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A Novel Approach for ESD Generator Modeling Using Deep Neural Network

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Agenda

- ❖ **Introduction**
  - ➢ System-level electrostatic discharge (ESD) problems
  - ➢ ESD generator modeling and simulation

- ❖ **Proposed Methodology for ESD Generator Modeling**
  - ➢ Introduction to neural networks
  - ➢ Deep neural network (DNN) parameter optimization
  - ➢ Verification results
  - ➢ Correlation with commercial ESD generators

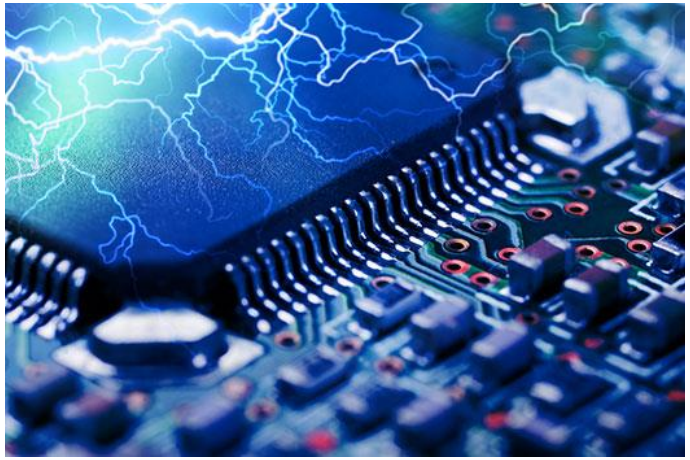
- ❖ **Conclusion**
- ❖ **Q & A**

System-level ESD Problems

- Electrostatic discharge (ESD) Source: Wikipedia
  - The sudden flow of electricity between two electrically charged objects by contact, dielectric breakdown
  - Short duration(0.1ns to 100ns), high voltage(~10kV), high current (1A to 30A) pulse
  - ESD sources: charged humans, charged cables (charger, USB, …), etc.
- System-level ESD problems in various electronic systems
  - High-speed operation, high complexity, and miniaturization

    ➔ **More sensitive to the ESD problems**

source: esdgoods.com



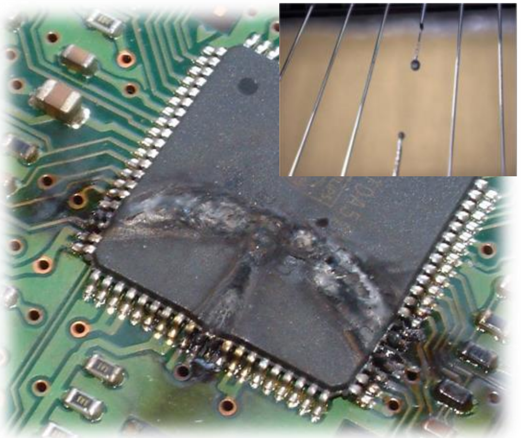
source: gotsige.com

ESD Failures

- Type of ESD failures
  - Hard failure: physical damages such as package burnt/cracked, melted wire bond.
  - Soft failure: system hang, reboot, and bluescreen due to logical error
- Cost and time losses to debug problems and figure out solutions

➔ **ESD simulation has to be conducted in the product design stage.**

Hard failure



source: datarecoverydublin.ie

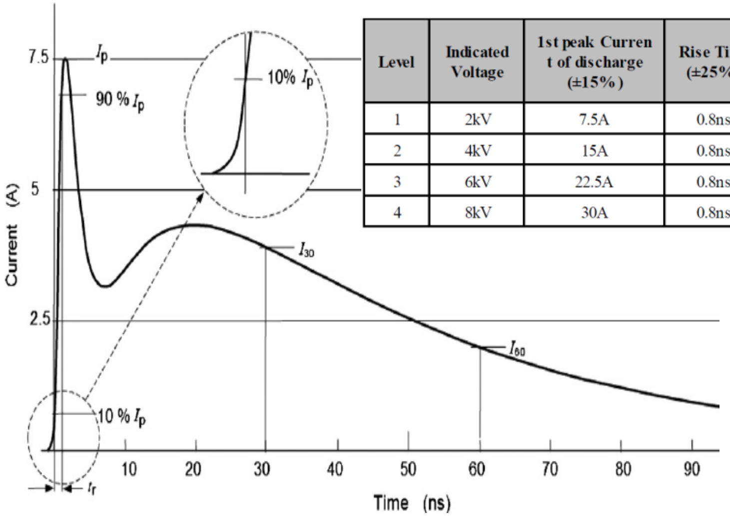
Soft failure

source: atchisonlibrary.org

ESD Generators

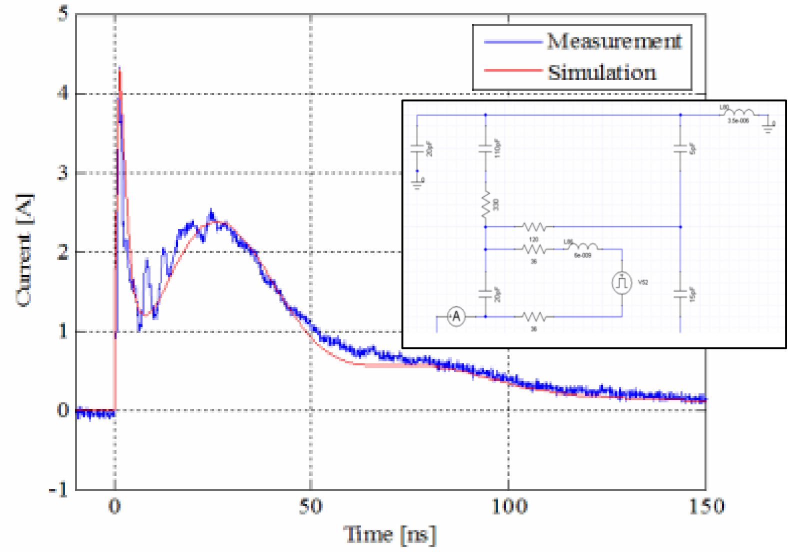
- ESD standard (IEC 61000-4-2) IEC: International Electrotechnical Commission
  - An assumption of that the source is an electrified human body discharge.
  - ESD generators have to meet the specified discharge waveform.
- The model of an ESD generator is required to perform an ESD simulation.
  - Many investigations (journals, conference papers) for developing ESD generator models

source: noiseken.com



Level	Indicated Voltage	1st peak Current of discharge (±15%)	Rise Time (±25%)	Current at 30ns (±30%)	Current at 60ns (±30%)
1	2kV	7.5A	0.8ns	4A	2A
2	4kV	15A	0.8ns	8A	4A
3	6kV	22.5A	0.8ns	12A	6A
4	8kV	30A	0.8ns	16A	8A

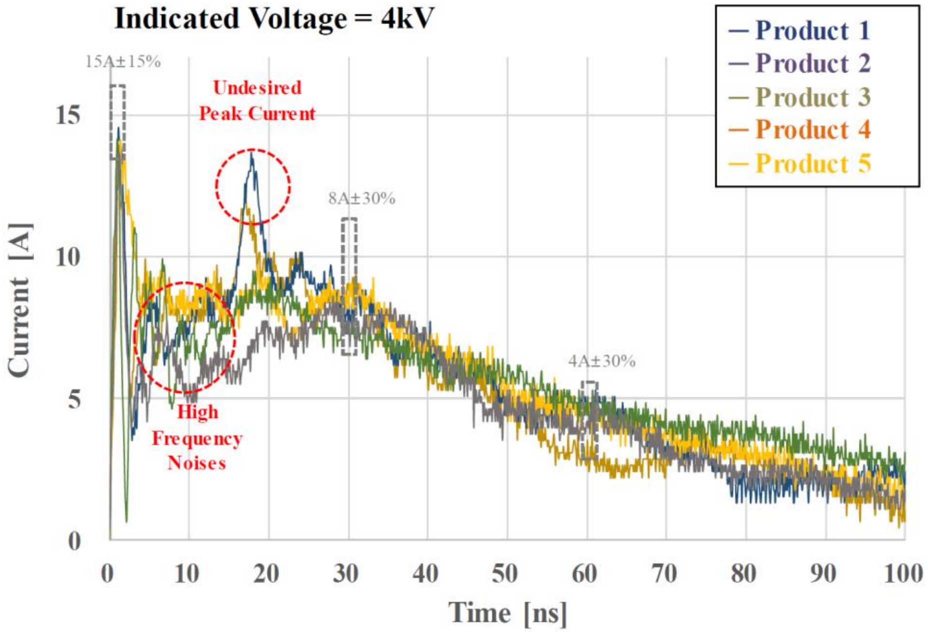
source: IEC 61000-4-2 Specification

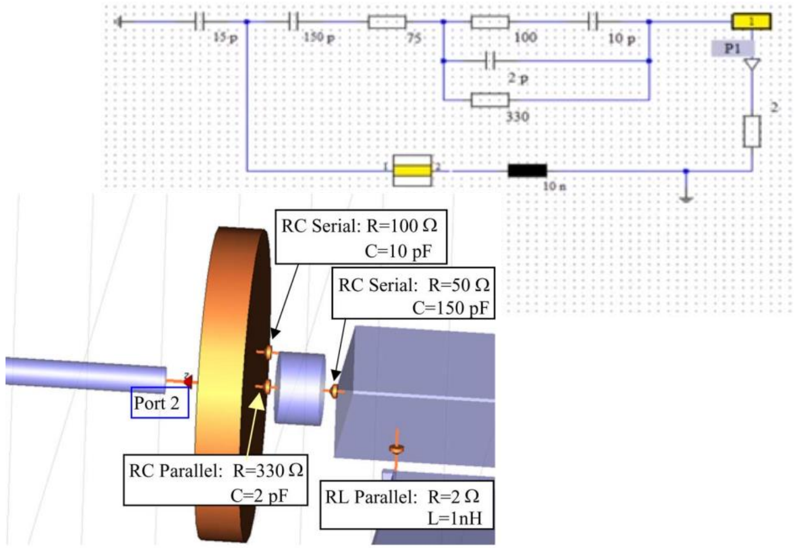


source: Seol Byongsu, *et al.*, EDAPS, 2008

Commercial ESD Generators

- Commercial ESD generators
  - All of commercial ESD generators satisfy IEC 61000-4-2 specification.
  - However, they have own characteristics such as peak current, high-frequency noises, etc.
    - ➔ Ironically, those undesired noises make ESD test failures in the laboratory test.
- Many investigations to improve the equivalent circuit model ESD generator, **however …**

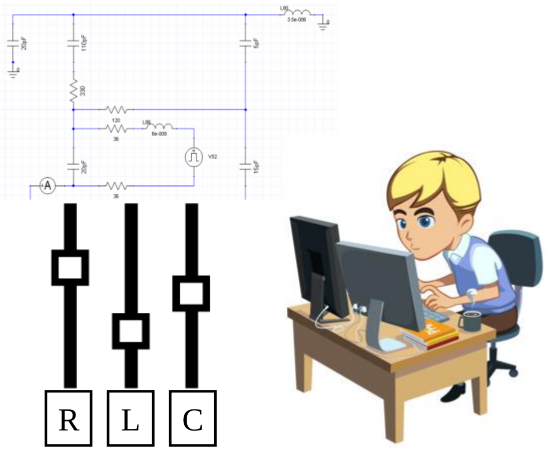




Source: S. Caniggia, et al., 2007

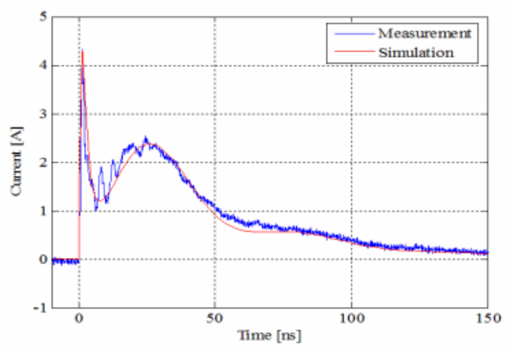
Proposed Methodology

- In the field, engineer tuned known model by adjusting passive components
  - Manually tuned the values of the components in the equivalent circuit model with multiple iterations
    - ➔ A time-consuming and tedious task for engineers
- Proposed methodology utilizes **"Deep Neural Network (DNN)"**
  - ➔ Component value extraction within few seconds once DNN is trained



source: kissclipart.com

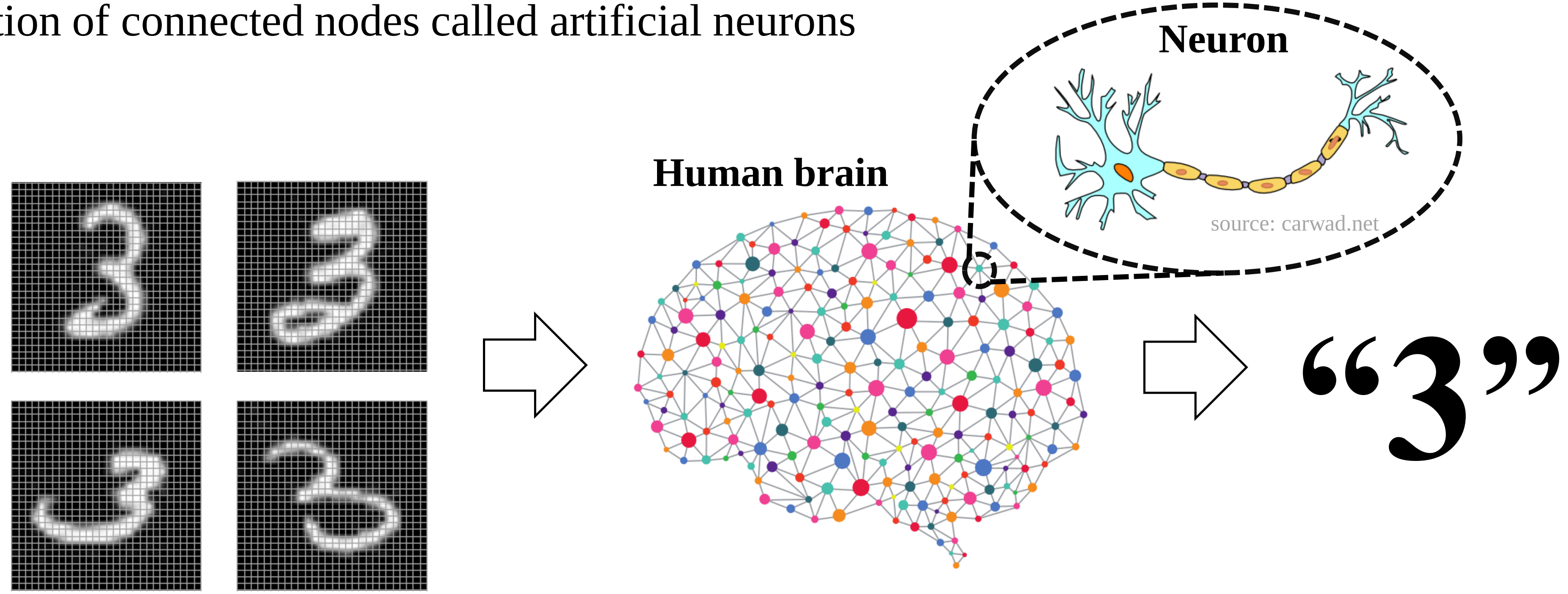
ESD current waveform



source: analyticsvidhya.com

Artificial Neural Network (ANN)

- Some problems are difficult to solve with conventional programming methodology
  - ➔ Computer vision, speech recognition, translation, AI, etc.
- ANNs are computing system inspired by the biological neural networks
  - Collection of connected nodes called artificial neurons

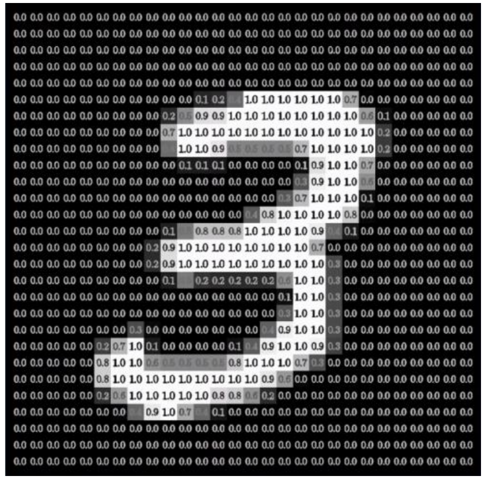


source: MNIST database

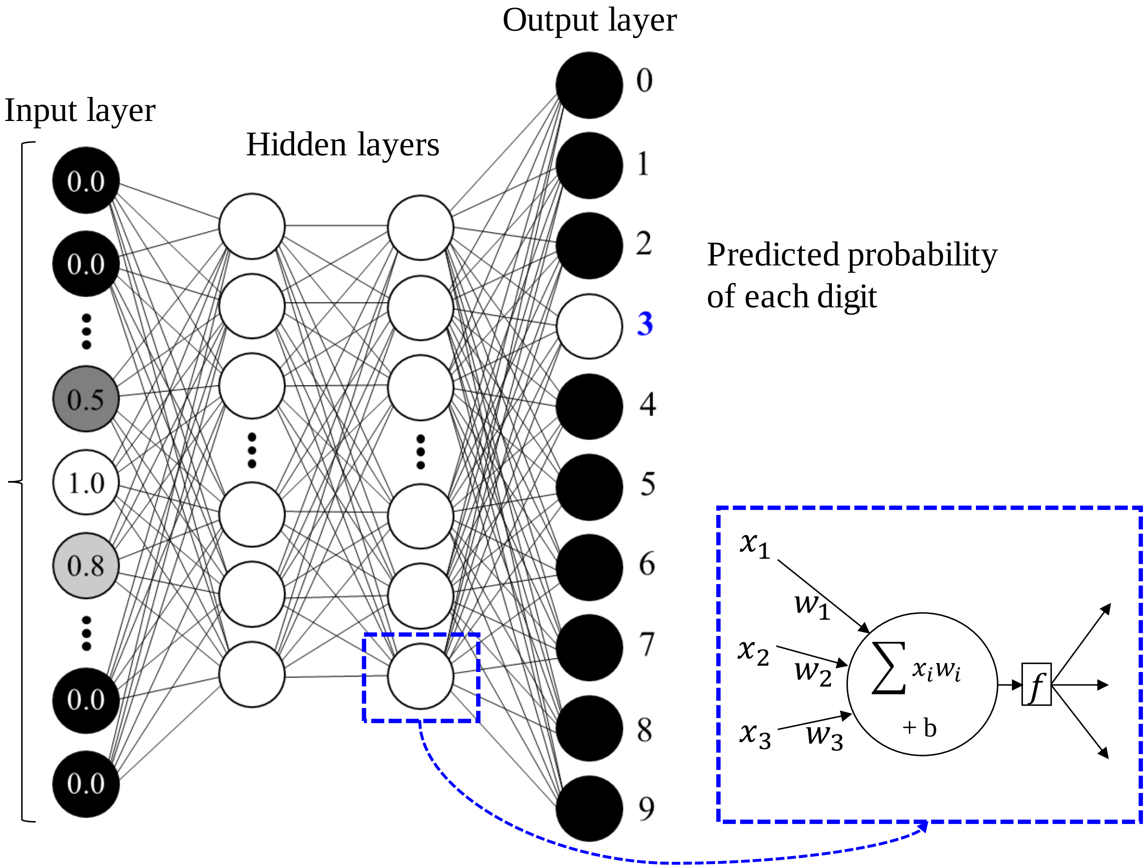
source: analyticsvidhya.com

Deep Neural Network (DNN)

- DNN has multiple hidden layers, and it is a kind of the ANNs.
- How works?

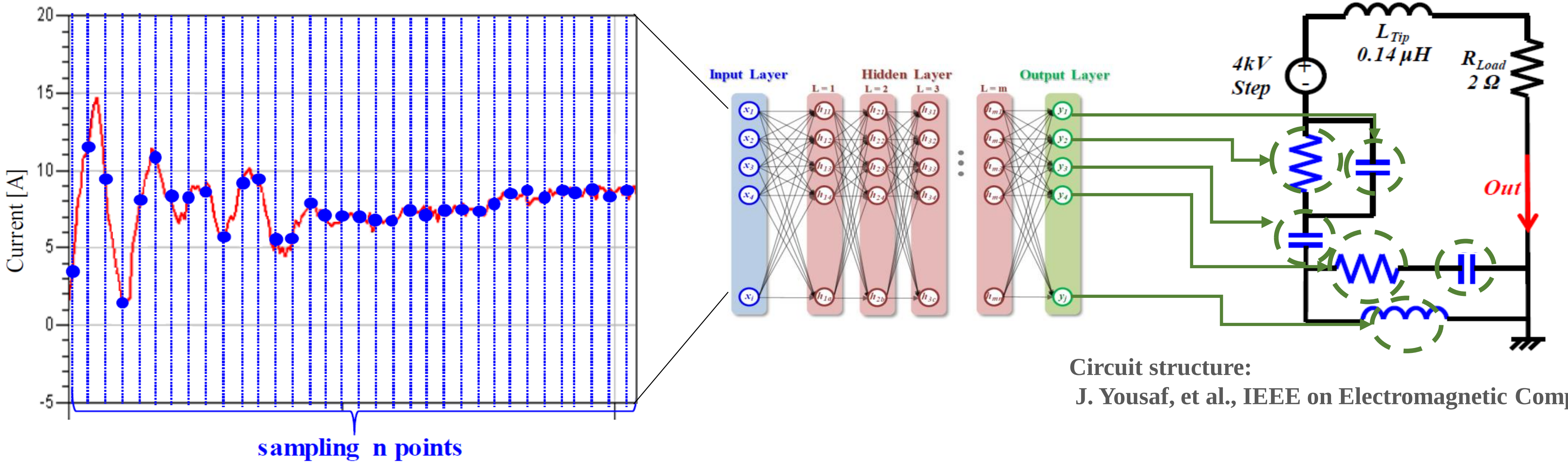


28 x 28 = 784 pixels



DNN Design for ESD Generator Modeling

- Without the machine learning, making ESD generator modeling program is very difficult
  - Hard to code logic of the program – it requires high-level knowledge about circuit
- Let's apply DNN to our problem

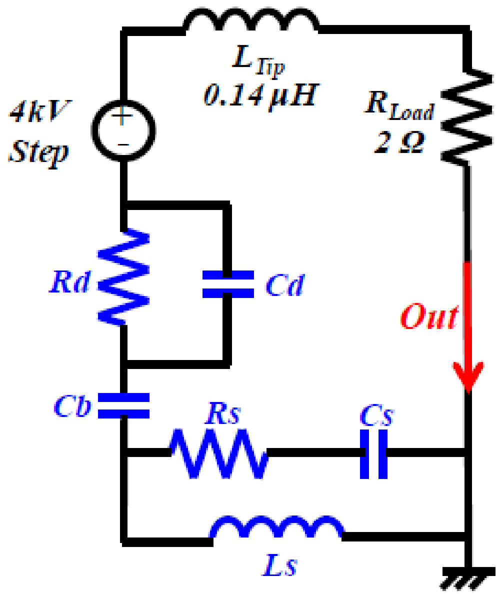


Circuit structure:
J. Yousaf, et al., IEEE on Electromagnetic Compatibility, 2018

- The DNN takes sampled waveforms as input
  - Each node in the input layer represents the current value of the corresponding sampling point
- The DNN predicts the passive components values that can generate a waveform similar to the input

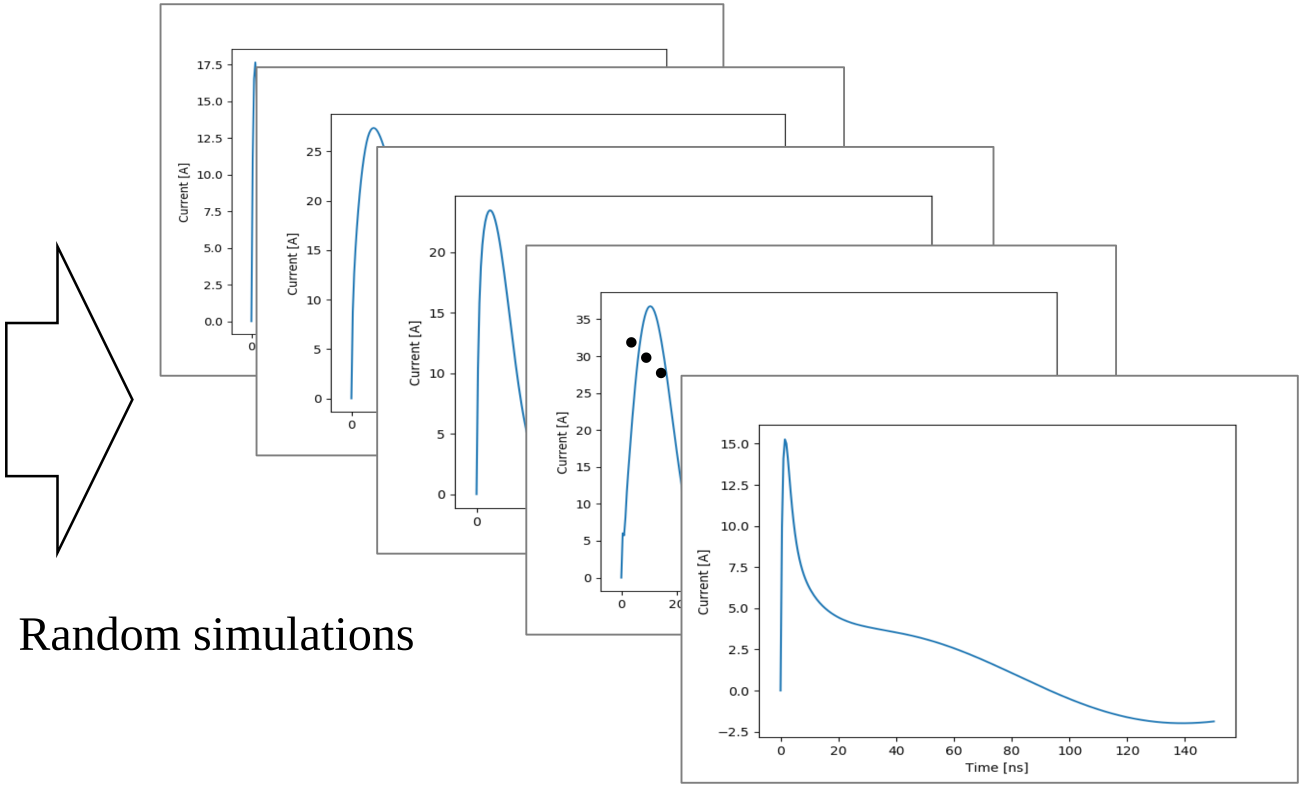
Dataset Generation

- When utilizing machine learning, one of the most difficult things is gathering reliable data
  - The dataset was generated using SPICE simulations with randomly selected passive components
- To keep reasonable exploration scope, we set parameter ranges based on the original model



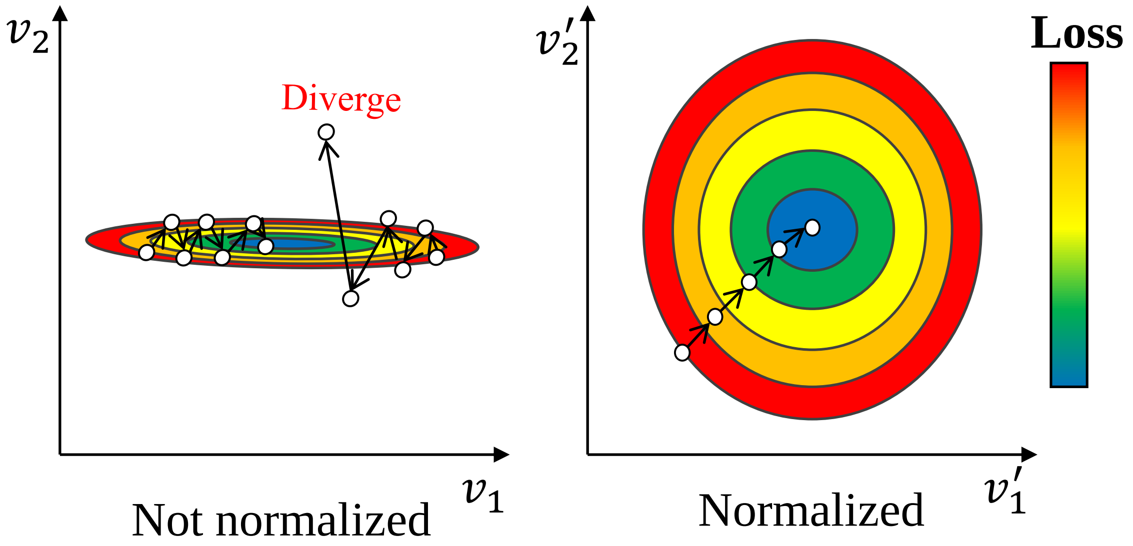
Component	Original value	**Proposed range**
Rd	330 Ω	**50-550 Ω**
Cd	3.45 pF	**0-60 pF**
Cb	150 pF	**0-600 pF**
Rs	95.6 Ω	**50-550 Ω**
Cs	14 pF	**0-100 pF**
Ls	1.7 μH	**0-10 μH**

Random simulations



Data Preprocessing

- Feature Scaling
  - A method used to standardize the range of features of data
  - Each feature is converted to the same scale to improve learning performance (learning speed, prevention of divergence)
  - In this study, all the values are normalized based on min-max normalization



Component	***Proposed range***
Rd	***50-550 Ω***
Cd	***0-60 pF***
Cb	***0-600 pF***
Rs	***50-550 Ω***
Cs	***0-100 pF***
Ls	***0-10 μH***

Ex. Rd = 100 Ω

Min-Max Normalization:

$$\frac{100-50}{550-50} = 0.1$$

Optimization of DNN Hyperparameters

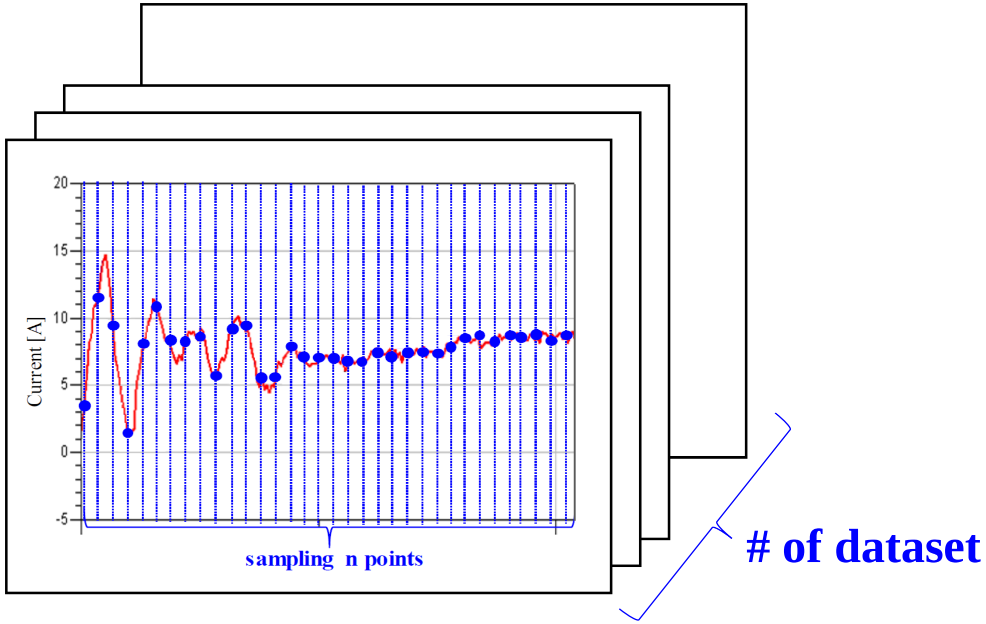
- DNN Hyperparameters?
  - Hyperparameters are properties that define a design of DNN model
  - To generate a good DNN model, you need to optimize the hyperparameters
  - Difficult or almost impossible to perfectly optimize DNN hyperparameters
  - Hyperparameters are interrelated to each other
- DNN hyperparameters
  - The size of a dataset
  - The number of hidden layers
  - Input resolution
  - Type of activation function
  - Learning rate
  - Optimization algorithm
  - Minibatch size

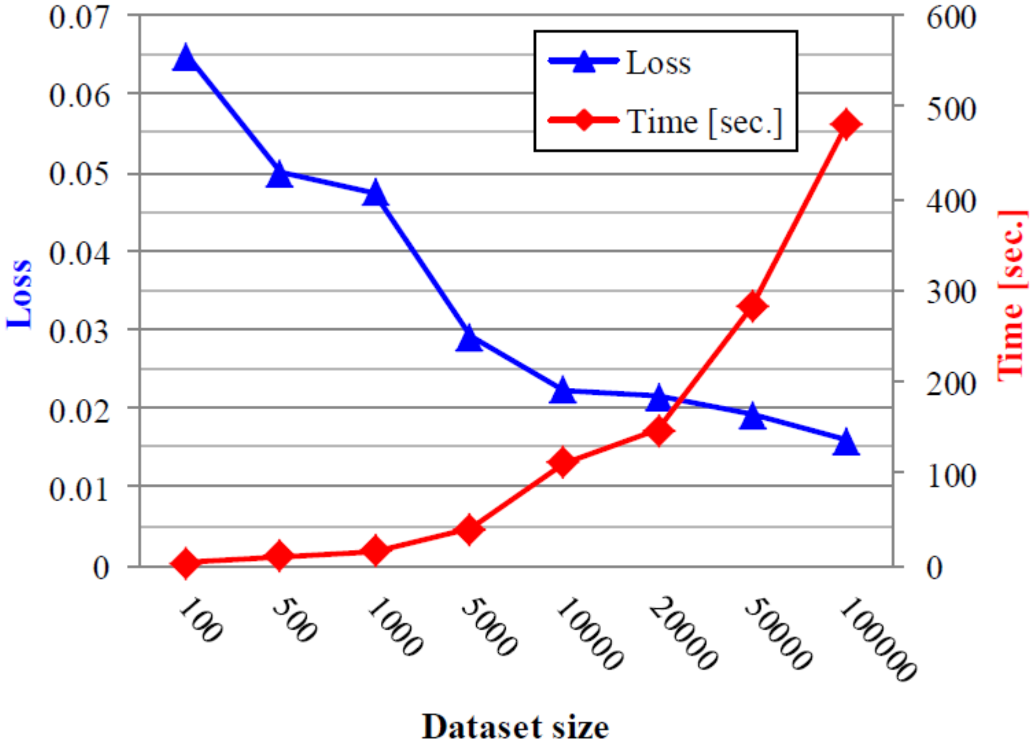
source: apigee.com

DNN Optimization (1): # of Dataset

- Dataset size makes a trade-off between accuracy and training time.
- Even though training time is increased, accuracy is also continuously increased

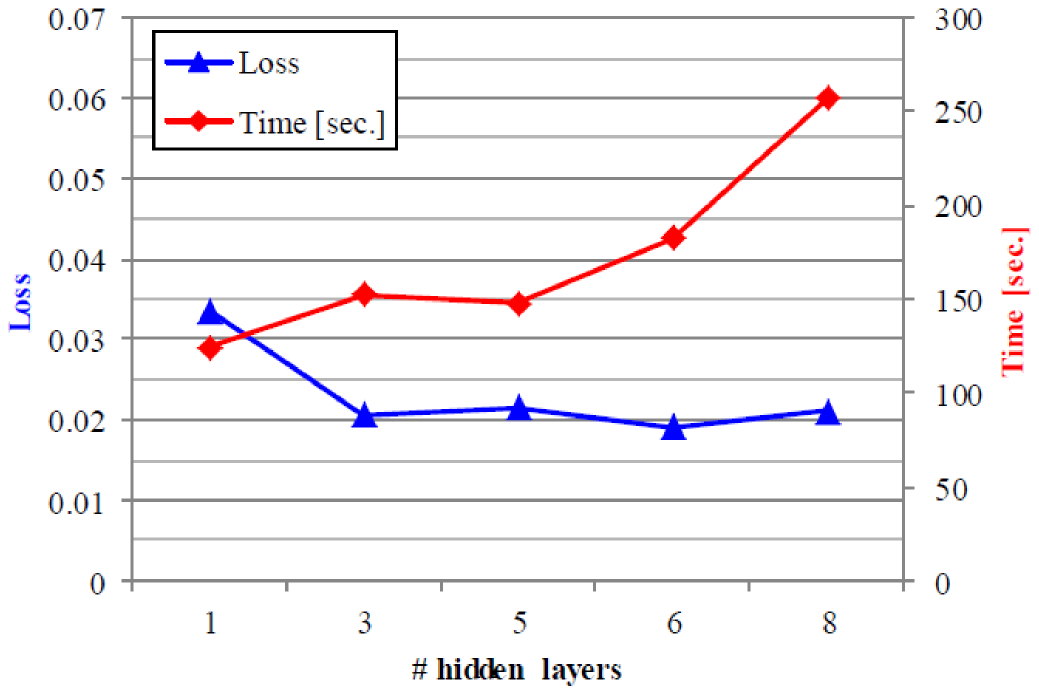
  ➔ 200,000 dataset for DNN training





DNN Optimization (2): # of Hidden Layers

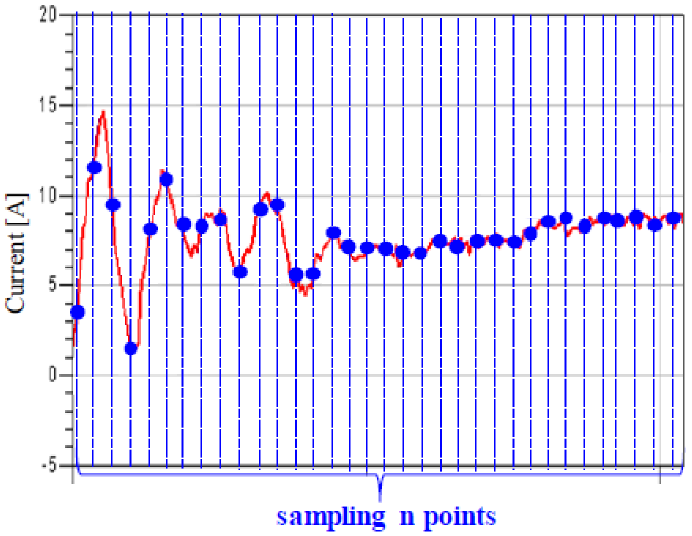
- The number of hidden layers can affect fitting performance.
- Accuracy is gradually saturated with increasing the number of hidden layers.

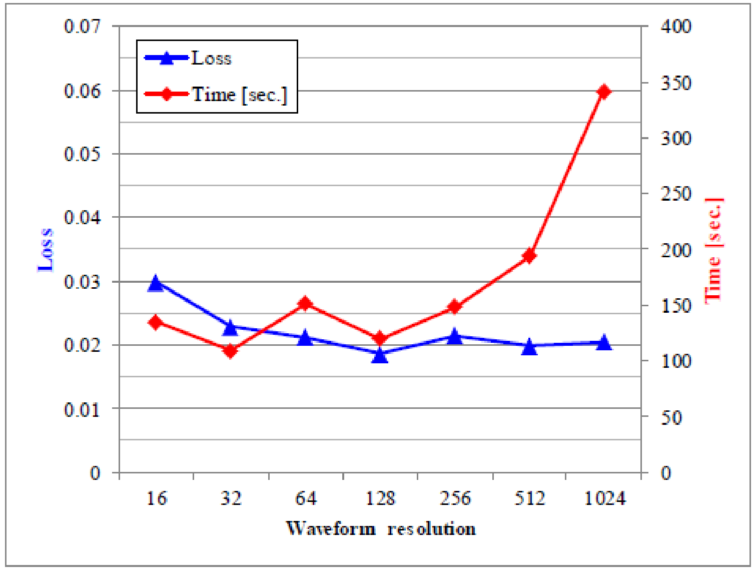


1 HL	3 HL	5 HL	6 HL	8 HL
Input layer (dimension: waveform resolution(256))				
FC 128	FC 128	FC 256	FC 128	FC 256
	FC 64	FC 128	FC 128	FC 256
	FC 32	FC 64	FC 64	FC 128
		FC 32	FC 64	FC 128
		FC 16	FC 32	FC 64
			FC 32	FC 64
				FC 32
				FC 32
Output layer (FC 6)				

DNN Optimization (3): Input Resolution

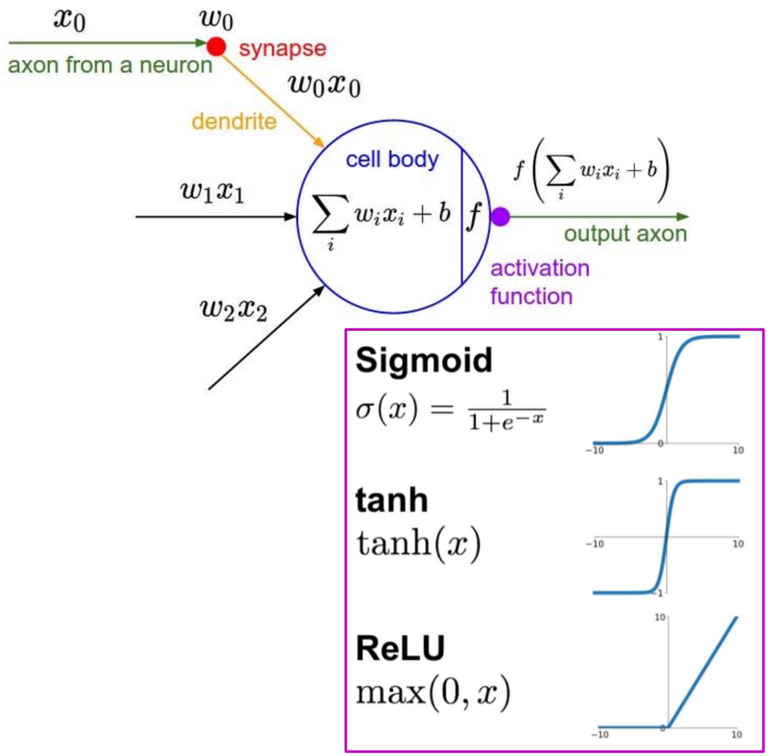
- Higher resolution doesn't guarantee the better performance for all cases.
  - Face recognition system: 8 x 8, 16 x 16, **32 x 32 (Best)**, 64 x 64, 128 x 128 (source: B.J. Boom, *et al.*, 2006)
  - Scene illumination classification using neural network: 64, **128 (Best)**, 256, 512, 1024, 2048 (source: M. H. Hesamian, et al., 2015)
- Accuracy is saturated at the 128 resolution.



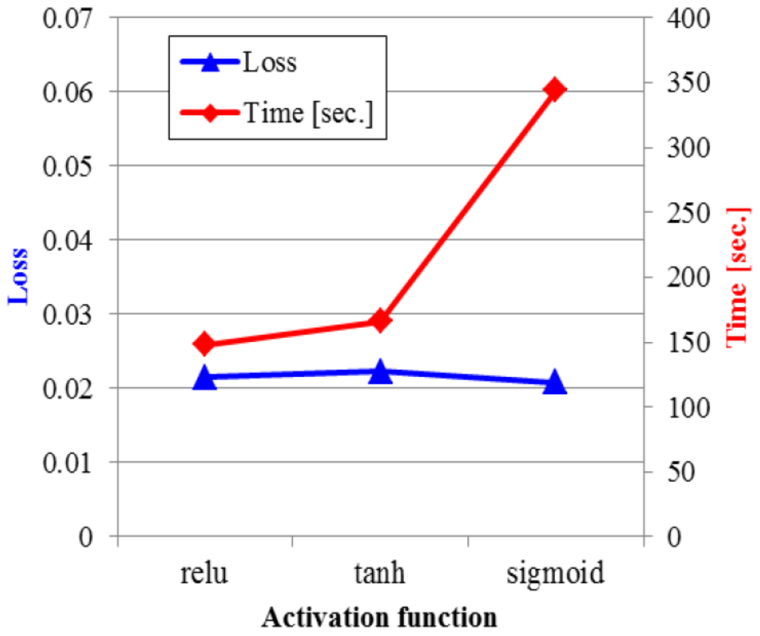


DNN Optimization (4): Type of Activation Function

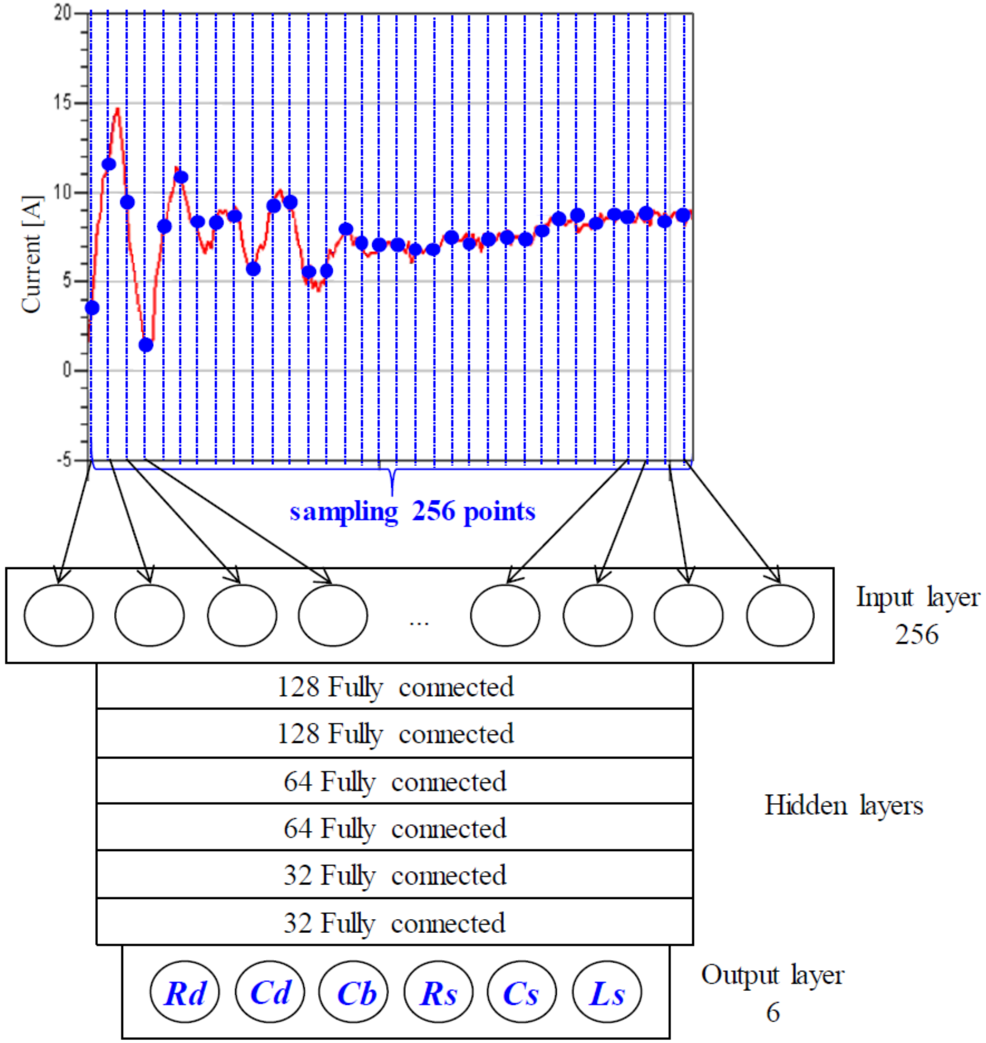
- Define propagation output of a neuron
- Different kinds of activation functions: ReLU, tanh, sigmoid
  - ➔ The shortest training time with ReLU



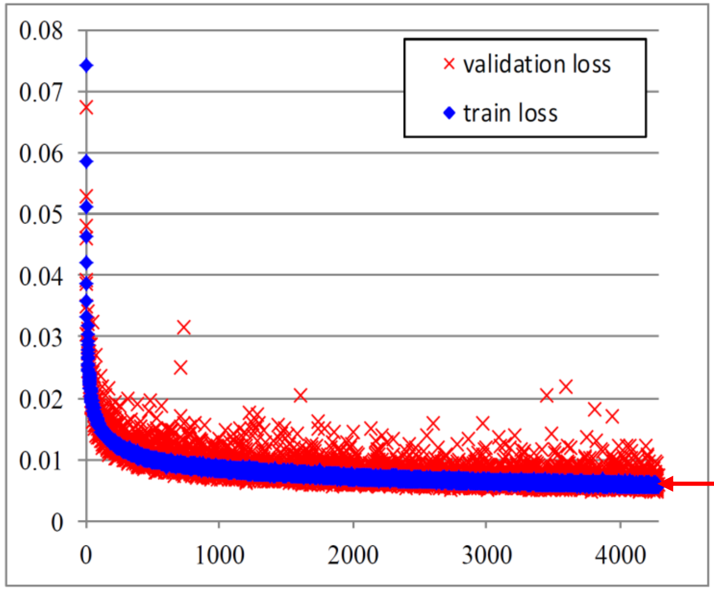
Source: medium.com



Proposed DNN Architecture



- The size of dataset: 200,000
- Overall layer depth: 8 layers
  (1 input layer, 6 hidden layers, 1 output layer)
- Input data resolution: 256
- Type of activation function: ReLU



Training time: 3 hours

Validation loss: 0.0074

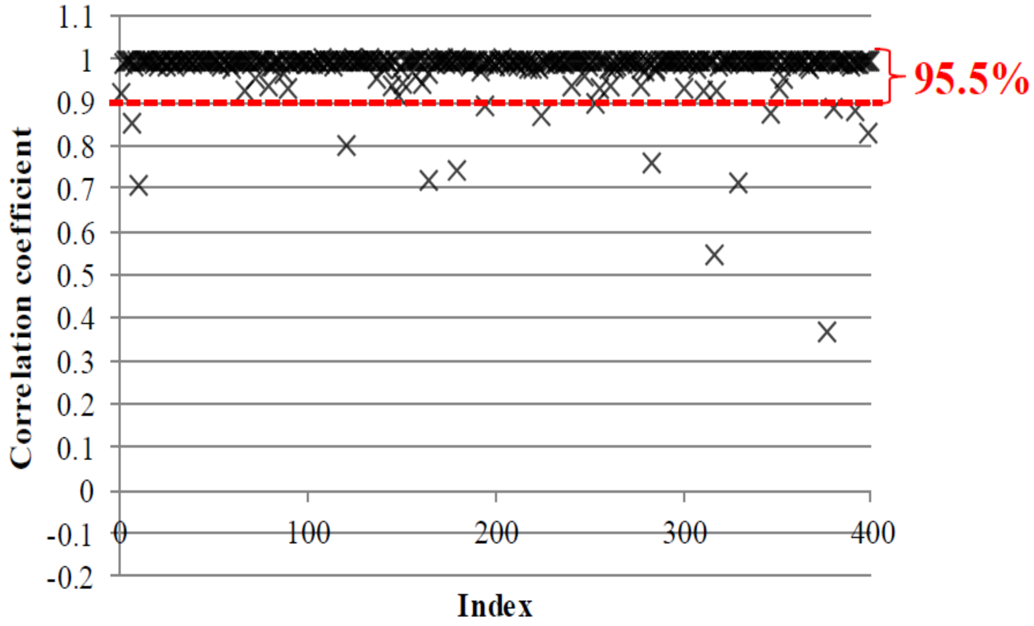
Verification Results

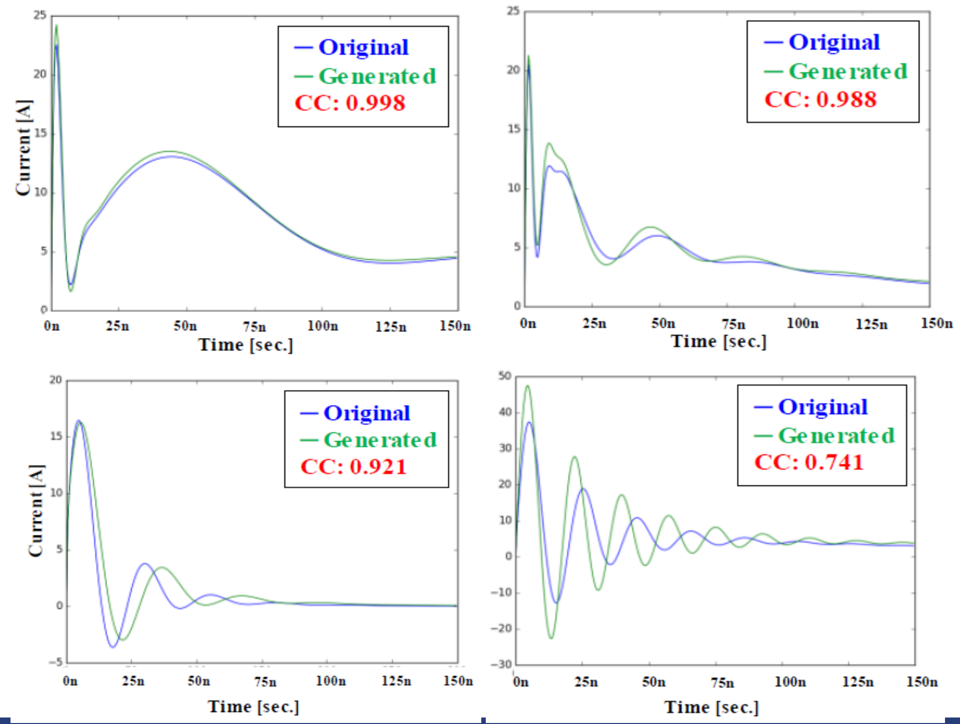
- Verified the DNN model with randomly generated 400 waveforms
- High correlation coefficient(Avg 0.98, > 0.9 for 95.5 %)
  - When the waveforms are similar, the correlation coefficient is close to one.

Correlation coefficient

$$\rho_{X,Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y}$$

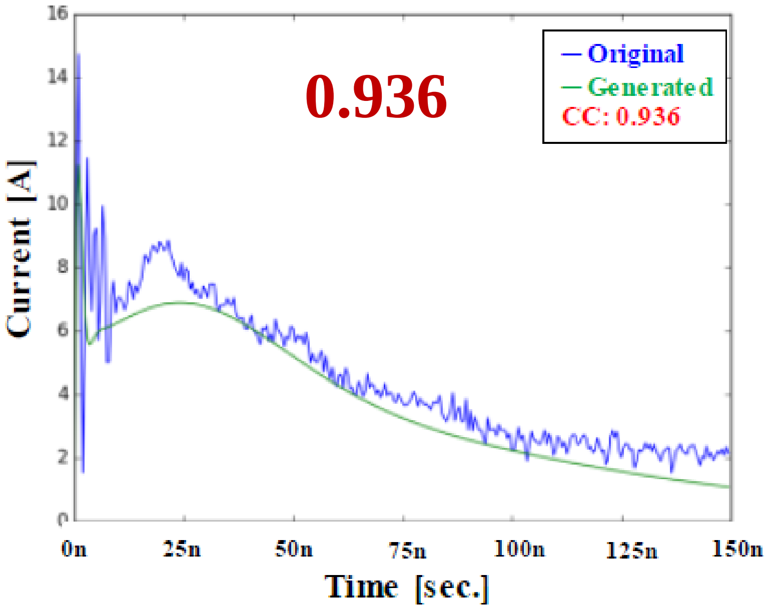
where:
σ is the standard deviation
μ is the mean
E is the expectation

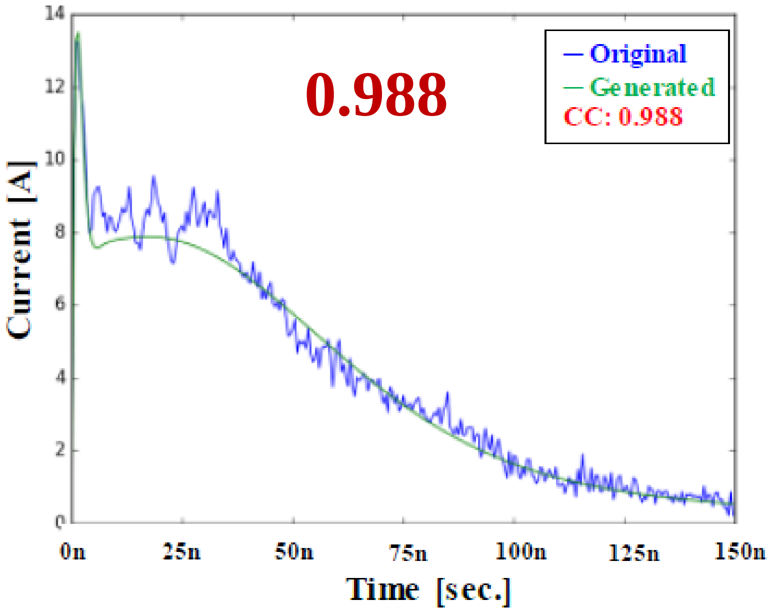


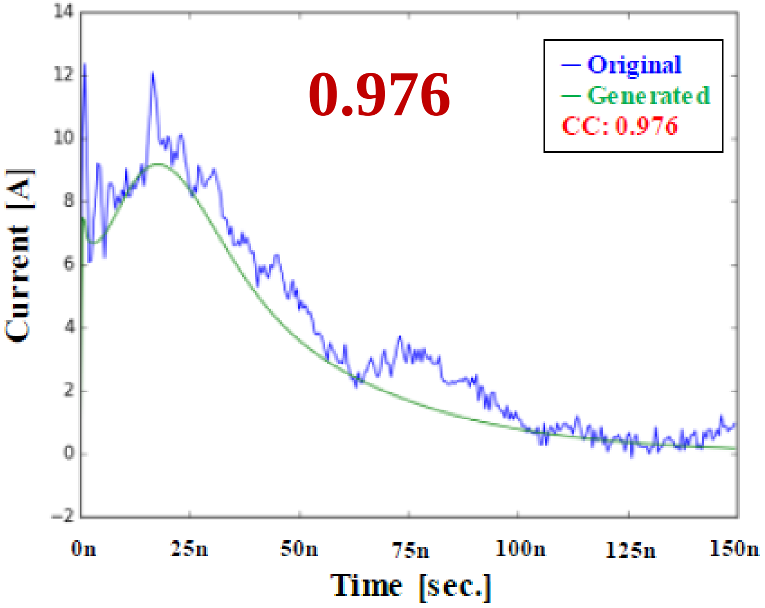


Correlation with Commercial ESD Generators

- Verified the DNN model with the measured waveforms from commercial ESD generators
- Good agreement with correlation coefficients of larger than 0.9
- Needs for enhanced circuit model for training to predict high-frequency noises







Conclusion

- Proposed the novel methodology for ESD generator modeling based on DNN
- Successfully predict equivalent circuit model for several ESD waveforms in a short time
- Also, verified with the measured waveforms of commercial ESD generators
- Possibility to improve accuracy with the enhanced circuit model in the DNN training
- Believe that the proposed methodology can be used in ESD simulation in the design stage

Q & A

Thank you for your attention.

Question or comment ?

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