AI/ML-Driven Device Modeling for Advanced Nodes, RF and Power Applications

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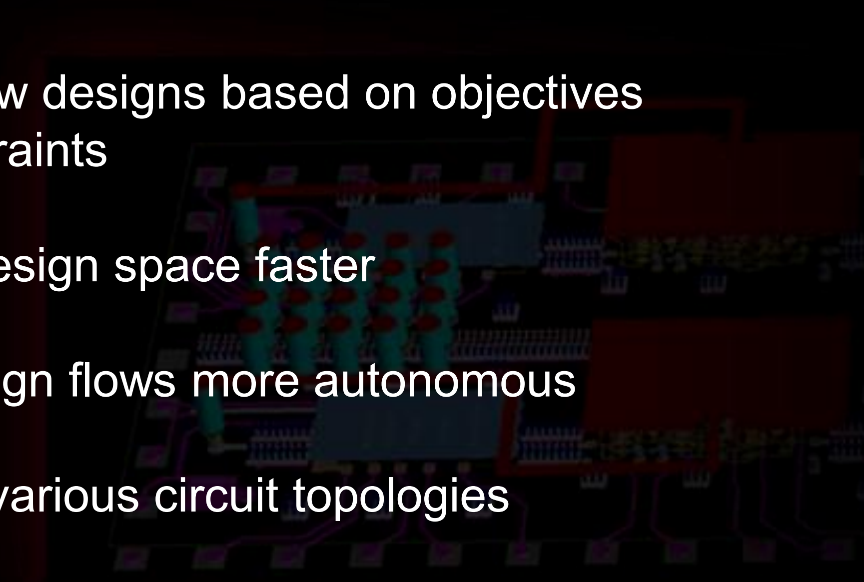
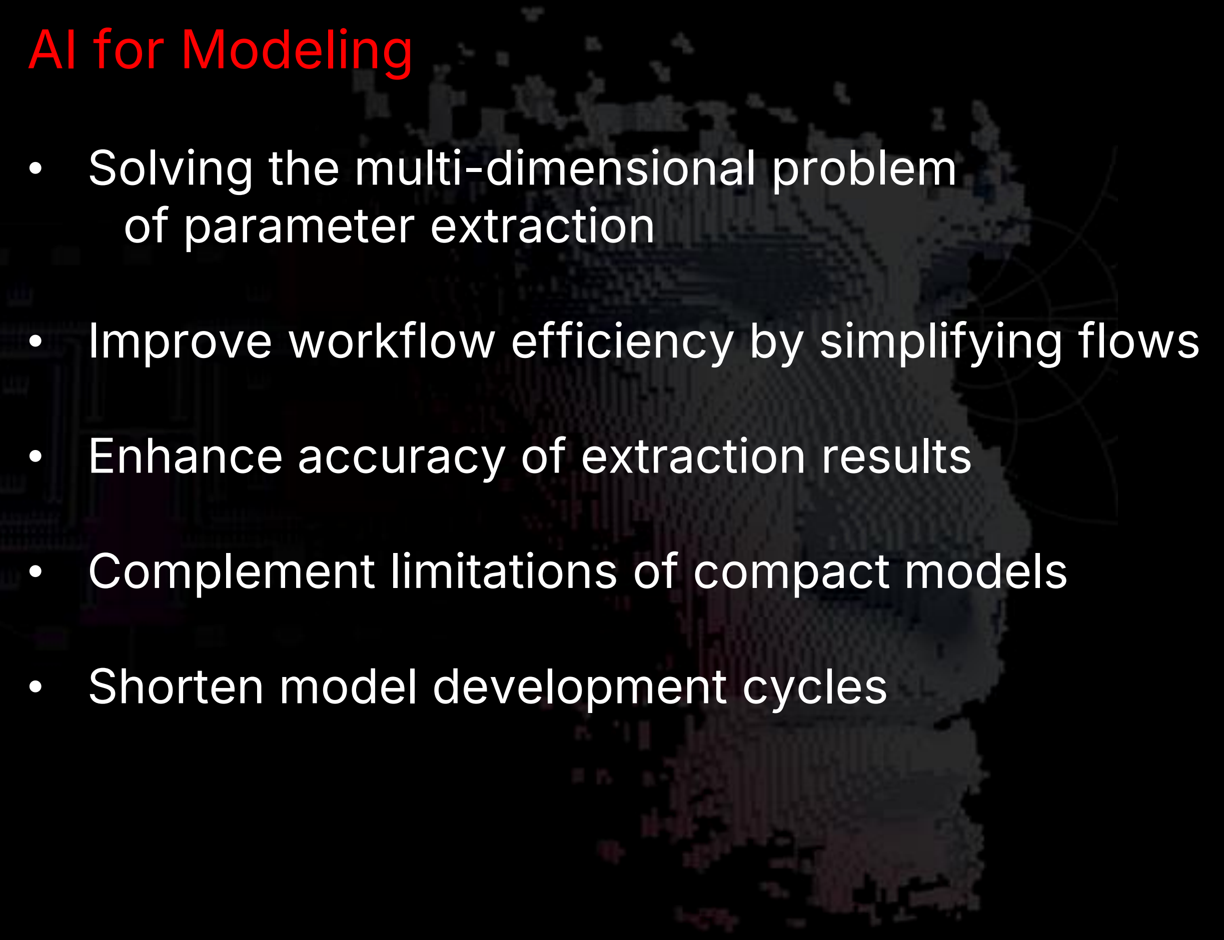
MOS-AK LatAm

Agenda

- Introduction: Device Modeling at Keysight
- AI/ML innovations in Device Modeling (DM)
  - ML Toolkit using Python, ML optimizer, and ANN toolbox
  - Full & Hybrid ANNs
- Applications:
  - Parameter extraction for advanced CMOS nodes
  - Model development for RF GaN- & GaAs-HEMTs
  - Modeling for SiC or IGBT power applications
- AI/ML efforts at Keysight:
  - Major Enhancements
  - EDAchat
  - EDA Copilots
- Conclusion
- Q&A

AI/ML Use-cases





AI for Design

- Create new designs based on objectives and constraints
- Explore design space faster
- Make design flows more autonomous
- Optimize various circuit topologies
- Solve design trade-offs in Digital/Analog/RF systems

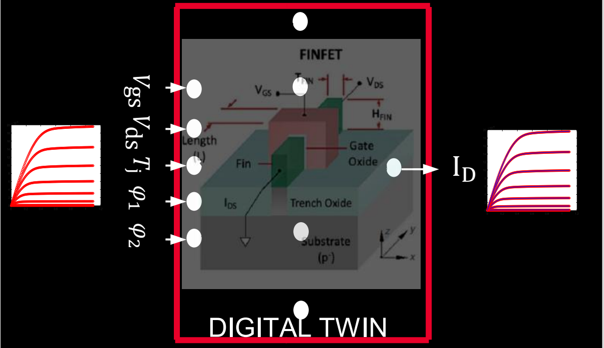
AI for Modeling

- Solving the multi-dimensional problem of parameter extraction
- Improve workflow efficiency by simplifying flows
- Enhance accuracy of extraction results
- Complement limitations of compact models
- Shorten model development cycles

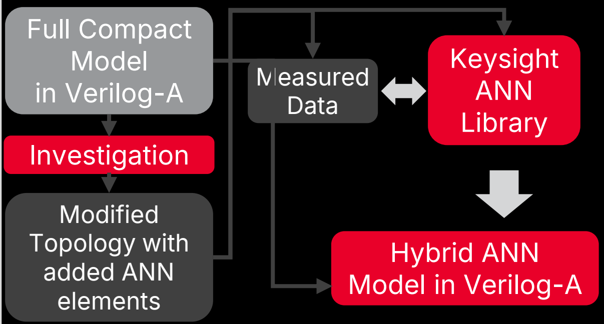
AI/ML solutions at Keysight

How can AI/ML techniques be successfully applied in Device Modeling?

ANN Toolbox



Hybrid ANN



Full Compact Model in Verilog-A

Investigation

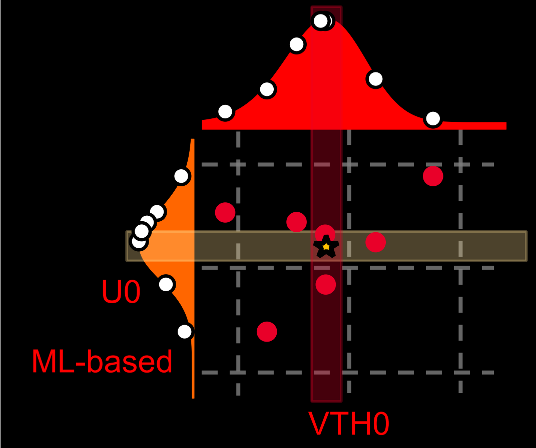
Modified Topology with added ANN elements

Measured Data

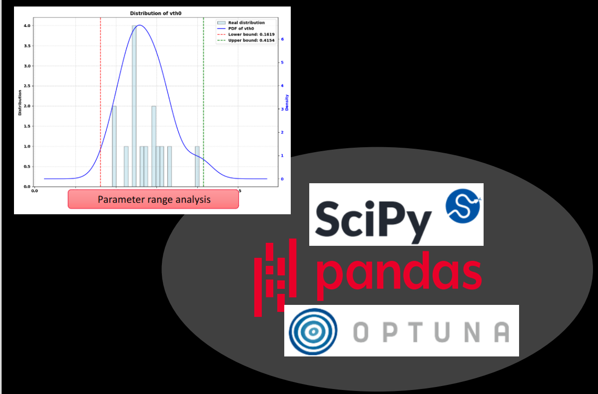
Keysight ANN Library

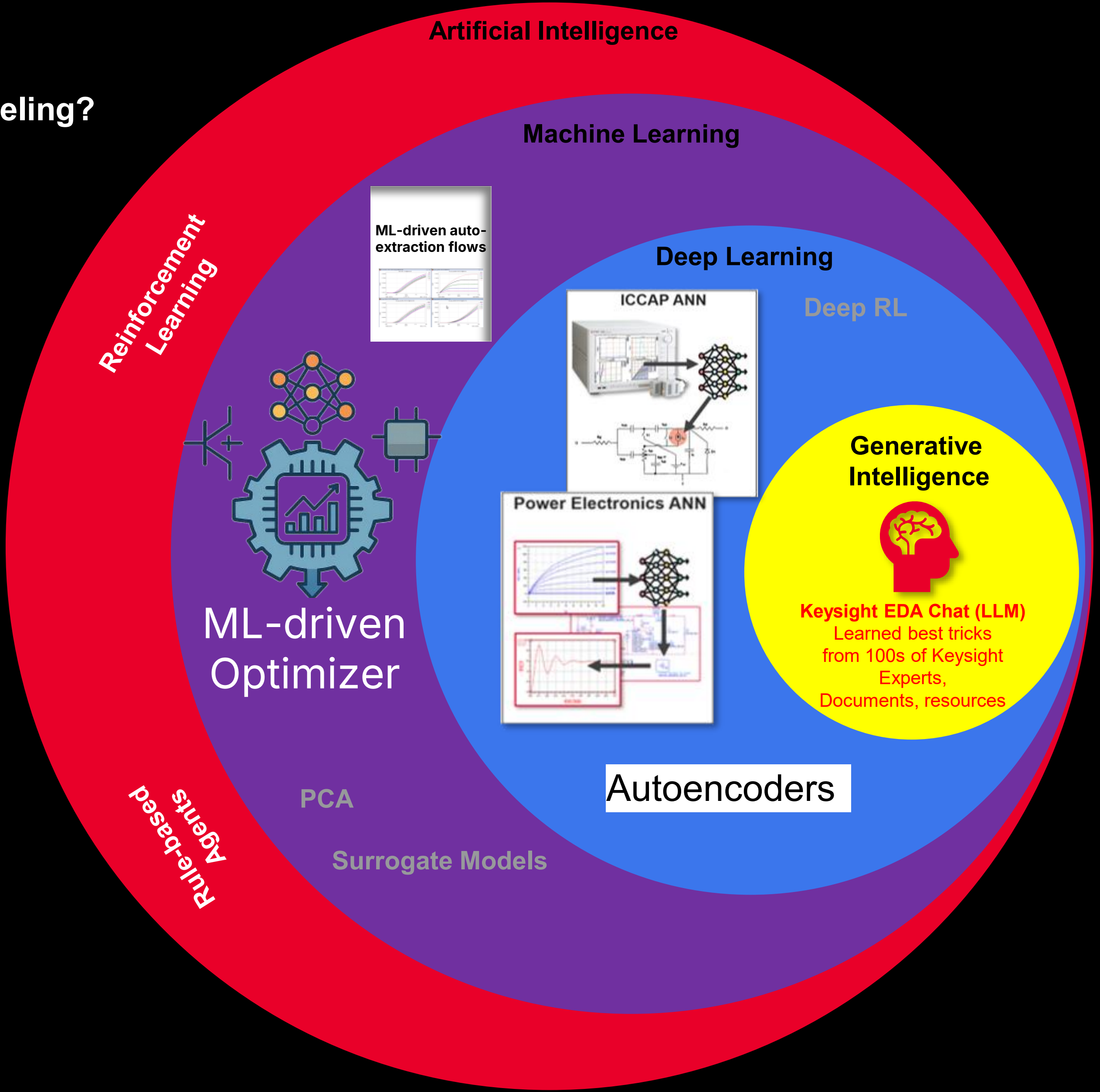
Hybrid ANN Model in Verilog-A

ML Optimizer



ML Toolkit





Artificial Intelligence

Reinforcement Learning

Rule-based Agents

Machine Learning

ML-driven auto-extraction flows

ML-driven Optimizer

PCA

Surrogate Models

Deep Learning

Deep RL

ICCAP ANN

Power Electronics ANN

Autoencoders

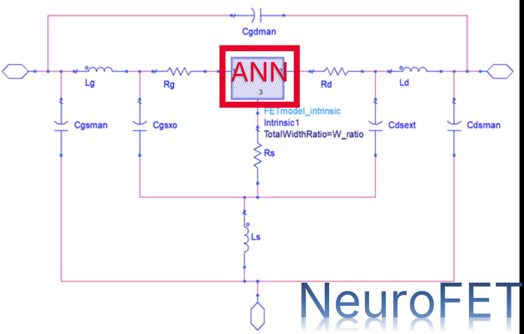
Generative Intelligence

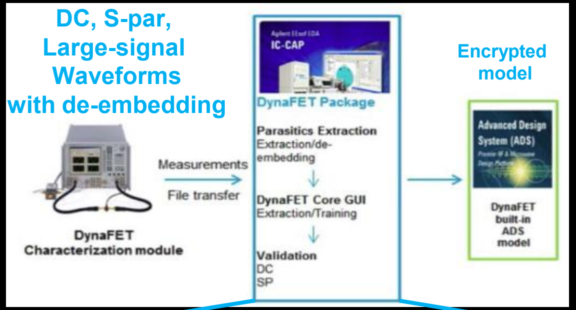
Keysight EDA Chat (LLM)
Learned best tricks from 100s of Keysight Experts, Documents, resources

Industry's First AI/ML Solutions in Device Modeling

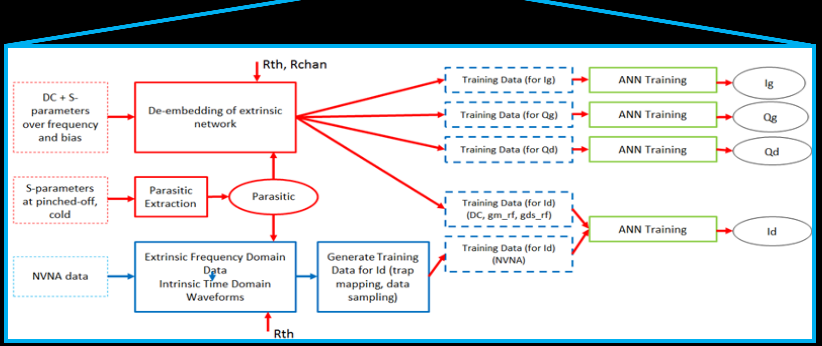
NeuroFET and DynaFET models

- NeuroFET: Similar to the RootFET, but with a polynomial replaced by an ANN. Intrinsic ANN consists of Train + Test splits:
  - Neuron Activation functions (Sigmoid/Hyperbolic tangent)
  - Training method (Quasi-Newton/Levenberg-Marquardt)
  - Number of hidden neurons
- DynaFET: NQS Large-signal III-V FET model offered an enhanced solution for GaN-HEMTs
  - Intrinsic model (ANN with thermal and trapping effects) + parasitic R, L, C
  - IV, S-par fitting done on large-signal waveform data from NVNA.

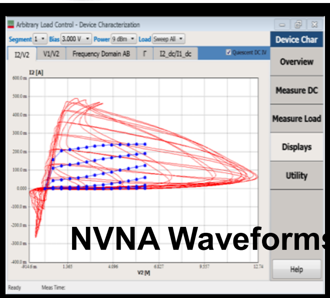



DC, S-par, Large-signal Waveforms with de-embedding

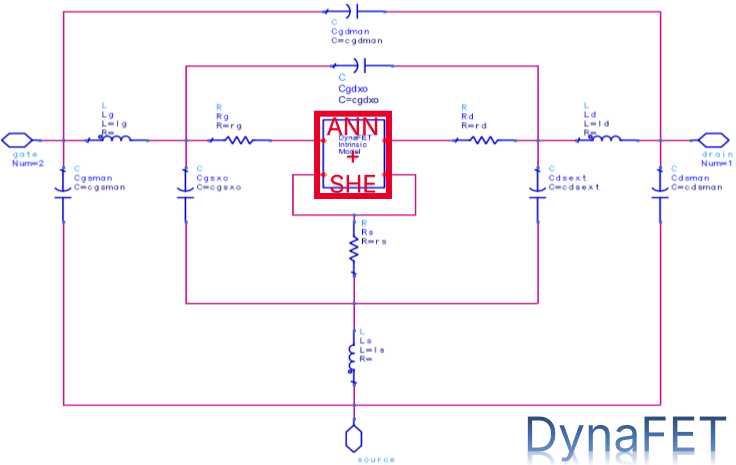
Encrypted model



NVNA



NVNA Waveforms

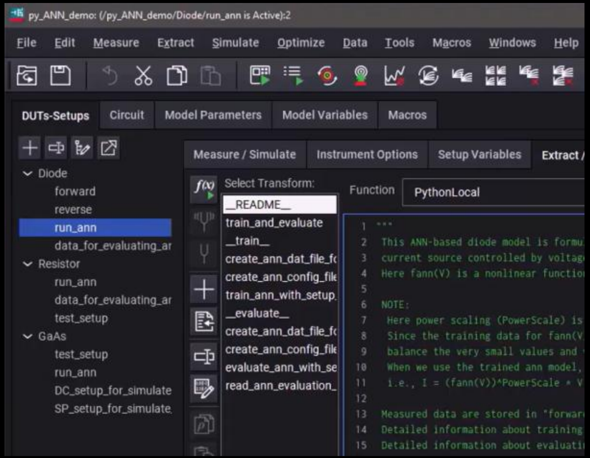


ANN Toolbox: GaAs-HEMT

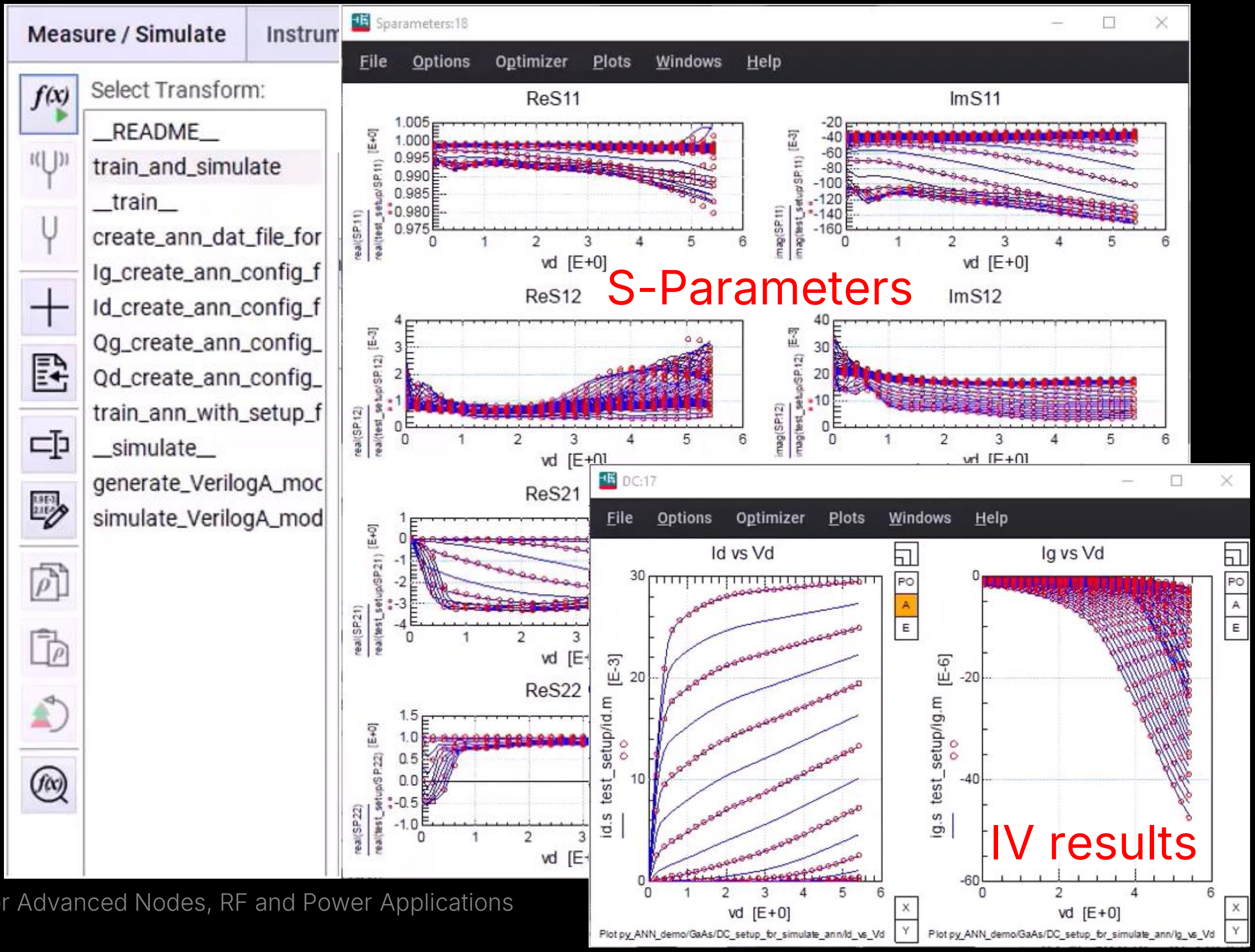
Data ➡ **ANN** ➡ **Model**

Keysight ANN Model Generator in IC-CAP

- Useful for quick point model generation at any design phase or when accurate models are unavailable
- Keysight ANN implementation generates ANN from partial derivative data and outputs Verilog-A SPICE model
- Consists of Python functions to
  - Train ANNs per input data
  - Evaluate ANN model
  - Output ANN eval circuit for simulation
- GaAs-HEMT as an example: 4 sub-ckt ANN models for Id/Ig/Qd/Qg combined



```
"""
This ANN-based diode model is formu
current source controlled by voltag
Here fann(V) is a nonlinear functio

NOTE:
 Here power scaling (PowerScale) is
 Since the training data for fann(V
 balance the very small values and
 When we use the trained ann model,
 i.e., I = (fann(V))^PowerScale * V

Measured data are stored in "forwar
Detailed information about training
Detailed information about evaluati
```

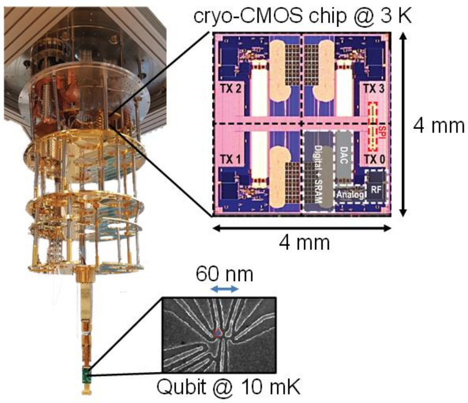


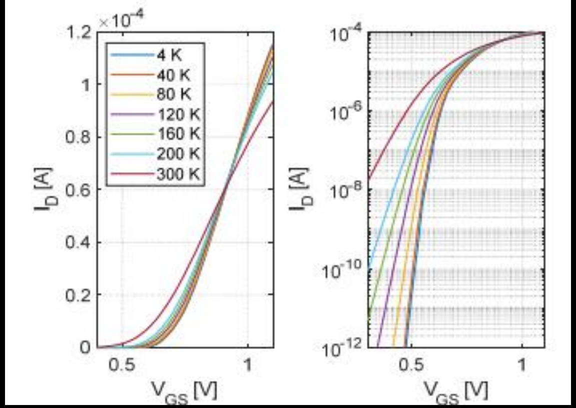
- Not used for replacing scalable compact models

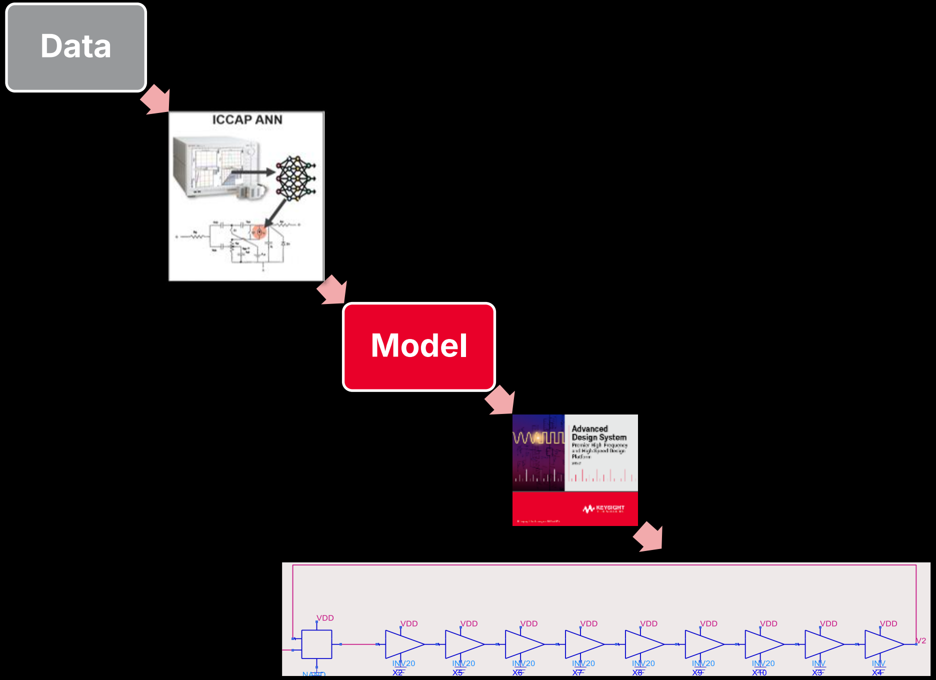
ANN Toolbox: Cryogenic CMOS modeling

Enabling models and circuits for Quantum Computing

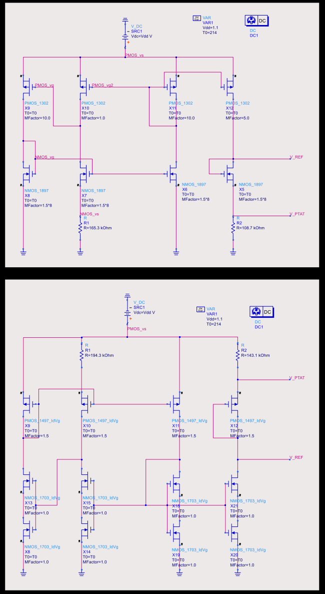
- Advanced node CMOS devices exhibit altered characteristics at very low temperatures
- Existing compact models may not fully capture freeze-out effects across all bias/temp ranges
- Extraction procedures are not straightforward

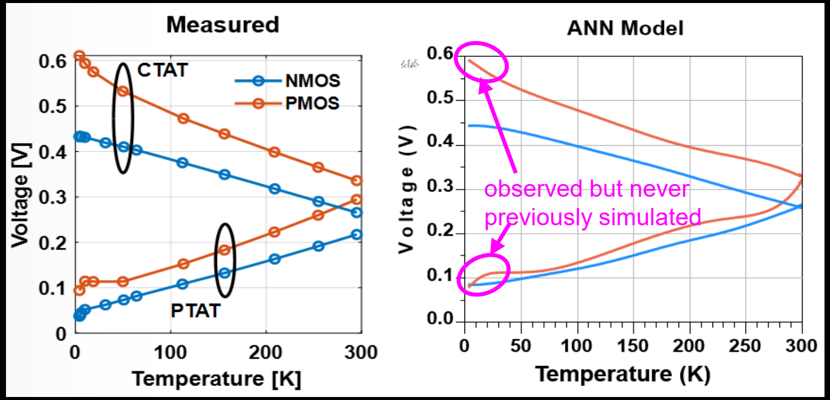





Data

Model



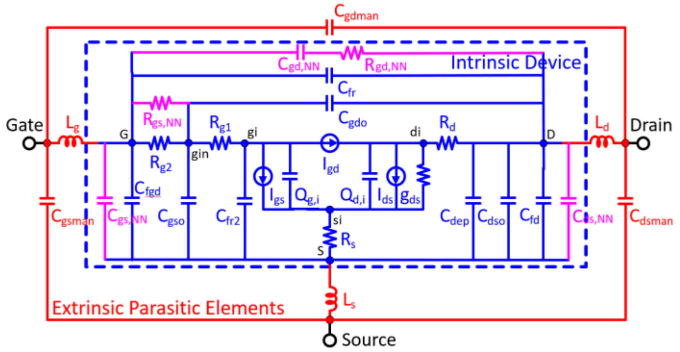


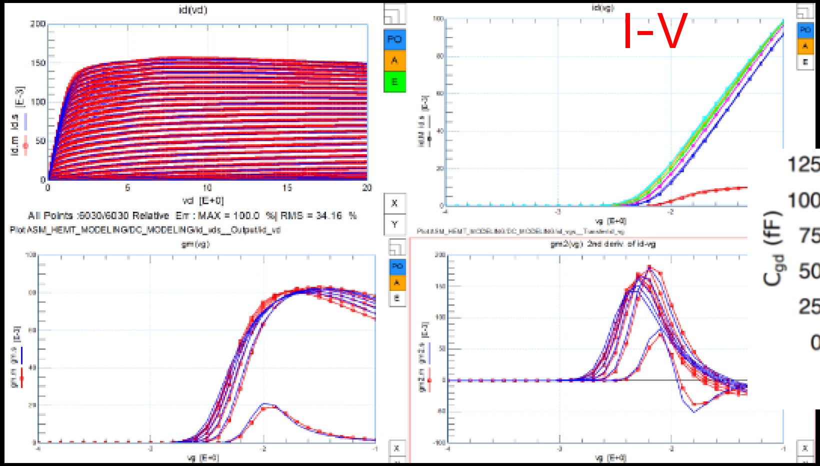
P.A. 't Hart, J. Xu, J. van Staveren, M. Babaie, D.E. Root, and F. Sebastiano, "Artificial Neural Network Modelling for Cryo-CMOS Devices", *IEEE 14th Workshop on Low Temperature Electronics (WOLTE)*, April 2021.

Hybrid ANN solution: GaN-HEMT devices

Problem: How to overcome the limitations of physics-based compact models?

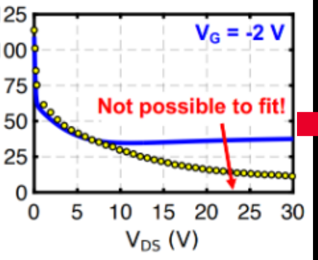
- Hybrid ANN modeling approach compensates for unmodeled non-linear physical behavior by incorporating additional R/C elements
  - ✓ Retain the physics-based core model and its ability to provide insights
  - ✓ Improves the overall accuracy of the model
  - × Requires expert investigation and validation.
- ASM-HEMT Cgd vs. Vds model fitting improved in ASM-HEMT by applying Hybrid-ANN

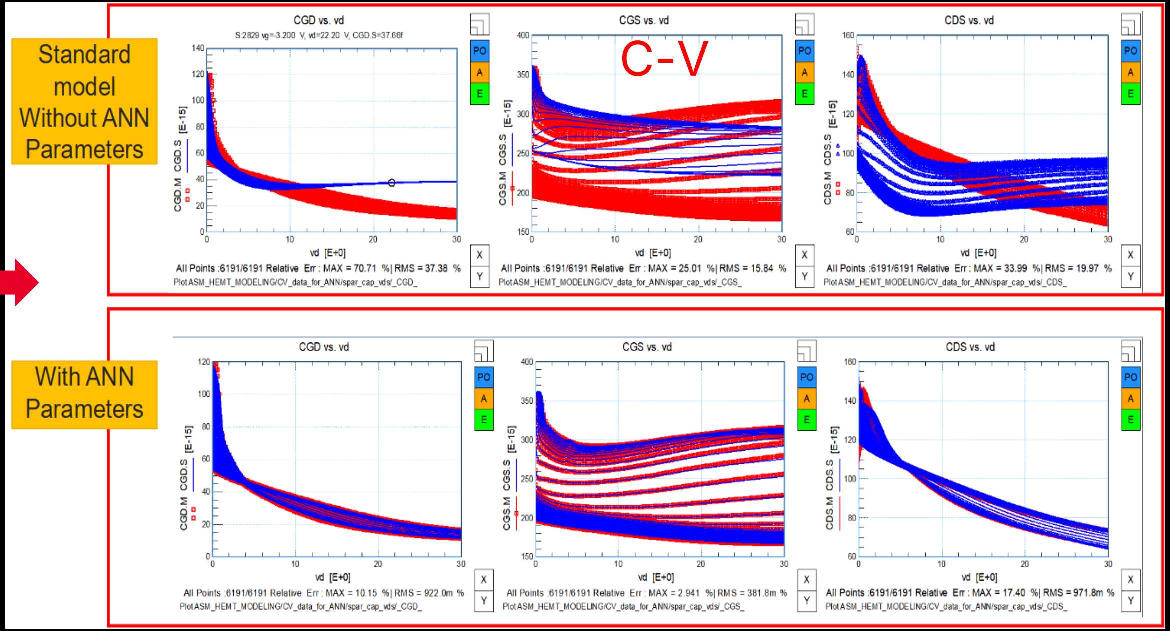




All Points :6030/6030 Relative Err : MAX = 100.0 %| RMS = 34.16 %

Plot ASM_HEMT_MODELING/DC_MODELING/id_ids__Output/id_vd





Standard model Without ANN Parameters

All Points :6191/6191 Relative Err : MAX = 70.71 %| RMS = 37.38 %

Plot ASM_HEMT_MODELING/CV_data_for_ANN/spar_cap_vds/_CGD_

All Points :6191/6191 Relative Err : MAX = 25.01 %| RMS = 15.84 %

Plot ASM_HEMT_MODELING/CV_data_for_ANN/spar_cap_vds/_CGS_

All Points :6191/6191 Relative Err : MAX = 33.99 %| RMS = 19.97 %

Plot ASM_HEMT_MODELING/CV_data_for_ANN/spar_cap_vds/_CDS_

With ANN Parameters

All Points :6191/6191 Relative Err : MAX = 10.15 %| RMS = 922.0m %

Plot ASM_HEMT_MODELING/CV_data_for_ANN/spar_cap_vds/_CGD_

All Points :6191/6191 Relative Err : MAX = 2.941 %| RMS = 381.8m %

Plot ASM_HEMT_MODELING/CV_data_for_ANN/spar_cap_vds/_CGS_

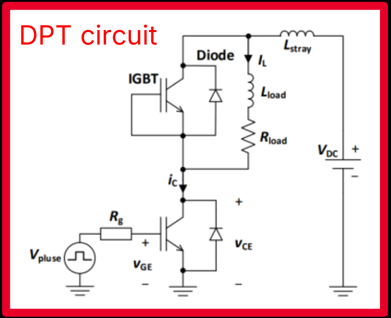
All Points :6191/6191 Relative Err : MAX = 17.40 %| RMS = 971.8m %

Plot ASM_HEMT_MODELING/CV_data_for_ANN/spar_cap_vds/_CDS_

R. P. Martinez et al., "A Hybrid Physical ASM-HEMT Model Using a Neural Network Based Methodology," 2024 IEEE BiCMOS and Compound Semiconductor Integrated Circuits and Technology Symposium (BCICTS), Fort Lauderdale, FL, USA, 2024, pp. 38-41,doi: 10.1109/BCICTS59662.2024.10745660

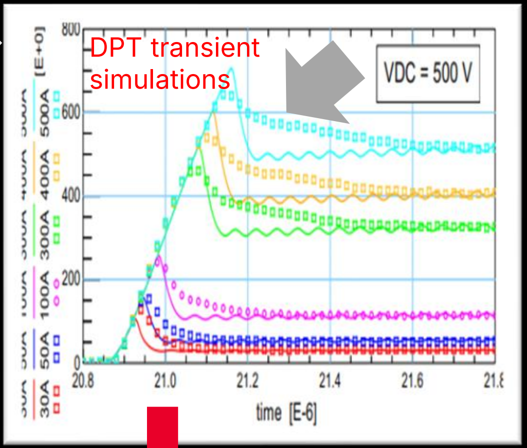
Hybrid ANN solution: IGBT Double Pulse Test (DPT)

Challenge: No bias-dependent model for reverse-recovery (RR) and lack of on-state cap model

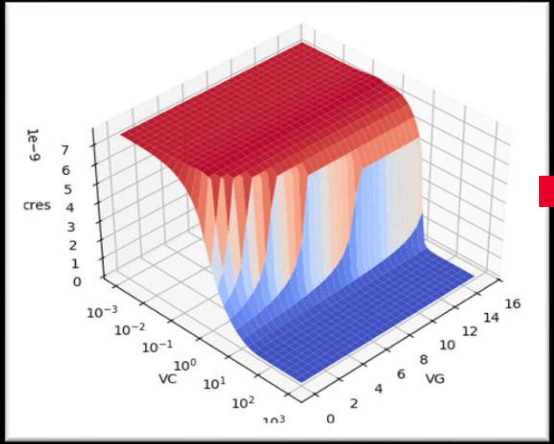


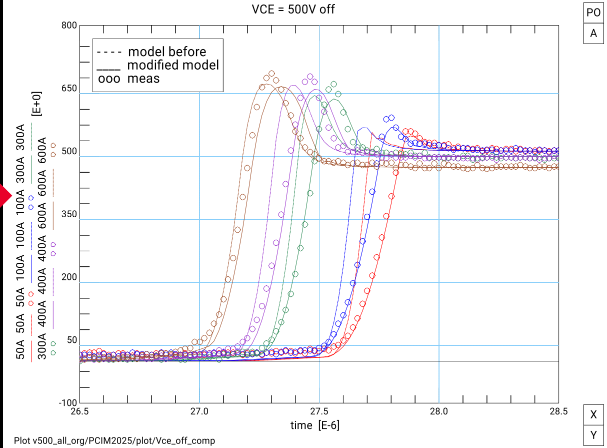
DPT circuit

- Model may fit in some bias conditions, but RR model itself is not bias-dependent.
- Hybrid ANN approach is used to create a bias-dependent equation to model RR of body diode @multibias →
- An empirical equation is used to extract the on-state capacitance ↓



DPT transient simulations



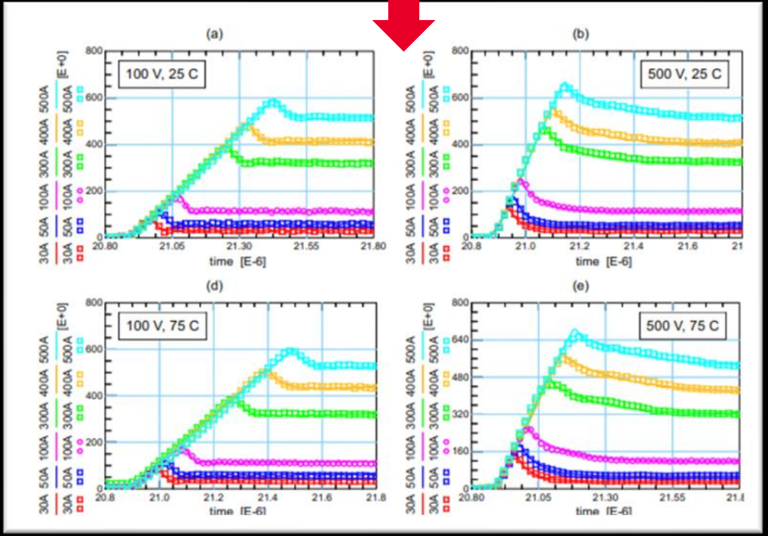


Shih, A., et al. "A Double Pulse Test Based IGBT On-State Capacitance Extrac-tion of ANN-assisted Hybrid Model." *PCIM Conference 2025; International Exhibition and Conference for Power Electronics, Intelligent Motion, Renewable Energy and Energy Management.* VDE, 2025.

$$C_{gc} = \frac{Cgc0}{(1-Fc)^{M}}(1+\left(\frac{M}{V_J(1-Fc)}\right)\cdot$$

$$(V_{CE}-Fc\cdot V_J))(1+tahn(\emptyset_2))$$

$$\emptyset_2 = P40 + P41\cdot V_{GE} - P111\cdot V_{CE}$$



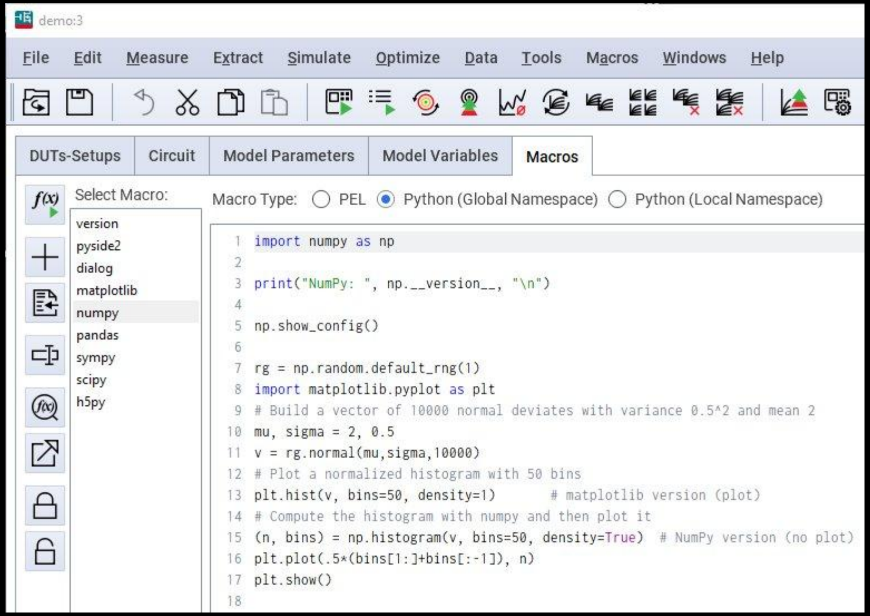
- Hybrid ANN models can be used to adjust the accuracy of encrypted models supplied by foundries
- ANN can overfit or underfit depending on its configuration (layers/neurons)

Python3 Interface

Enables an efficient and versatile programming experience, along with public ML libraries

Programming API in IC-CAP

- Python 3.12 support available for Macros and transforms
- Offers a powerful coding environment in addition to PEL
- Supports Optuna optimization framework, Keysight-pwdatatools, Scikit-RF, Seaborn, PyPDF etc.

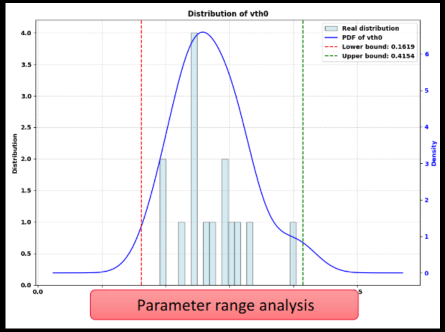


Macro Type: ○ PEL ● Python (Global Namespace) ○ Python (Local Namespace)

```
import numpy as np

print("NumPy: ", np.__version__, "\n")

np.show_config()

rg = np.random.default_rng(1)
import matplotlib.pyplot as plt
# Build a vector of 10000 normal deviates with variance 0.5^2 and mean 2
mu, sigma = 2, 0.5
v = rg.normal(mu,sigma,10000)
# Plot a normalized histogram with 50 bins
plt.hist(v, bins=50, density=1)       # matplotlib version (plot)
# Compute the histogram with numpy and then plot it
(n, bins) = np.histogram(v, bins=50, density=True)  # NumPy version (no plot)
plt.plot(.5*(bins[1:]+bins[:-1]), n)
plt.show()

```

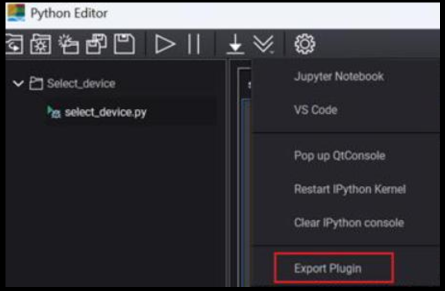
API & Utilities in MBP

- Python Editor supports task group for batch runs
- Utility for parameter boundary analysis from past models



Parameter range analysis

- Plugins for comparing model parameter values
- User-defined plugins for data manipulation, run flow etc.

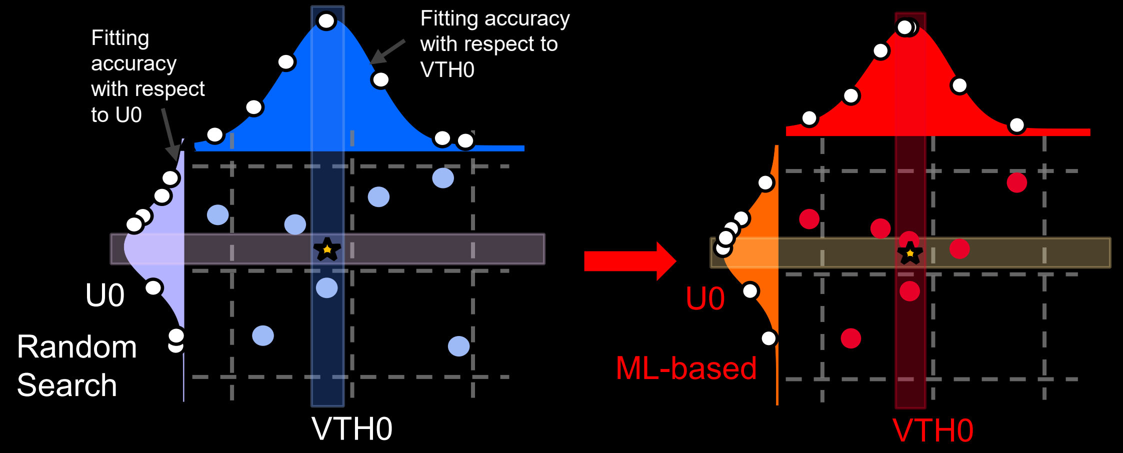


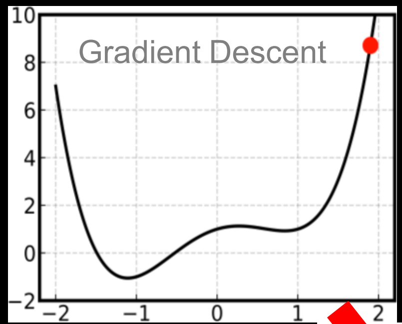
- Enables IPython interactive console and Jupyter Notebook

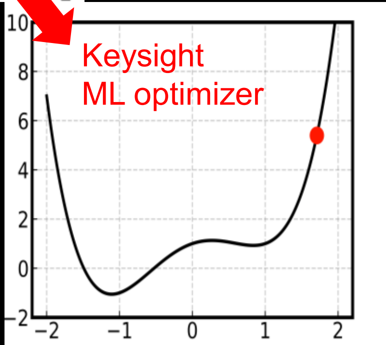
ML Toolkit: ML Optimizer

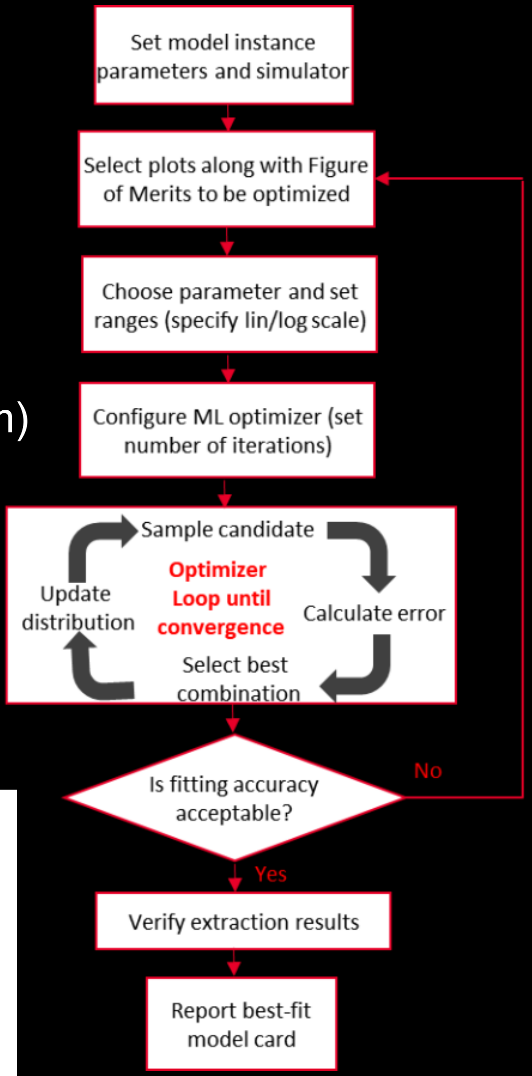
Supported in both IC-CAP 2025 and MBP 2026

- First commercial derivative-free ML-based optimizer introduced in IC-CAP 2025 for DM
- Derivative-based optimizers (e.g., Stochastic-Gradient, L-M) are inefficient
  - ×Fail to converge for >10 parameters
  - ×Leads to a complex flow with loops and inconsistent results
- ML optimizer based on past learning with forward guidance:
  - ✓Offers efficiency in high-dimensional spaces (W, T, Vg,..)
  - ✓faster convergence compared to other derivative-free optimizers (e.g. genetic, particle swarm)
  - ✓Special cost function (Δε) enhances robustness
  - ✓Reduces extraction time from days to hours/mins








Set model instance parameters and simulator

Select plots along with Figure of Merits to be optimized

Choose parameter and set ranges (specify lin/log scale)

Configure ML optimizer (set number of iterations)

Sample candidate

Calculate error

Select best combination

Update distribution

Optimizer Loop until convergence

Is fitting accuracy acceptable?

No

Yes

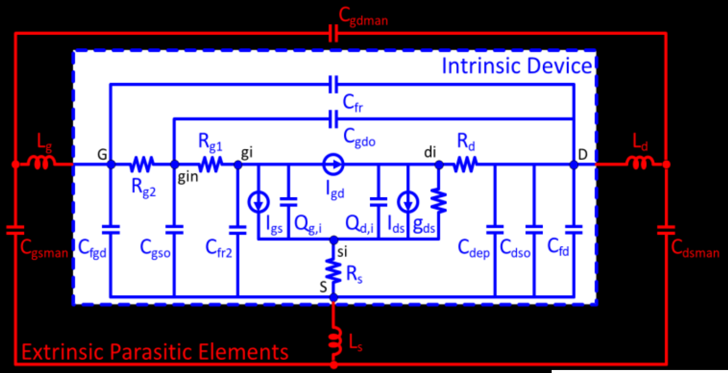
Verify extraction results

Report best-fit model card

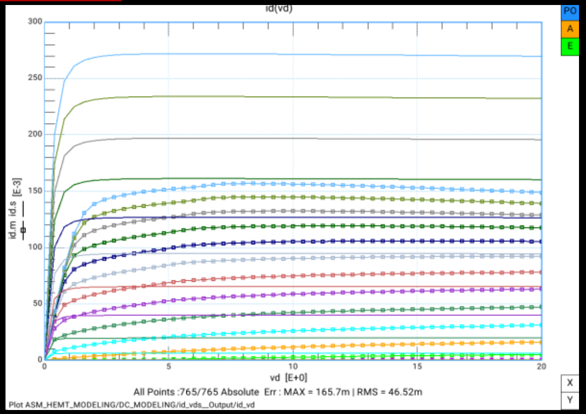
ML Toolkit: ASM-HEMT (GaN) Model Auto-extraction Flow

Problem: Optimize 35 parameters of a DC model with a 4×50 µm GaN-in-Si HEMT simultaneously

- Parameter extraction for ASM-HEMT begins with DC model parameter extraction
- Takes 7500 iterations to fit all 35 parameters at once in a single step.
- User just specifies the RMS error as exit criteria and number of iterations.
- ML optimizer helps automate modeling tasks for faster and consistent results.



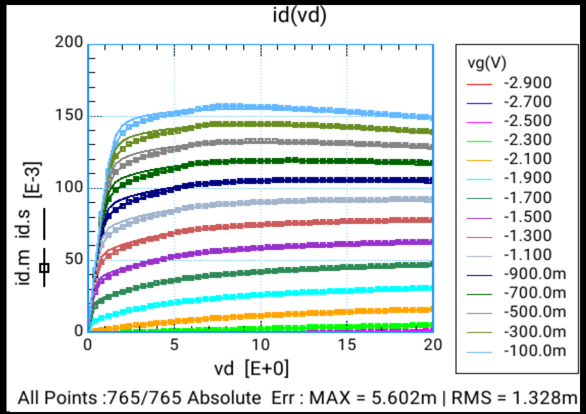
Starting point



All Points :765/765 Absolute Err : MAX = 165.7m | RMS = 46.52m

Plot ASM_HEMT_MODELING/DC_MODELING/id_vds__Output/id_vd

Results



All Points :765/765 Absolute Err : MAX = 5.602m | RMS = 1.328m

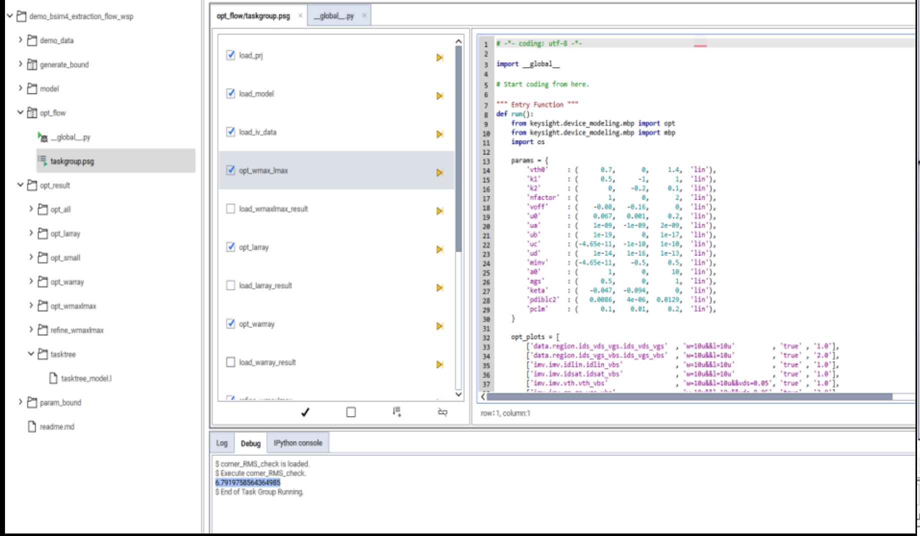
Parameter	Initial	Value
RTH0	32	31.8
VOFF	-2	-1.99
NFACTOR	300m	444m
U0	225m	182m
UA	200n	16.8n
UB	0.10a	0.04a
VSAT	200k	250k
LAMBDA	1.00m	1.50m
UTE	-750m	-100m
ETA0	50.0m	51.6m
VDSCALE	4	4.77
CDSCD	100m	49.1m
RSC	750u	456u
RDC	750u	627u
DELTA	3.5	2
THESAT	3	4
VSATACCS	75.0k	126k
NS0ACCS	500P	1.15E
NS0ACCD	500P	159P
U0ACCS	150m	175m
U0ACCD	150m	126m
MEXPACCS	3	2.71
MEXPACCD	3	2.9
IMIN	10.0f	620f
GDSMIN	100.0n	1.00p
UTES	-12.5	-10.6
UTED	-12.5	-7.03
IGDDIO	10.5	7.65
IGSDIO	10.5	14
NJGD	10	14.7
NJGS	10	7.97
RIGDDIO	75.0n	65.7n
RIGSDIO	50.0n	99.8n
RNJGD	8	11.8
RNJGS	25	24.7

R. P. Martinez *et al.*, "Compact Model Parameter Extraction via Derivative-Free Optimization," in *IEEE Access*, vol. 12, pp. 123224-123235, 2024, doi: 10.1109/ACCESS.2024.3453198

ML Toolkit: BSIM4 (Advanced CMOS Nodes) Model Auto-extraction Flow

Problem: Develop a full global model extraction flow

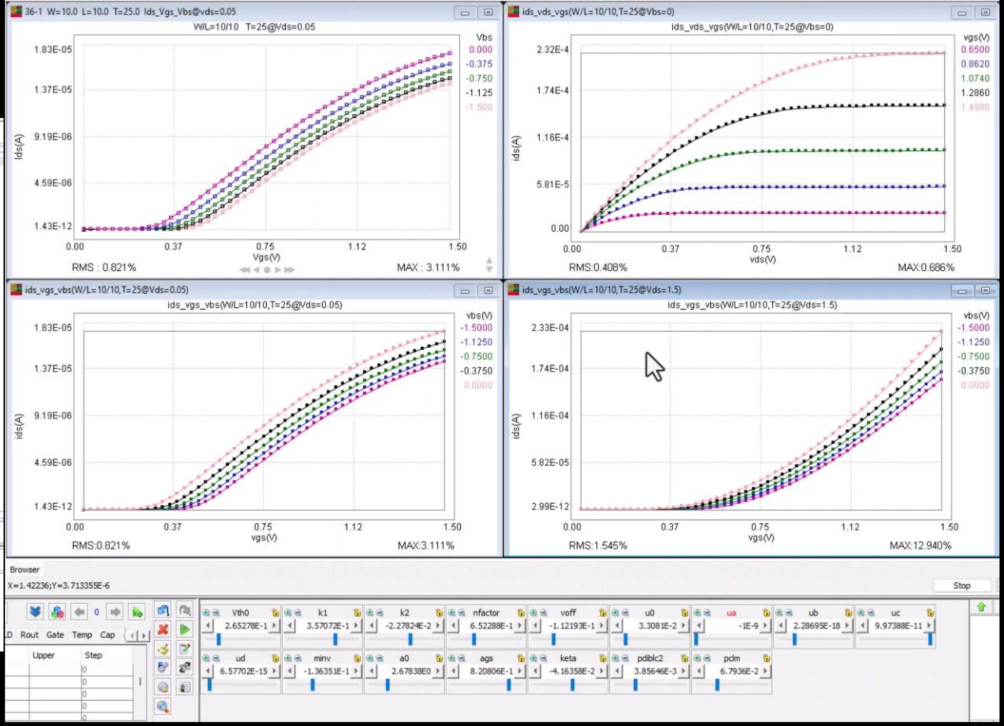
- Key device characteristics include Id-Vg, Id-Vd, Gm-Vg, Gds-Vd etc.
- Scaling plots such as Vtlin vs. L, Vtsat vs. W are also used
- Pre-defined parameter ranges are plugged inside the model
- Over 80+ parameters can be optimized simultaneously



☑ load_prj
☑ load_model
☑ load_iv_data
☑ opt_wmax_lmax
☐ load_wmaxlmax_result
☑ opt_larray
☐ load_larray_result
☑ opt_warray
☐ load_warray_result

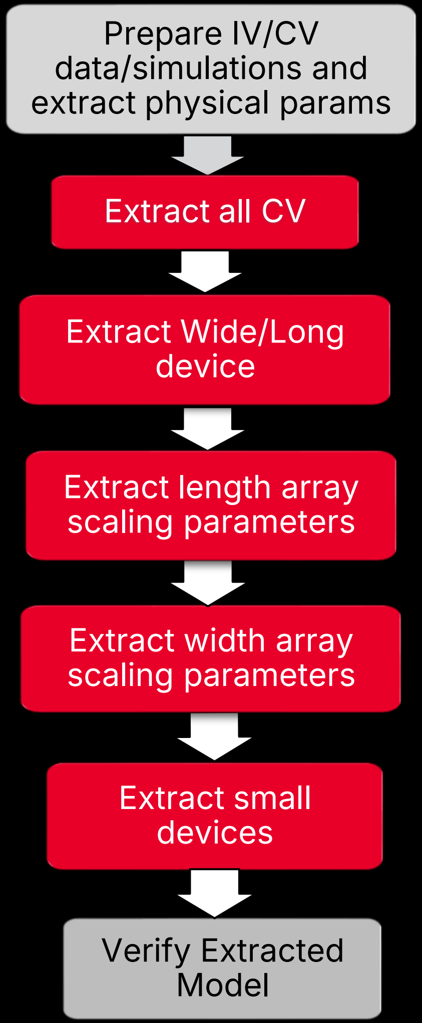
```
# -*- coding: utf-8 -*-

import __global__

# Start coding from here.

""" Entry Function """
def run():
    from keysight.device_modeling.mbp import opt
    from keysight.device_modeling.mbp import mbp
    import os

    params = {
        'vth0'     : (      0.7,       0,      1.4,  'lin'),
        'k1'       : (      0.5,      -1,        1,  'lin'),
        'k2'       : (        0,    -0.2,      0.1,  'lin'),
        'nfactor'  : (        1,       0,        2,  'lin'),
        'voff'     : (    -0.08,   -0.16,        0,  'lin'),
        'u0'       : (    0.067,   0.001,      0.2,  'lin'),
        'ua'       : (    1e-09,  -1e-09,    2e-09,  'lin'),
        'ub'       : (    1e-19,       0,    1e-17,  'lin'),
        'uc'       : (-4.65e-11,  -1e-10,    1e-10,  'lin'),
        'ud'       : (    1e-14,   1e-16,    1e-13,  'lin'),
        'minv'     : (-4.65e-11,    -0.5,      0.5,  'lin'),
        'a0'       : (        1,       0,       10,  'lin'),
        'ags'      : (      0.5,       0,        1,  'lin'),
        'keta'     : (   -0.047,  -0.094,        0,  'lin'),
        'pdiblc2'  : (   0.0086,   4e-06,   0.0129,  'lin'),
        'pclm'     : (      0.1,    0.01,      0.2,  'lin'),
    }

    opt_plots = [
        ['data.region.ids_vds_vgs.ids_vds_vgs'  , 'w=10u&&l=10u'          , 'true' , '1.0'],
        ['data.region.ids_vgs_vbs.ids_vgs_vbs'  , 'w=10u&&l=10u'          , 'true' , '2.0'],
        ['imv.imv.idlin.idlin_vbs'              , 'w=10u&&l=10u'          , 'true' , '1.0'],
        ['imv.imv.idsat.idsat_vbs'              , 'w=10u&&l=10u'          , 'true' , '1.0'],
        ['imv.imv.vth.vth_vbs'                  , 'w=10u&&l=10u&&vds=0.05', 'true' , '1.0'],
```

```
$ corner_RMS_check is loaded.
$ Execute corner_RMS_check.
6.7919758564364985
$ End of Task Group Running.
```



X=1.42236;Y=3.713355E-6

Vth0 2.65278E-1
k1 3.57072E-1
k2 -2.27824E-2
nfactor 6.52288E-1
voff -1.12193E-1
u0 3.3081E-2
ua -1E-9
ub 2.28695E-18
uc 9.97388E-11
ud 6.57702E-15
minv -1.36351E-1
a0 2.67838E0
ags 8.20806E-1
keta -4.16358E-2
pdiblc2 3.85646E-3
pclm 6.7936E-2



Prepare IV/CV data/simulations and extract physical params

Extract all CV

Extract Wide/Long device

Extract length array scaling parameters

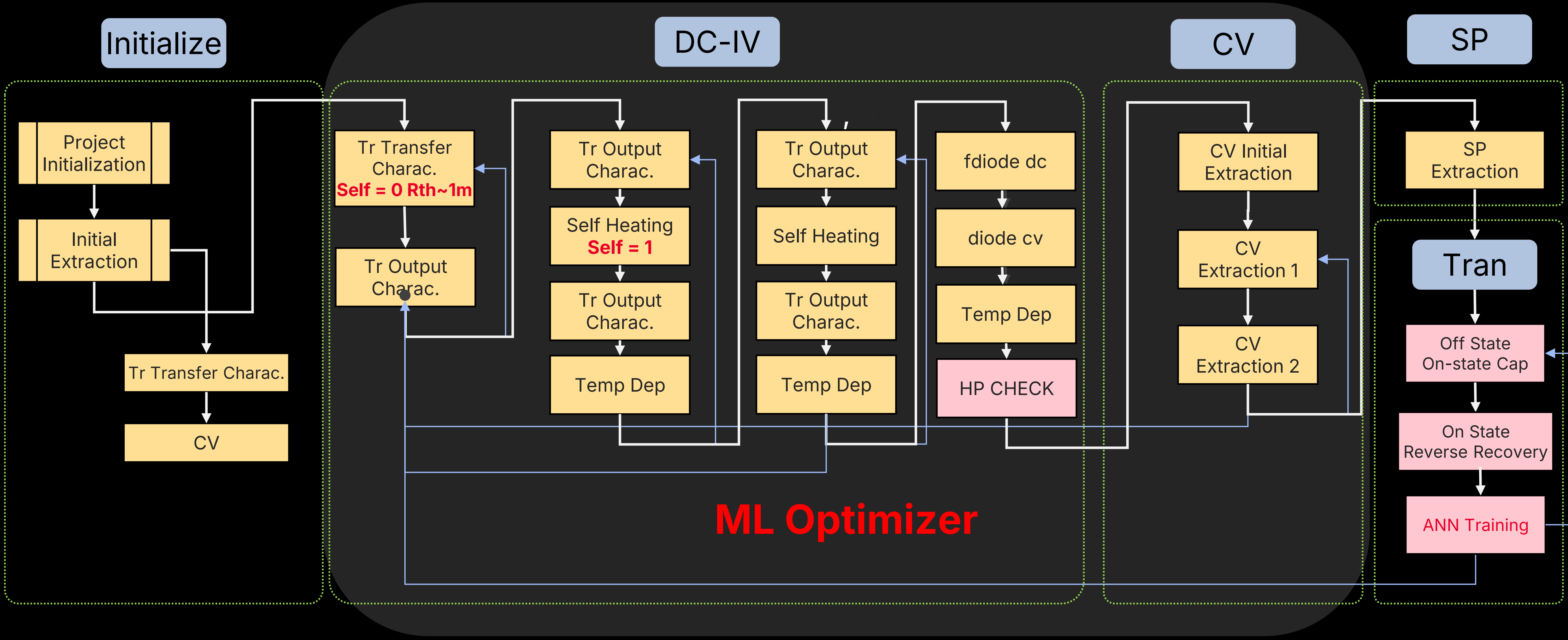
Extract width array scaling parameters

Extract small devices

Verify Extracted Model

ML Toolkit: Keysight PowerMOS (SiC) Model Auto-extraction Flow

All extraction steps finish in just 3 hours



Initialize

- Project Initialization
- Initial Extraction
- Tr Transfer Charac.
- CV

DC-IV

- Tr Transfer Charac. **Self = 0 Rth~1m**
- Tr Output Charac.

- Tr Output Charac.
- Self Heating **Self = 1**
- Tr Output Charac.
- Temp Dep

- Tr Output Charac.
- Self Heating
- Tr Output Charac.
- Temp Dep

- fdiode dc
- diode cv
- Temp Dep
- HP CHECK

CV

- CV Initial Extraction
- CV Extraction 1
- CV Extraction 2

SP

- SP Extraction

Tran

- Off State On-state Cap
- On State Reverse Recovery
- ANN Training

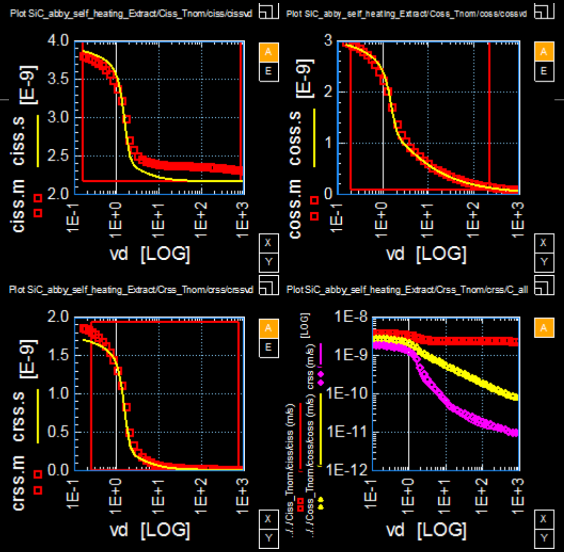
ML Optimizer

Automated run

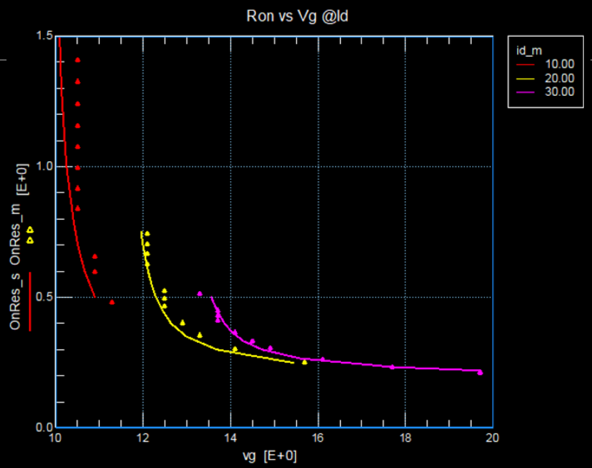
Partial (step-by-step) run

ML Toolkit: PowerMOS Model Auto-extraction results

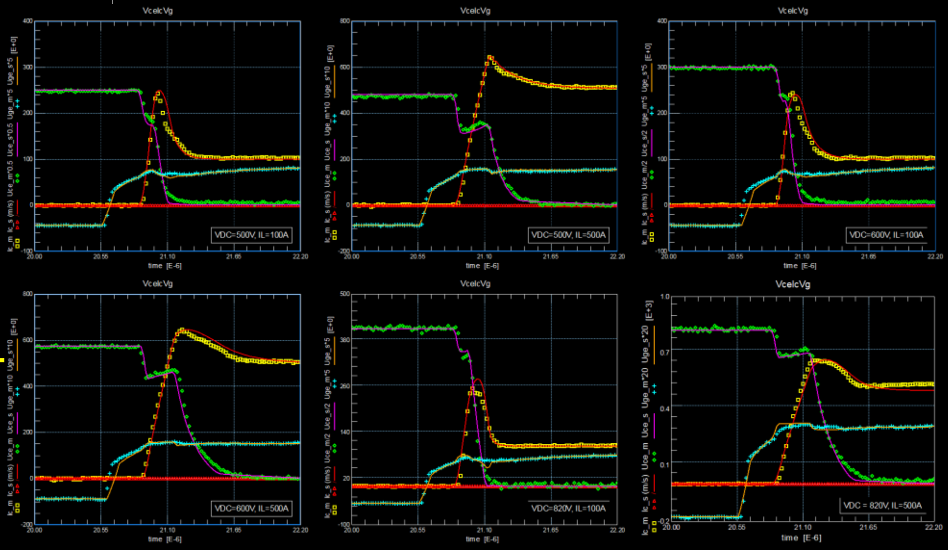
C-V Extraction



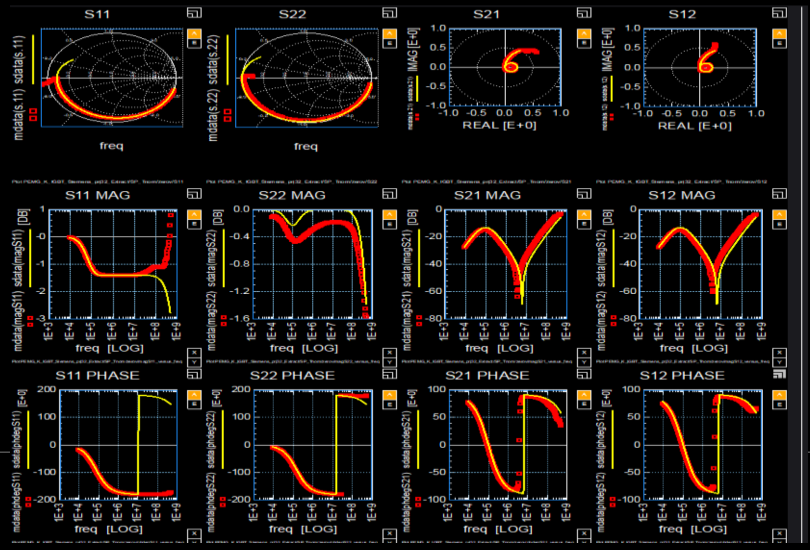
I-V Extraction

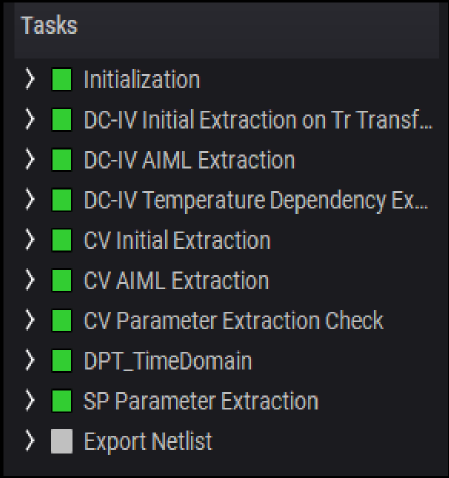


DPT On-state Cap Extraction



Parasitic Extraction (S-par)

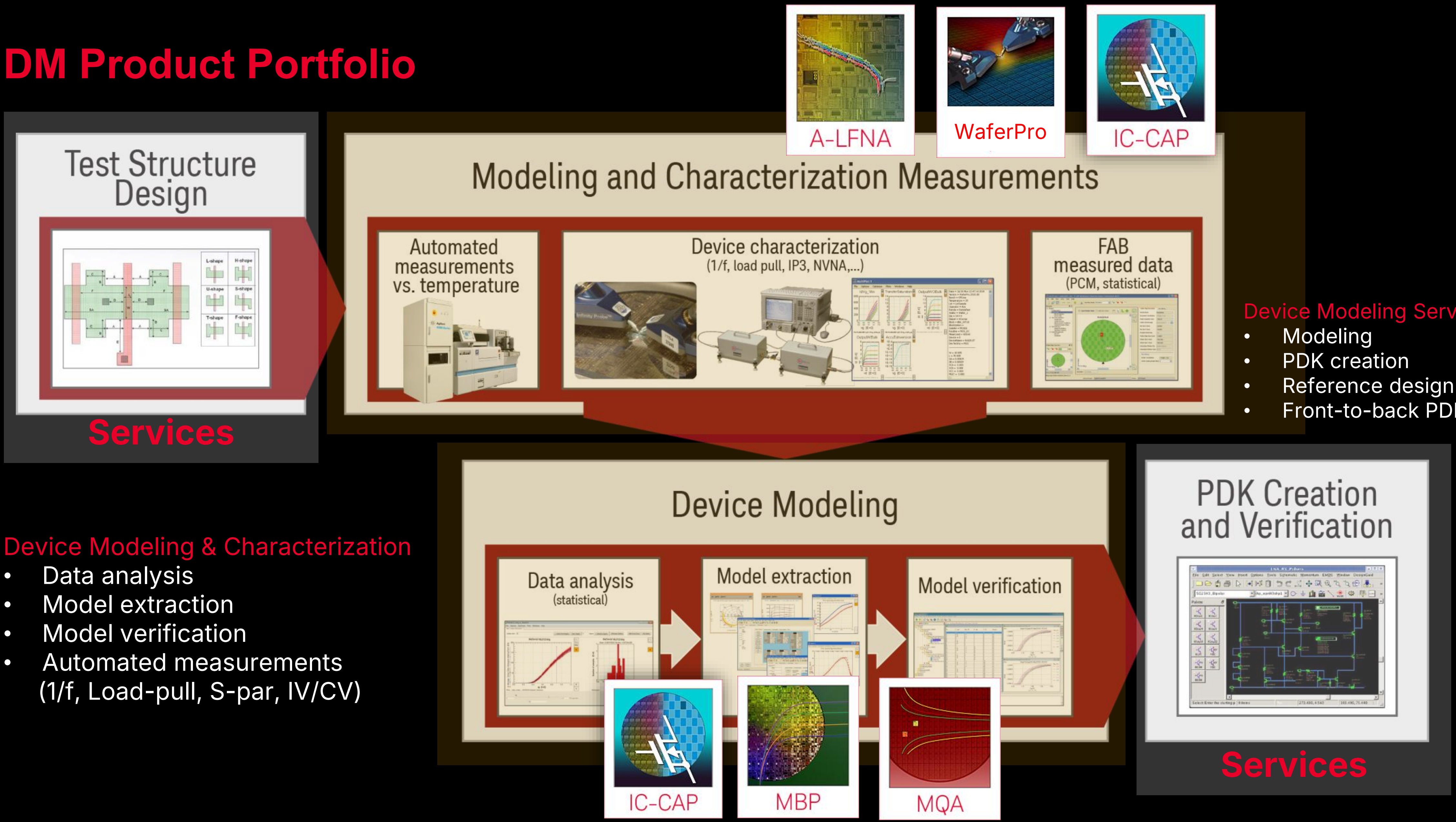



Tasks

- 🟩 Initialization
- 🟩 DC-IV Initial Extraction on Tr Transf...
- 🟩 DC-IV AIML Extraction
- 🟩 DC-IV Temperature Dependency Ex...
- 🟩 CV Initial Extraction
- 🟩 CV AIML Extraction
- 🟩 CV Parameter Extraction Check
- 🟩 DPT_TimeDomain
- 🟩 SP Parameter Extraction
- ⬜ Export Netlist

A. Shih, H. Zhang, S. Haensel and S. Lee, "A Double Pulse Test Based IGBT On-State Capacitance Extraction of ANN-assisted Hybrid Model," *PCIM Conference 2025; International Exhibition and Conference for Power Electronics, Intelligent Motion, Renewable Energy and Energy Management*, Nürnberg, Germany, 2025, pp. 1008-1014, doi: 10.30420/566541128.

DM Product Portfolio



A-LFNA

WaferPro

IC-CAP

Test Structure Design

Services

Modeling and Characterization Measurements

Automated measurements vs. temperature

Device characterization
(1/f, load pull, IP3, NVNA,...)

FAB measured data
(PCM, statistical)

Device Modeling

Data analysis
(statistical)

Model extraction

Model verification

IC-CAP

MBP

MQA

PDK Creation and Verification

Services

Device Modeling Services
- Modeling
- PDK creation
- Reference design flows
- Front-to-back PDK support

Device Modeling & Characterization
- Data analysis
- Model extraction
- Model verification
- Automated measurements
(1/f, Load-pull, S-par, IV/CV)

Resources

- What’s New in Device Modeling webpage:
  https://www.keysight.com/us/en/lib/resourc es/software-releases/whats-new-in-devicemodeling.html

- Recent blogs:
  - https://semiengineering.com/ai-meets-device-modeling-transforming-compact-modeling-with-machine-learning/
  - https://www.keysight.com/blogs/en/tech/sim-des/from-equations-to-intelligence

- Products:
  - W7009E: IC-CAP ANN modeling toolkit
  - W7301B: IC-CAP Model Generator Plus
  - W7300B: IC-CAP Device Modeling Platform
  - W6023E: MBP Machine Learning Toolkit
  - W6329B: MBP core, QA Express, and Machine Learning toolkit

Q & A

KEYSIGHT