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A Physics-Informed Deep Learning Framework for Performance Optimization of AlGaN/GaN HEMTs in High-Frequency RF Applications

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Abstract

AlGaN/GaN High Electron Mobility Transistors (HEMTs) are essential for high-frequency RF applications. However, designing HEMTs is difficult due to the complexity of the physical relationship between internal charges, device geometry, and reliability. The available standard simulation tools (TCAD) are accurate; however, they are too slow for testing thousands of design variations. In this study, we developed a Physics-Informed Neural Network (PINN) architecture to speed up this process. Initially, a reliable dataset is developed using calibrated TCAD simulations. During the training period, Poisson's equation residuals and the charge conversions were used. It generates consistent predictions of transconductance, breakdown voltage, cut-off frequency, and drain current. The proposed framework achieves a low prediction error and a significant reduction in the computational cost.

Keywords: AlGaN HEMT; Physics-Informed Neural Network (PINN); Wide Bandgap Semiconductors; TCAD.

How to Cite This Article

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Introduction

AlGaN/GaN High Electron Mobility Transistors (HEMTs) are used as key components in high-frequency and high-power RF applications. Their unique properties: wide bandgap, high breakdown field, and excellent electron transfer properties make it more suitable for such applications [1], [3], [6]. The polarization at the AlGaN/GaN heterointerface forms a Two-Dimensional Electron Gas (2DEG). It enables a high carrier density and current flow without traditional doping. It minimizes the channel resistance [2], [9].

However, performance optimization of such devices remains a challenging task. The designer needs to navigate a strong coupling of polarization electrostatics, gate geometry, and interface traps. Reliability in high-power applications can also be degraded due to gate instability and trapping effects [4], [5]. Improving one metric degrades the other. So, there is always a trade-off between the parameters.

Generally, Technology Computer-Aided Design (TCAD) is used for optimization. However, TCAD requires heavy computational power and a time-consuming nonlinear solver. The use of machine learning improves the speed, but the predictions are unrealistic [7], [8].

This work proposes a Physics-Informed Neural Network (PINN) architecture to bridge the gap between speed and accuracy. The charge conservation and electrostatic constraints are embedded into the loss function. This approach generates rapid predictions and steady performance. It simultaneously balances RF performance and reliability for next-generation GaN devices.

Device Physics Background

The AlGaN/GaN heterostructure is shown in Figure 1. A thin layer of AlGaN is grown on the top of GaN. The structural differences between these two layers generate spontaneous and piezoelectric polarization. It develops a fixed charge at the interface of two materials. This fixed charge creates a strong electric field that attracts electrons towards the interface. This process forms a dense sheet of electron charge, called the Two-Dimensional Electron Gas (2DEG).

Mathematically, polarization charge density is,

$$\sigma_{pol} = P_{AlGaN} - P_{GaN} + P_{pe} \qquad (1)$$

Where:
P_{AlGaN}= Spontaneous polarization of the AlGaN layer
P_{GaN}= Spontaneous polarization of the GaN layer
P_{pe}= Piezoelectric polarization
The 2DEG density is approximately expressed as,

$$n_{2DEG} = \frac{\sigma_{pol} - \sigma_{surf}}{q} \qquad (2)$$

Where:
σ_{pol}= Net polarization sheet charge density
σ_{surf}= Surface charge density due to traps
q= Electron charge
The trapping of electrons and their motion are determined by polarization and hot electron dynamics.

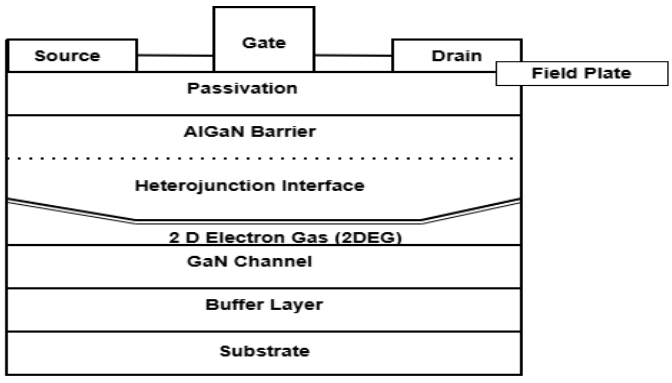

Fig. 1. *AlGaN/GaN Heterostructure*

RF Performance Metrics
Different metrics are used to evaluate the HEMT's capabilities.

- Drain Current (I_D) and Transconductance (g_m): Gate control of the channel.

- Breakdown Voltage (V_{BR}): Maximum power capacity of the device.
- Maximum Oscillation Frequency (f_{max}) and Noise Figure (NF): RF front-end applications.
- Cut-off Frequency (f_T): Intrinsic speed of the device.

It is expressed as,

$$f_T = \frac{g_m}{2\pi C_{gs}} \qquad (3)$$

Where:
g_m= Transconductance
C_{gs}= Gate-Source Capacitance

All these metrics are influenced by barrier composition, gate-length scaling, and interface trap density. However, the most dominant factor is the internal electric field profile. This parameter should be managed properly because crowding at the gate terminal degrades the breakdown reliability.

Methodology

This section describes the modelling for AlGaN/GaN HEMTs. It bridges the gap between physical simulation and optimization. Initially, a representative data set is generated by establishing a physics-based TCAD simulation environment. It reflects the structural and material variables. This data is used to train the Physics-Informed Neural Network (PINN).

TCAD-Based Device Modeling and Dataset Generation
A data set to capture the electrostatics and transport behaviour of AlGaN/GaN HEMTs was generated using 2D Technology Computer-Aided Design (TCAD). The drift-diffusion framework was used to perform the simulation. To calculate 2DEG sheet density, we integrated spontaneous and piezoelectric charge models at the interface. To model the carrier transportation, the field-dependent mobility model was used. The breakdown effect was predicted using the impact ionization model.

The Shockley–Read–Hall recombination and trap-assisted processes were incorporated to account for the interface and buffer trapping phenomena. To ensure the model is generalized for different designs, some primary parameters were varied across practical ranges for RF GaN technology, as shown in Table I.

Table 1. *Explored Parameter Space*

Parameter	**Symbol**	**Range**
Al Mole Fraction	x	0.15 – 0.35
AlGaN Barrier Thickness	tbar	15 – 30 nm
Gate Length	Lg	100 – 500 nm
Interface Trap Density	Dit	10^{11} – 10^{13} cm^{-2}

For each parameter combination, DC and small-signal simulations were performed to extract electrical and RF performance metrics. The dataset includes:

- Transfer and output characteristics
- Transconductance
- Cutoff frequency
- Breakdown voltage
- Peak electric field distribution.

Physics-Informed Neural Network Architecture

Standard machine learning methods have accelerated the semiconductor modeling process [7], [8]. However, due to the black-box approach, unrealistic results are generated. The Physics-Informed Neural Network (PINN) addresses these limitations. This network analyzes both the physical design of HEMT and its operating environments. Input to the network is expressed as a vector,

$$X = [x_{Al}, t_{AlGaN}, L_g, D_{it}, V_{GS}, V_{DS}] \qquad (4)$$

Where:
x_{Al}= Al mole fraction
t_{bar}= Barrier thickness

L_g= Gate length
D_{it}= Trap density
$V_{GS}$and V_{DS}= Applied gate and drain voltages
It allows the model to account for the following parameters. The model predicts performance parameters using these inputs. It is expressed as vector Y.

$$Y = [I_D, g_m, V_{BR}, f_T] \qquad (5)$$

To ensure the consistency of predictions, the training of the model is guided by the loss function:

$$L = L_{data} + \lambda_1 L_{Poisson} + \lambda_2 L_{charge} \qquad (6)$$

L_{data}represents the accuracy term. It minimizes the gap between the predictions and calibrated TCAD results.

$L_{Poisson}$ensures the output consistency of the model with Poisson's equation.

$L_{charge}$is the conservation constraint. It maintains the principle of charge conservation.

Automatic differentiation is used to calculate the physical residues during the training phase. It allows the network to self-correct based on the physical constraints.

Multi-Objective Optimization
We have found that the trained PINN replaces a traditional TCAD. The model performs predictions across thousands of design variations in seconds. This speed enables a true multi-objective optimization performance. But when the speed is improved, power handling is compromised.

To obtain a balanced trade-off between competing objectives, multi-objective optimization is used. The following objectives are considered:

Maximize: Cut-off frequency and breakdown voltage.

Minimize: Peak electric field in the device and noise figure.

The trained PINN model evaluates all these objectives at once. It generates a set of optimal solutions, called Petro Front. Each point in this front represents an optimal design. Many structural parameters are varied. It includes a variation in Al composition, barrier thickness, and gate length.

The device-level techniques are used to move the high electric field away from the gate terminal. This technique improves the breakdown reliability without affecting the high-frequency gain of the device [3], [11].

Results And Discussion

The performance of the proposed framework was validated against high-fidelity TCAD simulation data. This section evaluates the model's accuracy and provides the key design trade-offs.

Model Accuracy and Generalization
Figure 2 shows the comparison of PINN accuracy. The predicted results show consistency with TCAD data. The error in the drain current prediction remains below 2.5%, 3.5% for cut-off frequency, and less than 3% in breakdown voltage prediction. The proposed network maintains accuracy under unseen bias conditions.

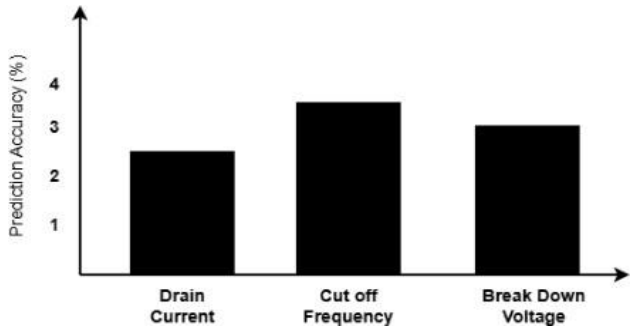

Fig. 2. *PINN Model Accuracy Across Key Metrics*

Figure 3 shows the extrapolation behaviour of the proposed model compared with the conventional neural network (conventional NN). The PINN maintains the agreement with the TCAD results even after the training period. However, the conventional NN shows deviation in the extrapolation region.

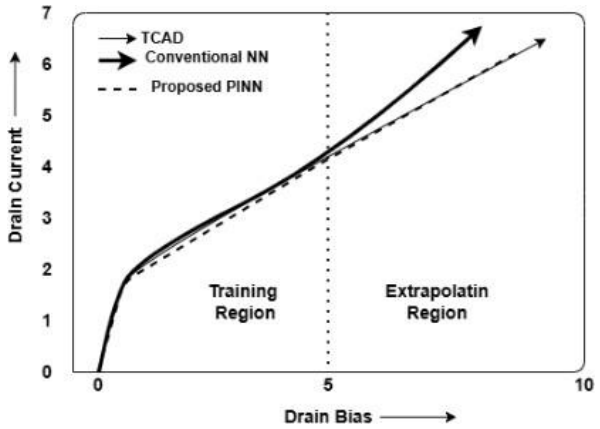

Fig. 3. *Extrapolation Behaviour of the PINN Model*

Optimization Insights

The optimization study reveals the effect of different design parameters on the device performance. An increase in the value of the Al mole fraction improves 2DEG density. Table II provides a summary of design constraints.

Table 2. *Primary Design Constraints*

Design Parameter	Optimal Value	Physical Impact
Al Mole Fraction (x)	≤ 0.30	Prevents Vbr degradation at high 2-DEG density
Barrier Thickness	~ 22 nm	Optimizes the trade-off between transconductance and field stress
Field Plate / Passivation	Structural	Smooths field peaks to boost breakdown [3], [11]
Trap Management	Passivation	Minimizes dispersion necessary to maintain RF linearity [4]

Reliability And Thermal Considerations

During high-power operations, the parameters such as gate degradation, charge trapping, and self-heating are responsible for the device reliability [4], [5]. The traps exist at the surface or within the buffer layer. They capture the charge carriers, reducing the device stability.

A high electric field generates heat in the device. It reduces carrier mobility and affects threshold voltage [10]. Electric field distribution can be controlled by using field plate structures and surface passivation techniques. It helps to improve the breakdown behaviour and maintain long-term stability [3], [11].

Conclusion

The model was trained using the TCAD data set. The proposed model exhibits close correlation with TCAD simulations and requires less computational overhead. The model was used for multi-objective optimization. The optimization study reveals that different design parameters affect the device performance. The proposed work demonstrates a practical approach for designing high-performance GaN HEMTs.

References

1. Chen, J., et al., “Output and Transfer Characteristics Prediction of GaN HEMTs on Silicon Substrate for Low-Voltage Applications,” *IEEE Transactions on Electron Devices*, 2025.
2. Dastider, A. G., et al., “Physics-Based Full-Band Transport Simulation of GaN HEMTs and Intrinsic Performance Limits,” 2025.
3. Rahman, T., and Lenka, T. R., “Enhanced Breakdown and RF Performance in Field-Plated AlGaN/GaN HEMTs for High-Power Applications,” 2025.
4. Ajayan, J., et al., “Reliability Issues and Degradation Mechanisms of p-GaN Gated AlGaN/GaN Power HEMTs: A Review,” *IEEE Access*, 2025.
5. Jia, M., et al., “Low-Temperature Sputtered AlN Cap Layer p-GaN HEMTs with Improved Gate Reliability,” *Materials Science in Semiconductor Processing*, 2025.
6. Jia, M., et al., “NiNx-Gate p-GaN HEMTs with Improved Threshold Stability and Breakdown Voltage,” *Microelectronics Journal*, 2025.
7. Peng, Y., et al., “Automated Parameter Extraction and Modeling for RF GaN HEMTs Using Machine Learning,” 2025.

8. Wang, X., et al., “Neural-Network-Based Switching and Dynamic Current Modeling of GaN HEMTs,” *Micromachines*, 2025.
9. Lee, J., Bayram, C., and Leburton, J.-P., “High-Field Transport Dynamics in Wide-Bandgap GaN Materials,” *IEEE Transactions on Electron Devices*, 2024.
10. Tijent, F. Z., et al., “Thermal Performance Enhancement and Heat Dissipation Strategies in GaN HEMTs,” 2024.
11. Xiang, X., et al., “AI-Assisted Field-Plate Design Optimization in GaN HEMTs,” *Advanced Theory and Simulations*, 2024.
12. Wang, Z., et al., “Quantum and Machine Learning Approaches for Modeling GaN Ohmic Contacts,” 2024.
13. Jazaeri, F., et al., “Design-Oriented Compact Modeling Techniques for AlGaN/GaN HEMTs,” 2024.
14. Bai, R., et al., “Ga-Polar Recessed-Gate AlGaN/GaN HEMTs for Millimeter-Wave High-Power Operation,” 2025.
15. Kilin, M., and Yasar, F., “GaN-Based HEMT Architectures with Advanced Passivation for Improved Leakage Control,” 2025.