Behavioral Modeling of Power Amplifiers Using Fully Recurrent Neural Networks

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Abstract — **This paper describes the first implementation of fully recurrent neural networks (FRNN) for behavioral modeling of power amplifiers. The proposed recurrent neural network model utilizes global feedbacks and full interconnections between neurons in hidden layers. The model has successfully been trained with W-CDMA signal. Then it is tested with not only W-CDMA signal but CDMA-IS95 and 2-tone signals as well. Good agreements between measured and modeled results have been achieved.**

Index terms — **Behavioral modeling, complementary cumulative probability density function (CCDF), peak to average ratio (PAR), recurrent neural networks (RNN), third-generation (3G) PA, wideband CDMA (W-CDMA).**

I. INTRODUCTION

Recently, Artificial Neural Networks (ANN) have been successfully used for the modeling, simulation and design of a wide variety of high frequency circuits used in telecommunication systems [1-3]. Neural networks can be trained from simulated or measured microwave data and subsequently used in circuit analysis and design stage. After being trained with microwave data, the neural networks can represent the behaviors they learnt and can give fast answers to the task they have learnt [4]. Since ANNs have the ability to model highly nonlinear input-output behaviors, they were also employed to model power amplifiers (PAs) operating under wide-band modulation and highly varying envelope signals such as wideband CDMA (W-CDMA) and CDMA2000 [5]. Those PAs usually exhibit strong memory effect that is difficult to take into account. Hence, the ANN-based models can be considered as a promising alternative to model PAs having strong memory effects along with high nonlinearity.

Recently, recurrent neural networks (RNN) have been employed to model microwave circuits [4,6]. In this paper, for the first time, a fully recurrent neural network (FRNN) is used to model microwave PAs operating under complex digitally modulated signals. FRNN is a type of dynamic neural networks having the capability of learning and then representing the input-output behavior of systems [7]. In theory, the RNNs with internal dynamics are more robust with respect to the information about the dynamic order of the system [7]. By using global feedbacks and local interconnections in FRNN, the ability of the network to model nonlinear dynamics of systems can be enhanced. Local interconnections are achieved by the introduction of interconnections between neurons in hidden layers, whereas global feedbacks are produced by the connections of the network outputs to the network inputs. Since the ability of modeling the nonlinear dynamic behaviors of systems is embedded in the hidden neuron interconnections and global feedbacks, the FRNN model can capture the memory effects and nonlinear behaviors of PAs as well.

In this work, FRNN is used to model a wireless PA module (PAM) driven by W-CDMA (uplink) signals. Input and output waveforms of the original PAM are used as training data. Conjugate gradient method is used in the training process. The validation of the model is then tested with not only W-CDMA signal but CDMA-IS95 (reverse link) and 2-tone signals as well. Good agreements between measured and modeled results have been achieved. This is an attempt to further extend the use of neural network techniques to the dynamic modeling of PAs driven by digitally modulated signals.

II. FRNN BEHAVIORAL MODEL OF PAs

A. Structure of the Neural Network

The structure of the FRNN used in this study is shown in Fig. 1. This model is used to identify nonlinear relationships between input and output of a PAM. The input layer includes a tapped-delay line (TDL) that is used to consider the history of input signal, which is needed for memory effect modeling. The hidden layer contains K neurons connected with each other. The output layer has one linear neuron and is connected to neurons in input layer through a TDL.

The appropriate value of the number of delays in TDL and the number of neurons in hidden layer are determined through optimization in training process. Further information concerning FRNN can be found in [7,8].

The dynamic input-output relationships of the network in Fig. 1 is described as

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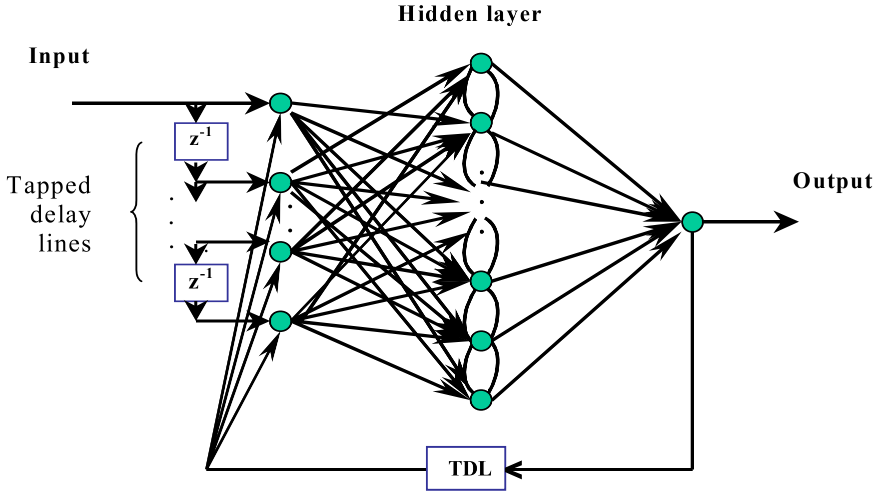

Fig. 1. Structure of the fully recurrent neural network behavioral model used in this study. (Delays in inter-connections between hidden neurons are assumed to be present although they are not shown).

$$y(n) = f_{ANN}[y(n-1), y(n-2), \cdots, y(n-p); x(n), x(n-1), \cdots x(n-q)] \quad (1)$$

where p and q stand for the memory depth of the PA under test, $\boldsymbol{x}$ and $\boldsymbol{y}$ are input and output of the network, respectively.

The RNNs with internal dynamics do not necessarily require an assumption about the order of the process dynamics. So they offer an advantage whenever knowledge about the system order does not exist [7]. This is also the common case when modeling PAs working with complex modulation signals having high PAR. The combination of local interconnections between hidden neurons and global feedbacks can enhance the ability of the neural networks to model nonlinear dynamic systems. Therefore, FRNNs with internal dynamics can be considered as a potential alternative to model PAs having strong memory effects along with high nonlinearity. After training process is completed, the FRNN behavioral models can give answers much faster than traditional simulation.

B. Training Process

The FRNN will not represent the nonlinear behaviors of microwave circuits unless it is trained by training data. The training process is defined as the computation of the weighting matrix and the threshold values of neurons in the neural networks so that the error function E (also called cost function) is minimized. The error function E, over an epoch, is defined by (2):

$$E = \frac{1}{N}\sum_{i}^{N}[y_d(i) - y(i)]^2 \quad (2)$$

where $y(i)$ represents the output of FRNN at instant *ith*, and $y_d(i)$ is the desired output at instant *ith*, N is the length of the training data.

In this work, the training process of the FRNN is performed using the measured time domain waveforms of the PAM driven by W-CDMA signal (3GPP uplink, DPCCH + 1DPDCH) at various power levels. The excitations used for generating testing data are different from those for generating training data. The behavioral model will offer high prediction accuracy since the model's parameters are identified using data captured when the PA is driven by complex digitally modulated signal that implies real operation condition.

A three-layer FRNN, as shown in Fig. 1, is used to build behavioral model for the PAM. The number of delays in TDLs and the number of neurons in hidden layer are determined through optimization. In this work, a FRNN having the number of delays in TDL for inputs $P_0 = 10$ and the number of hidden neurons $K_0 = 10$ is found to be suitable for the PAM. Hyperbolic-tangent functions were used as activation functions of hidden neurons. The delay value in feedback connections from output to network inputs is one unit.

The training data are gathered by exciting the PAM with a set of W-CDMA signals power levels (Pin = -10, -9,…, 5 dBm). Half of the measured data (-9, -7,…, 5 dBm) is used for training, and the other half (-10, -8,…, 4 dBm) is used for model verification.

Twelve-thousand (12K) sampled data from W-CDMA measurements were used to train the model and four-thousand (4K) sampled data were used to make cross-validation during the training process to guarantee the generality of the model. Conjugate gradient method was used in the training process. Fig. 2 shows typical convergence curve of the FRNN training process using W-CDMA signal.

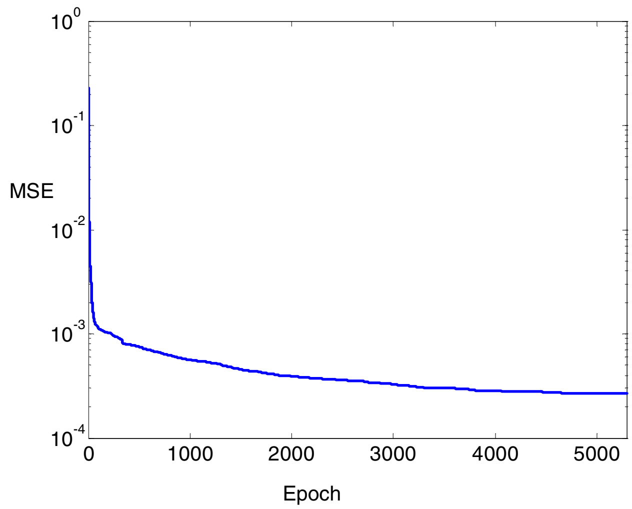

Fig. 2. Typical convergence curve of the training process.

C. Getting Data for Training

A 1-W peak PA for 3G wireless mobile phone was used in this study for model validation. It is WS2512 PAM (made by Wavics Inc.) operating at a 1.92 GHz – 1.98 GHz band. In this study, the WS2512 PAM was biased to operate in high-gain mode at carrier frequency of 1.92 GHz. The small signal gain of the WS2512 PAM is 27 dB and the output power at 1-dB gain compression is approximately 30 dBm.

A real-time two-channel sampling system consisting of a twin down-converter and a high-speed 12-bit two-channel A/D converter was built to capture time domain waveforms at input and output of the PAM simultaneously. The sampling system was carefully designed so that its two channels have almost identical characteristics. RF signals at input and output of PAM are first down-converted to an intermediate frequency using the twin down-converter. Two outputs of the twin down-converter are fed to the two-channel A/D converter. Output data of the A/D converter is directly stored into computer for data processing. The time-delay lag between the two channels is compensated using a computer program written in Matlab[R].

III. Validation of The Model

After being trained with W-CDMA signal, the proposed FRNN was validated with testing data sets that are different from those used in training process. Fig. 3 and Fig. 4 show the comparison between the results predicted by the FRNN and the measured ones for W-CDMA signals. Frequency spectrums of signals were plotted using *pwelch* function in Matlab[R]. Average testing error was calculated using the formula (3).

$$E_{percent} = \frac{1}{N}\sum_{i}^{N}\sqrt{[y_d(i) - y(i)]^2}.100 \quad (\%) \qquad (3)$$

Besides, to further demonstrate that the FRNN model represents the behavior of the PAM, the model was also tested with CDMA-IS95 signal (reverse, CCDF at 0.01% is 5 dB) and two-tone signal (having the PAR equals to 3 dB). Fig. 5 and Fig. 6 show the tested results for CDMA-IS95 and two-tone excitations. Even though the CDMA–IS95 and two-tone signals were not used to train the FRNN, the validation still gave satisfactory results.

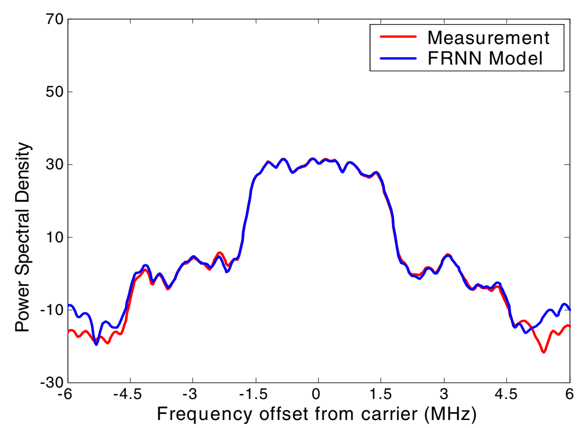

Fig. 3. PSD comparison between the FRNN behavior model and the measured data of W-CDMA (uplink, DPCCH + 1DPDCH, CCDF at 0.01% is 3.38 dB) at input power = 4 dBm (1.5-dB compression point), carrier frequency of 1.92 GHz.

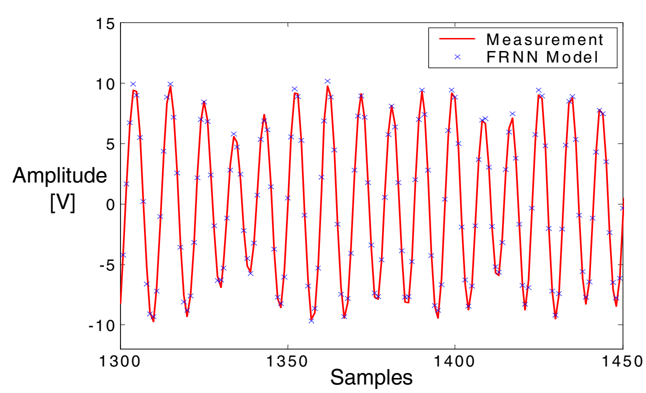

Fig. 4. Validation of the model with W-CDMA signal in time domain (Pin = 4 dBm). Average testing error = 3.349 %.

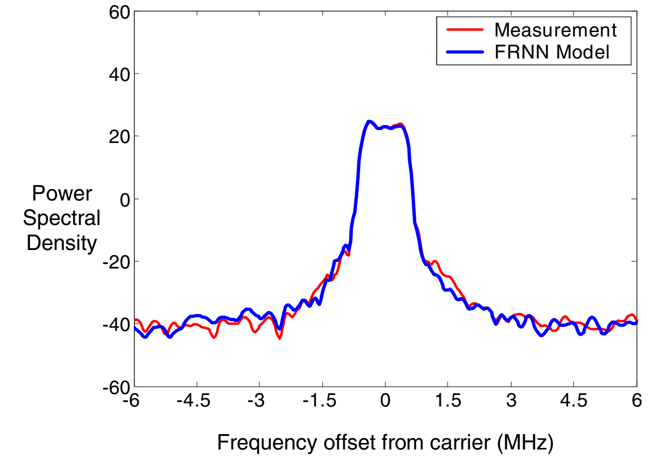

Fig. 5. PSD comparison between the FRNN behavior model and the measured data of CDMA-IS95 (reverse) at input power = -8 dBm, carrier frequency of 1.92 GHz.

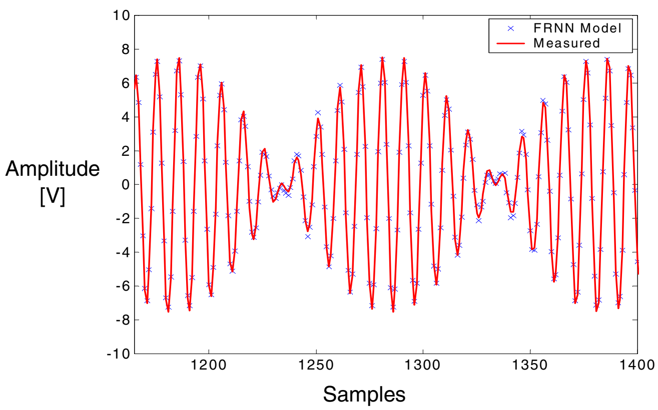

Fig. 6. Validation of the model with two-tone signal in time domain (Pin = - 1 dBm, spacing between tones = 1 MHz). Average testing error = 1.715 %.

IV. Conclusion

In this paper, for the first time, a fully recurrent neural network is used to model a PA driven by W-CDMA signal. Good agreements between measured and modeled results have been achieved showing the validation of the proposed model used in this study.

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