ANN Model For AlGaN/GaN HEMTs Constructed From Near-Optimal-Load Large-Signal Measurements

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***Abstract* — AlGaN/GaN HEMTs have a high potential for high-power applications at microwave frequencies. We developed a behavioural model corresponding to the operation condition as how this device will be used in power amplifiers, i.e., at a high output load. The model is based on time-domain large-signal measurements, and the representation format is an artificial neural network (ANN). AlGaN/GaN devices on sapphire are known to be temperature sensitive. Therefore, we also consider the incorporation of the self-heating effect in the behavioural model description.**

I. Introduction

GaN-based devices are extensively being pursued for potential applications in high-power microwave circuits [1]. Specific physical characteristics, such as pronounced temperature dependency, render the application of 'classical' modelling techniques, such as direct extraction, difficult. In this paper, we describe the construction of a behavioural model. This modelling approach has as advantage that it is completely based on (vectorial large-signal) measurements only and consequently that the precise equivalent scheme does not need to be known. The basic principle of the modelling procedure has been described in an earlier publication [2]. The contribution of this paper is the application of this method to AlGaN/GaN HEMTs, whereby two specific points of attention are the use of loadpull measurement data for model building, and the incorporation of the self-heating effect. The former is because AlGaN/GaN HEMTs have little or no gain when measured with a 50 Ohm load, and consequently there is no practical use of having a model at this 'standard' load condition. Therefore, in order to have a model that is ready to be used in actual applications, i.e., power amplifier designs, we constructed it from load-pull data. The second item, the self-heating effect, is known to be important in case of AlGaN/GaN HEMTs on sapphire substrates.

In Section II, details about the measurement set-up are described. The modelling procedure is reviewed and extended for its application to AlGaN/GaN HEMTs in Section III. Modelling results are shown and analysed in Section IV.

II. Experiment Design

As the modelling method is based on measurements only, the data gathering part can not be underestimated. The considered device is a 0.5 ∝m x 100 ∝m unpassivated AlGaN/GaN HEMT, fabricated by IEMN. Processing details and performance results can be found in Ref. [3]. In general, the optimal load for FET devices is a few Ohm, whereas the optimal load for GaN-based devices of this geometry is in the order of kOhm. Applying loads close to the edge of the Smith chart is a challenging task for metrology. In our set-up we combined passive and active loadpull. A passive tuner was used to apply a high load, and excursions from this position were realised using active injection. By automatically varying the amplitude and phase of the injection signal, we realised a range of 180 different loads, as represented on the Smith chart of Fig. 1.

At all these load conditions and at a fixed fundamental frequency (2.4 GHz), DC bias (V_{gsDC}= -0.6 V, V_{dsDC}= 25 V) and input power (14.5 dBm), the terminal voltages and currents of the device were measured using a Large-Signal Network Analyzer (LSNA) set-up [4]. The advantage of this instrument is that the four quantities (two terminal voltages and two terminal currents) are measured simultaneously, which implies that the phase relationships are conserved. This is important to be able to distinguish between current and charge contributions. The time-domain representation of these measured characteristics is the starting point for the behavioural modelling procedure, highlighted in the next Section.

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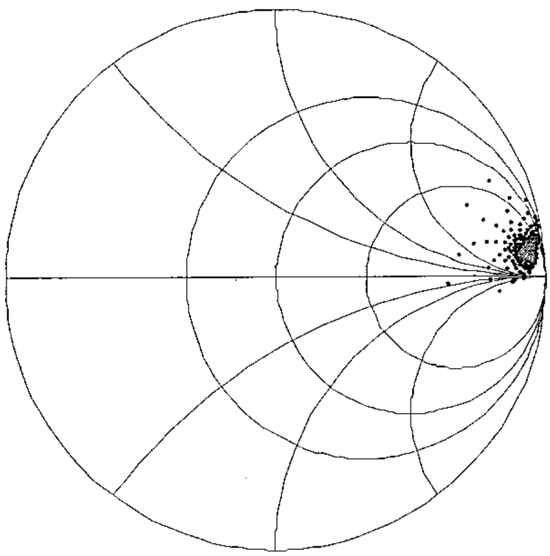

Fig. 1. Smith chart with overview of the 180 realised loads (denoted in dots).

III. Model Construction

A. Modelling Method

The basic principle of the modelling method [2] involves that the considered microwave two-port device can be described by equations of the form:

$$I_1(t) = f_1\left(V_1(t), V_2(t), \dot{V}_1(t), \dot{V}_2(t), \ddot{V}_1(t), \ddot{V}_2(t), \cdots, \dot{I}_1(t), \dot{I}_2(t), \cdots\right) \quad (1)$$
$$I_2(t) = f_2\left(V_1(t), V_2(t), \dot{V}_1(t), \dot{V}_2(t), \ddot{V}_1(t), \ddot{V}_2(t), \cdots, \dot{I}_1(t), \dot{I}_2(t), \cdots\right)$$

with $I_1(t)$ and $I_2(t)$ the terminal currents, $V_1(t)$ and $V_2(t)$ the terminal voltages, and the superscript dots representing the (higher order) time derivatives.

The objective of the modelling technique is to find the number of independent or state variables, and consequently to determine the functional relationships $f_1(.)$ and $f_2(.)$ by fitting the measured terminal currents to the state variables.

B. Modelling Procedure

The first step, as mentioned above, is collecting time-domain data at operating conditions that are realistic for the device use. The next step consists in determining the independent (or state) variables. Since we are considering a HEMT device, we can easily estimate that a good set of state variables be the terminal voltages, and the corresponding first and second order time derivatives. Otherwise, the 'embedding' technique, based on the 'false nearest neighbour' principle, can be executed to assess the necessary state variables [2,5].

To include the temperature dependency, we make use of the fact that the net dissipated power P_{net} is a good measure for the actual device temperature [6,7]. Therefore, we add P_{net} as 7th independent variable, and calculate it from: $P_{net} = P_{dc}*(1\text{-PAE})$ with PAE the power added efficiency.

Subsequently, the functional relationships $f_1(.)$ and $f_2(.)$ have to be determined. This is done by fitting the measured time-domain terminal currents towards the independent variables. The terminal voltages are measured, while the derived quantities, like the first and second order time derivatives, are calculated from the measurements. As fitting function, all types of analytical expressions are virtually possible. However, it can be advisable to bear the typical device characteristics in mind when selecting a particular analytical representation. For example, higher-order polynomials have exponential-like asymptotes, which might give cause to convergence problems. Therefore, we adopted the use of artificial neural networks (ANNs). The topology of the ANN is limited to one hidden layer, and the selected activation function is the sigmoid function due to its well-defined and smooth asymptotes. The ANN is initially trained using the back-propagation algorithm, and subsequently fine-tuned using the Newton-Raphson technique, as implemented in the NeuroModeler program, which is described in detail in Refs. [8]-[10].

IV. Modelling Results

A. ANN Model Results

We consider two alternatives: Model A is the model with 6 state variables included, whereas model B is the model with 6 + 1 ($=P_{net}$) state variables. The number of hidden neurons for both cases is 20. This number provides a good trade-off between model accuracy and complexity. The models have been trained using a set of 60 different load values, and have been tested by a different set of 60 loads.

Table I summarizes the test results, consisting of the average and maximal test errors for both currents. The table also lists the correlation coefficient, which is a measure for whether we selected the correct set of independent variables. The error levels are low, and the high correlation denotes that we have a good set of independent variables. We notice only a marginal improvement in terms of both correlation and test errors when P_{net} gets included. We will separately come back to this in the next Subsection.

Next, we implement the time-domain behavioural models in the ADS microwave circuit simulator by means of a symbolically defined device (SDD). The SDD allows the calculation of the (higher order) time derivatives of the terminal voltages during the simulation, enabling the evaluation of the expressions for the currents.

Fig. 2 shows the variation of the output power as function of the index number of the applied loads. Simulations were carried out at exactly the same excitation conditions as the measurements. We observe that the simulations are well capable to predict the correct output power.

Since the loads are varied automatically around a realistic start load, set by the passive tuner, the optimal load condition for maximal output power can straightforwardly be determined. Fig. 3 compares the measured and simulated time-domain waveforms of the terminal currents for the case of model B, at the optimal load condition. This load was not present in the training set of 60 loads. We notice that the modelling accuracy is excellent.

Table I: Overview of AlGaN/GaN HEMT results after training an ANN based on multi-load large-signal measurements. Model A is without and model B is with P_{net} included.

	Model A		Model B	
	I_1	I_2	I_1	I_2
correlation	0.9997		0.9998	
average error [%]	0.5	0.5	0.7	0.5
max. error [%]	5.5	4.0	4.4	2.9

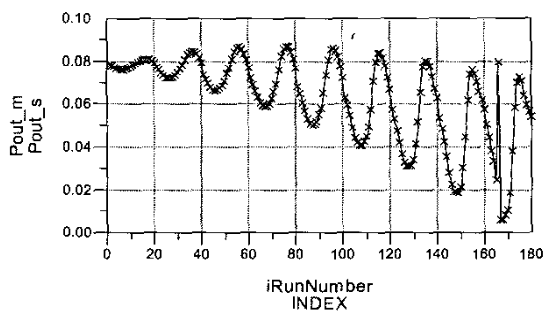

Fig. 2. Comparison of the measured (x) and modelled (solid line) output power [in W] as function of the index of the applied loads.

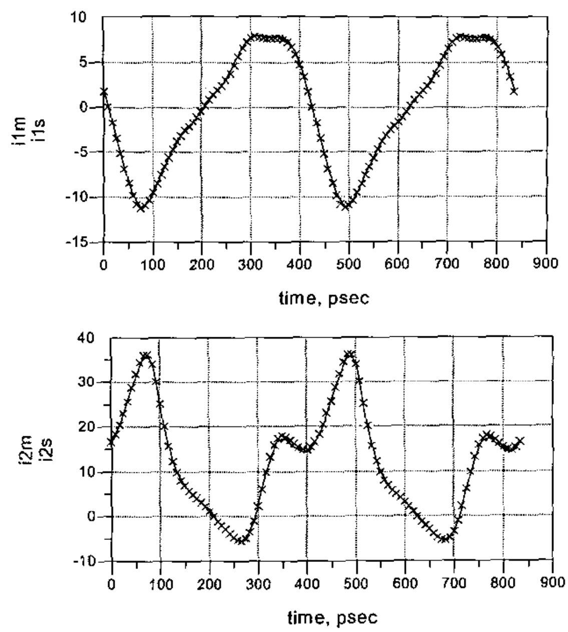

Fig. 3. Comparison of the measured (x) and modelled (solid line) terminal currents [in mA] at the optimal load condition Z_{load}=715+j522 Ohm.

B. Importance of P_{net}

We indicated above that including P_{net} as state variable has no significant influence on the model accuracy. The reason is that there are little DC current variations, and consequently P_{net} and temperature variations, within the considered training set, because the model is built from measurements at a fixed DC bias condition, and at load conditions that only occupy a small portion of the Smith chart. In this example, P_{net} varies between 195 mW and 310 mW.

To increase the variation in P_{net}, we also constructed a behavioural model from multi-bias large-signal measurements, as opposed to multi-load large-signal measurements. The device dimensions (1.5 µm x 100 µm) and the fundamental frequency (4 GHz) were slightly different in this case. Power-swept single-tone measurements were performed at gate voltages near V_T and near maximal g_m, and at drain voltages ranging between 2 V and 20 V, and this at three selected load conditions. After training the ANN, we found that the average errors decrease slightly (from 1.1% to 1.0% for I_1, and from 1.5% to 1.1% for I_2) when the self-heating effect is incorporated, although the variation in P_{net} is much higher (between 7.2 mV and 1.26 W). The limited effect of adding P_{net} to the model description is probably related to the fact that the considered device widths (100 µm) are very small in terms of high-power devices, and consequently that self-heating remains limited.

To illustrate that P_{net} can represent self-heating, we show in Table II the results of an ANN model for a 0.8 ∝m x 10 ∝m SiGe HBT [11], which is also a strong temperature dependent device. In this case as well, the training set was composed of a large range of DC biases and input powers. The corresponding P_{net} is ranging between 0 mW and 20 mW. From Table II, we notice a clear improvement in model accuracy in terms of both the average and maximum errors when adding a temperature-sensitive state variable.

Table II: Overview of SiGe HBT results after training an ANN based on multi-bias large-signal measurements. Model A is without and model B is with P_{net} included.

	Model A		Model B	
	I_1	I_2	I_1	I_2
correlation	0.9781		0.9998	
average error [%]	2.0	4.5	0.2	0.2
max. error [%]	32.6	58.8	2.7	2.9

V. Conclusion

A behavioural model for AlGaN/GaN HEMTs has been constructed from near-optimal-load time-domain large-signal measurements. We have shown that the artificial neural network representation gives accurate results when it gets evaluated at loads that were not part of the training set. The self-heating effect, although not essential for the considered device dimension, can be incorporated by an additional independent variable, being the net dissipated power. The resulting small ANN test error, and the excellent agreement with large-signal verification data show that this modelling approach is a valuable candidate to be used in actual power amplifier circuit design.

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