

MODELS by Sequential Sampling

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Abstract—This paper proposes a sequential sampling technique to generate efficiently multidimensional X-parameters models for microwave transistors, while guaranteeing X-parameters' validity and overcoming simulator convergence issues. The sequential sampling process selects a set of samples that are subsequently used to construct behavioral models with radial basis functions. The proposed method was compared with a tabular X-parameters model with cubic spline interpolation. The radial basis function models demonstrate very fast convergence and greater accuracy already for a few tens of samples. The proposed technique is illustrated for a GaAs HEMT using Curtice3 and Chalmers empirical model simulations as the data source.

Index Terms—X-parameters, sequential sampling, behavioral modeling, computer simulation

I. INTRODUCTION

PAST developments in measurement instrumentation allow to automatically gather large-signal response of high-frequency nonlinear devices. One way to characterize a device is to provide complex amplitudes of incident and reflected waves for a given set of Large Signal Operating Points (LSOPs) (frequency, incident wave power, bias voltages, etc.). Since this results in an extremely large problem size, the X-parametersTM concept was introduced [1]. This approach assumes that the higher-order harmonics are small enough to meet the superposition principle. Therefore, one can describe a nonlinear device at an LSOP by using only the ratios between wave components.

In the case of simulations of active elements, especially transistors, the data dimensionality is still an issue, despite using X-parameters. It results in high simulation and extraction cost. Therefore, global optimization is not feasible, and the optimal LSOP in amplifier design is determined in a number of subsequent stages in which only a subset of variables is used in optimization [2]. Moreover, a simulator error for a single sample may result in termination of the whole multidimensional simulator sweep. There are few ways to overcome this problem such as limiting the sweep ranges or performing multiple sweeps over smaller ranges and combining the results. However, each of these solutions involves a lot of additional resources and is not an optimal choice. Moreover,

X-parameters model validity-region is limited to the space where the superposition principle is met [3].

In this paper, we propose an accurate and efficient X-parameters modeling technique. It is used to construct X-parameters behavioral models with a small number of samples, and at the same time of handling errors related to lack of simulator convergence and violation of the linearity assumptions. The technique is based on sequential sampling and behavioral modeling using Radial Basis Function (RBF) models [4]. First, we investigate two common empirical GaAs HEMT models (i.e., Chalmers [5] and Curtice3 [6] models) with respect to their validity region using the sequential sampling. Then, for the same empirical models, we build the X-parameters RBF model and compare it with the standard tabular model interpolated with cubic spline functions.

II. METHOD DESCRIPTION

A. Modeling procedure

The X-parameters samples are usually chosen by selecting a set of points in the range of interest for each of the LSOP parameters, and then taking all possible combinations (tensor product data grid). Such Design of Experiments (DoE) are easy to interpolate but can take a lot of resources. However, not every sample brings the same amount of information. Therefore, the DoE can be optimized. In order to maximize the information gain, one can use active learning techniques and sequentially select the samples with the highest added information value.

For those purposes we use methods provided by the SURrogate MODELing (SUMO) toolbox [7]. It contains a set of techniques for automatic building of accurate metamodels with a limited number of samples. In this work, it was extended with a dedicated Matlab wrapper for the Agilent hpeesof-sim simulator. The toolbox provides a number of sequential sampling strategies (Voronoi, Kriging, Local Linear Approximation (LOLA), etc.). We use the LOLA-Voronoi sampling strategy [4], which implements a trade-off between exploration (filling up the space to sample as equally as possible) and exploitation (selecting data points in highly nonlinear regions). The LOLA method identifies non-linear regions by comparing the gradients at the neighboring samples, while the Voronoi tessellation maximizes the distances among the samples.

After evaluating new samples, the behavioral model is built. Several behavioral model types may be considered: Artificial Neural Networks, RBF, Kriging, etc. However, there is no universal model type and one has to tailor the model type to

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the measured or simulated device. For the considered transistor modeling in this work, RBF models were chosen, since they show good trade-off between extraction and evaluation times, as well as good accuracy.

The last step is evaluating the model towards a specified accuracy measure. If the model accuracy requirement is satisfied, the model extraction is stopped. Otherwise, the procedure requests new samples and the whole loop is repeated. This strategy prevents under- and over-sampling.

B. Assuring X-parameters model validity

There are two types of errors, which might occur during X-parameters extraction. The first one is a critical error, which occurs when the harmonic balance simulator does not converge to a solution. In CAD environments, such as Agilent's ADS, it results in aborting the whole simulation, which may be very costly in the case of a multidimensional sweep.

The second source of error is related to the violation of the X-parameters linearization assumption [3]. As a measure to quantify this error, one can use

$$e_X = \left| \frac{X(\Delta P_{ext} \in [-30, -20] \text{ dB})}{X(\Delta P_{ext} = -50 \text{ dB})} - 1 \right| \quad (1)$$

where ΔP_{ext} is the ratio between the extraction tone power and the fundamental tone power in dB scale. Although the error will diminish as the extraction tone power decreases, ΔP_{ext} should be kept in the range of $[-30, -20]$ dB [8]. In that case, the simulation will resemble the measurements, in which the response of the device to the very small extraction tone may be obscured by noise. The value of ΔP_{ext} in the denominator of (1) was set to -50 dB, as it is achievable in the measurements with averaging and at the same time meets the superposition principle [3]. However, in the simulation environment this value can be further decreased as the digital noise is significantly lower. In the standard X-parameter modeling approach, errors of X-parameter values cannot be identified during the simulation. Therefore, a custom post-processing must be done.

Using sequential sampling techniques, one can easily handle the described errors. If the evaluation of the sample results in an error, the sample is considered as failed, and is not used in the model building. However, it is still kept for the sequential sampler. While generating new samples, the algorithm fills up the variable space such that the new samples do not lie near the already evaluated ones. Apart from a good space filling, it prevents the algorithm from exploring the region with samples marked as failed.

III. RESULTS AND DISCUSSION

A. Model validity

We evaluated the proposed approach by using empirical transistor model simulations as the data source. We have extracted RBF models for each of the X-parameters' terms separately. This allowed us to investigate the validity region in more details, since we sample each of the terms independently from the others. The well-established Chalmers (extracted from measurements [9]) and Curtice3 models were selected for

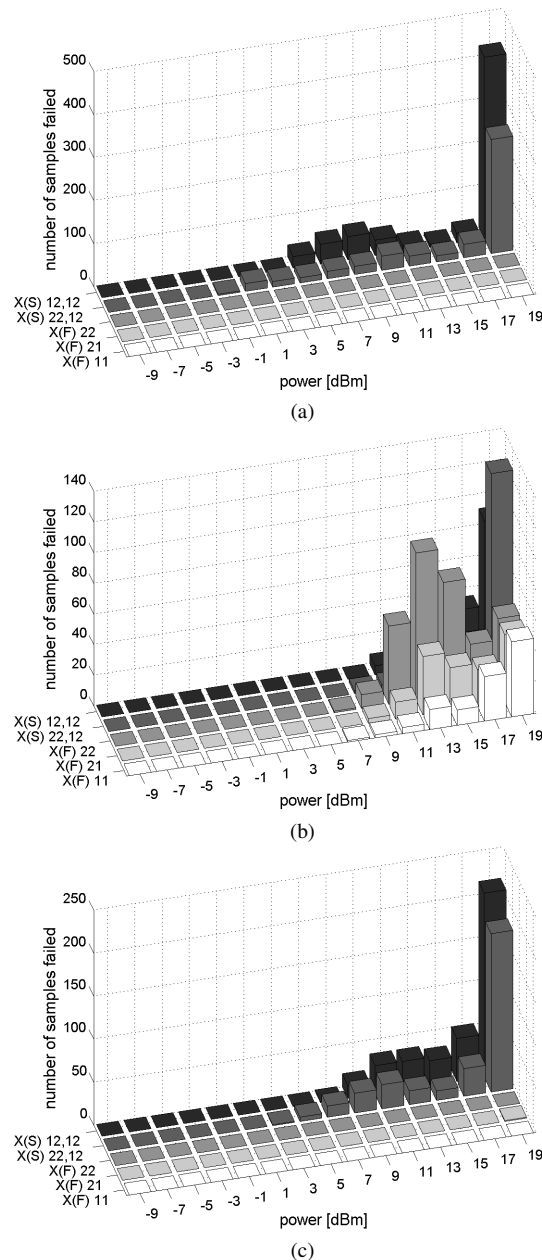


Fig. 1. Number of samples failed for different X-parameter terms as a function of the fundamental tone power in 2-dB bins; (a)- errors due to violating X-parameters linearization assumption for Chalmers model, (b) - errors in simulation for Curtice3 model, (c) - errors due to violating X-parameters linearization assumption for Curtice3 model.

this purpose. The following ranges were set for the samples (LSOPs): gate voltage $V_g \in [-0.4, 0.4]$ V, drain voltage $V_d \in [2, 6]$ V, fundamental tone frequency $f \in [2, 4]$ GHz, fundamental tone incident wave power $P \in [-10, 20]$ dBm. ΔP_{ext} was set to -20 dB. A 16-sample factorial design was used as the initial DoE [7]. The modeling stop criterion was the root relative square error equal to 0.05 in the cross-validation measure. The threshold value e_X (1), beyond which the sample was considered as failed due to violating the linearity assumption, was set to 1%.

Fig. 1 shows the number of failed samples as a function of the fundamental tone power with respect to the model

type, the error origin and the X-parameters term. There were no simulator errors during the Chalmers model evaluation. Contrary to the Curtice3 model, where the current is proportional to the third order polynomial of the gate voltage, the current in the Chalmers model saturates at higher power levels. Therefore, the harmonic balance simulator convergence can be preserved at high input power values. One can also notice that the number of errors grows non-monotonically as a function of power. This may indicate that the errors depend also on the other LSOP parameters. Therefore, the X-parameters validity region cannot be described by a simple hyperrectangle and sequential sampling techniques should be applied. One can also see that the number of errors related to the violation of linearity assumptions is strongly dependent on the X-parameters term. There are almost no errors in $X^{(F)}$ terms. This behavior might be explained by the relatively small influence of the extraction tone comparing to the main-tone incident-wave power.

B. Model accuracy

In order to assess the proposed modeling technique, it was compared with the standard ADS tabular model interpolated with the cubic spline functions. The tabular model was built on a tensor product grid with n equally distant points per variable, where $n \in [2, 10]$. The variable ranges were the same as for the model validity analysis, with exception to the fundamental tone power. It was limited to $[-10, 6]$ dBm range, which allowed to avoid the simulator convergence problems in the classical sweep, thus making models comparable.

The tabular and RBF models (X_m) have been compared with the empirical models (X_{ref}) using a validation dataset composed of $N = 10000$ random samples (x_i) with a uniform distribution. Then, the mean relative error (2) and the relative worst case error (3) were calculated.

$$e_{mean} = \frac{1}{N} \sum_{i=1}^N \left| 1 - \frac{X_m(x_i)}{X_{ref}(x_i)} \right| \quad (2)$$

$$e_{worst} = \max_{i \in [1, N]} \left| 1 - \frac{X_m(x_i)}{X_{ref}(x_i)} \right| \quad (3)$$

Fig. 2 shows the error comparison between the imaginary parts of the tabular and RBF X-parameters models extracted from the Chalmers model. Similar results were obtained for the real part, as well as for the models extracted from the Curtice3 model.

It can be perceived that the mean error is smaller for the RBF models. Especially when the response is smooth, as in $X_{21}^{(F)}$, the tabular model needs much more samples to achieve a performance similar to the RBF model. Moreover, the RBF models converge much faster. It proves the usability of the sequential sampling technique, in which the samples taken first usually carry the most of information. No major difference between the RBF and tabular models were observed for the worst case error levels.

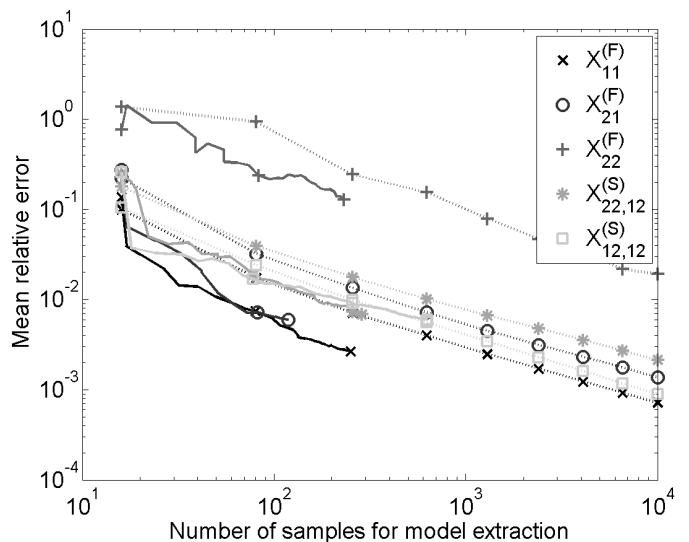


Fig. 2. Comparison between the mean relative errors for the imaginary part of the tabular (dotted lines) and the RBF model (solid lines) for the Chalmers model as a function of the number of samples used to build a model.

IV. CONCLUSIONS

We have presented an efficient and accurate modeling technique for X-parameters using sequential sampling in the model generation process and the RBF representation as behavioral model. The method has been proven useful to assure model validity over wide range of variable values. The constructed models showed fast convergence and smaller relative mean error even for a small number of samples.

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