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

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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 (RNN)
- Behavioral models of input-output drivers
- Capture the memory effect

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

<table>
<thead>
<tr>
<th>Min Error</th>
<th>Max Error</th>
<th>Average Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00005 dB</td>
<td>0.227 dB</td>
<td>0.0008 dB</td>
</tr>
</tbody>
</table>
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

\[
\text{COM@99.73\%: 3.87dB} \\
\text{delta_COM@3-5sig: 0.8; 1.32; 1.46dB}
\]
Data Efficient Signal Integrity Analysis

**Input:** circuit parameters
\[ x = (x_1, x_2, ..., x_n) \]

**Output:** eye height and width
\[ y = (y_{EH}, y_{EW}) \]

- Duo-DNN: Modeling the input-output
- DDQN: Searching for the informative input parameters
- IBIS-based Simulator: Labeling the generated input parameters

Or we can use GAN-based data augmentation module instead
- Retraining Duo-DNN with all inputs
## Experiment Results DDQN Data

<table>
<thead>
<tr>
<th>data type</th>
<th>amount</th>
<th>total amount</th>
<th>EH ACC</th>
<th>EW ACC</th>
</tr>
</thead>
<tbody>
<tr>
<td>original datasets</td>
<td>600</td>
<td>600</td>
<td>92.40%</td>
<td>96.50%</td>
</tr>
<tr>
<td>add random samples</td>
<td>400</td>
<td>1000</td>
<td>94.18%</td>
<td>97.24%</td>
</tr>
<tr>
<td>add DDQN samples</td>
<td>400</td>
<td>1000</td>
<td>94.70%</td>
<td>97.66%</td>
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<tr>
<td>continue add random samples</td>
<td>400</td>
<td>1400</td>
<td>94.94%</td>
<td>97.80%</td>
</tr>
<tr>
<td>continue add DDQN samples</td>
<td>400</td>
<td>1400</td>
<td>95.29%</td>
<td>98.05%</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>data type and amount</th>
<th>prediction accuracy</th>
<th>improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>original 50</td>
<td>75.85%</td>
<td>-</td>
</tr>
<tr>
<td>add 50 random data</td>
<td>81.94%</td>
<td>6.09%</td>
</tr>
<tr>
<td>add 50 synthetic data</td>
<td>85.89%</td>
<td>10.04%</td>
</tr>
<tr>
<td>add 100 random data</td>
<td>85.59%</td>
<td>9.74%</td>
</tr>
<tr>
<td>add 100 synthetic data</td>
<td>88.65%</td>
<td>12.80%</td>
</tr>
<tr>
<td>add 200 random data</td>
<td>87.23%</td>
<td>11.38%</td>
</tr>
<tr>
<td>add 200 synthetic data</td>
<td>91.40%</td>
<td>15.55%</td>
</tr>
</tbody>
</table>

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


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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