A Novel Low Complexity based PAPR Reduction in OFDM System

Ch. Sita Mahalakshmi[1], S.V. Kavya[2], J.Priyanka[3], M. Rama Krishna (MTech)[4],
[1]*B.Tech Students,* [2] *Assosciate Professor*
Department of Electronics and Communication Engineering,
Andhra Loyola Institute of Engineering and Technology, Vijayawada, Andhra Pradesh 520008, India.

Abstract - In this project the first module, problem of peak-to-average power ratio (PAPR) reduction in orthogonal frequency-division multiplexing (OFDM) based massive multiple-input multiple-output (MIMO) downlink systems. Specifically, given a set of symbol vectors to be transmitted to K users, the problem is to find an OFDM-modulated signal that has a low PAPR and meanwhile enables multiuser interference (MUI) cancelation. Unlike previous works that tackled the problem using convex optimization, we take a Bayesian approach and develop an efficient PAPR reduction method by exploiting the redundant degrees-of-freedom of the transmit array. The sought-after signal is treated as a random vector with a hierarchical truncated Gaussian mixture prior, which has the potential to encourage a low PAPR signal with most of its samples concentrated on the boundaries. A variational expectation-maximization (EM) strategy is developed to obtain estimates of the hyper parameters associated with the prior model, along with the signal. In addition, the generalized approximate message passing (GAMP) is embedded into the variational EM framework, which results in a significant reduction in computational complexity of the proposed algorithm. The draw backs of Module one will be corrected by considering the computationally efficient RCTF method Simulation results show our proposed algorithm achieves a substantial performance improvement over existing method.

Keywords - RCTF, PAPR, BER, OUT-OF-BAND interference.

I. INTRODUCTION

Wireless Communication is the transfer of information over a distance without the use of enhanced electrical conductors or “Wires”. The distances involved may be short (a few meters as in television remote control) or long (thousands or millions of kilometres for radio communications). It encompasses various types of fixed, mobile, and portable two-way radios, cellular telephones, Personal Digital Assistants (PDAs), and wireless networking.

One new modulation scheme which has received significant attention over the last few years is a form of multicarrier modulation called Orthogonal Frequency Division Multiplexing (OFDM). OFDM has been used for Digital Audio Broadcasting (DAB) and Digital Video Broadcasting (DVB) in Europe, and for Asymmetric Digital Subscriber Line (ADSL) high data rate wired links. OFDM has also been standardized as the physical layer for the wireless networking standard ‘HIPERLAN2’ in Europe as the IEEE 802.11a, standard in the US, promising raw data rates of between 6 and 54Mbps.

Massive multiple-input multiple-output(MIMO), also known as large-scale or very-large MIMO, is a promising technology to meet the ever-growing demands for higher throughput and better quality-of-service of next-generation wireless communication systems [3]. Massive MIMO systems are those that are equipped with a large number of antennas at the base station (BS) simultaneously serving a much smaller number of single-antenna users sharing the same time-frequency bandwidth. In addition to higher throughput, massive MIMO systems also have the potential to improve the energy efficiency and enable the use of inexpensive, low-power components. Hence, it is expected that massive MIMO will bring radical changes to future wireless communication systems.

In this project the first module, problem of peak-to-average power ratio (PAPR) reduction in orthogonal frequency-division multiplexing(OFDM) based massive multiple-input multiple-output(MIMO) downlink systems. Mainly, a set of symbol vectors to be transmitted to K users, the problem is identified an OFDM-modulated signal that has a low PAPR and meanwhile enables multiuser interference (MUI) cancelation. The EM-GAMP algorithm is one of the best solution to overcome this PAPR problem in OFDM signal. The sought-after signal is treated as a random vector with a Gaussian noise mixture, which has the potential to encourage a low PAPR signal with most of its samples concentrated on the boundaries. A variational expectation-maximization (EM) strategy is developed to obtain estimates of the hyper parameters associated with the prior model, along with the signal. In addition, the generalized approximate message passing (GAMP) is embedded into the variational EM framework.

But EM+GAMP which leads to complexity increases. Comparing to in-band distortion, out-band is more critical. It severely interference with the radio communication adjacent channel. So, reducing this problem we are introduce a technique called “RCTF”(Repetitive companding transform function).

International telecom union for radio frequencies (ITU- RF) has approved the bit error rate (BER) as performance evaluation parameter to get desired statistics of the signal. In OFDM, BER is gradually declined due to companding distortion and the sudden declination in BER performance is due to signal attenuation factor which compresses the original symbols. Minimization of OBI is another prominent factor to be considered and to successfully handle the problem of OBI a frequency-domain filtering is utilized in the latter stage. Finally, the compression of peak signals came into control by performing the companding and filtering approaches for multiple times respectively till to achieve the desired result.

Here OFDM system model is comprises of transmitter and receiver, while RCTF technique is deployed at transmitter end for PAPR reduction. Over- sampled Inverse IFFT operation is used to convert the complex vector in accurate manner. Here two constants K1 and K2 are used to switch the single and multiple operations in respective iteration level.

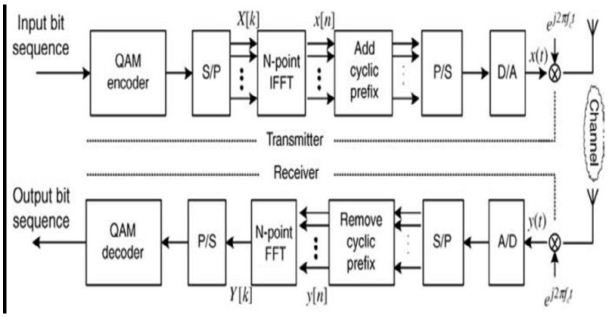


Figure 1: Block Diagram Of OFDM

Peak-to-Average Power Ratio (PAPR) Reduction - The main challenges of OFDM-based systems are the high peak-to-average power ratio (PAPR) of transmitted signals, resulting in signal distortion. OFDM modulation typically a large dynamic range because the phases of the sub-carriers are independent of each other. To avoid out-of-band radiation and signal distortion by using high-resolution DACs and linear power amplifier at the transmitter to accommodate the large peaks of OFDM signals, which leads to more expensive and power-inefficient.

PAPR is defined as the ratio of the peak power of the signal to its average power. Specifically, the PAPR at the m^thtransmit antenna is defined as

$$\text{PAPR}=\frac{maX_t|x(t)|^2}{E_t[|x(t)|^2]}\text{………………(1)}$$

LetE[x(t)] · denote the mathematical expectation and the amplitude, $||x||_2$denote the second norm of a vector.

When the number of transmit antennas is larger than the number of users, numerous ZF pre-coding matrices are available. By using this ZF pre-coding process, the MUI is removed and reduce the PAPR also.

In this paper, instead of designing the pre-coding matrix we directly search 'w' signal for reducing the PAPR and MUI cancelation.

II. EXISTING METHOD

A. EM-GAMP Introduction - In this project the first module, problem of peak-to-average power ratio (PAPR) reduction in orthogonal frequency-division multiplexing (OFDM) based massive multiple-input multiple-output (MIMO) downlink systems. Mainly, a set of symbol vectors to be transmitted to K users, the problem is identified an OFDM-modulated signal that has a low PAPR and meanwhile enables multiuser interference (MUI) cancelation. The EM-GAMP algorithm is one of the best solutions to overcome this PAPR problem in OFDM signal.In addition, the generalized approximate message passing (GAMP) is embedded into the variational EM framework, which results in a significant reduction in computational complexity of the proposed algorithm.

To facilitate our algorithm development, we introduce a noise term to model the mismatch between y and Ax, i.e.

$$y = Ax + \epsilon \quad \text{……. (2)}$$

Where ϵ denotes the noise vector and its entries are assumed to be i.i.d. Gaussian random variables with zero-mean and unknown variance β^{-1}. Here we treat β as an unknown parameter because the Bayesian framework allows an automatic determination of its model parameters and usually provides a reasonable balance between the data fitting error and the desired characteristics of the solution.

The graphical model of the proposed hierarchical is presented in Fig. 2(a). In general, Bayesian inference requires computing the logarithm of the prior. In this regard, (24) is an inconvenient form for inference.

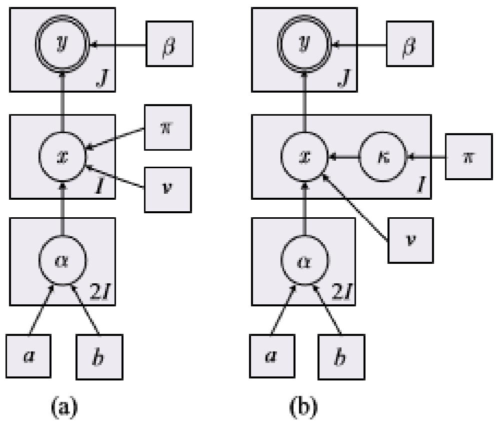


Figure 2: Graphical models for low-PAPR signal priors
(a) Original prior, (b) Modified prior

Here circles denoting hidden variables, double circles denoting observed variables and squares representing model parameters.

B. EM-GAMP Algorithm - A variational expectation-maximization (EM) algorithm is developed to obtain estimates of the hyper parameters associated with the prior model, along with the signal. In addition, the generalized approximate message passing (GAMP) technique [22] is employed to facilitate the algorithm development in the expectation step. This GAMP technique also helps significantly reduce the computational complexity of the proposed algorithm. Simulation results show that the proposed method presents a substantial improvement over the PTS algorithm in terms of both PAPR reduction and computational complexity.

i). Likelihood Function Approximation via GAMP -

Let z = {x, α1, α2, κ} denote all hidden variables appearing in our hierarchical model, and θ ≜β, v} denote the unknown deterministic parameters. As discussed in the previous subsection, the posterior of z can be approximated by a factorized form as follows

$p(x,\alpha_1,\alpha_2,\kappa|y;\beta,v)\approx q(x,\alpha_1,\alpha_2,\kappa)=q(x)q(\alpha_1)q(\alpha_2)q(\kappa)$)…..(3)

The approximate posteriors can be obtained as

$\ln q(x)=\langle \ln p\ (y, x, , \alpha_1, \alpha_2, \kappa; \beta, v)\rangle_{q(\alpha1)q(\alpha_2)q(\kappa)}$+const,… ………(3.1A)

$\ln q(\alpha_1)=\langle \ln p\ (y, x, \alpha_1, , \alpha_2, \kappa; \beta, v)\rangle_{q(x)q(\alpha_2)q(\kappa)}$+const, ……….(3.1B)

$\ln q(\alpha_2)=\langle \ln p\ (y, x, \alpha_1, , \alpha_2, \kappa; \beta, v)\rangle_{q(x)q(\alpha_1)q(\kappa)}$+const ……..(3.1C)

$\ln q(\kappa)=\langle \ln p\ (y, x, \alpha_1, , \alpha_2, \kappa; \beta, v)\rangle_{q(x)q(\alpha_1)q(,\alpha_2)}$+const ……(3.1D)

ii). Generalized approximate message passing (GAMP) -

GAMP is a very-low-complexity Bayesian iterative technique recently developed in [23] for obtaining approximate marginal posteriors and likelihoods. It therefore can be naturally embedded within the EM framework to provide an approximate posterior distribution of x and reduce the computational complexity, as shown in [20]. Specifically, the EM-GAMP framework of [25] proceeds in a double-loop manner: the outer loop (EM) computes the Q-function using the approximate posterior distribution of x, and maximizes the Q-function to update the model parameters (e.g. α1, α2, κ); the inner loop (GAMP) utilizes the newly estimated parameters to obtain a new approximation of the posterior distribution of x.

C. EM-GAMP Procedure -

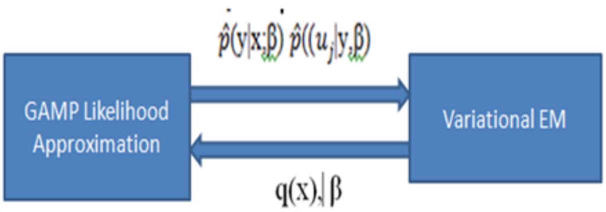


Figure 3: Variational EM-GAMP framework.

GAMP is a simplification of loopy BPand can be used to compute approximate marginal posteriors and likelihoods. Here we approximate the joint likelihood function p(y|x;β) as a product of approximate marginal likelihoods computed via the GAMP, i.e.

$p(y|x;\beta) \approx \hat{p}(y|x;\beta) \propto \prod_{i=1}^{I} N(x_i|\widehat{r_i,\tau_i^r})$ …..(3.2)

Where $N(x_i|\widehat{r_i,\tau_i^r})$is the approximate marginal likelihood obtained by the GAMP algorithm. To calculate r_i and τ_i^r, an estimate of the posterior q(x) and β is required as inputs to the GAMP algorithm (see the details of the GAMP algorithm provided below). Hence the GAMP algorithm can be embedded in the variational EM framework: given an estimate of q(x) and β, use the GAMP to obtain an approximation of the likelihood function p(y|x;β); with the approximation ˆ p(y|x;β), the variational EM proceeds to yield a new estimate of q(x) and β, along with estimates of other deterministic parameters (e.g. v) and posterior distributions for the other hidden variables (e.g. α1,α2,κ). This iterative procedure is illustrated in Figure 4.

Note that besides the approximation pˆ (y|x_i;β), GAMP also produces approximations for the marginal posteriors of the noiseless output u = $[u_1, u_2 \ldots, \ldots u_j]^T$ ≜Ax, which are given by

$p(u_j|y,\beta)\approx\hat{p}((u_j|y,\beta)\propto p((y_j|(u_j;\beta)N((u_j|\widehat{p}_j,\tau_j^p)$ ……(3.5)

Where $\widehat{p}_j$ and τ_j^p are quantities obtained from the GAMP algorithm.

Note that we can also treat {α1, α2, κ} as deterministic parameters.

i). E-Step: Update of Hidden Variables -

Update of q(x): As discussed above, p(y|x;β) is approximated as a factorized form of independent scalar likelihoods, which enables the computation of q(x) (3.1A). Specifically, using (3.1A) (3.5) can be simplified as

$\ln q(x)=\langle \ln p\ (y, x, , \alpha_1, \alpha_2, \kappa; \beta, v)\rangle_{q(\alpha1)q(\alpha_2)q(\kappa)}$ +const (3.6)

lnq(x) = −∞ otherwise. It can be seen that lnq(x) has a factorized form, which implies that hidden variables {xi} have independent posterior distributions. Also, it can be readily verified that the posterior q(xi) follows a truncated Gaussian distribution

$q\ (x_i) = \int \frac{N(x_i|\mu_i,\sigma_i^2)}{\emptyset_i}$ if $x_i \in [-v,v]$, 0 *otherwise* .... (3.7)

Where σ_i^2= variance

$\mu_{i,}$= Mean

$\emptyset_i$= Normalization constant

Update of q (α_1): Keeping only the terms that depend on α_1,the variational optimization of q (α_1) yields

$Lnq(\alpha_1)=\langle \ln p\ (x|\alpha_1, \alpha_2, \kappa; v)p(\alpha_1)\rangle_{q(x)q(\alpha_2)q(\kappa)}$ +const

$= \sum_{i=1}^{I} \langle \ln p\ (x_i|\alpha_{i1}, \alpha_{i2}, k_i; v)p(\alpha_{i1})\rangle_{q(x)q(\alpha_2)q(\kappa)}$ +const

Therefore $q(\alpha_1)$ follows a Gamma distribution

$q\ (\alpha_1)$ =Gamma $(\alpha_{i1}|\widehat{a_{i1}}, \widehat{b_{i1}})$ … (3.8)

with

$\widehat{a_{i1}} = a + \frac{1}{2}\langle k_i\rangle$

$\widehat{b_{i1}} = b + \frac{1}{2}\langle k_i\rangle\langle(x_i - v)^2\rangle$

Update of q (α_2): Following a procedure similar to the derivation of q (α_1), we have

$q\ (\alpha_2)$ =Gamma $(\alpha_{i2}|\widehat{a_{i2}}, \widehat{b_{i2}})$ ….. (3.9)

with

$\widehat{a_{i2}} = a + \frac{1}{2}(1 - \langle k_i\rangle$

$\widehat{b_{i2}} = b + \frac{1}{2}(1 - \langle k_i\rangle)\langle(x_i + v)^2\rangle$

ii). M-step: Update of deterministic Parameters:

As indicated earlier, in the variational EM framework, the deterministic parameters $\theta = \{\beta, v\}$ are estimated by maximizing the Q-function, i.e.

$\theta^{NEW} = {}^{max}_{\ \ \theta} Q\ (\theta, \theta^{old})$ ……. (3.10)

Update of β: We first discuss the update of the parameter β the inverse of the noise variance. Since the GAMP algorithm provides an approximate posterior distribution for the noise less output u ≜ Ax., we can simply treat u as hidden variables when computing the Q-function, i.e.

$Q(\beta,\beta^{(t)})= \sum_{j=1}^{J}\langle \ln p(y_j|u_j;\beta)\rangle_{p(\widehat{u_j|y},\beta)}$ +const …….(3.11)

The new estimate of data is obtained by maximizing the Q-function, which can be solved by setting the derivative of $Q(\beta,\beta^{(t)})$ with respect to β to zero.

Update of v: We now discuss how to update the boundary parameter v. The boundary parameter v can be updated by maximizing the Q-function with respect to v. Nevertheless, the optimization is complex since the Q-function involves computing the expectation of the normalization terms η_{il}, i = 1, 2, …..I, l = 1, 2 with respect to the posterior distributions p (α_{il}).The basic idea is to find an appropriate value of v such that the mismatch $\|y-A\hat{x}\|2$ is minimized, where ˆ x denotes the estimated signal which is chosen as the mean of the posterior distribution q(x).

Note that when the boundary parameter v is small, the mismatch could be large since there may not exist a solution to satisfy the constraint y = Ax. Therefore we can firstly set a small value of v, then gradually increase v by a step-size such that the mismatch keeps decreasing and eventually becomes negligible.

Algorithm 2: EM-GAMP -

EM-TGM-GAMP Initialization: β(0) = 10^3, $v^{(0)}$ = ‖y‖∞/‖A‖∞, initialize the means of q(x), q(α1), q(α2), q(κ) as 0, 1, 1, $\frac{1}{2}$1 respectively, set the variance of q(x) as 1, and set iteration number t = 0.

Repeat the following steps until t ≥ tMAX

1. Based on the mean and variance of q(x) and β(t), calculate the approximate distributions ˆ p(y|x;β(t))and ˆ p(uj|y,β(t)), j = 1,...,J,
2. Using the approximate likelihood ˆ p(y|x;β(t)), update the posteriors of hidden variables: q(x), q(α1), q(α2) and q(κ)
3. Compute the new estimate β(t+1) and obtain the v(t+1)
4. Increase t = t + 1 and return to step 1

III. PROPOSED METHOD

International telecom union for radio frequencies (ITU- RF) has approved the bit error rate (BER) as performance evaluation parameter to get desired statistics of the signal. In OFDM, BER is gradually declined due to companding distortion and the sudden declination in BER performance is due to signal attenuation factor which compresses the original symbols. Minimization of OBI is another prominent factor to be considered and to successfully handle the problem of OBI a frequency-domain filtering is utilized in the latter stage.

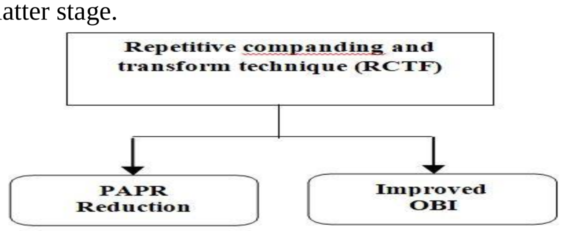


Figure 4: Iterative companding and transform technique and its mechanism

OFDM offers high data rate at one end and on other end its performance is badly impacted by PAPR. The above block diagram design intended to mitigate the peak values in accurate way. Here OFDM system model is comprises of transmitter and receiver, while RCTF technique is deployed at transmitter end for PAPR reduction. Over- sampled Inverse IFFT operation is used to convert the complex vector $X \in C^N$ in accurate manner. Here two constants K_1 and K_2 are used to switch the single and multiple operations in respective iteration level.

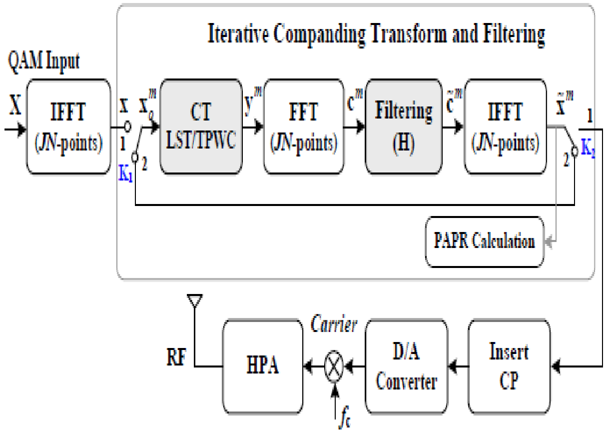


Figure 5: Block diagram of OFDM transmitter using RCTF technique.

If K_1 value is set to 1, then OFDM symbol $X \in C^{JN}$ is given as input to RCTF at the iteration, M=1 and these iterations are processed based on symbol-by-symbol process. In case, if both K_1 and K_2 are set to 2, then in that stage both companding and ICTF are used for the same OFDM symbol. In last iteration both constants values are set to 1 again to get the output as $\tilde{X}^m \in C^{JN}$ reactively. Assume $c^m \in C^{JN}$ and $\tilde{c}^m \in C^{JN}$ represented the frequency-domain OFDM symbol at mth iterative level (before and after filtering process). The proposed figure area as follows The proposed method intends to decrease the PAPR impact and achieves improved OBI performance. The presence companding noise and channel noise results in companding distortion. Finally, BER analysis is carried out using companding distortion. Two companding transform techniques is initialized by linear (LST) companding transform technique and non-linear companding scheme (TPCW).

i). Linear symmetrical transform (LST) - Linear symmetrical transform (LST) is a companding transform profile and its respective companding transform function is as follows

$$f(x) = (k.|x| + b).\mathrm{sgn}(x) \quad (1)$$

The above equation is composed of sign function and two parameters. These parameters are used to specify companding profile. PAPR reduction and improved BER is achieved by selecting the parameters in linear regions of companding profile. Average power alternation is concerned area in companding transform and by $k^2+\sqrt{\pi}.kb/\sigma+\frac{b^2}{\sigma^2}$ is used to maintain the average power in unchanged form. The decompanding function is notated as follows

$$f^{-1}(x)=\frac{|x|-b}{k}.\operatorname{sgn}(x) \qquad (2)$$

The PAPR and the transform gain G is defined as the ratio of the PAPR of original symbol to that of the companded symbol are as follows

$$PAPR_{LST}(db)=10\log\frac{\max_{n\in[0,JN-1]}\{|y_n|^2\}}{\frac{1}{JN}\sum_{n=0}^{JN-1}|y_n|^2}$$

$$=20\log\frac{k.v+b}{\sigma} \qquad (3)$$

$$G_{LST}(dB)=10\log\frac{PAPR_{org}}{PAPR_{LST}}=20\log\frac{k.v+b}{\sigma} \qquad (4)$$

Two-Piecewise Companding (TPWC) - There are four classified companding transform profiles in both linear and non-linear way, Linear Nonsymmetrical Transform (LNST) has achieved best results in terms of PAPR reduction and BER performance over remaining companding transform profiles. The companding function is as follows

$$f(x)=\begin{cases} u_1|x|.\operatorname{sgn}(x) & |x|\le v \\ (u_2|x|+s).\operatorname{sgn}(x), & |x|>v^1 \end{cases} \qquad (5)$$

$$For\, u_1>1,\ 0<u_2<1,\ s=(u_1-u_2)v>0\ \ and\ \ 0\le v\le V$$

is the cutoff point with $V=\max_{0\le n\le JN-1\{|x_n|\}}$ with maximum value $V=\max_{0\le n\le JN-1\{|x_n|\}}$

The de-companding function of TPWC is given by

$$f^{-1}(x)=\begin{cases} \frac{1}{u_1}|x|.\operatorname{sgn}(x) & |x|\le u_1 v \\ \left(\frac{1}{u_2}|x|-s\right).\operatorname{sgn}(x), & |x|>u_1 v \end{cases} \qquad (6)$$

For a single TPWC-CT approach, Its achievable PAPR is given by

$$PAPR_{TPWC}(dB)=20\log\frac{u_2V+s}{\sigma} \qquad (7)$$

The corresponding transform gain G is written by

$$G_{TPWC}(dB)=20\log\frac{V}{u_2V+s} \qquad (8)$$

Companding Distortion Analysis:

i). Companding noise - The BER performance in RCTF procedure is investigated. Based on Buss gang theorem for real and complex Gaussian Signal, the companded signal can be approximately decomposed into two parts the attenuated signal component and companding noise, ρ_n ,i.e $y_n=SAF\times x_n+\rho_n$ Thus, the transmitted symbol with 'm' iterations using ICTF can be approximately decomposed $x_n^m=SAF^m\times x_n+\rho_n$

ii). Channel noise - Improved BER is achieved even in the absence of de-compounding operation at receiver end. The necessary theoretical analysis as follows;

a) RCTF-LST - At receiver end, When de-compounding operation is performed and if m=1 (Iteration 1) the received signal is as follows

$$\tilde{x}_n=f^{-1}\left(f(x_n)+\omega_n\right)=x_n+\frac{\omega_n}{k} \qquad (9)$$

Where ω_n =channel noise

If number of iterations increased then it results in noise,

$$e_n^{(m)}=\left|\omega_n/k^m\right| \qquad (10)$$

As a result, it is preferable to abandon the decompanding at the receiver. It is noteworthy that this is quite advantageous for practical OFDM systems.

b) RCTF-TPWC - RCTF-TPWC analysis is carried out in same way as RCTF-LST. Assuming that m iterative de-companding operations are performed at the receiver, the recovery error is approximately given by

$$e_n^{(m)}=\begin{cases} \left|\omega_n/u_1^m\right|, n\in\phi_1(v) \\ \left|\omega_n/u_2^m\right|, n\in\phi_2(v) \end{cases} \qquad (11)$$

IV. SIMULATION RESULT

To better evaluate the PAPR reduction performance, we plot the CCDF of the PAPR for respective schemes in Fig. 6(a). The number of trials is chosen to be 1000 in our experiments. Note that PAPRs associated with all M antennas are taken in account in calculating the empirical CCDF. it reduces the PAPR by 2dB The SER performance of respective schemes is shown in Fig. 6(b), We observe that the proposed algorithm incursan SNR-performance loss of 2.5 dB and 1.7 dB (at SER = 10−3) compared to the ZF and FITRA schemes, respectively.

Assume that, the number of subcarriers is N=128 using quaternary phase shift keying (QPSK) or 16 Quadrature amplitude modulation (16-QAM). Over sampling j=4 is used in proposed work to accurate PAPR estimation.

BER performance is analyzed in both the AWGN channel and multipath fading channels (RACIAN and SUI) are applied. A CP with length of ¼ symbols is inserted to control ICF. ICTF achieves better PAPR reduction (6.57dB

PAPR reduction is achieved) over traditional CT techniques and ICF. The impact of PAPR reduction technique on OFDM system is observed using BER and OBI.

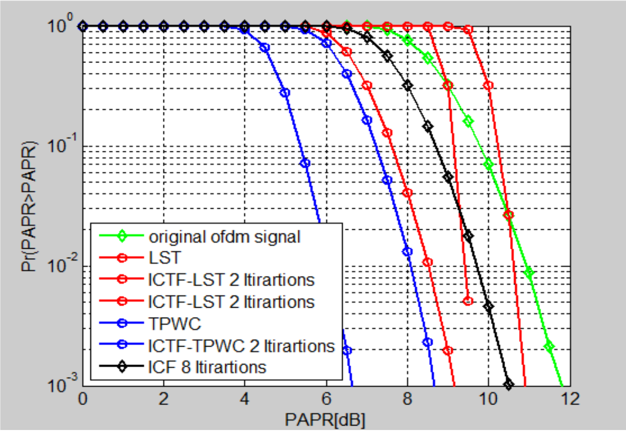
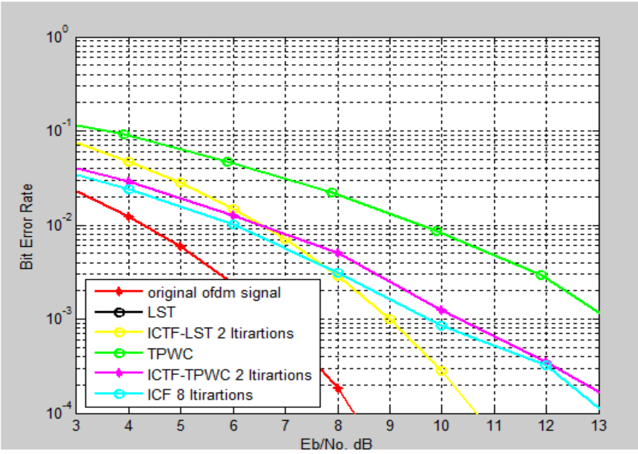
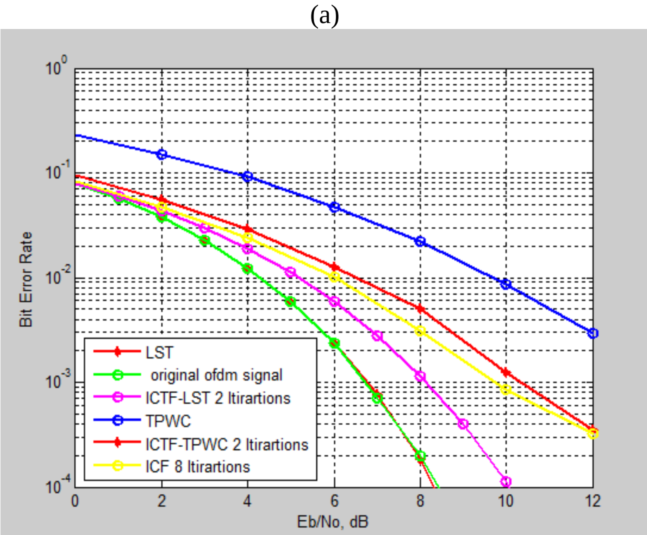


Figure 6: CCDF statistics of OFDM symbol for different PAPR-reduction schemes (N=1024, QPSK, and the over-sampling ratio J=4).



(a)



(b)

Figure 7: BER comparison for different PAPR-reduction schemes through AWGN channel for OFDM system (N=1024, QPSK).

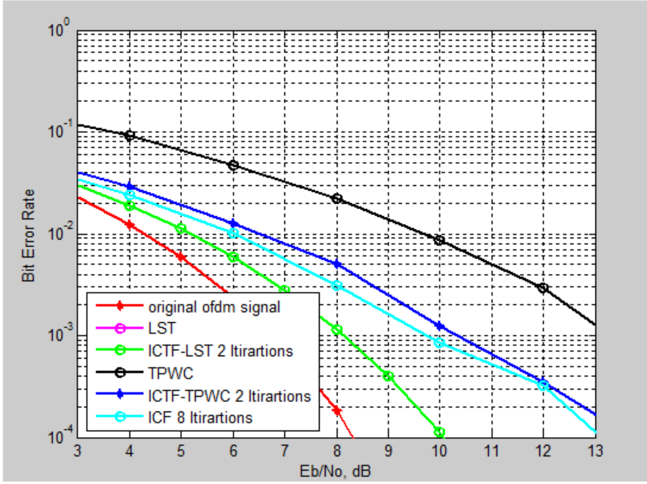


Figure 8: BER comparison for different PAPR-reduction schemes through Rician fading channel for OFDM system (N=1024, QPSK).

V. CONCLUSION

We considered the problem of joint PAPR reduction and multiuser interference (MUI) cancelation in OFDM based massive MIMO downlink systems. ICTF is an equipped approach has ability to reduce PAPR and improved BER performance. Both AWGN channel and SUI channel for reliability and efficiency. ICTF achieves good results over conventional techniques. The proposed ICTF technique not only obtains significant PAPR reduction with improved BER and OBI performance, but also dramatically decreases the iterations number. In addition, ICTF procedure can also be extended to other well-known linear and nonlinear companding profiles. The proposed algorithm also demonstrates a fast convergence rate, which makes it attractive for practical real-time systems.

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