A Deep Learning Space Mapping Based Enhancement of Compact Models for Accurate Prediction of Trapping in GaN HEMTs from DC to mm-Wave Frequency

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***Abstract* — In this work, a deep learning space mapping technique has been developed to enable standard compact models to account for sporadic trapping effects in AlGaN/GaN high electron mobility transistors (HEMTs). In the proposed technique, an artificial neural network (ANN) is used to map the input feature space spanning the geometrical, material, bias, and trap-related parameters of a rigorous physics-based model (fine model) of the HEMT to the input feature space of a compact model (coarse model). Consequently, the space mapping augmented compact model is able to retain the high computational efficiency of the standard compact model while gaining the capacity to account for the effects of interface and bulk traps in the HEMT responses from DC to millimeter wave frequencies. In this work, the compact model considered is the industry standard advanced SPICE model for GaN HEMTs (ASM-HEMT).**

***Keywords* — Admittance parameters, artificial neural networks, bulk and interface traps, compact model, coarse model, fine model, deep learning, space mapping.**

I. Introduction

AlGaN/GaN high electron mobility transistors (HEMTs) play a vital role in modern wireless communication and radar systems because of their attractive properties such as high output power density in mm-wave frequency band, high chemical/mechanical/thermal stability, and high voltage withstanding capacity. GaN HEMTs are commonly used in numerous nonlinear radio frequency (RF) circuits, such as power amplifiers, mixers, and oscillators [1]. However, these devices exhibit strong trapping/de-trapping effects, which significantly degrade the circuit performance at mm-wave frequencies. Hence, there is an urgent need to develop accurate but efficient compact models that can capture the performance degradation of HEMT devices from DC all the way to mm-wave frequencies due to multiple traps in the different device locations (bulk traps and interface traps).

Unfortunately, standard physics-based compact models such as the Advanced SPICE Model for GaN HEMTs (ASM-HEMTs) and MIT virtual source GaN HEMT (MVSG) do not account for trapping effects in the device [2], [3]. In contrast, technology computer-aided design (TCAD) simulations effectively evaluate trapping/de-trapping effects over a vast trap variability albeit at massive computational time costs. Therefore, existing compact models are forced to iteratively tune their input parameters to best fit the GaN HEMT responses obtained from the TCAD simulations. In this way, the compact models can indirectly account for sporadic trapping/de-trapping effects. However, this approach is highly labor-intensive and time-consuming. In recent years, machine learning (ML) has emerged as a promising alternative in the fast quantification of electronic devices [4], [5]. Several reports have demonstrated that ML-based surrogate models can faithfully emulate the performance of intrinsic field effect transistor devices as analytic functions of the geometrical, physical, material, bias, and trap-related parameters [5].

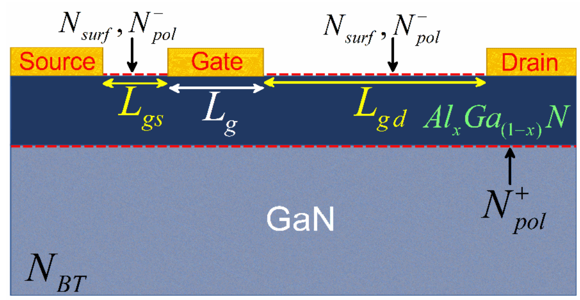

Fig. 1. Schematic of GaN HEMT with bulk and interface traps for DC and small signal Y-parameter analysis.

In this work, a deep learning space mapping technique is developed to incorporate TCAD-evaluated trapping/de-trapping effects of GaN HEMTs into any standard compact model framework. To that end, first, a TCAD model (fine model) is developed that is able to evaluate the effect of interface and bulk traps with different trap locations from the valance band (VB) and conduction band (CB). Such a capability is absent in standard compact models (e.g., the ASM-HEMT compact model). Thereafter, a space mapping artificial neural network (ANN) is used to map the geometrical, material, bias, and trap-related parameters or features of the fine model to the input parameter or features of the compact model (coarse model) [6], [7] such that the error between the device responses obtained from the fine and coarse models are minimized. Consequently, the space mapping augmented compact model will now be able to predict the advanced trap-related effects on the large signal current-voltage (I-V) characteristics and small signal admittance (Y) parameters of GaN HEMTs without compromising on their inherent computational efficiency. The proposed method is generic enough to be used for any compact model. It also does not require access to or altering the compact model in any way. All features, functionalities, and flexibility of the industry-standard compact model are retained, and this allows perfect backward compatibility.

II. Development of Deep Learning Space Mapping Augmented Compact Model

A. Problem Statement

Consider an AlGaN/GaN HEMT device as shown in Fig. 1 where bulk traps are present in the GaN buffer layer and interface traps are present at the passivation dielectric/AlGaN interface [8]. The performance of this HEMT device will be studied within an N-dimensional input parameter space where the variability in each of the N device parameters of interest (p_i) is expressed as

$$p_i = \left(\frac{p_{i,\min} + p_{i,\max}}{2}\right) + \left(\frac{p_{i,\max} - p_{i,\min}}{2}\right)\lambda_i; \quad 1 \le i \le N \tag{1}$$

In (1), [$p_{i,min}$, $p_{i,max}$] is the interval of support for the i-th parameter and λ_i is an uniformly distributed random variable lying the range [-1, 1]. Let the device terminal characteristics of interest be described as $X(\boldsymbol{\lambda})$ where X can refer to either DC large-signal characteristics or small-signal Y-parameters and $\boldsymbol{\lambda}$ = [λ_1, λ_2, …, λ_N]. Now, when predicting the device terminal characteristics, $X(\boldsymbol{\lambda})$, for different values of $\boldsymbol{\lambda}$ (i.e., different values of the device parameters), repeated rigorous physics-based simulations of a TCAD model (fine model) will be required at prohibitively high computational time costs.

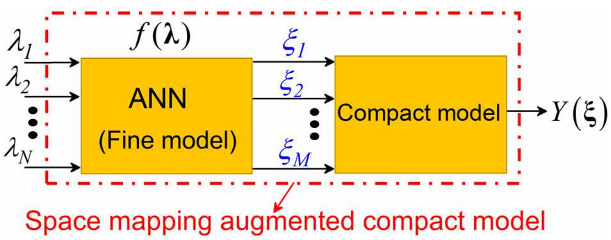

Fig. 2. Deep space mapping neural network augmented compact model.

B. Proposed Space Mapping Augmented Compact Model

In order to shrink the prohibitively high time costs of the fine model simulations, standard compact models (coarse models) such as the ASM-HEMT model can be used. The coarse models emulate the device terminal characteristics as analytic functions of the geometrical, material, and bias parameters [2]. Hence, the coarse models can predict the device terminal characteristics at significantly smaller time costs than the fine model. Let the parametric variability in the fine model of (1) be mirrored in the coarse model using M input parameters. These input parameters are described as

$$q_j = \left(\frac{q_{j,\min} + q_{j,\max}}{2}\right) + \left(\frac{q_{j,\max} - q_{j,\min}}{2}\right)\xi_j; \quad 1 \le j \le M \tag{2}$$

where [$q_{j,\min}$, $q_{j,\max}$] is the interval of support for the j-th parameter and ξ_j is the uniformly distributed random variable lying in the range [-1, 1]. The corresponding device terminal characteristics predicted by the coarse model is given as $Y(\boldsymbol{\xi})$ where $\boldsymbol{\xi}$ = [ξ_1, ξ_2, …, ξ_M]. The main limitation of existing coarse models is that they are unable to capture the sporadic trapping/de-trapping effects in HEMT devices at different locations and hence, lack the necessary level of model fidelity.

In this paper, a space mapping approach is proposed to incorporate the fine model-evaluated trapping/de-trapping effects of GaN HEMTs into the coarse model frameworks. The block diagram describing this approach is provided in Fig. 2. It is seen from Fig. 2 that there exists a nonlinear mapping from the input parameters of the fine model to that of the coarse model given as

$$\boldsymbol{\xi} = f(\boldsymbol{\lambda}) \tag{3}$$

The objective of the proposed space mapping approach is to identify the mapping function of (3) such that the error between the device terminal characteristics predicted by the coarse and fine models is minimized. In this paper, the mapping function of (3) is identified using a deep ANN, this ANN is referred to as the space mapping ANN.

Table 1. Fine model parameters for DC/small signal Y-parameter with uniform variability embedded within the GaN HEMT

Device Parameters	**Range**
N_{surf} (donor trap density at interface)	1.2×10^{13} cm^{-2} ± 10%
N_{BT} (acceptor trap density in GaN bulk)	5×10^{17} cm^{-3} ± 10%
$E_{D,trap}$ (donor trap level)	0.4 eV ± 10%
$E_{A,trap}$ (acceptor trap level)	0.4 eV ± 10%
x (Al mole fraction)	0.25 ± 10%
L_g (gate length)	0.7 µm ± 10%
L_{gs} (gate to source length)	0.7 µm ± 10%
L_{gd} (gate to drain length)	2 µm ± 10%
V_{gs} (gate to source voltage)	[-5 - 0] V
V_{ds} (drain to source voltage)	[0 - 10] V
Frequency	[0.5 - 50] GHz

C. Training the Space Mapping ANN

In order to train the deep space mapping ANN, a dataset consisting of K data points described as $\{\boldsymbol{\lambda}^{(k)}, X(\boldsymbol{\lambda}^{(k)})\}_{k=1}^{K}$ is used. In the dataset, $\boldsymbol{\lambda}^{(k)}$ = [$\lambda_1^{(k)}$, $\lambda_2^{(k)}$,…, $\lambda_N^{(k)}$] are the values of the input parameters to the fine model for the k-th data point. The result of the fine model for the k-th data point, $X(\boldsymbol{\lambda}^{(k)})$, is extracted from a TCAD simulation. Let the predicted output of the space mapping ANN for each data point, $\boldsymbol{\lambda}^{(k)}$ be equal to $z(\mathbf{w}, \mathbf{b}, \boldsymbol{\lambda}^{(k)})$ where $(\mathbf{w}, \mathbf{b})$ are the set of weights and bias terms in the ANN. The loss function of the ANN is the mean square error between the results of the fine and coarse models at the training data points expressed as

$$F_{loss} = \frac{1}{K}\sum_{k=1}^{K}\left(X(\boldsymbol{\lambda}^{(k)}) - Y(z(\mathbf{w}, \mathbf{b}, \boldsymbol{\lambda}^{(k)}))\right)^2 \tag{5}$$

Next, the space mapping ANN will tune the set of weights and bias terms $(\mathbf{w}, \mathbf{b})$ to solve the optimization problem

$$\left(\mathbf{w},\mathbf{b}\right)_{opt} = \underset{\mathbf{w},\mathbf{b}\in\Re}{\arg\min} \frac{1}{K}\sum_{k=1}^{K}\left(X(\boldsymbol{\lambda}^{(k)}) - Y(z(\mathbf{w},\mathbf{b},\boldsymbol{\lambda}^{(k)}))\right)^2 \quad (6)$$

Once the space mapping ANN is trained, the combination of this ANN and the compact model of Fig. 2 forms the space mapping augmented compact model. The value of this augmented compact model is that it can emulate the device terminal characteristics obtained from the fine model in the presence of advanced trapping/de-trapping effects with minimal computational overheads.

Table 2. Coarse model parameters for DC/small signal Y-parameter with uniform variability embedded within the device

Device Parameters	**Range**
V_{OFF} (cut-off voltage)	-3 V ± 10%
U_0 (low field mobility)	2.5 m^2/V-s ± 10%
V_{SAT} (saturation velocity)	112760 m/s ± 10%
$V_{satacces}$ (saturation velocity for access region)	406610 cm/s ± 10%
η_0 (DIBL parameter)	2.08 ± 10%
N_{FACTOR} (subthreshold slope factor)	4.75 ± 10%
THESAT (velocity saturation parameter)	5.93 V^{-2} ± 10%
L_g (gate length)	0.7 μm ± 10%
L_{gs} (gate to source length)	0.7 μm ± 10%
L_{gd} (gate to drain length)	2 μm ± 10%
V_{gs} (gate to source voltage)	[-5 - 0] V
V_{ds} (drain to source voltage)	[0 - 10] V
Frequency	[0.5 - 50] GHz

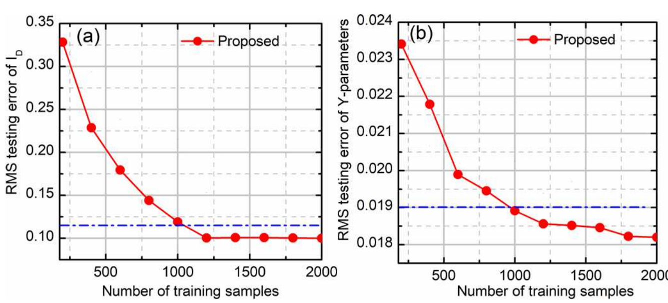

Fig. 3. RMS testing error decay with increasing number of training points for (a) drain current, and (b) Y-parameters which is averaged across all Y-parameters.

III. Results and Discussion

In this section, the AlGaN/GaN HEMT structure of Fig. 1 is considered. The variability in the input parameter space for fine and coarse models is provided in Table 1 and 2 respectively. The device terminal characteristics of interest are the DC I-V characteristics and small signal Y- parameters in the bandwidth [0.5-50] GHz. For accuracy analysis, the above device characteristics are predicted by the fine model (Sentaurus TCAD), coarse model (ASM-HEMT), and the proposed space mapping augmented coarse model described in Section II.

The proposed space mapping ANN uses a training dataset of K = {200, 400, 600, 800, 1000, 1200, 1400, 1600} Latin hypercube sampling points and a common testing dataset of 1000 points. Moreover, it uses three hidden layers of 100 neurons each, the Adam optimizer, and the ReLU activation function for training. The decay of the root mean square (RMS) testing error for the drain current (I_D) using proposed approach with the increasing number of training points is shown in Fig. 3 (a). A total of 1015 training points and 200 epochs are required to achieve a prescribed testing error tolerance of 0.12, as observed in Fig 3(a). The predictive accuracy of the space mapping augmented compact model compared to that of the standard compact model is illustrated using the scatter plot of Fig. 4(a). Fig. 4(a) also clearly demonstrates the inaccuracy in the standard coarse model arising from its inability to account for the bulk and interface traps. For further accuracy analysis, the variation of drain current with drain-to-source voltage (V_{ds}) and the gate-to-source voltage (V_{gs}) at different points in the input parameter space using all three models of above is displayed in Fig. 5.

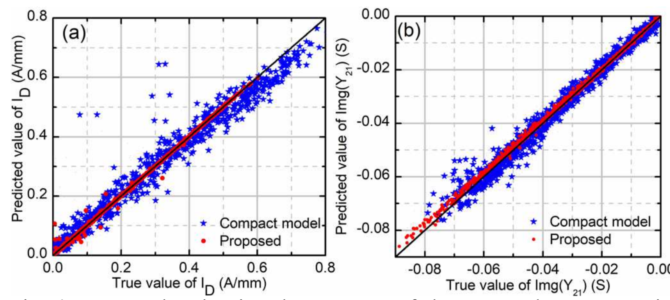

Fig. 4. Scatter plot showing the accuracy of the proposed space mapping augmented compact model and the standard compact model (a) drain current using 1015 training samples (b) imaginary part of Y_{21} using 985 training samples at 1000 testing points.

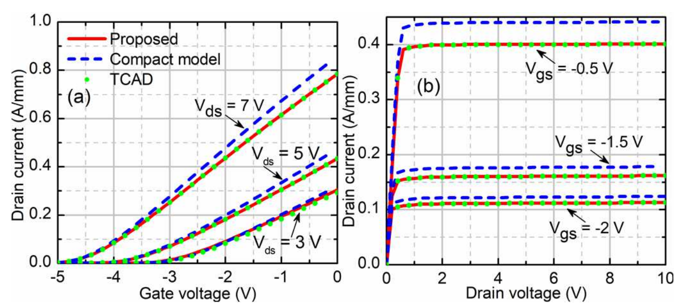

Fig. 5. Validation of drain current (I_D) with respect to (a) gate voltage (V_G), and (b) drain voltage (V_D) for TCAD, compact model, and proposed approach evaluated at distinct input space.

For the device Y-parameters, the same space mapping ANN architecture and training approach as above is used with the only difference being that frequency is now an added input. The decay of the RMS testing error averaged across all Y-parameters for the proposed approach with the increasing number of training points is shown in Fig. 3(b). It is noted

Table 3. The incurred computational cost for device terminal performance

Models	**RMS error w.r.t. TCAD**		**Standard deviation of error w.r.t. TCAD**		**Execution time (Time for a single device characteristic evaluation)**	**Speedup w.r.t. TCAD**
	I_D	Y-parameter	I_D	Y-parameter		
TCAD	-	-	-	-	180 sec	-
Compact model	0.2518	0.2548	12.7 x 10^{-3}	2.1 x 10^{-3}	4 msec	45,000
Proposed	0.1806	0.1287	8.4 x 10^{-3}	0.9 x 10^{-3}	5.3 msec	33,962

from Fig. 3(b) that a total of 985 training points and 200 epochs are sufficient to achieve a prescribed testing error tolerance of 0.019. The predictive accuracy of the space mapping augmented compact model compared to that of the standard compact model is illustrated using the scatter plot of Fig. 4(b). Finally, in Fig. 6, the variation of the small signal admittance parameters Y_{11} and Y_{21} with frequency for different points in the input parameter space using all three models above is displayed. It is clear from Fig. 6 that the proposed space mapping augmented coarse model is able to match the accuracy of the fine model even though the standard coarse model cannot.

Finally, in Table 3, the incurred time cost of all the three models of above for predicting the device terminal characteristics is recorded. It is concluded from Table 3, and Figs. 3-6, that the proposed space mapping augmented compact model retains the high computational efficiency of the standard coarse model while matching the accuracy of the fine model. In fact, the proposed space mapping augmented compact model adds a miniscule 1.3 milliseconds to the execution time of the standard compact model while substantially the accuracy is improved significantly by using the proposed approach. In effect, the space mapping augmented coarse model can include the effects of the bulk and interface traps at virtually negligible run-time costs. Of course, training the space mapping ANN requires additional time cost. However, this cost is a one-time cost unlike the fine model where the time cost is multiplied by the number of observation points in the input parametric space (usually in the order of thousands).

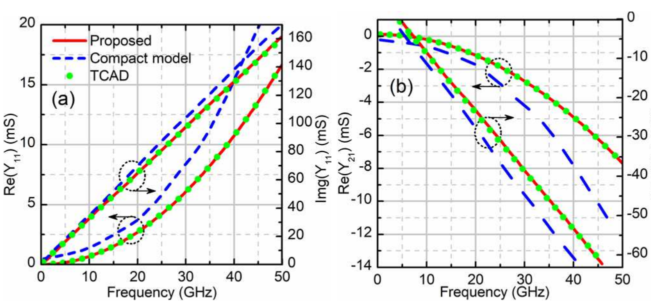

Fig. 6. Validation of small-signal admittance parameters (a) Y_{11}, and (b) Y_{21} for TCAD, compact model, and proposed method.

IV. Conclusion

In this paper, a deep learning space mapping technique is developed to enhance the capabilities of standard compact models (e.g., the ASM-HEMT model) to accurately predict the effects of bulk and interface traps on the device terminal characteristics. In particular, a space mapping ANN is combined with the compact model to ensure that by simply pre-processing the input parameter space of the compact model, it will be able to match the accuracy of a rigorous physics-based fine model when considering advanced trapping/de-trapping effects in GaN HEMTS at minimal loss of computational efficiency.

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