Self-Sensing Digital Predistortion of RF Power Amplifiers for 6G Intelligent Radio

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***Abstract*— The future intelligent communication systems will dynamically adjust the transmitted signal according to the radio environment and human behavior, which will lead to the rapid change of the characteristics of power amplifier (PA) and bring new challenges for digital predistortion (DPD). In this letter, a novel self-sensing DPD (SS-DPD) technique is proposed to linearize PA driven by fast time-varied signals. By automatically sensing the features of input signal and integrating them into the neural network, the proposed model is capable of linearizing the PA operated in such time-varied scenarios without updating DPD coefficients. Furthermore, the polynomial basis functions are embedded into neural network to reduce the complexity. Experimental results on a Doherty PA driven by the fast time-varied signal show that the proposed method can achieve good performance constantly with low complexity.**

***Index Terms*— Digital predistortion (DPD), intelligent radio, neural network, power amplifier (PA).**

I. Introduction

INTELLIGENCE will be the development goal of future communication system, to make more efficient use of limited communication resources. Specifically, future communication networks are expected to sense the characteristics of human behavior and radio environment, in order to automatically optimize the transceiver configurations [1], [2]. For instance, digital baseband adjusts the average power, modulation scheme, and bandwidth that are defined by the standards of the baseband signal, according to the demand of the user's data rate and spectrum detection, so as to effectively utilize resources, as shown in Fig. 1. Thus, the input signal is fast time-varied. As a result, the power amplifier (PA) will exhibit dynamic characteristics, which will pose challenges to the linearization technique. Digital predistortion (DPD) is a widely employed linearization method that enables PA to operate in high-efficiency mode while maintaining high linearity. In such intelligent radio scenarios, the conventional DPD methods cannot adapt to the rapid change of input signal, leading to the failure of linearization.

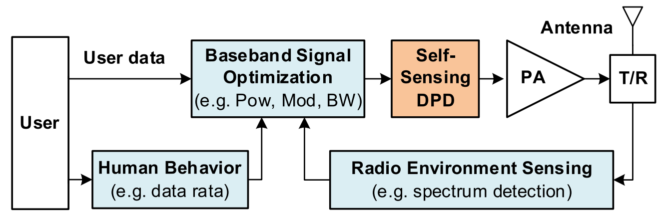

Fig. 1. Intelligent radio scenario in the future.

In the literature, some DPD methods have been proposed to try to solve this issue. Power adaptive DPD was proposed in [3], which employs dynamic coefficients to compensate for the dynamic distortion of the PA caused by multiple power levels. Data-clustering-assisted DPD was proposed in [4] for linearizing a large number of transmitter states only with a small set of coefficients. In [5], a heterogeneous neural network (HNN) was proposed for modeling enormous transmitter states by employing only one model. However, all of the above methods still require real-time configuration information from the transmitter, which might limit their applications in future intelligent scenarios.

In this letter, a novel self-sensing DPD (SS-DPD) technique is proposed for intelligent radio system. SS-DPD is a single-input–single-output (SISO) structure that requires no additional input information. The features of the transmitted signal will be self-sensed and modeled into the integrated model of neural network and polynomial-basis functions, which can realize intelligent functionality with low complexity. Experimental results provide a good validation for the proposed idea.

II. Proposed Method

A. PAs Driven by Fast Time-Varied Input Signal

PAs exhibit dynamic distortion when driving by fast time-varied input signals. In particular, the average power, peak-to-average power ratio (PAPR), and bandwidth of the signal affect the operating state of PAs. For conventional DPD methods, it is necessary to extract a separate model for each state, which will be costly. Besides, the transmitter needs to pass the label of the signal into the DPD module in real time to update the coefficients. In the case of fast time-varied signal, the switch of DPD coefficients cannot timely keep up with the changes of the signals. To solve this problem, DPD modules need to be more intelligent. Therefore, we propose to make the DPD model autonomously sense the change of signal, i.e., SS-DPD.

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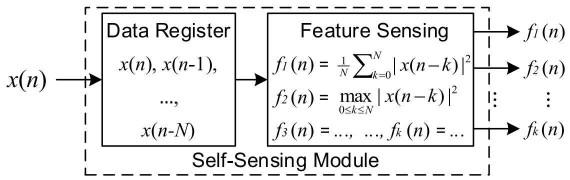

Fig. 2. Structure of self-sensing module.

B. Self-Sensing Module

To realize the functionality of SS-DPD, the model is required to be able to sense the current operating state according to the input signal, which can be simplified as a pattern recognition task. Usually, a neural network can achieve this goal [6], but it will significantly increase the model complexity and cost too much. Therefore, we propose to insert the predetermined functions into a simplified neural network instead of directly employing complex neural network to realize this task. In general, the overall features of input signal, e.g., average power, have a great influence on the characteristics of PA, and thus, it is feasible to employ these features in the model.

Based on this idea, the self-sensing module can be constructed, as shown in Fig. 2. The data register stores the latest samples of the input signal. Feature sensing block employs these data to calculate the overall features. Here, two time-domain and one frequency-domain features are taken, for example, as the output of the self-sensing module. The calculation function can be expressed by the following equation:

$$f_1(n) = \frac{1}{N}\sum_{k=0}^{N}|x(n-k)|^2 \quad (1)$$

$$f_2(n) = \max_{0\le k\le N}|x(n-k)|^2 \quad (2)$$

$$f_3(n) = \max(\mathrm{FFT}([x(n),\ldots,x(n-N)])) \quad (3)$$

where N is the size of data register, $x(n)$ is the data restored in the data register, FFT[·] represents the fast Fourier transform, and $f_1(n)$–$f_3(n)$ are the calculated average power, maximum power, and maximum power spectral density value at instant n, respectively. In a neural network model, the flexible connection is able to find the combination relationship of these features, e.g., the combination of $f_1(n)$ and $f_2(n)$ is related to the PAPR and the combination of $f_1(n)$ and $f_3(n)$ is related to the bandwidth. Therefore, the output of the self-sensing module can effectively reflect the current operating state of PA.

C. Proposed Model

When PA is driven by fast time-varied signals, although the properties of PA are dynamically changing, some basic characteristics can be shared. Based on this concept, the characteristics of PA can be divided into static and dynamic ones. The static characteristics are relatively simple, only depending on the input signal, which can be well represented by the polynomial basis functions. The dynamic characteristics depend not only on the input signal but also on the signal features, and thus, the neural network is a promising option with high flexibility to better fit it. Therefore, the complete structure of the proposed model is shown in Fig. 3, including dynamic neural network and static polynomial block.

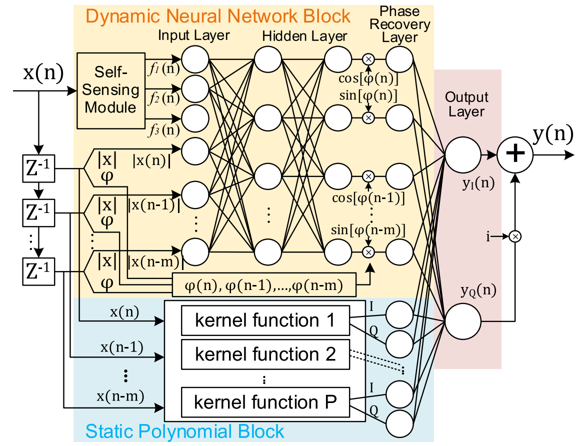

Fig. 3. Structure of the proposed model.

The upper part is the dynamic neural network block, which integrates the self-sensing module. The output of the self-sensing module, along with the input signal, is injected into the input layer. The neural network adopts a vector decomposition structure [7]. The input is the amplitude of the signal, and the nonlinearity is generated by the activation function through the hidden layers. The phase information is recovered with the linear weighting in the phase recovery layer [7]. The relationship trained by the dynamic block can be expressed as follows:

$$y(n) = F[x(n),\ldots,x(n-m),\ f_1(n),\ f_2(n),\ f_3(n)] \quad (4)$$

where m is the memory depth, $y(n)$ is the output of dynamic block, and $F[\cdot]$ is the function trained by a neural network that is able to automatically find the relationship between input features and output. Thus, the model can adapt to the change of input signal and realize the self-sensing function.

The lower part is the static polynomial block, similar to [8], which employs the polynomial basis functions. The input signal is first transformed by the kernel function to produce nonlinearity. According to the prior knowledge of PA, the kernel function can choose the basis function of the polynomial model, e.g., memory polynomial (MP) model [9]. The output of kernel function is divided into real and imaginary parts and connected to the output layer. Since the self-sensing features are not included, this block mainly fits the static characteristics.

The output layer merges the signals of two blocks, the whole model can be built in a neural network, and all the weights can be trained by the neural network optimization algorithm together.

When DPD carries out, the input signal will be fed into the model. In the dynamic neural network block, the self-sensing module automatically calculates the input signal to generate output features, in order to tune the output of the model. Finally, the proper predistorted signal will be generated and fed into PA.

The proposed model has the following advantages: 1) the self-sensing module can automatically extract the overall features of the input signal and realize SS-DPD; 2) the static characteristics are compensated by a polynomial block, which reduces the complexity; and 3) the dynamic characteristics are tuned by a neural network block, improving the performance.

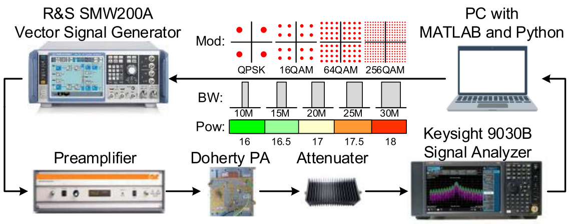

Fig. 4. Testbench setup.

TABLE I
BASEBAND SIGNALS CONFIGURATIONS

Attributes	Configurations
Power (i = 1-5)	16, 16.5, 17, 17.5, 18 dBm
Bandwidth (j = 1-5)	10, 15, 20, 25, 30 MHz
Modulation (k = 1-4)	QPSK, 16QAM, 64QAM, 256QAM

III. MEASUREMENT RESULT

To validate the proposed method, a testbench was set, as shown in Fig. 4. The baseband signals with different configurations were generated by utilizing MATLAB according to 5G NR standards. The signals were labeled as (i: power, j: bandwidth, and k: modulation). The configuration is shown in Table I. There are in total $5 \times 5 \times 4 = 100$ signals with different PAPRs distributed from 8.0 to 10.3 dB. The device under test (DUT) was a Doherty PA [10] using two CGH40010 GaN transistors operating at 2.4 GHz. The vector signal generator downloaded the signals from PC. After preamplifier, the signals were injected into the PA. The signal analyzer captured the output signals after an attenuator and sent back to PC for signal processing. For each signal, 6000 points were used for training, while 10 000 points were used for validation.

To compare and prove the effectiveness of the proposed method, the tests were conducted in four scenarios: 1) full DPD: train a separate model for each signal using generalized MP (GMP) [11]; 2) fixed DPD: train a fixed model using GMP by the signal (3, 5, and 4) to linearize all states; 3) HNN-based DPD [5]: train a model by HNN with predetermined labels; and 4) proposed DPD: train a model by putting all signal together to let the model automatically sense signal features and relate it to the output signal. All of the above DPD methods employ iterative learning control (ILC) [12] algorithm for coefficient extraction. The memory depth was set as 2. For the GMP model, the nonlinear order was set as 8 for aligned envelope and 2 for the lagging and leading envelope, and the lagging and leading memory was set as 1. The HNN model has two hidden layers with 15 neurons each. The proposed model has two hidden layers with nine neurons each in the neural network block and 18 kernel functions in the polynomial block.

The normalized mean square error (NMSE) and adjacent channel power ratio (ACPR) of four DPD methods are shown in Figs. 5 and 6, respectively. In the figures, full DPD achieves the best performance. For fixed DPD, most of the signals cannot be linearized well. The HNN-based DPD and the proposed DPD can obtain good performance, similar to that of full DPD. However, HNN-based DPD requires to know the label of the signals in advance, while the proposed DPD can realize signal self-sensing function.

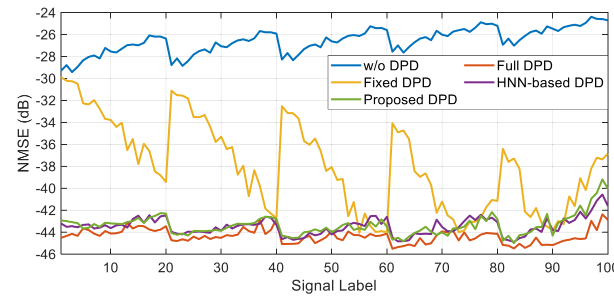

Fig. 5. NMSE performance. (The signal labels were flattened into one dimension, as $20 \times (i-1) + 4 \times (j-1) + k$, [for $i = 1{-}5$, $j = 1{-}5$, and $k = 1{-}4$].)

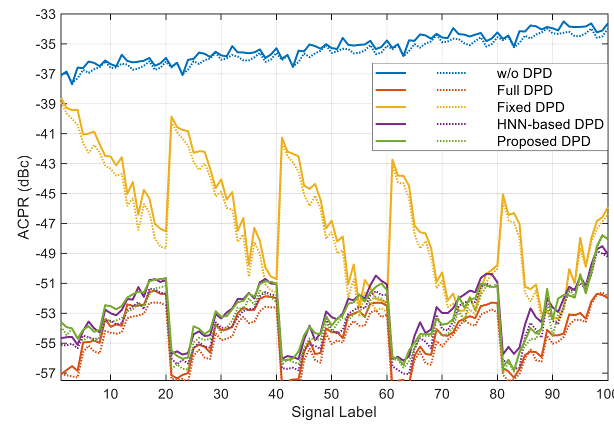

Fig. 6. ACPR performance. Solid line: ACPR (left). Dashed line: ACPR (right).

TABLE II
COMPLEXITY COMPARISON OF FOUR DPD METHODS

DPD Method	Number of Coefficients	Number of FLOPs [13]	Self-Sensing Function
Full DPD [11]	39×100	310×100	No
Fixed DPD [11]	39	310	No
HNN-based DPD [5]	422	810	No
Proposed DPD	237	466+100	Yes

The number of coefficients and floating-point operations (FLOPs) [13] for four DPD methods is shown in Table II. It is worth mentioning that the proposed DPD method introduces additional complexity in the self-sensing module. The calculation of $f_1(n)$ and $f_2(n)$ only deals with the latest signal at most of the time, leading to low consumption. $f_3(n)$ calculates FFT, which consumes thousands of FLOPs. However, the bandwidth changes relatively slowly in practice, which means that FFT can be calculated every few hundred points. Thus, the total average consumption for self-sensing block can be less than 100 FLOPs. As a result, the proposed DPD method still consumes the least FLOPs, but it possesses the functionality of self-sensing, making it very suitable for linearization method in intelligent radio scenarios.

IV. CONCLUSION

In this letter, a novel SS-DPD technique is proposed to linearize PA driven by fast time-varied signals. The features of the input signal are sensed and added to the proposed model. Thus, the model can automatically adapt with the rapid changes of input signals to keep good linearization performance. The experimental results show that the proposed method has great potential in future intelligent radio scenarios.

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