IEM-based Tone Injection for Peak-to-Average Power Ratio Reduction of Multi-carrier Modulation

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Abstract

Tone Injection (TI) scheme significantly reduces the peak-to-average power ratio (PAPR) of Multicarrier Modulation (MCM). However, the computational complexity of the TI scheme rises exponentially with the extra freedom constellation number. Therefore, a novel immune evolutionary mechanism-based TI scheme is proposed in this paper to reduce the computational complexity. By restraining undesirable degeneracy during the processing, this IEM scheme can dramatically increase the population fitness. Monte Carlo results show that proposed IEM-based TI scheme can achieve a significant PAPR and BER improvement with a low complexity.

1. Introduction

Multicarrier modulation (especially orthogonal frequency division multiplexing) has widely used in a number of standard systems, including the 3GPP LTE, IEEE 802.11 a/g/n standard, and WiMAX standard, due to the merits of robustness to the selective fading and high spectral efficiency, etc [1]-[3].

However, the inherent high peak-to-average power ratio (PAPR) of MCM systems causes large signal distortion and inefficiency of the power amplifier (due to large back-off). Numerous PAPR reduction methods are thus obtainable in the references (see [4]-[8] and the references therein), among these solutions, tone injection (TI) [2], [9]-[15] is a distortion-less scheme that can reduce the PAPR dramatically without side information transmission or extra data rate loss. It uses hexagonal constellation [9] or extended constellations [10] to achieve a lower PAPR. However, the implementation requires solving an integer-programming problem, which belongs to a NP-hard problem. Therefore, one has to produce a good suboptimal solution, such as clipping projection [11], [15], cross-entropy [12], tabu search [13] and linear programming [14].

Inspired by quantum-inspired evolutionary algorithm [16] successfully utilized to resolve combinatorial optimization problem, a basic immune evolutionary algorithm is introduced in [17]. However, since degeneracy is not completely eliminated, it can be improved further. Consequently, in order to achieve better system performance, this paper introduces immune mechanism [18], [19] to the quantum computing. To preserve evolutionary mechanism's advantages, a novel immune evolutionary mechanism (IEM) is utilized for restraining the degeneracy during evolution, which improves the algorithmic efficiency and reduces the complexity. Thus, new IEM TI schemes are developed for PAPR reduction. Furthermore, in this paper, we use a specially hexagonal constellation to eliminate power increase caused by conventional tone injection. Monte Carlo results confirm the IEM-TI achieves significant improvement in BER and PAPR with a low complexity.

The outline of the rest in this paper is organized as follows. The MCM Model and problem formulation are described in Section II. Section III summarizes the concepts and principles of quantum computing and immune mechanisms. By introducing immune mechanism to the quantum computing, Section IV puts forth the proposed schemes to search the extra freedom constellation for TI. Section V presents the performance evaluation. Conclusion is summarized in Section VI.

2. MCM Model and Problem Formulation

2.1 MCM Model and PAPR Definition

For a N subcarriers MCM system with quadrature amplitude modulation (QAM), the outputs of the inverse discrete Fourier transform (IDFT) of signal X_k is given by

$$x_n = \frac{1}{\sqrt{LN}} \sum_{k=0}^{LN-1} X_k \exp\left(\frac{j \cdot 2\pi kn}{LN}\right), \qquad n=0,1,\dots,LN-1. \tag{1}$$
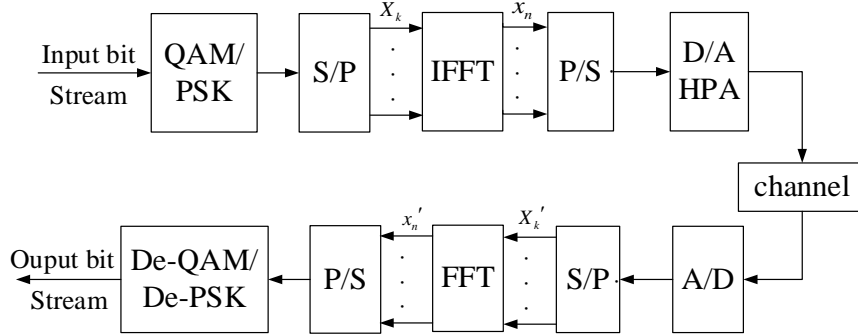

Fig. 1. Diagram of a traditional MCM system.

The PAPR definition in transmitted MCM signal can be expressed as

$$PAPR = 10 \cdot \log_{10} \frac{\max\limits_{0 \le n < NL-1}\left\{|x_n|^2\right\}}{E\left[|x_n|^2\right]} \ (dB). \tag{2}$$

Here, the $E[.]$ denotes the expectation operation (Note that during the simulations, it is will be replaced by its mean value as a further simplification). Furthermore, as shown in [20], in order to keep a good approximation to the continuous signals, the MCM signal must oversampled by a factor that larger than 4.

2.2 Tone Injection for PAPR Reduction

Mapping the original MCM constellation to several equivalent constellations, tone injection [2] can use any of the equivalent constellation to carry the same information. Mathematically, for an M-ary square QAM signal, the symbols after TI scheme can be expressed as [2]

$$x_n' = \frac{1}{\sqrt{n}} \sum_{k=0}^{N-1} \left(X_k + p_k \cdot \Delta + jq_k \cdot \Delta\right) \exp\left(\frac{j2\pi n}{LN}\right), \tag{3}$$

where $\sqrt{M}$ represent the level per dimension, p_k and q_k are integers, and d is the minimum distance of the constellation points. In addition, literature [3] shows that in order to keep the BER performance at the receiver maintain the same level, Δ must be larger than $d\sqrt{M}$.

On one hand, taking the complexity problem into account, assume only one candidate constellation for each MCM symbol can be chosen to shift, then, the optimization problem in TI scheme can be given by

$$\min f(b) = \left|x_n'(b)\right|^2$$
$$subject\ to : b \in \{0,1\}^N. \tag{4}$$

Equation (4) has been proven to be a non determined-polynomial-time complete problem. Therefore, an efficient IEM-TI scheduling scheme will be proposed in next section.
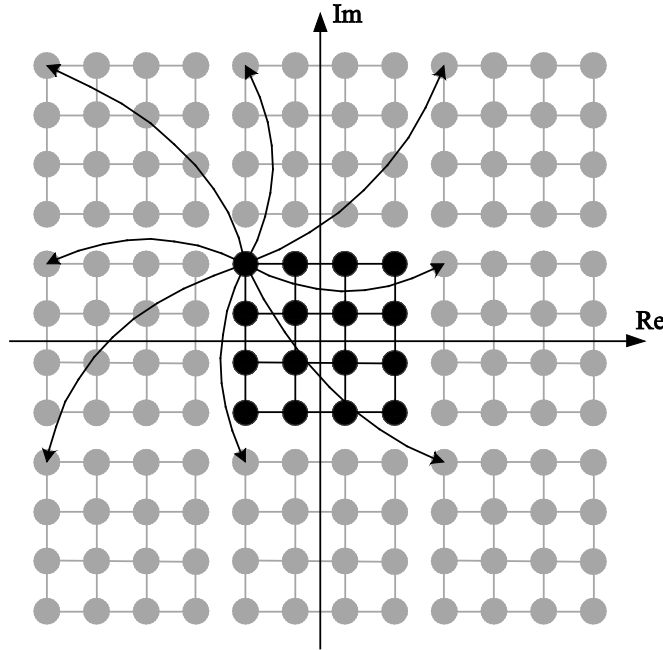

Fig. 2. Constellation expansion with eight replications for a MCM symbol.

On the other hand, considering that hexagonal lattice [21] is the most dense packing in two dimensions. Therefore, in order to reduce the PAPR without increasing the signal power, a hexagonal constellation (HC) is introduced to TI [9]. In this case, for each constellation point, the decision region is $\sqrt{3}d^2/2$, and the new transmit signal can then be expressed as

$$x'_{nHC} = x_{nHC} - \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} b_k X_{kHC} e^{j2\pi nk/LN},$$ (5)

where x_{nHC} is the same as x_n in Eq. (1) and b_k is defined in Eq. (4). In addition, the $X_{kHC} = X_k + p_k \cdot \Delta + jq_k \cdot \Delta$.

2.3 Cubic Metric in MCM Systems

It has been shown in [22] that for a real power amplifier (PA) in a cellular handset, the cubic metric (CM) can predict the power capability reduction effectively. Since its accuracy in many devices and signals, 3GPP members chosen CM as a method to determine PA power derating. This method has shown [23] a better performance than the PAPR to predict derating for the WCDMA and LTE signals. The CM in a typical MCM system is defined as

$$CM = \frac{RCM - RCM_{ref}}{K},$$ (6)

note that the *RCM* denote the raw cubic metric. The *RCM* for a given signal $d(t)$ can be defined as follows.

$$RCM = 20\log\left[rms\left[\left(\frac{|d(t)|}{rms[d(t)]}\right)^3\right]\right],\qquad(7)$$

where $rms[d(t)]$ is the root-mean-square of a given signal $d(t)$.

Here, the parameter K and RCM_{ref}, shown in [23], are introduced to complete estimate of the power derating required to meet a certain adjacent channel leakage ratio (ACLR). For example, the values of parameter RCM_{ref} and K in LTE downlink are 1.52dB and 1.56, respectively. Based on this, in this paper, the *CM* performance of the proposed IEM scheme are also tested.

3. Concepts of Evolutionary and Immune Mechanisms

In order to puts forth the proposed scheme for PAPR reduction, in this Section we will first introduce the concepts and principles of quantum computing and immune mechanisms.

3.1 Basics of Quantum Computing

In conventional computing, one bit is either in the state-'1' or state-'0'. The quantum analogue is a Quantum bit or a Q-bit. Note that a Q-bit is probably in the state-'1' or state-'0', or in any superposition of these two states. The state $|\Psi\rangle$ can be defined as

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle, or\ \ |\Psi\rangle = \begin{bmatrix}\alpha\\\beta\end{bmatrix},\qquad(8)$$

where α and β are the probability of the Q-bit in the corresponding state-'1' or state-'0', and $|\alpha|^2 + |\beta|^2 = 1$. In other words, a Q-bit defines an angle θ, where $\cos(\theta) = |\alpha|$ and $\sin(\theta) = |\beta|$. A Q-bit individual is denoted as a string of V in Q-bits [14]

$$|\Psi\rangle = \begin{bmatrix}\alpha_1 & |\alpha_2 & |\cdots & |\alpha_V\\\beta_1 & |\beta_2 & |\cdots & |\beta_V\end{bmatrix},\qquad(9)$$

where $|\alpha_i|^2 + |\beta_i|^2 = 1, i = 1, 2, \ldots V$. Moreover, quantum gate (denote as the Q-gate) [16], [18] is proposed to update the Q-bit individuals of the probabilities of α and β. Here, note that this Q-gate is a reversible gate and can be denoted as a unitary operator Z acting on the Q-bit basis states satisfying $Z^\dagger Z = ZZ^\dagger$, where $Z^\dagger$ is the hermitian adjoint of Z. A system with s Q-bits can represent 2^s states at the same time. By updating these states with a certain Q-gate, the best solution is obtained.

3.2 Immune Mechanism

Immune concepts and methods in an evolutionary process aim to find the optimal solution

by using the locally characteristic information. Local information can be utilized to restrain useless and reduplicated work and involve in the global searching, in order to remove the blind mutation. The immune algorithm, like the immune phenomenon in nature, refrains degeneracy in evolutionary process, which, in turn, making the population fitness rising steadily [19]. The immunity operation can be achieved by two steps [24], [25]: 1) vaccination; 2) Immune selection. The former can raise the average fitness of population and the latter can prevent the useless and repetitive work, e.g., deterioration. These two steps can be described as follows.

- *Vaccination*
  Assume the individual *x* is a potential solution (bit sequence) for an integer optimization problem. Vaccination of *x* means to modify some bits of *x* according to the priori knowledge to increase the probability of increased fitness. In the next Section, we will give the general steps to realize it.

- *Immune Selection*
  First, if the vaccination individual [19] has worse fitness value than the original one (parent), then the parent not the vaccination individual will participate the next competition. The current and parent populations are sorted based on individual fitness and the contribution to the diversity of the population. The individuals whose fitness value are better than the average and differ greatly from the best individual will survive with a larger probability. Note that this step not only guarantees the effective transmission of evolutionary information but also keeps the diversity of population.

In Section 4, the vaccination schedule and the selection method will compared with other methods by simulations.

4. The Proposed Algorithm and Its Complexity

By introducing immune mechanism to the quantum computing, in this section, we first give the general Immune Evolutionary Mechanism (IEM) steps, and then put the IEM to the TI method for PAPR reduction.

4.1 Immune Evolutionary Mechanism

For general integer optimization problem using the IEM, in every generation, both the fitness and bit values of the solutions are compared. For example, if one solution b_i is better than another one b_j and if the bit values differ, then the Q-gate operator is used to update the corresponding bits. Therefore, the worse solution b_j moves slightly toward to the better one b_i. In addition, to prevent this operation being irreversible, elitism is introduced [18]. The elitist at generation $t+1$ is achieved by the optimal solution in the t generation. Since the elitist is compared with every individual, the information collected during search evolution is not only maintained at the individual level but also periodically communicated to the entire population.

Similar to other probabilistic evolutionary methods, at generation t, IEM retains Q-bit individuals at the size of *pop*, e.g., $Q(t) = \{q_1^t, q_2^t, ..., q_{pop}^t\}$, where q_i^t is the Q-bit individual

$$q_i^t = \begin{bmatrix} \alpha_{i1}^t & \alpha_{i1}^t & \cdots & \alpha_{iV}^t \\ \beta_{i1}^t & \beta_{i1}^t & \cdots & \beta_{iV}^t \end{bmatrix}. \tag{10}$$

Here, the length of the Q-bit individual is defined as V, where $i=1,2,\ldots,V$. In principle, the IEM method is iteratively running in three steps:

Step 1. By observing the Q-gate to generate the random binary solutions in $P(t)$, where $B(t) = \{b_1^t, b_2^t, \ldots, b_{pop}^t\}$ and $b_i^t = \{b_{i1}^t, b_{i2}^t, \ldots, b_{iV}^t\}$ at generation t. In the PAPR problem, the binary value b_{ik}^t is determined by

$$b_{ik}^t = \begin{cases} -1, & if \ \left|\alpha_{ik}^t\right|^2 > random[0,1) \\ 1, & if \ \left|\alpha_{ik}^t\right|^2 < random[0,1) \end{cases}. \tag{11}$$

Step 2. Performing immuning on $B(t)$ to increase the fitness of population.

   Vaccination: it can be achieved by the following steps: 1) Revise the phase information of the selected individual according to the vaccination schedule; 2) Remove the overlapping individuals in the past or current population(for b_j^t, if $b_j^t = b_i^t$ or $b_j^t = b_i^{t-n}$, which means b_j^t already chosen in the population), then regenerate a new individual. After that, calculate the fitness value of the corresponding individual.

   To modify the IEM-based TI candidate we need follow these steps to implement: based on all fitness value list the population; Then, pick the individual phase information with great difference to the best one (maximum r bits). By using the following equation, it can be quickly achieve the corresponding fitness value for the purpose of the complexity reduction,

$$f_{modified} = f_{original} - 2b_{ir} \cdot x^r \tag{12}$$

By using Eq. (12), different individuals can be obtained.

   Immune selection: this step can be achieved by the following procedures: sort the current and parent population based on individual fitness and the contribution to the diversity of the population, so that the fitness value better than the average and greatly differ from the best individual can survive.

Step 3. Modifying the probabilities α and β by using Q-gate to update the Q-bit individuals. The Q-gate can be expressed as

$$\begin{bmatrix} \alpha_{ij}^{t+1} \\ \beta_{ij}^{t+1} \end{bmatrix} = \begin{bmatrix} \cos\left(\Delta\theta_{ij}^t\right) & -\sin\left(\Delta\theta_{ij}^t\right) \\ \sin\left(\Delta\theta_{ij}^t\right) & \cos\left(\Delta\theta_{ij}^t\right) \end{bmatrix} \cdot \begin{bmatrix} \alpha_{ij}^t \\ \beta_{ij}^t \end{bmatrix}, \tag{13}$$

where $\Delta\theta$ is the rotation angle parameter of each Q-bit. Fig. 1 shows the rotation gate of individuals. Note that $\Delta\theta$ can control the convergence speed, large $\Delta\theta$ may converge to a local optimum solutions. Ref. [16] give a details design method of $\Delta\theta$.
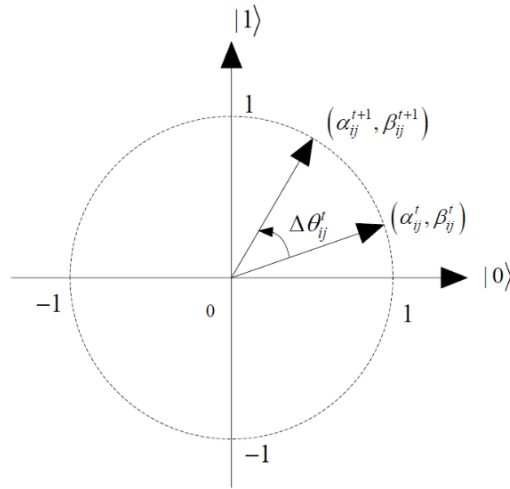
Fig. 3. Rotation gate for *Q*-bit individuals.

4.2. Structure of the Proposed IEM

The structure of IEM can now be summarized as follows:

Procedure IEM

$t \leftarrow 0$

1. *initialize $Q(t)$, all qubits are set to $1/\sqrt{2}$*
2. *make $B(t)$ by observing the states of $Q(t)$ from Eqs. (10) and (11)*
3. *evaluate $B(t)$ and store the best solutions among $B(t)$ into $B_{best}(t)$*

   while *(not termination-condition)* **do**

   $t \leftarrow t + 1$

4. *make $B(t)$ by observing the states of $Q(t-1)$ and Eq. (11)*
5. *perform Immune (Step 2 and Eq.(12)) on $B(t)$*
6. *evaluate $B(t)$ by using Eq. (14)*
7. *update $Q(t)$ using Q-gates:(see Eq. (13) and APPENDIX) **learn_model**$(B_i^t, B_{best,i}^t, Q_i^t)$*
8. *store the best solutions among $B(t-1)$ and $B(t)$ into $B_{best}(t)$*
9. *store the best solution **b** among $B_{best}(t)$*
10. **if** *(migration-condition)* **then**

    *migrate **b** or b_i^t to $B(t)$ globally or locally, respectively*

    end if

end while

A description of the *learning model* in detail are given in the Appendix. In the procedure, the best solutions in generation *t*-1 among $B_{best}(t$-1) and *t* among $B(t)$ are chosen and compared

to the best in $B_{best}(t)$, the better one will be stored into new best solution b. Note that the algorithm running in the **while** loop until meet the termination condition.

Each solution must set a fitness function. Clearly, the candidate constellation in (5) maintain the average power unchanged. Therefore, the fitness function of the IEM-TI MCM may be expressed as

$$fitness(b_i) = \min_{0 \leq n \leq NL-1} \left| x'(b_i) \right|^2. \tag{14}$$

Moreover, in IEM-TI, the not termination-condition is that $PAPR(x'(b_i))$ larger than the predetermined threshold and the migration-condition is $PAPR(x'(b_i))$ meets the requirement or maximum iteration number is achieved.

4.3. Analysis of the Computational Complexity

The sample number determines the total computational complexity when a population based PAPR searching method (see [10], [11], and [13]) is used. If the population size and generation value and are *pop* and *Gen*, then, its complexity can be shown as the number of samples, e.g., $pop \times Gen$ (Here, each sample is calculated with a $O(NlogN)$ multiplications in fast Fourier transform). Note that this complexity analysis covers any population search-based PAPR reduction schemes.

In addition, for a given $f_{original}$, N additions is needed in Equation (11) to obtain $f_{modified}$. Therefore, compared with other methods, IEM increases the addition complexity while maintain the multiplication complexity constant. Next Section will show the performance evaluation of these schemes by simulations.

5. Performance Evaluation

In this section, the performance of the IEM-TI algorithm is evaluated by simulating 10^5 MCM symbols under quadrature amplitude modulation with a 256 subcarriers. The system simulation parameters are given in **Table 1**.

Table 1. Simulation Environment

System Parameter	Simulation Environment
Modulation Scheme	64-QAM
subcarriers number	256 subcarriers
SSPA	6.5 dB saturation point, p=3
Oversampling factor	4
Q-bit angle	$\Delta\theta = 0.01\pi$

Furthermore, three population-based schemes, cross-entropy (CE-TI) [12], Parallel TS-TI [13], and linear programming(LP-TI) [14] are chosen for comparison. "IEM1" and "IEM2" in the figures are given in Appendix.
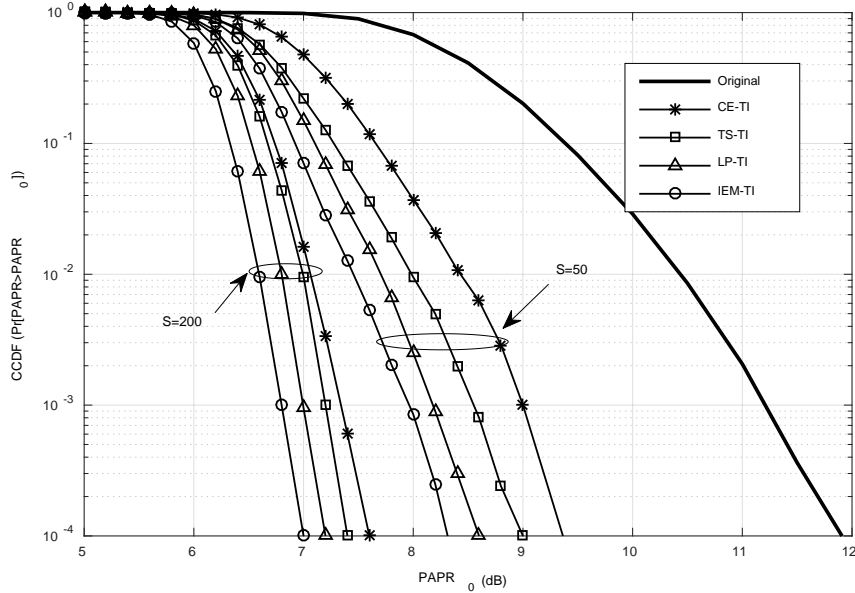
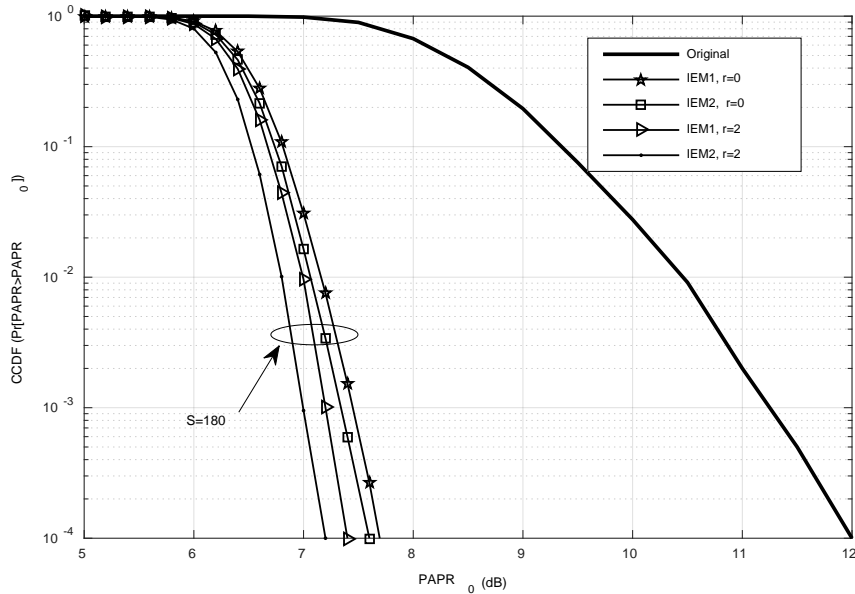**Fig. 4.** PAPR for various TI techniques in various scenarios.

Fig. 5. CCDF of PAPR with S=180 of the IEM1 and IEM2.

Figs. 4 and **5** depicts the PAPR reduction of various schemes.(Here, the parameter of the parallel TS in [13] as described below. The number in parallel is *pop*=4 and the *move*=11. Hence, the search number of parallel TS is *pop* multiply *move*. In addition, the crossover search number is given by c=C_4^2=6. Similarly, we can obtain the search number under one iteration of the parallel TS is *pop*×*move*+*c*=50) As shown, the proposed IEM-TI schemes

outperform the other schemes with the same computational complexity. Specially, to obtain a fixed PAPR level at generation value S=50, the proposed IEM scheme shows better performance than the CE-TI, Parallel TS-TI and the LP-TI schemes. When a sixty population size and the three generation value are used, the IEM1 and IEM2 schemes with r=2 gains about 0.5 dB, as compared to IEM1 and IEM2 with r=0, respectively. Complexity comparisons are shown in **Table 2**.

Table 2. Complexity at 10^{-3} PAPR

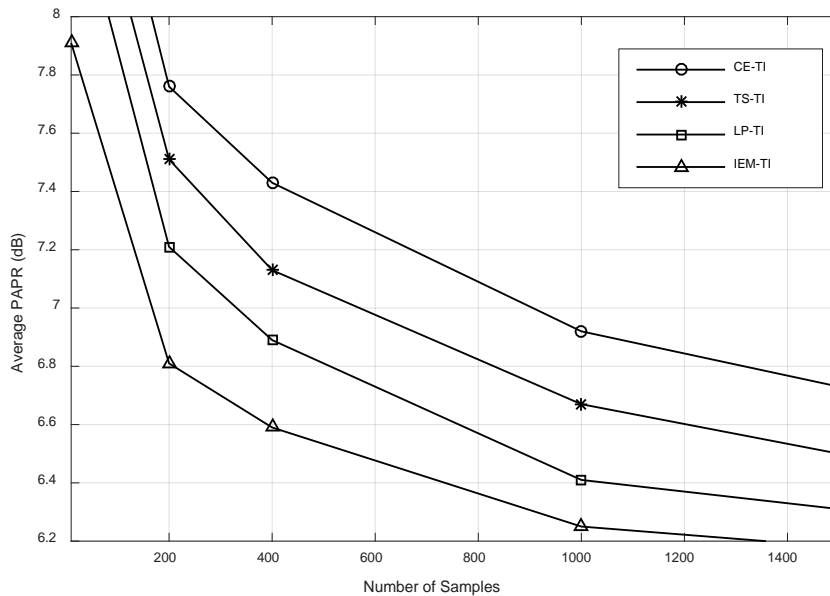| Algorithm	Number of Samples	PAPR
CE-TI	150	8.07dB
Parallel	$[(11\times4)+6]\times3$=150	7.91dB
LP-TI	150	7.58dB
IEM-TI,r=0	50×3=150	7.05dB

Fig. 6. PAPR for CCDF at 10^{-3} vs computational complexity for various schemes.

Fig. 6 compares the CCDF of PAPR with CE-TI, Parallel TS-TI, LP-TI and IEM schemes for the same complexity. The IEM schemes achieve much smaller PAPR than other schemes. Although the PAPR performance is improved with increase of the samples, the PAPR of IEM-TI with 400 samples is only less 0.3 dB than that of 1200 samples. Therefore, 400 samples can be a suitable choice for our proposed IEM schemes. **Fig. 7** shows the comparison of cubic metric. As seen, the IEM-based TI scheme also plays a good CM performance during the simulations.
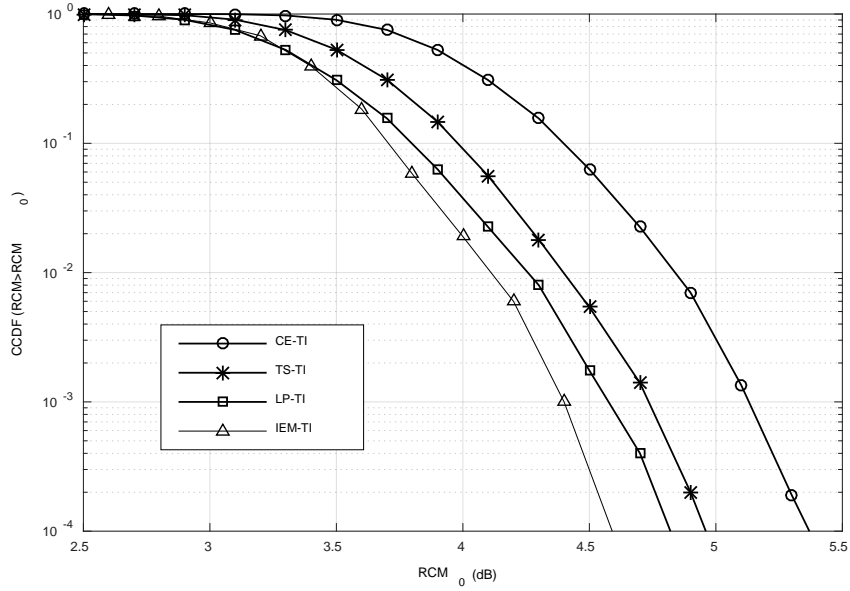
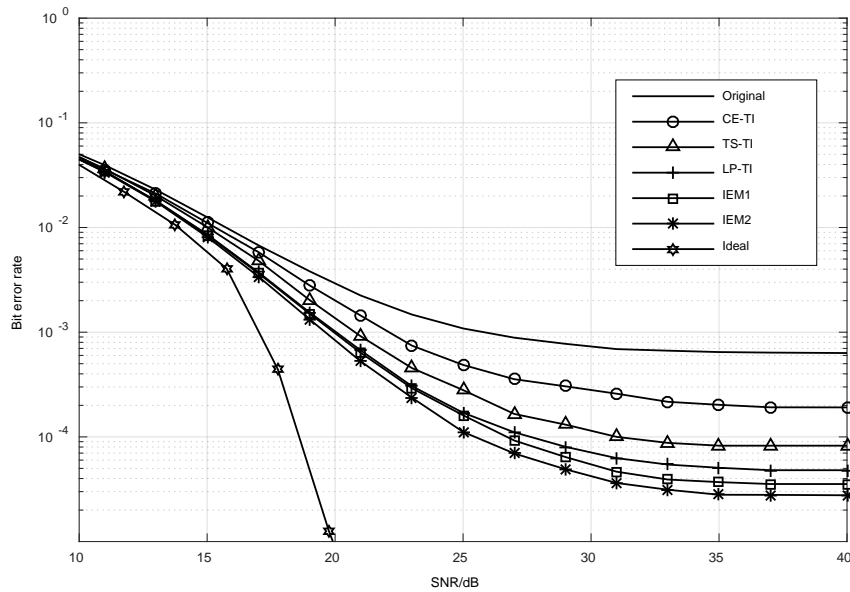**Fig. 7.** CCDFs of the raw cubic metric comparison for various schemes.

Fig. 8. BER of the various schemes with 6.5 dB SSPA saturation point, 64QAM and 256 subcarriers.

Finally, **Fig. 8** compares the BER performance versus E_b/N_0 of different schemes under hexagonal constellation with solid state power amplifier (SSPA), with comparison to that of the original OFDM scheme. Note that the SSPA model, i.e., Rapp model, can be expressed by [1]

$$y(t) = \frac{x(t)}{\left[1 + \left(\frac{|x(t)|}{C}\right)^{2p}\right]^{(1/2p)}} \tag{15}$$

where the parameter C, $x(t)$ and $y(t)$ and are the saturating point of the SSPA, input signal and output signal, respectively. Here, the parameter p controls the AM/AM sharpness of the power amplifier. In the simulations, we choose C=6.5 dB and p=3. The number of samples in all PAPR schemes are set to 200. As seen in Fig. 6, to obtain a 10^{-3} BER performance of MCM system, the required E_b/N_0s of the CE-TI, Parallel TS-TI, LP-TI, IEM1 and IEM2 under SSPA are 22.1 dB, 20.8 dB, 19.9 dB, 19.8 dB and 19.5 dB, respectively. Since side information is eliminated by the hexagonal constellation, therefore, the proposed scheme is propitious to the application.

6. Conclusion

While TI is an effective PAPR reduction technique, its computational complexity rises exponentially with the extra equivalent constellation number. To remedy this, a new immune and evolutionary mechanism-based global strategy is presented. It utilizes the vaccination and selection schedules to remove the duplicated work during the search. Monte Carlo simulation results demonstrate that the new algorithm can obtain a better PAPR improvement and lower computational complexity than other schemes.

Appendix

In this section, the *learning model* are described as follows:

Algorithm 1: *learning model*($B_i^t, B_{best,i}^t, Q_i^t$)

---

for all i do

  if $f\left(B_i^t\right) > f\left(B_{best,i}^t\right)$ **then**

  $Q_i^t \leftarrow rotate\ Q_i^t\ towards\ \ B_{best,i}^t\ using\ \ \Delta\theta$

  else

  $Q_i^t \leftarrow rotate\ Q_i^t\ towards\ \ B_{best,i}^t\ using\ \ -\Delta\theta$

  end if

end for

Algorithm 2: *learning model*($B_i^t, B_{best,i}^t, Q_i^t$)

---

for $j = 1$ to V **do**

  if $B_{ij}^t \neq B_{best,i,j}^t$ **then**

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if $B_{ij}^t = 1$ then

$Q_i^t \leftarrow rotate\ Q_i^t\ towards\ \ B_{best,i,j}^t\ \ using\ \ \Delta\theta$

else

$Q_i^t \leftarrow rotate\ Q_i^t\ towards\ \ B_{best,i,j}^t\ \ using\ \ -\Delta\theta$

end if
  end if
end for

ACKNOWLEDGMENT

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