

# REDUCED-COMPLEXITY DIGITAL PREDISTORTION FOR MASSIVE MIMO

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## ABSTRACT

A novel reduced-complexity digital predistortion (DPD) solution is presented in this paper. The proposed DPD can suppress the unwanted distortions due to power amplifier (PA) nonlinearity and I/Q modulator impairments in direct conversion transmitters using reduced-bandwidth filtered basis functions. Moreover, the DPD parameter estimation is based on very simple decorrelation based closed-loop processing and reduced-bandwidth observation, thus further reducing the overall complexity. The proposed DPD can be used in large array or massive MIMO systems with large number of radio transceivers and PAs, where reducing the complexity of the DPD processing is very critical.

*Index Terms*— 5G, Digital Predistortion, Direct Conversion Transmitters, I/Q imbalance, Massive MIMO, Power Amplifiers.

## 1. INTRODUCTION

Massive MIMO is anticipated to be one of the key enablers of enhanced spectral and energy efficiency in future wireless communication systems [1]. The usage of a large number of antennas at the transmitter, each of which has its own RF chain, implies an urgent need for reducing the cost and size of these RF chains, while maximizing their energy efficiency at the same time. Direct conversion transmitters, typically used in most mobile devices, are considered a good candidate due to their small form factor, and reduced bill of materials [2]. However, such transmitter architectures typically have their own challenges, such as I/Q imbalance, local oscillator (LO) leakage, etc [2]. Moreover, using large and power hungry linear power amplifiers (PAs) is practically impossible in massive MIMO transmitters. Low cost, small size and highly energy-efficient, and therefore highly nonlinear PAs operating close to saturation, are expected to be adopted.

Some recent studies have investigated the impact of hardware impairments, such as PA nonlinearities, I/Q imbalance, etc, on massive MIMO transmitters [3–8]. These studies show that such impairments can significantly degrade both the spectral efficiency and the energy efficiency, both of which are fundamental objectives of massive MIMO. In [3], the analysis was based on the assumption that appropriate compensation algorithms have been applied and thus the authors focused only on the residual hardware impairments. Meanwhile, in [4], the out-of-band radiations due to PA nonlinearity is analyzed in both single antenna and massive MIMO transmitter scenarios, assuming a memoryless polynomial model for each PA unit. It was shown that the adjacent channel leakage ratio (ACLR) due to PA nonlinearity in the massive MIMO scenario is, on average, equal to the single antenna scenario when transmitting with the same total

sum-power. This implies that when a highly nonlinear PA is used per RF chain, as mentioned earlier, significant out-of-band distortion can occur in massive MIMO transmitters that can easily interfere with neighboring transmissions and/or violate spurious emission limits, as also demonstrated in [5]. Moreover, the unwanted emissions become even worse when the I/Q modulator impairments interact with the PA nonlinearity as demonstrated in [9], in the context of single antenna transmitters.

In terms of the impact of hardware impairments on the transmitted signal quality, it has also been shown in [5] that the error vector magnitude (EVM) degradation due to PA nonlinearity can compromise the spectral efficiency of the massive MIMO base station, where at least 6 dB backoff was shown to be required in order to reach the maximum targeted data rate. Moreover, in [6], the authors demonstrated that when practical PA models are used in a massive MIMO base station, the signal to interference and noise ratio (SINR) at the user receiver can be significantly degraded. On the other hand, impairments resulting from the I/Q modulator have also been shown in [8] to have an impact on the system performance in large array systems, where it was demonstrated that in case of a MIMO transmitter with 20 RF chains, I/Q imbalance per RF chain degrades the overall EVM. It was also shown that sufficient I/Q imbalance pre-compensation can result in around 13 dB enhancement in the EVM, which can be directly translated into enhanced spectral efficiency.

Applying backoff to overcome the PA distortion is not an attractive solution since it requires using larger PAs operating in the linear region. As a result, the cost and size of each RF chain will increase and the energy efficiency will decrease, which directly translates to an increased running cost in terms of power supply and cooling. A better solution is to use smaller PAs that operate more efficiently close(r) to saturation, while using a low complexity linearization method to reduce both the in-band and the out-of-band distortion per RF chain. This is the main scope of this paper.

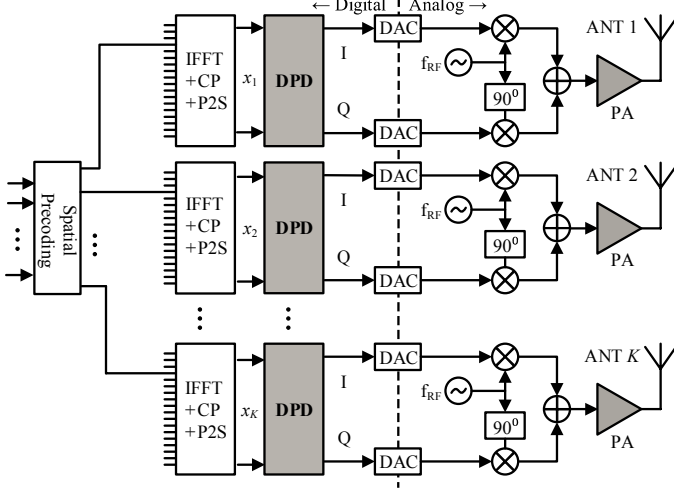
## 2. LOW COMPLEXITY DPD CONCEPT

Digital predistortion (DPD) is considered the most widely used and effective linearization technique, both from performance and flexibility points of view [10]. However, the reason why classical DPD techniques might be considered unfit for massive MIMO is primarily due to the large additional complexity in terms of the required digital front-end processing in the transmitter main path, as well as the extra hardware and processing required in the feedback receiver(s). On the other hand, and as discussed in the previous section, there is clear need for a DPD solution that can tackle both the PA and I/Q modulator impairments, while at the same time having feasible running complexity, especially when adopted in a per RF chain or per-antenna manner as illustrated in Fig. 1.

In this paper, a novel reduced-complexity DPD solution that can jointly tackle the PA nonlinearity, I/Q imbalance, and LO leakage in direct conversion transmitters is proposed. The proposed DPD builds

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This work was supported by the Academy of Finland under the projects 288670, 284694, and 301820, and by Tekes, Nokia Bell Labs, Huawei Technologies Finland, TDK-EPCOS, Pulse Finland and Saskaen Finland under the 5G TRx project.



**Fig. 1.** OFDM-based massive MIMO transmitter with DPD, assuming a direct conversion architecture per RF chain and per-antenna PA units. Only the main transmitter paths are shown in this figure.

on the structure in [9], while using lower rate filtered basis functions in the DPD main path, thus significantly reducing the running complexity of the DPD. Moreover, a novel closed-loop parameter estimation solution building on reduced-bandwidth observation of the PA output signal, combined with highly simple correlation type of processing, is described. It is worth mentioning that the idea of using filtered basis functions has been introduced earlier in [11, 12] in the context of ILA-based learning, and only PA nonlinearity was considered. In summary, the complexity reduction achieved by the proposed DPD solution is fourfold and can be summarized as

- Filtered basis functions are used in the DPD main processing path, thus reducing the baseband processing sample rate, as well as the cost and sampling rate of the DACs.
- Reduced-bandwidth observation of the PA output can be adopted, through the feedback receiver, thus reducing the required sampling rate of the ADC in the feedback path.
- The proposed DPD learning utilizes a closed loop estimation solution which is less sensitive to noisy observations in the feedback receiver, compared to widely-used ILA based DPD learning [13]. This implies the option of using simpler, and lower cost components in the feedback receiver.
- The proposed DPD parameter estimation and adaptation algorithm builds on simple decorrelation-based processing that does not require computationally demanding operations (e.g., matrix inversions, etc).

It is noted that the mutual coupling between the antenna ports has been ignored in this work, assuming sufficient isolation, in order to simplify the processing. However, it is considered an interesting aspect for future work in this research field.

### 3. INJECTION-BASED JOINT PA AND I/Q MODULATOR DPD PROCESSING STRUCTURE

The proposed DPD is based on the well-known parallel Hammerstein (PH) structure [14] whose baseband equivalent static nonlinear (SNL) basis functions read  $x(n)|x(n)|^{p-1}$ , where  $x(n)$  is the complex baseband input signal, and  $p$  is the nonlinearity order of the

corresponding basis function. These basis functions are then filtered and decimated to a lower sample rate. The decimation filter is a LPF  $\tilde{f}_n$  whose bandwidth is less than  $P$  times the bandwidth of the original baseband signal  $x(n)$ , where  $P$  is the maximum nonlinearity order of the DPD. The DPD running complexity is thus greatly reduced due to the reduction in the required sample rate in the rest of the processing chain. Meanwhile, the linearization is focused only on the passband of the decimation filter  $\tilde{f}_n$ , while the distortion lying in the filter stopband is assumed to be filtered out by the RF transmit filter. The filtered basis functions are then orthogonalized [15] for better numerical properties and stability when used in the adaptive filtering and parameter estimation context.

The key idea of the proposed injection-based DPD concept is to inject a proper additional low-power cancellation signal into the direct conversion transmitter input, such that the level of the distortions due to PA nonlinearity, I/Q imbalance, and LO leakage at the PA output is reduced. An appropriate digital injection signal can be obtained by adopting a widely linear transformation of the previously mentioned orthogonal filtered basis functions, denoted by  $s_p(n)$ , as also illustrated in Fig. 2. However, only the distortion terms are injected in this architecture, which implies that the linear non-conjugated term  $s_1(n)$  is not injected, which thus further reduces the complexity of the proposed DPD. The PA input signal  $\tilde{x}(n)$ , with DPD included, reads then

$$\tilde{x}(n) = x(n) + \sum_{\substack{p=3 \\ p \text{ odd}}}^P \alpha_{p,n} \star s_p(n) + \sum_{q=1}^Q \beta_{q,n} \star s_q^*(n) + c, \quad (1)$$

where  $\star$  denotes convolution,  $P$  and  $Q$  are the nonlinearity orders of the main and conjugate branches respectively, and  $c$  is an appropriate constant added to suppress the LO leakage at the PA output. The nonlinearity order  $Q$  can, in general, be assumed to be less than  $P$ , and thus the total number of the DPD filters is not substantially larger than in any ordinary PH structure, while still having the ability to efficiently suppress both the PA and the I/Q modulator induced distortions. The achievable suppression of the unwanted distortion products depends directly on the selection and optimization of the DPD filter coefficients  $\alpha_{p,n}$ ,  $\beta_{q,n}$ , and the constant  $c$ . This is addressed in detail in the next section.

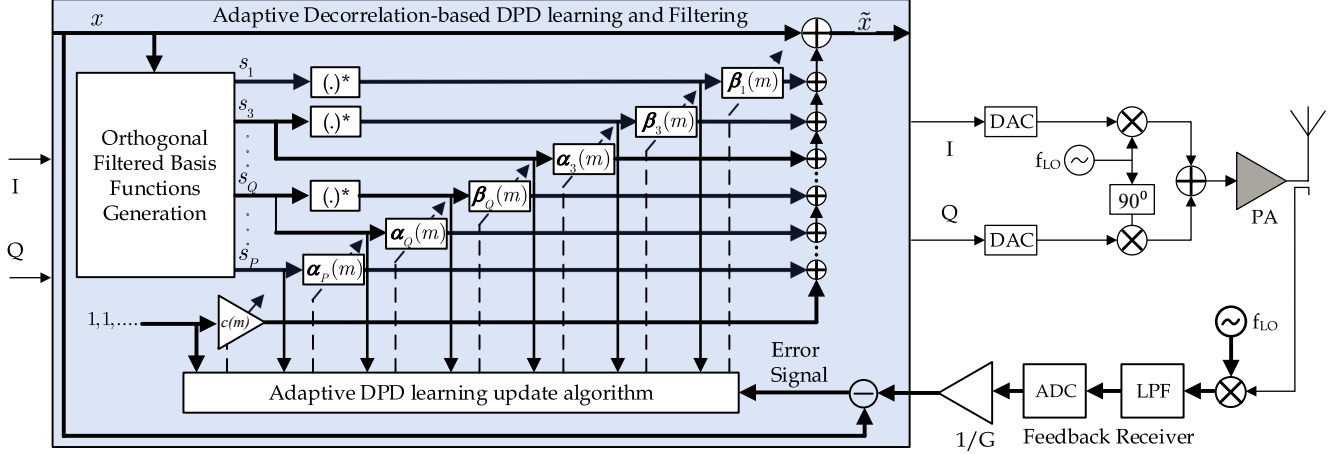
### 4. DECORRELATION-BASED DPD PARAMETER LEARNING

In this section, we formulate a computationally feasible and highly efficient closed-loop estimation algorithm for learning the proposed DPD filter coefficients, based on the decorrelation principle [16]. The DPD parameter optimization task is formulated here as minimizing the correlation between the distortion at the PA output due to PA nonlinearity, I/Q imbalance, and LO leakage, and the orthogonalized filtered SNL basis functions discussed in the previous section. The specific basis function used for LO leakage mitigation is simply a vector of ones whose complex gain  $c$  in (1) is then estimated using the decorrelation principle as well.

The filtered baseband equivalent nonlinear distortion observed at the PA output, denoted by  $e(n)$ , can be calculated as follows

$$e(n) = [f_n \star y(n)/G] - x(n) \quad (2)$$

where  $y(n)$  is the baseband equivalent PA output signal, and  $G$  is the complex linear gain of the PA which is assumed to be known using simple estimation techniques, e.g., least squares. The observation is



**Fig. 2.** Block diagram of the proposed DPD adopting closed-loop learning. Thick lines correspond to complex I/Q processing.

filtered by the LPF  $f_n$ , which has the same bandwidth as the filter  $\bar{f}_n$  used for basis function generation [11, 12]. This implies that the proposed solution requires only a narrowband feedback observation, thus reducing the complexity of the feedback receiver as explained earlier. Closed-loop DPD learning is in fact less sensitive, compared to ILA-based solutions, to any sort of mismatch between the filters  $f_n$  and  $\bar{f}_n$  used for filtering the observation and the basis functions, respectively [13], which implies more flexibility in the design and implementation of these two filters.

The decorrelation-based learning principle is then applied using the filtered basis functions  $s_p(n)$  and their complex conjugates. As the name suggests, the learning is based on finding the DPD filter coefficients  $\alpha_{p,n}$ ,  $\beta_{q,n}$ , and  $c$  that minimize the correlation between the extracted nonlinear distortion at the PA output,  $e(n)$ , and the corresponding basis function samples, as also illustrated in Fig. 2. Then, assuming an estimation block size of  $M$  samples and DPD filter memory depths of  $N_p$  and  $N_q$  per each of the filtered basis functions, the following vectors and matrices, which stack the necessary samples and the corresponding DPD filter coefficients within processing block  $m$ , can be defined:

$$\mathbf{s}_p(n_m) = [s_p(n_m) \dots s_p(n_m - N_p)], \quad (3)$$

$$\bar{\mathbf{s}}_q(n_m) = [s_q^*(n_m) \dots s_q^*(n_m - N_q)], \quad (4)$$

$$\mathbf{S}_p(m) = [\mathbf{s}_p(n_m)^T \dots \mathbf{s}_p(n_m + M - 1)^T]^T, \quad (5)$$

$$\bar{\mathbf{S}}_q(m) = [\bar{\mathbf{s}}_q(n_m)^T \dots \bar{\mathbf{s}}_q(n_m + M - 1)^T]^T, \quad (6)$$

$$\mathbf{b}(m) = [1 \ 1 \ \dots \ 1]^T, \quad (7)$$

$$\mathbf{S}(m) = [\mathbf{S}_3(m) \ \mathbf{S}_5(m) \ \dots \ \mathbf{S}_P(m), \quad (8)$$

$$\bar{\mathbf{S}}_1(m) \ \bar{\mathbf{S}}_3(m) \ \dots \ \bar{\mathbf{S}}_Q(m) \ \mathbf{b}(m)],$$

$$\boldsymbol{\alpha}_p(m) = [\alpha_{p,0}(m) \ \alpha_{p,1}(m) \ \dots \ \alpha_{p,N_p}(m)]^H, \quad (9)$$

$$\boldsymbol{\beta}_q(m) = [\beta_{q,0}(m) \ \beta_{q,1}(m) \ \dots \ \beta_{q,N_q}(m)]^H, \quad (10)$$

$$\bar{\boldsymbol{\alpha}}(m) = [\boldsymbol{\alpha}_3(m)^T \ \boldsymbol{\alpha}_5(m)^T \ \dots \ \boldsymbol{\alpha}_P(m)^T, \quad (11)$$

$$\boldsymbol{\beta}_1(m)^T \ \boldsymbol{\beta}_3(m)^T \ \dots \ \boldsymbol{\beta}_Q(m)^T \ c^*(m)^T]^T,$$

where  $n_m$  denotes the index of the first sample of block  $m$ . The block-adaptive decorrelation-based DPD coefficient update, with learning rate  $\mu$ , then reads

$$\bar{\boldsymbol{\alpha}}(m+1) = \bar{\boldsymbol{\alpha}}(m) - \mu [\mathbf{e}(m)^H \mathbf{S}(m)]^T, \quad (12)$$

where  $\mathbf{e}(m) = [e(n_m) \dots e(n_m + M - 1)]^T$  is the error signal vector, while  $\mathbf{S}(m)$  denotes the filter input data matrix, all within the processing block  $m$ . The obtained new DPD coefficients  $\bar{\boldsymbol{\alpha}}(m+1)$  are then applied on the next block of  $M$  samples. It is clear from (12) that the proposed DPD parameter estimation requires very simple correlation type of computations which makes the solution quite attractive for the target application. As a special case with  $M = 1$ , the learning rule corresponds to sample-adaptive instantaneous decorrelation between the adopted basis function samples and the distortion at the PA output, while for  $M > 1$  the correlation is measured over the block of  $M$  samples for each iteration. In general, the coefficient update in (12) resembles largely the classical least-mean square (LMS) algorithm, and thus, e.g., the step-size selection is straightforward.

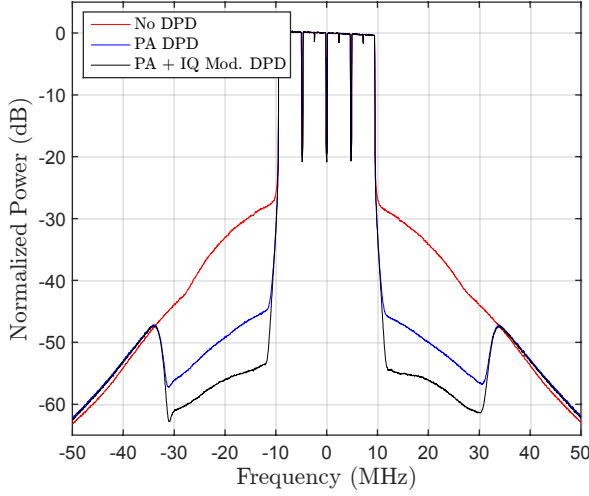
## 5. SIMULATION RESULTS AND ANALYSIS

In this section, a quantitative performance analysis of the proposed DPD solution is presented using Matlab simulations with practical measured models for mobile-like PAs designed for low-cost devices. A typical massive MIMO base station may easily transmit at a total power in the order of  $+40 \dots +46$  dBm. Thus, if assuming 100 antennas per base station, each antenna/PA transmits then at roughly  $+20 \dots +26$  dBm. Consequently, the PA model used for simulating a single arbitrary RF chain of a massive MIMO transmitter is a ninth-order PH model that has been identified using measurements with a true mobile PA transmitting at  $+22$  dBm. I/Q imbalance and LO leakage are also included in the simulations, where the amplitude and phase imbalances are 7% and  $5^\circ$  respectively. The nonlinearity orders  $P$  and  $Q$  of the DPD are 9 and 3 respectively, and the DPD memory depths  $N_p$  and  $N_q$  are equal to 1 (i.e., 2 memory taps per filter). The learning block-size  $M$  used by the proposed DPD is  $10k$  samples, and 30 block adaptive iterations are used. In order to evaluate the performance of the DPD in a quantitative manner, both the inband waveform purity and the adjacent channel interference due to spectral regrowth are quantified using the error vector magnitude (EVM), and the ACLR, respectively [17].

Fig. 3 shows the normalized PSD of a contiguous LTE-A type of carrier aggregation (CA) scenario composed of four 5 MHz OFDM(A) component carriers (CCs), with and without DPD processing. Iterative clipping and filtering based peak to average power

**Table 1.** CA simulation scenario with four 5 MHz CCs, Tx power = +22 dBm, composite PAPR = 8.22 dB.

	EVM [%]	ACLR L / R (dBc)
Without DPD	7.7068	31.7923 / 32.6808
With PA DPD	5.8584	48.1204 / 48.9318
With PA + IQ Mod. DPD	0.8075	55.9932 / 55.5335



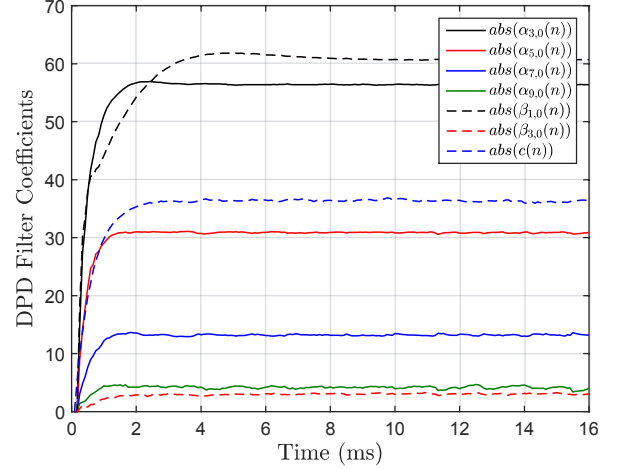
**Fig. 3.** Baseband equivalent spectra, with and without DPD, of a contiguous intraband CA transmitter with four 5 MHz OFDM carriers and 16-QAM subcarrier modulation. The PA model is a ninth order PH PA with memory extracted from a real mobile PA at +22 dBm. I/Q imbalance and LO leakage are also included.

ratio (PAPR) reduction approach [18] is also applied to the transmit signal, prior to the DPD stage. Moreover, filtered basis functions are used where the DPD running bandwidth and feedback observation bandwidth are both limited to 3 times the signal bandwidth (i.e., ACLR measurement zone) instead of 9 (DPD nonlinearity order). The quantitative performance results in this scenario are reported in Table 1, where the ACLR is measured over the adjacent 20 MHz channels. Also a PA-only DPD is simulated, for reference, where the conjugated basis functions are excluded. A significant improvement in both the EVM and ACLR is achieved when using the proposed DPD, despite its remarkable simplicity. It is noted that incorporating the I/Q image suppression into the DPD processing has particularly clear impact on the achievable EVM performance. Fig. 4 presents an example of the coefficient behavior of the proposed DPD, during the learning phase, evidencing fast and reliable convergence.

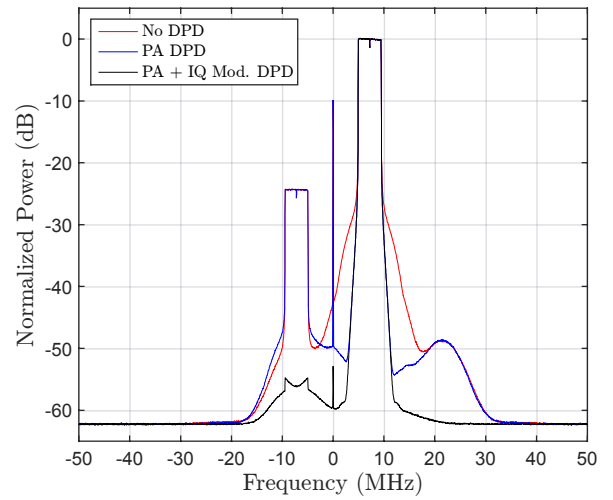
Meanwhile, another simulation example is provided in Fig. 5, where three of the four CCs are deliberately switched off to better visualize the I/Q image component and LO leakage before and after applying the proposed DPD. Excellent suppression of the mirror image and LO leakage due to I/Q modulator impairments, in addition to the adjacent spectral regrowth due to the PA nonlinearity is achieved.

## 6. CONCLUSIONS

A reduced-complexity digital predistortion (DPD) was proposed in this paper that can jointly mitigate the unwanted distortions due to



**Fig. 4.** Convergence of the first memory taps of the different DPD filters using a single realization of a contiguous intraband CA transmitter with four 5 MHz OFDM carriers and 16-QAM subcarrier modulation.



**Fig. 5.** Baseband equivalent spectra, with and without DPD, of a contiguous intraband CA transmitter with only one out of the four 5 MHz OFDM carriers switched on, while the remaining three are switched off.

transmitter power amplifier and I/Q modulator imperfections. The proposed solution facilitates reduced sampling rate both in the DPD main path processing, as well as in the feedback observation path. Moreover, the proposed solution is based on a simple closed-loop learning algorithm with decorrelation type of computations. These advantages make the solution very attractive to massive MIMO transmitters where a large number of PA units are used, each requiring a separate DPD. Practical simulations using measured models of off-the-shelf PAs, and I/Q modulator imperfections, show that the proposed solution gives excellent linearization results in terms of both EVM and ACLR. The proposed DPD allows for the usage of small, cheap, and highly efficient analog components in massive MIMO transmitters without sacrificing the system performance.

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