Advancing mm-Wave GaN Technology Through Innovative Modeling Approaches

Ph.D. Dissertation Defense by:

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May 15th, 2024

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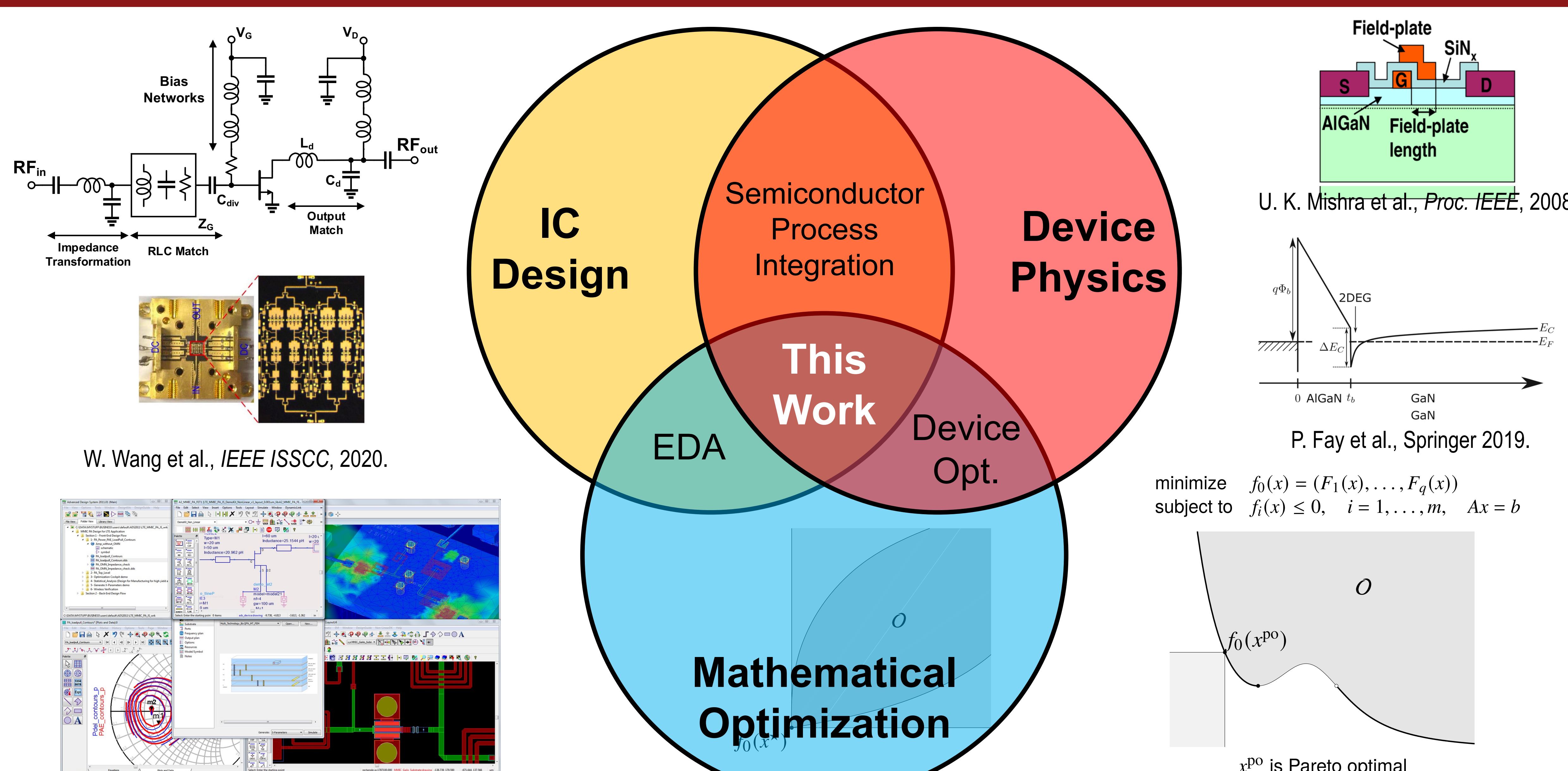
Outline

- Introduction to GaN Technology
- Lending Derivative-Free Optimization to Device Modeling
- A Hybrid Physical ASM-HEMT Model
- Summary of Contributions

Ph.D. Dissertation Topic: Intersection of Multiple Fields



Gallium Nitride: Reshaping Technology and Society

Optoelectronics

LED Lightning

Headlights

MicroLED

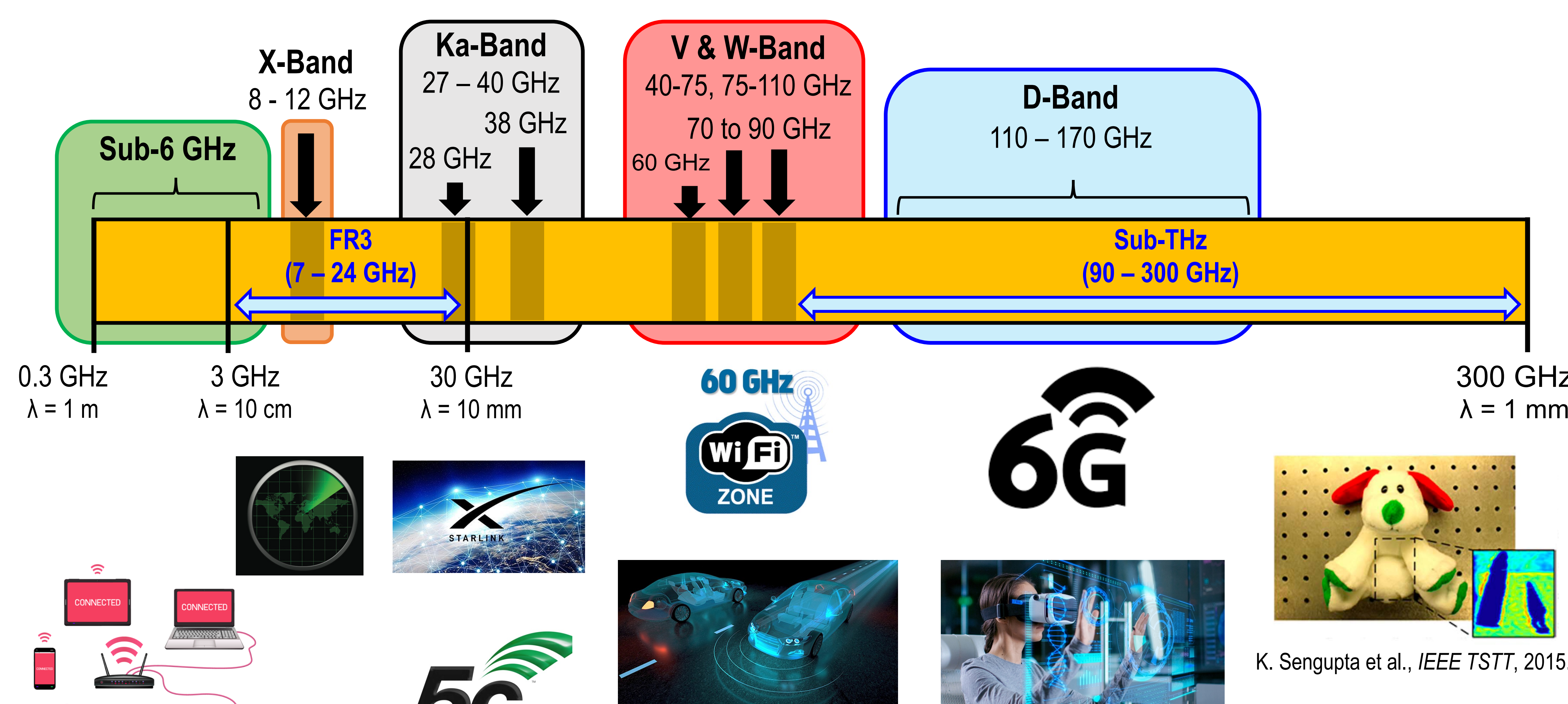
μLEDs

Lasers

The Royal Swedish Academy of Sciences has decided to award the
2014 NOBEL PRIZE IN PHYSICS
to:
Isamu Akasaki, Hiroshi Amano
and Shuji Nakamura

2014 Nobel Prize in Physics

RF Spectrum: Wireless Applications (Beyond-5G)



Keysight, App. Note, 2024.

Samsung, White Paper, 2020.

K. Sengupta et al., *IEEE TSTT*, 2015.

Key Device Metrics for mm-Wave Amplifiers

Difficult to Optimize for all Four at mm-Wave

Gain

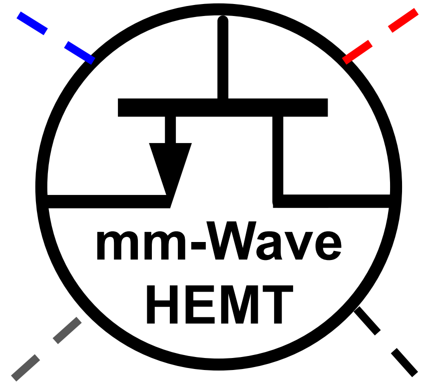
$$G = \frac{P_{\text{RF,out}}}{P_{\text{RF,in}}}$$

- High electron mobility

Output Power

$$P_{\text{out}} = \frac{V_{\text{swing}} I_{\text{swing}}}{8} = \frac{2(V_{\text{DD}} - V_{\text{kn}}) I_{\text{kn}}}{8}$$

- Large current / voltage swing



PAE

$$\text{PAE} = \frac{P_{\text{RF,out}} - P_{\text{RF,in}}}{P_{\text{DC}}} = \left(1 - \frac{1}{G}\right) \frac{P_{\text{RF,out}}}{P_{\text{DC}}}$$

- High gain and output power
- Low T_j and P_{DC}

Linearity

$$\text{OIP}_3 = 10 \log_{10} \left(\frac{2}{3} \frac{g_{\text{m1}}^3 R_{\text{L}}}{g_{\text{m3}}} \right) + 30$$

AM-AM / AM-PM Distortion

- Flat transconductance (g_m)
- Constant C_{gs}, C_{gd}

Low Dispersion is Required

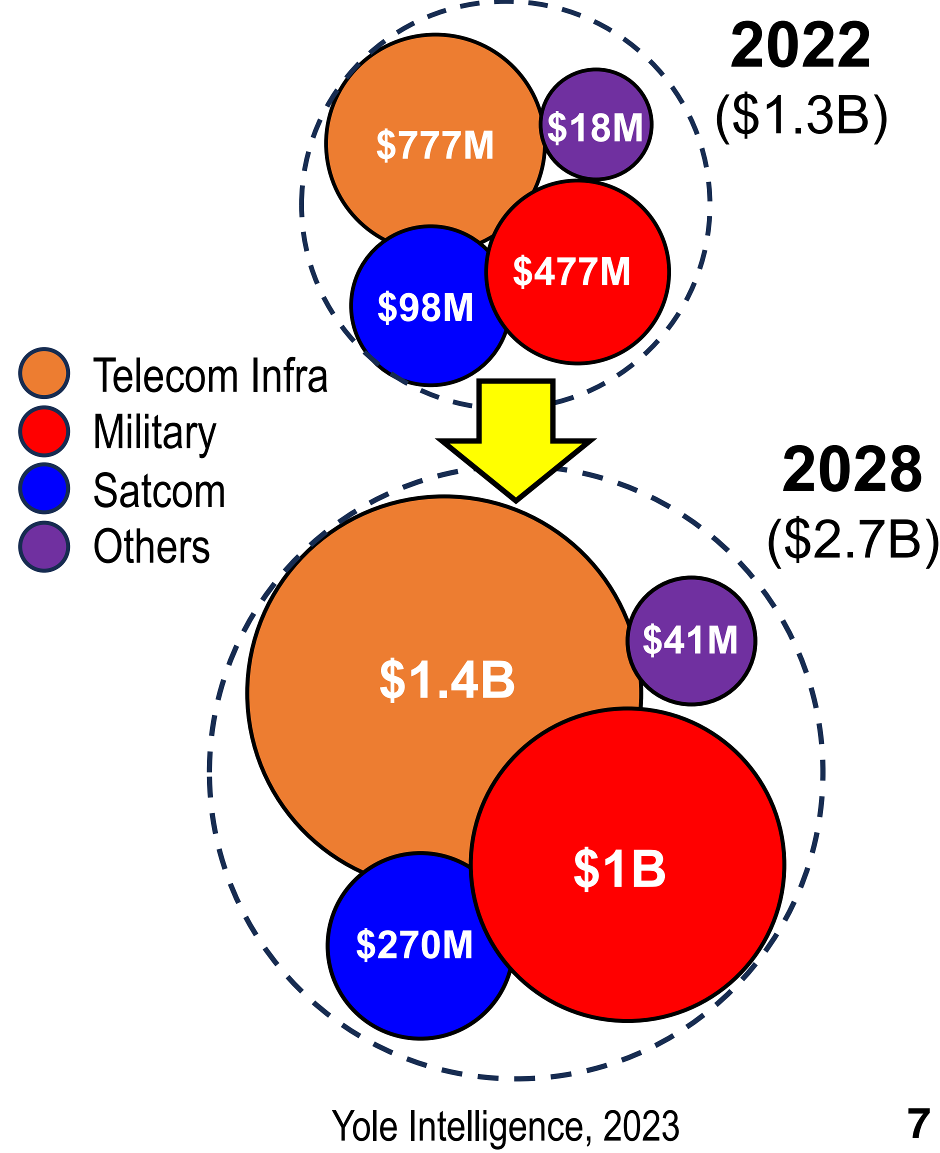
GaN Technology Addresses High-Performance Needs

- **GaN transistors 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·s)	1500	5400	8500	**2000***
Peak Saturation Velocity, v_{sat} ($x10^7$ cm/s)	1	3.3	2.0	**2.5**
2DEG Density, n_s ($x10^{13}$ 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}·v_{sat} /2π)	1	5.8	2.7	**28**

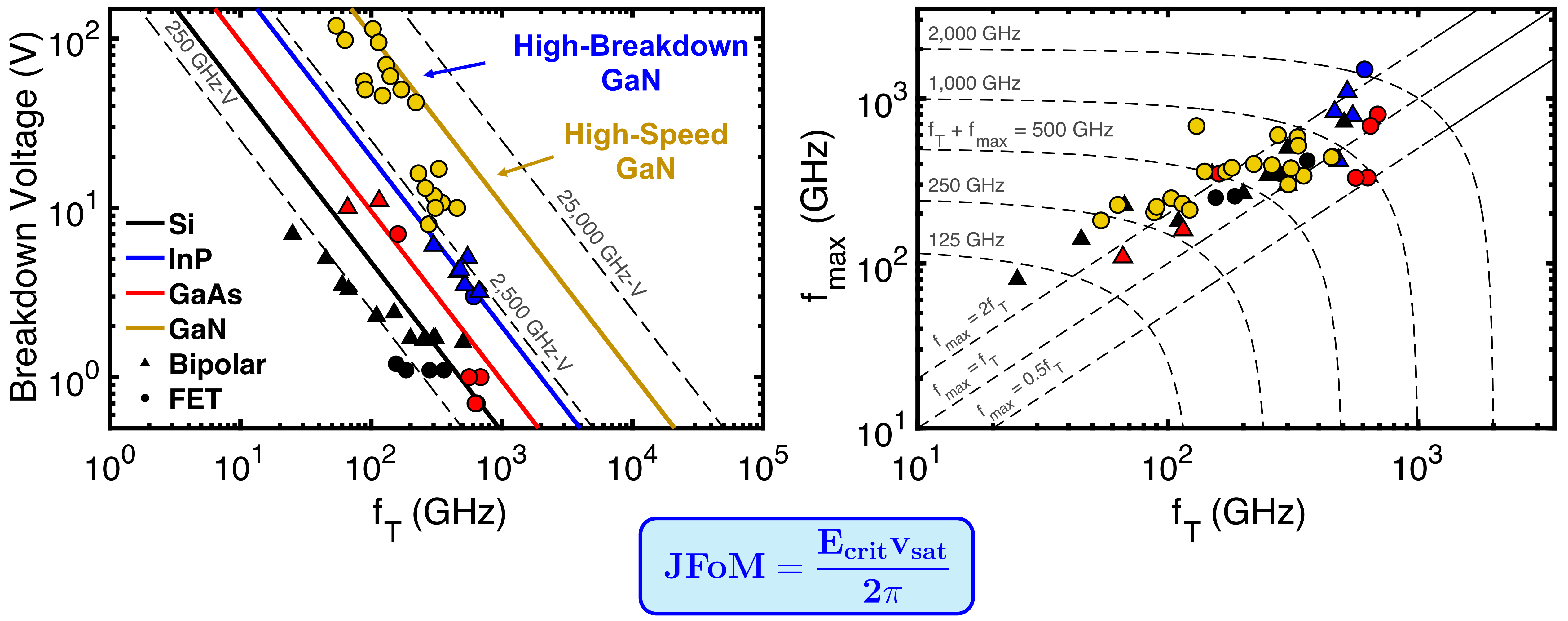
*2DEG Mobility



Yole Intelligence, 2023

State-of-the-art f_T / f_{max} Performance Survey

- **Fundamental trade-off in f_T / f_{max} and breakdown voltage:** “Johnson Limit”

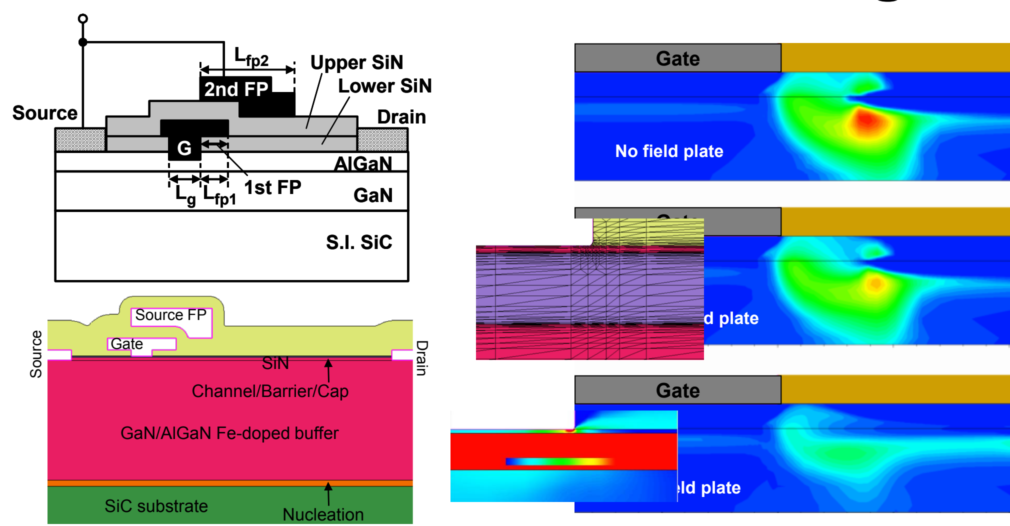


$$\mathrm{JFoM} = \frac{E_{crit} v_{sat}}{2\pi}$$

K. Woo, M. Noshin, Z. Bian, R. P. Martinez *et al.*, *JPhys Materials*, 2024.

Challenges Hindering GaN's Theoretical Limit

Electric-Field Crowding

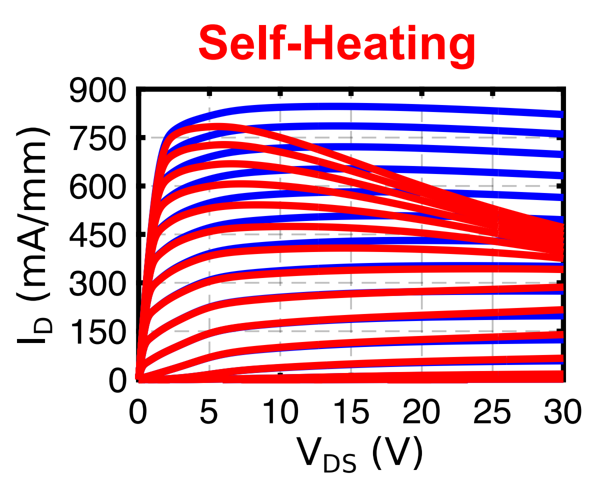


Y. Ando et al., IEEE IEDM, 2005.

N. Braga, Synopsis.

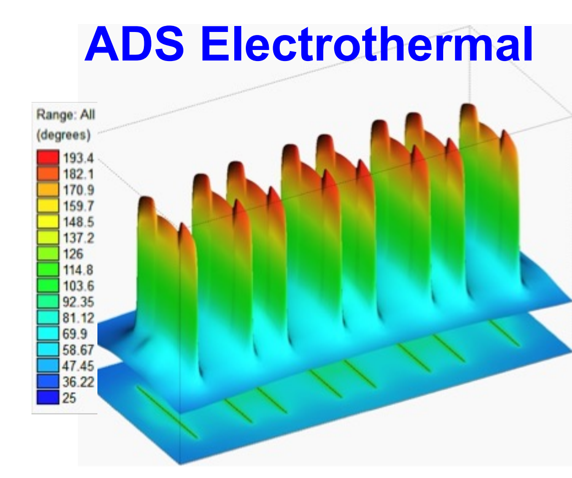
Thermal Effects

Self-Heating



R. P. Martinez, M. Iwamoto, and S. Chowdhury, *IEEE TMTT*, 2024.

ADS Electrothermal



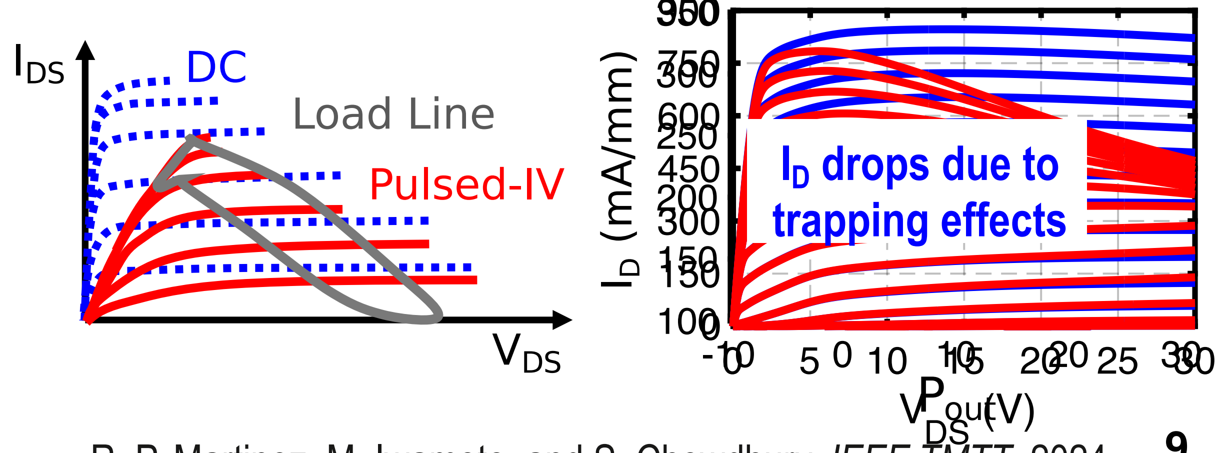
R. P. Martinez, S. Boyd, and S. Chowdhury, submitted.

G_m Non-Linearity

I_D
Bias Point
V_{GS}
g_{m1}
g_{m3}
"∞ OIP_3"
Flat g_{m1}
Zero g_{m3}
V_{in}
I_{Out}
Aux
$I_{D,M1}$
$I_{D,M2}$
M_1
M_2
$V_{bias,1}$
$V_{bias,2}$

R. P. Martinez, B. Murmann, and S. Chowdhury, *IEEE TED*, 2023.

Trapping Effects



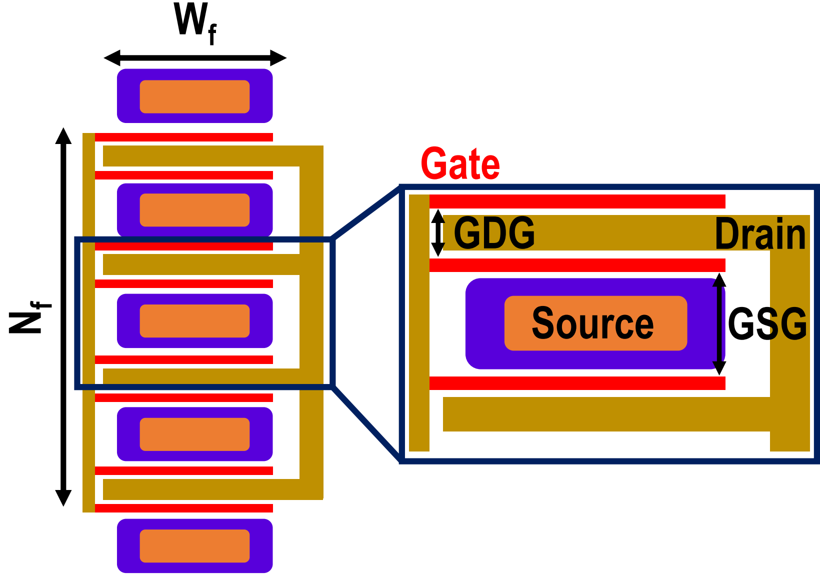
R. P. Martinez, M. Iwamoto, and S. Chowdhury, *IEEE TMTT*, 2024.

Motivation: Addressing Two Major Challenges in GaN

- **Improve accuracy and reduce extraction time in GaN models**
  - Takes weeks to months to extract a device model
  - Some models are unable to capture the strong device nonlinearities

C_{gdman}
Intrinsic Device
C_{fr}
C_{gdo}
Gate L_g G R_{g1} gi di R_d D L_d Drain
R_{g2} gin I_{gd}
$R_{ds,ext}$
I_{gs} $Q_{g,i}$ $Q_{d,i}$ I_{ds} g_{ds}
C_{gsman} C_{fgd} C_{gso} C_{fr2} si C_{dep} C_{dso} C_{fd} C_{dsman}
R_s $C_{ds,ext}$
S
L_s
Extrinsic Parasitic Elements
200+ model parameters
Source

- **Optimize P_{out}, PAE, linearity, and thermal at mm-wave**
  - Devices are optimized for high f_{max} / P_{out}
  - Obtaining a good designs takes multiple iterations



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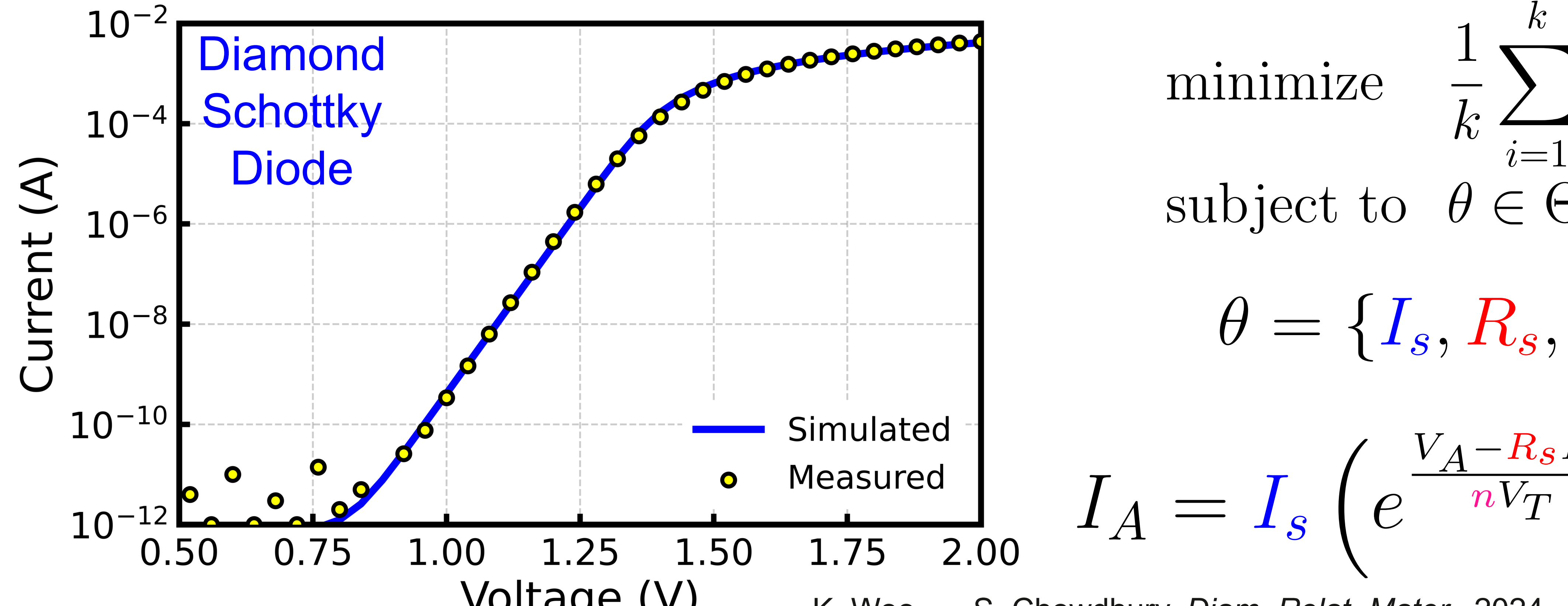
The Parameter Extraction Problem in Device Models

- **Device model parameter extraction involves adjusting the parameters of a model to align with data from a semiconductor device**
- **Typical compact / TCAD device models do not have simple formulas**
  - Given by running a SPICE / TCAD simulation and depends on 10s of parameters



$$\text{minimize} \quad \frac{1}{k}\sum_{i=1}^{k}\mathcal{L}(\hat{y}, y)$$

$$\text{subject to} \quad \theta \in \Theta$$

$$\theta = \{I_s, R_s, n\}$$

$$I_A = I_s\left(e^{\frac{V_A - R_s I_A}{n V_T}} - 1\right)$$

K. Woo,…, S. Chowdhury, *Diam. Relat. Mater.*, 2024.

Extracting the ASM-HEMT DC Model with 30+ Parameters

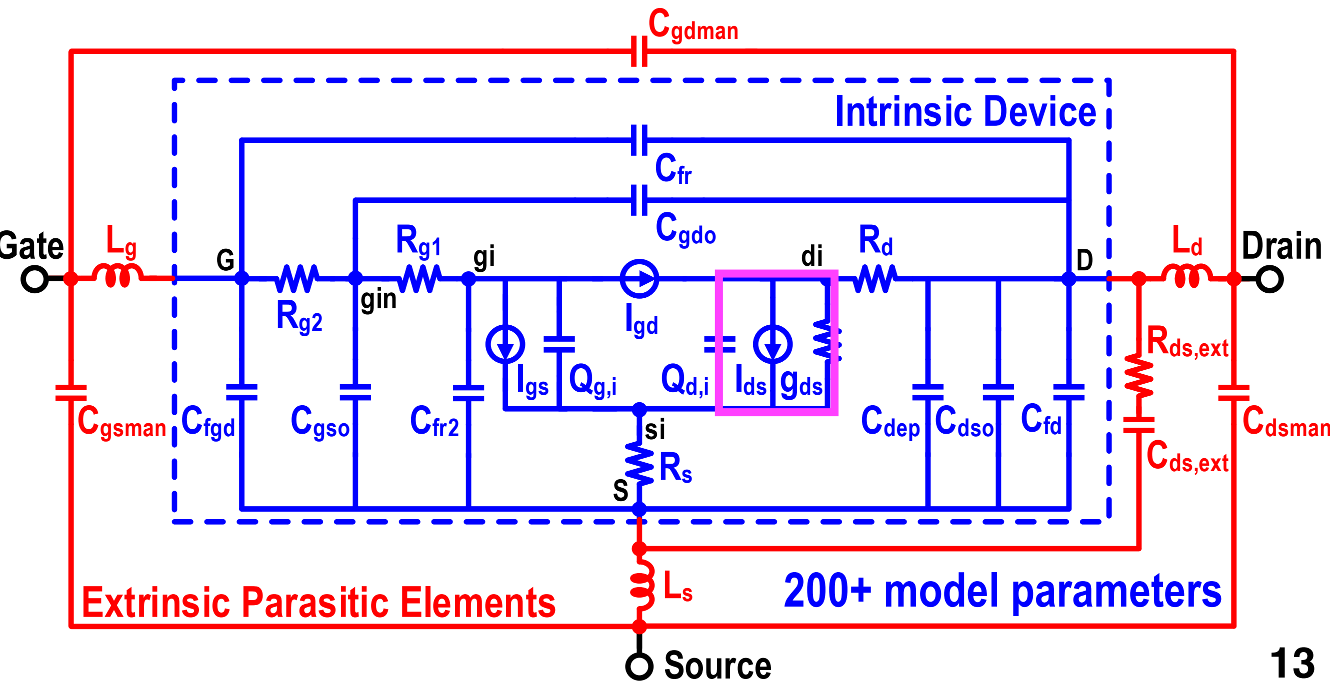
- **Compact models represent mathematically the electrical behavior of semiconductor devices (primarily used for IC design)**
- **ASM-HEMT:** Surface-potential-based physical compact model

Problem: Requires adjusting 30+ model parameters to fit the DC model

GaN Device Cross-Section

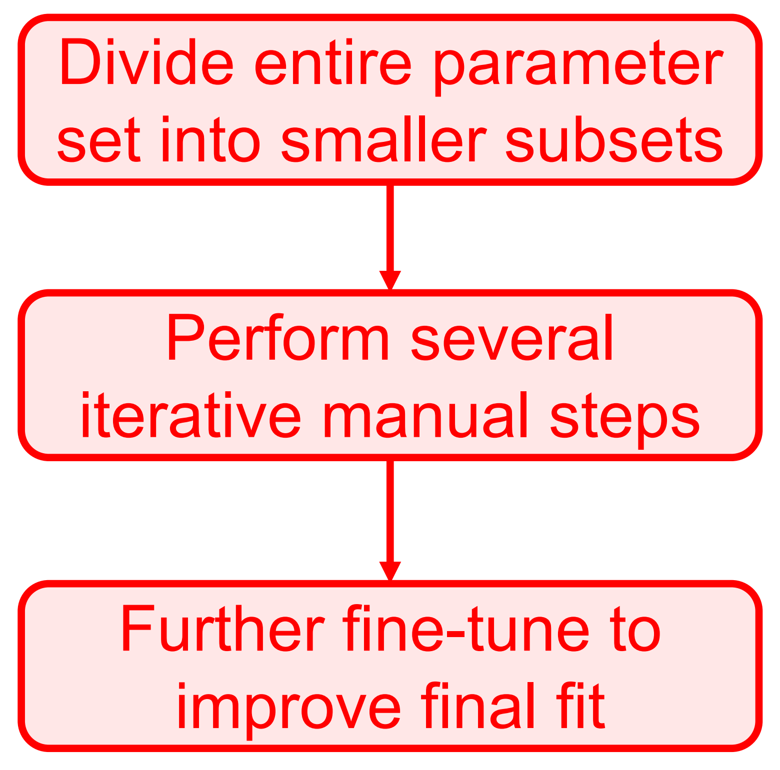
Source
Gate
Drain
R_s
R_g
R_d
C_{gs}
C_{gd}
AlGaN
2DEG
R_{accs}
I_{ds}
g_{ds}
R_{accd}
C_{ds}
GaN
SiC Substrate

ASM-HEMT Equivalent Circuit Model



Manual Fitting: The 30-Year Norm in Parameter Extraction

- **Typical approach for parameter extraction is extremely time-consuming**
  - Takes several days or weeks, and does not guarantee a satisfactory fit
- **Divide-and-conquer approach to parameter extraction**

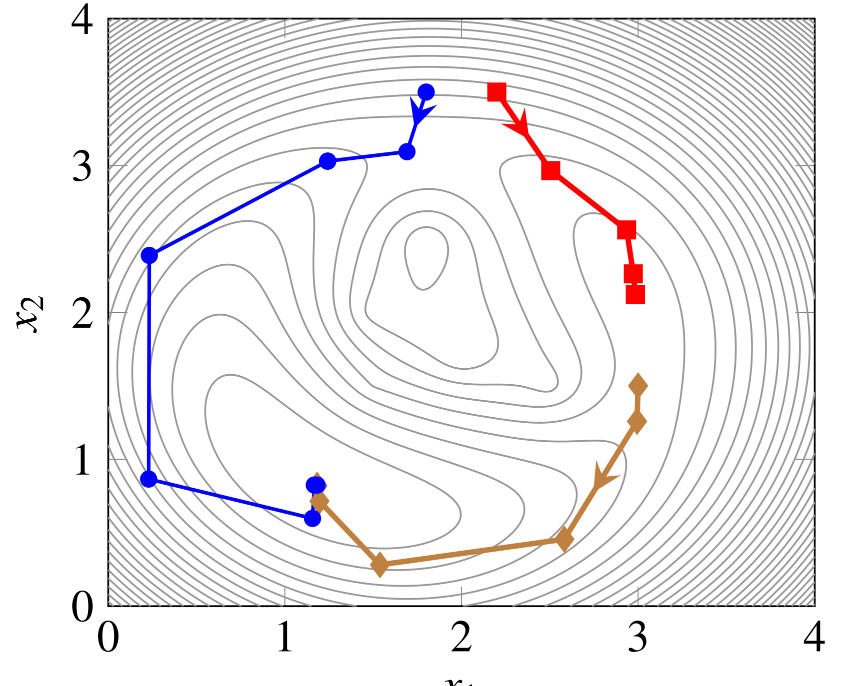


"SPICE Monkeying"

"SPICE Monkeying," DALL·E 3, OpenAI.

Levenberg-Marquardt Algorithm for Parameter Extraction

- **Combines gradient descent with least squares to optimize parameters**
- **Gradients are difficult to obtain (require numerical approximations)**
  - Requires knowing how a small change in each parameter affects the output
- **Becomes inefficient with tens of model parameters**
- **Can get stuck in local minima of high-dimensional landscapes**



Levenberg-Marquardt Iteration

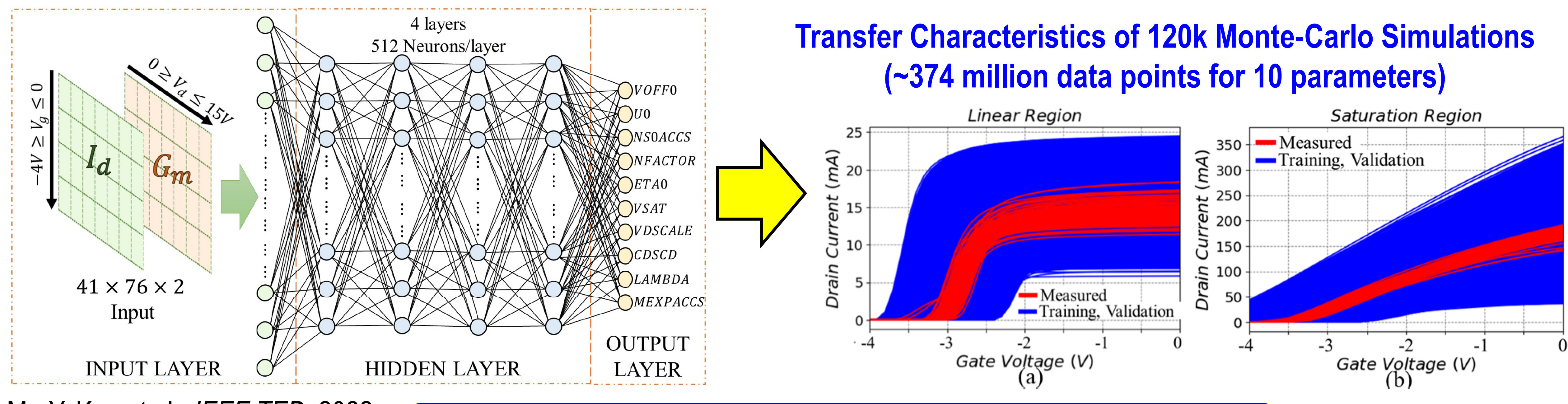
$$\text{minimize} \quad \left\| f(\theta^{(k)}) + Df(\theta^{(k)})(\theta - \theta^{(k)}) \right\|^2 + \lambda^{(k)} \left\| \theta - \theta^{(k)} \right\|^2$$

$$\theta^{(k+1)} = \theta^{(k)} - \left(Df(\theta^{(k)})^T Df(\theta^{(k)}) + \lambda^{(k)} I \right)^{-1} Df(\theta^{(k)})^T f(\theta^{(k)})$$

S. Boyd and L. Vandenberghe, Cambridge Univ. Press, 2018.

Prior Works Addressing This Issue Using Deep Learning

- **Recent works have trained a neural network that takes simulated data as input and outputs the model parameters**
- **Challenges:** Extensive simulations required, precise parameter range knowledge needed, and not resilient to outliers (measurement error)

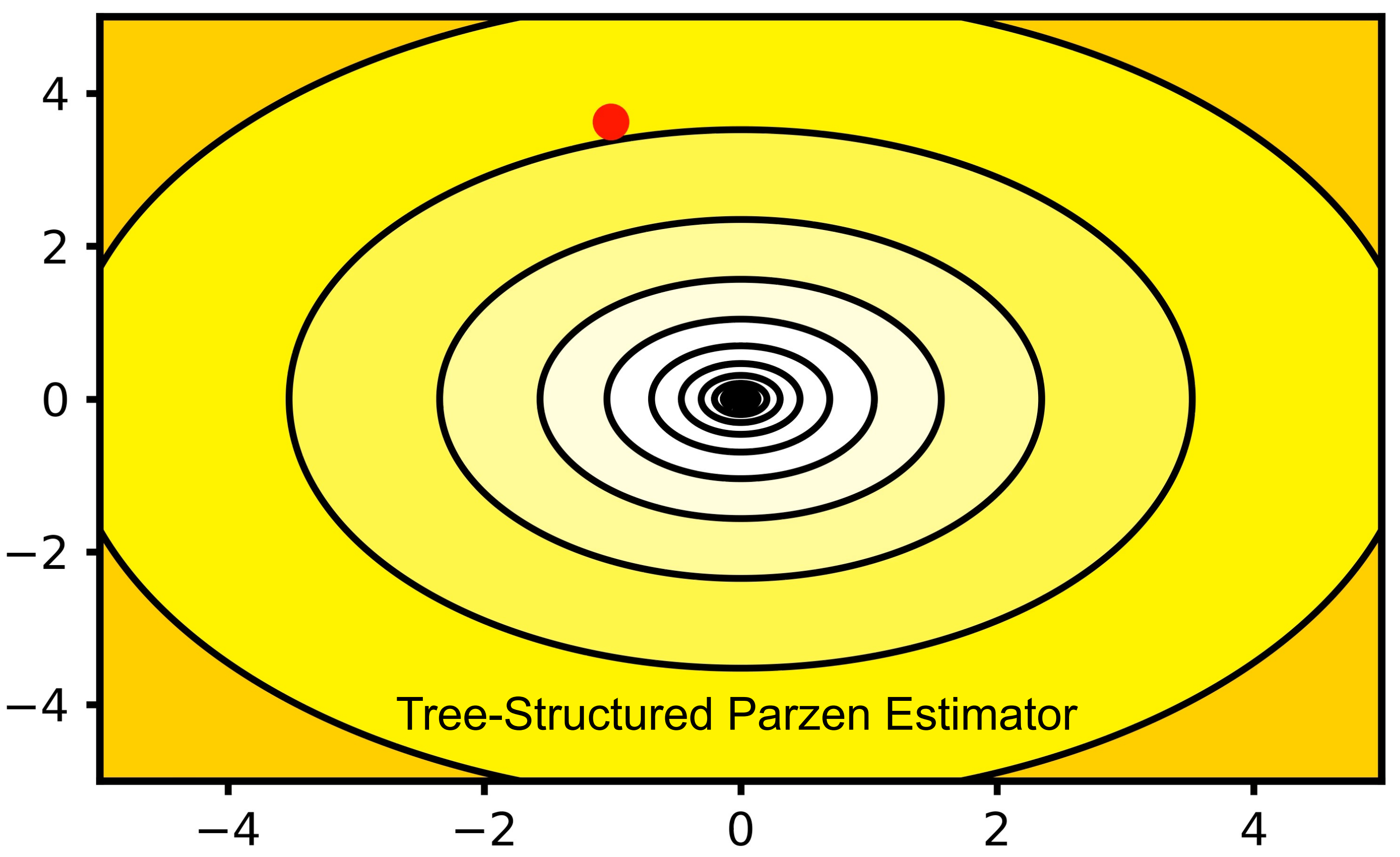


M. -Y. Kao et al., *IEEE TED*, 2022.
F. Chavez et al., *IEEE EDL*, 2023.

Q: How can we extract model parameters efficiently, without thousands of simulations, yet covering a broad range of possible values?

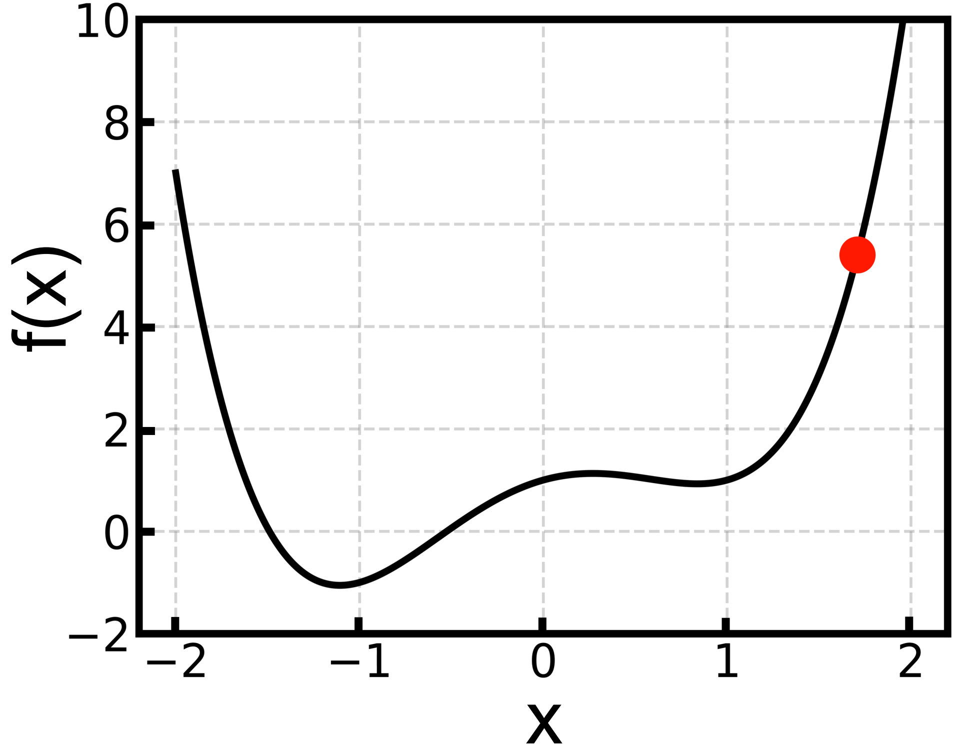
Proposed Solution: Derivative-Free Optimization

- **Methods that approx. minimize a function only using the objective value**
- **Obtains a nearly optimal fit with fewer simulations than a full-grid search**
- **Performs well with 10's of parameters but less effective beyond 100+**

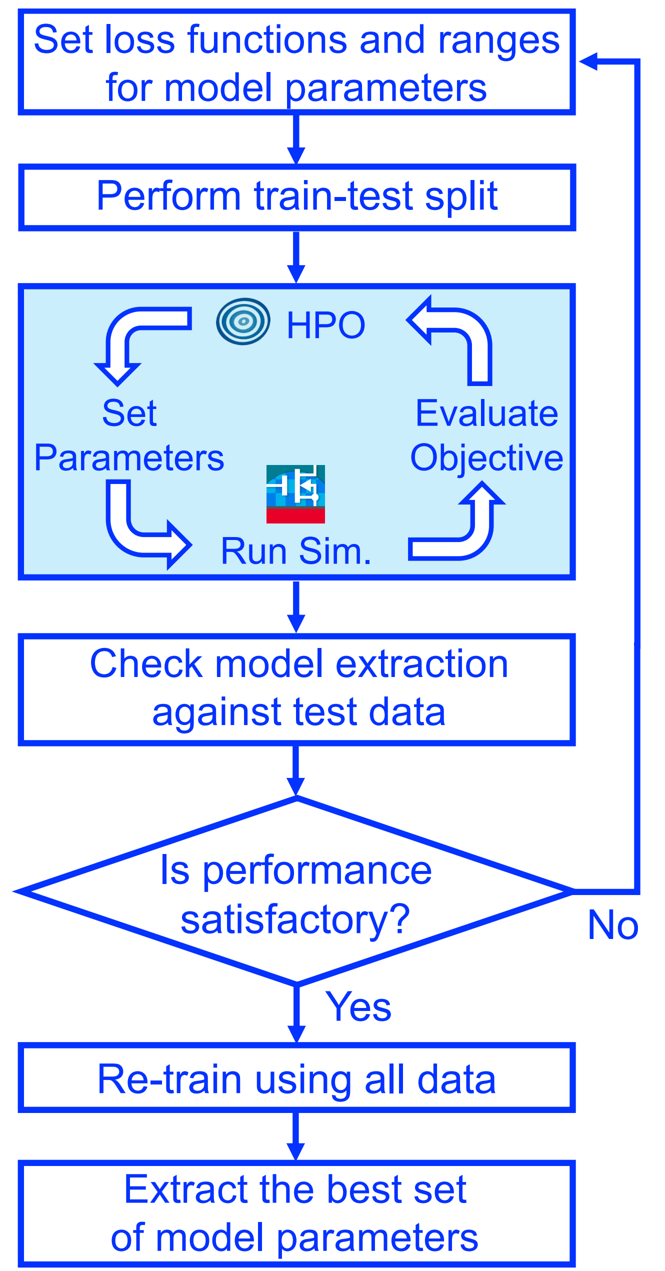


How Does Derivative-Free Optimization Work?

- **Explore:** Sample broadly to identify promising parameter areas
- **Refine:** Focus on top 20-30% best-performing parameters
- **Adapt:** Gradually learn and adapt to distribution of most effective parameters
- **Reevaluate:** Use past results to test new parameters or optimize known ones



Proposed Approach for Parameter Extraction



- **Addresses the limitations of manual fitting and deep learning approaches**
  - Little to no human effort is required for extraction
- **Reduces extraction time from weeks / months to a few hours (Intel i9-9900 CPU @ 3.1 GHz)**
  - A "good fit" is obtained within a few thousand trials

"Monkey Using Good ML," DALL·E 3, OpenAI.

Choosing the Right Loss Function for Parameter Extraction

Loss function selection is motivated by three device modeling issues:

1) Ensure consistent model performance across different orders of magnitude
2) Guide the optimization process to prioritize regions of particular interest
3) Reduce sensitivity to outliers and measurement errors

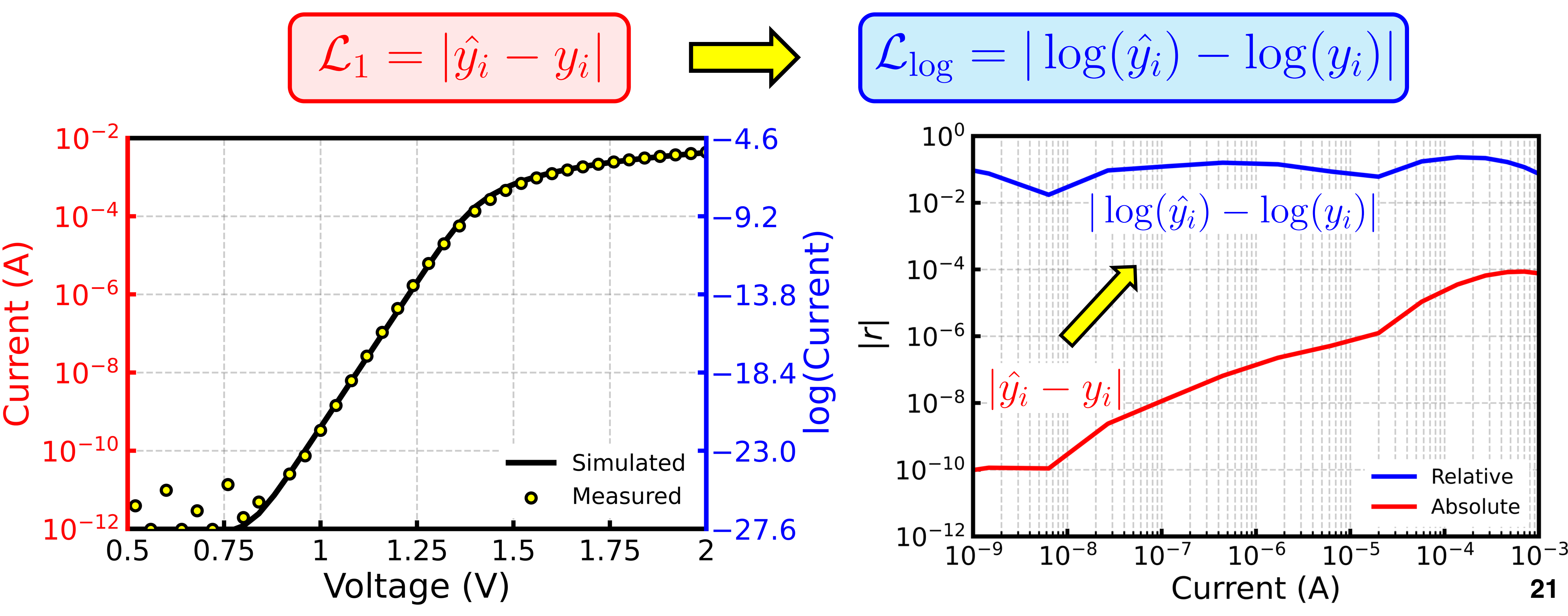
$$\begin{aligned} &\text{minimize} \quad \frac{1}{k}\sum_{i=1}^{k}\mathcal{L}(\hat{y}, y) \\ &\text{subject to} \quad \theta \in \Theta \end{aligned}$$

$$\mathcal{L}_{\text{clip}}(\hat{y}, y) = \begin{cases} u^2 & \text{if } |u| \leq \delta_i \\ \delta_i^2 & \text{if } |u| > \delta_i \end{cases}$$

$$u = \left| \log\left(1 + \frac{\hat{y}_i}{\epsilon_i}\right) - \log\left(1 + \frac{y_i}{\epsilon_i}\right) \right|$$

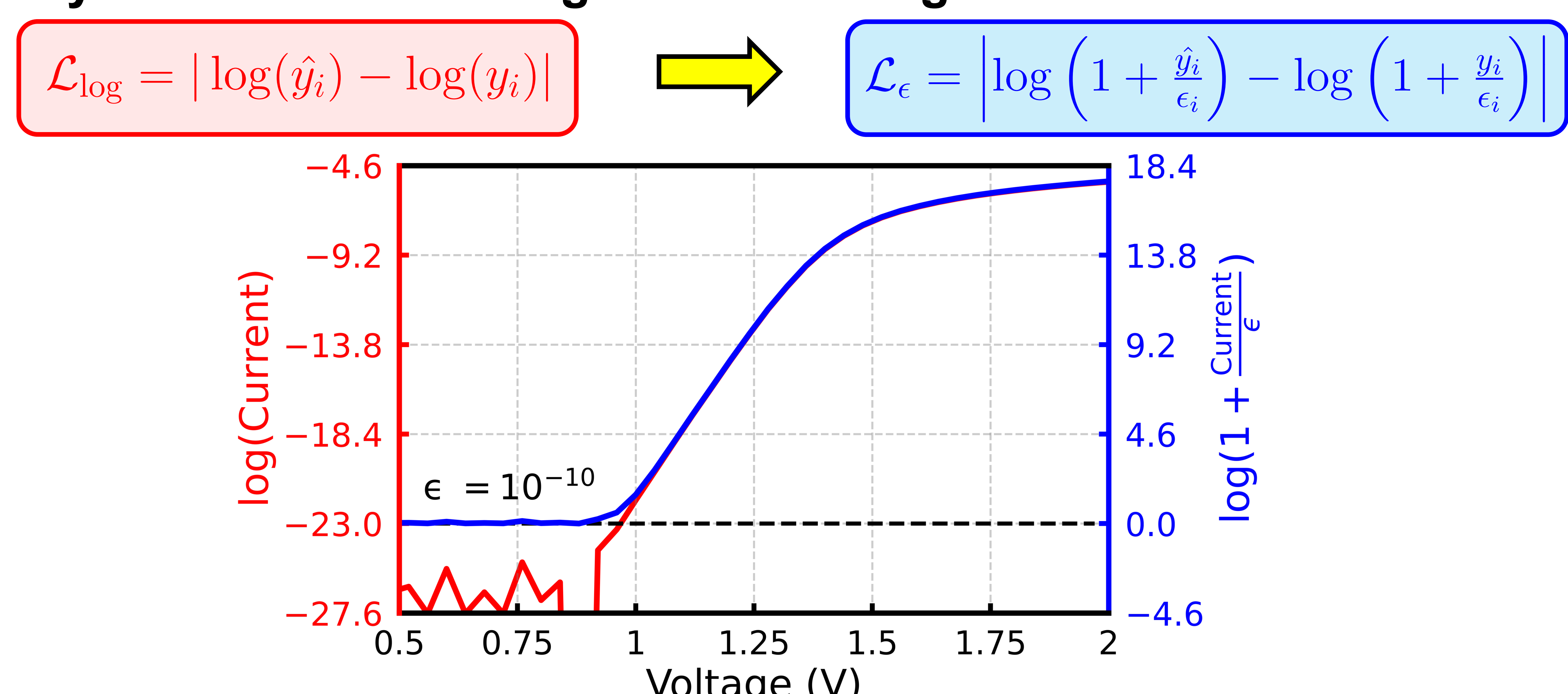
Importance of Relative Error in Device Modeling

- **Want to fit model across a wide range of values (e.g., 10 μA to 100 mA)**
- **Absolute Error**: Large values dominate while small values are ignored
- **Relative Error**: Uniform assessment across different scales of data



Prioritizing Key Operational Regions

- **Guide optimization process by prioritizing key regions of interest while deprioritizing less critical areas (e.g., below noise floor)**
- **Modify loss function to target model fitting above a certain threshold**

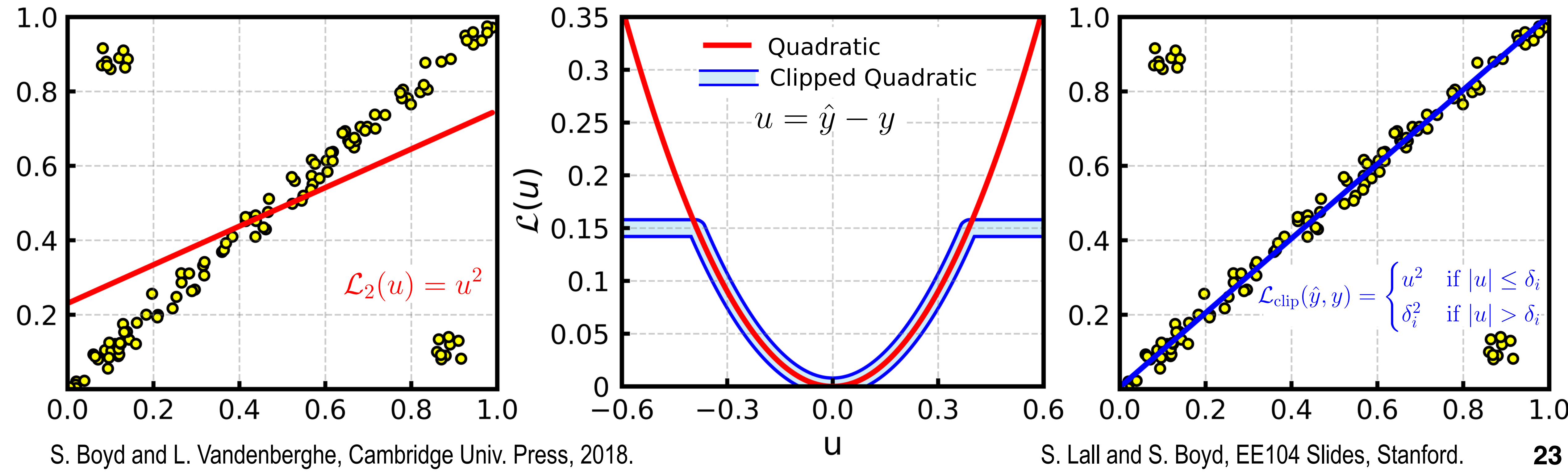


Robust Penalty Functions: Resiliency Against Outliers

- **Robust penalty function "clips" any |u| > δ_i (treats them as outliers)**
- **Reduces overall sensitivity to outliers and measurement errors**

$$\mathcal{L}_2(y, \hat{y}) = u^2$$

$$\mathcal{L}_{\text{clip}}(\hat{y}, y) = \begin{cases} u^2 & \text{if } |u| \le \delta_i \\ \delta_i^2 & \text{if } |u| > \delta_i \end{cases}$$

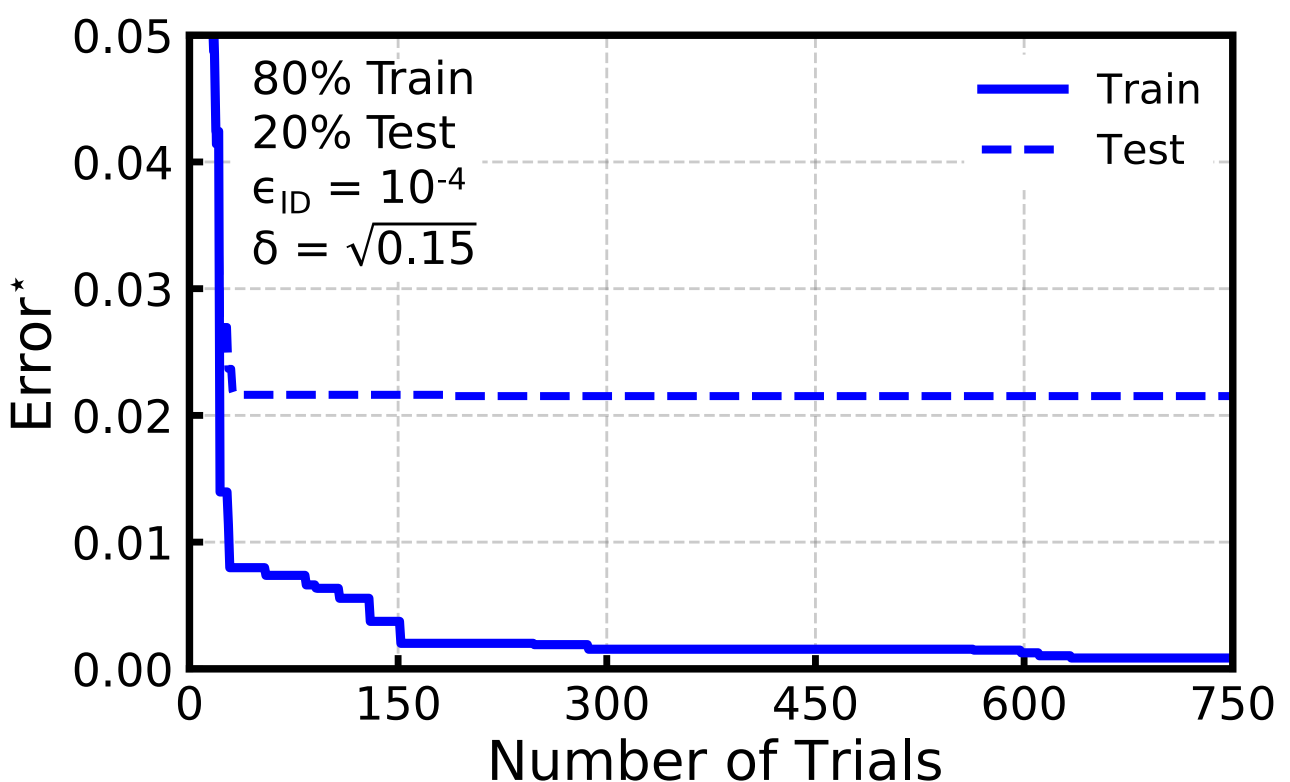


S. Boyd and L. Vandenberghe, Cambridge Univ. Press, 2018.

S. Lall and S. Boyd, EE104 Slides, Stanford.

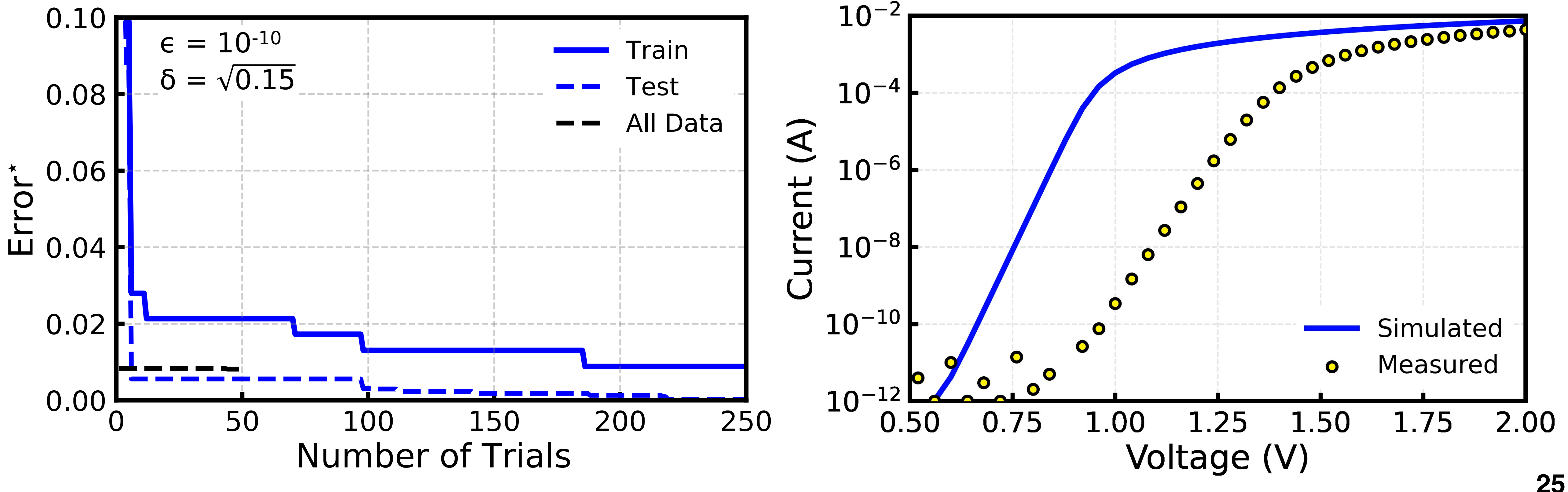
Assessing Model Fit Through Train / Test Split

- **Problem:** Need to judge model fit when extracting tens of model parameters
  - Model should perform reliably across various I / V's and unseen bias conditions
- **Consider a problem with 35 parameters and 35 measurements**
  - Model shows improved training performance with more trials, but no improvement on test data beyond 30 trials



Diamond Schottky Diode Example

- **Example of a diamond Schottky diode using the SPICE diode model**
- **Three parameters:** n (ideality factor), I_s (saturation current), R_s (series resistance)
  - V = 0.48 to 2 V (ΔV_D = 400 mV): 39 measurements
- **An excellent fitting in < 250 trials, resulting in an error of 0.01 (for I > 10^{-10})**

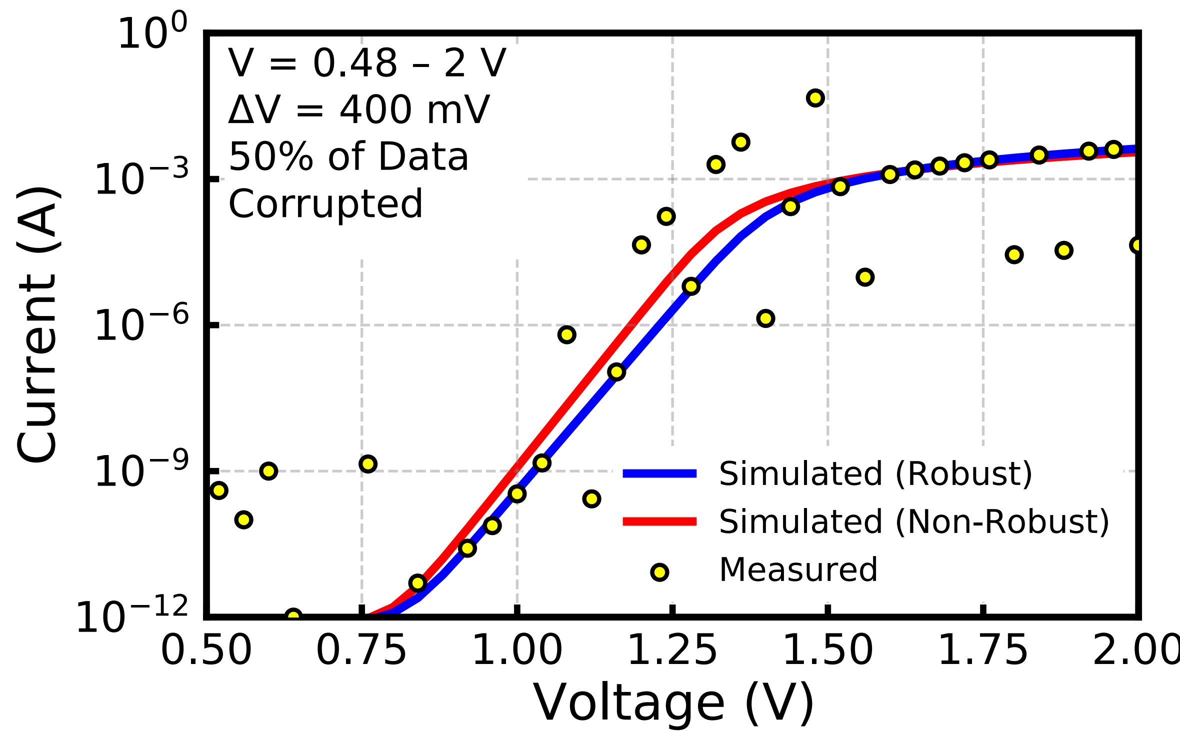


Diamond Schottky Diode Example: Robust to Outliers

- **We intentionally corrupt 50% of the diode's measurements**
- **Comparing two loss functions:** With and without penalty function
- **Proposed loss function accurately fitted the model (0.756 vs. 0.011)**

$$\mathcal{L}_{2,\epsilon}(\hat{y}, y) = \left| \log\left(1 + \frac{\hat{y}_i}{\epsilon_i}\right) - \log\left(1 + \frac{y_i}{\epsilon_i}\right) \right|^2$$

$$\mathcal{L}_{\text{clip}}(\hat{y}, y) = \begin{cases} u^2 & \text{if } |u| \leq \delta_i \\ \delta_i^2 & \text{if } |u| > \delta_i \end{cases}$$



Modeling a 150 nm GaN High-Electron-Mobility Transistor

- **High-performance 150 nm GaN HEMT process on a SiC substrate**
  – Primarily targets 5G and mm-wave applications (Ku, Ka, Q-band)
- **Modeled Devices:** 4x50 µm and 8x50 µm GaN HEMTs (L_G = 150 nm)

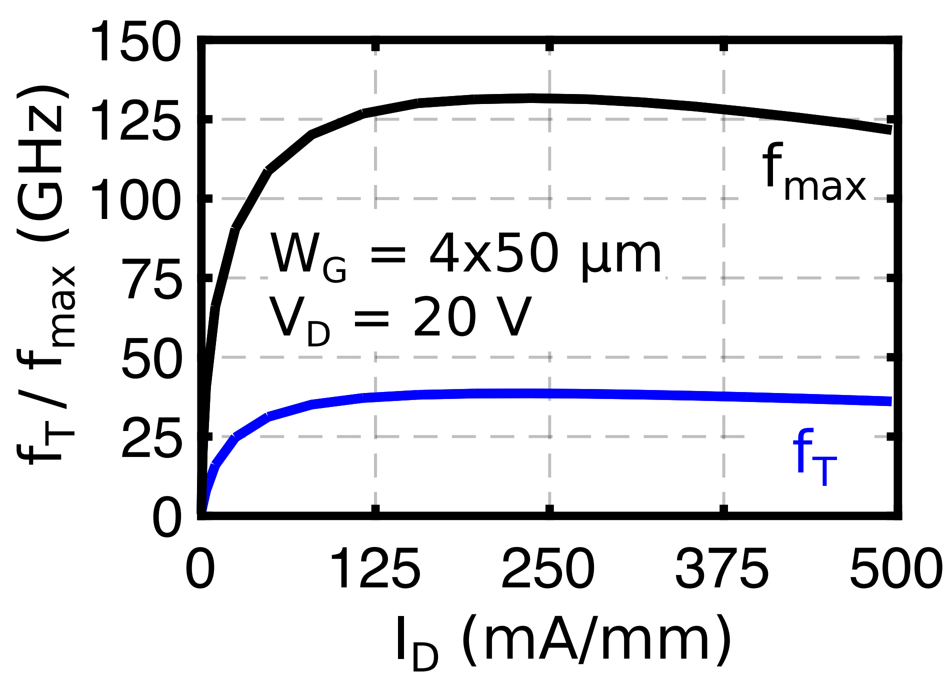
DC Characteristics & NVNA Data

W_G = 8x50 µm
f = 100 MHz

I_D (mA/mm)
1400
1200
1000
800
600
400
200
0

0 10 20 30 40 50 60
V_D (V)

Small-Signal Metrics

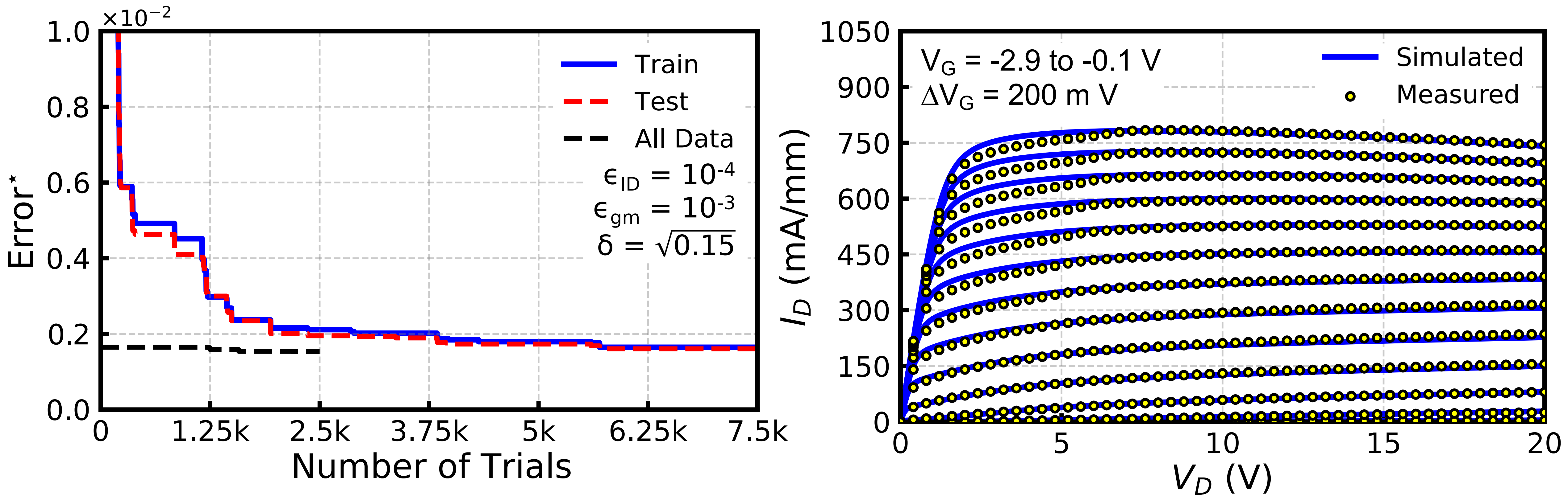


Special thanks to J. Xu for helping with NVNA measurements

R. P. Martinez, M. Iwamoto, and S. Chowdhury, *IEEE TMTT*, 2024.

4x50 μm GaN HEMT Example: Adjusting 35 Parameters

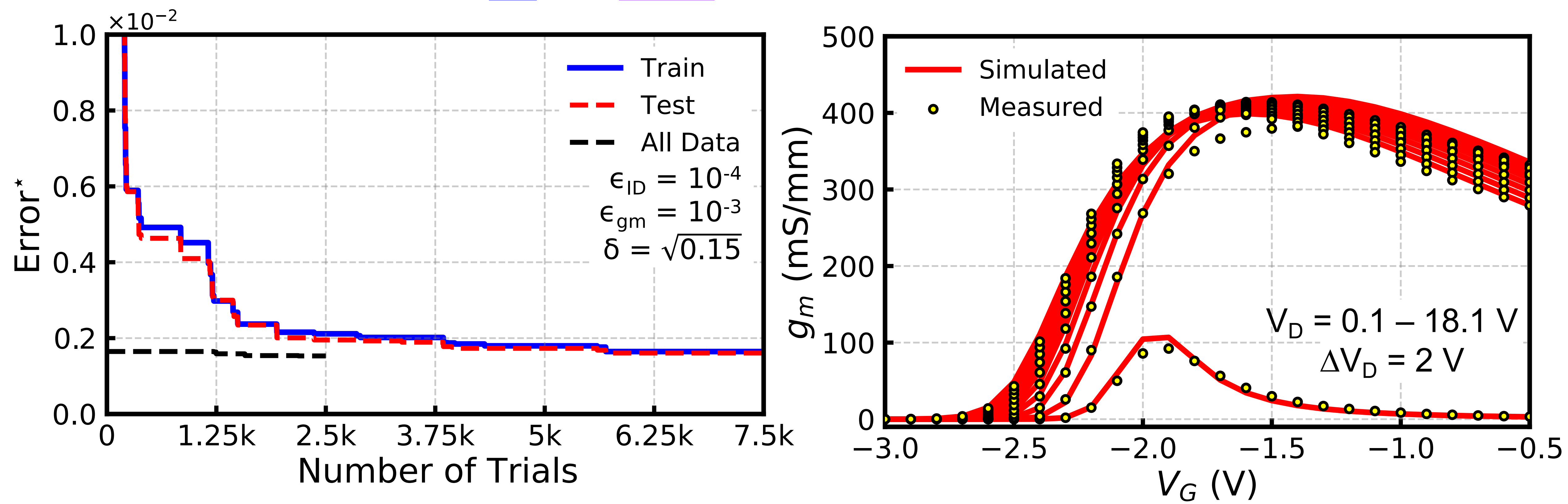
- **Simultaneously adjusted 35 model parameters to fit ASM-HEMT DC Model**
  - V_D = 0 to 20 V (ΔV_D = 0.1 V), V_G = -3 to -0.1 V (ΔV_G = 0.1 V): 6,030 measurements
- **Used a scalarizer (multi-obj. → single-obj.):** $\mathcal{L}_{\text{total}} = w_1 \mathcal{L}_{I_D} + w_2 \mathcal{L}_{g_m}$
- **Excellent fit achieved in < 6,000 trials, resulting in an I_D error of 1.25e-3**



R. P. Martinez, M. Iwamoto, S. Boyd, and S. Chowdhury, *IEEE Access*, 2024.

4x50 µm GaN HEMT Example: Adjusting 35 Parameters

- **Simultaneously adjusted 35 model parameters to fit ASM-HEMT DC Model**
  - V_D = 0 to 20 V (ΔV_D = 0.1 V), V_G = -3 to -0.1 V (ΔV_G = 0.1 V): 6,030 measurements
- **Excellent fit achieved in < 6,000 trials, resulting in a g_m error of 2.17e-3**
- **< 5% of simulations (6k vs. 120k) required compared to DL approach**

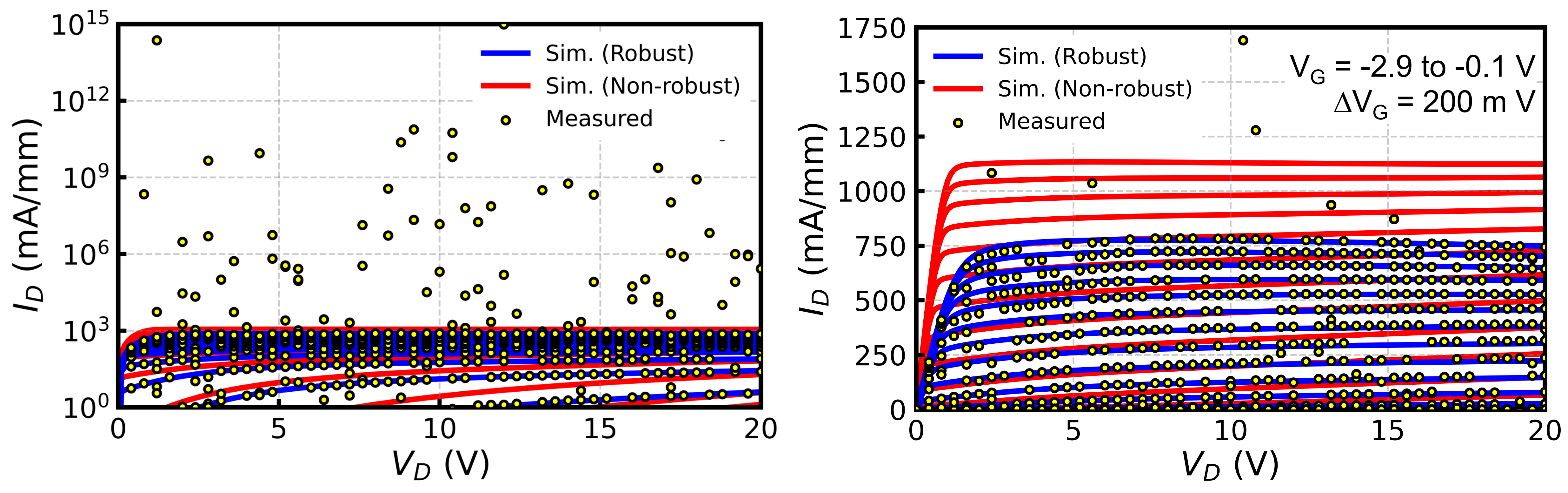


F. Chavez et al., *IEEE EDL*, 2023.

R. P. Martinez, M. Iwamoto, S. Boyd, and S. Chowdhury, *IEEE Access*, 2024.

GaN HEMT Robust Example: Corrupting 25% of Data

- **Repeated same extraction but now corrupted 25% of measurements**
  - Corrupted data follows a normal (Gaussian) distribution with μ = 0 and σ = 10
- **Robust loss function achieved good fit achieved in < 4,000 trials, while non-robust loss function resulted in a poor I_D fit (0.00127 vs. 0.325)**



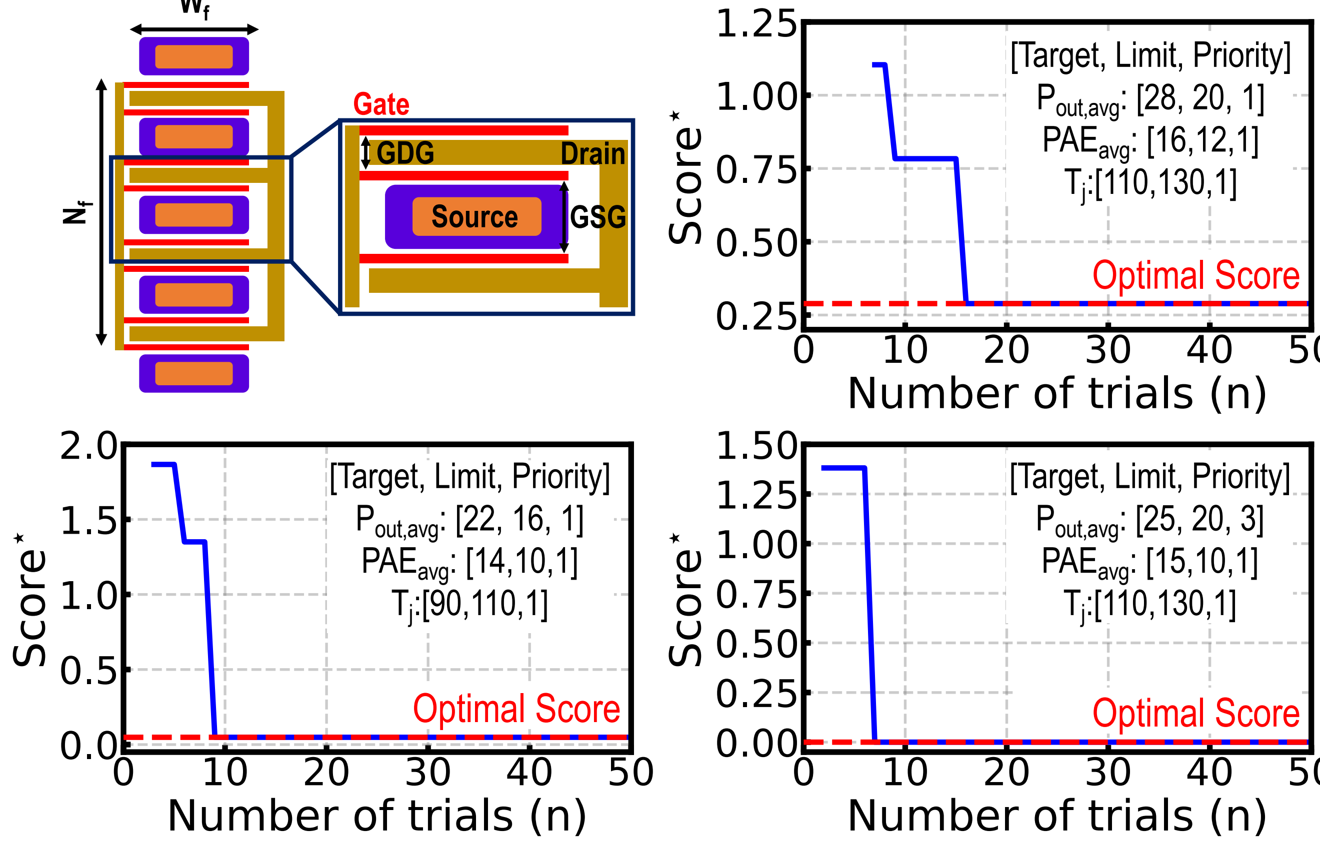
R. P. Martinez, M. Iwamoto, S. Boyd, and S. Chowdhury, *IEEE Access*, 2024.

Robust Pareto Design for GaN HEMT Sizing

Robust Pareto design methodology for sizing GaN HEMTs for PA applications, utilizing DFO to identify Pareto optimal designs

Multi-Objective Optimization

Optimal Score Reached in < 4% of 672 Designs



R. P. Martinez, S. Boyd, and S. Chowdhury, submitted.

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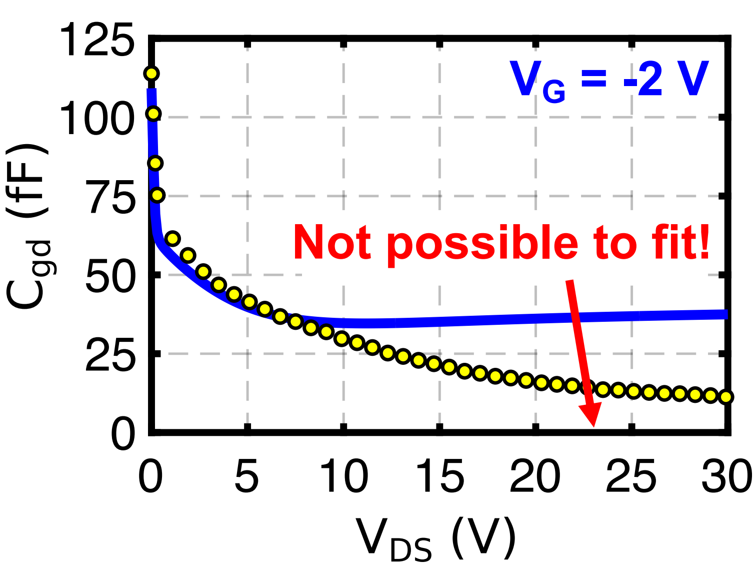
ASM-HEMT Model Limitations for C-V Characteristics

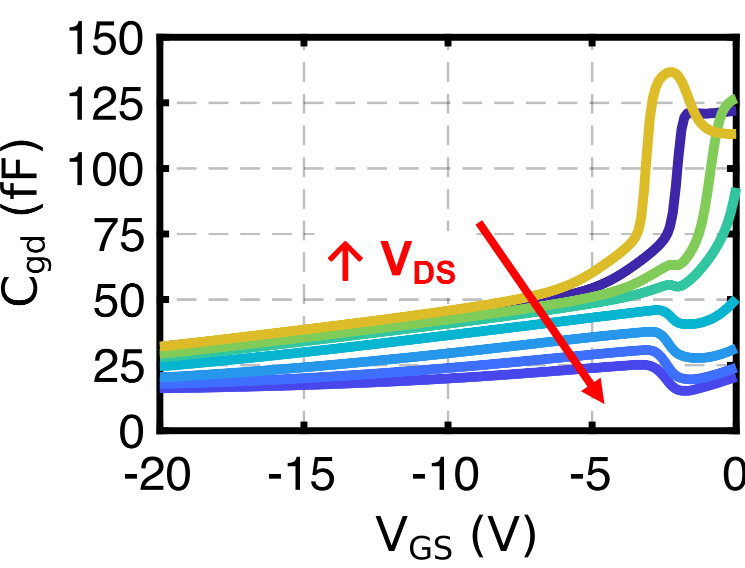
- **Problem:** ASM-HEMT fails to capture CV non-linearities of the device
  - – DFO and manual approaches are unable to fit measured CV curves
- **Most results in the literature only show fitting at one V_D bias point**
  - – Nonlinear behavior in scaled HEMTs isn't modeled properly (in most models)

Accurate modeling of device nonlinearities results in improved prediction of S-parameters, AM-PM / IM distortion, ACPR / EVM

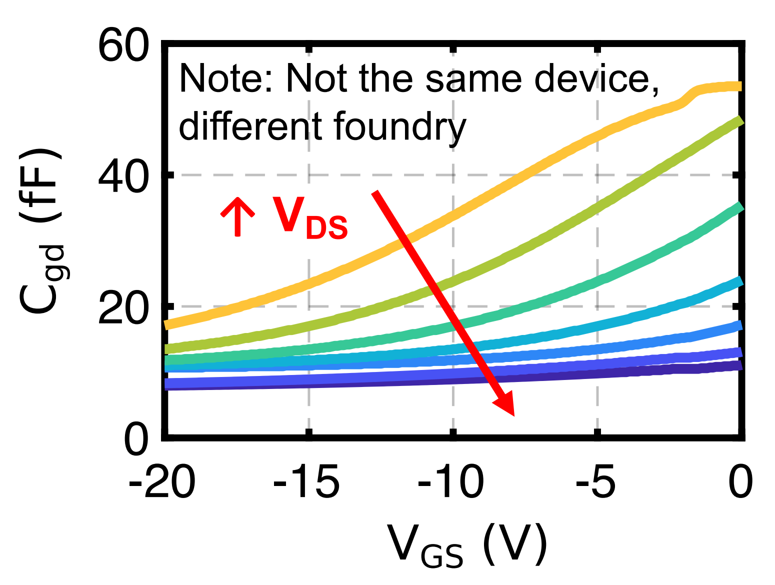
ASM-HEMT Model



C_{GD} Measured Data



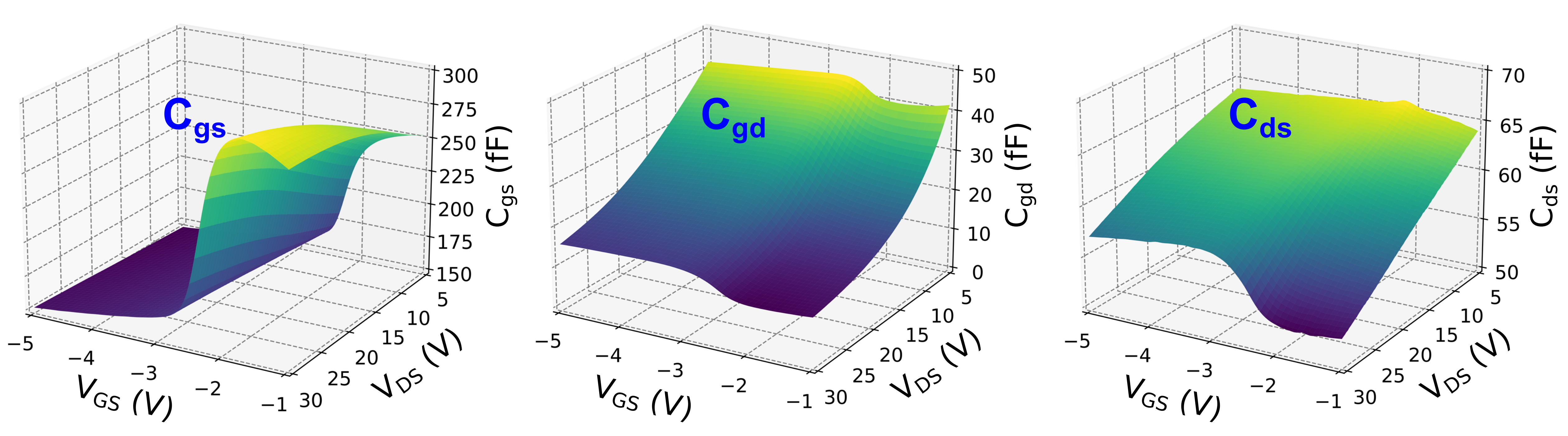
Foundry Model Simulation



Solution: Enhancing the ASM-HEMT Model Framework

- **Two-step approach to enhancing ASM-HEMT model framework:**
  1) Find <u>limitations</u> where the model fails to capture complex nonlinear behavior
  2) <u>Compensate</u> for physical behavior not captured by ASM-HEMT framework

Nonlinear Junction Capacitances of 4x50 µm GaN HEMT



Modifying the ASM-HEMT 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**

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

"Compensating"
(Uses a Neural Network)

Implemented through Verilog-A

Modifying the ASM-HEMT 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

Intrinsic **Overlap** **Depletion** **Fringe** **"Compensating"**

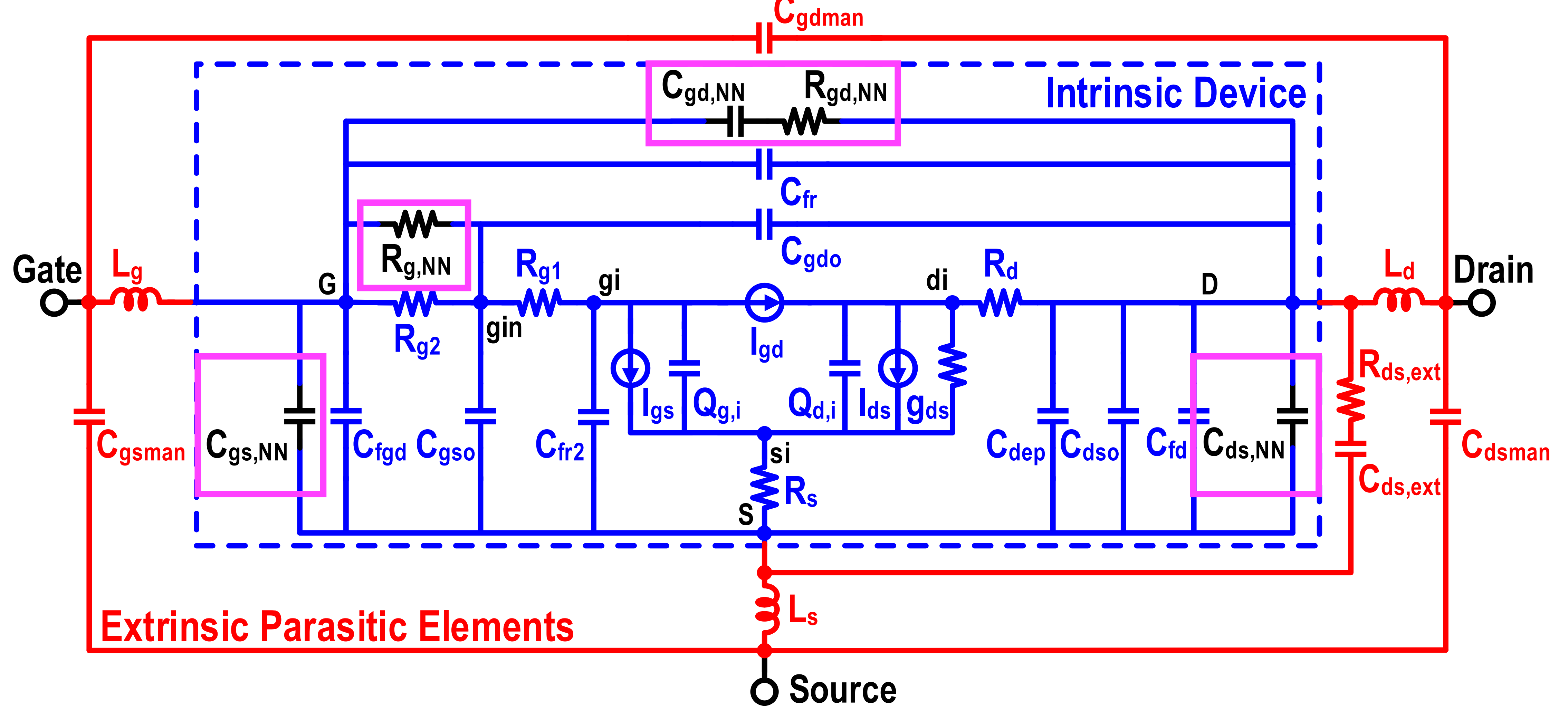
$$Q_D = Q_{\mathrm{di}} + \int C_{\mathrm{dso}}\, dV_{\mathrm{DS}} + Q_{\mathrm{dep}} + \int C_{\mathrm{fd}}\, dV_{\mathrm{DS}} + \int C_{\mathrm{ds,NN}}\, dV_{\mathrm{DS}}$$

(Uses a Neural Network)

Implemented through Verilog-A

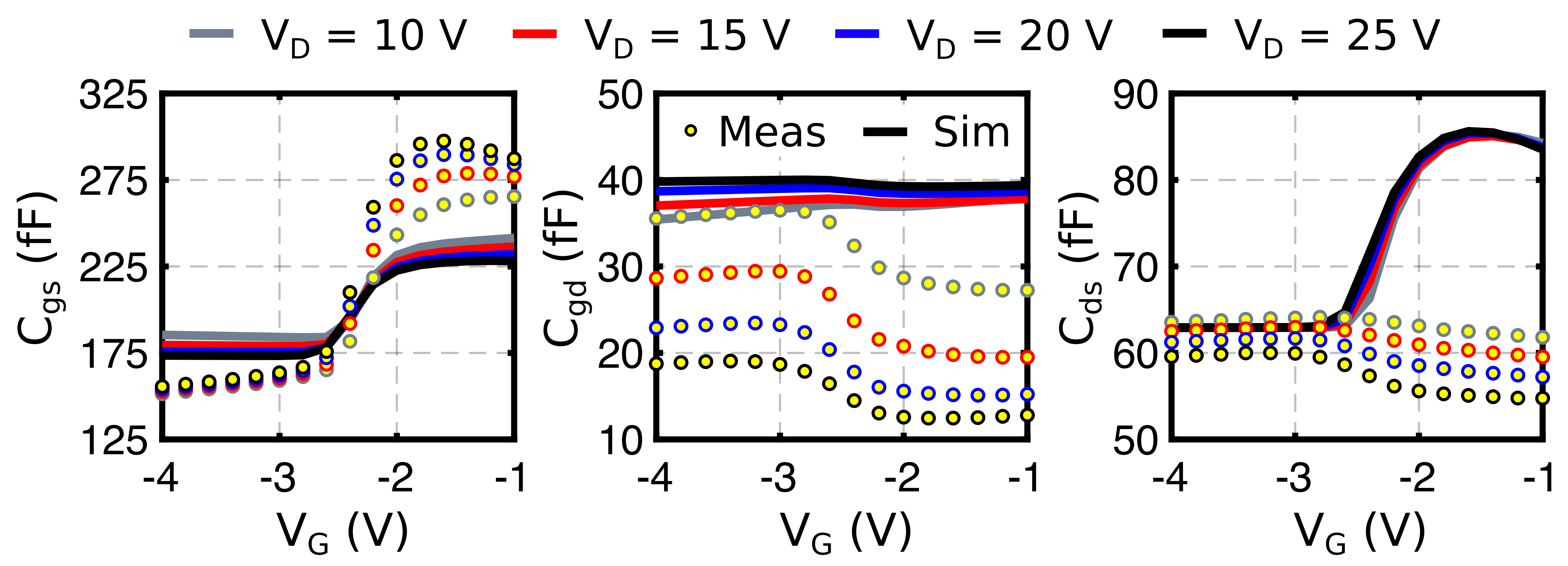
Equivalent Circuit Model for Hybrid ASM-HEMT Model

- Intrinsic, extrinsic, and modified circuit elements in hybrid ASM-HEMT
- Modified circuit elements compensate for unmodeled physical behavior



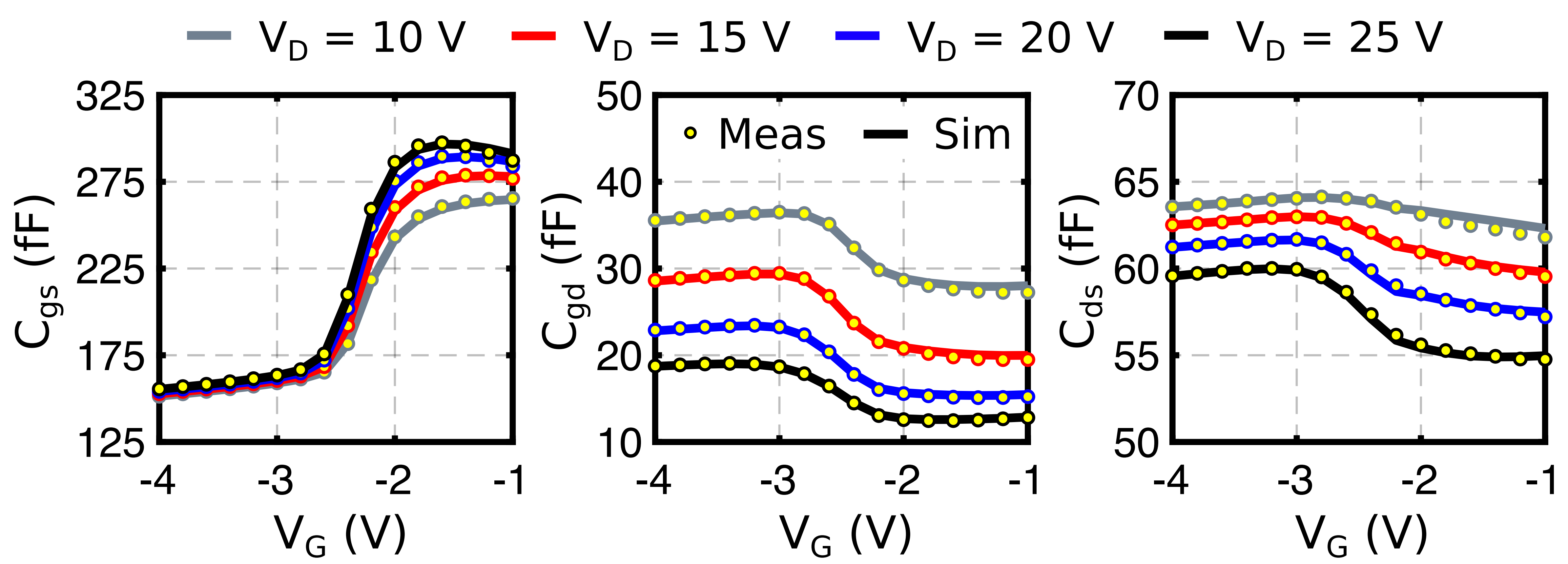
Baseline Model Fails to Model Junction Capacitances

- **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)**



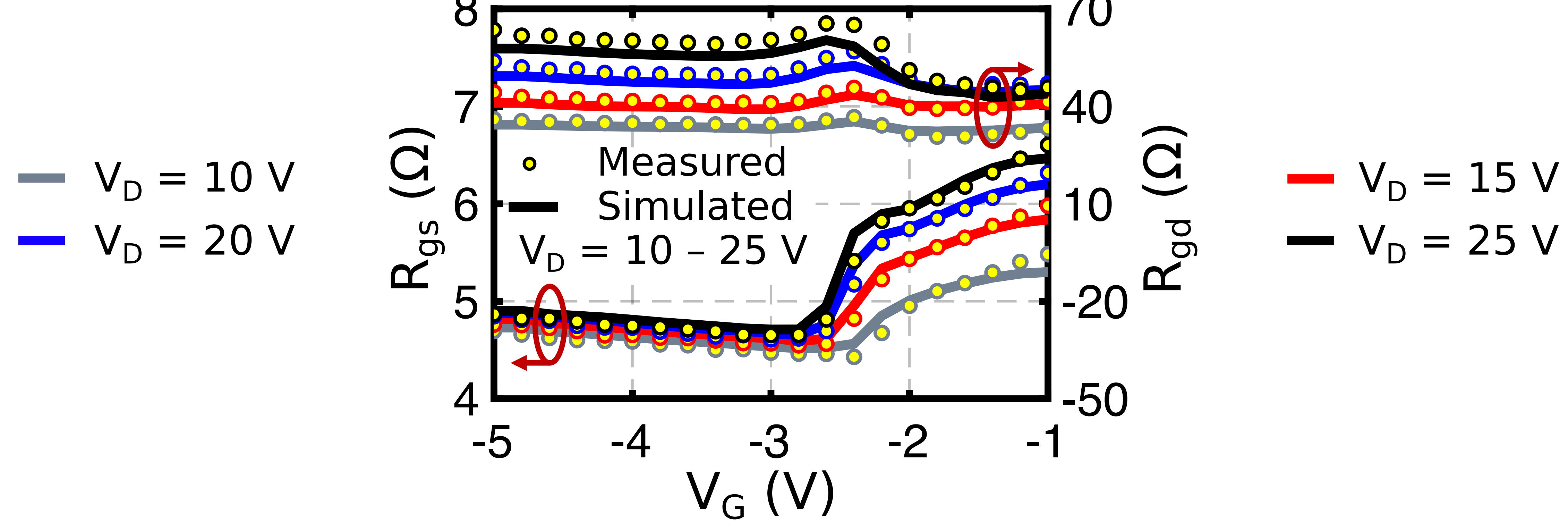
Improved Capacitance Fitting Using Hybrid Approach

- **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**

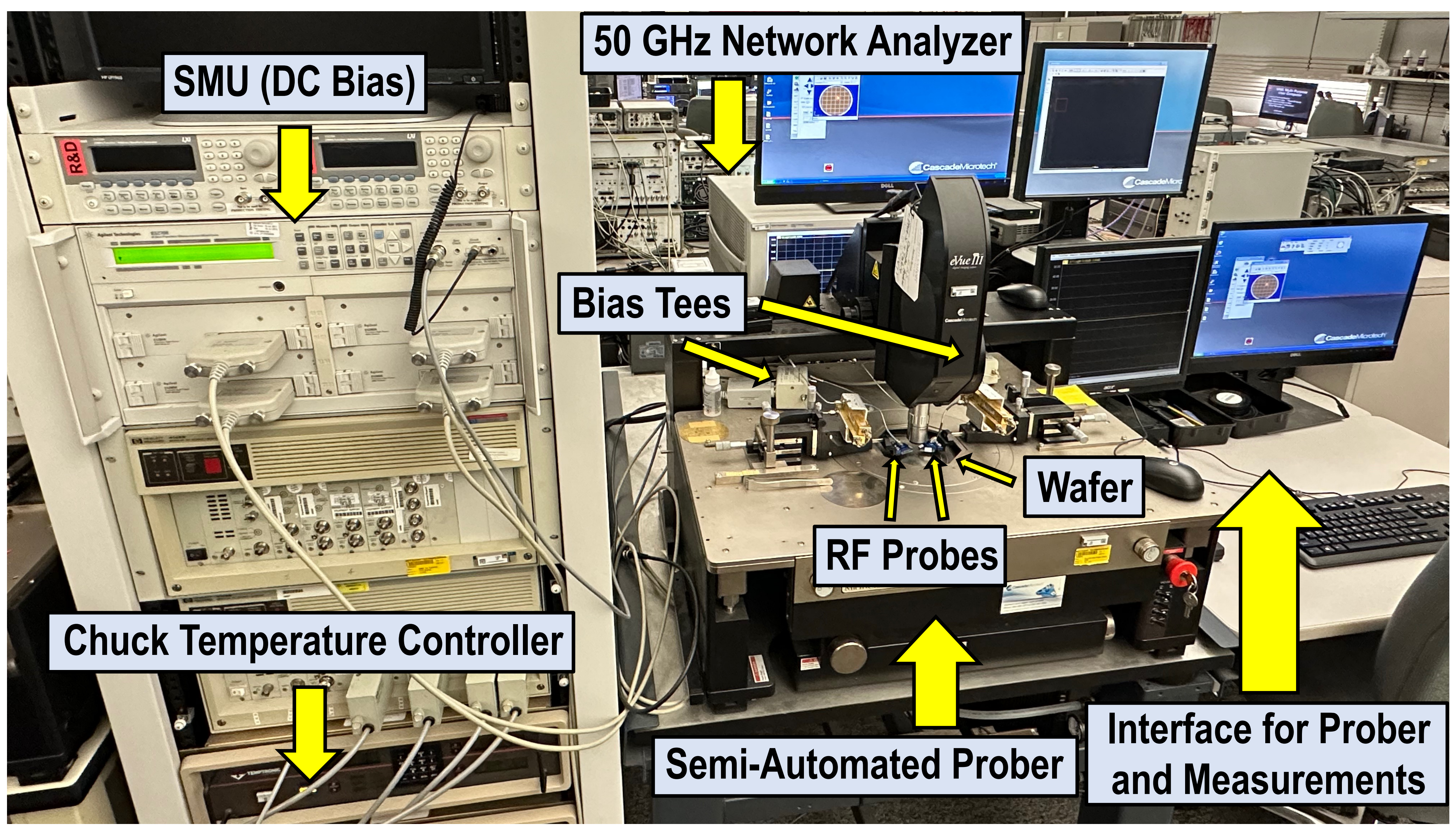


Improved Resistance Fitting Using Hybrid Approach

- **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**



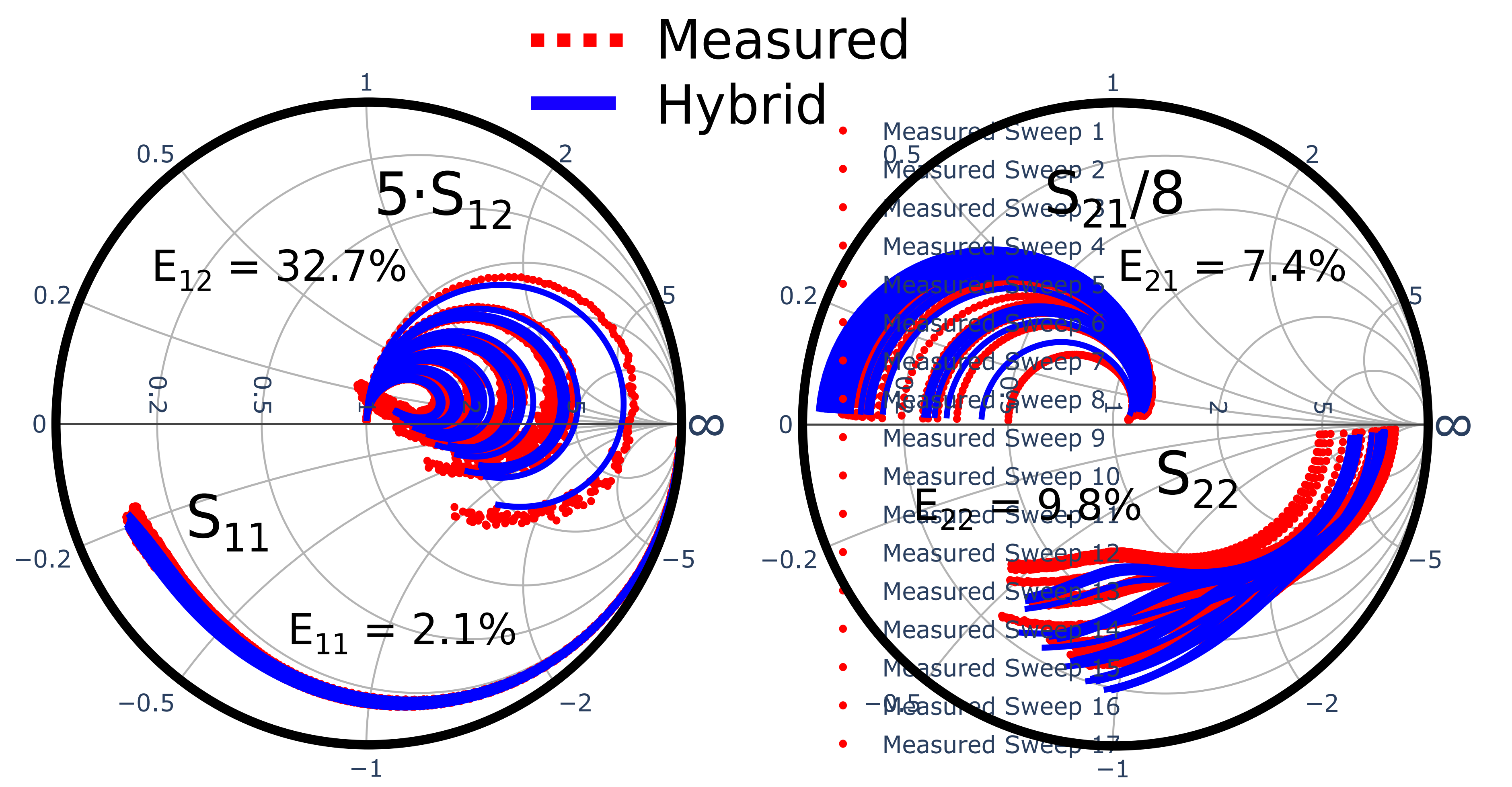
Set-up for S-parameter Modeling and Validation



Courtesy of M. Iwamoto (Keysight Technologies MML)

S-parameter Model Validation (100 MHz – 50 GHz)

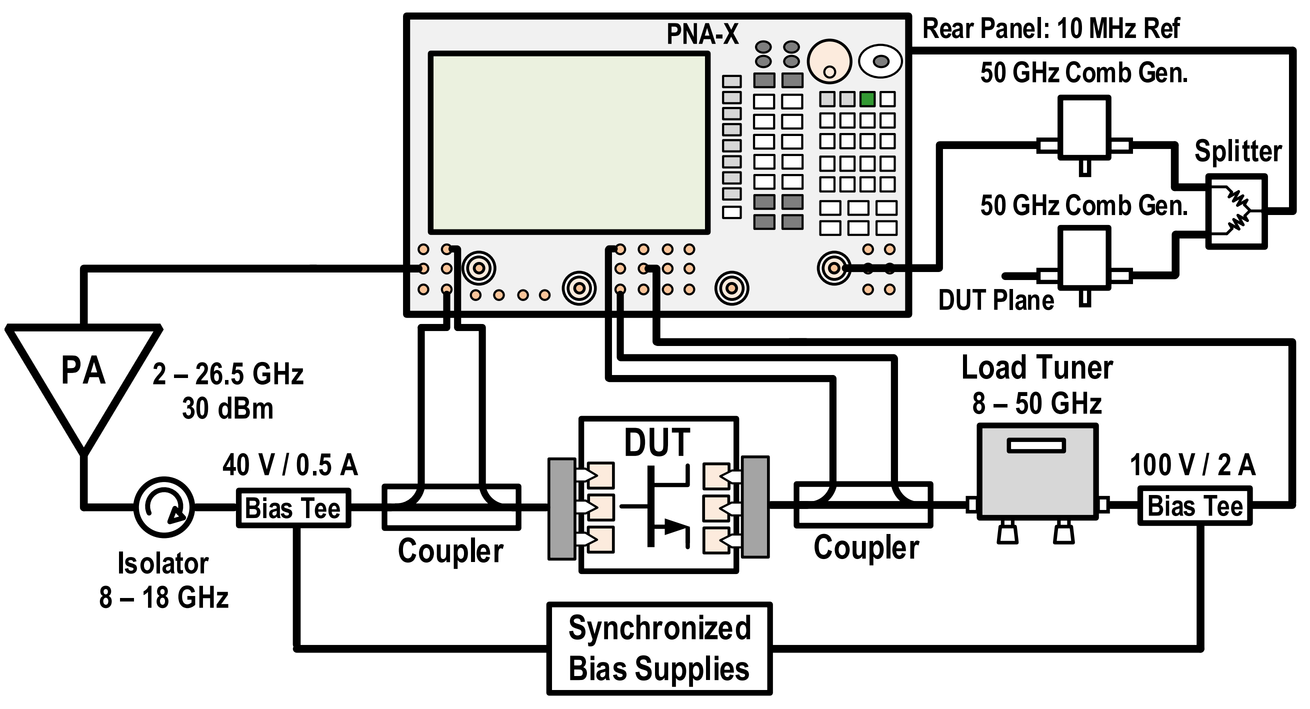
- **Good agreement between measured and simulated S-parameters**
  - V_D = 5 – 25 V (ΔV_D = 5 V), V_G = -2.2 to -1 V (ΔV_G = 0.2 V), I_D = 15 – 500 mA/mm



Set-up for Non-linear Validation (X-parameters + LP)

- Built 8 – 50 GHz load-pull system from scratch (difficult but worth it!)
- Fundamental load-tuner and NVNA set measurement frequency range
- Driver amplifier + isolator limit how much P_{out} we can present to the DUT

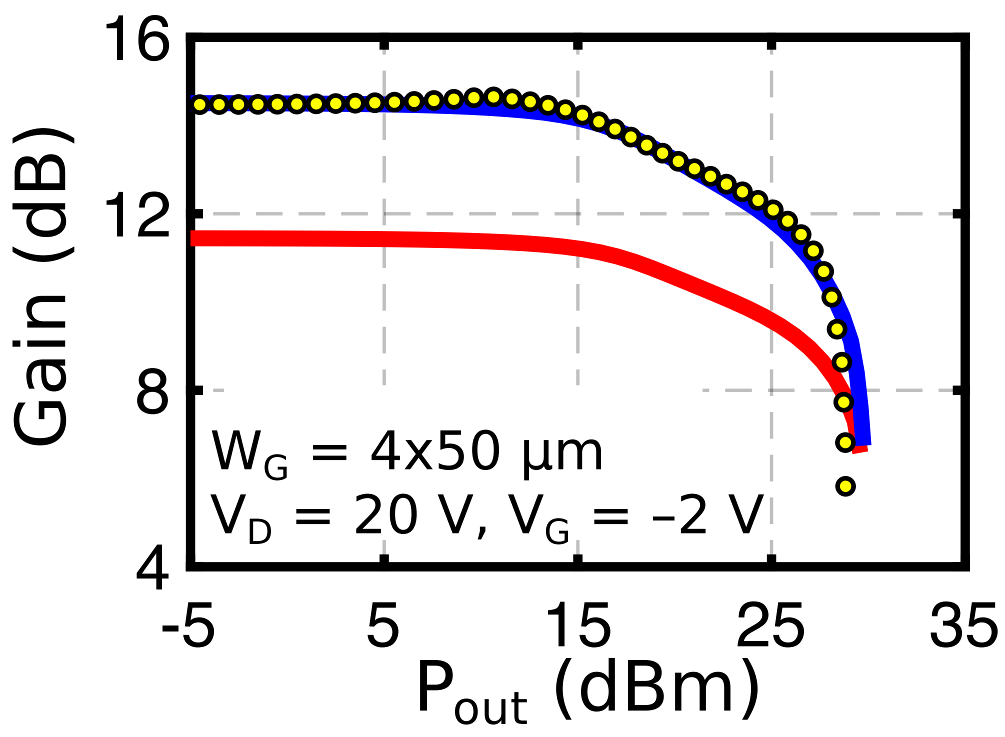
SMU (DC Bias)
Power Sensor
Chuck Temperature Controller
50 GHz Network Analyzer
Bias Tees
Load Tuner
Couplers
DUT
Comb Generators
RF Probes
Power Amplifier
Manual Prober
E-Cal

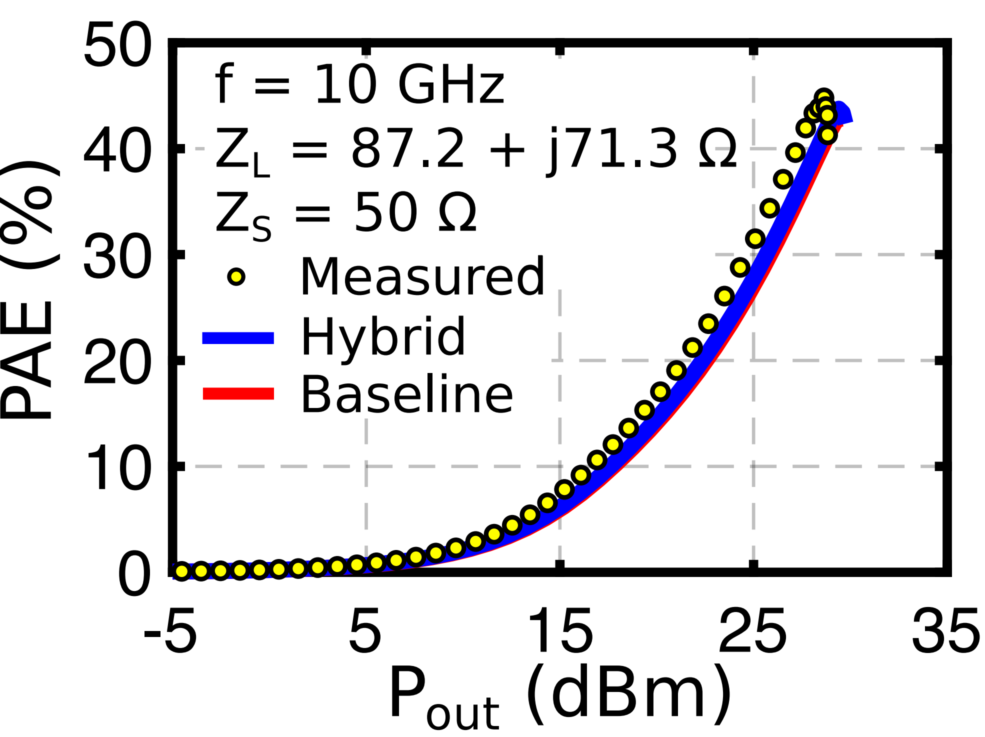


Special thanks to C. Gillease, M. Culver, A. Cognata, and M. Iwamoto

Large-Signal Non-linear Validation for 4x50 µm HEMT

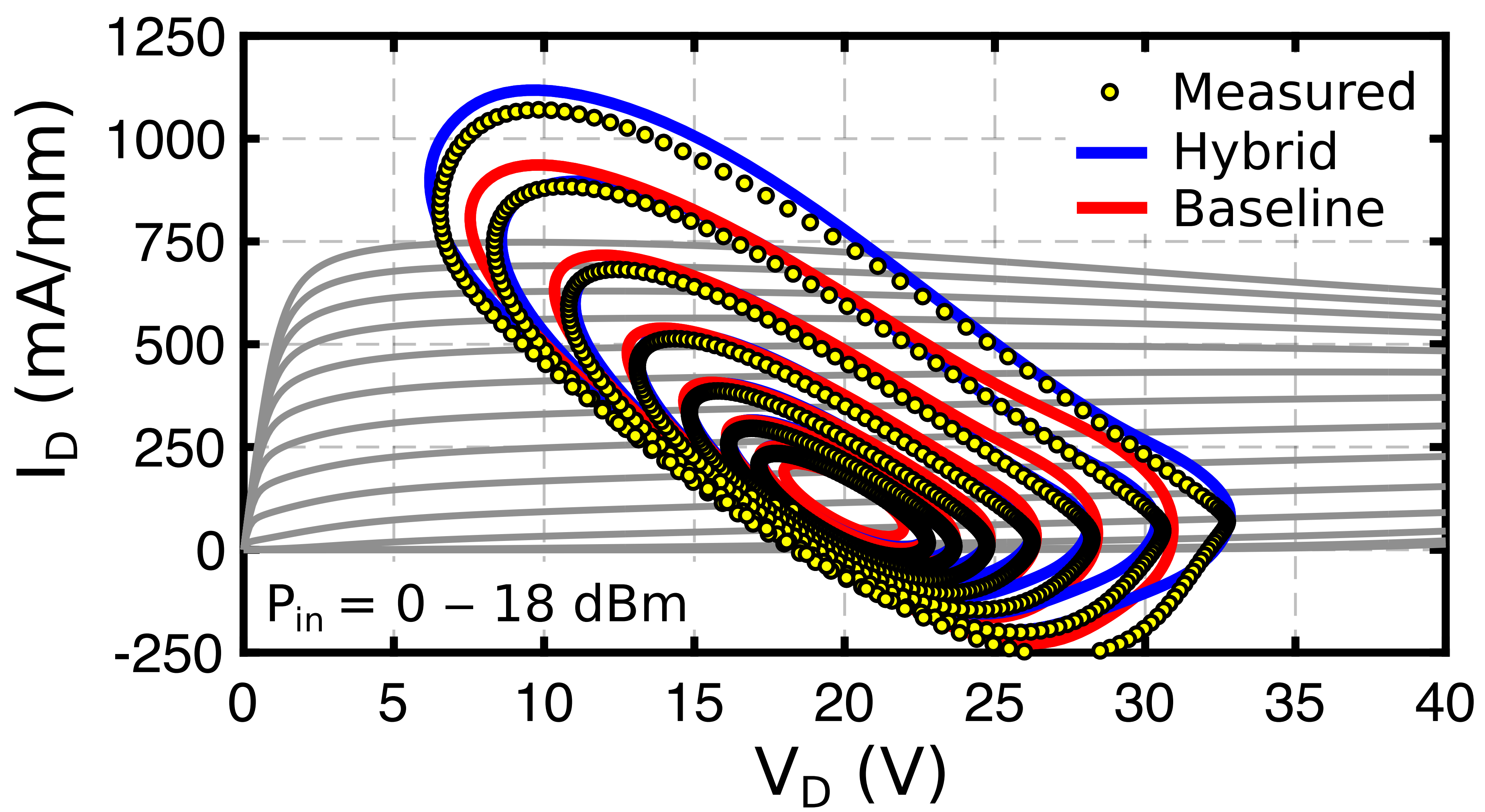
- **Hybrid model accurately predicted gain compression and PAE**
- **Baseline model resulted in a poor fit for gain compression**
  - Baseline model confined to a narrow V_{DS} range due to existing limitations





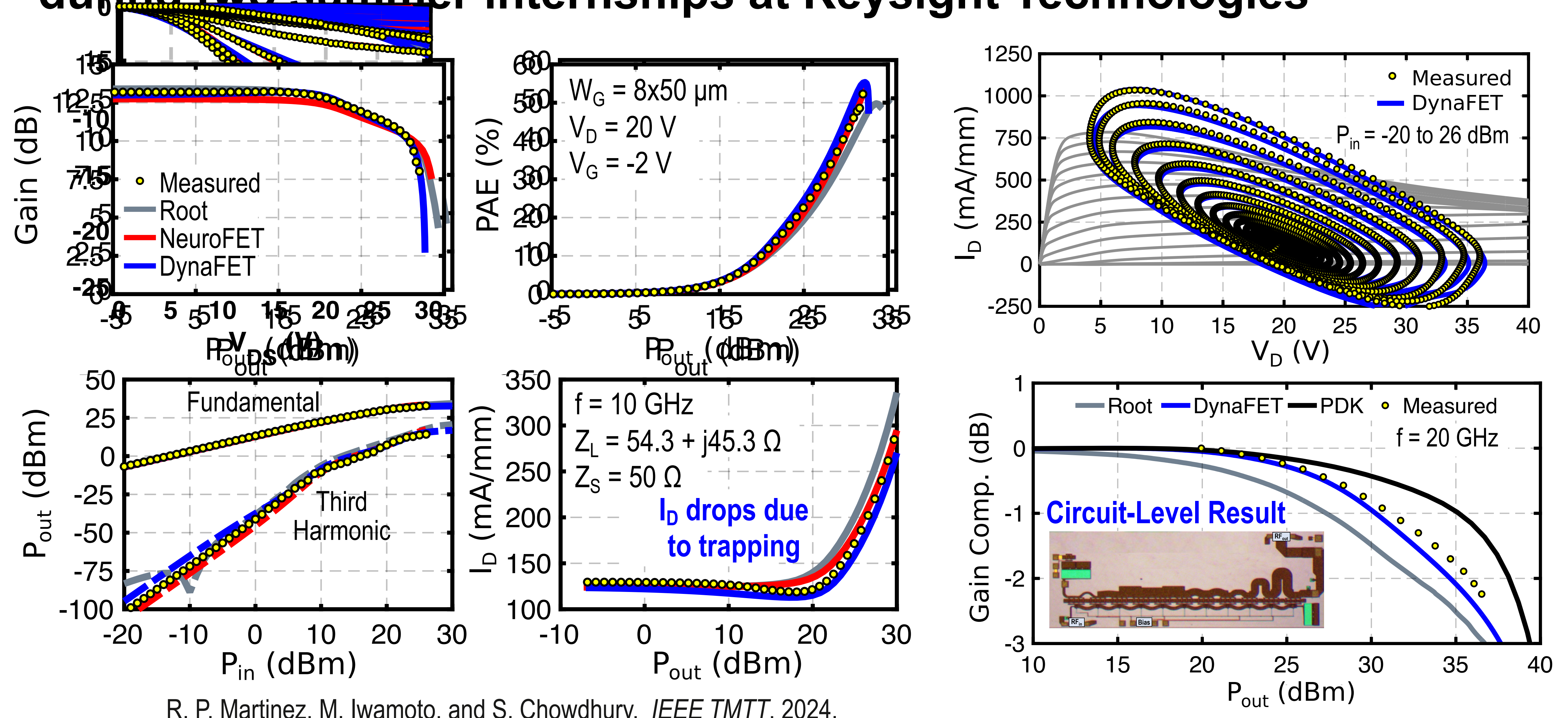
Measured / Simulated Dynamic Load-Lines

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



Assessment of Three Measurement-Based Models

- **Previously extracted and validated <u>three</u> measurement-based models during two summer internships at Keysight Technologies**



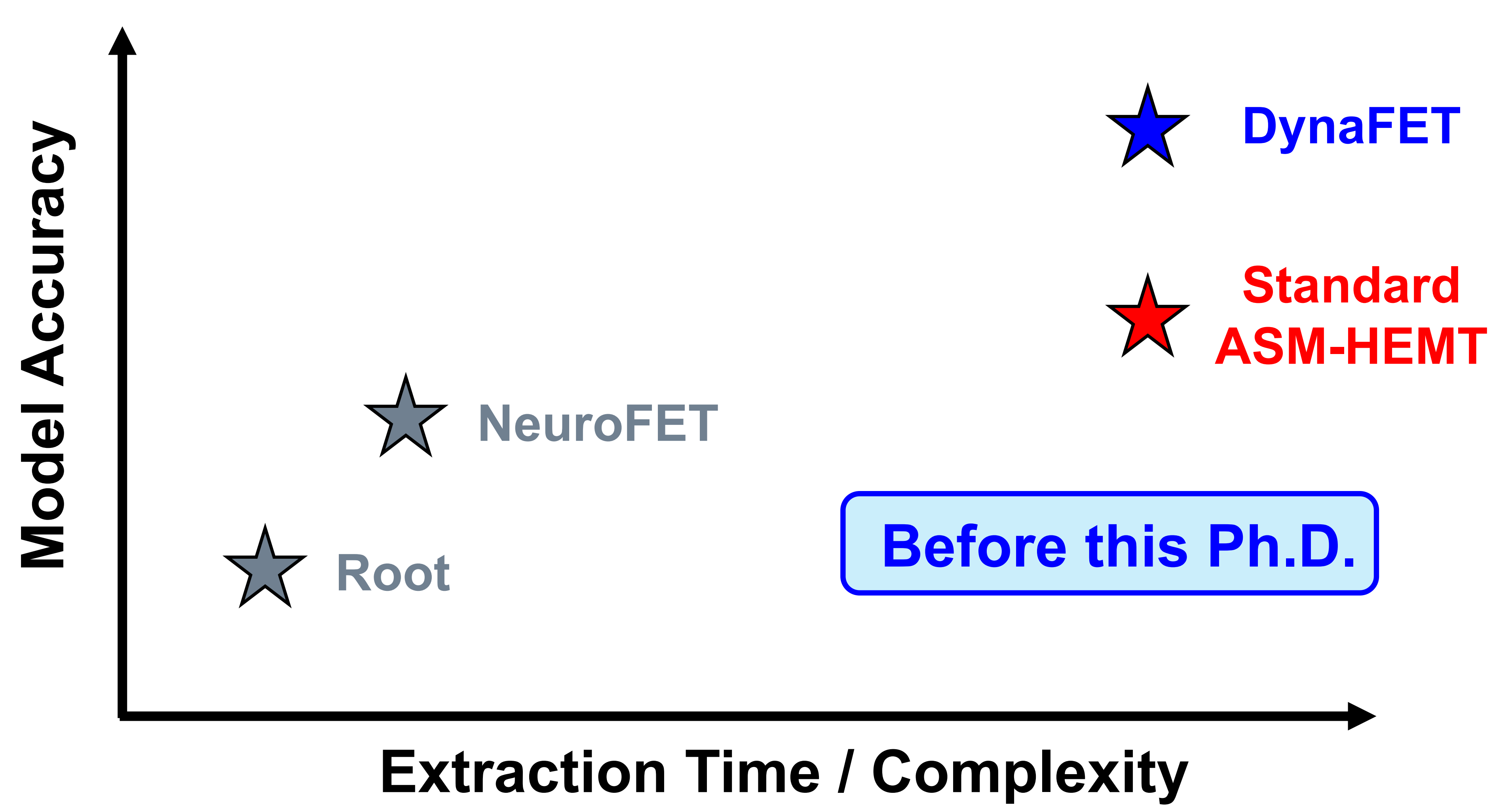
R. P. Martinez, M. Iwamoto, and S. Chowdhury, *IEEE TMTT*, 2024.

Outline

- Introduction to GaN Technology
- Lending Derivative-Free Optimization to Device Modeling
- A Hybrid Physical ASM-HEMT Model
- **Summary of Contributions**

Contributions of this Ph.D. to GaN Device Modeling

- **Improved ASM-HEMT accuracy while greatly reducing extraction time**
- **Methods are model-agnostic:** Applicable to Silicon & III-V technologies



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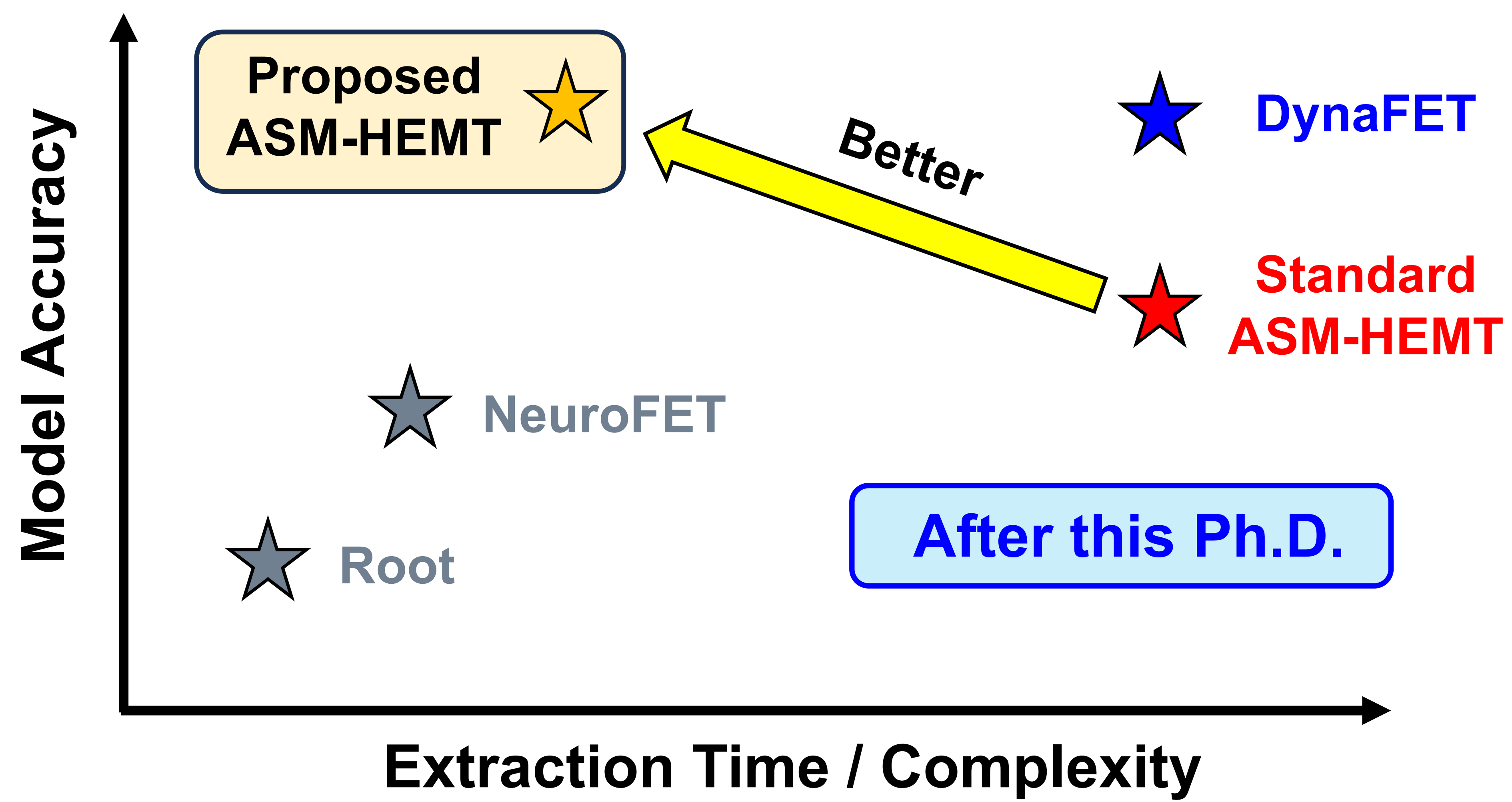

Summary of Contributions

- **Assessed the strengths and limitations of measurement-based models**
- **Proposed a new parameter extraction method based on derivative-free optimization along with a loss function**
- **Introduced a new hybrid approach in the ASM-HEMT model to improve fitting of non-linear capacitances and intrinsic resistances**
- **Improved standard ASM-HEMT model extraction flow by addressing its current limitations**
- **Introduced a robust Pareto design (multi-objective optimization) approach for selecting GaN HEMT designs in the context of 5G**

All code developed for this presentation will be made available on GitHub under an open-source license to benefit the device modeling community

Journal Publications

1) **R. P. Martinez**, M. Iwamoto, K. Woo, Z. Bian, R. Tinti, S. Boyd, and S. Chowdhury, “Compact Model Parameter Extraction via Derivative-Free Optimization,” IEEE Access, vol. 12, pp. 123224-123235, Sep. 2024, doi: 10.1109/ACCESS.2024.3453198.
2) **R. P. Martinez**, S. Boyd, and S. Chowdhury, “Robust Pareto Design of GaN HEMTs for Millimeter-Wave Applications,” under review.
3) K. Woo, Z. Bian, M. Noshin, and **R. P. Martinez**, M. Malakoutian, B. Shankar, S. Chowdhury, “From wide to ultrawide-bandgap semiconductors for high power and high frequency electronic devices,” *J. Phys.: Mater*, vol. 7, no. 2, pp. 022003, Mar. 2024, doi:10.10882515-7639ad218b.
4) **R. P. Martinez**, M. Iwamoto, J. Xu, C. Gillease, S. Cochran, M. Culver, A. Cognata, N. Wagner, P. Pahl, and S. Chowdhury, “Assessment and Comparison of Measurement-Based Large-Signal FET Models for GaN HEMTs,” *IEEE Trans. Microw. Theory Techn.*, vol. 72, no. 5, pp. 2692-2703, May 2024, doi:10.1109/TMTT.2023.3349172.
5) H. Lu, M. Zhang, L. Yang, B. Hou, **R. P. Martinez**, M. Mi, J. Du, L. Deng, M. Wu, S. Chowdhury, X. Ma, Y. Hao, “A Review of GaN RF Devices and Power Amplifiers for 5G Communication Applications,” *Fundam. Res.*, Nov. 2023, doi:10.1016/j.fmre.2023.11.005.
6) **R. P. Martinez**, D. J. Munzer, B. Shankar, B. Murmann, and S. Chowdhury, “Linearity Performance of Derivative Superposition in GaN HEMTs: A Device-to-Circuit Perspective,” *IEEE Trans. Electron Devices*, vol. 70, no. 5, pp. 2247-2254, May 2023, doi:10.1109/TED.2023.3259383.
7) X. Y. Zhou, M. Malakoutian, R. Soman, Z. Bian, **R. P. Martinez**, and S. Chowdhury, “Impact of Diamond Passivation on fT and fmax of mm-wave N-polar GaN HEMTs,” *IEEE Trans. Electron Devices*, vol. 69, no. 12, pp. 6650-6655, Dec. 2022, doi: 10.1109/TED.2022.3218612.

Conference Publications

1) **R. P. Martinez**, M. Iwamoto, A. B. Morgado, Y. Li, R. Tinti, J. Xu, E. Schmidt, Z. Song, N. Wagner, P. Pahl, A. Petr, and S. Chowdhury, "A Hybrid Physical ASM-HEMT Model Using a Neural Network-Based Methodology," in *Proc. IEEE BiCMOS Compound Semicond. Integr. Circuits Technol. Symp.*, Oct. 2024, pp. 38-41, doi: 10.1109/BCICTS59662.2024.10745660.

2) **R. P. Martinez**, M. Iwamoto, J. Xu, P. Pahl, and S. Chowdhury, "Benchmarking Measurement-Based Large-Signal FET Models for GaN HEMT Devices," in *Proc. IEEE Radio Freq. Integr. Circuits Symp. (RFIC)*, San Diego, CA, USA, 2023, pp. 1-4, doi: 10.1109/RFIC54547.2023.10186170.

3) B. Shankar, **R. P. Martinez**, P. Zuk, and S. Chowdhury, "A di/dt Triggered Self-Powered Unidirectional DC Circuit Breaker for both GaN and SiC platform for 400 V DC Applications," in *Proc. IEEE Energy Convers. Congr. Expo (ECCE)*, Detroit, MI, USA, 2022, pp. 1-4, doi: 10.1109/ECCE50734.2022.9947482.

4) B. Shankar, K. Zeng, B. Gunning, **R. P. Martinez**, C. Meng, J. Flicker, A. Binder, J. R. Dickerson, R. Kaplar, and S. Chowdhury, "Movement of Current Filaments and its Impact on Avalanche Robustness in Vertical GaN P-N diode Under UIS stress," in *Proc. 80th Device Res. Conf. (DRC)*, 2022, pp. 1-2, doi: 10.1109/DRC55272.2022.9855818.

5) B. Shankar, Z. Bian, K. Zeng, B. Gunning, C. Meng, **R. P. Martinez**, J. Flicker, A. Binder, J. R. Dickerson, R. Kaplar, and S. Chowdhury, "Study of Avalanche Behavior in 3 kV GaN Vertical P-N Diode Under UIS Stress for Edge-termination Optimization," in *Proc. IEEE Int. Rel. Phys. Symp. (IRPS)*, 2022, pp. 2B.2-1-2B.2-4, doi: 10.1109/IRPS48227.2022.9764525.

6) **R. P. Martinez**, D. J. Munzer, X. Zhou, B. Shankar, E. Schmidt, K. Wildnauer, B. Murmann, and S. Chowdhury, "Best Practices to Quantify Linearity Performance of GaN HEMTs for Power Amplifier Applications," *in Proc. IEEE 8th Workshop Wide Bandgap Power Devices Appl. (WiPDA)*, 2021, pp. 259-262, doi: 10.1109/WiPDA49284.2021.9645120.

7) X. Zhou, **R. P. Martinez**, B. Shankar, and S. Chowdhury, "Design of Ka-Band Doherty Power Amplifier Using 0.15 μm GaN on SiC Process Based on Novel Complex Load Modulation," in *Proc. IEEE 8th Workshop Wide Bandgap Power Devices Appl. (WiPDA)*, 2021, pp. 259-262, doi: 10.1109/WiPDA49284.2021.9645125.

8) B. Shankar, K. Zeng, B. Gunning, K. J. Lee, **R. P. Martinez**, C. Meng, X. Zhou, J. Flicker, A. Binder, J. R. Dickerson, R. Kaplar, and S. Chowdhury, "On-Wafer Investigation of Avalanche Robustness in 1.3kV GaN-on-GaN P-N Diode Under Unclamped Inductive Switching Stress," in *Proc. IEEE 8th Workshop Wide Bandgap Power Devices Appl. (WiPDA)*, 2021, pp. 259-262, doi: 10.1109/WiPDA49284.2021.9645154.

Conference Publications / Oral and Poster Presentations

9) R. Kaplar, A. Allerman, A. Armstrong, … , **R. P. Martinez**, K. Zeng, D. Ji, S. Chowdhury, O. Aktas, and J. Cooper, “Vertical GaN Power Electronics-Opportunities and Challenges,” APS March Meeting, 2021.
10) R. Kaplar, A. Allerman, A. Armstrong, … , **R. P. Martinez**, K. Zeng, D. Ji, S. Chowdhury, O. Aktas, and J. Cooper, “Development of High-Voltage Vertical GaN PN Diodes,” *in IEDM Tech. Dig.*, San Francisco, CA, 2020, pp. 5.1.1-5.1.4, doi: 10.1109/IEDM13553.2020.9372079.
11) R. Kaplar, A. Allerman, B. Gunning, M. Crawford, G. Pickrell, A. Armstrong, … , S. Chowdhury, K. Zeng, and **R. P. Martinez**, “Development of High-Voltage Vertical GaN PN Diodes,” Virtual MRS Spring/Fall Meeting, 2020.

Oral and Poster Presentations

1) **R. P. Martinez**, M. Iwamoto, J. Xu, P. Pahl, and S. Chowdhury, “Benchmarking Measurement-Based Large-Signal FET Models for GaN HEMT Devices,” Oral Presentation at 2023 IEEE Radio Frequency Integrated Circuits Symposium (RFIC), San Diego, CA, USA, June 2023.
2) **R. P. Martinez**, B. Murmann, and S. Chowdhury, “Linearity Performance Metrics of GaN HEMTs” Invited talk at SystemX November Conference, Stanford, CA, USA, 2022.
3) **R. P. Martinez**, D. J. Munzer, X. Zhou, B. Shankar, E. Schmidt, K. Wildnauer, B. Murmann, and S. Chowdhury, “Best Practices to Quantify Linearity Performance of GaN HEMTs for Power Amplifier Applications,” Oral Presentation at 2021 IEEE Workshop on Wide Bandgap Power Devices and Applications, Nov. 2021.
4) **R. P. Martinez**, D. J. Munzer, X. Zhou, B. Shankar, E. Schmidt, K. Wildnauer, B. Murmann, and S. Chowdhury, “Best Practices to Quantify Linearity Performance of GaN HEMTs for Power Amplifier Applications,” Poster Presentation at SystemX November Conference, Stanford, CA, USA, 2021.
5) **R. P. Martinez** and S. Chowdhury, “RF Linearity of GaN HEMTs for Mm-Wave Applications,” Oral Presentation at Spring Stanford-Nagoya Seminar (with Nobel Laureate: Prof. Hiroshi Amano), 2021.
6) **R. P. Martinez**, R. Soman, D. Ji, B. Ercan, K. Zeng, and S. Chowdhury, “Study of Wide Bandgap (GaN) Device Characterization and Modeling” Poster Presentation at SystemX November Conference, Stanford, CA, USA, 2019.

Acknowledgments (Funding Information)

- **This work was funded by:**
  - Stanford Graduate Fellowship in Science & Engineering
  - Dionisio Garza Medina Fellowship
  - Keysight Technologies through the Stanford SystemX Alliance

Acknowledgments: Ph.D. Quals & Defense Committee

Prof. Srabanti Chowdhury

Prof. Stephen Boyd

Dr. Masaya Iwamoto

Prof. Zerina Kapetanovic

Prof. Tsachy Weissman

Prof. Boris Murmann

Acknowledgments WBG Lab @ Stanford University

Maliha Noshin
Kelly Woo
Zhengliang Bian
Jackson Meng
Seungbin Jeong
Bhawani Shankar
Ashley Jun
Ana Banzer Morgado
Jeongkyu Kim
Rohith Soman
Mohamad Malakoutian
Ke Zeng
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Nish Sinha
Hayao Kasai
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Swaroop Kommera
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