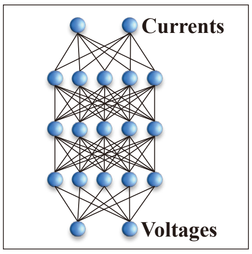

Deep Learning based Model for Millimeter Wave GaN HEMTs

Kenya NISHIGUCHI*, Takeshi KAWASAKI, and Masahiro TANOMURA

Millimeter-wave GaN HEMTs are expected to be used in higher-capacity wireless communications, but the large nonlinear components such as short-channel effects, have challenges in creating the large-signal models that are essential for amplifier fabrication. In this report, we have developed an innovative model that an artificial neural network (ANN) is applied only to the current source to avoid over-fitting issues. To create this model, pulsed I-Vs/S-parameters measurement data up to 120 GHz were used. The proposed model is the first to demonstrate large-signal power performances at 71 GHz in high accuracy.

Keywords: GaN HEMT, amplifier, neural network, model

1. Introduction

The millimeter-wave band is expected to be utilized for high-capacity communication systems and high-resolution radar systems because of its wide bandwidth and high frequency[(1)]. To realize millimeter-wave band applications, a highly accurate large-signal model for millimeter-wave GaN HEMTs is required.

For large-signal GaN HEMT models, compact models, such as the Angelov model[(2)] and the AMCAD model,[(3),(4)] have been commonly used. These models consist of lumped elements, such as current sources, resistors, inductances, and capacitances, with bias and frequency dependencies described by functions that can calculate DC, small-signal, and large-signal behaviors. However, it has been very difficult to represent the current-voltage (I-V) waveform of a millimeter-wave GaN HEMT as functions because the nonlinear waveform shows extraordinary complexity due to short-channel effects*[1] and other factors.

Recently, artificial neural network (ANN)-based models have attracted much attention as large-signal models that can represent such high nonlinearity.[(5)–(7)] ANN models have been applied to sub-6-band GaN HEMTs for base stations, and some studies report the representation of memory effects. However, it is difficult to apply an ANN to a millimeter-wave band model because measured data of millimeter wave S-parameters*[2] are unstable due to their low signal-to-noise ratio. It will cause an overfitting problem when the measured data is directly taken as the training data of deep learning.

In this work, we propose an ANN modeling flow optimum for millimeter-wave GaN HEMTs. We have developed an ANN model, in which only a current source with low noise effects represented by an ANN. Parasitic elements are extracted from the S-parameters at each bias point using small-signal equivalent circuits and represented by nonlinear functions to avoid noise effects. Resistances and inductances are extracted from the lumped elements of the data points near the load line.

This ANN model has successfully elaborated the I-V waveforms affected by the current collapse and short-channel effects, and the S-parameters in the millimeter-wave band.

2. Large-signal ANN Modeling

The proposed large-signal model for millimeter-wave GaN HEMTs is shown in Fig. 1. Capacitances (C_{gs}, C_{gd}, C_{ds}) were modeled by nonlinear functions, and only current sources in the center were modeled by an ANN. As shown in the modeling flow in Fig. 2, these models require the calculation of built-in potentials V_{gsi}, V_{gdi}, and V_{dsi}.[(8)]

This section is organized as follows: In section 2-1, the extraction of small-signal equivalent circuit parameters and calculation of built-in potentials are explained. In section 2-2, capacitance modeling is explained in detail. In section 2-3, current source modeling is explained, and ANN modeling performance is demonstrated and discussed.

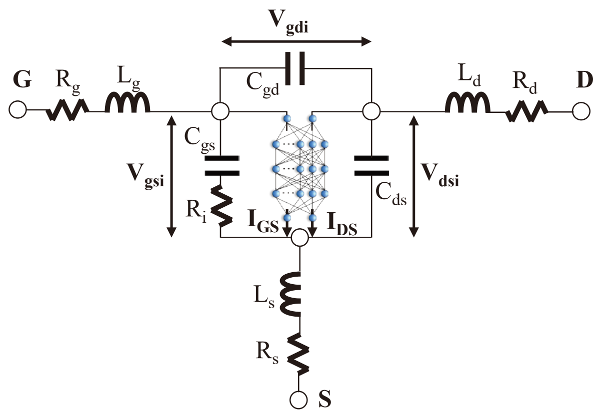

Fig. 1. Large-signal ANN model for millimeter-wave GaN HEMTs

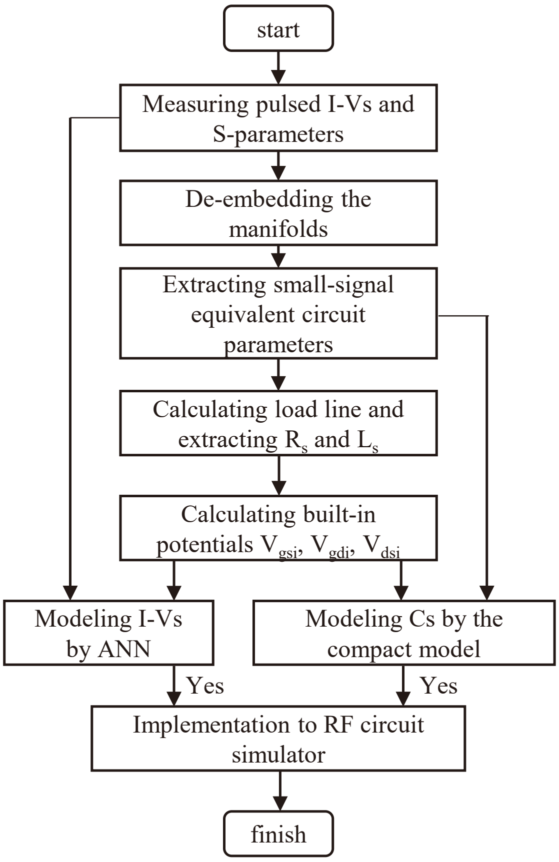

Fig. 2. Modeling flow of the ANN model

2-1 Small-signal parameters extraction and calculation of intrinsic potentials

The pulsed I-Vs and S-parameters (1–120 GHz) were measured. After manifolds*3 were de-embedded from the measurements, parameters of the small-signal equivalent circuit were extracted using the small-signal model at all the bias points shown in Fig. 3. To determine each resistance (R_g, R_s, R_d) and inductance (L_g, L_s, L_d), a load line with a maximum output power from the I-V waveforms was assumed by calculation, and parameters at the bias points near the load line were extracted. In addition, the median values of (R_g, R_s, R_d) and (L_g, L_s, L_d) at the extracted bias points were used for the ANN model. This method provides highly accurate results for large-signal calculations. The built-in potentials are expressed as follows:

$$V_{dsi} = V_{DS} - I_{DS} * (R_s + R_d) - I_{GS} * R_s \quad \cdots\cdots\cdots\cdots (1)$$

$$V_{gsi} = V_{GS} - I_{DS} * R_s - I_{GS} * (R_g + R_s) \quad \cdots\cdots\cdots\cdots (2)$$

$$V_{gdi} = -(V_{DS} - V_{GS} - I_{DS} * R_d). \quad \cdots\cdots\cdots\cdots\cdots\cdots (3)$$

2-2 Capacitance modeling

Bias-dependent parameters for each capacitance (C_{gs} vs V_{gsi}, C_{gd} vs V_{gdi}, and C_{ds} vs V_{dsi}) are used as follows:

$$A = C_0 + (C_1 - C_0) * \frac{(1+\tanh(a*(V_i+V_m)))}{2} \quad \cdots\cdots\cdots\cdots (4)$$

$$C_{model} = A - C_2 * \frac{\left(1+\tanh\left(b*\left(V_i+V_p\right)\right)\right)}{2} \quad \cdots\cdots (5)$$

where C_0, C_1, C_2, V_m, and V_p are the fitting parameters and V_i is the built-in potential for each C.(3),(4) The error function is defined as follows:

$$\varepsilon = \sum_{k=1}^{N} \frac{|C_{meas} - C_{sim}|}{C_{meas}} \quad \cdots\cdots\cdots\cdots\cdots\cdots (6)$$

where C_{meas} and C_{sim} are the measured C and simulated C respectively, and N is the total number of data points.

2-3 ANN current source modeling

To model the current source, a fully connected ANN with three hidden layers as shown in Fig. 4 was trained with I-V waveforms. The sigmoid function was selected as an activation function.

$$\sigma(x) = \frac{1}{1+e^{-x}}. \quad \cdots\cdots\cdots\cdots\cdots\cdots (7)$$

Training was performed using TensorFlow,*4 and the optimization method was based on the optimization function ADAM*5 provided by TensorFlow.

Figure 5 shows the I-V waveforms measured and simulated by the ANN and compact models. The ANN model fully represents the measured I_{DS} waveforms. In

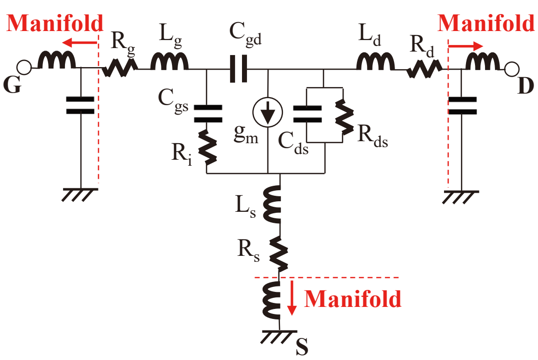

Fig. 3. Small-signal model for GaN HEMTs

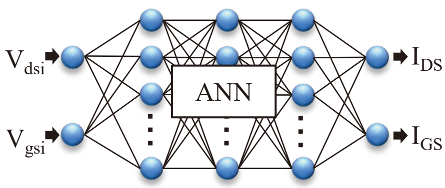

Fig. 4. ANN for I-V waveforms

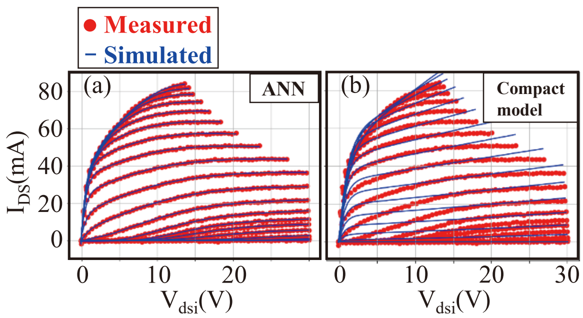

Fig. 5. I-V waveforms of (a) ANN model and (b) Compact model

contrast, the conventional compact model has large deviations from the measured values. These results indicate the powerful modeling ability of an ANN.

3. ANN Model Verification

The millimeter-wave GaN amplifier fabricated to verify the calculation accuracy of the ANN model is shown in Photo 1. The amplifier consists of a GaN HEMT, an input matching network, and an output matching network.

The developed model was implemented using Verilog-A*[6] in an RF circuit simulator (ADS*[7]). Figure 6 shows a comparison between the measured and simulated DC/S- parameters. The waveforms of I_{DS}-V_{DS} and I_{GS}-V_{DS}, and small-signal characteristics over a wide frequency range of 1–120 GHz were well modeled.

Figure 7 (a) shows the large-signal characteristics of the 71 GHz amplifier at Z_{source} = 50 + 0j Ω and Z_{load} = 50 + 0j Ω. The measured and simulated values of output power P_{out}, transducer gain Gain, and power added efficiency PAE at 71 GHz agreed well. In addition, Fig. 7 (b) shows the large-signal characteristics of the impedance-matched amplifier at Z_{source} = 117.2 + 38.4j Ω and Z_{load} = 51.2 + 28j Ω. The simulated values also agreed well with the measured values. These figures show that even with different impedances, the ANN model can calculate large-signal characteristics with high accuracy. Through the above-mentioned comparisons, it is shown that the ANN model can simulate the DC, S-parameters, and large-signal behaviors for millimeter-wave GaN HEMT performance with high accuracy.

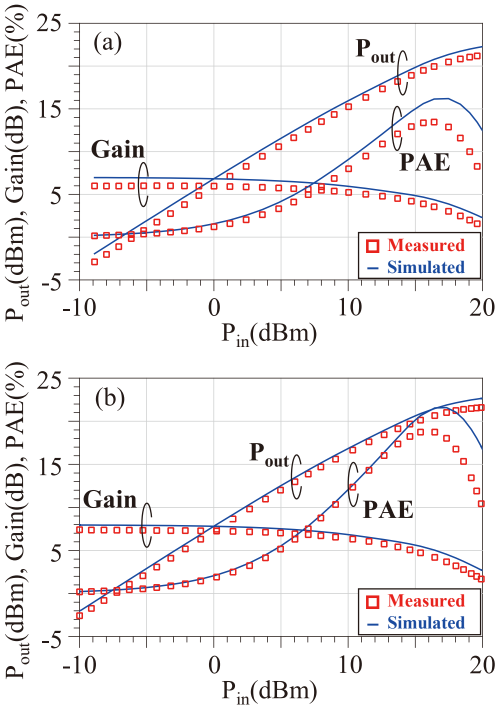

Fig. 7. Measured and ANN-simulated large signal performances for different impedances at 71 GHz. The impedances at (a) Z_{source} = 50 + 0j Ω and Z_{load} = 50 + 0j Ω, and (b) Z_{source} = 117.2 + 38.4j Ω and Z_{load} = 51.2 + 28j Ω

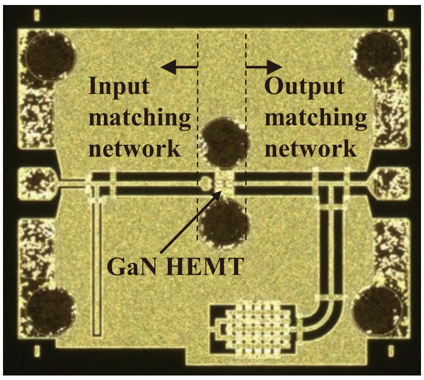

Photo 1. Millimeter-wave GaN amplifier

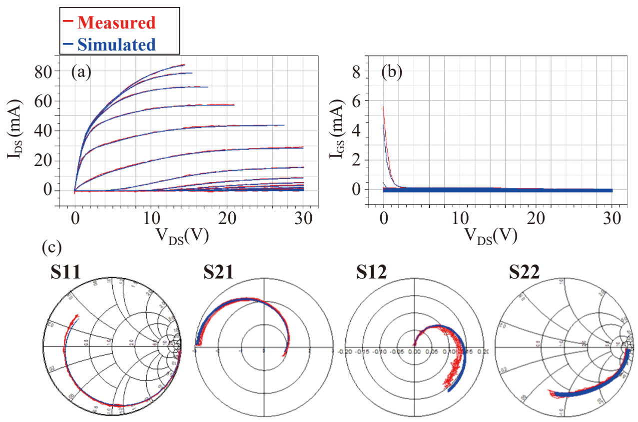

Fig. 6. Measured and ANN-simulated DC/S-parameters

4. Conclusion

We have developed the world's first large-signal model for millimeter-wave GaN HEMTs based on an ANN. To avoid overfitting problems, we applied an ANN only to the current sources of the compact model. Pulsed I-Vs/S-parameters measurement data up to 120 GHz were used to extract the parameters for the ANN.

The ANN has successfully modeled I-V waveforms with high accuracy, exceeding the performance of the conventional compact model. To verify the accuracy of the proposed modeling, we have implemented the ANN-based model in an RF circuit simulator using Verilog-A and found excellent agreement between the measured and calculated values of DC/small signal over a wide frequency range of 1–120 GHz. Furthermore, we have fabricated a 71 GHz amplifier and also found large-signal characteristics to be in good agreement. Since this model enables highly sophisticated high-frequency circuit design, we expect a higher performance of high-frequency amplifiers in the future.

Technical Terms

*1 Short-channel effects: A general term for the effects when the gate length is further reduced. Drain leakage current under the gate increases substantially.

*2 S-parameters (scattering parameters): A set of the circuit network parameters that describe the characteristics of high-frequency circuits.

*3 Manifold: A circuit (pad) that is used to evaluate HEMTs.

*4 TensorFlow: A Google-developed software library for machine learning. TensorFlow is a registered trademark of Google LLC.

*5 ADAM (adaptive moment): A kind of optimization algorithm.

*6 Verilog-A: A programming language that requires a compiler. Useful for modeling analog circuits.

*7 ADS (Advanced Design System): A circuit simulator developed by Keysight Technologies.

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