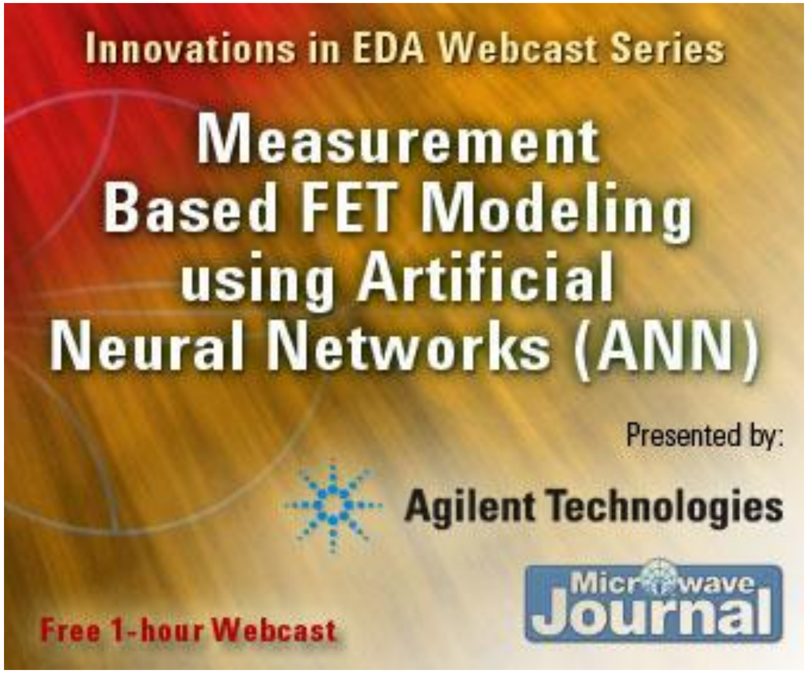
Welcome



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Agilent Technologies, Inc.

Agilent Technologies

February 7, 2012

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

Jianjun Xu and David E. Root

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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:

(1) Data Acquisition

(2) Advanced ANN Training

(3) Compiled Nonlinear Model

Agilent NeuroFET

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

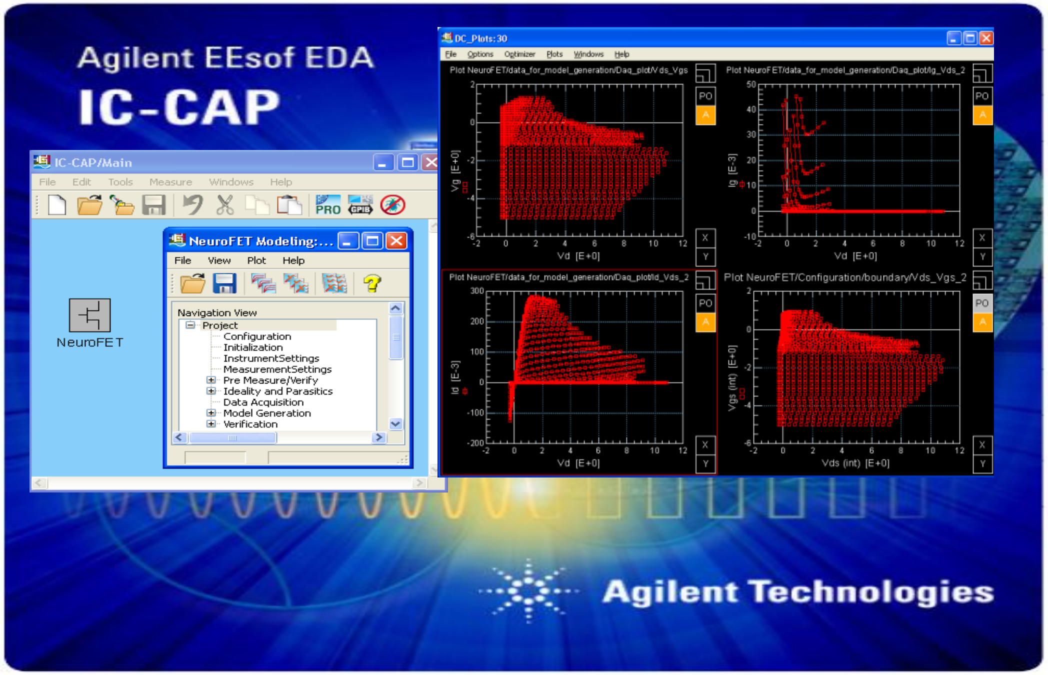
NeuroFET components

(1) Automated, adaptive characterization system for FETs

VNA

DC

Agilent IC-CAP



Data Acquisition:

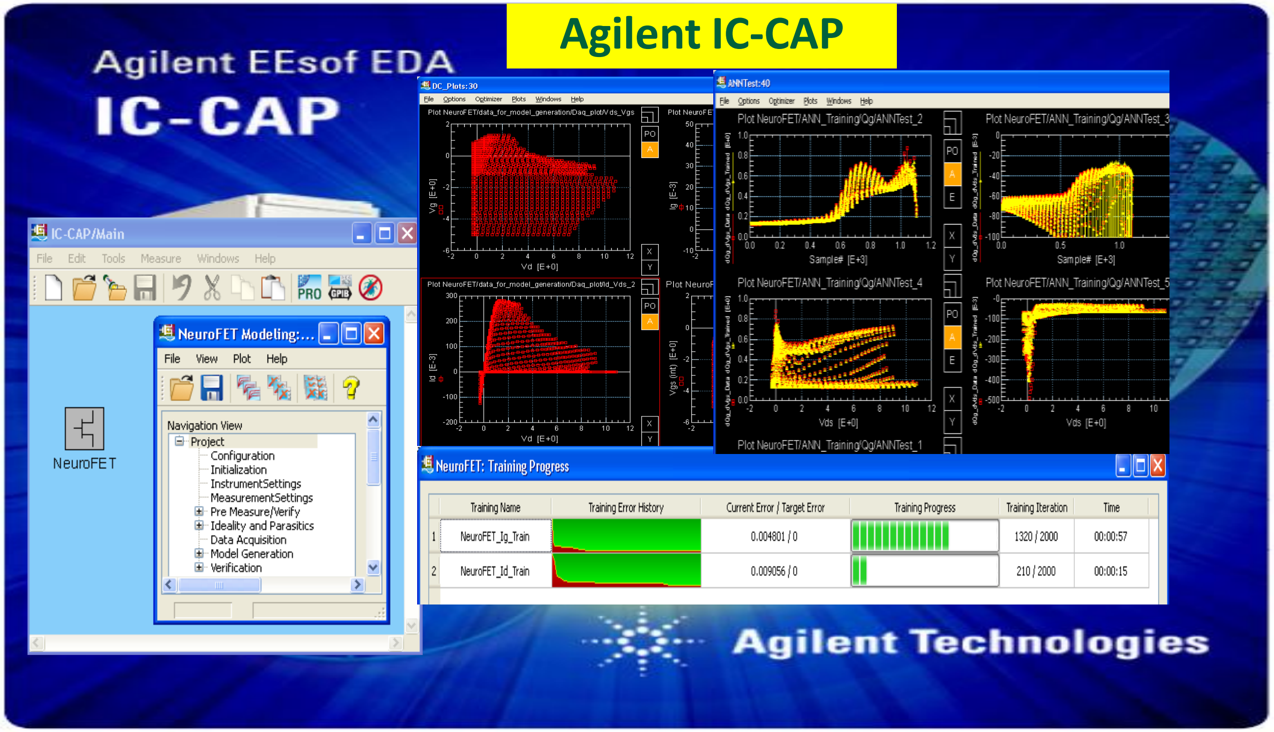
Benefits:

Supports common gate and common source layouts

Minimizes impact of device degradation during characterization

NeuroFET components

(2) Unique and powerful Agilent ANN Training Technology



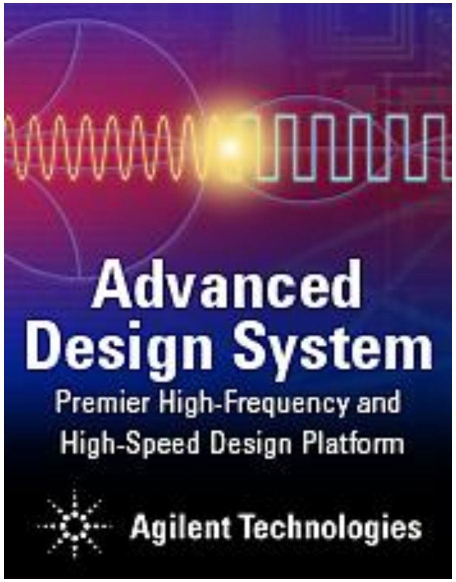
Model Generation

Benefits:

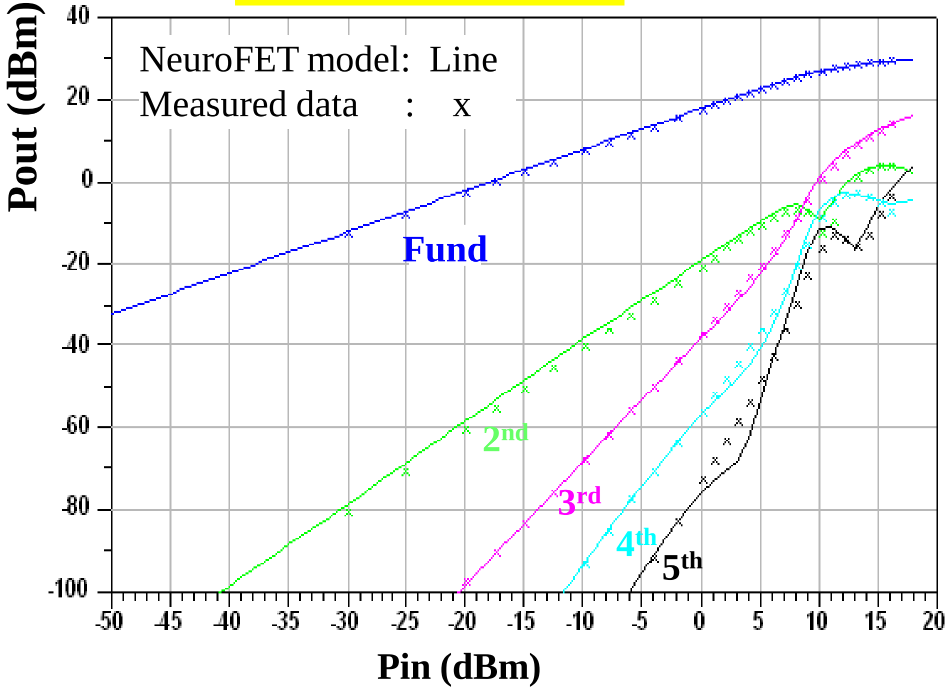
- Advanced ANN training creates accurate & general model functions
- Same flow can fit very different looking device characteristics

NeuroFET components

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



Agilent ADS



Nonlinear Simulation And Design

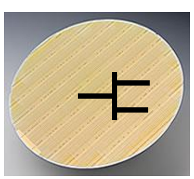
Benefits:

- 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

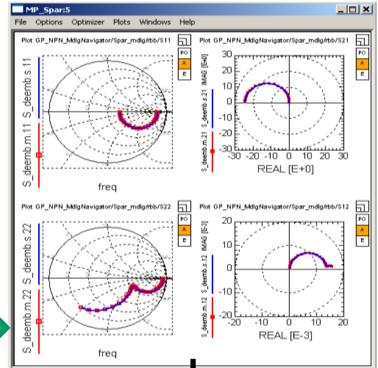
Conventional Transistor Modeling Flow

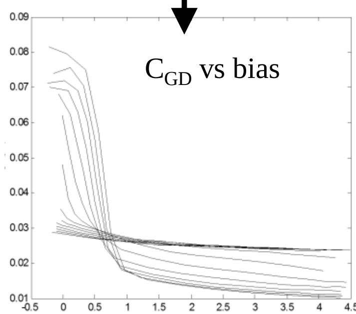
VNA

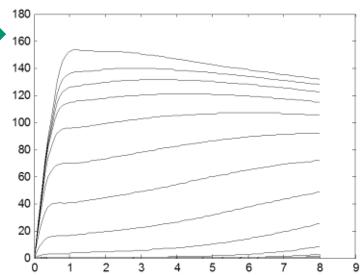
DC



Device Characterization







DC + S-parameter

Equation formulation
Physical or Empirical

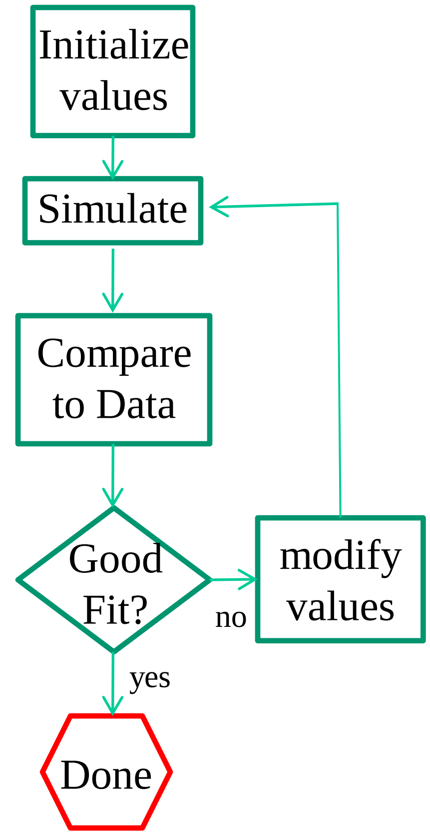
$$Q_G = -WL\sqrt{2q\varepsilon N_D}\left(\sqrt{(\phi - V_{GS})} + \sqrt{(\phi - V_{GD})}\right)$$

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

$$I_D = \frac{W\mu q N_D a}{\varepsilon L}\left(V_{DS} - \frac{2}{3}\left[\sqrt{\frac{2\varepsilon}{qN_D a^2}}\left((\phi - V_{GD})^{3/2} - (\phi - V_{GS})^{3/2}\right)\right]\right)$$

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

Parameter Extraction
Optimization



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!

Alternative: *Measurement-based models*

"The Device knows best!"

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

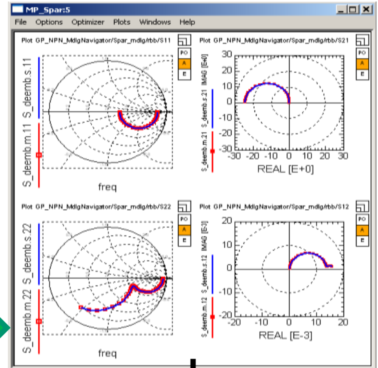
- Table-based models (e.g. HP/Agilent FET (Root) Model)
- Artificial Neural Network (ANN) models (e.g. NeuroFET)

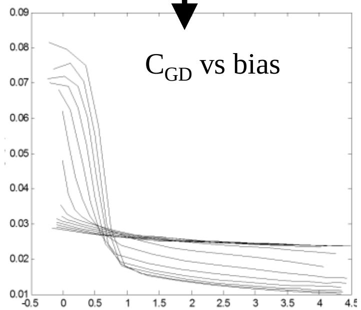
Models can be both general and accurate

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

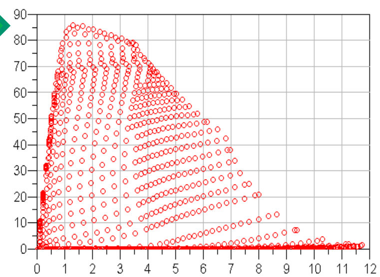
NeuroFET: Measurement-Based FET Modeling using ANNs

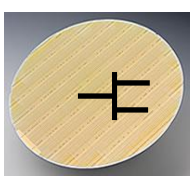
VNA





DC



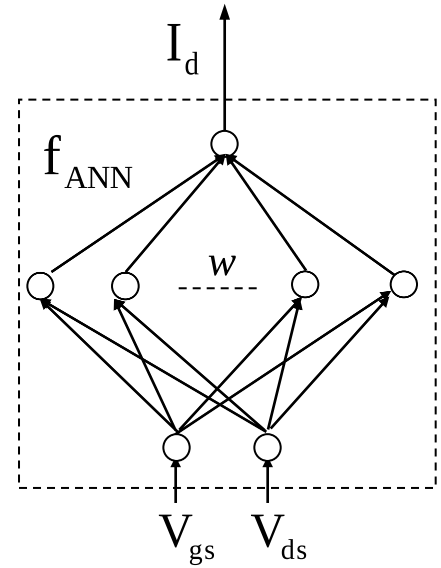


Device Characterization

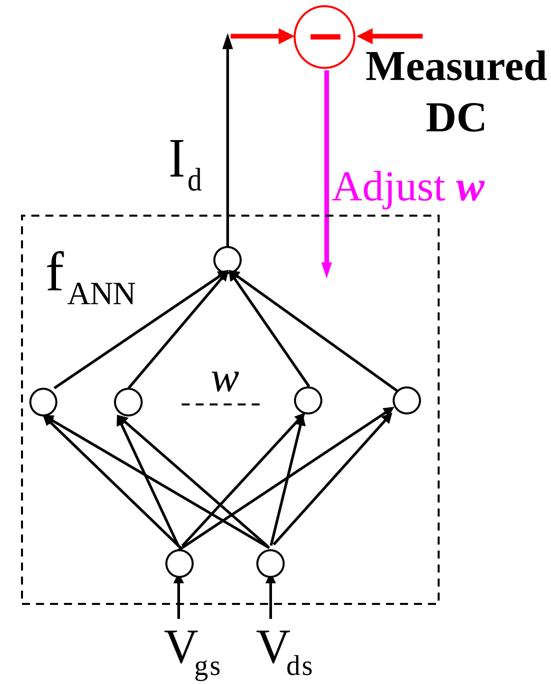
DC + S-parameter

Equation formulation using ANN

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



ANN Training



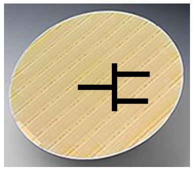
Advantages:

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

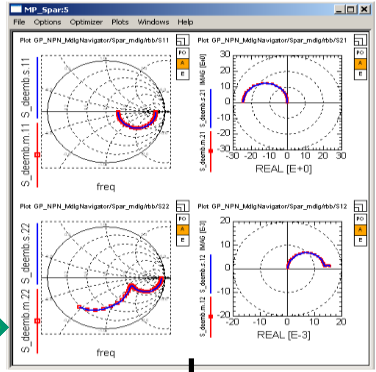
NeuroFET: Measurement-Based FET Modeling using ANNs

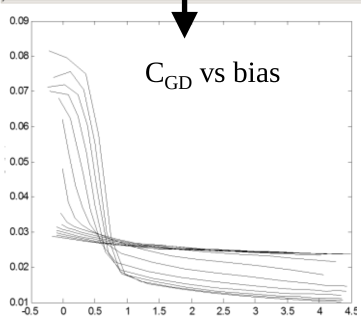
VNA

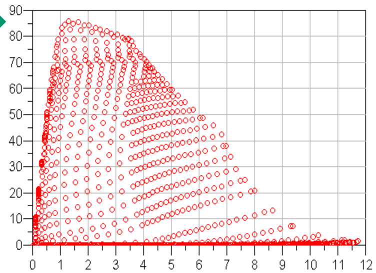
DC



Device Characterization



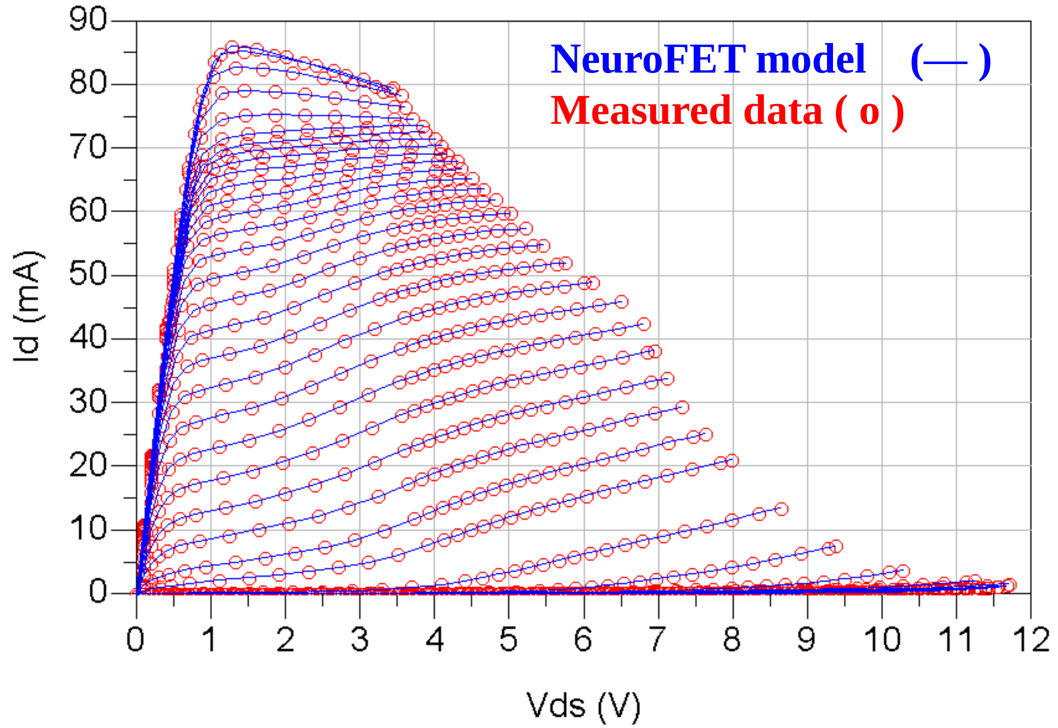




DC + S-parameter

Equation formulation using ANN

ANN Training



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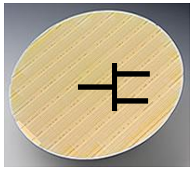
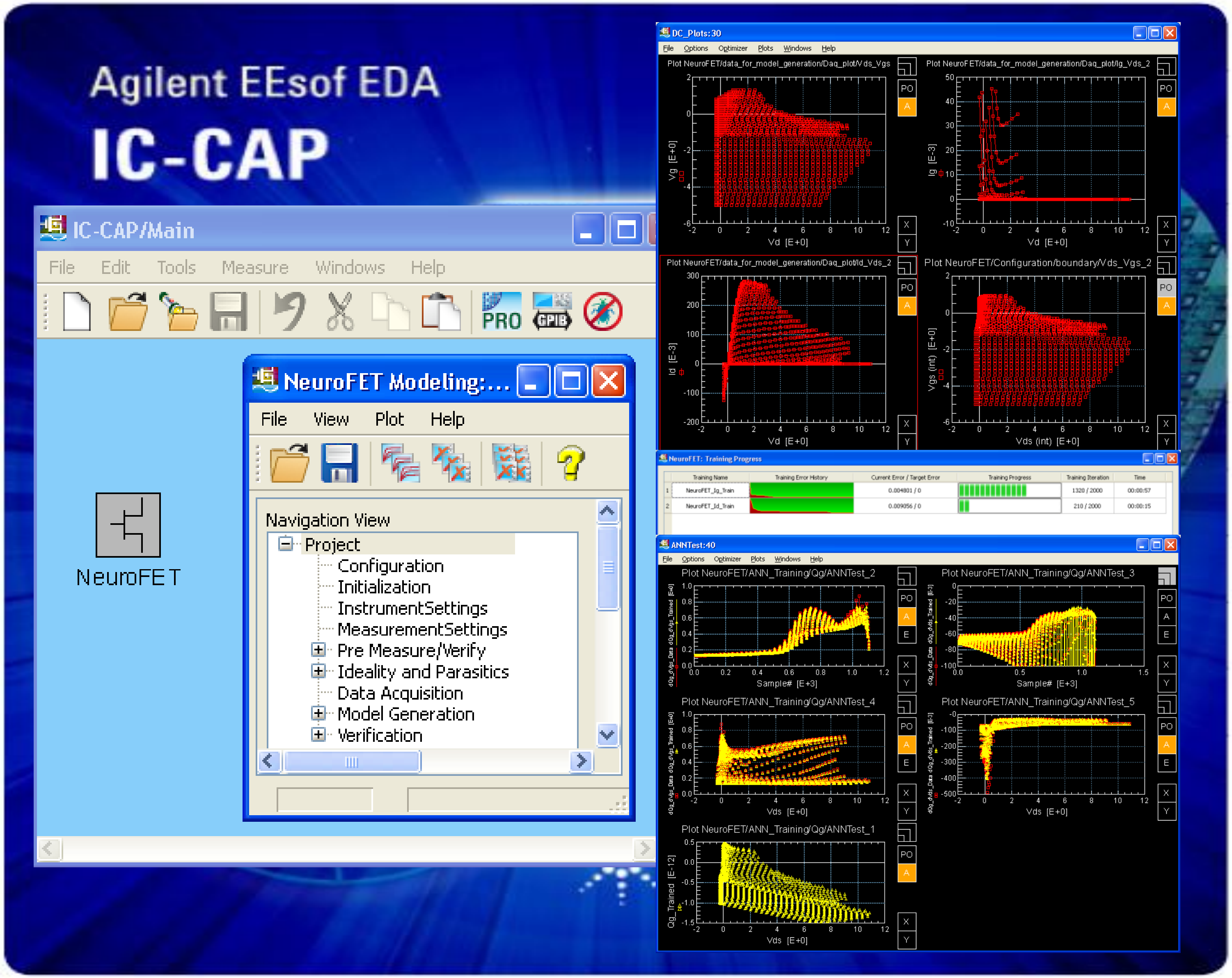
NeuroFET: Measurement-Based FET Modeling using ANNs

VNA

DC



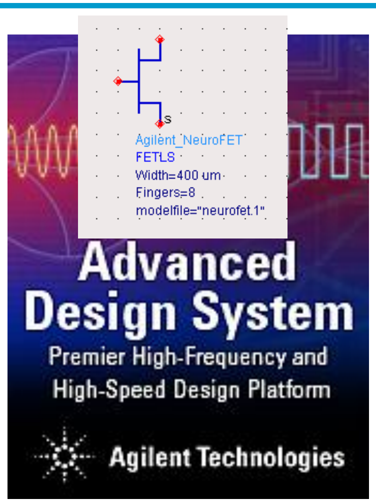
Device Characterization

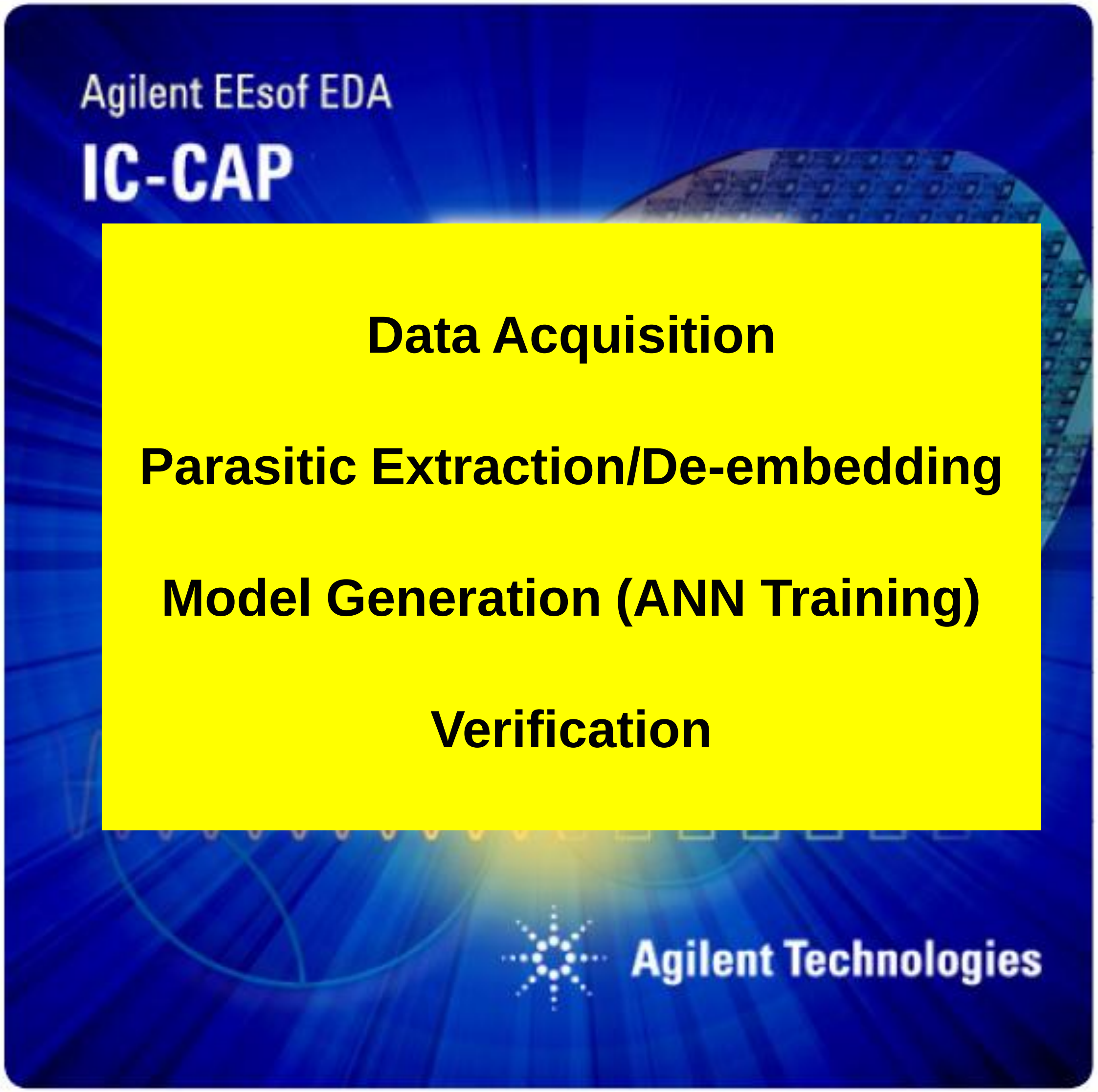


IC-CAP: NeuroFET Modeling Flow

VNA

DC





Data Acquisition

Parasitic Extraction/De-embedding

Model Generation (ANN Training)

Verification

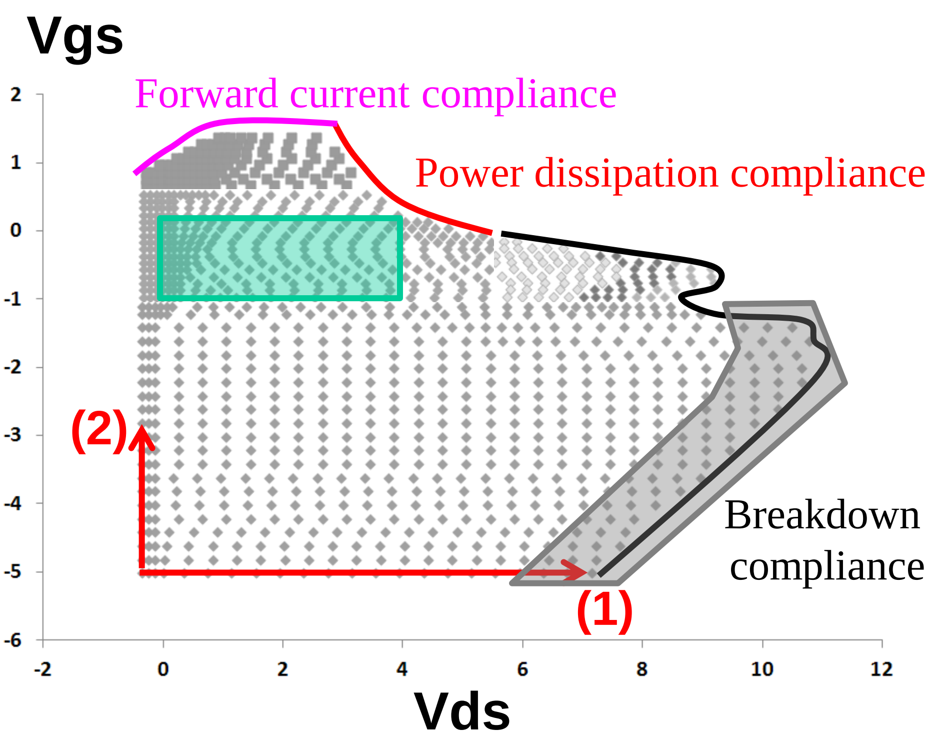
NeuroFET: Data Acquisition

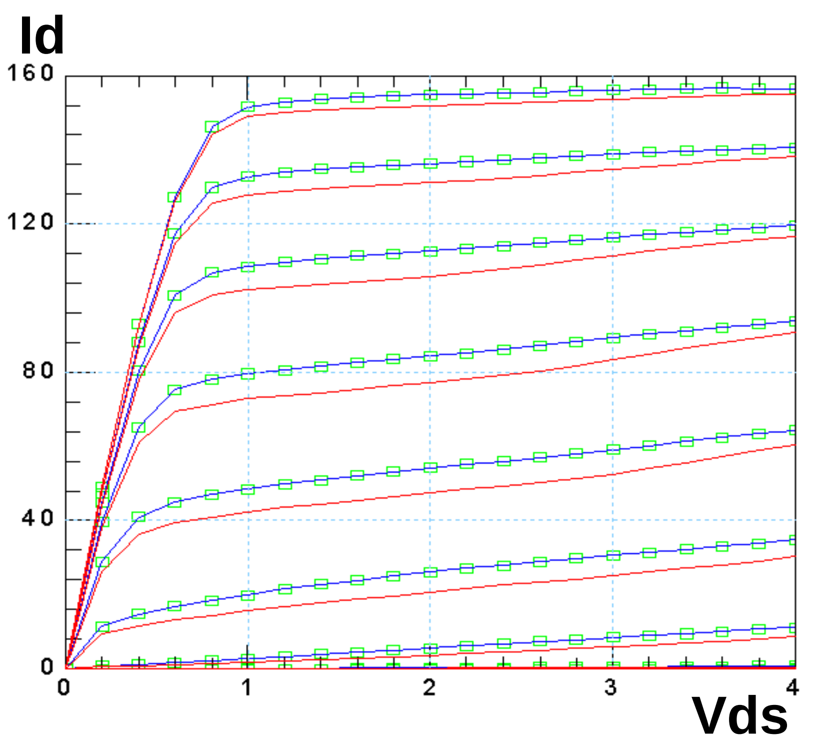
Why is a good Data Acquisition Routine important?

For measurement-based model,

(1) it is important to get data everywhere.

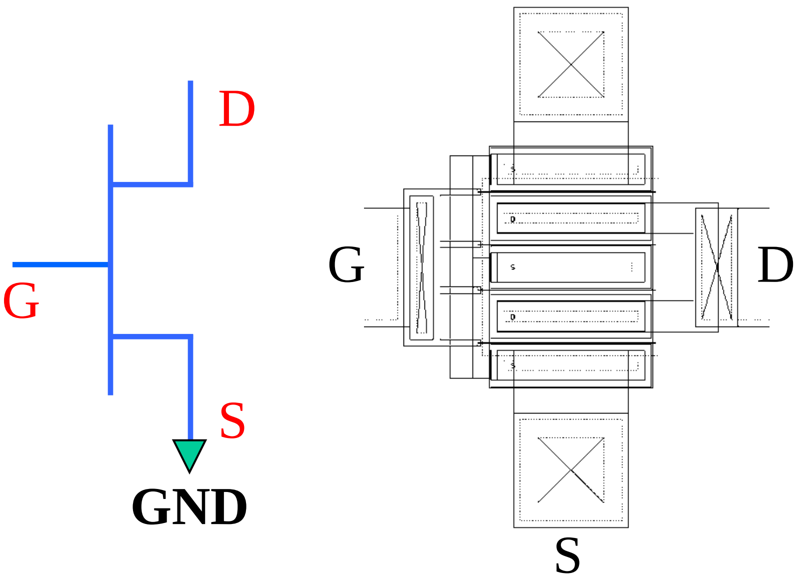
(2) the acquisition routine should be intelligent and flexible to preserve the device for integrity.



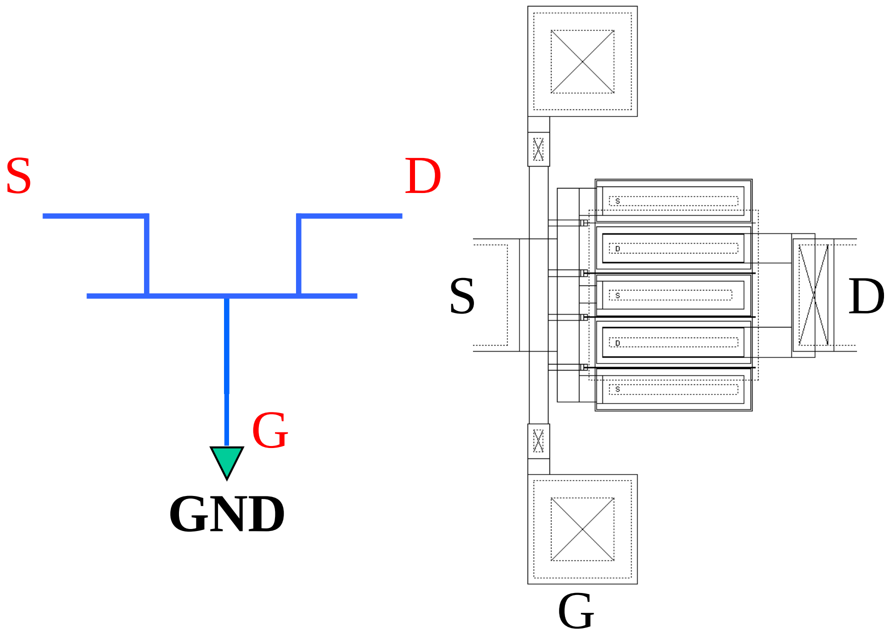


NeuroFET: Data Acquisition

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

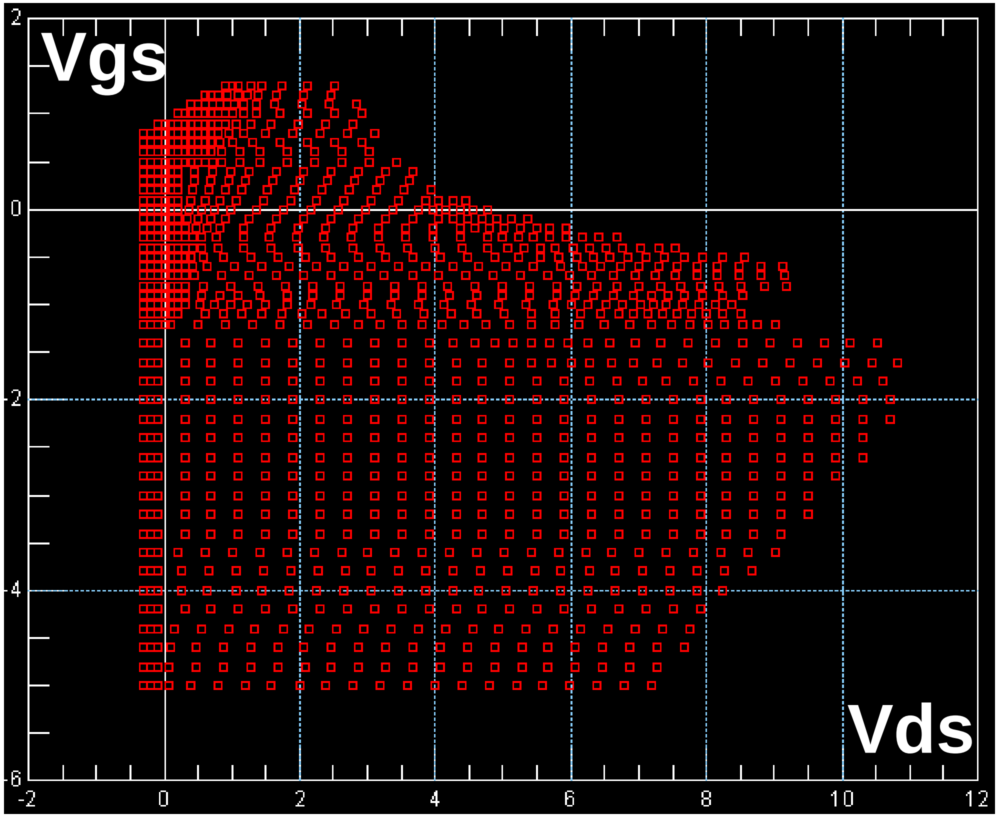


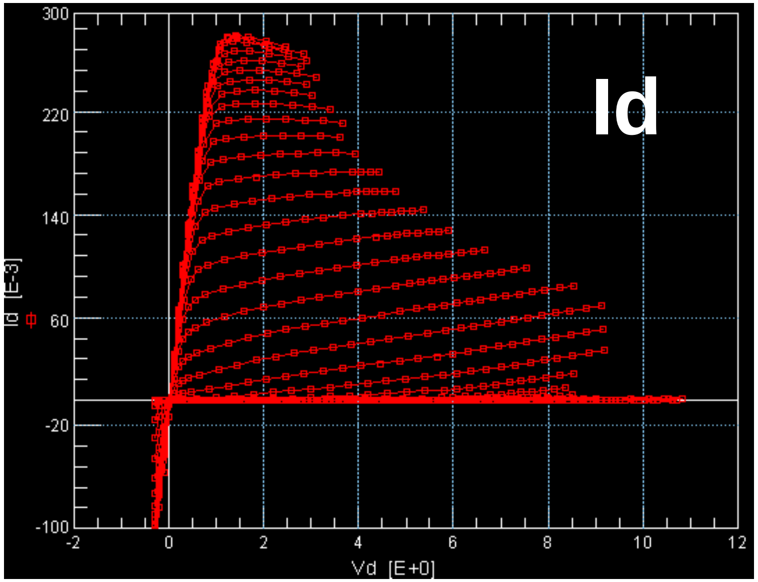
Common-Source FET
(for Amplifier Application)

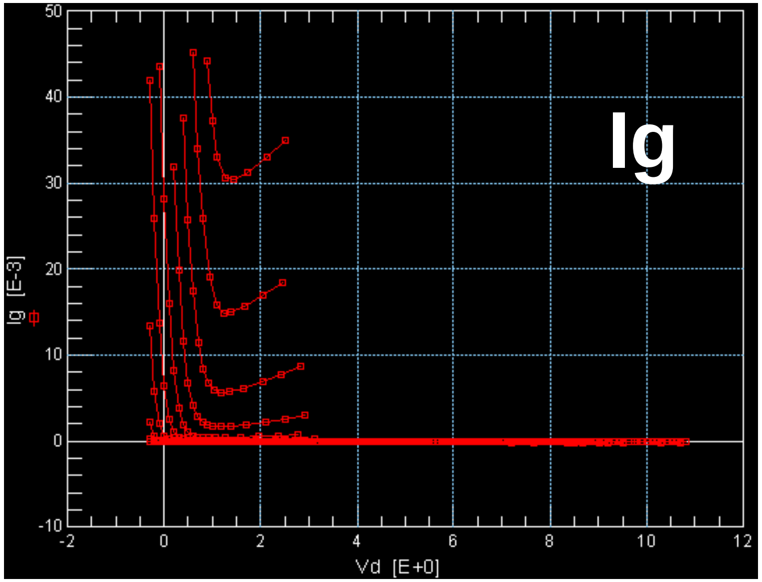


Common-Gate FET
(for Mixer/Switch Applications)

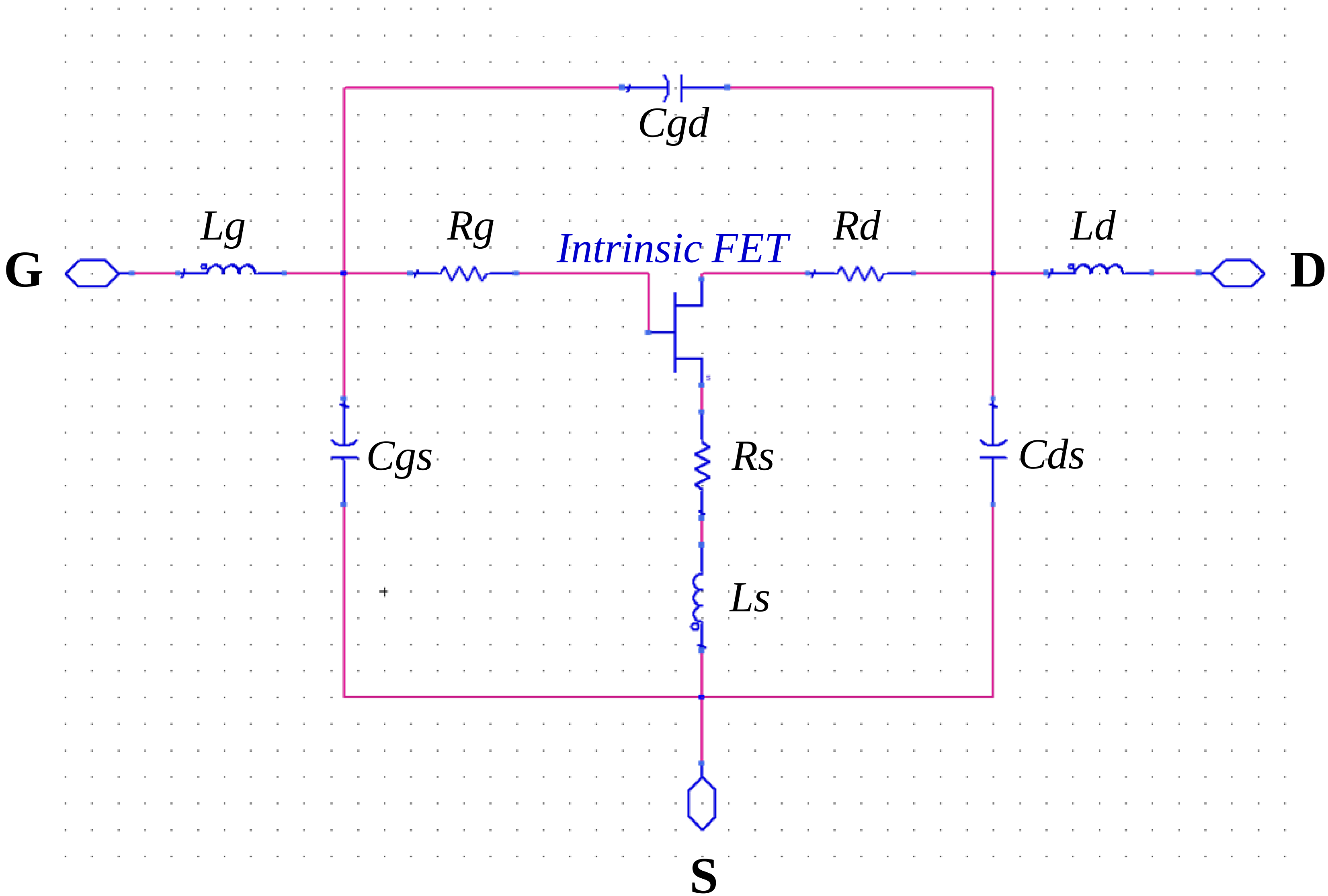
NeuroFET: Data Acquisition



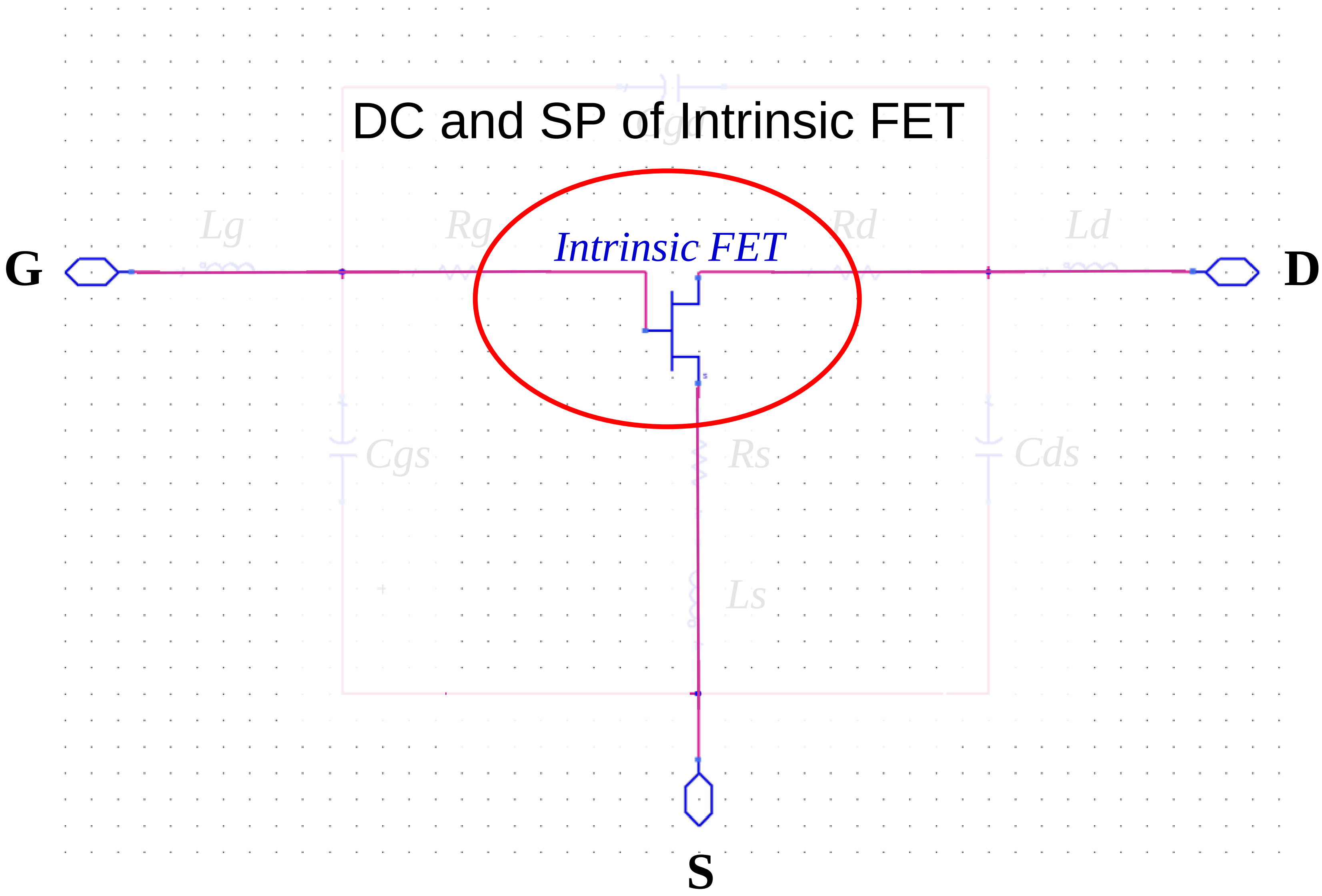




NeuroFET Model

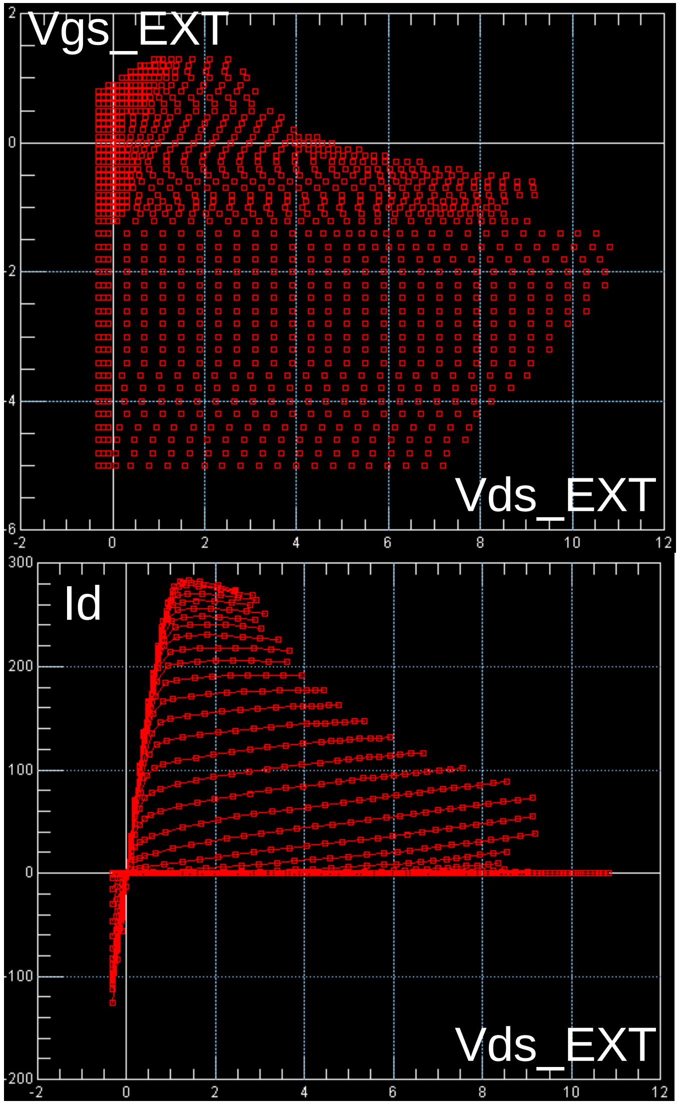


NeuroFET: Parasitic Extraction & De-embedding

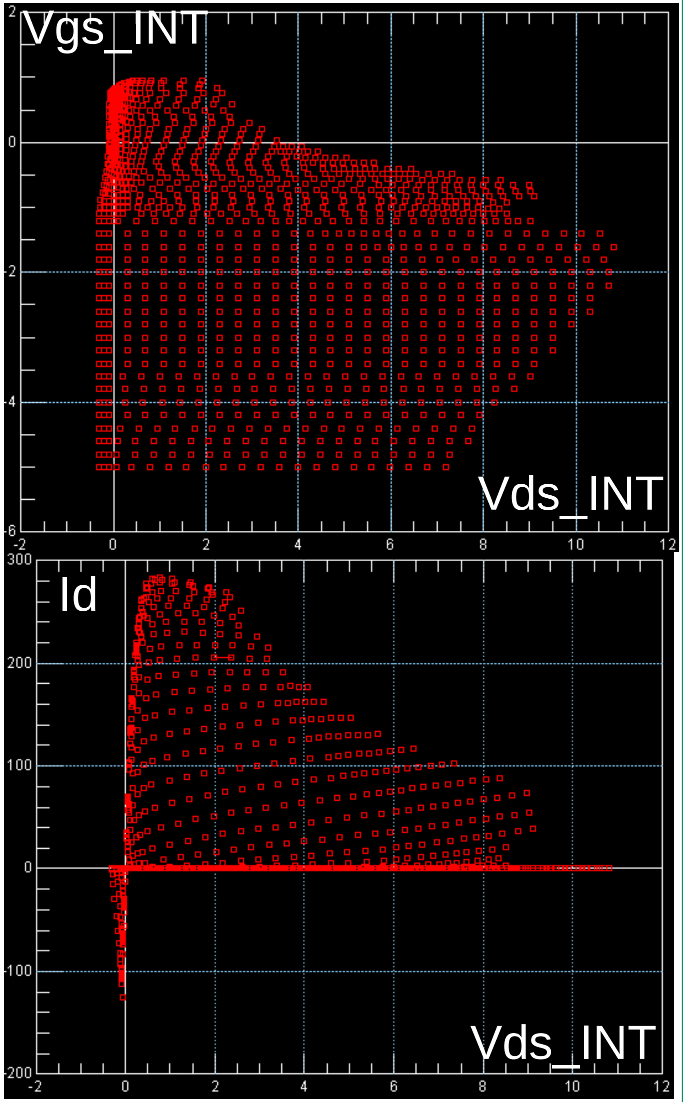


Before and After De-embedding

Extrinsic

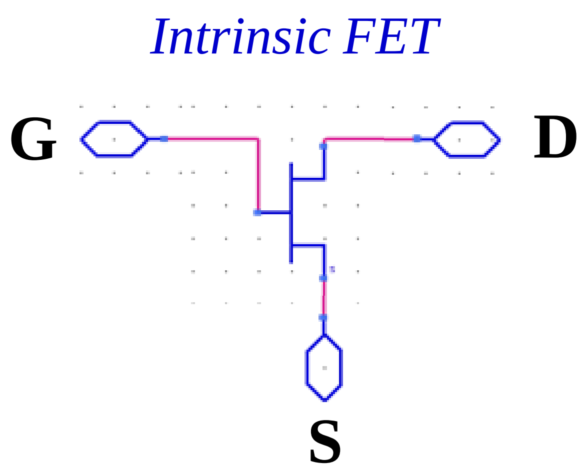


Intrinsic



Agilent Technologies

NeuroFET: Intrinsic Model



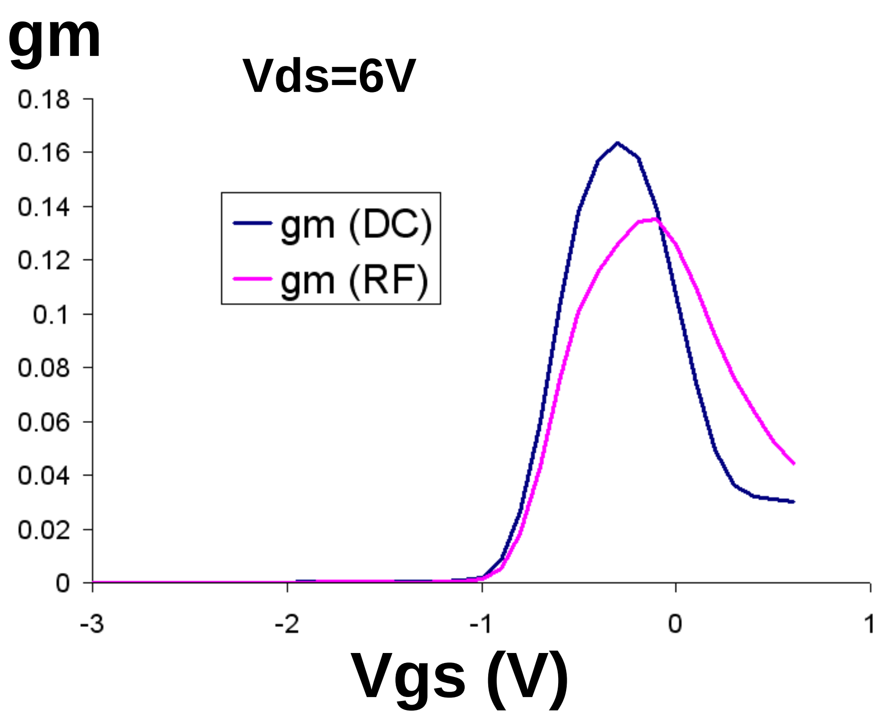
NeuroFET (Intrinsic) is a non-quasi-static model that accounts for

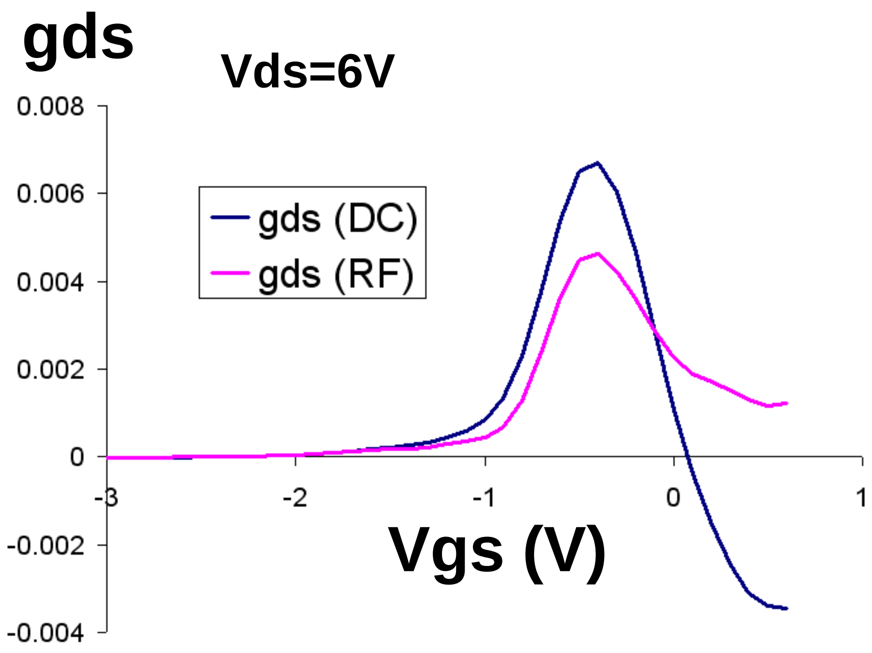
(1) Static I-V characteristics

(2) Terminal charges

(3) Frequency dispersion

Frequency dispersion of small-signal characteristics

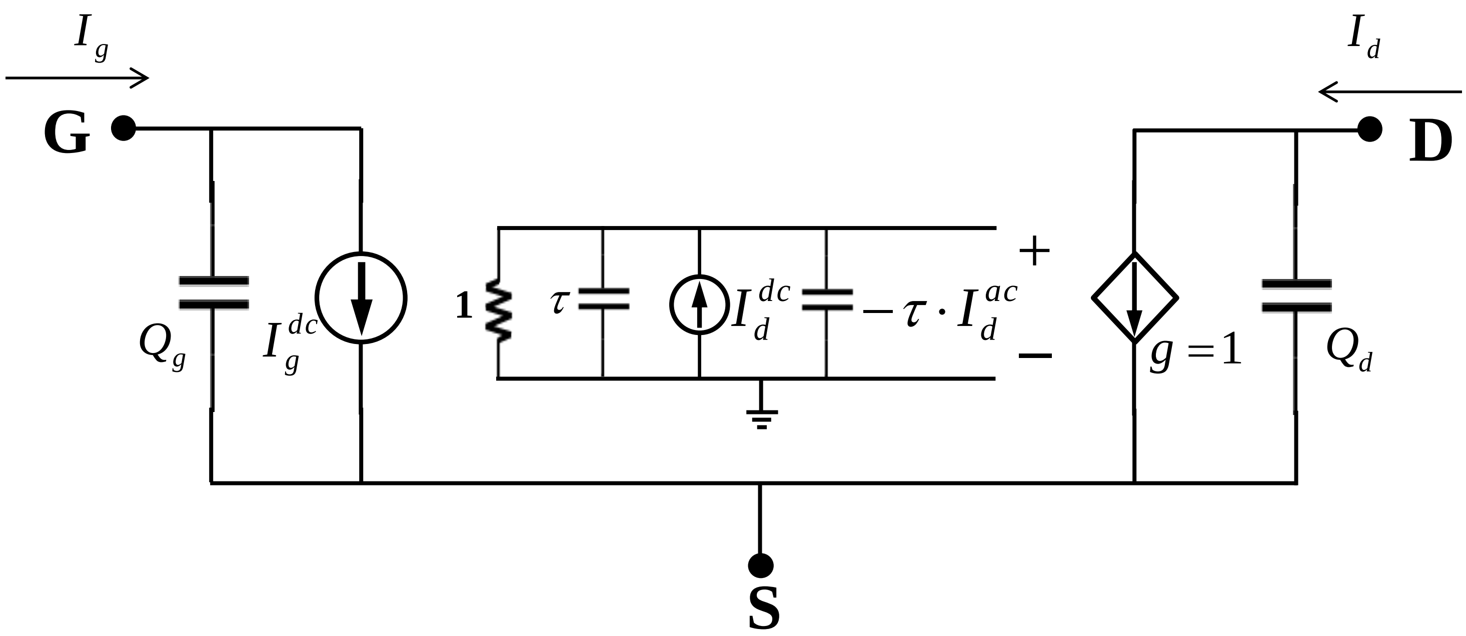




NeuroFET: Intrinsic Model Formulation

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

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



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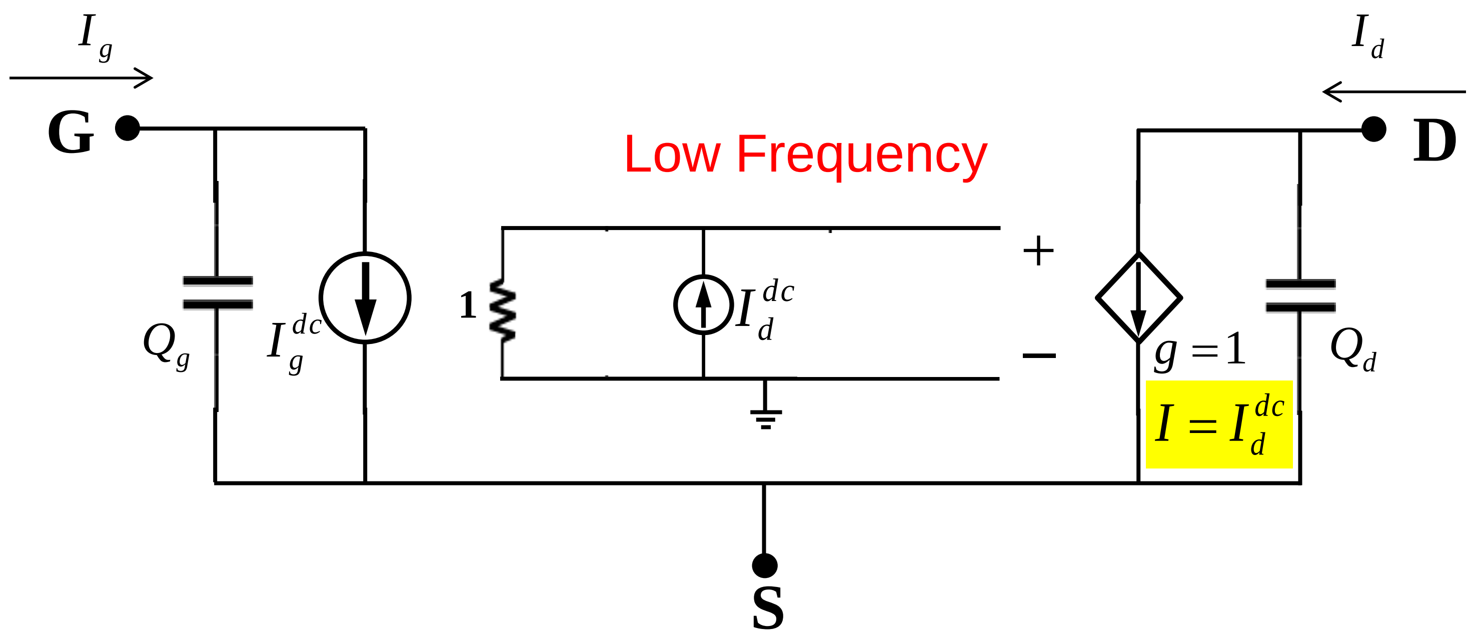

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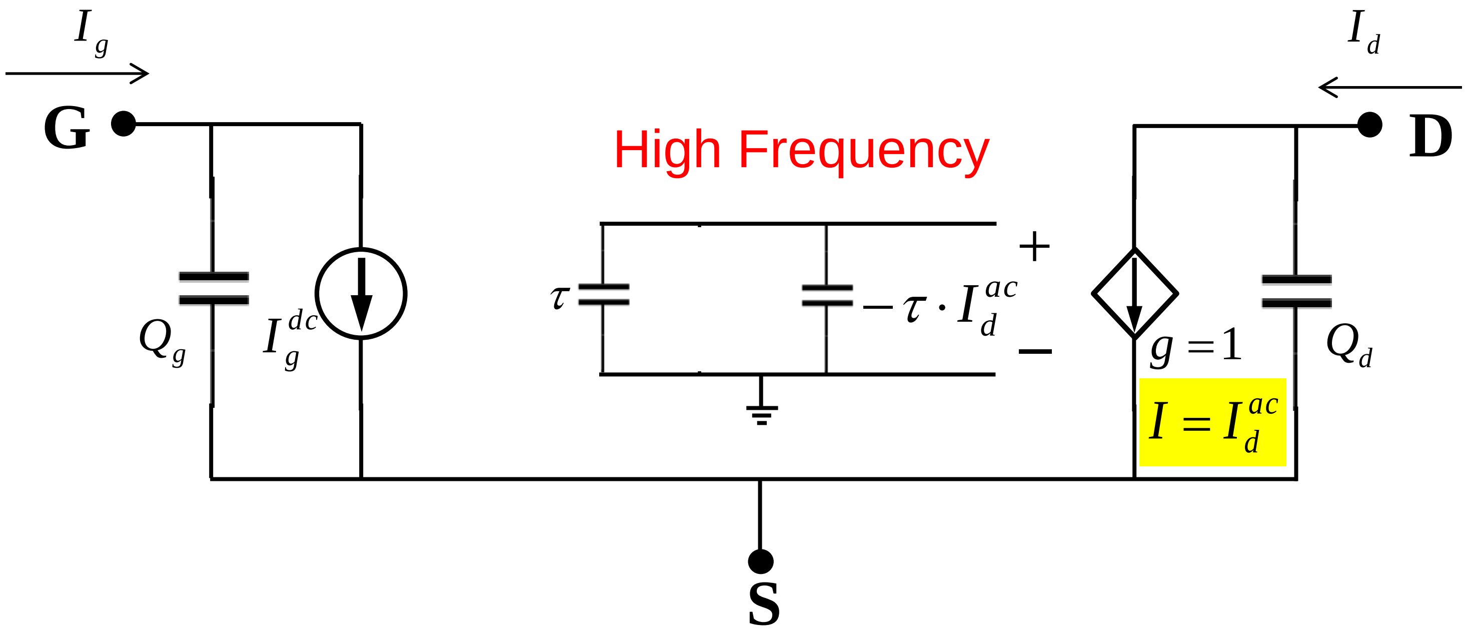
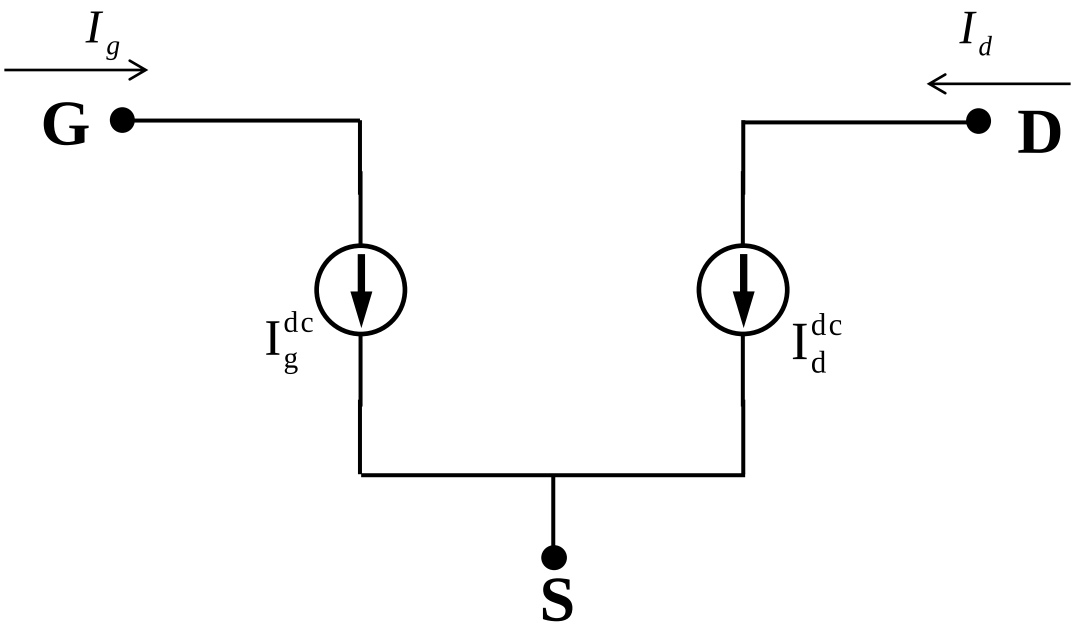


NeuroFET: Intrinsic Model
- DC

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

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

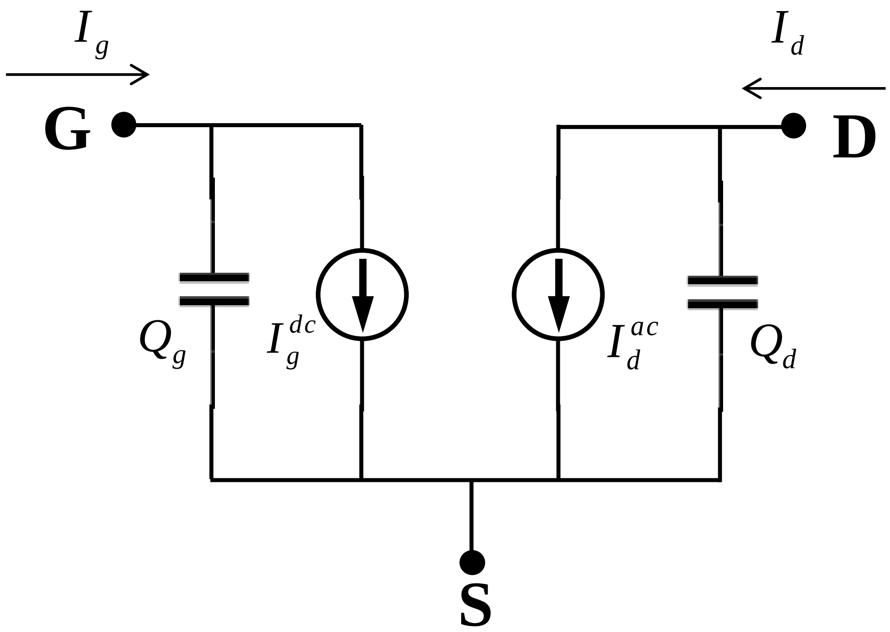


NeuroFET: Intrinsic Model

- RF

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

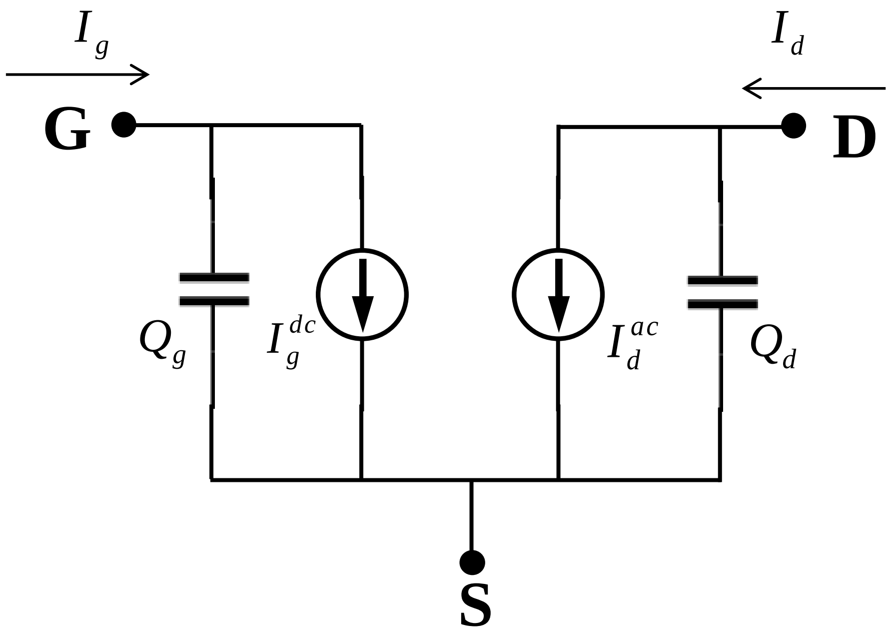
$$I_d(t) = I_d^{ac}(V_{gs}(t), V_{ds}(t)) + \frac{dQ_d(V_{gs}(t), V_{ds}(t))}{dt}$$



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)

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

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

$$\Downarrow$$

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

$$\frac{\partial Q_d}{\partial V_{gs}} = \frac{Imag(Y_{21})}{\omega} \qquad \frac{\partial Q_d}{\partial V_{ds}} = \frac{Imag(Y_{22})}{\omega} \qquad V_{gs},\ V_{ds}$$

$$\Downarrow$$

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

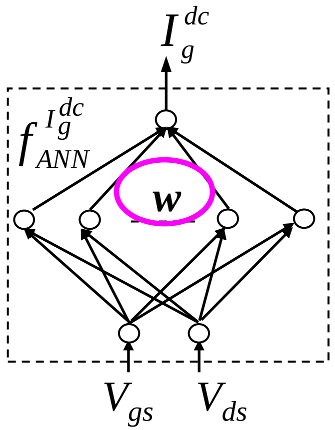
$$\frac{\partial I_d^{ac}}{\partial V_{gs}} = Real(Y_{21}) \qquad \frac{\partial I_d^{ac}}{\partial V_{ds}} = Real(Y_{22}) \qquad V_{gs},\ V_{ds}$$

$$\Downarrow$$

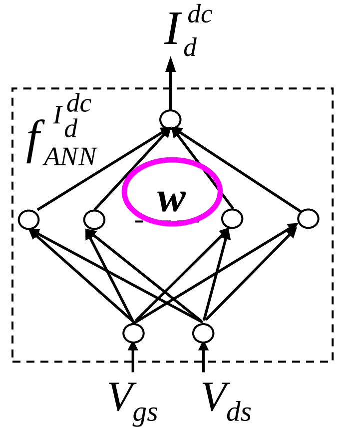
$$I_d^{ac}(V_{gs}, V_{ds})$$

Constitutive Relations are Modeled by ANNs

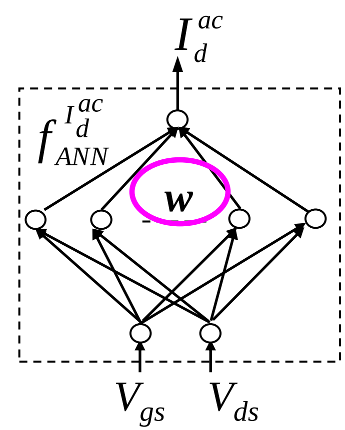
$$I_g^{dc} = f_{ANN}^{I_g^{dc}}(V_{gs}, V_{ds}, \mathbf{w})$$



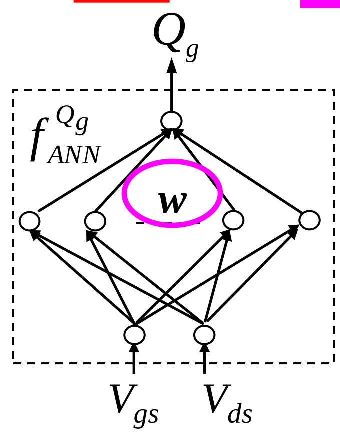
$$I_d^{dc} = f_{ANN}^{I_d^{dc}}(V_{gs}, V_{ds}, \mathbf{w})$$



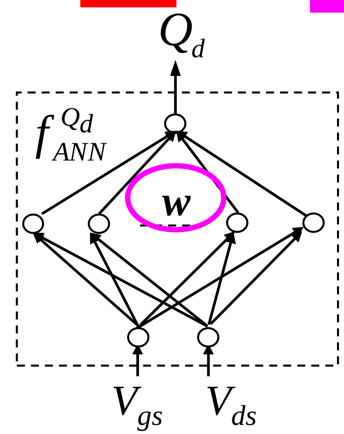
$$I_d^{ac} = f_{ANN}^{I_d^{ac}}(V_{gs}, V_{ds}, \mathbf{w})$$



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

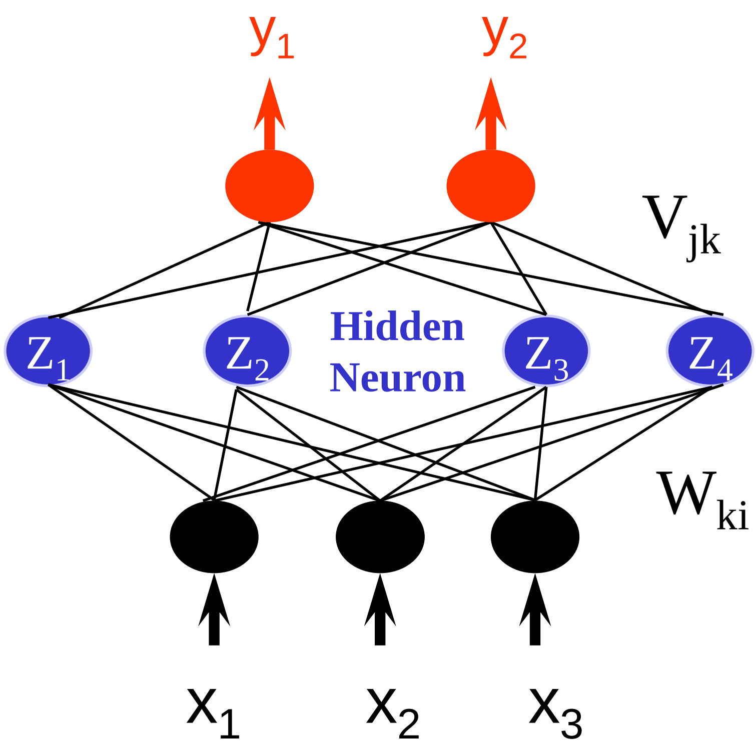


$$Q_d = f_{ANN}^{Q_d}(V_{gs}, V_{ds}, \mathbf{w})$$



Artificial Neural Networks (ANNs)

$y_1 = f_1(x_1, x_2, x_3)$ $y_2 = f_2(x_1, x_2, x_3)$



Outputs

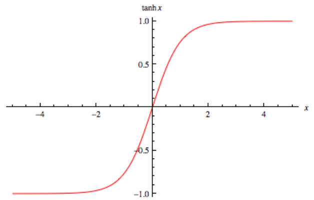
↑

$$y_j = \sum_k V_{jk} Z_k$$

↑

Hidden Neuron Output

$$Z_k = \tanh\left(\sum W_{ki} x_i\right)$$



↑

Parameters $w = [W_{ki}, V_{jk}]$

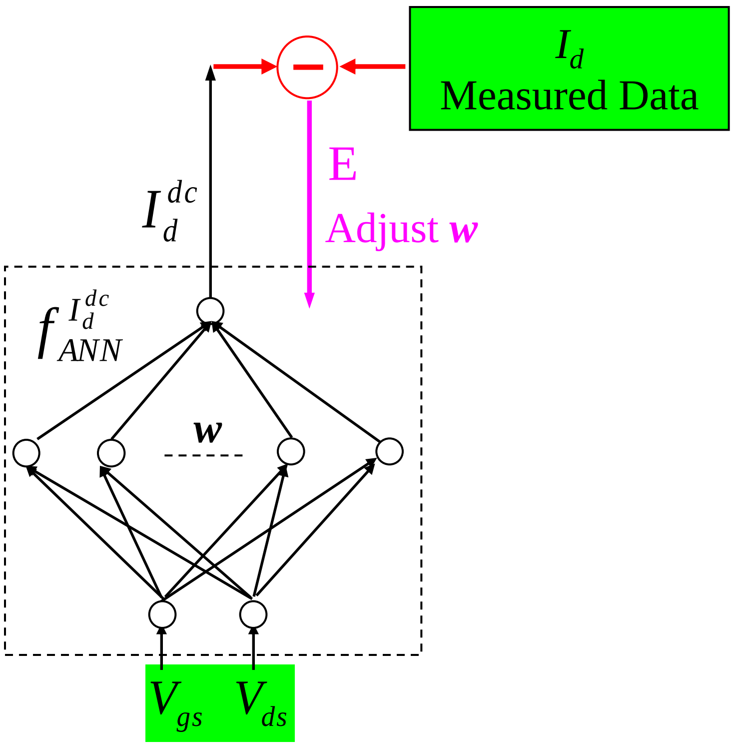
Inputs

- 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

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



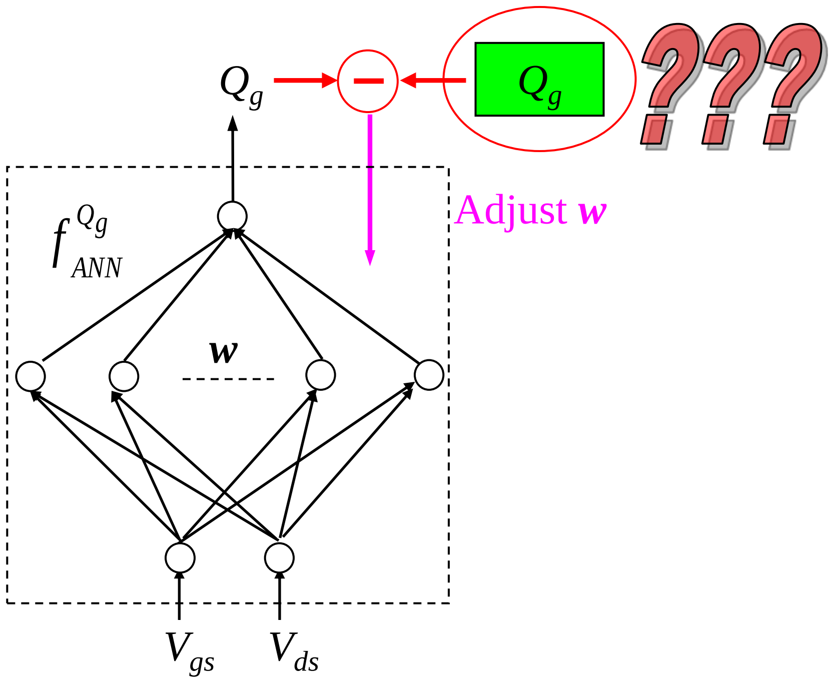
Model Training (Q_g)
- Adjoint Neural Network Training

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

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

$$V_{gs},\ V_{ds}$$

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



Model Training (Q_g)
- Adjoint Neural Network Training

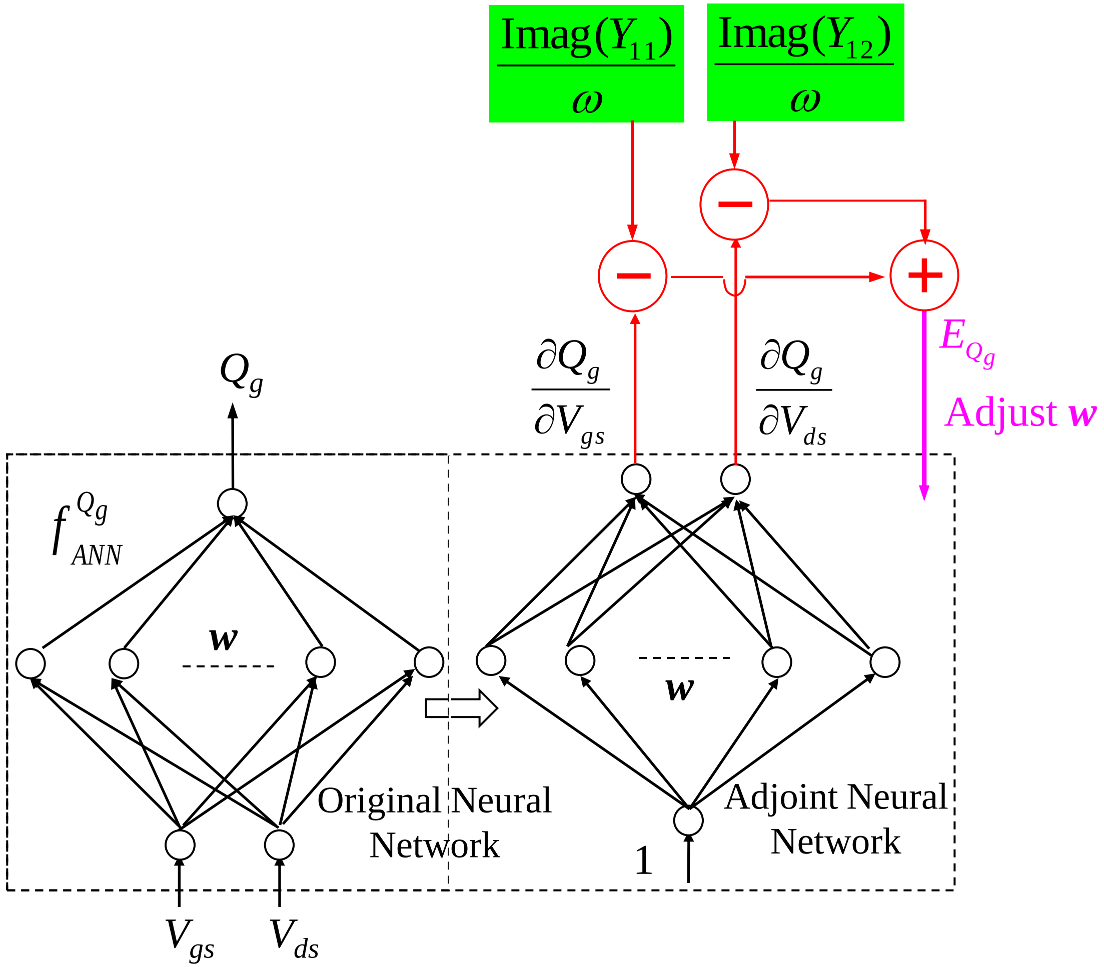
$$\frac{\partial Q_g}{\partial V_{gs}} = \frac{Imag(Y_{11})}{\omega}$$

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

$$V_{gs},\ V_{ds}$$

⇓

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



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.

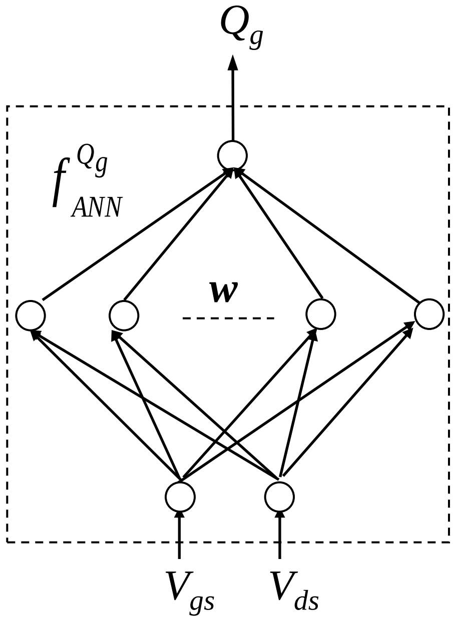
Model Training (Q_g)
- Adjoint Neural Network Training

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

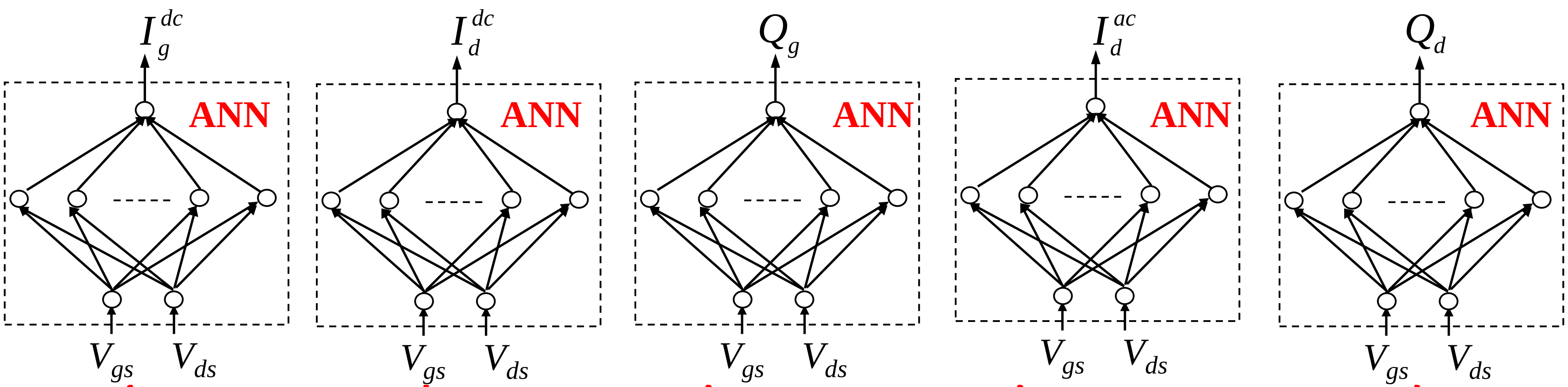
$$\frac{\partial Q_g}{\partial V_{ds}} = \frac{Imag(Y_{12})}{\omega}$$

$$V_{gs},\ V_{ds}$$

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



NeuroFET: Intrinsic Model

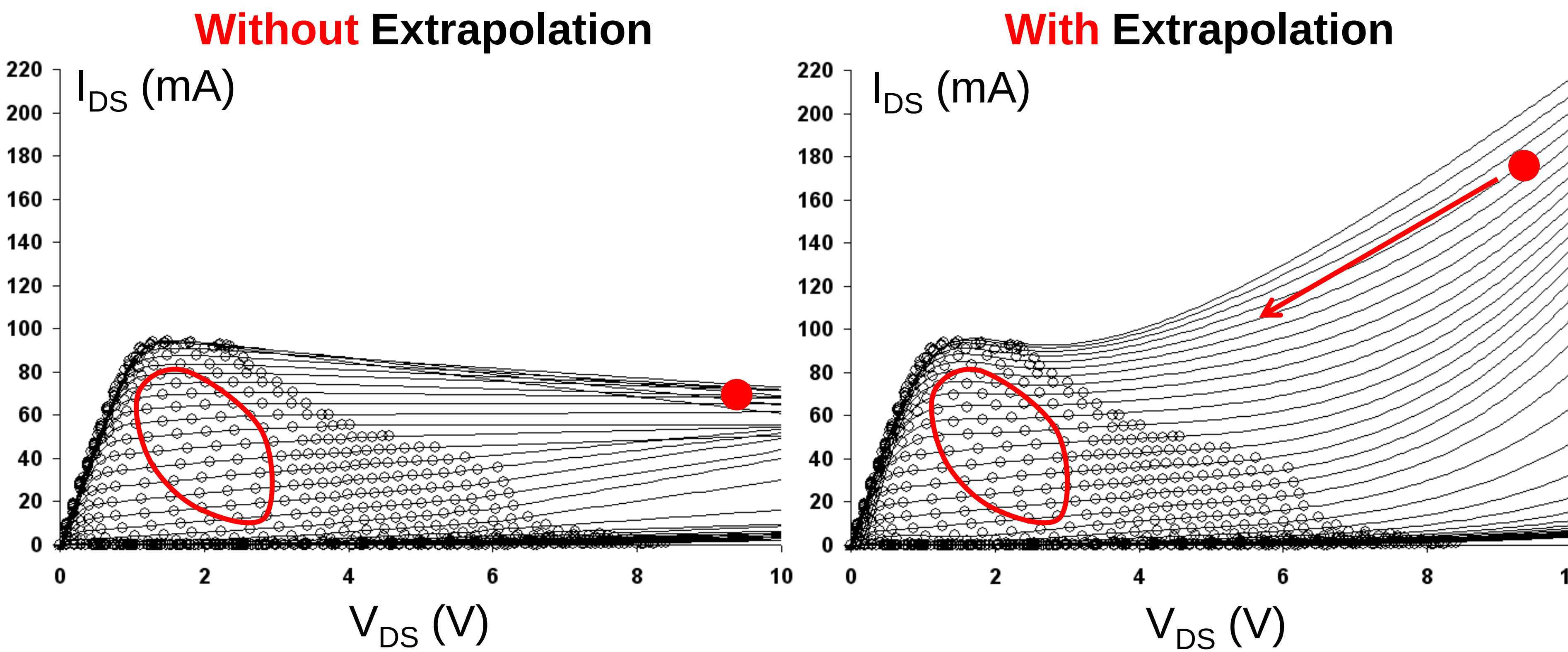


$$I_g(t) = I_g^{dc}(V_{gs}(t), V_{ds}(t)) + \frac{dQ_g(V_{gs}(t), V_{ds}(t))}{dt}$$

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

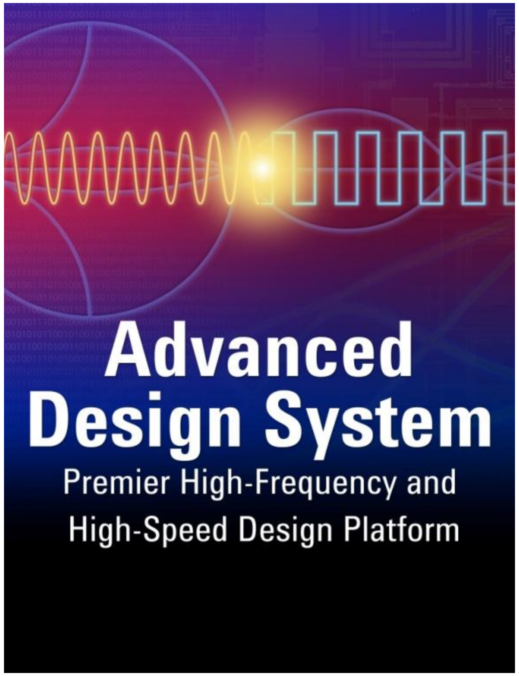
Advanced Model Extrapolation Routine

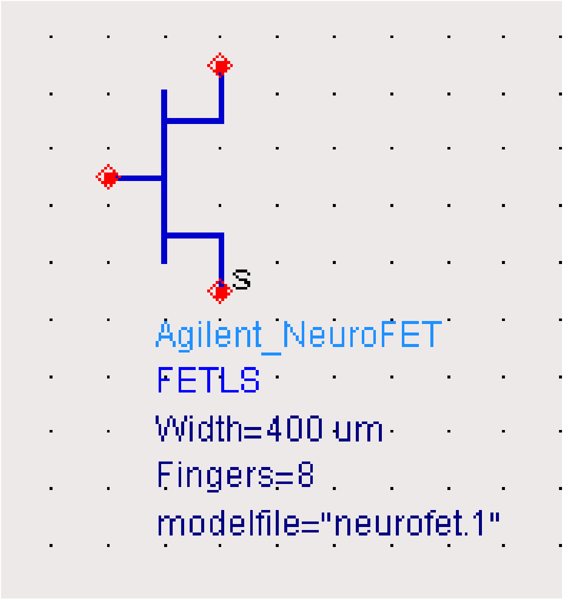
- for robust convergence



○ Measured Data (training data)

NeuroFET Model is compiled into ADS





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

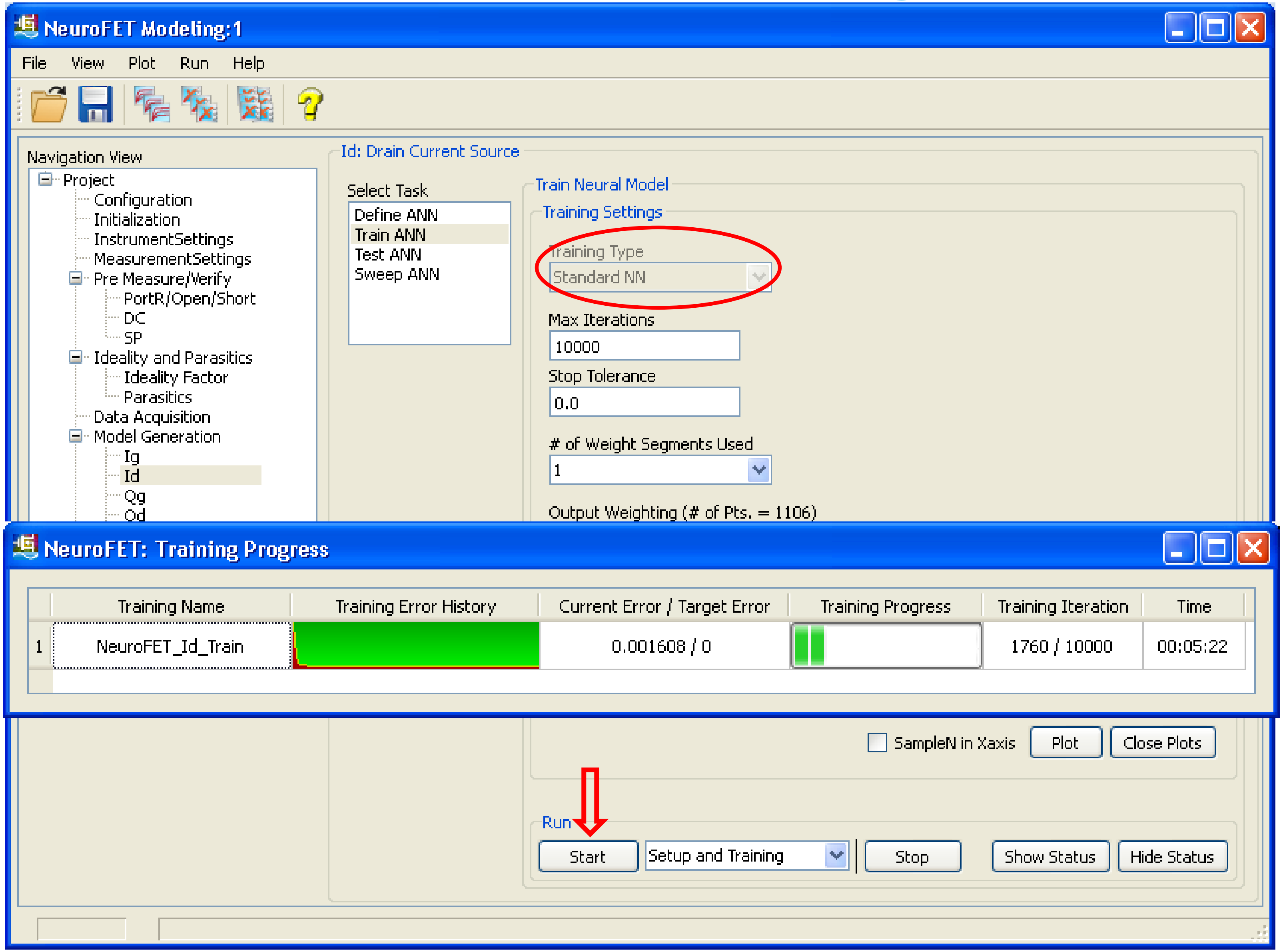
- **Same use model as any other transistor model.**
- **Model has simple scaling rules with gate width and number of fingers.**

Example 1

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

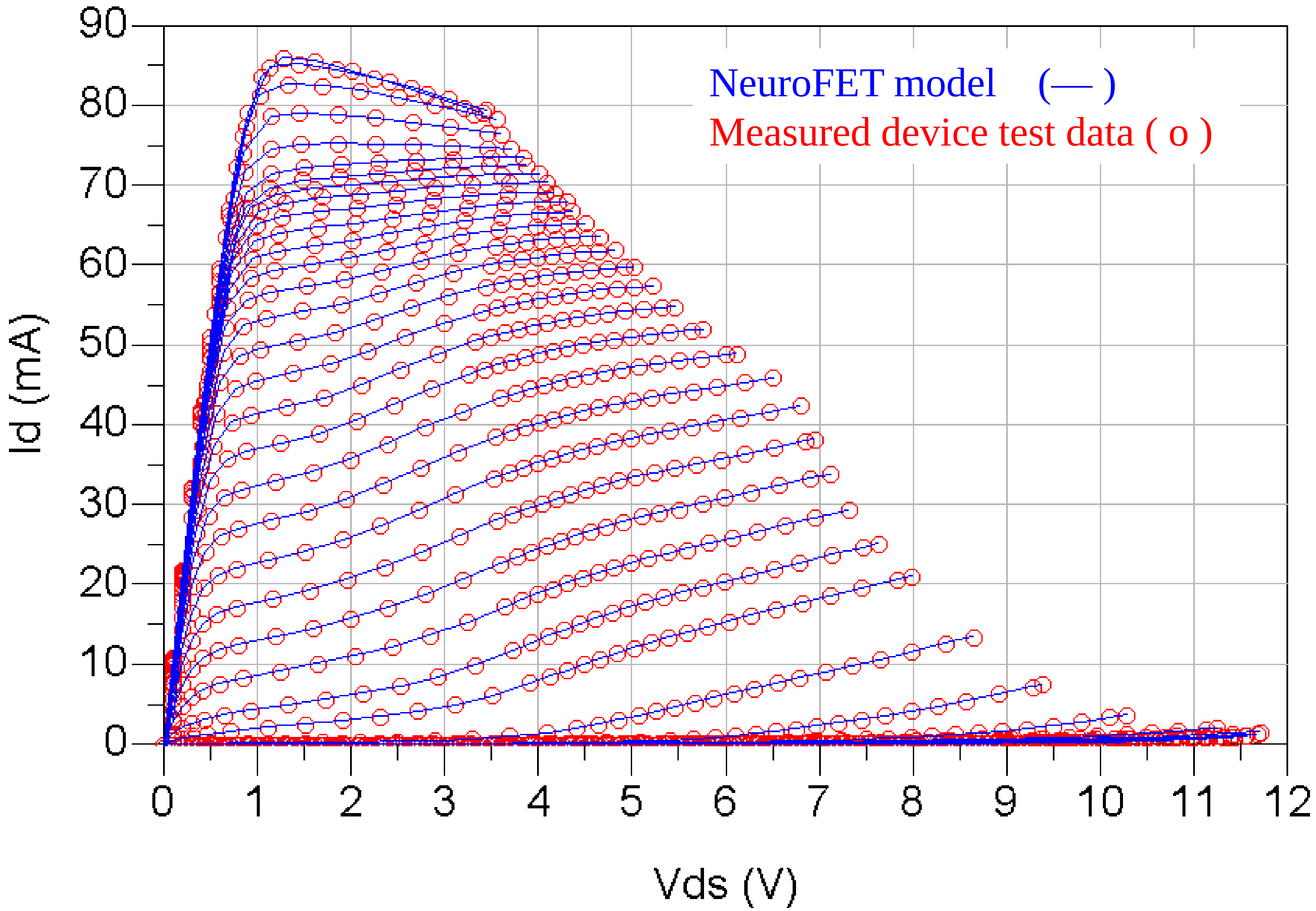
- DC IV
- $Q_{g,}$ $Q_{d,}$ and I_d^{ac}
- S-parameters versus bias and frequency
- One-tone Harmonic Distortion
- Two-tone Intermodulation

NeuroFET: Training I_d^{dc}

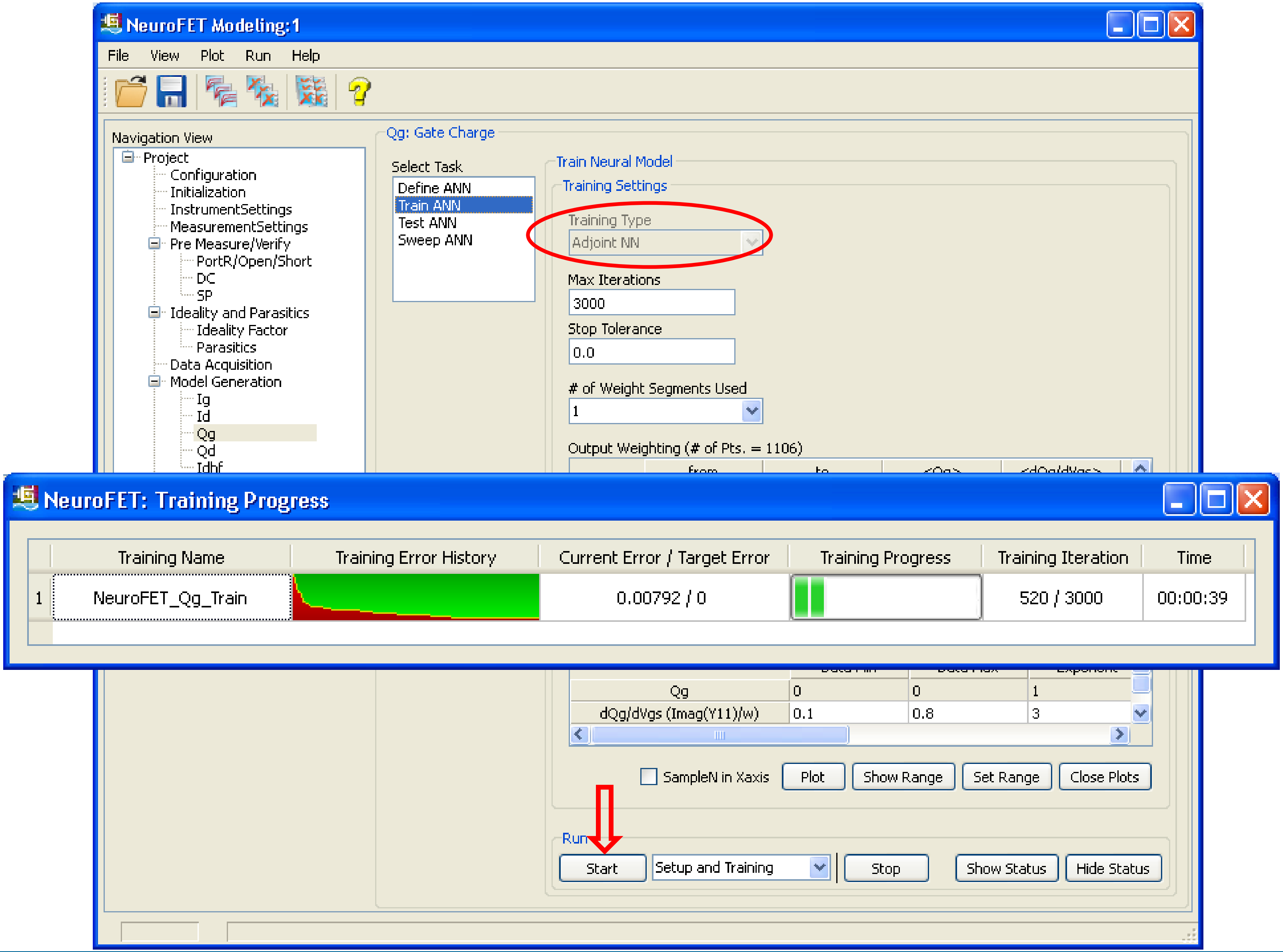


Model Validations

- DC



NeuroFET: Training Q_g



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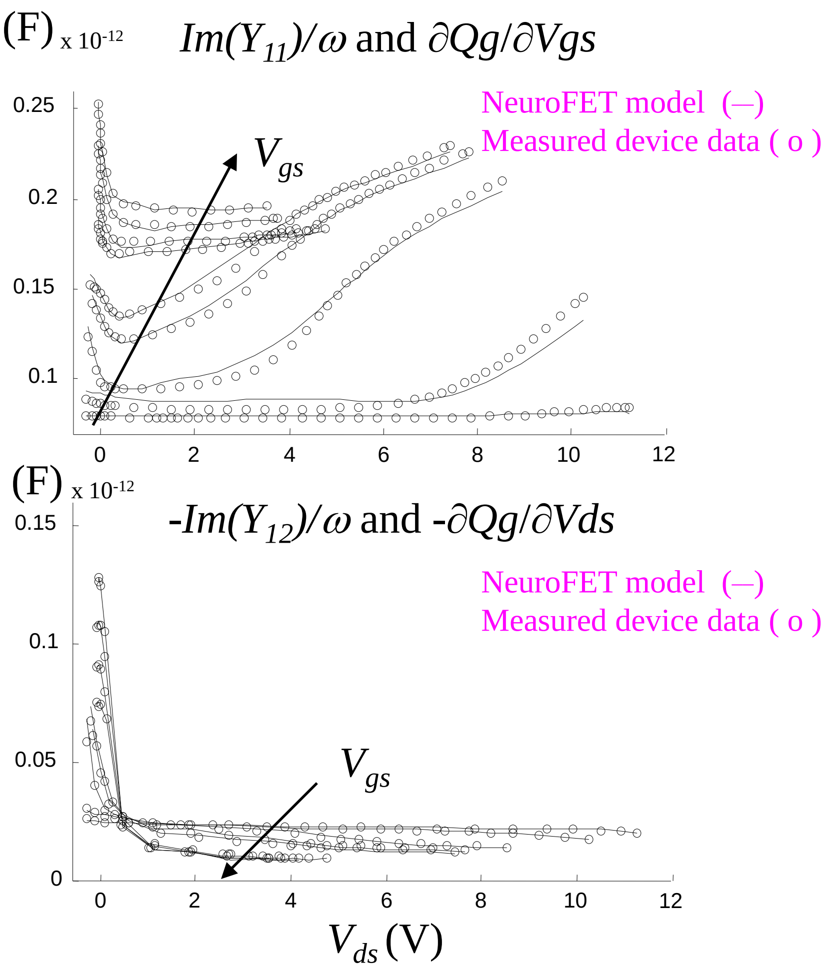
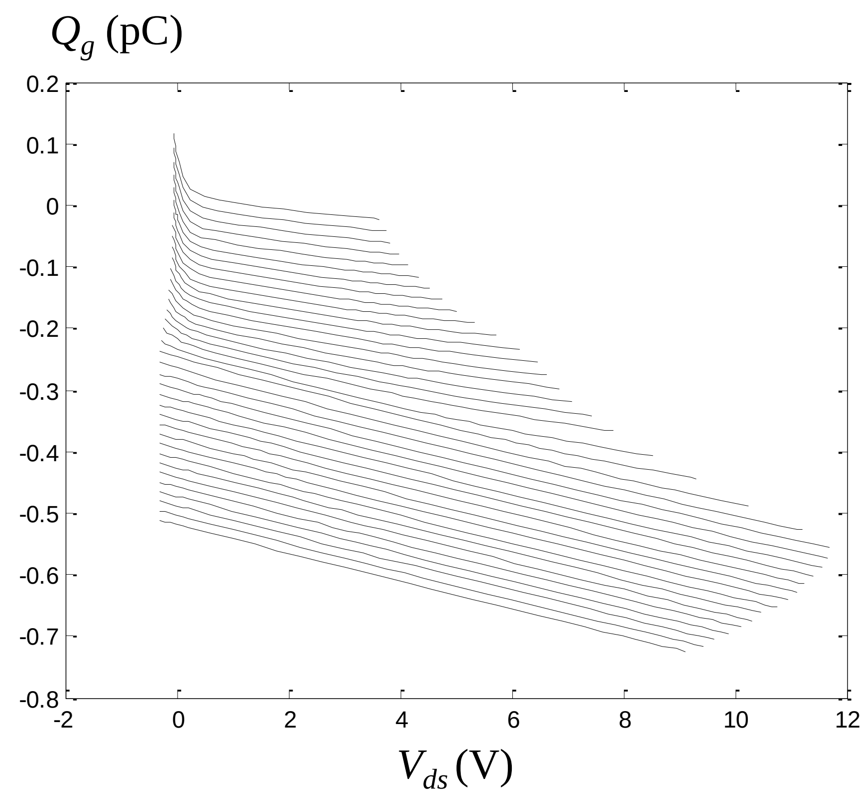
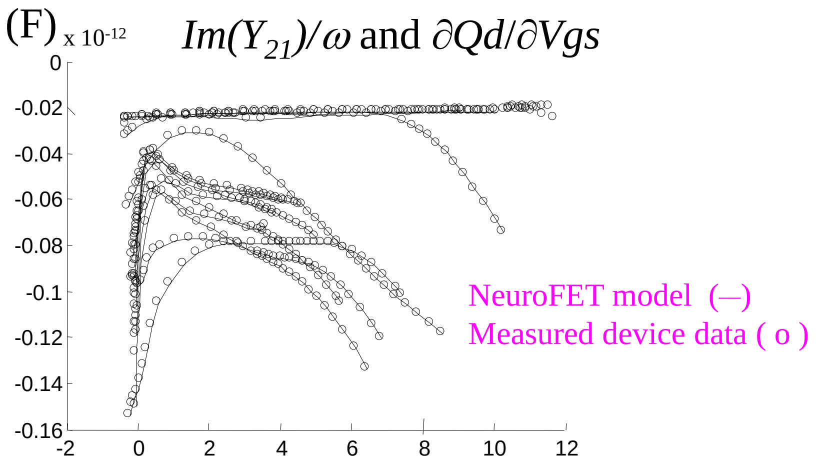
Model Validations
-Charge Q_g

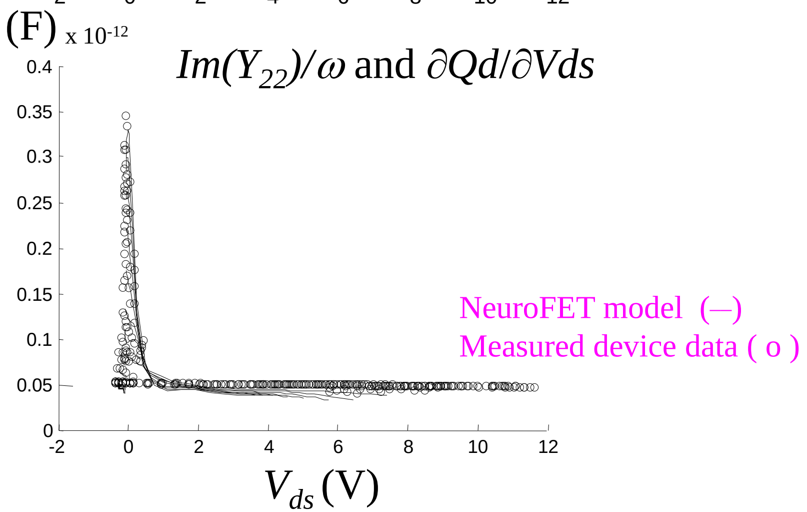


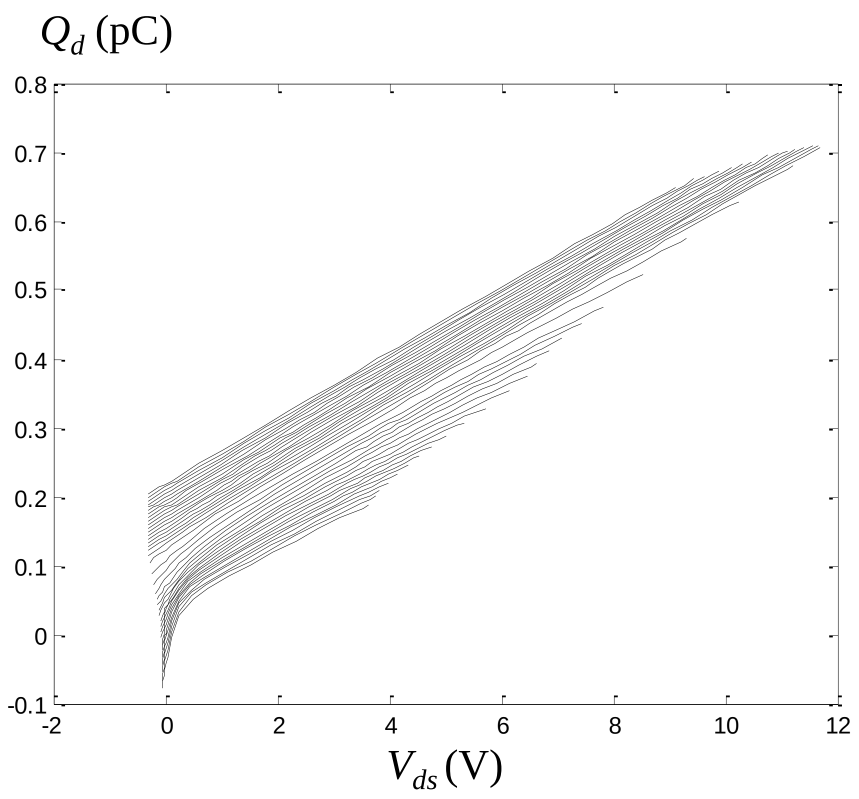


Agilent Technologies

Model Validations
-Charge Q_d



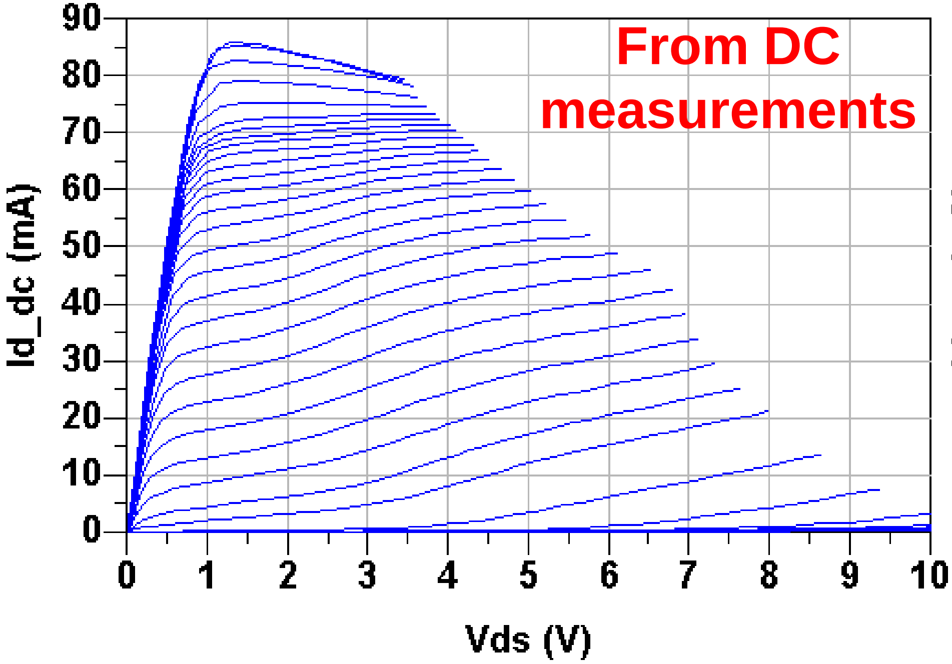




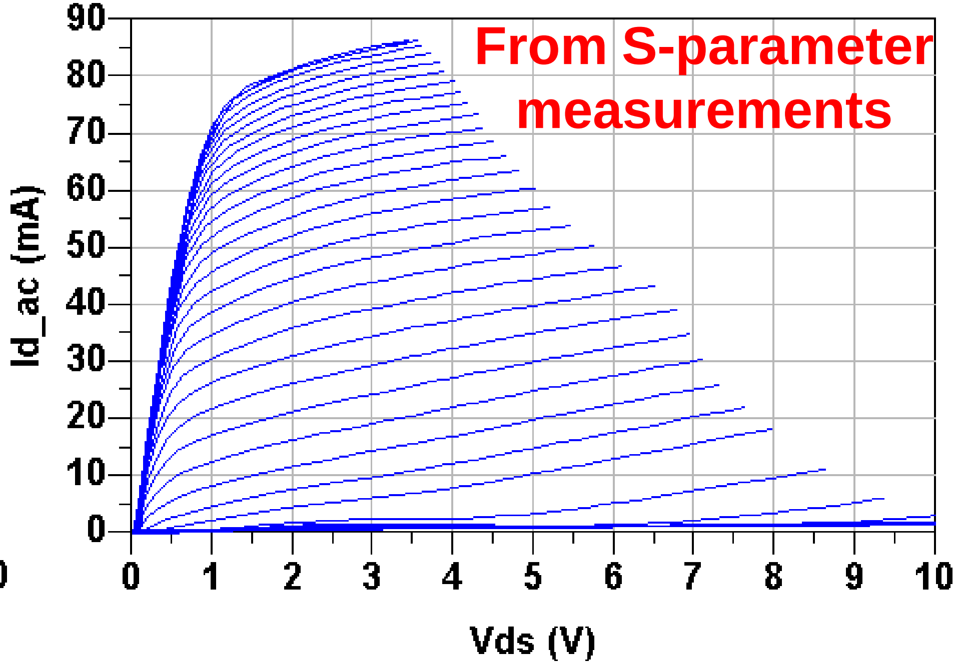
Model Validations

- I_d^{ac}

I_d^{dc}

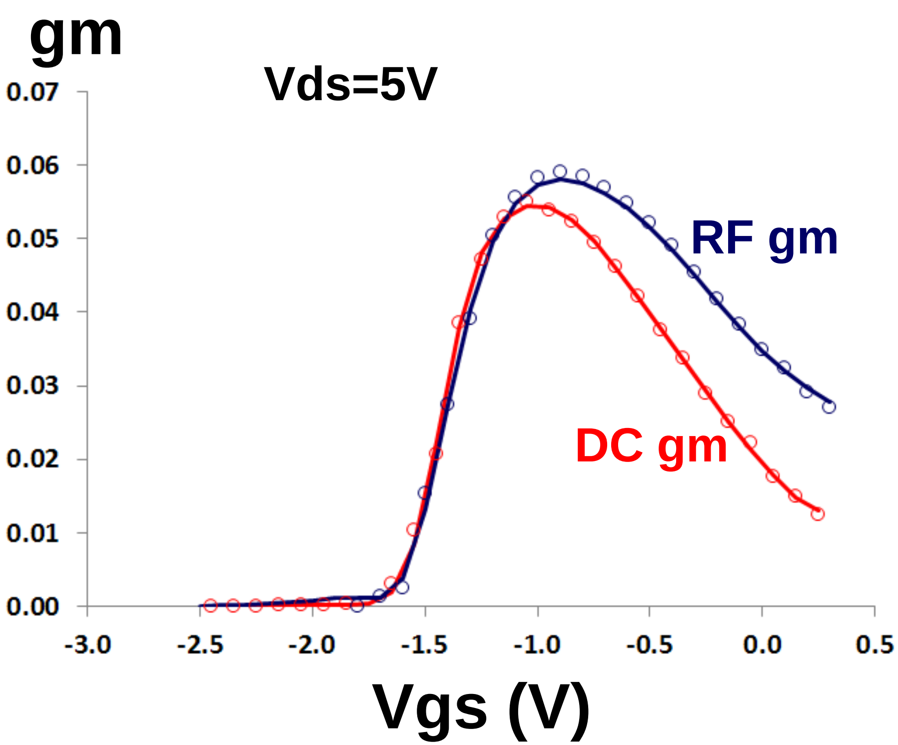


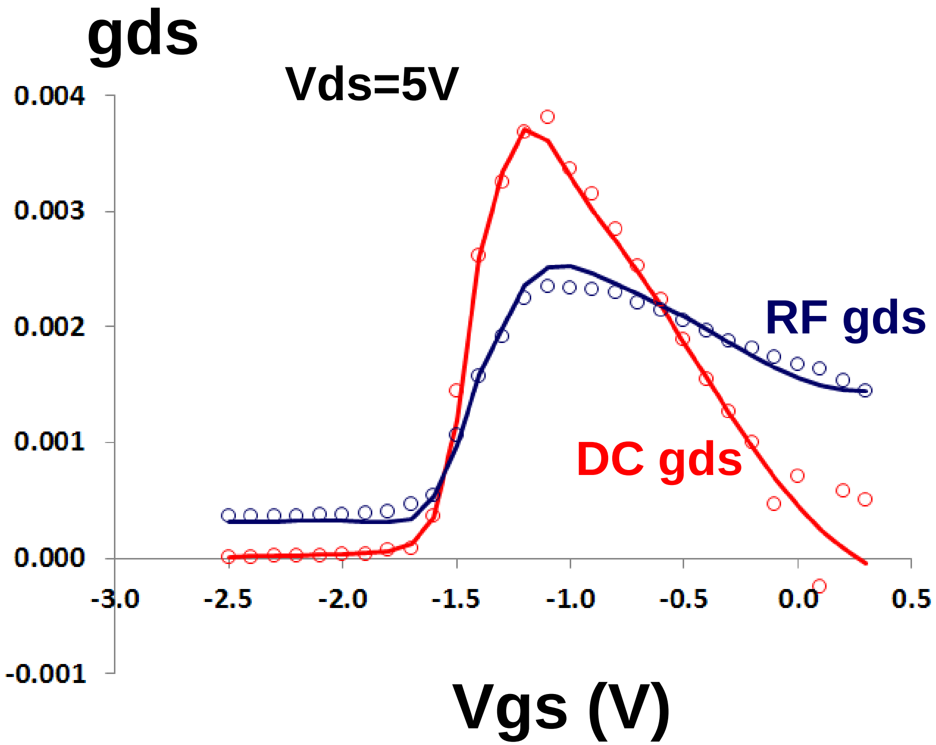
I_d^{ac}



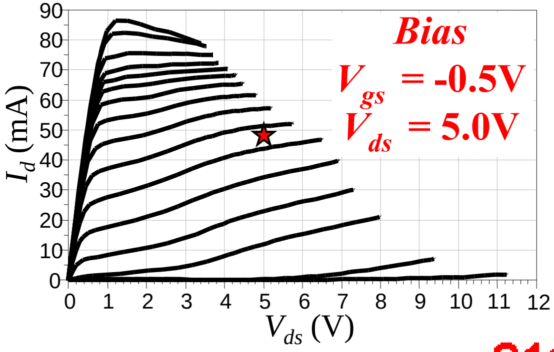
Frequency dispersion of small-signal characteristics

NeuroFET (—)
Measured data (o)



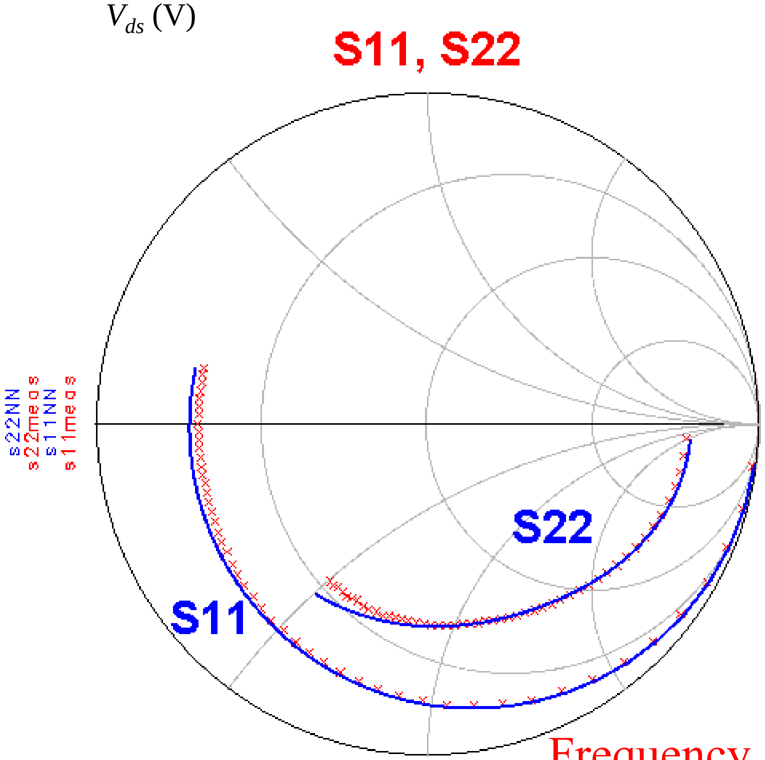


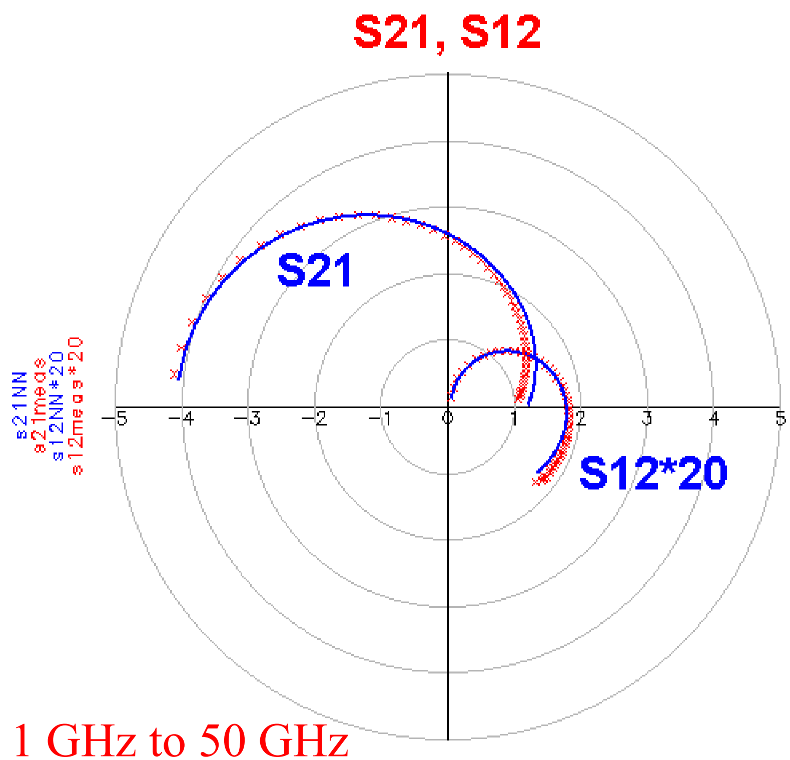
Model Validations
- S parameters



NeuroFET model (—)

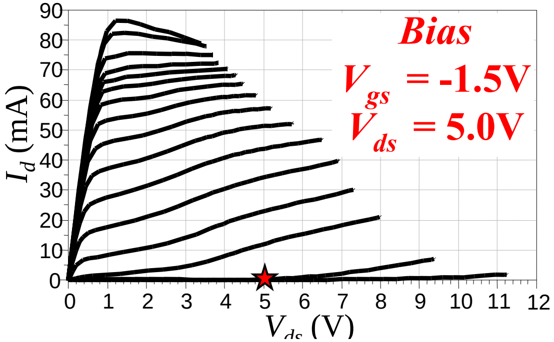
Measured device test data (x)





Frequency : 1 GHz to 50 GHz

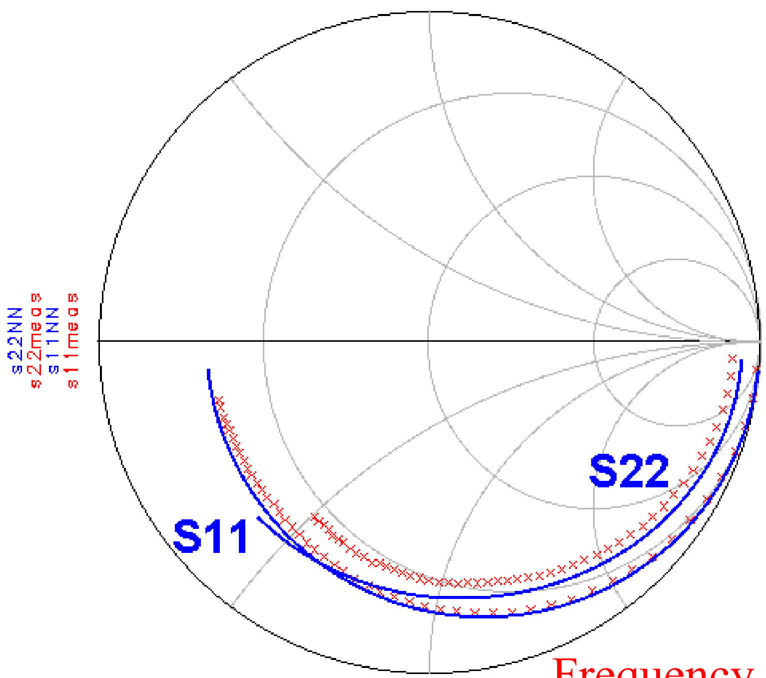
Model Validations
- S parameters



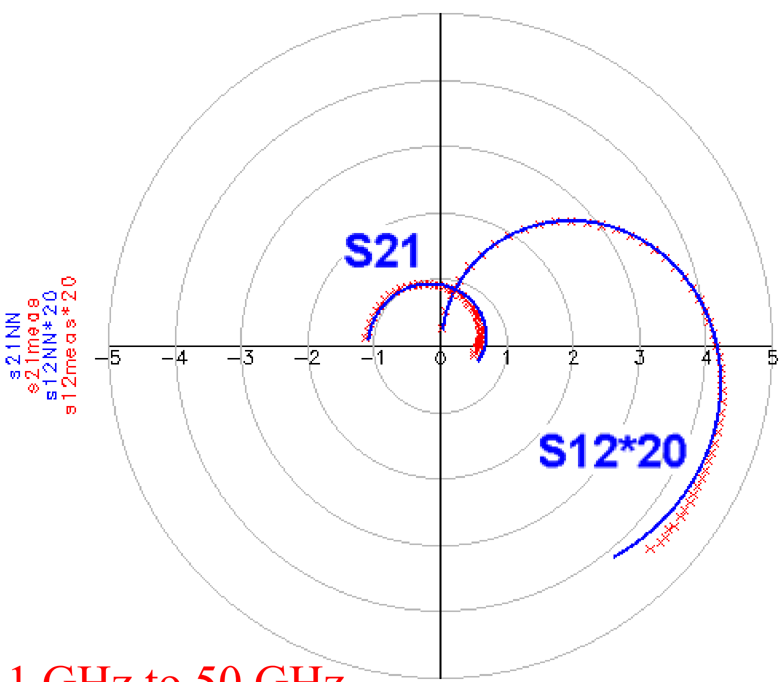
NeuroFET model (—)

Measured device test data (x)

S11, S22

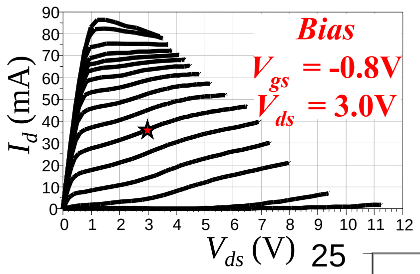


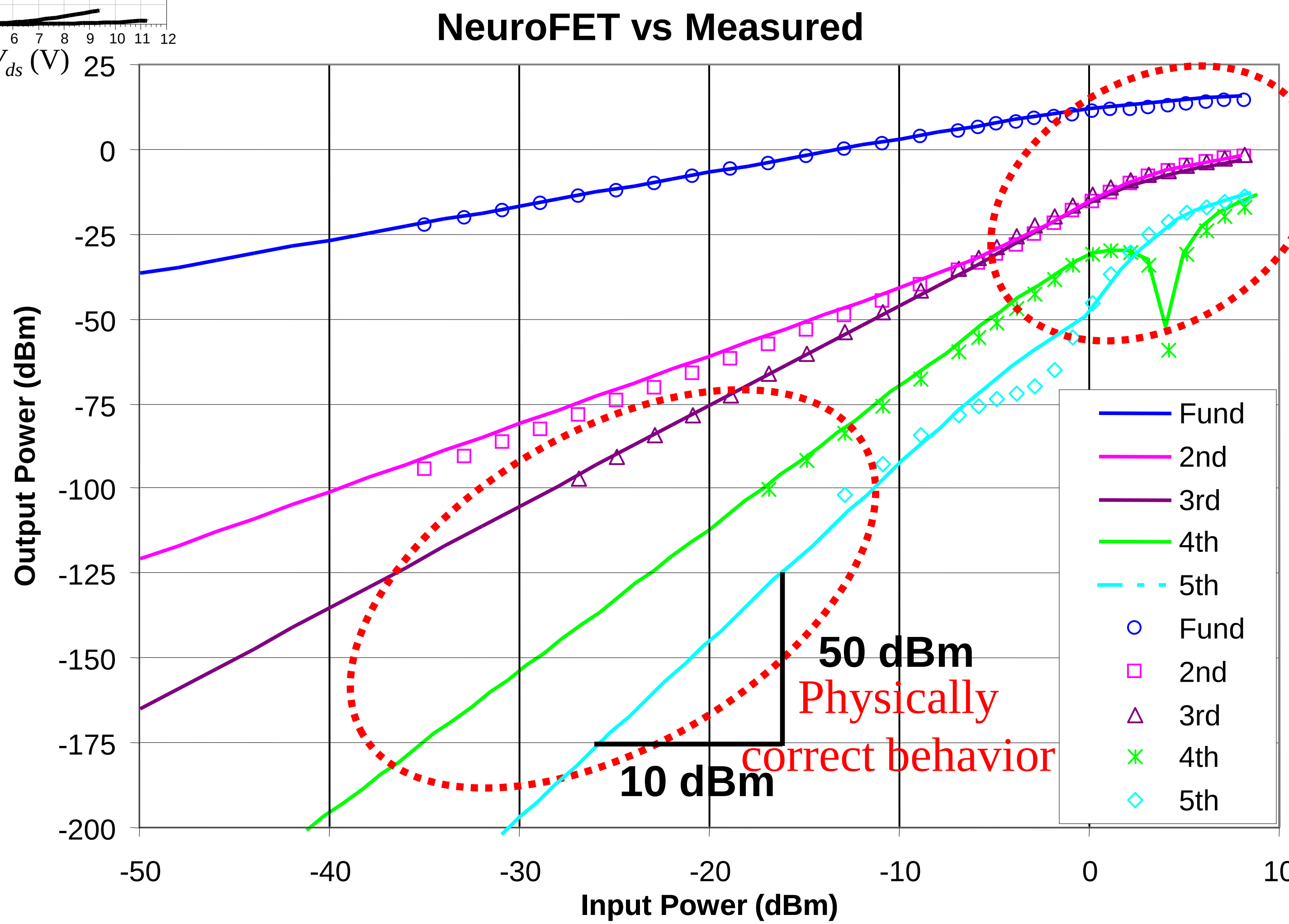
S21, S12



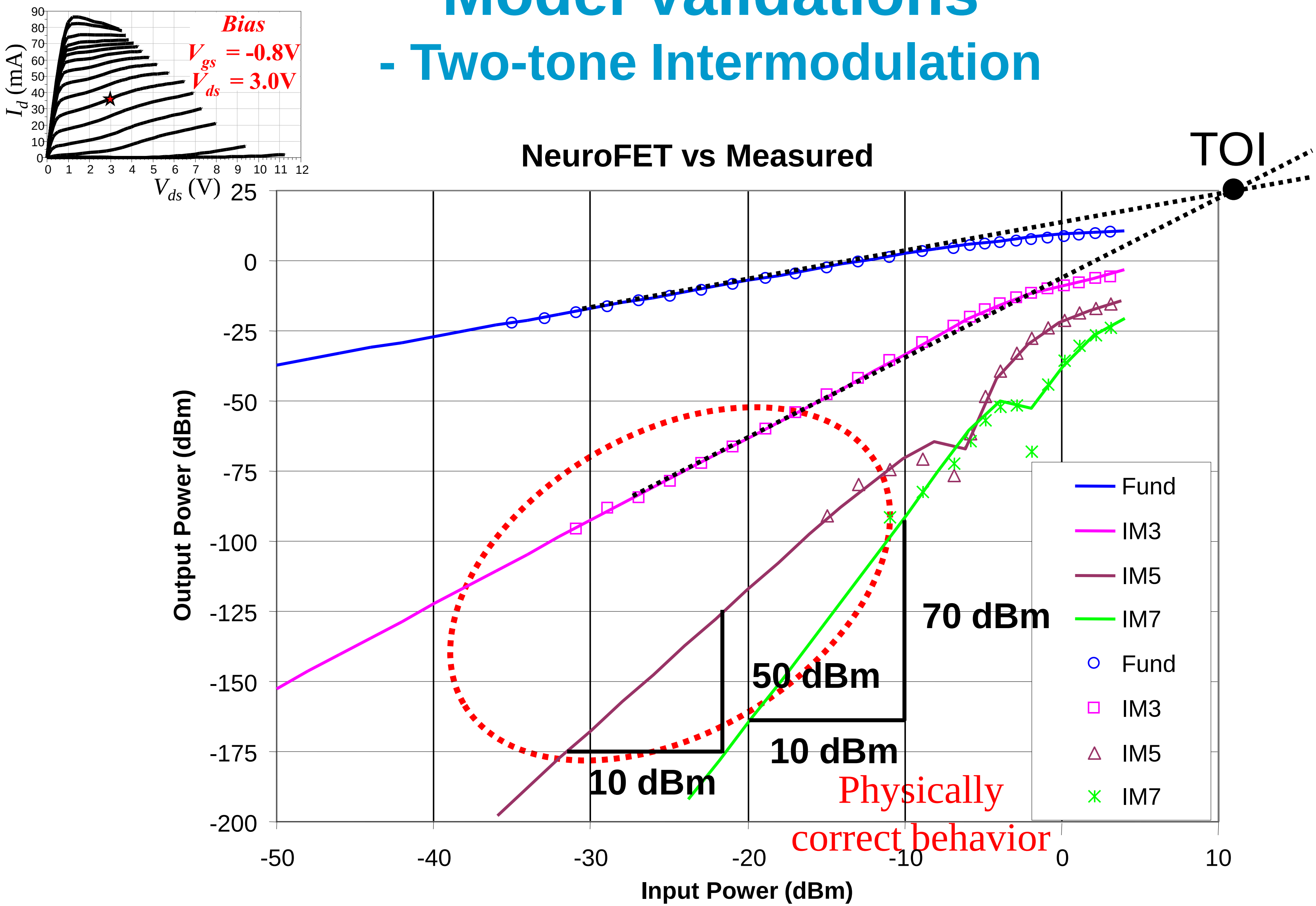
Frequency : 1 GHz to 50 GHz

Model Validations
- One-tone Harmonic Distortion





Model Validations
- Two-tone Intermodulation



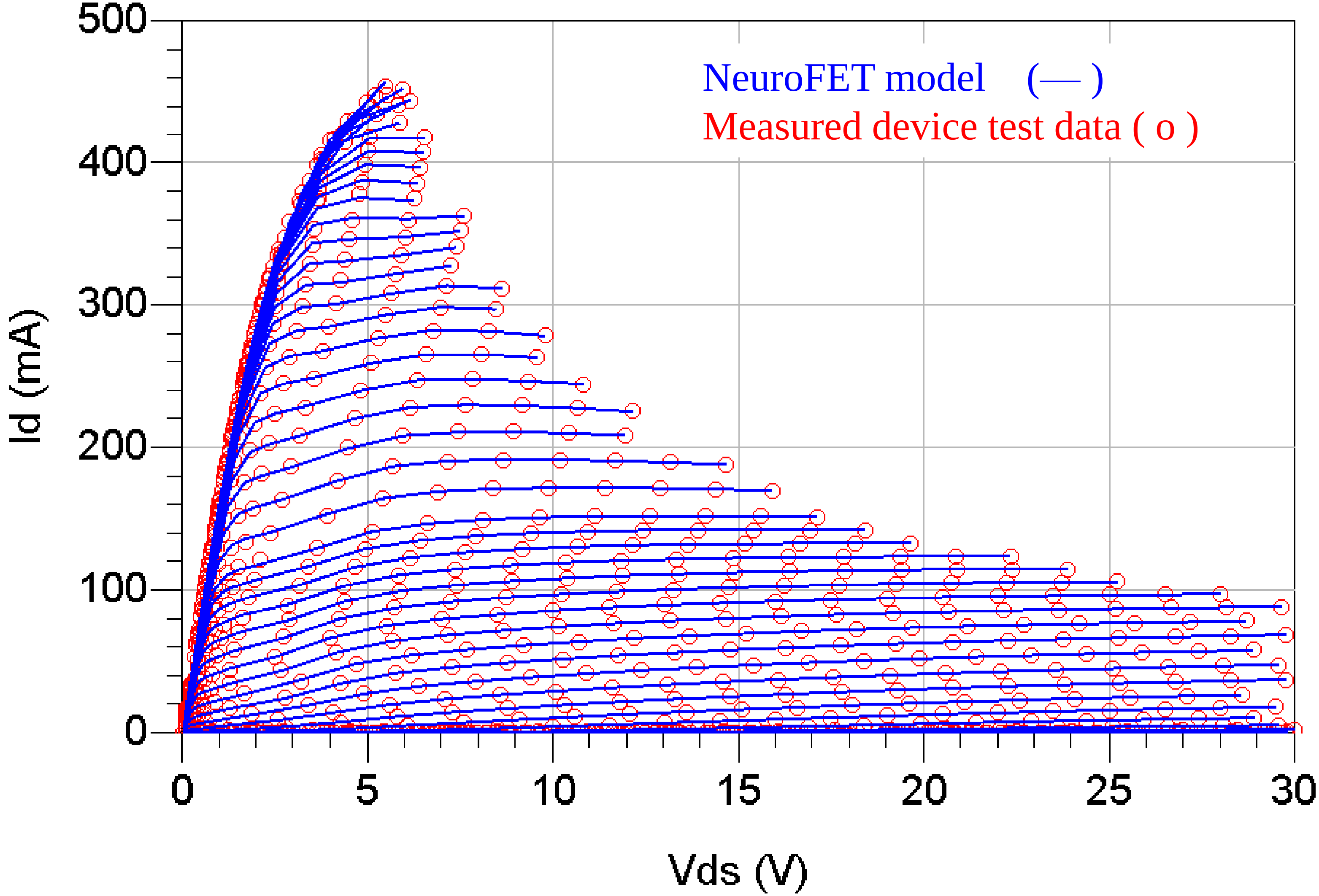
Example 2

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

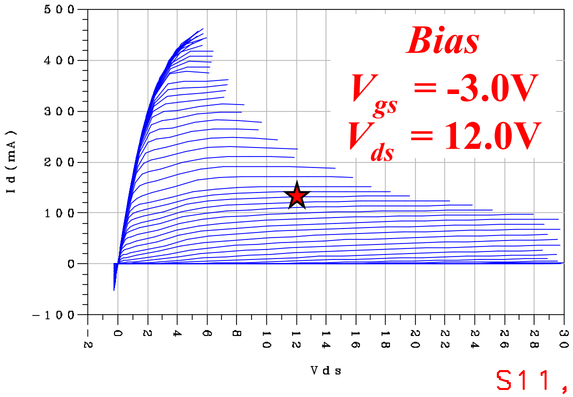
- DC IV
- S-parameters versus bias and frequency
- One-tone Harmonic Distortion
- Two-tone Intermodulation

Model Validations

- DC

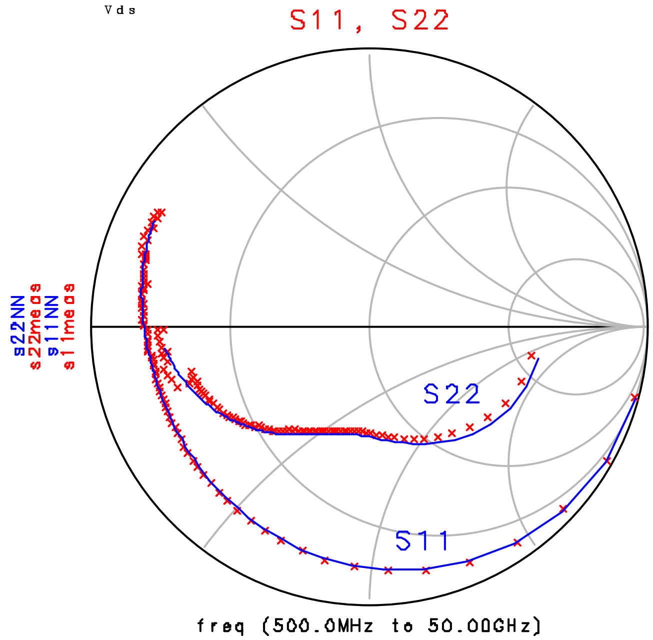


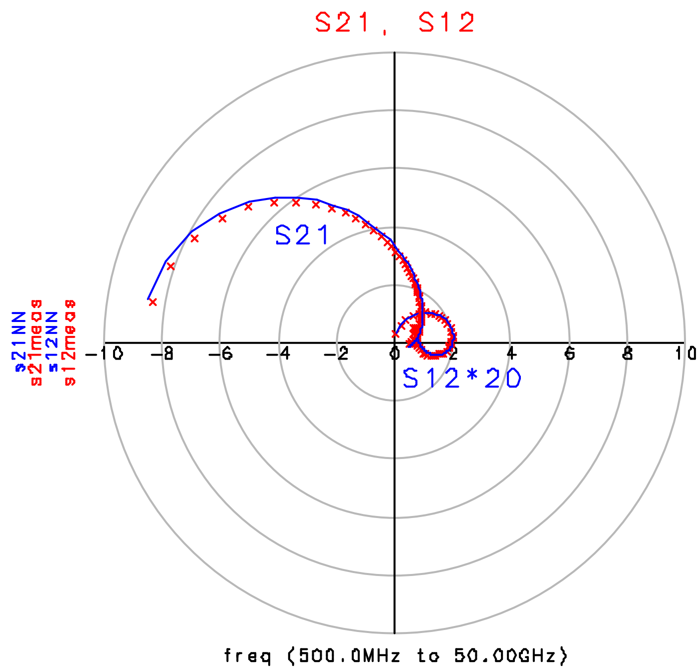
Model Validations
- S parameters



NeuroFET model (—)

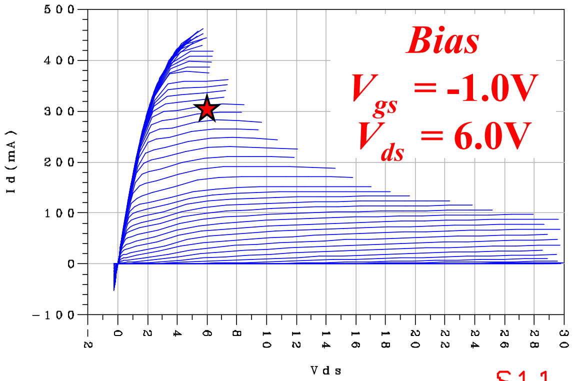
Measured device test data (x)





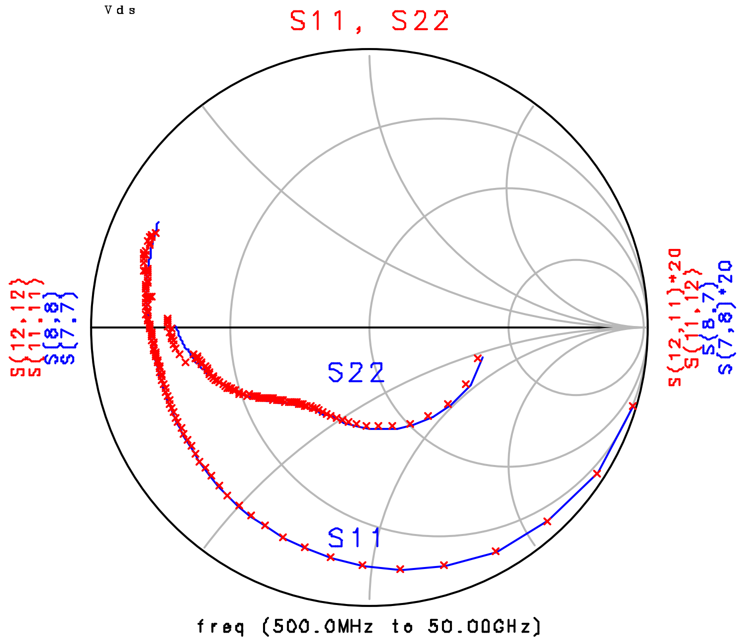
Frequency : 0.5 GHz to 50 GHz

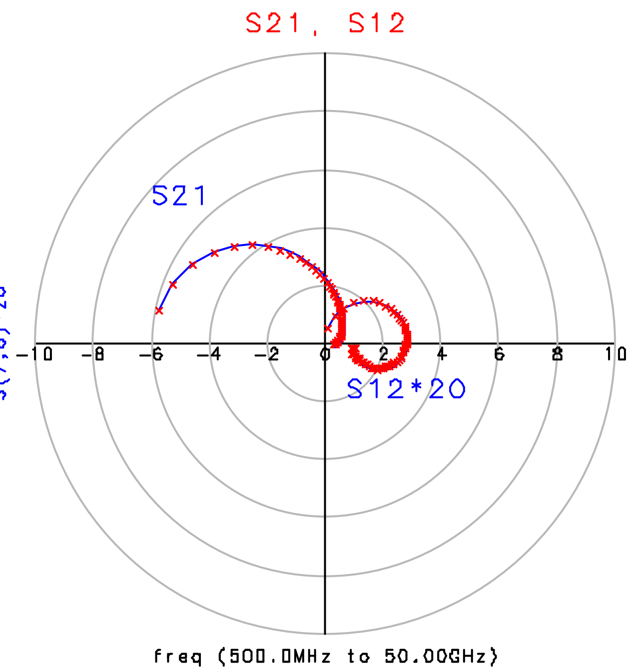
Model Validations
- S parameters



NeuroFET model (—)

Measured device test data (x)

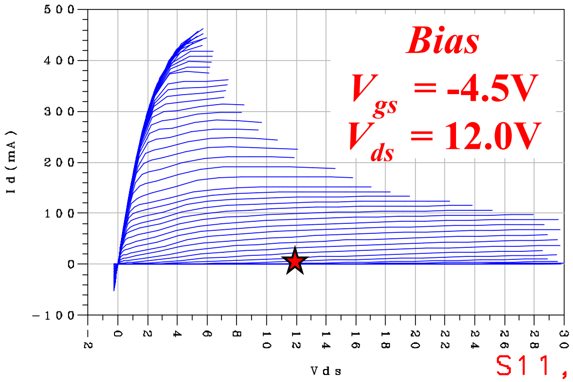




Frequency : 0.5 GHz to 50 GHz

Agilent Technologies

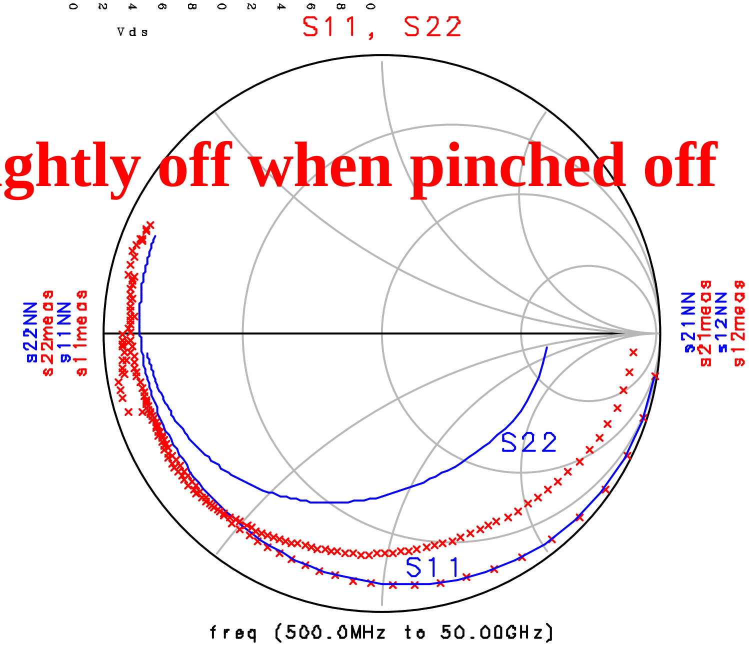
Model Validations
- S parameters

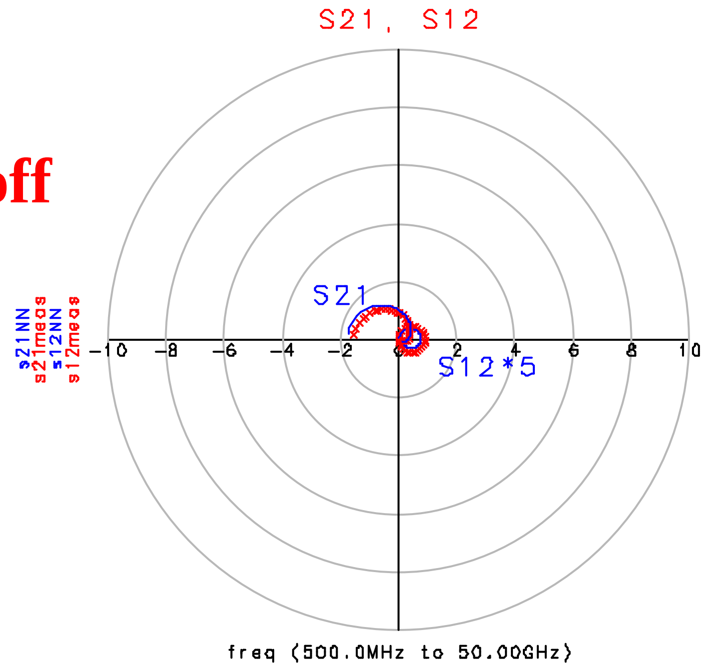


NeuroFET model (—)

Measured device test data (x)

S_{22} is slightly off when pinched off

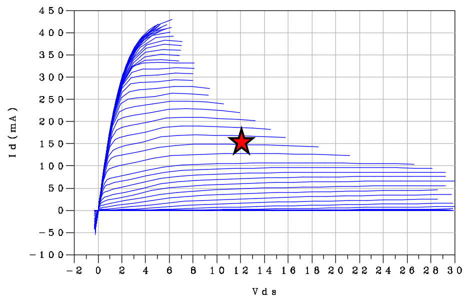




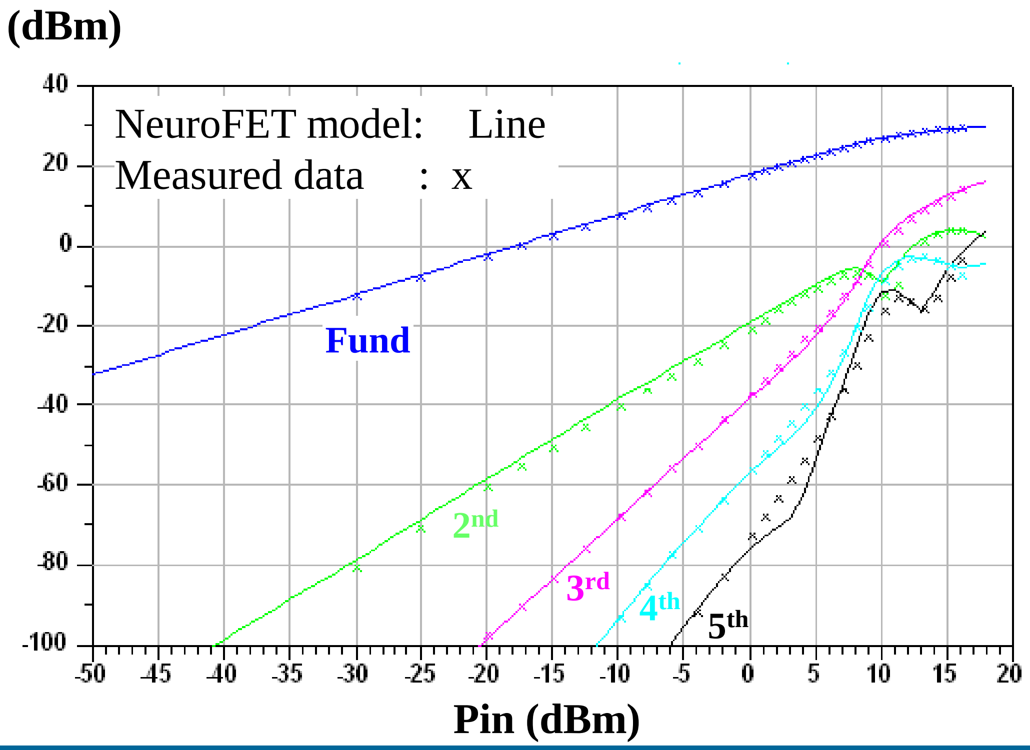
Frequency : 0.5 GHz to 50 GHz

Model Validations

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

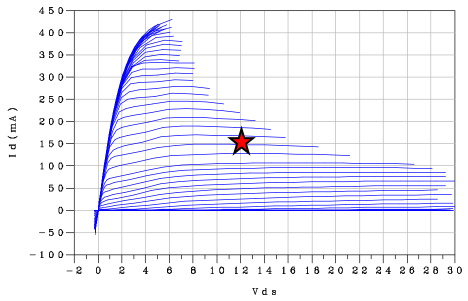


Bias
V_g = -2.5V
V_d = 12.0V

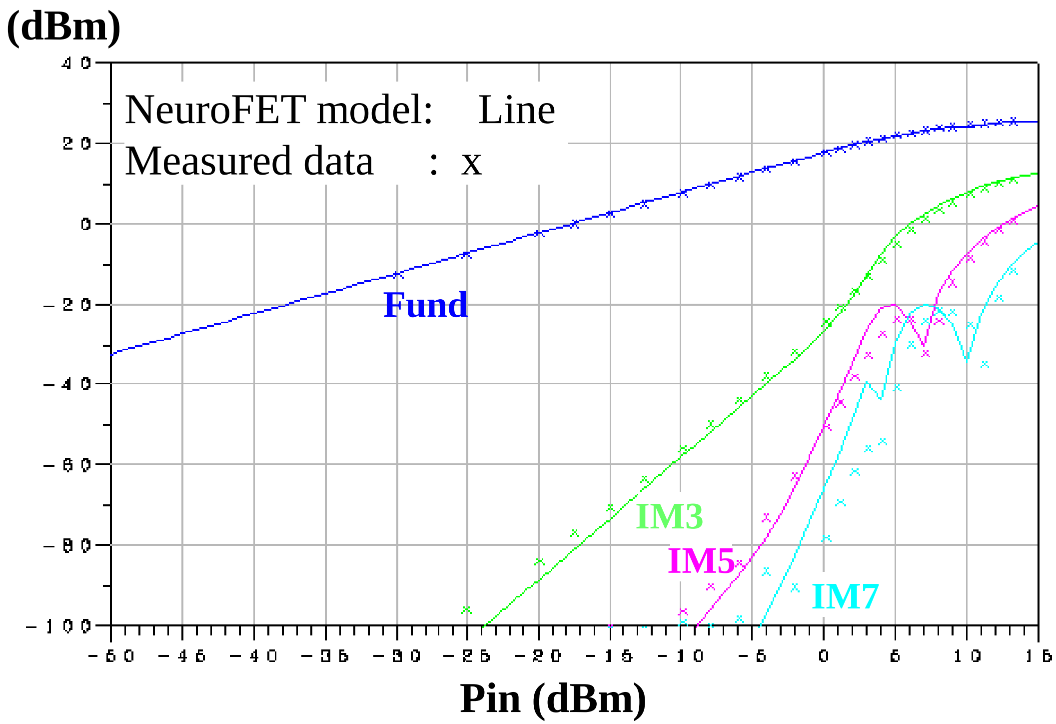


Model Validations

- 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

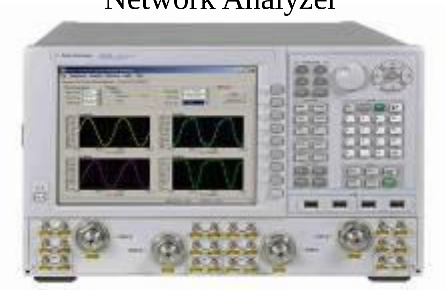
References

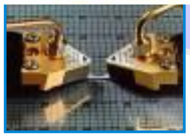
- J. Xu, D. Gunyan, M. Iwamoto, A. Cognata, and D. E. Root, "Measurement-Based Non-Quasi-Static Large-Signal FET Model Using Artificial Neural Networks," 2006 IEEE MTT-S Int. Microwave Symp. Dig., San Francisco, CA, USA, June 2006.
- J. Xu, D. Gunyan, M. Iwamoto, J. Horn, A. Cognata, and D. E. Root, "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 Technologies

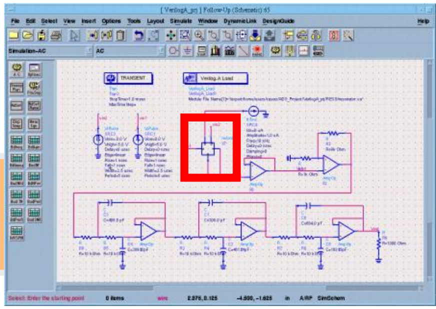
Agilent measurement-based modeling and design solutions

Agilent Nonlinear Vector Network Analyzer





Electronic design automation software

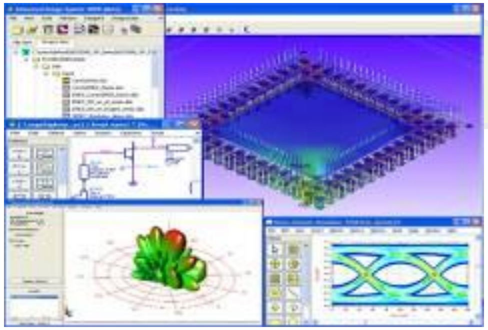


Measurements

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

Dr. Hongxiao Shao
Skyworks

Dr. Peter Zampardi
Skyworks

You can find more webcasts
www.agilent.com/find/eesof-innovations-in-eda
www.agilent.com/find/eesof-webcasts-recorded