Neural Networks for Modeling Nonlinear Memoryless Communication Channels

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***Abstract*— This paper presents a neural network approach for modeling nonlinear memoryless communication channels. In particular, the paper studies the approximation of the nonlinear characteristics of traveling-wave tube (TWT) amplifiers used in satellite communications. The modeling is based upon multilayer neural networks, trained by the odd and even backpropagation (BP) algorithms. Simulation results demonstrate that neural network models fit the experimental data better than classical analytical TWT models.**

***Index Terms*—Neural networks, satellite communications, TWT amplifiers.**

I. Introduction

SEVERAL nonlinear channels (e.g., satellite communication channels) [1] are equipped with memoryless nonlinear devices such as traveling-wave tube (TWT) amplifiers. These devices exhibit two kinds of nonlinearities, amplitude distortion (AM/AM conversion) and phase distortion (AM/PM conversion). Two equivalent frequency-independent representations have been proposed for these nonlinearities [1], [12]. These representations are amplitude-phase (A-P) and in-phase and quadrature (I-Q). Several analytical models such as Bessel and rational functions have been proposed for these nonlinear distortions.

This paper adaptively models these nonlinear functions using the odd and even backpropagation (BP) algorithms [9]. These supervised learning procedures use the measured TWT input and output signals for iteratively adjusting the neural network weights.

The simulation results indicate that the neural net approach performs better than classical approximation techniques. Furthermore, a change in the TWT characteristic can be tracked by the neural net since the net is adaptive. This yields a new model which has adapted to this change. The neural net can approximate all types of TWT's with the same basic structure (only the weights change). The neural architecture has few parameters (e.g., only 15 scalar parameters are needed to model the AM/AM conversion of an Intelsat TWT amplifier). Moreover, this architecture can be implemented rapidly in parallel for both the learning and generalization phases. This paper focuses on the experimental application of neural networks to the TWT approximation problem. The theoretical neural network learning behavior for the TWT modeling problem is studied in [3]. Reference [3] investigates the explicit influence of the neural network parameters on the learning and convergence behavior of the BP algorithm.

The paper is organized as follows. Section II reviews classical analytical models for approximating TWT characteristics. Section III presents several simulation examples and a comparison of the neural net approach to classical methods.

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II. Analytical Models of TWT Amplifiers

Let the input wave $x(t)$ be expressed as $x(t) = r(t)\cos(\omega_0 t + \theta(t))$, where ω_0 is the carrier frequency, and $r(t)$ and $\theta(t)$ are the modulated envelope and phase, respectively.

In the A-P representation, the TWT output is given by

$$y(t) = A(r(t))\cos(\omega_0 t + \theta(t) + \phi(r(t))) \tag{1}$$

where $A(r)$ and $\phi(r)$ are the amplitude and phase nonlinear distortions, respectively. These functions are approximated by analytical expressions for several purposes (e.g., performance analysis of the communication channel, simulations, etc.). Table I presents some of these classical A-P models.

In the I-Q representation, the TWT output is given by its in-phase and quadrature components:

$$p(t) = P(r(t))\cos(\omega_0 t + \theta(t)) \tag{2}$$

$$q(t) = -Q(r(t))\sin(\omega_0 t + \theta(t)). \tag{3}$$

$P(r)$ and $Q(r)$ are the in-phase and quadrature nonlinearities, respectively.

Table II presents some proposed analytical models for approximating these nonlinearities.

The analytical models are parameterized with relatively few parameters. The parameter evaluation requires an optimization process to fit the experimental data. For more details about the choice and the range of these parameters, see the references in Tables I and II.

These models have some limitations. In particular, they are only suited for TWT characteristics with specific asymptotic behaviors: Saleh's A-P model requires that, for large input amplitude r, $A(r)$ is proportional to $(1/r)$ and $\phi(r)$ approaches a constant. In Berman–Mahle's phase formula, $\phi(r)$ approaches $k_3 r^2$ for large r. Saleh's I-Q formulas are proportional to $(1/r)$ for large r, while those of Hetrakul–Taylor approach constants. Thus, TWT's without these specific asymptotic behaviors cannot be well approximated by those models. Furthermore, classical models are not adaptive. A change in the TWT characteristic cannot be tracked by these models unless a new optimization is performed.

TABLE I
ANALYTIC MODELS FOR THE A-P REPRESENTATION

Model	AM/AM	AM/PM
Saleh [12]	$A_1(r) = \frac{\alpha_a r}{1+\beta_a r^2}$	$\phi_1(r) = \frac{\alpha_p r^2}{1+\beta_p r^2}$
Berman-Mahle [2]	-	$\phi_2(r) = k_1(1-\exp(-k_2 r^2)) + k_3 r^2$
Thomas et al. [14]	$A_2(r) = 10^{\alpha\left(\cos\left(\log\left(\frac{r}{r_s}\right)/\beta\right)-1\right)}$ for $r > r_s$ $= r$ for $r < r_s$	-

TABLE II
ANALYTIC MODELS FOR THE I-Q REPRESENTATION ($J_n(\cdot)$ IS THE MODIFIED BESSEL FUNCTION OF THE FIRST KIND OF ORDER n)

Model	In-phase	Quadrature
Saleh [12]	$P_1(r) = \frac{\alpha_p r}{1+\beta_p r^2}$	$Q_1(r) = \frac{\alpha_q r^3}{(1+\beta_q r^2)^2}$
Hetrakul-Taylor [5]	$P_2(r) = C_1 r \exp(-C_2 r^2)\, J_0(C_2 r^2)$	$Q_2(r) = S_1 r \exp(-S_2 r^2)\, J_1(S_2 r^2)$

III. NEURAL NETWORK APPROACH

A. Learning Process

This paper uses the odd and even BP algorithms [7], [9] to model the TWT nonlinearities. These algorithms exactly generate odd and even functions, respectively. Let $g(x)$ denote the nonlinear function to be approximated. The learning process presents to the neural network a pair $(x_i,\, g(x_i))$ of the TWT input–output measured data. The BP algorithm adjusts the neural weights so as to reduce the error between the network output and the desired output. This procedure is repeated until the error reaches a minimum and the weights no longer change significantly (i.e., the algorithm converges). A two-layer structure is used in the simulations below. The structure is composed of a scalar input, N odd (or even) neurons in the first layer, with a sigmoidal activation function, and a scalar output, with the identity function as the activation function: 1–N–1 network. The two-layer structure was motivated by the universal approximation property [6]. The number of neurons N is chosen sufficiently large for a good approximation. However, N should not be very large so as to not increase the computational complexity. The single-neuron case with the error surface and the optimal solution is studied analytically in detail in [3].

B. Simulation Results

I-Q Representation: This section models the I-Q representation of a Hughes 261-H Intelsat IV TWT amplifier. A 1–5–1 odd network is used for each nonlinearity with the hyperbolic tangent as the activation function. Thus, each neural net achieves (by construction) an odd function which is bounded and indefinitely differentiable.

Thirteen points were used for the measured training data for each of the in-phase and quadrature conversions, respectively [5]. Figs. 1(a) and 2(a) plot these data points (whose x coordinates are positive) and their symmetries with respect to the origin. Note that, since odd neural nets give by construction odd functions, the networks need not be trained using data points with negative x coordinates.

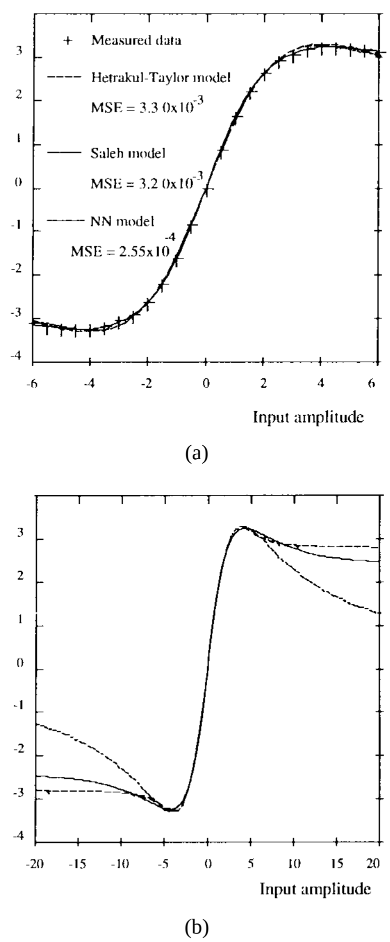


Fig. 1. In-phase conversion models. (a) In-phase amplitude. (b) In-phase amplitude.

Fig. 1(a) shows the simulation results for the in-phase nonlinearity. At each step of the odd BP algorithm, one of the 13 pairs of data points is selected randomly and presented to the network. The approximation performance of the (1–5–1) network is better than that of Saleh's model and the Hetrakul–Taylor model (see Table III). Fig. 1(b) shows the approximation function behavior for high-input amplitude

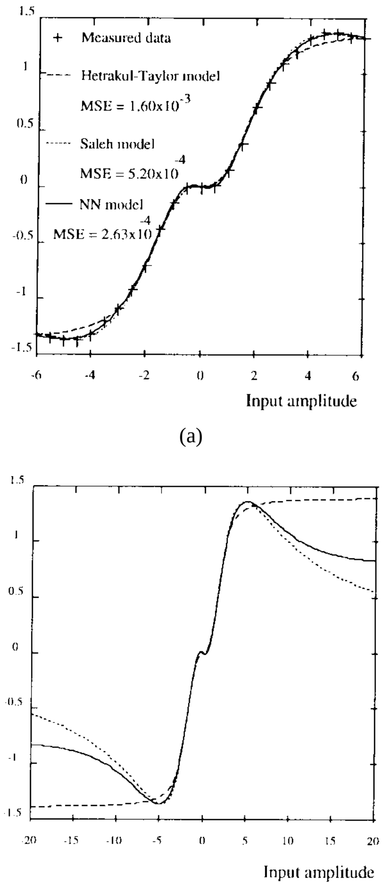


Fig. 2. Quadrature conversion models. (a) Quadrature amplitude. (b) Quadrature amplitude.

TABLE III
MSE PERFORMANCE OF THE DIFFERENT MODELS

Model	In-phase	Quadrature	AM/AM	AM/PM
NN	2.55×10^{-4}	2.63×10^{-4}	9×10^{-5}	3.4×10^{-5}
Saleh	3.20×10^{-3}	5.20×10^{-4}	1.40×10^{-4}	1.38×10^{-4}
Hetrakul-Taylor	3.30×10^{-3}	1.60×10^{-3}	-	-
Thomas et al.	-	-	2.00×10^{-4}	-
Berman-Mahle	-	-	-	8.00×10^{-4}

values (outside the learning data basis). The neural net approximation function is odd, bounded, and approaches a positive constant as x increases. The neural net outperforms classical models for the quadrature nonlinearity as well (Fig. 2).

A-P Representation: This section models the A-P representation of an Intelsat IV TWT amplifier [2]. For the AM/AM and AM/PM conversions, a 1–5–1 odd network and a 1–5–1 even network were used, respectively (Fig. 3). The training data were composed of 13 points, respectively. Again, neural networks outperform classical models (see Table III).

Fig. 4 represents the learning curves of neural network models.

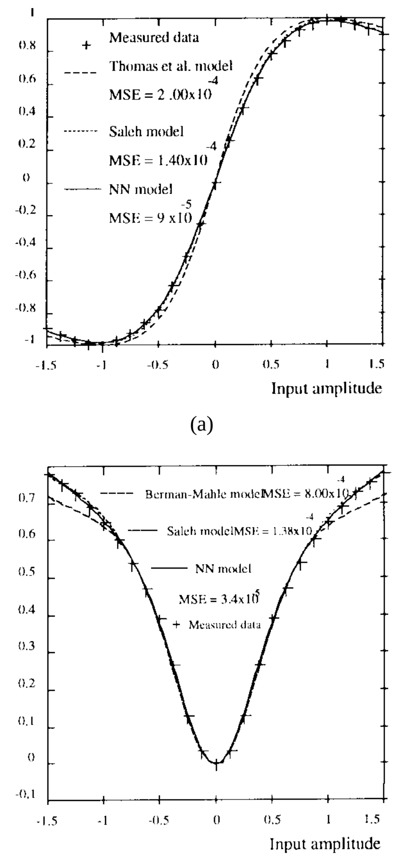


Fig. 3. AM/AM and AM/PM conversion models. (a) Output amplitude. (b) Output phase.

C. Comments on Neural Network Models

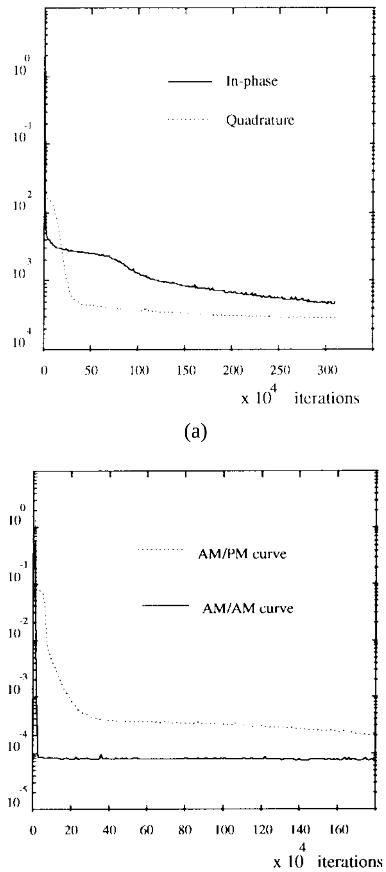
The simulation results show that neural network models yield a good fit to TWT measured data. The neural net approximation MSE was always smaller than that of classical models (see Table III).

The neural net approximation functions have several mathematical properties which are important for satellite channel simulations: the functions are bounded and indefinitely differentiable. They approach an asymptote for high-input values and do not oscillate. They can be strictly odd or even, and are able to approximate complicated nonlinearities.

The computational complexity of these neural net architectures (order of 15 scalar parameters) is comparable to some classical models (such as the Shimbo–Pontano model [13]), and is greater than others (e.g., the Saleh model [12]). The neural net can be implemented in parallel, resulting in a large reduction of the computation time (for both learning and generalization).

The neural net approach offers the same basic architecture (e.g., a 1–5–1 network), to approximate a wide variety of TWT's (only the weight values change from one model to another). This property is very important for laboratory simulations or for the future analytical study of the effects of memoryless nonlinear channels on data transmission.

Our adaptive method allows the tracking of changes in the TWT characteristic. These changes may be caused by internal or external factors (e.g., temperature, gravitation, etc.). The



(a)

(b)

Fig. 4. Learning curves. (a) MSE. (b) MSE.

neural network approach can approximate the TWT characteristics even if it is embedded in a digital channel with memory (i.e., no direct access to the TWT input–output signals) [7]. The technique has been used for channel characterization and fault detection in digital satellite communications [8].

IV. Conclusion

This paper has presented a neural network approach for modeling nonlinear memoryless communication channels. Computer simulations of the neural networks yielded approximations to the TWT characteristics with a smaller MSE than classical techniques. The neural net approach provides the same simple basic structure for modeling a wide variety of memoryless nonlinearities (only the values of the weights change from one TWT model to another). The neural network computation complexity is comparable to some classical models. Finally, neural net models can be implemented in parallel, allowing faster computation for both learning and generalization.

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