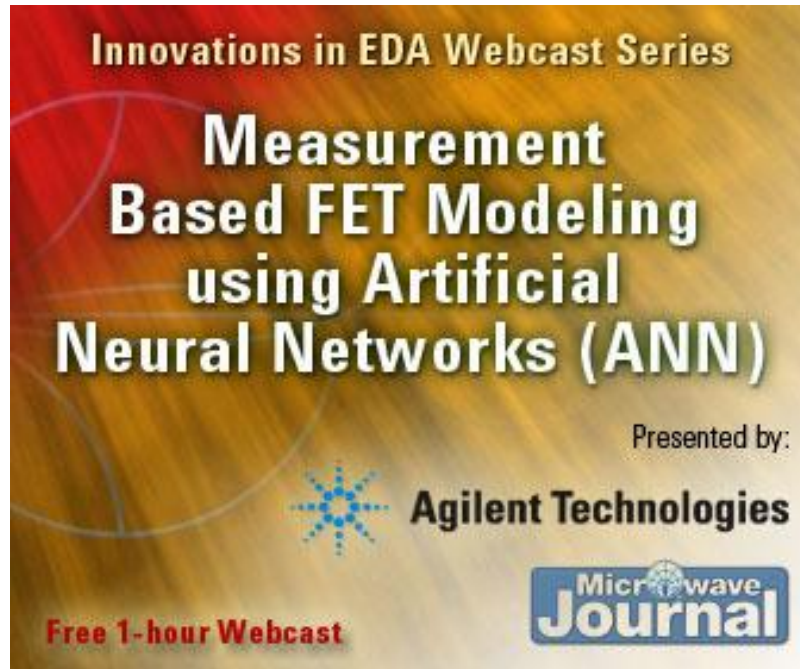


Welcome



Jianjun Xu



David Root

Modeling and Measurement Technology Program (MMTP)
Measurement Research Laboratories
Agilent Technologies, Inc.

Measurement-Based FET Modeling using Artificial Neural Networks (ANNs)

Jianjun Xu and David E. Root



Modeling and Measurement Technology Program (MMTP)
Measurement Research Laboratories
Agilent Technologies, Inc.

Presentation Outline

- Introduction
- NeuroFET Modeling Flow Details
- Examples and Model Validation
- Summary

Introduction

“All models are wrong, but some are useful.”

- statistician George Box

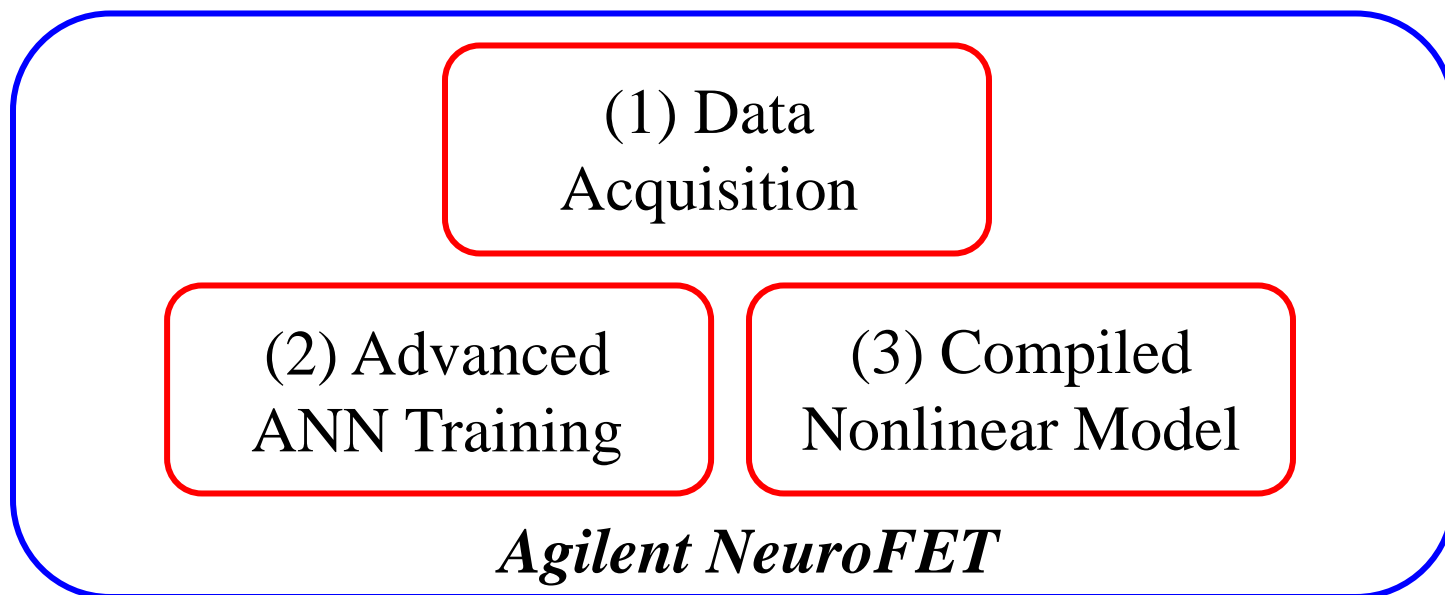
*“All models are approximations.
Some models are useful.”*

- attributed to Mike Golio and others

Purpose of Webinar

Introduce Agilent's first measurement-based modeling solution based on artificial neural networks (ANN) – *NeuroFET*

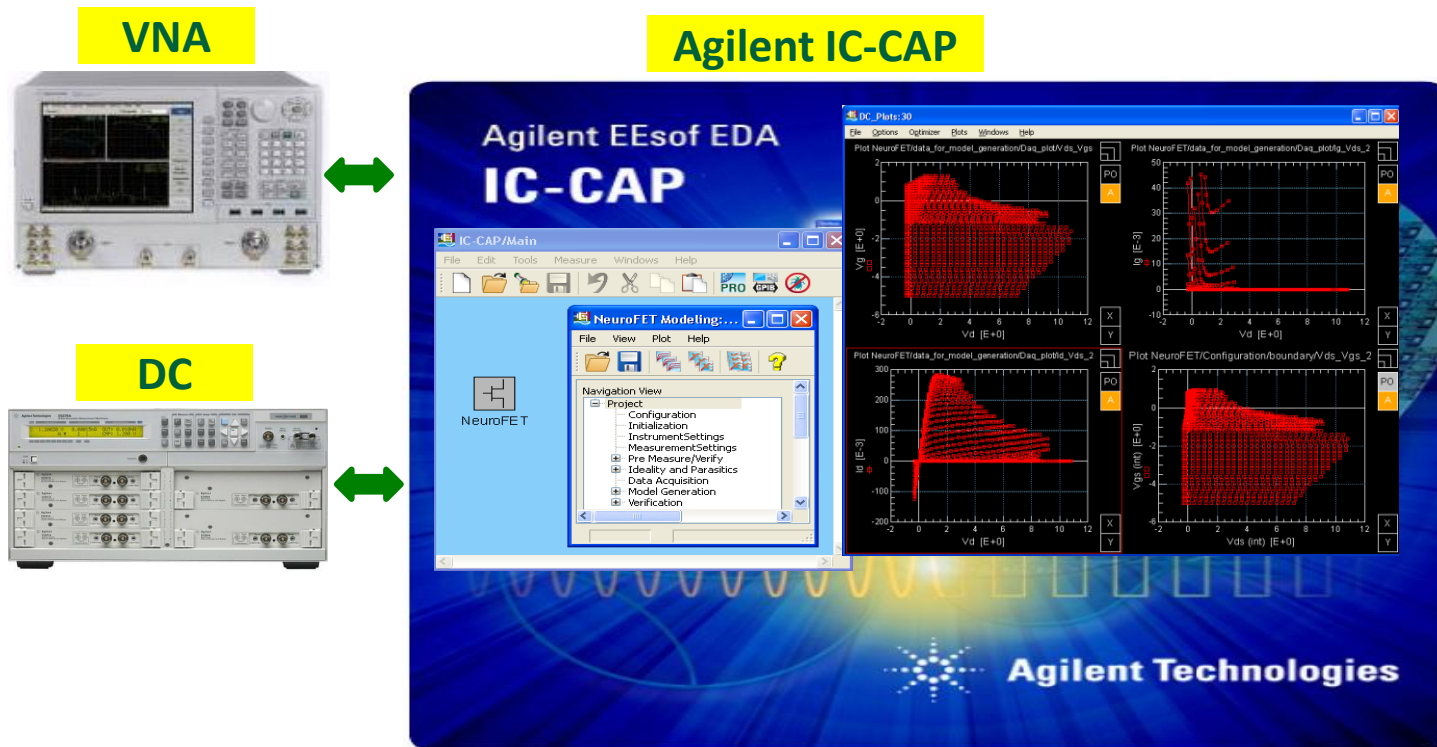
Three interoperable components:



- Agilent developed each component; designed them to work together
- Deployed for Agilent proprietary III-V MMIC technology at HFTC
- Commercialized in collaboration with Agilent EEs of EDA Division

NeuroFET components

(1) Automated, adaptive characterization system for FETs



Benefits:

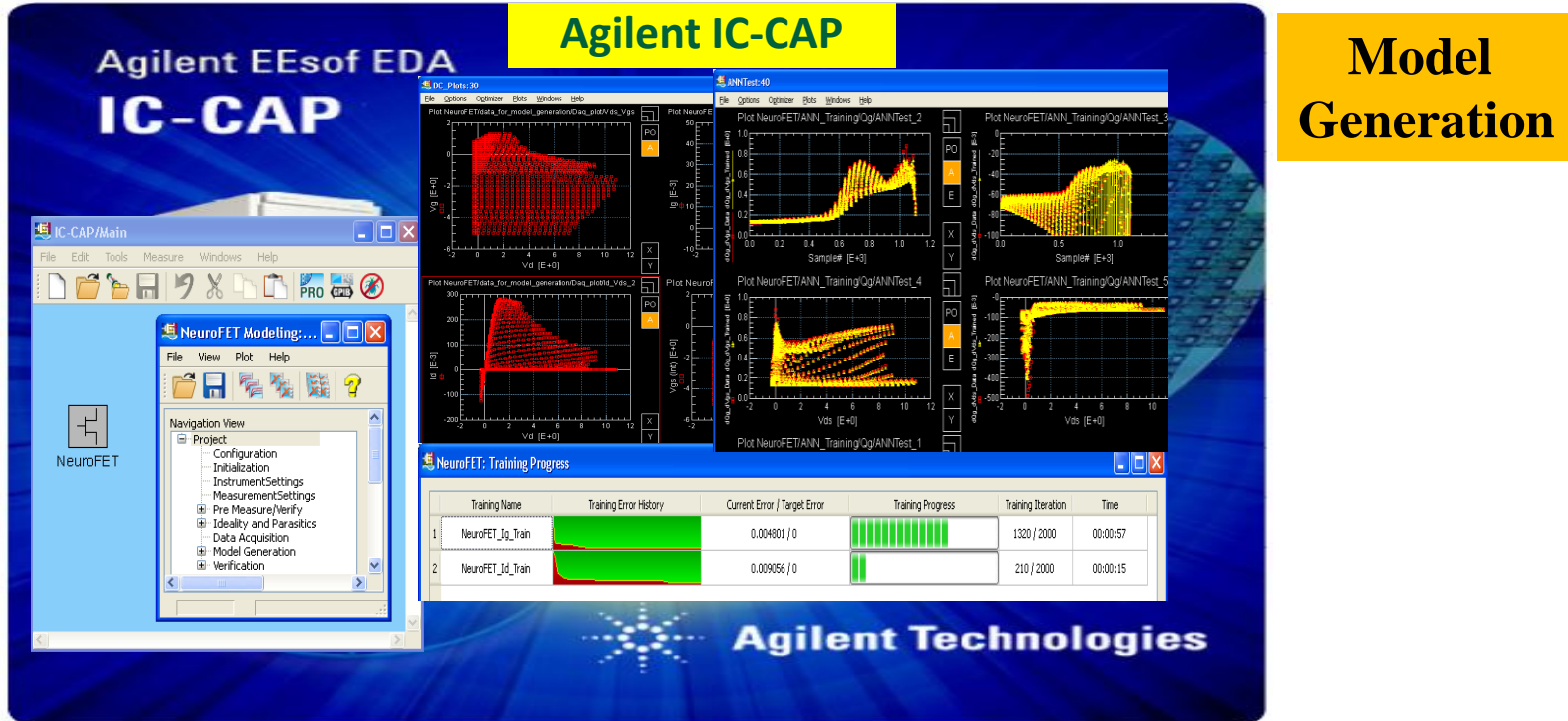
Supports common gate and common source layouts

Minimizes impact of device degradation during characterization

Data Acquisition:

NeuroFET components

(2) Unique and powerful Agilent ANN Training Technology



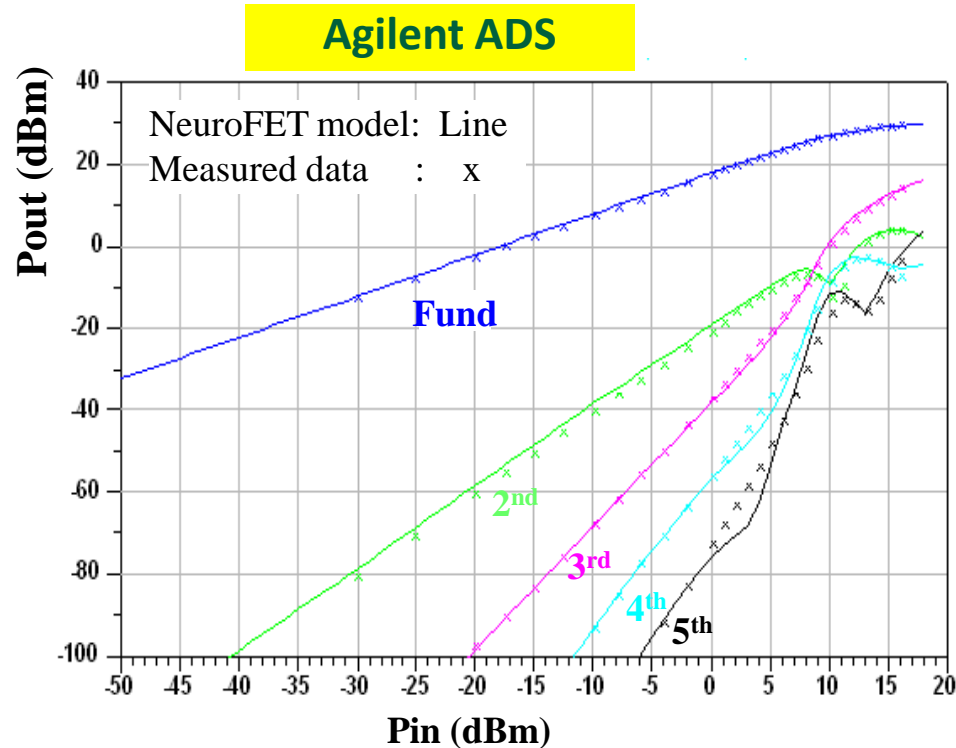
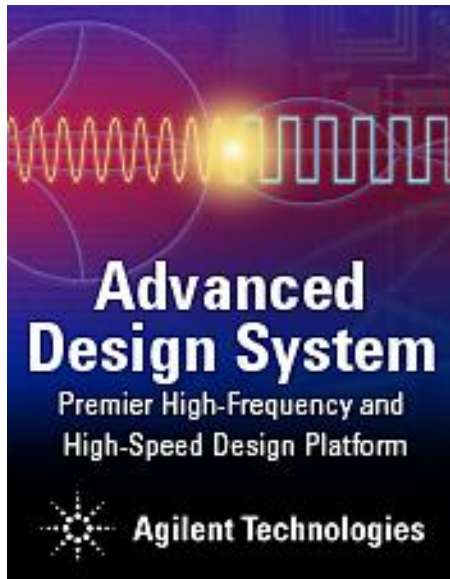
**Model
Generation**

Benefits:

- Advanced ANN training creates accurate & general model functions
- Same flow can fit very different looking device characteristics

NeuroFET components

(3) Built-in (compiled) nonlinear transistor model in ADS

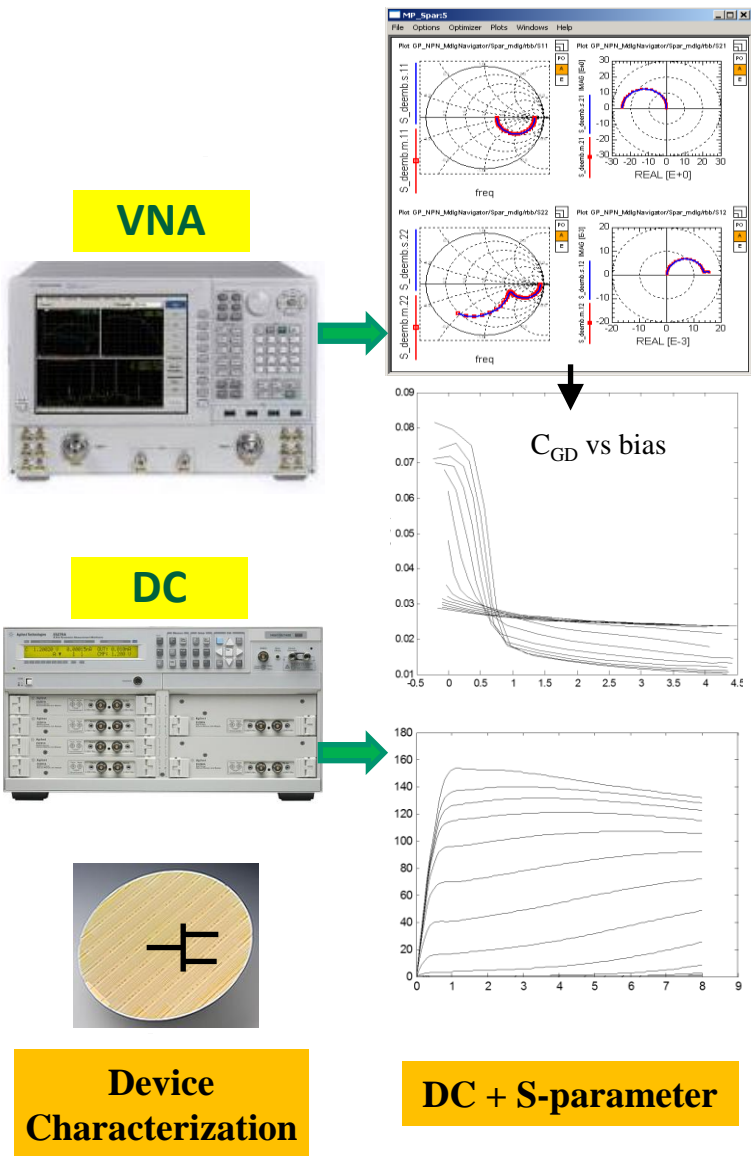


Nonlinear
Simulation
And Design

Benefits:

- Fast & accurate nonlinear simulation with robust convergence
- Model usable in all bias conditions (even $V_{DS} \leq 0$ for switch / mixers)
- Model works for HEMT, MESFET and other types of FETs

Conventional Transistor Modeling Flow



Equation formulation Physical or Empirical

$$Q_G = -WL\sqrt{2q\epsilon N_D} \left(\sqrt{(\phi - V_{GS})} + \sqrt{(\phi - V_{GD})} \right)$$

$$Q_G = C_{gs0} V_{bi} \left(1 - \frac{V_{GS}}{V_{bi}} \right)^\eta + C_{gd0} V_{GD}$$

$$I_D = \frac{W\mu q N_D a}{\epsilon L}$$

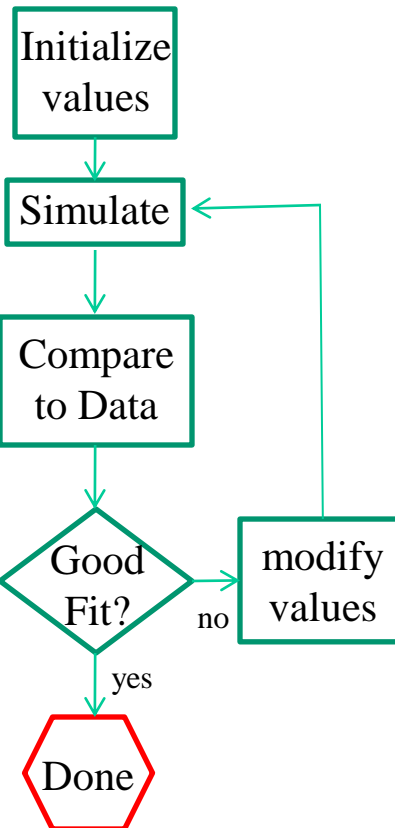
$$\left(V_{DS} - \frac{2}{3} \left[\sqrt{\frac{2\epsilon}{qN_D a^2}} \left((\phi - V_{GD})^{3/2} - (\phi - V_{GS})^{3/2} \right) \right] \right)$$

$$I_D = \left(\sum_{n=1}^3 A_n V_{GS}^n \right) \tanh(\gamma V_{DS})$$

Drawbacks:

- Expert intensive (Ph.D.)
- Time consuming: *years* to develop, *days* to extract
- Technology dependent; hard to maintain
- Optimization not always well-posed; constrained
- May never get good results!

Parameter Extraction Optimization



Alternative: *Measurement-based models*

“The Device knows best!”

Directly construct nonlinear model functions from data
(DC + S-parameters)

- Table-based models (e.g. HP/Agilent FET (Root) Model)
- **Artificial Neural Network (ANN) models (e.g. NeuroFET)**

Models can be both general and accurate

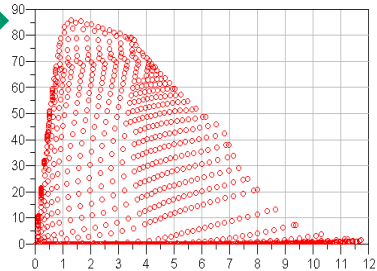
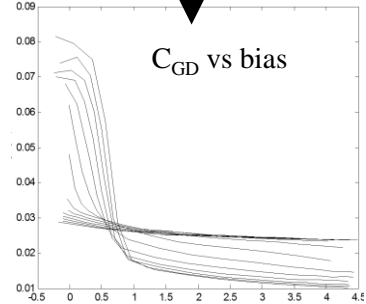
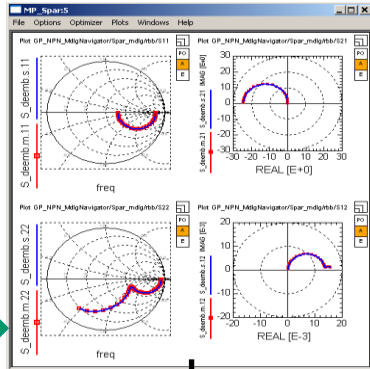
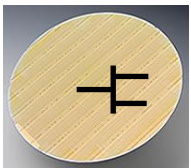
Conventional I-V, Q-V model development and
parameter extraction replaced by ANN training

NeuroFET: Measurement-Based FET Modeling using ANNs

VNA



DC

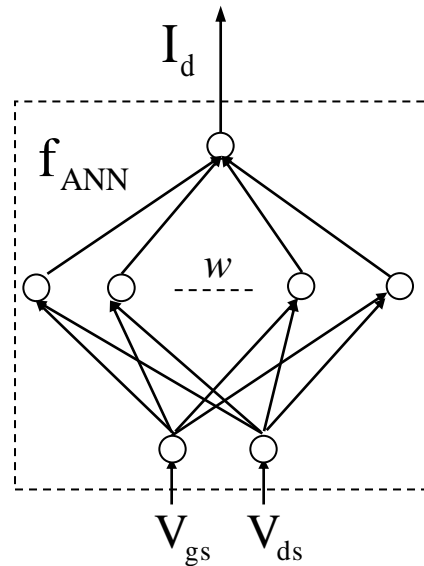


DC + S-parameter

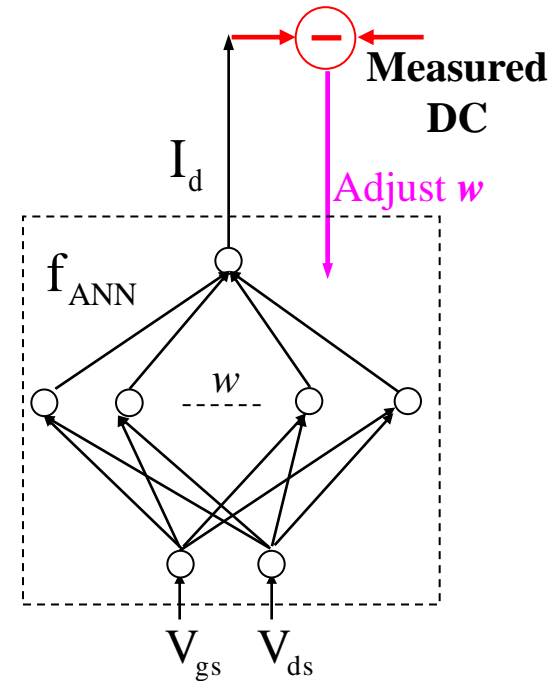
Device Characterization

Equation formulation using ANN

$$I_d = f_{ANN}(V_{gs}, V_{ds}, w)$$



ANN Training



Advantages:

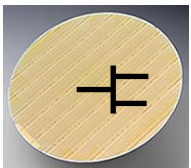
- Model is general and accurate
- Easy to extract (train)
- Technology independent; easy to maintain
- The model computation is fast
- Infinitely differentiable and smooth

NeuroFET: Measurement-Based FET Modeling using ANNs

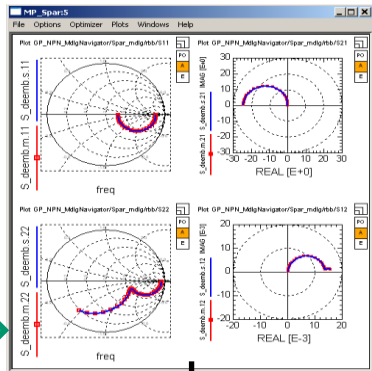
VNA



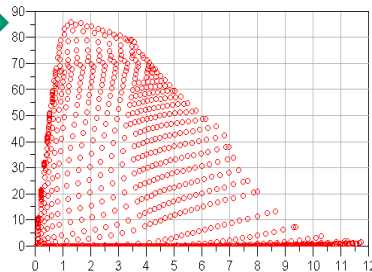
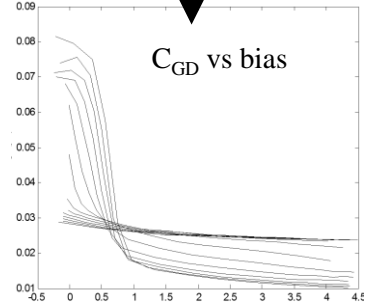
DC



Device Characterization



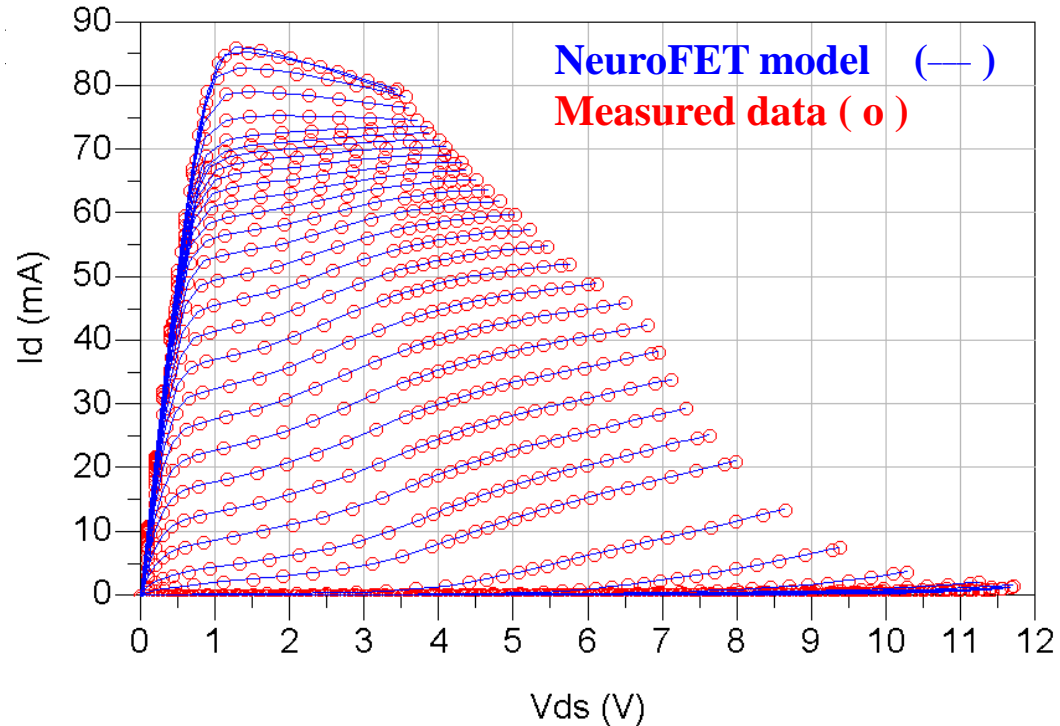
C_{GD} vs bias



DC + S-parameter

Equation formulation using ANN

ANN Training



Advantages:

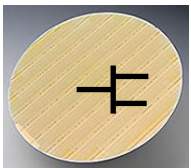
- Model is general and accurate
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- The model computation is fast
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NeuroFET: Measurement-Based FET Modeling using ANNs

VNA

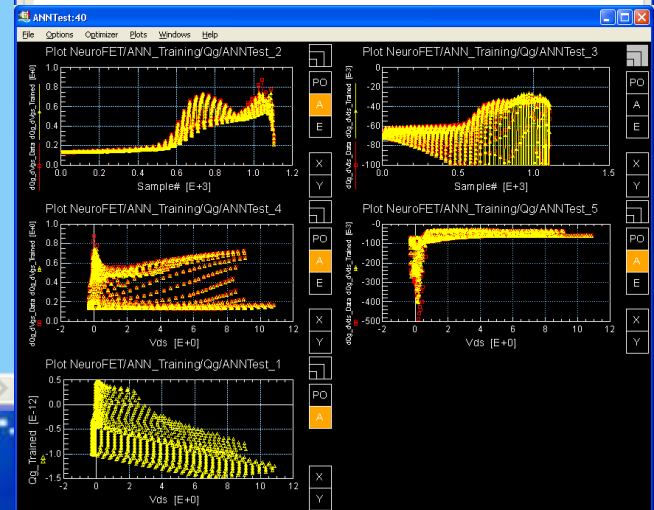
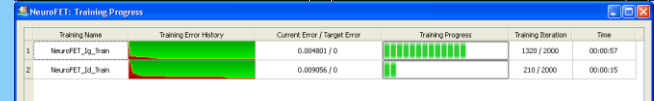
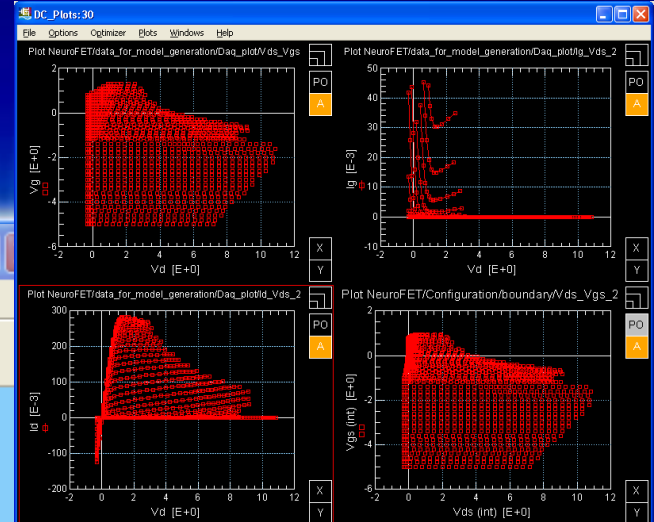


DC



Device Characterization

Agilent EEs of EDA
IC-CAP



IC-CAP: NeuroFET Modeling Flow

VNA



DC



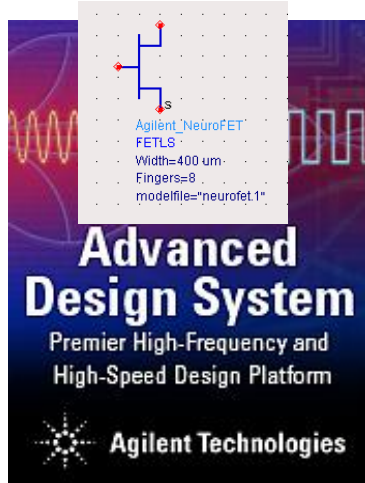
Agilent EEsof EDA
IC-CAP

Data Acquisition

Parasitic Extraction/De-embedding


Model Generation (ANN Training)

Verification



Agilent 'NeuroFET'
FETLS
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Advanced Design System
Premier High-Frequency and High-Speed Design Platform

 **Agilent Technologies**



Agilent Technologies



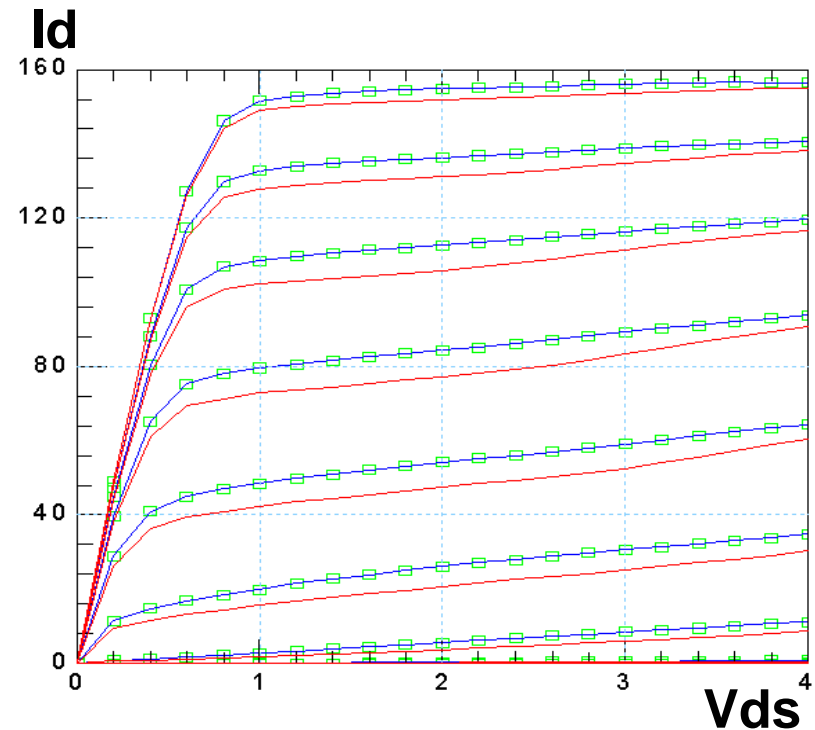
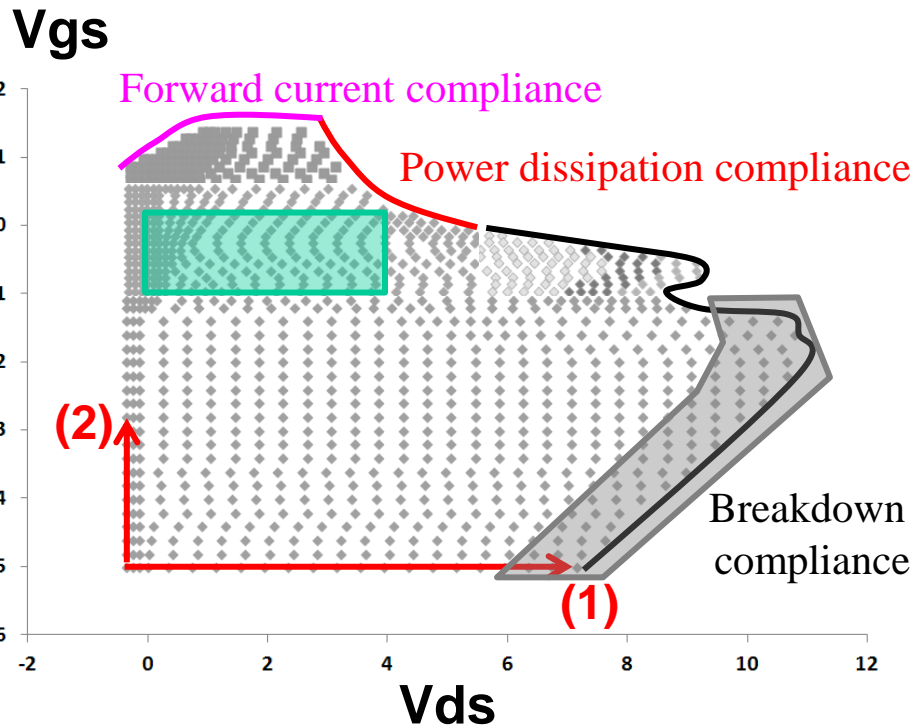
Agilent Technologies

NeuroFET: Data Acquisition

Why is a good Data Acquisition Routine important?

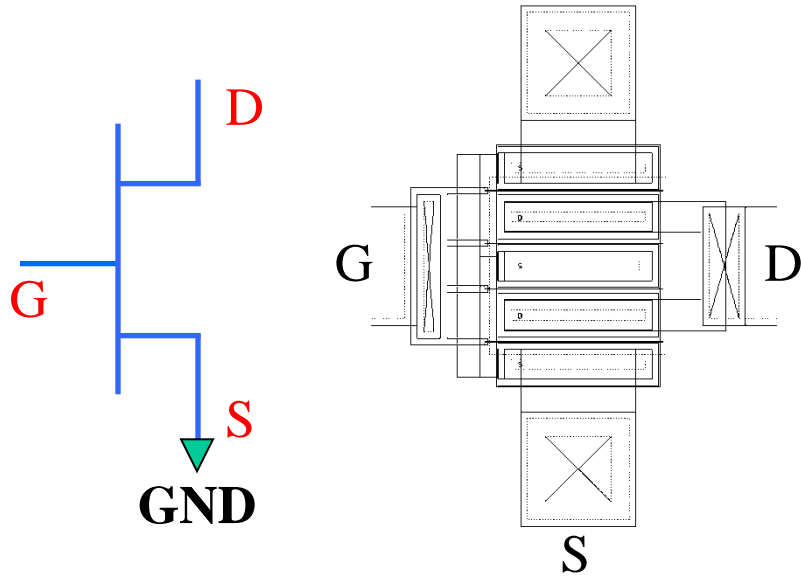
For measurement-based model,

- (1) it is important to get data everywhere.
- (2) the acquisition routine should be intelligent and flexible to preserve the device for integrity.

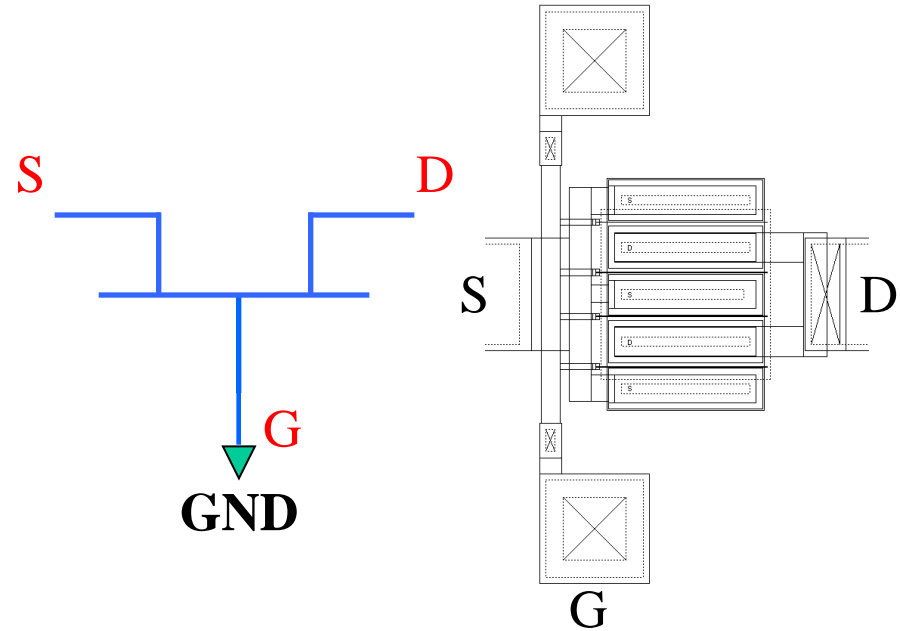


NeuroFET: Data Acquisition

It works for both **common-source FET** and **common-gate FET**

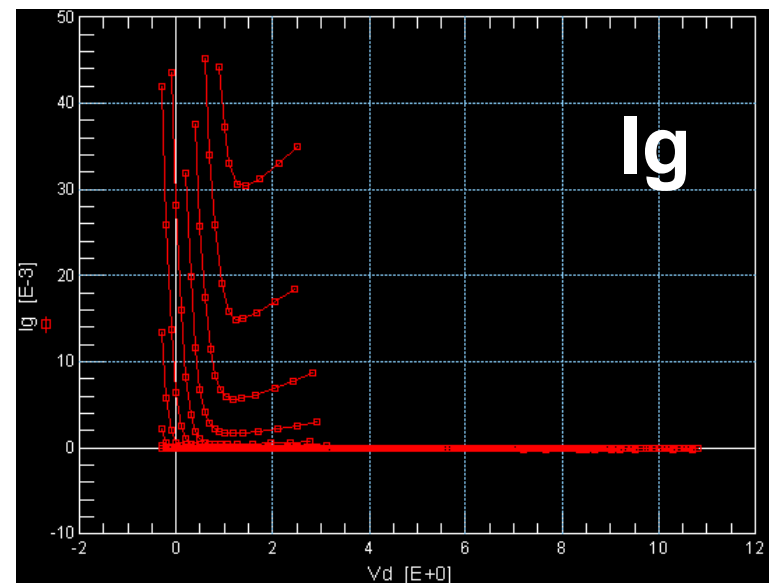
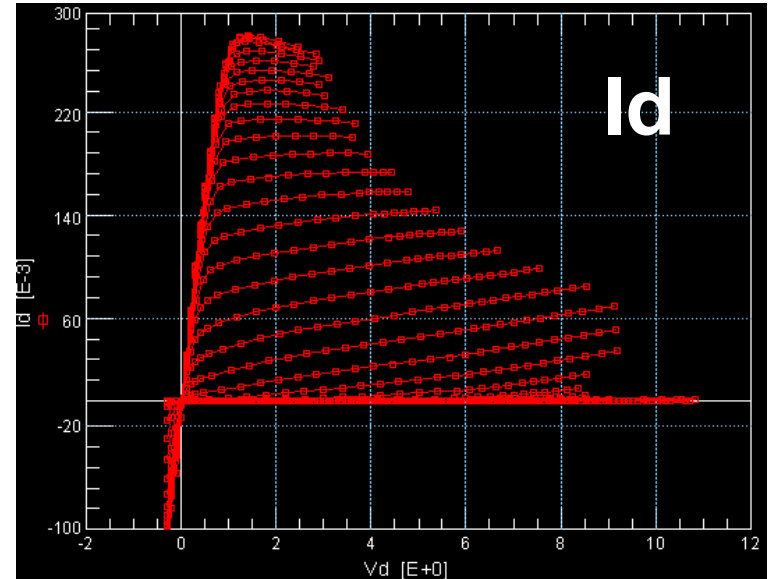
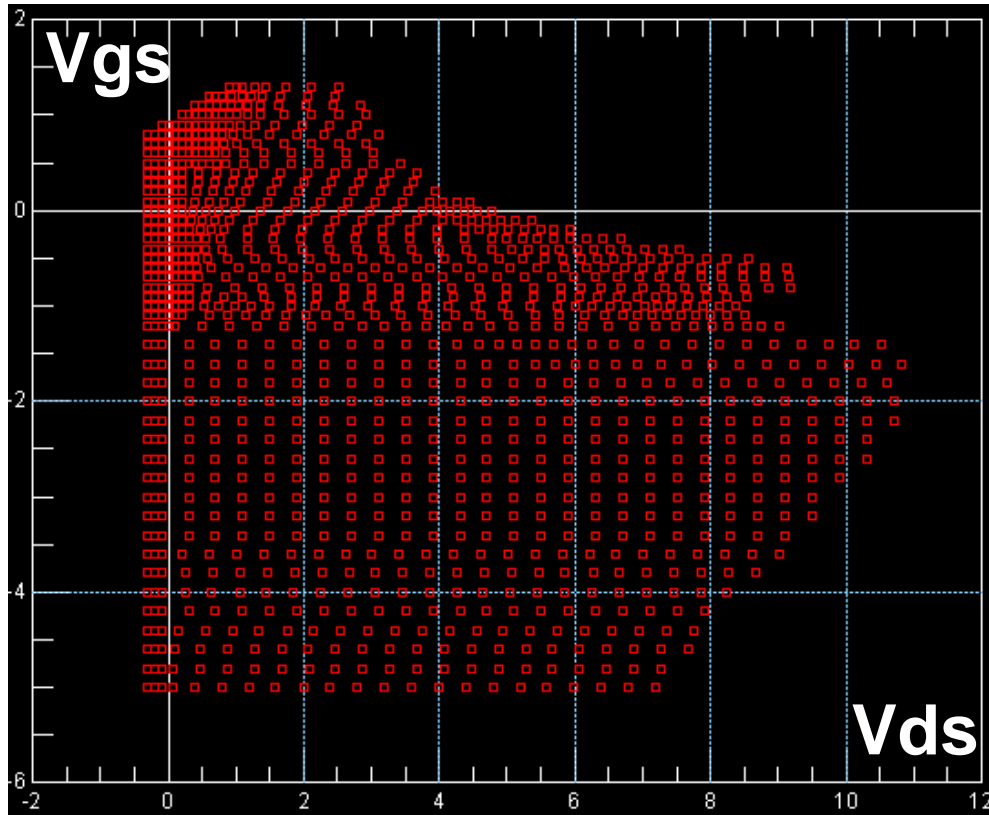


Common-Source FET
(for Amplifier Application)

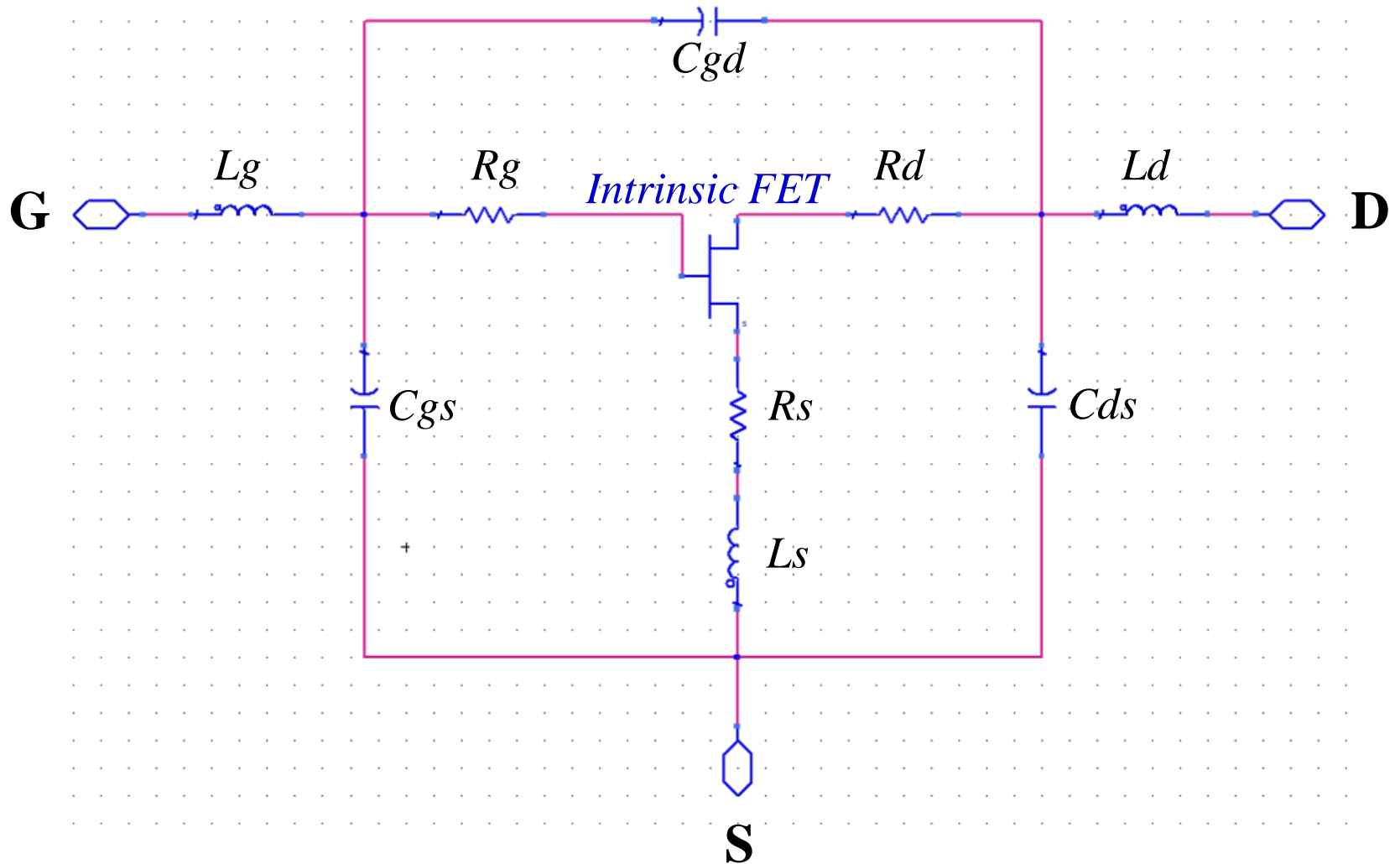


Common-Gate FET
(for Mixer/Switch Applications)

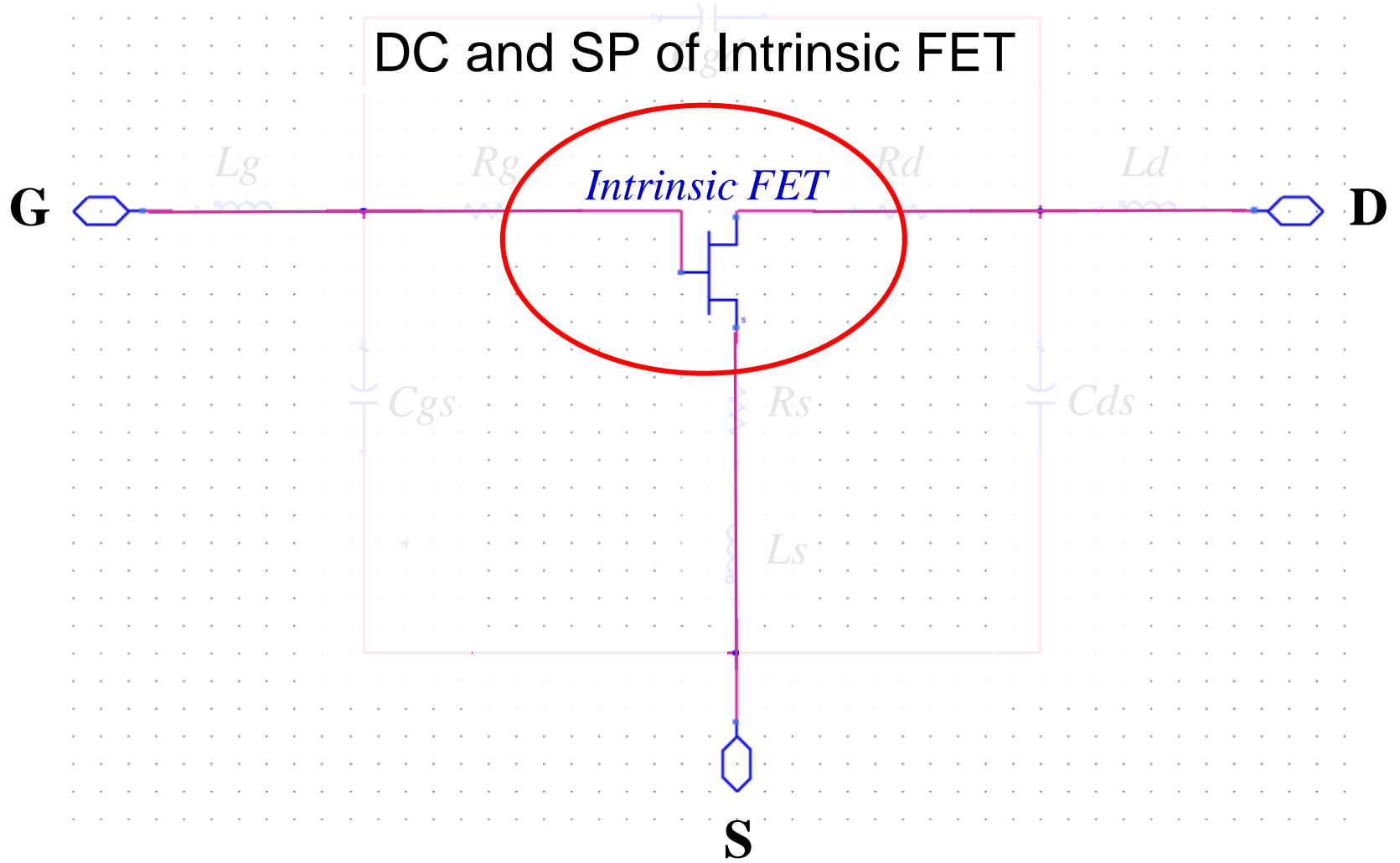
NeuroFET: Data Acquisition



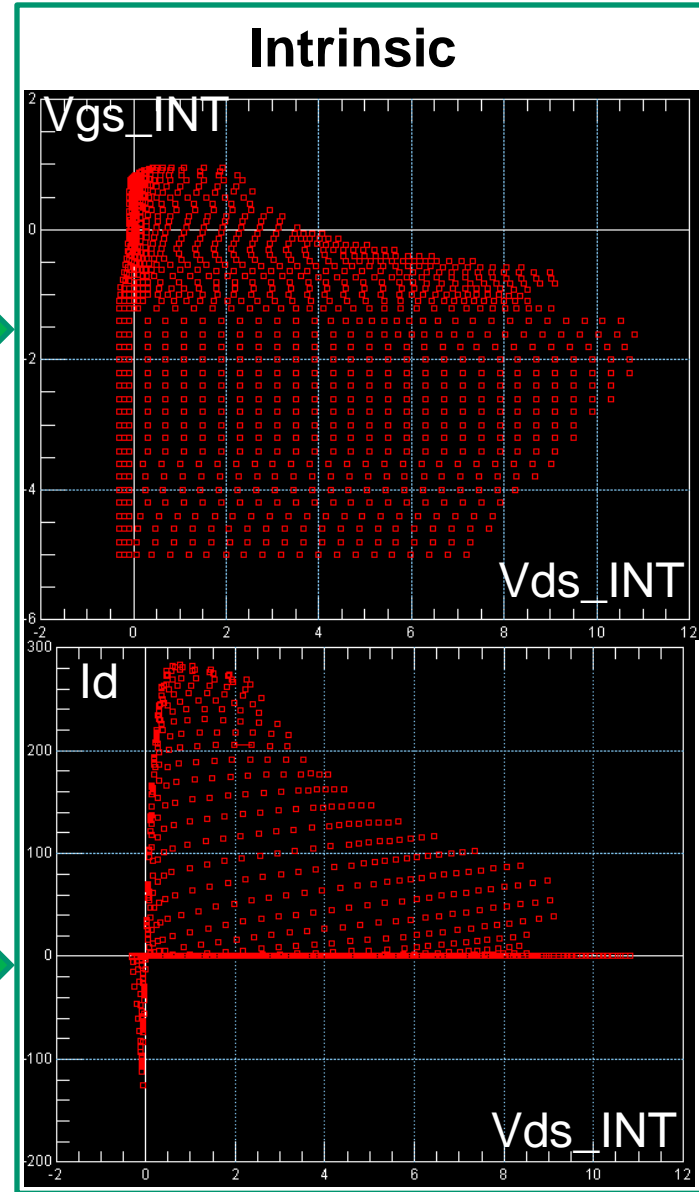
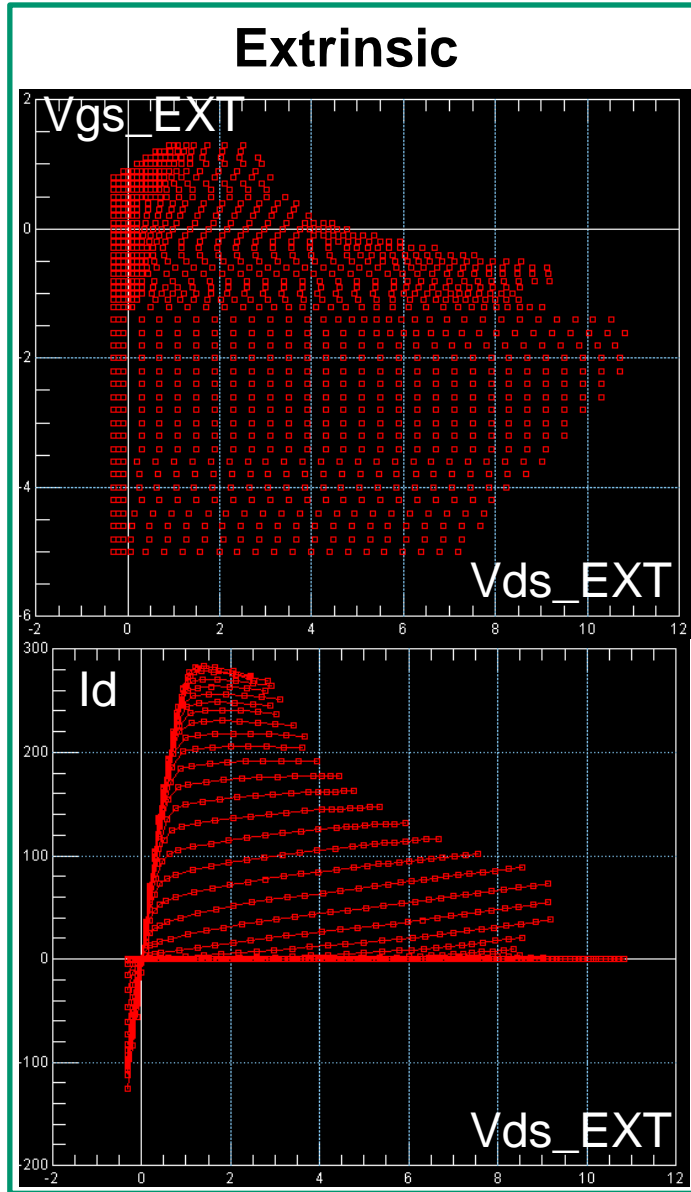
NeuroFET Model



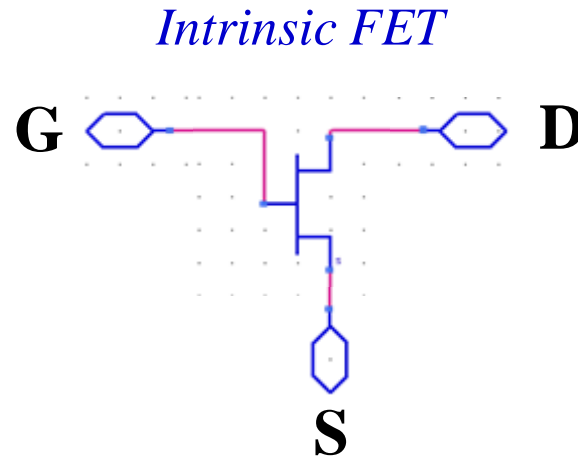
NeuroFET: Parasitic Extraction & De-embedding



Before and After De-embedding



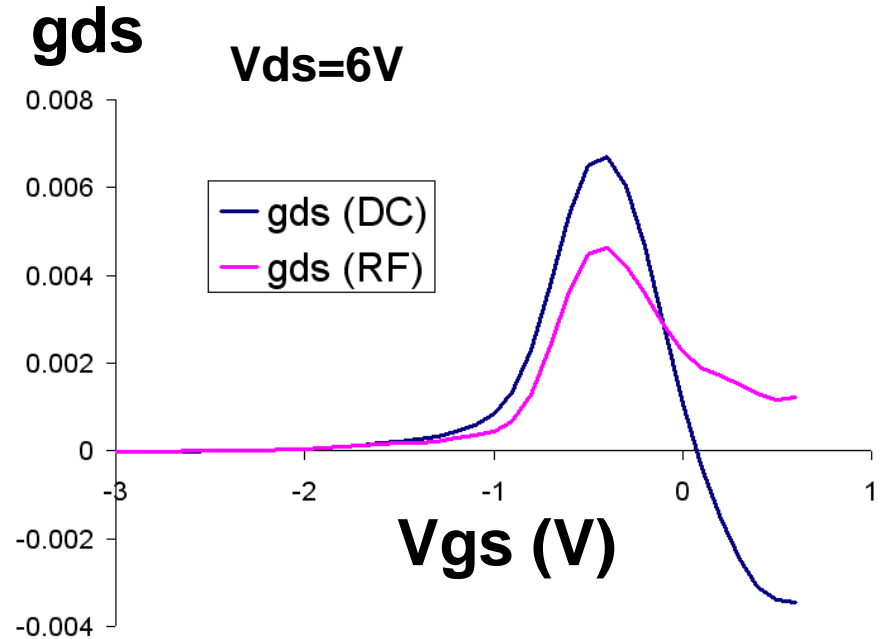
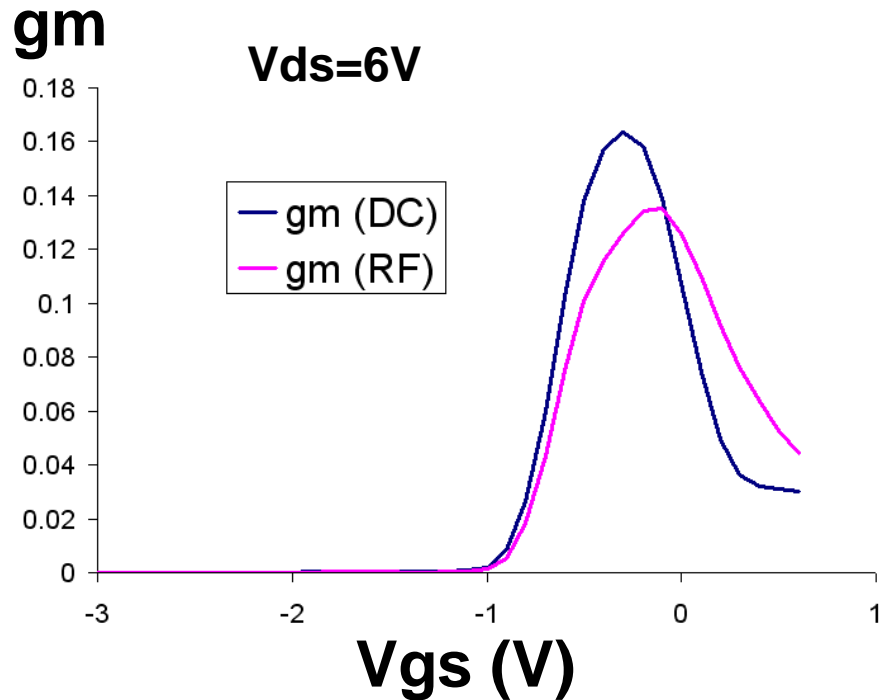
NeuroFET: Intrinsic Model



NeuroFET (Intrinsic) is a non-quasi-static model that accounts for

- (1) Static I-V characteristics
- (2) Terminal charges
- (3) Frequency dispersion

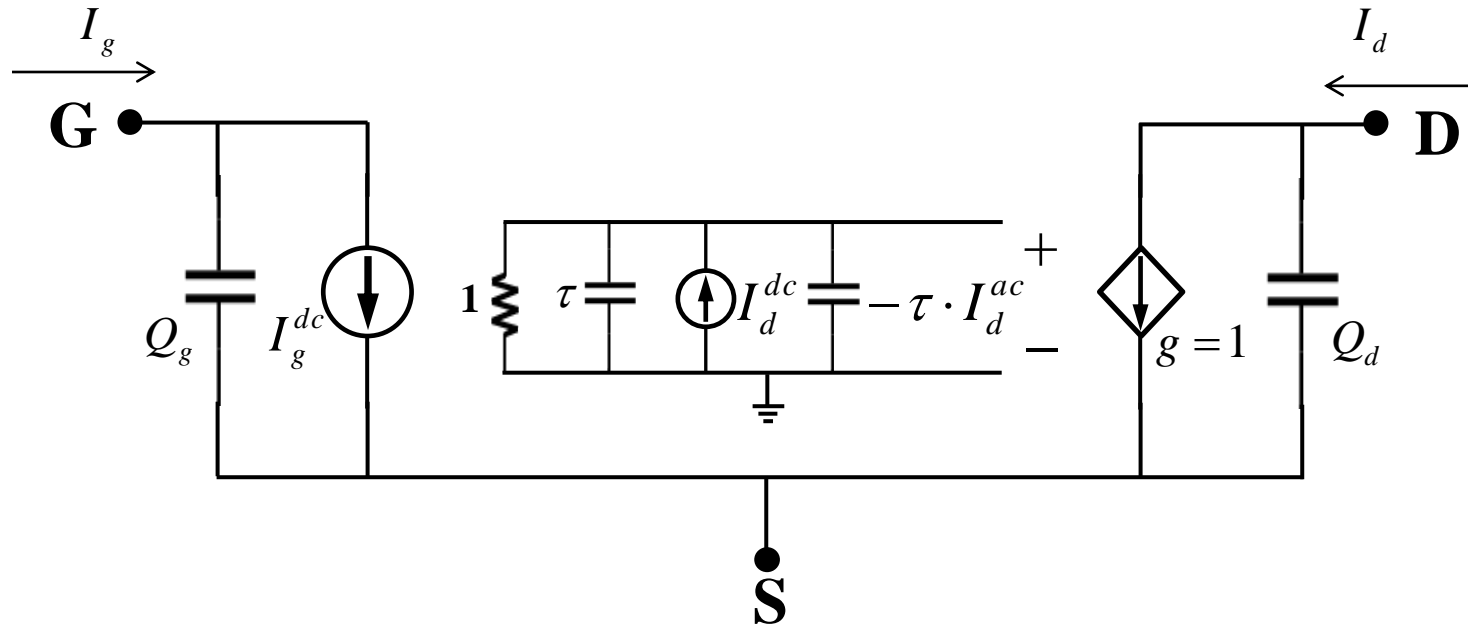
Frequency dispersion of small-signal characteristics



NeuroFET: Intrinsic Model Formulation

$$I_g(t) = I_g^{dc}(V_{gs}(t), V_{ds}(t)) + \frac{dQ_g(V_{gs}(t), V_{ds}(t))}{dt}$$

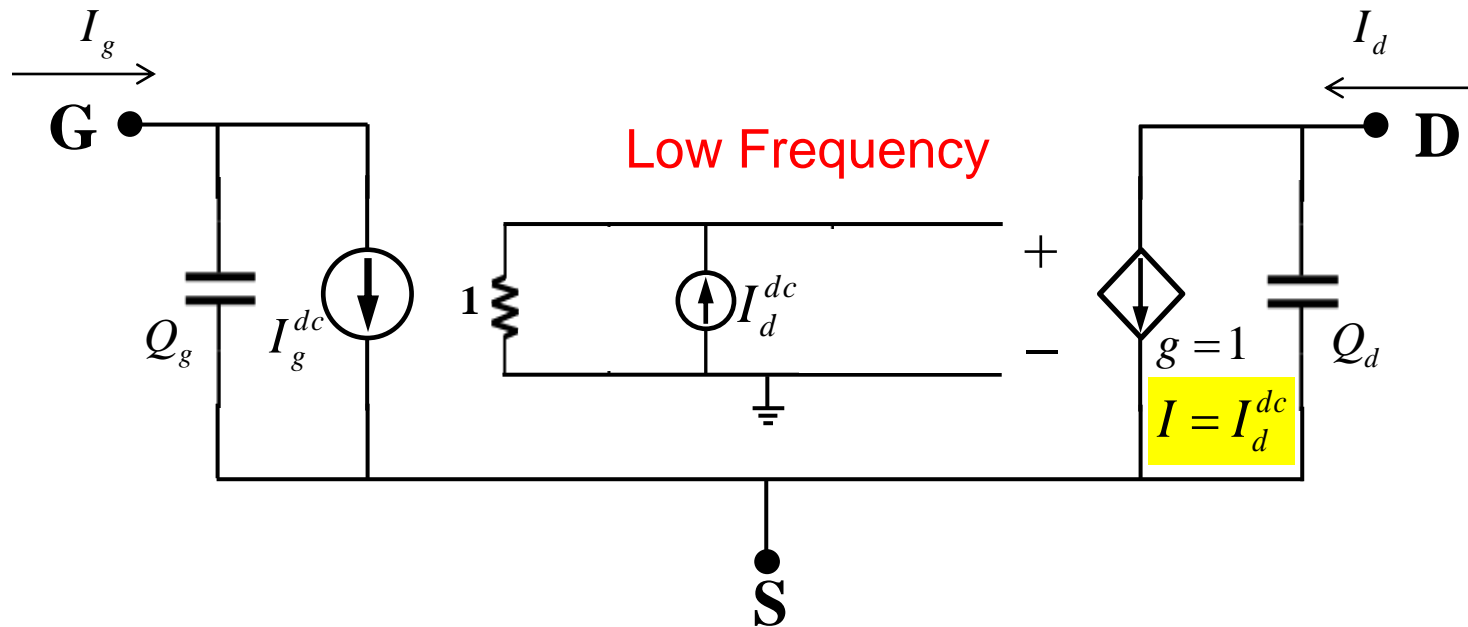
$$I_d(t) + \tau \frac{dI_d(t)}{dt} = I_d^{dc}(V_{gs}(t), V_{ds}(t)) + \tau \frac{dI_d^{ac}(V_{gs}(t), V_{ds}(t))}{dt} + \frac{dQ_d(V_{gs}(t), V_{ds}(t))}{dt} + \tau \frac{d^2Q_d(V_{gs}(t), V_{ds}(t))}{dt^2}$$



NeuroFET: Intrinsic Model Formulation

$$I_g(t) = I_g^{dc}(V_{gs}(t), V_{ds}(t)) + \frac{dQ_g(V_{gs}(t), V_{ds}(t))}{dt}$$

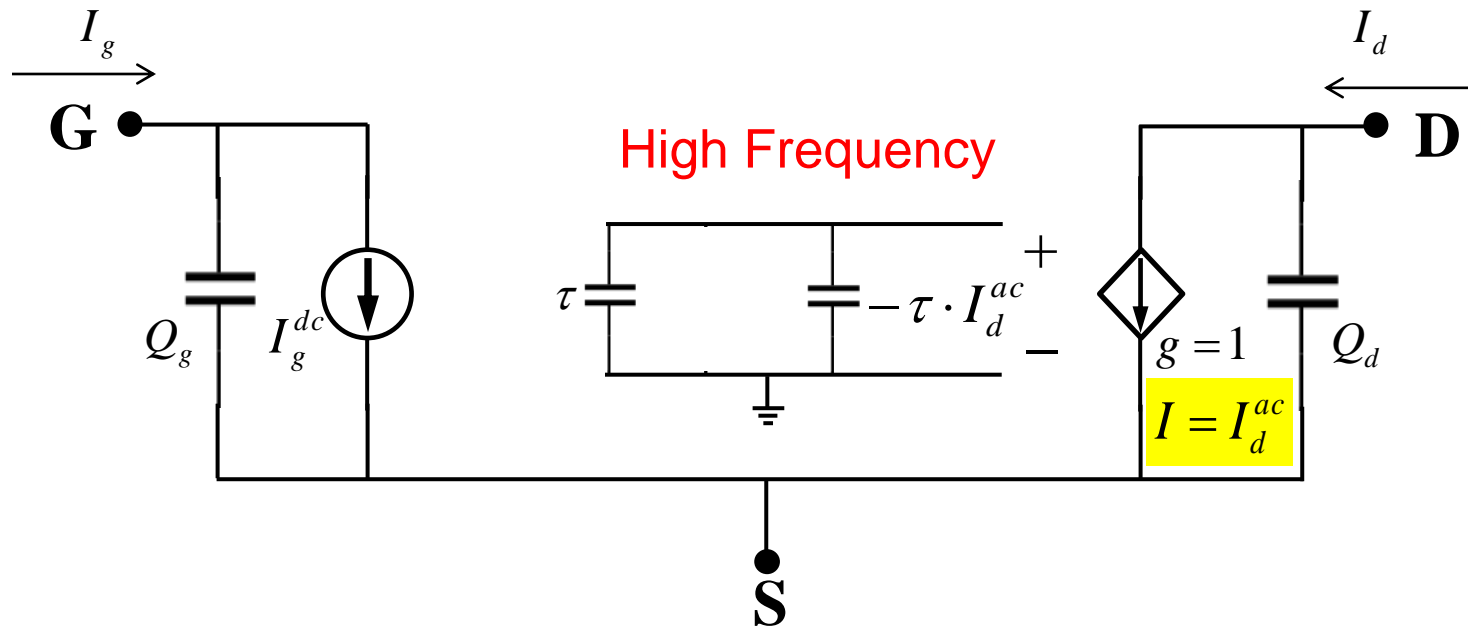
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NeuroFET: Intrinsic Model Formulation

$$I_g(t) = I_g^{dc}(V_{gs}(t), V_{ds}(t)) + \frac{dQ_g(V_{gs}(t), V_{ds}(t))}{dt}$$

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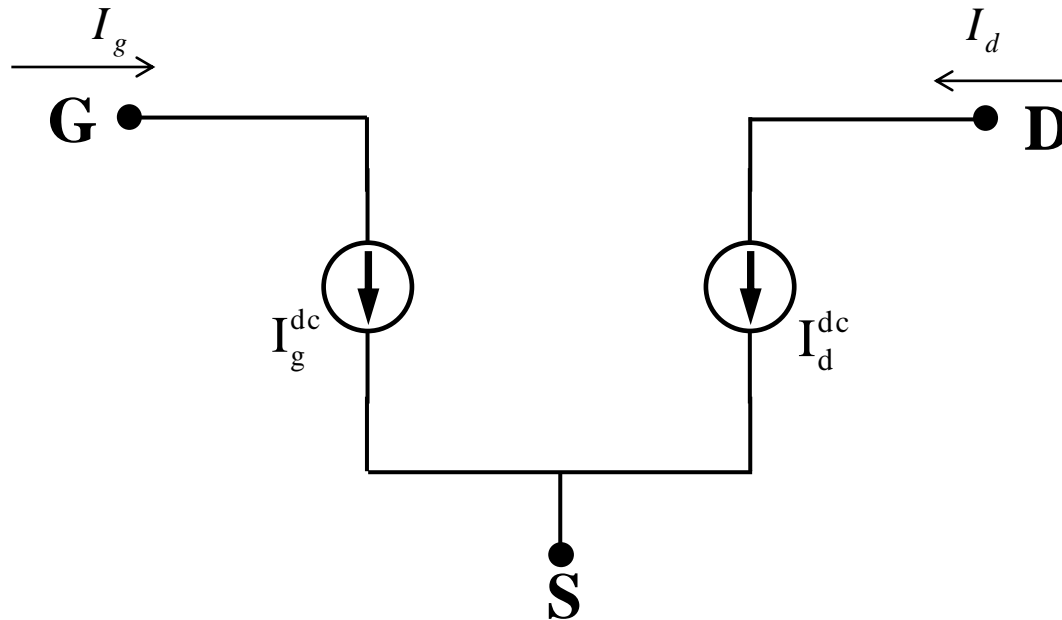


NeuroFET: Intrinsic Model

- DC

$$I_g = I_g^{dc}(V_{gs}, V_{ds})$$

$$I_d = I_d^{dc}(V_{gs}, V_{ds})$$

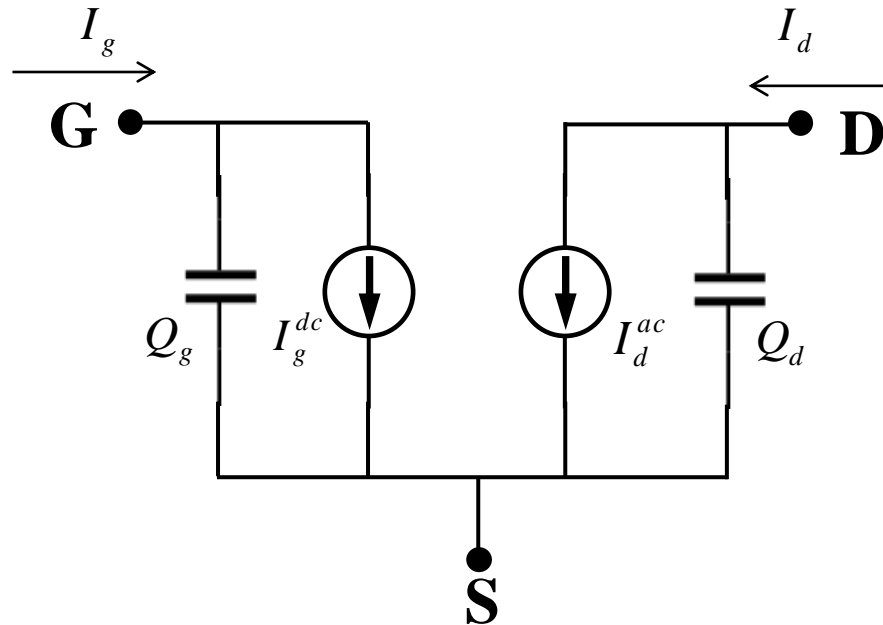


NeuroFET: Intrinsic Model

- RF

$$I_g(t) = I_g^{dc}(V_{gs}(t), V_{ds}(t)) + \frac{dQ_g(V_{gs}(t), V_{ds}(t))}{dt}$$

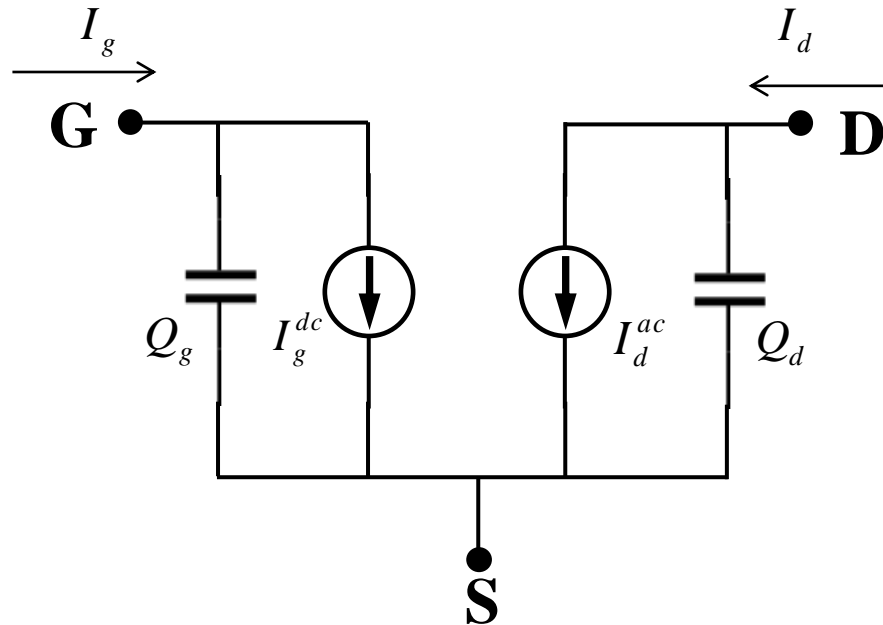
$$I_d(t) = I_d^{ac}(V_{gs}(t), V_{ds}(t)) + \frac{dQ_d(V_{gs}(t), V_{ds}(t))}{dt}$$



NeuroFET: Intrinsic Model

- RF (small signal)

$$\begin{bmatrix} \frac{\partial I_g^{dc}}{\partial V_{gs}} + j\omega \frac{\partial Q_g}{\partial V_{gs}} & \frac{\partial I_g^{dc}}{\partial V_{ds}} + j\omega \frac{\partial Q_g}{\partial V_{ds}} \\ \frac{\partial I_d^{ac}}{\partial V_{gs}} + j\omega \frac{\partial Q_d}{\partial V_{gs}} & \frac{\partial I_d^{ac}}{\partial V_{ds}} + j\omega \frac{\partial Q_d}{\partial V_{ds}} \end{bmatrix} = \begin{bmatrix} Y_{11} & Y_{12} \\ Y_{21} & Y_{22} \end{bmatrix}$$



NeuroFET: Intrinsic Model

- RF (small signal)

$$\begin{bmatrix} \frac{\partial I_g^{\text{dc}}}{\partial V_{gs}} + j\omega \frac{\partial Q_g}{\partial V_{gs}} & \frac{\partial I_g^{\text{dc}}}{\partial V_{ds}} + j\omega \frac{\partial Q_g}{\partial V_{ds}} \\ \frac{\partial I_d^{\text{ac}}}{\partial V_{gs}} + j\omega \frac{\partial Q_d}{\partial V_{gs}} & \frac{\partial I_d^{\text{ac}}}{\partial V_{ds}} + j\omega \frac{\partial Q_d}{\partial V_{ds}} \end{bmatrix} = \begin{bmatrix} Y_{11} & Y_{12} \\ Y_{21} & Y_{22} \end{bmatrix}$$

$$\begin{aligned} \frac{\partial Q_g}{\partial V_{gs}} &= \frac{\text{Imag}(Y_{11})}{\omega} \\ \frac{\partial Q_g}{\partial V_{ds}} &= \frac{\text{Imag}(Y_{12})}{\omega} \\ &V_{gs}, V_{ds} \end{aligned}$$

$$Q_g(V_{gs}, V_{ds})$$

$$\begin{aligned} \frac{\partial Q_d}{\partial V_{gs}} &= \frac{\text{Imag}(Y_{21})}{\omega} \\ \frac{\partial Q_d}{\partial V_{ds}} &= \frac{\text{Imag}(Y_{22})}{\omega} \\ &V_{gs}, V_{ds} \end{aligned}$$

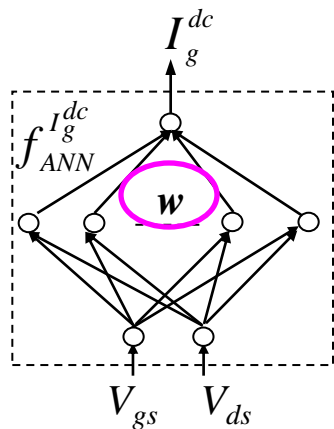
$$Q_d(V_{gs}, V_{ds})$$

$$\begin{aligned} \frac{\partial I_d^{\text{ac}}}{\partial V_{gs}} &= \text{Real}(Y_{21}) \\ \frac{\partial I_d^{\text{ac}}}{\partial V_{ds}} &= \text{Real}(Y_{22}) \\ &V_{gs}, V_{ds} \end{aligned}$$

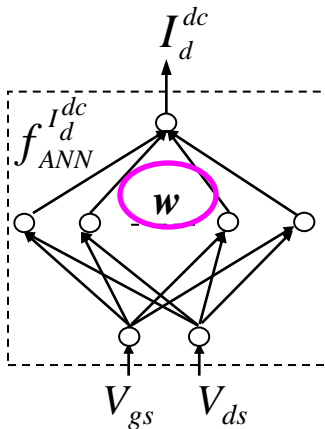
$$I_d^{\text{ac}}(V_{gs}, V_{ds})$$

Constitutive Relations are Modeled by ANNs

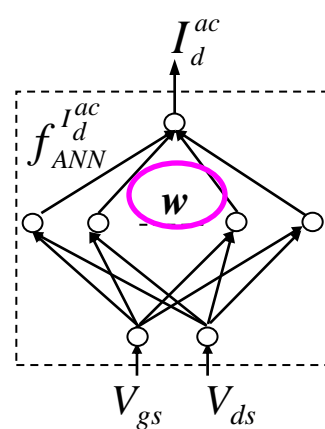
$$I_g^{dc} = f_{ANN}^{I_g^{dc}}(V_{gs}, V_{ds}, \mathbf{w})$$



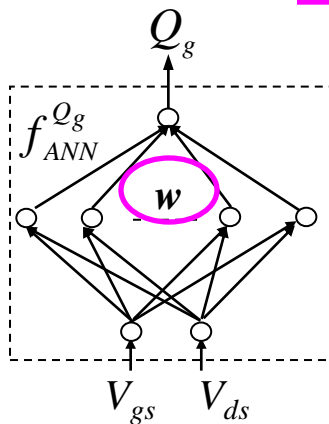
$$I_d^{dc} = f_{ANN}^{I_d^{dc}}(V_{gs}, V_{ds}, \mathbf{w})$$



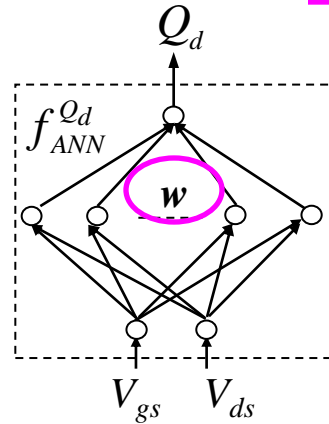
$$I_d^{ac} = f_{ANN}^{I_d^{ac}}(V_{gs}, V_{ds}, \mathbf{w})$$



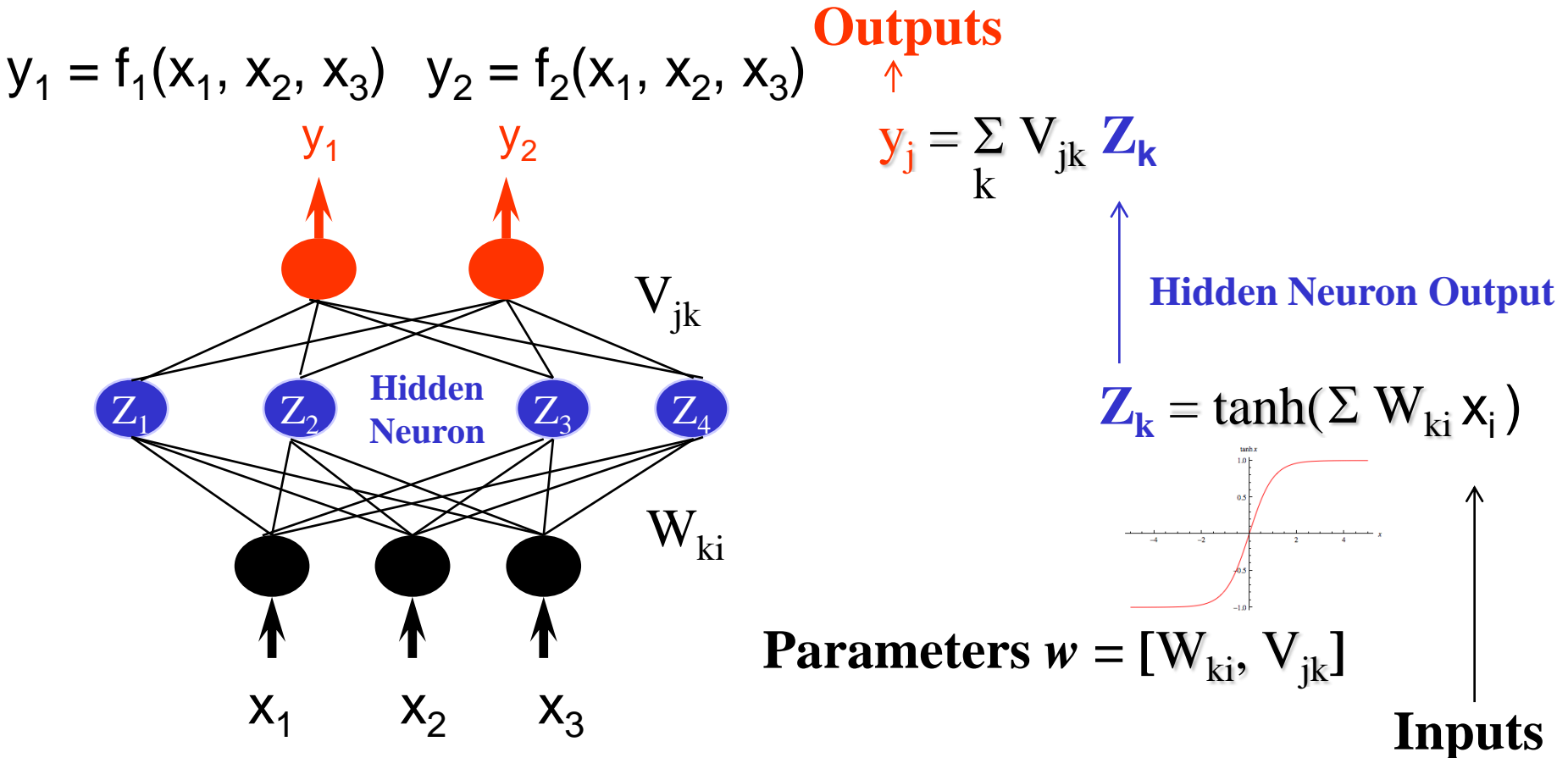
$$Q_g = f_{ANN}^{Q_g}(V_{gs}, V_{ds}, \mathbf{w})$$



$$Q_d = f_{ANN}^{Q_d}(V_{gs}, V_{ds}, \mathbf{w})$$



Artificial Neural Networks (ANNs)

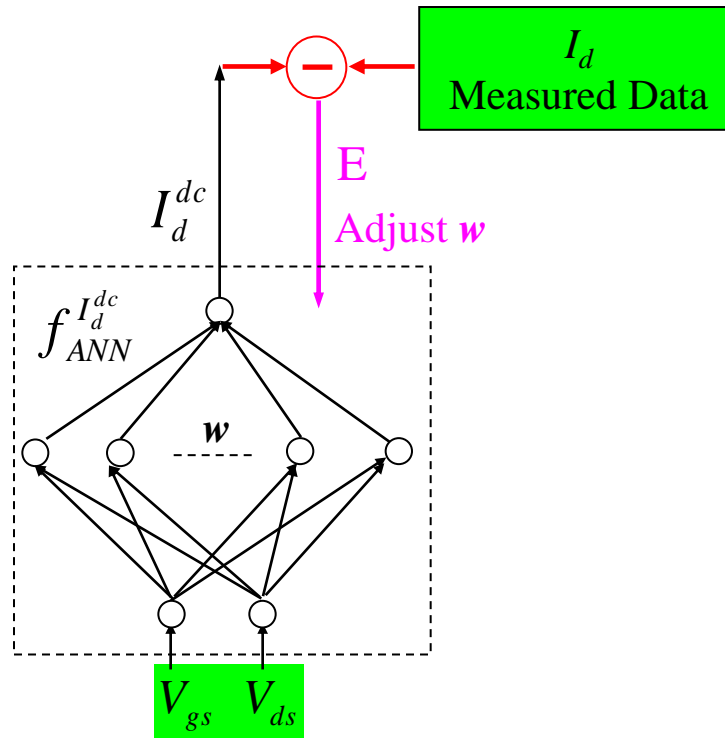


- Universal Approx. Thm: Can fit any nonlinear function of many variables
- The model computation is very fast.
- Infinitely differentiable.
- Can be trained on non-gridded data in any number of dimensions.

Model Training (I_g^{dc} I_d^{dc})

- Standard Neural Network Training

$$I_d^{dc} = f_{ANN}^{I_d^{dc}}(V_{gs}, V_{ds}, w)$$



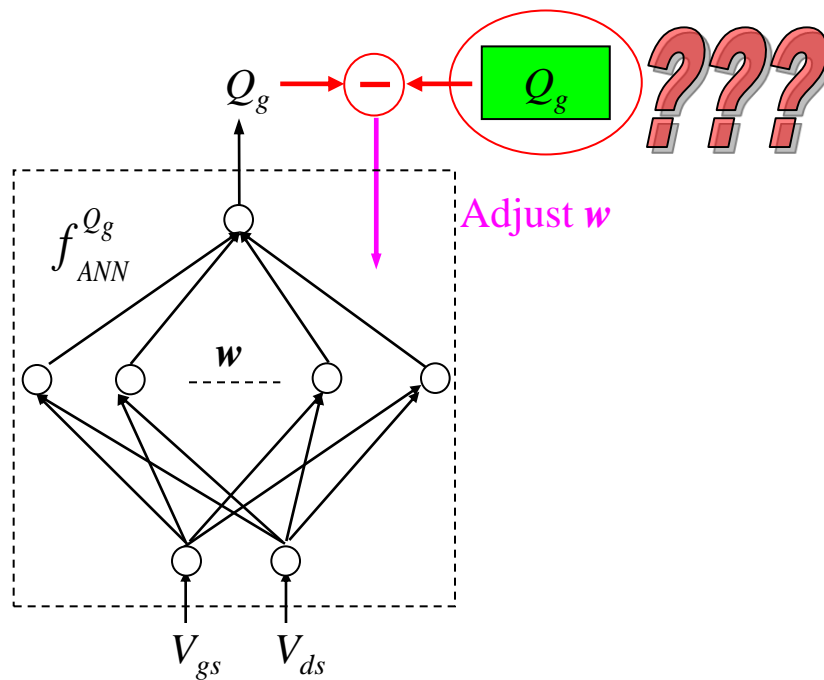
Model Training (Q_g)

- Adjoint Neural Network Training

$$\frac{\partial Q_g}{\partial V_{gs}} = \frac{\text{Imag}(Y_{11})}{\omega}$$
$$\frac{\partial Q_g}{\partial V_{ds}} = \frac{\text{Imag}(Y_{12})}{\omega}$$

V_{gs}, V_{ds}

$$Q_g = f_{ANN}^{Q_g}(V_{gs}, V_{ds}, \mathbf{w})$$



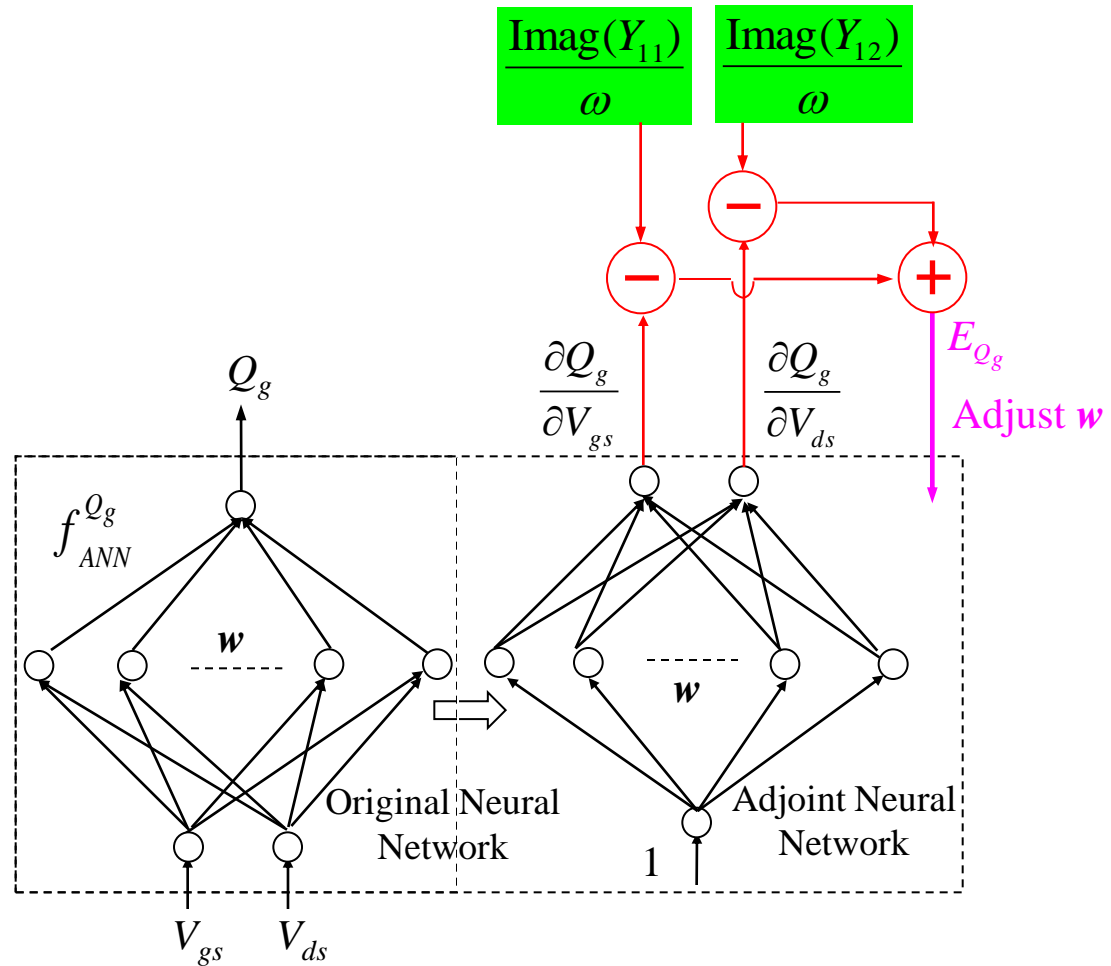
Model Training (Q_g)

- Adjoint Neural Network Training

$$\frac{\partial Q_g}{\partial V_{gs}} = \frac{\text{Imag}(Y_{11})}{\omega}$$

$$\frac{\partial Q_g}{\partial V_{ds}} = \frac{\text{Imag}(Y_{12})}{\omega}$$

$$Q_g = f_{ANN}^{Q_g}(V_{gs}, V_{ds}, \mathbf{w})$$



Jianjun Xu, M.C.E. Yagoub, Runtao Ding and Q.J. Zhang,
 "Exact adjoint sensitivity analysis for neural based microwave modeling and design,"
IEEE Transactions on Microwave Theory and Techniques, vol. 51, pp.226-237, 2003.

Model Training (Q_g)

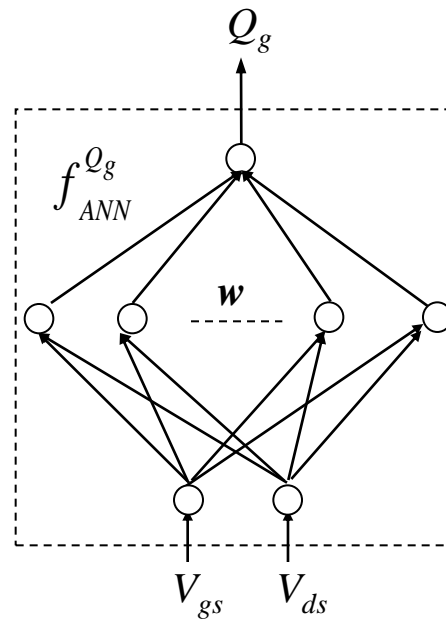
- Adjoint Neural Network Training

$$\frac{\partial Q_g}{\partial V_{gs}} = \frac{\text{Imag}(Y_{11})}{\omega}$$

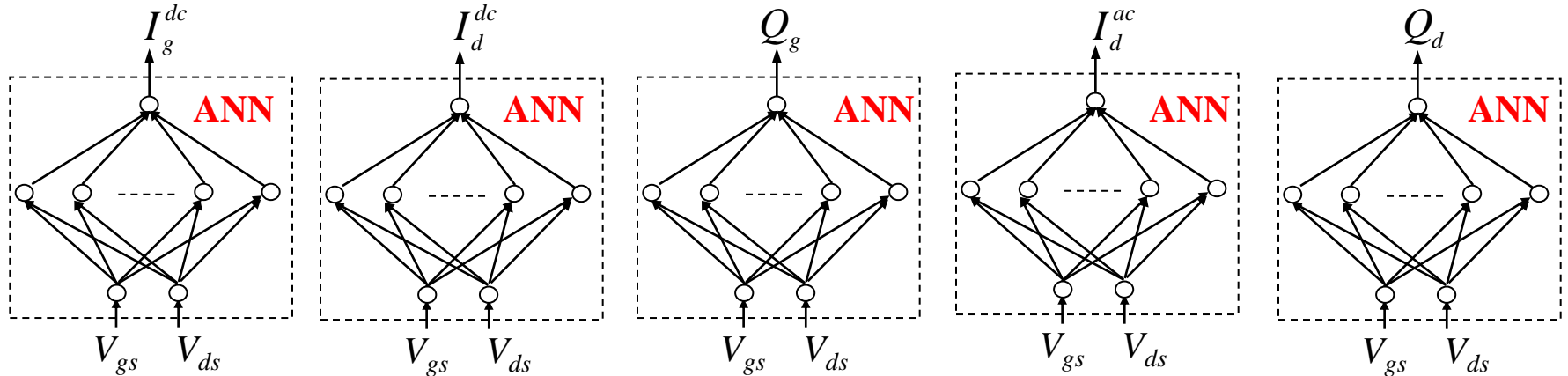
$$\frac{\partial Q_g}{\partial V_{ds}} = \frac{\text{Imag}(Y_{12})}{\omega}$$

V_{gs}, V_{ds}

$$Q_g = f_{ANN}^{Q_g}(V_{gs}, V_{ds}, \mathbf{w})$$



NeuroFET: Intrinsic Model



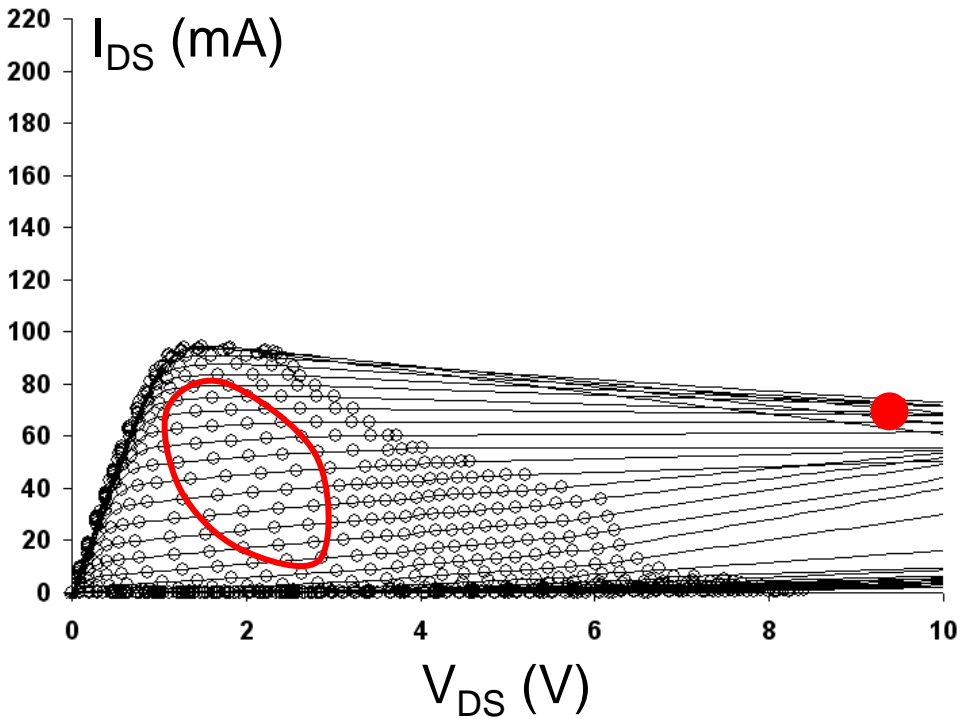
$$I_g(t) = I_g^{dc}(V_{gs}(t), V_{ds}(t)) + \frac{dQ_g(V_{gs}(t), V_{ds}(t))}{dt}$$

$$I_d(t) + \tau \frac{dI_d(t)}{dt} = I_d^{dc}(V_{gs}(t), V_{ds}(t)) + \tau \frac{dI_d^{ac}(V_{gs}(t), V_{ds}(t))}{dt} + \frac{dQ_d(V_{gs}(t), V_{ds}(t))}{dt} + \tau \frac{d^2Q_d(V_{gs}(t), V_{ds}(t))}{dt^2}$$

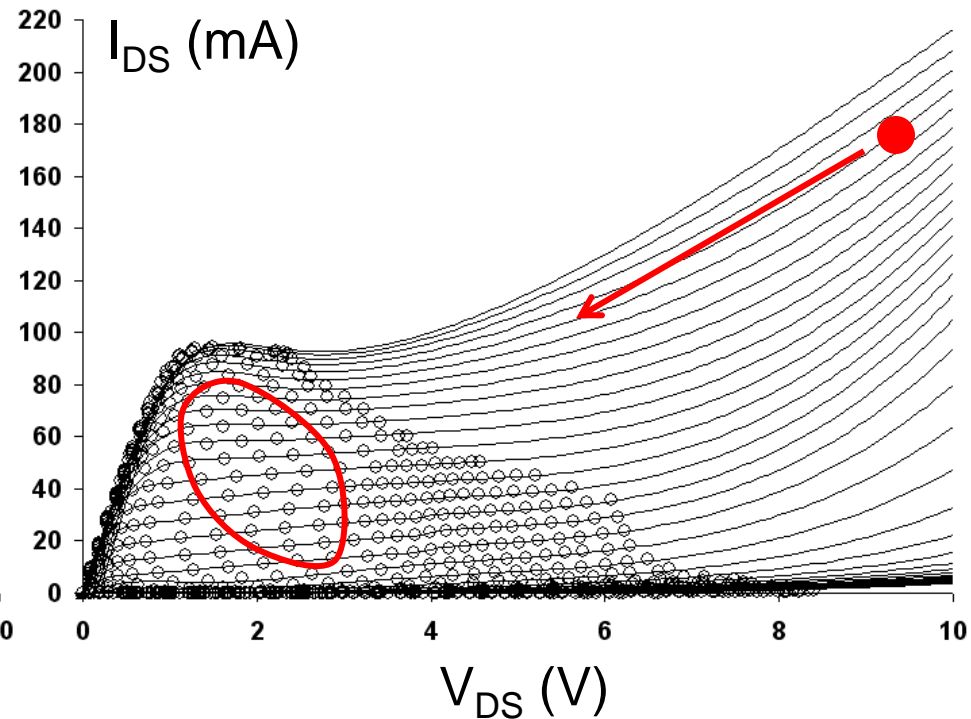
Advanced Model Extrapolation Routine

- for robust convergence

Without Extrapolation

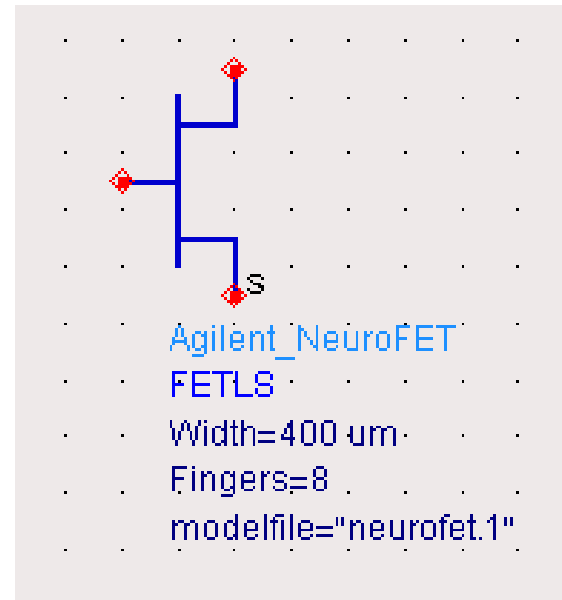
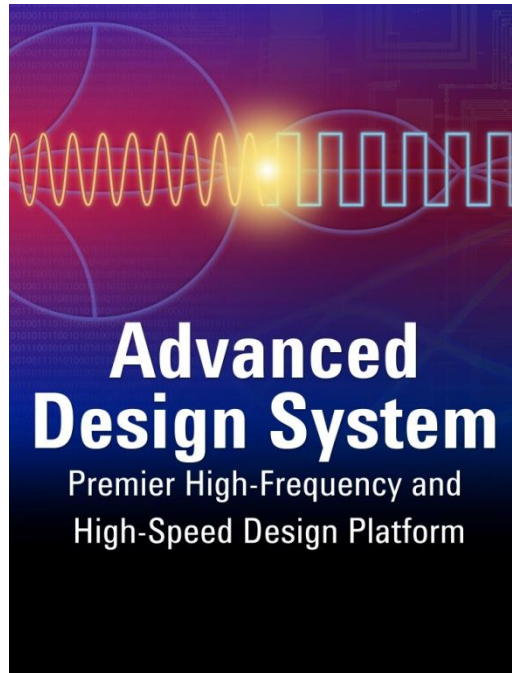


With Extrapolation



○ Measured Data (training data)

NeuroFET Model is compiled into ADS



**The model, together with extrapolation routine,
is compiled into ADS.**

- **Same use model as any other transistor model.**
- **Model has simple scaling rules with gate width and number of fingers.**

Example 1

A 0.25um GaAs pHEMT device (Width=150um) was extracted:

- DC IV
- Q_g , Q_d , and I_d^{ac}
- S-parameters versus bias and frequency
- One-tone Harmonic Distortion
- Two-tone Intermodulation

NeuroFET: Training I_d^{dc}

The screenshot displays the NeuroFET Modeling software interface. The main window is titled "NeuroFET Modeling: 1" and features a menu bar (File, View, Plot, Run, Help) and a toolbar. The left sidebar shows a "Navigation View" tree with categories like Configuration, Initialization, InstrumentSettings, MeasurementSettings, Pre Measure/Verify, Ideality and Parasitics, Data Acquisition, and Model Generation. The "Model Generation" category is expanded, showing sub-items: Ig, Id (selected), Qg, and Od. The main workspace is titled "Id: Drain Current Source" and contains a "Select Task" list with options: Define ANN, Train ANN (highlighted), Test ANN, and Sweep ANN. To the right, the "Train Neural Model" section includes "Training Settings" with a dropdown menu for "Training Type" set to "Standard NN" (circled in red), "Max Iterations" set to 10000, "Stop Tolerance" set to 0.0, and "# of Weight Segments Used" set to 1. Below these settings, it indicates "Output Weighting (# of Pts. = 1106)".

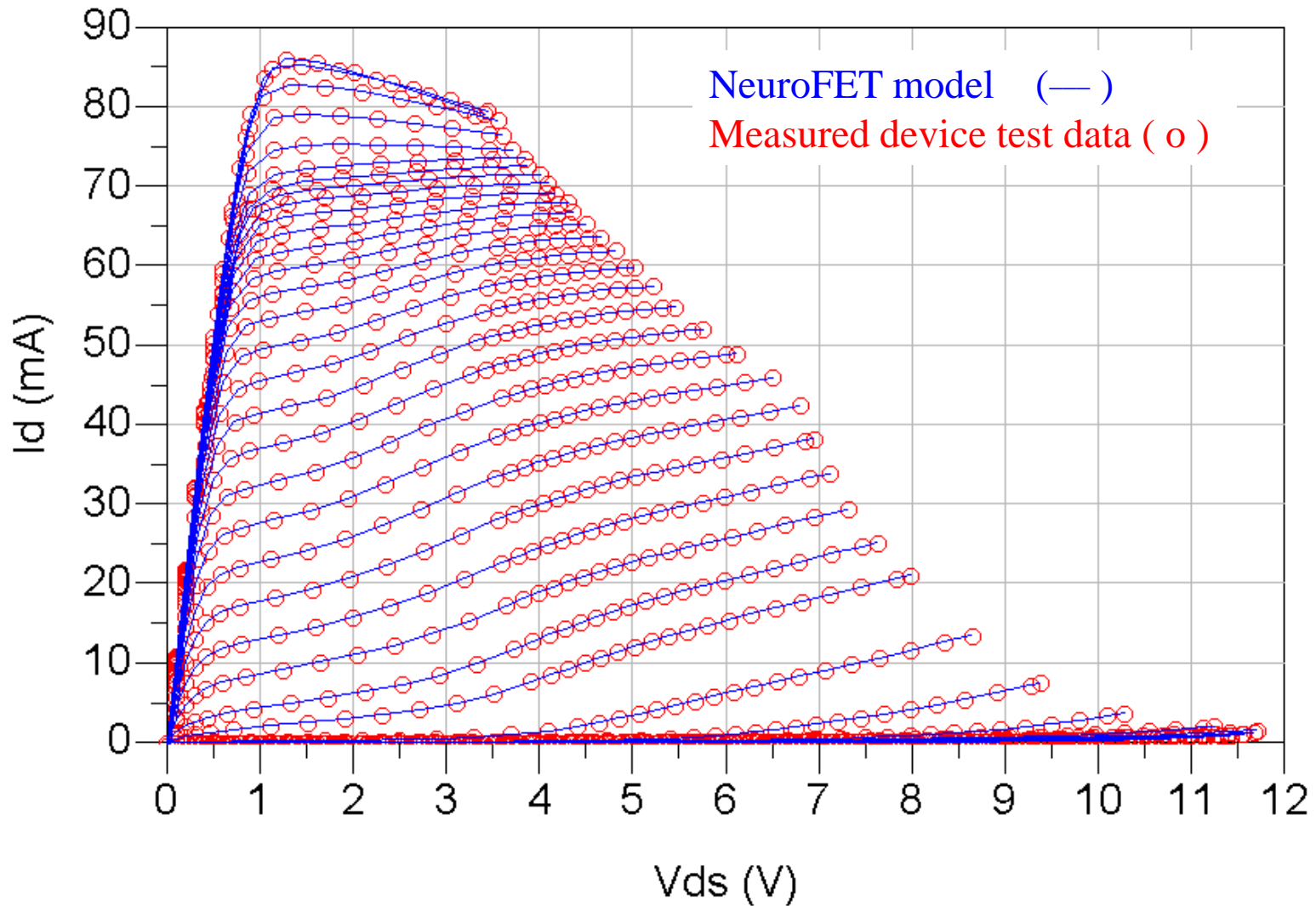
Below the main window is a "NeuroFET: Training Progress" window. It contains a table with the following data:

	Training Name	Training Error History	Current Error / Target Error	Training Progress	Training Iteration	Time
1	NeuroFET_Id_Train		0.001608 / 0		1760 / 10000	00:05:22

At the bottom of the training progress window, there are control buttons: "Run" (with a red arrow pointing to it), "Start", "Setup and Training" (with a dropdown arrow), "Stop", "Show Status", and "Hide Status". There are also checkboxes for "SampleN in Xaxis" and buttons for "Plot" and "Close Plots".

Model Validations

- DC



NeuroFET: Training Q_g

NeuroFET Modeling: 1

File View Plot Run Help

Navigation View

Project

- Configuration
- Initialization
- InstrumentSettings
- MeasurementSettings
- Pre Measure/Verify
 - PortR/Open/Short
 - DC
 - SP
- Ideality and Parasitics
 - Ideality Factor
 - Parasitics
- Data Acquisition
- Model Generation
 - Ig
 - Id
 - Qg
 - Qd
 - Idbf

Qg: Gate Charge

Select Task

- Define ANN
- Train ANN
- Test ANN
- Sweep ANN

Train Neural Model

Training Settings

Training Type: Adjoint NN

Max Iterations: 3000

Stop Tolerance: 0.0

of Weight Segments Used: 1

Output Weighting (# of Pts. = 1106)

from	to	<Qg>	<dQg/dVgs>

NeuroFET: Training Progress

Training Name	Training Error History	Current Error / Target Error	Training Progress	Training Iteration	Time
1 NeuroFET_Qg_Train		0.00792 / 0		520 / 3000	00:00:39

Run

Qg	0	0	1
dQg/dVgs (Imag(Y11)/w)	0.1	0.8	3

SampleN in Xaxis

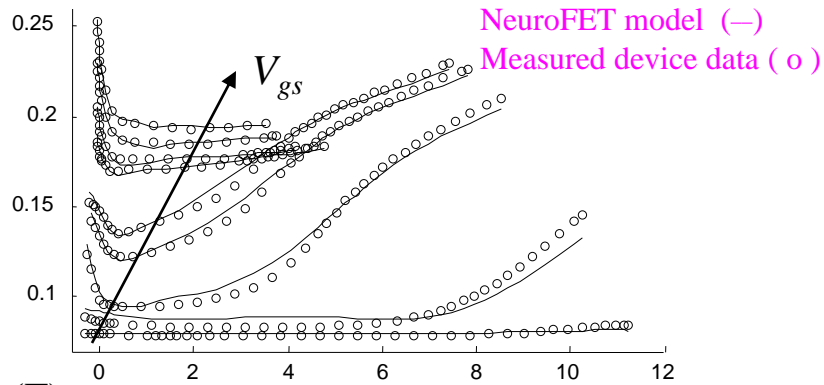
Plot Show Range Set Range Close Plots

Start Setup and Training Stop Show Status Hide Status

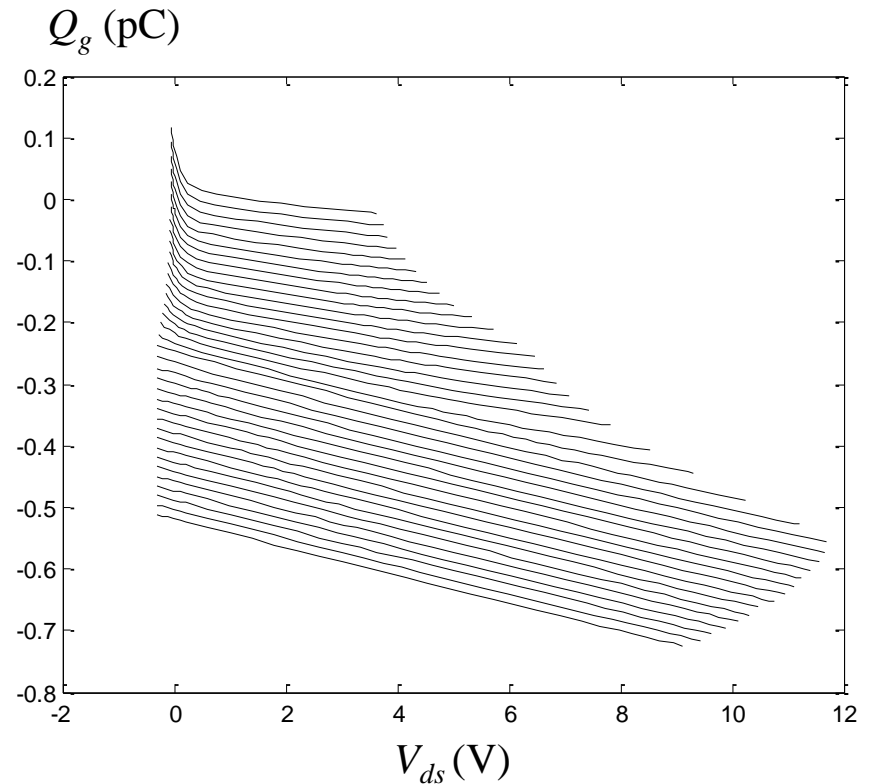
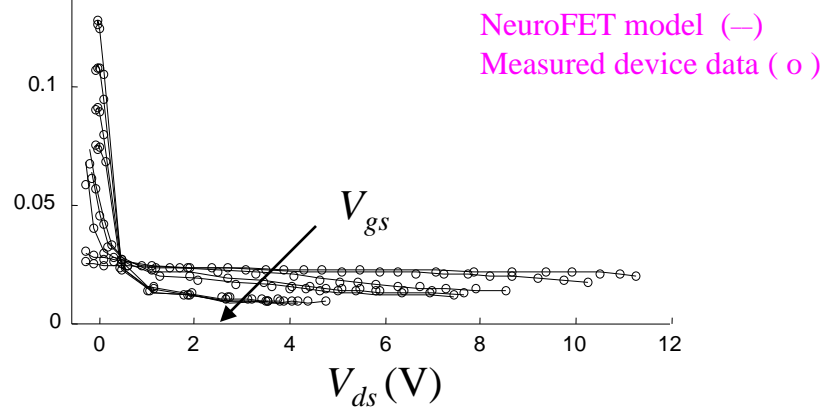
Model Validations

-Charge Q_g

(F) $\times 10^{-12}$ $Im(Y_{11})/\omega$ and $\partial Q_g/\partial V_{gs}$

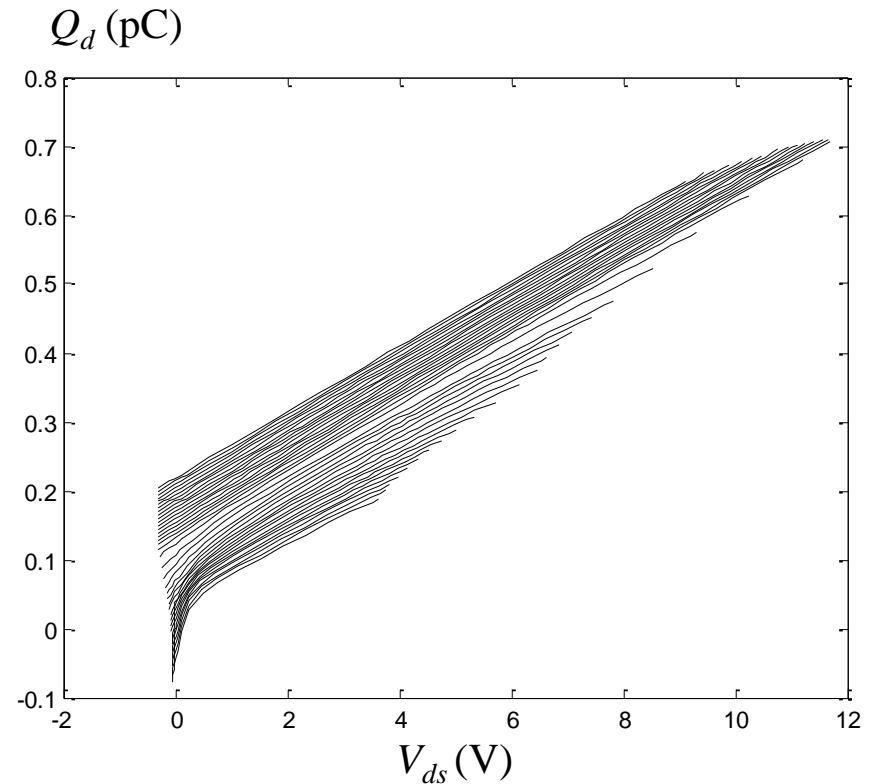
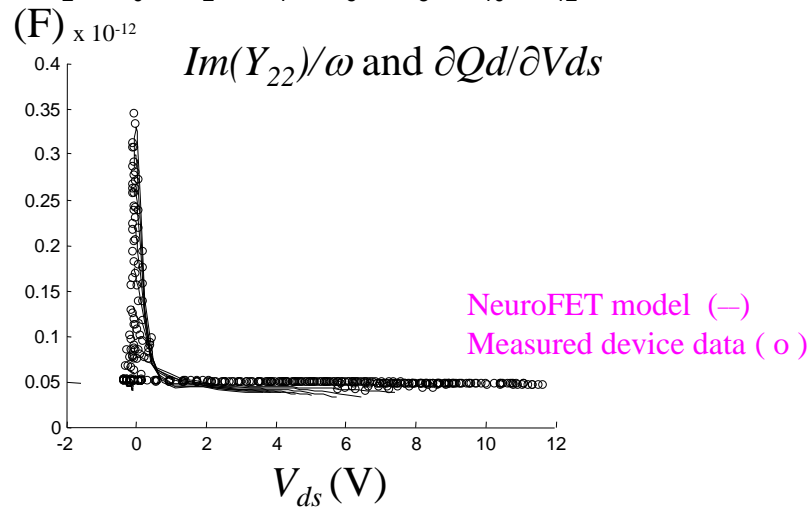
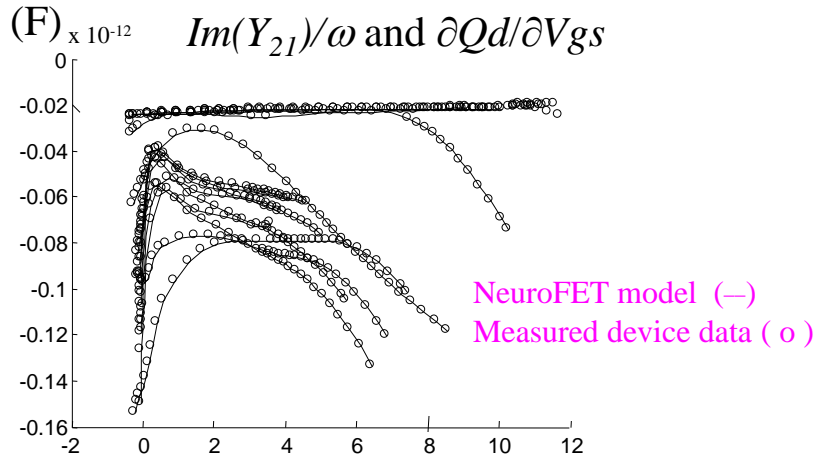


(F) $\times 10^{-12}$ $-Im(Y_{12})/\omega$ and $-\partial Q_g/\partial V_{ds}$



Model Validations

-Charge Q_d

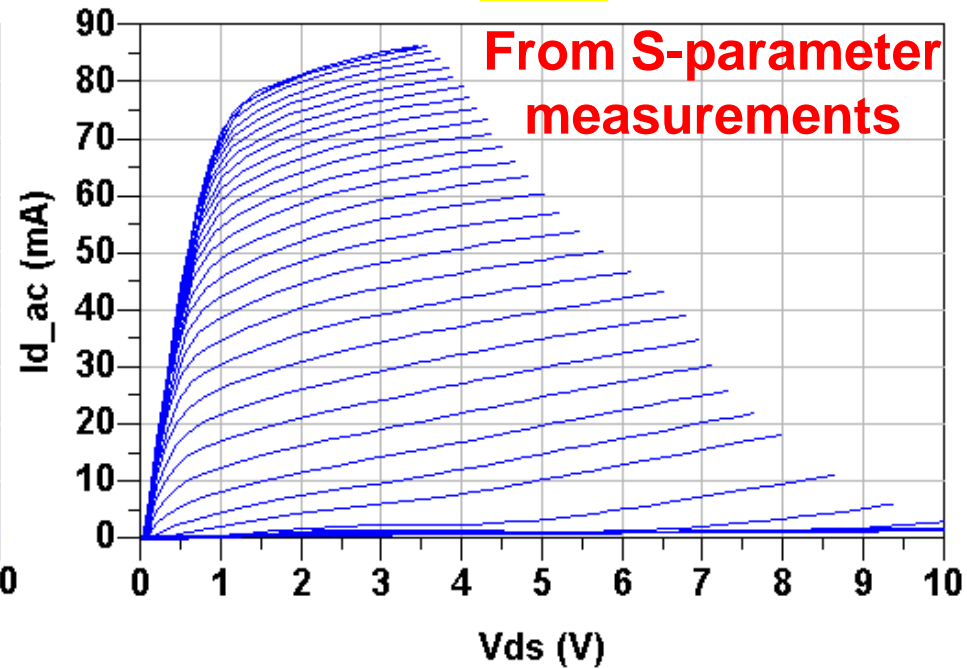
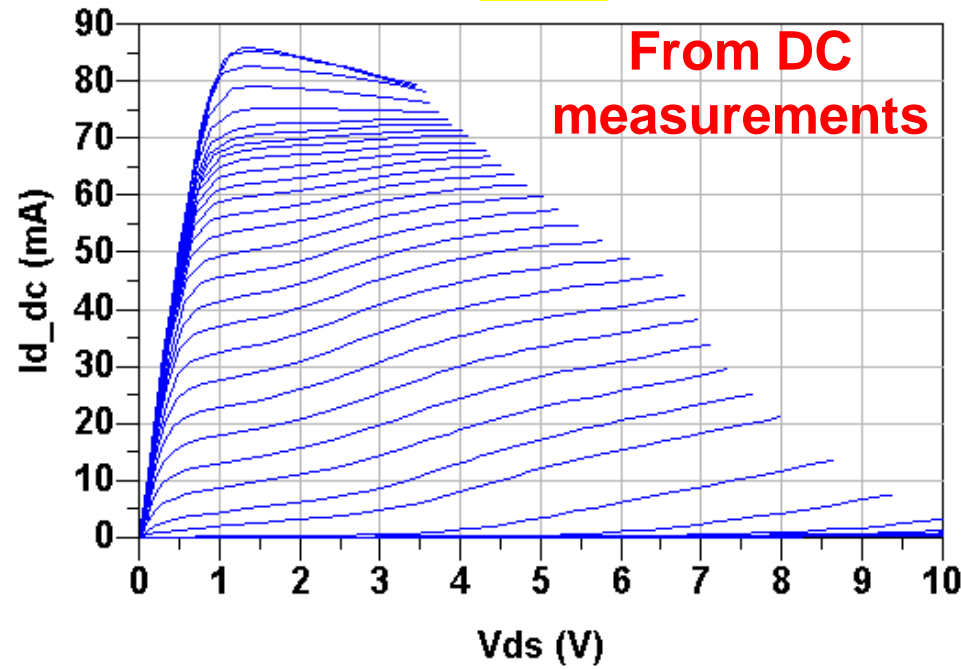


Model Validations

$$- I_d^{ac}$$

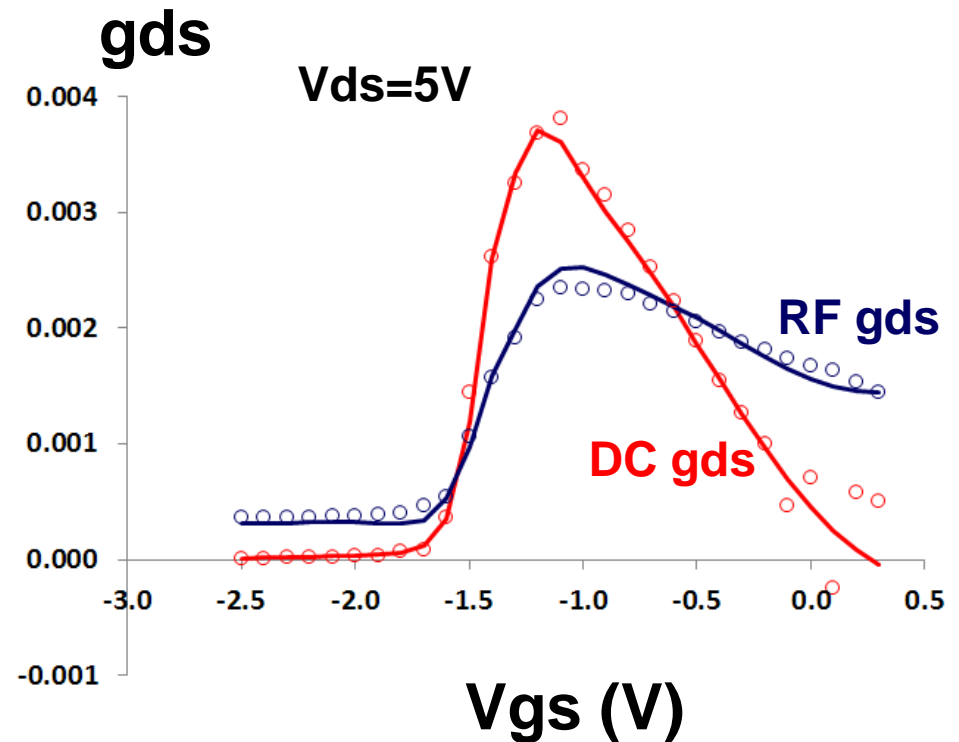
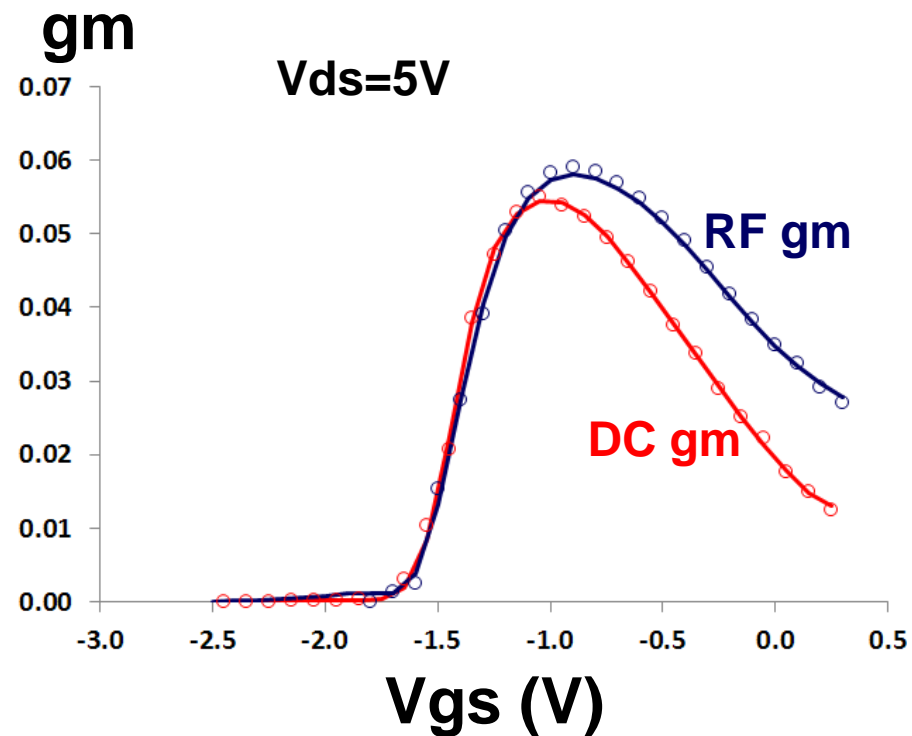
$$I_d^{dc}$$

$$I_d^{ac}$$



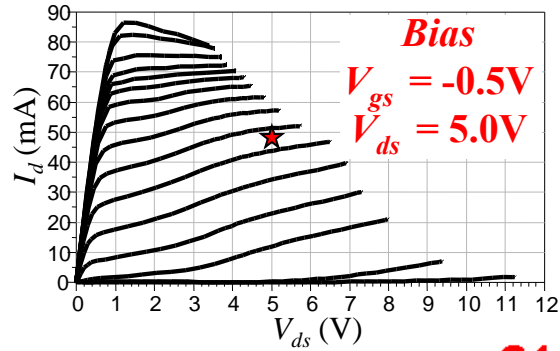
Frequency dispersion of small-signal characteristics

NeuroFET (—)
Measured data (o)



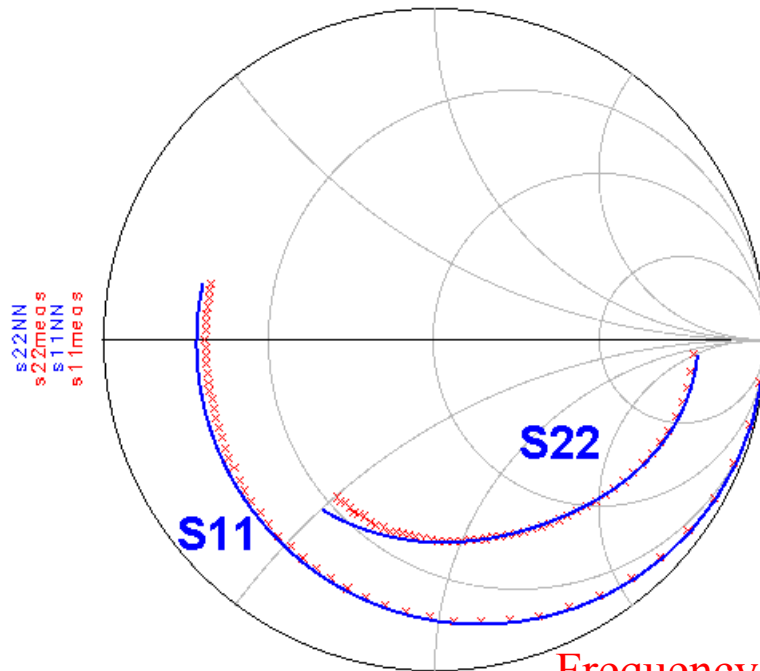
Model Validations

- S parameters

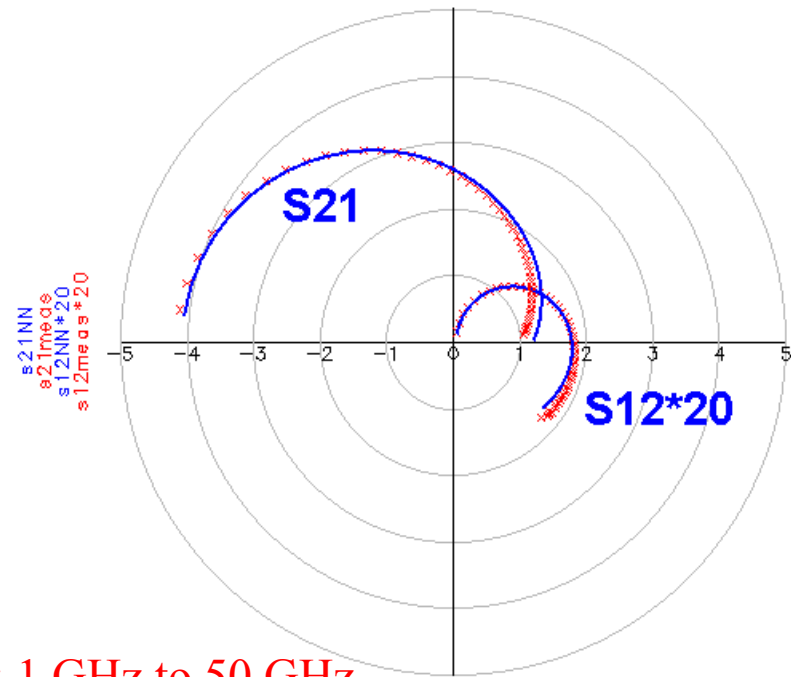


NeuroFET model (—)
 Measured device test data (x)

S11, S22



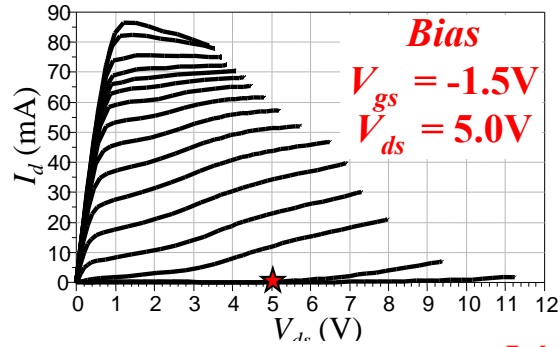
S21, S12



Frequency : 1 GHz to 50 GHz

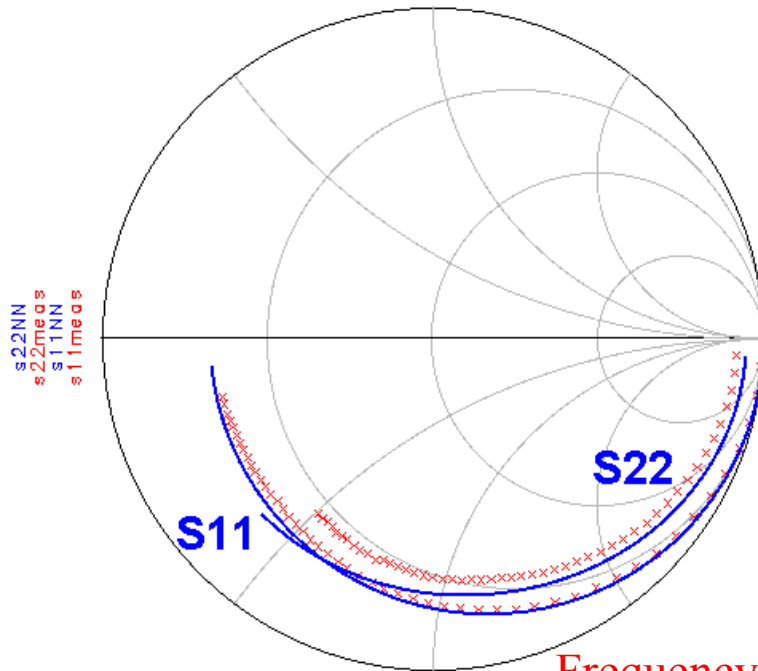
Model Validations

- S parameters

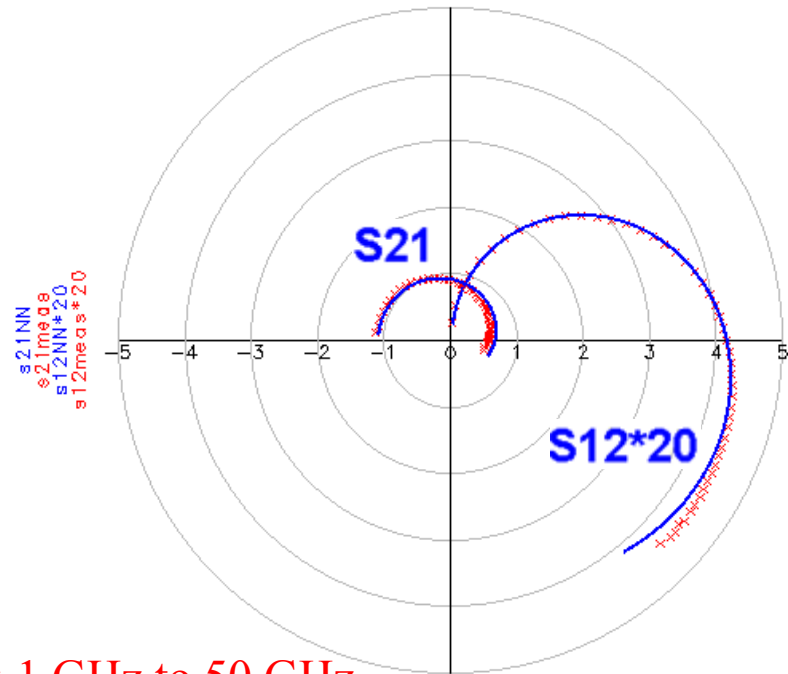


NeuroFET model (—)
 Measured device test data (x)

S11, S22



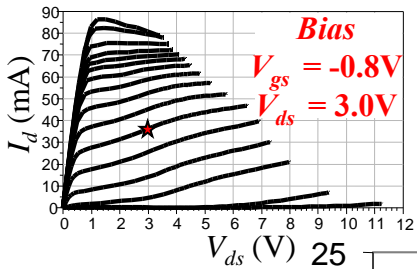
S21, S12



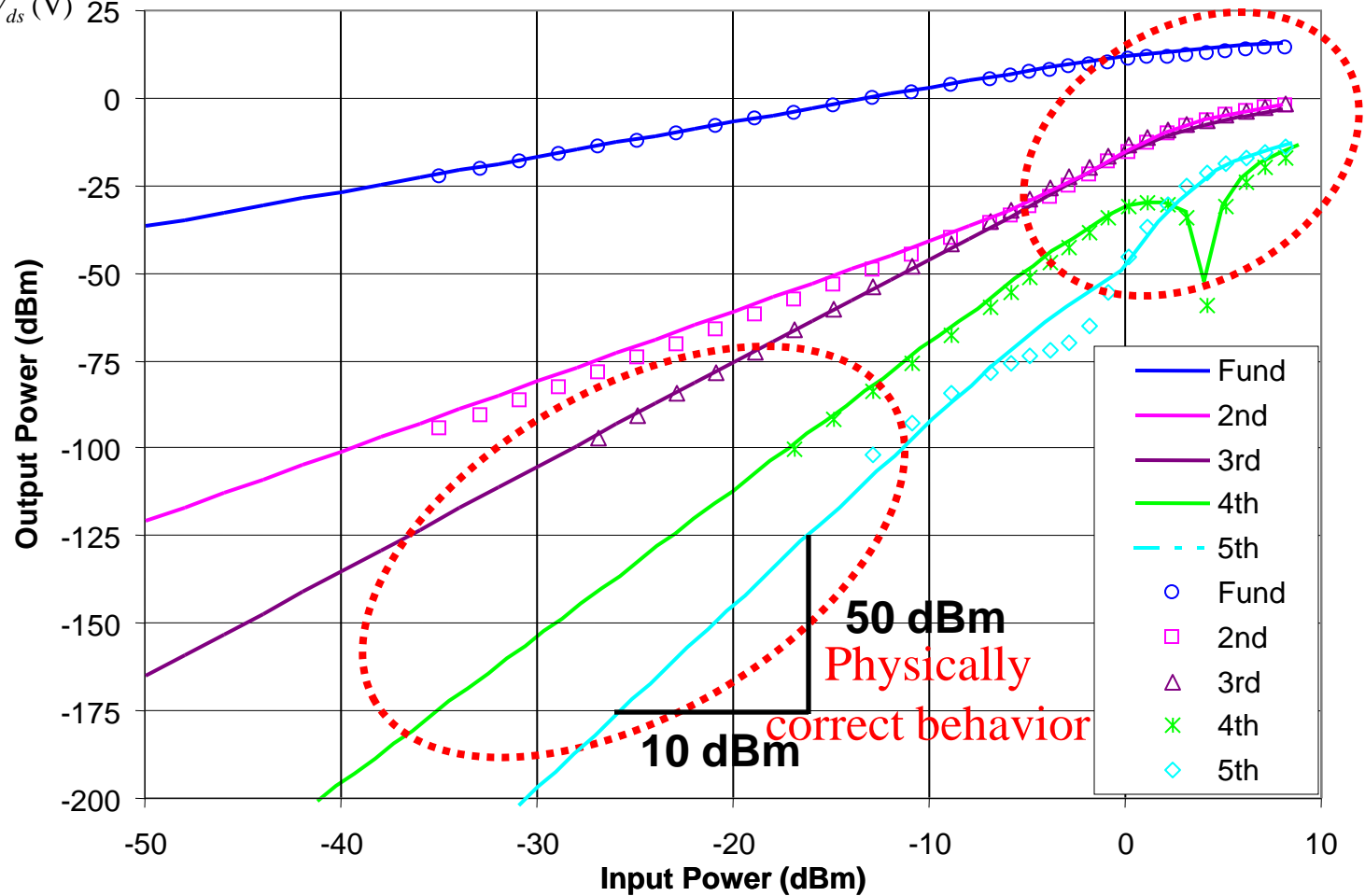
Frequency : 1 GHz to 50 GHz

Model Validations

- One-tone Harmonic Distortion

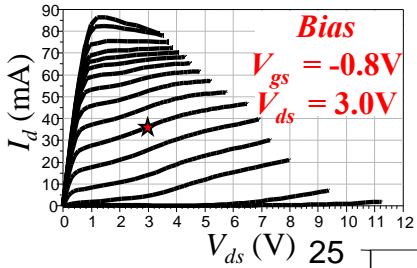


NeuroFET vs Measured

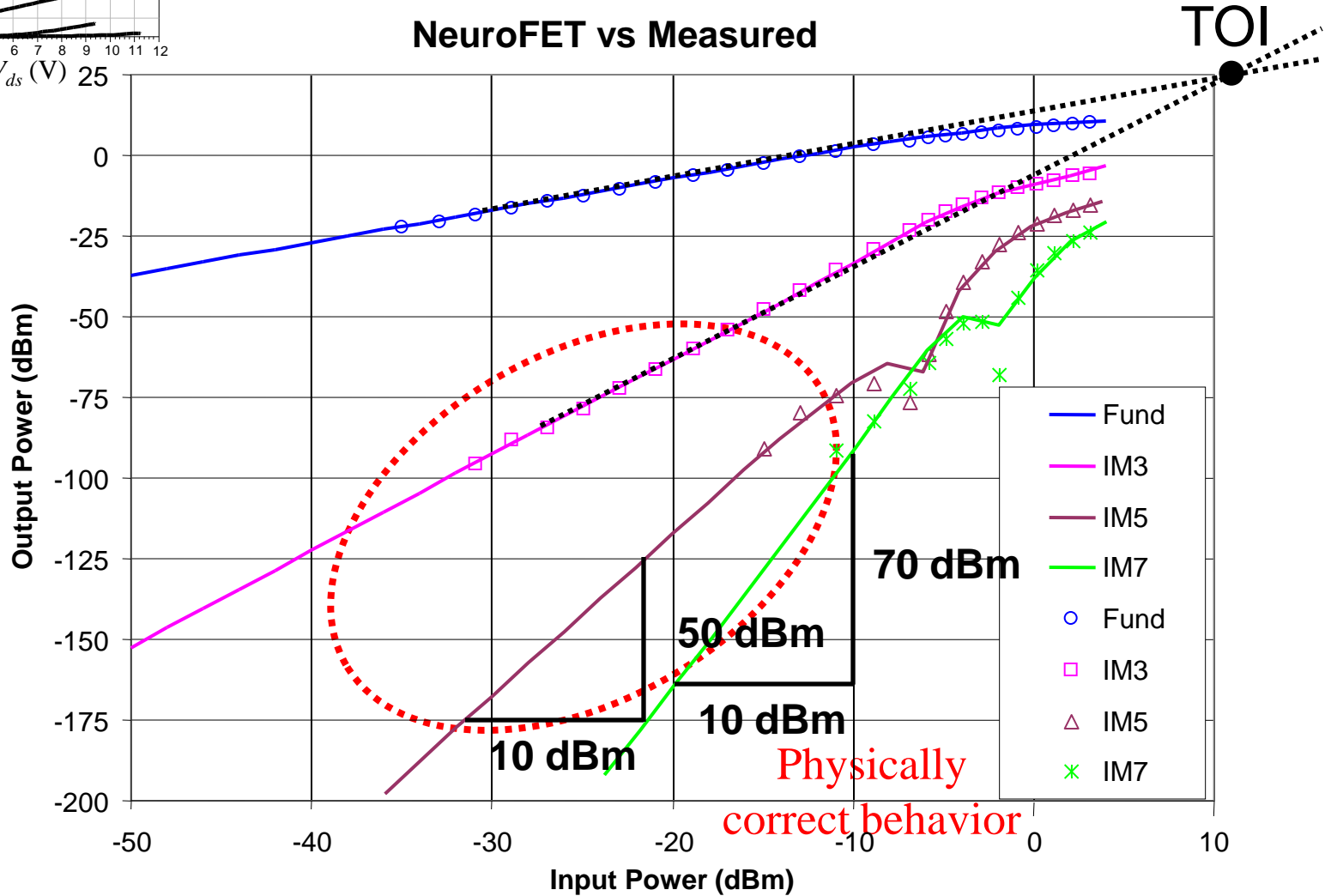


Model Validations

- Two-tone Intermodulation



NeuroFET vs Measured



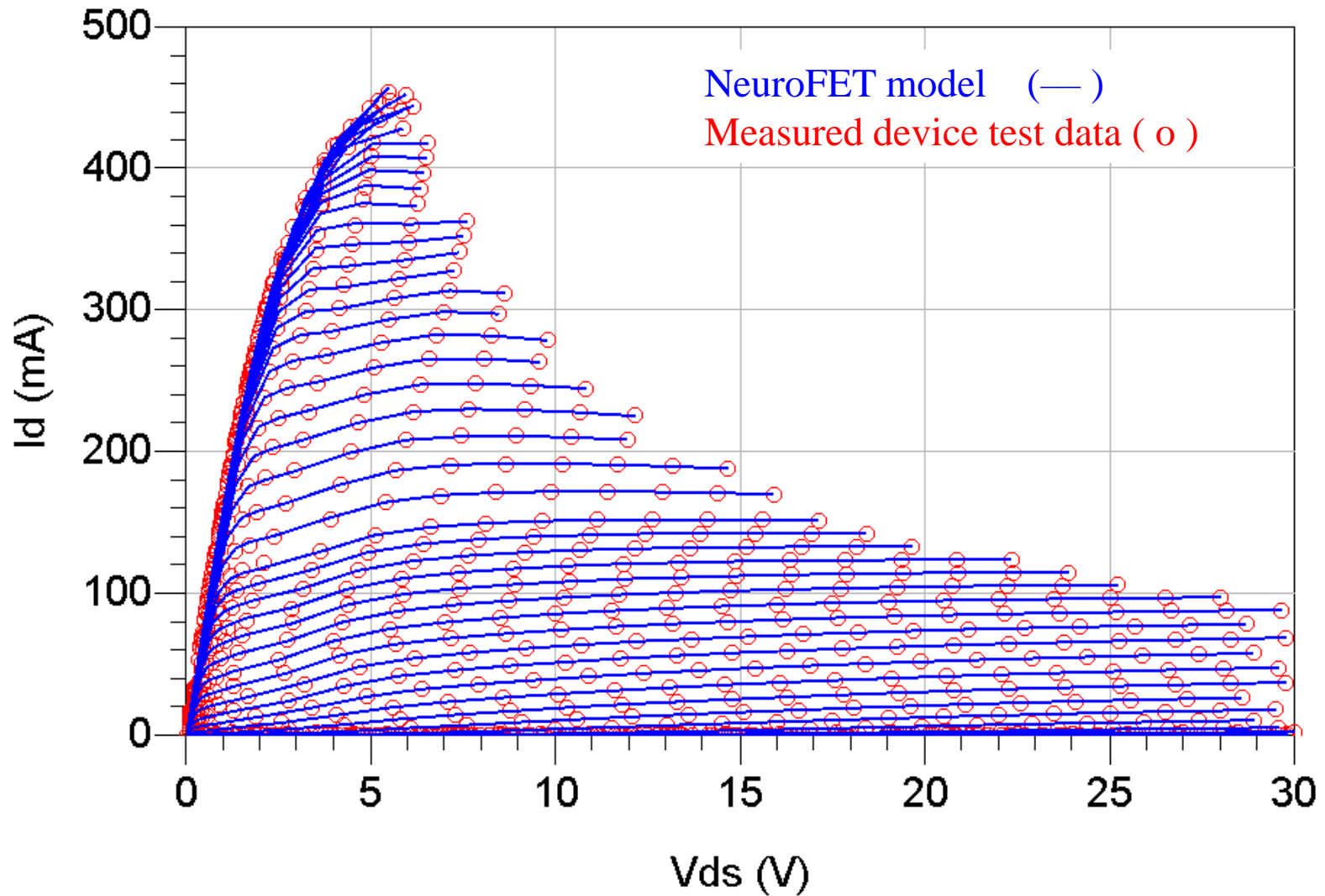
Example 2

A 0.25 μ m GaN HEMT device (Width=400 μ m) was extracted:

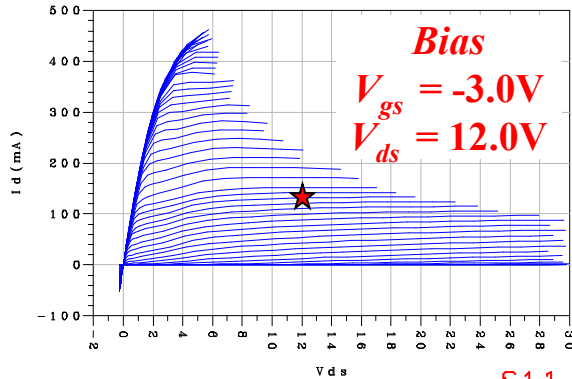
- DC IV
- S-parameters versus bias and frequency
- One-tone Harmonic Distortion
- Two-tone Intermodulation

Model Validations

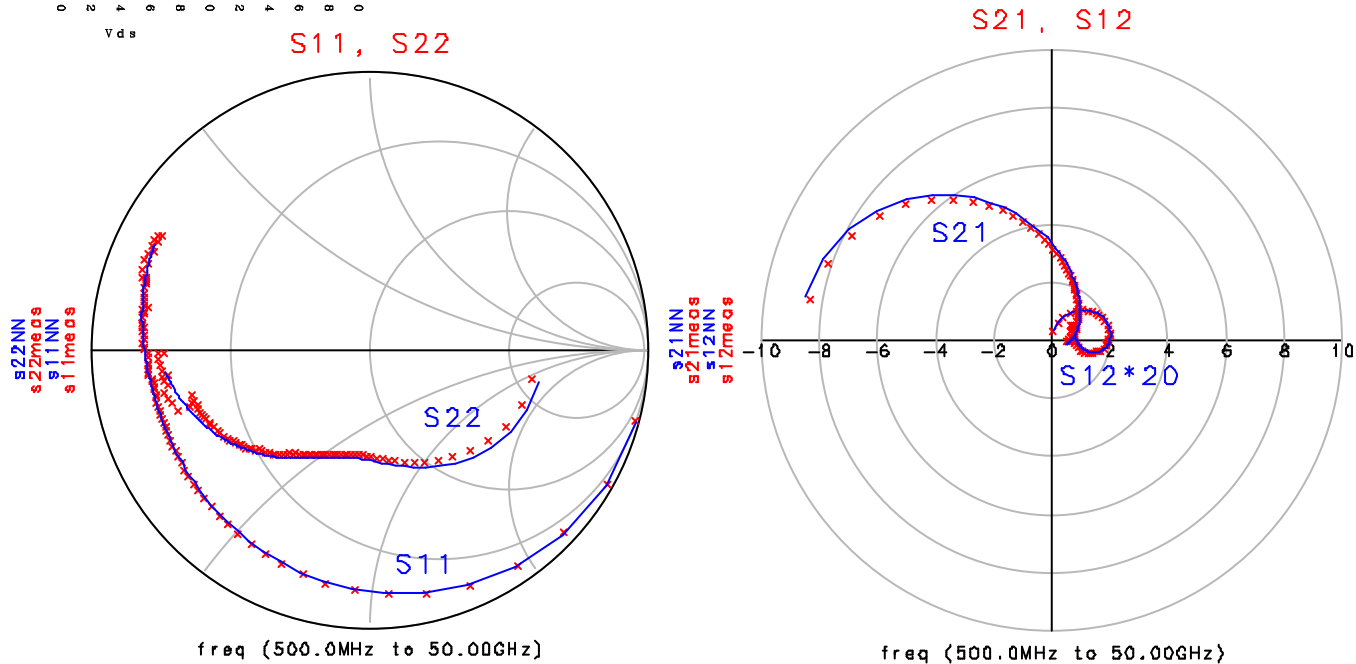
- DC



Model Validations - S parameters



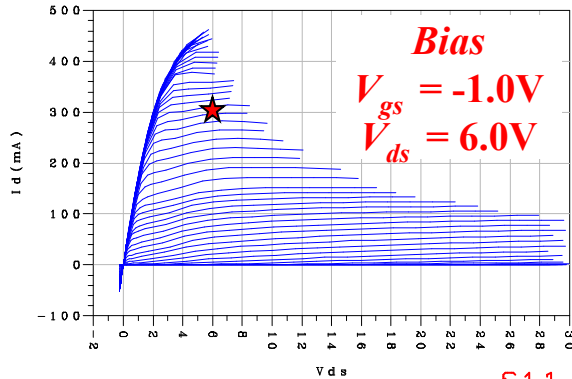
NeuroFET model (—)
 Measured device test data (x)



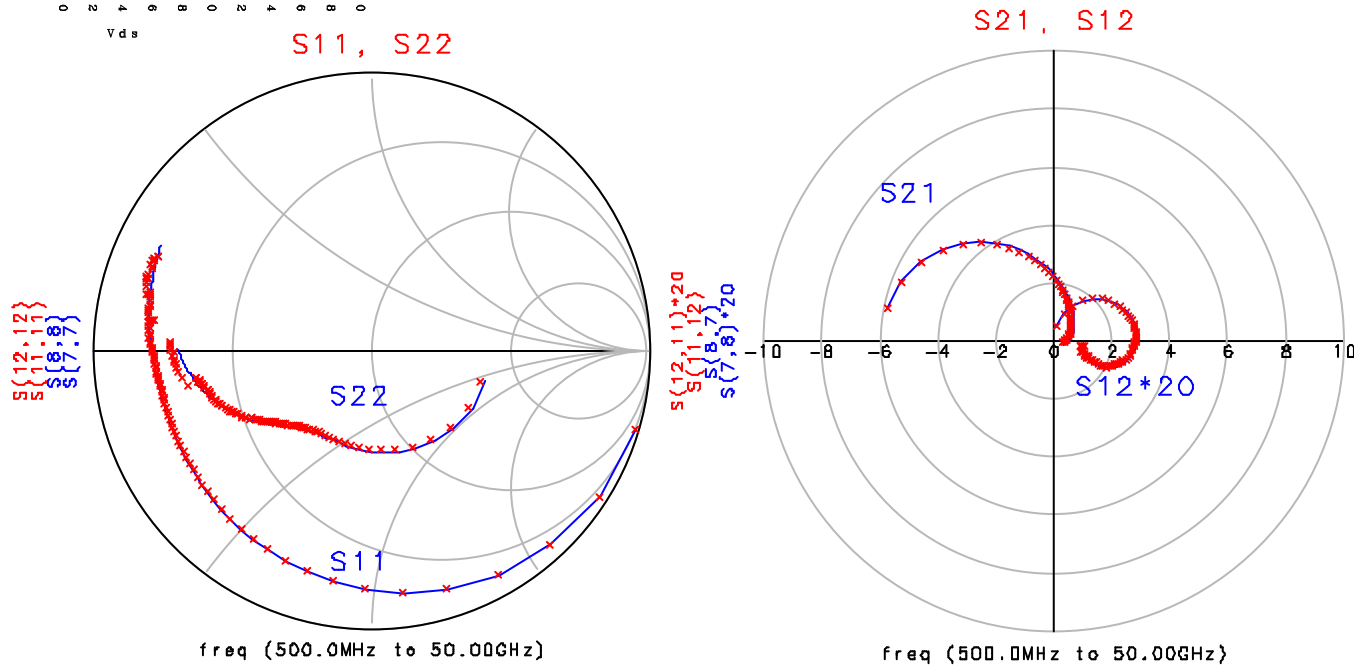
Frequency : 0.5 GHz to 50 GHz

Model Validations

- S parameters

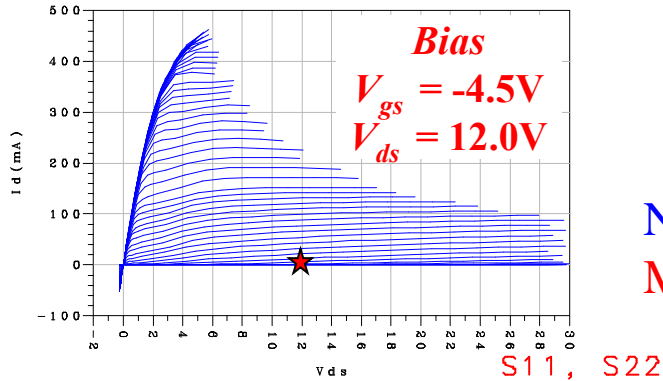


NeuroFET model (—)
 Measured device test data (x)



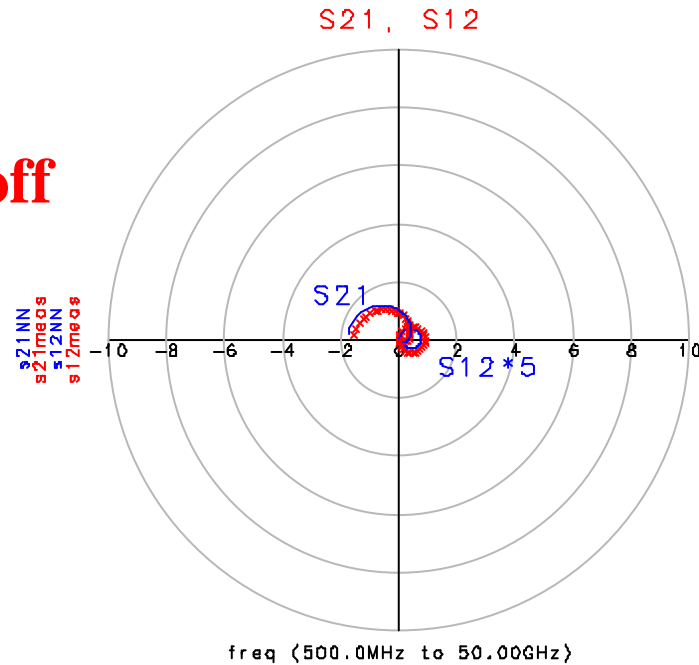
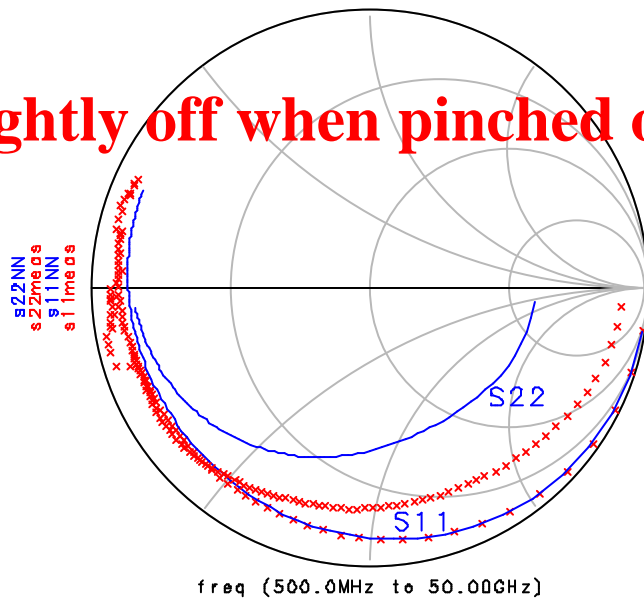
Frequency : 0.5 GHz to 50 GHz

Model Validations - S parameters



NeuroFET model (—)
 Measured device test data (x)

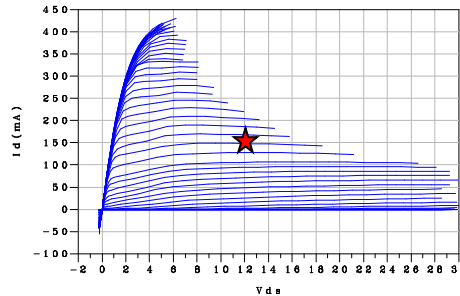
S_{22} is slightly off when pinched off



Frequency : 0.5 GHz to 50 GHz

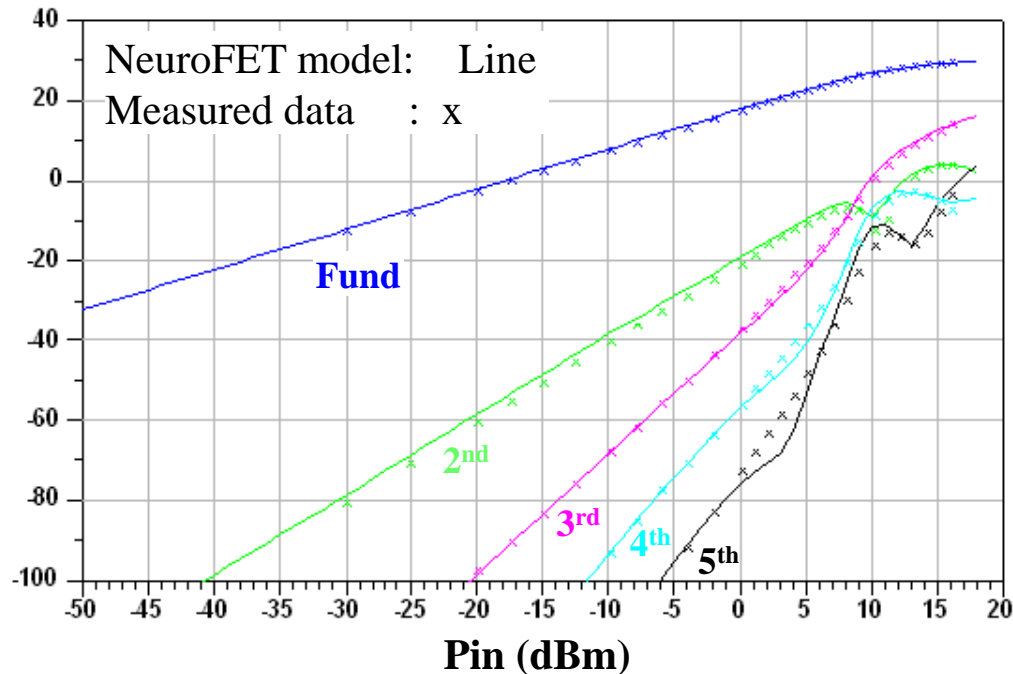
Model Validations

- One-tone Harmonic Distortion (Freq=2GHz)



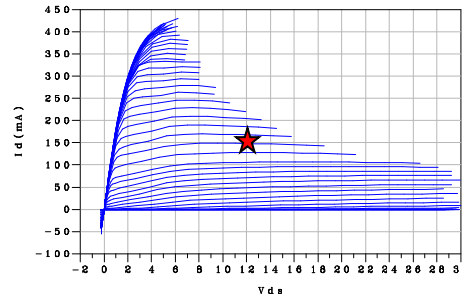
Bias
 $V_g = -2.5V$
 $V_d = 12.0V$

(dBm)

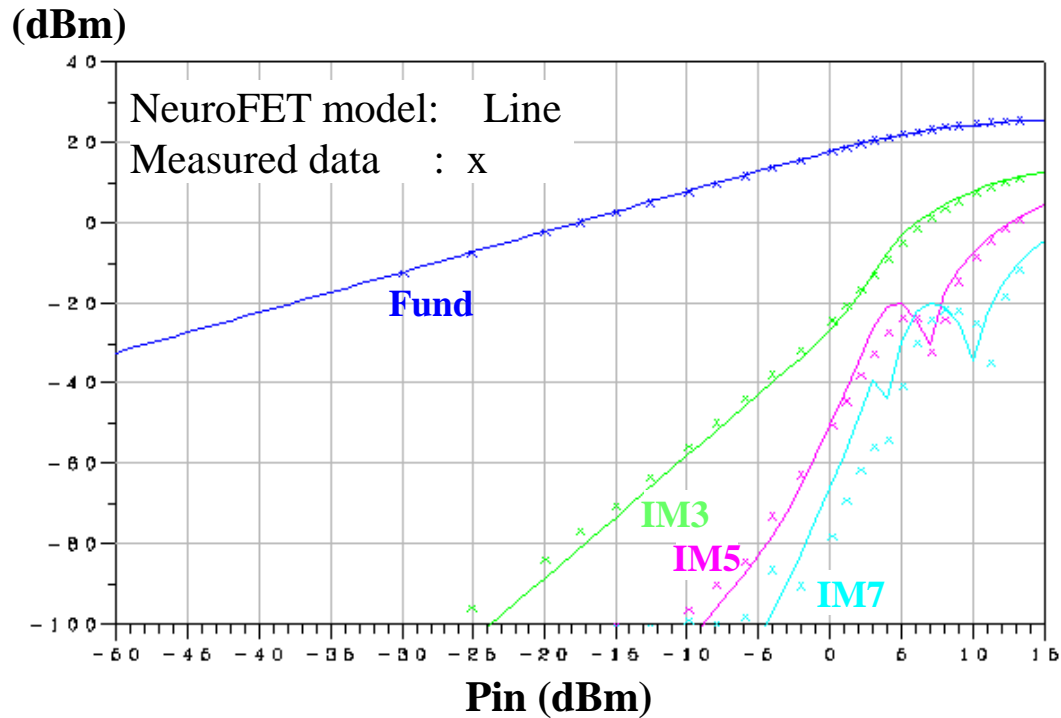


Model Validations

- Two-tone Intermodulation (Freq1=2GHz, Freq2=2.005GHz)



Bias
 $V_g = -2.5V$
 $V_d = 12.0V$



Summary: *NeuroFET*

Easy to use, fast to simulate, accurate

- Flexible, automated, data acquisition system takes data where needed
 - Minimizes impact of device degradation on resulting model
- Advanced Agilent ANN-training creates accurate & general model functions
- Compiled ADS model works for HEMT, MESFET and other types of FETs
 - Robust DC and RF convergence, compared to table-based models; fast to simulate
 - Improved distortion simulation compared to table-based models
 - Better power-added efficiency (PAE) and S-parameters versus bias over the entire range of device operation, compared to many compact models for wide range of technologies
 - Model can be used in all bias conditions (including $V_{DS} \leq 0$ for mixers and switches)
- Instrument control and powerful ANN training available in Agilent's ICCAP Modeling Software
- FET simulation model available in Agilent's Advanced Design System (ADS), the industry standard RF simulator

References

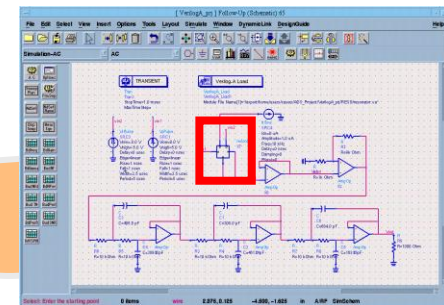
- J. Xu, D. Gunyan, M. Iwamoto, A. Cognata, and D. E. Root, "Measurement-Based Non-Quasi-Static Large-Signal FET Model Using Artificial Neural Networks," 2006 IEEE MTT-S Int. Microwave Symp. Dig., San Francisco, CA, USA, June 2006.
- J. Xu, D. Gunyan, M. Iwamoto, J. Horn, A. Cognata, and D. E. Root, "Drain-Source Symmetric Artificial Neural Network-Based FET Model with Robust Extrapolation Beyond Training Data," 2007 IEEE MTT-S Int. Microwave Symp. Dig., Honolulu, HI, USA, June 2007.
- J. Xu, J. Horn, M. Iwamoto, and D. E. Root, "Large-signal FET model with multiple time scale dynamics from nonlinear vector network analyzer data," IEEE MTT-S International Microwave Symposium Digest, May, 2010.
- J. Xu, M.C.E. Yagoub, R. Ding, and Q.J. Zhang, "Exact adjoint sensitivity analysis for neural based microwave modeling and design," IEEE Transactions on Microwave Theory and Techniques, vol. 51, pp.226-237, 2003.
- D. E. Root, J. Xu, J. Horn, and M. Iwamoto, "The Large-Signal Model: theoretical foundations, practical considerations, and recent trends," in **Nonlinear Transistor Model Parameter Extraction Techniques**, Cambridge University Press, 2011, eds. Rudolph, Fager, & Root
- D.J.McGinty, D.E.Root, and J.Perdomo, "A Production FET Modeling and Library Generation System," in IEEE GaAs MANTECH Conference Technical Digest, San Francisco, CA, July, 1997 pp. 145-148.
- D.E.Root, D.McGinty, B.Hughes, "Statistical Circuit Simulation with Measurement-Based Active Device models: Implications for Process Control and IC Manufacturability," 1995 GaAs IC Symposium Technical Digest, San Diego, pp. 124-127.
- Root, D.E., Fan, S., Meyer, J. "Technology Independent Non Quasi-Static FET Models by Direct Construction from Automatically Characterized Device Data" 21st European Microwave Conf. Proceedings, Stuttgart, Germany, Sept 1991, pp 927-932.

Agilent measurement-based modeling and design solutions

Agilent Nonlinear Vector Network Analyzer



Electronic design automation software



Measurements

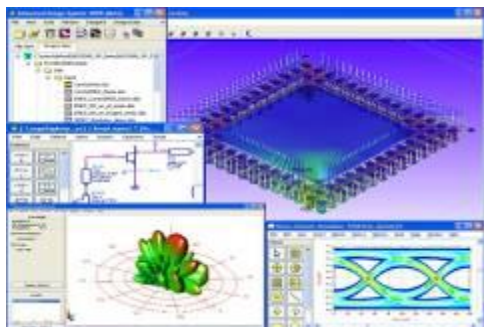
Simulation & Design

Modeling

Customer Applications

Examples:

- HP/Agilent (Root) models
- AgilentHBT model and extraction module
- X-parameters / NVNA
- *NeuroFET*



Where to find Information about NeuroFET

- IC-CAP NeuroFET Webpage:

<http://www.agilent.com/find/eesof-neurofet>

- IC-CAP Device Modeling Software:

<http://www.agilent.com/find/eesof-iccap>

Questions and Answers

You are invited



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