Hybrid Compact Modeling Strategy: A Fully-Automated and Accurate Compact Model with Physical Consistency

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OUTLINE

- **Introduction**
- **Proposed Hybrid Compact Model**
  - **Bidirectional Physics-based Compact Model Generator - Neural Networks (PMG-NN)**
  - **Deep Global Correction - Neural Networks (DGC-NN)**
- **Conclusions**

Physics-based Compact Model (Physics-CM)

Easy, fast

Compact Models

Drift-Diffusion equations

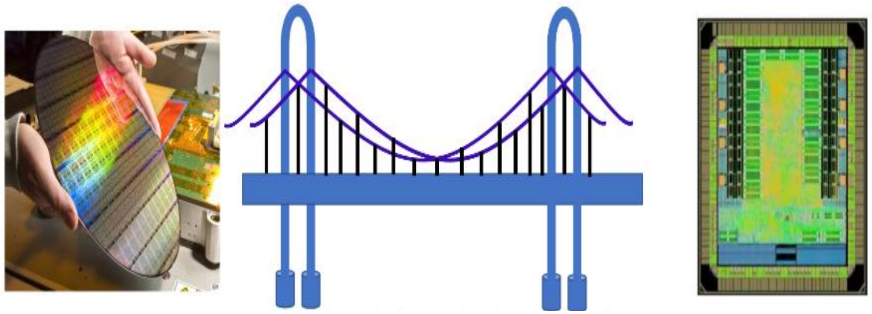
Hydrodynamic equations

Quantum Monte Carlo methods

Green's functions methods

Schrödinger equations

Complex, Slow



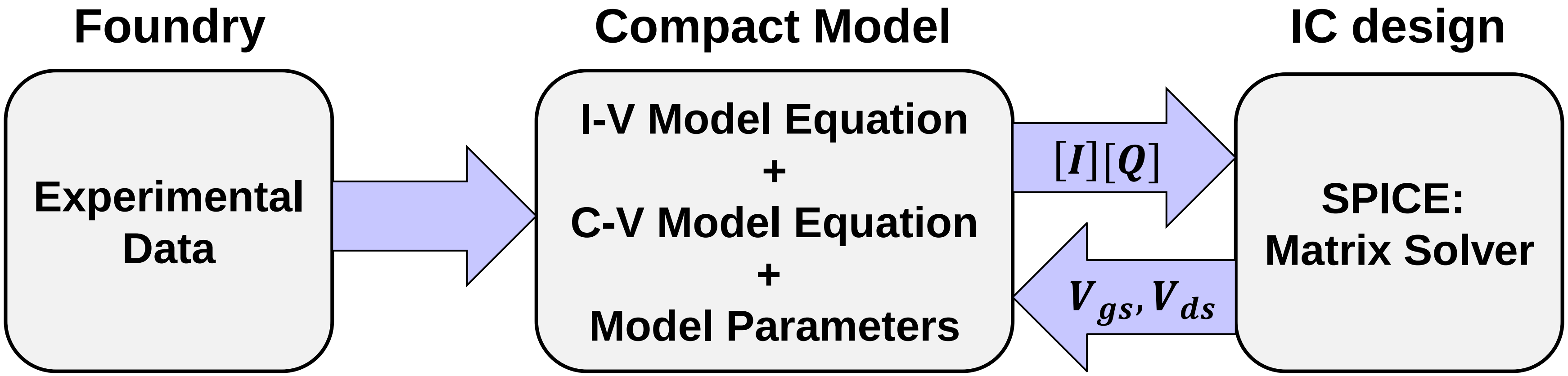
Foundry Compact Model IC design

▲ Hierachy of transport models [1] ▲ Role of the compact model [2]

- **There are various transport models used to explain the behavior of semiconductor devices**
- **Compact model is the simplest and fastest model**
- **Compact model serves as a bridge between the foundry and IC design**

[1] Vasileska, Dragica, Stephen M. Goodnick, and Gerhard Klimeck. Computational Electronics: semiclassical and quantum device modeling and simulation. CRC press, 2017.
[2] Dabhi, Chetan Kumar. Compact Modeling of FinFET and FDSOI FET: GIDL, Noise, RF and Negative Capacitance Effect. Diss. Doctoral dissertation, INDIAN INSTITUTE OF TECHNOLOGY KANPUR, 2021.

Physics-based Compact Model

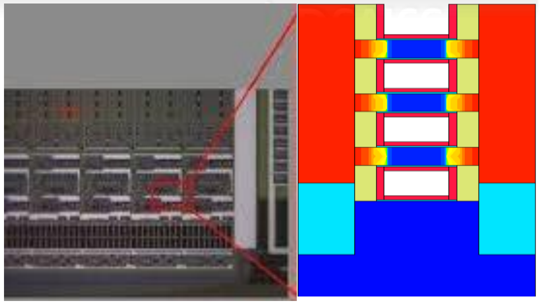


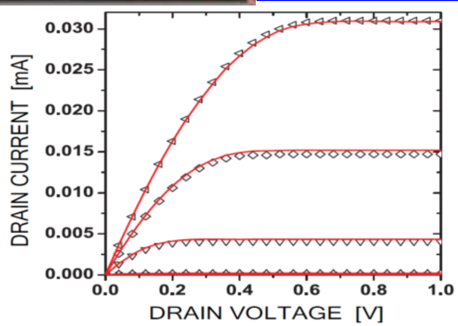
▲ Detail role of the compact model [2]

- **Compact Model = Simple Model for Circuit Sim.**
  - A series of closed-form mathematical equations
  - Input: terminal voltages
  - Output: branch currents, terminal charges

Physics-based Compact Model

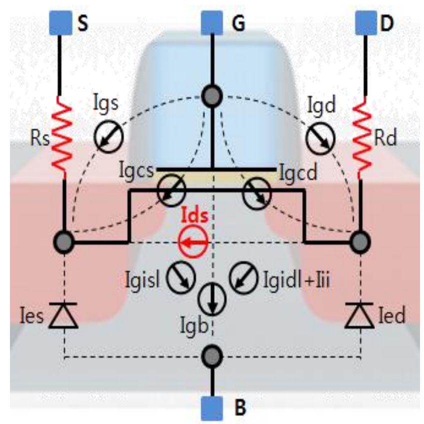
Process, Device





Compact Model = Model Parameters + Equations

Equivalent Circuit



Analytical Equation

$$\boldsymbol{I_{ds}} = KP\frac{W}{L}\cdot\left(V_{gs} - V_{th0} - \frac{F_B(\boldsymbol{R_d}, \boldsymbol{R_s})}{2}V_{ds}\right)\cdot V_{ds}$$

Verilog-A language

```
module FinFET(G,D,S,B);
parameter   real   KP;
parameter   real   Vth0;
parameter   real   FB;

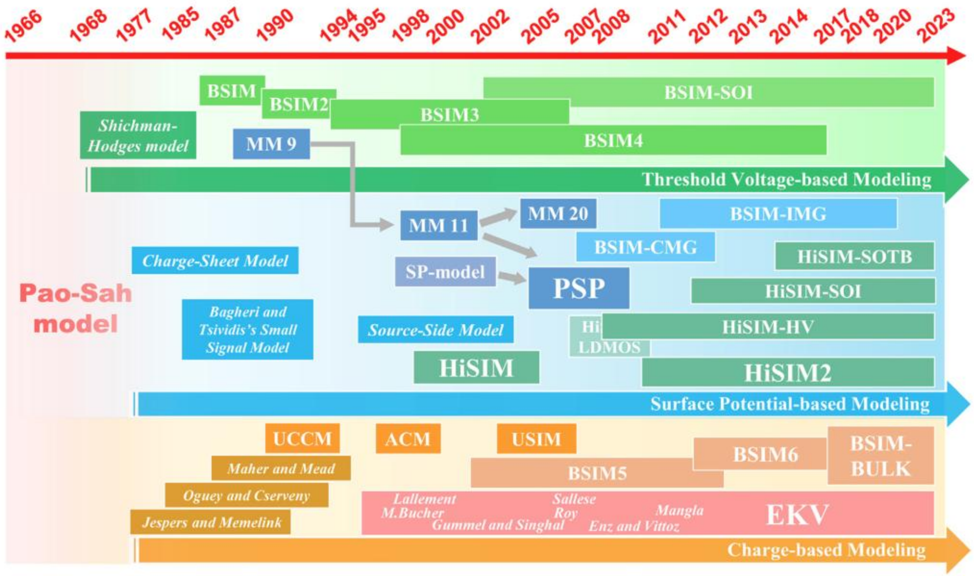
I(ds) <+ KP *W/L*(Ve)*Vds;
```

→ **Model Parameters**

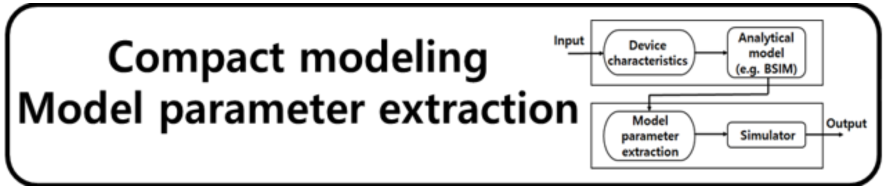
→ **Equations**

- **Experimental data: I-V and C-V under various process and bias conditions**
- **Compact model: an equivalent circuit consisting of many model parameters and equations**
- **Accurate compact model is important for circuit sim.**

Issue 1. Developing Closed-form Eq.



▲ Evolution chart of mainstream compact models [3]



$$\frac{\partial^2\psi}{\partial x^2}+\frac{\partial^2\psi}{\partial y^2}=\frac{q}{\varepsilon_{\mathrm{ch}}}\left(\frac{n_i^2}{N_{ch}}e^{\frac{\psi-V_{ch}}{v_T}}+N_{ch}\right)$$

$$v_G-v_o-v_{ch}=-q_m+\ln(-q_m)+\ln\left(\frac{q_t^2}{e^{q_t}-q_t-1}\right)$$

$$v_o=v_{FB}-q_{dep}-\ln\left(\frac{2qn_i^2A_{ch}}{v_TC_{ins}N_{ch}}\right) \quad (3)$$

$$q_t=(q_m+q_{dep})r_N \quad (4)$$

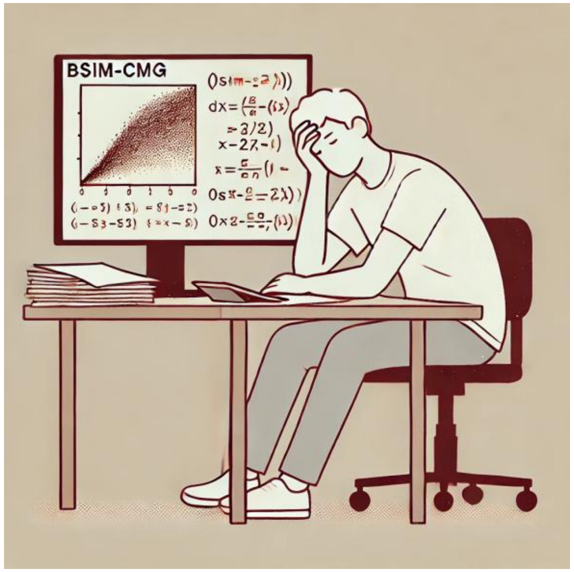
$$i_{DS}=-\int_{q_{m,S}}^{q_{m,D}}q_m\frac{dv_{ch}}{dq_m}dq_m \quad (8)$$

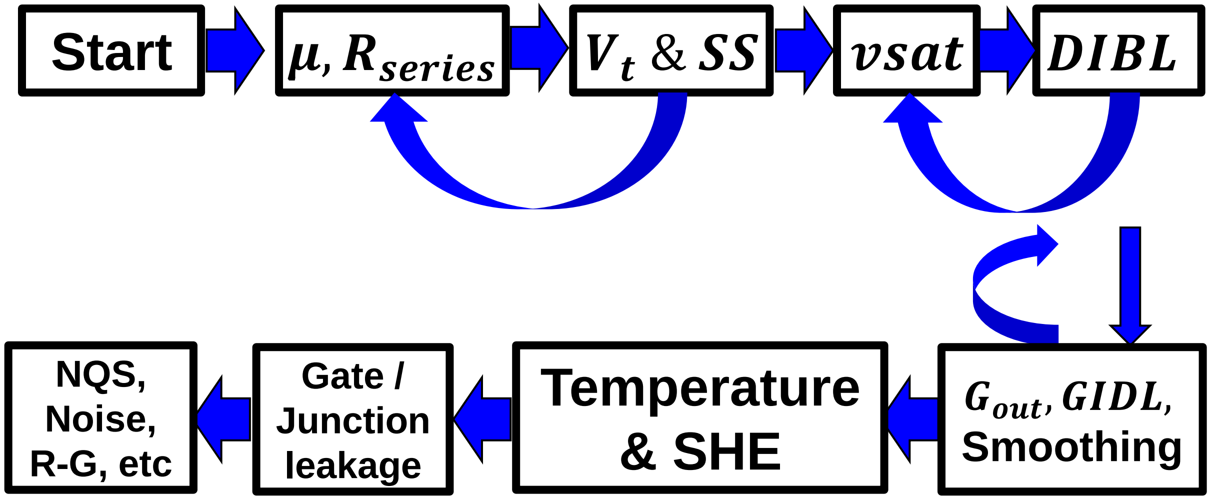
▲ BSIM-CMG compact model [4]

- **Researchers have difficulty in developing closed-form equations of emerging devices (> 2~3 years)**
- **Bottleneck of design technology co-optimization**

[3] Li, Xufan, et al. "Overview of emerging semiconductor device model methodologies: From device physics to machine learning engines." *Fundamental Research* (2024).
[4] A. Dasgupta and C. Hu, "BSIM-CMG compact model for IC CAD: From FinFET to gate-all-around FET technology," J. Microelectronic Manuf., vol. 3, Dec. 2020, Art. no. 20030402, doi: 10.33079/jomm.20030402.

Issue 2. Model Parameter Extraction



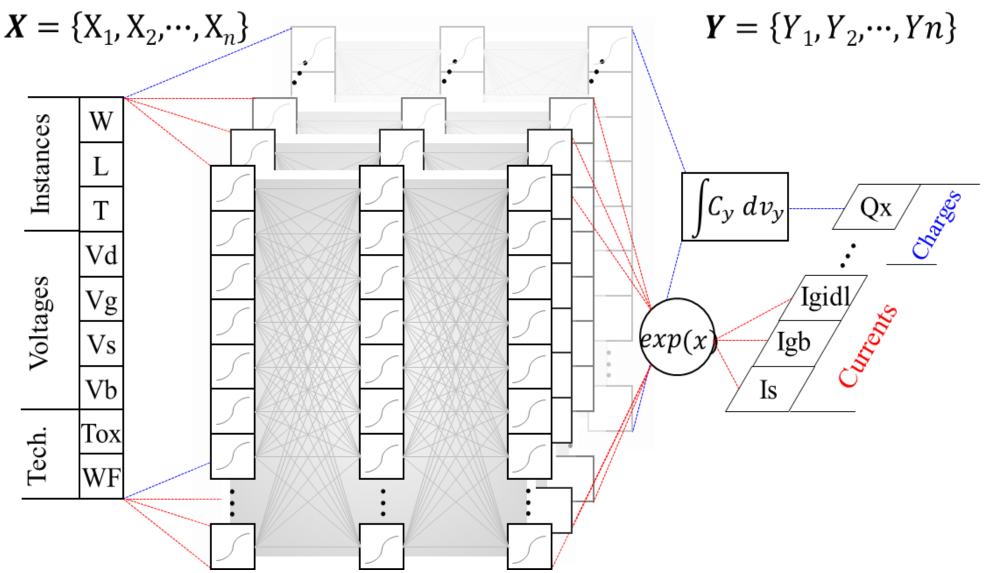


▲ Extraction flow of BSIM-CMG model parameters [5]

- **Recently, there are many sub-models with over 2,000 model parameters**
- **Extracting these model parameters requires a lot of time and modeling efforts (days to weeks)**

[5] BSIM-CMG110.0.0Technical Manual. Accessed: Jan. 01, 2016. [Online]. Available: https://bsim.berkeley.edu/models/bsimcmg/

ANN-based Compact Model (ANN-CM)



$$Y = W_3 \times g(W_2 \times g(W_1 \times X + B_1) + B_2) + B_3$$

$$I_{XY} = I_0 \times 10^{(Y_{XY})} \times V_{ds} \quad \text{(DC)}$$

$$Q_X = Q_0 * Y_{Q_X}$$

$$I_x = -\frac{dQ_x}{dt} \quad \text{(Transient)}$$

▲ ANN-based compact model

- Deterministic ML model can be represented as closed-form equation
- ANN can be converted to compact model using Verilog-A
- Technology independent, accurate, automatic
- Strong candidate for the future compact model

Physics-CM to Hybrid-CM using ML

Model		Physics-CM	ANN-CM	Hybrid-CM
Base Equations		Physics-based, Empirical parameters	MLP matrix, Activation function	Physics-based, Empirical parameters
Available Models		Various models (GIDL, noise, SHE...)	I-V, C-V (Under active development)	Various models (GIDL, noise, SHE...)
Modeling Time	Development	Slow (> 2~3 years.)	Fast (< 2 hours)	Fast (< 2 hours)
	MPE	Slow (a few weeks)		Fast (a few minutes)
Perf.	Accuracy	Low	High	High
	Model coverage	Narrow	Wide	Wide
Interpretability (User-friendly)		High	Low	High
Application		Foundry, reliability sim.	DTCO, emerging device sim.	Foundry, DTCO

- We propose **Hybrid-CM** based on Physics-CM
- Hybrid-CM has **various** sub-models, **interpretability**, **fast** modeling time, **high** accuracy and **wide** model coverage

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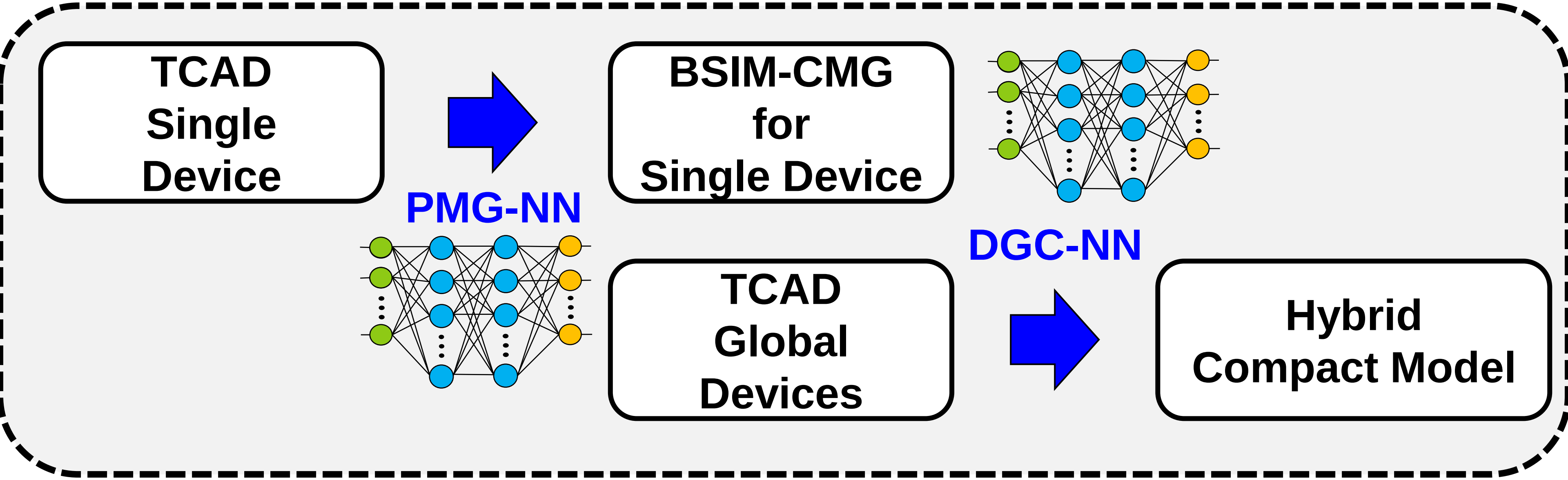
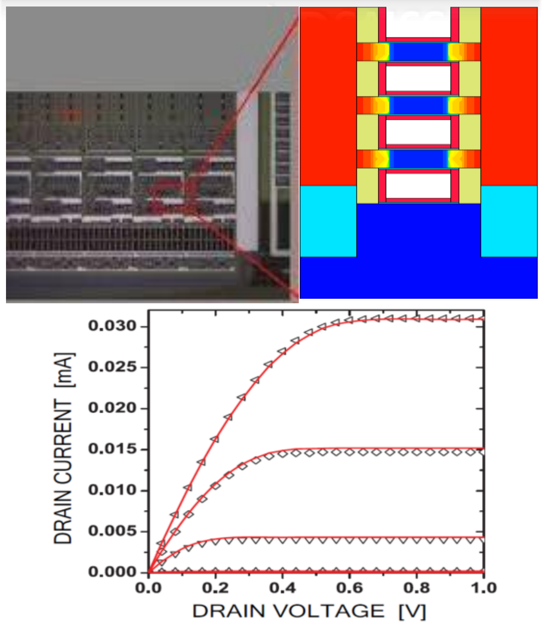
Proposed Hybrid-CM Workflow



- Physics-CM generator-NN (PMG-NN) can automate model parameter extraction
- Deep global correction-NN (DGC-NN) can correct model equations

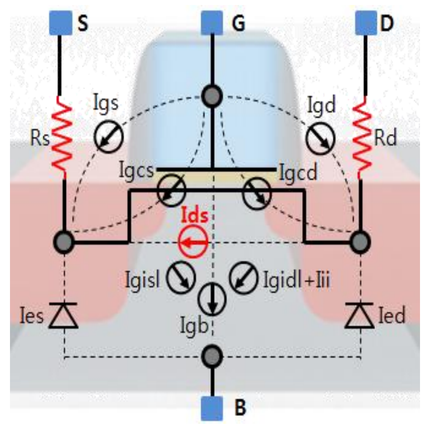
Physics-CM Generator-NN (PMG-NN)

Process, Device



Compact Model = Equations + Model Parameters

Equivalent Circuit



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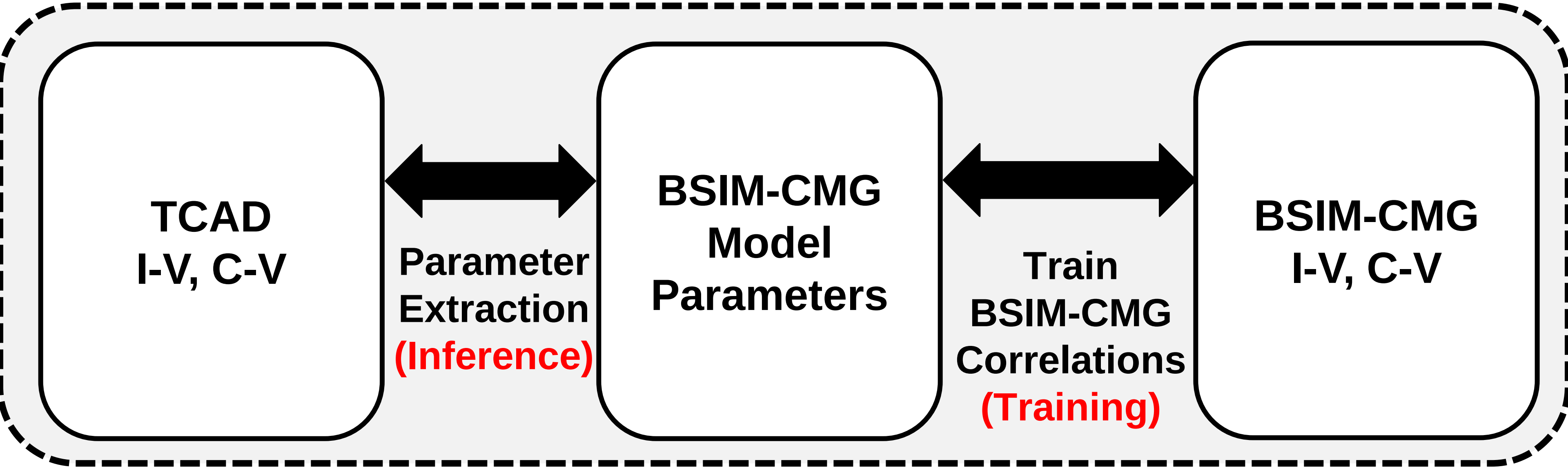
```

Model Parameters

Equations

- **Significant model parameter extraction time**
- **PMG-NN automatically extract model parameters**

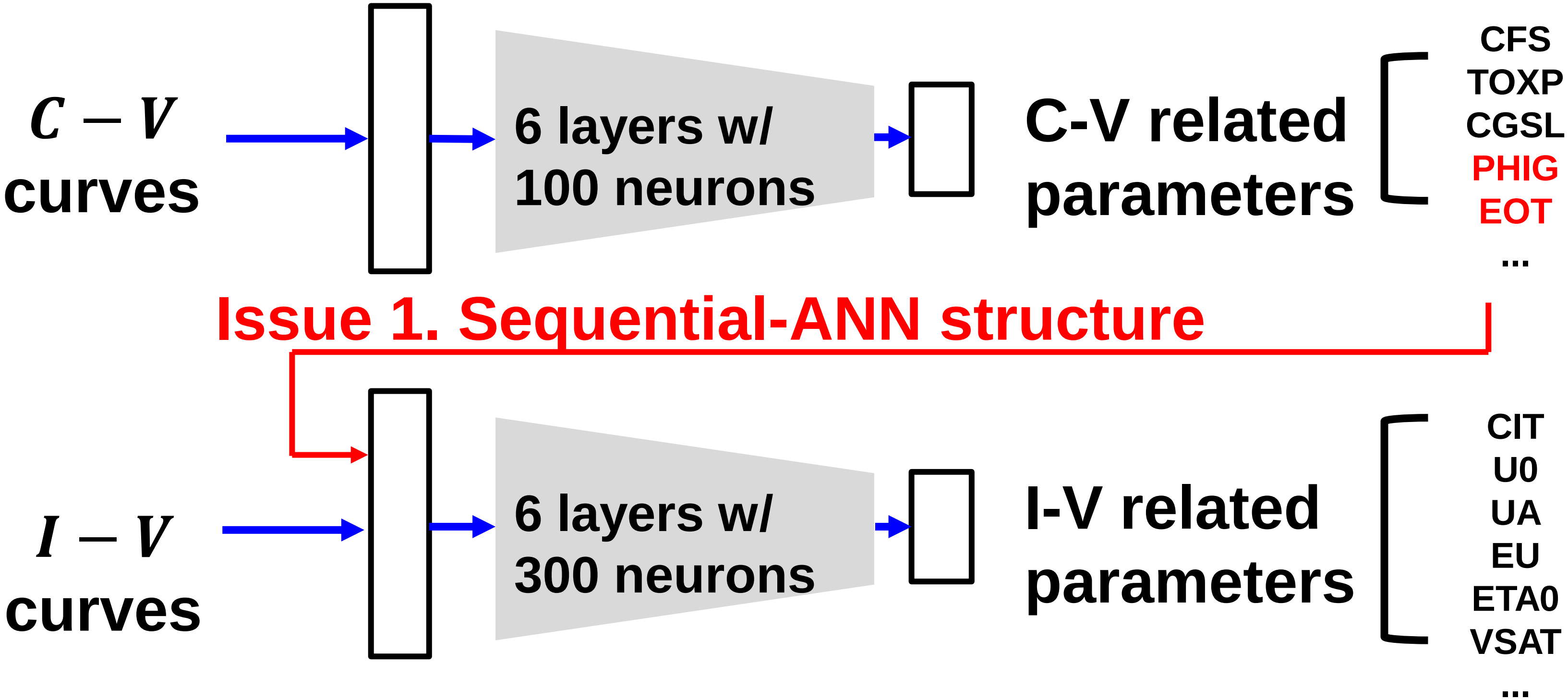
PMG-NN Workflow



- **(Training) Train the correlations between BSIM-CMG model parameters and BSIM-CMG I-V and C-V**

- **(Inference) Automatically extract BSIM-CMG model parameters that fit the TCAD I-V and C-V**

Issues of Conventional PMG-NN [6]



- Can't consider I-V and C-V simultaneously for PHIG, EOT
- Series of inefficient training data generation, NN-training, inference steps (Sequential-ANN structure)

➢ This structure slows down the overall flow significantly

[6] Kao, Ming-Yen, et al. "Deep learning-based BSIM-CMG parameter extraction for 10-nm FinFET." *IEEE Transactions on Electron Devices* 69.8 (2022): 4765-4768.

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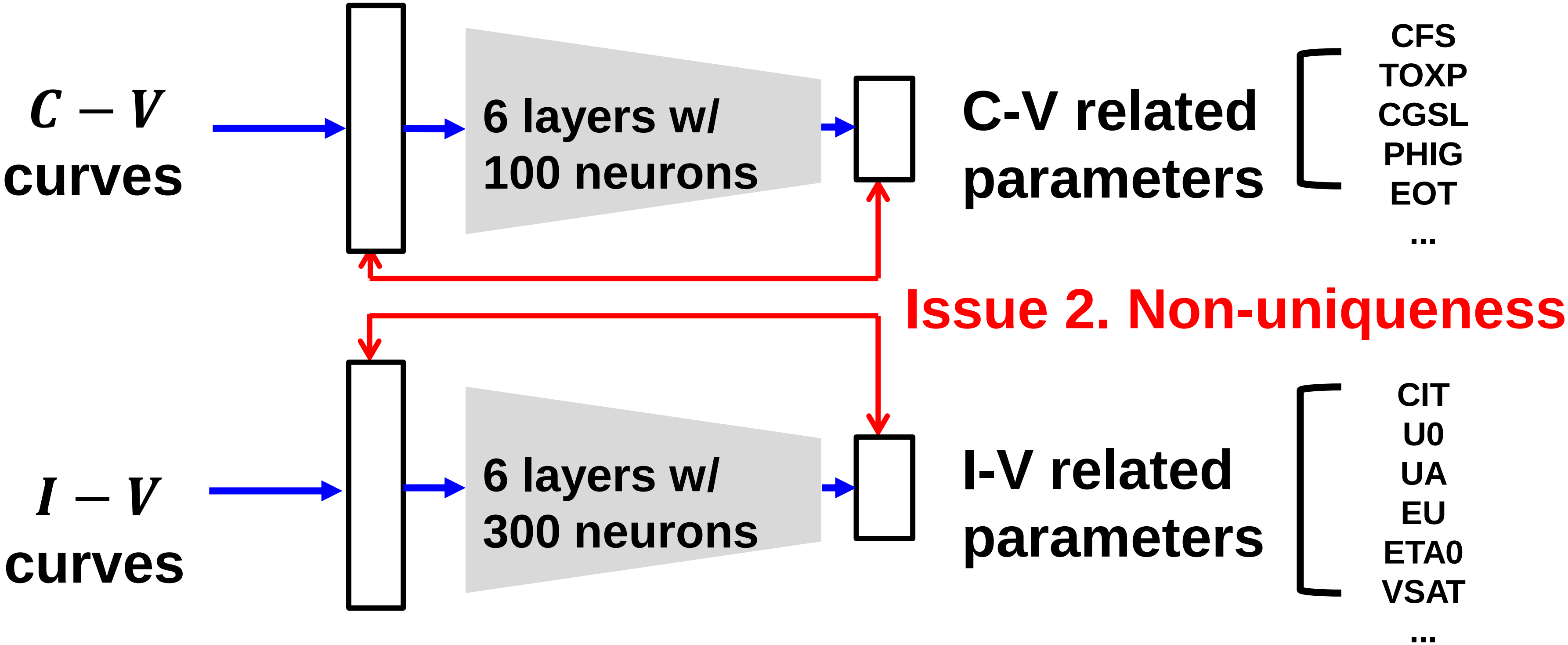
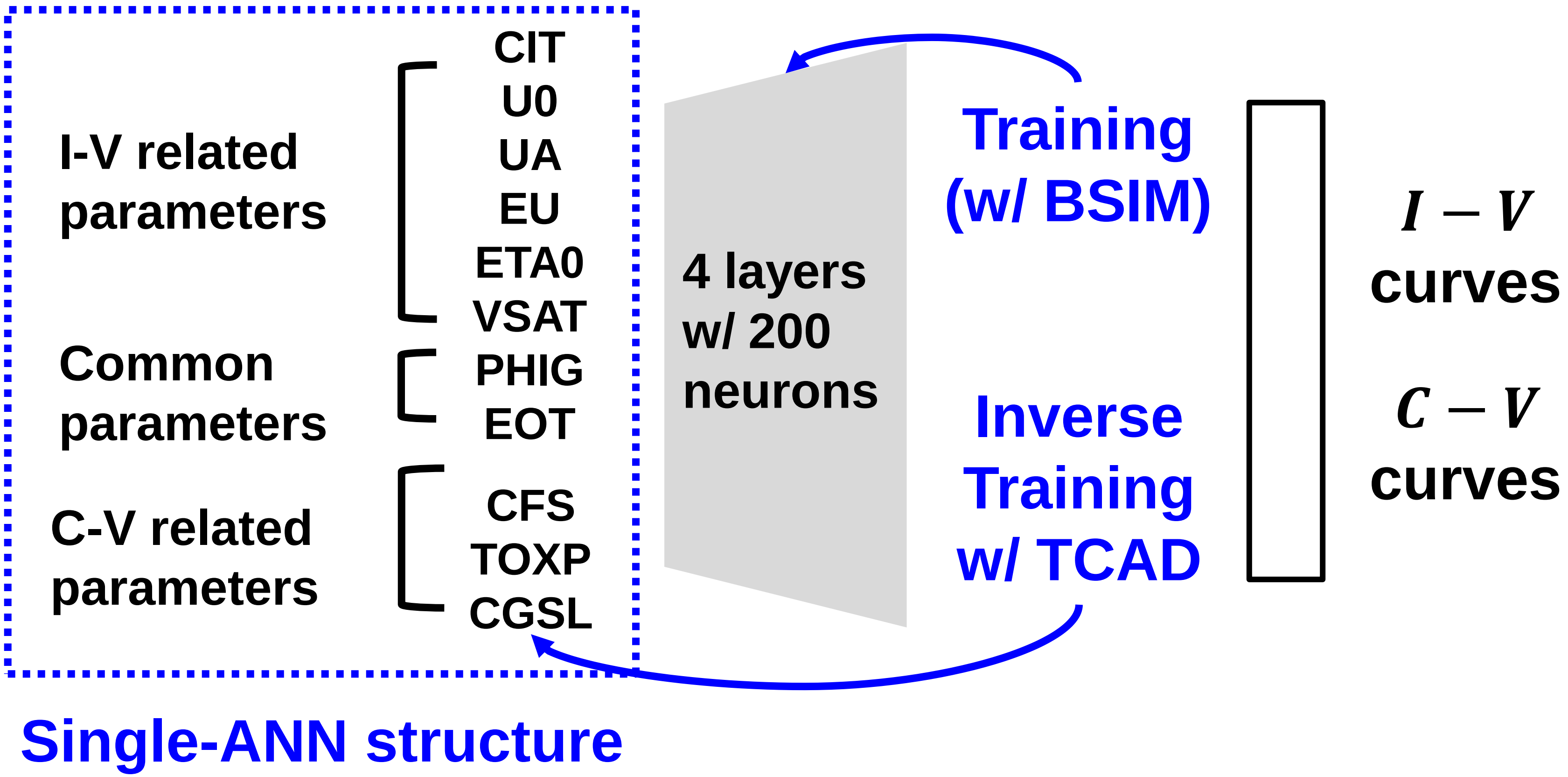


- **Multiple sets of model parameters can generate similar I-V and C-V curves (Non-uniqueness)**
  - **Increasing nonlinearity and challenging to achieve training convergence**
  - **Difficult to extract a wide range of training data**

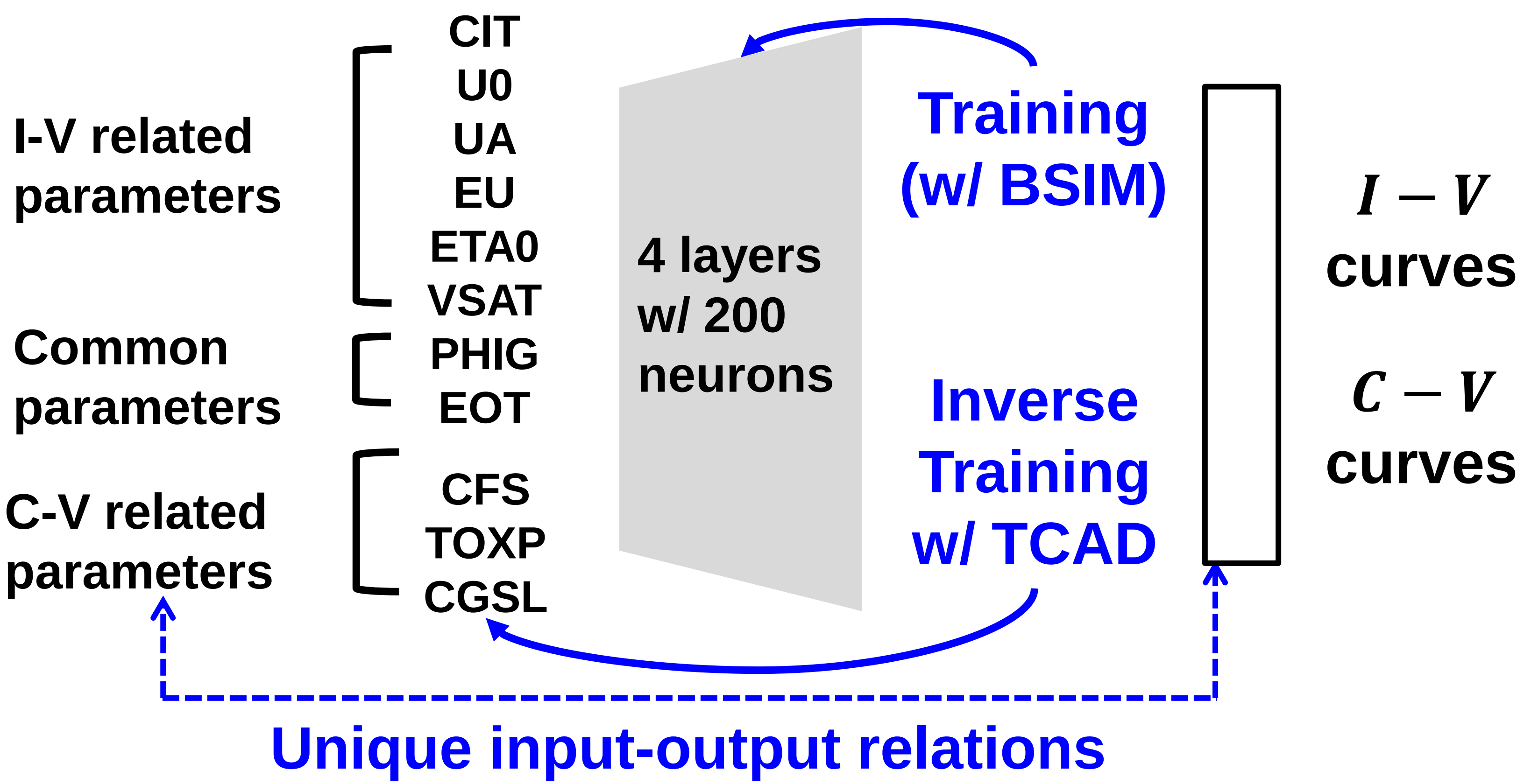
[6] Kao, Ming-Yen, et al. "Deep learning-based BSIM-CMG parameter extraction for 10-nm FinFET." *IEEE Transactions on Electron Devices* 69.8 (2022): 4765-4768.

Proposed Bidirectional PMG-NN



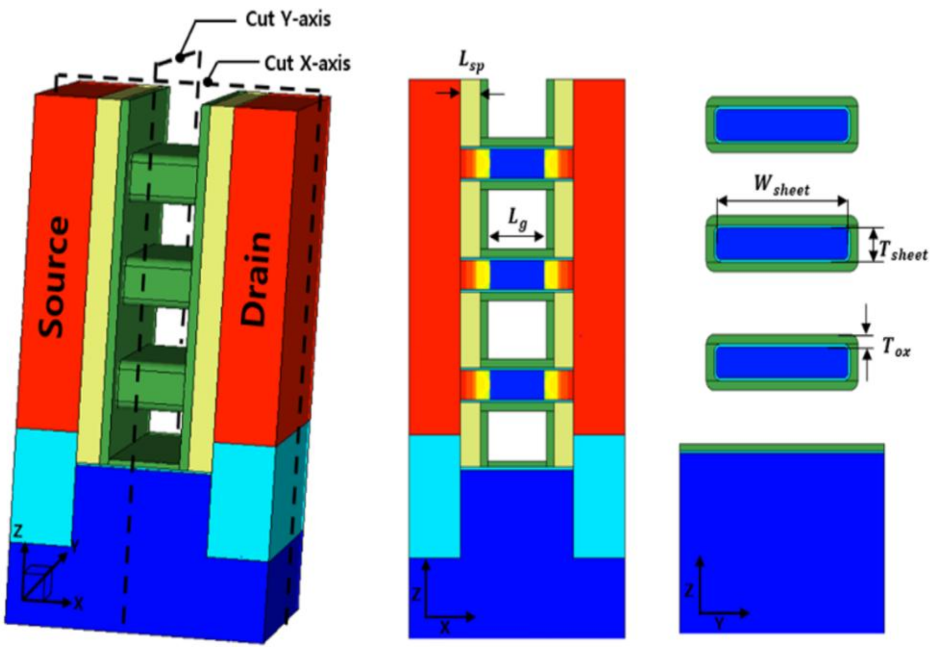
- **Single-ANN structure**
  - ➢ **One-step training data generation and NN training**
  - ➢ **Optimal MPE considering both I-V and C-V**

Proposed Bidirectional PMG-NN

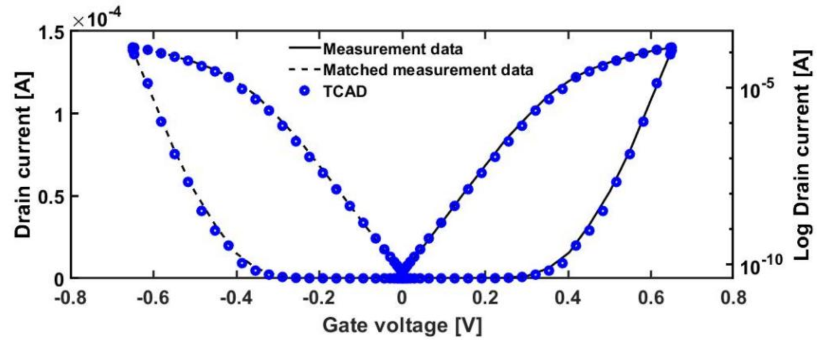


- Unique input-output relations
  - ➢ (Training) Significantly improves the training efficiency
  - ➢ (Inference) MPE with inverse training

TCAD Simulation Setup



	Parameters		Nominal values
Global variables	L_g [nm]		12
	T_{sheet} [nm]		5
	W_{sheet} [nm]		25
	L_{sp} [nm]		4
	EOT [nm]		0.6
Local variables	C_{doping} $[cm^{-3}]$	NMOS	1.4e16
		PMOS	2e16
	SD_{doping} $[cm^{-3}]$	NMOS	4e20
		PMOS	3e20
	Work function [ev]	NMOS	4.51
		PMOS	4.71



- **The NSFETs were designed and simulated using Synopsys TCAD [7]**
- **We calibrated TCAD model with measurement NSFET [8], achieving an 99% accuracy**

[7] Sentaurus Device User Guide, Version P-2019.03, Synopsys, Mar. 2019
[8] N. Loubet et al., "Stacked nanosheet gate-all-around transistor to enable scal ing beyond FinFET," in Proc. VLSI Symp. Dig., Jun. 2017, pp. T230-T231, doi: 10.23919/VLSIT.2017.7998183.

PMG-NN Dataset (100,000 BSIM samples)

	Parameter	Min	Max		Parameter	Min	Max
1	phig	4.18	4.42	9	CIT	1e-4	1
2	cratio	0.05	0.95	10	vsat	5000	95000
3	eot	3e-11	5.7e-10	11	rdsw	5	95
4	QMFACTOR	-50	50	12	eu	0.2	3.8
5	QMTCENCV	-50	50	13	etamob	0.5	9.5
6	CGSL	1e-15	1e-8	14	u0	8e-4	15.2e-3
7	PCLMCV	0.01	10	15	ua	0.024	0.456
8	CGEOA	0.1	1.9	16	ksativ	0.17	3.23
				17	pclm	0.01	10
				18	eta0	0.05	0.95
				19	cdsc	1e-6	1e-1
				20	cdscd	1e-6	1e-1
				21	psat	0.15	2.85

▲ C-V related parameters

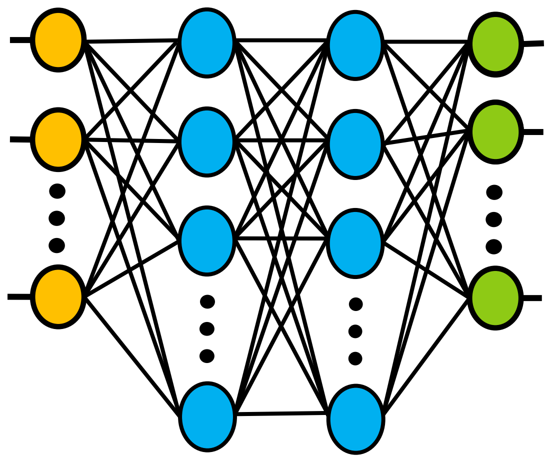
▲ I-V related parameters

- **21 model parameters** were selected
- **Much wider variation of 90%**, compared to previous studies with a 10% variation

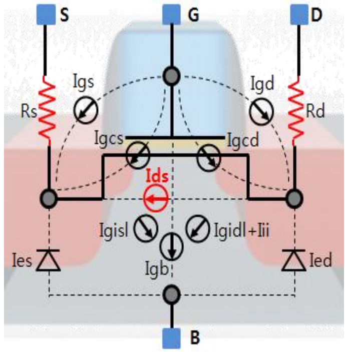
Bidirectional PMG-NN Training

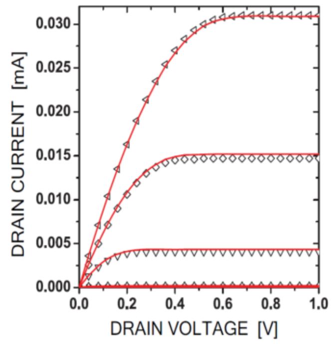
BSIM-CMG parameters

phig, cratio, eot, qmfactor, qmtcencv, cgsl, pclmcv, cgeoa, cit, vsat, rdsw, eu, etamob, u0, ua, ksativ, pclm, eta0, cdsc, cdscd, psat



BSIM-CMG I-V, C-V



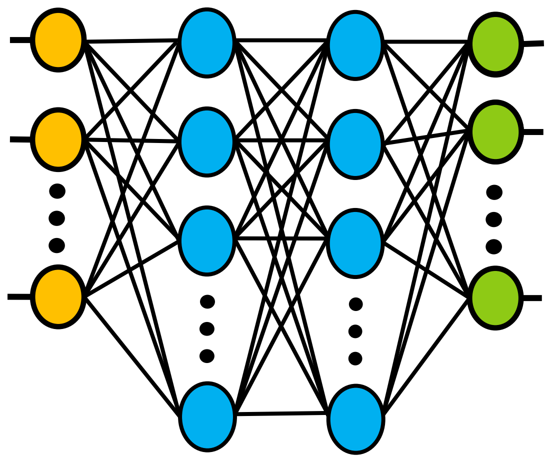


- **Train correlations in BSIM-CMG (Training)**
  - **- Input: BSIM-CMG model parameters (21 inputs)**
  - **- Output: BSIM-CMG I-V, C-V curves (total 56 outputs)**
  - **- Training data: 100,000 BSIM-CMG samples (80% train, 20% valid)**
  - **- NN size: (200 - 200 - 200 - 200), Iterations: 100,000**

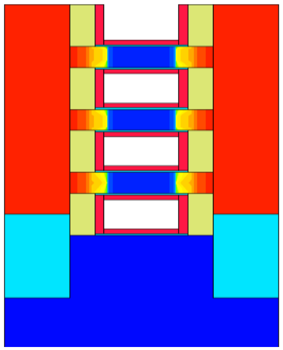
Bidirectional PMG-NN Inference

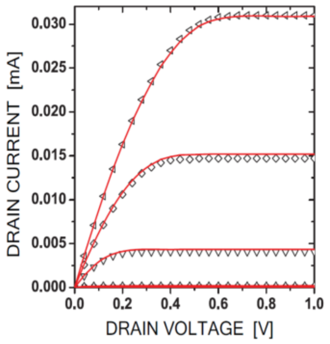
BSIM-CMG parameters

phig, cratio, eot, qmfactor, qmtcencv, cgsl, pclmcv, cgeoa, cit, vsat, rdsw, eu, etamob, u0, ua, ksativ, pclm, eta0, cdsc, cdscd, psat



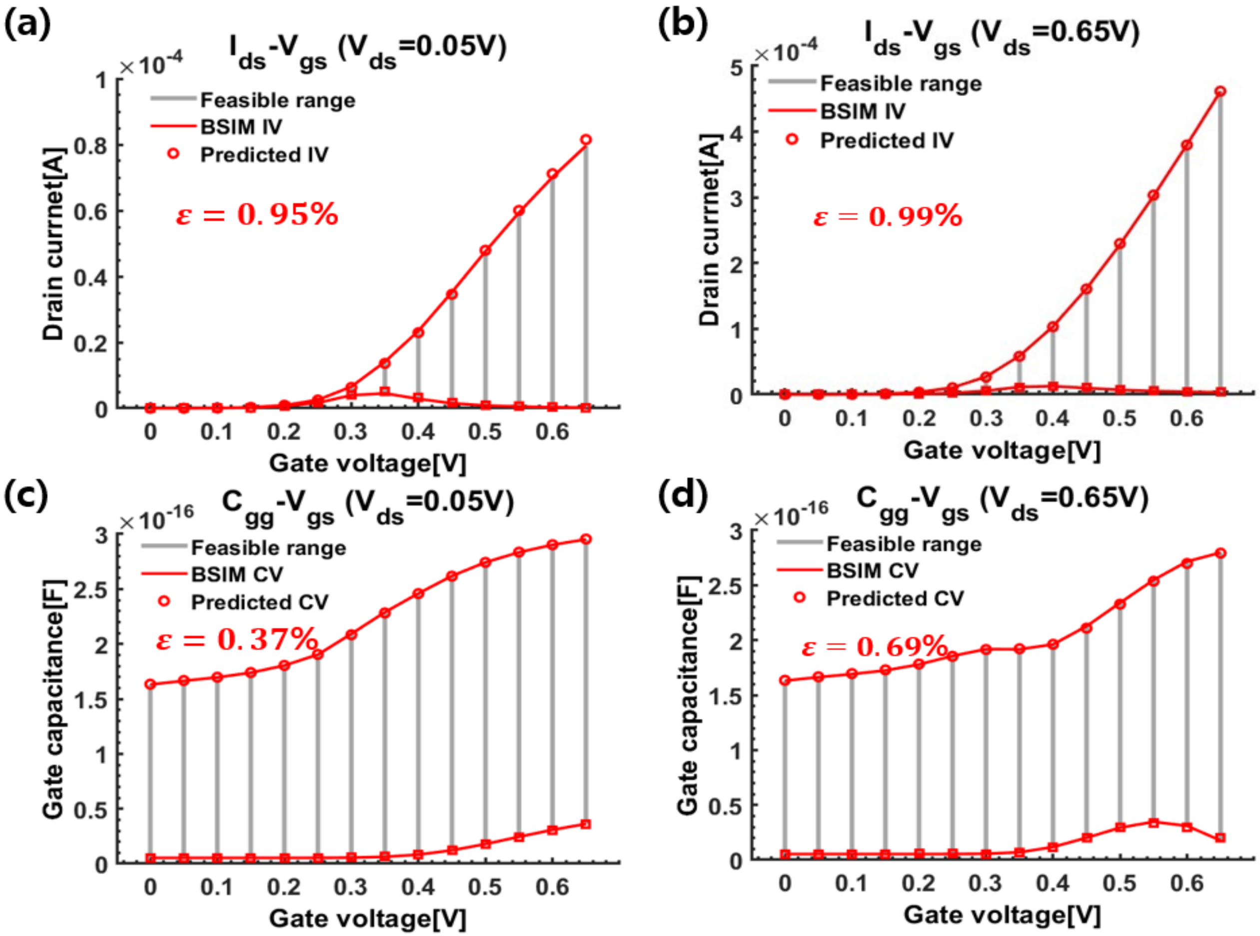
TCAD I-V, C-V





- **Model parameter extraction (inference)**
  - **- Input: BSIM-CMG model parameters (21 inputs)**
  - **- Output: TCAD I-V and C-V curves (total 56 outputs)**
  - **- Iterations: 1,000**

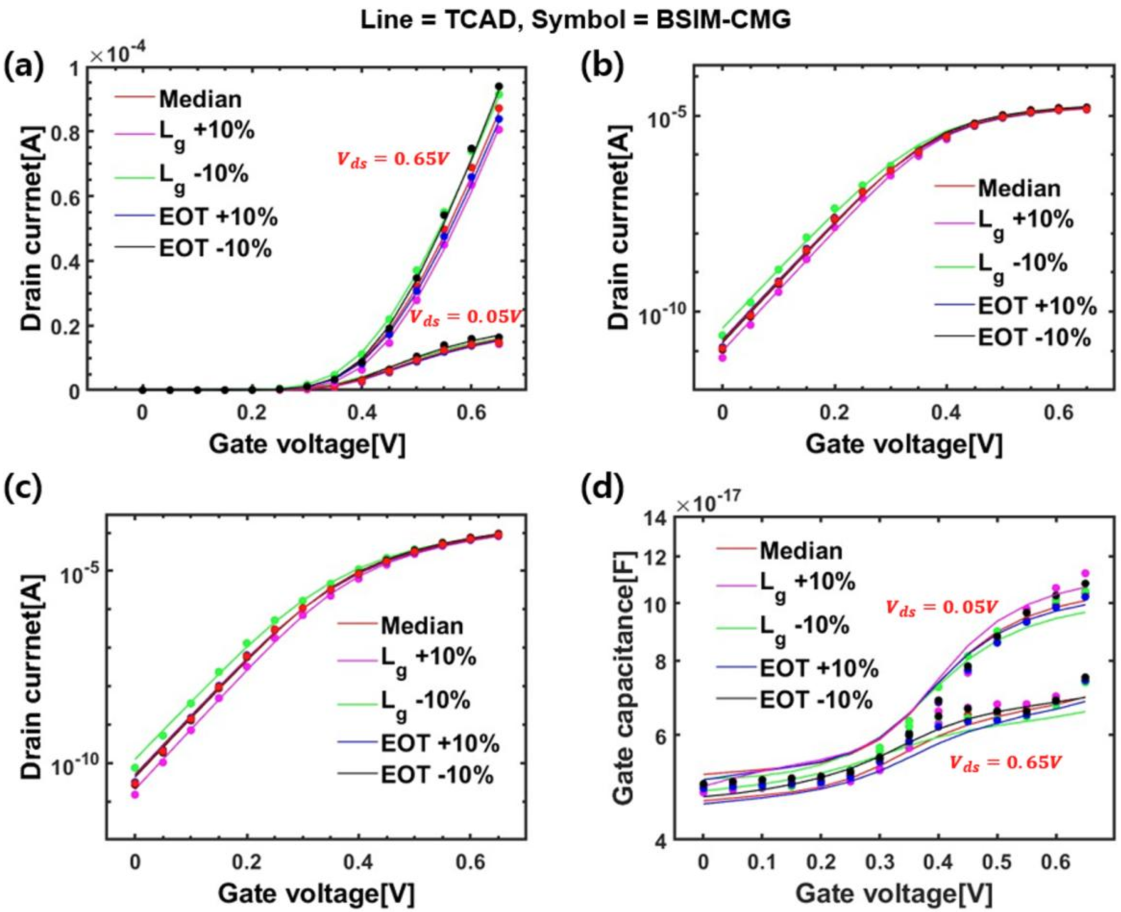
Model Validation of PMG-NN



◀ **Training Results**

- **Within the trained range and feasible shape, we can generate a BSIM-CMG that satisfies desired I-V and C-V with less than 1% error**

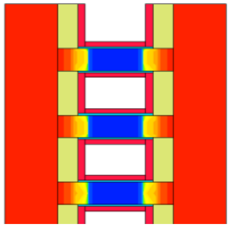
Model Validation of PMG-NN

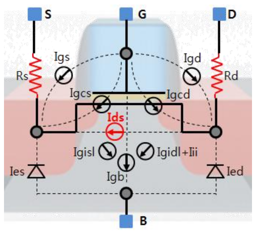


◀ Inference Results

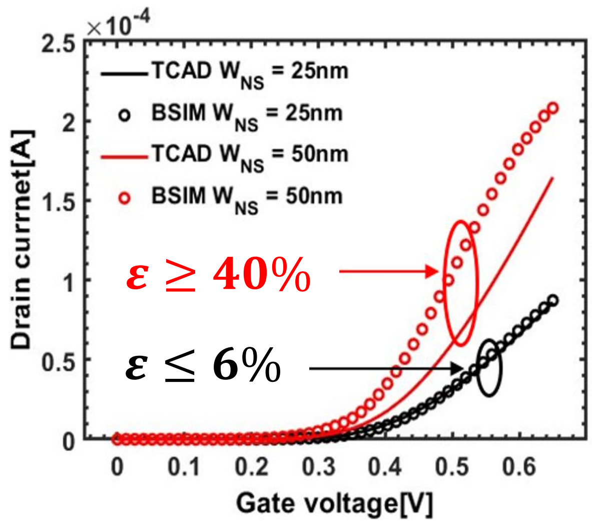
- TCAD data can be fitted with over 94% accuracy
- PMG-NN can reduce modeling time to just a few minutes, compared to the MPE flow which takes days to weeks

Model Mismatches in Global Devices





Global Variation



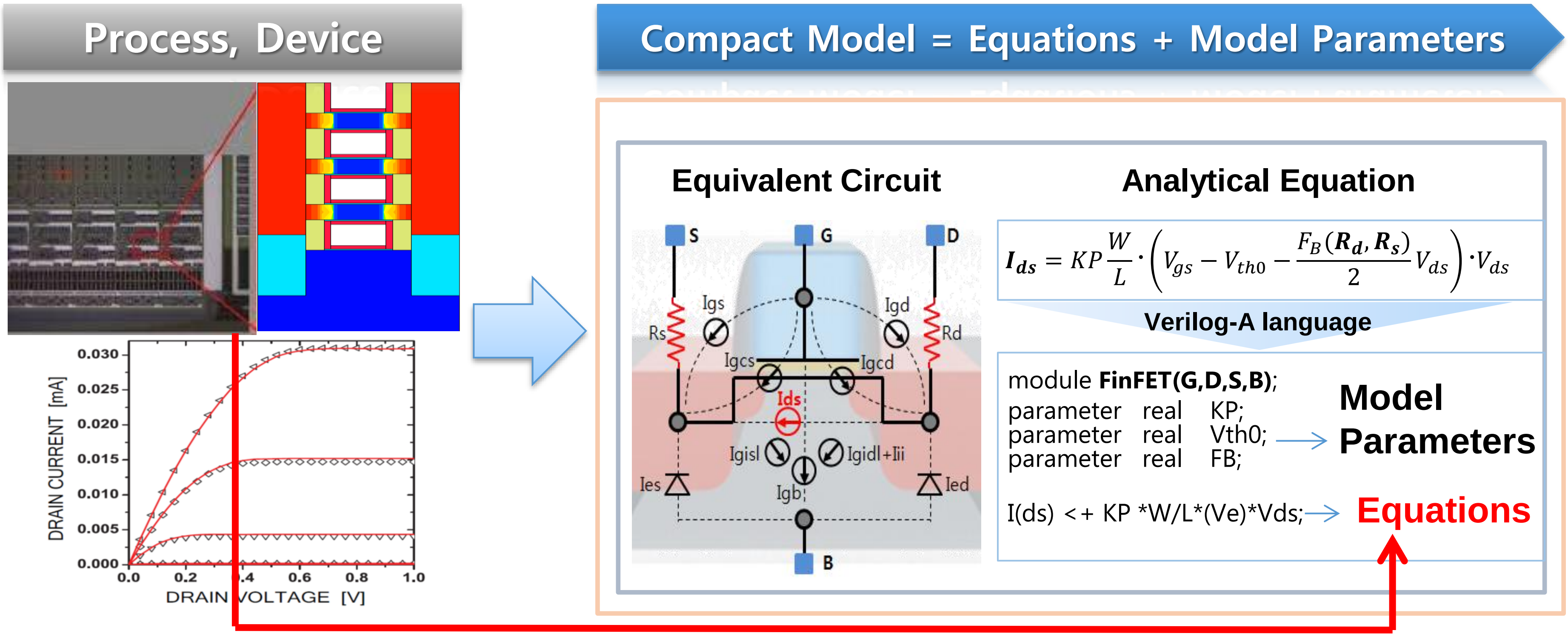
▲ Model mismatch caused by variations in process parameters

	Min	Max	Nominal
L_g	12 nm	20 nm	12 nm
T_{NS}	4 nm	6 nm	5 nm
W_{NS}	20 nm	50 nm	25 nm
C_{doping}	1e16	5e16	1e16
SD_{doping}	1e20	5e20	4e20

▲ Our DGC-NN TCAD datasets for 100 global devices

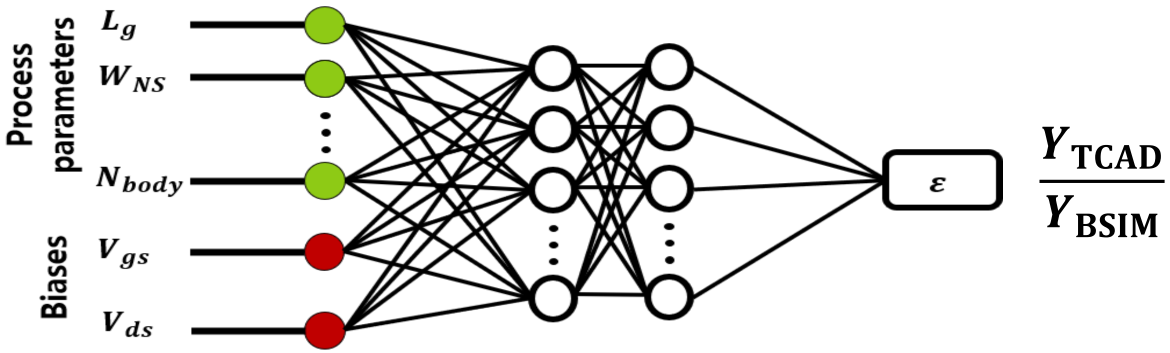
- Hard to generate a compact model for global devices accurately
- For various process and doping variables, the error increased by more than 40%

Deep Global Correction - NN (DGC-NN)



- For now, fully explaining the behavior of nano-scale devices under various process conditions using only physics-CM is impossible
- DGC-NN automatically corrects model equations to address accuracy, model coverage issues

Proposed DGC-NN Training



$$Loss = \frac{1}{N}\sum\left(\varepsilon(X) * Y_{BSIM}(X) - Y_{TCAD}(X)\right)^2$$

- **Find correction terms (Training)**

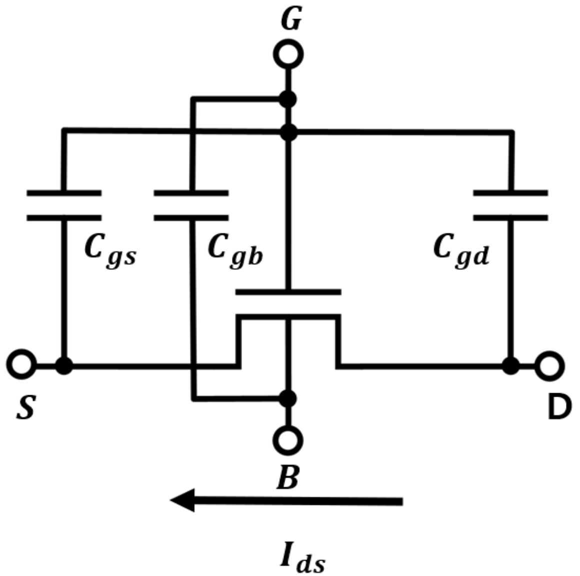
  - Input: $L_g, W_{NS}, T_{NS}, N_{SD}, N_{BODY}, V_{gs}, V_{ds}$ (7 inputs)

  - Output: Y_{TCAD}/Y_{BSIM} ($Y = I_{ds}$ (I-V), C_{gg}, C_{gd}, C_{gs}(C-V))

  - Training data: 100 TCAD and BSIM-CMG samples (80% train, 20% valid)

  - NN size: (25 - 20), Iterations: 500,000

Proposed DGC-NN Inference (Verilog-A)



$$I_{ds} = I_{BSIM} + I_{BSIM} * (\varepsilon_1 - 1)$$

$$C_{gg} = \frac{\partial Q_g}{\partial V_g}_{BSIM} + \frac{\partial Q_g}{\partial V_g}_{BSIM} * (\varepsilon_2 - 1)$$

$$C_{gd} = \frac{\partial Q_g}{\partial V_d}_{BSIM} + \frac{\partial Q_g}{\partial V_d}_{BSIM} * (\varepsilon_3 - 1)$$

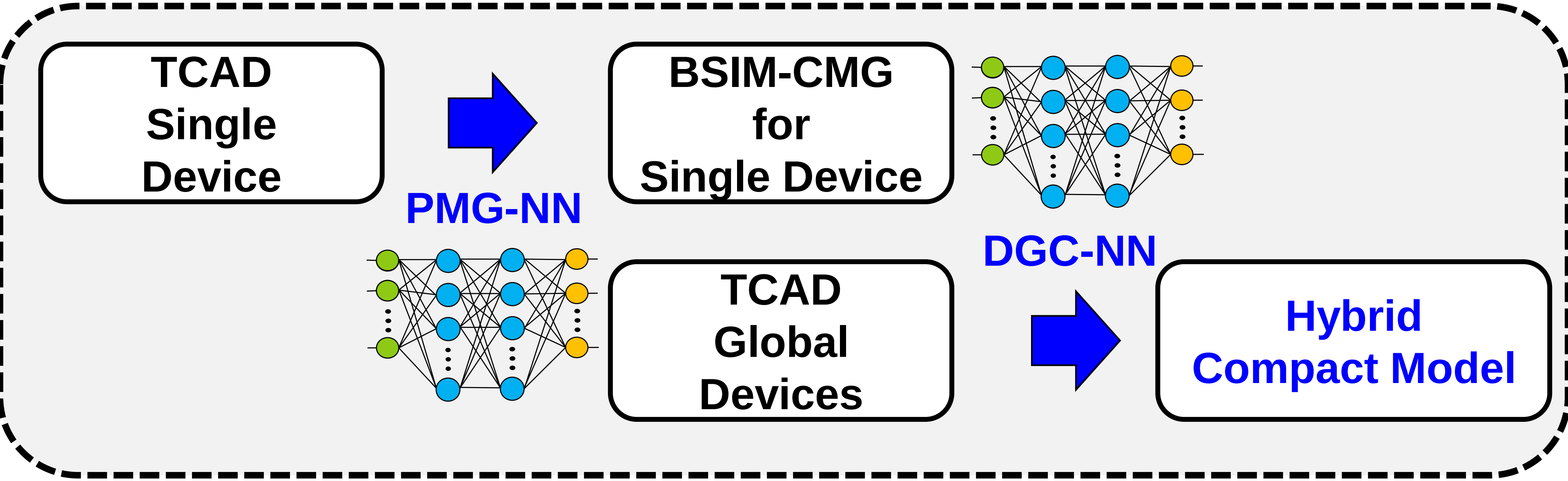
$$C_{gs} = \frac{\partial Q_g}{\partial V_s}_{BSIM} + \frac{\partial Q_g}{\partial V_s}_{BSIM} * (\varepsilon_4 - 1)$$

$$C_{gb} = C_{gg} - C_{gd} - C_{gs}$$

▲ Hybrid compact model w/ global correction terms

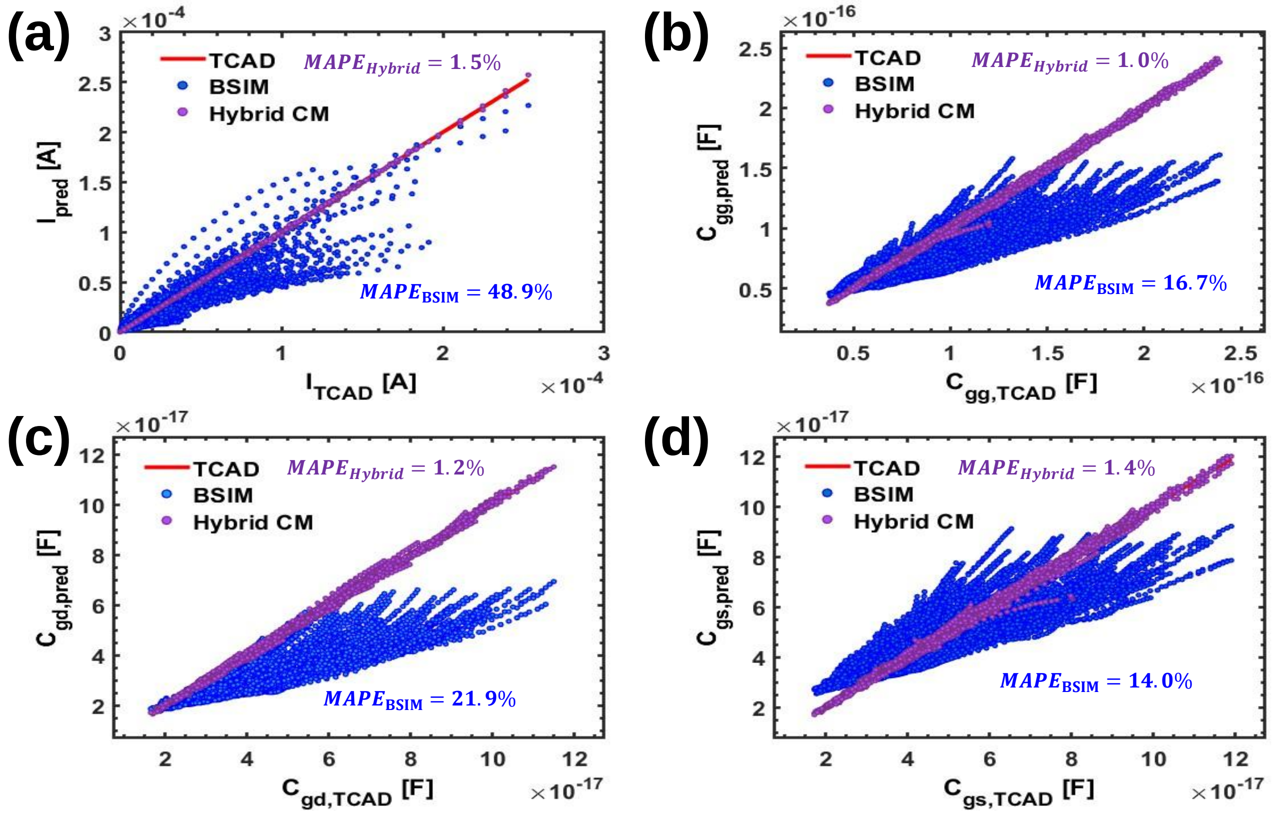
- **Add correction terms at the final stage of BSIM-CMG to correct the electrical characteristics**
- **Can be integrated into BSIM-CMG [8] through Verilog-A language**

Recap: Hybrid Compact Model



- **Proposed hybrid compact model where neural networks and physics equations work together**

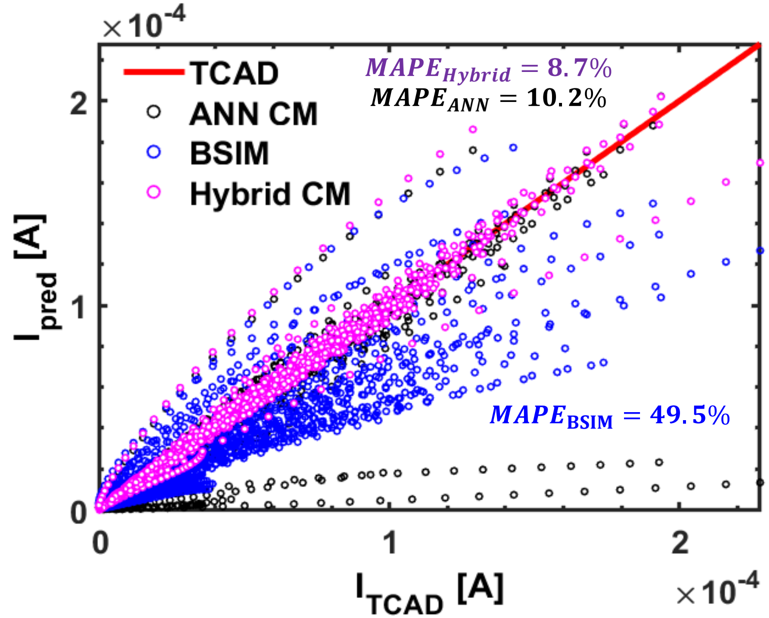
Model Validation of Hybrid -CM



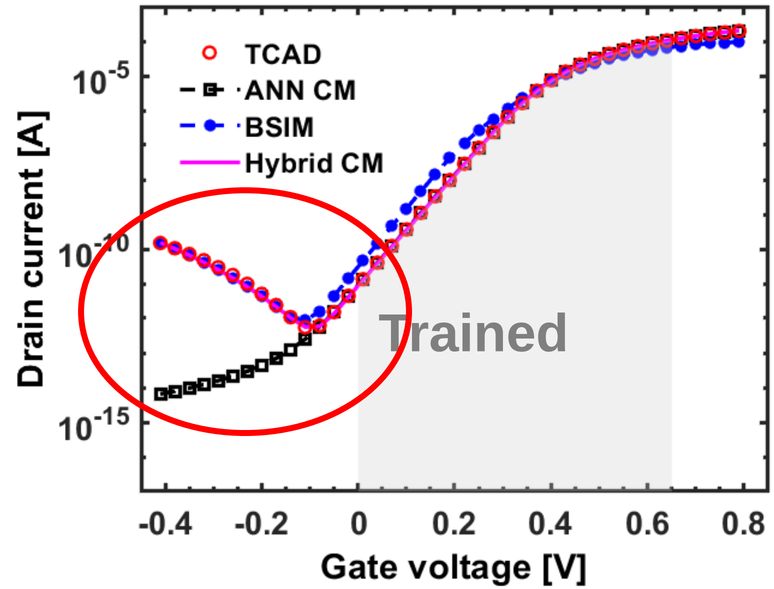
▲ Fitting results of (a) I_{ds}, (b) C_{gg}, (c) C_{gd} and (d) C_{gs}

- **Hybrid-CM shows much higher fitting accuracy than BSIM-CMG: 98.5% in I-V (vs. 50.1%), 98.8% in C-V (vs. 82.5%)**

Model Validation of Hybrid -CM



▲ I-V Fitting results of unseen process conditions



▲ I-V Fitting results of unseen operation conditions

- Hybrid-CM has **the highest prediction accuracy** for unseen test devices: 91.3% (vs. 50.5%, 89.8%)
- **It can maintain physical consistency** even under unseen operation conditions ($V_{gs} < 0\ V$) using GIDL sub-model

Conclusions

- **Bidirectional PMG-NN can reduce a few weeks of modeling time to just a few minutes**

- **DGC-NN enables global device modeling with over 98.5% accuracy, previously unachievable with only physics-CM**

- **The proposed Hybrid-CM brings fitting capability and automation to the physics-CM**

- **The Hybrid-CM can play a crucial role in both DTCO and the foundry business**

Thank you
for your attention

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