Guaranteed Locally-Stable Macromodels of Digital Devices via Echo State Networks

2006 IEEE Electrical Performance of Electronic Packaging

Guaranteed Locally-Stable Macromodels of Digital Devices via Echo State Networks

I. S. Stievano, C. Siviero, I. A. Maio, F. G. Canavero

Dip. Elettronica, Politecnico di Torino C. Duca degli Abruzzi 24, 10129 Torino, Italy

Ph. +39 011 5644184, Fax +39 011 5644099 (e-mail igor.stievano@polito.it)

Abstract: The assessment of signal integrity effects in high-speed digital systems requires accurate and efficient IC macromodels. The proposed methodology is based on parametric relations that are expressed in terms of discrete-time Echo State Networks. This approach overcomes the stability limitations of traditional parametric macromodels used so far. Applications of Echo State Networks to the modeling of real devices exhibiting a complex dynamical behavior are discussed.

1 Introduction

Nowadays, the availability of accurate and efficient macromodels of digital integrated circuits (ICs) input and output buffers is a key resource for the assessment of signal integrity and electromagnetic compatibility effects in fast digital circuits via numerical simulation. Buffer macromodels are usually based on simplified equivalent circuits derived from the information on the internal structure of devices. The most important example of the equivalent circuit approach is provided by the Input/output Buffer Information Specification (IBIS) [1]. Recently, other approaches to IC macromodeling, that supplement the IBIS resource and provide improved accuracy for recent device technologies, have been proposed [2, 3]. These approaches are based on the estimation of suitable parametric relations from port voltage and current responses to a suitable set of stimuli applied to the IC ports.

The parametric relations used so far for the generation of IC models have been sought for within the class of discrete-time Nonlinear Auto Regression with eXtra input (NARX) parametric relations expressed in terms of gaussian or sigmoidal expansions. This choice arises from the large availability of methods for parameter estimation, as well as from the nice features of these models to approximate *almost any* nonlinear dynamical system [4]. NARX parametric relations have been proven to accurately reproduce the behavior of a wide class of commercial devices [2, 3]. Besides, they turn out to be very compact, thus leading to models with a very small size. Owing to this, the estimated models, implemented in a simulation environment, are very efficient and allow simulation speed-ups on the order of $10 \div 1000$ w.r.t. physical descriptions of devices. In spite of these advantages, NARX relations have some inherent limitations. Mainly: *(i)* local stability of models cannot be easily imposed *a-priori* or even during the training process without impacting on model accuracy (model stability is verified at the end of the estimation process by validating the model). *(ii)* Fully nonlinear optimization algorithms are required for the computation of model parameters (depending on the specific algorithm used for parameter estimation, the estimation time may not be negligible); besides, the model accuracy depends on the initial guess of parameters and on local minima of the cost function. *(iii)* Higher order dynamical effects may not be readily represented by these models. It is worth remarking that locally unstable models must be avoided, even if they well reproduce the reference responses used in the model estimation. In fact, numerical simulation of these models for different signal and load conditions may lead to poor results.

In order to address the previous limitations, along with the requirement of avoiding the use of complex model structures, impacting on the simulation efficiency, model representations based on the recently-proposed Echo State Networks (ESNs) [7, 8, 9] technique are assessed. ESNs are discrete-time relations defined by a nonlinear state-space equation, whose stability can be easily enforced *a-priori* and whose parameters can be effectively estimated by means of the solution of a standard linear least squares problem. ESNs provide a very good compromise between model accuracy and model efficiency for the modeling of real systems with a complex dynamic behavior, and are good candidates to be used for the modeling problem at hand.

For the sake of simplicity, the discussion is based on single-ended output buffers. The results, however, are extensible to input ports and different device technologies. A macromodel for output buffers reproduces the electric behavior of the port current $i(t)$ and voltage $v(t)$ variables and is defined by the following two-piece relation [2].

$$i(t) = w_H(t)i_H(v(t), d/dt) + w_L(t)i_L(v(t), d/dt) \qquad (1)$$

where i_H and i_L are submodels describing the nonlinear dynamic behavior of the port in the fixed high and low logic states, respectively, and w_H and w_L are weighting signals describing state transitions (they play the same role of internal non measurable variables driving the buffer state). In addition, as discussed in [10], submodels i_H and i_L are conveniently expressed as a sum of a static and a dynamic component as follows:

$$i_{H,L}(v(t), d/dt) = \bar{\imath}_{H,L}(v(t)) + \hat{\imath}_{H,L}(v(t), d/dt) \tag{2}$$

The estimation of model (1) amounts to selecting a model representation for the dynamic components of submodels $\hat{\imath}_H$ and $\hat{\imath}_L$ and to computing the model parameters. It is worth noting that the selection of the model representation along with a good algorithm for the estimation of model parameters are the most critical steps of the modeling process. In fact, once the dynamic components $\hat{\imath}_H$ and $\hat{\imath}_L$, and therefore i_H and i_L, are completely defined, the computation of the weighting coefficients w_H and w_L in (1) is carried out by a simple linear inversion of the model equation. This is done from voltage and current waveforms recorded during state transitions events, as suggested in [2].

Finally, the last step of the modeling process amounts to coding the model equations in a simulation environment. This can be done by representing equations (1) and (2) in terms of an equivalent circuit and then implementing the equivalent as a SPICE-like subcircuit. The circuit interpretation of model equations is a standard procedure that is based on the use of controlled-current sources for the static contributions, and on resistors, capacitors, and controlled source elements for the dynamic components. As an example, the SPICE-like implementation of a generic nonlinear dynamic parametric model is discussed in [2]. As an alternative, model (1) can be directly plugged into a mixed-signal simulation environment by describing model equations via hardware description languages likes Verilog-AMS or VHDL-AMS.

2 Echo State Networks

This Section briefly discusses the generation of IC output port models by means of ESNs. A comprehensive discussion on ESNs can be found in [7] and references therein. This class of models is described by a nonlinear discrete-time state-space equation that is able to approximate a wide class of nonlinear dynamic systems. As an example, for the dynamic component $\hat{\imath}_H(v(t), d/dt)$ of (2), an ESN parametric representation writes

$$\begin{cases} \mathbf{x}(k) = \mathbf{f}\left(\mathbf{A}\mathbf{x}(k-1) + \mathbf{b}v(k-1)\right) \\ \hat{\imath}_H(k) = \mathbf{c}^T \left[\mathbf{x}^T(k), v(k)\right]^T \end{cases} \tag{3}$$

where k is the discrete-time variable and vector $\mathbf{x} = [x_1, ..., x_N]^T$ collects the N internal state variables. Typical values of N are in the range $[20, 500]$ and the nonlinear multivariate mapping $\mathbf{f}$ consists of the collection of sigmoidal functions. In this study, $\mathbf{f} = [\tanh(\cdot), ..., \tanh(\cdot)]^T$. The parameters of the model are the square matrix $\mathbf{A}$ and the vectors $\mathbf{b}$ and $\mathbf{c}$.

The estimation of the entire set of parameters in (3) requires the solution of a fully nonlinear optimization problem. This feature, along with the large number of unknown parameters involved in a state-space equation, would limit the applicability of this approach. Besides, nonlinear algorithms lead to the same possible dynamic instability of models observed in the estimation of NARX relations.

In order to address the previous limitations, the methodology proposed in [7] amounts to adapting only the weights of the network-to-output connections, *i.e.,* the parameters in vector $\mathbf{c}$, thus leading to the solution of a linear least squares problem. The other parameters, *i.e.,* matrix $\mathbf{A}$ and vector $\mathbf{b}$, are defined *a-priori* in a way that allows the inclusion in the model of a large number of randomly generated dynamics, hopefully including those of the original system under modeling. In particular, matrix $\mathbf{A}$ is chosen to satisfy the "echo state" property, which means that for each input sequence, model (3) must present a unique sequence of state variables, thus leading to locally stable models.

ESNs designed as outlined in this Section have several strengths. They are stable by construction, they rely on a simple linear estimation algorithm and have been effectively used to approximate the nonlinear dynamic behavior of complex dynamical systems possibly with chaotic behavior or higher order dynamical effects [7].

3 Numerical results

In this Section, the methodology for the generation of IC macromodels based on both NARX parametric relations and on ESNs is applied to a commercial device. The device is the output port of a Texas Instruments transceiver, whose HSPICE physical description is available from the official website of the vendor. The lumped circuit equivalent of the IC package is provided by the supplier as well. The example device is an 8-bit bus transceiver with four independent buffers (model name SN74ALVCH16973, power supply voltage VDD=1.8 V). The example device operates at 167 Mbps, i.e., the bit time is 6 ns. The HSPICE simulations of the physical model are assumed as the reference curves hereafter and are used for both generating the estimation signals and the validation responses.

In this study, two modeling examples are developed. They are based on the same device, and either include or exclude the device package.

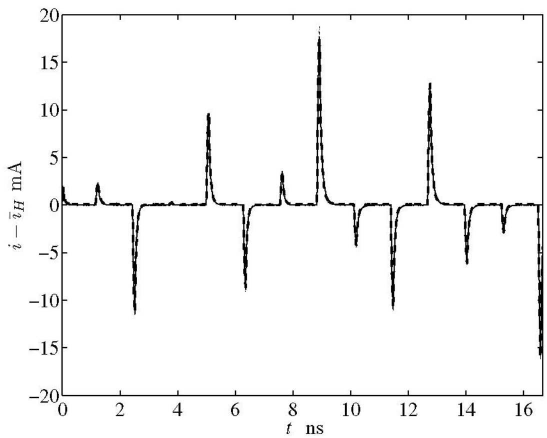

Figure 1: Validation test: dynamic component of the port current responses for the device of example 1. Three curves (barely distinguishable) are shown: the reference (solid), responses of the ESN models with $N = 30$ (dashed), and responses of NARX models (dotted). See text for details.

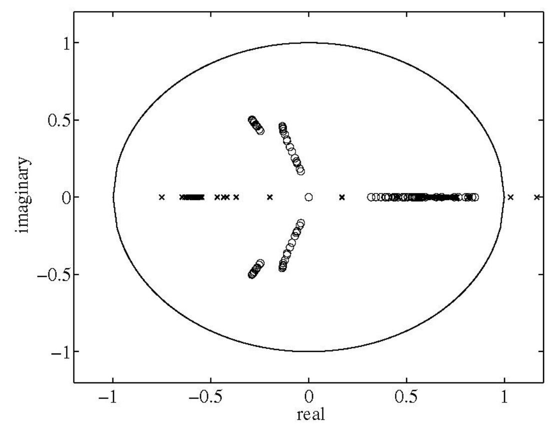

Figure 2: Comparison of eigenvalues of the linearized model. The eigenvalues are computed for each point explored during the transient simulation of example 1. Circles: eigenvalues of the ESN model; crosses: eigenvalues of the NARX models.

Example 1

In the first example, the proposed modeling methodology is applied to the characterization of the silicon part of the output port of the example device. No package information is included in the reference physical description of the transceiver. For this example, different models are estimated. In one case, eight different NARX models are obtained by means of the application of either static [5] or recurrent [6] estimation algorithms. All this models have 5 basis functions and a dynamic order 2. The second case refers to several ESN models with a number of internal states $N = 30$ that are estimated as outlined in Sec. 2 with random initializations.

In order to assess the quality of the different estimated models, a validation test circuit consisting of the driver under modeling forced in fixed high state and loaded by the series connection of a resistor and a voltage source, is considered. The voltage source produces a multilevel signal spanning the range of possible operating voltages. The test conditions (driver in high state) and the output variable (dynamic component of the port current) are adopted for the sake of simplicity, and not limiting the validity of our conclusions, that were also checked on the complete model (1).

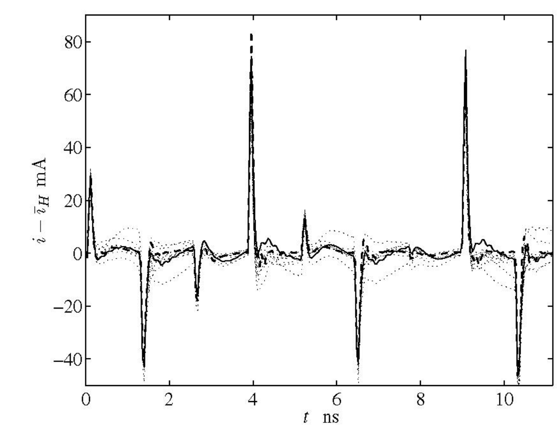

Figure 3: Dynamic component of the port current responses for the example 2 validation test. Solid line: reference, dashed line: ESN models with $N = 30$; dotted lines: NARX models.

Figure 1 compares the dynamic component of the reference output port current response and the responses of models of two different classes. The responses of several ESN models (whose estimation differs only for a random initialization of the states matrix) coincide, and are represented as one curve with dashed line in Fig. 1. The coincidence of responses is a clear indication of the adequacy of ESN models to represent the dynamics of the device under modeling, irrespective of the particular choice of matrix A. The second class of tested models is represented by NARX models, of which eight different realizations have been generated by the application of different estimation algorithms [5, 6]. The responses of these NARX models coincide, and are represented as one curve with dotted line in Fig. 1. From the exact superposition of curves in Fig. 1, it is clear that both models (ESN and NARX) are adequate to reproduce the reference behavior.

For an additional performance evaluation, we addressed ourselves to the assessment of model stability, by means of an analysis of the eigenvalues of the linearized model. The eigenvalues are computed for each point explored by the voltage and current responses during the transient simulations of a validation test [11]. Figures 2 compares the eigenloci of the linearized model equation for the dynamic component of i_H, for ESN (circles) and NARX (crosses) models. This figure clearly shows that all the eigenvalues of the ESN model are located within the unitary circle, as expected, since such model is stable by construction. On the other hand, NARX models, although reproducing the device reference responses very well, have a potential dynamic instability (see the eigenvalues lying outside the unitary circle of Fig. 2), since no constraint on the model stability is imposed during model estimation.

The CPU time required by the estimation of ESN models (relying on the solution of a linear least squares problem) is much less than the time required for the estimation of NARX models via the solution of nonlinear optimization problems. On the other hand, NARX models, that are generally smaller in size, are more efficient. However, for the devices of interest, like the one of this example, ESN models with a limited number of internal states (*e.g.,* $N = 30$) are a good compromise, leading to a limited efficiency penalty and a good accuracy level.

Example 2

The second example is aimed at testing the performance of ESN models for silicon buffers mounted in their package, whose parasitics may be responsible for higher order dynamical effects.

Figure 3 compares the dynamic component of the reference output port current response with the responses of ESN and NARX models. The same set of experiments devised for example 1 have been carried out and the main results are summarized below. The responses of ESN models (whose estimation differs only for a random initialization of the states matrix) are represented as one curve with dashed line in Fig. 3. The coincidence of responses is a confirmation of the robustness of ESN models, irrespective of the particular values assumed for the state system parameters. As a comparison, the dotted lines of Fig. 3 represent eight different realizations of NARX models (differing by the estimation methods [5, 6] and their initialization): the variability of the curves is an indication of the difficulty for NARX models to reproduce much richer (*i.e.,* higher order) dynamics, as the ones introduced by the die package of this example.

4 Conclusions

This paper addresses the generation of locally-stable macromodels of digital ICs. The advocated approach is based on the so-called Echo State Networks that are state space relations whose parameters can be effectively computed via standard linear techniques from device port responses. This approach has been validated by modeling some realistic example devices exhibiting higher order dynamical effects.

References

[1] I/O Buffer Information Specification (IBIS) Ver. 4.1, on the web at `http://www.eigroup.org/ibis/-ibis.htm`, Jan. 2004.

[2] I. S. Stievano, F. G. Canavero, I. A. Maio, "Parametric Macromodels of Digital I/O Ports," *IEEE Trans. on Advanced Packaging*, Vol. 25, No. 2, pp. 255–264, May 2002.

[3] I. S. Stievano, I. A. Maio, F. G. Canavero, "Mπ*log* Macromodeling via Parametric Identification of Logic Gates," *IEEE Trans. on Advanced Packaging*, Vol. 27, No. 1, pp. 15–23, Feb. 2004.

[4] J. Sjöberg et al., "Nonlinear black-box modeling in system identification: a unified overview," *Automatica*, Vol. 31, No. 12, pp. 1691–1724, 1995.

[5] M. T. Hagan, M. Menhaj, "Training feedforward networks with the Marquardt algorithm," *IEEE Trans. on Neural Networks*, Vol. 5, No. 6, pp. 989–993, Nov. 1994.

[6] Y. H. Fang, M. C. E. Yagoub, F. Wang, Q. J. Zhang, "A new macromodeling approach for nonlinear microwave circuits based on recurrent neural networks," *Proc of 2000 IEEE MTT-S Int. Microwave Symp.*, 2000.

[7] H. Jaeger, "The Echo State Approach to Analyzing and Training Recurrent Neural Networks," GMD - German National Research Institute for Computer Science, GMD Report 148, 2001.

[8] D. Prokhorov, "Echo state networks: appeal and challenges," Proc of *International Joint Conference on Neural Networks*, Vol. 3, pp. 1463–1466, 31 July – 4 Aug. 2005.

[9] M. Salmen, P. G. Ploger, "Echo State Networks used for Motor Control," *International Conference on Robotics and Automation*, pp. 1953–1958, 18–22 April 2005.

[10] I. S. Stievano, I. A. Maio, F. G. Canavero, C. Siviero, "Reliable Eye-Diagram Analysis of Data Links via Device Macromodels," *IEEE Trans. on Advanced Packaging*, Vol. 29, No. 1, pp. 31–38, Feb. 2006.

[11] C. Alippi, V. Piuri, "Neural Modeling of Dynamic Systems with Nonmeasurable State Variables", *IEEE Trans. on Instrumentation and Measurement*, Vol. 48, No. 6, pp. 1073–1080, Dec. 1999.