Neural Networks and next generation wireless amplifiers

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Abstract. The aim of this paper is to highlight the relevance of the neural network paradigm application for the modeling of next generation wireless amplifiers, which behave mostly nonlinearly due to the new highly-efficient modulation techniques. A model that has the capability to learn and predict the dynamic behavior of nonlinear amplifiers based on a Time-Delayed Neural Network (TDNN), is proposed. The model can be trained with input/output device measurements or simulations, and a very good accuracy can be obtained in the device characterization easily and rapidly. These properties make this kind of models specially suitable for new wireless communications amplifiers that require speed, good model accuracy and simplicity in model building, to reduce the time-to-market in the development process. The TDNN model has been validated with Power Amplifier (PA) time-domain simulations.

Keywords. Neural networks, amplifier model, wireless communications

1 Introduction

The development of RF components for new generation wireless communications devices, i.e. third generation (3G) mobile phones, needs new accurate and speed modeling of its components [1]. The new highly-efficient modulation techniques designed for the new communication standards have triggered new challenging issues in the modeling and design of their components, because existing techniques have become not suitable anymore for modeling the new amplifiers behavior [2], related to the memory phenomena. In the time-domain, memory effects cause the output of the amplifier to deviate from the desired linear output characteristic when the signal changes, resulting in a deterioration of the whole system performance. Moreover, in wireless communications, the transmitter amplifier can even introduce nonlinearities in the signal when operating near its maximum output power [3].

A technique that is receiving increasing attention for the development of electronic devices models is the Neural Network (NN) approach [4] since model tailoring to the element under study only needs a training procedure based on simulated or measured input-output time or frequency domain datasets. The model is considered as a black-box in the sense that no knowledge of the internal structure is required and the modeling information is completely included in the device external response. Due to this feature, the model parameters can be effectively estimated from measured response or simulated results, in an effective and timely manner.

The aim of this paper is to highlight the relevance of the NN paradigm application for the modeling of next generation wireless amplifiers. This paper presents a new neural network-based model that can be used for nonlinear RF/Microwave elements modeling, using a NN which takes into account device nonlinearity and memory effects. The proposed approach is tested with an amplifier simulation data.

The organization of the paper is the following: in the next Section, the neural network-based device modeling approach is briefly presented; in Section 3 we present the proposed NN model; in Section 4 the training and validation results are shown. Finally, the conclusions and future work are reported in Section 5 and 6, respectively.

2 Neural network-based device modeling

At present, the usefulness of simulators is limited in many practical cases by the characteristics of the component models that are used. If a model becomes too complex, simulation speed as well as accuracy decrease significantly. It is also possible that it is very hard to construct an accurate model because of device physics, as is often the case with relatively new power transistor technologies. A possible solution is to build generic black-box models describing the electrical behavior of a generic component, expressing measured behavior of an object with equations that are function of the independent variables that control the object's behavior [5]. The model parameters can be calculated based upon measured data or on simulated data.

These kind of models have become the object of extensive research during the last few years [6]. In particular for the modeling of amplifiers with memory effects [7], two main approaches have been proposed lately: polynomial models [8] and NN-based models. However, the polynomial method has the disadvantage of possible convergence problems when extrapolating the data and the polynomial order constraints the model applicability.

Recently NNs have been preferred over other methods because of their speed in implementation and accuracy, and they have been successfully applied to several RF and Microwave applications [9]. By profiting from their potential to learn the circuit behavior based on simulated or measured records of its input and output signals, they were used in nonlinear modeling and design of many microwave circuits and systems.

Neural network-based models can nowadays be seen as a potential alternative to model amplifiers having medium-to-strong memory effects along with high-order nonlinearity. Modern high-capacity links involve large signal bandwidths, and therefore amplifier models should also take into account the amplifier distortion due to both the amplitude and the bandwidth of the input signal [10]. However, many of the actual proposals involve complicated network topologies and special training algorithms that make execution time very long. Furthermore, most of these models demand an expert user for the creation and manipulation of the model.

For example, for the modeling of the nonlinear behavior of microwave components in the frequency-domain, the work in [11] proposes the use of describing functions for the device behavior, which are fitted to the measurements using NNs. For training this model, special frequency-domain nonlinear measurements of the device behavior are needed, obtained using a special equipment named Nonlinear Network Measurement System (NNMS), which is not always available in any laboratory. It also proposes the use of many small neural networks, trained simultaneously, which introduces the problems of how to divide the variables intro different models, how to coordinate the learning and how to mix the results at the output, all of them affecting model speed.

In [12] a power amplifier is modeled, in the time-domain, but including also the temperature (self-heating) as a controlling variable, therefore influencing the neural model with the internal physics of the device considered. This way, it is not a general model, it strongly depends on the device physics and technology, therefore limiting its use. For example, for some devices the temperature influence may be not so important to take into account and in that case the model becomes useless.

A different approach is presented in [13] where the idea is to model a communication system, handling complex (real and imaginary part) input/output signals. The model proposed needs a network topology that represents both parts of the signal, needing special signals measurements. This model is application-dependent, also influenced by the type of device modeled. It is a model particularly suited for representing communication systems elements. But if the idea is to model a generic amplifier, and the only available measurements are input and output device power, it could not be used.

Differently from all the above mentioned approaches, we would like to have, instead, a model that could be trained with simple and standard time-domain measurements easily generated in a lab, and formed by one single network which learns in a standard way and has no special feature to make slow its speed of convergence, if it has enough data to generalize. The model should not consider explicitly a particular physical or technological feature of the device (i.e. the temperature influence on the output behavior; the material used to build it) but implicitly, inside the input/output measurements that are used for training the model. The idea is to have a kind of "plug-and-play" model, which could be used to model any kind of device or circuit. In this paper we propose a model that accounts for all these desired characteristics. Our proposal in explained in detail in the next Section.

3 Time-delayed neural network model

Many topologies of NNs are reported in the literature for the modeling of different types of circuits and systems, with different kinds of linear and nonlinear behavior [14]. However, not any NN type and topology can be used for the representation of a system which has a nonlinear behavior and is dynamic, intending by dynamic not only that the device characteristic varies over time but also that it depends on past values of its controlling input variables. For the representation of this kind of systems, Time-Delayed NNs (TDNN) should be used, because the continuous time system derivatives can be approximated by time-delays of the input/output variables in the discrete time [15]. Due to this reason a TDNN model has been chosen for the model, having nonlinear activation functions in the hidden layer.

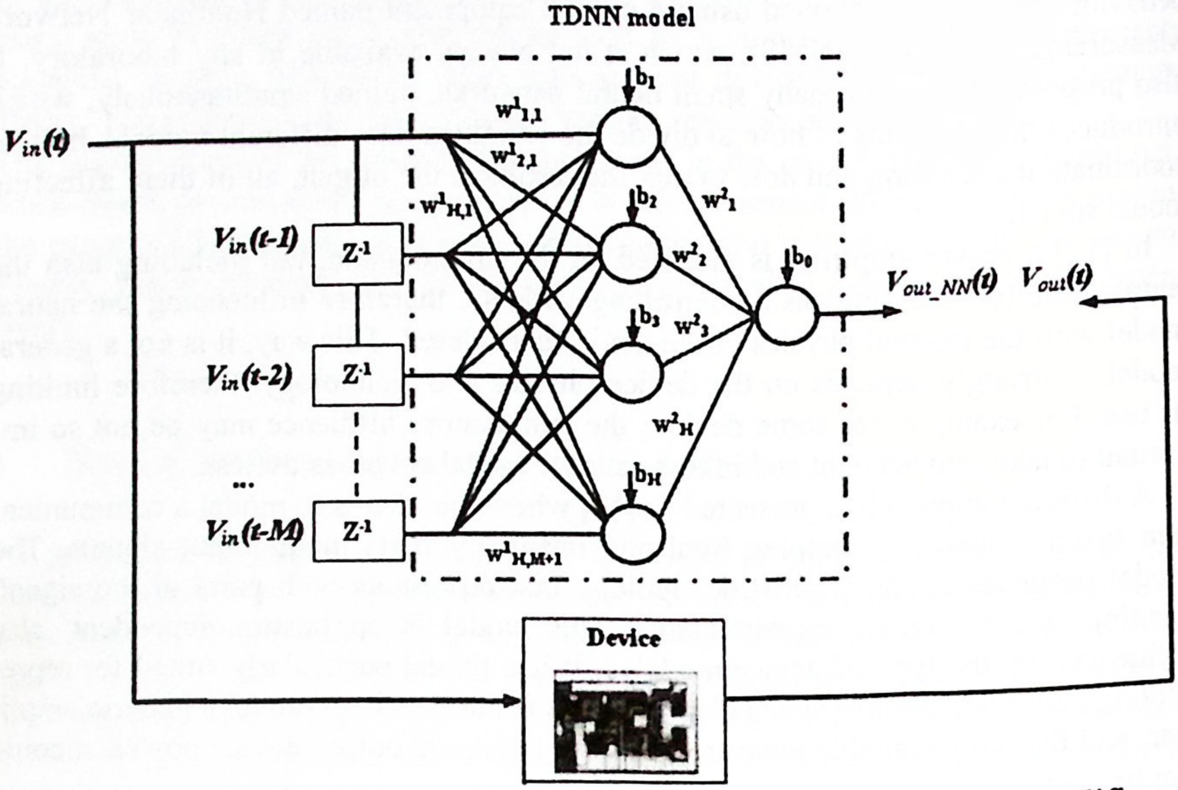

Fig. 1. Time-delayed Neural Network (TDNN) model for a power amplifier.

The model has the classical topology for universal approximation, three layers: the input variable and its delayed samples (in the case of a power amplifier, the input is only one variable, input power), the nonlinear hidden layer and a linear combination of the hidden neurons outputs at the output neuron (for a power amplifier, output power). All neurons have bias values, which allows to have more degrees of freedom for the learning algorithm and therefore more parameters that can be optimized to better represent the system. To improve network accuracy and speed up learning, the inputs are normalized to the domain of the hidden neurons nonlinear activation functions. M is memory depth or the number of delayed input samples; it represents the accuracy in the characterization bandwidth shaping. H is the number of hidden neurons chosen to perform the best fitting of the training waveforms. The architecture of the TDNN is shown in figure 1, while equation 1 presents its corresponding input-output analytical expression.

$$V_{out\_NN}(t) = b_0 + \sum_{h=1}^{H} w_h^2 f\left(b_h + \sum_{k=0}^{M} w_{h,k+1}^1 V_{in}(t-k) \right) \quad (1)$$

To build a model of a power amplifier, the TDNN model is trained with device input/output time-domain measurements. The input and output power waveforms are expressed in terms of their discrete samples in the time-domain. The tap delay Z^{-1} between successive samples must be a multiple or equal to the data sampling time T_s, and it is calculated as $MT_s = M/F_s$, being F_s the data sampling frequency. The network parameters are optimized using a second-order backpropagation algorithm. The Levenberg-Marquardt algorithm [15] has been chosen due to its good performance and speed in execution. To evaluate the TDNN learning accuracy, the mean square error (mse) is calculated, using equation 2, being T the number of input/output pairs in the training set.

$$mse = \frac{1}{T}\sum_{k=1}^{T} e(k)^2 = \frac{1}{T}\sum_{k=1}^{T}\left(V_{out}(k) - V_{out\_NN}(k)\right)^2 \qquad (2)$$

The good generality property of a neural network says that it must perform well on a new dataset distinct from the one used for training. A very small value of the mean square error on training does not necessarily imply that a good model has been obtained and that it can generalize good to new inputs. Even excessive training (number of epochs or iterations) on the learning phase could make performance to decrease, causing the over-fitting phenomenon. That is why, to avoid it, we divide the total amount of data available from measurement/simulation into training and validation subsets, all equally spaced. We have used the "early-stopping" technique [17], where if there is a succession of training epoch in which performance improves only for the training data and not for the validation data, over-fitting has occurred and the learning is terminated. The model training and validation results are shown in the next Section.

4 Training and validation results

The learning procedure is performed fitting the input/output voltages waveforms of the device to the TDNN model. In this study, the training procedure is performed based on simulations of a dynamic time-domain characterization of a power amplifier, using an amplitude single-sideband modulated signal. The input and output waveform appear in figure 2.

The initialization of the network is an important issue for training the TDNN with the back-propagation algorithm, that is why the initial weights and biases of the network are calculated using the Nguyen-Widrow initial conditions [18], instead of a purely random initialization.

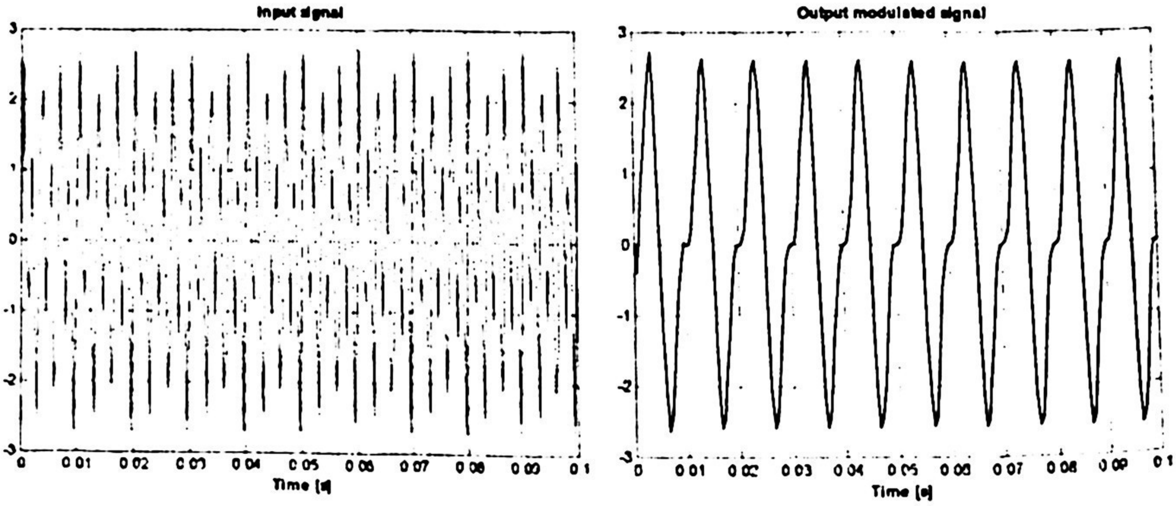

Fig. 2. Amplifier input (left) and output (right) signal.

In this study, we have made a comparison among several possible models to try to find the best topology for the neural model, regarding the amount of memory for the model (number of delayed inputs), the number of hidden neurons and its activation function. The aim of this comparison is to highlight the relevance of the inclusion of memory in this kind of models compared with a static (or not memory at all) model. That is why we compare the static model (no memory, only 1 input) against models having an arbitrarily number of delays: on the one hand, 1 delayed input (that is to say, 2 inputs to the network) and on the other hand, 3 delayed inputs (4 inputs to the model).

Then, we have chosen two possible nonlinear activation functions for the hidden layer, the hyperbolic tangent (traditionally used in the electronics field for modeling the behavior of nonlinear devices) and the sigmoid function. We have chosen them because they allow representing a dynamic system of almost any order, without knowing the system order beforehand. The only difference among them is their input interval. In fact the results confirm the fact that both of them can be used for the model, without substantial difference in the results.

Finally, to help in the election of the number of hidden neurons, models having 3, 5 and 10 hidden units are compared. The number of hidden neurons is important, because when the model is implemented inside a circuit simulator, a large number of hidden units could make simulation time significantly longer and complicate model implementation.

The results of the comparisons are presented in Table 1. These numbers are the results of executing twice each model, choosing for the comparison the higher approximation mean square error (mse). Looking at the results, the error in every column diminish as more hidden units are added, and along each row, it further decreases as more delayed input samples are included in the model.

As can be seen, the results from both types of activation functions are very close. Concerning the number of hidden neurons, the minimum mse for this problem (marked with *) can be reached with a neural network having 5 hidden units and 3 delayed input samples (a total of 4 inputs). Therefore we have identified the preferred topology for TDNN model of the power amplifier under study (marked in bold) as a model having sigmoid or hyperbolic tangent activation function (in the simulations, the sigmoid has been used), 5 hidden units and 4 inputs. The results that are shown from now on refer to this topology.

Activation function	H	No memory	1 delayed sample	3 delayed samples
Hyperbolic tangent	3	1.4094	1.2141	1.1935
	5	0.3970	0.7030	0.0003*
	10	0.0052	0.0003*	0.0003*
Sigmoid	3	1.4196	1.3461	0.8229
	5	0.3968	0.7106	0.0003*
	10	0.0053	0.0003 *	0.0003*

Table 1. Comparisons among the mean square errors (mse) obtained after training possible TDNN model topologies (* = 0.000324749).

The number of points T in each training and validation dataset is 2001 (the total data interval is 1 second). For the training set, data at a different close frequency than the training data has been used. The results of the learning phase of the best model are shown in Fig. 3. The mean square error (mse) of the model reached after 39 epochs was 0.000324749 for the training set, and 0.0819 for the validation set, as shows Fig. 4.

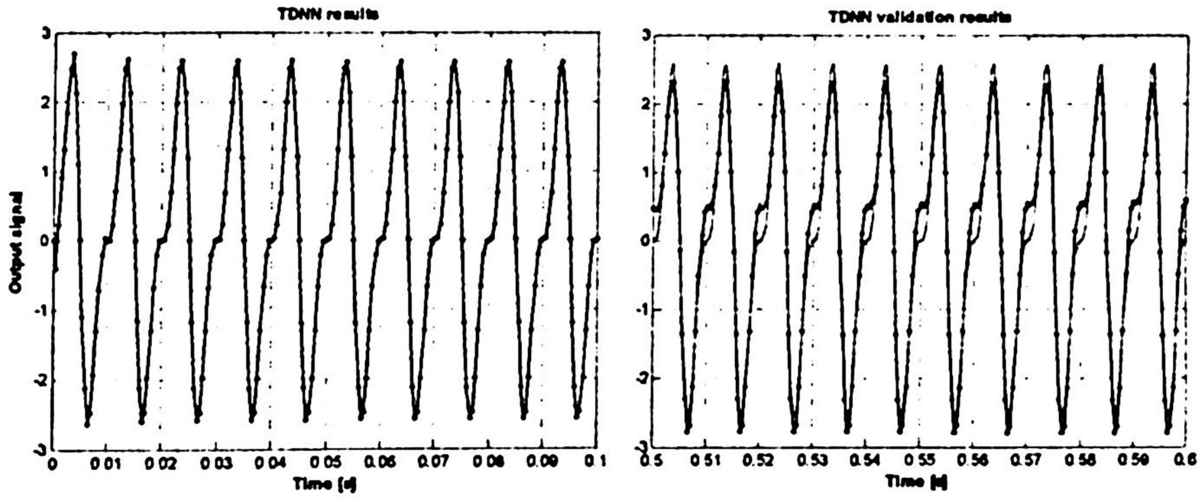

Fig. 3. Results of the TDNN model. Training data (left) and validation data (right)

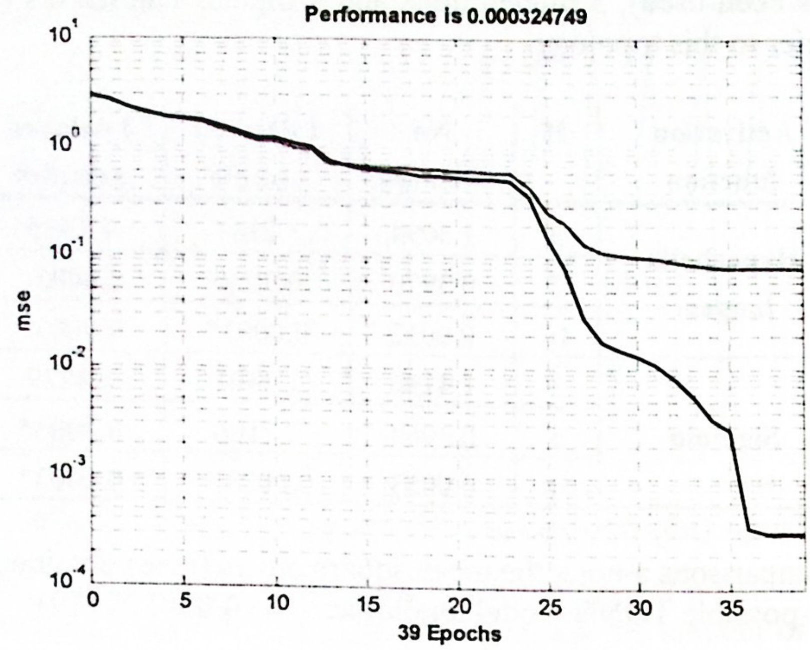

Fig. 4. MSE of the training dataset during the learning phase.

5 Conclusions

In this paper, a new model that has the capability to learn and predict the dynamic behavior of nonlinear power amplifiers, based on a Time-Delayed Neural Network (TDNN), has been proposed. The model is very general because it is not restricted by device technology nor application constraints.

A comparison study among different model topologies has shown the relevance of using delayed input samples to the model to improve accuracy in the model representation and reduce the mean square error.

Validation and accuracy of the TDNN model in the time-domain showed good agreements between the model output data and simulations. The TDNN model can be trained with input/output device measurements or simulations, and a very good accuracy can be obtained in the device characterization easily and rapidly.

These properties make this kind of models specially suitable for new wireless communications devices modeling, which are mostly nonlinear, and require speed, accuracy and simplicity when designing and building the model.

6 Future Work

We are actually developing a free software tool that allows building a TDNN model for a generic device, training it with device measurements or simulations, and after the learning phase is finished, it will generate a black-box model which could be loaded and used inside any commercial electronic circuit simulator for RF/Microwave applications.

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