

# **Artificial Intelligence and Machine Learning for RF and Microwave Design: *practical technologies for present and future applications***

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# Outline

- **Introduction to AI, ML and ANN**
- **ANN for electronic device modeling**
- **ANN for electronic behavioral modeling**
- **Summary**

# Outline

- **Introduction to AI, ML and ANN**
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- ANN for electronic behavioral modeling
- Summary

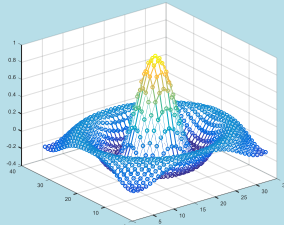
# AI and ML

## AI

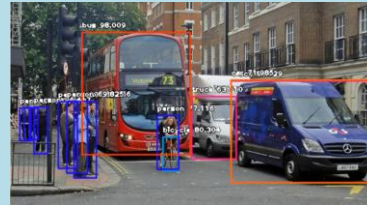
### ML

#### Supervised Learning

##### Regression

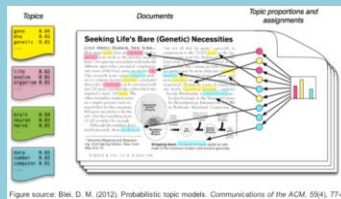


##### Image classification

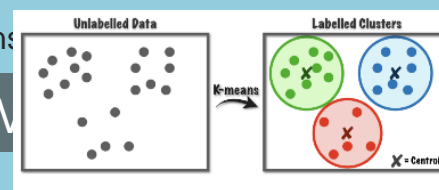


Face recognition  
Speech to text  
Text translation

#### Unsupervised Learning



Topic Modeling

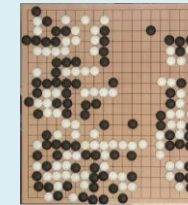


Clustering

#### Reinforcement Learning



Video games



Alpha Go



Stock trading



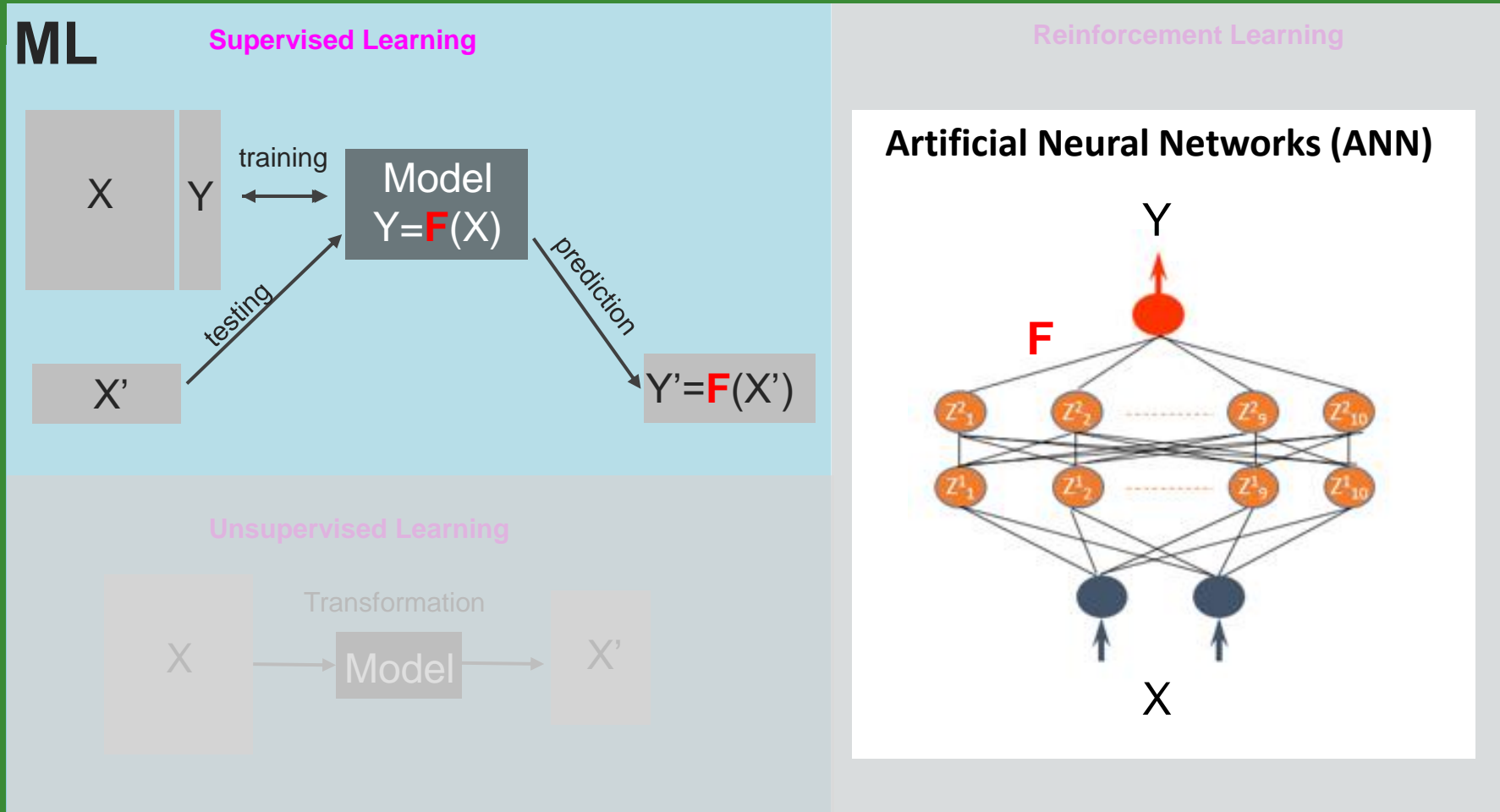
Walking, jumping, etc.



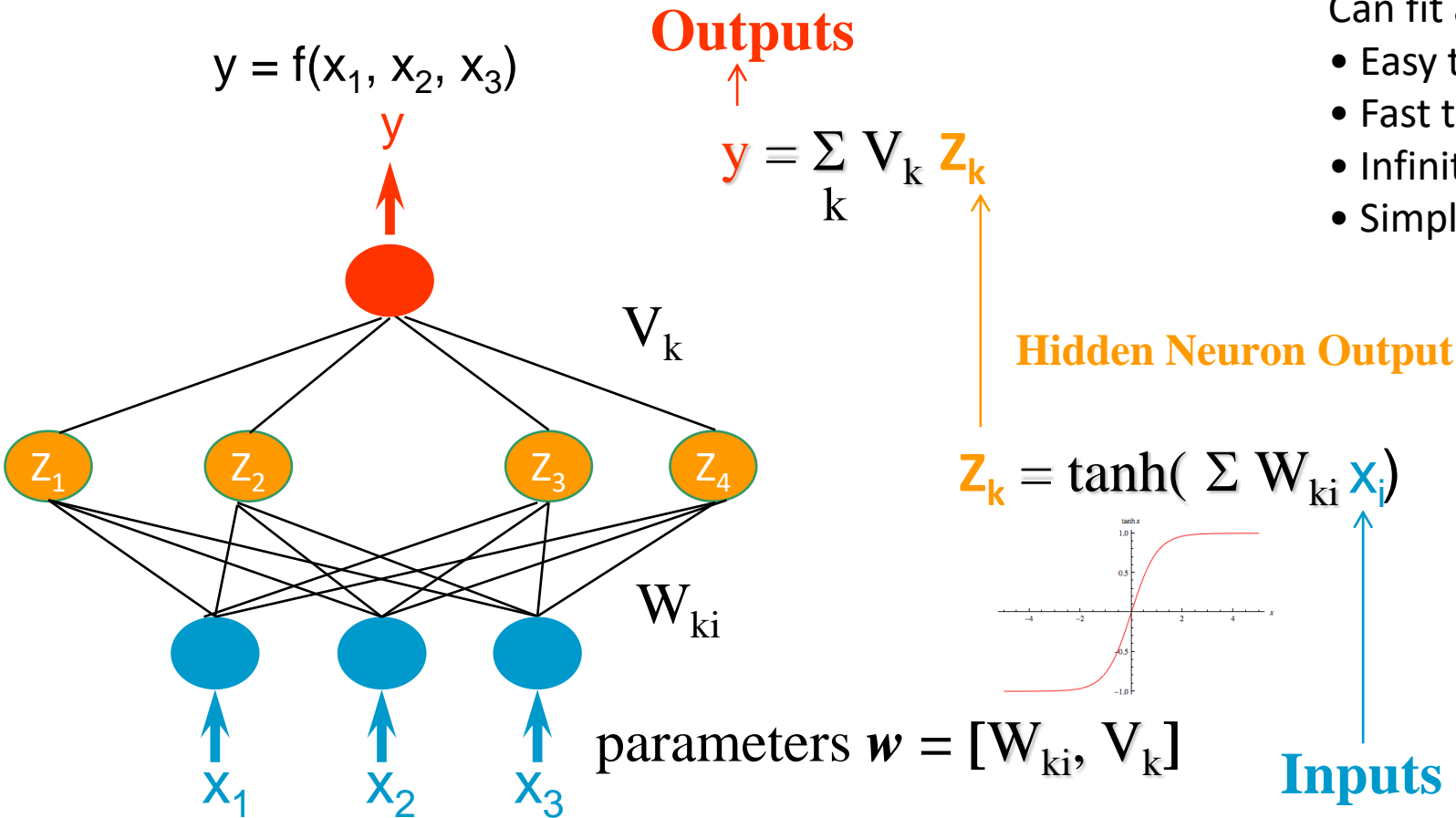
Self-driving cars

# AI and ML

AI



# Introduction to Artificial Neural Networks (ANN)

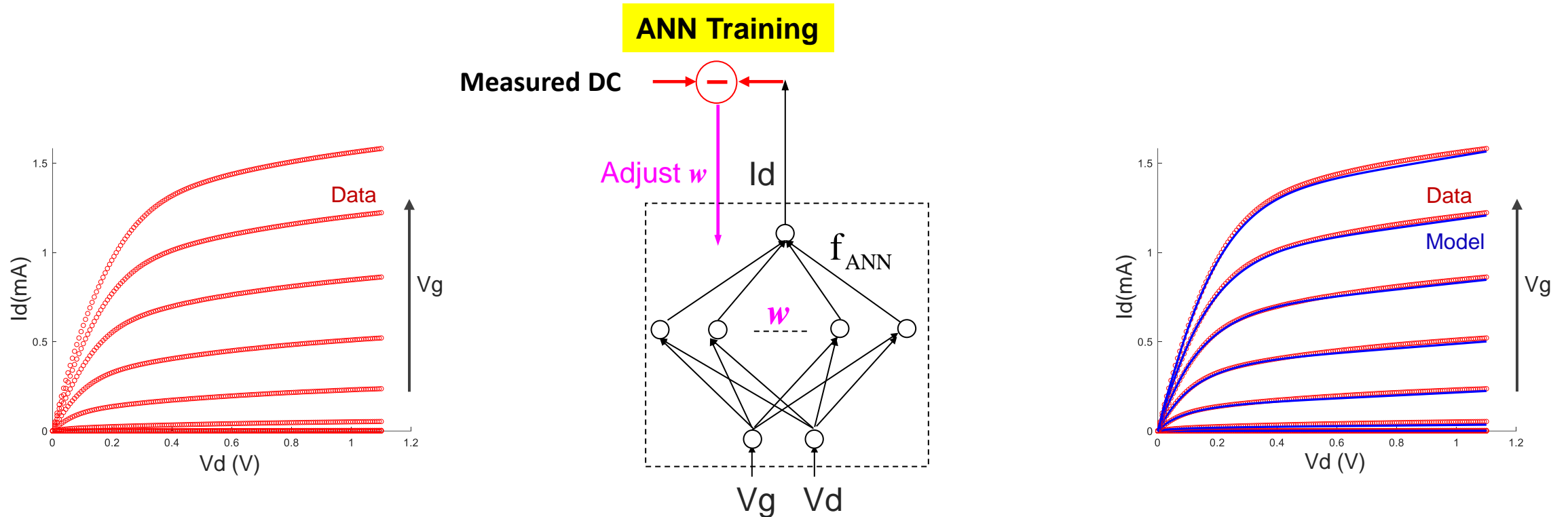


## Universal approximation Theorem:

Can fit any nonlinear function of many variables

- Easy to train *on scattered data*
- Fast to evaluate
- Infinitely differentiable
- Simple link (Verilog-A, ONNX, ...) to Simulators

# Introduction to Artificial Neural Networks (ANN)



Well-known training methods (e.g. back-propagation)

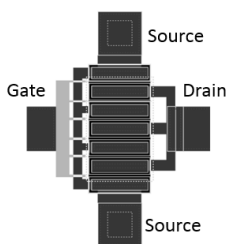
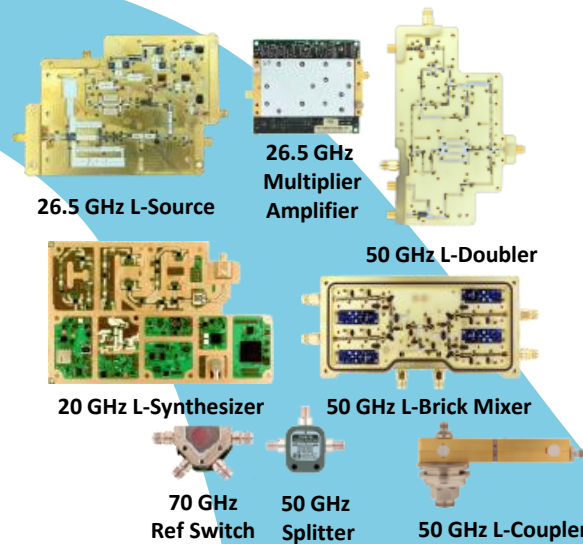
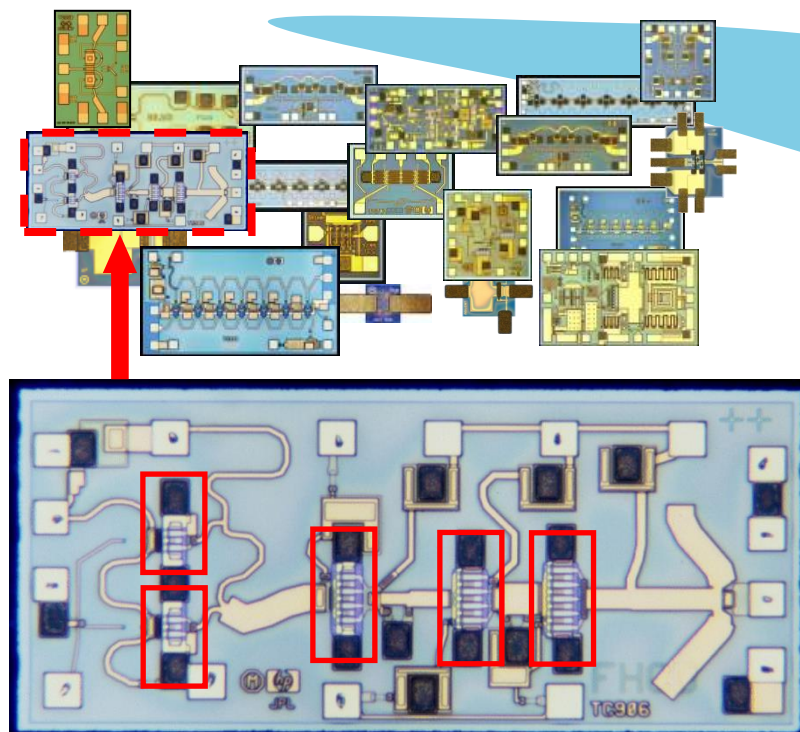
- No equation development needed
- No user-defined parameter extraction strategy

# Outline

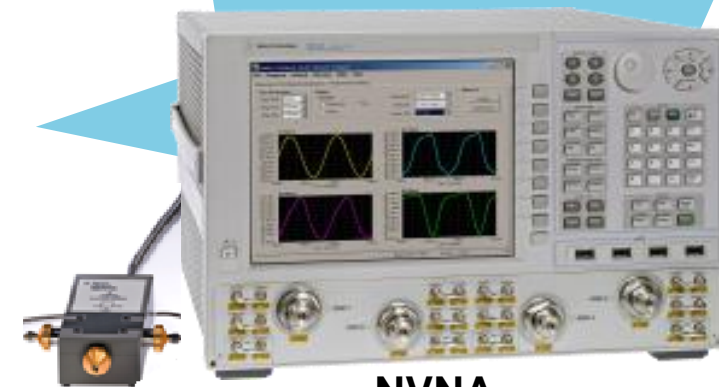
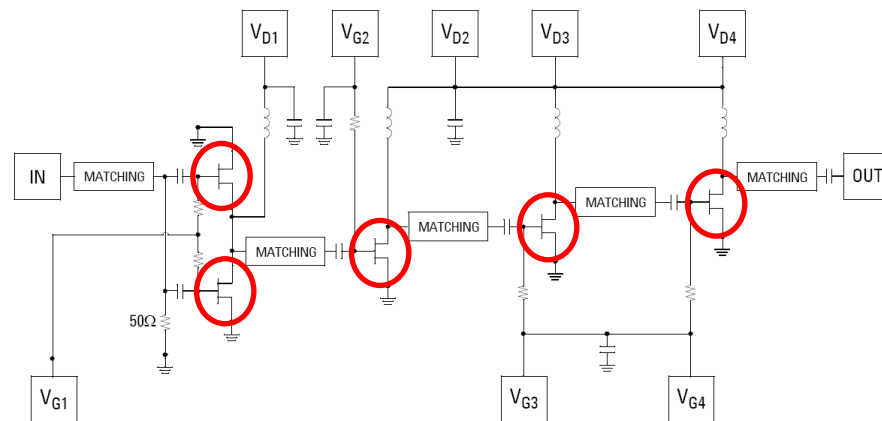
- Introduction to AI, ML and ANN
- **ANN for electronic device modeling**
- ANN for electronic behavioral modeling
- Summary



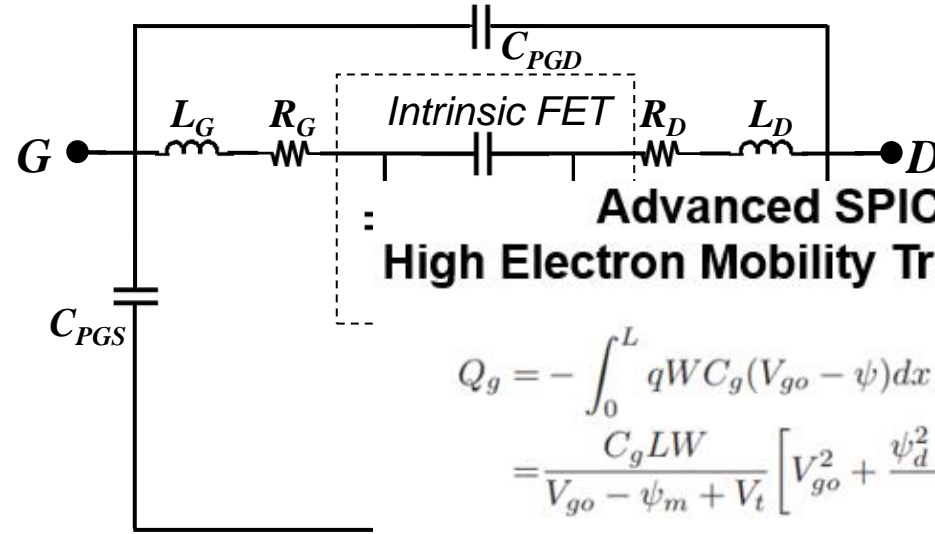
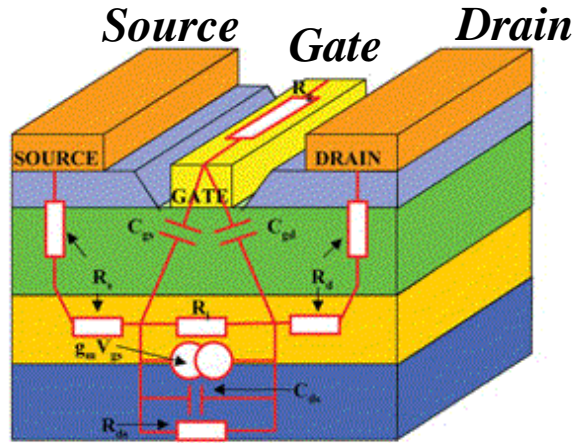
# Device Modeling



**Device Model**



# Conventional Device Modeling Flow



**Advanced SPICE Model for High Electron Mobility Transistor (ASM-HEMT)**

$$Q_g = - \int_0^L qWC_g(V_{go} - \psi)dx$$

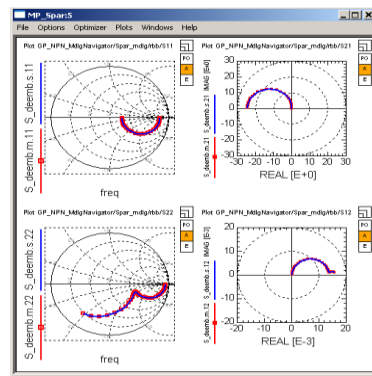
$$= \frac{C_g LW}{V_{go} - \psi_m + V_t} \left[ V_{go}^2 + \frac{\psi_d^2 + \psi_s^2 + \psi_d \psi_s}{3} - V_{go}(\psi_d + \psi_s - V_t) - V_t \psi_m \right]$$

$$I_{ds} = \frac{\mu_{eff} C_g}{\sqrt{1 + \theta_{sat}^2 \psi_{ds}^2}} \frac{W}{L} (V_{go} - \psi_m + V_{th}) (\psi_{ds}) (1 + \lambda V_{ds,eff})$$

$$E_{f,unified} = V_{go} - \frac{2V_t \ln \left( 1 + e^{\frac{V_{go}}{2V_t}} \right)}{\frac{1}{H(V_{go,p})} + (C_g/qD)e^{-\frac{V_{go}}{2V_t}}}$$

$$H = \frac{V_{go} + V_t [1 - \ln(\beta V_{gon})] - \frac{\gamma_0}{3} \left( \frac{C_g V_{go}}{q} \right)^{2/3}}{V_{go} \left( 1 + \frac{V_t}{V_{god}} \right) + \frac{2\gamma_0}{3} \left( \frac{C_g V_{go}}{q} \right)^{2/3}}$$

VNA

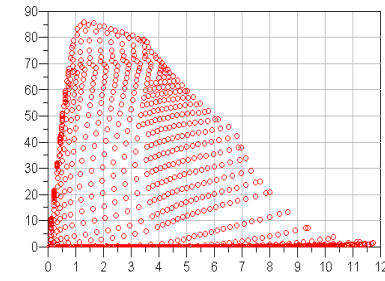


$Q_{GS}$

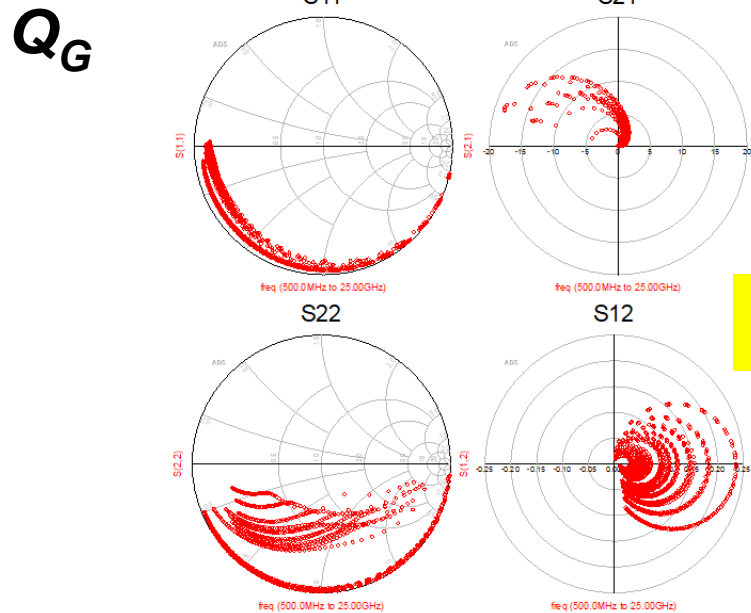
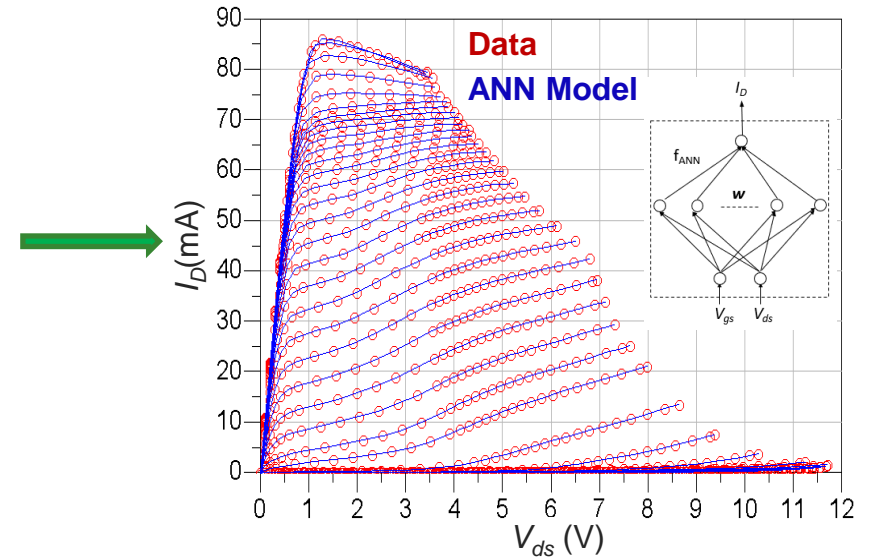
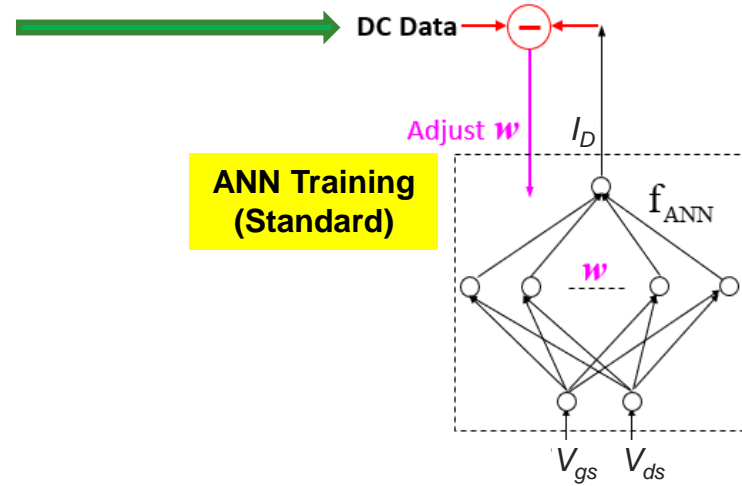
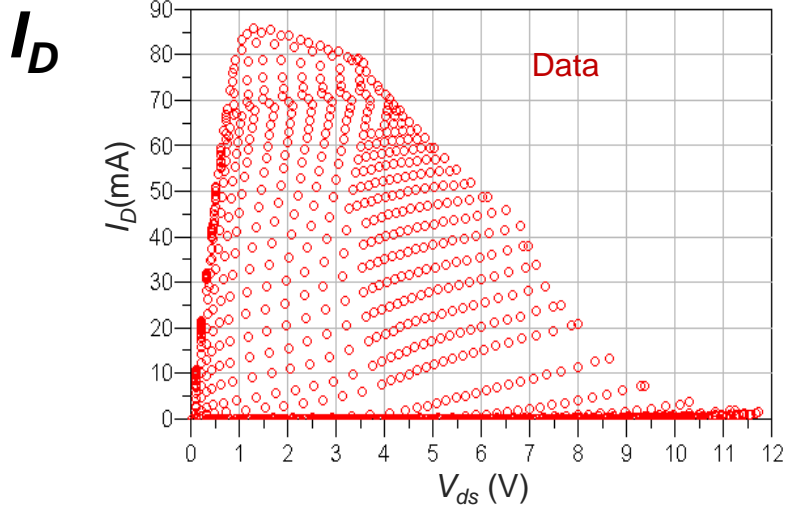
ANN Training

$I_{DS}$

DC



# ANN Training

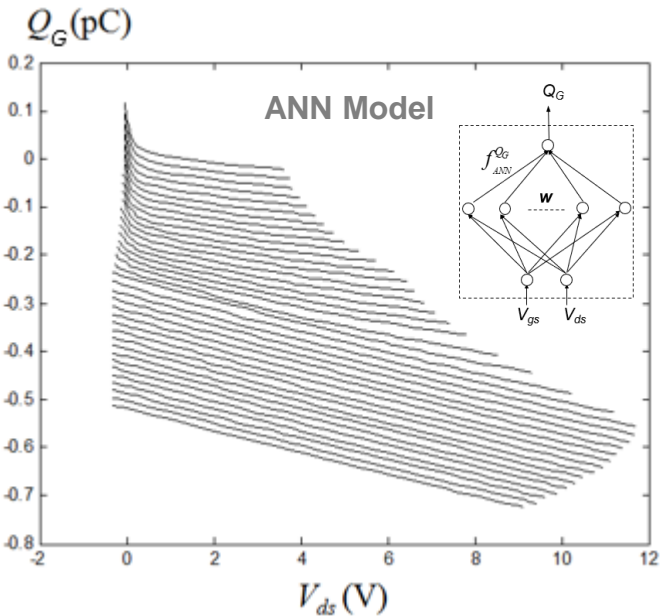
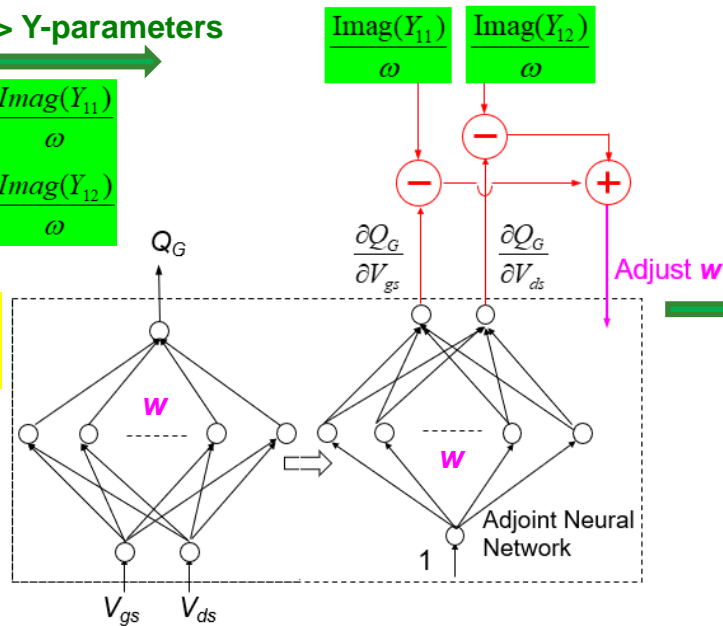


S-parameters -> Y-parameters

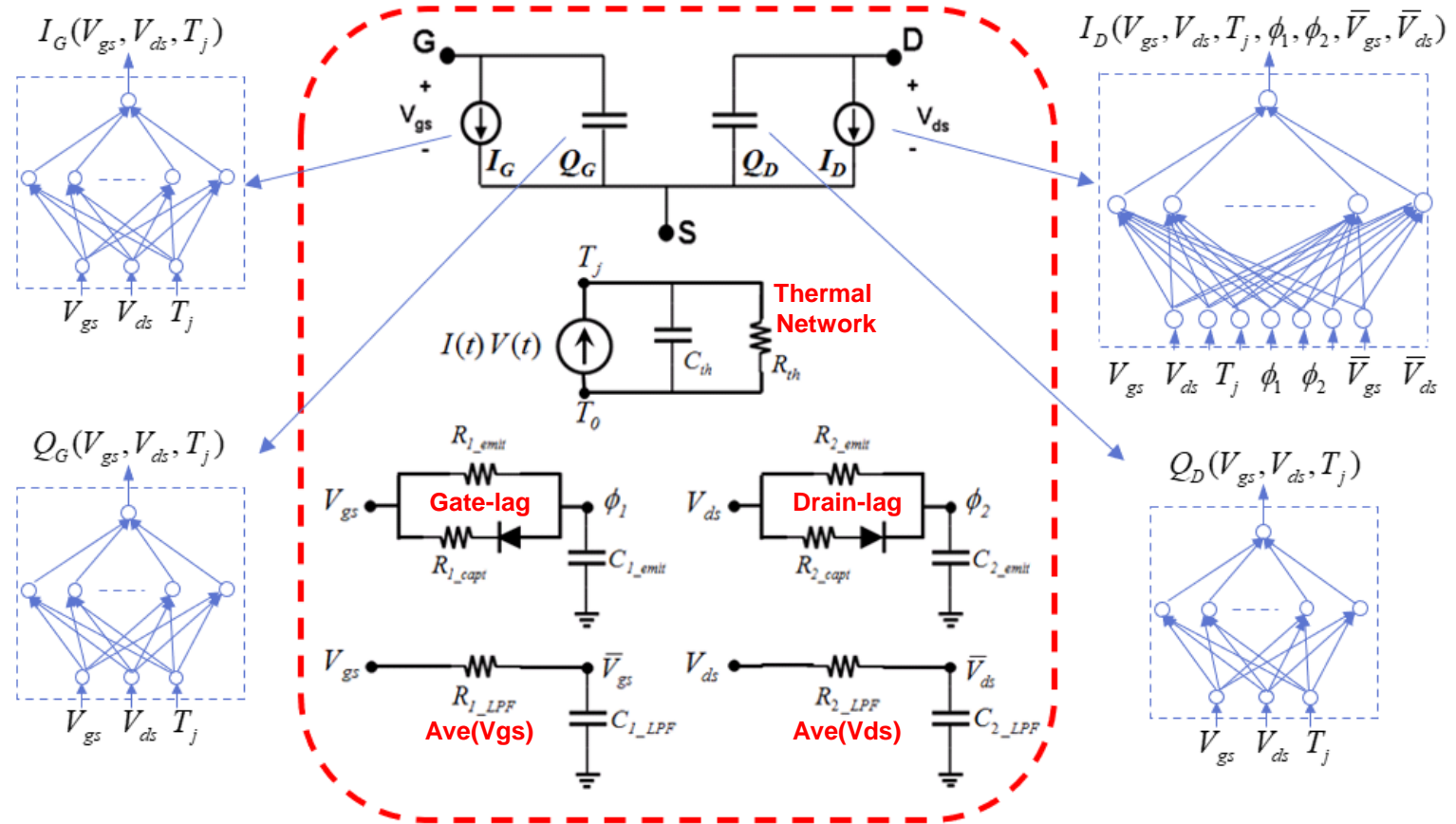
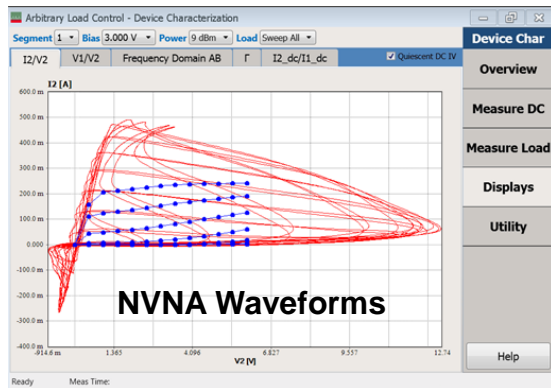
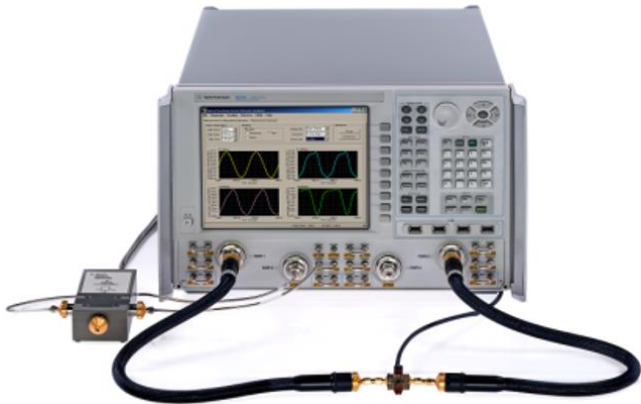
$$\frac{\partial Q_G}{\partial V_{gs}} = \frac{\text{Imag}(Y_{11})}{\omega}$$

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

ANN Training (Adjoint [1])



# ANNs in DynaFET [2] model for GaN transistors



➤ Richer data necessary to identify complicated dynamics

➤ ANNs used to model the detailed, general, multi-variate coupling

➤ **One global model** that predicts, simultaneously:

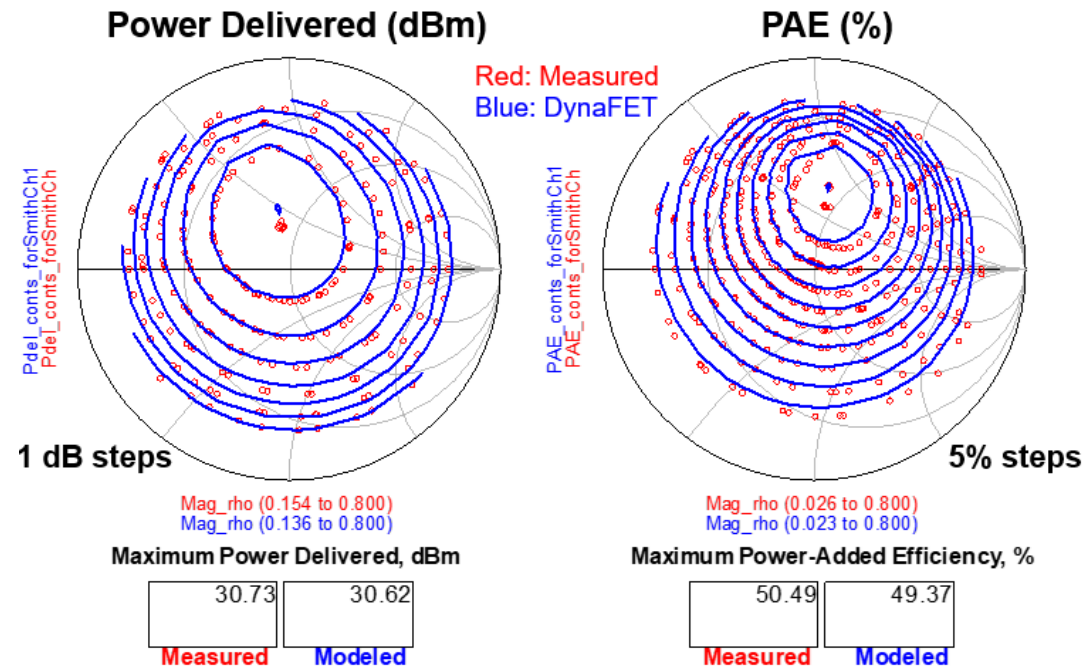
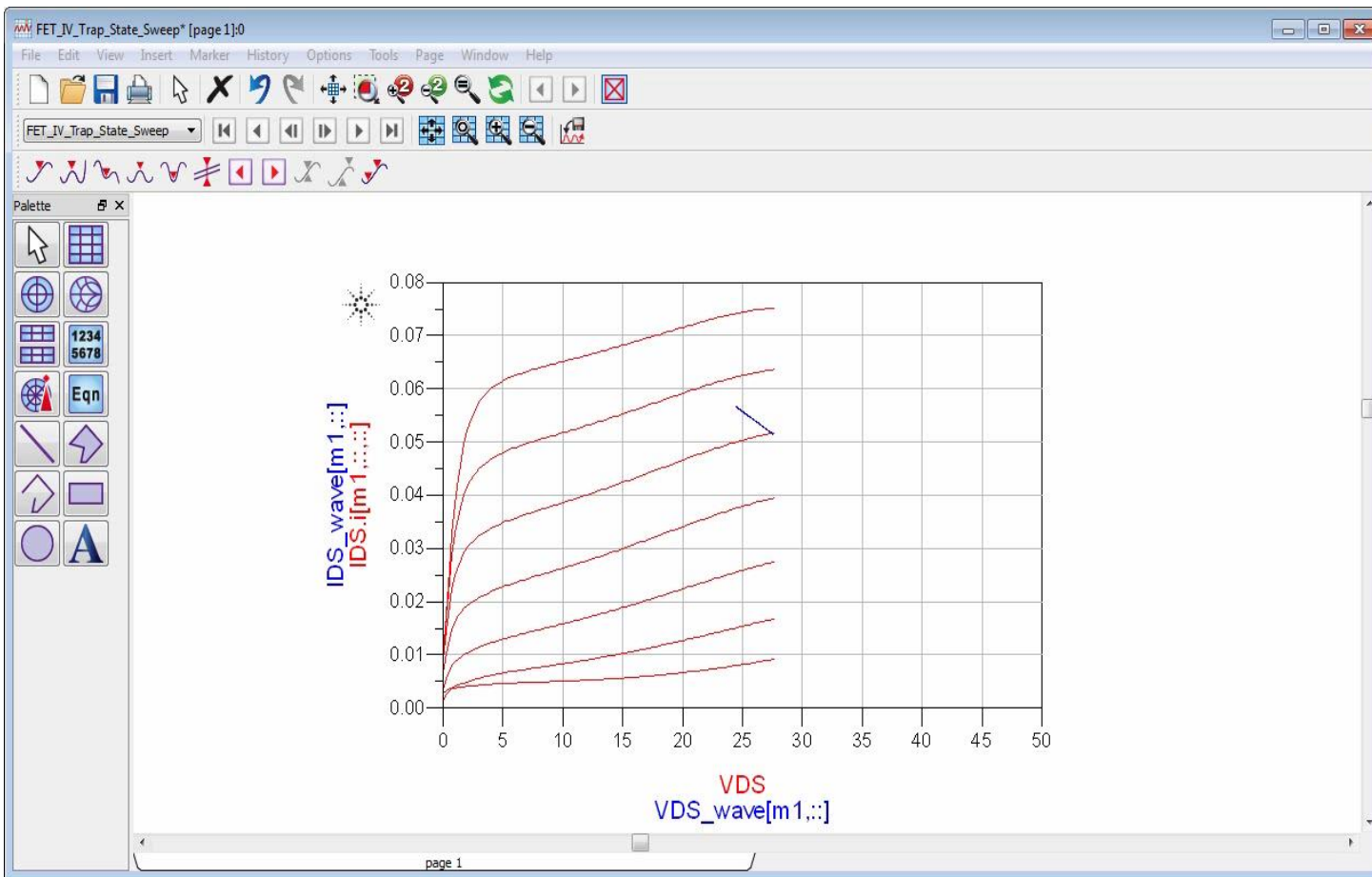
- Accurate and general
- No additional assumptions (e.g., backgating/virtual gate)

- DC and S-parameters
- Large-signal nonlinearities (distortion, load-pull, PAE)
- Long-term memory effects
- No application-specific model tuning needed

# DynaFET model for GaN transistors [2]

Raytheon 6x60 $\mu$ m GaN HFET

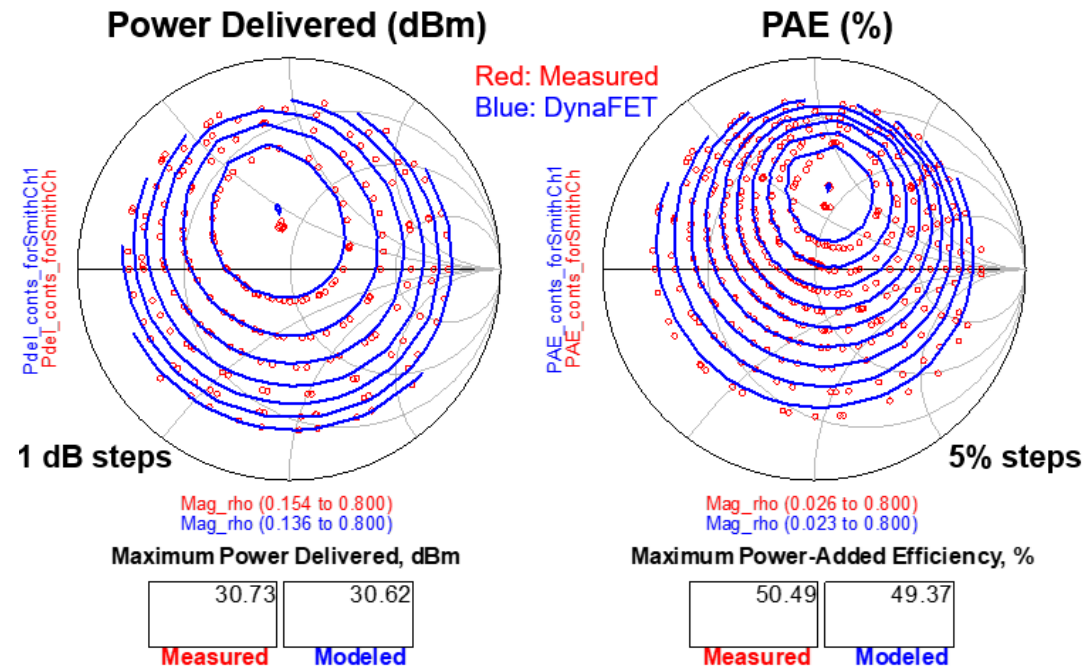
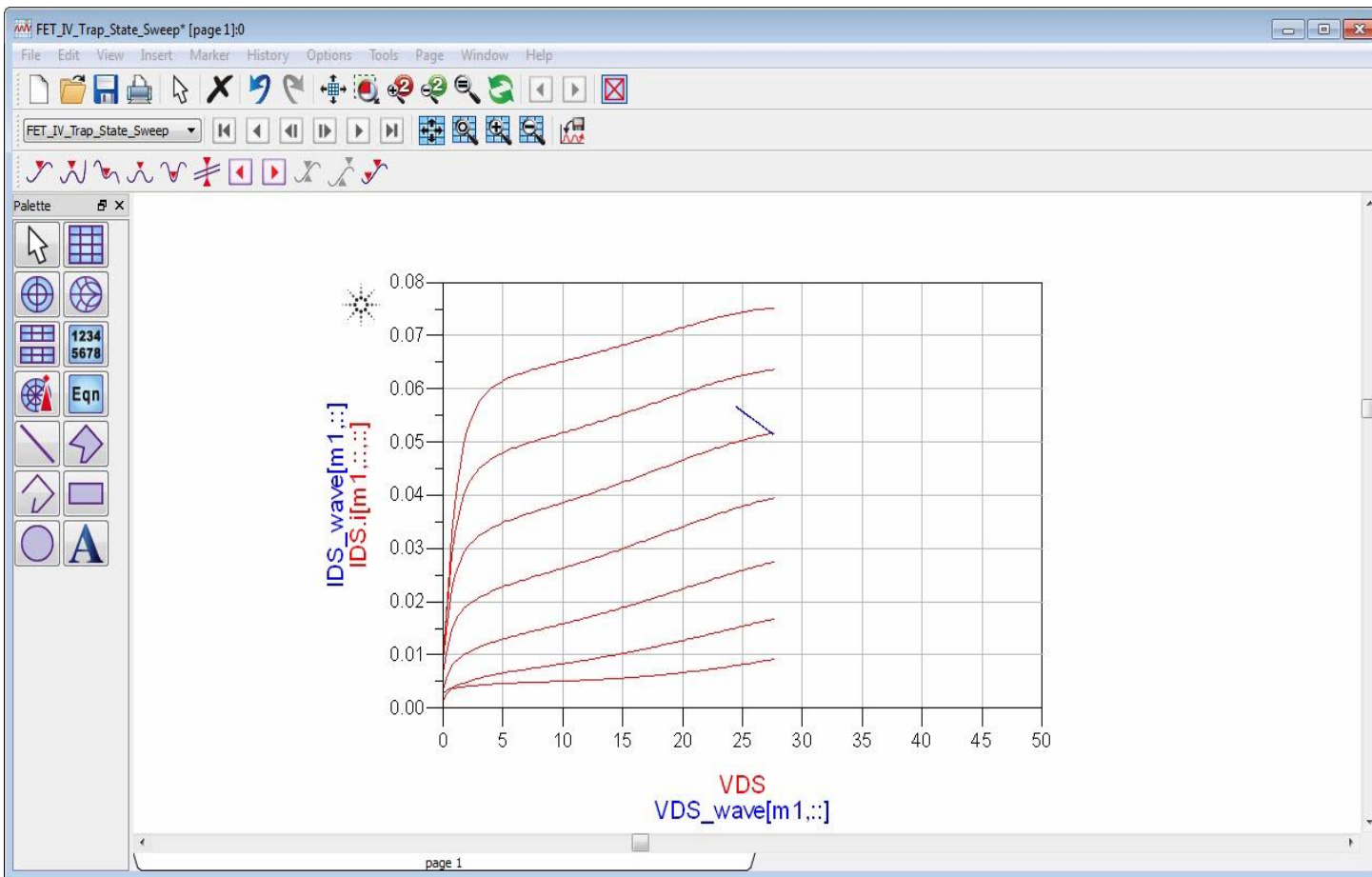
Model Validations – Load-pull Contours  
fund=10GHz, @Vd=12V, Id=54mA, Pin=24dBm



# DynaFET model for GaN transistors [2]

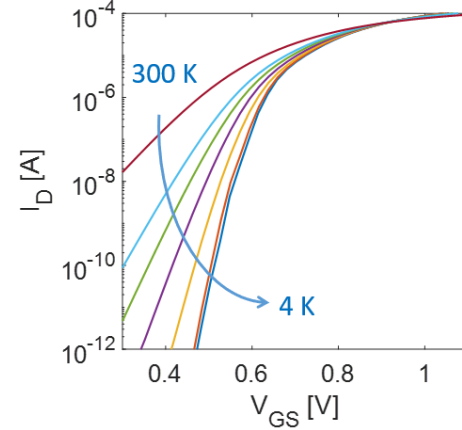
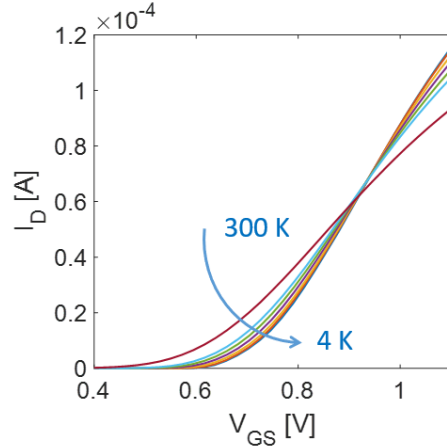
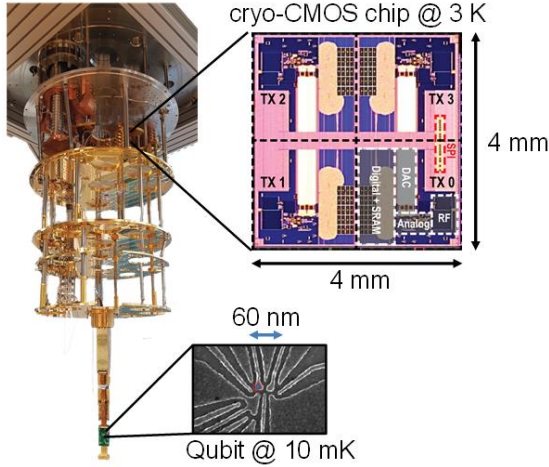
Raytheon 6x60 $\mu$ m GaN HFET

Model Validations – Load-pull Contours  
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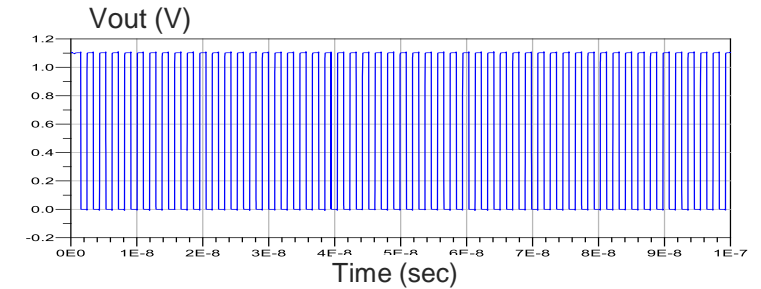
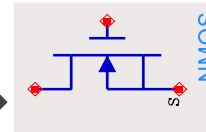
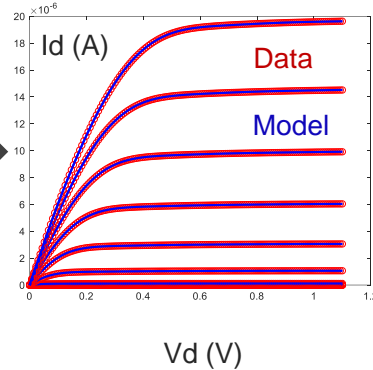
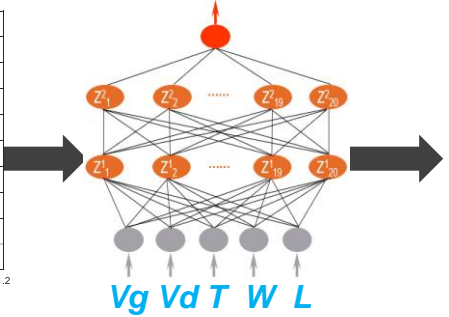
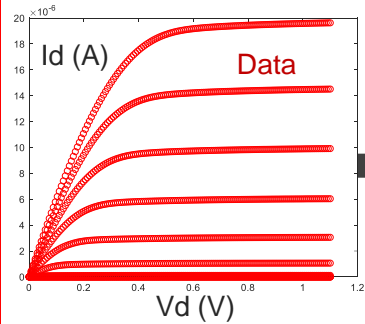
# ANN for Cryogenic CMOS Modeling [3]

Enabling circuit simulations for quantum control applications

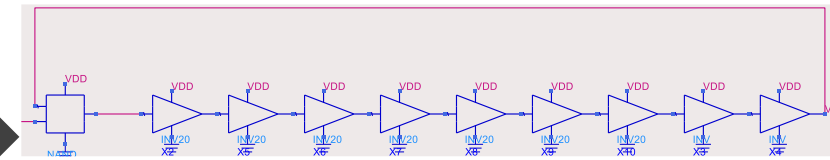
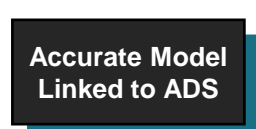
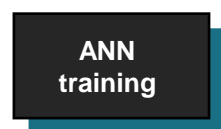
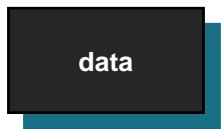


- Device characteristics at cryogenic temperatures are different from those at room temperature
- Existing models and extraction procedures may not be effective
- So far, there is not yet consensus on a standard cryo-CMOS model

$$I_d = I_d^{ANN}(V_g, V_d, T, W, L)$$



Cryo Work Flow

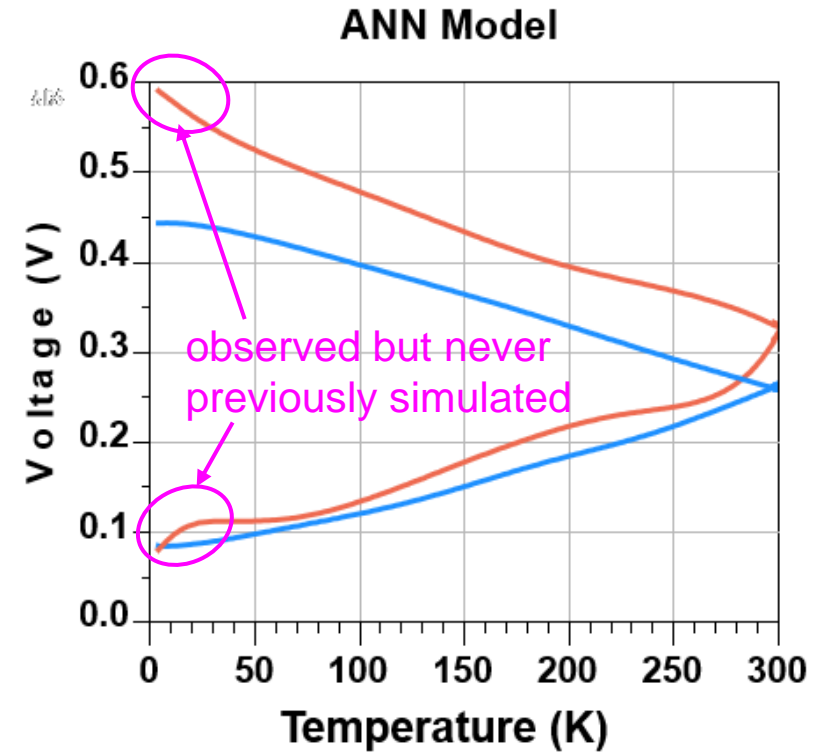
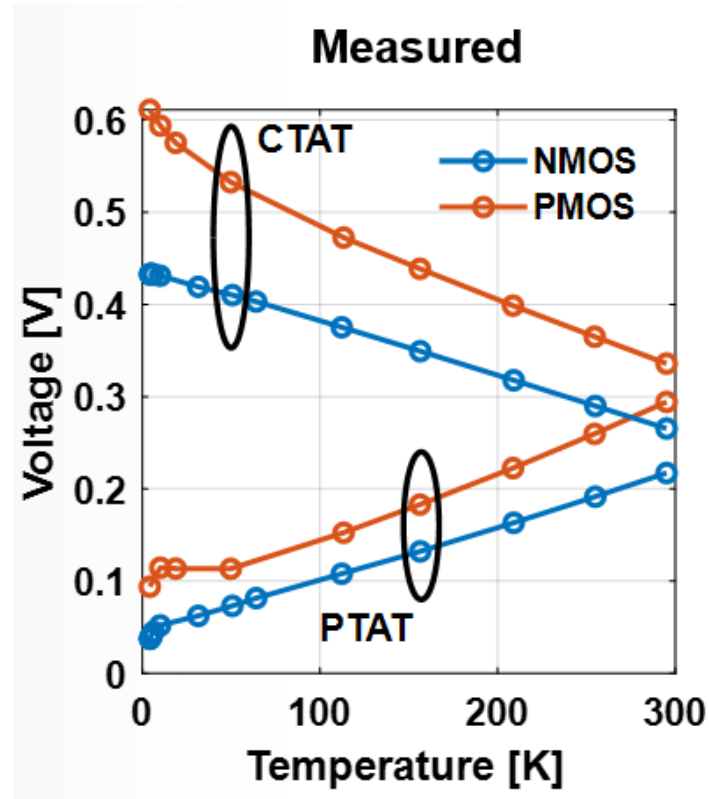
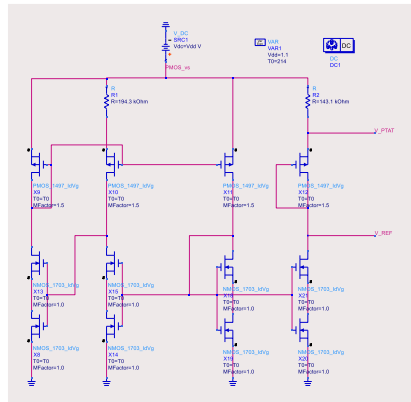
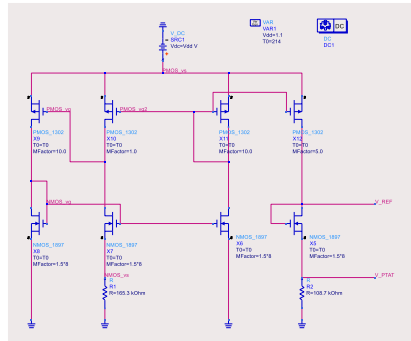
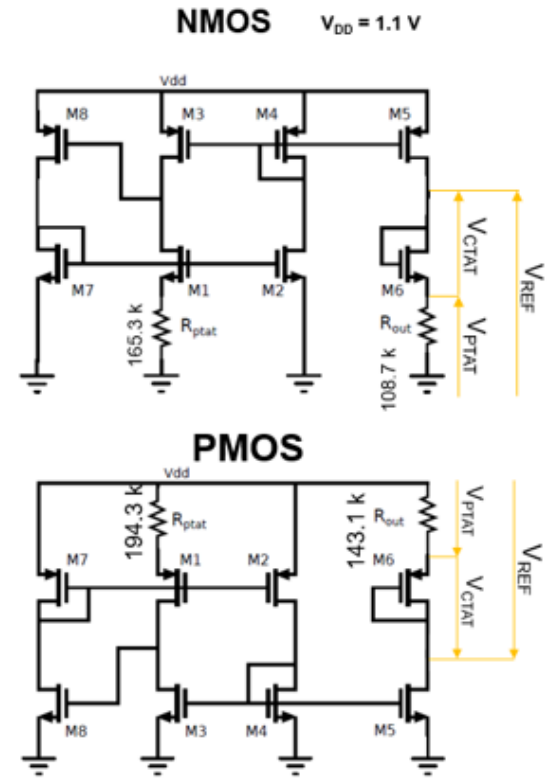


Design and Simulate Cryogenic Circuits

# ANN for Cryogenic CMOS Modeling [3]

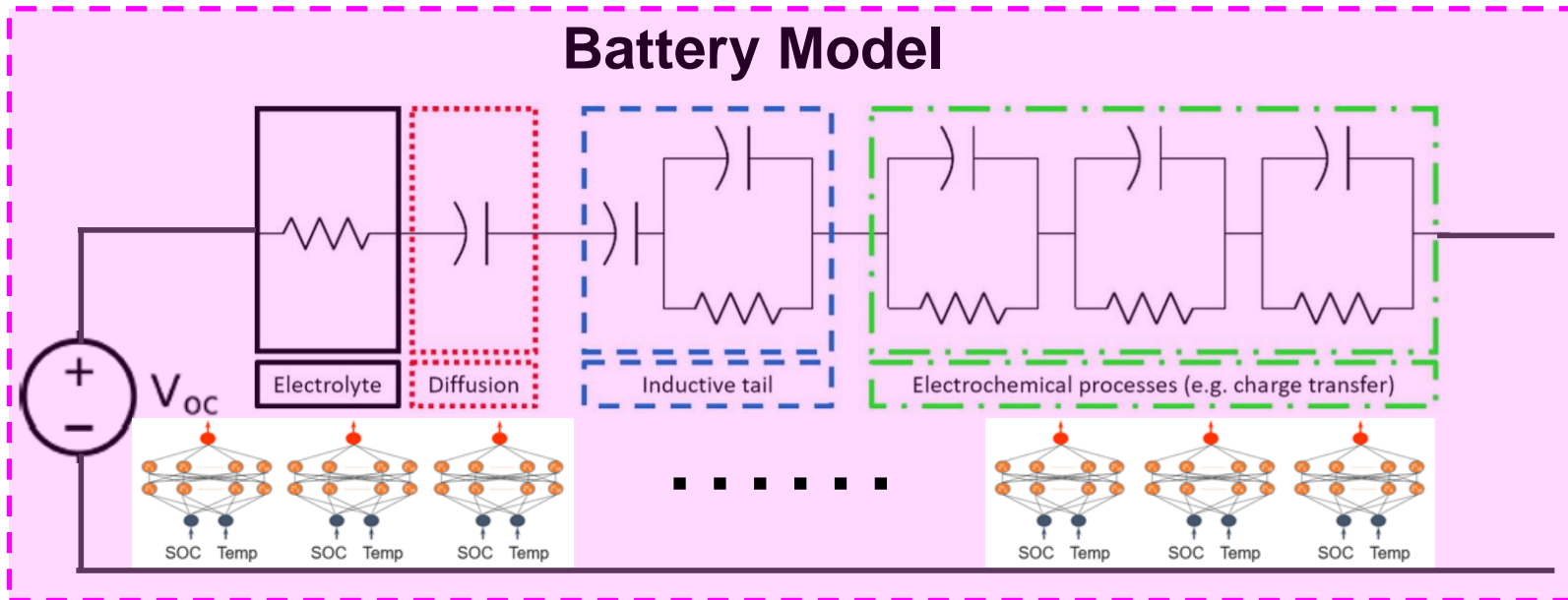
## Voltage Reference Circuits

## Keysight ADS implementation with ANN models





# Battery Modeling [4]



emulation



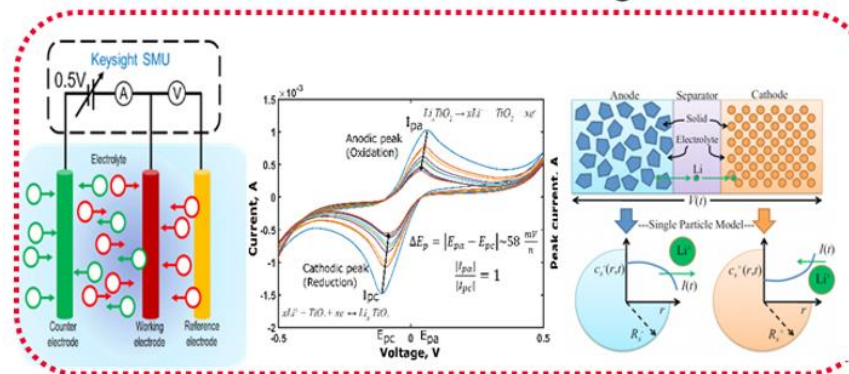
prediction / battery management system



parameter extraction / classification



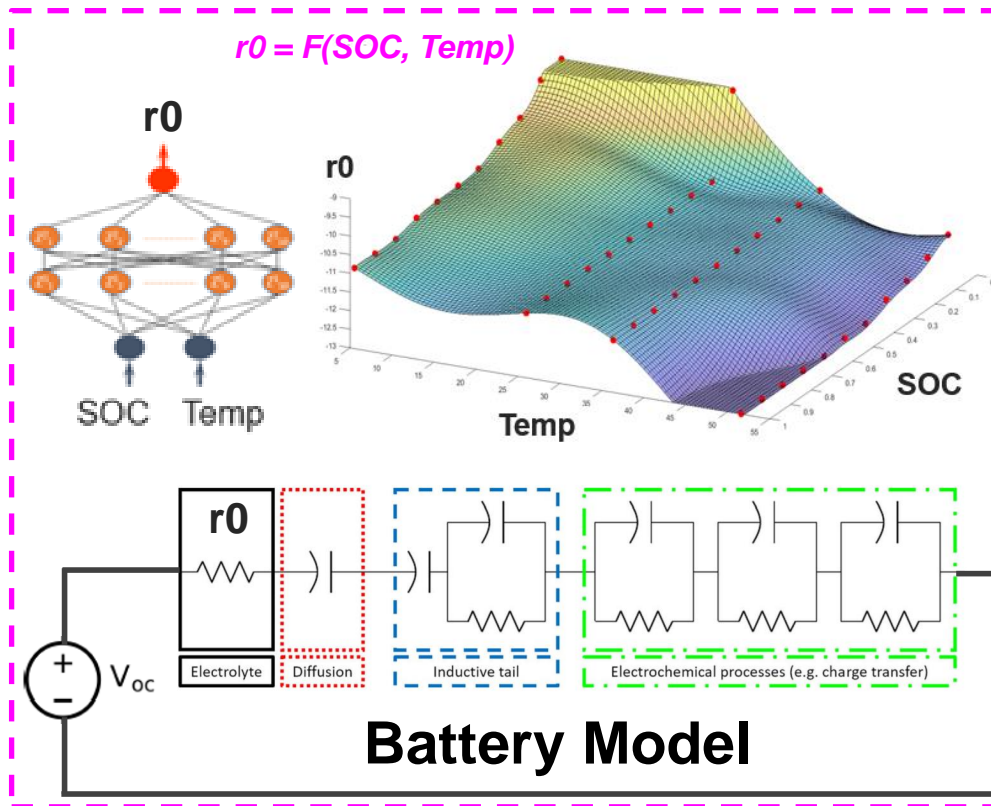
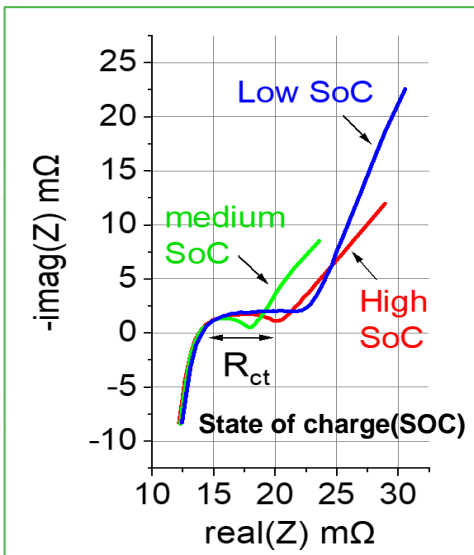
electrochemical modelling



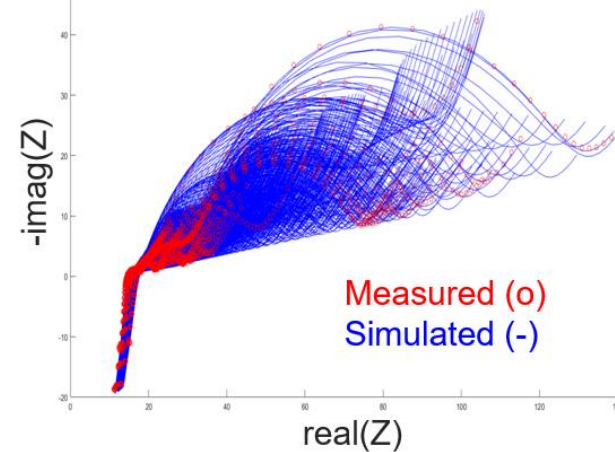
# Battery Modeling [4]



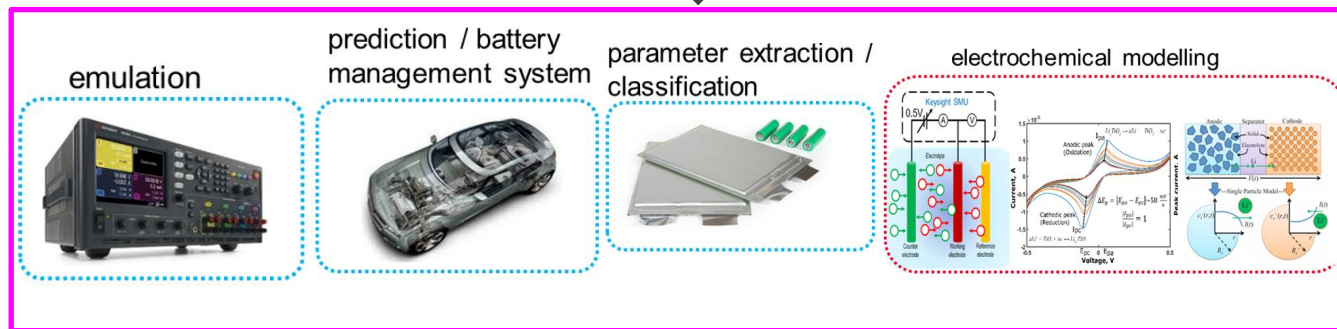
Electrochemical Impedance Spectroscopy (EIS)



Predicting the battery's behavior at different Temperature and State of charge (SOC)



Keysight Battery Test System



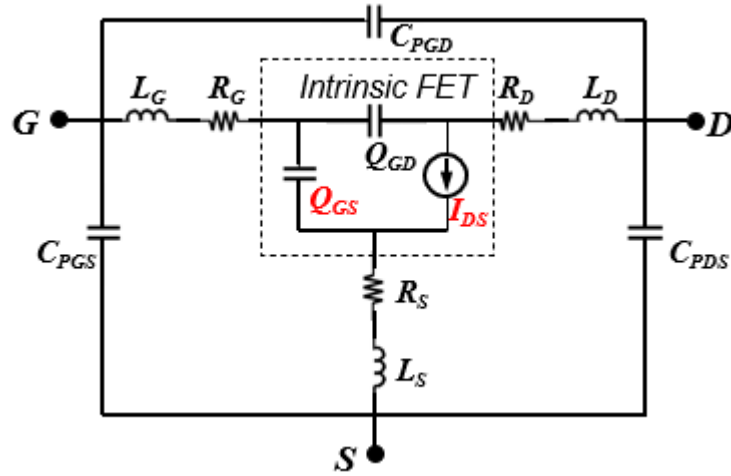
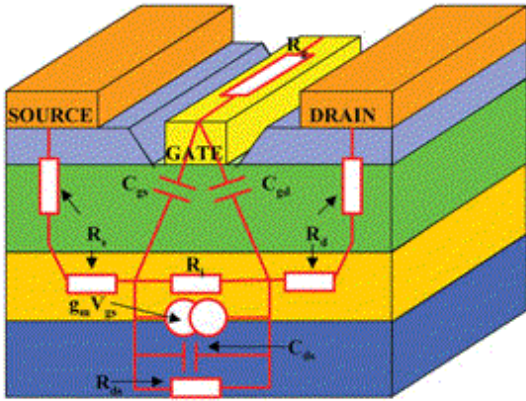
[4] M. Kasper et al, "Calibrated Electrochemical Impedance Spectroscopy and Time-Domain Measurements of a 7 kWh Automotive Lithium-Ion Battery Module with 396 Cylindrical Cells", *Batteries & Supercaps* published by Wiley-VCH GmbH, 2022.



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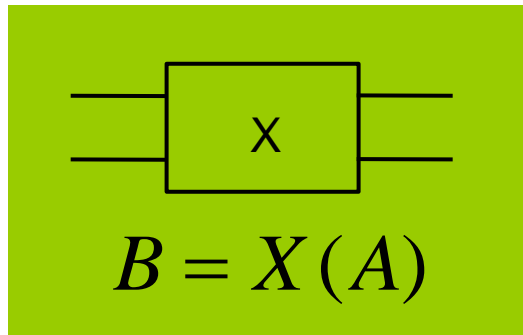
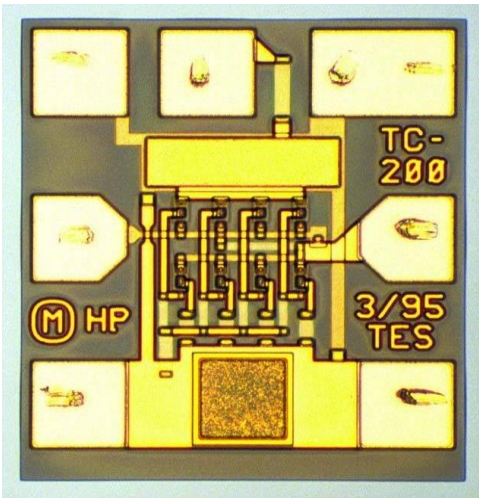
# Behavioral Modeling



**Device Model**

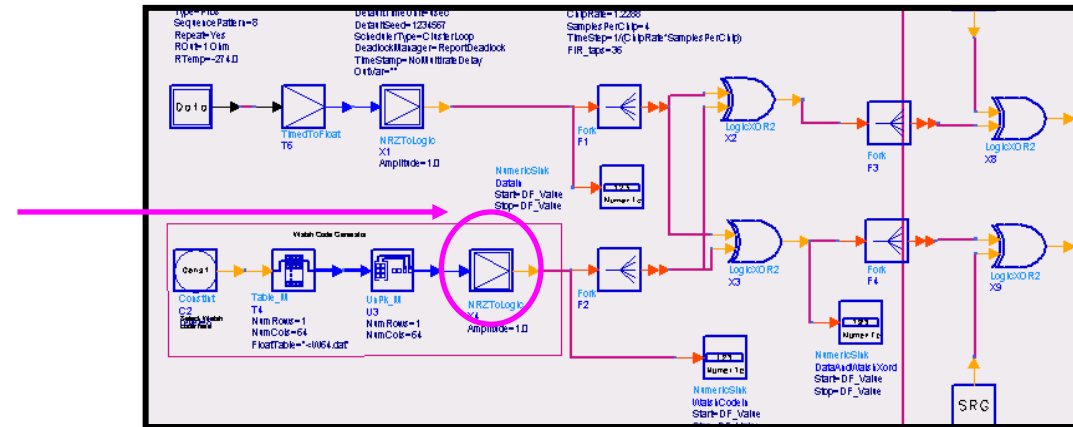
$$Q_{GS} = -C_{gs0} V_{bi} \left( I - \frac{V_{GS}}{V_{bi}} \right)^\eta$$

$$I_{DS} = \left( \sum_{n=0}^3 A_n \cdot V_{GS}^n \right) \cdot \tanh(\gamma \cdot V_{DS})$$

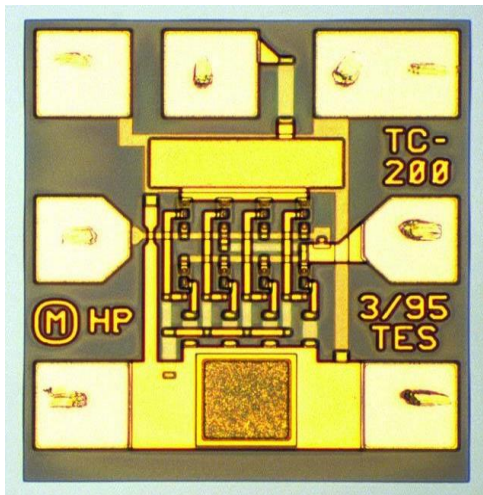


**Behavioral Model**

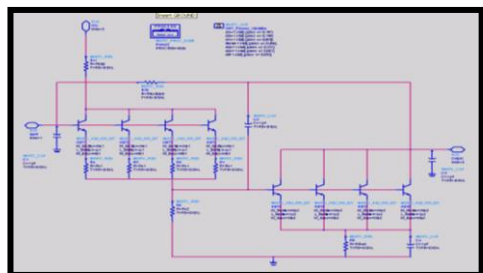
## Design of Front End Module or IC



# Behavioral Modeling



Actual Circuit



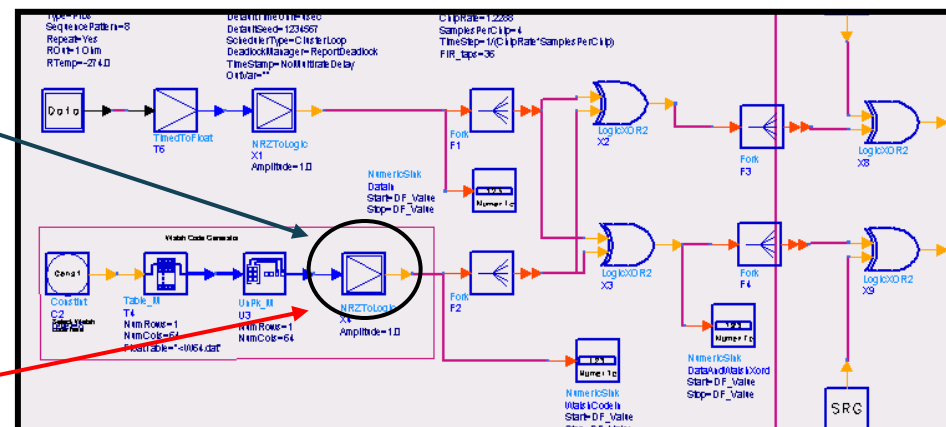
Detailed Circuit Model (SPICE/ADS) of IC

## Measurement-Based Model

- Circuit model may not exist
- Circuit models may be inaccurate
- Completely protect design IP

Generate Behavioral Model

## Design of Front End Module or IC

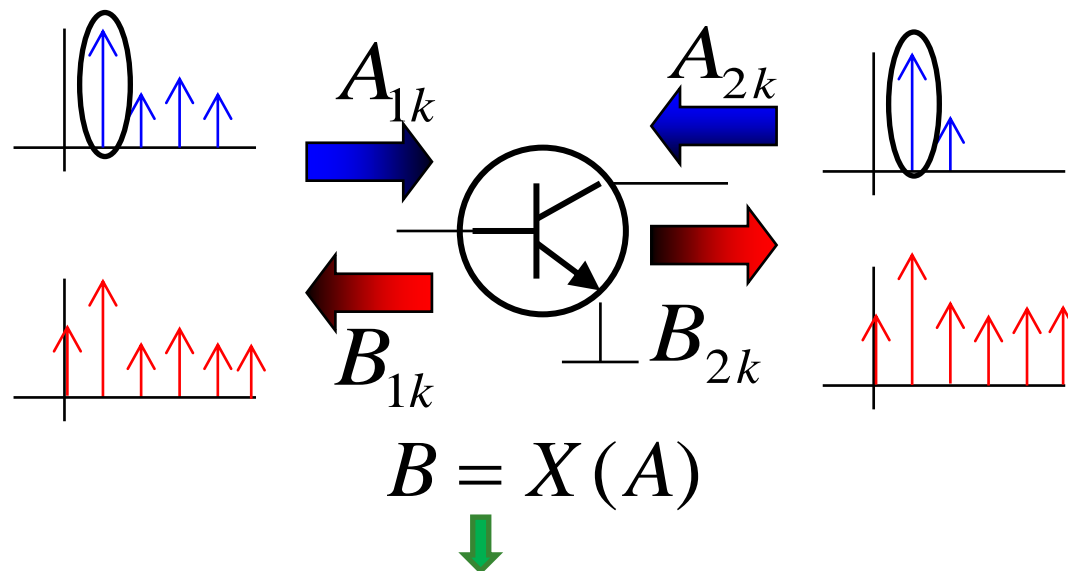


## Simulation-Based Model

- Detailed circuit simulation is too slow
- Design system before building IC
- Completely protect design IP
- Do more in simulator than possible on instrument

# ANN for Frequency Domain Behavioral Modeling

## Load-dependent X-parameter Model [6]



$$B_{p,k} \cong X_{p,k}^{(F)}(LSOP)P^k + \sum_{(q,m)>(1,1)} X_{p,k;q,m}^{(S)}(LSOP)P^{k-m}A_{q,m} + \sum_{(q,m)>(1,1)} X_{p,k;q,m}^{(T)}(LSOP)P^{k+m}A_{q,m}^*$$

- Spectral linearization around  $LSOP=[ Bias, Freq, |A_{1,1}|, real(A_{2,1}), imag(A_{2,1}) ]$
- $P = e^{j\phi(A_{11})}$  Phase of A11
- Outputs assuming all harmonics are matched
- Cross-frequency mismatch sensitivity terms

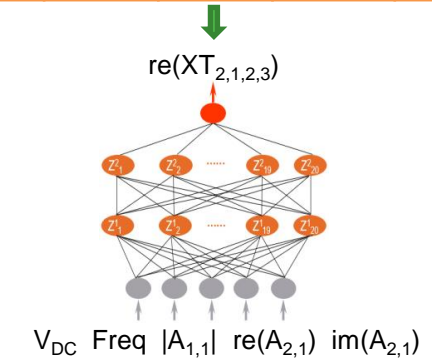
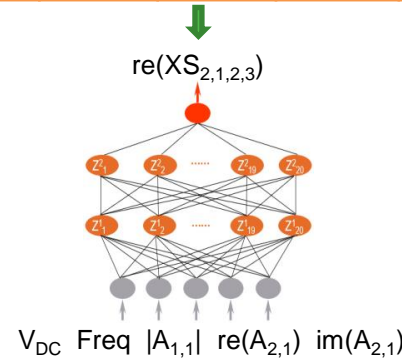
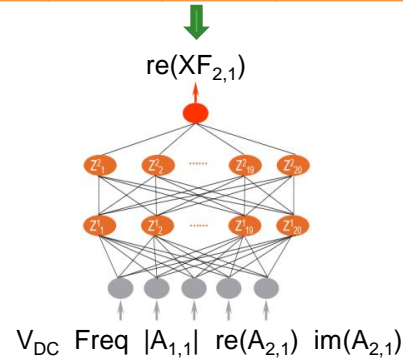
# ANN for Frequency Domain Behavioral Modeling

$$B_{p,k} \cong X_{p,k}^{(F)} (LSOP) P^k + \sum_{(q,m)>(1,1)} X_{p,k;q,m}^{(S)} (LSOP) P^{k-m} A_{q,m} + \sum_{(q,m)>(1,1)} X_{p,k;q,m}^{(T)} (LSOP) P^{k+m} A_{q,m}^*$$

VDC	Freq	A1,1	Real(A2,1)	Imag(A2,1)	Real(XF2,1)
2.0	1e9	0.0375	0.0316	-0.123	0.0315
5.0	2e9	0.0467	0.1643	-0.588	0.1041
8.0	3e9	0.1470	0.5623	-0.963	-0.3162
...	...	...	...	...	...

VDC	Freq	A1,1	Real(A2,1)	Imag(A2,1)	Real(XS2,1,2,3)
2.0	1e9	0.0375	0.0316	-0.123	0.0015
5.0	2e9	0.0467	0.1643	-0.588	0.2102
8.0	3e9	0.1470	0.5623	-0.963	-0.1116
...	...	...	...	...	...

VDC	Freq	A1,1	Real(A2,1)	Imag(A2,1)	Real(XT2,1,2,3)
2.0	1e9	0.0375	0.0316	-0.123	-0.6031
5.0	2e9	0.0467	0.1643	-0.588	-0.5104
8.0	3e9	0.1470	0.5623	-0.963	0.2316
...	...	...	...	...	...



## Current limitations:

- Gridded data structure forces high volume of data measurement, some conditions are hard or difficult (device damage) to measure
- Accurate simulation requires a large table of data
- Time to load data file is long and Memory usage is large
- Results may depend on particular simulator capabilities to read tables and interpolation algorithms

## Benefits of replacing tables with ANNs:

- Data can be taken as needed for accuracy (e.g., adaptively) and as may be constrained by device operation
- Discrete data is converted to smooth functions for further applications downstream (optimization, system simulation, hierarchical modeling, Digital Twin)

## Downside of ANNs for X-parameter modeling:

- Training times may be long, requiring parallel training infrastructure (Keysight unpublished work)



# ANN for Frequency Domain Behavioral Modeling

WJ FP2189 1W HFET

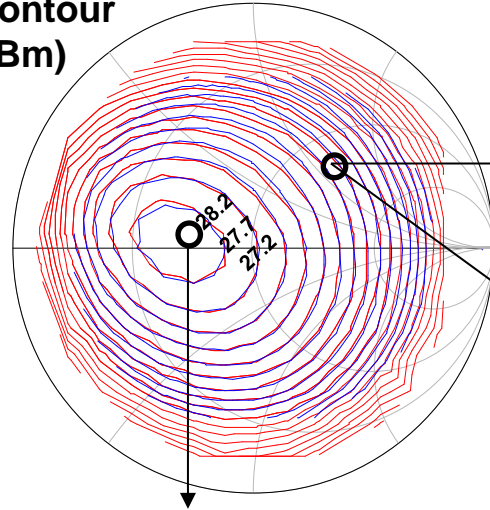
Model Validations  
 fund=2GHz, @Vd=8V,  
 Id=250mA, Pin=12dBm

The results of unpublished ANN-based X-parameter model is virtually identical to the table-based results first published [8] shown in these plots.

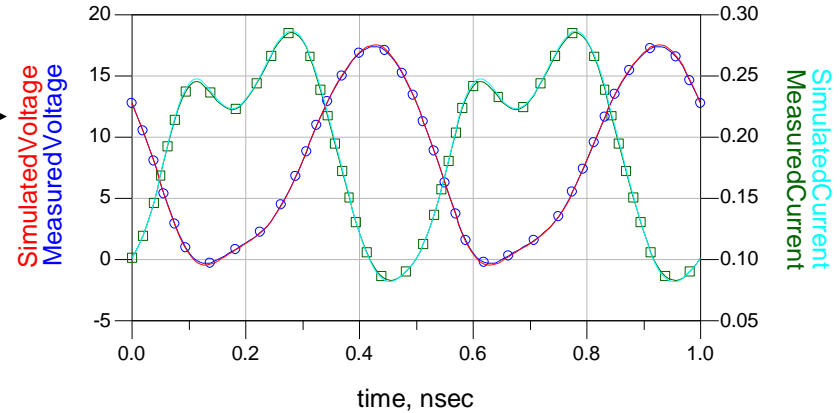
Measurements

ANN based X-parameter Simulation

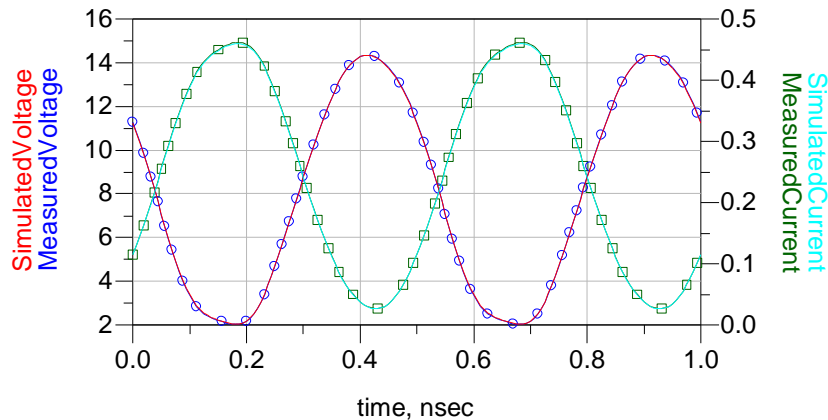
$P_{out}$  Contour (dBm)



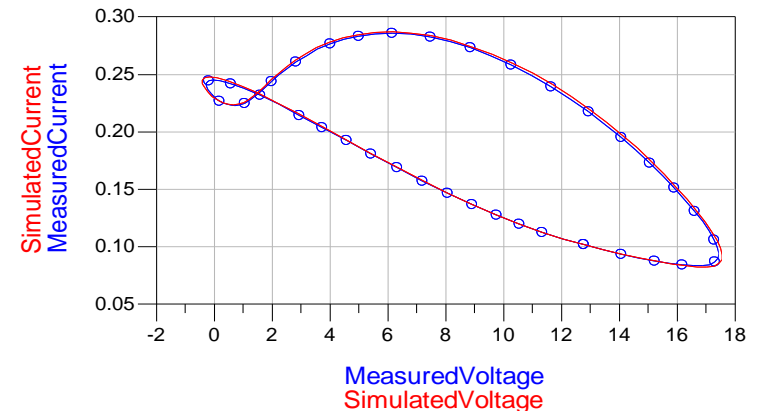
Measured and Simulated Voltage and Current Waveforms



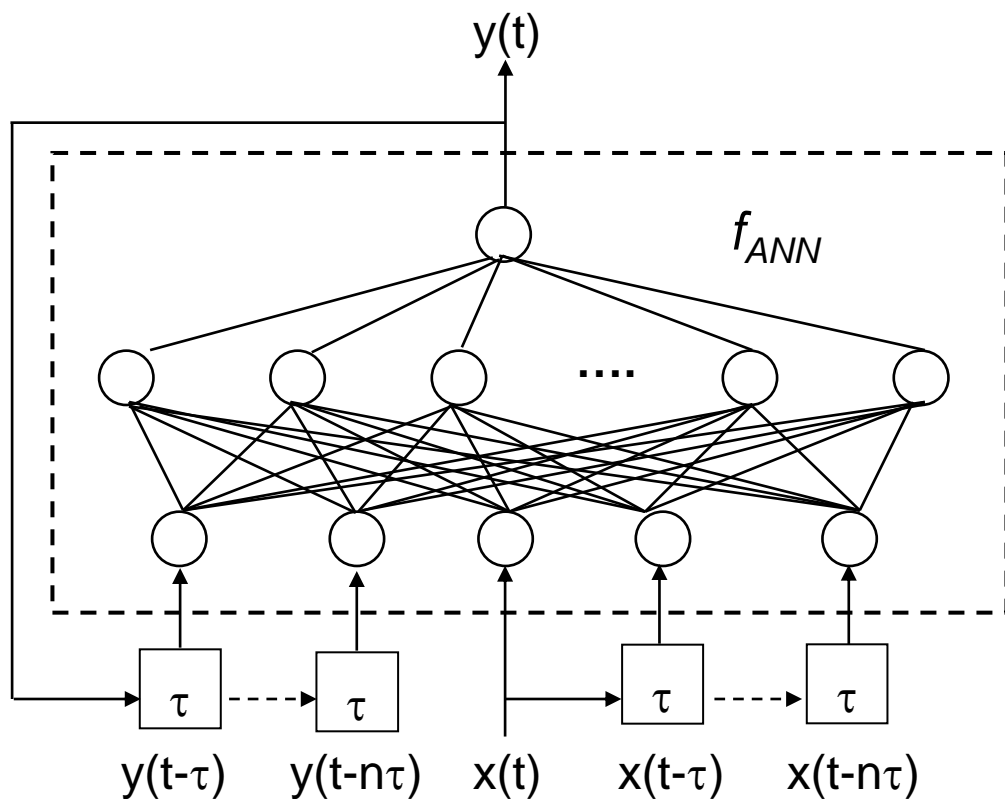
Measured and Simulated Voltage and Current Waveforms



Measured and Simulated Dynamic Load Line

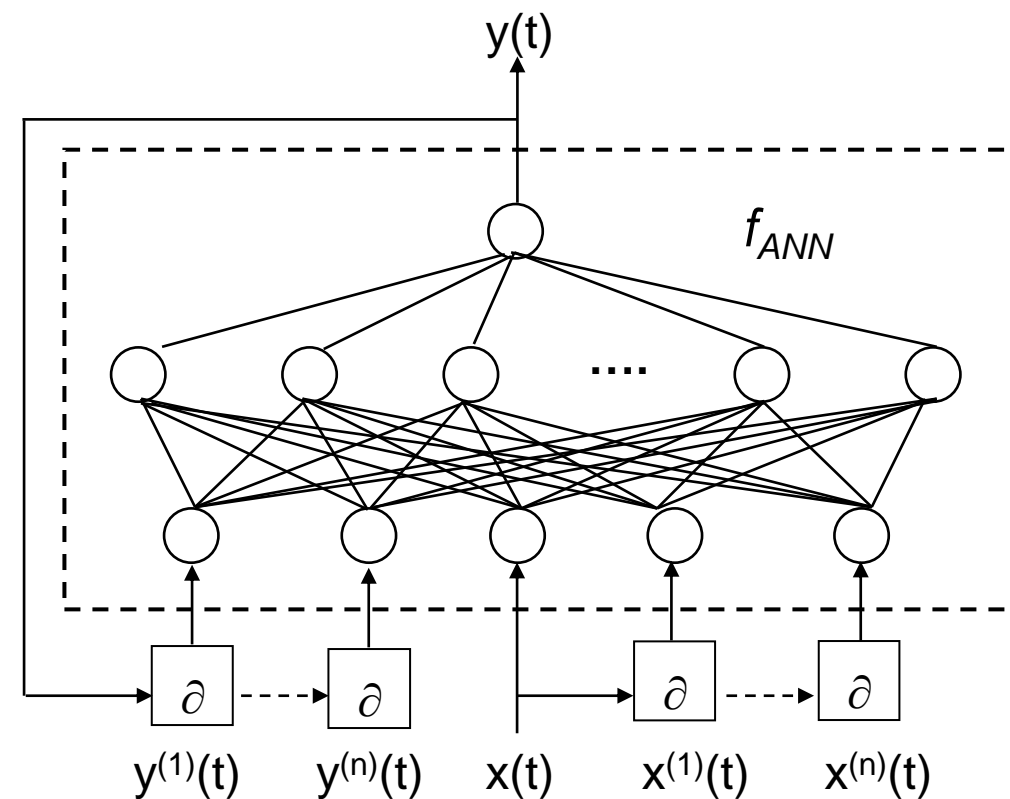


# ANN for Time Domain Behavioral Modeling



**Recurrent Neural Network (RNN)**

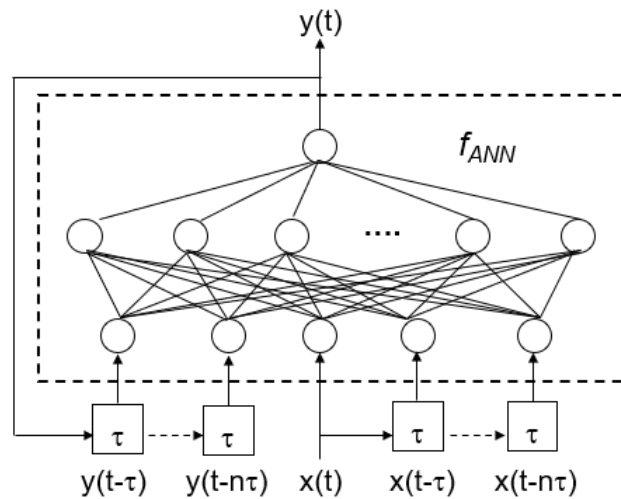
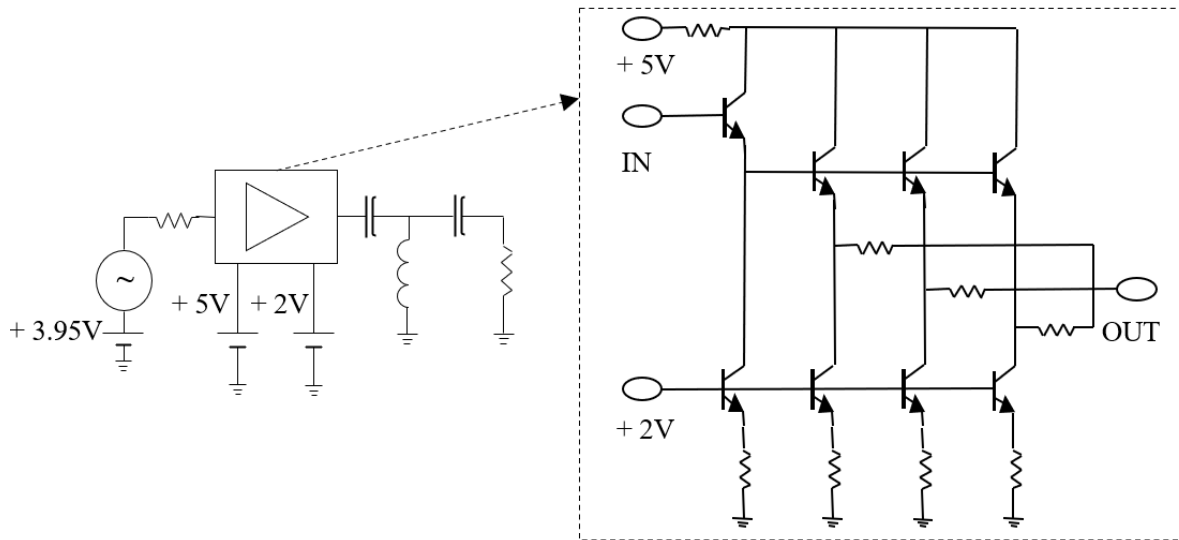
$$y(t) = f_{ANN}(y(t - \tau), \dots, y(t - n\tau), x(t), x(t - \tau), \dots, x(t - n\tau))$$



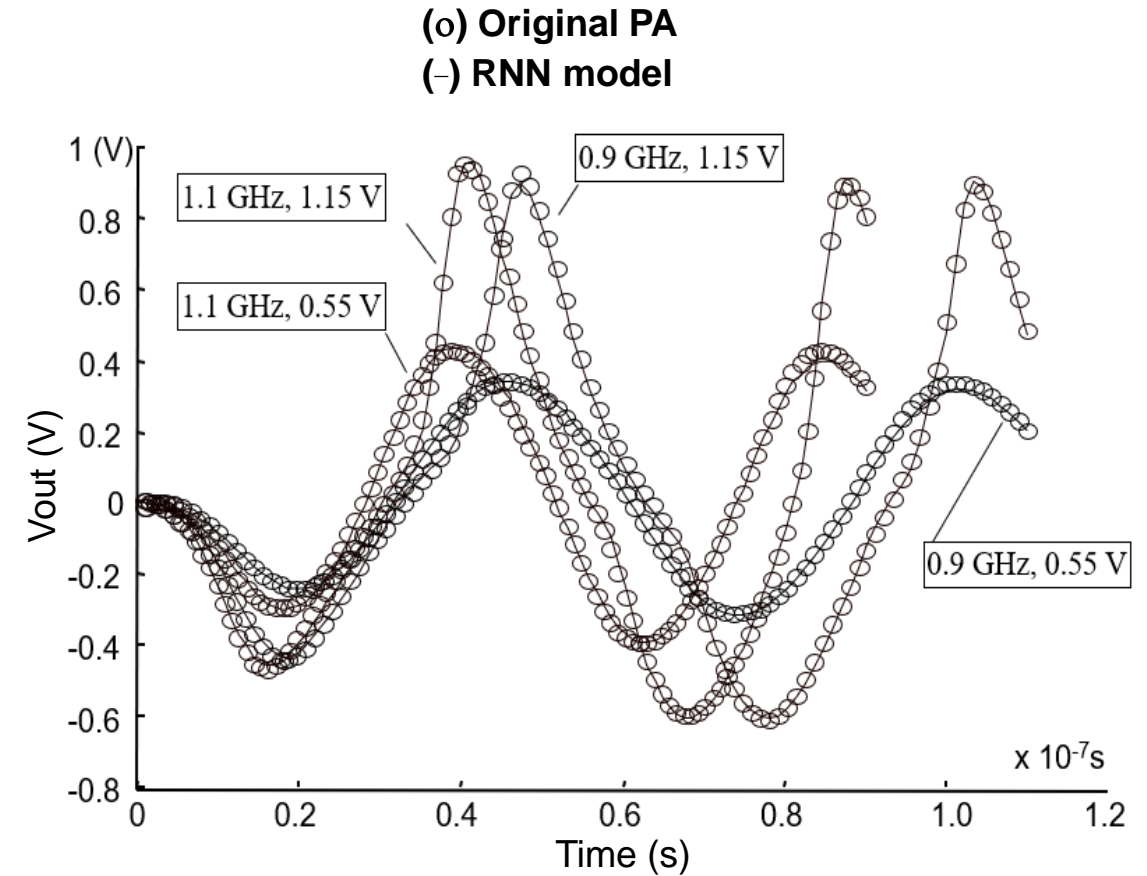
**Dynamic Neural Network (DNN)**

$$y(t) = f_{ANN}(y^{(1)}(t), \dots, y^{(n)}(t), x(t), x^{(1)}(t), \dots, x^{(n)}(t))$$

# ANN for Time Domain Behavioral Modeling [7]



**Recurrent Neural Network (RNN)**



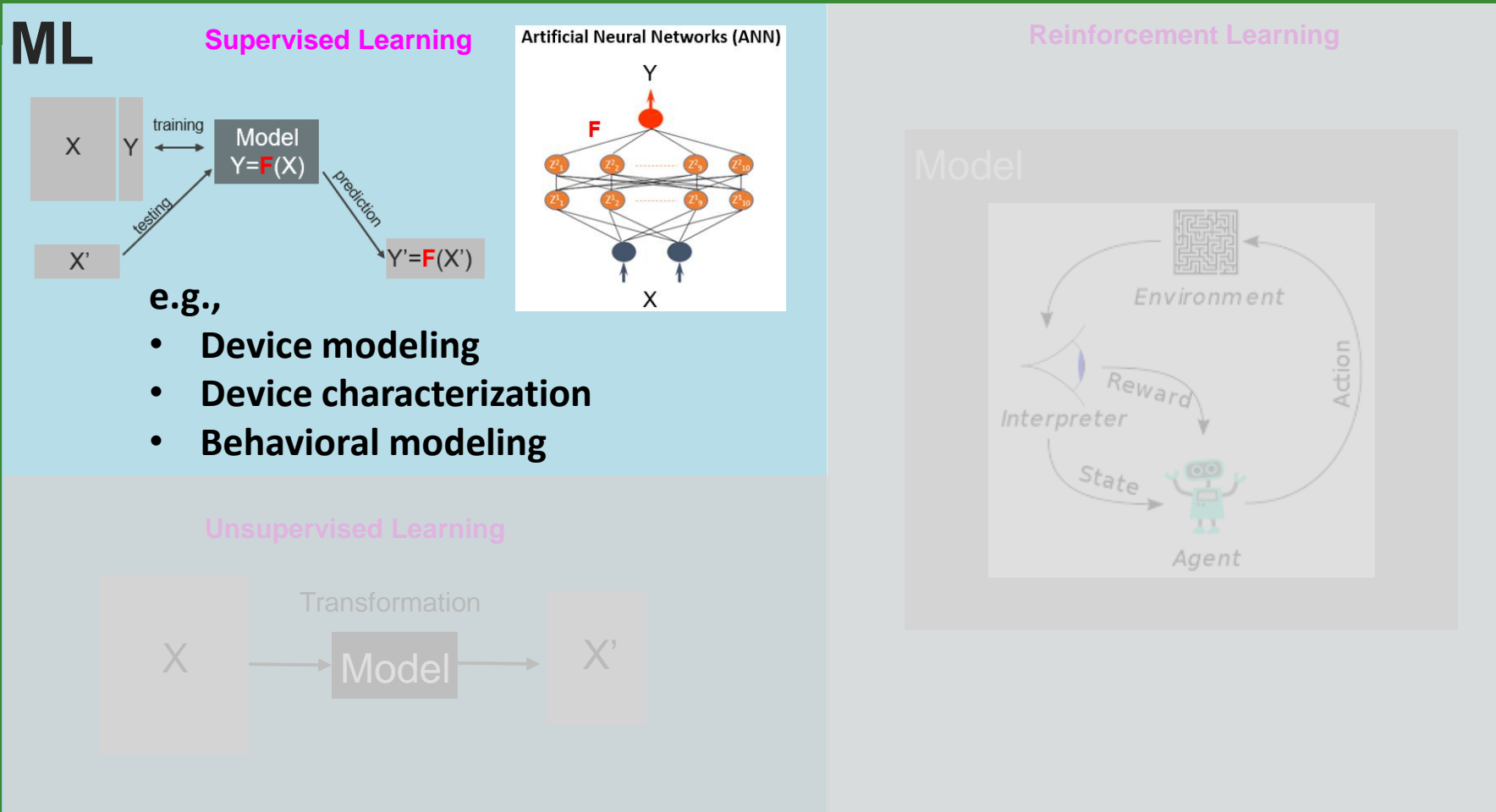
	RNN Model	Original PA
CPU Time for evaluation of 900 different sets of input-output waveforms	10 seconds	177 seconds

# Outline

- Introduction to AI, ML and ANN
- ANN for electronic device modeling
- ANN for electronic behavioral modeling
- **Summary**

# Summary

## AI

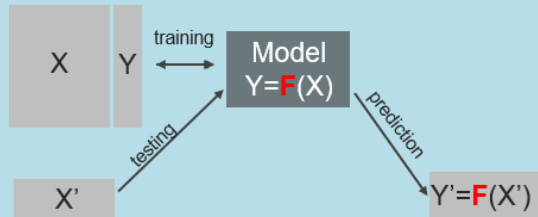


# Summary

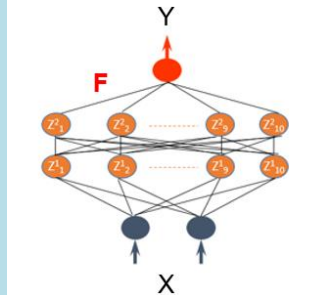
## AI

### ML

#### Supervised Learning



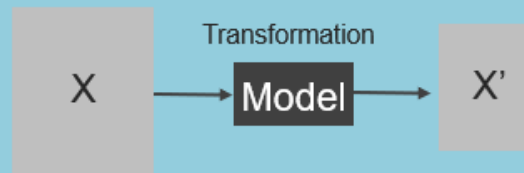
Artificial Neural Networks (ANN)



e.g.,

- Device modeling
- Device characterization
- Behavioral modeling

#### Unsupervised Learning

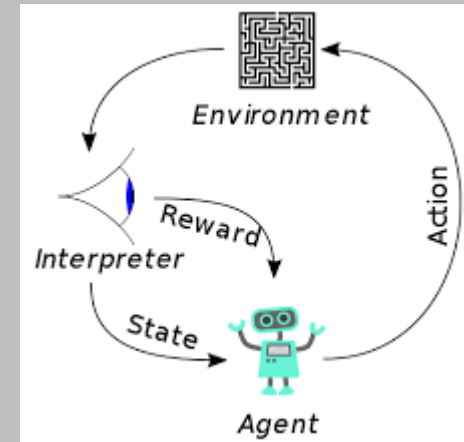


e.g.,

- **Automatic Circuit Tuning**  
Automates the post-fabrication circuit tuning process

#### Reinforcement Learning

### Model



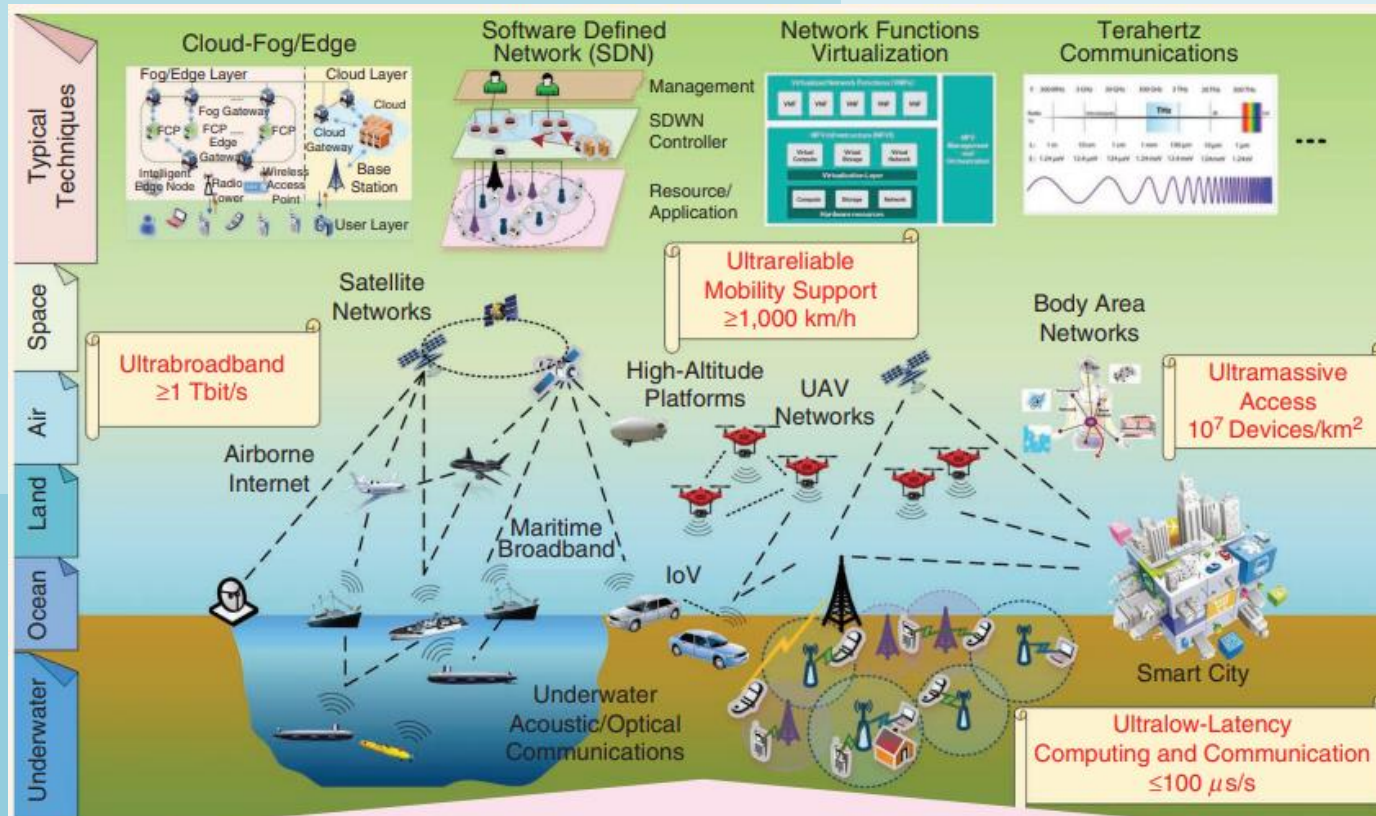
e.g.,

- **Optimization and multi-physics**  
Exploration and exploitation for design problems with many variables

# Future Potential

AI

ML



6G  
Network  
[8]

- Make more optimized and adaptive data-driven decisions
- Alleviate communication challenges
- Meet requirements from emerging services

**Thank you!**