Advanced Embedded Passives Technology Consortium

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Neural Network Approaches to Electromagnetic Based Modeling of Embedded Passives and Their Applications

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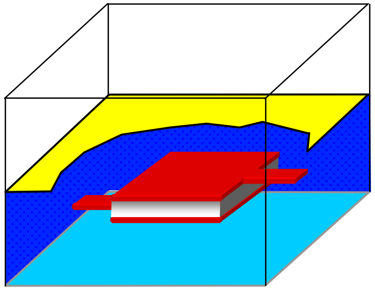
Outline

- Introduction
- Neural network based modeling approaches
  - Pure neural network model
  - EC-NN model
  - SSE-NN model
  - EC-SSE-NN model
- Embedded passive models
- Use of models in circuit simulation
- Conclusions

Embedded Passives and EM-based Models

At high frequencies, EM behavior of embedded passives becomes prominent. Models representing the EM effects of embedded passives are important for efficient circuit design.

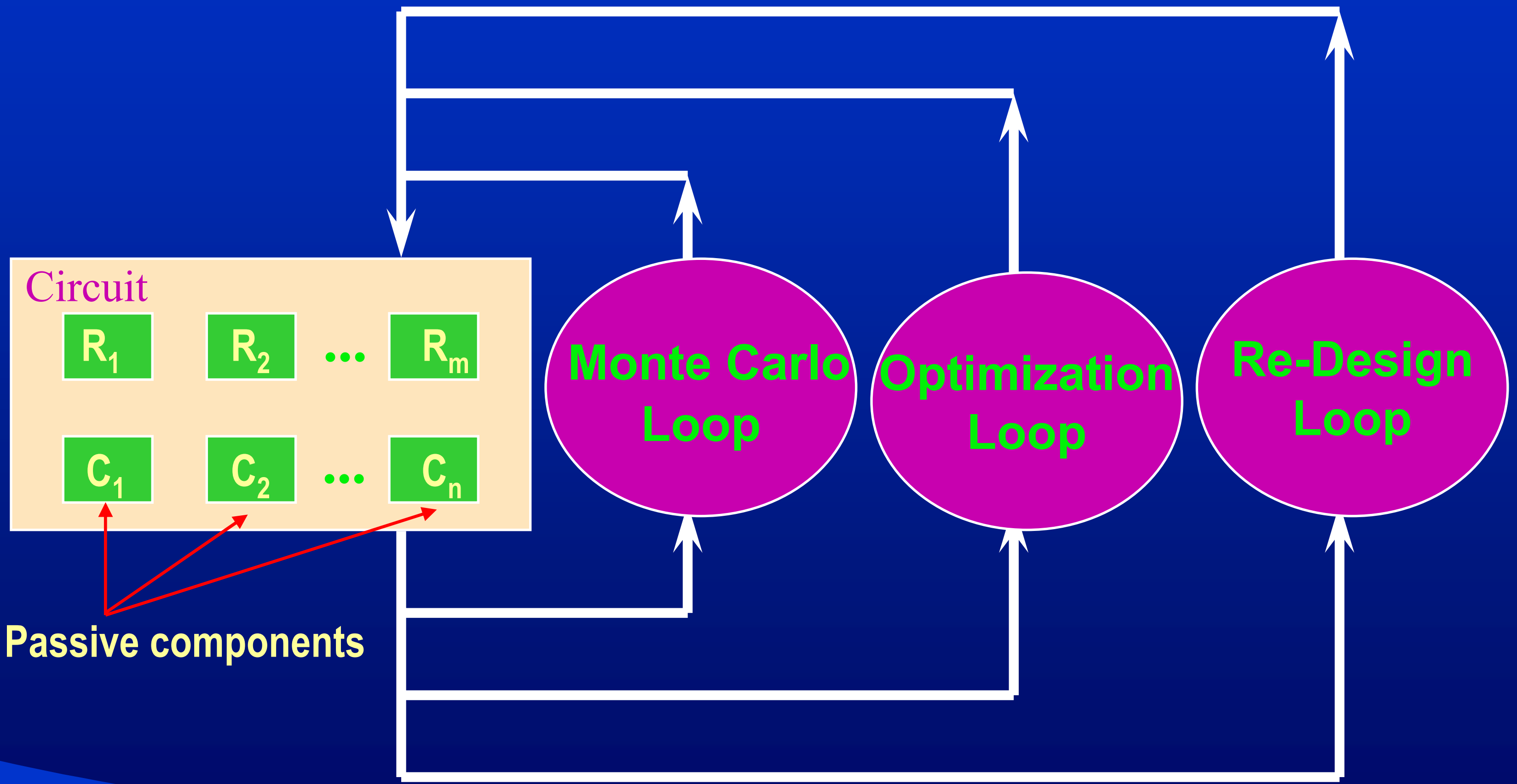
EM Behavior of Embedded Passives



Slow EM simulation

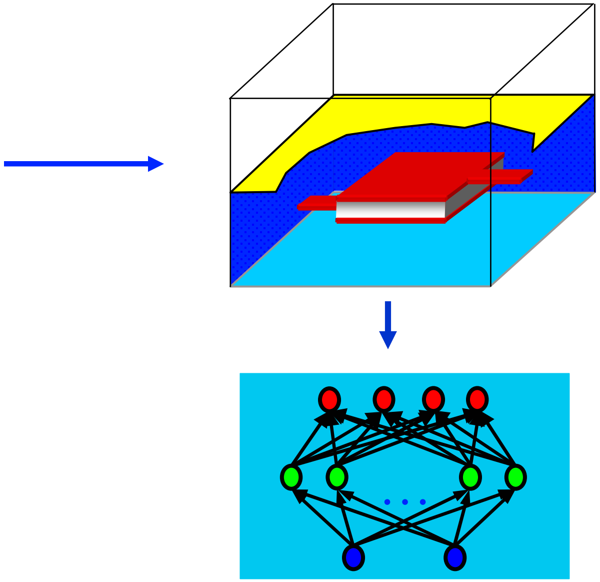
Circuit and System Design

High level circuit design requires repetitive use of component models.



Embedded Passives and EM-based Models

EM Behavior of Embedded Passives



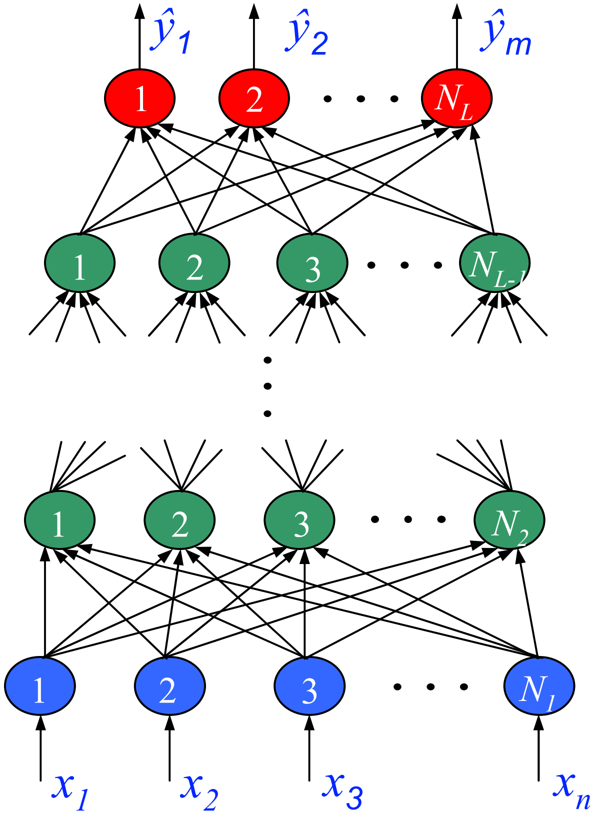
Slow EM simulation

Fast EM-based neural network model

Features of Neural Network Model

- Neural networks can learn and generalize from EM data of embedded passives. Trained neural networks become models representing the embedded passives
- Neural models provide the EM behavior with the speed of empirical or equivalent models
- Recent advances in NN research allow the use of existing knowledge for efficient modeling.
- Neural models can be plugged into high-level circuits and systems for efficient frequency/time-domain computer-aided design.

The Typical MLP Neural Network Structure



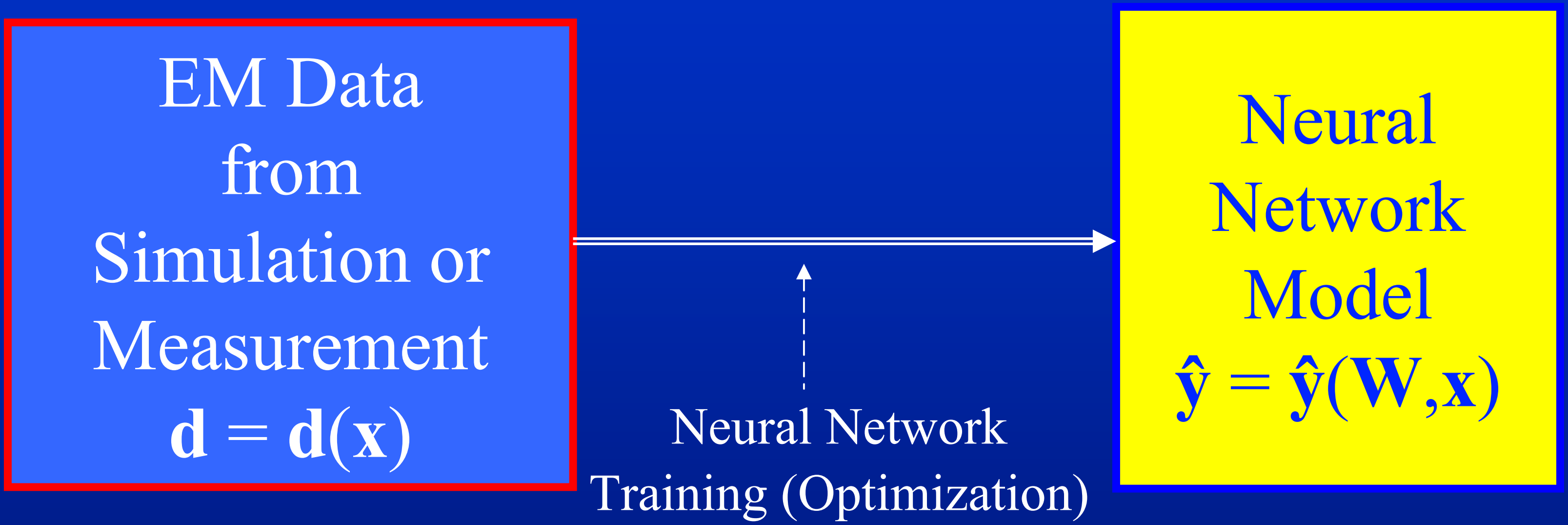
Layer *L*
(Output layer)

Layer *L - 1*
(Hidden layer)

Layer *2*
(Hidden layer)

Layer *1*
(Input layer)

Basic Neural Network Training



EM Data
from
Simulation or
Measurement
$\mathbf{d} = \mathbf{d}(\mathbf{x})$

Neural Network
Training (Optimization)

Neural
Network
Model
$\hat{\mathbf{y}} = \hat{\mathbf{y}}(\mathbf{W},\mathbf{x})$

Training Objective:

$$\underset{\mathbf{W}}{\text{minimize}} \sum_{\mathbf{x}} (\hat{\mathbf{y}} - \mathbf{d})^2$$

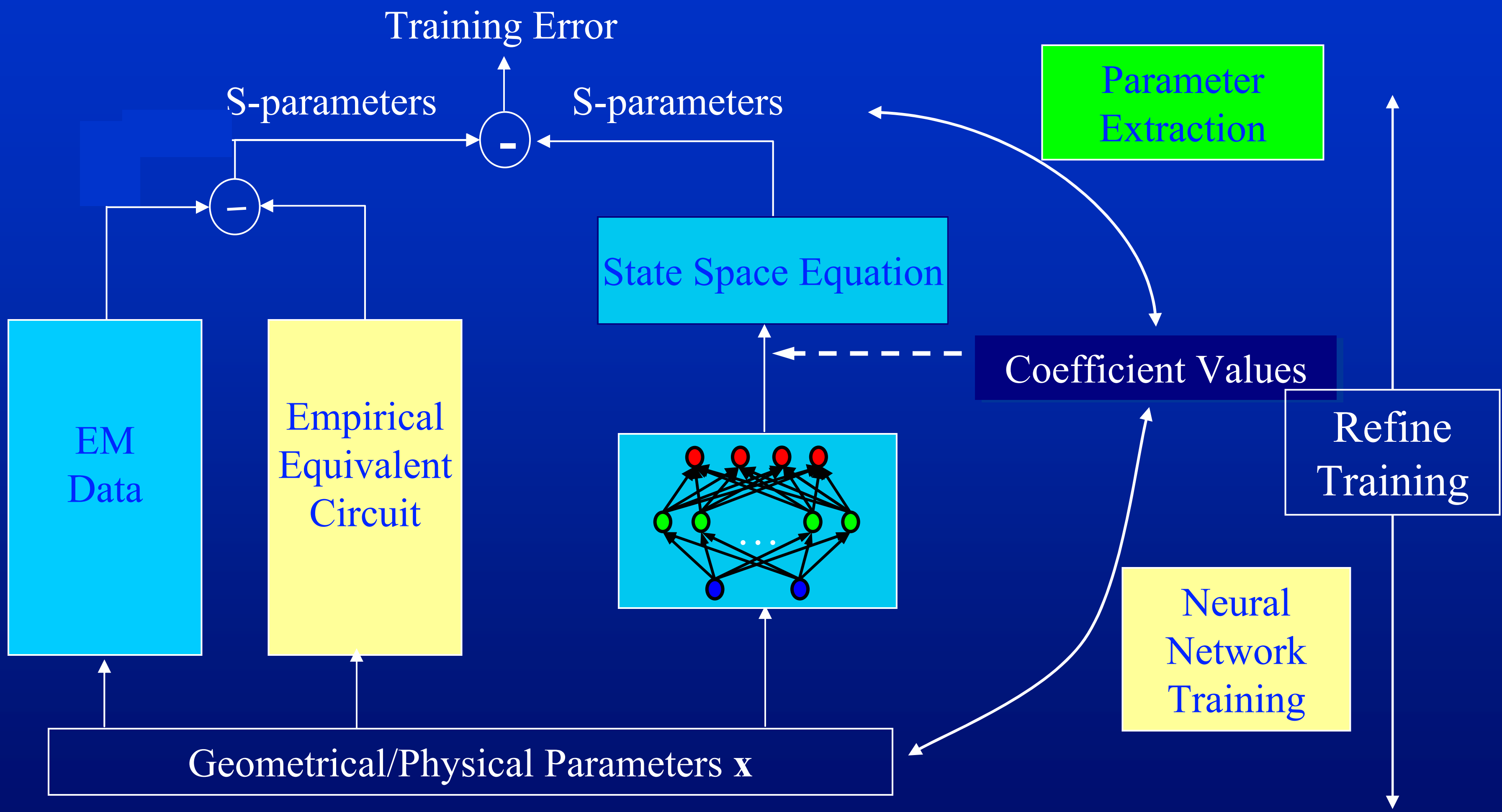
Acronym

- EM: Electromagnetic
- NN: Neural Network
- EC: Equivalent Circuit
- SSE: State-Space Equations

Neural Network Modeling Methods for EM Based Embedded Passive Models

Method	Pure NN	EC-NN	SSE-NN	EC-SSE-NN
Additional parts in model	N/A	Equivalent circuit	State space equation	Equivalent circuit and state space equation
Training data	S-parameter	S-parameter	S-parameter	S-parameter
Accuracy	User desired	Bounded by EC	User desired	User desired
Design environment	Frequency Domain	Frequency/Time Domain	Frequency/Time Domain	Frequency/Time Domain
Existing EC model	N/A	Needed	N/A	Optional
Number of optimization procedures In training	1	2-3	2-3	2-3

Combined Model Structure and Training Process



Training Error

S-parameters

S-parameters

Parameter Extraction

State Space Equation

Coefficient Values

Refine Training

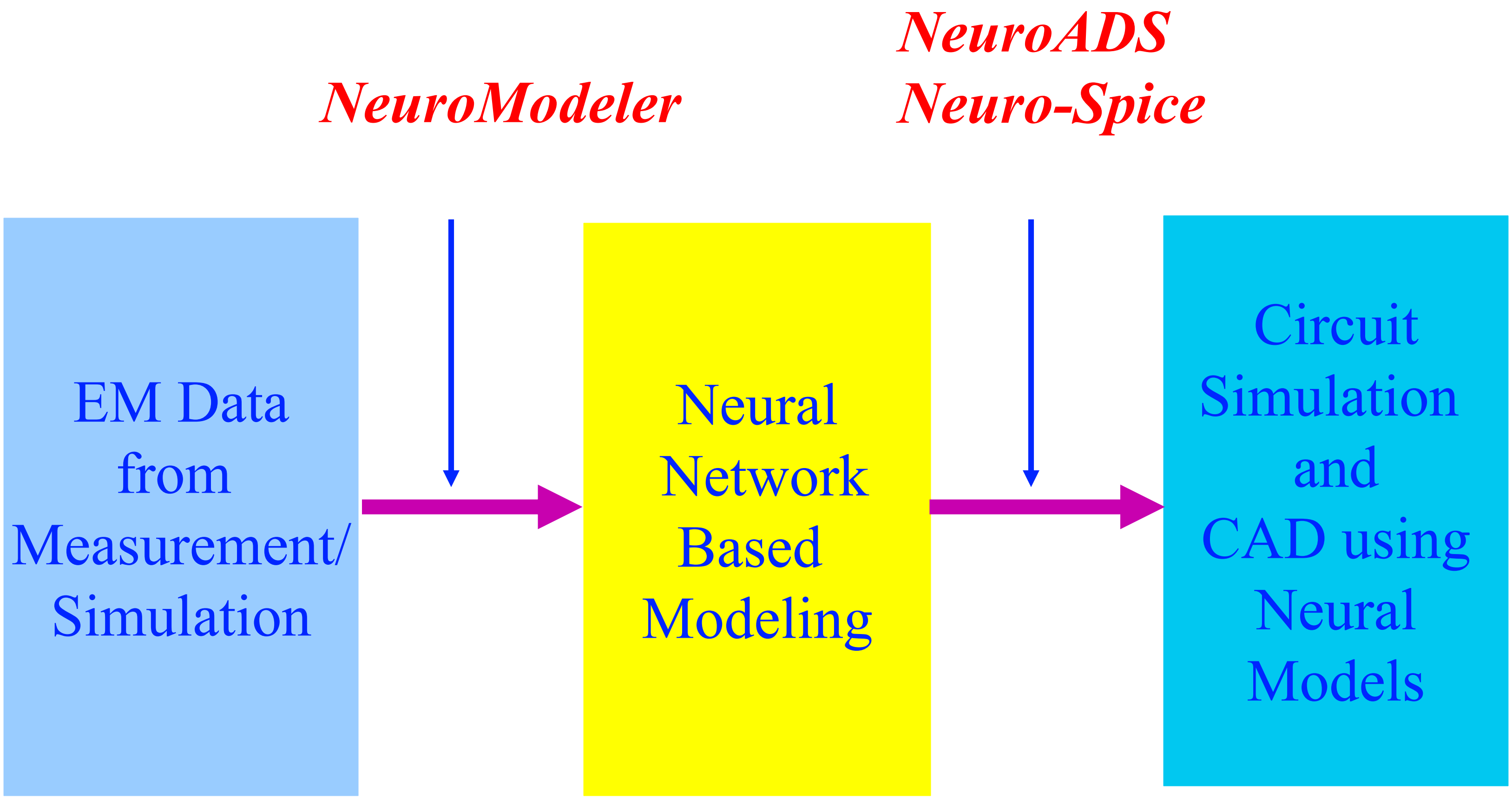
EM Data

Empirical Equivalent Circuit

Neural Network Training

Geometrical/Physical Parameters **x**

EM Based Modeling and Use in Circuit Simulators



NeuroModeler

NeuroADS
Neuro-Spice

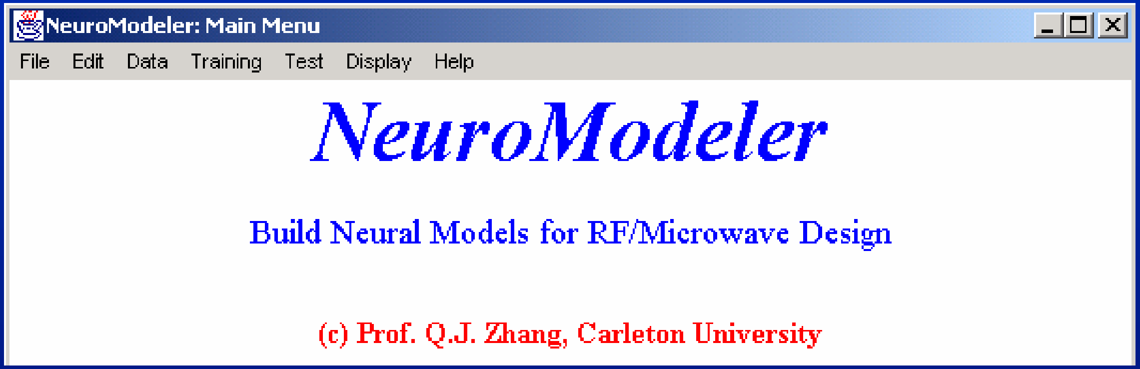
EM Data from Measurement/ Simulation

Neural Network Based Modeling

Circuit Simulation and CAD using Neural Models

Use of NeuroModeler for Training Neural Networks

- Define neural network structure
- Train neural network model to learn EM data
- Test neural network model with testing data



NeuroModeler

Build Neural Models for RF/Microwave Design

(c) Prof. Q.J. Zhang, Carleton University

- Export neural network model into Matlab, C, Java, Microsoft Excel, and Hspice format.

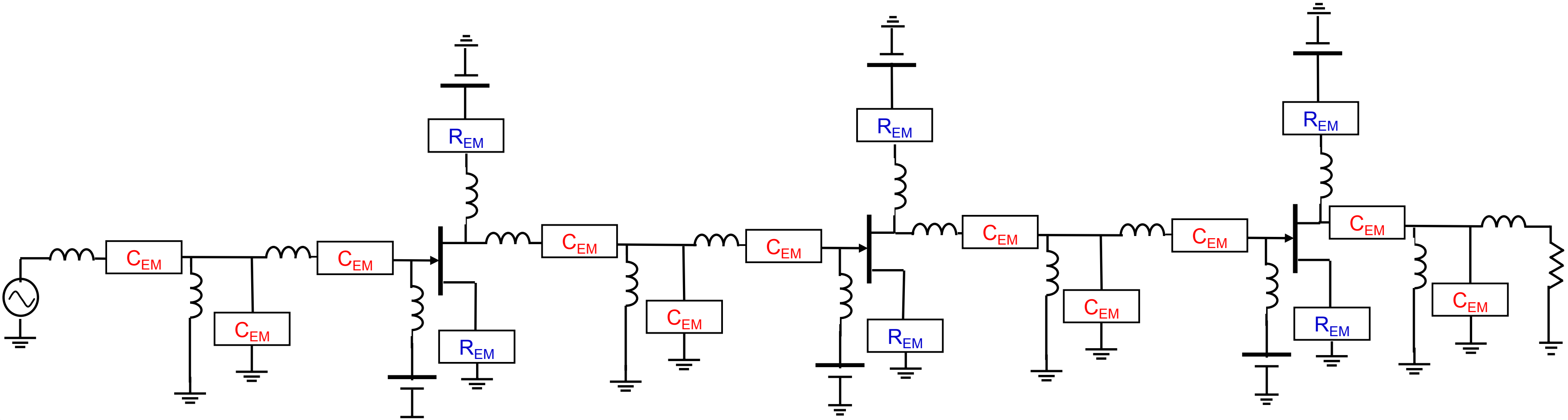
Using EM based Neural Model in Agilent-ADS: through interface program *NeuroADS*

Trained neural models of embedded passives can be plugged into Agilent-ADS design environment for circuit simulation and optimization

Amplifier example:

R_{EM}: EM based neural network model for embedded resistor from Sonnet data.

C_{EM}: EM based neural network model for embedded capacitor from Ansoft-HFSS data.

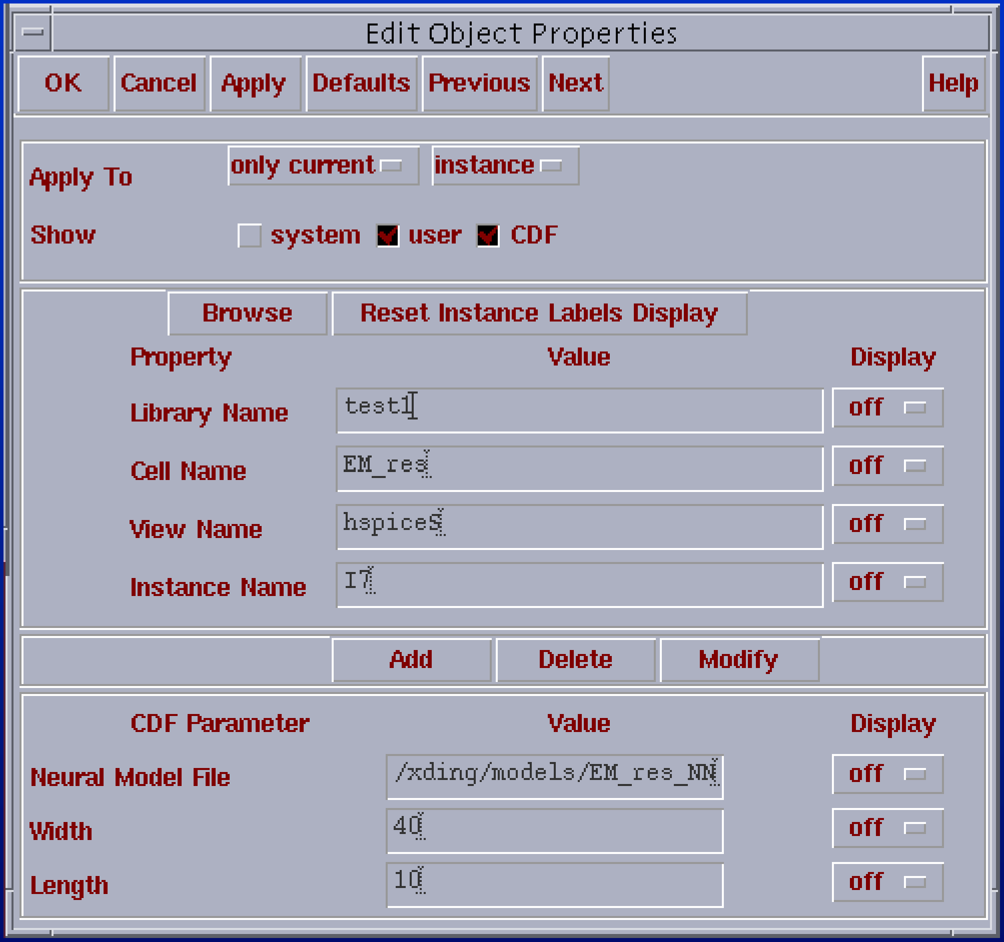


Using EM Based Neural Model in *Hspice:* *With Netlist for NN Exported from NeuroModeler*

```
*************************************
** filename: EM_RES_NN.S
** Department of Electronics
** Carleton University
***********************************
***Resistor EC-NN Model ***
.subckt &1 In Out
******Neural Network Structure******
*Neuromod input scaling
.param x1='-1.0+(2.0)*(&2-(35.0))/((55.0) - (35.0))'
.param x2='-1.0+(2.0)*(&3-(8.0))/((12.0) - (8.0))'
*Neuromod calculating hidden neurons
.param w10=0.062397
.param w11=0.424936
.param w12=-0.370152
.param z1='1.0/(1.0+exp(-1.0*(w10+x1*(w11)+x2*(w12))))'
.param w20=-3.23649
.param w21=0.72697
.param w22=-1.68496
.param z2 ='1.0/(1.0+exp(-1.0*(w20+x1*(w21)+x2*(w22))))’
……
```

```
……
.param t80 = -1.57952
.param t81 = 16.2157
.param NN_Out3= 't80+(y8-(0.0))*((t81) - (t80))/((1.0)-(0.0))‘

******END of Neural Network Model Structure******

******Equivalent Circuit Topology******

L1 In  n1  NN_Out_3
C1 n1 n2  NN_Out_1
C2 n1  0  NN_Out_2
C3 n2  0  NN_Out_2
L2 n2 Out NN_Out_3
******END of Equivalent Circuit ******

.ENDS &1
```

Using EM-based Neural Model in Cadence: Part of Neural Model Definition in *Cadence*



Edit Object Properties

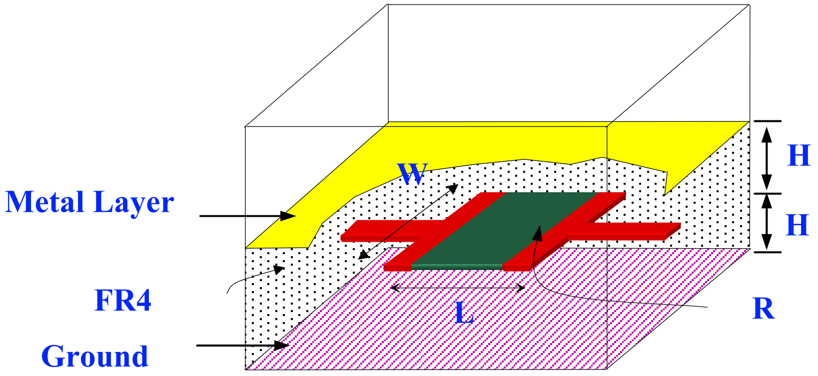
Apply To: only current, instance

Show ☐ system ☑ user ☑ CDF

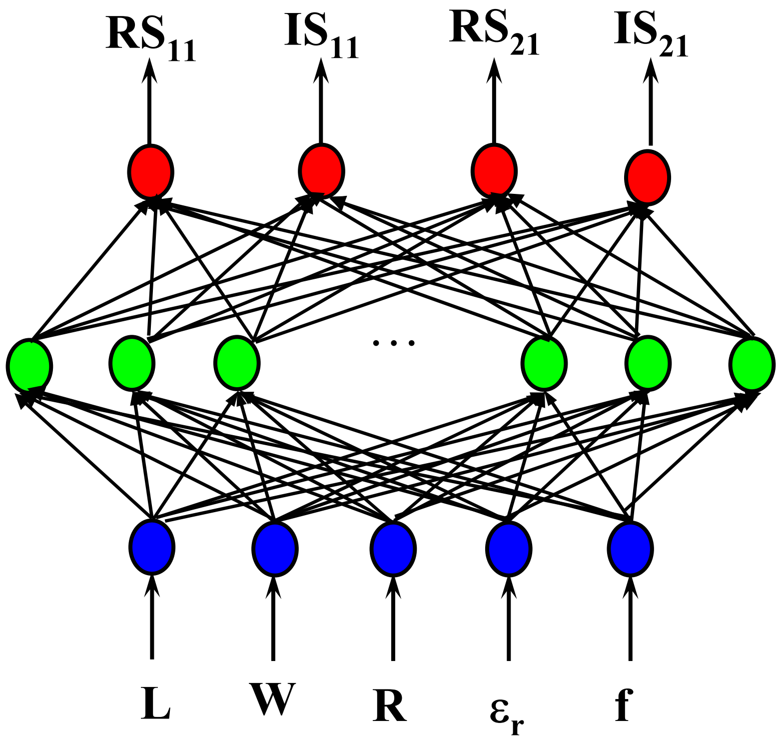
Property	Value	Display
Library Name	test1	off
Cell Name	EM_res	off
View Name	hspiceS	off
Instance Name	I7	off

CDF Parameter	Value	Display
Neural Model File	/xding/models/EM_res_NN	off
Width	40	off
Length	10	off

Example: Pure Neural Network Model of Embedded Resistor



EM data is generated from Sonnet. Length (L), width (W), resistivity (R),substrate dielectric (ε_r), and frequency (f) are EM model inputs, respectively.

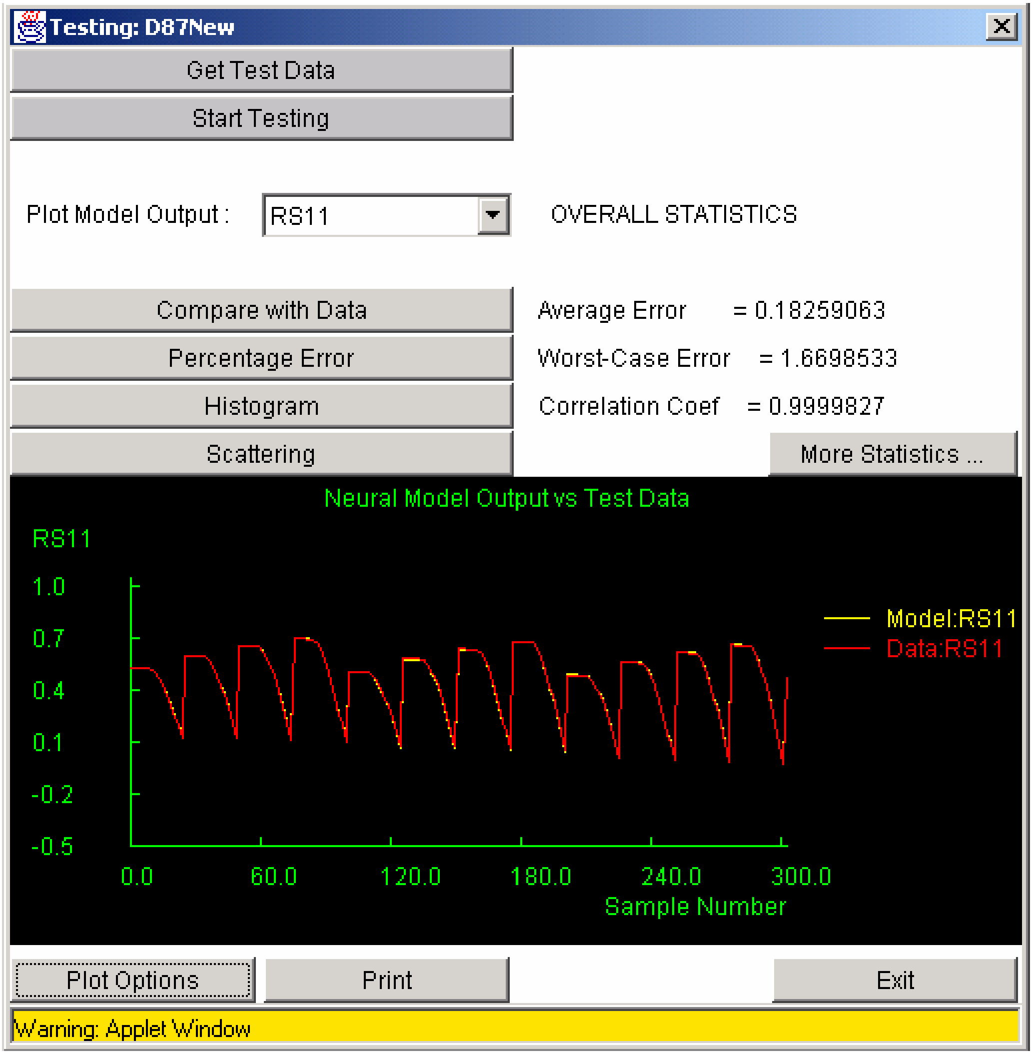


Neural model representing EM behaviors is developed using ***NeuroModeler.***

Set of Pure Neural Network Models for Embedded Resistors

EM Resistor Model	W(mils)	L (mils)	εr	R (ohm)
2L_01	6~20	6~20	1~7	200~1000
2L_02	6~20	18~30	1~7	200~1000
2L_03	6~20	28-40	1~7	200~1000
2L_04	6~20	6~20	7~10	200~1000
2L_05	6~20	18~30	7~10	200~1000
2L_06	6~20	28-40	7~10	200~1000
2L_07	18~30	6~20	1~7	200~1000
2L_08	18~30	18~30	1~7	200~1000
2L_09	18~30	28~40	1~7	200~1000
2L_10	18~30	6~20	7~10	200~1000
2L_11	18~30	18~30	7~10	200~1000
2L_12	18~30	28~40	7~10	200~1000

Accuracy for Pure Neural Network Model Example



Testing: D87New

Plot Model Output : RS11

OVERALL STATISTICS

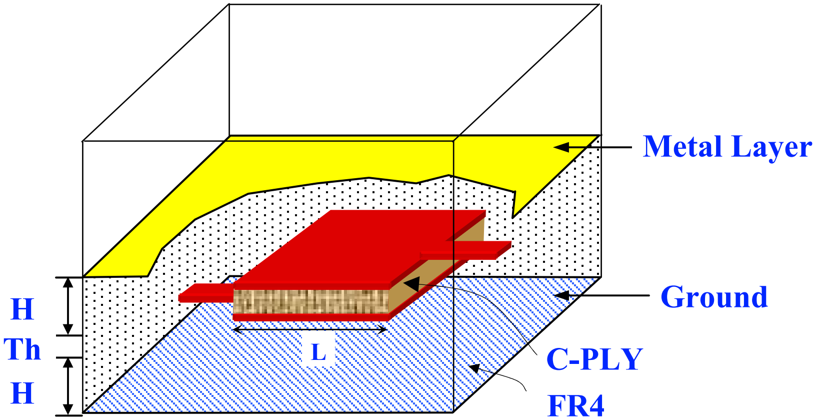
Average Error = 0.18259063

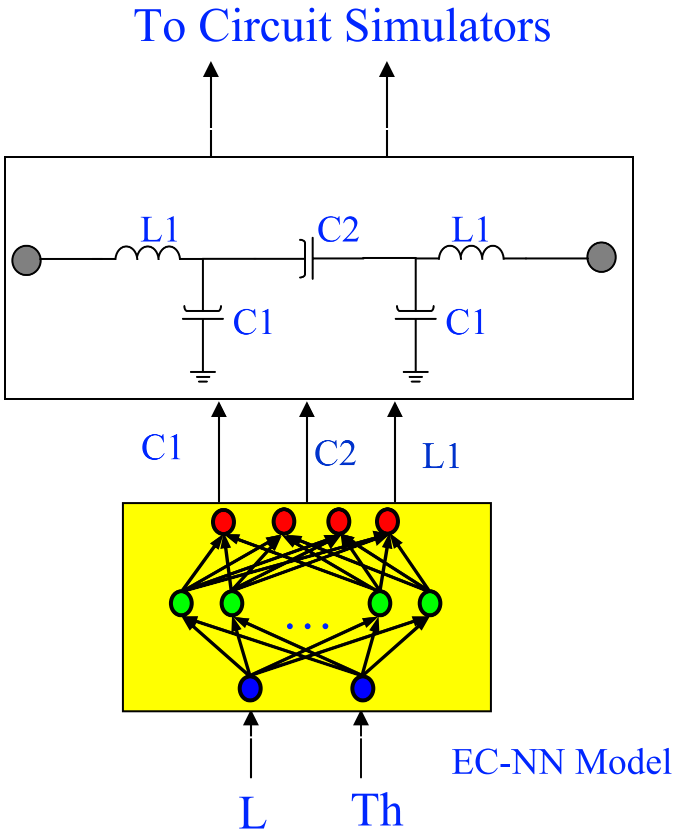
Worst-Case Error = 1.6698533

Correlation Coef = 0.9999827

Warning: Applet Window

Example: EC-NN Model for Embedded Capacitor



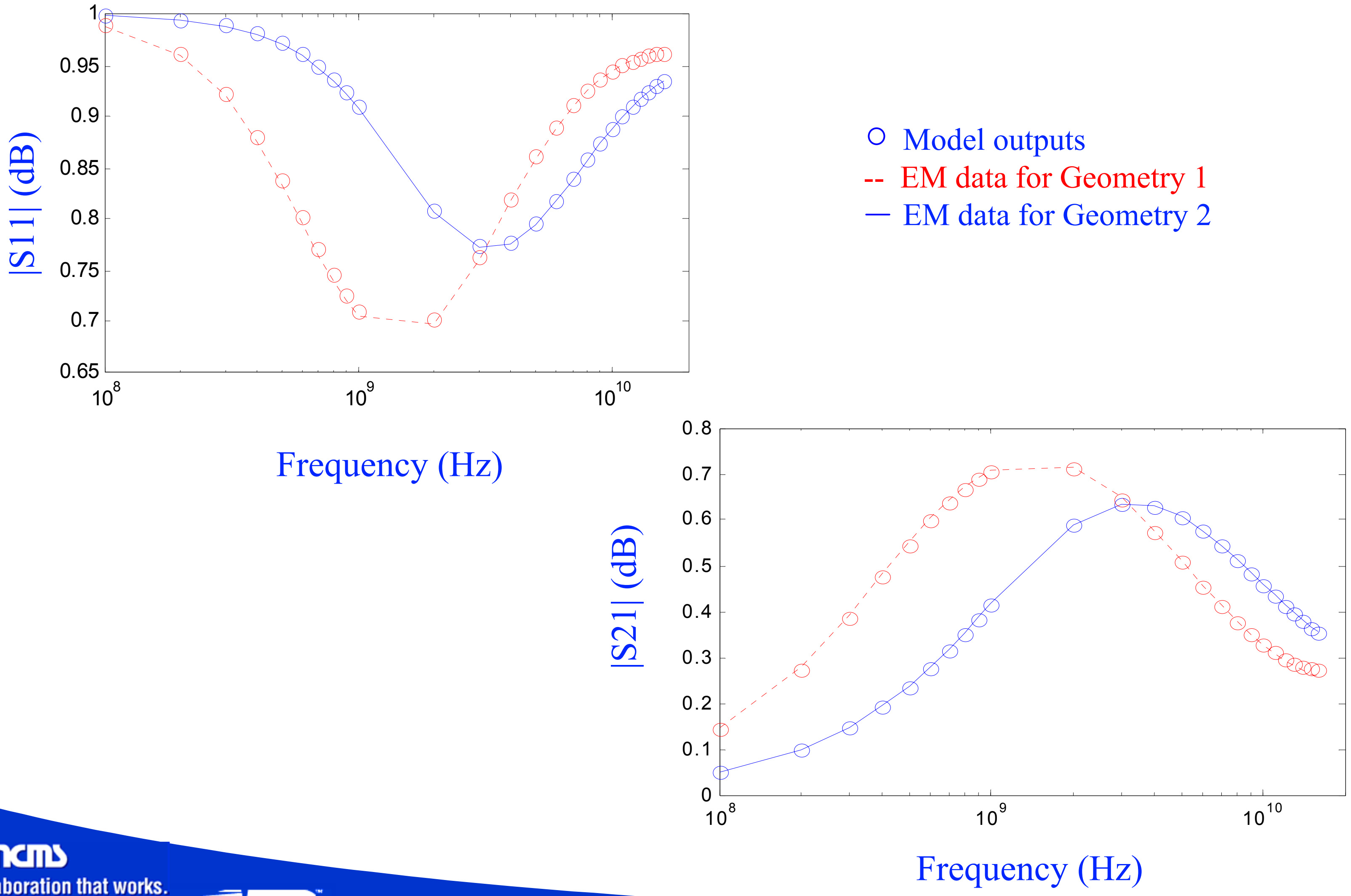


EM data are generated from Ansoft-HFSS. Geometrical parameters such as length, and thickness are used as variables.

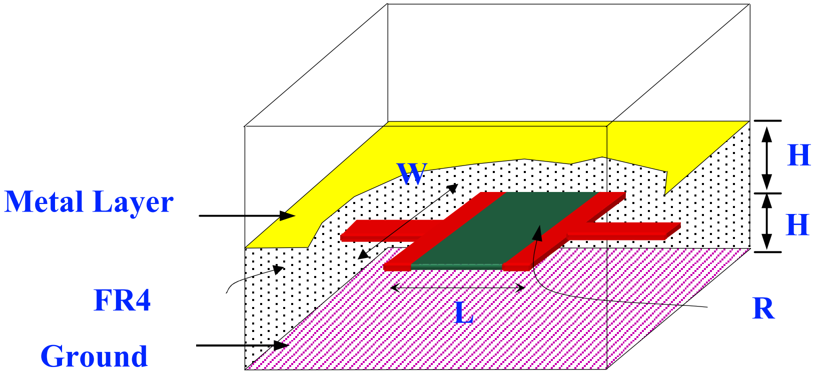
Set of EC-NN Models for Embedded Capacitors

EM Capacitor	L(mil)	Th(mil)	H(mil)	Parameter extraction variables
Cap_S_H3	10 - 60	0.2~0.7	3	C1, C2, L1
Cap_M_H3	70 - 150	0.2~0.7	3	C1, C2, L1
Cap_L_H3	160 - 300	0.2~0.7	3	C1, C2, L1
Cap_S_H5	10 - 60	0.2~0.7	5	C1, C2, L1
Cap_M_H5	70 - 150	0.2~0.7	5	C1, C2, L1
Cap_L_H5	160 - 300	0.2~0.7	5	C1, C2, L1
Cap_S_H10	10 - 60	0.2~0.7	10	C1, C2, L1
Cap_M_H10	70 - 150	0.2~0.7	10	C1, C2, L1
Cap_L_H10	160 - 300	0.2~0.7	10	C1, C2, L1

Example of EC-NN Capacitor Models



Example: EC-SSE-NN Model for Embedded Resistor

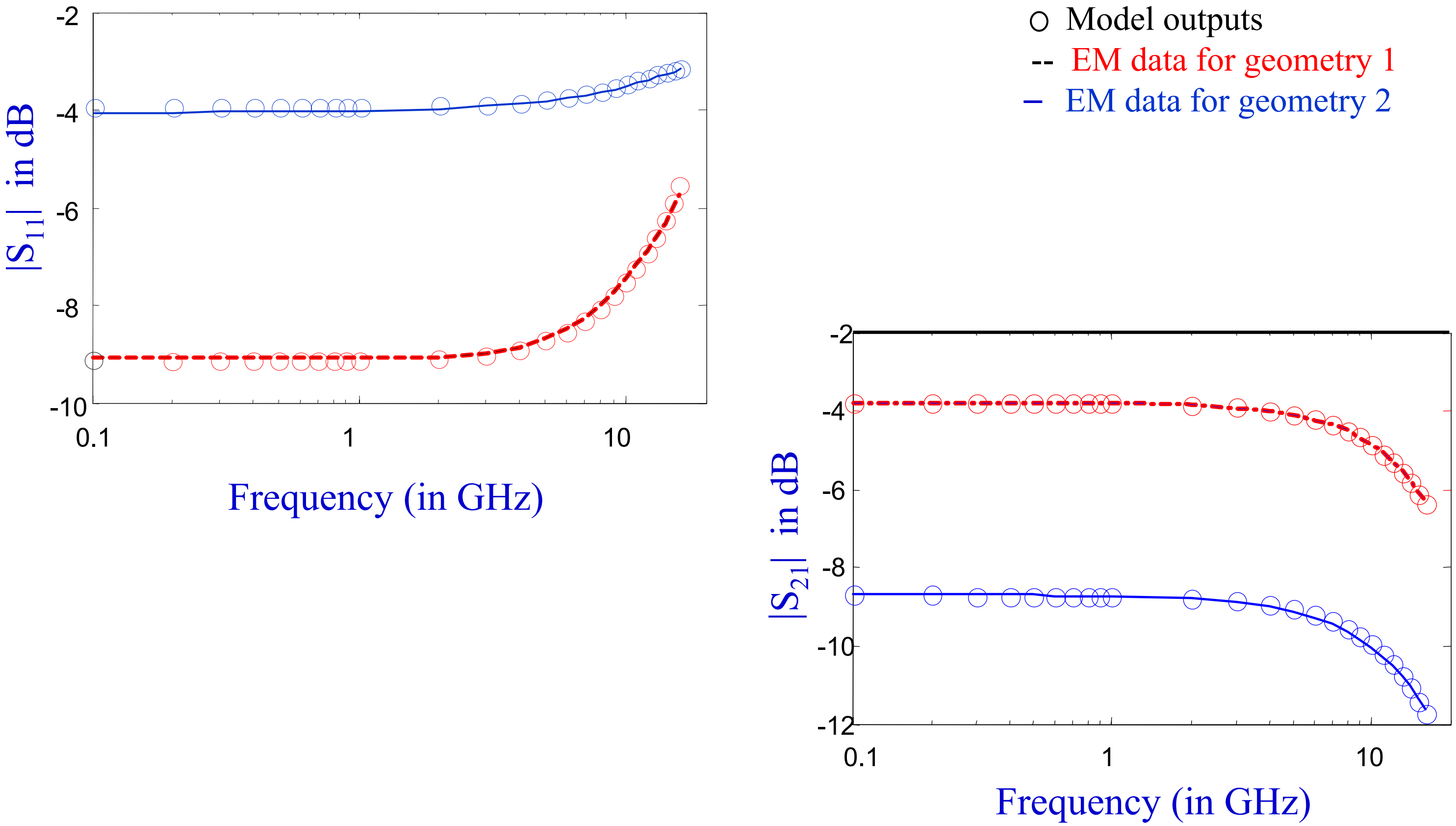


EM data is generated from Sonnet.
Length (L), width (W), resistivity (R), and frequency (f) are varied for EM data generation.

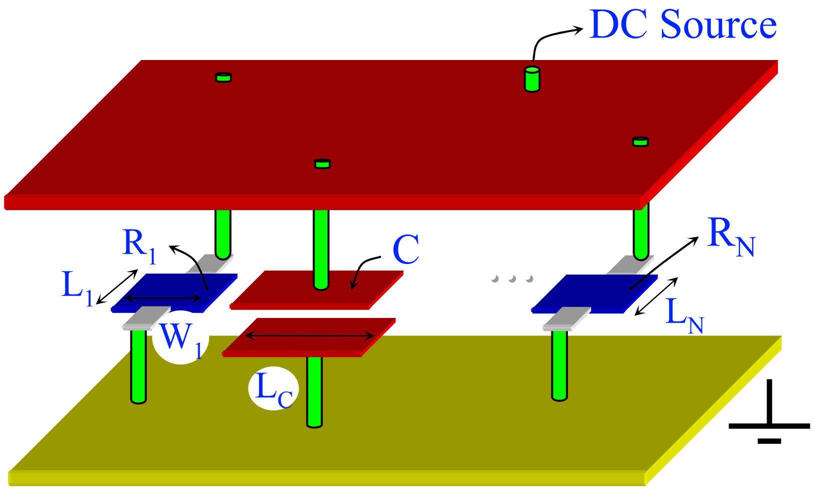
Set of EC-SSE-NN Models for Embedded Resistors

EM Resistor	W(mil)	L(mil)	R	H(mil)	Formulations for Parameter Extraction
Res_S_H3	10 - 60	10 - 60	40 -100	3	2^{nd} SSE
Res_M_H3	60 - 150	60 - 150	40 -100	3	2^{nd} SSE
Res_L_H3	150 - 300	150 - 300	40 -100	3	2^{nd} SSE
Res_S_H5	10 - 60	10 - 60	40 -100	5	2^{nd} SSE
Res_M_H5	60 - 150	60 - 150	40 -100	5	2^{nd} SSE
Res_L_H5	150 - 300	150 - 300	40 -100	5	2^{nd} SSE
Res_S_H10	10 - 60	10 - 60	40 -100	10	2^{nd} SSE
Res_M_H10	60 - 150	60 - 150	40 -100	10	2^{nd} SSE
Res_L_H10	150 - 300	150 - 300	40 -100	10	2^{nd} SSE

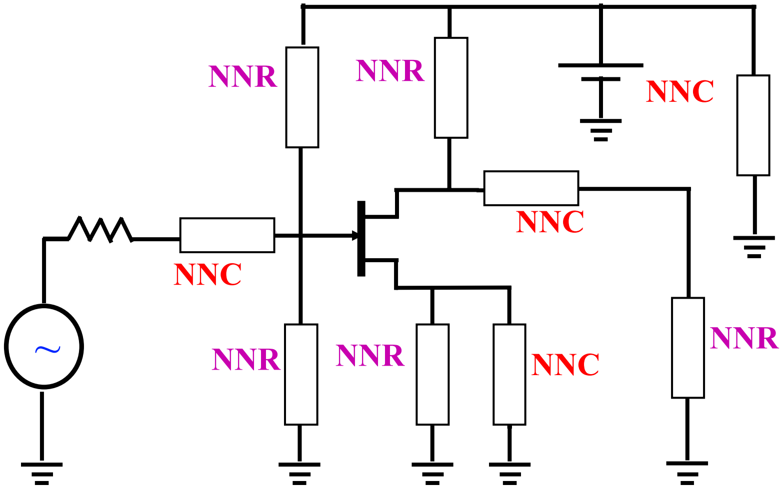
Example of EC-SSE-NN Resistor Models



Circuit Design Example: Amplifier Example



3-D illustration of circuit with several embedded components.



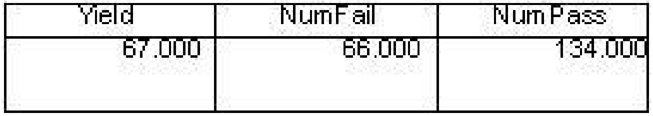
All the passive components are represented by our neural models.

NNR: Embedded resistor neural model

NNC: Embedded capacitor neural model

Circuit Design Example: Amplifier Example

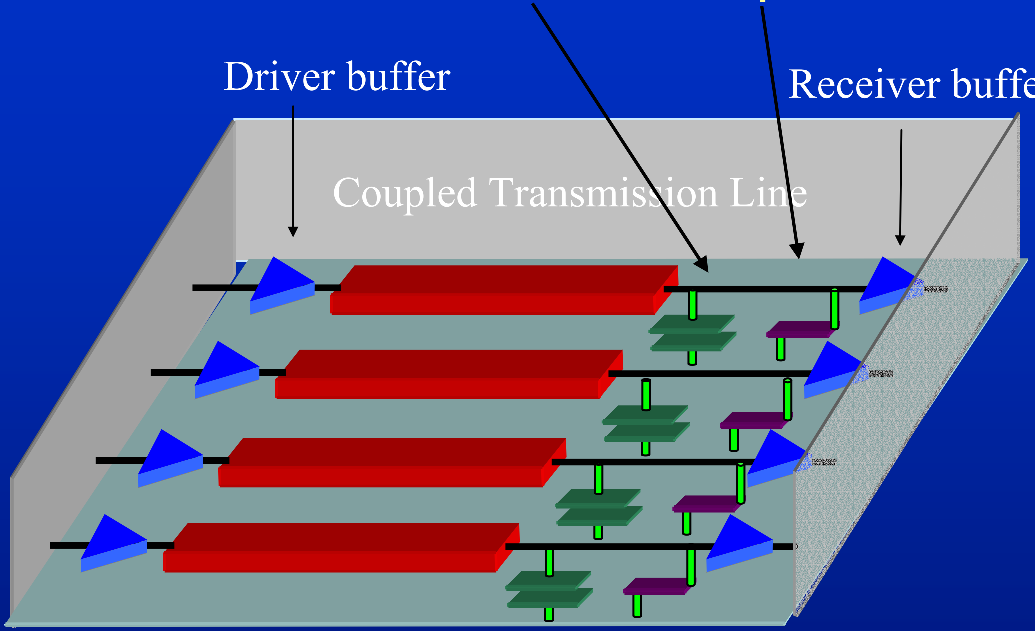
Whenever optimization changes R/C geometry, the corresponding neural model is called. The computation time for 200 outcomes of the amplifier Monte-Carlo simulation using our neural models is 4.3 minutes, compared to 3.5 hours if using EM simulators just for all the embedded passive simulations.



Yield	NumFail	NumPass
67.000	66.000	134.000

Variables (mils)	After Nominal Opt.	After Yield Opt.
L_1	9.6985	9.8996
W_1	17.9367	16.9530
L_2	14.7502	15.2313
W_2	8.2589	8.6287
L_3	27.8129	27.0229
W_3	10.6673	10.2715
L_4	19.2965	19.7036
W_4	15.3901	15.5325
L_5	28.2486	27.8934
W_5	9.9595	10.0364
Yield	29%	67%

Signal Integrity Example



Embedded resistors and capacitors

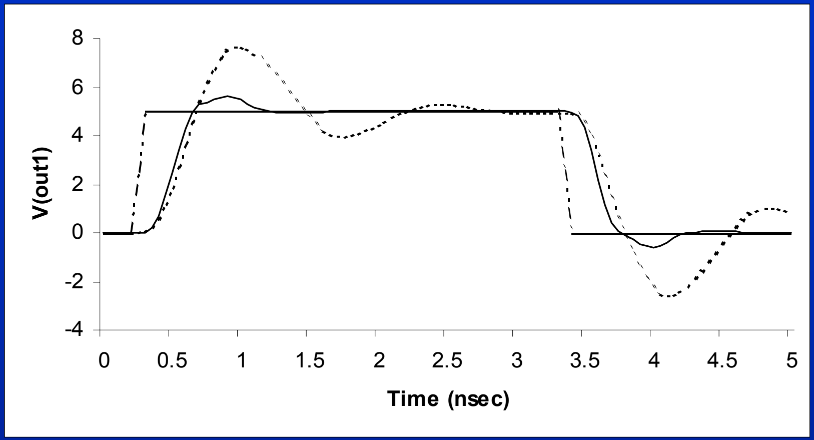
Driver buffer

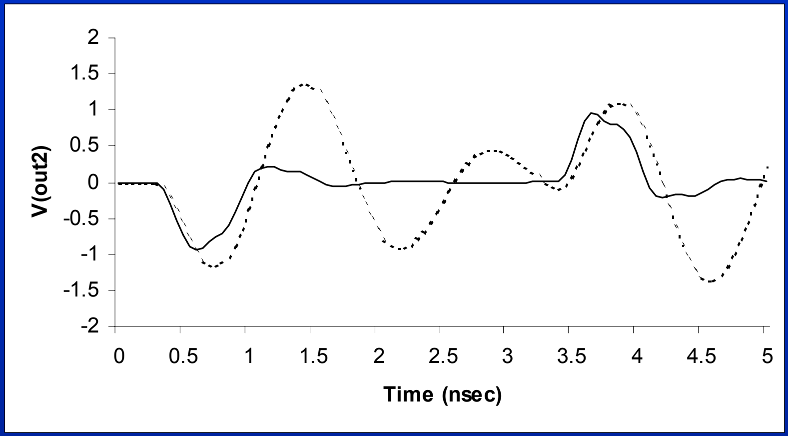
Receiver buffer

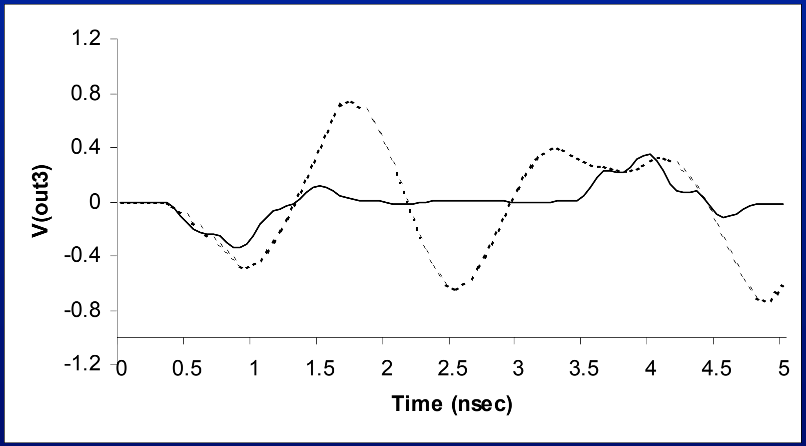
Coupled Transmission Line

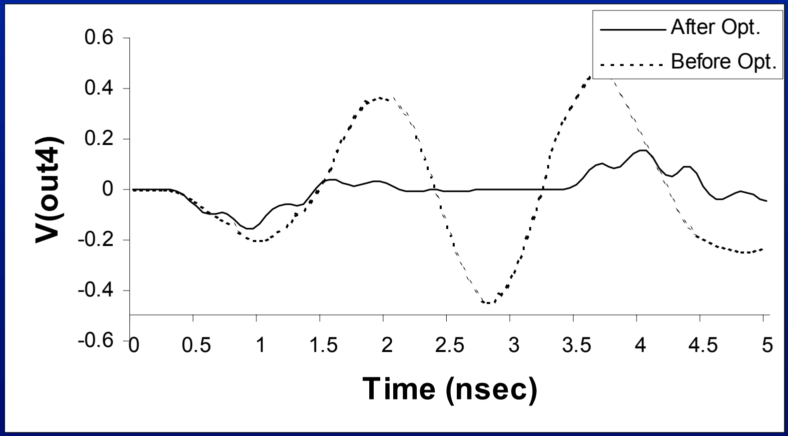
Three dimensional illustration of signal integrity analysis of multilayer circuit with embedded resistors and capacitors as coupled transmission line terminations. The driver/receiver buffers are nonlinear.

Signal Integrity Optimization in Time Domain

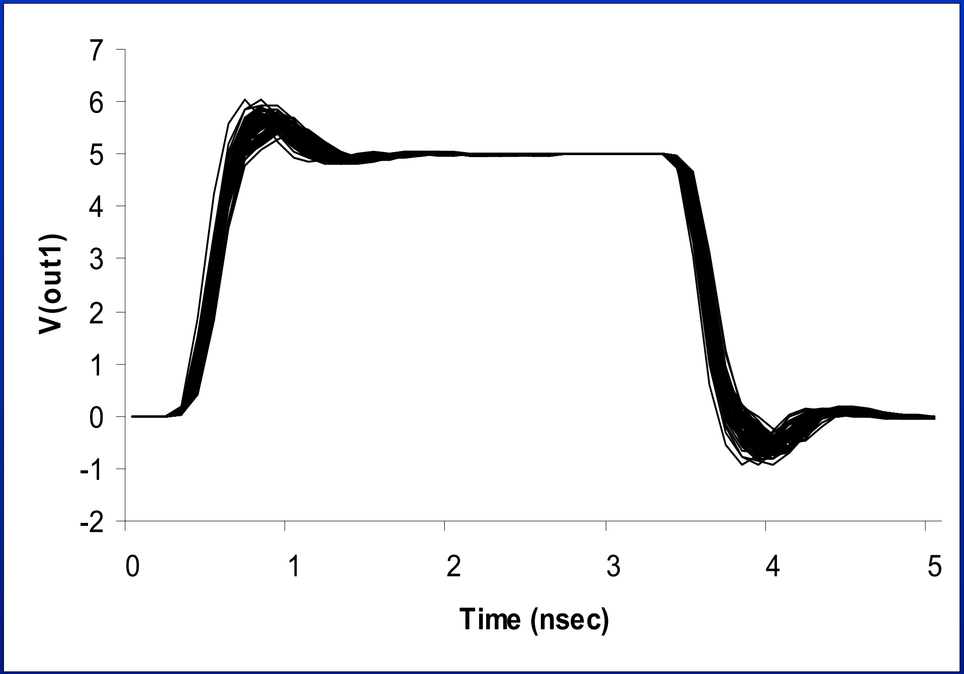








Monte-Carlo Analysis



500 output curves vs. time for *Hspice* Monte-Carlo analysis of the 4-coupled transmission line network using our combined EC-SSE-NN models of embedded passives. *Hspice* simulation time for Monte-Carlo analysis of the entire circuit with eight embedded passives using EC-SSE-NN model is 7.75 minutes as compared to 5 hours required by EM simulator just for simulating the passive components.

Conclusions

- Four neural network modeling approaches for embedded passives are developed, addressing various cases of frequency- and time-domain EM based modeling.
- The neural models have EM behavior, but model evaluation is much faster than direct EM simulations.
- EM based neural models can provide high frequency response of embedded passives to be used for high-level circuit simulation in frequency- or time-domains.
- Circuit optimization, statistical analysis, and yield optimization with EM effects can be performed with respect to geometrical/physical design variables of the embedded passives, enhancing effectiveness of high-frequency/high-speed electronic design.

Conclusions

- Use of the models help increase design efficiency due to
  use of accurate high-frequency EM effects
  faster neural model evaluation compared to direct EM simulation

- Automatic neural network training speeds up model development time, compared to conventional manual trial and error based model development. The helps reducing design cost.

- Using EM based neural network model, circuit optimization, statistical design and yield optimization become more effective. This helps increase design accuracy, shorten design cycle, and speedup time-to-market.