Linearizing RF Power Amplifiers Using Adaptive RPEM Algorithm

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Abstract. This paper proposes the adaptive indirect learning architecture (ILA) based digital predistortion (DPD) technique using a recursive prediction error minimization (RPEM) algorithm for linearizing radio frequency (RF) power amplifiers (PAs). The RPEM algorithm allows the forgetting factor to vary with time, which makes the predistorter (PD) parameter estimates more consistent and accurate in steady state, and hence reduces mean square errors. The proposed DPD technique is evaluated with respect to the error vector magnitude (EVM) and the adjacent channel power ratio (ACPR). The simulated PA Wiener model is used to validate the efficiency of the proposed algorithms. The simulation results have confirmed the improvement of the proposed adaptive RPEM ILA based DPD in terms of EVM and ACPR.

Keywords: Power amplifier · RPEM algorithm · Linearizing

1 Introduction

The development of future wireless communication systems, e.g., the fifth generation (5G) or beyond, continuously demands higher data rates and larger user capacities, which faces significant challenges. It requires not only wideband transceiver architecture, but also higher-order modulation schemes. The signals of these systems characterized by non-constant envelopes and high peak-to-average power ratio (PAPR), leading to stringent linearity requirements for signal amplification. In the meantime, the power dissipation of the future communication systems must be remained as low as possible [1]. To cope with these challenges, high efficiency and linear radio frequency (RF) power amplifiers (PAs) are indispensable components. Unfortunately, due to the inherent

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nonlinear behavior of PAs, efficiency and linearity requirements often conflict each other. In order to provide highly-efficient power conversion, PAs should be driven into the saturation region. However, the saturated PAs produce not only in-band distortion but also result in spectral regrowth that interferes the adjacent frequency band channels. Consequently, the spectra utilization efficiency is reduced. In contrast, the nonlinear distortion can be mitigated by a traditional back-off approach, but this generates low power efficiency due to high PAPR of the transmitted signals. In order to maintain a low level of distortion without sacrificing the system energy efficiency requirement, PA linearization techniques are often used [2]. Thanks to its flexibility and excellent linearization performance, baseband digital predistortion (DPD) has been recognized as one of the most cost-effective linearization techniques [3–9], and it also tends to be popularly and widely used in wireless transmitters for the next generation wireless communication systems. In this scheme, a predistorter (PD) block is placed in front of a PA. The PA input signal is pre-distorted by the PD whose transfer function is the inverse of that of the PA. Ideally, the cascade of the PD and PA behaves as a linear amplification system and the original input is amplified by a constant gain.

In practice, the PA characteristics change with time due to process, supply voltage, and temperature (PVT) variations. In order to track time-varying change in the PA characteristics, an adaptive DPD using cost-effective learning architectures has become one of the most preferred choices. There are two commonly and widely used learning architectures for PD parameter identification: indirect learning architecture (ILA) [10–12] and direct learning architecture (DLA) [8,9,13,14]. Although DLA is more robust than ILA in terms of noise at the PA output and can provide unbiased parameter estimates, it is more complex identification process since the adaptive algorithms used in DLA require many iterations to find a set of parameters that minimizes the optimization criterion [3]. For these reasons, the adaptive ILA is most often used for identifying the PD parameters in RF PAs [3]. The adaptive ILA using least mean squares (LMS) for linearizing PAs was developed in [15]. The advantage of LMS is its simple implementation. However, it provides inaccurate estimation and has slow convergence since increasing the step size parameter leads instability problems. Moreover, it is also sensitive to the scaling of the input signal, making it very hard to choose a proper step size [15]. In order to obtain faster convergence of the adaptation, authors in [10,12] proposed the adaptive ILA using recursive least squares (RLS). It is worth noting that the choice of forgetting factor λ is often essential to make a good trade-off between the convergence and accuracy. For RLS, a decrease in the forgetting factor λ leads to its sensitivity to noise and a larger fluctuation of parameter estimates [16], resulting in inefficiency linearization performance.

In this paper, we propose an adaptive ILA using recursive prediction error minimization (RPEM) algorithm to linearize PAs, which allows time-varying forgetting factor λ. Thus, the RPEM algorithm reduces the fluctuation of the PD parameter estimates, speeds up the convergence, mitigates the steady-state mean square error and hence minimizes the total nonlinear distortion at the PA output. As a result, the adaptive ILA with RPEM effectively compensate the nonlinear distortion of the PA even if the PA characteristics changes due to PVT drift and other factors such as type of signals, high-order modulation schemes, input power levels etc. The rest of the paper is organized as follows. Section 2 proposes the one using RPEM. Simulation results are presented in Sect. 3. Conclusions are finally drawn in Sect. 4.

2 Proposed Adaptive ILA Using RPEM for Linearizing RF Power Amplifiers

Figure 1 shows the block diagram of the ILA-based DPD technique, where a post-distorter (or training) block is used to identify the postinverse of the PA. The baseband signal $u(n)$ is fed to the predistorter, which generates a signal $x(n)$ that is a PA input. The PA output signal is normalized by a linear gain G_0, producing the normalized output $z(n)$, i.e., $z(n) = \frac{y(n)}{G_0}$. The postdistorter model has the input $z(n)$ and the output $z_{\mathrm{p}}(n)$. Its parameters are identified by minimizing the error signal $e(n) = x(n) - z_{\mathrm{p}}(n)$ using the adaptive algorithms. Note that both the PD and postdistorter models are identical. Thus, when the coefficients of the postdistorter are identified, they are directly copied to the PD model. This process is repeated iteratively until the ILA linearization has converged. At convergence, the cascaded PD and PA system behaves linearly. Since the MP models have owned low computational cost, satisfactory accuracy, and easy hardware implementation, they have become promising choices and been widely applied for behavioral modeling and predistortion of PAs exhibiting nonlinear memory effects [2,4,12,17]. Therefore, both the PD and postdistorter

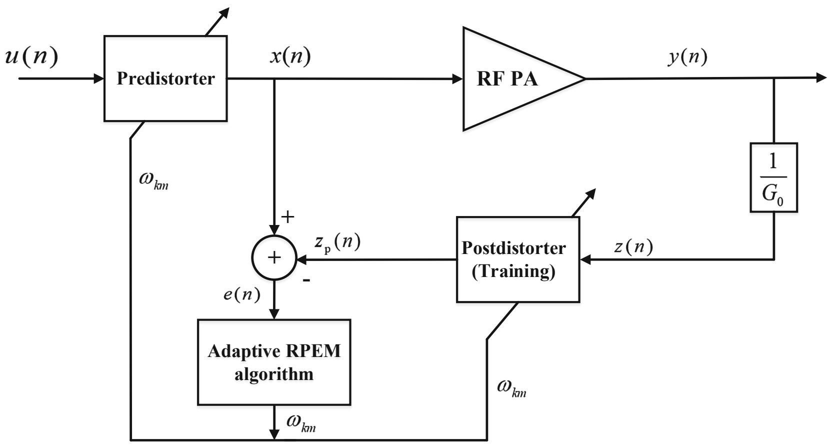


Fig. 1. Block diagram of Indirect learning architecture (ILA) using the proposed RPEM adaptive algorithm.

are modeled by the same MP model that has Q as the nonlinearity order and P as memory depth, and ω_{km} as coefficients. The input and output relation of the PD model is given by

$$x(n) = \sum_{k=1}^{Q} \sum_{m=0}^{P} \omega_{km} u(n-m) |u(n-m)|^{k-1} = \omega^{\mathrm{T}} \phi(n), \tag{1}$$

where

$$\omega = [\omega_{10}, \ldots, \omega_{Q0}, \ldots, \omega_{1P}, \ldots, \omega_{QP}]^{\mathrm{T}}, \tag{2}$$

and

$$\phi(n) = [\phi_{10}(n), \ldots, \phi_{Q0}(n), \ldots, \phi_{1P}(n), \ldots, \phi_{QP}(n)]^{\mathrm{T}} \tag{3}$$

with

$$\phi_{km}(n) = u(n-m)|u(n-m)|^{k-1}. \tag{4}$$

The symbol T indicates the matrix transpose.

The input and output of the postdistorter model can be expressed by

$$z_{\mathrm{p}}(n) = \sum_{k=1}^{Q} \sum_{m=0}^{P} \omega_{km} z(n-m) |z(n-m)|^{k-1} = \omega^{\mathrm{T}} \mathbf{z}(n), \tag{5}$$

where ω is defined as in (2) and

$$\mathbf{z}(n) = [z_{10}(n), \ldots, z_{Q0}(n), \ldots, z_{1P}(n), \ldots, z_{QP}(n)]^{\mathrm{T}} \tag{6}$$

with

$$z_{km}(n) = z(n-m)|z(n-m)|^{k-1}. \tag{7}$$

The prediction error $e\,(n, \omega)$ is defined by

$$e\,(n, \omega) = x(n) - z_{\mathrm{p}}(n) = x(n) - \omega^{\mathrm{T}} \mathbf{z}(n). \tag{8}$$

The adaptive algorithms are derived by minimizing corresponding lost functions that refer to scalar-valued functions of all the prediction errors $e\,(n, \omega)$.

The coefficient vector ω of the predistorter is estimated by using the Gauss-Newton RPEM algorithm in [16] that minimizes the following cost function.

$$f_L\,(\omega) = \lim_{L \to \infty} \frac{1}{L} \sum_{l=1}^{L} \mathrm{E}\left\{e^2\,(l, \omega)\right\}, \tag{9}$$

where $e(l, \omega)$ is given as in (8).

The formulation of the RPEM algorithm is derived in [16], which requires the negative gradient of $e\,(l, \omega)$ with respect to ω. From (8), the negative gradient is given by

$$-\frac{\partial e\,(n, \omega)}{\partial \omega} = \mathbf{z}^{\mathrm{T}}(n). \tag{10}$$

When applying the RPEM algorithm [16] for PA linearization, the adaptive ILA-based DPD using RPEM algorithm is described in Algorithm 1, where ρ also is

Algorithm 1. The proposed adaptive ILA-based DPD technique using RPEM.

Initialize: $n = 0, \lambda_0, \lambda(0), \mathbf{P}(0) = \rho\mathbf{I}$.
for $n = 1$ to $\mathrm{L} - 1$ **do**
  $x(n) = \omega^{\mathrm{T}}(n-1)\phi(n)$
  $y(n) = F_{\mathrm{PA}}\left\{x(n)\right\}.$
  $z(n) = \frac{y(n)}{G_0}$
  $z_p = \omega^{\mathrm{T}}(n-1)\mathbf{z}(n)$
  $e(n) = x(n) - z_{\mathrm{p}}(n)$
  $\lambda(n) = \lambda_0\lambda(n-1) + 1 - \lambda_0$
  $\mathbf{k}(n) = \frac{\mathbf{P}(n-1)\mathbf{z}(n)}{\lambda(n)+\mathbf{z}^{\mathrm{T}}(n)\mathbf{P}(n-1)\mathbf{z}(n)}$
  $\mathbf{P}(n) = \frac{1}{\lambda(n)}\left[\mathbf{P}(n-1) - \mathbf{k}(n)\mathbf{z}^{\mathrm{T}}(n)\mathbf{P}(n-1)\right]$
  $\omega(n) = \omega(n-1) + \mathbf{k}(n)e(n).$
End For

a positive constant and $\lambda(n)$ is a forgetting factor that tends exponentially to 1 as $n \to \infty$. λ_0, $\lambda(0)$ and $\mathbf{P}(0)$ are initial variables designed by users. Typically chosen values for λ_0 and $\lambda(0)$ are $\lambda_0 = 0.99$ and $\lambda(0) = 0.95$ [16].

It is crucial that the evaluation criteria should be adopted to clearly validate the performance of PA behavioral modeling and DPDs. Therefore, this part defines the figures of merit for performance evaluation. The most commonly used criteria are normalized mean square error (NMSE) in time domain, adjacent channel power ratio (ACPR) in frequency domain, and error vector magnitude (EVM) that are defined as in [3,18].

Firstly, NMSE is an estimator of the overall difference between the predicted and measured signals in time domain. It is often defined in decibels as

$$\mathrm{NMSE} = 10\log_{10}\left(\frac{\sum\limits_{n=1}^{N}\left(\left|y[n] - x[n]\right|\right)^2}{\sum\limits_{n=1}^{N}\left(\left|x[n]\right|\right)^2}\right), \tag{11}$$

where $x(n)$ is the experimental output (or desired output) of the DUT, and $y(n)$ is the output obtained from the model.

Moreover, ACPR is the ratio between the total adjacent channels' powers to the main channel signal power. It describes the degree of the signal regrowth into neighbouring channels. Since the ACPR characterizes the maximum power allowed to be radiated outside the allocated band, it plays a very important role in wireless radio standards. The ACPR is often expressed in decibels as

$$\mathrm{ACPR} = 10\log_{10}\left(\frac{\int_{\mathrm{B_{adj}}}\left|Y(f)\right|^2}{\int_{\mathrm{B_{ch}}}\left|Y(f)\right|^2}\right) \tag{12}$$

where $|Y(f)|$ denotes the power spectrum of the measured output signal $y(n)$, $\mathrm{B_{adj}}$ and $\mathrm{B_{ch}}$ refer to the bandwidth of the adjacent and main channels, respectively.

The EVM is a measure criterion that quantifies the imperfection to the output signal when compared to the input one. It describes the in-band distortion of the PA and is defined as

$$\mathrm{EVM} = \sqrt{\frac{\sum_{j=0}^{L}\left[\left(I_j - \hat{I}_j\right)^2 + \left(Q_j - \hat{Q}_j\right)^2\right]}{\sum_{j=0}^{L}\left[I_j^2 + Q_j^2\right]}} \tag{13}$$

where I_j and Q_j are the ideal output signal in-phase and quadrature components, and $\hat{I}_j$ and $\hat{Q}_j$ are their output measured counterparts, respectively.

3 Simulation Results

In order to demonstrate the proposed DPD linearization method, we tested a simulated PA that is modeled by a Wiener model consisting of a FIR filter followed by memoryless nonlinearity model. The coefficients of the FIR filter are as in [19–21]

$$h_0 = 0.7692, h_1 = 0.1538, h_2 = 0.0769. \tag{14}$$

For the memoryless nonlinearity model, we use Saleh's model [22], which is defined by

$$y(n) = \frac{\alpha_a \left|v(n)\right|}{1 + \beta_a |v(n)|^2} e^{j\angle\left[v(n) + \frac{\alpha_\varphi |v(n)|^2}{1+\beta_\varphi |v(n)|^2}\right]}, \tag{15}$$

with

$$v(n) = h_0 x(n) + h_1 x(n-1) + h_2 x(n-2), \tag{16}$$

where $x(n)$ and $y(n)$ are the input and output of the simulated PA, respectively, and $v(n)$ is the input of Saleh model. The parameters of Saleh model are as in [19]

$$\alpha_a = 20, \beta_a = 2.2, \alpha_\varphi = 2, \beta_\varphi = 1. \tag{17}$$

The transmitted symbols are modulated by 16-QAM with 3.84 MHz bandwidth. The input modulated signal is filtered by a raised cosine pulse shaping filter with the roll-off factor of 0.22.

The AM/AM and AM/PM characteristics computed at the instantaneous samples of the PA input and output, are shown in Fig. 2. It is clear that the simulated PA suffers from the nonlinearity and memory effects. Figure 3 shows the gain performance of the simulated PA with the average input power. One can observe that the gain in linear region is about 26 dB. The average input power at 1 dB compression point and at 3 dB are around −1 dBm and 4.3 dBm, respectively.

The MP model is used to model nonlinear behavior of the PA. In order to reduce the computational complexity, the orders (N and M) of the MP model are optimized by using a performance-based sweeping method [17]. Figure 4 shows

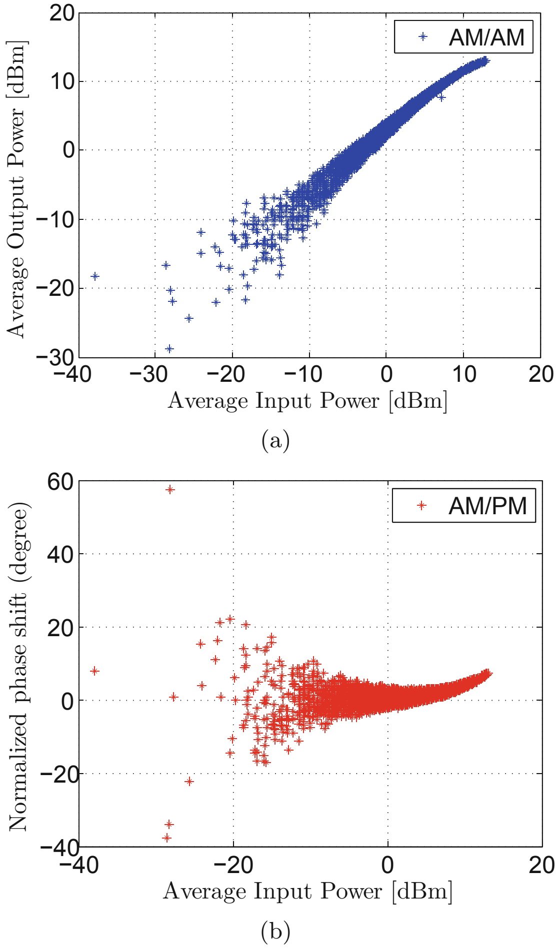


Fig. 2. The PA characteristics. (a) AM/AM. (b) AM/PM.

the NMSE performance versus the orders of the PA model. From this figure, we can see that the optimal values of N and M are $N = 5$ and $M = 2$, respectively, in order to achieve a good trade-off between the best NMSE and computational complexity.

In order to validate the proposed DPD, the RPEM algorithm is initialized when $\lambda_0 = 0.99$, $\lambda(0) = 0.95$ and the initial weight vectors $\omega(0)$ have a first element as 1 and the others as 0. In this simulation, the ACPR values are measured at the upper adjacent channels, corresponding to frequency offsets of 5 MHz.

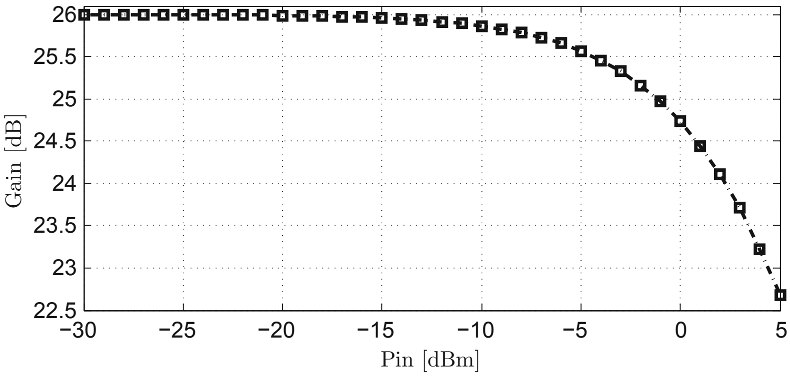


Fig. 3. Gain versus average input power of simulated PA.

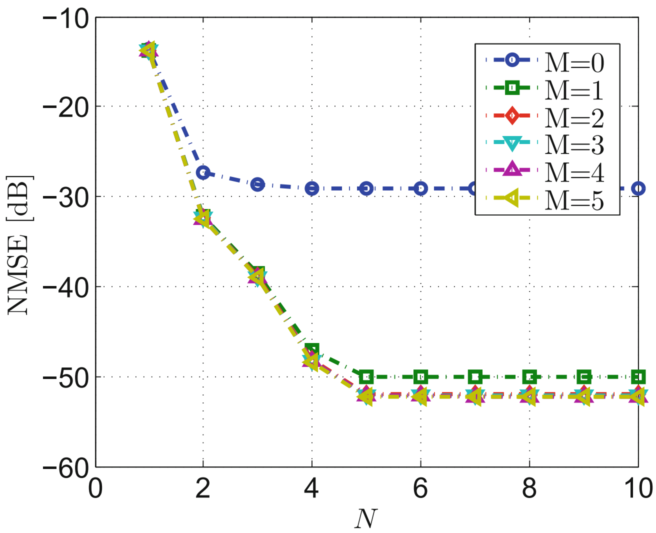


Fig. 4. NMSE versus N and M.

Figure 5 shows effectiveness in canceling the spectral regrowth of the proposed approach. for the input power of -4 dBm. It can be seen that there is a significant spectral regrowth reduction after DPD. The adaptive RPEM algorithm converges after 10-K samples, as shown in Fig. 6.

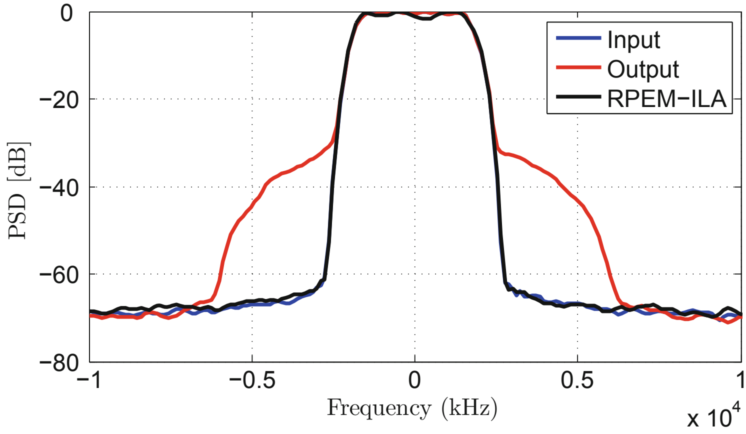


Fig. 5. Power spectral density (PSD) of the PA output before and after DPD using various adaptive algorithms with the input power of -4 dBm.

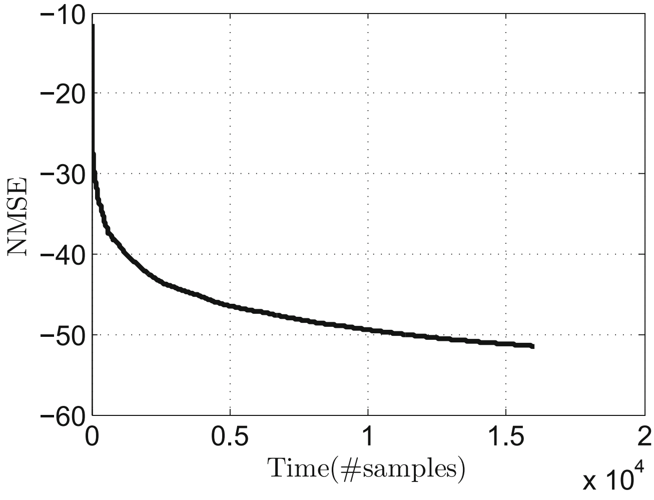
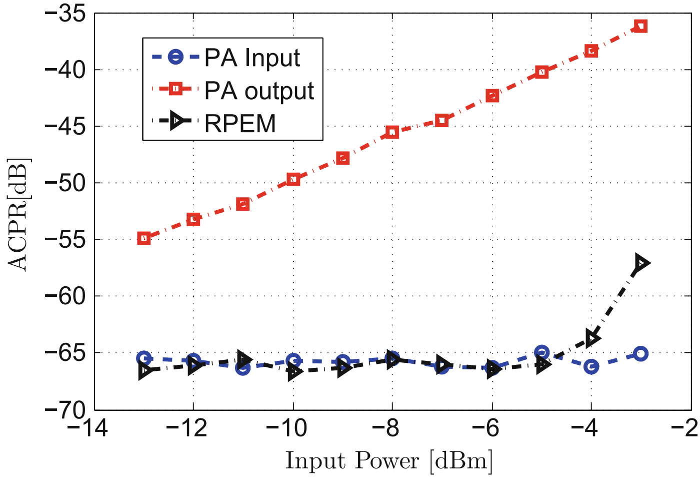
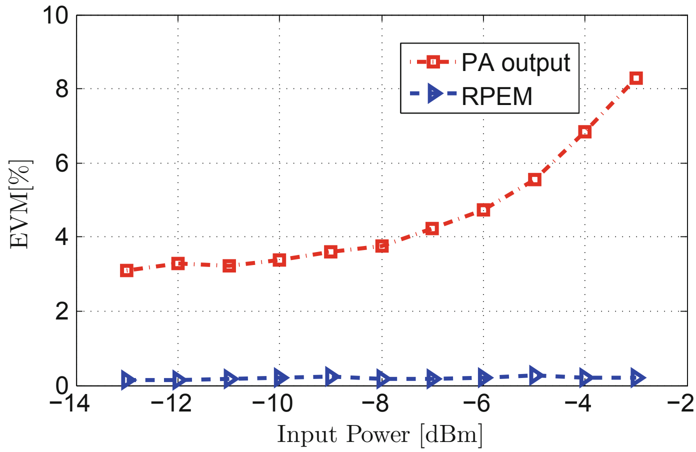


Fig. 6. Learning curves for adaptive RPEM algorithms.

Figures 7(a) and (b) respectively show the ACPR and EVM performance of the proposed DPD for various input power levels. From these figures, one can observe that the proposed DPD technique shows a significant performance improvement in terms of ACPR and EVM. It obtains the ACPR values almost equal to those of input. Furthermore, after applying RPEM-ILA, the EVM values are significantly reduced and less than 0.26%, which shows excellent performance in in-band distortion mitigation. This is because the RPEM algorithm makes



(a)



(b)

Fig. 7. ACPR and EVM performance after the proposed DPD using adaptive RPEM algorithm. (a) ACPR. (b) EVM.

the PD coefficient estimates more consistent and precise in steady state. The simulation results have clarified the improvements of the proposed technique compared with LMS [15] and RLS-based [10,12] ILA methods.

4 Conclusions

In this paper, an adaptive ILA linearization using the RPEM algorithm has been proposed. Thanks to the time-varying forgetting factor, the PD coefficient estimates are consistent and accurate in steady state, leading to speed up the convergence, reduce the NMSE, and minimize the total nonlinear distortion at the PA output. The simulation results confirm that the nonlinear distortion of the PA operated under different conditions (for example, the different input powers), can be almost fully compensated by employing the adaptive ILA with RPEM. In other words, the proposed DPD technique effectively linearizes the PA even if its characteristics change. So, this approach provides a very promising solution for future wireless communication system where the PA characteristics change due to the type of signal, high-order modulation, working condition, etc. The future works will target the optimization, hardware implementation and more detail analysis results of the proposed linearization technique.

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