An Enhanced Temporal Compressive Resource Allocation Technique for PLC Systems

Yan F. Coutinho, Guilherme R. Colen, Moisés V. Ribeiro

***Abstract*— This work introduces enhanced versions of the temporal compressive resource allocation technique, which is applied for power line communication systems when the periodically time varying behavior of electric power systems is taken into account. The enhancements are accomplished by introducing two changes that increase the effectiveness of the resource allocation process based on rate adaptation. The first change refers to the use of the minimum signal-to-noise ratio of each set of microslots for preventing symbol error rate peaks in some microslots. The second change imposes the use of the normalized signal-to-noise ratio matrix to estimate the correlation among microslots since it is a more reliable parameter to provide such type of information. Numerical results, based on a comparison between the full enhanced version, a partial enhanced version and the original technique, show that both enhanced versions are capable of fulfilling symbol error rate upper bound with reduced data rate loss penalty in comparison to the original one. Also, the use of the normalized signal-to-noise ratio matrix results in higher computational complexity reduction.**

***Keywords*— Bit loading, power line communication, resource allocation, rate adaptation.**

I. Introduction

Resource allocation has an important role in modern telecommunication systems because it allows us to efficiently and effectively share the available channel resources among multi-users and multi-servers demanding multi-services (e.g., real-time and non-real-time). Due to the necessity of more channel resources for satisfying staggering demands for data communications, the electric power systems, again, is being considered for addressing part of these demands. Regarding Power Line Communication (PLC) systems, the orthogonal frequency division multiplexing (OFDM) scheme [1], [2] is widely adopted by reason of the unique characteristics of PLC channels, such as frequency selectivity, periodically time varying behavior, and impulsiveness (i.e., colored behavior) of additive noise [3]. As a result, improving the performance of OFDM-based PLC systems is an important issue to be addressed.

OFDM-based PLC systems, similar to xDSL ones, operate in the baseband. It means that a baseband version of the OFDM scheme – hermitian symmetric OFDM (HS-OFDM) – with bit loading, which is commonly called discrete multitone modulation (DMT), can be applied. In this scheme, the frequency domain representation of an OFDM symbol is mapped to exploit the hermitian symmetric property of the discrete Fourier transform (DFT) and to ensure that the corresponding time domain representation of such symbol is a real finite-length sequence that can be transmitted through the baseband.

Regarding resource allocation in PLC systems, those based on microslots – which exploit the periodically time varying behavior of these channels – were advanced in [4]. However, the resource allocation technique introduced in [4] is not feasible for real-time implementation due to the great computational complexity and the necessity of performing data exchanges among transceivers and receivers.

In order to circumvent those issues, [5] and [6] introduced low-cost resource allocation techniques that are, respectively, called Temporal Compressive Resource Allocation (TCRA) and Spectral Compressive Resource Allocation (SCRA). Both techniques exploit the behavior of electric power grids with the advantage of offering a variable trade-off between performance and computational complexity. In [5], the existing relationships in the time domain of PLC channels were taken into account to significantly reduce the computational complexity in exchange for small reductions in data rate, considering a dynamic resource allocation process. Regarding [6], solutions were proposed for performing resource allocation by exploiting the existing correlation among the normalized signal-to-noise ratio (nSNR) associated with consecutive subcarriers. Also, [6] introduced a solution for the combination of the SCRA and TCRA techniques, called Spectral-Temporal Compressive Resource Allocation (STCRA), in which existing relationships in time and frequency domains are jointly exploited. Those three techniques – TCRA, SCRA, and STCRA – result in suboptimal solutions that may be close to the optimum one under constraint related to computational complexity.

The TCRA technique takes advantage of small differences among consecutive mains cycles, which is considered a quasi-linear periodically time varying (LPTV) behavior of PLC channels. The quasi-LPTV assumption in TCRA [5] is a little bit different from the assumption of LPTV in [4]. In practice, the former assumption is much more realistic since the PLC channel can vary due to load dynamics. As a consequence, the assumption of quasi-LPTV behavior results in the violation of a symbol error rate (SER) upper bound in TCRA as well as in other techniques. In fact, the peaks on the SER related to the TCRA technique certainly result in the reduction of the effective data rate since retransmissions may be requested more often. Another source of data rate degradation in the use of TCRA concerns the way in which the channel correlation

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is evaluated, which relies on the use of multichannel nSNR (nm-SNR) or data rate. The use of one of these parameters can result in loss of information[1]. However, such information is useful for efficiently characterizing the correlation between microslots, which is considered a relevant feature for performing resource allocation in PLC channels.

Aiming to address the aforementioned problems related to TCRA, this work introduces and analyzes two main modifications to the technique. The first modification focuses on ensuring that the peak SER does not violate an imposed SER upper bound. The second one contemplates the use of a distinct correlation coefficient within a cycle of the mains signal in order to guarantee that the resource allocation process makes use of more reliable information. These modifications lead to two versions of the Enhanced Temporal Compressive Resource Allocation (ETCRA) technique. The first version, called ETCRA, applies both modifications. The second version, called partial ETCRA, utilizes only the modification regarding the assurance of an SER upper bound, maintaining the original correlation evaluation. Numerical results show that the former version achieves lower data rates, however with greater reductions on computational complexity compared to the latter one. Furthermore, both enhanced versions ensure a non-violation of an SER upper bound. As a result, both enhanced versions improve the overall performance of the resource allocation process in PLC systems.

II. Problem Formulation

Let us assume a baseband LPTV PLC channel with a coherence time T_c and a PLC system based on the HS-OFDM scheme. Also, microslots are defined in the time interval duration denoted by T_γ, such that the PLC channel is modeled as linear time invariant (LTI) during these intervals since the constraint $T_\gamma \ll T_c$ is fulfilled. For each cycle of the mains signal, there are M microslots. With that in mind, the vectorial representation of the channel impulse response (CIR) during the m^{th} microslot can be denoted by $\mathbf{h}[m] = [h_0[m], h_1[m], \cdots, h_{L_h-1}[m]]^T$, in which L_h is the length of the CIR and $(\cdot)^T$ denotes the transpose operator. Thus, the DFT of the zero-padded version of the CIR in the m^{th} microslot is given by $\mathbf{H}[m] = [H_0[m], H_1[m], \cdots, H_{2N-1}[m]]^T = \mathbf{W}_{2N}[\mathbf{h}[m]^T \mathbf{0}_{2N-L_h}^T]^T$, where $\mathbf{W}_{2N} \in \mathbb{C}^{2N\times 2N}$ is the DFT matrix and $\mathbf{0}_{2N-L_h}$ is the $(2N-L_h)$-length column vector composed of zeros. The noise is modeled as an additive, stationary and zero-mean Gaussian random process with frequency representation within the m^{th} microslot given by $\mathbf{V}[m] = [V_0[m], V_1[m], \cdots, V_{2N-1}[m]]^T$, where $V_k[m]$ is a random variable that models the additive noise at the k^{th} subchannel such that $\mathbb{E}\{V_k[m]V_j[m]\} = \mathbb{E}\{V_k[m]\}\mathbb{E}\{V_j[m]\}$ for $k \neq j$, $\mathbb{E}\{V_k[m]\} = 0$ and $\mathbb{E}\{\cdot\}$ denotes the expectation operator. In this work, we assume that the additive noise is a colored Gaussian random process. For the sake of simplicity, we use $\mathbf{\Lambda}_{|\mathbf{H}[m]|^2} \triangleq \mathbf{diag}\{|H_0[m]|^2, |H_1[m]|^2, \cdots, |H_{2N-1}[m]|^2\}$ and $\mathbf{\Lambda}_{\sigma^2_{\mathbf{V}[m]}} \triangleq \mathbf{diag}\{\sigma^2_{V_0[m]}, \sigma^2_{V_1[m]}, \cdots, \sigma^2_{V_{2N-1}[m]}\}$, in which $\sigma^2_{V_k[m]}$ is the noise variance in the k^{th} subchannel for the m^{th} microslot and $\mathbf{diag}\{\cdot\}$ denotes a diagonal matrix. Based on that, the nSNR matrix, which represents the subchannel signal-to-noise ratios (SNRs) when unit energy is applied to each subchannel at the transmitter, is expressed as

$$\begin{aligned}\mathbf{\Lambda}_{\overline{\gamma}[m]} &\triangleq \mathbf{diag}\Big\{\overline{\gamma}_0[m], \overline{\gamma}_1[m], \cdots, \overline{\gamma}_{2N-1}[m]\Big\} \\ &= \mathbf{\Lambda}_{|\mathbf{H}[m]|^2}\mathbf{\Lambda}^{-1}_{\sigma^2_{\mathbf{V}[m]}}\,.\end{aligned} \tag{1}$$

As a consequence, based on [5], the nm-SNR in the m^{th} microslot is given by

$$\overline{\gamma}[m] = \mathbf{det}\Big(\mathbf{I}_{2N} + \mathbf{\Lambda}_{\overline{\gamma}[m]}\Big)^{\frac{1}{2N}} - 1\,, \tag{2}$$

where $\mathbf{I}_{2N} \in \mathbb{R}^{2N\times 2N}$ and $\mathbf{det}(\cdot)$ denote, respectively, the $2N$-size identity matrix and the determinant operator.

The optimum resource allocation which maximizes the data rate during the m^{th} microslot can be represented by

$$\Big[\mathbf{\Lambda}_{b^o[m]}, \mathbf{\Lambda}_{E^o[m]}\Big] = f\Big(\mathbf{\Lambda}_{\overline{\gamma}[m]}, E_t, \Gamma, \beta\Big)\,, \tag{3}$$

in which $f(\cdot)$ is a greedy rate adaptive algorithm [7] that performs the resource allocation; $\mathbf{\Lambda}_{b^o[m]} = \mathbf{diag}\{b_0^o[m], b_1^o[m], \ldots, b_N^o[m]\}$ is the matrix of bits allocated for performing data communication through the m^{th} microslot; $\mathbf{\Lambda}_{E^o[m]} = \mathbf{diag}\{E_0^o[m], E_1^o[m], \ldots, E_N^o[m]\}$ is the energy allocated to the m^{th} microslot; $b_k^o[m]$ and $E_k^o[m]$ are, respectively, the number of bits and the energy allocated at the m^{th} microslot at the k^{th} subchannel; E_t is the total energy to be shared among microslot; $\Gamma \in \mathbb{R}_+$ is the gap factor from the Shannon capacity that defines an SER upper bound; and β is the bit granularity for the resource allocation problem, i.e., the number of bits allocated in each iteration of the greedy algorithm. Note that the baseband data communication means that the total transmission power is allocated only to N subcarriers (not to $2N$). Therefore, $\mathbf{\Lambda}_{b^o[m]} \in \mathbb{Z}^{N\times N}$ and $\mathbf{\Lambda}_{E^o[m]} \in \mathbb{R}^{N\times N}$.

The optimal data rate for the m^{th} microslot is denoted as

$$R^o[m] = \frac{\mathrm{Tr}\big(\mathbf{\Lambda}_{b^o[m]}\big)}{T_{\mathrm{sym}}}\,, \tag{4}$$

where $\mathrm{Tr}(\cdot)$ is the trace operator, $T_{\mathrm{sym}} = (2N + L_{cp})/F_s$ is the time duration of an HS-OFDM symbol, L_{cp} is the length of the cyclic prefix and F_s is the sampling frequency.

Thereby, the attained optimal data rate needs to be periodically updated and, as a consequence, computational complexity is significantly increased. However, according to [5], the existing relationship among successive cycles of the mains signal as well as inside each one of them in the time domain can be exploited for reducing such complexity associated with the resource allocation in OFDM-based PLC systems. In this sense, the TCRA technique establishes a trade-off between data rate and computational complexity. However, despite the gains made by the TCRA technique, we point out that the lack of an SER constraint analysis may result in a reduced effective data rate, which can affect the overall performance. Another issue regards the use of $\overline{\gamma}[m]$ or $R^o[m]$ in order to evaluate

[1] According to data-processing inequality in the field of Information Theory, the processing of a data can reduce the amount of information associated with it.

the correlation among microslots. Such usage may represent a loss of important channel information since these parameters are a consequence of considerable processing.

To deal with the aforementioned problems, Section III introduces the modifications that lead to both ETCRA and partial ETCRA techniques, which ensure that the SER upper bound is totally satisfied during the resource allocation process applied to LPTV channels.

III. Enhanced Temporal Compressive Resource Allocation

Let us assume the existence of $N_c \in \mathbb{N}^*$ consecutive cycles of the mains signal, each one containing M microslots. According to [5], there are three distinct cases for resource allocation, which are, for the sake of simplicity, briefly described as follows:

- Case #1: the existing relationship among microslots inside only one cycle of the mains signal is exploited for resource allocation purposes.
- Case #2: the relationship among microslots of distinct cycles of the mains signal is exploited.
- Case #3: exploits both relationships among M microslots inside one cycle and among N_c cycles of the mains signal to reduce the complexity associated with the resource allocation problem.

It is important to emphasize that for the TCRA technique, in [5] the PLC channel is considered quasi-LPTV, i.e., with small variations from one cycle to the other, hence the argument of using different cases of microslot grouping. However, as in [4], this work considers that the channel is non-variant between consecutive cycles. Consequently, a different application of these cases must be considered. Case #1 can be normally applied. Case #2 has already a natural application since two consecutive mains cycles are identical. Therefore, there is no point in considering case #2 to analyze the reduction of computational complexity. Since case #3 is a combination of cases #1 and #2, it becomes senseless as well, even if it is the case applied in practice. Accordingly, the computational complexity reduction must be evaluated based only on case #1.

As [5] considers the PLC channel quasi-LPTV, during a real-time application, it is not possible to know perfectly the nSNR of all microslot for the current mains cycle or the following ones. As a consequence, $\mathbf{\Lambda}_{b[m]}$ and $\mathbf{\Lambda}_{E[m]}$ must be chosen based on the first microslot within the set of microslots, which are defined using the Set Partition Procedure and replicated on the remaining microslots belonging to this set. This procedure is well discussed in [5]. However, it is notable that such an approach may cause peaks on the SER associated with the remaining microslots belonging to the set, which can eventually violate the SER constraint applied to the resource allocation problem. The proposed enhancement focuses on the replacement of $\mathbf{\Lambda}_{b[m]}$ and $\mathbf{\Lambda}_{E[m]}$ associated with the first microslot of the set and the adoption of the worst nSNR for each subcarrier within the set of microslots instead. This is a conservative choice that ensures the non-violation of SER constraint. The worst nSNR matrix related to the l^{th} set of microslots is expressed as

$$\mathbf{\Lambda}_{\mathbf{\Psi}_l} = \mathbf{diag}\big\{\Psi_{l,0}, \Psi_{l,1}, \ldots, \Psi_{l,N-1}\big\}, \tag{5}$$

where $\Psi_{l,k}$ is the worst nSNR[2] associated with the k^{th} subchannel belonging to the l^{th} set of microslots. Note that

$$\Psi_{l,k} = \min_{j} \overline{\gamma}_k\big[\mathcal{S}_l\{j\}\big], \tag{6}$$

in which $\min(\cdot)$ is the minimal operator, $\mathcal{S}_l$ denotes the group of microslots belonging to the l^{th} set, $j \in \mathbb{N} \mid 1 \leq j \leq \text{card}(\mathcal{S}_l)$ and $\text{card}(\cdot)$ is the cardinality of a set. Therefore, the bit and energy allocation applied to all microslots of the l^{th} set is obtained by

$$\Big[\mathbf{\Lambda}_{b_l}, \mathbf{\Lambda}_{E_l}\Big] = f\Big(\mathbf{\Lambda}_{\mathbf{\Psi}_l}, E_t, \Gamma, \beta\Big), \tag{7}$$

in which $f(\cdot)$ defines the resource allocation technique.

Moreover, a modification is also introduced in the Set Partition Procedure. In [5], the correlation is evaluated using $\overline{\gamma}[m]$ or $R^o[m]$, and the microslot with a correlation higher than a chosen threshold are grouped in the same set. However, this correlation does not allow us to efficiently exploit the richness of information associated with all subchannels since these parameters are outcomes of substantial processing. Therefore, we suggest the replacement of $\overline{\gamma}[m]$ or $R^o[m]$ for $\mathbf{\Lambda}_{\overline{\gamma}[m]}$ on the correlation evaluation since it carries much more information of all subchannels. The suggested parameter is denoted as $\mathbf{\Lambda}_{\overline{\gamma}[m]}$ by reason of being much more representative for the current state conditions of the PLC channel in the m^{th} microslot. It is important to emphasize that, although the modified correlation evaluation has greater computational complexity, the Set Partitioning Procedure is applied only once, in case there is no change in the channel state information (CSI) during the Bit Loading Procedure, as explained in [5]. This implies that the complexity added by the modified correlation is minimal, compared to complexity additions to the Bit Loading Procedure, which is applied significantly more often in the resource allocation process. Hence, the correlation coefficient can be defined as follows:

$$\Phi(\tau) \triangleq \frac{\text{Tr}\Big(\mathbf{\Lambda}_{\overline{\gamma}[m]}\mathbf{\Lambda}_{\overline{\gamma}[m+\tau]}\Big)}{\sqrt{\text{Tr}\Big(\big(\mathbf{\Lambda}_{\overline{\gamma}[m]}\big)^2\Big)}\sqrt{\text{Tr}\Big(\big(\mathbf{\Lambda}_{\overline{\gamma}[m+\tau]}\big)^2\Big)}}, \tag{8}$$

in which $\tau \in \mathbb{Z} \mid 0 \leq \tau < M - 1$.

The two aforementioned changes in the TCRA technique result in the so-called ETCRA. Based on [5], the steps for implementing ETCRA are detailed in Algorithm 1. However, a distinct approach can be made by considering only the modification displayed in (6) and adopting the correlation using $\overline{\gamma}[m]$ instead of $\mathbf{\Lambda}_{\overline{\gamma}[m]}$. For the sake of simplicity, this technique is called partial ETCRA.

IV. Numerical Results

This section discusses a comparative analysis between TCRA, partial ETCRA, and ETCRA techniques based on a set

[2]The minimum operation is applied as a conservative approach for fulfilling a target SER and, as a consequence, some data rate reduction can be observed.

Algorithm 1: The ETCRA technique.

input :
$\mathbf{\Lambda}_{\overline{\gamma}[m]}$ is the diagonal matrix of nSNRs for the Set Partitioning Procedure
M is the number of microslots within one cycle of the mains signal
$\alpha \in \mathbb{R}$ is a threshold which determines the sets of microslots
E_t is the maximum energy to be distributed among microslots
Γ is the gap from the Shannon capacity curve
β is the bit granularity of the resource allocation problem
output:
$\mathbf{\Lambda}_{b_l}$ is the matrix corresponding to the number of bits allocated in each set of microslots
$\mathbf{\Lambda}_{E_l}$ is the matrix corresponding to the energy allocated in each set of microslots

begin
  while *PLC system on* **do**
    for $\tau = 0$ *to* $M-1$ **do**
      $\Phi(\tau) \triangleq \frac{\mathrm{Tr}\left(\mathbf{\Lambda}_{\overline{\gamma}[m]}\mathbf{\Lambda}_{\overline{\gamma}[m+\tau]}\right)}{\sqrt{\mathrm{Tr}\left(\left(\mathbf{\Lambda}_{\overline{\gamma}[m]}\right)^2\right)}\sqrt{\mathrm{Tr}\left(\left(\mathbf{\Lambda}_{\overline{\gamma}[m+\tau]}\right)^2\right)}}$;
    end
    $L_{\mathcal{S}}^a = M$;
    for $l = 1$ *to* $L_{\mathcal{S}}^a$ **do**
      $\mathcal{S}_l^a = \{l-1+\tau \mid \Phi(\tau) \geq \alpha,\ 1 \leq l+\tau \leq M\}$;
    end
    $\mathcal{S}_l^b, L_{\mathcal{S}} \leftarrow \min L_{\mathcal{S}}^a$, in which
      $\bigcup_{l=1}^{L_{\mathcal{S}}} \mathcal{S}_l^b = \{0, 1, \cdots, M-1\}$;
    for $l = 1$ *to* $L_{\mathcal{S}}$ **do**
      $\epsilon_{\mathcal{S}_l} = \min_j(\overline{\gamma}[\mathcal{S}_l^b\{j\}])$;
      $\mathcal{S}_l = \{\ \emptyset\ \}$;
    end
    for $p = 0$ *to* $M-1$ **do**
      $l_p^* = \{l \mid \mathcal{S}_l^b \cap \{p\} \neq \{\emptyset\}\}$;
      $q = \arg\max_j(\epsilon_{\mathcal{S}_{l_p^*}\{j\}})$;
      $\mathcal{S}_{l_p^*}\{q\} = \mathcal{S}_{l_p^*}\{q\} + \{p\}$;
    end
    while *CSI do not change* **do**
      for $l = 1$ *to* $L_{\mathcal{S}}$ **do**
        for $k = 0$ *to* $N-1$ **do**
          $\Psi_{l,k} = \min_j \overline{\gamma}_k\left[\mathcal{S}_l\{j\}\right]$;
        end
        $\mathbf{\Lambda}_{\Psi_l} = \mathbf{diag}\{\Psi_{l,0}, \Psi_{l,1}, \ldots, \Psi_{l,N-1}\}$;
        $\left[\mathbf{\Lambda}_{b_l}, \mathbf{\Lambda}_{E_l}\right] = f\left(\mathbf{\Lambda}_{\Psi_l}, E_t, \Gamma, \beta\right)$;
      end
      for $l = 1$ *to* $L_{\mathcal{S}}$ **do**
        Apply $\mathbf{\Lambda}_{b_l}$ and $\mathbf{\Lambda}_{E_l}$ in other elements of $\mathcal{S}_l$;
      end
    end
  end
end

of measured data. The data set is constituted by PLC channel estimates and additive noise measurements obtained from a measurement campaign carried out in seven residences in the city of Juiz de Fora, Brazil. The covered frequency band is between 1.7 and 100 MHz. Also, 232 measures were obtained with the use of the HS-OFDM scheme with $N = 2048$ subchannels and a cyclic prefix of $L_{cp} = 512$ samples, as described in [8]. The number of microslots during a time interval corresponding to one cycle of the mains signal is $M = 32$ and the time interval of each microslot is equal to $T_\gamma = (1/f_0)/M \approx 520\ \mu$s, where $f_0 = 60$ Hz is the mains frequency. The value of M complies with the coherence time of the in-home PLC channel.

The performance comparisons are presented in terms of data rate loss ratio and computational complexity reduction ratio. The data rate loss ratio is expressed as

$$\eta = 1 - \frac{R_c}{R^o}\,, \tag{9}$$

where R^o denotes the optimal data rate obtained by the greedy rate adaptive algorithm in all (M) microslots and R_c refers to the data rate obtained with TCRA, partial ETCRA or ETCRA.

On the other hand, the computational complexity reduction ratio is given by

$$\rho = 1 - \frac{L_{\mathcal{S}}}{M}\,, \tag{10}$$

in which $L_{\mathcal{S}}$ is the number of times TCRA, partial ETCRA, or ETCRA are applied during the resource allocation problem, whereas M is the total number of microslots used by the optimal resource allocation. Note that only case #1 was considered for the TCRA technique.

As in [5], the threshold $\alpha \in \mathbb{R} \mid 0 \leq \alpha \leq 1$ is used to analyze the impact of using different values for the correlation coefficient (i.e., $\Phi(\tau) \geq \alpha$) on data rate loss ratio and computational complexity reduction ratio. Note that $\alpha = 0$ implies on the grouping of all microslots in a single set (consequently, $\rho \cong 0.97$), and $\alpha = 1$ implies the absence of grouping and, therefore, the creation of M sets in the Set Partitioning Procedure ($\rho = 0$).

First of all, let us analyze the complementary cumulative distribution function (CCDF) of the data rate loss ratio and computational complexity reduction ratio for the mentioned techniques. Fig. 1 shows the CCDF of data rate loss ratio for $\alpha = 0.2$ and $\alpha = 0.9$. Such values of α were chosen in order to better exemplify the implications of the variation of such parameter when values close to its extremes are taken into account. It is notable that, for all techniques, the variation of α affects η directly. Higher values of α imply a microslot grouping closer to its optimal and lower data rate loss. On the other hand, lower values of α suggest the same allocation for all microslots and, consequently higher data rate loss, as illustrated in Fig. 1. We can observe that ETCRA yields higher η than TCRA, which is an expected outcome given the modification presented in (6) being a trade-off between η and ρ with an SER constraint guarantee. Considering the partial ETCRA, it is clear that this approach has intermediate performance between the two other techniques and, also, is more sensitive to variations in α.

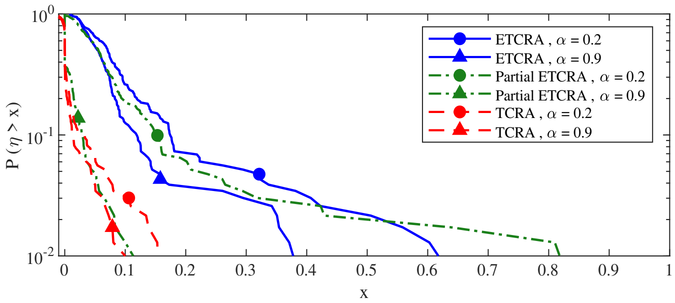

Fig. 1: CCDF of data rate loss ratio.

Regarding computational complexity, Fig. 2 portrays a comparison between the three techniques by showing the CCDF of computational complexity reduction ratio for the same values of α as in Fig. 1. Perceive that ETCRA undergoes almost negligible changes in view of the variations in α. TCRA and partial ETCRA, on the contrary, produces more distinct probabilities from each other regarding variations in α (note that both curves are more distant from each other). Such a result showed in Fig. 2 illustrates properly the trade-off offered by the ETCRA technique, where it yields higher data rate loss, however with a higher reduction to computational complexity. It also portrays the computational complexity reduction yielded with the use of the modified correlation.

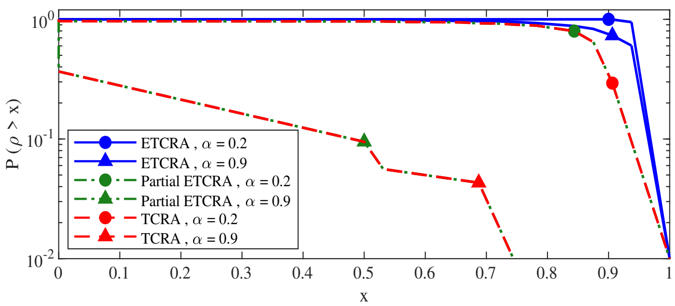

Fig. 2: CCDF of computational complexity reduction ratio.

Finally, we present a discussion regarding SER, which is the main focus of the modifications brought by the enhanced techniques. An SER upper bound is imposed on the system as [7] thoroughly describes. This constraint is evaluated based on the gap from the Shannon capacity curve (Γ) and can be expressed as

$$\xi_b = 4Q\left(\sqrt{3\Gamma}\right), \tag{11}$$

where $Q(.)$ is the tail distribution function of the standard normal distribution (i.e., Q-function) and the gap is set as $\Gamma = 9$ dB (resulting on $\xi_b = 2.1 \times 10^{-6}$). Note that this constraint can be applied in every subchannel.

Fig. 3 portrays the simulated SER using a quadrature amplitude modulation (QAM) scheme over an additive white Gaussian noise (AWGN) channel for all three techniques in comparison with the SER constraint defined by (11). Again, the chosen values of α were the same as in Figs. 1 and 2. Note that, regardless of the chosen α, both partial ETCRA and ETCRA achieve SER values lower than the predefined SER constraint for all microslots, with partial ETCRA being closer to the SER upper bound. On the other hand, TCRA violates the SER upper bound in most microslots for both values of α.

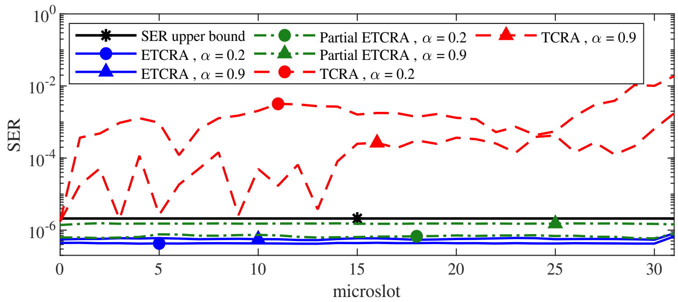

Fig. 3: SER per microslot.

V. CONCLUSION

This work introduced ETCRA and partial ETCRA, which are enhanced versions of TCRA, for ensuring that an SER upper bound is not violated. The enhancements are of great importance, since failure to comply with an SER upper bound results in loss of effective data rate due to the necessity of retransmissions that may be required for achieving an acceptable performance of OFDM-based PLC systems. Similar to TCRA, numerical results showed that ETCRA offers a trade-off between data rate and computational complexity and yields data rates relatively lower than those obtained with TCRA, when both modifications are taken into account. In addition, by considering the partial ETCRA, it was shown that the new way of evaluating correlation results in higher reductions of computational complexity. Finally, it was shown that TCRA violates the SER upper bound established by the gap from the Shannon capacity curve in several microslots, while both enhanced techniques successfully ensure the fulfillment of it.

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