# A Deep Learning Space Mapping Based Enhancement of Compact Models for Accurate Prediction of Trapping in GaN HEMTs from DC to mm-Wave Frequency

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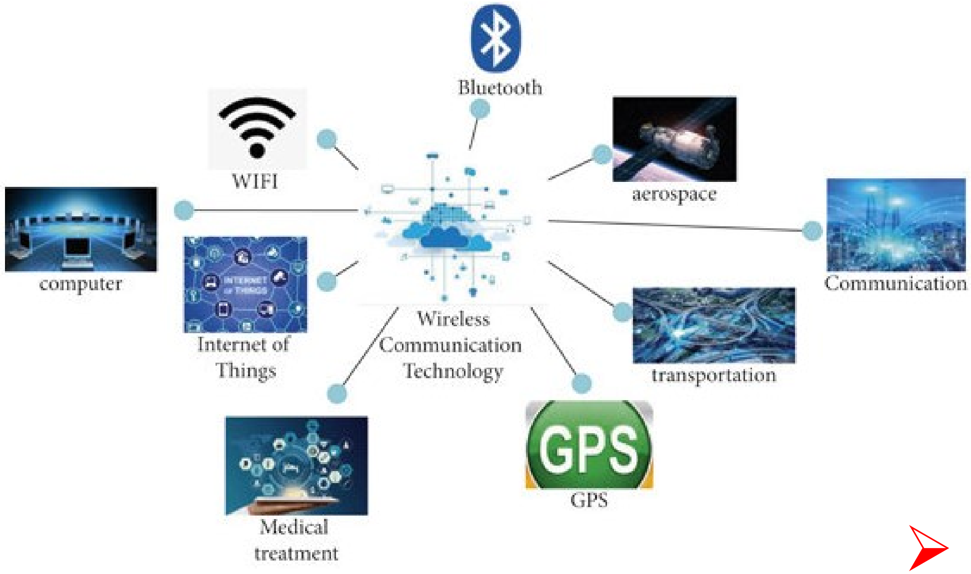
# Outline

- Introduction
- Limitations of Compact Models
- Premise of Proposed Methodology
- Proposed: Space Mapping (SM) based Enhancement of Compact Model
- Numerical Example and Discussion
- Summary

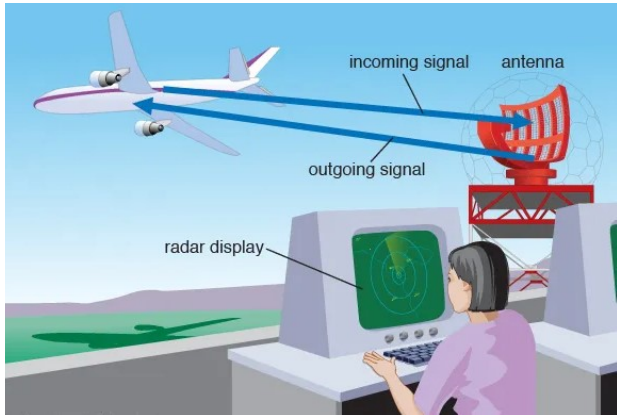
# Introduction



➢ AlGaN/GaN HEMTs are used in




1. Modern wireless communication technologies




2. Radar systems


3. Low noise amplifier (LNA)

Due to its ability to provide:

- ➢ High gain
- ➢ Fast switching speed
- ➢ Better power handling capacity
- ➢ Low noise figure

➢ More reliability issues like gate lag, drain lag, current collapse, and frequency dispersion will appear due to trapping

- Robust design optimization
- Reliability based design optimization
- Yield optimization

→ Reliable electronics design and automation (EDA) tools

# Various EDA Tools



**Physics Based Solver: Technology Computer Aided Design (TCAD)**

- Solves fundamental PDEs using FEM/FDTD
- Highly accurate
- Computationally too slow
- Accurate trapping/de-trapping models possible

**Compact Models: ASM HEMT and MSVG**

- Simple and user friendly
- Analytically map terminal characteristic to device geometrical, material, and bias parameters
- Accurate only around calibration points
- Extremely fast

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# Limitations of Compact Models

**Limitations of Compact Models**

→ Multiple trap locations, different trap energy levels can not be incorporated

→ Can't capture large device parameter variations

→ Performance of HEMTs show large deviations from DC to sub-Terahertz frequencies due to trapping effect

<u>To address this</u>

Input parameters $\lambda_1$ … $\lambda_N$ → **Physics Solvers** → True device characteristic → **Compact Models** → Predicted device characteristics

Physics Solvers: extracts the true device terminal characteristics in presence of traps

Compact Models: tune fitting parameters to mimic the true characteristics

Repeated physics solver simulations (very slow)

Repeated subsequent calibrations (very slow)

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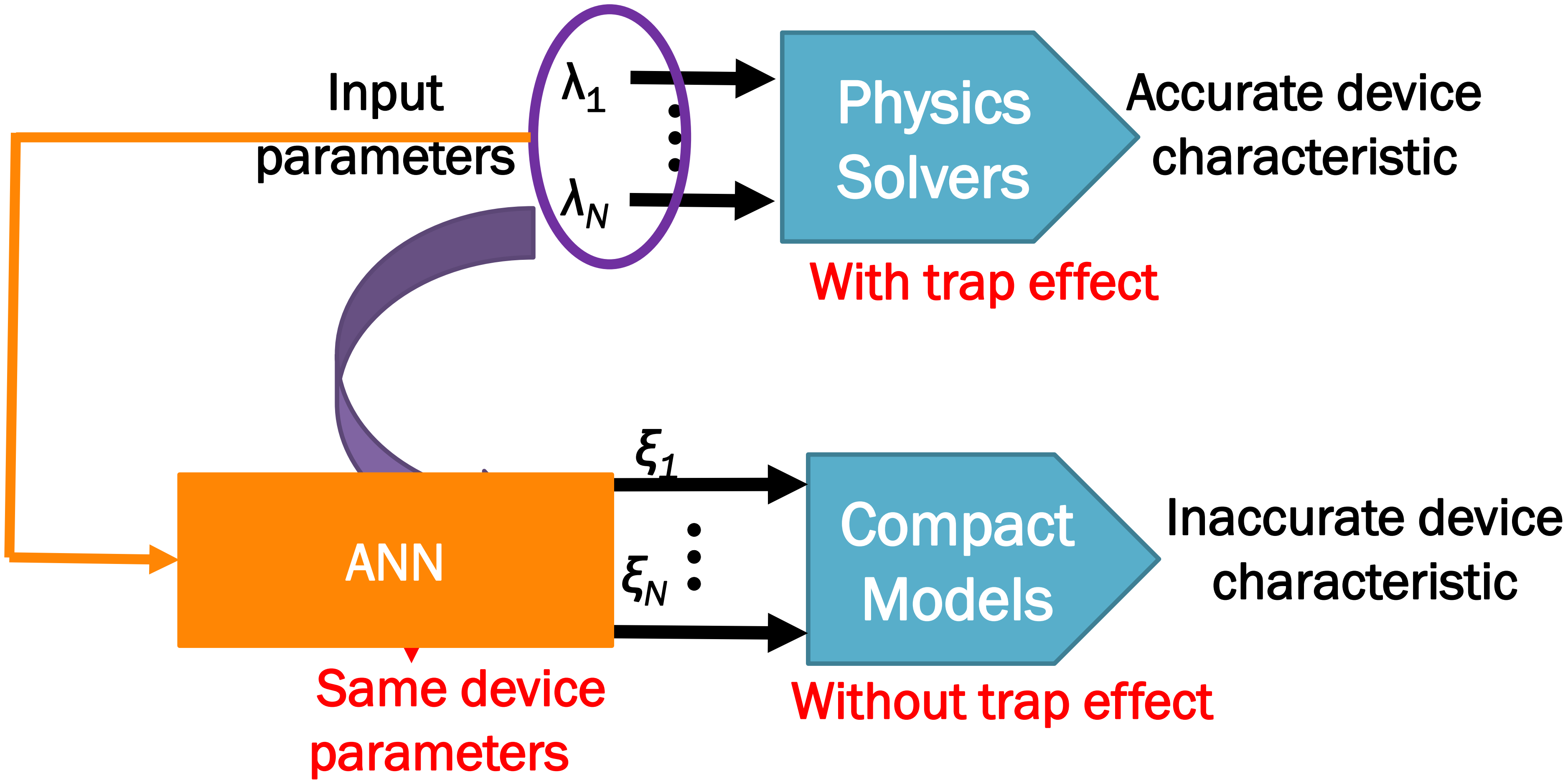
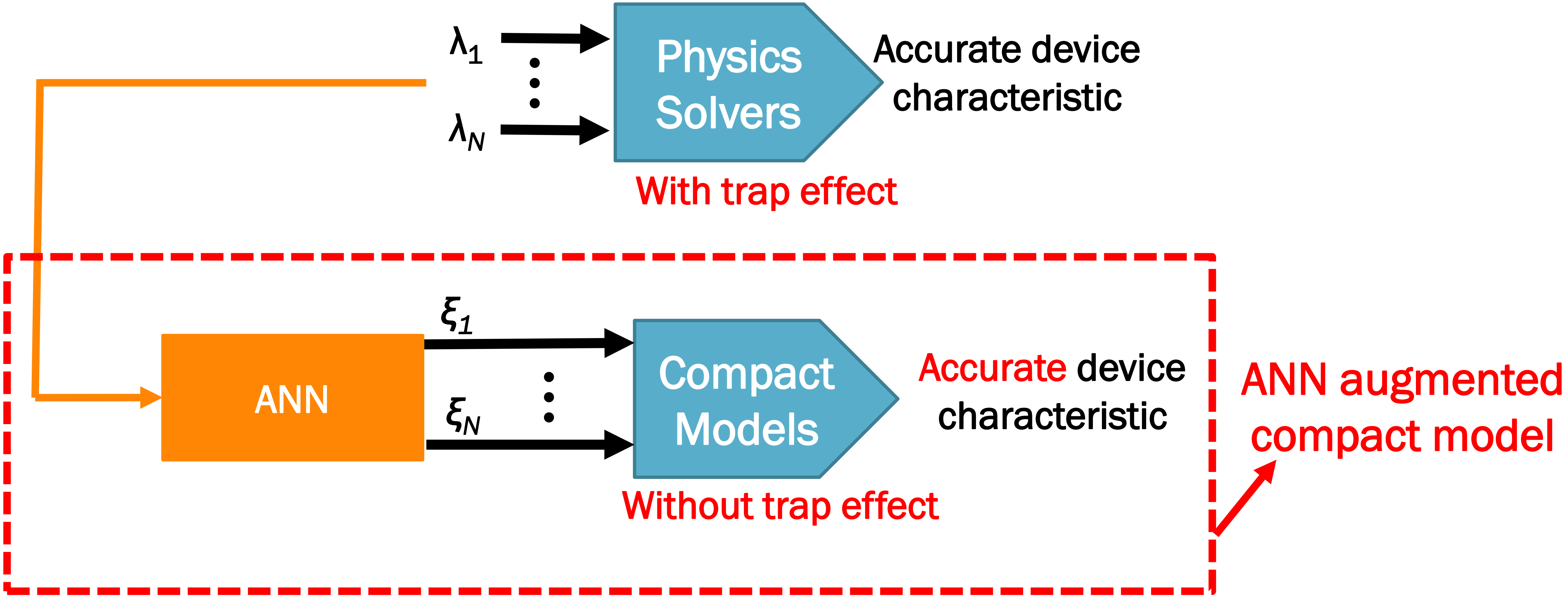
# Prelims of Proposed Methodology



# Prelims of Proposed Methodology





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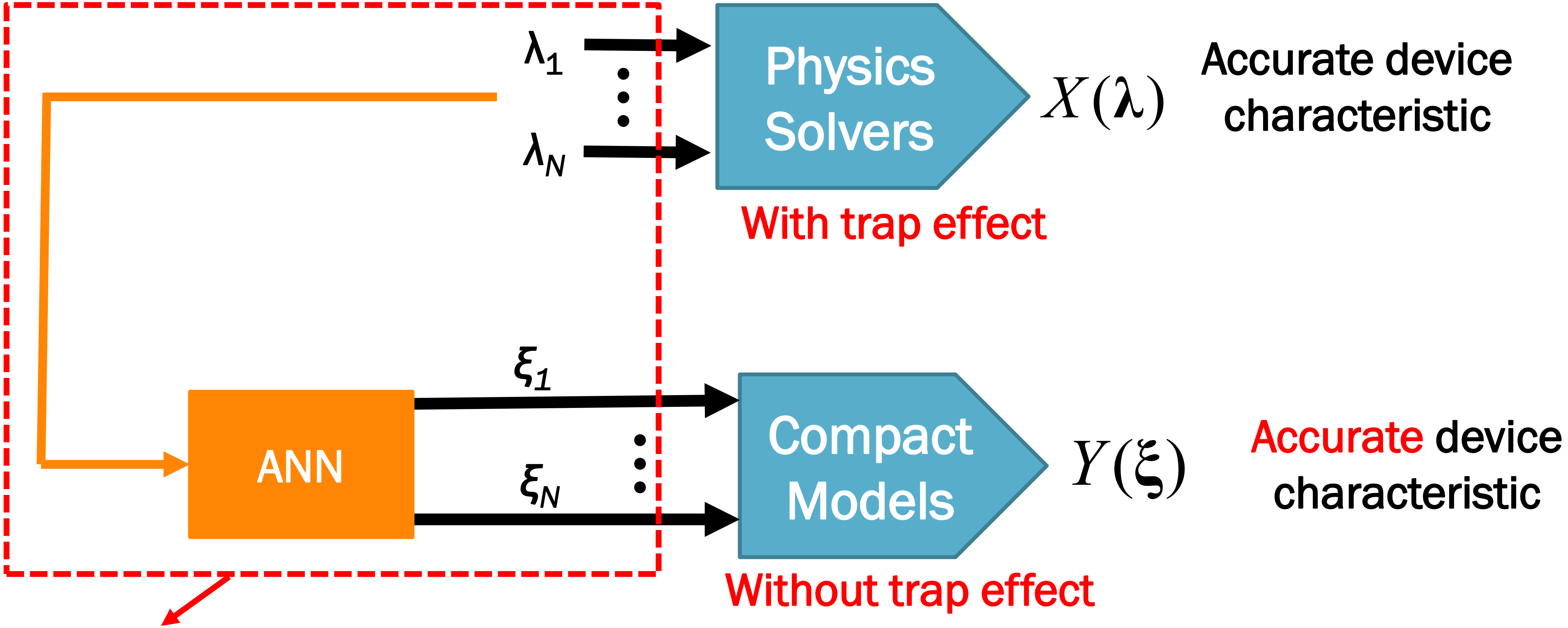
# SM Enhanced Compact Model




Space Mapping (SM) ANN

$$\xi = f(\lambda)$$

Coarse model input parameters

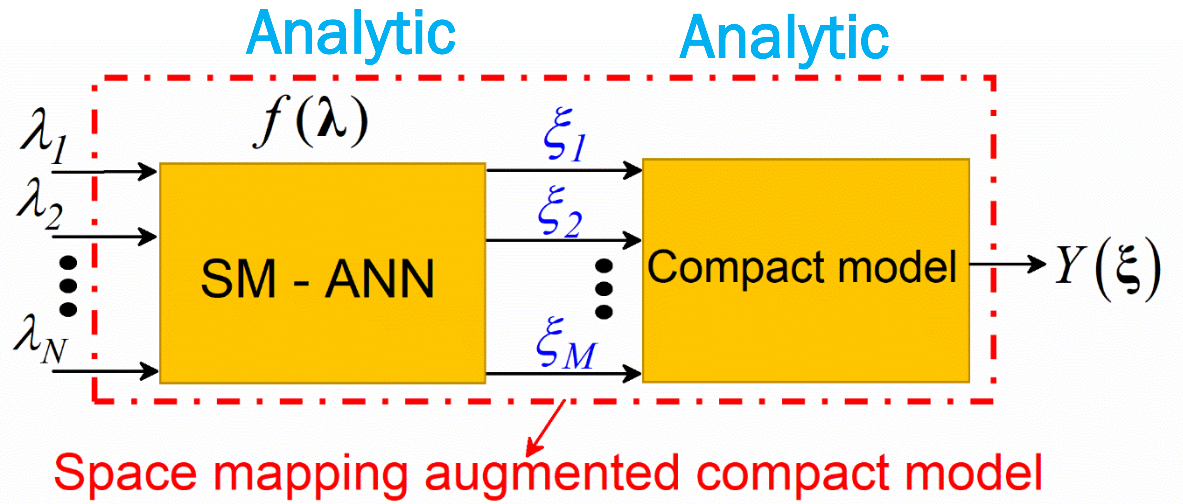
Fine model input parameters

# Training of Space Mapping ANN

Now tuning the set of weights and bias terms (w, b) to solve the optimization problem

$$(\mathbf{w},\mathbf{b})_{opt} = \underset{\mathbf{w},\mathbf{b}\in\Re}{\arg\min} \frac{1}{K}\sum_{k=1}^{K}\left(X(\boldsymbol{\lambda}^{(k)}) - Y(z(\mathbf{w},\mathbf{b},\boldsymbol{\lambda}^{(k)}))\right)^2 \quad (4)$$

Once the space mapping ANN is trained




Minimal computational overheads...!!!

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# Numerical Example and Discussion

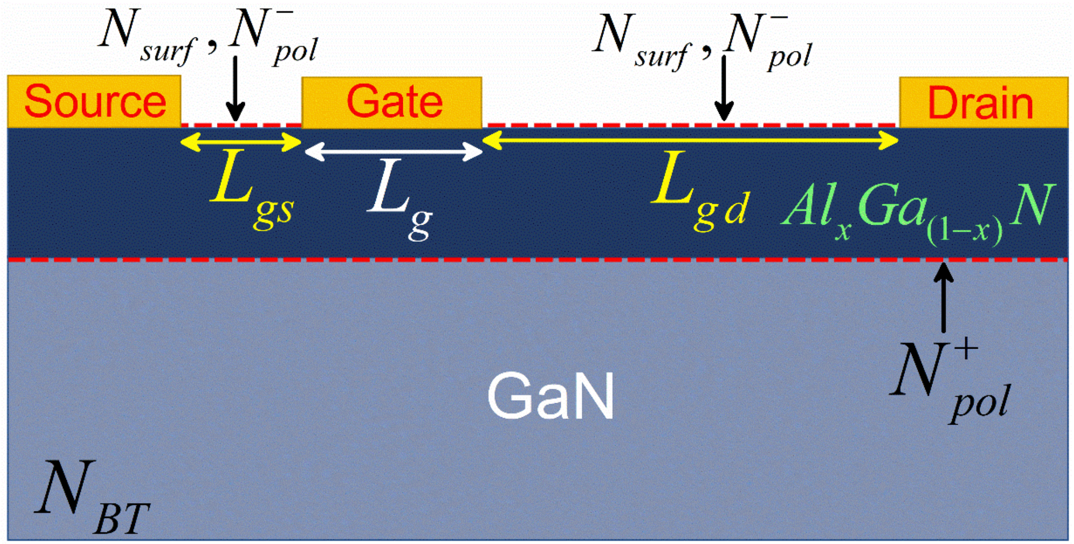


Fig. 1. Schematic of GaN HEMT with bulk and interface traps for DC and small signal Y-parameter analysis.

Table 1. Fine model (TCAD) parameters

| Device Parameters | Range (uniform distribution) |
|---|---|
| $N_{surf}$ (donor trap density at interface) | $1.2\times10^{13}$ cm$^{-2}$ ± 10% |
| $N_{BT}$ (acceptor trap density in GaN bulk) | $5\times10^{17}$ cm$^{-3}$ ± 10% |
| $E_{D,trap}$ (donor trap level) | 0.4 eV ± 10% |
| $E_{A,trap}$ (acceptor trap level) | 0.4 eV ± 10% |
| x (Al mole fraction) | 0.25 ± 10% |
| $L_g$ (gate length) | 0.7 µm ± 10% |
| $L_{gs}$ (gate to source length) | 0.7 µm ± 10% |
| $L_{gd}$ (gate to drain length) | 2 µm ± 10% |
| $V_{gs}$ (gate to source voltage) | [-5 - 0] V |
| $V_{ds}$ (drain to source voltage) | [0 - 10] V |
| Frequency | [0.5 - 50] GHz |

# Numerical Example and Discussion



Table 2. Coarse model (ASM-HEMT) parameters

| Device Parameters | Range (uniform distribution) |
|---|---|
| $V_{OFF}$ (cut-off voltage) | -3 V ± 10% |
| $U_0$ (low field mobility) | 2.5 $m^2$/V-s ± 10% |
| $V_{SAT}$ (saturation velocity) | 112760 m/s ± 10% |
| $V_{sataccs}$ (saturation velocity for access region) | 406610 cm/s ± 10% |
| $\eta_0$ (DIBL parameter) | 2.08 ± 10% |
| $N_{FACTOR}$ (subthreshold slope factor) | 4.75 ± 10% |
| THESAT (velocity saturation parameter) | 5.93 $V^{-2}$ ± 10% |
| $L_g$ (gate length) | 0.7 µm ± 10% |
| $L_{gs}$ (gate to source length) | 0.7 µm ± 10% |
| $L_{gd}$ (gate to drain length) | 2 µm ± 10% |
| $V_{gs}$ (gate to source voltage) | [-5 - 0] V |
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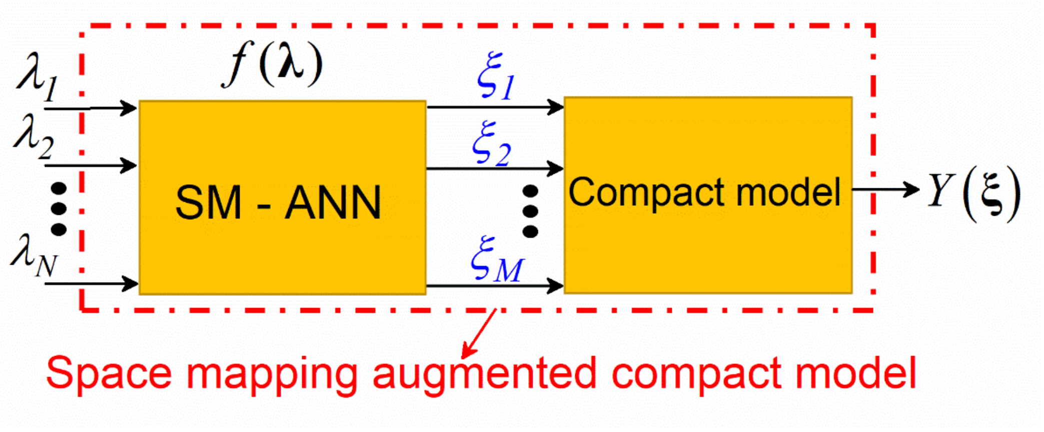
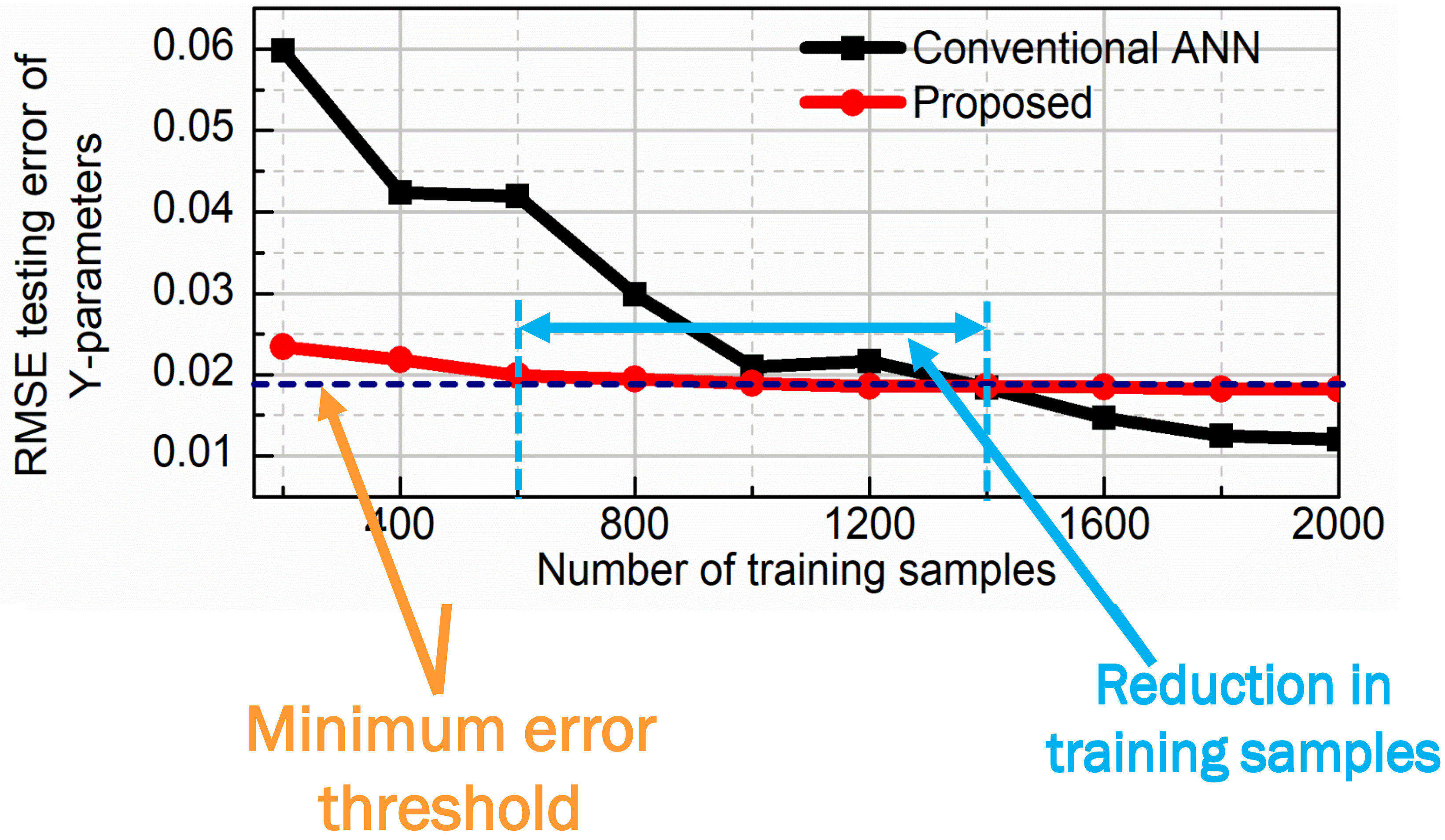



Fig. 2. Deep space mapping neural network augmented compact model.

# Numerical Example and Discussion

- Testing error decay plot




Hidden layers = 3
# neurons = 100 (each layer)
# epochs = 200
Activation function = ReLU
Optimizer = Adam

# Numerical Example and Discussion



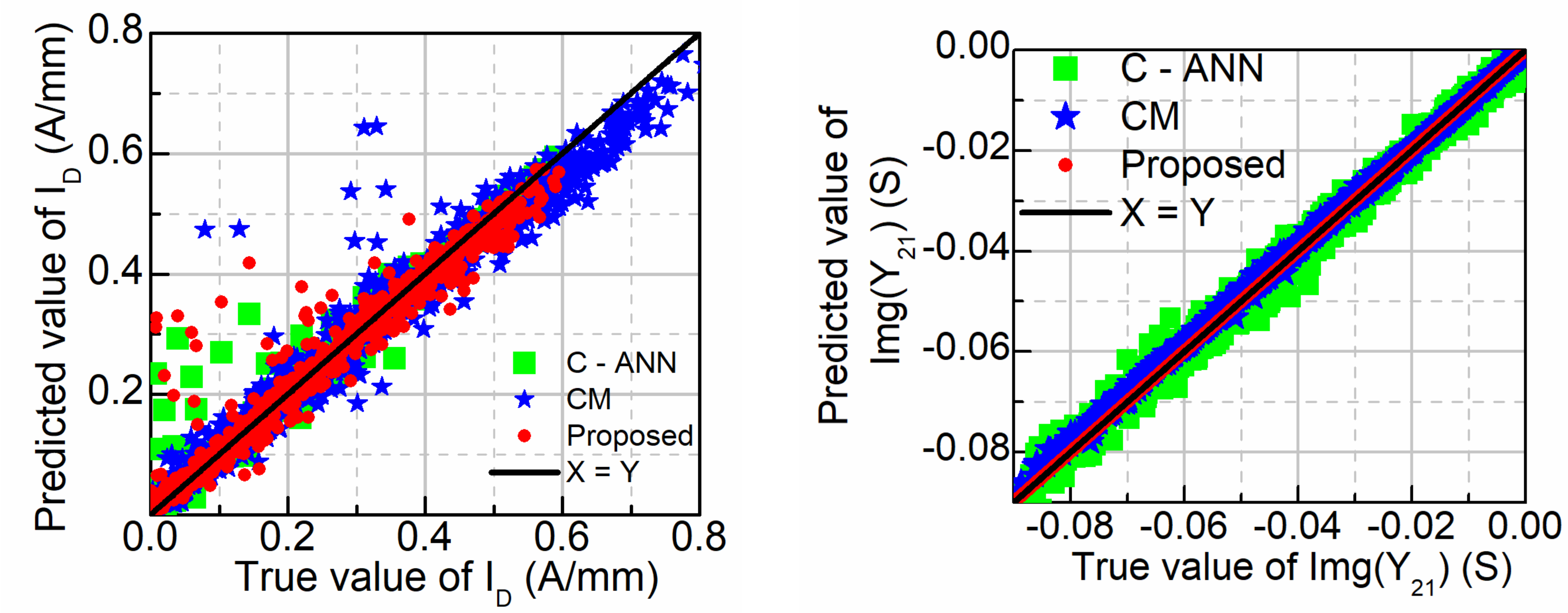



Fig. 3. Scatter plot showing the accuracy of the proposed space mapping augmented compact model w.r.t. Conventional ANN (C - ANN) and the standard compact model (CM) (a) drain current using 1015 training samples and (b) imaginary part of $Y_{21}$ using 985 training samples at 1000 testing points.

# Numerical Example and Discussion

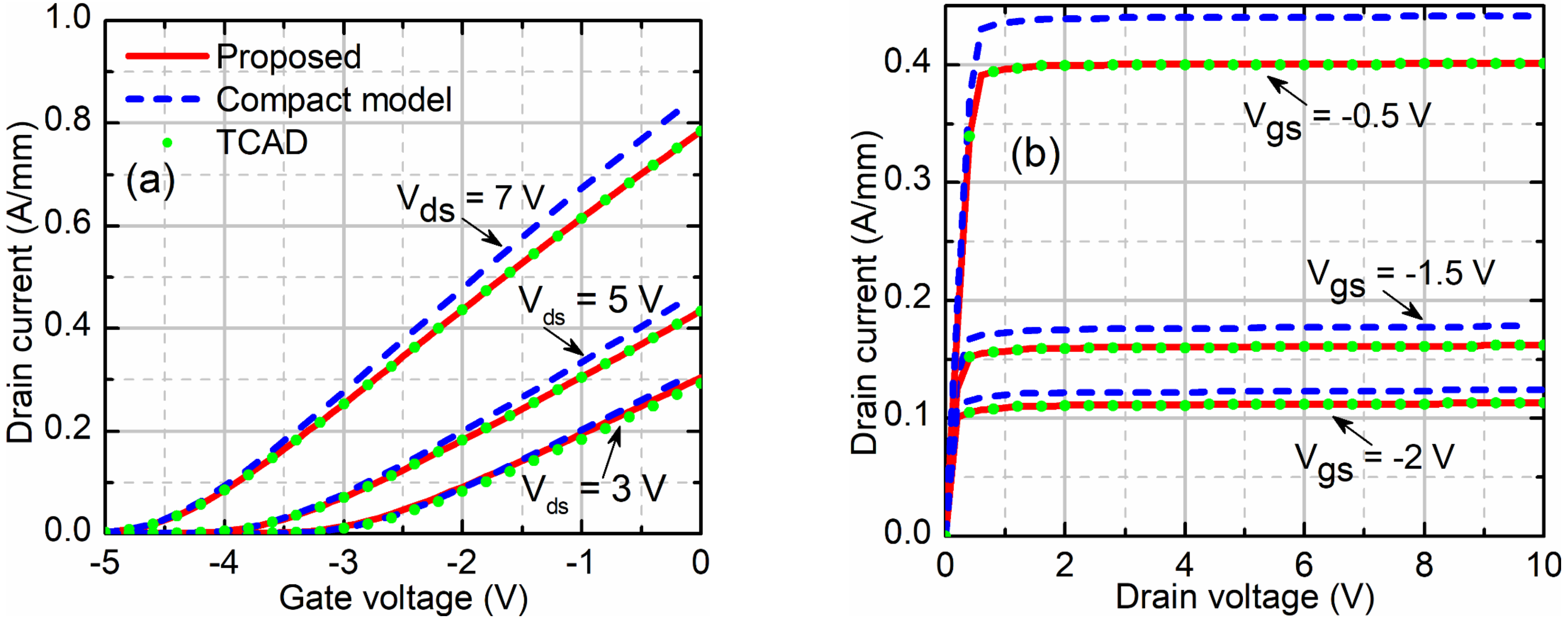



**Fig. 4. Validation of drain current ($I_D$) with respect to (a) gate voltage ($V_G$), and (b) drain voltage ($V_D$) for TCAD, compact model, and proposed approach evaluated at different corner points.**

Corner points for Fine Model: ($N_{surf}$=1.08×$10^{13}$, $N_{BT}$= 5.5×$10^{17}$, $E_{D,trap}$=0.44eV, $E_{A,trap}$=0.44eV, x=0.275, Lg=0.77 µm, Lgs=0.63 µm Lgd=1.8 µm)

Corner points for Coarse Model: (Voff=-2.7, Uo=2.25, Vsat=101484, Vsataccs=365949, η0=1.872, Nfactor=5.225, THESAT=6.523, Lg=0.77 µm, Lgs=0.63 µm Lgd=1.8 µm)

# Numerical Example and Discussion



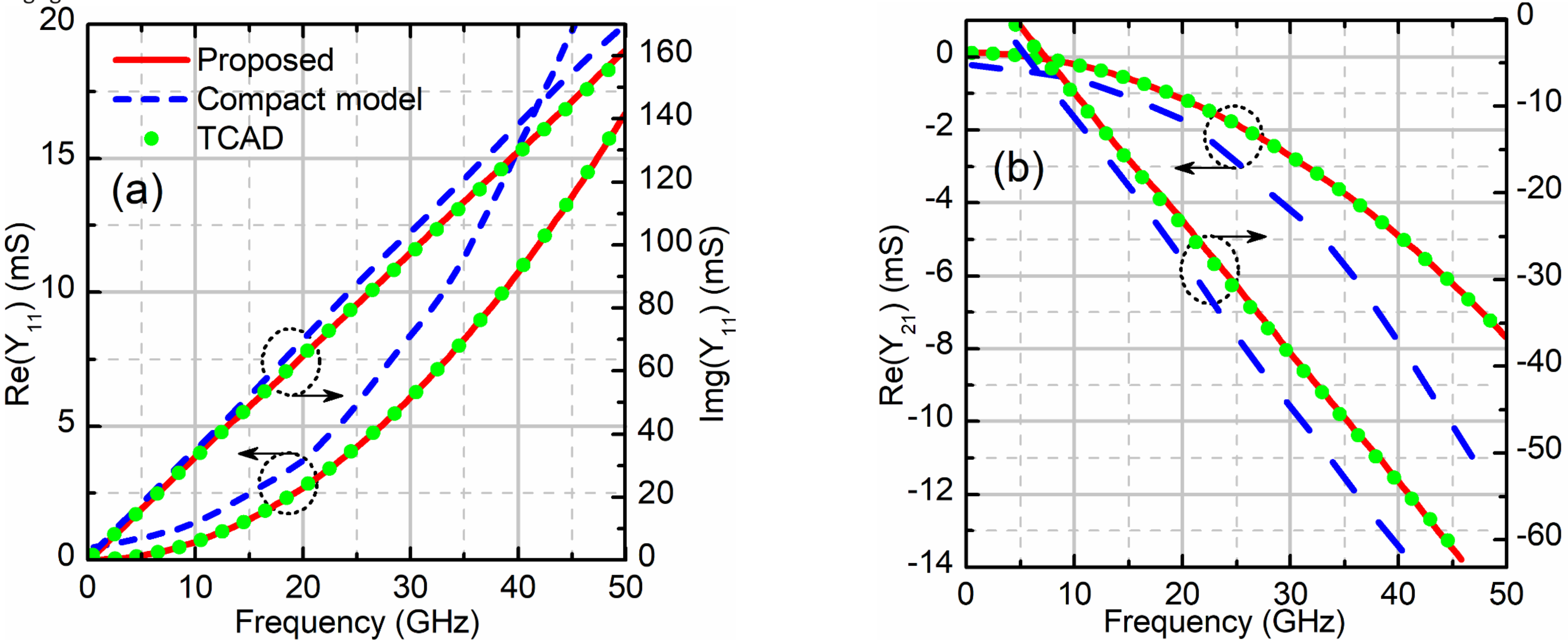



Fig. 5. Validation of small-signal admittance parameters (a) $Y_{11}$, and (b) $Y_{21}$ for TCAD, compact model, and the proposed method.

Corner points for Fine Model: ($N_{surf}$=1.08×$10^{13}$, $N_{BT}$= 5.5×$10^{17}$, $E_{D,trap}$=0.44eV, $E_{A,trap}$=0.44eV, x=0.275, Lg=0.77 μm, Lgs=0.63 μm Lgd=1.8 μm)

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# Numerical Example and Discussion



Table 3. The incurred computational cost for device terminal performance

| Models | RMS error w.r.t. TCAD (average calculated at 1000 sampling point) | | Standard deviation of error w.r.t. TCAD (average calculated at 1000 sampling point) | | Execution time (Time for a single device characteristic evaluation) | Speedup w.r.t. TCAD |
|---|---|---|---|---|---|---|
| | $I_D$ | Y-parameter | $I_D$ | Y-parameter | | |
| TCAD | - | - | - | - | 180 sec | - |
| Compact model | 0.2518 | 0.2548 | $12.7 \times 10^{-3}$ | $2.1 \times 10^{-3}$ | 4 msec | 45,000 |
| Proposed | 0.1806 | 0.1287 | $8.4 \times 10^{-3}$ | $0.9 \times 10^{-3}$ | 5.3 msec | 33,962 |

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# Summary

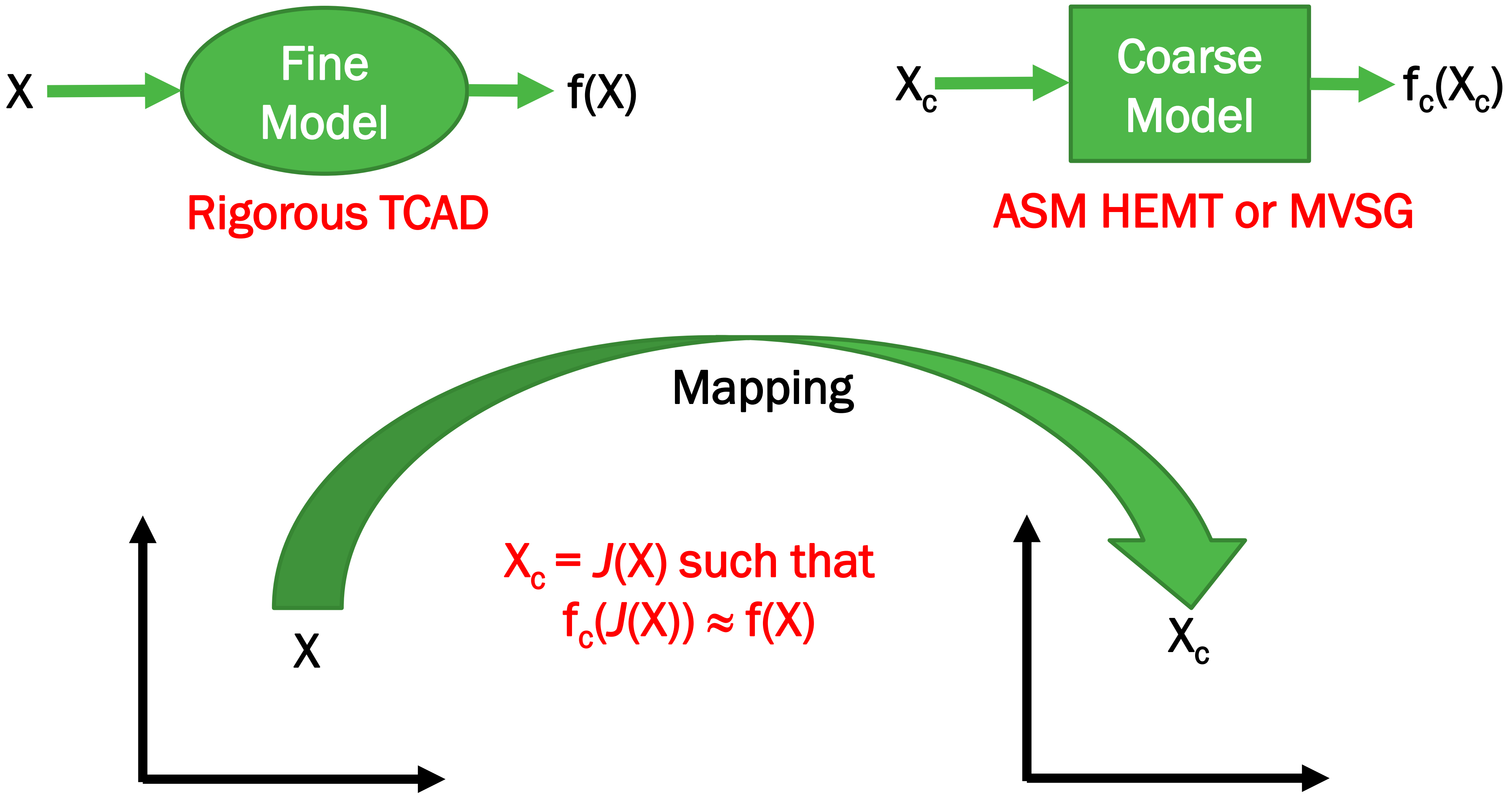
- Complicated trapping effects (bulk and interface traps) have been included to enhance the capabilities of existing industry standard compact models
- All features, functionalities, and flexibility of the industry-standard compact model are retained, and this allows perfect backward compatibility
- Space mapping augmented compact model is faster than Conventional ANN, and physics based TCAD model

# Acknowledgement



Thank You

# Space Mapping (SM)



# Training of Space Mapping ANN



Consider a dataset consisting of *K* data points described as

$$\{\boldsymbol{\lambda}^{(k)}, X(\boldsymbol{\lambda}^{(k)})\}_{k=1}^{K}$$

Input parameters to fine model for the *k*-th data point

Device terminal characteristics such as current and Y-parameters

$$F_{loss} = \frac{1}{K}\sum_{k=1}^{K}\left(X(\boldsymbol{\lambda}^{(k)}) - Y(z(\mathbf{w}, \mathbf{b}, \boldsymbol{\lambda}^{(k)}))\right)^2$$

Predicted output of the space mapping ANN for each data point, $\lambda^{(k)}$