NONLINEAR COMPENSATION BY SUPPORT VECTOR MACHINE APPROACH

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ABSTRACT

A new adaptive predistortion method for compensation of unknown linear and nonlinear distortion in a high power amplifier (HPA) is investigated by a data-based approach using the support vector regression (SVR). The proposed approach can construct an inverse model of the nonlinear HPA by learning procedure using training input-output data samples. An on-line adaptive algorithm for updating the parameters of the SVR machines is also given to reduce the computational burden of the batch processed optimization. By comparing with an ordinary look-up table scheme, it is shown that the proposed data-based approach can attain improved suppression of the power spectrum of the amplifier output outside the input frequency band caused by the nonlinear distortions.

1. INTRODUCTION

In the orthogonal frequency division multiplexing (OFDM) communication systems, the signal has widely changeable amplitudes dependently of transmitted symbols, the nonlinearity compensation is essentially needed to improve the distortion. The technique allows bandwidth efficient modulation schemes to be used with nonlinear HPA with small degradation in bit error rate performance relative to a purely linear transmitter system. In addition, the technique adapts to changes in the nonlinearity of the HPA which could be caused by changes to the input power, carrier frequency, aging, temperature, or component replacement.

Previous predistortion techniques include analog feedback, analog feedforward, and digital table-lookup mapping. The analog techniques have been limited by narrow operating bandwidth, extreme sensitivity of HPA variations, instabilities, and in some techniques the requirement for additional RF amplifiers. The digital mapping techniques have been limited by the massive amount of storage required for a sufficiently accurate mapping to be stored, and by degradation caused by discontinuity of the table-based mapping [2, 3, 4]. In addition, inverse modeling approach of a nonlinear PHA has been proposed by using a Volterra series analysis [5, 6, 7, 8, 9, 10, 11], and digital techniques

based on neural networks have also been developed [12].

The purpose of this paper is to present a predistortion scheme based on the SVM which is one of powerful tools for constructing a nonlinear input-output mapping on the basis of a given number of training samples [1]. By using the data-based approach, we construct an inverse model for nonlinear high power amplifier (HPA) to compensate nonlinear and linear distortions in an adaptive way.

2. DESIGN PROBLEM FOR HPA PREDISTORTION

Nonlinearity compensation for HPA is needed in the orthogonal frequency division multiplexing (OFDM) communication systems, since the OFDM signal has an information in the instantaneous amplitude which changes in wide range corresponding to the transmitted symbols. In this paper, we take a predistortion scheme where an inverse system is designed so that the input-output relation is linearized.

Let (a_n, b_n) be a transmitted symbol, and let $d_n = a_n + jb_n$. The baseband OFDM signal generated from the symbols can be described by

$$\begin{aligned} s(t) &= \sum_{n=-N/2}^{N/2-1} (a_n + jb_n) \{ \cos(2\pi n f_0 t) + j \sin(2\pi n f_0 t) \} \\ &= \sum_{n=-N/2}^{N/2-1} d_n e^{j2\pi n f_0 t} = s_I(t) + j s_Q(t) \end{aligned} \quad (1)$$

The input-output relation of the predistorter located at the input of the HPA can be expressed by

$$z(t) = z_I(t) + j z_Q(t) = H(k s(t)) \quad (2)$$

where k is an arbitrary nominal gain of the HPA. The output of the nonlinear HPA with input signal $z(t)$ is given as

$$y(t) = y_I(t) + j y_Q(t) = G(z(t)) \quad (3)$$

The role of the predistortion is to design $H(\cdot)$ for an unknown nonlinear HPA $G(\cdot)$ so that

$$G(H(k s(t))) = k s(t) \quad (4)$$

can be satisfied. The amplitude and phase characteristics of HPA is a function of the absolute value and phase of the complex input signal $z(t)$, as described by

$$G(z(t)) = \text{Amp}(|z|)e^{j[\angle z + \Phi(|z|)]} \quad (5)$$

Now the design problem is how to implement the predistorter $H(\cdot)$ for the uncertain HPA $G(\cdot)$. The predistorter has two inputs for real and imaginary parts and also two outputs. Then the $H(\cdot)$ consists of two-input single-output subsystems $H_I(\cdot)$ and $H_Q(\cdot)$ described by

$$H_I(ks(t)) = \text{Re}(H(ks(t))) = \text{Re}(z(t)) = z_I(t) \quad (6)$$

$$H_Q(ks(t)) = \text{Im}(H(ks(t))) = \text{Im}(z(t)) = z_Q(t) \quad (7)$$

However it can be proved that the construction of either $H_I(\cdot)$ or $H_Q(\cdot)$ is sufficient for the predistortion satisfying (4). Since it follows from the property of HPA (5) that $G(e^{j\theta}z(t)) = e^{j\theta}G(z(t))$, the predistorter satisfies that

$$H(-jks(t)) = -jH(ks(t)) \quad (8)$$

Therefore, if we input the signal $-jks(t)$ to $H_I(\cdot)$, then it holds that

$$\begin{aligned} H_I(-jks(t)) &= \text{Re}(H(-jks(t))) = \text{Re}(-jz(t)) \\ &= \text{Re}(z_Q(t) - jz_I(t)) = z_Q(t) \end{aligned} \quad (9)$$

then we have

$$H_Q(ks(t)) = H_I(-jks(t)) \quad (10)$$

As a result, we only need to update either $H_I(\cdot)$ or $H_Q(\cdot)$ by changing the input signal, as shown in Fig.1.

3. SVR-BASED PREDISTORTION OF HPA

3.1 Inverse Modeling by Support Vector Regression

Fig.1 gives a schematic diagram for the proposed adaptive predistortion scheme for a nonlinear HPA by constructing an inverse model by a support vector regression (SVR) obtained from the training input-output data set. The amplifier ordinarily includes uncertain memoryless saturation type of nonlinearity and uncertain low-pass dynamics in input and output parts of the amplifier. k is a nominal gain, and $n(t)$ is a zero-mean white noise. The aim is to construct a nonlinear input-output inverse model for the HPA with the above uncertainties by taking the SVR-based approach using a finite number of training samples, so that $s_{\text{out}}(t) = k \cdot s(t)$ can be realized.

As clarified in the previous section and shown in Fig.1, the input to SVR may be either real or imaginary part of the amplifier output $s_{\text{out}}(t)$. In the following, we use the real part of $s_{\text{out}}(t)$ and define it by $s_{\text{out},I}(t)$. Let the $n-1$ training data samples be denoted by

$$\mathbf{x}_i = [s_{\text{out},I}(iT), \dots, s_{\text{out},I}((i-m+1)T)] \quad (11)$$

$$y_i = \hat{z}_I((i-d)T) \quad \text{for } i = 1, \dots, n-1 \quad (12)$$

Figure 1: Adaptive predistortion of HPA nonlinearity by SVR

where T is a sampling interval, d is a delay, m is the dimension of the input vector $\mathbf{x}_i$. T will be omitted for simplicity of notation.

3.2 Off-line SVR Approach

Let the training input-output data be given by $(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_n, y_n)$. The aim is to obtain a regression function as

$$y = f(\mathbf{x}, \theta) = \langle \mathbf{w}, \mathbf{x} \rangle + b \quad (13)$$

which provides the model output predicting an actual output. By introducing a linear ε -insensitive loss function denoted by

$$L_{1,\varepsilon}(y, f(\mathbf{x}, \mathbf{w})) = \max(0, |y - f(\mathbf{x}, \mathbf{w})| - \varepsilon) \quad (14)$$

we can take the structural risk function given by

$$\min_{\mathbf{w}} \left\{ \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^n L_{1,\varepsilon}(y_i, f(\mathbf{x}_i, \mathbf{w})) \right\} \quad (15)$$

where the first term corresponds to the model complexity and the second term indicates the empirical risk due to the regression error. The above minimization can be described as the primary problem as

$$\begin{aligned} \min_{\mathbf{w}} \quad & \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^n (\xi_i + \hat{\xi}_i) \\ \text{subject to} \quad & \begin{cases} y_i - \langle \mathbf{w}, \mathbf{x}_i \rangle - b \leq \varepsilon + \xi_i \\ \langle \mathbf{w}, \mathbf{x}_i \rangle + b - y_i \leq \varepsilon + \hat{\xi}_i \\ \xi_i \geq 0, \quad \hat{\xi}_i \geq 0, \quad i = 1, \dots, n \end{cases} \end{aligned} \quad (16)$$

where ξ_i and $\hat{\xi}_i$ are the non-negative slack variables.

By introducing the Lagrangian multipliers, we can transform the primary problem into its dual problem stated as:

$$\max_{\alpha} W(\alpha) = -\frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (\alpha_i - \hat{\alpha}_i)(\alpha_j - \hat{\alpha}_j) \langle \mathbf{x}_i, \mathbf{x}_j \rangle$$

$$\begin{aligned}
& -\varepsilon \sum_{i=1}^n (\alpha_i + \hat{\alpha}_i) + \sum_{i=1}^n y_i (\alpha_i - \hat{\alpha}_i) \\
\text{subject to } & \begin{cases} \sum_{i=1}^n (\alpha_i - \hat{\alpha}_i) = 0 \\ 0 \leq \alpha_i \leq C, \quad 0 \leq \hat{\alpha}_i \leq C \end{cases} \quad (17)
\end{aligned}$$

For the purpose of extension to the nonlinear regression problem, a mapping $\varphi(\mathbf{x})$ from the input vectors $\mathbf{x} \in \mathcal{X}$ to a high-dimensional feature space $\varphi \in \Phi$ is introduced, [1] as

$$\begin{aligned}
y_t &= f(\mathbf{x}_t, \boldsymbol{\theta}) \\
&= \langle \mathbf{w}, \boldsymbol{\varphi}_t \rangle + b = \sum_{i=1}^{n-1} (\alpha_i - \hat{\alpha}_i) \langle \boldsymbol{\varphi}_i, \boldsymbol{\varphi}_t \rangle + b \\
&= \sum_{i=1}^{n-1} (\alpha_i - \hat{\alpha}_i) K(\mathbf{x}_i, \mathbf{x}_t) + b \quad (18)
\end{aligned}$$

where $K(\mathbf{x}_i, \mathbf{x}_t)$ is introduced to estimate the inner product $\langle \boldsymbol{\varphi}_i, \boldsymbol{\varphi}_t \rangle$ in the feature space implicitly without performing the nonlinear mapping from the input space $\mathbf{x} \in \mathcal{X}$ into feature space $\varphi \in \Phi$ [1], where a variety of kernels have been proposed, for instance, radial-basis functions and polynomial functions.

The SVM approach can be formulated as a convex problem by (17) and (18). In the nonlinearity predistortion case, in which the nonlinearity of amplifiers can be expressed by an odd degree of polynomial function of input signal, we can decide that $b = 0$ in (18). Furthermore, $\alpha_i - \hat{\alpha}_i$ can be replaced by one variable, for instance, β_i , so we also define β_i as α_i again. When the data set consisting of n input-output training samples given by (11) and (12), from the above consideration and the Kuhn-Tucker optimality conditions, we can show that the dual problem (17) can be rewritten in the next alternative expression as

$$\begin{aligned}
\max_{\boldsymbol{\alpha}^{(n)}} W(\boldsymbol{\alpha}^{(n)}) &= \max_{\boldsymbol{\alpha}^{(n)}} \sum_{i=1}^n \alpha_i^{(n)} y_i \\
&- \frac{1}{2} \sum_{i,j=1}^n \alpha_i^{(n)} \alpha_j^{(n)} K(\mathbf{x}_i, \mathbf{x}_j) - \varepsilon \sum_{i=1}^n |\alpha_i^{(n)}| \\
\text{subject to } & 0 \leq |\alpha_i^{(n)}| \leq C \quad \text{for } i = 1, \dots, n \quad (19)
\end{aligned}$$

Some of $\{\alpha_i^{(n)}\}$ are zero, but some of them take non-zero values which correspond to the support vectors $\{\mathbf{x}_i\}$. By solving the above problem, the output $\hat{y}_t$ of the optimal SVM has an expression form as

$$\hat{y}_t = \sum_{i=1}^n \alpha_i^{(n)} K(\mathbf{x}_i, \mathbf{x}_t) \quad (20)$$

where $K(\mathbf{x}_i, \mathbf{x}_t)$ is a kernel function satisfying the Mercer's conditions. As described later, we adopt a polynomial type of kernel as $K(\mathbf{x}_i, \mathbf{x}_t)$, which seems suitable to description of an inverse model of the Volterra series systems.

3.3 SVM-Based Adaptive Algorithms

In this section, an adaptive algorithm for updating the parameters in the SVM on every instant when new input-output data is obtained. It is assumed that the SVM parameters $\{\alpha_i^{(n-1)}\}$ are given by solving the maximization problem (19) using the $n-1$ input-output training samples. When new input-output data are added at n -th time instant, the issue is how to update and calculate the new SVM parameters which can maximize the performance.

We show an adaptive scheme for updating the old parameters $\alpha_1^{(n-1)}, \alpha_2^{(n-1)}, \dots, \alpha_{n-1}^{(n-1)}$ to the new parameters $\alpha_1^{(n)}, \alpha_2^{(n)}, \dots, \alpha_n^{(n)}$. The algorithm consists of two steps: In the first step, we calculate $\{\alpha_n^{(n-1)}\}$ first, so that the criterion $W(\alpha_n^{(n-1)})$ can be maximized with respect to only $\alpha_n^{(n-1)}$, on the condition that other $\alpha_1^{(n-1)}, \alpha_2^{(n-1)}, \dots, \alpha_{n-1}^{(n-1)}$ are remained fixed at the values previously obtained. Its solution is given as follows:

$$\begin{aligned}
\frac{\partial W(\alpha_n^{(n-1)})}{\partial \alpha_n^{(n-1)}} &= e_n^{(n-1)} - \alpha_n^{(n-1)} K(\mathbf{x}_n, \mathbf{x}_n) \\
-\varepsilon \text{sign}(\alpha_n^{(n-1)}) &= 0 \quad (21)
\end{aligned}$$

where

$$e_n^{(n-1)} = y_n - \hat{y}_n^{(n-1)} \quad (22)$$

$$\hat{y}_n^{(n-1)} = \sum_{i=1}^{n-1} \alpha_i^{(n-1)} K(\mathbf{x}_i, \mathbf{x}_n) \quad (23)$$

Then it follows from (21) that

$$\alpha_n^{(n-1)} = \min \left[C, \frac{|e_n^{(n-1)}| - \varepsilon}{K(\mathbf{x}_n, \mathbf{x}_n)} \right] \text{sign}(e_n^{(n-1)}) \quad (24)$$

Now we can have all the parameters $\{\alpha_i^{(n-1)}\}$ for $i = 1, 2, \dots, n$, however, they should further be updated by the new data set $\{y_n, \mathbf{x}_n\}$ already obtained at n -th instant.

In the next step, we update $\alpha_i^{(n-1)}$ to new parameters $\alpha_i^{(n)}$ for $i = 1, \dots, n$ as

$$\alpha_i^{(n)} = \alpha_i^{(n-1)} + \Delta \alpha_i^{(n)} = \alpha_i^{(n-1)} + \eta_i \frac{\partial W(\alpha_n^{(n-1)})}{\partial \alpha_i^{(n-1)}} \quad (25)$$

where

$$\frac{\partial W(\alpha_n^{(n-1)})}{\partial \alpha_i^{(n-1)}} = e_i^{(n)} - \varepsilon \text{sign}(\alpha_i^{(n-1)}) \quad (26)$$

$$e_i^{(n)} = e_i^{(n-1)} - \alpha_n^{(n-1)} K(\mathbf{x}_n, \mathbf{x}_i) \quad (27)$$

where $e_i^{(0)} = y_i$.

The optimal step size η_i can also be determined so that the criterion $W(\alpha_n^{(n-1)} + \Delta\alpha_n^{(n)})$ can be maximized, then we have

$$\eta_i = \frac{1}{K(\mathbf{x}_i, \mathbf{x}_i)} \quad \text{for } i = 1, \dots, n \quad (28)$$

Thus the updated parameters given by the second step is expressed as

$$\begin{aligned} \alpha_i^{(n)} &= \alpha_i^{(n-1)} + \frac{1}{K(\mathbf{x}_i, \mathbf{x}_i)} \\ &\cdot [e_i^{(n-1)} - \alpha_n^{(n-1)} K(\mathbf{x}_n, \mathbf{x}_i) - \varepsilon \text{sign}(\alpha_i^{(n-1)})] \\ &\quad i = 1, \dots, n \end{aligned} \quad (29)$$

Thus the adaptive algorithm executed at every instant when the sample data is given can be summarized as

Step 1: Let $n = 1$, $\alpha_1^{(0)} = 0$ and $\hat{y}_1^{(0)} = 0$.

Step 2: Obtain the new data $\mathbf{x}_n, y_n$, as (11) and (12).

Step 3: Calculate $e_n^{(n-1)}$ by using (22). If $e_n^{(n-1)} \leq \varepsilon$, set $\alpha_n^{(n)} = 0$ and $n = n + 1$, and go to Step 2, otherwise go to Step 4.

Step 4: Calculate the parameters $\alpha_n^{(n-1)}$ by using (24).

Step 5: Calculate the perturbations for all parameters $\Delta\alpha_n^{(n-1)}$ by using (25), (26) and (28), and update them, although the parameters $\alpha_i^{(n-1)} = 0$ are not updated.

Step 6: Calculate the criterion $W(\alpha_n^{(n)})$ from (19). If $W(\alpha_n^{(n)}) \geq W(\alpha_{n-1}^{(n-1)})$, then let $n = n + 1$ and go to Step 2, otherwise do not update the parameters and set $\alpha_n = 0$ and $n = n + 1$ and go to Step 2.

3.4 Case with Quadratic ε -Insestive Loss Function

In this section, we take an alternative quadratic ε -insestive loss function given as

$$L_\varepsilon(y, f(\mathbf{x}, \mathbf{w})) = \max(0, (y - f(\mathbf{x}, \mathbf{w}))^2 - \varepsilon) \quad (30)$$

then, the structural risk function is expressed by

$$\min_w \left\{ \|\mathbf{w}\|^2 + C \sum_{i=1}^n L_\varepsilon(y_i, f(\mathbf{x}_i, \mathbf{w})) \right\} \quad (31)$$

By introducing the slack variables as in (16) and the Lagrange multiplier as in (17), and executing some manipulation as in (19), we can describe the dual problem for (31) as follows:

$$\begin{aligned} \max_{\alpha_n^{(n)}} W(\alpha_n^{(n)}) &= \max_{\alpha_n^{(n)}} \sum_{i=1}^n \alpha_i^{(n)} y_i \\ &- \frac{1}{2} \sum_{i,j=1}^n \alpha_i^{(n)} \alpha_j^{(n)} [K(\mathbf{x}_i, \mathbf{x}_j) + (1/C)\delta_{ij}] \\ &- \varepsilon \sum_{i=1}^n |\alpha_i^{(n)}| \end{aligned} \quad (32)$$

Then, by solving the above problem, the output $\hat{y}_s(t)$ of the optimal SVM has the same expression form as (20).

By skipping its details, we will show the adaptive algorithm for updating the SVR scheme in the quadratic cost function. Let the input/output data set $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_n, y_n)$ be given. When a new input/output data is given, a new support vector is selected as follows:

Step 1: Let the input/output data set $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_n, y_n)$ be given, and let the n_{sv} support vectors are obtained as

$$\alpha = [K + (1/C)I]^{-1} \mathbf{y} \quad (33)$$

where n_{sv} is a number of the support vectors, K is a kernel matrix with a element $K(\mathbf{x}_i, \mathbf{x}_j)$, and $\mathbf{y} = (y_1, \dots, y_{n_{sv}})$.

Step 2: A new data set $\mathbf{x}_s, y_s$ is obtained, and the number of data set becomes $n_{sv} + 1$.

Step 3: If $y_s - \sum_{i=1}^{n_{sv}} \alpha_i K(\mathbf{x}_s, \mathbf{x}_i) \leq \varepsilon'$, go to Step 2, otherwise go to Step 4.

Step 4: Calculate the parameters $\alpha_{n_{sv}+1}$ as

$$\alpha_{n_{sv}+1} = [K_{n_{sv}+1} + (1/C)I_{n_{sv}+1}]^{-1} \mathbf{y}_{n_{sv}+1} \quad (34)$$

where all of the data set $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_{n_{sv}}, y_{n_{sv}})$ are used, and $\mathbf{y}_{n_{sv}+1}$.

Step 5: Deleting i th data set from $n_{sv} + 1$ data sets, we calculate n_{sv} support vectors as follows:

$$\alpha_{n_{sv}}^{(-i)} = [K_{n_{sv}}^{(-i)} + (1/C)I_{n_{sv}}]^{-1} \mathbf{y}_{n_{sv}}^{(-i)} \quad (35)$$

where the calculation for $\alpha_{n_{sv}}^{(-i)}$ uses the data sets $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_{i-1}, y_{i-1}), (\mathbf{x}_{i+1}, y_{i+1}), \dots, (\mathbf{x}_{n_{sv}+1}, y_{n_{sv}+1})$, and let $\mathbf{y}_{n_{sv}}^{(-i)} = (y_1, \dots, y_{i-1}, y_{i+1}, \dots, y_{n_{sv}+1})$.

Step 6: From the $n_{sv} + 2$ candidates for the support vector obtained in Step 4 and Step 5, find the support vector α such that

$$\alpha^T (K + (1/C)I) \alpha \quad (36)$$

is minimized. Thus, exchanges of the support vectors are executed.

4. SIMULATION RESULTS

In this simulation, we investigate the effectiveness of the proposed SVM-based approach to compensation of linear and nonlinear distortions of HPA, which is frequently used in OFDM transmission systems. The OFDM is one of the multi-carrier modulations as given

by (1), where f_0 is a fundamental carrier frequency and $T = 1/f_0$ is a sampling interval. Since the signal has widely changeable amplitudes dependently of transmitted symbols, the nonlinearity compensation is essentially needed to improve the distortion.

(a) *Compensation of memoryless nonlinear distortion*

We consider the nonlinear HPA given by

$$\text{Gain: } A(z) = \frac{|z|}{(1 + |z|^{2b})^{1/2b}}$$

$$\text{Phase: } \Phi(z) = \frac{\pi}{3} \frac{|z|^2}{1 + |z|^2}$$

where z is the amplitude of the input to HPA and $b = 3$. The algorithm in Section 3.4 was applied to the simulation. The setup for the simulation is summarized as follows: $s(t)$ is 64QAM-OFDM signal, the number of carriers is $N = 1405$, and the FFT size is 2048. The size of the regression vector $\mathbf{x}_i$ is chosen $m = 3$, and the delay is chosen $d = 1$. The kernel is selected as the polynomial type given by $K(\mathbf{x}_1, \mathbf{x}_2) = (a\mathbf{x}_1^T \mathbf{x}_2 + 1)^p$ where $a = 2.5$ and $p = 3$. The constant parameters in the design of the SVM are chosen as $C = 1$, $\varepsilon = 10^{-6}$ and $\varepsilon' = 10^{-2}$. These constants are determined as follows: The constant C relating with regularization can be chosen from a maximum value among actually calculated α_i by changing C from larger to smaller one. The constant a in the kernel can be given from the magnitude of the inner product of the support vectors and input vectors. The appropriate constants m , d and p can be determined so that the sum of the squares error $e^2(t)$ may be minimized. It will be noticed that m and d are smaller than the case with dynamics in HPA.

The predistortion performance is evaluated by the reduction of the output power spectra outside the transmission frequency band caused by high nonlinearity of HPA. The results are compared to a case with no predistortion scheme (see Fig.2) and a case with an ordinary table-lookup scheme (see Fig.3). The proposed SVR based method can improve the predistortion by 50dB from the no predistortion case and by 18dB from the table lookup scheme (see Fig.4).

(b) *Compensation of both nonlinear and linear distortions*

In this simulation, it is assumed that the nonlinear amplifier has linear dynamical distortion in its input and output parts as shown in Fig.5, where $A(j\omega)$ and $B(j\omega)$ are lowpass filters respectively. The setup for the simulation is summarized as follows: The transmitted signal $S_{IN}(t)$ is the 64QAM-OFDM signal same as the former simulations. The number of carriers, the size of FFT are also the same. The delay is chosen as $d = 3$, the dimension of the regressor vector is chosen as $m = 6$. The kernel is given by $K(\mathbf{x}_1, \mathbf{x}_2) = (a\mathbf{x}_1^T \mathbf{x}_2 + 1)^p$, where $a = 5$ and $p = 7$. The constants in design for the SVM are chosen by

Figure 2: Output power spectrum: No predistortion

Figure 3: Output power spectrum: Predistortion by ordinary table lookup scheme

Figure 4: Output power spectrum: Proposed SVR

$C = 1$ and $\varepsilon = 10^{-5}$. These constants needed in the SVM approach can also be determined similarly as in the case (a).

The predistortion performance is also evaluated by the reduction of the output power spectra outside the transmission frequency band. The proposed SVR based method can improve the predistortion by 30dB. It should be remarked that the appropriate values of d , m and p given from minimization of the squares error are larger than those in the case (a) with no dynamics. However we can use the same structure of the SVM predistorter. The recovered 64-QAM symbols are plotted in Fig.7 obtained in a case without predistortion, and in Fig.8 obtained by the proposed adaptive SVR based predistortion. The detection performance can also be improved as well as the leakage of output power spectra.

Figure 5: Nonlinear structure of HPA with dynamics

Figure 6: Output power spectrum: Proposed SVR

5. CONCLUSION

The new adaptive predistortion algorithm has been presented on the basis of the nonlinear input-output modeling using the data-based SVR, which has effectiveness in compensation of uncertain nonlinear and linear distortions in HPA used in OFDM systems.

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Figure 7: De-mapped signal of 64QAM: No predistortion

Figure 8: De-mapped signal of 64QAM: Proposed SVR

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