Nonlinear Statistical Modeling of Large-Signal Device Behavior

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ABSTRACT — **A novel technique for modeling the nonlinear statistics of large- and small- signal device model parameters is proposed. It features transformation of individual random variables and introduces a new criterion for optimum statistical variable transformation based on Quantile-Quantile plots. Subsequently, multivariant methods are applied to build an inherently nonlinear statistical model. The models are easily implemented into current CAD tools and are suited to accurately predict yield in the presence of process variations and process shifts. Results for devices and MMIC circuits operated under small- and large signal excitation validate the accuracy of the method.**

I. INTRODUCTION

The success of a MMIC product ultimately is measured by its profitability. Critical factors in that respect are time-to-market and yield. The key to optimizing both is the ability to simulate process variations *a priori*, at an early stage of a design. By predicting the circuit's sensitivity to process variations the design can be "centered" to the manufacturing process or, in other words, made robust. This way, yield constraints and performance can be balanced to reduce the number of design-cycles and to maximize yield [1][2].

Deviations from the nominal behavior due to process variations have been accounted for by either tuning relevant parameters to their estimated limits (worst-case scenario) or by performing a Monte-Carlo analysis with estimated parameter deviations (±σ-method). Both approaches lack any assessment of parameter correlation and can result in physically impossible model parameter sets. The use of multivariant linear statistical methods enables the modeling of correlation but assume the same distribution fuction for all random variables [3] [4]. For an accurate yield estimate the statictical model has to include the nonlinear relationships between all random variables. [9]

We propose individual transformation of each random variables to overcome the inaccuracies of linear parametric models and to avoid shortcomings associated with higher order regression. A new criterion for an optimal transformation function is proposed. Finally, the statistics of the transformed variables can be accurately described by the principal components [7] resulting in an intrinsically nonlinear statistical model.

II. NONLINEAR STATISTICAL DEVICE MODELING

Step I: Mapping

We use standard in-process RF and DC measurements from active and passive process control monitor structures to extract the parameters for the standard small-signal model [5] and for the empirical large-signal Materka-Model [6]. In the large-signal case, measurements include maximal Drain current (IMAX), saturation drain current (IDSSP), pinch-off voltage (VP), peak transconductance (GMP), and source/drain resistance (RS/RD). For the extraction of model parameter, a two level optimizing procedure has been developed that take the respective measurement conditions of the process control monitor structures into consideration. After thus mapping the measured coupon data to the Materka-parameters, they subsequently will be treated as the random variables.

Step II: Transformation

A simple yet powerful transformation function is used to achieve a normal distribution for each transformed random variable x_i (with p_i being the respective parameter):

$$f(x_i) = x_i^{\,p_i}$$

Also, a new criterion has been developed that assesses the success of the transformation: the transformation function's parameter are chosen to maximize the multiple correlation coefficient R^2 of the transformed data's inverse Gaussian probability function (Q-plot/normal plot) [7]. With this transformation, we are able to use a linear regression model for the transformed data and to calculate the parameters for the statistical model in a closed form. This is a big advantage over a true nonlinear statistical model, which requires an iterative technique. By using an individual transformation function for each Materka-parameter the model is capable of accounting for nonlinear and non-Gaussian joint probabilities.

Step III: Eigenvalue Decomposition

For the linear model of the transformed data we determine the minimum number of independent dimension by Eigenvalue Decomposition.

Step IV: Principal Factor Model

The correlation matrix of the transformed random variables is orthogonalized via principal component regression.

The model building process is fully automated: the software queries the database with coupon measurements and performs the statistical model building process for small-signal device models, large-signal device models and passive components for different processes. The model parameter files are automatically updated and are accessed by the CAD library components. Summary pages for different processes can be accessed by the design community via the intranet.

Results

As an example, figure 1 shows the simulated scatterplots of two Materka-Model parameters, Idss vs. SL. The simulation shows the ability of the proposed technique to accurately account for nonlinear correlation between model parameters, which is visible in the shape and density distribution of the scatterplots.

The strength of the proposed technique is also illustrated in figure 2; here, for a one-stage ideally terminated Class-F amplifier the differences in yield prediction for a given PAE-limit is shown for the simulation with correct mean and standard deviation but no correlation between the statistical parameters and for the proposed model. The simulated yield can be considerably different depending on the actual limit; for example, for a lower PAE control limit of 78% the new model predicts a yield of 5% which is rigorously different from the previous model which predicts 20%.

Fig. 3 shows the input match of a low noise amplifier simulated with the standard small signal model, the according to the proposed technique centered model, and measured data. The standard small signal model is based on a single device which was considered typical within a one-standard deviation range. Where the original model predicts a pronounced minimum at 37 GHz not seen in the measured data, the proposed model is in very good agreement with the actual data. By taking into account the variability of the manufacturing process the mean behavior of the MMIC and its statistics can be accurately be predicted.

The statistics of drain current vs. output power of two-stage power amplifier are illustrated as a scatterplot in fig. 4. The simulated data are in good agreement with the measured data (not shown here).

V. CONCLUSION

A statistical modeling technique has been proposed that utilizes optimum individual variable transformation based on a novel criterion involving the Inverse Gaussian Probability function. The method makes use of readily available data, features an inherently nonlinear statistical model, and can accurately recreate means, standard variations, and nonlinear correlations of the device model’s parameter. In conjunction with a Monte-Carlo Simulator it accurately predicts circuit sensitivity to process variation and circuit yield, and thus allows for yield optimization.

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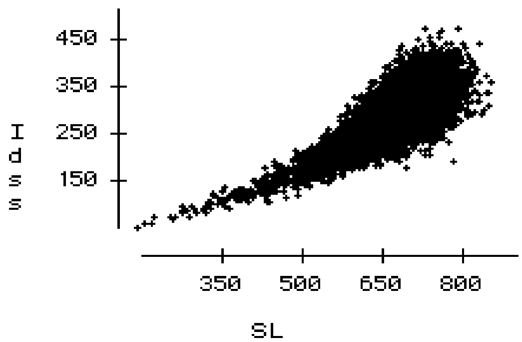

Fig. 1: Simulated Scatterplot of Materka-Parameters Idss vs. SL which accurately matches the data in its statistical moments and the nonlinear correlation

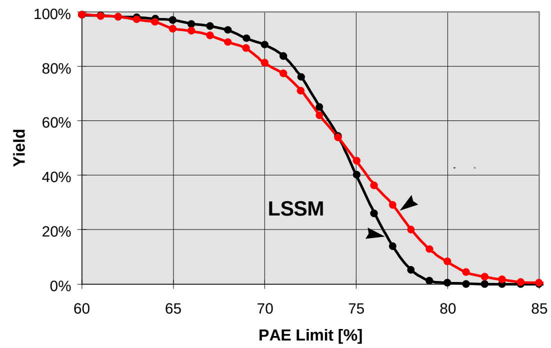

Fig 4: Complementary Cumulative Distribution Function for a Monte-Carlo analysis (MC) without considering nonlinear correlation and for the proposed statistical model (LSSM).

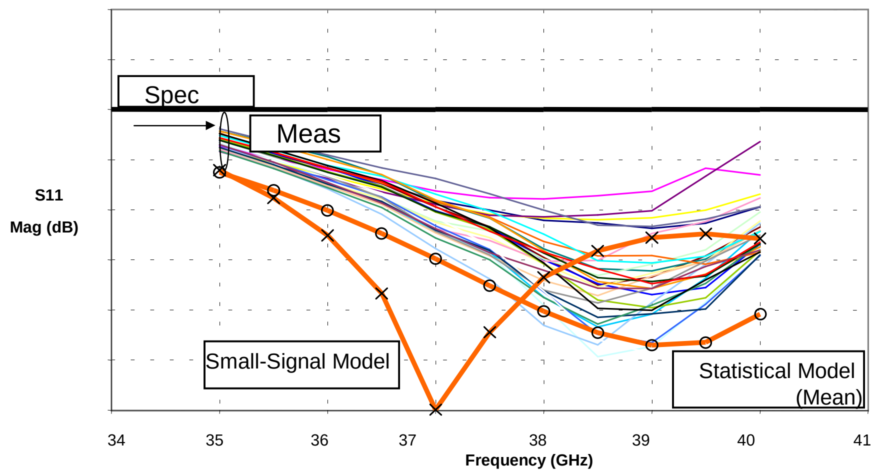

Fig. 2: Input Match for a Low Noise Amplifier vs. Frequency; shown are the simulation with the standard small signal model (based on one device), the mean behavior simulated with a centered/statistical model, and measured data

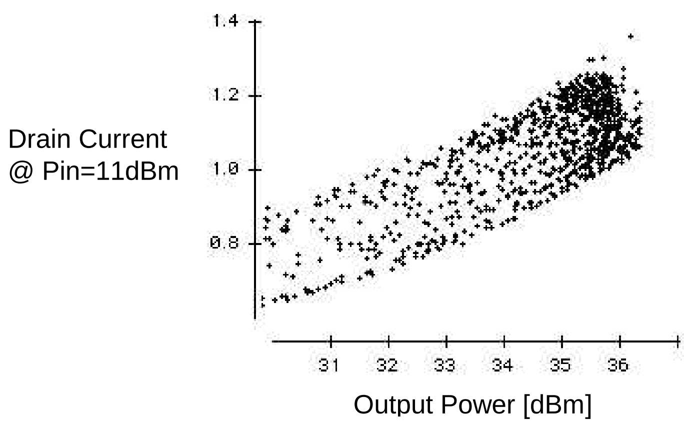

Figure 3: Drain Current vs. Output Power at 11dBm Input Power for a 2 stage, 50% PAE, C-Band 0.25um T-gate PHEMT power amplifier MMIC with a total periphery of 9.4mm (half chip) predicting the measured data (not shown here).

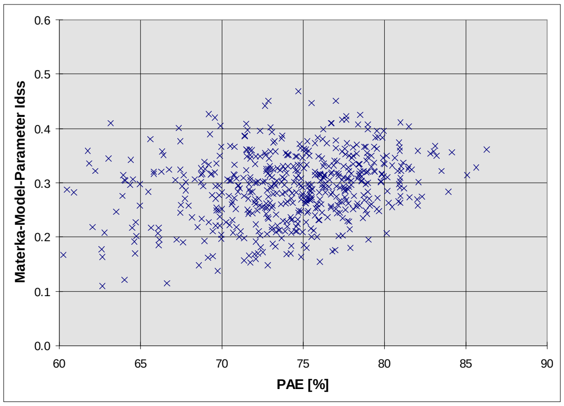

Fig.5: Materka-parameter Idss vs. PAE of a ideally terminated class F amplifier for a simple Monte Carlo simulation.

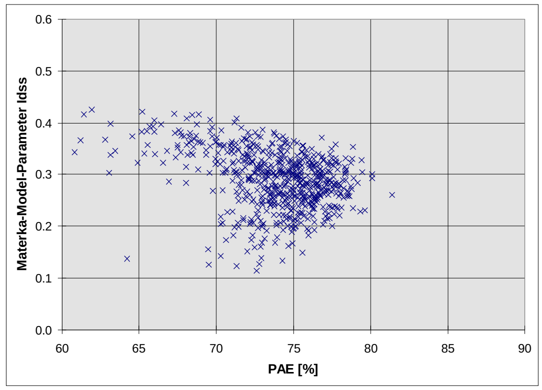

Fig.6: Materka-parameter Idss vs. PAE of a ideally terminated class F amplifier for the proposed statistical large signal model