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Neural Network based 5G Power Amplifier Modeling on MATLAB

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Abstract—Fifth-generation wireless communication systems face significant challenges in the characterization and linearization of radio frequency (RF) power amplifiers (PAs), particularly when high peak-to-average ratio waveforms are introduced. Recently, artificial neural networks (ANNs) have accomplished outstanding achievements in various fields including PAs behavioral modeling. In this paper, a theoretical demonstration of ANNs competence in PAs modeling is presented. Moreover, a preliminary performance comparison between different ANN architectures is also given to indicate that long-short term memory (LSTM) neural network (NN) is an promising approach in PAs characterization.

Index Terms—Behavioral modeling, MLP, LSTM, time delay, complex envelope.

I. INTRODUCTION

In 5G's physical layer, being able to balance between the linearity and efficiency of RF PAs is difficult since high efficient PAs are commonly nonlinear. The creation of precise identification models for the nonlinear devices is essential in order to make it easier to use computing tools and to satisfy the need of reconfigurability. Physical models and behavioral models are frequently used. In order to track and observe the system's static nonlinear behavior as well as its dynamics, which are referred to as memory effects, behavior modeling usually builds the mathematical nonlinear modeling function by capturing the system's input and output responses when driven by significant time-varying signals [1]. The most powerful model among behavioral models is Volterra series model. However, the number of coefficients in Volterra formalism is huge, and the set of static parameters has to be extracted for each input configuration (input power, frequency range and step, etc.).

To address these above issues and inspired by the development of artificial intelligence (AI) in communication domain, numerous NN-based models have been investigated. Among the AI approaches, deep learning or particularly, convolutional neural network (CNN) and recurrent neural network (RNN) have proven their capability in wireless communication. Nonetheless, there have been limited studies, which applied deep learning to obtain behavioral modeling and linearization for nonlinear PAs. The reasons are: i) the output layer of CNN classifier gives a decision rather than constructing signal, and ii) the current RNNs are specifically designed for natural language processing, which seems to violate the causality law if used for modeling PAs.

This work aims to explain how a NN can execute the similar

function as a behavioral model for PAs, and to compare the performances of multilayer perceptron (MLP) NN, time delay NN (TDNN), and LSTM NN in PA modeling.

II. THEORETICAL DEVELOPMENT

A. Shallow NN for PA Modeling

In MATLAB, common shallow NN consists of an input layer, a hidden layer structure, and an output layer. The model inputs are the I/Q components and also comprises the time delay blocks into the spatial structure of input layer to implement memory effects, as the real-valued time-delay (RVT) architecture NN model in [2]. TDNN is selected for studying in this work.

B. Deep NN for PA Modeling

Instead of using single hidden layer, deep NN is constructed over two hidden layers to simulate the PA's behaviors. Different from the shallow NN, deep NN can build more complex structures by varying the number of layers with relatively low complexity. However, when the PA shows complicated characteristics, the number of used parameters to simulate PA's behavior raises. It is obvious that deep NN has to utilize more weights for PA modeling execution. Thus the complexity of deep NN grows correspondingly. In this work, only MLP and LSTM NNs are studied to compare with conventional methods and shallow NN in modeling an PA.

C. Justification of the NN

In this demonstration, let's consider a baseband memory polynomial (MP) [3] model described by the following expression:

$$\begin{aligned} y_{MP} &= \sum_{l=0}^M \sum_{k=1}^N a_{lk} x(n-l) |x(n-l)|^{k-1} \\ &= \sum_{l=0}^M \sum_{k=1}^N a_{lk} I(n-l) (I^2(n-l) + Q^2(n-l))^{(k-1)/2} \\ &\quad + j \sum_{l=0}^M \sum_{k=1}^N a_{lk} Q(n-l) (I^2(n-l) + Q^2(n-l))^{(k-1)/2} \end{aligned} \quad (1)$$

where $x(n) = I(n) + jQ(n)$, $|x(n)| = (I^2(n) + Q^2(n))^{1/2}$.

To simplify demonstration, an investigation is taken on the NN architecture shown in Fig. 1. The output of each neuron in the hidden layer in Fig. 1 is equal to the bias plus the sum of the product of the input signals and corresponding weights,

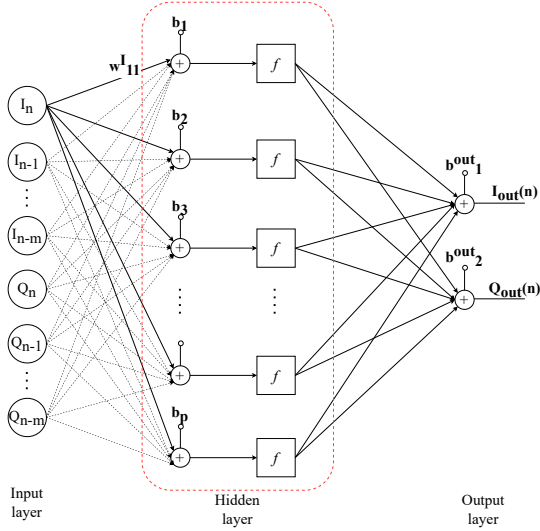


Fig. 1: Diagram of feed forward shallow neural network

then the output at any layer in NN is determined by applying activation function. For example, if the activation function is hyperbolic tangent sigmoid (*tansig*), the signal at the output layer of NN is expressed as:

$$y_{NN} = \sum_{m=0}^M \sum_{h=0}^{2H} w_{im}^I d_h I(n-m) X^{2h} + j \sum_{m=0}^M \sum_{h=0}^{2H} w_{im}^Q d_h Q(n-m) X^{2h} + c \quad (2)$$

while $X = (\sum_{m=0}^M w_{ij}^I I(n-m))^2 + (\sum_{m=0}^M w_{ij}^Q Q(n-m))^2$, i denotes the i th neuron of hidden layer, m denotes the *memory*th sample, and c stands for the mixed power terms.

Comparing (1) with (2), the proposed neural network is able to generate a richer and more complex basis function set rather than the memory polynomial model. Furthermore, with a similar approach, LSTM is also proven that it could be used to model the power amplifier behaviors.

III. SIMULATION RESULTS

A virtual wideband PA model designed in [4] is taken as a reference. That PA model is a memory polynomial model with the nonlinear order 5 and memory depth 2. The input signal for PA is generated by using MATLAB toolbox, the output signal is taken from the reference PA. The NNs will not represent the nonlinear behavior of PAs unless they are trained by simulated data. The dataset is divided into subsets: training, validation, and test set. The accuracy of models is evaluated in terms of normalized mean square error (NMSE). The other criterion also considered is the number of coefficients to indicate the complexity of each approach.

As shown in Fig. 2 and Table I, the best NMSE value among these methods is TDNN model with -50.4 dB, and the corresponding number of coefficients is 92. Meanwhile, MLP and LSTM NN have lower performances. It can be explained

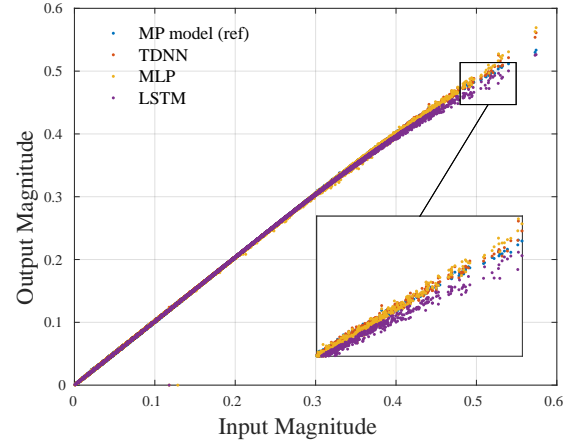


Fig. 2: AM-AM comparison of modeling between the reference PA and NN models

TABLE I: Modeling performance and complexity of methods

Method	NMSE (dB)	Num. of coefficients
TDNN	-50.4	92
MLP	-43.3	647
LSTM	-40.5	1250

that: the data fed to MLP NN and TDNN is in a matrix that has input vector of three pairs I and Q , however these values in MLP NN are independent while in TDNN, the input signal has a causality relation based on time delay blocks in its architecture. With LSTM NN, one pair of I and Q is used without preprocessing. Due to its architecture, LSTM still gives the appropriate approximation for PA characterization.

IV. CONCLUSION

In this paper, a comparison of PA behavioral NN-based models was carried out. Although LSTM NN can perform satisfactorily in PA modeling, the number of total coefficients remains large compared with other NNs or conventional behavioral models. Improving modeling performance and reducing the complexity of LSTM NN architecture are essential tasks to inspect in future research.

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