

A Large-Signal Statistical Model and Yield Estimation of GaN HEMTs Based on Response Surface Methodology

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Abstract—A novel nonlinear large-signal equivalent circuit statistical model of GaN HEMTs based on response surface methodology (RSM) is proposed in this letter. Thirty-four GaN HEMTs from 10 batches are measured and all the parameters in the large-signal equivalent circuit model are extracted by an in-house parameters extraction program. We choose the four most sensitive parameters of the drain-source current model and the gate charge model. The statistical method is modeled by using response surface methodology to change the range of the four parameters. The statistical model is implemented in Agilent-ADS and three S-band GaN HEMT power amplifier are designed by using the established statistical model for validation. The results show that good accuracy has been achieved by comparing measured and simulated output power (Pout) and power added efficiency (PAE). This method is simple and accurate for GaN HEMT power amplifier design and yield estimation.

Index Terms—GaN HEMT, large signal, power amplifier, response surface methodology, statistical model.

I. INTRODUCTION

GaN HEMTs are known to be promising devices for power amplifier in recent years. Due to the variations in process, design of GaN MMIC requires accurate statistical models of the variations in the GaN HEMTs' performance that enable the designer to perform yield-oriented design of microwave and millimeter-wave integrated circuits. The current statistical models are mostly small-signal equivalent circuit [1]–[5]. Recently, a few works have been proposed to accurately describe the large-signal statistical model [6]–[8]. These modeling methods are based on Monte Carlo simulation. However, Monte Carlo simulation needs a large number of simulated data, is a random algorithm, and can not control the varying range of parameters. A quick large-signal model was proposed to evaluate sensitivity of process tolerances [9], the authors got the changing range of the device's performances by changing the range of the model parameters. However, the parameters they obtained were

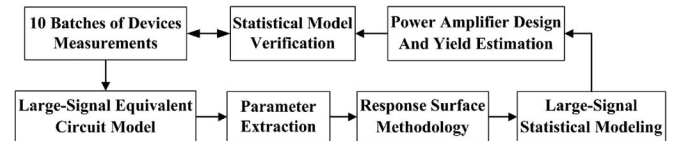


Fig. 1. The large-signal statistical modeling methodology.

only from one device, the parameters became bigger or smaller altogether, which can not be mixed freely.

In this letter, we present a novel large-signal statistical-modeling method which is simple and accurate. The statistical-modeling methodology is depicted in Fig. 1. Firstly, the large-signal equivalent circuit parameters (ECPs) are extracted from DC and S-parameter measurements. We use RSM on the four most sensitive parameters of the large-signal empirical equivalent circuit model. The statistical model was implemented in Agilent-ADS software, the large-signal performances (Pout and PAE) have been simulated and compared with the measured results to verify the statistical model. Finally, three S-band GaN HEMT power amplifiers are designed by using the established statistical model for verification.

II. THE LARGE-SIGNAL STATISTICAL MODEL

The large-signal performances (Pout and PAE) of thirty-four GaN HEMTs (0.25 μm GaN HEMT on SiC substrate with $4 \times 100 \mu\text{m}$ gate width) have been measured from 10 batches for establishing a statistical model. All the parameters of an improved Angelov large-signal model [10] have been extracted including the nonlinear drain-source current model and the nonlinear gate charge model.

The proposed modeling approach was applied to the database of extracted equivalent-circuit parameters [11] for the GaN HEMT. Four most sensitive parameters (I_{PK} , V_{PK1} , C_{gs0} , C_{gd0}) are chosen as variables in the statistical model, whereas the other parameters were fixed for simple analysis. The values of the four parameters are shown in Fig. 2.

The extracted parameters were analyzed using RSM [12], which provides statistical models that help in understanding the interactions among the parameters that should be optimized. The parameters were fitted to a second-order polynomial model. In general, the second-order model is as follows:

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1, j \leq i}^k \beta_{ij} x_i x_j \quad (1)$$

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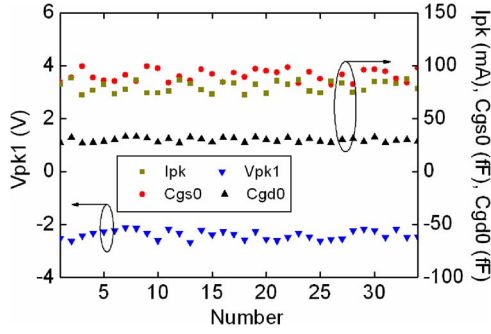


Fig. 2. The variability of sensitive model parameters.

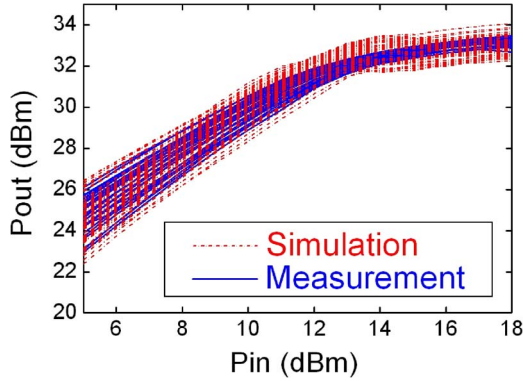


Fig. 3. Comparison between simulated and measured Pout at input power of 5–18 dBm.

y is the sum of the known response value, k is the number of parameters at each point, β_0 is the constant coefficient, β_i is the linear coefficient, β_{ij} is the coefficient of interaction effect, and x_i and x_j are the coded values of variables i and j , respectively. If the maximum value of one parameter is X_H , and the minimum value is X_L , any intermediate value X can obtain by the symbolic value C

$$C = \frac{(X - a)}{b} \quad (2)$$

$$a = \frac{(X_H + X_L)}{2} \quad (3)$$

$$b = \frac{(X_H - X_L)}{2} \quad (4)$$

$$X = b \times C + a. \quad (5)$$

The value of C changes in the range from -1 to 1 . As can be seen in Fig. 3, the variability of the model parameters are almost in the range of $\pm 10\%$, and the typical fluctuation of parameters are about $\pm 10\%$ in process, so we take parameters' changes in three states, i.e., -10% , 0 and 10% . Then, we can get a combination of $81(3^4)$ sets of states, which can reflect all the variations of these four parameters. The advantages of the proposed method are fast and simple, with less parameters and good convergence when simulated in software ADS, and the range of parameters can be controlled artificially.

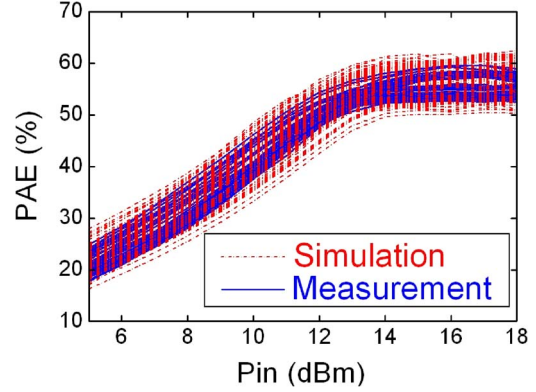


Fig. 4. Comparison between simulated and measured PAE at input power of 5–18 dBm.

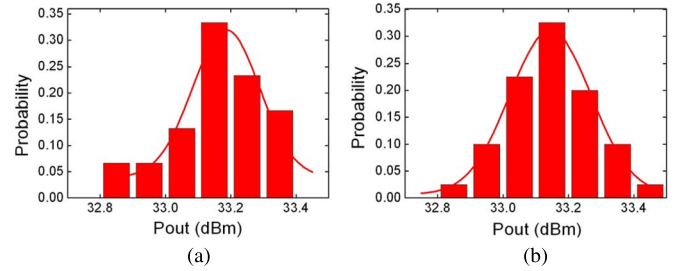


Fig. 5. Probability distribution of simulated and measured results. (a) Measured Pout. (b) Simulated Pout.

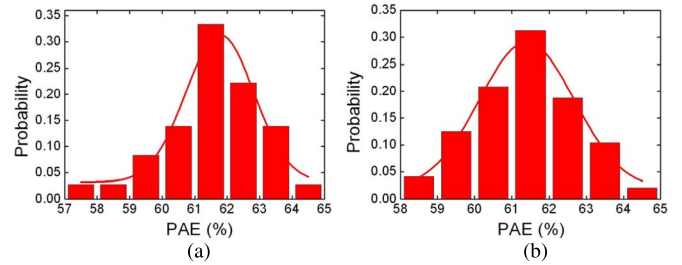


Fig. 6. Probability distribution of simulated and measured results. (a) Measured PAE. (b) Simulated PAE.

III. MODEL VALIDATION AND DISCUSSION

The GaN HEMT statistical model was implemented in Agilent-ADS software, biased at $V_{gs} = -2.8$ V, $V_{ds} = 28$ V. The 81 simulated results were compared to the measured results with the input power from 5 to 18 dBm, at the frequency of 3 GHz. The results show that the large-signal performances (Pout and PAE) were reproduced accurately, as shown in Figs. 3. and 4.

The probability distribution of Pout and PAE have been depicted in Figs. 5 and 6, each of them shows an almost normal distribution. Since the sample capacities of simulated results are larger than the measured ones, the standard deviations of simulated results are bigger than the measured ones. These just illustrate that the measured data have been contained in the statistical model. These results show that the statistical model is accurate.

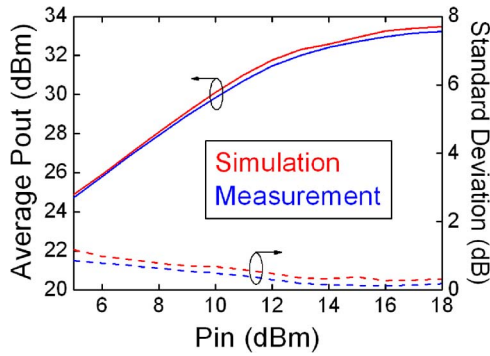


Fig. 7. Median and standard deviation of simulated and measured Pout.

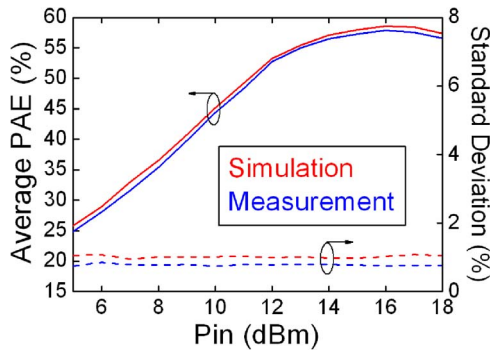


Fig. 8. Median and standard deviation of simulated and measured PAE.

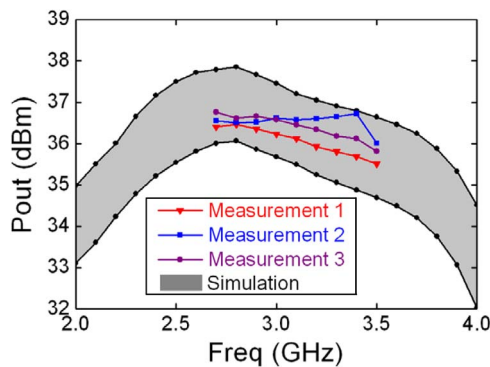


Fig. 9. Measured and average simulated Pout in the simulated area.

The medians and standard deviations of simulated and measured results have been shown in Figs. 7. and 8. The medians are very similar, whereas the standard deviations of simulated results are bigger than the measured results, this is precisely because the sample size of simulated results are larger and more dispersed than the measured results.

IV. POWER AMPLIFIER DESIGN AND YIELD ESTIMATE

Three AB-class 2.7–3.5 GHz single-stage HEMT amplifiers have been designed and measured at the same bias with the statistical model ($V_{gs} = -2.8$ V, $V_{ds} = 28$ V), and the input power is 24 dBm [13]. 81 times simulations were performed in ADS of the frequency bandwidth from 2 to 4 GHz, the simulated results (Pout and PAE) are shown in Figs. 9 and 10. The measured results are contained in the envelope of the simulated results (gray area). These show that this model is accurate and suitable for yield estimation.

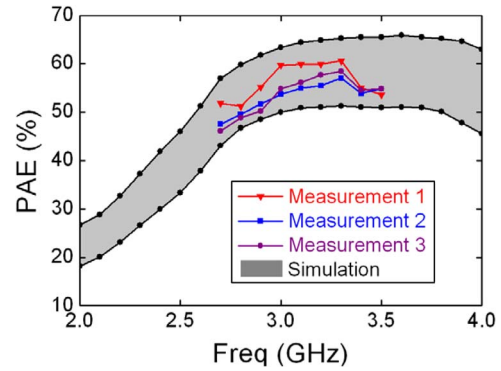


Fig. 10. Measured and average simulated PAE in the simulated area.

V. CONCLUSION

A novel nonlinear large-signal statistical-modeling method for GaN HEMTs has been presented. The technique uses response surface methodology to obtain the range of the four most sensitive parameters of the drain-source current model and the gate charge model. This method is fast and simple, at the same time, accurate. The statistical model was used to design and analyze three S-band power amplifiers. As a result, this large-signal statistical model can use for circuit yield estimation with good accuracy.

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