

Systematic behavioral modeling of nonlinear microwave/RF circuits in the time domain using techniques from nonlinear dynamical systems

David E. Root¹, John Wood¹, Nick Tuffillaro², Dominique Schreurs³, and Alexander Pekker¹

(1) Agilent Technologies, Microwave Technology Center, Santa Rosa, CA

(2) Agilent Laboratories, Palo Alto, CA

(3) K.U.Leurven, Div. ESAT-TELEMIC Leuven-Heverlee, Belgium

Abstract

A powerful and systematic approach to behavioral modeling of nonlinear microwave/RF circuits in the time domain is presented, integrating several techniques from nonlinear dynamical systems analysis. Algorithms based on information-theoretic principles help determine efficient trade-offs between model accuracy, speed, and complexity. Models are constructed from large-signal microwave measurements or simulations, and are integrated into a commercial nonlinear circuit simulator. A simulation speedup of more than an order of magnitude has been achieved.

Keywords

Behavioral modeling, time series analysis, black-box modeling, nonlinear circuit simulation, large-signal

Introduction

The difficulty of simulating, at the transistor level, complex nonlinear microwave and RF circuits under large-signal conditions, often presents a significant productivity bottleneck for design engineers. The computational complexity and computer memory demands of such problems result in very long simulation times, sometimes exceeding several days or more. These burdens become prohibitive when designing complex modules and microwave/RF sub-systems built upon many of these circuits; it is often impossible to simulate these systems in a nonlinear simulator at the transistor or fundamental component level.

One solution to these problems is provided by behavioral modeling, in which entire circuits, nonlinear functional blocks, or selected components of a subsystem, are replaced by much simplified, but sufficiently accurate models. This enables simulation at the higher level of abstraction while still representing, accurately, the effect of the nonlinear blocks in the overall system performance.

This paper focuses on a new, general, and systematic time-domain approach based on integrating several techniques developed in the study of nonlinear dynamical systems. This “black-box” approach integrates experiment design, elements

of nonlinear time series analysis including variable selection and embedding, and multi-variate functional approximation methods.

Generality is a big advantage of the present modeling approach. The procedures for excitation, analysis, model generation, and simulator implementation are generic; they work for amplifiers, mixers, and other components of arbitrary number of terminals. The models are not confined to use in steady-state conditions, as are most of the frequency domain formulations for microwave applications. Moreover, the procedure works for arbitrarily strong nonlinearities, unlike common microwave approaches based on Volterra analysis or similar variants.

The Models

The present models are formulated as nonlinear ordinary differential equations which are most easily implemented in commercial simulators. The variables are the embeddings of the outputs ($y(t)$ and derivatives) and the inputs ($u(t)$ and derivatives). The outputs are assumed to be measurable functions of the (unknown) state, $x(t)$, and the inputs. The nonlinear function, f , defines the differential equation implicitly. The actual procedure used in this work is to choose one of the outputs, say $y(t)$, or else its highest order derivative, and fit that to all the other terms in equation (1) considered as independent variables.

$$f(y(t), \dot{y}(t), \ddot{y}, \dots, u(t), \dot{u}(t), \dots) = 0 \quad (1)$$

$$\dot{x}(t) = g(x(t), u(t)) \quad (2)$$

$$y(t) = h(x(t), u(t)) \quad (3)$$

The resulting models work in all simulator domains, dc, ac-small-signal, harmonic balance, envelope, and full transient analysis. The technique has a firm theoretical basis in nonlinear dynamics. This helps understand the conditions under which the approach is valid and gives strong pointers towards future developments. It has resulted in fewer ad hoc assumptions (such as model order) compared with other recent time domain techniques (1).

Procedure

A flow-chart of the behavioral modeling procedure is given in Figure 1. A nonlinear component, say a broad-band amplifier, is selected to be represented by a behavioral model. A circuit model of the component at the transistor level, if it is available, can be used to generate the data needed for the behavioral model by using the nonlinear simulator as a virtual instrument. Alternatively, recent nonlinear measurement systems (2) can be used to provide the data needed for the modeling toolbox to create the behavioral model. Both virtual and measurement-based behavioral models have their advantages. Simulation-based behavioral models significantly reduce the design cycle by enabling module design before the constituent ICs are even manufactured. In fact this methodology is used in the Agilent Technologies Microwave Technology Center for its module designs based on GaAs ICs which are also designed and manufactured at this center (8). Such “virtual” or simulation-based behavioral models allow bottoms up design and comparison among different ICs competing for use in the same system block diagram. Alternatively, nonlinear waveform data is used to construct the model directly from carefully engineered large-signal excitations. Results have been reported at the device and circuit level in (2) and (3). The measurement-based approach allows accurate large-signal data to be used for design without the compounding effects of propagating errors from (perhaps several layers of) approximate modeling at lower hierarchical levels.

Next, the range of operation expected of the component in the design is specified. For the amplifier this usually involves the frequency band of interest and the power levels of the signals. This helps determine the set of excitations, or experiments, used to stimulate the DUT to produce the data needed to generate the behavioral model. In the work reported here, experiments were designed to inject large-amplitude tones,

swept over frequency, from 1 to 4 GHz, at the input and the output of the amplifier simultaneously. The input and output tones were offset slightly in frequency in order to help cover the state space of the model. That is, as shown in Equation (1), the models depend not only on the instantaneous inputs impressed on the external terminal but also on the time derivatives of these signals (and perhaps the time derivatives of the output signals as well) considered as independent variables. The set of excitations, or experiment design, must take into account the need to generate enough sample points for each independent variable to generate an accurate model.

Other excitations, such as modulated communication signals (e.g. W-CDMA) can also be used. Excitations can be true random or pseudo-random, and need not be limited to periodic or few tones like in many frequency-domain approaches. Criteria for excitations to produce transportable models, capable of being used in very different simulation environments (such as non-50 ohm impedances) can be formulated. This is unlike other modern methods which are valid only for small departures from known impedance (usually 50 ohms) environments (4).

The results of stimulating the component with the above excitations, either by the simulator in the case of the virtual model or by the measurement system in case of a measurement-based model, are stored in the form of several time series. That is, the selected input and resulting output signals, as well as several orders of their time derivatives, are saved as waveforms evaluated at sampled times. Characteristic of our approach is the use of these derivative embeddings, where different experiments may be sampled at different time intervals. Most applications of nonlinear time series are based on fixed time interval sampling and lag embeddings (7). Derivative embeddings and non-constant time samples help generate nonlinear models which work over a broad frequency range with different time scales. The time series are then read into a behavioral modeling toolbox created in MATLAB. The toolbox can therefore use the same procedure to generate behavioral models whether the data comes from a simulator or from actual nonlinear measurements.

The algorithms for choosing the actual dynamical variables for the resulting model are based on the principle of False Nearest Neighbors (FNN) (6). The algorithm is applied to a suitably de-correlated subset of the time series data in order to estimate the minimum number of variables involving inputs, outputs, and their time derivatives needed to model the dynamics as observed in the data. This algorithm is based on information-theoretic principles which help determine efficient trade-offs between model accuracy, speed, and complexity. This is in contrast to other approaches which use ad hoc methods or don't explicitly consider procedures to

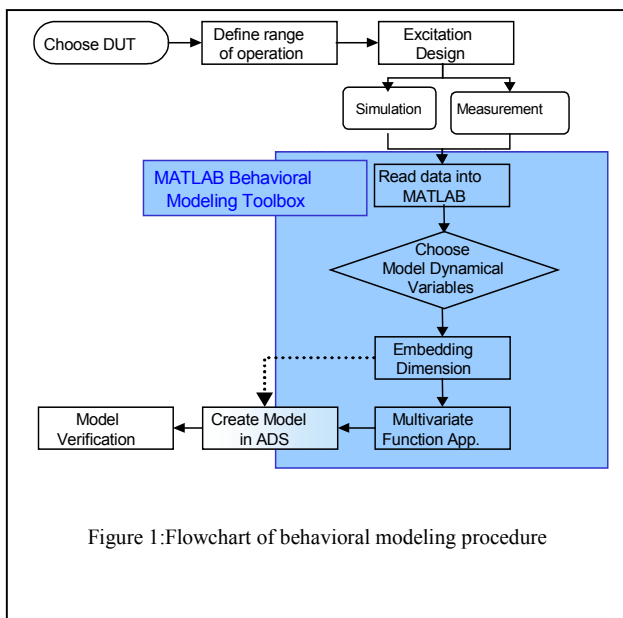


Figure 1: Flowchart of behavioral modeling procedure

determine the order of the time-domain model. The FNN algorithm starts with the input and output waveforms and systematically adds time derivative waveforms to the candidate embeddings until the output is accurately represented by a single-valued function of the selected set of variables. The set of variables, which usually includes the input signals, selected time derivatives, and in the case of feedback models, derivatives of the output waveforms, is the final embedding. This technique results in a model of vastly lower complexity than the original nonlinear system.

The next step is to fit the outputs as nonlinear functions of the inputs and the other embedding variables. Several techniques have been investigated. Multivariate polynomials and radial basis functions have been used and reported in (2). Figure (2) shows the results of an HBT amplifier model constructed from time domain data and using a radial basis function for the output function. The accuracy for the gain compression characteristic is within $\frac{1}{2}$ dB over the entire range of compression, over 5dB.

In this work we have also implemented artificial neural networks (ANNs) to provide the functional approximations. These functions generally provide smoother fits and are expected to give better predictions of distortion than radial basis functions. We have found ANNs are also extremely good functions for measurement-based modeling at the device level (5). The behavioral models generated with ANN functions also tend to extrapolate well over frequency and power. This is shown in figures (3) and (4) where a simple amplifier circuit behavioral model is derived with excitations within the range of the magenta box. The model is derived as above and ANN functions are used to fit the determined embedding. The model is then excited by signals outside the range of the training data and the results are compared to independent simulations of the underlying circuit model. Figures (3) and (4) show that the behavioral model is very accurate compared to the circuit model from which it was generated, and its extrapolation is also sensible when compared to the circuit model behavior outside the range over which the behavioral model was trained.

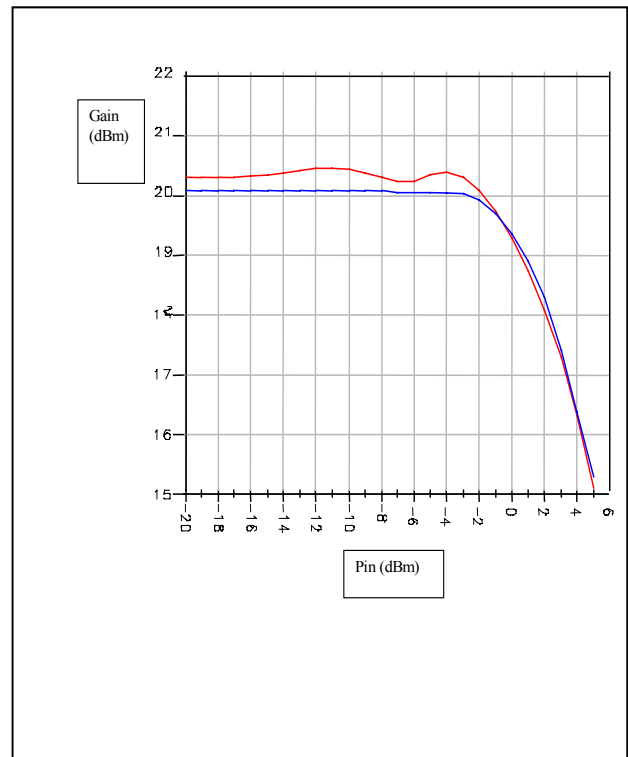


Figure 2: Simulated gain compression curves from behavioral model (red) versus nonlinear circuit model (blue) for an actual MMIC HBT-based amplifier circuit. The behavioral model simulated more than 10 times faster than the circuit model from which it was constructed.

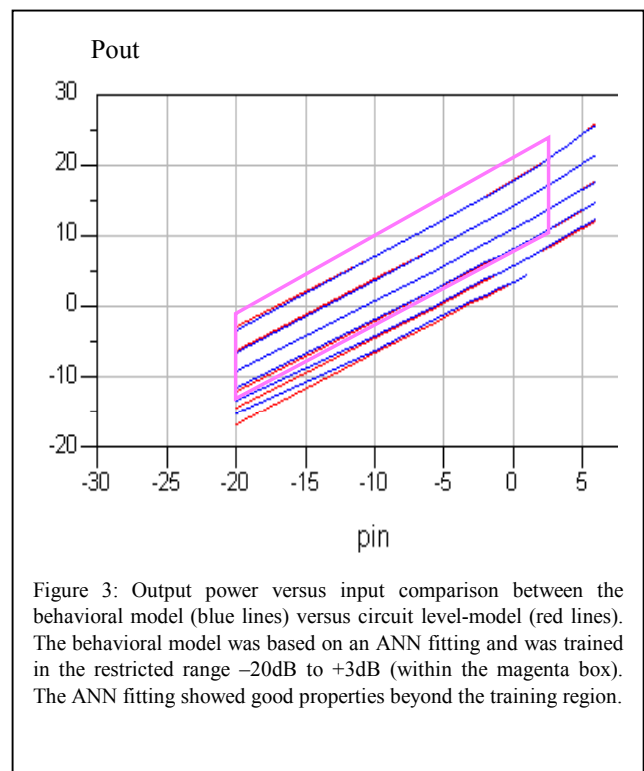


Figure 3: Output power versus input comparison between the behavioral model (blue lines) versus circuit level-model (red lines). The behavioral model was based on an ANN fitting and was trained in the restricted range -20 dB to $+3$ dB (within the magenta box). The ANN fitting showed good properties beyond the training region.

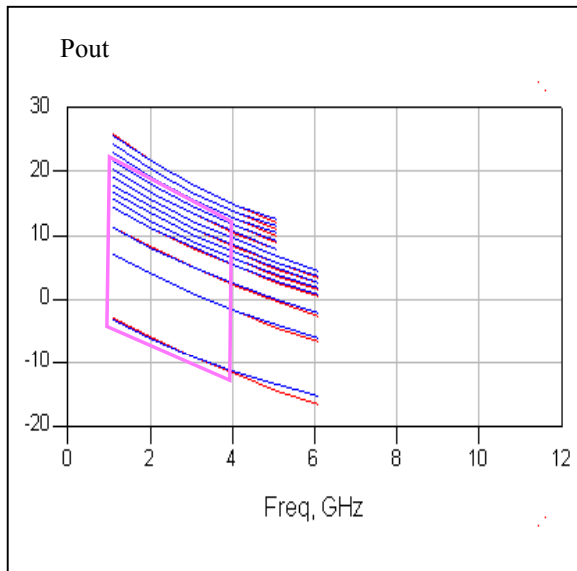


Figure 4: Output Power versus frequency comparison between the behavioral model (blue lines) and the circuit-level model (red lines) of the amplifier. The behavioral model was based on an ANN fitting and was trained in the restricted range of 1 to 4 GHz, indicated by the magenta boxed region. The ANN fitting showed good extrapolation properties beyond the training region.

Conclusions

A powerful, general, and systematic approach to behavioral modeling of microwave and RF nonlinear circuits in the time domain has been presented. It is based on sound, fundamental theory and techniques developed in the study of nonlinear dynamical systems. The models are attached to a commercial nonlinear microwave simulator. Models have been generated from transistors and complex nonlinear microwave ICs, using either novel large-signal microwave data or simulation. Simulation speedup of over an order of magnitude and dramatic memory reductions have been demonstrated. This technique enables complete and accurate simulation of complex modules and circuits in all simulation modes, including transient analysis, harmonic balance, and transient-envelope.

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