between the mount of clipping distortion and the achievable PAPR level ratio.

In the proposed CS-based scheme, regarding to our strategy of dropping out the clipped samples, the measurement matrix excludes clipped samples that are random in nature. For instance, Fig. 6, demonstrates an example of the random sensing patterns where the estimated missed samples instances correspond to clipping events.

Fig. 7, shows the PAPR performance for clipped and unclipped OFDM and OFDM-SIM schemes according to different N_s and CR values. As shown, all unclipped schemes exhibit nearly the same PAPR levels around 11 dB. On the other hand, an extremely low PAPR about 2 dB is achieved through applying the clipping technique with $CR = 1$ (0 dB) on the conventional OFDM and the proposed OFDM-SIM schemes. Moreover, less than 2 dB PAPR is attained at $CR = 0.8$. For, example, as shown in Fig. 7, the proposed OFDM-SIM without clipping with N_s=5 archives about 9.8 dB PAPR value, while this value is reduced to be about 1.9 dB using the proposed OFDM-SIM with N_s=5 and $CR = 0.8$. Which clearly highlight the superiority of the proposed scheme with the clipping technique in alleviating the PAPR issue.

The BER performance comparisons of the proposed scheme, the unclipped SIM scheme, the coded-OFDM [19] under both AWGN and a slowly fading channel is shown in Fig. 8, and Fig. 9, respectively. The simulations in Fig. 8, and Fig. 9 are performed with $\text{CR} = 1$, and $\text{PAPR} = 2$ dB for the clipped schemes. As shown in these figures, the proposed scheme outperforms corresponding coded-OFDM scheme under the same effective SE and PAPR level. Thanks to the enhanced sparsity structure of the proposed scheme, the sparsity based-spectral estimation exhibits higher noise immunity than conventional coding protection.

Anyway, in terms of BER, the proposed scheme outperforms the clipped and coded-OFDM scheme. Moreover, Fig.8 shows comparisons among the different simulation results for the different schemes and the theoretical analysis results of the theoretical upper bound of error. These comparisons indicate the accuracy of the upper bound theoretical analysis of error, where all the compared simulations respect this theoretical upper bound. Also, the simulating error probability respects theoretical upper bound of error as shown in Fig.8. More specifically, by regarding IAA performance, the proposed clipped SIM-OFDM ($Ns = 5$) outperforms corresponding coded and clipped OFDM (BPSK) by about 6 dB. Also, the clipped SIM-OFDM ($Ns = 12$) outperforms the corresponding the coded and clipped OFDM (QPSK) with about 8 dB gain. The introduced BER performance gain may be exploited for further reducing PAPR levels lower than 2 dB through applying lower clipping ratios as (CR=0.8).

However, by observing the performance difference between the two followed estimators IAA and MIAA, it seems that MIAA trades the gain of IAA by the computational complexity. It reduces the number of samples involved in the processing on the cost of gain reduction. IAA approach exhibits better performance than MIAA by about 4 dB.

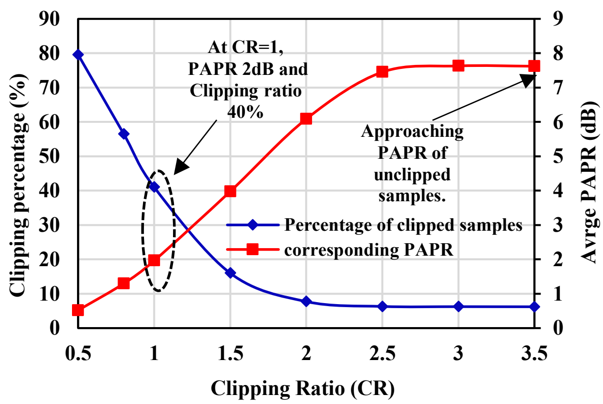

Figure 5: **Impact of clipping ratio on the Percentage of affected samples & average PAPR.**

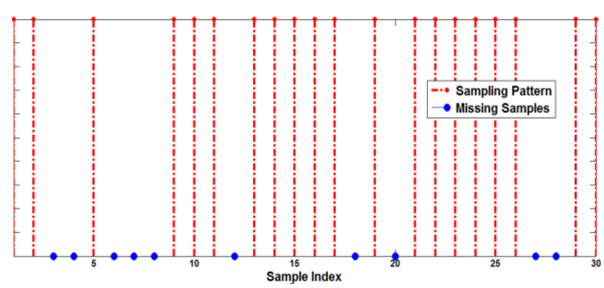

Figure 6: **Example of sensing pattern in time domain, where the missed samples corresponds to clipping instances.**

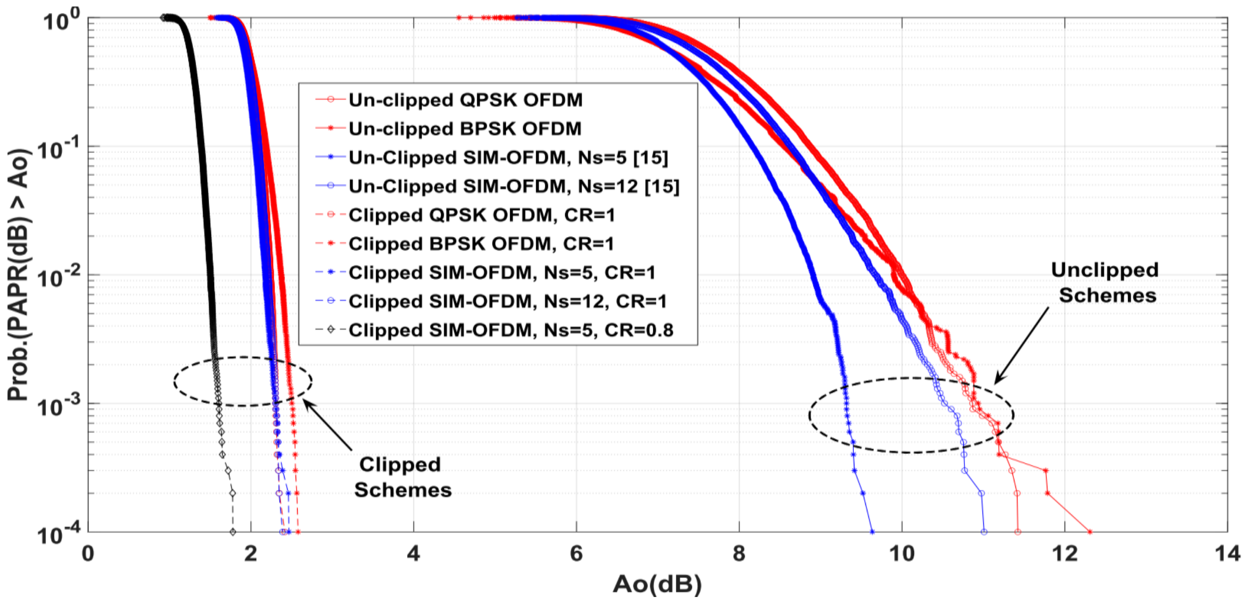

Figure 7: **PAPR comparisons**

This can be justified due to some errors in detecting the truly clipped samples at receiver side in the presence of additive noise as demonstrated in Fig.10. As shown in the figure, there are 105 clipped samples from 256 sample in this symbol. By regarding the samples of largest amplitude as a clipped or missed, we have 28 of un-correctly estimated clipped samples from the estimated 105 samples. However, that performance may be enhanced through following more sophisticated algorithms in detecting clipped samples indices. Also, the noise sensitivity increases under reduced number of measurements where the lower bound of the number of measurements (samples) is in reverse proportional to the operating SNR.

The BER performance under Rayleigh fading channel is demonstrated in Fig.9. With the IAA approach, the proposed clipped SIM-OFDM ($Ns = 5$) outperforms the corresponding coded and clipped OFDM (BPSK) by about 8 dB. However, the performance of both IAA and MIAA estimators seems almost the same. This can be justified by regarding that the deep fading effect dominates over the noise and clipping distortions even for wide range of SNRs values.

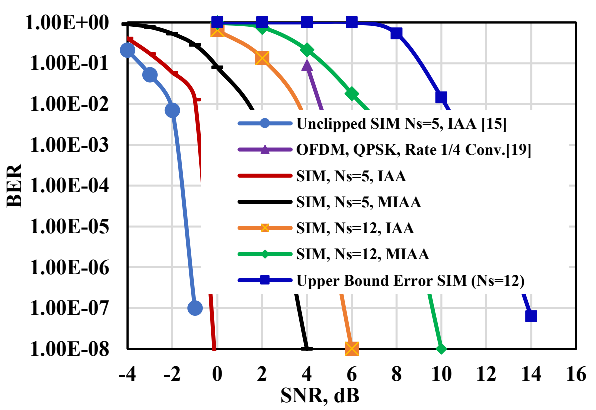

Figure 8: **BER under AWGN channel**

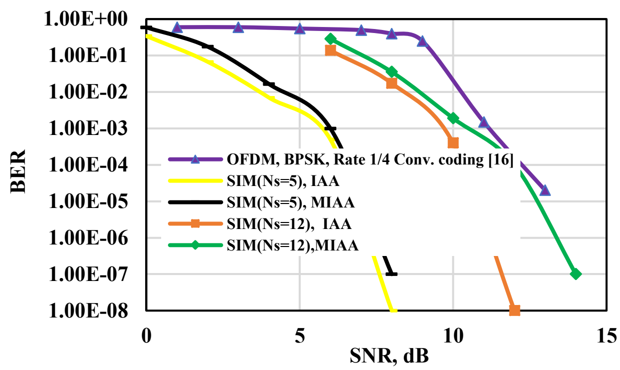

Figure 9: **BER under slowly fading Rayleigh**

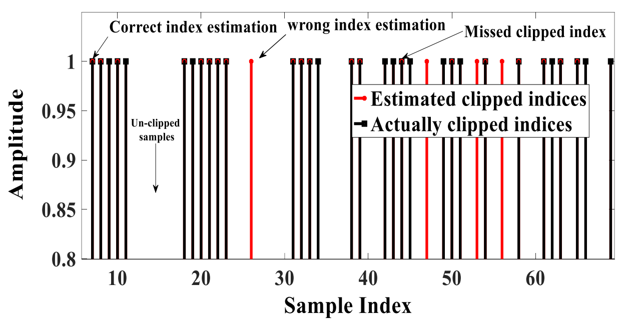

Figure 10: **Errors in estimating the clipped samples indices, ($CR = 1$, clipping 105 samples from 256, with 28 sample index error)**

VII. CONCLUSIONS

In this paper, an improved OFDM-SIM is introduced as an energy efficient multicarrier scheme for IoT communications. Mainly, the explicit sparsity in frequency domain of OFDM-SIM which provides a higher degree of freedom is exploited in the proposed scheme to enhance the performance in terms of EE. In particular, a novel clipping-CS based PAPR reduction technique for OFDM-SIM is proposed in this paper. Considering the complexity constraints for IoT devices, the simple and low complex clipping method is used to alleviate the PAPR issue. Moreover, supported with the inherent sparsity of the received OFDM-SIM signal, CS is introduced to deal with clipping noise and to help in the signal recovery process. Furthermore, in this paper the information-theoretic limits on sparsity recovery are exploited to derive an upper bound measure of BER. The simulation results demonstrate that the proposed scheme significantly enhance the system performance in terms EE, PAPR reduction and BER compared to the conventional clipped coded-OFDM. As a future work, the possibility of utilizing the proposed scheme for other OFDM system through guaranteeing the sparsity in other domains in addition to time domain can be investigated.

REFERENCES

[1] M. H. Alsharif, A. H. Kelechi, S. Kim, I. Khan, J. Kim, and J. H. Kim, "Enabling Hardware Green Internet of Things: A Review of Substantial Issues," *IEEE Access,* 2019.

[2] M. Shirvanimoghaddam, K. Shirvanimoghaddam, M. M. Abolhasani, M. Farhangi, V. Z. Barsari, H. Liu*, et al.*, "Towards a green and self-powered Internet of Things using piezoelectric energy harvesting," *IEEE Access,* vol. 7, pp. 94533-94556, 2019.

[3] L. Cho, X.-H. Yu, C.-Y. Chen, and C.-Y. Hsu, "Green OFDM for IoT: Minimizing IBO subject to a spectral mask," in *2018 IEEE International Conference on Applied System Invention (ICASI)*, 2018, pp. 5-8.

[4] E. Basar, "Index modulation techniques for 5G wireless networks," *IEEE Communications Magazine,* vol. 54, pp. 168-175, 2016.

[5] N. Ishikawa, S. Sugiura, and L. Hanzo, "Subcarrier-index modulation aided OFDM-will it work?," *IEEE Access,* vol. 4, pp. 2580-2593, 2016.

[6] E. Basar, M. Wen, R. Mesleh, M. Di Renzo, Y. Xiao, and H. Haas, "Index modulation techniques for next-generation wireless networks," *IEEE Access,* vol. 5, pp. 16693-16746, 2017.

[7] M. Elsayed, H. S. Hussein, and U. S. Mohamed, "Fully generalised spatial modulation," in *2018 35th National Radio Science Conference (NRSC)*, 2018, pp. 274-282.

[8] H. S. Hussein and M. Elsayed, "Fully-quadrature spatial modulation," in *2018 IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom)*, 2018, pp. 1-5.

[9] H. S. Hussein, M. Elsayed, U. S. Mohamed, H. Esmaiel, and E. M. Mohamed, "Spectral efficient spatial modulation techniques," *IEEE Access,* vol. 7, pp. 1454-1469, 2018.

[10] E. J. Candès and M. B. Wakin, "An introduction to compressive sampling [a sensing/sampling paradigm that goes against the common knowledge in data acquisition]," *IEEE signal processing magazine,* vol. 25, pp. 21-30, 2008.

[11] A. K. Fletcher, S. Rangan, and V. K. Goyal, "Necessary and sufficient conditions for sparsity pattern recovery," *IEEE Transactions on Information Theory,* vol. 55, pp. 5758-5772, 2009.

[12] E. C. Marques, N. Maciel, L. Naviner, H. Cai, and J. Yang, "A review of sparse recovery algorithms," *IEEE Access,* vol. 7, pp. 1300-1322, 2018.

[13] H. Ochiai and H. Imai, "On the distribution of the peak-to-average power ratio in OFDM signals," *IEEE transactions on communications,* vol. 49, pp. 282-289, 2001.

[14] M. Salah, O. A. Omer, and U. S. Mohamed, "Joint compressive sensing framework for sparse data/channel estimation in non-orthogonal multicarrier scheme," *journal of engineering science (JES),* vol. 44, pp. 537-554, 2016.

[15] M. Salah, O. A. Omer, and U. S. Mohamed, "Compressive sensing approach in multicarrier sparsely indexing modulation systems," *China Communications,* vol. 14, pp. 151-166, 2017.

[16] M. Salah, O. A. Omer, and U. S. Mohammed, "Spectral Efficiency Enhancement Based on Sparsely Indexed Modulation for Green Radio Communication," *IEEE Access,* vol. 7, pp. 31913-31925, 2019.

[17] B. Liu, S. Liu, Y. Rui, L. Gui, and Y. Wang, "A low-complexity compressive sensing algorithm for PAPR reduction," *Wireless personal communications,* vol. 78, pp. 283-295, 2014.

[18] H. Ochiai and H. Imai, "Performance analysis of deliberately clipped OFDM signals," *IEEE Transactions on communications,* vol. 50, pp. 89-101, 2002.

[19] M. Y. El-Ganiny, H. M. ElAttar, M. A. A. Dahab, and T. A. Elgarf, "Improved coding gain of clipped OFDM signal using avalanche effect of AES block cipher," in *2017 IEEE Pacific Rim Conference on Communications, Computers and Signal Processing (PACRIM)*, 2017, pp. 1-6.

[20] K.-H. Kim, H. Park, J.-S. No, H. Chung, and D.-J. Shin, "Clipping noise cancelation for OFDM systems using reliable observations based on compressed sensing," *IEEE Transactions on Broadcasting,* vol. 61, pp. 111-118, 2014.

[21] F. Yang, J. Gao, S. Liu, and J. Song, "Clipping noise elimination for OFDM systems by compressed sensing with partially aware support," *IEEE Transactions on Broadcasting,* vol. 63, pp. 103-110, 2016.

[22] E. Soujeri, G. Kaddoum, M. Au, and M. Herceg, "Frequency index modulation for low complexity low energy communication networks," *IEEE Access,* vol. 5, pp. 23276-23287, 2017.

[23] A. Ali, A. Al-Rabah, M. Masood, and T. Y. Al-Naffouri, "Receiver-based recovery of clipped OFDM signals for PAPR reduction: A Bayesian approach," *IEEE access,* vol. 2, pp. 1213-1224, 2014.

[24] J. Gao, F. Yang, and S. Liu, "Clipping noise cancellation for OFDM systems based on priori aided compressed sensing," in *2016 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*, 2016, pp. 1-4.

[25] J. Zheng and H. Lv, "Peak-to-average power ratio reduction in OFDM index modulation through convex programming," *IEEE Communications Letters,* vol. 21, pp. 1505-1508, 2017.

[26] E. Memisoglu, E. Basar, and H. Arslan, "Low complexity peak-to-average power ratio reduction in OFDM-IM," in *2018 IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom)*, 2018, pp. 1-5.

[27] S. Queiroz, W. Silva, J. P. Vilela, and E. Monteiro, "Maximal Spectral Efficiency of OFDM with Index Modulation under Polynomial Space Complexity," *arXiv preprint arXiv:1908.02860,* 2019.

[28] E. Başar, Ü. Aygölü, E. Panayırcı, and H. V. Poor, "Orthogonal frequency division multiplexing with index modulation," *IEEE Transactions on Signal Processing,* vol. 61, pp. 5536-5549, 2013.

[29] A. R. Bahai, M. Singh, A. J. Goldsmith, and B. R. Saltzberg, "A new approach for evaluating clipping distortion in multicarrier systems," *IEEE Journal on Selected Areas in Communications,* vol. 20, pp. 1037-1046, 2002.

[30] M. J. Azizipour and K. Mohamed-pour, "Clipping noise estimation in OFDM systems: A greedy-based approach," *AEU-International Journal of Electronics and Communications,* vol. 80, pp. 36-42, 2017.

[31] H. Ochiai and H. Imai, "Performance of the deliberate clipping with adaptive symbol selection for strictly band-limited OFDM systems," *IEEE Journal on selected areas in communications,* vol. 18, pp. 2270-2277, 2000.

[32] R. E. Carrillo, A. B. Ramirez, G. R. Arce, K. E. Barner, and B. M. Sadler, "Robust compressive sensing of sparse signals: a review," *EURASIP Journal on Advances in Signal Processing,* vol. 2016, p. 108, 2016.

[33] N. Li, W. Chen, and P. Li, "Stable Recovery of Signals From Highly Corrupted Measurements," *IEEE Access,* vol. 6, pp. 62865-62873, 2018.

[34] P. Stoica, D. Zachariah, and J. Li, "Weighted SPICE: A unifying approach for hyperparameter-free sparse estimation," *Digital Signal Processing,* vol. 33, pp. 1-12, 2014.
[35] P. Stoica, P. Babu, and J. Li, "SPICE: A sparse covariance-based estimation method for array processing," *IEEE Transactions on Signal Processing,* vol. 59, pp. 629-638, 2010.
[36] S. Sahnoun, P. Comon, and A. P. da Silva, "A greedy sparse method suitable for spectral-line estimation," 2016.
[37] J. A. Tropp, "Greed is good: Algorithmic results for sparse approximation," *IEEE Transactions on Information theory,* vol. 50, pp. 2231-2242, 2004.
[38] G.-O. Glentis and A. Jakobsson, "Efficient implementation of iterative adaptive approach spectral estimation techniques," *IEEE Transactions on Signal Processing,* vol. 59, pp. 4154-4167, 2011.
[39] Z. Shaeiri, M.-R. Karami, and A. Aghagolzadeh, "Enhancing the sufficient condition of sparsity pattern recovery," *Digital Signal Processing,* vol. 81, pp. 43-49, 2018.
[40] C. Aksoylar and V. Saligrama, "Information-theoretic characterization of sparse recovery," in *Artificial Intelligence and Statistics*, 2014, pp. 38-46.