

# Hardware and AI/ML: Applications of SIPI & IBIS

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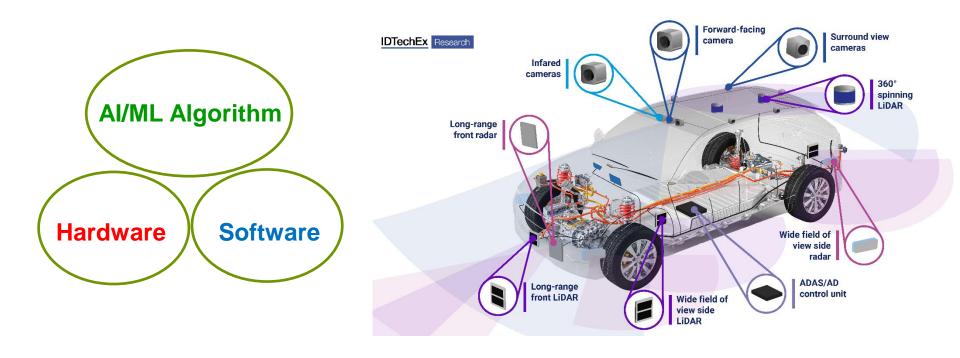
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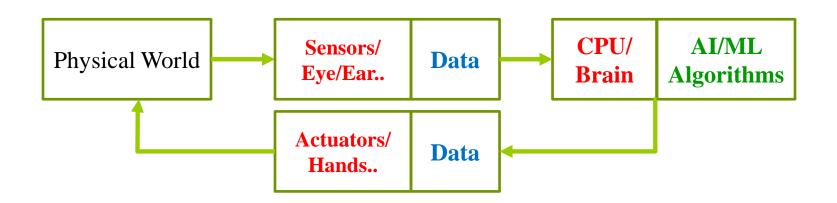
Asian IBIS Summit @ Tokyo, JAPAN November 14, 2023

## Agenda

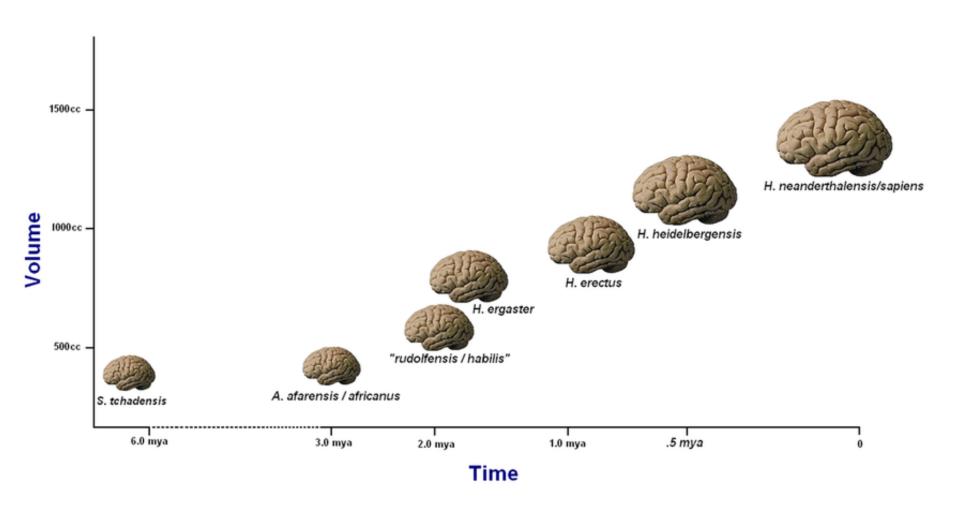
- Hardware Plays Critical Roles in AI/ML
- Human vs Silicon Evolutions
- SIPI Demands & Challenges
- AI/ML and Hardware Can Help Each Other
- SIPI AI/ML Case Studies
  - Placement optimization of decoupling capacitors
  - PDN Impedance Prediction (CNN-GA)
  - Eye-diagram-metrics prediction with DNN
  - Eye-diagram generation with RNN
- IBIS AI/ML Usage Cases
  - IBIS + AI/ML for SIPI design and simulations
    - IBIS keywords are very useful as AI/ML parameters
  - Use AI/ML to generate more accurate IBIS models

# **Hardware Plays Critical Roles in AI/ML**



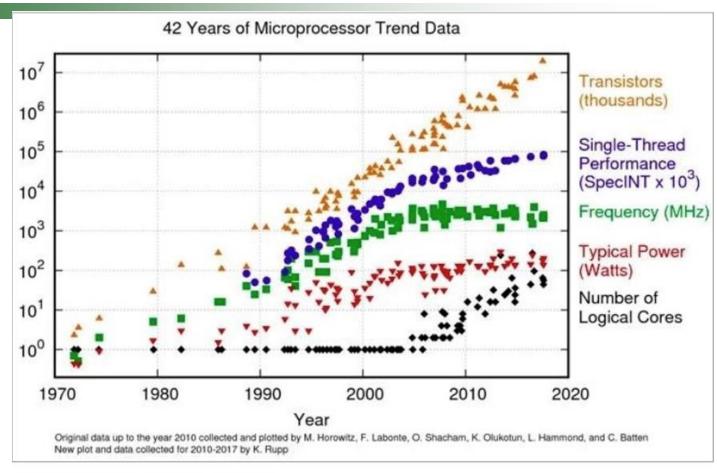


#### **Human Evolution Over Millions Years**



3X increase over 6 million years

#### Silicon Evolution in 42 Years



Source: M. Horowitz, et al. 2010, K. Rupp, 2017.

Figure 20 Tradeoffs in MPU performance after the power limit was reached.

#### 10^7 X increase over 42 years!

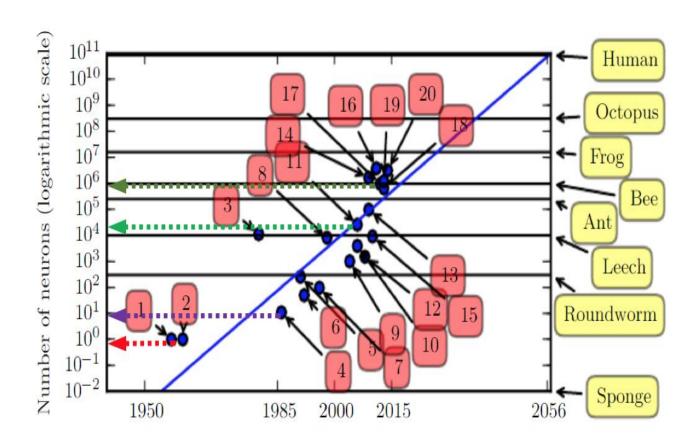
## **Machine vs Living Creatures**

Multi-GPU convolutional neural network (2012)

GPU accelerated convolutional neural network (2006)

Early back-propagation network (1986)

Perception (1958)



**Neural Network Size Grows with Hardware Advancement** 

Ivan Goodfellow et al.

Silicon/Hardware is evolving much faster, but still fall behind Human

## Signal Integrity Demands & Challenges

#### Relentless Advancement – Switch Silicon Bandwidth



102.4T? 2010 2012 2014 2018 2020 12 Years 7 Switch Generations (80x) 4 SerDes Speeds (10x) 51.2T 4 Switch Radix Increases (8x) 25.6T 12.8T 6.4T 3.2T Switch Silicon BW 640G 1.28T SerDes Speed 10G 28G 56G 112G # SerDes x128 x256 x512 x64 QSFP28 QSFPDD56 Optics QSFP+ QSFPDD800

Figure 3 Relentless advancement – switch silicon bandwidth

Reference: OIF Next Generation CEI-224G Framework https://www.oiforum.com/wp-content/uploads/OIF-FD-CEI-224G-01.0.pdf

# **Power Integrity Demands & Challenges**

#### Relentless Advancement – 80x BW over 12 Years

Represents a combination of multiple chip families and architectures to provide historical context and future projections Fixed Box Power Breakdown

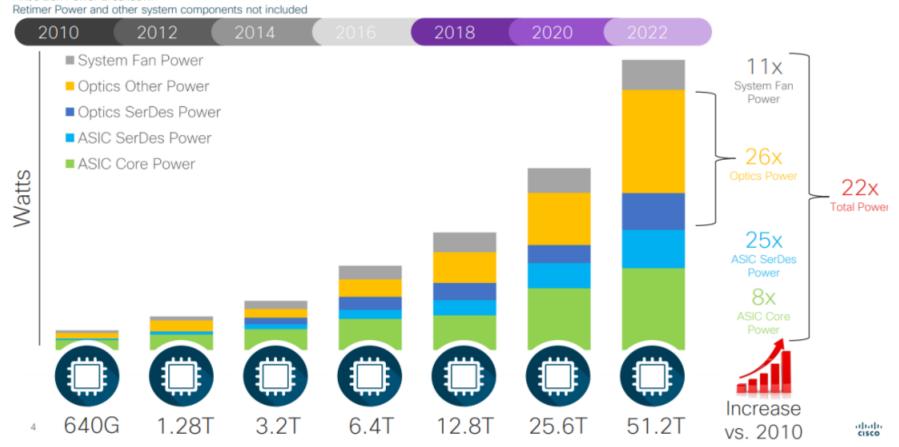
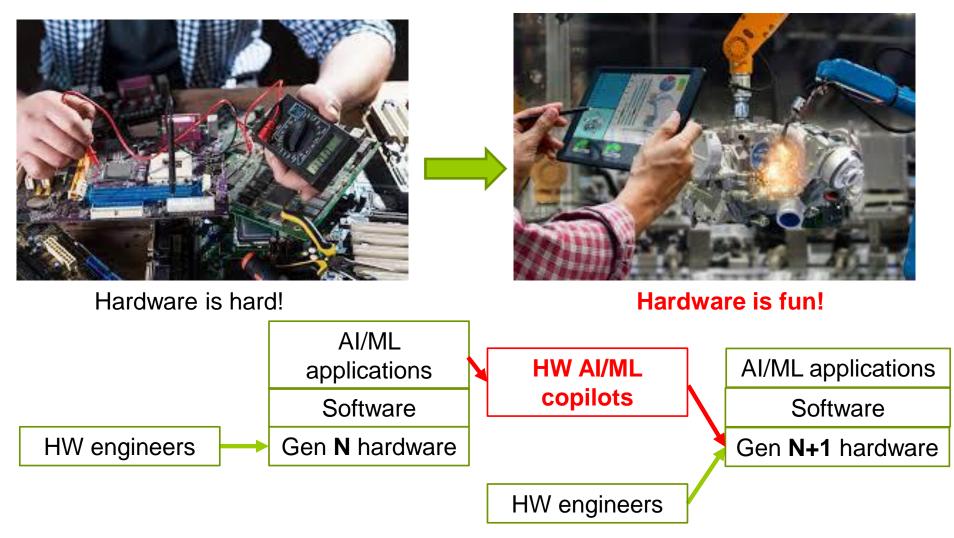


Figure 4 Relentless advancement – 80x BW over 12 years

Reference: OIF Next Generation CEI-224G Framework https://www.oiforum.com/wp-content/uploads/OIF-FD-CEI-224G-01.0.pdf

# AI/ML and Hardware Can Help Each Other



Advanced HW AI/ML copilots are expected to significantly improve the hardware design. This will enable a positive feedback loop between Hardware Design and AI/ML applications.

#### More Advanced Hardware for AI/ML



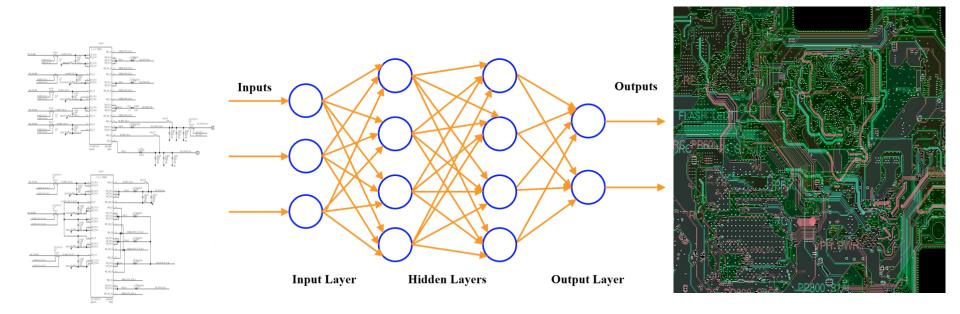






Current Silicon/Hardware cannot meet exponential growth of Al/ML! nVidia is a \$T dollar company now. We need more advanced hardware!

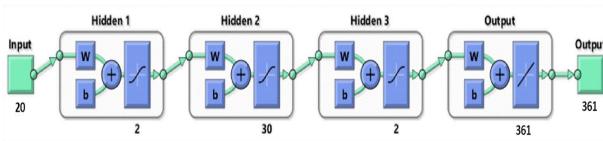
## More Powerful AI/ML for Hardware Design



Mark Hayter, Plenary Talk, 2018 IEEE EMC Symposium, Singapore

**Schematic** 

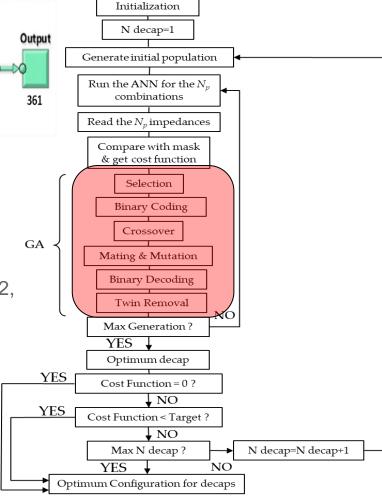
#### **Case Study: Optimization for Decap Placement (ANN-GA)**



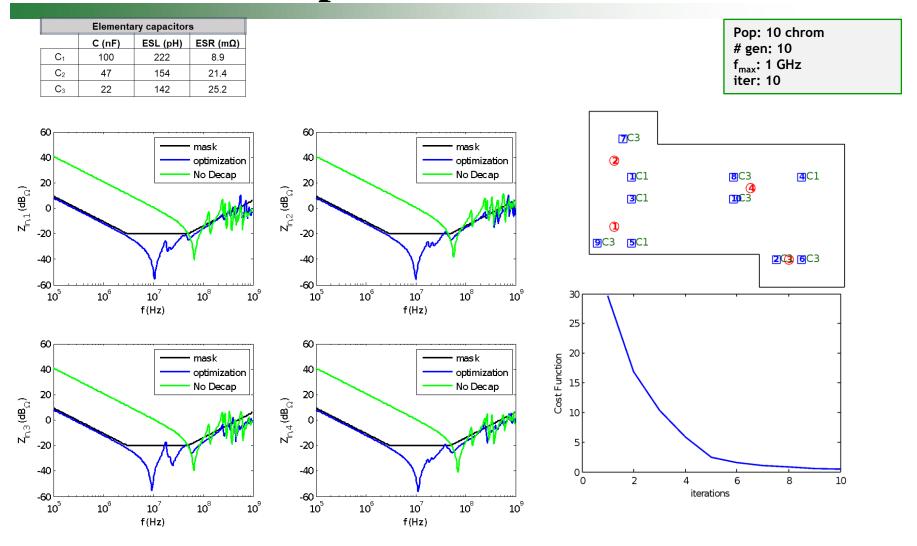
Input: decaps value and location

#### **Output**: PDN impedance

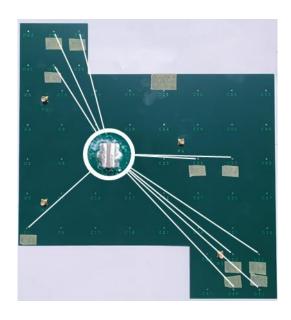
- The final architecture consists on 3 hidden layer (width of 2, 30 and 2, respectively)
- The output layer has size of 361: the values of Zin(f) at the 361 frequency points of the spectrum



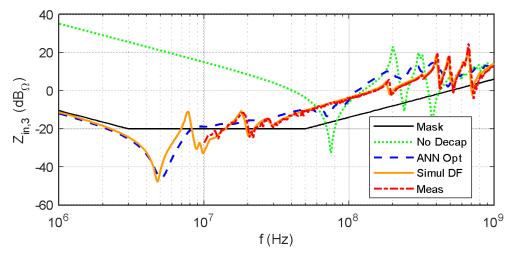
# **Results of the Optimization**



## **Lab Validations**



Decap locations in the real board

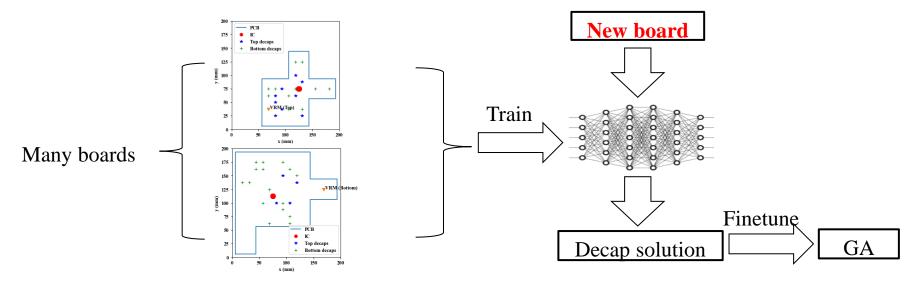


#### Z<sub>in</sub> at Port 3:

- from ANN-GA
- from measurement
- from simulation

## **Case Study: PDN Impedance Prediction (CNN-GA)**

Deep learning to optimize Decap placement given any: board shape, stack-up, IC location, and # of decaps

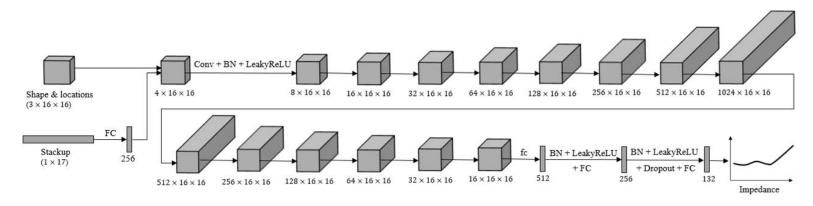


Two step approach: trained network + fine tune (GA)

Use the predicted solution by the DRL as a seeded solution of the GA

# Case Study: PDN Impedance Prediction

#### Convolutional neural network (CNN) structure:



- Training: 1.3M board
- Testing: 10K board
- Training time: 80 hours (1 NVIDIA Tesla K80 GPU)

# Case Study: PDN Impedance Prediction

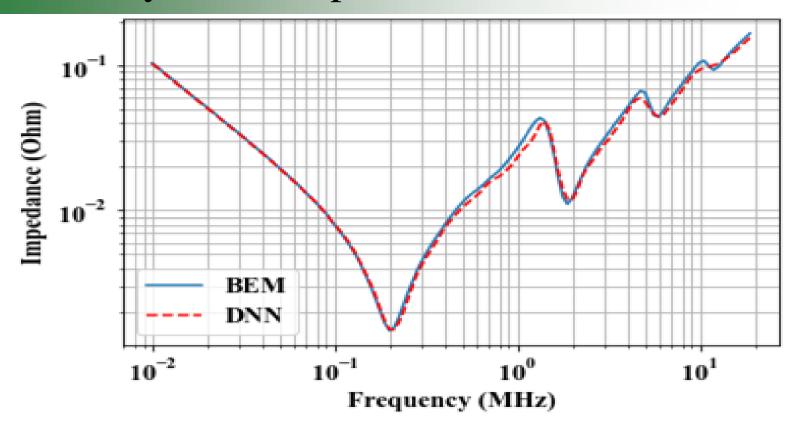
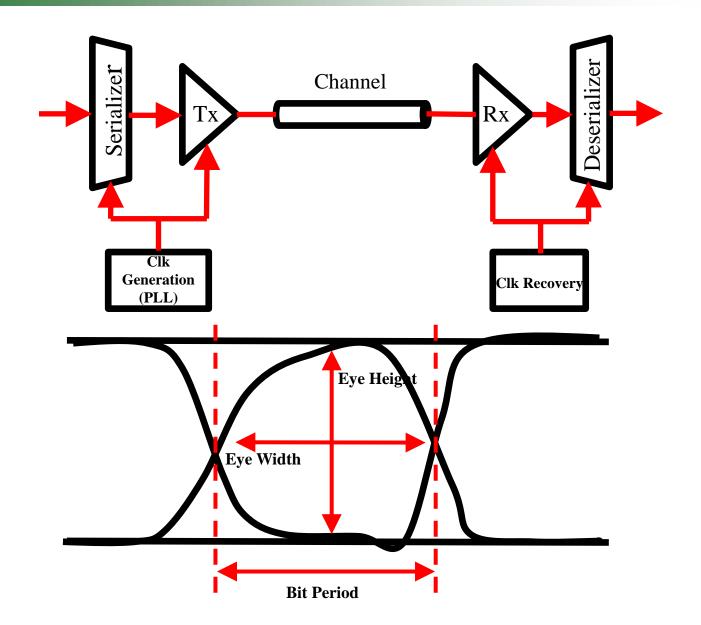


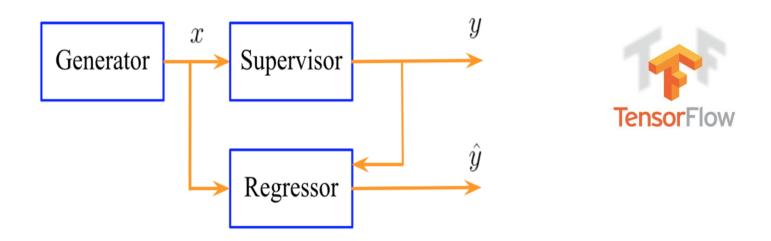
TABLE 2 Time comparison

Methods	Case 1	Case 2
Full-wave simulation	35 min	40 min
Boundary element method	10 s	30 s
Deep neural network	0.1 s	0.1 s

## Case Study: ML in High-Speed Channel Modeling

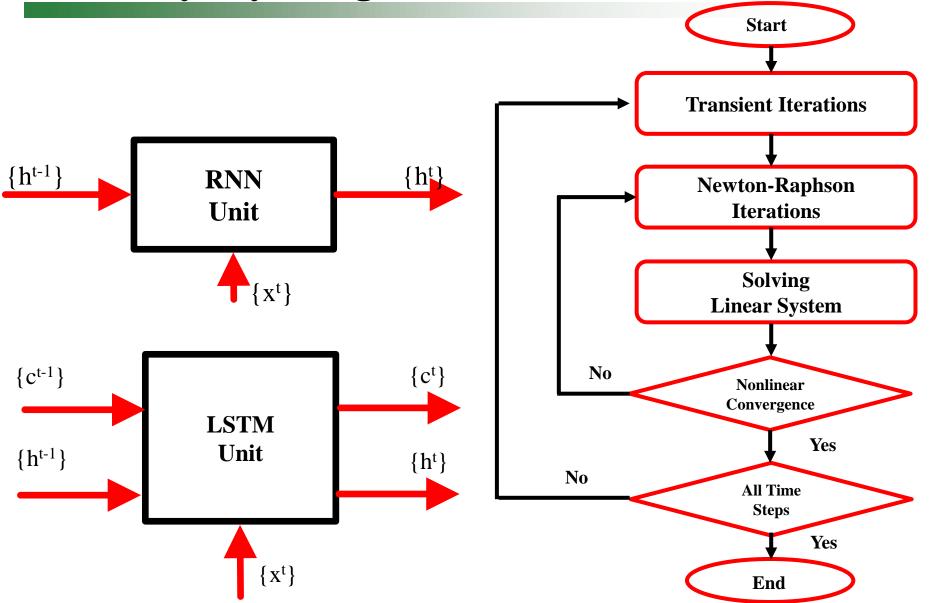


## Case Study: Eye-diagram-metrics Prediction with DNN

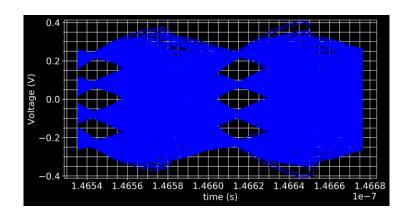


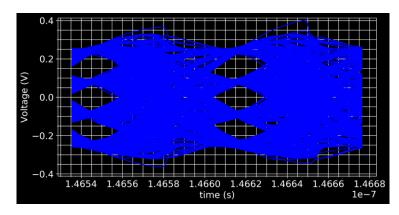
- Generator creates a set of input parameters for a high-speed channel, stored in  $\{x\}$ .
- Supervisor returns eye height or width y based on  $\{x\}$ .
- The learning process is essentially the selection of the right regression function  $f(\{x\}, \{\theta\})$  where  $\{\theta\}$  contains the parameters to be learned, such that the prediction made by  $f(\{x\}, \{\theta\})$  approximates the value returned by the supervisor uniformly over all possible input  $\{x\}$ .
- Regression method in this work includes linear, support vector, and DNN regressions.

## Case Study: Eye-diagram-metrics Prediction with RNN



## **Eye Diagram Generation with a PAM4 Example**





#### **Circuit Simulator**

**LSTM Network** 

T. Nguyen, T. Lu, K. Wu, J. Schutt-Aine, "Transient simulations of high-speed channels with recurrent neural network," in IEEE Transactions on Computer Aided Design of Integrated Circuits and Systems.

## IBIS + AI/ML for SIPI Design and Simulations

- **IBIS keywords** are very useful as AI/ML input parameters
- This is an active research field and here are some publications:
  - Comparison of Machine Learning Techniques for Predictive Modeling of High-Speed Links, Hanzhi Ma; Er-Ping Li; Andreas C. Cangellaris; Xu Chen, 2019 IEEE 28th Conference on Electrical Performance of Electronic Packaging and Systems (EPEPS)
  - PAM-4 Behavioral Modeling using Machine Learning via Laguerre-Volterra Expansion, Xinying Wang; Thong Nguyen; Jose E. Schutt-Aine, 2020 IEEE 11th Latin American Symposium on Circuits & Systems (LASCAS)
  - Self-Evolution Cascade Deep Learning Model for High-Speed Receiver Adaptation, Bowen Li; Brandon Jiao; Chih-Hsun Chou; Romi Mayder; Paul Franzon, IEEE Transactions on Components, Packaging and Manufacturing Technology, Year: 2020 | Volume: 10, Issue: 6

#### Use AI/ML to generate more accurate IBIS models

- This is a relatively new research field, and it belongs to **generative AI**.
- Presentation from Prof Huang at the Hybrid IBIS Summit at 2023 IEEE Symposium on EMC+SIPI

#### USB3.0 IBIS-AMI Model Construction based on Measurement and Neural Network

Jiahuan Huang (Missouri S&T EMC Lab, USA)

Junho Joo (Missouri S&T EMC Lab, USA)

Hank Lin (ASUS, Taiwan)

Bin-Chyi Tseng (ASUS, Taiwan)

Will Chan (ASUS, Taiwan)

Chulsoon Hwang (Missouri S&T EMC Lab, USA)

[Presented by Jiahuan Huang]

# THANK YOU! & QUESTIONS?

Please contact me at

yangzhip@mst.edu or zhipingyang@JAY-Plus.com

#### **Abbreviations**

- GA: Genetic Algorithm
- ANN: Artificial Neural Network
- CNN: Convolutional Neural Network
- RNN: Recurrent Neural Network
- DNN: Deep Neural Networks
- LSTM: Long Short-Term Memory

## **Publications**

- [A] Stefano Piersanti, Riccardo Cecchetti, Carlo Olivieri; Francesco de Paulis; Antonio Orlandi; Markus Bueker, **Decoupling Capacitors Placement at Board Level Adopting a Nature-Inspired Algorithm**, in Electronics 2019, Volume 8, Issue 7, October 2019, available online: <a href="https://www.mdpi.com/2079-9292/8/7/737/pdf">https://www.mdpi.com/2079-9292/8/7/737/pdf</a>
- [B] Francesco de Paulis; Riccardo Cecchetti; Carlo Olivieri; Stefano Piersanti; Antonio Orlandi; Markus Bueker, Efficient Iterative Process based on an Improved Genetic Algorithm for Decoupling Capacitor Placement at Board Level, in Electronics 2019, Volume 8, Issue 11, available online: https://www.mdpi.com/2079-9292/8/11/1219/pdf
- [C] R. Cecchetti, F. de Paulis, C. Olivieri, A. Orlandi, M. Buecker, "Effective PCB Decoupling Optimization by Combining an Iterative Genetic Algorithm and Machine Learning" in Electronics 2020, Volume. 9, Issue 8, August 2020, available online: <a href="https://www.mdpi.com/2079-9292/9/8/1243">https://www.mdpi.com/2079-9292/9/8/1243</a>
- [D] F. de Paulis, R. Cecchetti, C. Olivieri and M. Buecker, "Genetic Algorithm PDN Optimization based on Minimum Number of Decoupling Capacitors Applied to Arbitrary Target Impedance," 2020 IEEE International Symposium on Electromagnetic Compatibility & Signal/Power Integrity (EMCSI), Reno, NV, USA, 2020, pp. 428-433, doi: 10.1109/EMCSI38923.2020.9191458. "Best SIPI Symposium Paper Award"
- [E] Lu, Tianjian, Ju Sun, Ken Wu, and Zhiping Yang. "High-speed channel modeling with machine learning methods for signal integrity analysis." IEEE Transactions on Electromagnetic Compatibility 60, no. 6 (2018): 1957-1964.
- [F] Nguyen, Thong, Tianjian Lu, Ju Sun, Quang Le, Ken We, and Jose Schut-Aine. "Transient simulation for high-speed channels with recurrent neural network." In 2018 IEEE 27th Conference on Electrical Performance of Electronic Packaging and Systems (EPEPS), pp. 303-305. IEEE, 2018.
- [G] L. Zhang, J. Juang, Z. Kiguradze, B. Pu, S. Jin, S. Wu, Z. Yang, and C. Hwang, "Fast PDN Impedance Prediction using Deep Learning", submitted to International Journal of Numerical Modeling: Electronic Networks, Devices and Fields.
- [H] J. Juang, L. Zhang, Z. Kiguradze, B. Pu, S. Jin, S. Wu, Z. Yang, and C. Hwang, "A Modified Genetic Algorithm for the Selection of Decoupling Capacitors in PDN Design", accepted to IEEE EMC+ SIPI 2021.
- [I] L. Zhang, J. Juang, Z. Kiguradze, B. Pu, S. Jin, S. Wu, Z. Yang, and C. Hwang, "Efficient DC and AC Impedance Calculation for Arbitrary-shape and Multi-layer PDN Using Boundary Integration," IEEE Trans. Electromagn. Compat., to be submitted.
- [J] L. Zhang, J. Juang, Z. Kiguradze, S. Jin, S. Wu, Z. Yang, J. Fan, C. Hwang, "PCB-Level Decap Placement Using Deep Reinforcement Learning", IEEE Trans Microw Theory Tech., to be submitted.