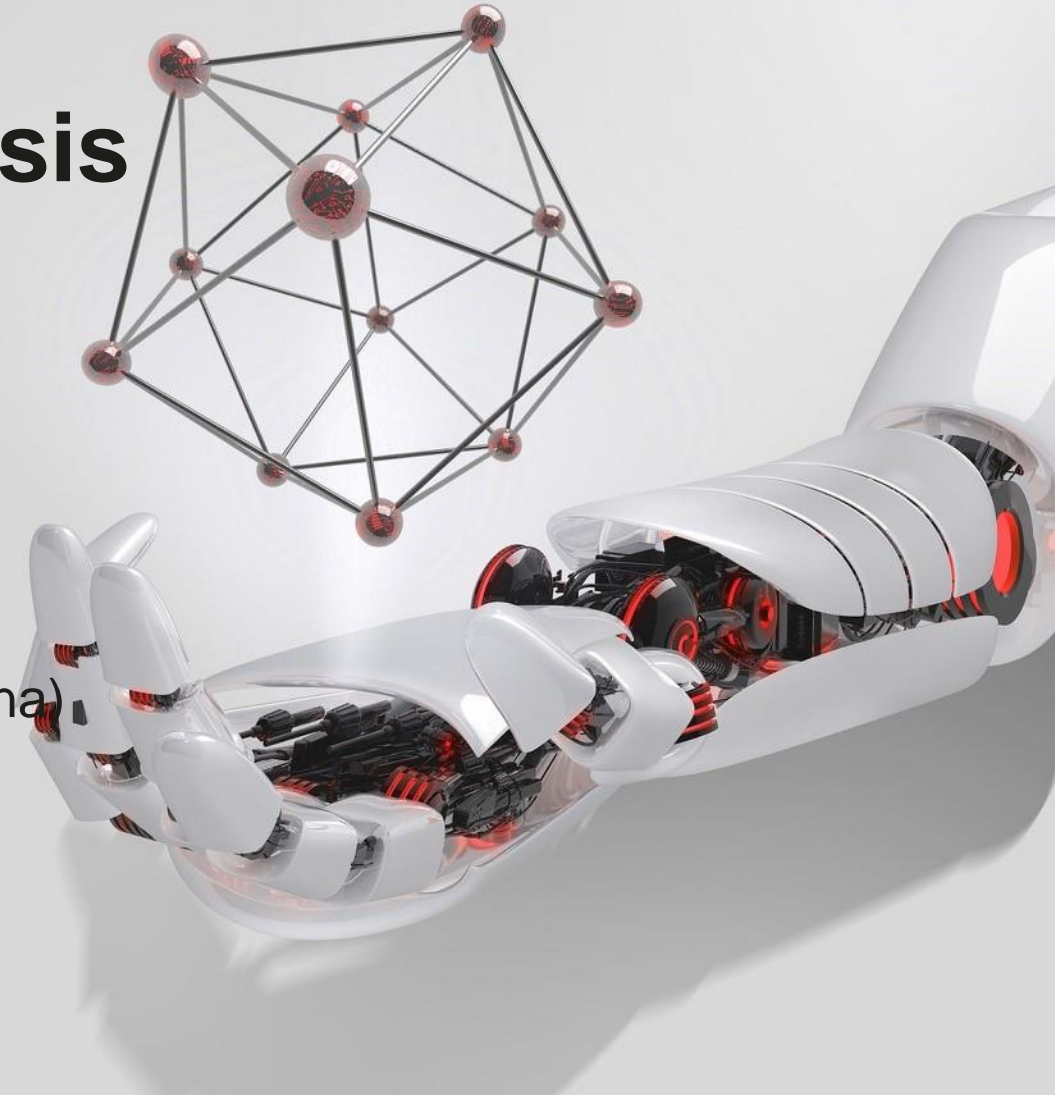


AI on SI: Data Efficient Analysis and Manufacturing Process Variation Analysis

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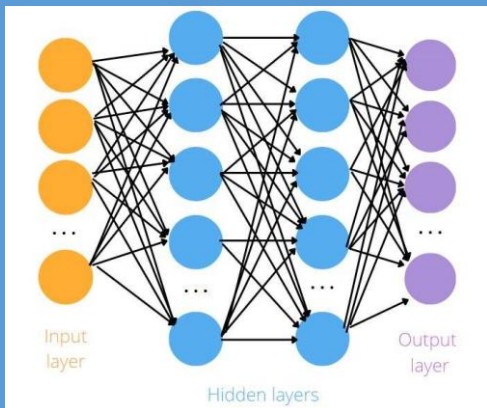
Asian IBIS Virtual Summit (China)
November 4, 2022



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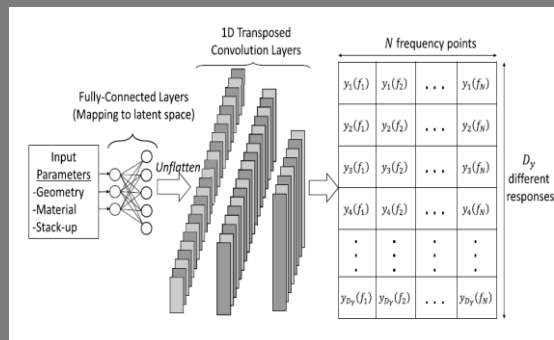
1. Background: AI in signal integrity
2. Challenges
3. Application 1: Manufacturing process variation analysis
4. Application 2: Data efficient signal integrity analysis
5. Conclusion

Background: AI in Signal Integrity



Deep NN (DNN)

- Target Impedance Violation
- Eye Diagram Modeling
- Current Prediction

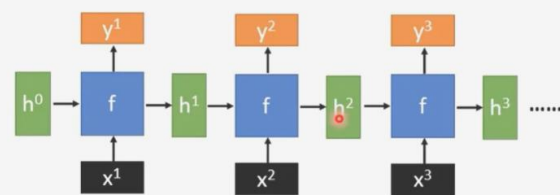


Transposed CNN (TCNN)

- Capture the resonant inductor behavior
- Predicting the S/Z-parameters

Recurrent Neural Network

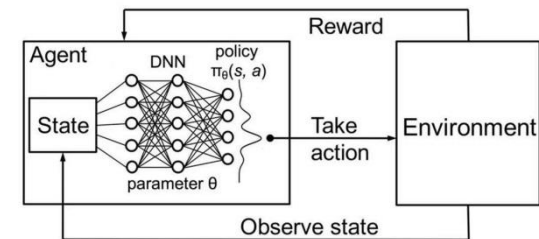
- Given function $f: h^t, y = f(h, x)$ h and h^t are vectors with the same dimension



Recurrent NN (RNN)

- Behavioral models of input-output drivers
- Capture the memory effect

DEEP REINFORCEMENT LEARNING



Reinforcement Learning

- Chip floorplan
- Wire Interconnect for PCB
- Microwave Device Design

Challenges

Manufacturing Process Deviation

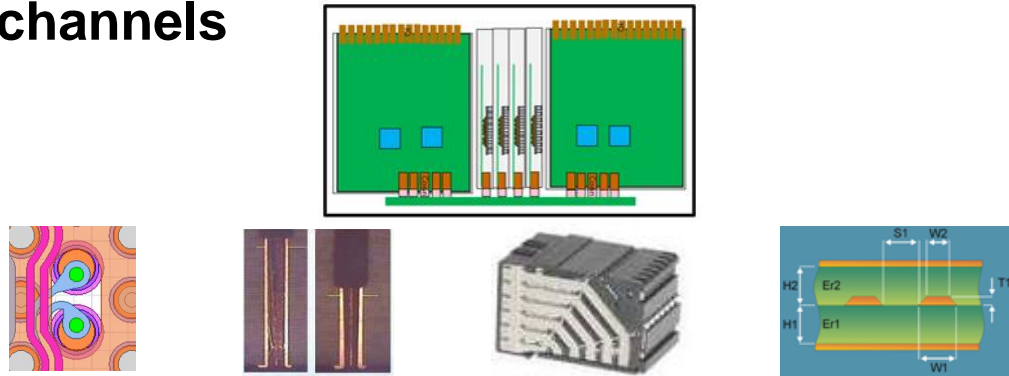
- Current estimated margin makes it difficult to design higher-rate systems
- The manufacturing processing variation is hard to quantify
- The variation of system performance might be considered by the impact of multi-factor coupling
- A large amount of simulations and test data are required
- Challenge: How can we use limited data to estimate system performance under the influence of multiple processing variables?

System Optimization

- Simulation for each system setup takes long time
- Multiple correlated parameters => large search space
- Traditional traversing methods not possible
- Machine learning based methods require a lot of training data
- Challenge: How can we reduce the required training data?

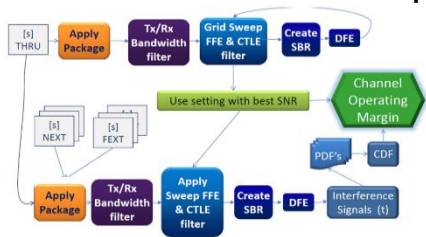
Manufacturing Process Deviation Analysis

Manufacturing coupling variables for channels



Model used: Channel Operating Margin (COM)

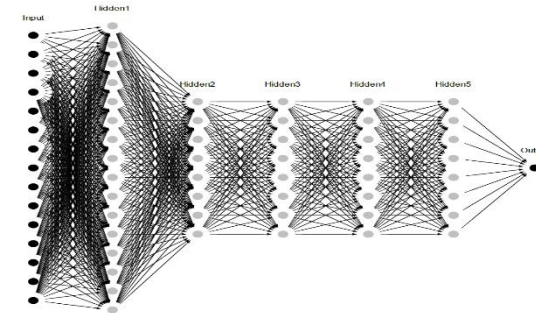
* IBIS model can be used for similar application as well



Steps

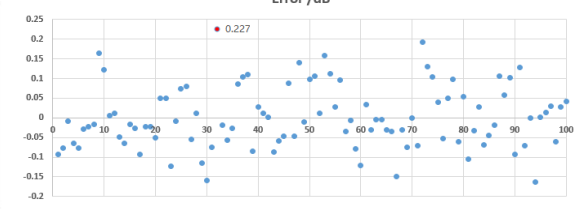
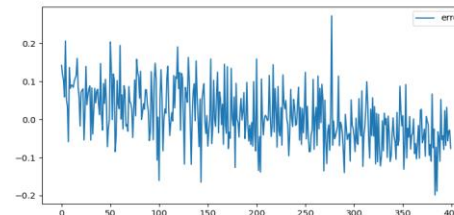
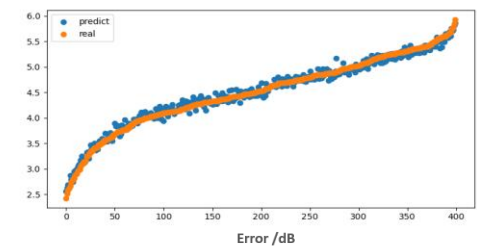
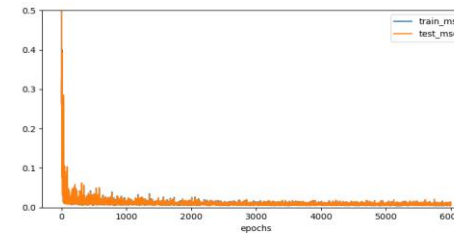
- Select variables for training
- Construct end-to-end links automatically
- Calculate COM values for training S parameters
- Predict massive COM values

DNN training



Input: processing variables

Output: COM values for certain link



Min Error	Max Error	Average Error
0.00005 dB	0.227 dB	0.0008 dB

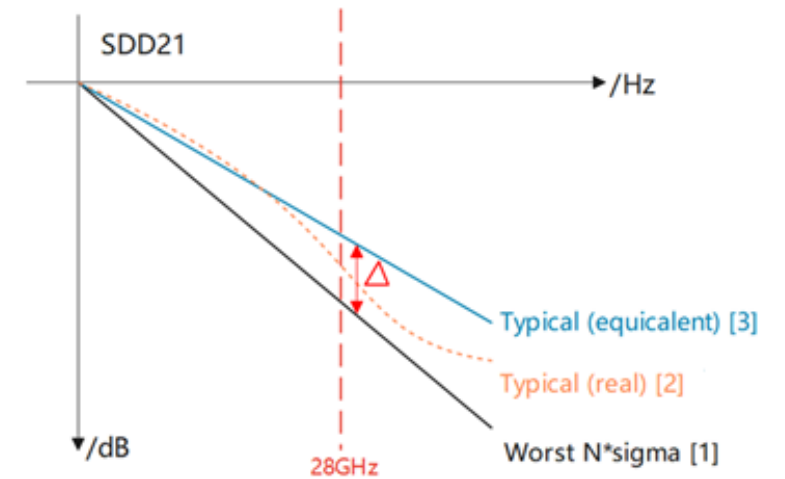
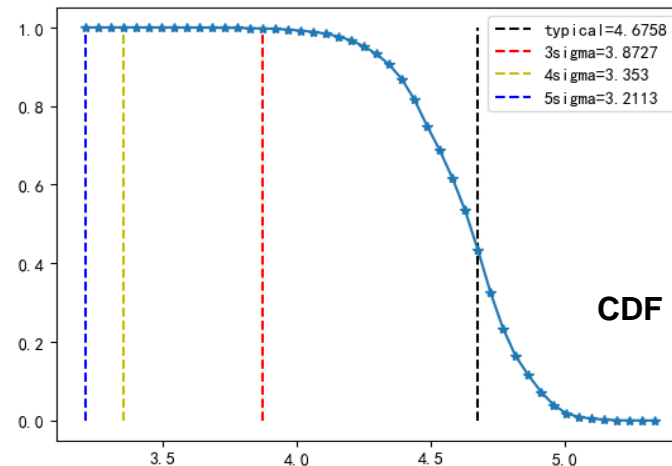
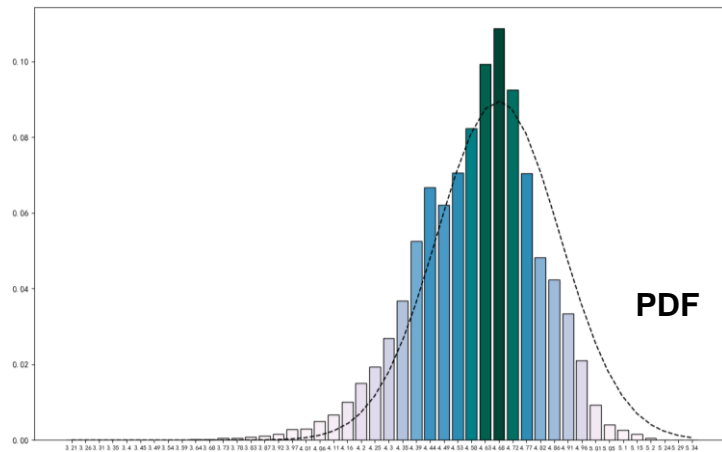
Manufacturing Process Deviation Results

DNN Prediction

- **Millions** of COM values for channels can be predicted from limited training samples **in seconds**
- Bounds of COM values @ N sigma can be given according to PDF and CDF
- Performance of certain channel can be derived by comparing typical COM with the worst N sigma COM

typ COM=4.68dB, best COM=5.5dB
worst COM=2.67dB, 3sigma COM=3.87dB

COM@99.73%:3.87dB
delta_COM@3-5sig:0.8;1.32;1.46dB



Experiment Results DDQN Data

data type	amount	total amount	EH ACC	EW ACC
original datasets	600	600	92.40%	96.50%
add random samples	400	1000	94.18%	97.24%
add DDQN samples	400	1000	94.70%	97.66%
continue add random samples	400	1400	94.94%	97.80%
continue add DDQN samples	400	1400	95.29%	98.05%

Compared to randomly adding training samples, expanding training datasets with samples generated by DDQN is more efficient in training SI analysis model.

Experiment Results Synthetic Data

data type and amount	prediction accuracy	improvement
original 50	75.85%	-
add 50 random data	81.94%	6.09%
add 50 synthetic data	85.89%	10.04%
add 100 random data	85.59%	9.74%
add 100 synthetic data	88.65%	12.80%
add 200 random data	87.23%	11.38%
add 200 synthetic data	91.40%	15.55%

Compared to original small datasets , synthetic samples can improve **15.55%** of the prediction accuracy of SI analysis network.

Conclusion and Next Steps

Contributions:

- Uncertainty analysis based on information theory
- Improve the prediction accuracy of SI analysis
- Realize SI analysis based on a small amount of training datasets
- Derive Insertion Loss deviation resulting from manufacturing process variation

Next steps:

- Apply proposed methods on broader range of electronic circuit design tasks

Reference

Swaminathan M, Torun H M, Yu H, et al. Demystifying machine learning for signal and power integrity problems in packaging[J]. IEEE Transactions on Components, Packaging and Manufacturing Technology, 2020, 10(8): 1276-1295.

Peizhi Lei, Chong Wang, Jie Zheng, Jienan Chen “Generative Query Reinforcement Active Learning Networks: A Sample-Free Method”, Reviewed by IEEE Transactions on Neural Networks and Learning Systems, 2022

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