

A Hybrid Physical ASM-HEMT Model Using a Neural Network-Based Methodology

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Outline



- **Motivation**
- **Hybrid Physical Modeling**
- **Model Extraction Flow**
- **Model Validation**
- **Summary**

GaN Addresses High-Performance Needs



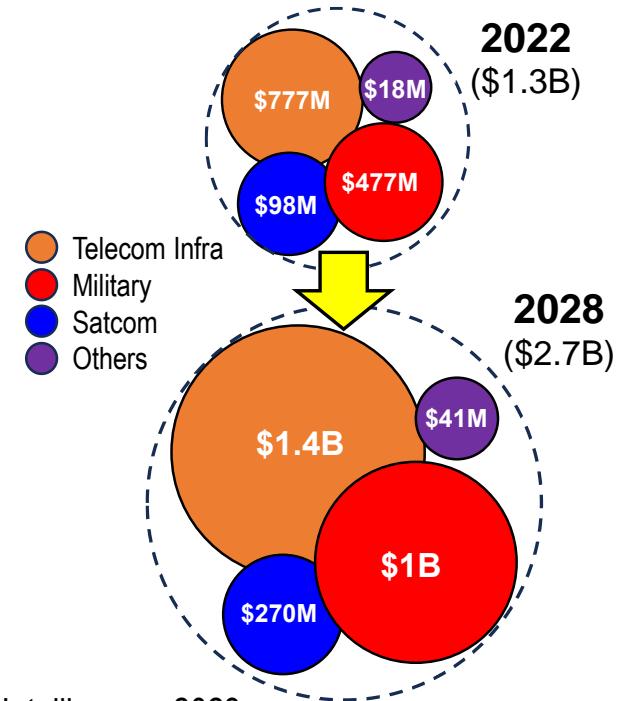
- GaN HEMTs provide high P_{out} & PAE at mm-wave frequencies

Properties of RF Semiconductors

Material Properties	Si	InP	GaAs	GaN
Bandgap, E_g (eV)	1.12	1.34	1.42	3.49
Critical Breakdown Field, E_{crit} (MV/cm)	0.3	0.5	0.4	3.3
Mobility, μ ($cm^2/V \cdot s$)	1500	5400	8500	2000*
Peak Saturation Velocity, v_{sat} ($\times 10^7$ cm/s)	1	3.3	2.0	2.5
2DEG Density, n_s ($\times 10^{13}$ cm^{-2})	N/A	0.3	0.2	> 1.5
Thermal Conductivity, k (W/cm·K)	1.3	0.7	0.5	2
Dielectric Constant, ϵ_s	11.7	12.5	12.9	9.5
Johnson FoM Relative to Si ($E_{crit} \cdot v_{sat} / 2\pi$)	1	5.8	2.7	28

*2DEG Mobility

RF GaN Market Forecast



Yole Intelligence, 2023

Measurement vs. Physics-Based Models



- Two prevalent modeling schemes at opposite ends of the spectrum
- Various trade-offs: None satisfy a modeling engineer's [ideal wish list](#) 😞

Key Features	Measurement-Based	Physics-Based
CMC approved	X	✓
Good physical behavior outside extraction range	X	✓
Geometry Scalable	~	✓
Fast extraction / training time	~	~
Early availability during process development	✓	X
Does not require process information	✓	X
One-size-fit-all modeling solution	✓	X

Hybrid Physical Modeling Methodology



Physical Model

- Captures basic device physics
- Show good physical responses when simulated beyond the measurement range

ANN Model

- Early availability during process development
- Can fit complex nonlinear measured data
- Short model development time for new technologies

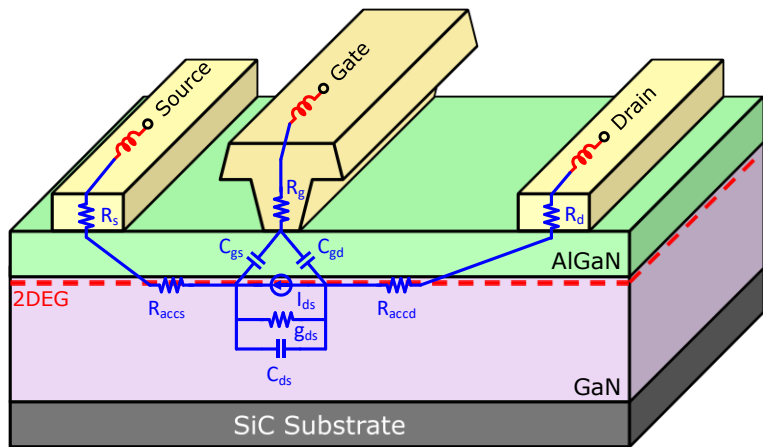
Hybrid Model:

- Combine physical model with neural networks
- Maintains physics with increased accuracy

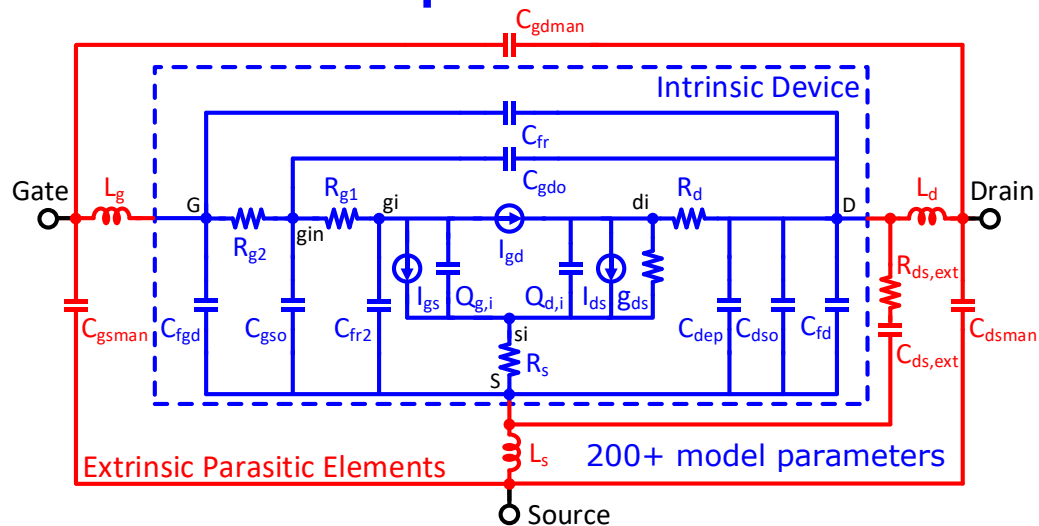
The Advanced SPICE Model for HEMTs

- **ASM-HEMT:** Surface-potential-based physical compact model
- **Model effectively captures a range of device non-idealities:**
 - Self-heating, mobility degradation, DIBL, velocity saturation, trapping, etc.

GaN Device Cross-Section



ASM-HEMT Equivalent Circuit Model

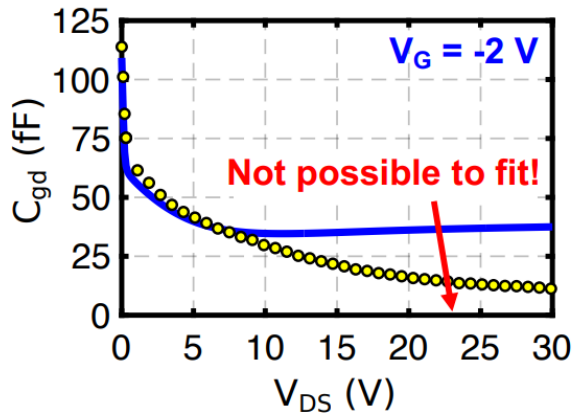


Model Limitations for C-V Characteristics

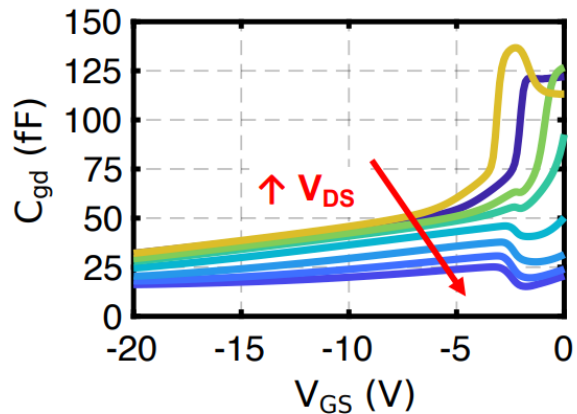


- Problem:** ASM-HEMT fails to capture CV non-linearities of the device
 - Unable to fit measured CV curves using various approaches
- Most results in the literature only show fitting at one V_D bias point**
 - Nonlinear behavior in HEMTs isn't modeled properly (in most models)

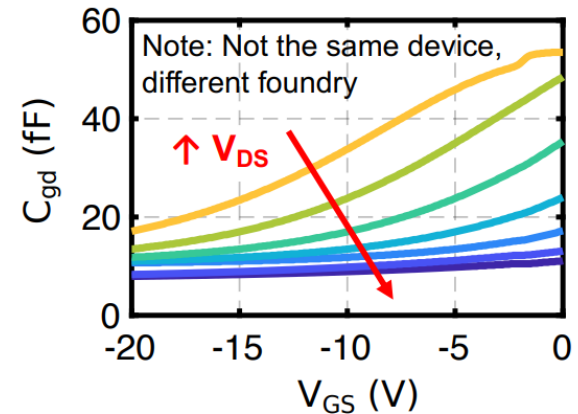
ASM-HEMT Model



C_{GD} Measured Data



Foundry Model Simulation



Modifying the Gate Charge Framework



- Overlap capacitances are treated as **constant** capacitances
- C_{gs}/C_{gd} formulation **insufficient** to model V_{DS} -dependent non-linearities
- **Hybrid**: We **compensate** for unmodeled nonlinear physical behavior by incorporating additional model parameters into ASM-HEMT framework

Hybrid ASM-HEMT Gate Charge Formulation

Intrinsic

Overlap

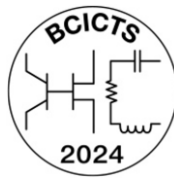
Fringe

$$Q_G = Q_{gi} + \int C_{gso} dV_{GS} + \int C_{gdo} dV_{GD} + Q_{fr} + \int C_{fgd} dV_{GS} + \int C_{gs,NN} dV_{GS} + \int C_{gd,NN} dV_{GD}$$

“Compensating” (Uses a Neural Network)

Implemented through Verilog-A

Modifying the Drain Charge Framework



- Overlap capacitances are treated as **constant** capacitances
- C_{ds} formulation **insufficient** to model V_{DS} -dependent non-linearities
- **Hybrid**: We **compensate** for unmodeled nonlinear physical behavior by incorporating additional model parameters into ASM-HEMT framework

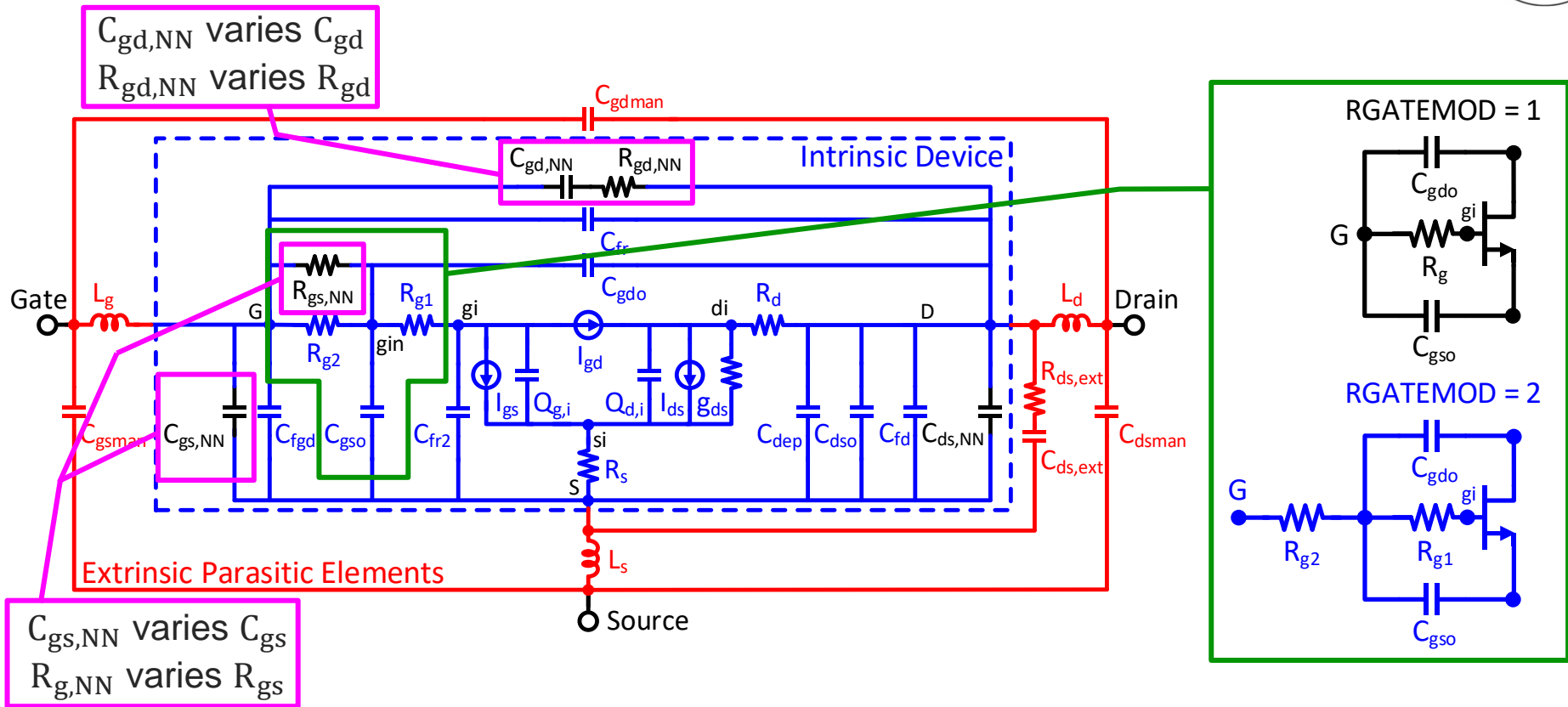
Hybrid ASM-HEMT Drain Charge Formulation

$$Q_D = \underbrace{Q_{di}}_{\text{Intrinsic}} + \underbrace{\int C_{dso} dV_{DS}}_{\text{Overlap}} + \underbrace{Q_{dep}}_{\text{Depletion}} + \underbrace{\int C_{fd} dV_{DS}}_{\text{Fringe}} + \underbrace{\int C_{ds,NN} dV_{DS}}_{\text{“Compensating”}}$$

(Uses a Neural Network)

Implemented through Verilog-A

Hybrid ASM-HEMT Model Equivalent Circuit

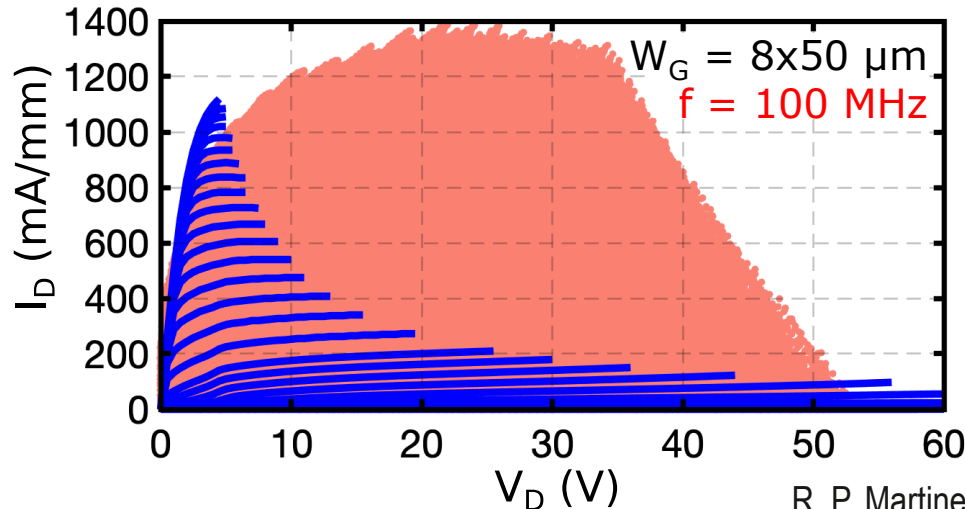


Modeling a 150-nm GaN HEMT

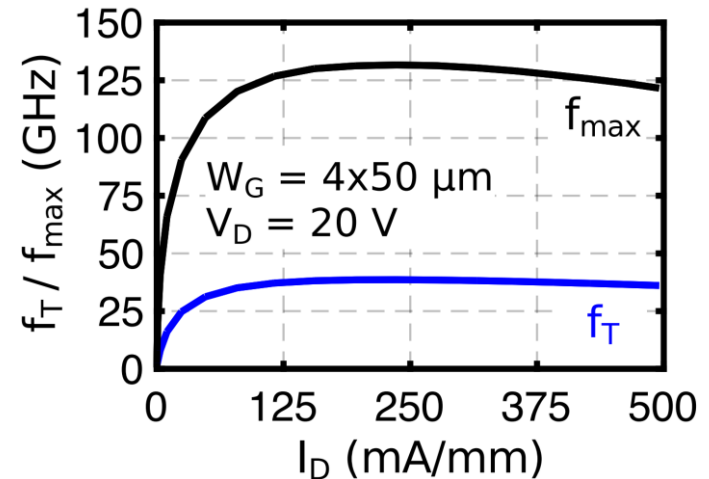


- **High-performance GaN HEMT process on a SiC substrate**
 - Primarily targets 5G and mm-wave applications (Ku, Ka, Q-band)
- **Device Geometry:** 4x50 μm GaN HEMT ($L_G = 150$ nm)

DC Characteristics & NVNA Data



Small-Signal Metrics



R. P. Martinez et al., *IEEE TMTT*, 2024.

Extracting the ASM-HEMT DC Model

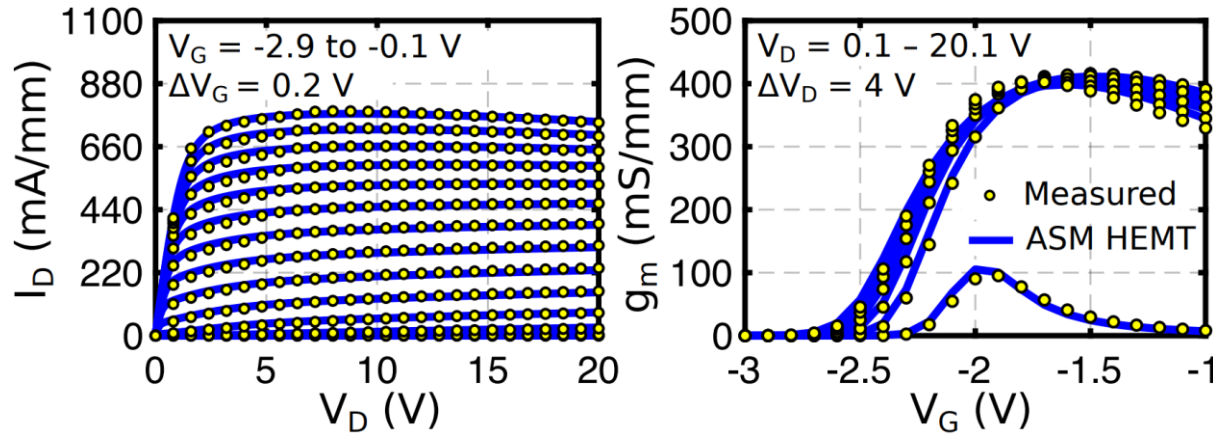
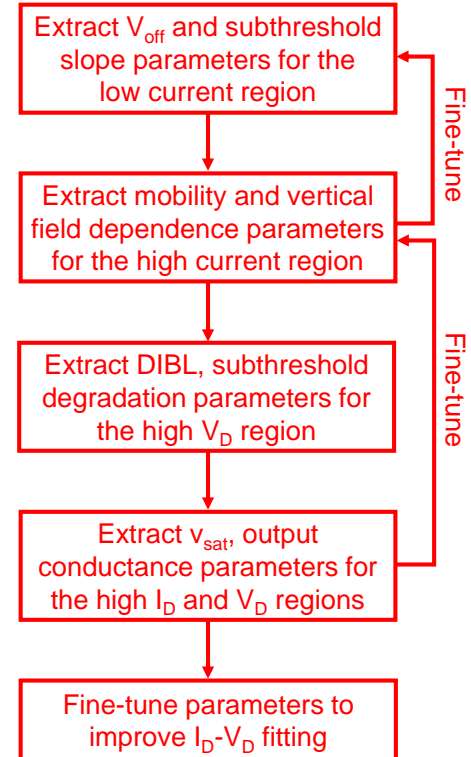


1) Follow the manual flow of ASM-HEMT RF extraction package in IC-CAP (this work)

- Divide the parameter set into smaller subsets

2) Extract the DC model via derivative-free optimization (no manual efforts)

Manual Extraction Flow



S. A. Ahsan et al., *IEEE JEDS*, 2017.

Extracting the ASM-HEMT DC Model

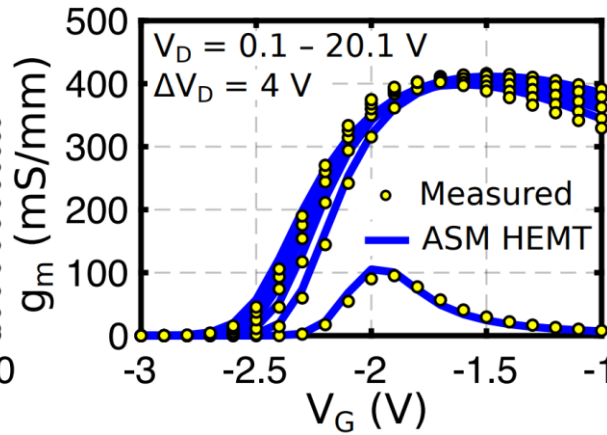
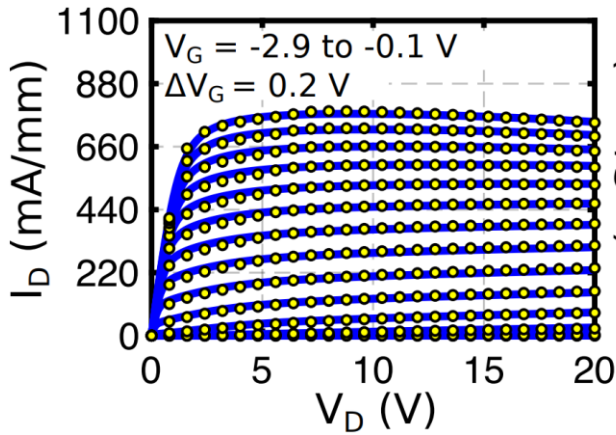
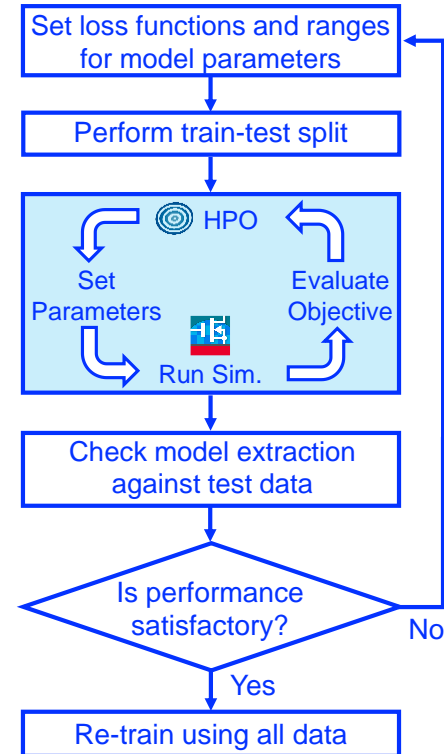


1) Follow the manual flow of ASM-HEMT RF extraction package in IC-CAP

2) Extract the DC model via derivative-free optimization (no manual efforts)

– Reduce extraction time from weeks to hours!

Automatic Extraction Flow



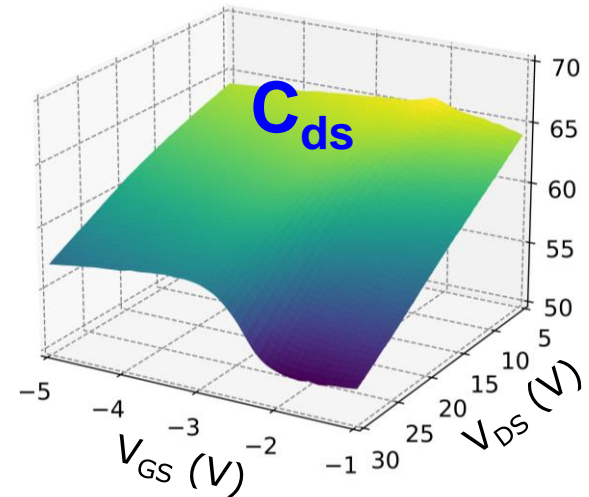
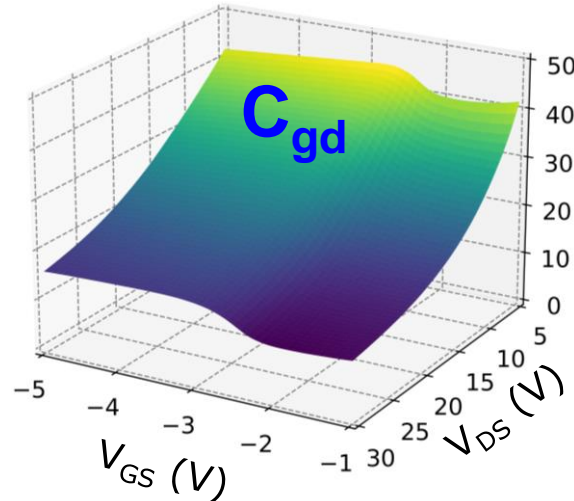
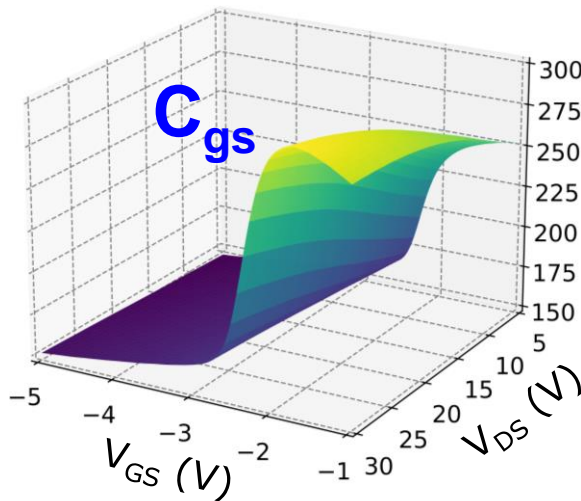
R. P. Martinez et al., *IEEE Access*, 2024.

Measurements Needed for Hybrid Model



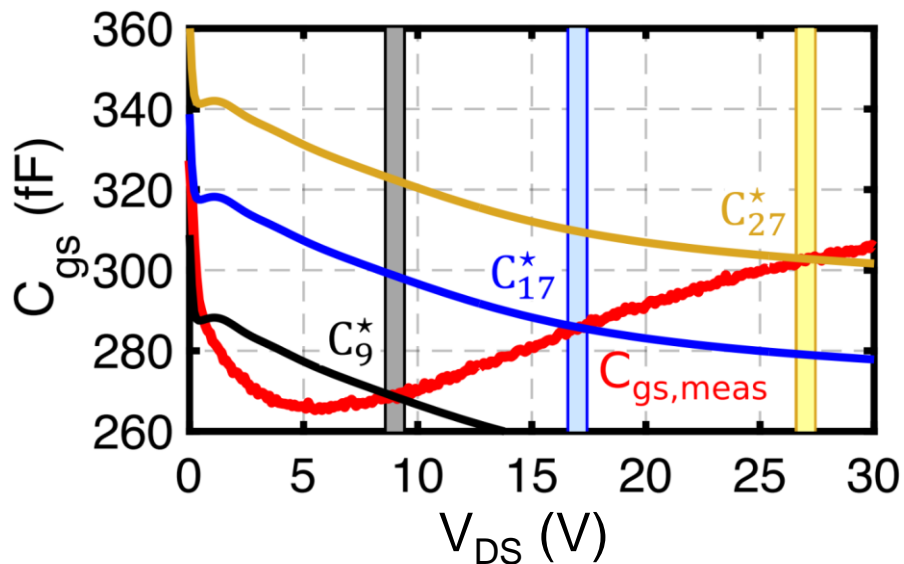
- **S-parameters were measured for a wide range of bias conditions**
 - $V_D = 0 - 30 \text{ V}$ ($\Delta V_D = 200 \text{ mV}$), $V_G = -5 \text{ to } -1 \text{ V}$ ($\Delta V_G = 100 \text{ mV}$) at $f = 10 \text{ GHz}$
- **Dataset used to extract model parameters in the hybrid model**

Nonlinear Junction Capacitances of 4x50 μm GaN HEMT



Obtaining Training Data for Hybrid Model

- **Goal:** Identify best model parameter value that aligns simulated results with measured device characteristics at each bias condition
- **Logical sequence was established:** $C_{GD} \rightarrow C_{GS} \rightarrow C_{DS}$



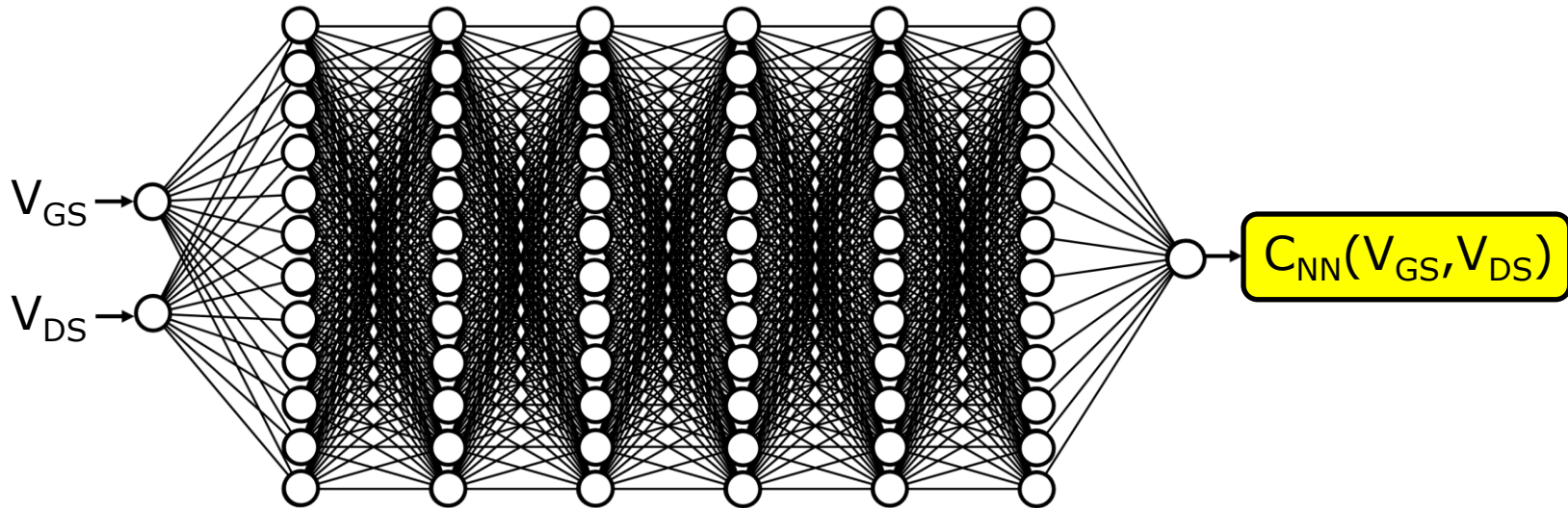
- **Minimize relative error at each bias using Levenberg-Marquardt:**

$$\text{minimize}_{C_{ASM,param}} \left| \frac{C_{sim}(V_{GS}^{(i)}, V_{DS}^{(j)}, C_{ASM,param}) - C_{meas}(V_{GS}^{(i)}, V_{DS}^{(j)})}{C_{meas}(V_{GS}^{(i)}, V_{DS}^{(j)})} \right|$$

Neural Network Training for Hybrid Model



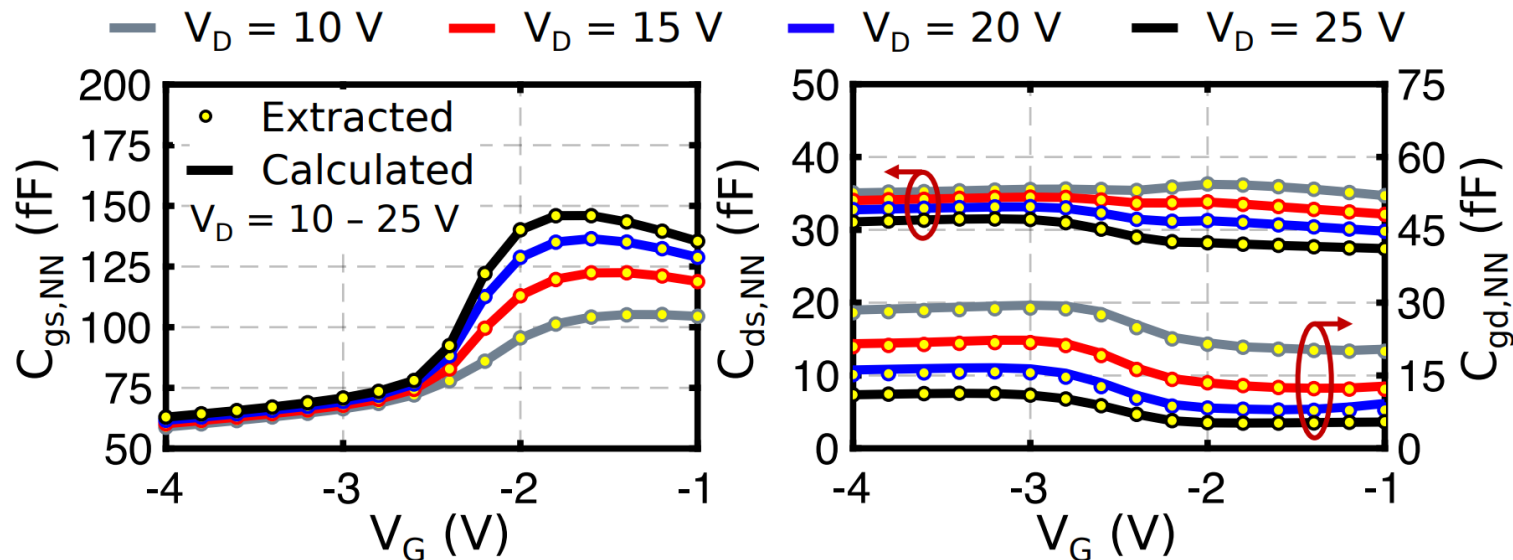
- **Neural network predicts hybrid model parameter at each bias**
 - Incorporated in Verilog-A model (replaces constant model parameter)
 - 6 hidden layers, 12 neurons each; Root Mean Square Error as loss function
- **Keysight's ANN Toolkit in IC-CAP is used to train neural network**



Neural Network Output for Hybrid Model

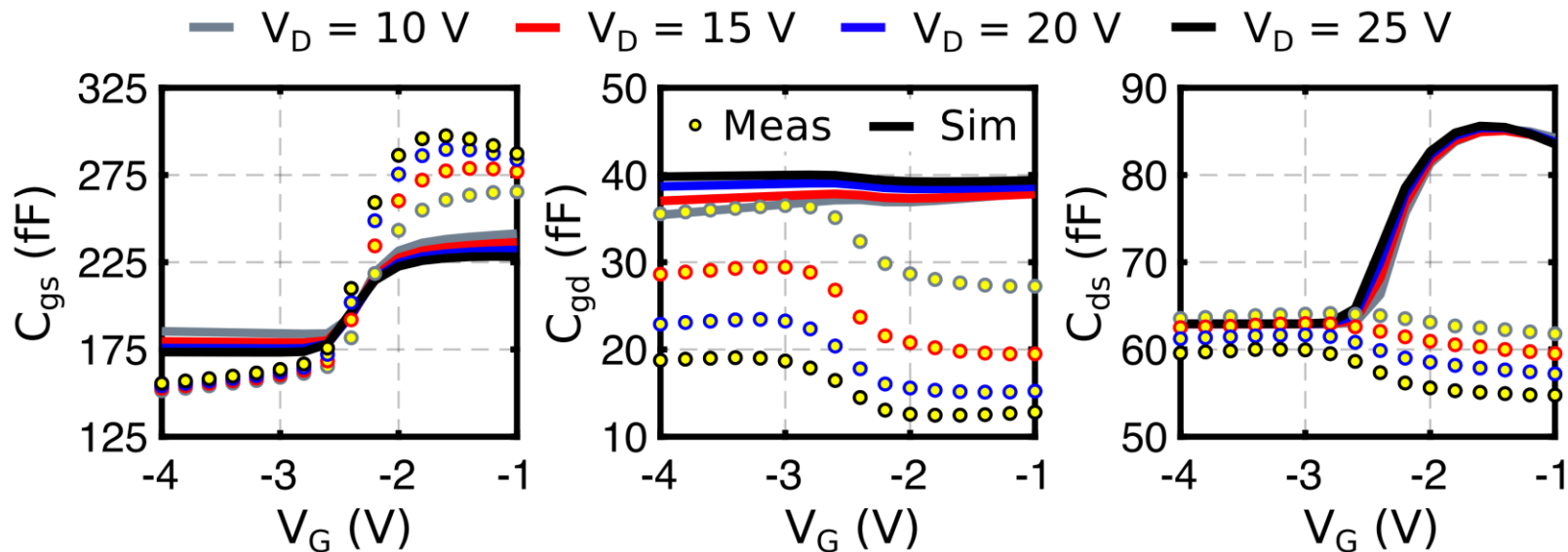


- Extracted capacitance model parameters that minimize error between simulated and measured C-V characteristics
- Neural network output shows good agreement as a function of bias



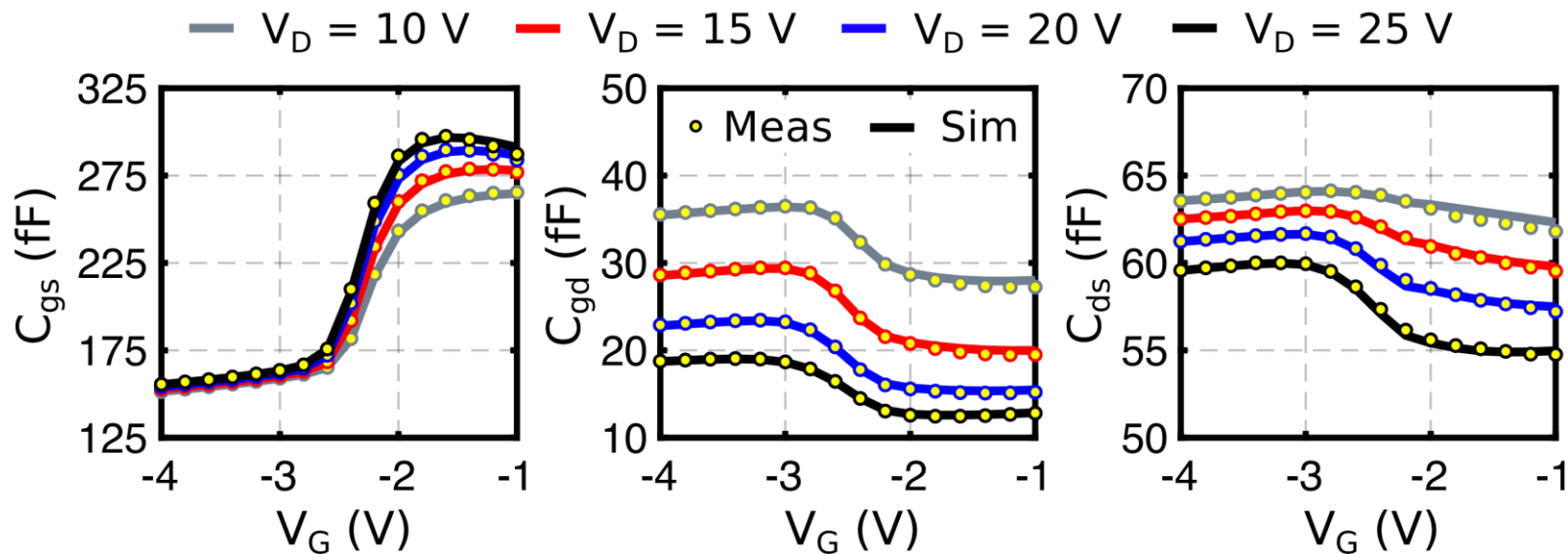
Baseline Model Fails to Model Capacitances

- **Baseline Model:** Unmodified model tailored to fit CV characteristics starting at $V_{DS} = 0$ V
- **Unable to fit V_{DS} -dependence for all three CV curves (limited range)**



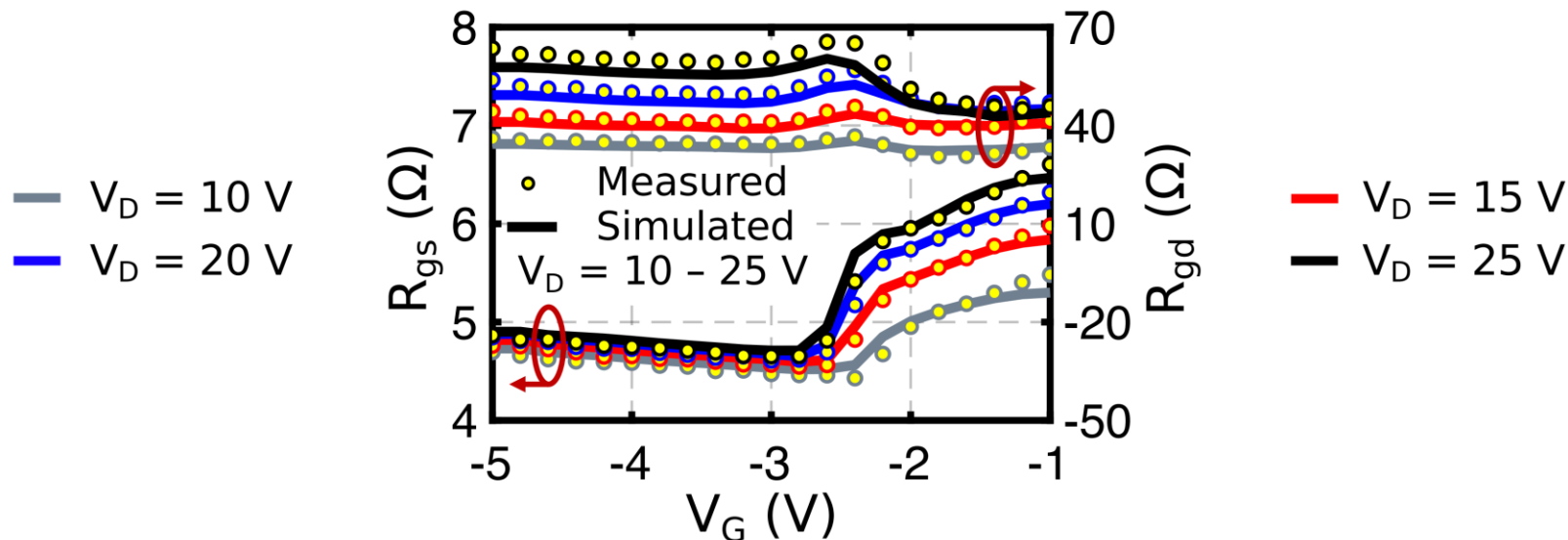
Improved Fitting Using Hybrid Approach

- **Hybrid Model:** Incorporates “compensating” circuit elements to fit capacitances through a neural network (6 hidden layers, 12 neurons)
- **Fitting of capacitances improved greatly as a function of V_G and V_D**

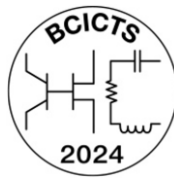


Improved Fitting Using Hybrid Approach

- **Hybrid Model:** Incorporates “compensating” circuit elements to fit resistances through a neural network (6 hidden layers, 12 neurons)
- **Fitting of resistances improved greatly as a function of V_G and V_D**



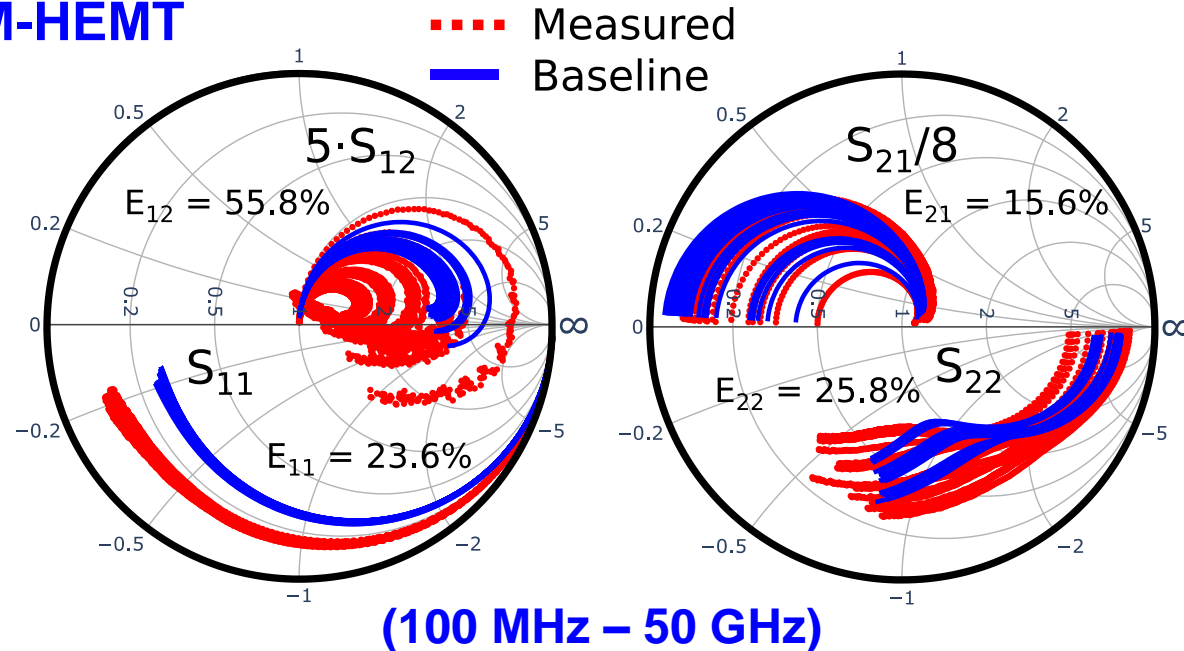
S-parameter Model Validation



- Mismatch between measured and simulated S-parameters

- $V_D = 5 - 25$ V ($\Delta V_D = 5$ V), $V_G = -2.2$ to -1 V ($\Delta V_G = 0.2$ V), $I_D = 15 - 500$ mA/mm

Baseline ASM-HEMT

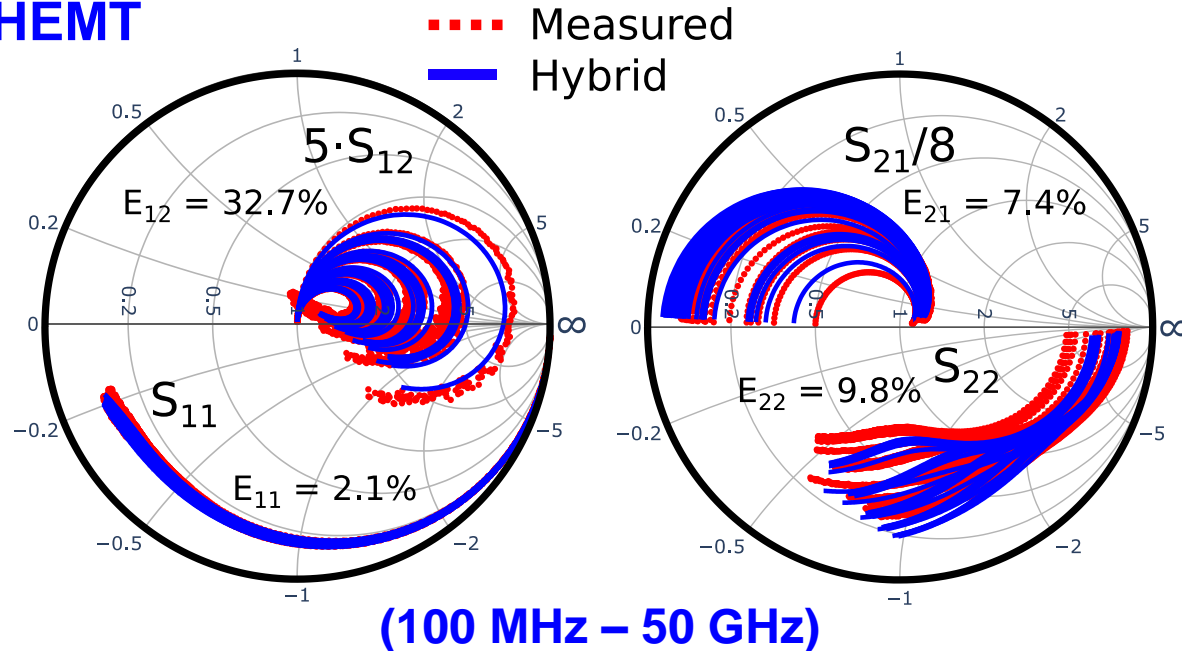


S-parameter Model Validation



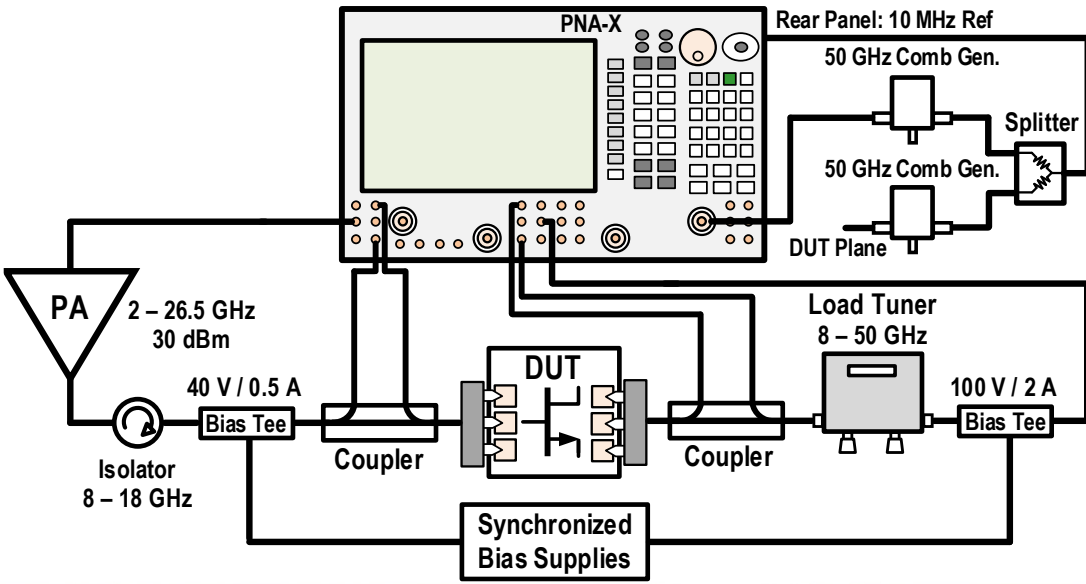
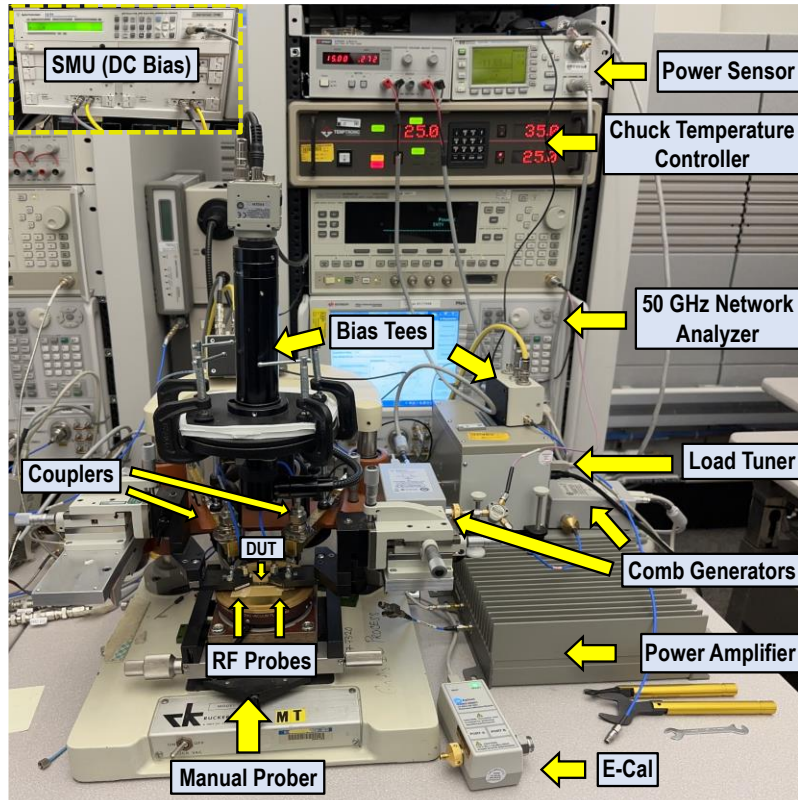
- **Good agreement between measured and simulated S-parameters**
 - $V_D = 5 - 25$ V ($\Delta V_D = 5$ V), $V_G = -2.2$ to -1 V ($\Delta V_G = 0.2$ V), $I_D = 15 - 500$ mA/mm

Hybrid ASM-HEMT



Set-up for Non-linear Validation

- Fundamental load-tuner and NVNA set measurement frequency range
- Driver amplifier + isolator limit how much power we can present to the DUT

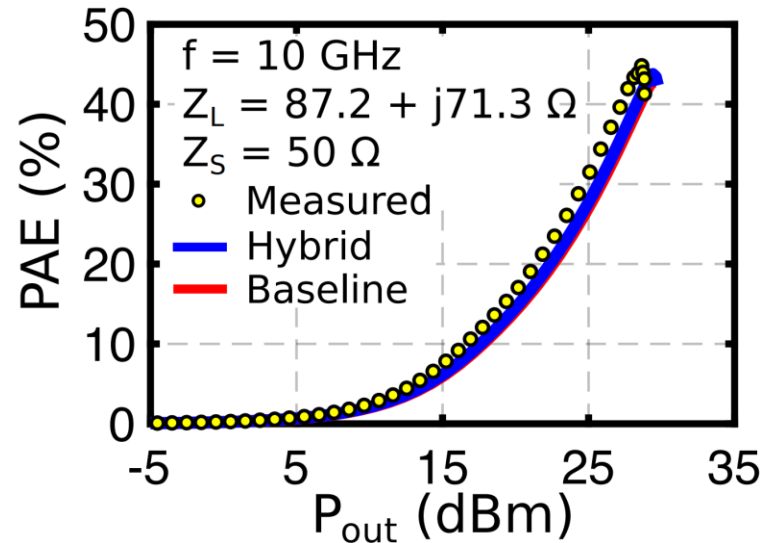
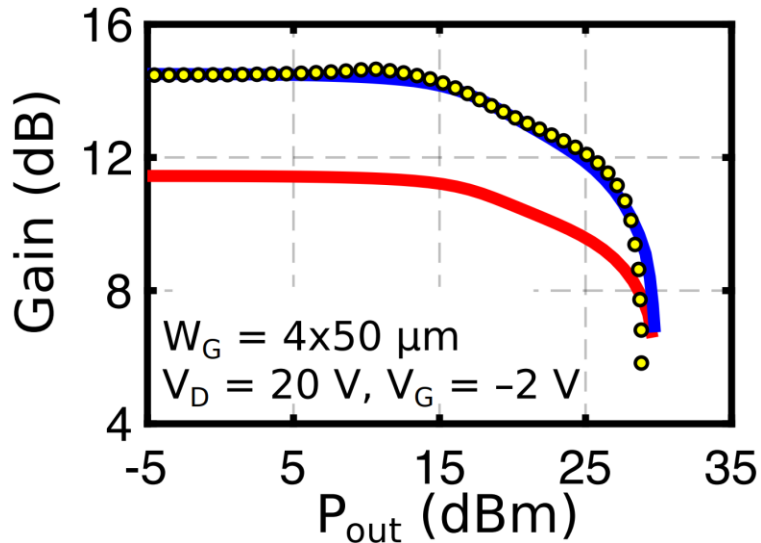


R. P. Martinez et al., *IEEE TMTT*, 2024.

Large-Signal Non-linear Validation



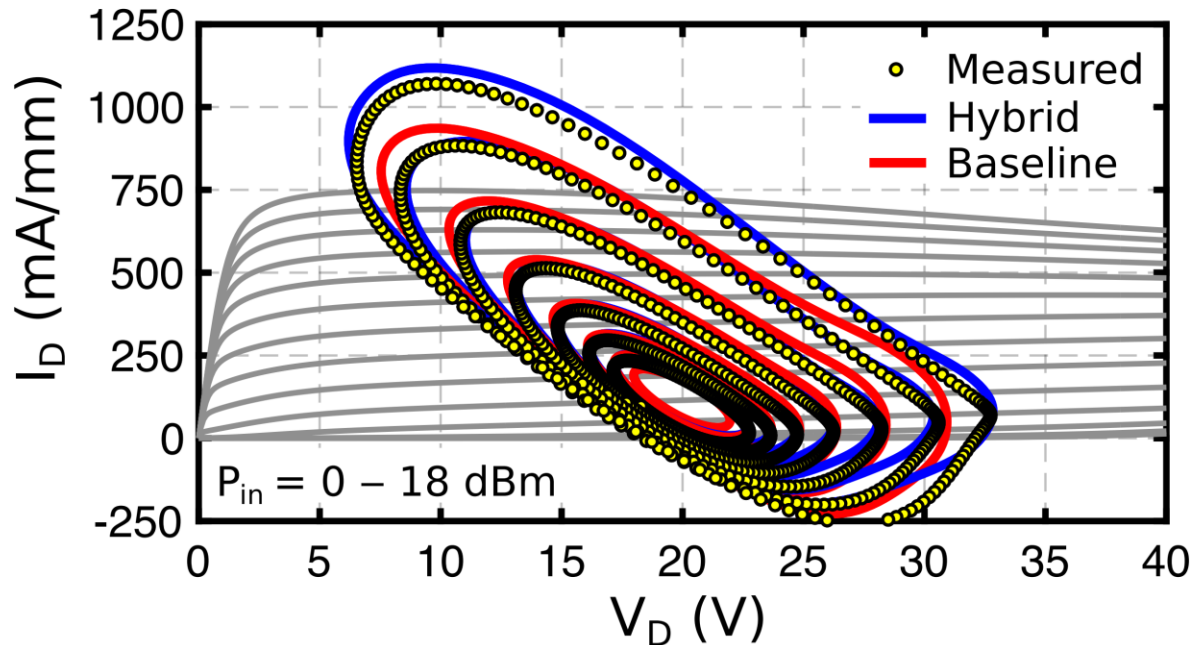
- Hybrid model **accurately predicted** gain compression and PAE
- Baseline model resulted in a **poor fit** for gain compression
 - Baseline model confined to a narrow V_{DS} range due to existing limitations



Dynamic Load-Line Validation



- Dynamic load-lines accurately predicted by hybrid ASM-HEMT model
- Baseline model yields poor results due to poor fitting of capacitances



Summary



- Introduced GaN technology and modeling schemes
- Evaluated strengths and limitations of measurement and physics-based models
- Proposed hybrid physical approach using ASM-HEMT model to improve fitting of capacitances and resistances
- Model validated against S-parameters, X-parameters, and dynamic load lines

Code and detailed documentation to be available in IC-CAP 2025 to benefit the device modeling community