Machine Learning for EMC Engineering

Prof. Christian Schuster, Hamburg University of Technology (TUHH)

Conference on Artifical Intelligence in Engineering, December 2, 2020

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VDE-Studie

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Künstliche Intelligenz«

1992

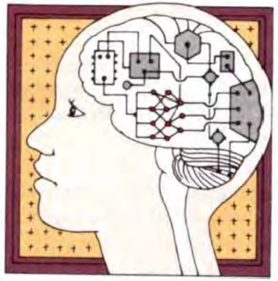
How Neural Networks Learn from Experience

Networks of artificial neurons can learn to represent complicated information. Such neural networks may provide insights into the learning abilities of the human brain

by Geoffrey E. Hinton

The brain is a remarkable computer. It interprets imprecise information from the senses at an incredibly rapid rate. It discerns a whisper in a noisy room, a face in a dimly lit alley and a hidden agenda in a political statement. Most impressive of all, the brain learns—without any explicit instructions—to create the internal representations that make these skills possible.

Much is still unknown about how the brain trains itself to process information, so theories abound. To test these hypotheses, my colleagues and I have attempted to mimic the brain's learning processes by creating networks of artificial neurons. We con-



ons, and they express the electrical output of a neuron as a single number that represents the rate of firing—its activity.

Each unit converts the pattern of incoming activities that it receives into a single outgoing activity that it broadcasts to other units. It performs this conversion in two stages. First, it multiplies each incoming activity by the weight on the connection and adds together all these weighted inputs to get a quantity called the total input. Second, a unit uses an input-output function that transforms the total input into the outgoing activity [see "The Amateur Scientist," page 170].

1988

Artificial Neural Networks

John J. Hopfield

Introduction

The following text is taken from an invited talk at the 1987 IEDM in Washington, DC, by Dr. John J. Hopfield, Professor of chemistry and biology at the California Institute of Technology. This talk has been transcribed for publication in *IEEE Circuits and Devices Magazine*. It covered the computational characteristics of neurobiological systems and attempted to show how these systems might be described in terms of equivalent electrical circuits. Silicon integrated circuits have been fabricated based on these circuit descriptions, and results have been obtained that are remarkably similar to the most simple neural networks. This is a fascinating field of study and illustrates the possibilities of improved understanding of neural systems by applying concepts from an apparently disparate field, namely, electrical circuits and computer science. And, of course, a long-term goal is to configure a computer to operate with the advantageous characteristics of neural networks.

Some Questions

I will attempt to answer five questions associated with artificial neural networks:

- Why are some people—who may be either visionaries or lunatics—interested in artificial neural networks?
- What are artificial neural networks, from the point of view of electronic circuits? How do such networks compute?
- How can they be programmed and how can they be made to solve particular problems?
- Can interesting problems actually be put on such networks?

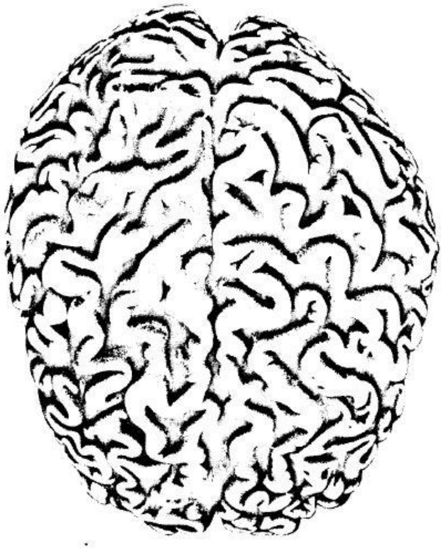


Fig. 1 A top view of the human brain. The computations are carried out in a surface layer about 2 mm thick.

decisions.) If we then compare—counting the hardware components used and multiplying by the number of clock cycles it takes to do things—we find that for arithmetic silicon VLSI—even discounting its speed—is a million times more effective than our brains.

1958

Psychological Review
Vol. 65, No. 6, 1958

THE PERCEPTRON: A PROBABILISTIC MODEL FOR INFORMATION STORAGE AND ORGANIZATION IN THE BRAIN[1]

F. ROSENBLATT

Cornell Aeronautical Laboratory

If we are eventually to understand the capability of higher organisms for perceptual recognition, generalization, recall, and thinking, we must first have answers to three fundamental questions:

1. How is information about the physical world sensed, or detected, by the biological system?
2. In what form is information stored, or remembered?
3. How does information contained in storage, or in memory, influence recognition and behavior?

and the stored pattern. According to this hypothesis, if one understood the code or "wiring diagram" of the nervous system, one should, in principle, be able to discover exactly what an organism remembers by reconstructing the original sensory patterns from the "memory traces" which they have left, much as we might develop a photographic negative, or translate the pattern of electrical charges in the "memory" of a digital computer. This hypothesis is appealing in its simplicity and ready intelligibility, and a large family of theoretical brain

HOW WILL ML AFFECT EMC ENGINEERING?

Outline

1. EMC

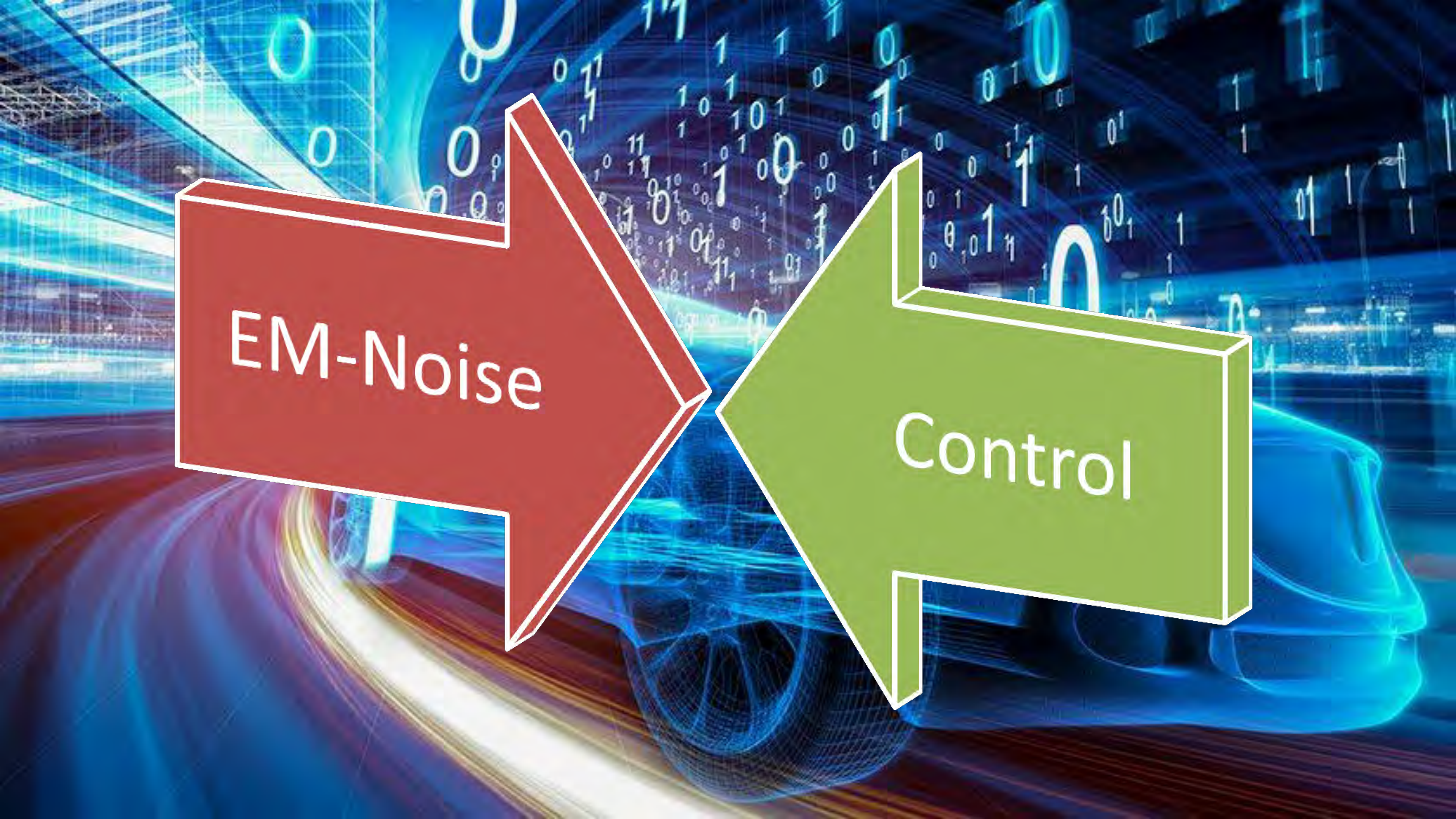
2. EMC Engineering

3. ML in EMC

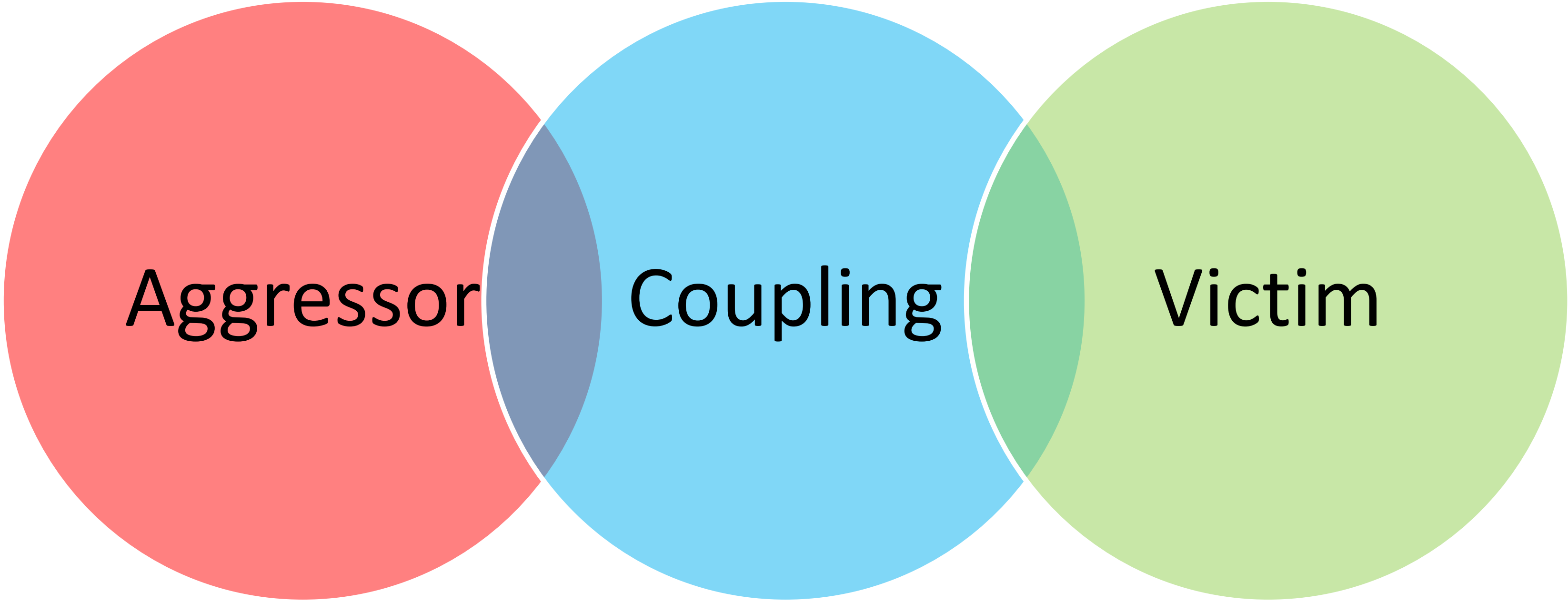
4. Conclusions

Outline

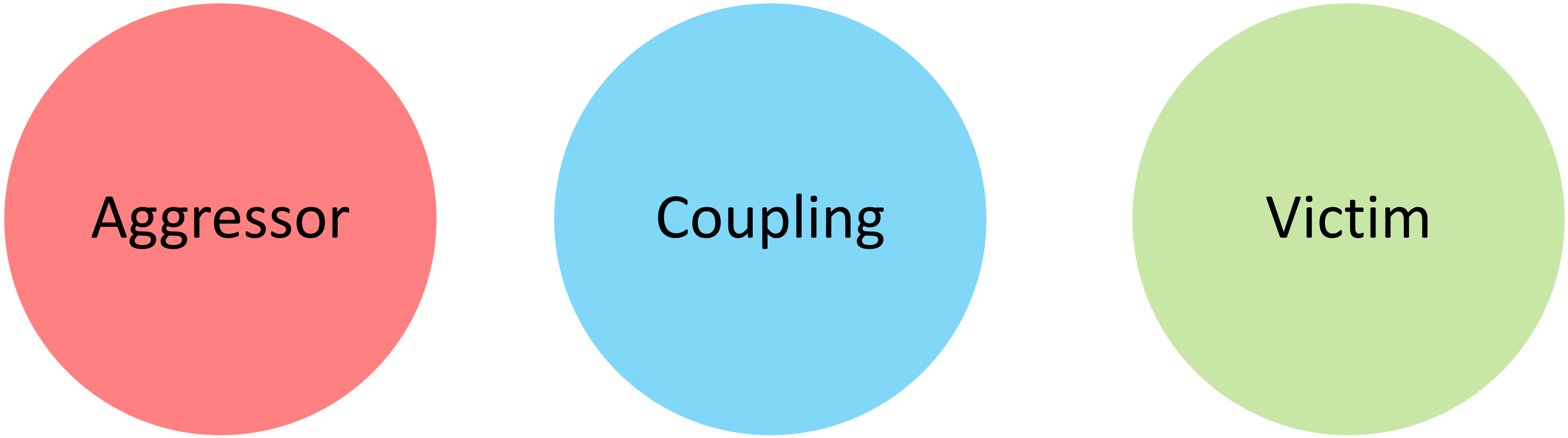
1. EMC
2. EMC Engineering
3. ML in EMC
4. Conclusions


EM-Noise
Control

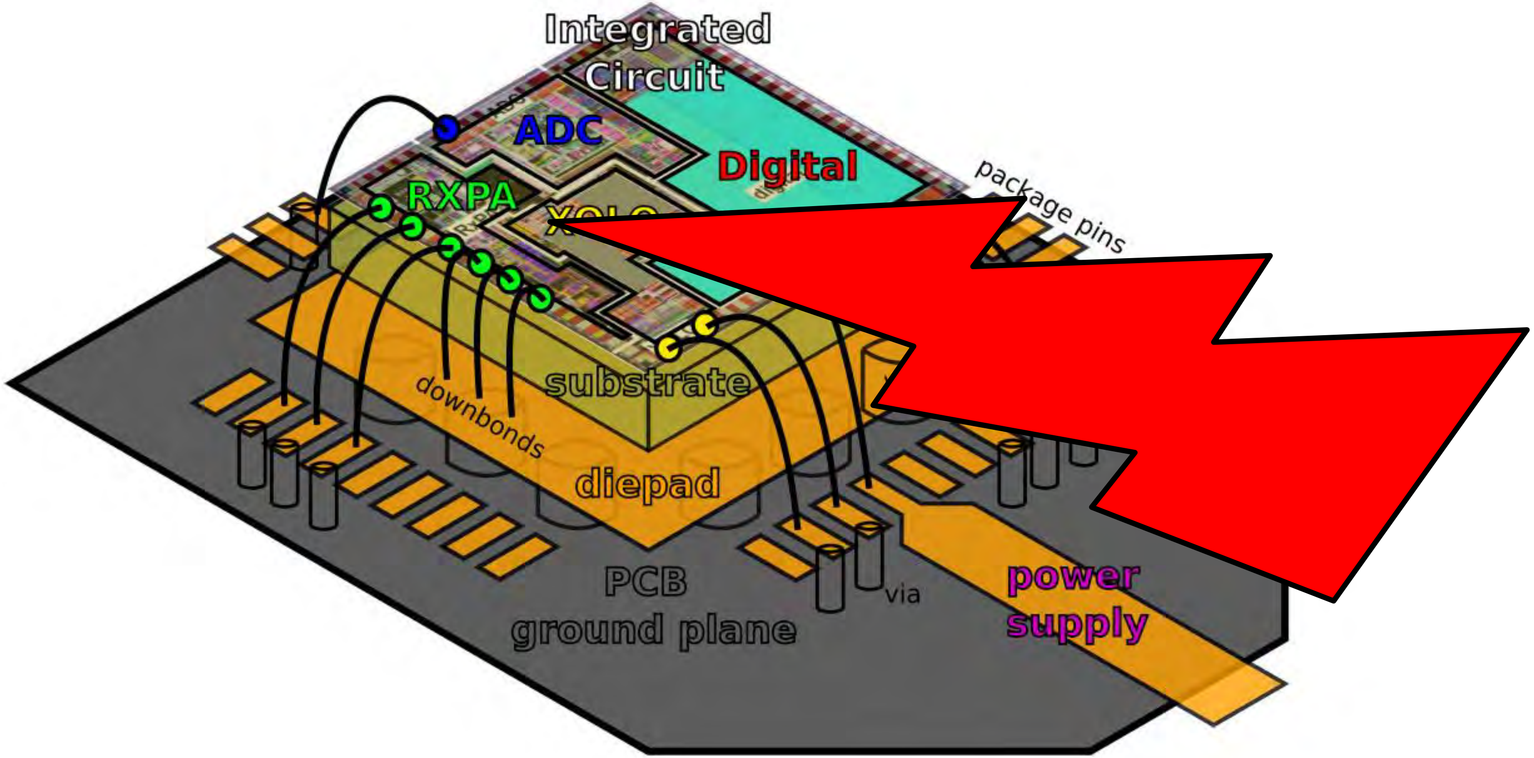
Insufficient EMC



Sufficient EMC

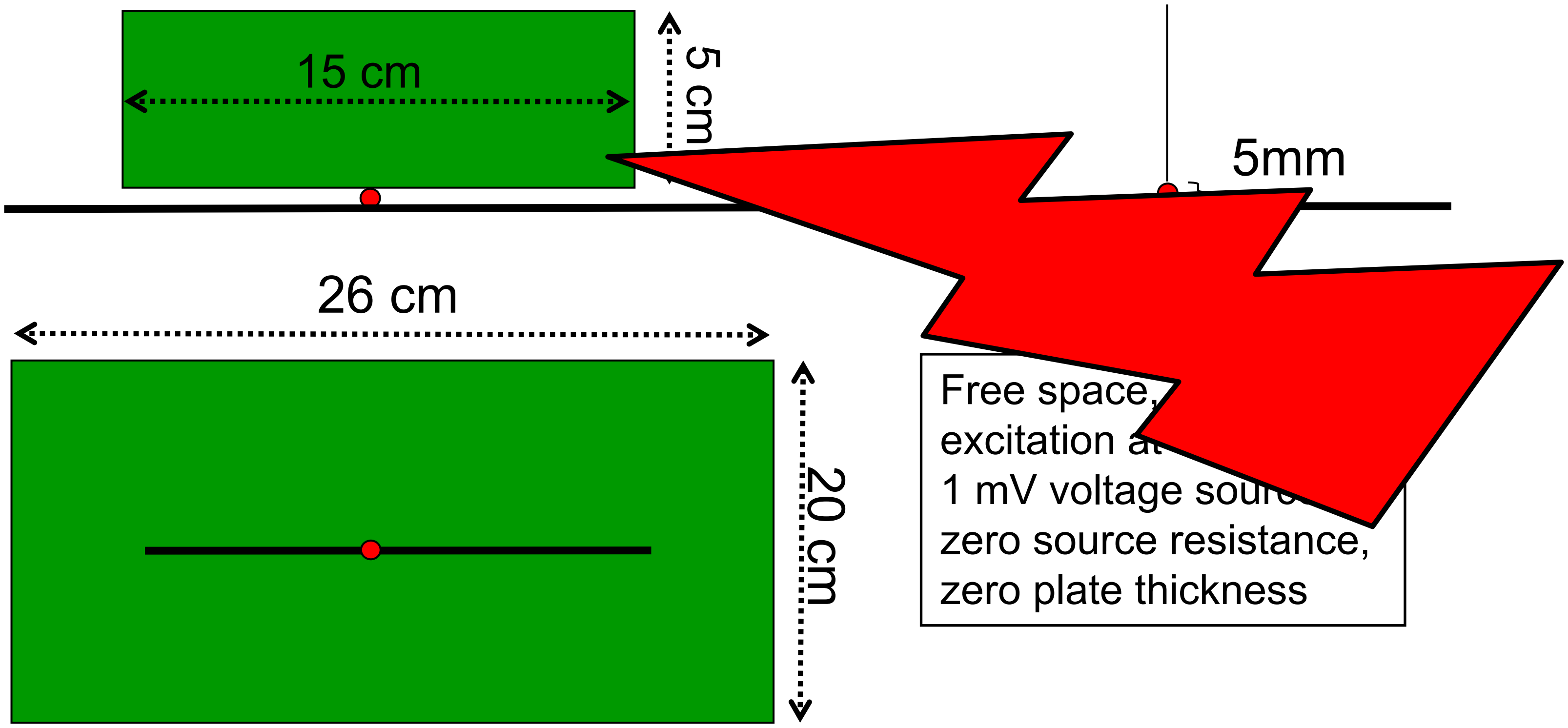


Coupling on RFIC



Ö. F. Yildiz et al.: „Sensitivity Analysis and Empirical Optimization of Cross-Domain Coupling on RFICs using Polynomial Chaos Expansion “, IEEE Symposium on EMC, 2017

Radiation from PCBs



Free space, excitation at 1 mV voltage source, zero source resistance, zero plate thickness

Where does EMC matter?

Outline

1\. EMC

2\. EMC Engineering

3\. ML in EMC

4\. Conclusions

Outline

1. EMC
2. EMC Engineering
3. ML in EMC
4. Conclusions

EMC Engineering

1. Specify requirements for system, then subsystem, then component levels

2. Design / verify from component level up

3. Assemble and test

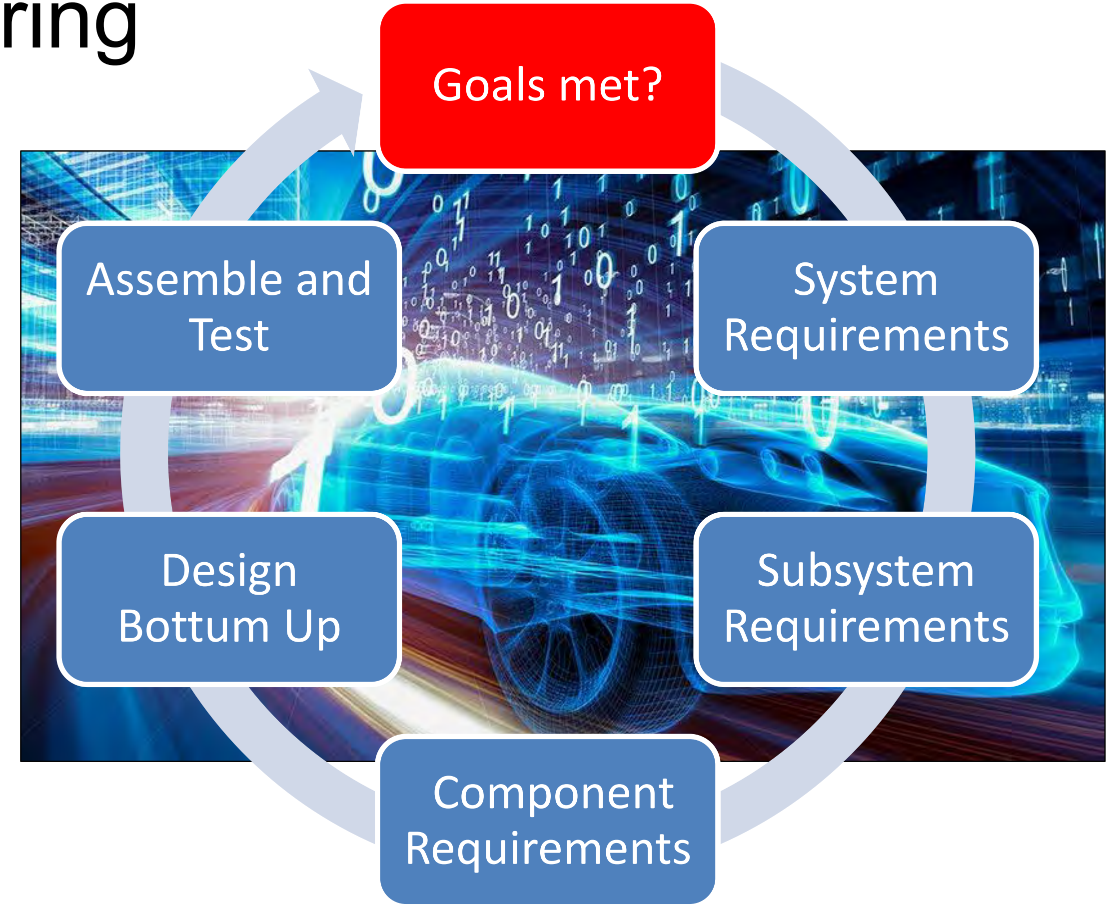


Image: www.mobilitaet-von-morgen.de

Internal vs. External Goals for EMC

INTERNAL:

SI, PI, and EMI fulffill design specifications

EXTERNAL:

Product passes EMC tests

Image: www.mobilitaet-von-morgen.de

EMC "Bug Fixing"

1. You locate the aggressor

2. You identify the coupling mechanism

3. You think of mitigation techniques

Image: www.mobilitaet-von-morgen.de

4. You implement one of them and hope for the best ☺!

EMC "Bug Fixing"

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2. **You identify the coupling mechanism**
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Image: www.mobilitaet-von-morgen.de

Modeling in EMC

➔ A model (from Latin “modulus“ = scale, measure) is a simplified, abstract “view“ of a complex reality.

➔ Models are used to know, understand, or predict the reality the model represents.

➔ By definition models have a limited range of validity.

➔ Models for EMC are usually based on the foundations given by physics (“physics-based”).

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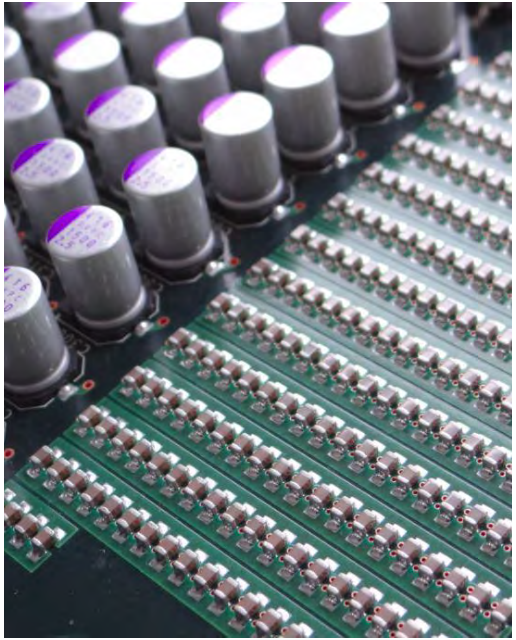
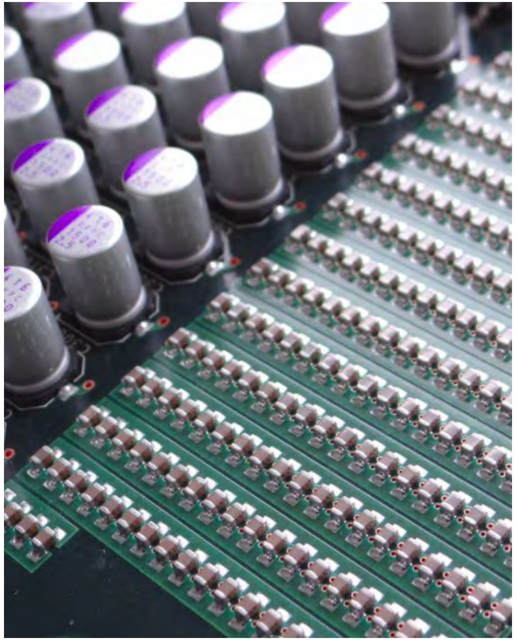
- ➔ **Models for EMC are usually based on the foundations given by physics (“physics-based”).**

PB Modeling of Reality

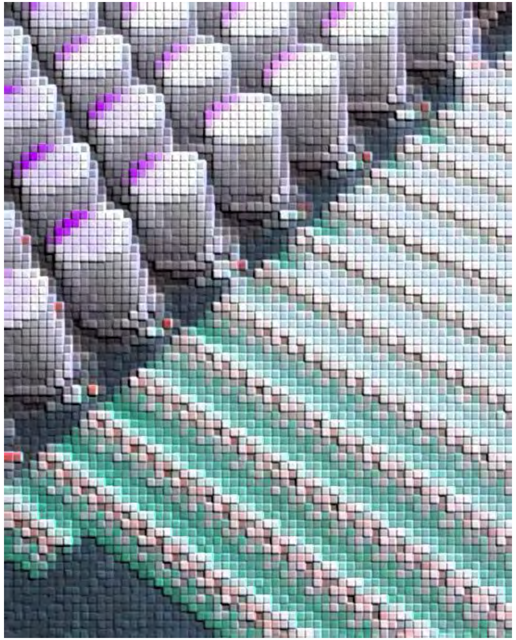


???

PB Modeling of Reality



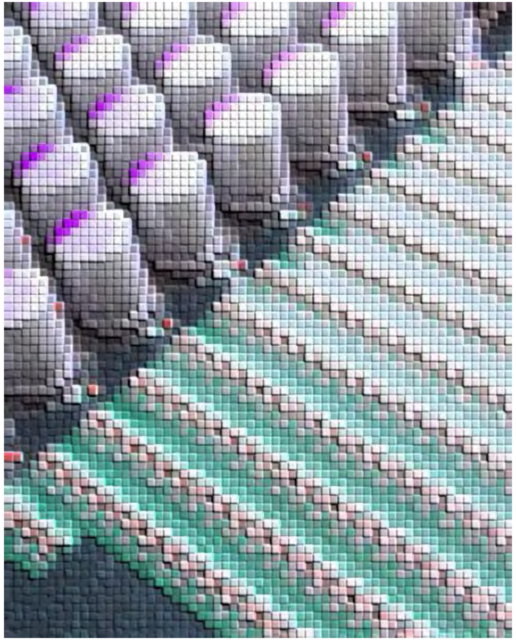
Physics-Based Model



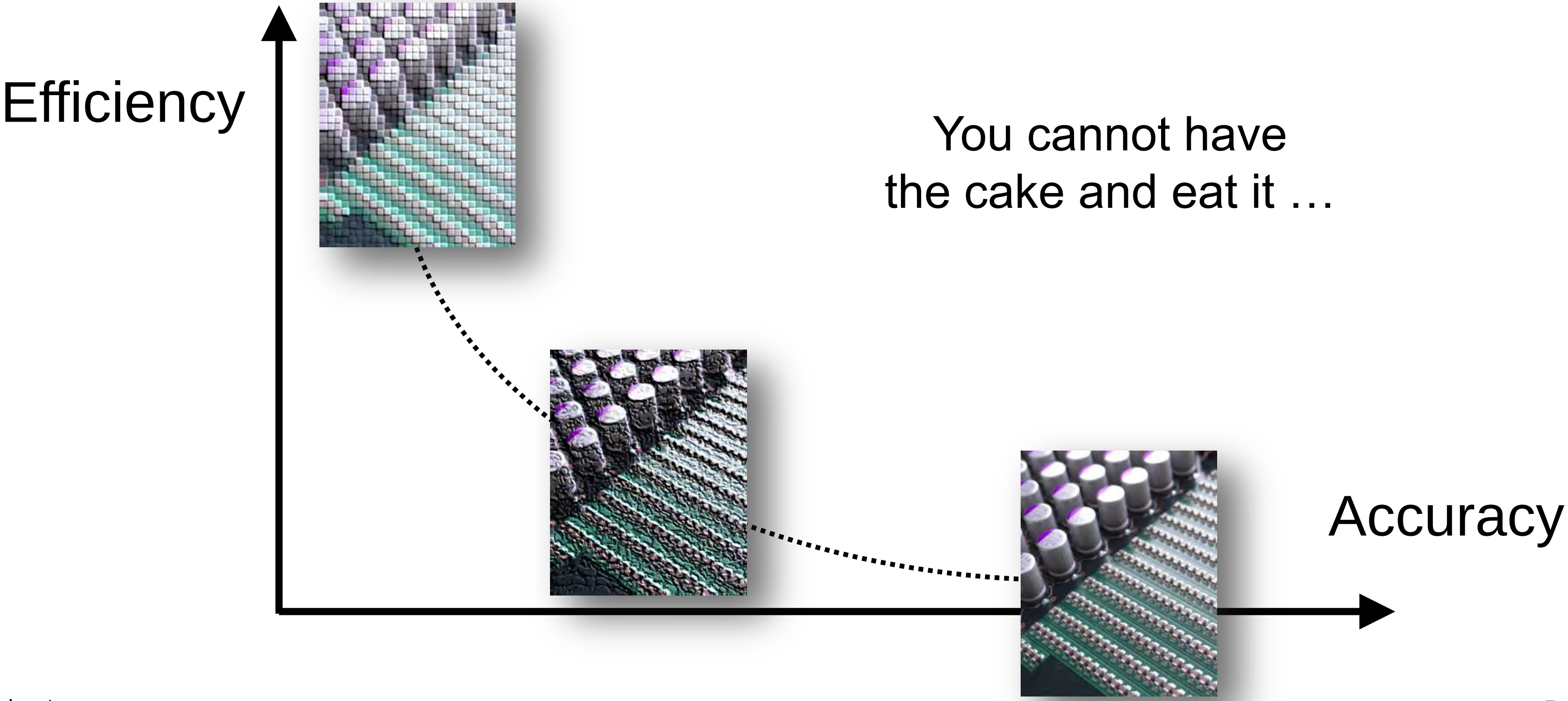
Features of PB Models

- ➔ No need for data / training
- ➔ Correct in a physical way
- ➔ Solution space $\rightarrow \infty$
- ➔ Sometimes tough to generate
- ➔ Sometimes tough to compute
- ➔ Lots of correlation to hardware

Physics-Based Model



The PB Modeling Dilemma



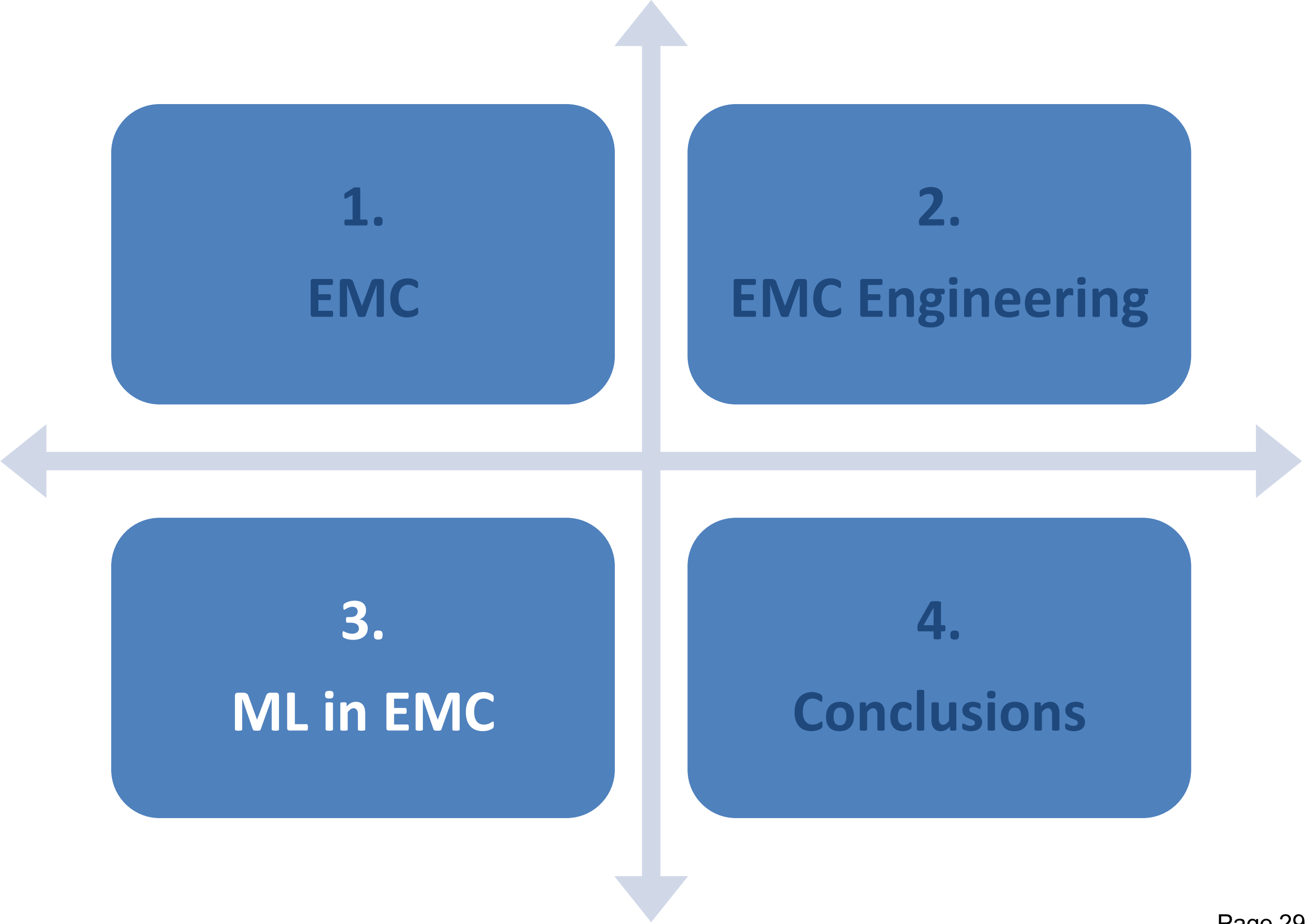
You cannot have
the cake and eat it …

THERE IS NO PB TOOL TODAY THAT CAN REPLACE EMC TESTS

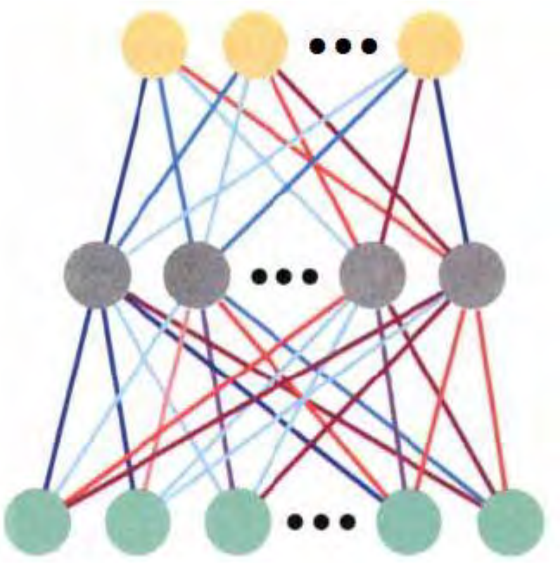
Outline

1. EMC
2. EMC Engineering
3. ML in EMC
4. Conclusions

Outline



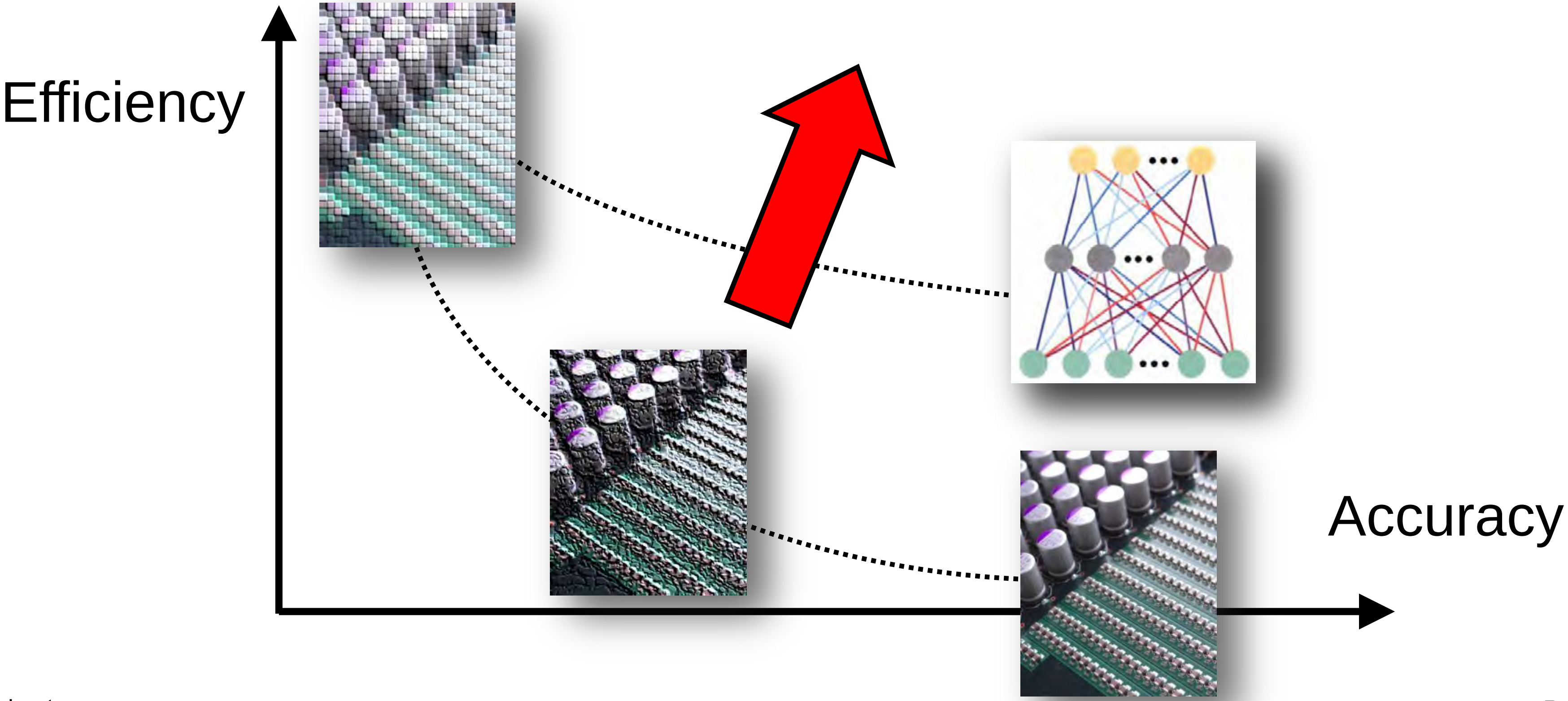
Features of ML Based Models



- ➔ Need for data / training
- ➔ Correct in a statistical way
- ➔ Solution space depends …
- ➔ Sometimes tough to generate
- ➔ Often simple to compute
- ➔ Little correlation to hardware

Image from: G. Hinton: „How Neural Networks Learn from Experience“, Scientific American 1992

The PB Modeling Dilemma – Resolved?



Challenges of ML Methods

- ➔ Reducing complexity (curse of dimensionality)
- ➔ Selecting the proper ML method (model)
- ➔ Making sufficent training data available
- ➔ Dealing with inductive (learning) bias
- ➔ Keeping training and validation data distinct
- ➔ Avoiding both overfitting and underfitting

Application of ML Methods in EMC

IEEE TRANSACTIONS O

Model

Artificial Neural Network

IEEE TRANSACTIONS ON COMPONENTS, PACKAGING AND MANUFACTURING TECHNOLOGY, VOL. 6, NO. 6, JUNE 2016 873

Eye Height/Width Prediction From *S*-Parameters Using Learning-Based Models

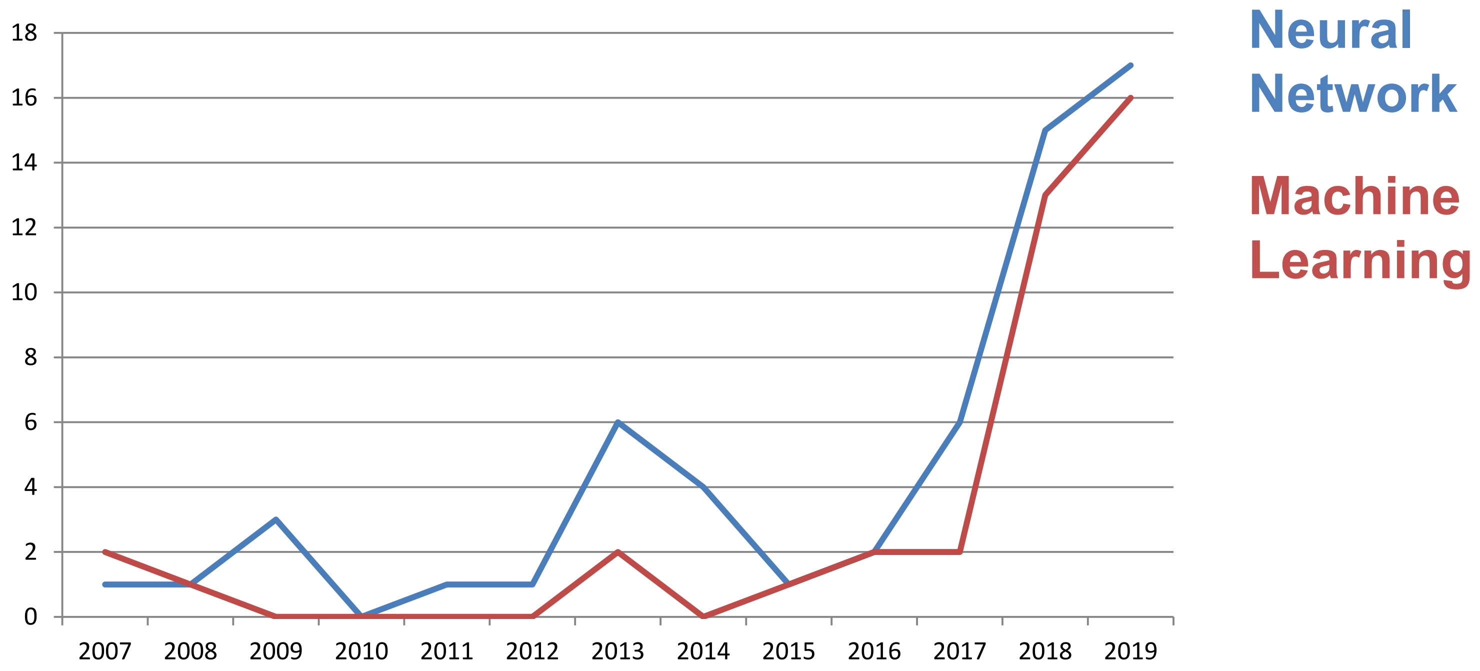
Nikita Ambasana, *Student Member, IEEE*, Gowri Anand, Bhyrav Mutnury, *Senior Member, IEEE*, and Dipanjan Gope, *Senior Member, IEEE*

IEEE TRANSACTIONS ON ELECTROMAGNETIC COMPATIBILITY 1

Prediction of MRI RF Exposure for Implantable Plate Devices Using Artificial Neural Network

Jianfeng Zheng, *Member, IEEE*, Qianlong Lan, Xingyao Zhang, Wolfgang Kainz, *Member, IEEE*, and Ji Chen, *Senior Member, IEEE*

ANN/ML Publications in EMC Transactions



Full text search in the IEEE Transaction on EMC by IEEE Xplore by year.

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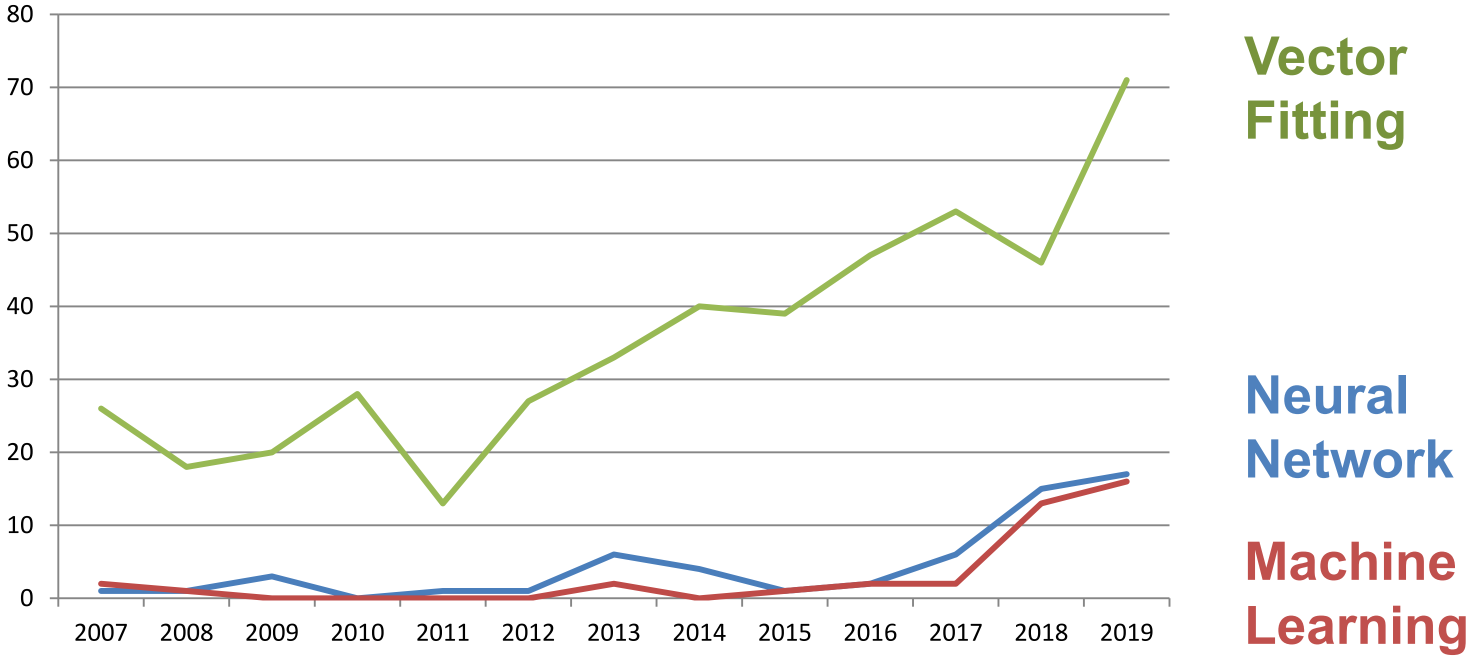

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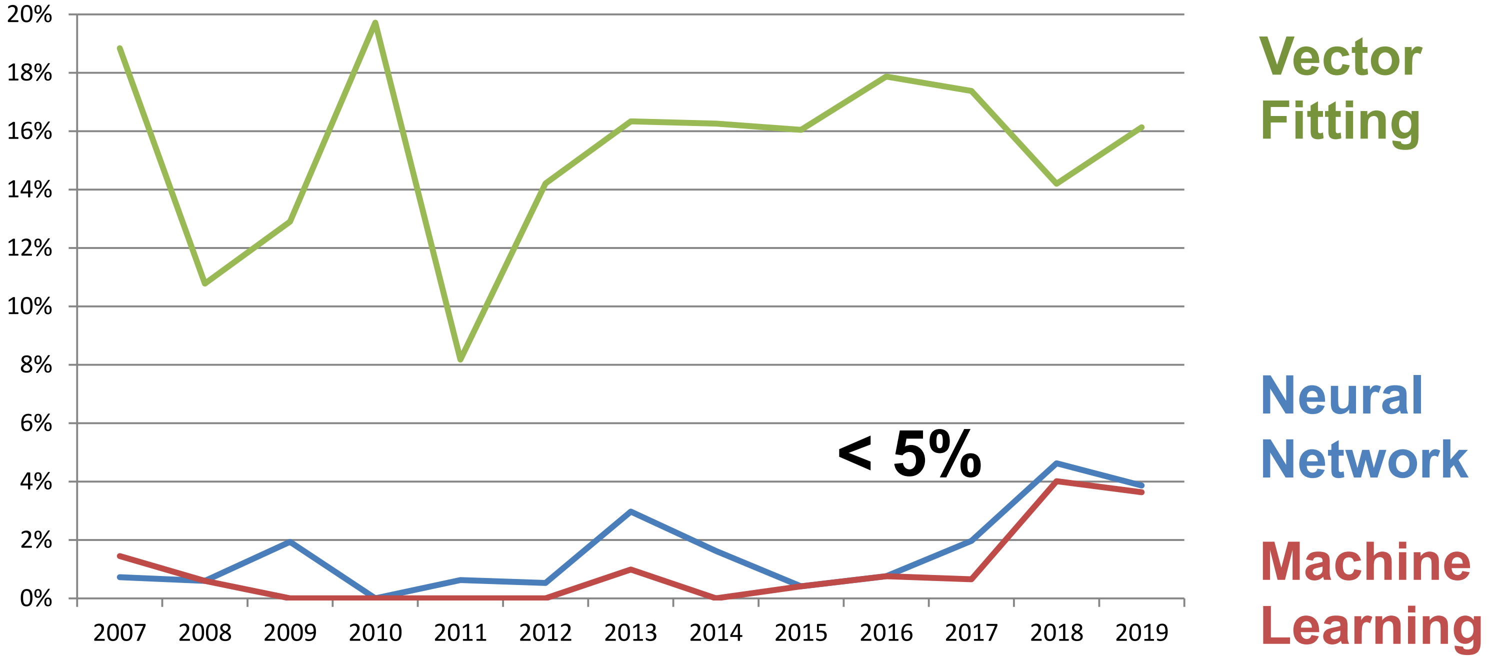

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Application of ANNs in EMC

IEEE TRANSACTIONS ON ELECTROMAGNETIC COMPATIBILITY, VOL. 55, NO. 2, APRIL 2013 385

A New ANN-Based Modeling Approach for Rapid EMI/EMC Analysis of PCB and Shielding Enclosures

Vijay Devabhaktuni, *Senior Member, IEEE*, Charles F. Bunting, *Senior Member, IEEE*, David Green, *Student Member, IEEE*, David Kvale, *Member, IEEE*, Lakshman Mareddy, *Student Member, IEEE*, and Vignesh Rajamani, *Member, IEEE*

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Application #1

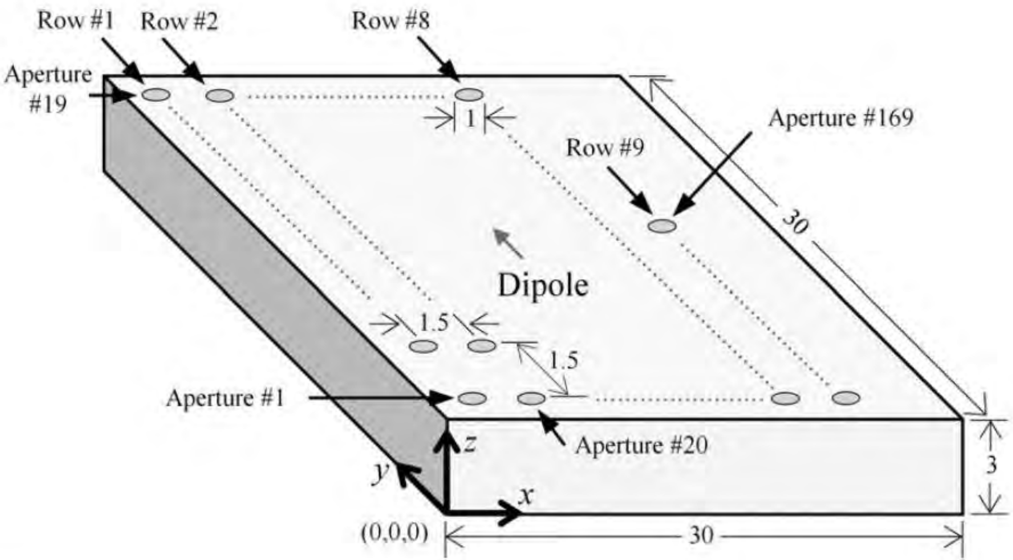

Fig. 3. Rectangular cavity with circular aperture enclosing a dipole source at its center. All dimensions are in centimeter.

Application #1

1 design parameter

2 input nodes
(1 for total area of ap.,
1 for numer of ap.)

1 hidden layer

Sigmoid activation

169 test sets

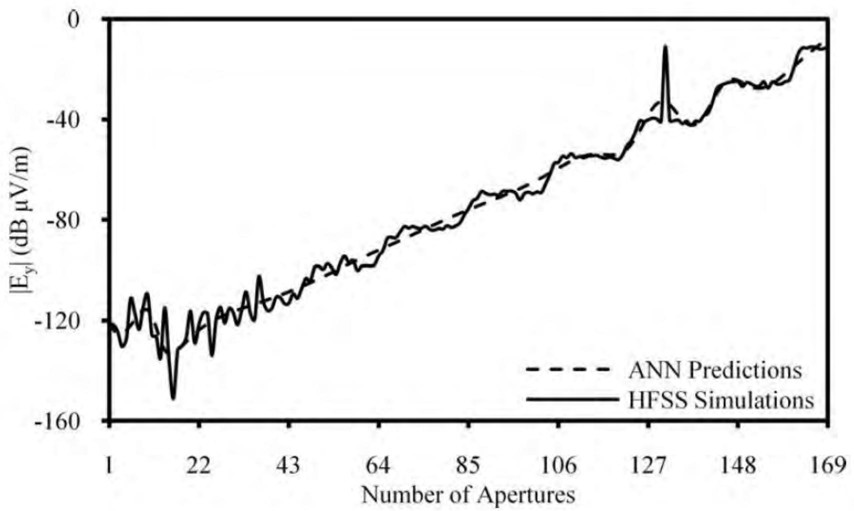

Fig. 5. Comparison of radiated emissions versus number of apertures relationship between the ANN model predictions and HFSS simulations.

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Application #2

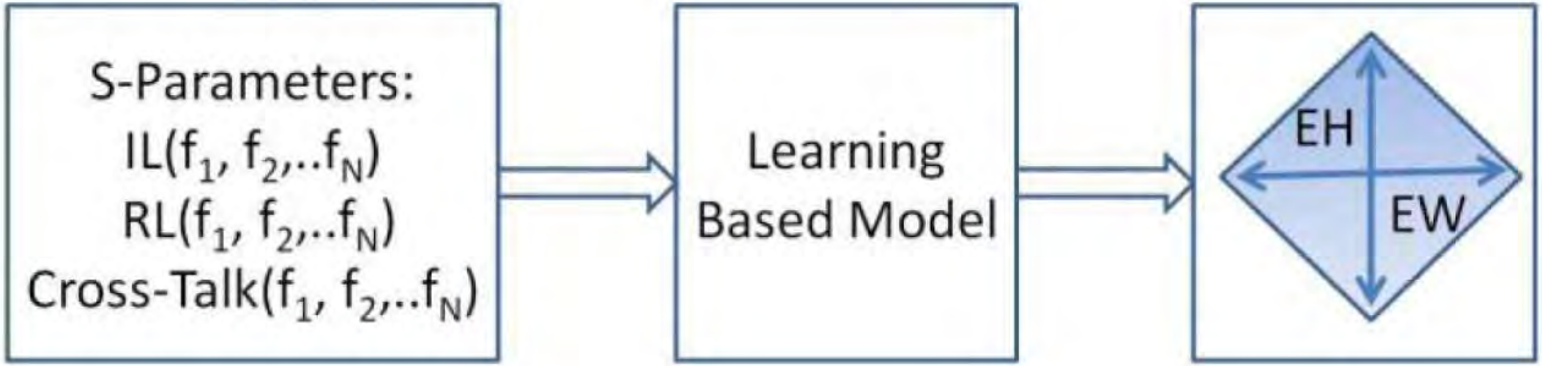

Fig. 6. Top-level block diagram of information flow in the proposed mapping methodology.

Application #2

7 design parameters

34 input nodes
(17 for IL, 17 for FEXT)

1 hidden layer with
10 neurons

Sigmoid activation

129 test sets

TABLE III

SATA 3.0 PREDICTION ERROR METRIC VALUES
[ε, μ, AND δ AS PER (7)–(9)]

EH	DoE (79 Sets)			RTS (49 Sets)		
Modeling Technique	ε (%)	μ (mV)	δ (mV)	ε (%)	μ (mV)	δ (mV)
ANN	1.6	1.4	11.5	2.2	2.3	16.0
SVM	1.0	1.3	5.3	1.4	1.7	11.9
EW	DoE (79 Sets)			RTS (52 Sets)		
Modeling Technique	ε (%)	μ (ps)	δ (ps)	ε (%)	μ (ps)	δ (ps)
ANN	0.6	0.4	3.0	0.5	0.3	1.2
SVM	0.7	0.5	2.5	0.5	0.3	1.4

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Application #3

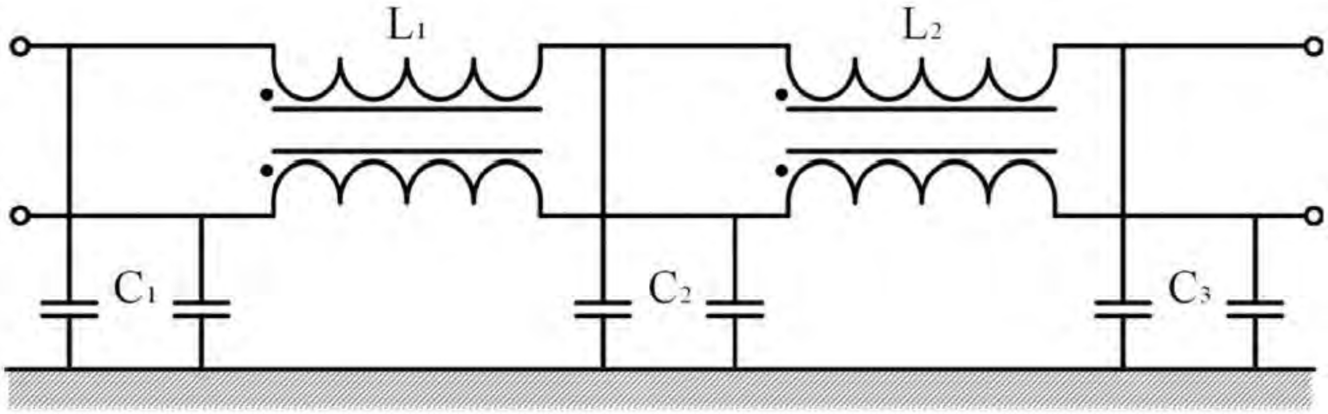


Fig. 1. Topology of an EMI filter.

Application #3

15 design parameters

15 input nodes
(for element values)

1 hidden layer with
60 neurons

Sigmoid activation

262 test sets

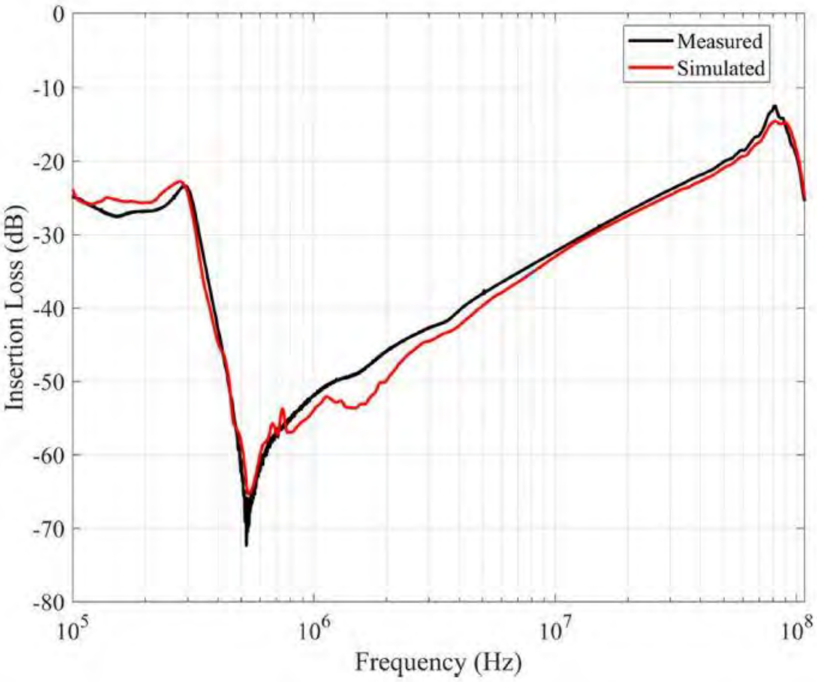
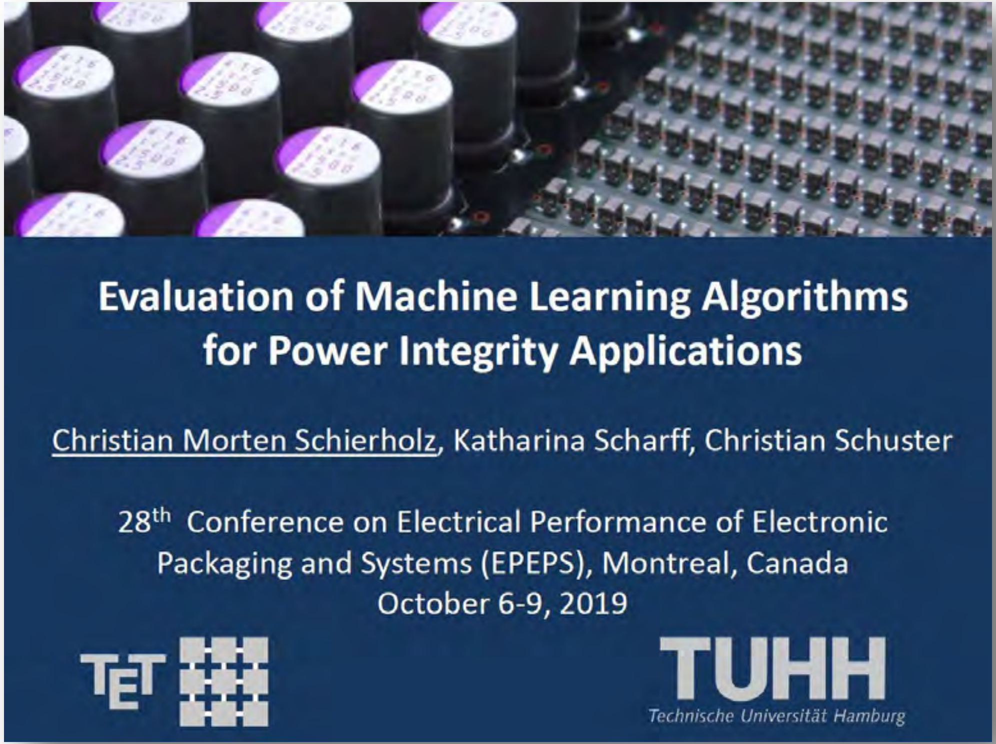
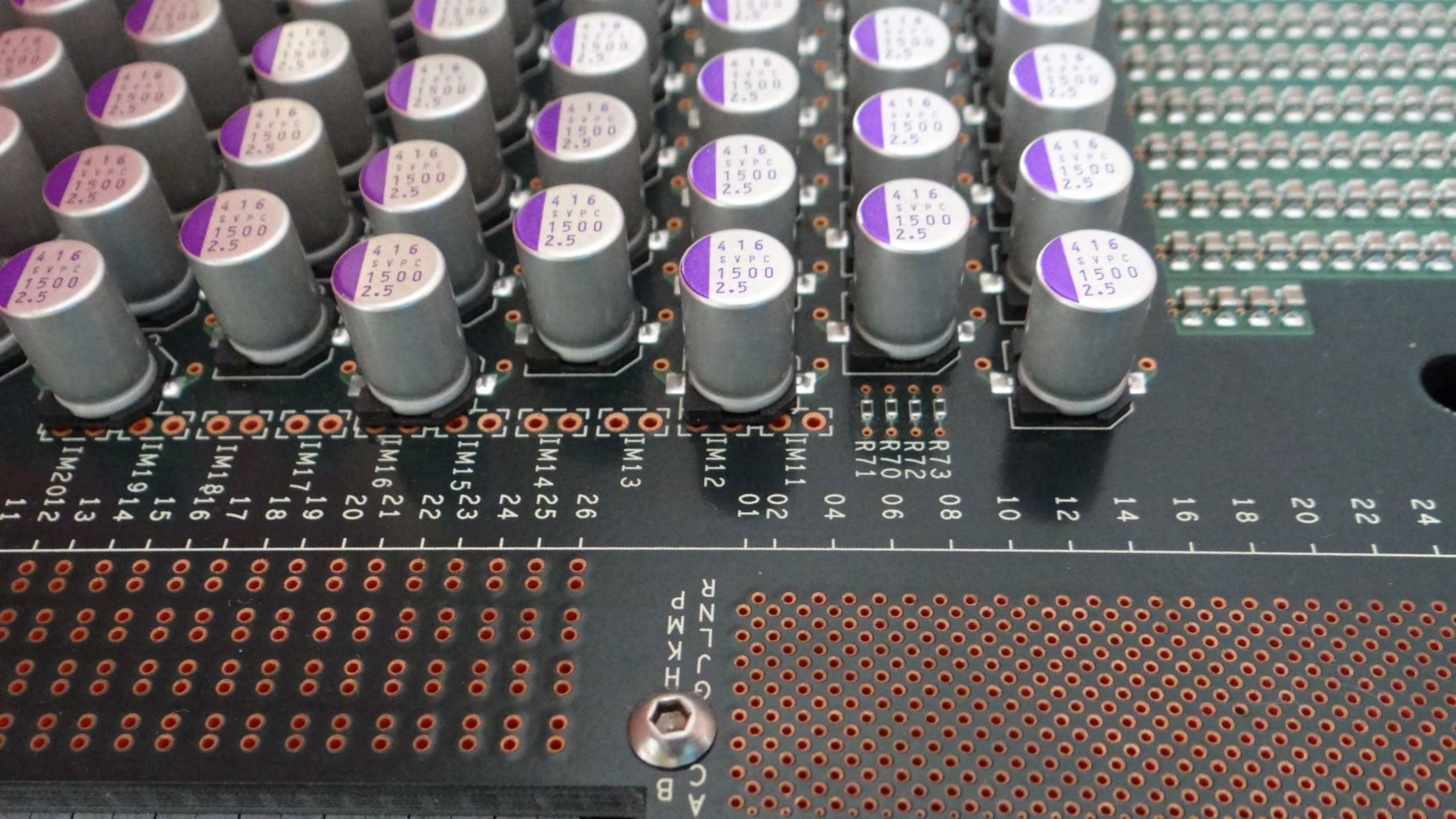


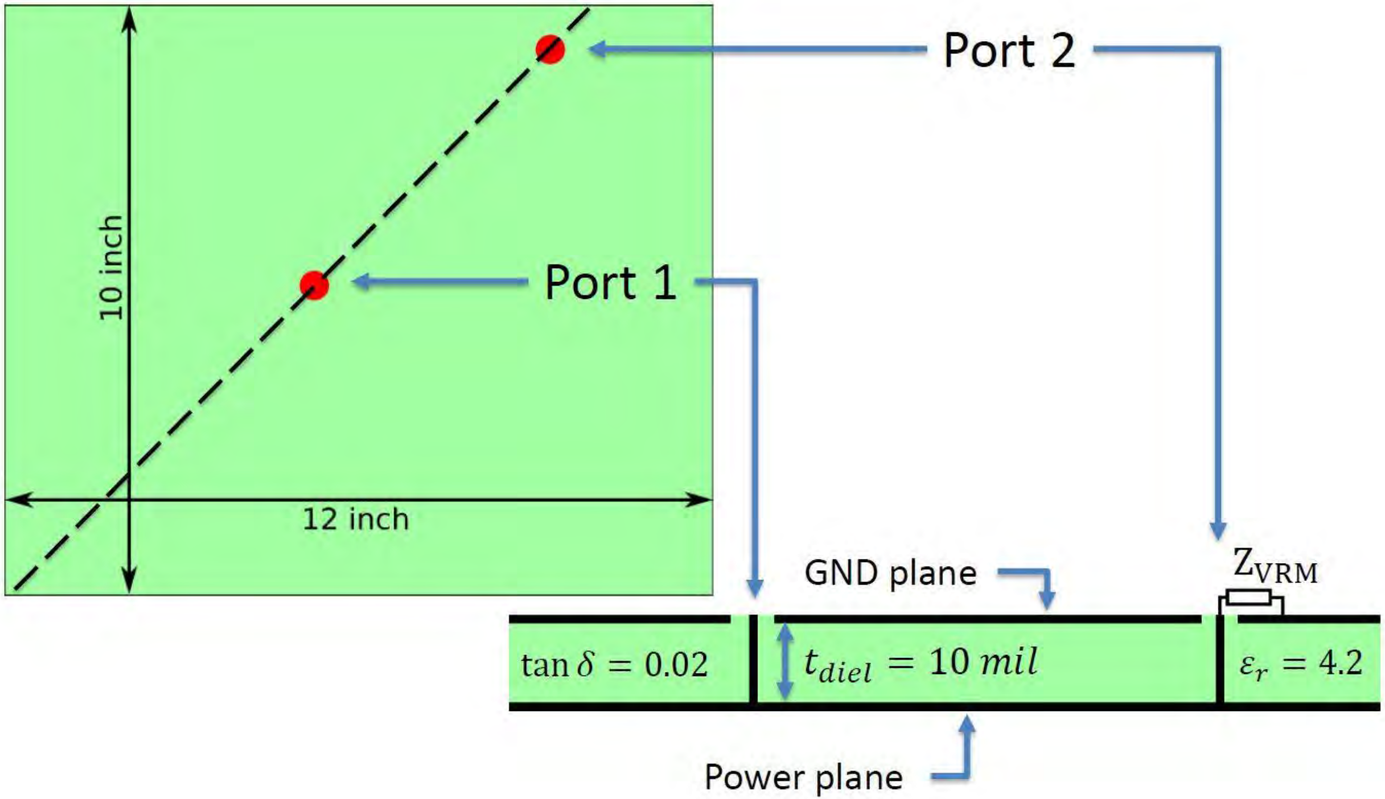
Fig. 6. Comparison of insertion loss curves of first validating sample obtained by measurement and multi-output ANN simulation.

ANNs for Power Delivery Network Design

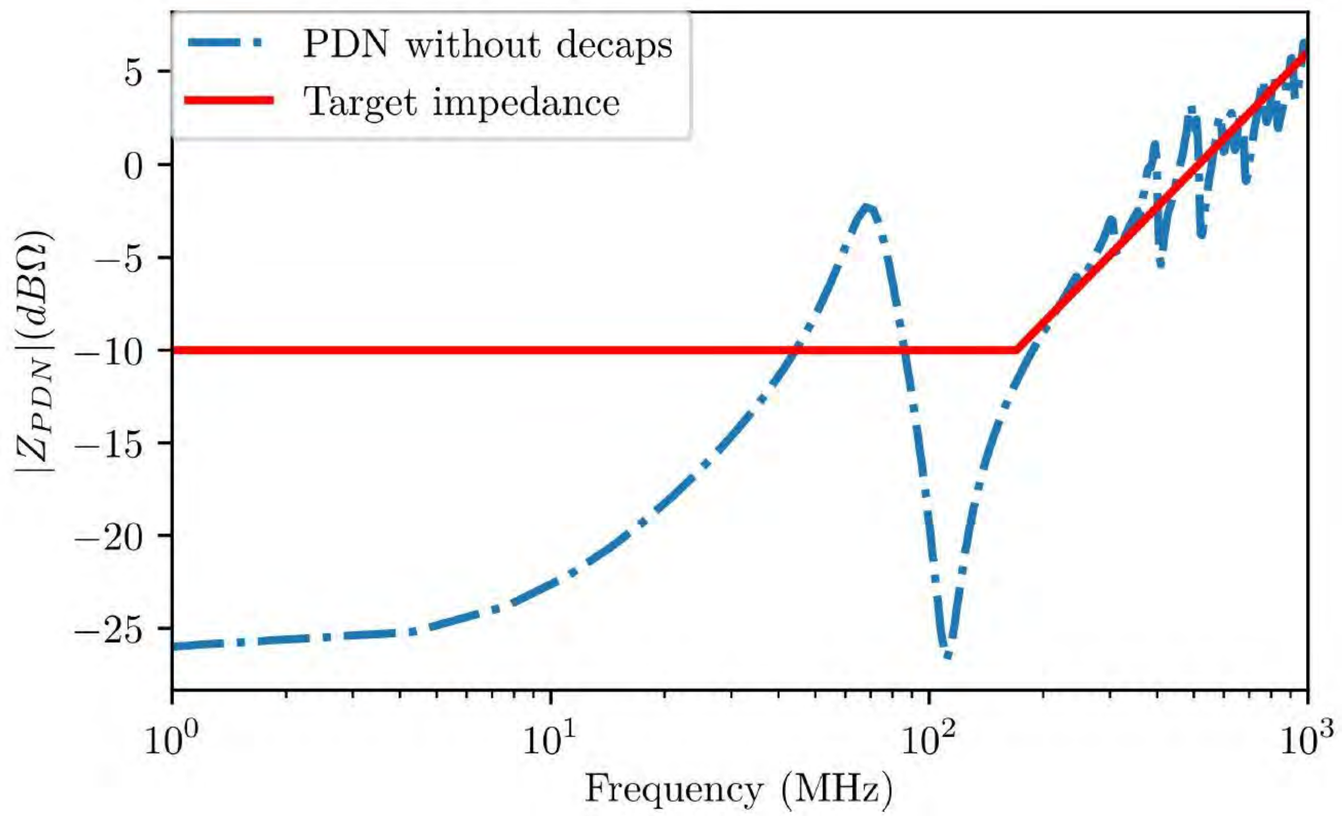



416
SVPC
1500
2.5
IM20
IM19
IM18
IM17
IM16
IM15
IM14
IM13
IM12
IM11
R71
R70
R72
R73
11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26
01 02 04 06 08 10 12 14 16 18 20 22 24

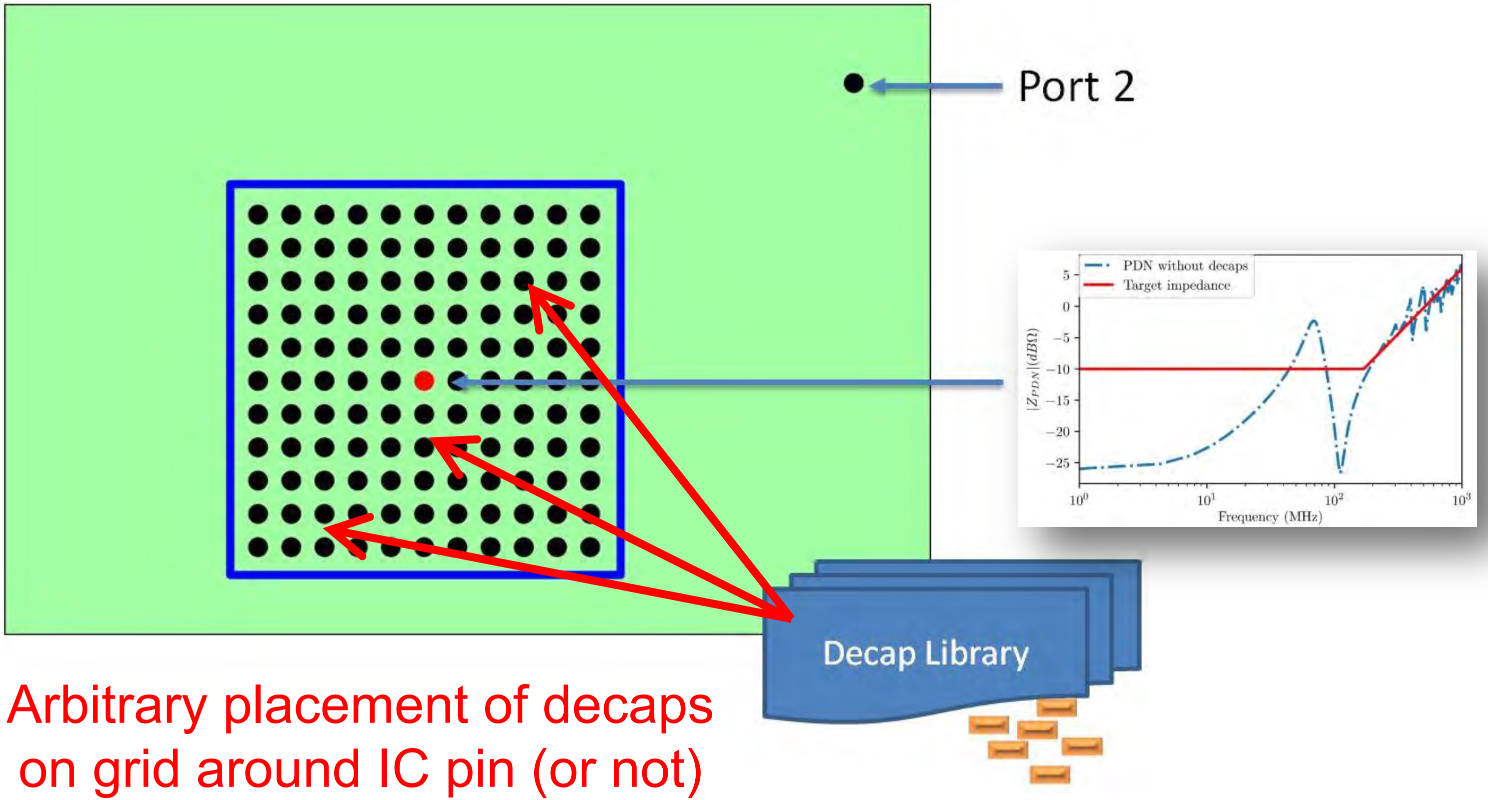
Goal: Decouple a 2-Layer PCB …



.. such that the target impedance is met

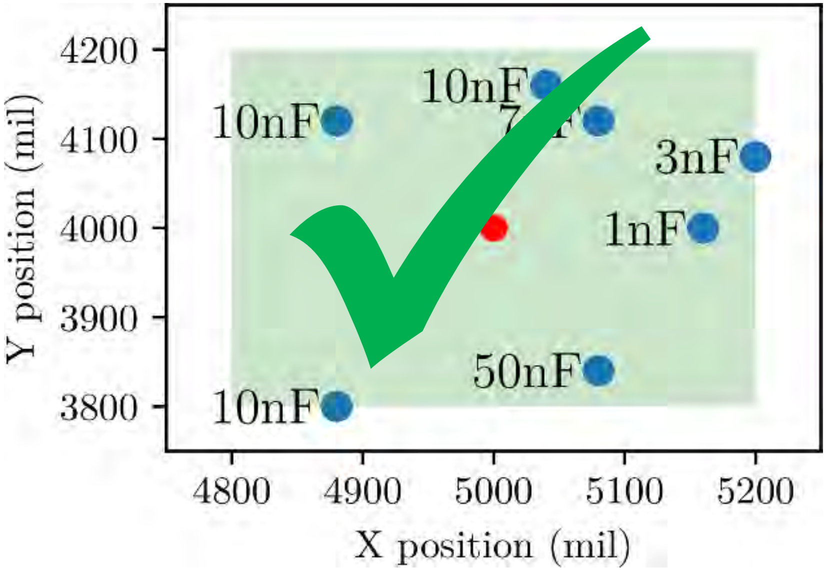


Formulation as a Classification Problem

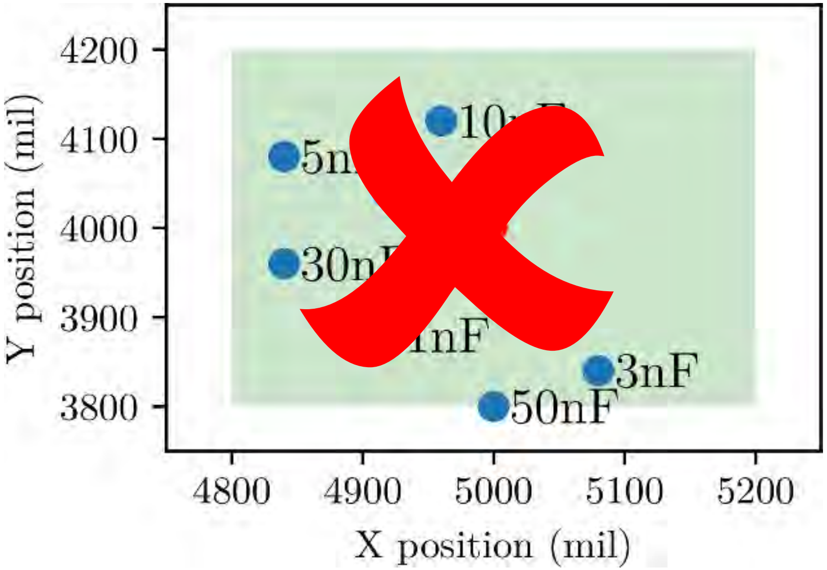


Arbitrary placement of decaps on grid around IC pin (or not)

Example

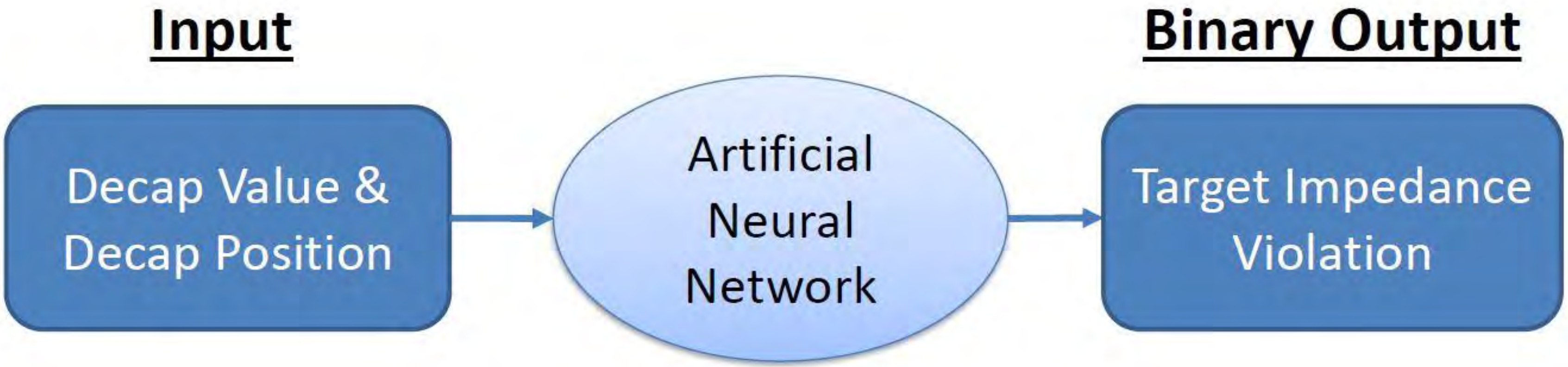


4200
4100
4000
3900
3800
Y position (mil)
10nF
10nF
3nF
1nF
50nF
10nF
4800
4900
5000
5100
5200
X position (mil)

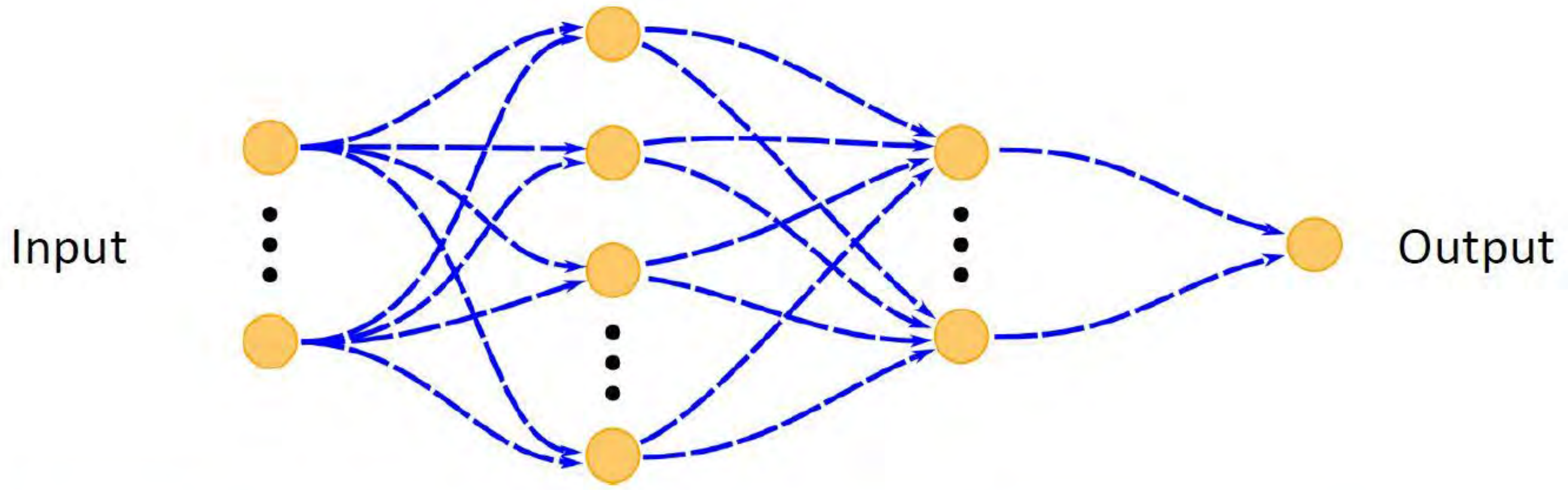


4200
4100
4000
3900
3800
Y position (mil)
3nF
50nF
4800
4900
5000
5100
5200
X position (mil)

Design of the ANN

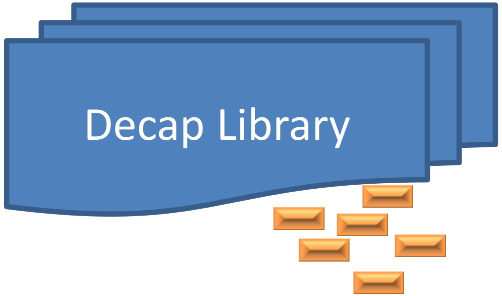


Design of the ANN



# neurons	60 to 121	15	5	1
Activation function	Identity	Relu	Relu	Logistic

Generation of Training Data



Capacitance (nF)	ESR (mΩ)	ESL (nH)
1 to 9 (step width = 1)	50	0.28
10 to 50 (step width = 10)	50	0.28
70	50	0.28

	FEM (Commercial)	CONMLSS (TUHH)	ANN prediction
CPU Time for 100 simulations	14 h	60 min	40 ms

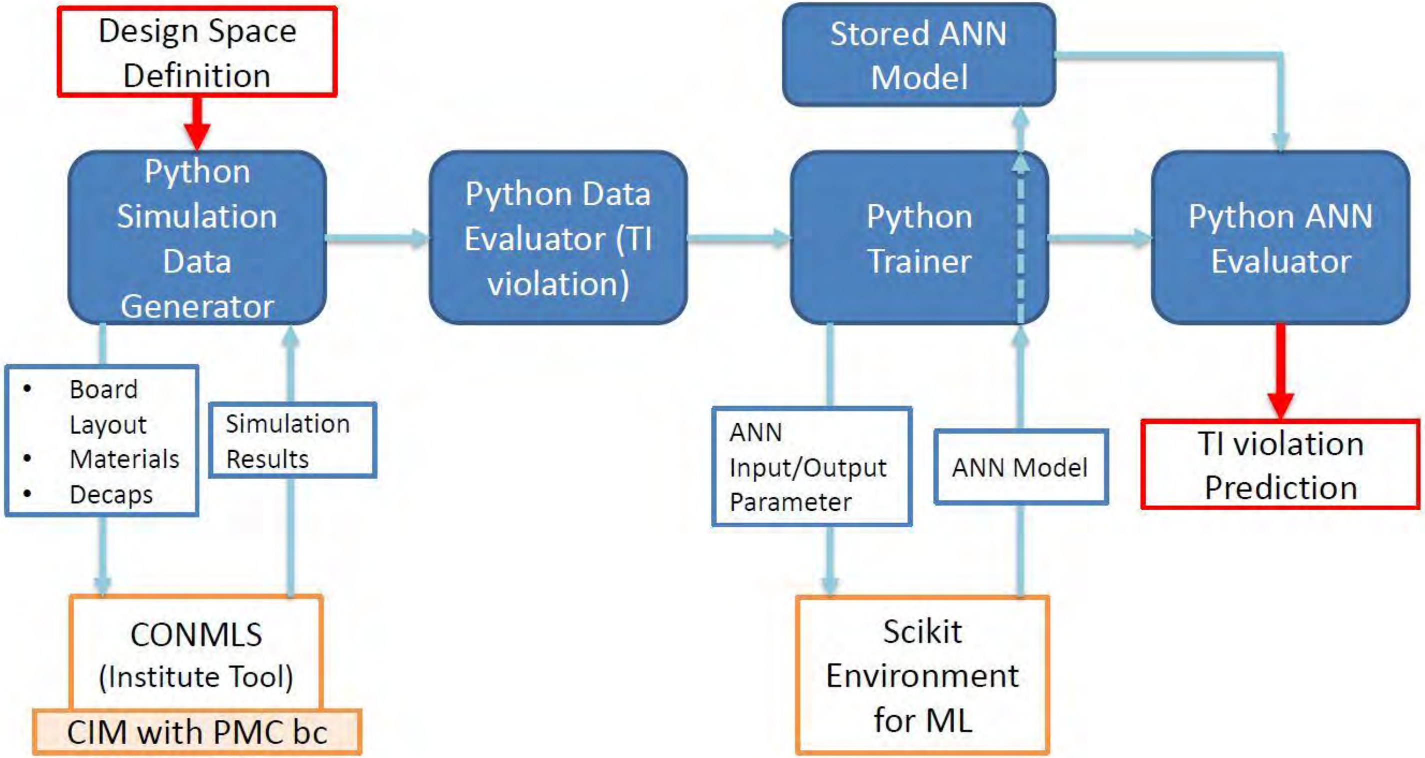
Factor > 1‘000‘000!

Split Training ↔ Test Data

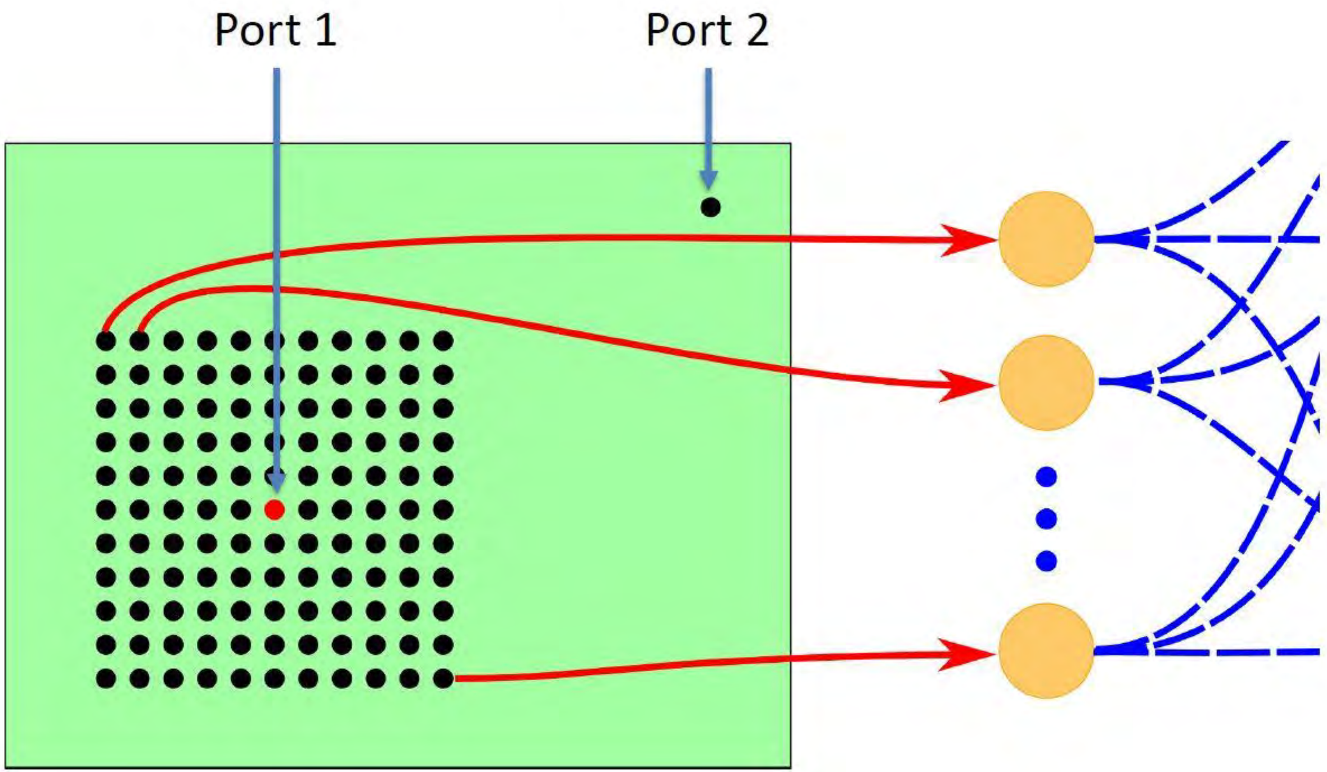
Training Samples	Testing Samples
11 200 (80%)	2 800 (20%)

14 000 Samples Total

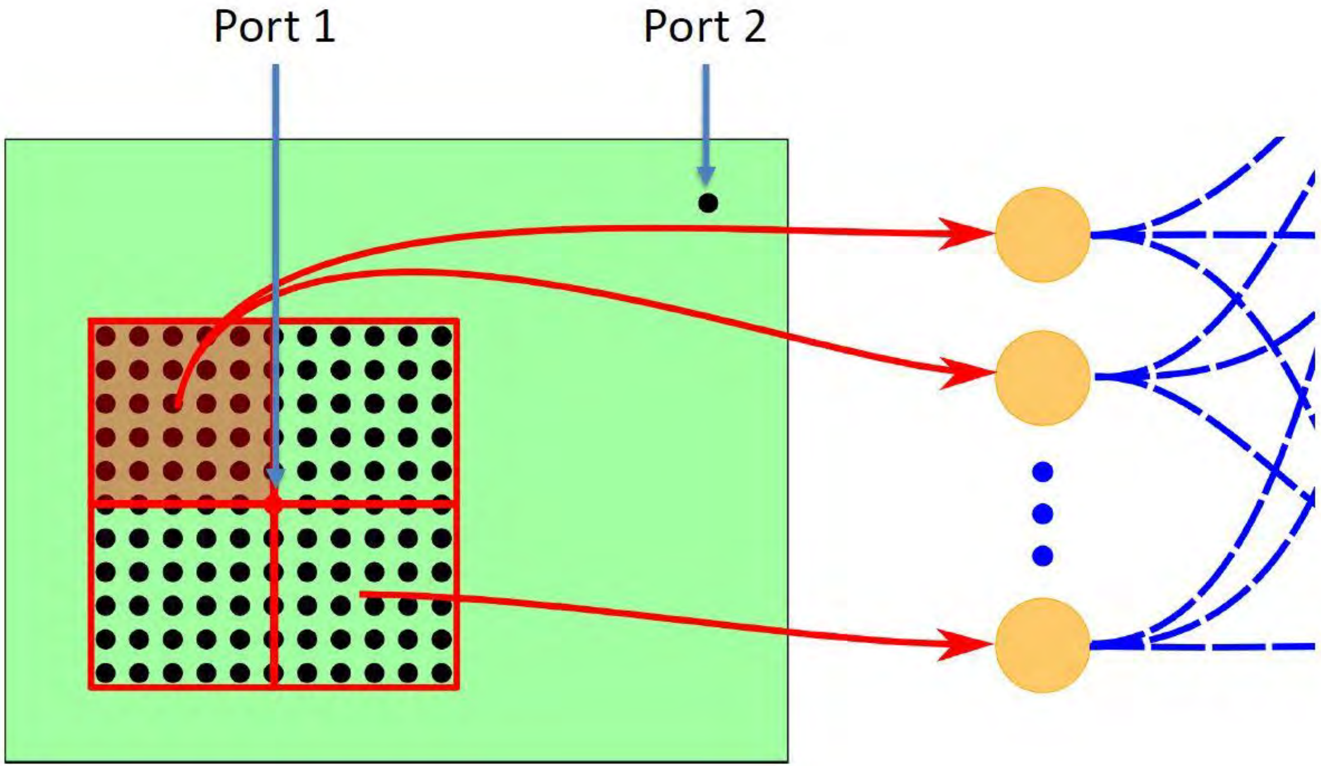
Training Environment



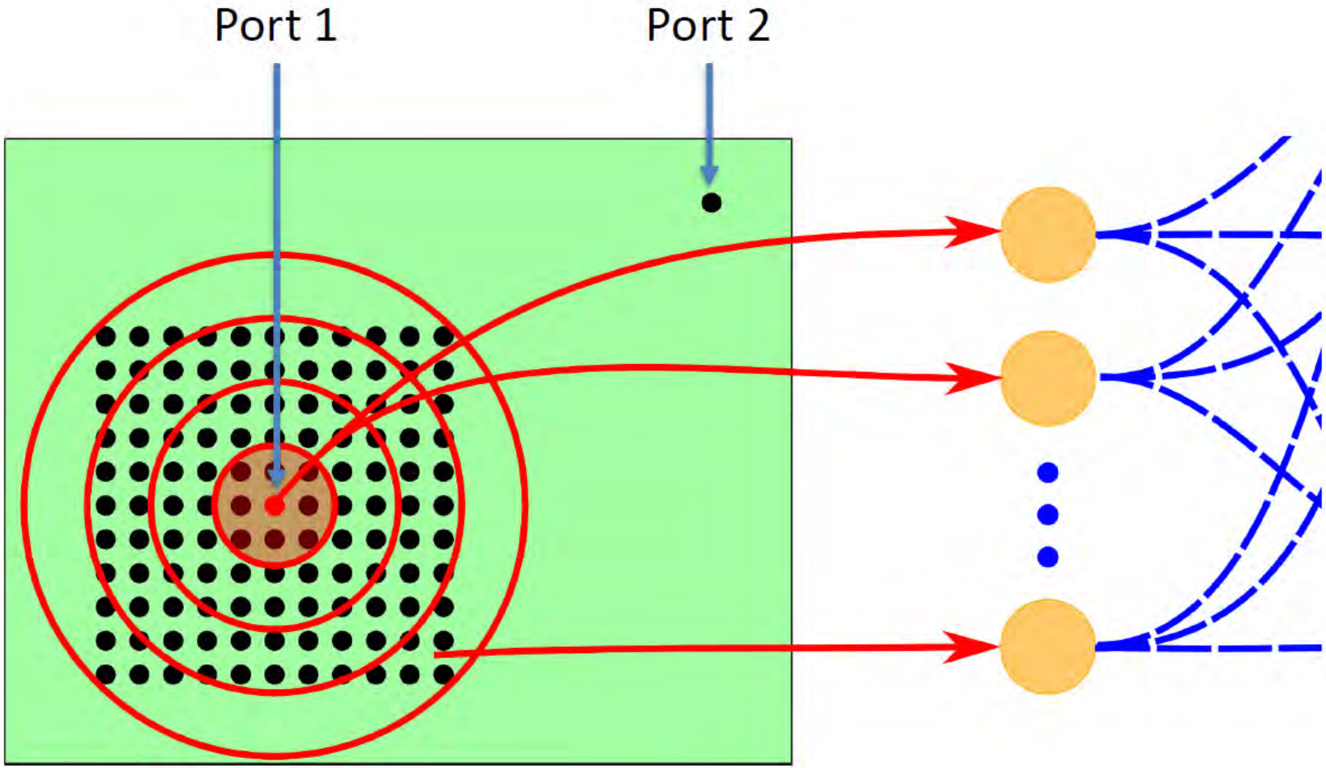
Direct (No) Pre-Processing



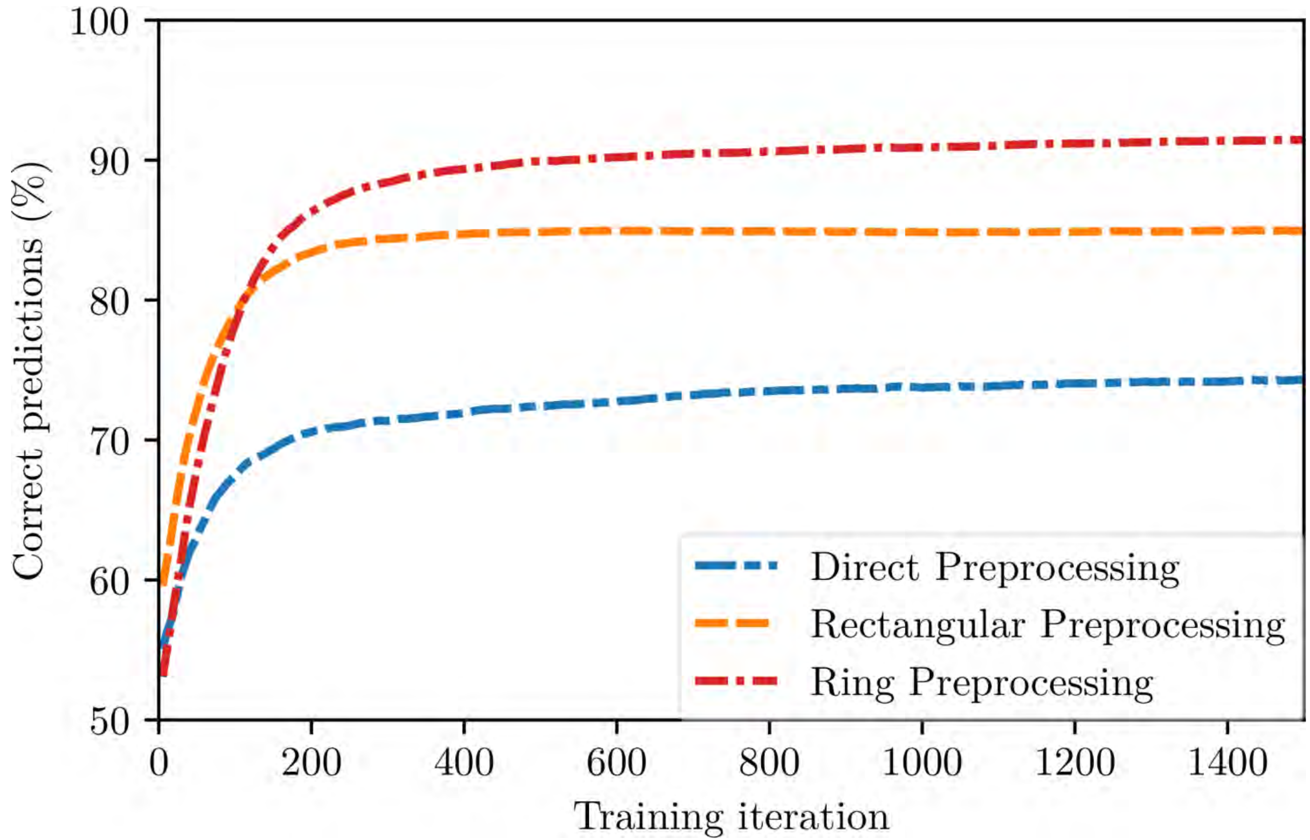
Rectangular Pre-Processing



Ring Pre-Processing



Results



100
90
80
70
60
50
Correct predictions (%)
0
200
400
600
800
1000
1200
1400
Training iteration
Direct Preprocessing
Rectangular Preprocessing
Ring Preprocessing

Effect of Split Training ↔ Test Data

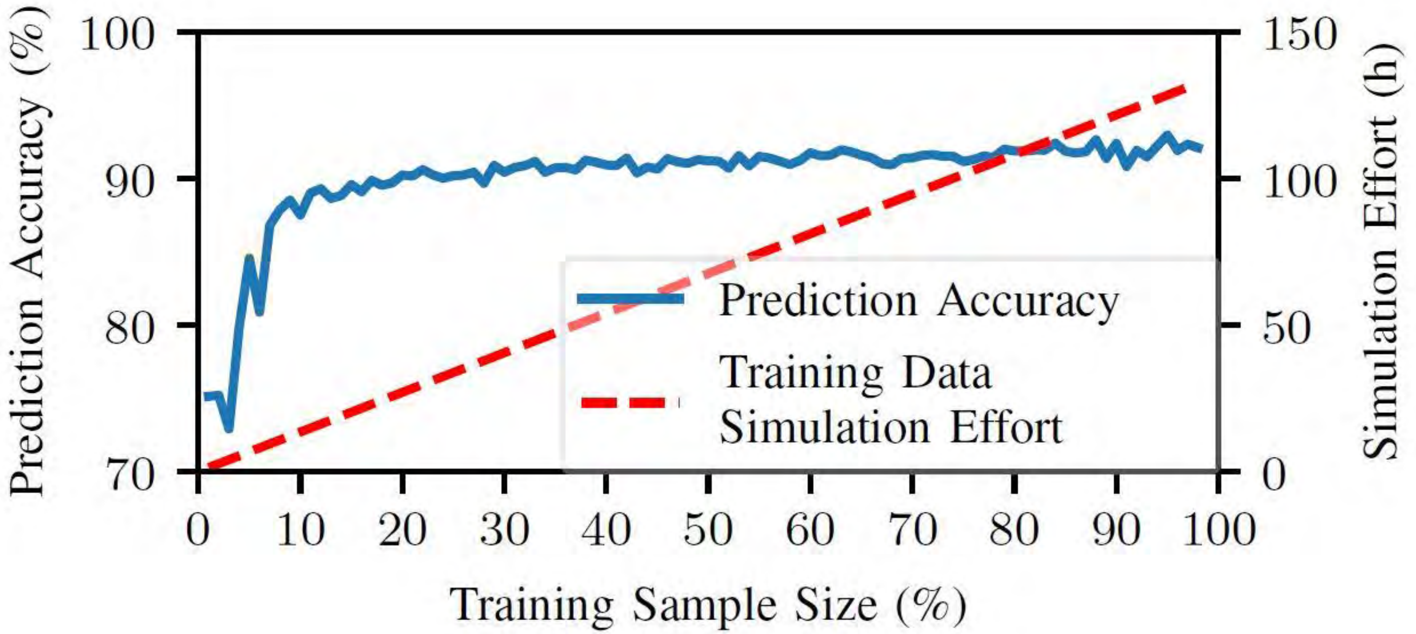
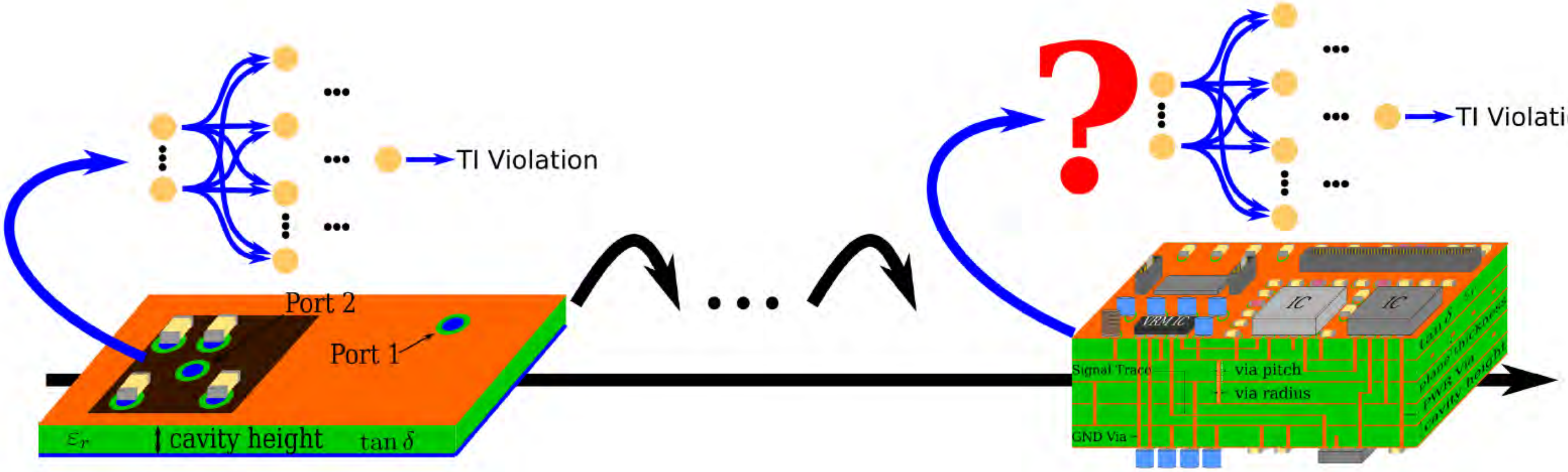


Image from M. Schierholz et al.: "Comparison of Collaborative versus Extended Artificial Neural Networks for PDN Design", submitted to IEEE SPI 2020

Summary: Our ANNs for PDN Design ..

- ➔ reached > 90 % prediction accuracy,
- ➔ required considerable training (data, time),
- ➔ solved more or less only one problem,
- ➔ but did so 1‘000‘000 times faster than full-wave tools,
- ➔ which is more than encouraging and, hence,
- ➔ will be the subject of further research at TUHH.

How far can we go with this?



Outline

1. EMC

2. EMC Engineering

3. ML in EMC

4. Conclusions

Outline

1. EMC

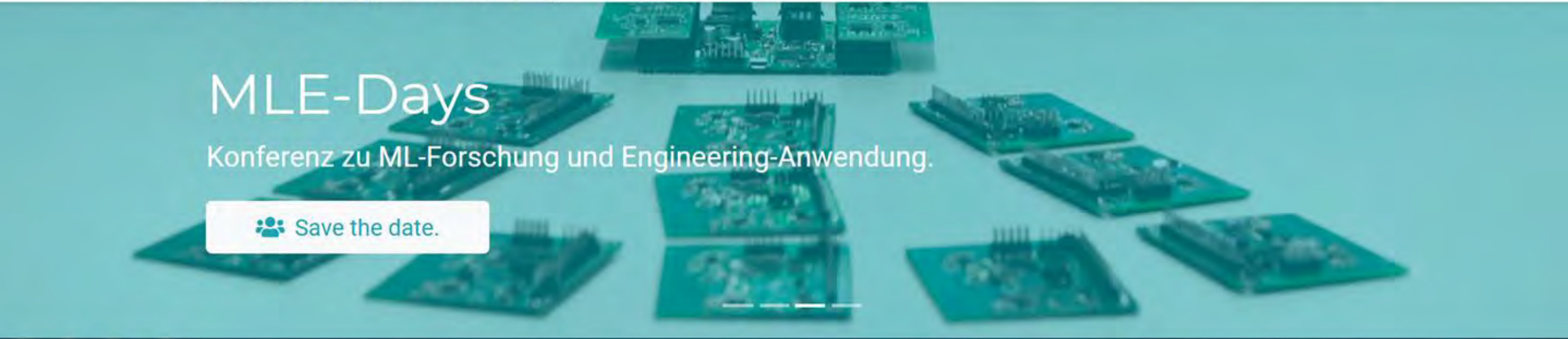
2. Models in EMC

3. ANNs in EMC

4. Conclusions

HOW WILL ML AFFECT EMC ENGINEERING?

... INTERESTING BUT LARGELY OPEN QUESTION!



MLE-Days

Konferenz zu ML-Forschung und Engineering-Anwendung.

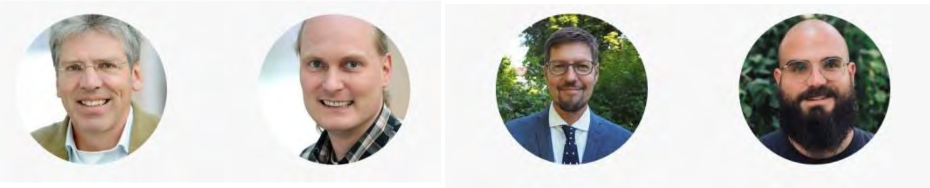
Save the date.

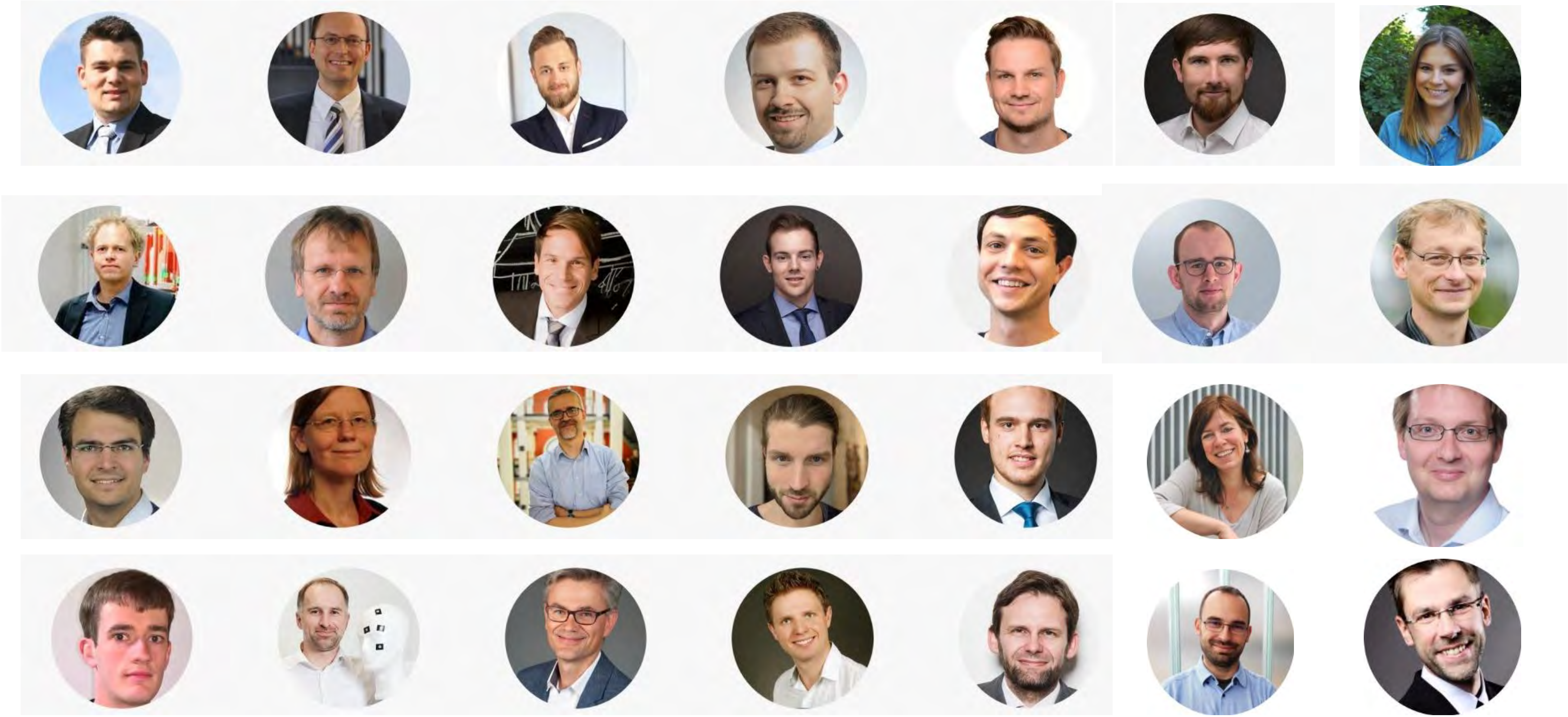
MLE

Machine Learning in Engineering

MLE ist eine Initiative zur Bündelung der Kompetenzen im Bereich Machine Learning an der Technischen Universität Hamburg mit dem Ziel des Wissenstransfers in Richtung Wirtschaft und Industrie.

MLE@TUHH:






THANK YOU!
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