# Neural Based Dynamic Modeling of Nonlinear Microwave Circuits

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***Abstract*** **— A neural network formulation for modeling nonlinear microwave circuits is achieved in the most desirable format, i.e., continuous time-domain dynamic system format. The proposed dynamic neural network (DNN) model can be developed directly from input-output data without having to rely on internal details of the circuit. An algorithm is developed to train the model with time or frequency domain information. A circuit representation of the model is proposed such that the model can be incorporated into circuit simulators for high-level design. Examples of dynamic-modeling of amplifiers, mixer and their use in system simulation are presented.**

## I. INTRODUCTION

Artificial Neural Networks (ANN) have recently been recognized as a useful tool in RF and microwave CAD [1][2]. This paper addresses the applications of ANN to nonlinear modeling and design, which could be an important area because of the increasing need for efficient CAD algorithms in high-level and large-scale nonlinear microwave design. Several methods have been studied recently, such as the behavioral based neural network [3] and discrete recurrent neural network methods [4]. These works demonstrated neural networks as a useful alternative to the conventional behavioral or equivalent circuit based approaches [5][6]. The ANN approach has the potential to learn the nonlinear behavior from measured or simulated input-output data, avoiding otherwise manual effort of developing equivalent circuit topology. The universal approximation property of ANN provides a theoretical basis of representing the full analog behavior of the circuit with good accuracy. The evaluation of the ANN from input to output is very fast [3][4]. However, because of the specific formats of the existing methods, the potential of neural networks is still not fully realized due to difficulties in their incorporations in circuit simulators or in establishing relations with large-signal measurement, or potential curse of dimensionality in multi-tone simulations.

The most ideal format to describe nonlinear dynamic models for circuit simulation is the continuous time-domain format, e.g., the popularly accepted dynamic current-charge format in many harmonic balance simulators. This format in theory best describes the fundamental essence of nonlinear behavior, and in practice is most flexible to fit most or nearly all needs of nonlinear microwave simulation, a task not yet achieved by the existing ANN techniques. In the neural network community, such type of networks has been studied, e.g., Hopefield network, recurrent network, etc. [7]. However they were mainly oriented for digital signal processing such as binary-based image processing, or system control with online correction signals from a physical system [7]. They are not directly suitable for microwave modeling. We must address continuous analog signals and our CAD method must be able to predict circuit behavior off-line.

For the first time, an exactly continuous time-domain dynamic modeling method is formulated using neural networks for large-signal modeling of nonlinear microwave circuits. The model, called dynamic neural network (DNN) model, can be developed directly from input-output data without having to rely on internal details of the circuit. An algorithm is described to train the model with time or frequency domain information. A circuit representation is proposed such that the model can be incorporated into circuit simulators for high-level design. Examples of dynamic-modeling of amplifiers, mixer and their use in system simulation are presented.

## II. DYNAMIC NEURAL NETWORK MODELING OF NONLINEAR CIRCUITS: FORMULATION AND DEVELOPMENT

### *A. Original Circuit Dynamics*

Let $\boldsymbol{u}$ and $\boldsymbol{y}$ be vectors of the input and the output signals of the nonlinear circuit respectively. The original circuit can be generally described in state equation form,

$$\begin{aligned}\dot{x}(t) &= \varphi(x(t), u(t)) \\ y(t) &= \psi(x(t), u(t))\end{aligned} \qquad (1)$$

where $x$ is a $N_S$-vector of state variables and $N_S$ is the number of states. For a circuit with many components, (1) could be a large set of nonlinear differential equations. For system level simulation including many circuits, such detailed state equations are too large, computationally



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expensive, or even unavailable at system level. Therefore, a simpler (reduced order) model approximating the same dynamic input-output relationships is needed.

### *B. Formulation of Dynamic Neural Network Model*

We propose a DNN formulation of a reduced order representation of the original circuit. Let $n$ be the order of the reduced model, $n < N_S$. Let $v_i$ be a $n_y$-vector, $i = 1,2,...,n$, and $n_y$ is the number of outputs of the model. Let $f_{ANN}$ represent a static multilayer perceptron neural network [1] with input neurons representing $y$, $u$, their derivatives $d^i y/dt^i$, $i=1, 2, ..., n-1$, and $d^k u/dt^k$, $k=1,2, ..., n-1$; and the output neuron representing $d^n y/dt^n$. The proposed DNN model is

$$\begin{aligned} \dot{v}_1(t) &= v_2(t) \\ &\vdots \\ \dot{v}_{n-1}(t) &= v_n(t) \\ \dot{v}_n(t) &= f_{ANN}(v_n(t), v_{n-1}(t), \cdots, v_1(t), u^{(n-1)}(t), \cdots, u(t)) \end{aligned} \quad (2)$$

where $u^{(k)}(t) = d^k u/dt^k$, and the input and output of the model is $u(t)$ and $y(t) = v_1(t)$, respectively.

The overall DNN model (2) is in a standardized format for typical nonlinear circuit simulators. For example, the left-hand-side of the equation provides the charge ($Q$) or the capacitor part, and the right-hand-side provides the current ($I$) part, which are the standard representation of nonlinear components in many harmonic balance simulators. The order $n$ (or the number of hidden neurons in $f_{ANN}$) represents the effective order (or the degree of nonlinearity) of the original circuit that is visible from the input-output data. Therefore the size of the DNN reflects the internal property of the circuit rather than external signals, and as such the model does not suffer from curse of dimensionality in multi-tone simulation.

### *C. Model Training*

Our DNN model will represent a nonlinear microwave circuit only after we train it with data from the original circuit. We use training data in the form of input/output harmonic spectrums (obtainable by simulation or measurement). Let $U(\omega)$, and $Y(\omega)$ be such input and output spectrums respectively, $\omega \in \Omega$, where $\Omega$ is the set of spectrum frequencies. The training data is generated using a variety of input samples, leading to a set of data $U_m(\omega)$, $Y_m(\omega)$, where $m$ is the sample index, $m=1, 2, ..., M$, and $M$ is the total number of samples.

*Initial Training:* We first train the static ANN part of the DNN model, i.e., $f_{ANN}$, in time-domain directly or indirectly using time-domain information. Suppose $A(\omega, t)$ represents the coefficients of Inverse Fourier Transform. The training data for $f_{ANN}$ can be derived from,

$$y_m^{(i)}(t) = \sum_{\omega \in \Omega} \frac{\partial^i A(\omega, t)}{\partial t^i} \cdot Y_m(\omega) \quad (3)$$

The initial training is illustrated in Fig. 1. This process is computationally efficient (without involving harmonic balance simulation) and can train the $f_{ANN}$ from a random (unknown) start to an approximate solution.

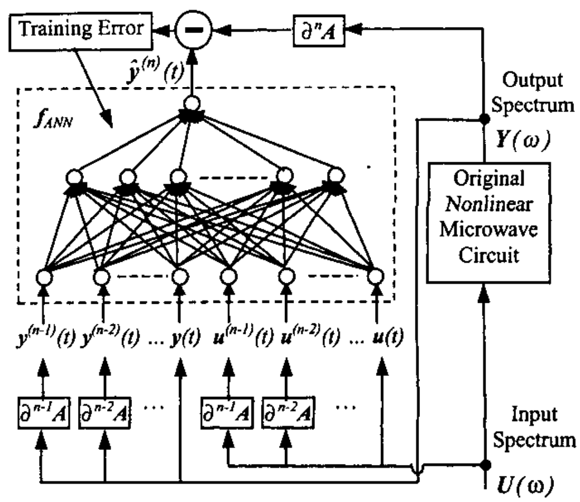


Fig. 1. *Initial training* to train the static multilayer perceptron part $f_{ANN}$ in time-domain using spectrum data, where $\partial^i A$ is the time derivative operator corresponding to (3).

*Final Training:* The DNN model is further refined using results from initial training as starting point. Final training is done in frequency-domain involving harmonic balance solutions of the DNN model. The error function for training is,

$$E = \frac{1}{2} \sum_{m=1}^{M} \sum_{\omega \in \Omega} \left\| \hat{Y}_m(\omega) - Y_m(\omega) \right\|^2 \quad (4)$$

where $\hat{Y}_m(\omega)$ and $Y_m(\omega)$ represent spectrum from model and $m^{th}$ sample of training data, respectively. In order to achieve the harmonic solutions $\hat{Y}_m(\omega)$ from the DNN model, we apply differentiation over the $f_{ANN}$ using the adjoint neural network method [8]. The resulting derivatives fit the Jacobian matrix of harmonic balance equations.

### *D. Use of Trained DNN Model in Existing Simulators*

An exact circuit representation of our DNN can be derived as shown in Fig. 2. In this way the trained model can be incorporated into available simulation tools for high-level circuit and system design.

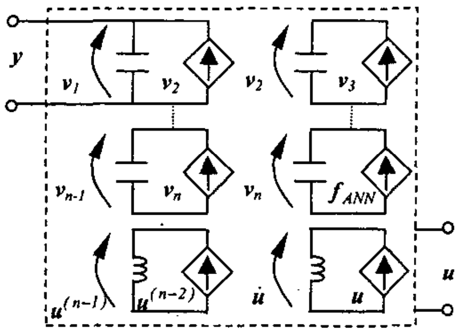


Fig. 2. Circuit representation of the DNN model.

## III. Dynamic-Modeling Examples

### *A. Amplifier Modeling*

This example shows the modeling of nonlinear effects of an amplifier using the DNN technique. The amplifier internally has a 3-stage class B topology with 9 NPN transistors modeled by Agilent-ADS nonlinear models Q34 and Q37, and HP AT 41411[9].

We train our DNN to learn the input-output dynamics of the amplifier. We choose a hybrid 2-port formulation with $u=[v_{in}, i_{out}]^T$ as input, and $y = [i_{in}, v_{out}]^T$ as output.

The training data for the amplifier is gathered by exciting the circuit with a set of frequencies (0.95 ~ 1.35GHz, step-size 0.05GHz), powers (-30 ~ -14 dBm, step-size 2 dBm), and load impedances (35 ~ 65 Ohms, step-size 10 Ohms). In initial training, Fourier transform sampling frequencies ranged from 47.5 to 67.5GHz. Final training is done with optimization over harmonic balance such that modeled harmonics match original harmonics. We trained the model in multiple ways using different number of hidden neurons and orders ($n$) of the model as shown in Table I. Testing is performed by comparing our model (implemented using Fig. 2) with original amplifier in ADS, with different set of signals never used in training, i.e., different test frequencies (0.975 ~ 1.325GHz, step-size 0.05 GHz), powers (-29 ~ -15 dBm, step-size 2 dBm) and loads (40, 50, 60 Ohms). The model is compared with original circuit in both time and frequency domains, and excellent agreement is achieved. Fig. 3 shows examples of spectrum comparisons.

Table I. Amplifier: DNN Accuracy From Different Training

| No. of Hidden Neurons In Training | Testing Error |
|---|---|
| 40 | 4.2E-3 |
| 50 | 2.9E-3 |
| 60 | 3.6E-3 |

| Order $n$ In Training | Testing Error |
|---|---|
| 2 | 5.3E-3 |
| 3 | 2.9E-3 |
| 4 | 1.5E-2 |

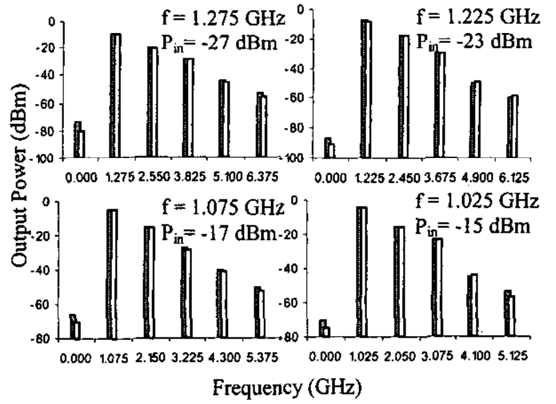


Fig. 3. Amplifier output: Spectrum comparison between DNN (▨) and original circuit (□) at load = 50 Ω. Excellent agreement is achieved even though such data were never used in training.

### *B. Mixer Modeling*

This example illustrates DNN modeling of a mixer. The circuit internally is a Gilbert cell with 14 NPN transistors in ADS [9]. The dynamic input and output of the model is $u=[v_{RF}, v_{LO}, i_{IF}]^T$ and $y = [i_{RF}, v_{IF}]^T$. For example, the static multilayer perceptron part of the $v_{IF}$ model is

$$v_{IF}^{(n)}(t) = f_{ANN}(v_{IF}^{(n-1)}(t), v_{IF}^{(n-2)}(t), \cdots, v_{IF}(t), v_{RF}^{(n-1)}(t), v_{RF}^{(n-2)}(t), \cdots, v_{RF}(t), v_{LO}^{(n-1)}(t), v_{LO}^{(n-2)}(t), \cdots, v_{LO}(t), i_{IF}^{(n-1)}(t), i_{IF}^{(n-2)}(t), \cdots, i_{IF}(t)) \quad (5)$$

The training data is gathered in such way: RF input frequency and power level changed from 11.7 to 12.1GHz with step-size 0.05GHz and from -45 dBm to -35 dBm with step-size 2dBm respectively. LO signal is fixed at 10.75 GHz and 10dBm. Load is perturbed by 10% at every harmonic in order to let the model learn load effects. The DNN is trained with different number of hidden neurons and orders ($n$) as shown in Table II. Testing is done in ADS using input frequencies (11.725 ~ 12.075GHz, step-size 0.05GHz) and power levels (-44, -42, -40, -38, -36 dBm). The agreement between model and ADS is achieved in time and frequency domains even though those test information was never seen in training. Fig. 4 illustrates examples of test in time-domain.

Table II. Mixer: DNN Accuracy From Different Training

| No. of Hidden Neurons In Training | Testing Error |
|---|---|
| 45 | 8.7E-4 |
| 55 | 4.6E-4 |
| 65 | 6.5E-4 |

| Order $n$ In Training | Testing Error |
|---|---|
| 2 | 2.7E-3 |
| 3 | 1.4E-3 |
| 4 | 4.6E-4 |

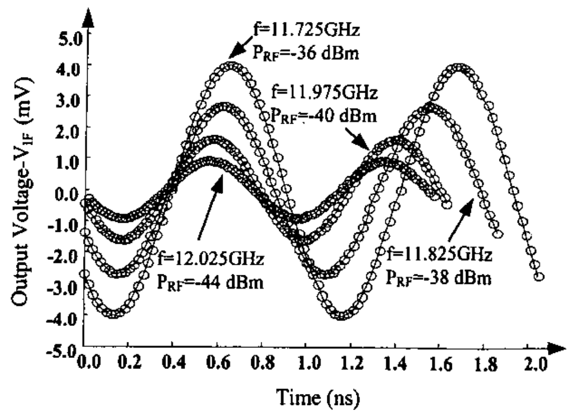


Fig. 4. Mixer $V_{IF}$ output: Time-domain comparison between DNN (o) and original circuit (–). Good agreement is achieved even though such data were never used in training.

*C. Nonlinear Simulation of DBS Receiver System*

To further confirm the validity of the proposed DNN, we also trained a DNN representing another amplifier (gain stage amplifier), and combined the three trained DNNs of mixer and amplifiers into a DBS receiver sub-system [10], where the amplifier trained in section *A* is used as output stage. The system solved by ADS harmonic balance simulation with original system in Fig. 5(a) is compared with that using DNN models of amplifiers and mixer in Fig. 5(b). The overall system solution using DNNs matches that of the original system as shown in Fig. 6.

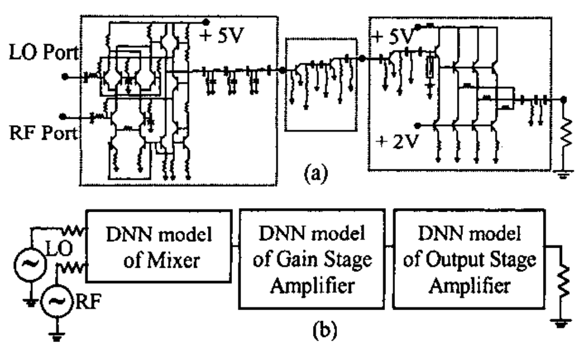


Fig. 5. DBS receiver sub-system: (a) connected by original detailed equivalent circuit in ADS, (b) connected by our DNNs

We also performed Monte-Carlo analysis of the system under random sets of RF input frequencies and power levels. The statistics from the DNN based system simulation matches that from the original system, and the CPU for 1000 analyses of the system using DNN versus using original circuits is 3.94 *vs.* 6.52 hours, showing efficiency of the DNN based system simulation. The proposed DNN retains the advantages of neural network learning, speed, and accuracy as in existing techniques; and provides further advantages of being theoretically elegant and practically suitable for diverse needs of nonlinear microwave simulation, e.g., standardized implementation in simulators, suitability for both time and frequency domain applications, and multi-tone simulations.

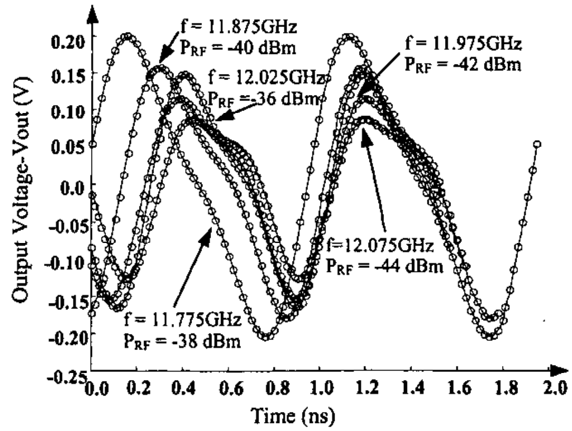


Fig. 6. DBS system output: Comparison between system solutions using DNN models (o) and ADS simulation of original system (–). Excellent agreement is achieved even though these nonlinear solutions were never used in training.

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