Comparison of Direct Learning and Indirect Learning Predistortion Architectures

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***Abstract*— Power amplifiers in a communication system are inherently nonlinear. Digital predistorters can compensate these nonlinearity effects. In this paper, two memory polynomial predistorters including direct and indirect learning architectures are compared with each other. To the best of our knowledge, no similar comparisons have been published. Both of these architectures are special cases of the self-tuning control. We have modeled predistorters and analysed nonlinear effects of a power amplifier and their digital compensation by using Matlab™. Simulation results show that the memory polynomial model has convergence problems at large amplitudes and also problems of accuracy of representation. We observed that the results of the compensation depend also on the amplitude, not only on the frequency. The results of the linearisation show that the direct learning architecture achieves a better performance in almost all cases.**

I. Introduction

The modeling of nonlinear systems is difficult because no general theory exists, which would allow us to define relations binding a system's inputs and outputs [1]. Nonlinear distortion can be caused for example by power amplifiers (PA), mixers, and oscillators. PAs normally operate close to saturation, so as to maximize power efficiency. This saturation is a nonlinear effect and also distorts the complex envelope of the fundamental frequency component. Because of the nonlinear operation the superposition principle is not, in general, valid. Nonlinearities cause three unwanted effects to the transmitted data including spectral spreading [2], intersymbol interference (ISI), and constellation warping [3] or distortion of constellation diagram.

In the future, quadrature amplitude modulation (QAM) and orthogonal frequency division multiplexing (OFDM) modulation methods will be more commonly used. These modulation methods have nonconstant envelopes. It can be also assumed that nonlinearities have memory due to wide bandwidth. However, it is not guaranteed that the nonlinear power amplifier with memory can amplify a constant envelope without introducing significant distortion. Thus, PA memory effects can no longer be ignored.

Predistortion has been in use for many years particularly in the satellite and microwave industries [4]. A predistorter (PD) is a functional block that precedes a nonlinear device such as the PA. The signal of the input passes through the predistorter whose characteristic is an inverse of the power amplifier. In the last twenty years, many articles on digital predistortion have been published. Several memoryless predistorters [5]-[10] are presented in the literature, but predistorters with memory are much less known in these research fields. There are only a few predistorters with memory which are based on direct learning architecture [11], [13]. Indirect learning algorithm is a more common architecture than the direct learning architecture [14]-[19].

Indirect and direct learning architectures are special cases of the inverse control. Additionally, the inverse control is a special case of the self-tuning control. Kalman (1958) has originally proposed the self-tuning controller and its working was later clarified by Åström and Wittenmark (1973) [21]. Direct learning means that the estimate of the input-output relation of the power amplifier is estimated, and the predistortion is obtained directly by "pre-inverting" the PA characteristics. Indirect learning means that a postdistorter first derives a postinverse of the nonlinear model without any predistorter and then the postdistorter is used as a predistorter and the postdistorter is removed. Inversion of a nonlinear system may not be possible: not all linear or nonlinear systems possess an inverse, and many systems can be inverted only for a restricted amplitude range of input [22, p. 123]. Invertible nonlinear model transformation must be a bijection, i.e., there is one-to-one correspondence between the input and the output.

In [23], it was shown that the indirect learning [17] model can be used at least in Wiener-Hammerstein, Wiener, and parallel Wiener systems. Crosscorrelation predistorters based on the direct and indirect learning architectures are discussed in [12]. The simulation results show that the performance is improved by using both direct and indirect learning scheme, except for the crosscorrelation PD based on the indirect learning architecture and large standard deviation. In that paper, no performances of the mean-square error (MSE) are compared. In [13], two drawbacks that affect the performance of the indirect learning model were mentioned. First, the measurement of PA's output could be noisy, thus, the adaptive algorithm converges to biased values. Second, the nonlinear filters cannot be commuted, i.e., the identified adaptive inverse model is actually a postinverse model. Thus, placing a copy of this model in front of the nonlinear device does not guarantee a good preinverse model for the nonlinear device. These drawbacks are not in the direct learning architecture.

In this paper, we concentrate on two memory polynomial predistorters, which are special cases of Volterra series including indirect [14] and direct learning [11] architectures. We compare these architectures with each other by using Matlab simulations. To the best our knowledge, this kind of comparisons have been not published previously. Results show that nonlinearities can be compensated if the amplitude of the input signal is lower than the saturation level. Results also show that the direct learning PD performs in general better than the indirect learning PD. The reasons are discussed.

The remainder of the paper is organized as follows. In Section II, we compare the self-tuning controller with direct and indirect learning architectures. Predistorter models are presented in Section III. Finally, simulations results are shown.

II. Comparison of the Self-Tuning Controller with Direct and Indirect Learning Architectures

Direct [11] and indirect [17] learning architectures and the estimation of the PA and PD model are implemented in a different way. But their architectures do not differ so much as thought. Both these architectures are special cases of the self-tuning control. The self-tuning controller is illustrated in Fig. 1. It is called self-tuning because it has the ability to tune its own parameters [20, p. 8]. In this technique, parameters of the unknown plant or PA are estimated by using a recursive parameter identification algorithm. In the controller design block, these parameters are fed to an automatic design algorithm that sets the parameters of the controller. The self-tuning controller has two loops including an inner and an outer loop. The inner loop consists of the conventional controller, but with alternating parameters, and the outer loop consists of the indentifier and design box which adjust these controller parameters [20]. The controller receives both the input signal and the output signal of the plant [20]. This technique is very flexible because the controller could be an input controller, or a controller within the feedback loop, or both [25, p. 364].

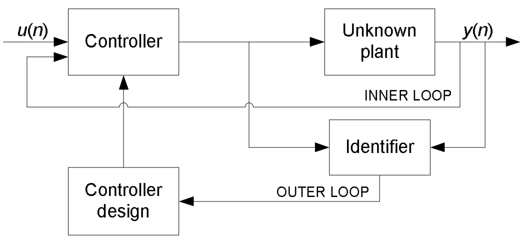

Fig. 1. Self-tuning controller.

Two different models exist for an adaptive inverse control including an indirect learning and a direct learning system. If these two models are compared with the self-tuning controller, the following observatios can be made. If we remove the inner loop in Fig. 1, we see that the residual model is similar to the indirect learning model in Fig. 2. In the indirect learning model, the identifier is a postdistorter and the design block is simple copying as in Fig. 2. In the direct learning model, the identifier is a direct estimator and a design block is the predistortion calculator as noted in Fig. 3. Thus, the identifier in Fig. 1 can model both indirect and direct learning models. The indirect learning model is the same as the self-tuning control with inverse modeling and the direct learning model is the same as the self-tuning control with direct modeling. It is claimed that the self-tuning controller is totally different from an inverse controller [25, p. 368]. However, we can conclude that the inverse control is a special case of the self-tuning controller.

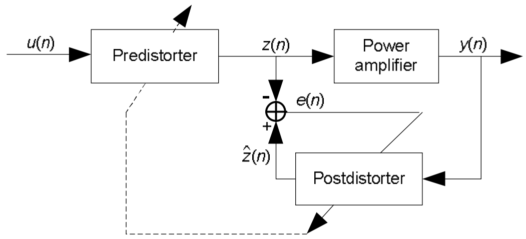

Fig. 2. Indirect learning architecture.

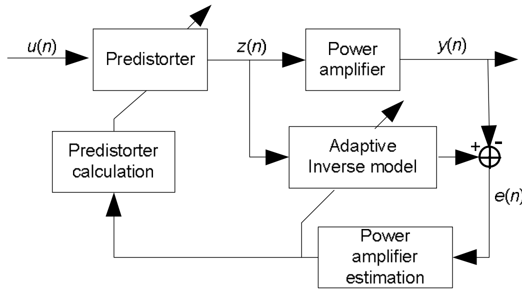

Fig. 3. Direct learning architecture.

III. Predistorter Models

Power amplifiers are modeled by using memory polynomial model in [11] and [17]. The memory polynomial [11] model is the special case of the Volterra series. The memory polynomial can be viewed as a compromise between the memoryless nonlinearity and the full Volterra nonlinearity. It is computationally effective [17]; the number of needed coefficients is on the order of $K(Q+1)$, where K is the nonlinearity order of the polynomial and Q is the length of the memory. The memory polynomial power amplifier can be described by

$$y(n) = \sum_{k=1}^{K} \sum_{q=0}^{Q} c_{kq} z_{n-q} |z_{n-q}|^{k-1} \qquad (1)$$

where y is the output signal of the PA, z is the output signal of the predistorter, and c_{kq} are the coefficients of the PA model.

A. Direct Learning Architecture

In the direct learning [11] architecture in Fig. 3, the PA model is first modeled by using memory polynomial similar to (1). Secondly, the inverse of the PA model is calculated.

Predistortion function can be solved by defining z signal from (1). Thus, PD function can be expressed as [23]

$$z(n) = \frac{1}{\beta_0(|z(n)|)}\left(u(n) - \sum_{q=0}^{Q} \beta_q(|z(n-q)|)z(n-q)\right) \quad (2)$$

where $\beta_0 = \sum_{k=1}^{K} c_{k0}|z(n)|^{k-1}$. In the first iteration, $z(n)$ and $z(n-q)$ are replaced with $u(n)$ and $u(n-q)$ in both β_0 and β_q. Some iterations are needed so that the algorithm converges. This digital memory polynomial predistorter scheme is illustrated in Fig. 4.

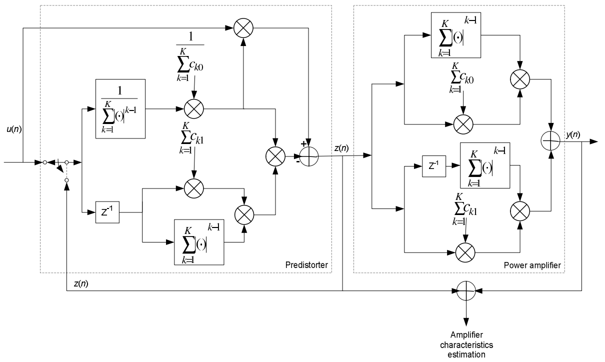

Fig. 4. Digital memory polynomial predistorter scheme (Q = 1) based on Kim's model.

B. Indirect Learning Architecture

Indirect learning [17] architecture uses two identical memory polynomial models for the predistorter and the postdistorter, as seen in Fig. 2. The predistorter parameters are defined by using a linear least squares (LS) method. It is possible because the model is linear in the unknown parameters a_{kq}. Thus, property of separability [26, p. 257] can be used. Next an LS procedure is discussed. First, u_{kq} sequence is defined as [17]

$$u_{kq}(n) = \frac{y(n-q)}{G}\left|\frac{y(n-q)}{G}\right|^{k-1} \quad (3)$$

Then we have [17]

$$\mathbf{z} = \mathbf{U}\mathbf{a} \quad (4)$$

where $\mathbf{z} = [z(0), \ldots, z(N-1)]$, $\mathbf{U} = [\mathbf{u}_{10}, \ldots, \mathbf{u}_{K0}, \ldots, \mathbf{u}_{1Q}, \ldots, \mathbf{u}_{KQ}]$, $\mathbf{u}_{kq} = [u_{kq}(0), \ldots, u_{kq}(N-1)]^T$, and $\mathbf{a} = [a_{10}, \ldots, a_{K0}, \ldots, a_{1Q}, \ldots, a_{KQ}]^T$. Thus, $z(n)$ can be expressed as

$$z(n) = \sum_{k=1}^{K}\sum_{q=0}^{Q} a_{kq}u(n) \quad (5)$$

and it is linear in the paramaters a_{kq}. The least-squares solution for (4) is

$$\hat{\mathbf{a}} = (\mathbf{U}^{\mathrm{H}}\mathbf{U})^{-1}\mathbf{U}^{\mathrm{H}}\mathbf{z}, \quad (6)$$

where $(\cdot)^{\mathrm{H}}$ denotes a complex conjugate transpose.

IV. Simulations

A. Simulation Model

Next the simulation models are presented and results are shown. Two different memory polynomial predistorters models have been modeled including direct learning [11], [23] and indirect learning [17] architectures. In both models, the transmitted data was a step-ramp signal when the characteristics of the PA was simulated and the signal is upconverted the frequency 0.4. The step-ramp signal increases in steps and the width of the step is $Q+1$ in which way we are able to fill in the memory of the amplifier model.

When the MSE is defined by using a simulation, the transmitted data are a Gaussian random noise, whose root mean square (rms) value is 0.3 or 1.0. These models are designed so that the compensation does not achieve desired results if the maximum amplitude of the input signal is greater than the saturation level. Thus, the input signal is set lower than the saturation level by using the rms value. The length of the transmitted signal is set to 8000 samples. The coefficients of the amplifiers are the same as in [17], as shown in Table I. These coeffiecients are extracted from an actual Class AB power amplifier. We use an iteration procedure in the direct learning model. In the initial state, the first coefficient of the predistorter (a_{10}) is one and others are zeros ([1 0 0 ... 0]).

TABLE I

Coefficients (c_{kq}) of the Power Amplifier

c_{10}	c_{30}	c_{50}
1.0513+0.0904j	-0.0542-0.2900j	-0.9657-0.7028j
c_{11}	c_{31}	c_{51}
-0.0680-0.0023j	0.2234+0.2317j	-0.2451-0.3735j
c_{12}	c_{32}	c_{52}
0.0289-0.0054j	-0.0680-0.0023j	0.1229+0.1508j

In both simulation models, the amplitude modulation - amplitude modulation (AM/AM), amplitude modulation - phase modulation (AM/PM) characteristics and a MSE value are calculated in the following way

$$y_{\text{AM/AM}}(n) = \sqrt{(\text{Re}[y(m)])^2 + (\text{Im}[y(m)])^2} \quad (7)$$

$$u_{\text{AM/AM}}(n) = \sqrt{(\text{Re}[u(m)])^2 + (\text{Im}[u(m)])^2} \quad (8)$$

$$y_{\text{AM/PM}}(n) = \arg(y(m)) \quad (9)$$

$$\hat{J} = \frac{1}{L}\sum_{n=1}^{L}|y(p) - u(l)|^2 \quad (10)$$

where $n = 1, 2, 3, \ldots$, $m = Q+1, 2Q+2, 3Q+3, \ldots, N-(Q+1)$, $p = Q+1, Q+2, Q+3, \ldots, N-(Q+1)$, $l = d, d+1, d+2, \ldots, N-d$, d is the delay parameter, and Re$(\cdot)$ is the real part of the signal, Im$(\cdot)$ is the imaginary part of the signal, L is the length of the output of the PD, and u is the input signal of the predistorter, as seen in Fig. 2.

B. *Comparison of the Direct Learning Predistorter with Indirect Learning Predistorter*

Fig. 5 illustrates AM/AM and AM/PM characteristics as 3D figure. Frequencies are normalized by the sampling rate. In the linear case, phase shifts are constant and nonlinear characteristics are clearly seen in the nonlinear case.

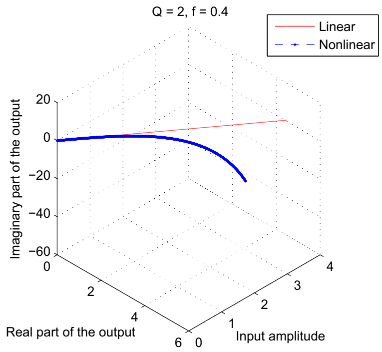

Fig. 5. AM/AM and AM/PM characteristics in the nonlinear and linear case in 3D figure, rms value = 0.3.

Next, the MSE is shown as a function of the number of the iterations in Figs. 6, 7, and 8. The delay parameter is fixed to the optimal delay (d), thus, $d = Q+1$ as seen in (10). A direct learning model achieves smaller MSE than an indirect learning model in all cases. The performance of the indirect learning models is better only in the first or second iterations. It can be seen that the MSE of the indirect learning model converges faster in the first iterations. These results show also that the iteration procedure is not needed in an indirect learning model because the performance does not improve after the second iteration.

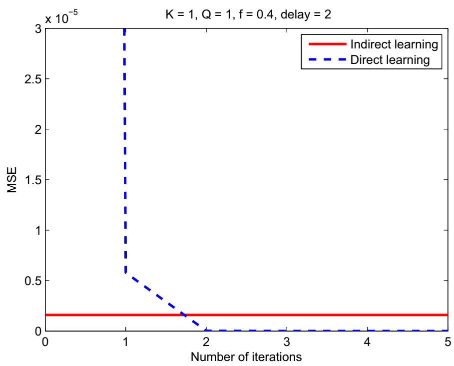

Fig. 6. Comparisons of Ding's and Kim's model on optimal delay in the linear case with memory, $K = 1$, $Q = 1$, rms value = 0.3, and $f = 0.4$.

In Fig. 9, the AM/PM characteristics of the PA and the PD and PA entity are shown for the indirect learning model when $f = 0.4$ and rms values are 0.3 and 1.0. It can be seen that the result of the compensation improves significantly when the rms value is 0.3 instead of the rms value is 1.0. Thus, we can conclude that the result of the compensation depends also on the amplitude distribution, not only on the frequency.

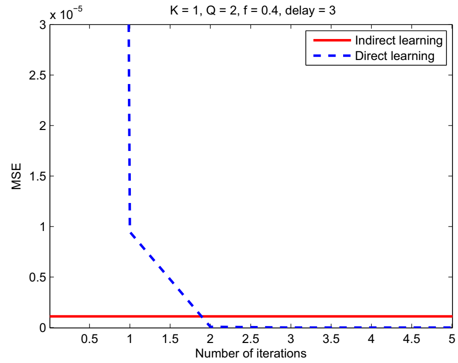

Fig. 7. Comparisons of Ding's and Kim's model on optimal delay in the linear case with memory, $K = 1$, $Q = 2$, rms value = 0.3, and $f = 0.4$.

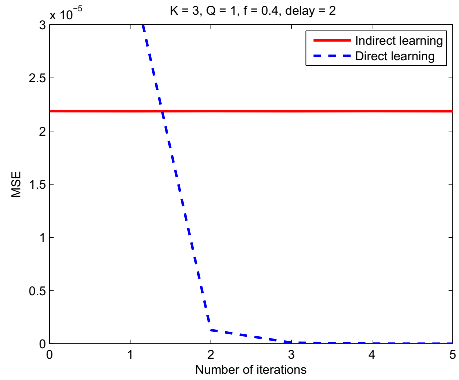

Fig. 8. Comparisons of Ding's and Kim's model on optimal delay in the nonlinear case with memory, $K = 3$, $Q = 1$, rms value = 0.3, and $f = 0.4$.

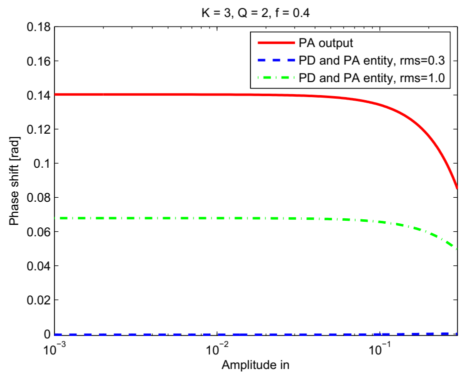

Fig. 9. AM/PM characteristics for the PA and the PA and PD entity, $K = 3$, $Q = 2$, $f = 0.4$, and rms value = 0.3 and 1.0.

We can conclude that the direct learning model performs in almost all cases better than the indirect learning model. The indirect learning method is based on the assumption that the commutation is valid, which is not valid in the nonlinear system. That is one reason why the MSE is larger in the indirect learning case than in the direct learning case. Additionally, the direct learning method has more degrees of freedom than the indirect learning method because the predistorter of the direct learning scheme is time-variant [23] although the PA is time-invariant. Furthermore, the direct learning model has own coefficients of the predistorter at each time sample. The indirect learning model is time-invariant if the amplifier is time-invariant. In the indirect learnign model, the predistorter model is employed directly based on the input and output signal of the PA [24]. The coefficients of the PA need to be known or estimated in order to define the predistortion function in the direct learning model [11]. The predistorter based on the indirect learning model is estimated by using an LS method and this estimation does not need an iterative process. In the direct learning model, the estimation of the memory polynomial predistortion function is based on an iterative process. These differences are surely one reason for the difference in the performance.

V. Conclusions

In this paper, digital memory polynomial predistorters were applied to mitigate nonlinearities of the power amplifiers. In this paper, the main attention was given to two memory polynomial predistorters including direct [11], [23] and indirect [17] learning architectures. These architectures are compared with each other. Both of these architectures are special cases of the self-tuning control. Simulation results showed that direct and indirect learning PD models do not work if the input amplitude is too high. The commutability is not valid unless there is a special reason for that. The post-inverse should be close to the pre-inverse. An invertible nonlinear model transformation must be a bijection, i.e., there is a one-to-one correspondence between the input and the output. Simulation results show also that the direct learning model performs better than indirect learning model in almost all cases. We also observed that the results of the compensation depend also on the amplitude, not only on the frequency. In future work, it is interesting to compare the complexity of these two predistorters architectures with each other.

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