ETH zürich

Power Electronic Systems Laboratory

ANN Powered Models for Magnetic Components

ECPE Online Workshop
Steps towards Design Automation and Artificial Intelligence in Power Electronics
December 3, 2021

Thomas Guillod[1] and J. W. Kolar[1]

[1] Power Electronic Systems Laboratory, ETH Zurich, Switzerland

Acknowledgements

- Dr. P. Papamanolis
- Dr. D. Rothmund
- Dr. F. Krismer

ETH zürich

- Haoran Li
- Evan Dogariu
- Dr. D. Serrano
- Prof. Minjie Chen

PRINCETON UNIVERSITY

- Andrew Nadler
- Prof. C. R. Sullivan

DARTMOUTH ENGINEERING

- Dr. Min Luo

plexim electrical engineering software

- Gianfranco Mauro
- Dr. K. Leong
- Dr. M. Kasper
- Dr. G. Deboy

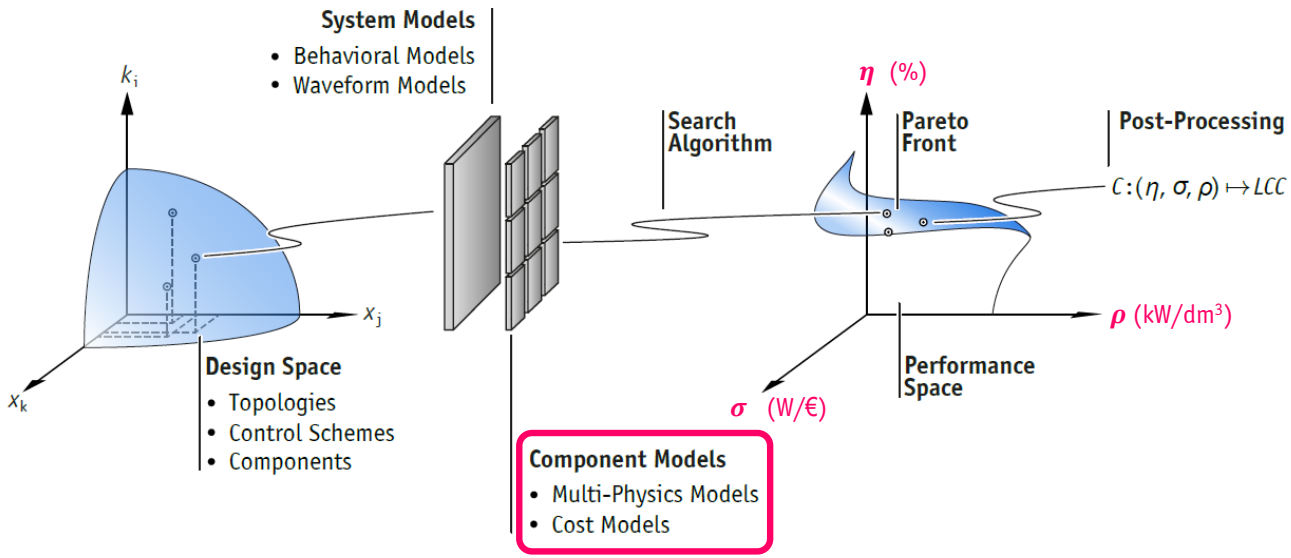
infineon

Swiss National Science Foundation

State-of-the-Art

Numerical models
Semi-numerical

▶ Multi-Objective Optimization



- **Advantages**
  - Efficiency, power density, costs, reliability, etc.
  - Virtual prototyping → time to market
- **Requirements**
  - Optim. algorithms & objectives
  - Models & material parameters

[Adapted from R. Burkart, PhD Thesis, ETHZ, 2016]

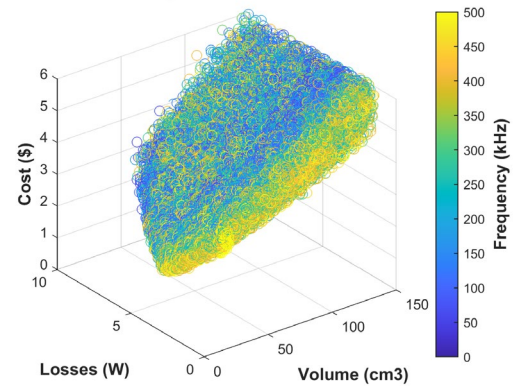
▶ Magnetic Model Properties

- **Modeling goals**
  - Accurate & robust
  - Versatile & comprehensive
  - Extensible & adaptable
  - Simple implementation & fast evaluation
  - Ability to “debug”
  - Give “physical” insights

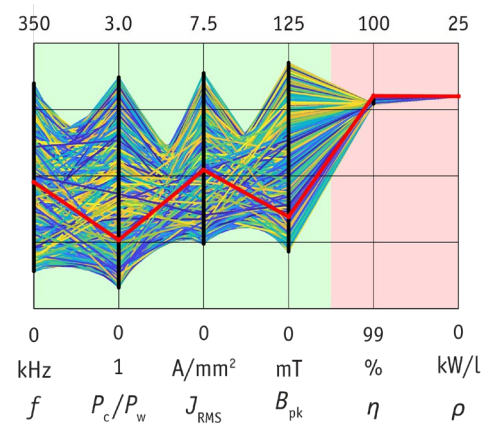
- **Model properties**
  - Multi-physics
  - Space dependent / dynamic
  - Multivariable (input & output)
  - Constrained (explicit & implicit)
  - Mixed-integer (discrete variables)
  - Non-linear / non-convex
  - Discontinuous / no explicit gradient
  - No explicit solution
  - Lack of first principle model

- **Magnetic modeling is intrinsically difficult**

Complex Trade-Off

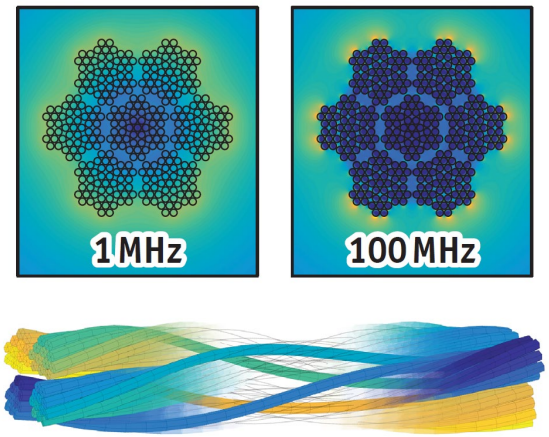


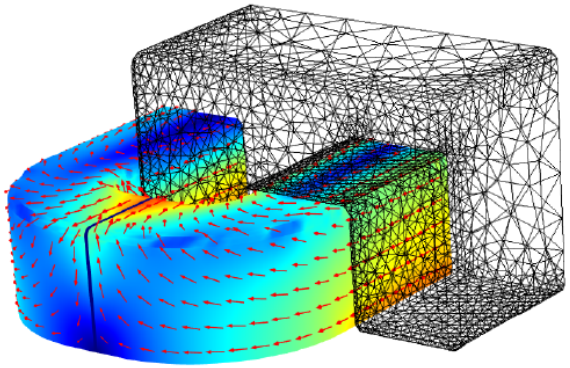
Design Space Diversity



▶ Full Numerical Model

- **Based on fundamental equations**
  - Maxwell
  - Heat transfer
  - Navier–Stokes
- **Methods**
  - FEM/FVM
  - FDM/FDTD
  - PEEC/MoM
- **Properties**
  - Highest accuracy
  - High modelling effort
  - High computational effort

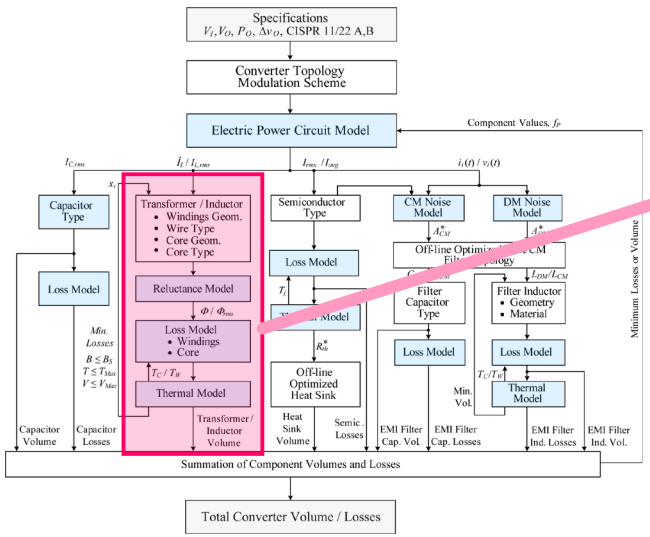


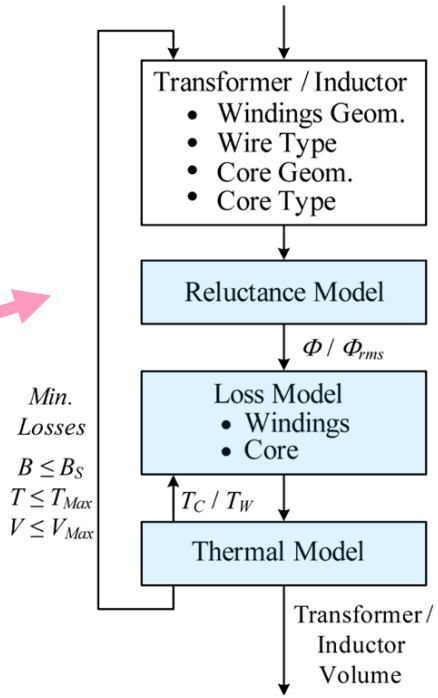


- **Useful for final validation, difficult for optimization**
- **Lack of first principle models (e.g., core losses)**

▶ Semi-Numerical Model

- **Modelling approach**
  - Many analytical equations
  - Thermal-loss coupling
  - Numerical solution
- **Properties**
  - High accuracy
  - Medium modelling effort
  - Medium computational effort





- **Easy to integrate in a full converter model**
- **Typical choice for optimization**

[Adapted from R. Burkart, PhD Thesis, ETHZ, 2016]

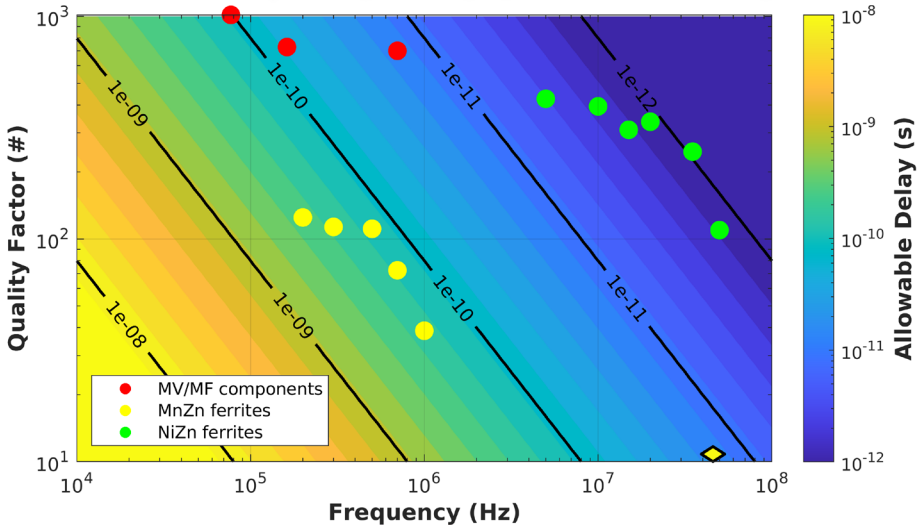
Fundamental Limits

Measurements
Tolerances

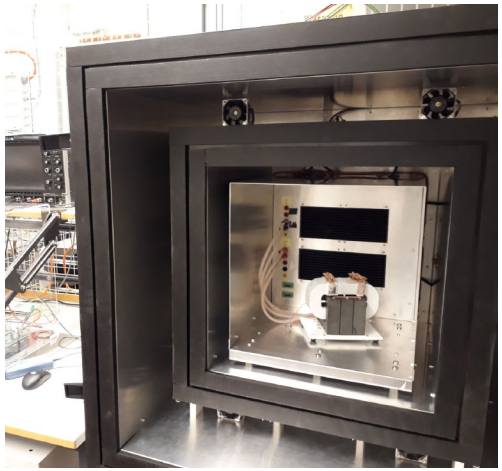
▶ Limitations: Measurement Uncertainties

- **Challenges**
  - HF harmonics
  - High efficiencies
  - Reactive power
- **Potential solutions**
  - Calibration against “ideal” reference
  - Reactive power compensation
  - Calorimetric measurement (transient / steady-state)

Max. Current/Voltage Delay @ 5% Loss Accuracy



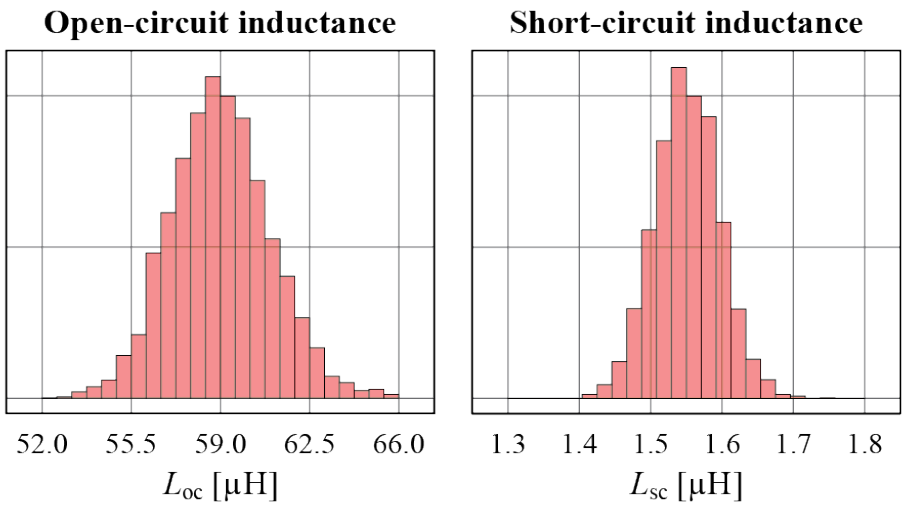
Calorimetric Meas.

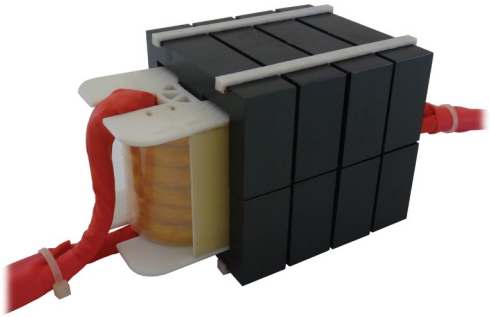


- **Typically: 5-25% for magnetic components**
- **Error analysis (statistical and systematic errors)**

▶ Limitations: Material & Geometrical Tolerances

- **Tolerances**
  - Material batch (e.g., core, Litz wire)
  - Construction tolerances
  - How representative is the prototype?
- **Example**
  - 20kW / 100kHz MF transformer
  - Equivalent circuit tolerances
  - Monte-Carlo method



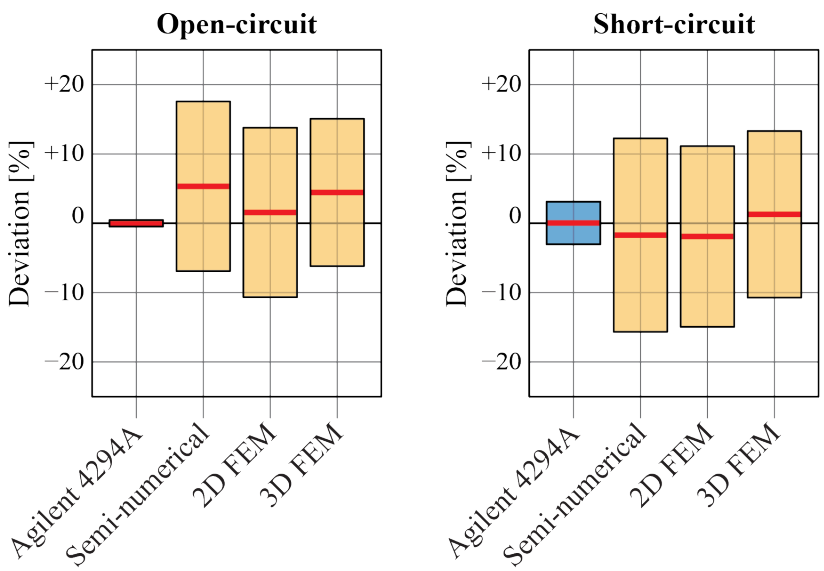


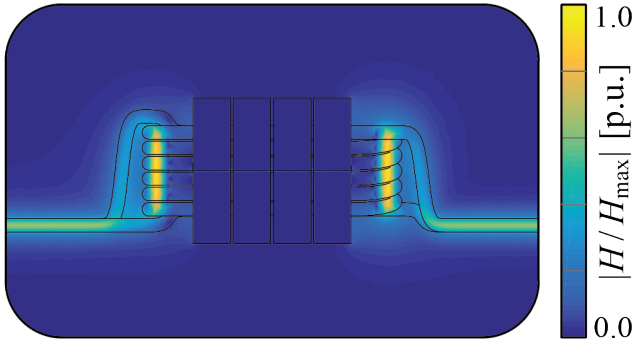
- **Batch to batch variations are not negligible**

[Adapted from T. Guillod, Springer Electr Eng, 2017]

▶ Limitations: Material & Geometrical Tolerances

- **Tolerances**
  - Material batch (e.g., core, Litz wire)
  - Construction tolerances
  - How representative is the measurement?
- **Example**
  - 20kW / 100kHz MF transformer
  - Equivalent circuit uncertainties
  - Monte-Carlo method





- **In this case neither the models nor the measurements are the bottleneck**

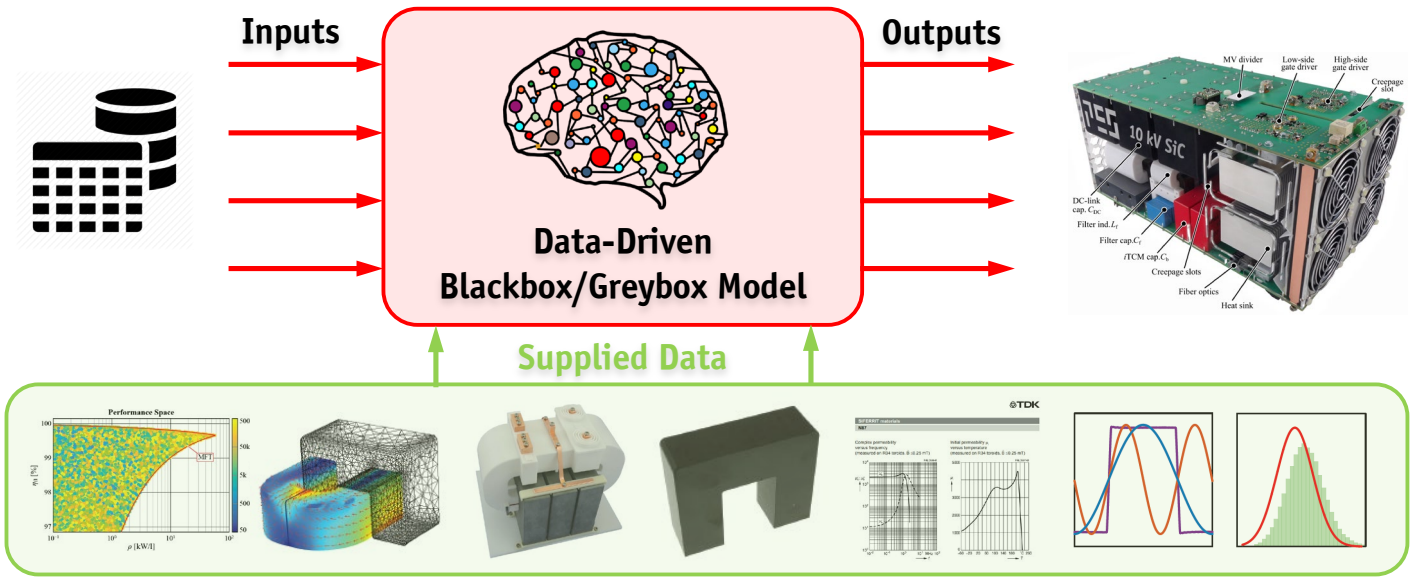
[Adapted from T. Guillod, Springer Electr Eng, 2017]

Neural Network Models

Properties
Workflows

▶ Data-Driven Model

- **Modelling approach**
  - Measurements
  - Simulation data
  - Datasheets
- **Properties**
  - Versatile methods
  - Limited physical meaning
  - Limited validity range
- **Methods**
  - Interpolation (e.g., loss map)
  - Model fitting (e.g. Steinmetz)
  - Machine learning

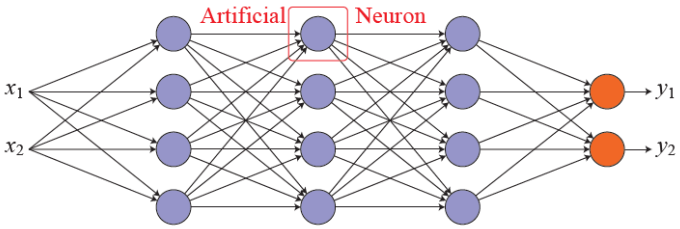


- **New class of model for magnetic?**

[Theoretical background: S. Skansi, Introduction to Deep Learning, 2018]

▶ Artificial Neural Networks

- **Main categories**
  - Supervised learning ➔ labeled/scored data
  - Unsupervised learning ➔ raw data
  - Reinforcement learning ➔ feedback loop learning
  - Shallow ANN ➔ basic modelling
  - Deep ANN ➔ complex modeling



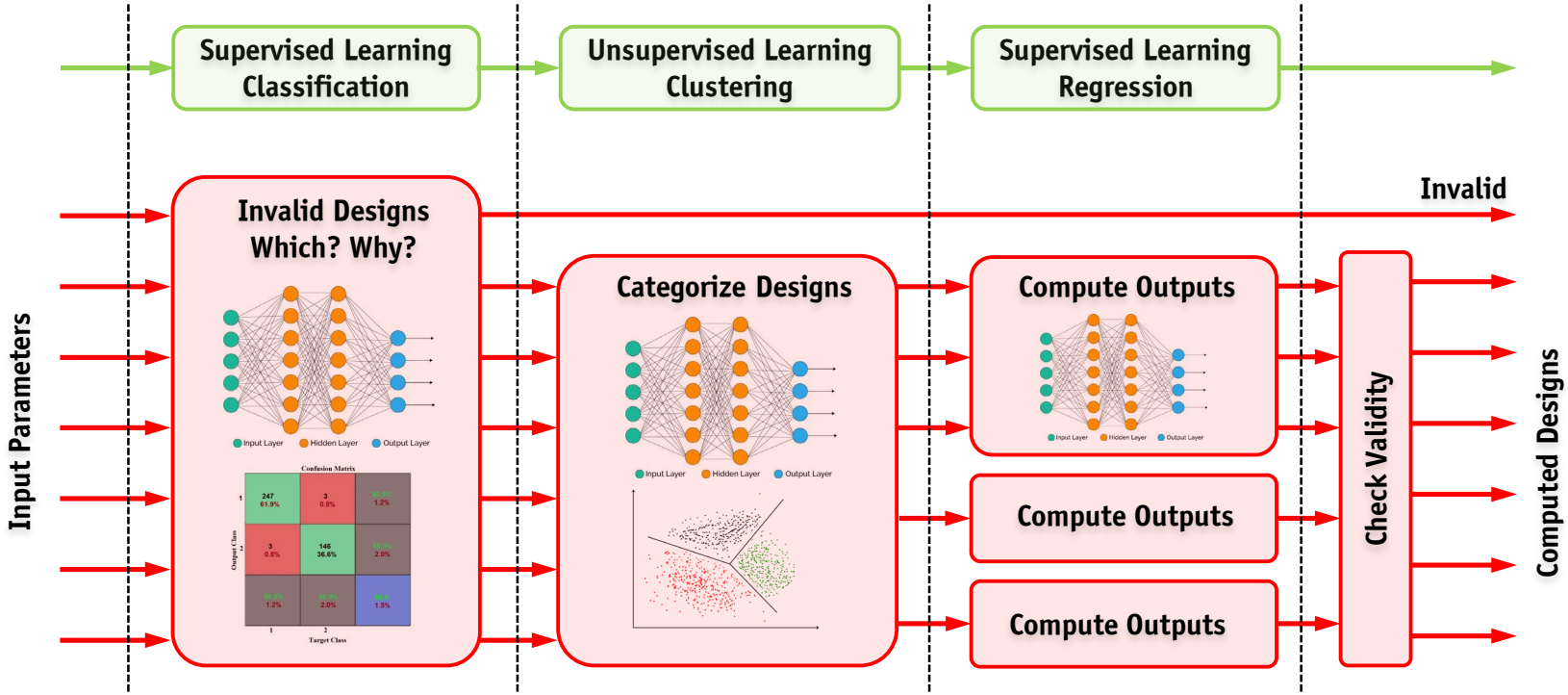
- **Many variations**
  - MLP: regression, classification ➔ modelling
  - GAN: generation, regression, classification ➔ complex modelling
  - CNN: image processing ➔ field pattern, geometry, etc.
  - RNN: time series ➔ waveform, ODE, etc.

- **Properties**
  - Extremely flexible & versatile
  - Low computational cost at evaluation
  - Large / complex datasets
  - Noisy / incomplete datasets

[Theoretical background: S. Skansi, Introduction to Deep Learning, 2018]

▶ Deep Learning for MF Transformers

- **Goal**
  - Comprehensive MF transformer model
  - Complete black box model
- **Deep learning**
  - Many hidden layers (dense, sparse, dropout)
  - Classification, clustering, and regression

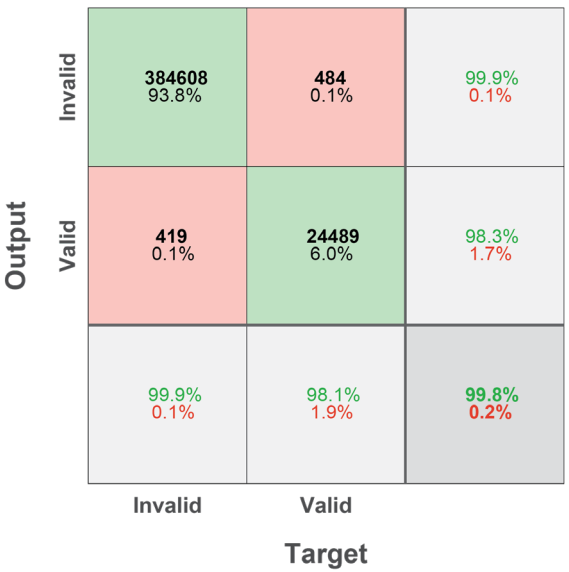


▶ Deep Learning for MF Transformers

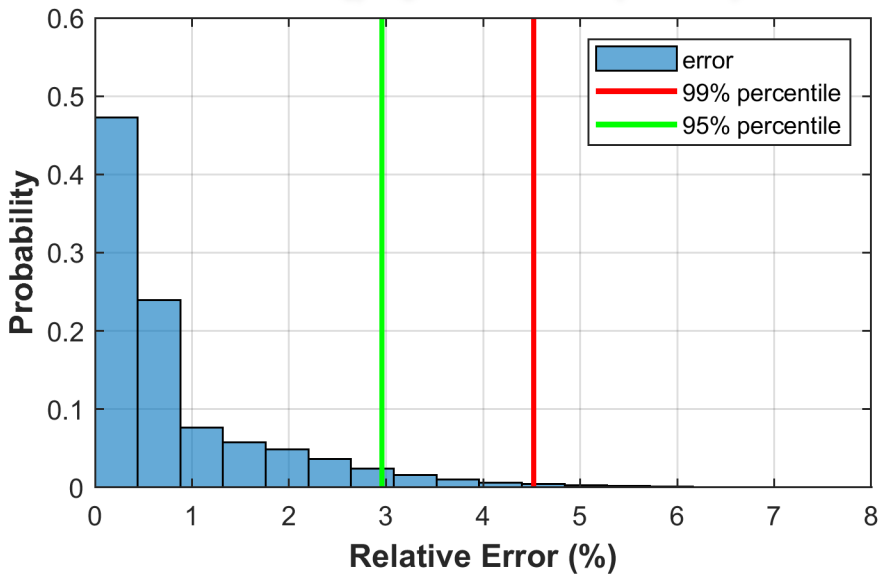
- **Dataset**
  - Semi-numerical simulation data
  - Coupled loss-thermal model
  - Different geometries & materials
  - Power, voltage, frequency, etc.

- **Deep learning (TensorFlow)**
  - 410'000 designs for classification
  - 50'000 valid designs for clustering/regression
  - 20 inputs (geometry, material, applied waveform, etc.)
  - 11 outputs (equivalent circuit, losses, temperature, etc.)

Classification error (test set)



Clustering/regression error (test set)

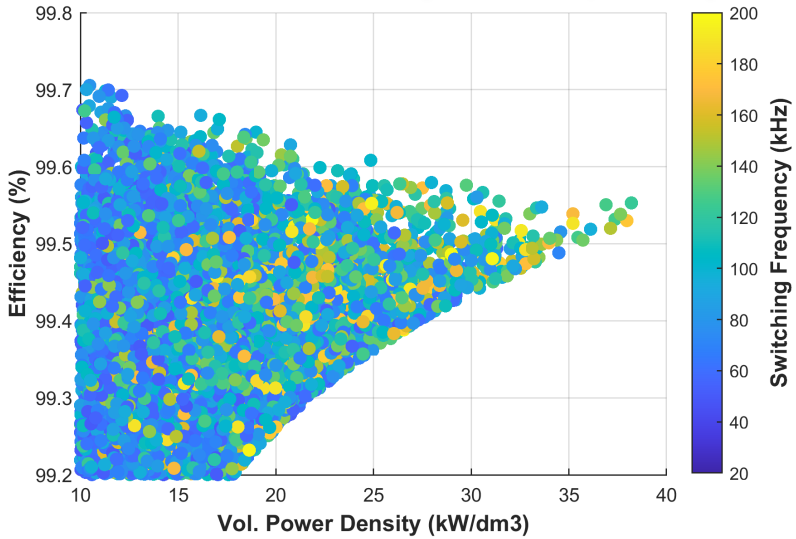


- **ANNs can handle the complexity of magnetic components**

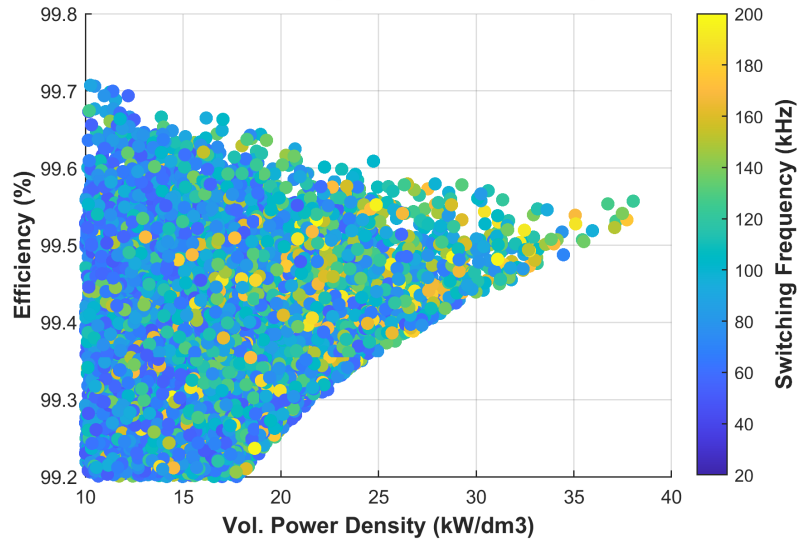
▶ Deep Learning for MF Transformers

- **4.5 kW / 200V / 100V**
  - Brute force grid search
  - ANN vs. semi-numerical model
- **ANN model**
  - Accuracy is not a problem
  - Extremely fast

Semi-numerical model (60min computation)

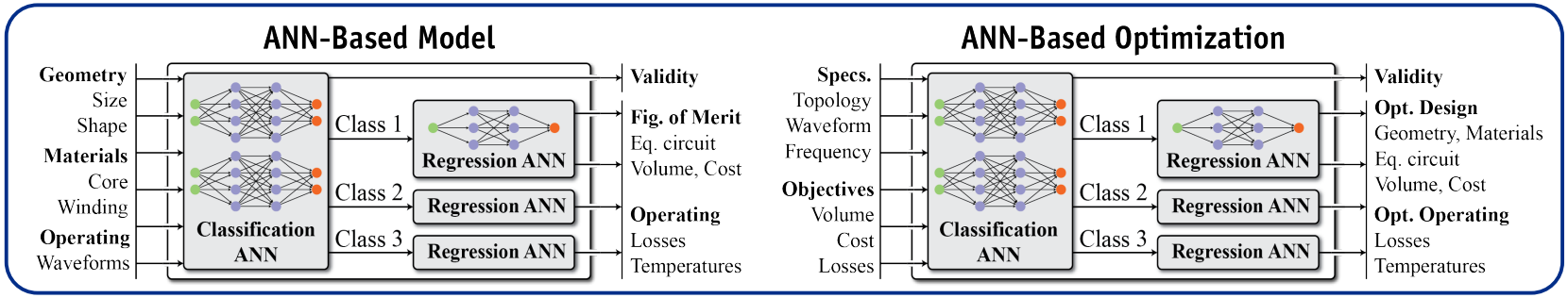


ANN model (0.3s computation)

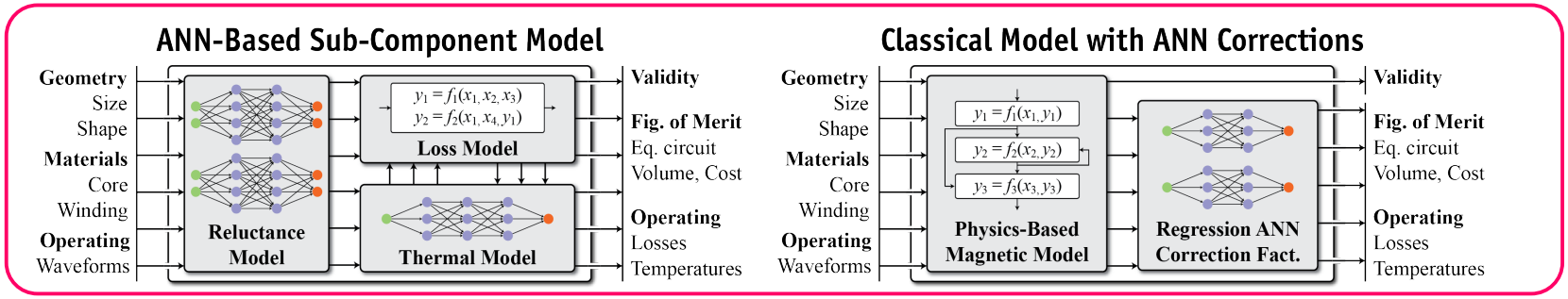


- **Large training dataset is required**
- **Better ANN modeling workflow?**

▶ ANN Workflows



Full-ANN



Hybrid-ANN

- We understand (most of) the physics of magnetic components!
- Are 100% data-driven approaches really optimal?
- Hybrid workflows are promising

[Adapted from T. Guillod, IEEE OJPEL, 2020]

AI-mag

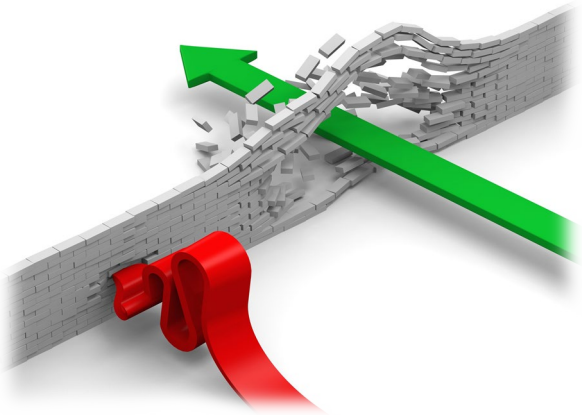
Inductor Modeling and Design
Artificial Neural Network
Finite Element Method

Inductor Design Tool
ANN-Powered

[Adapted from T. Guillod, IEEE OJPEL, 2020]

▶ ANN-Powered Inductor Design Tool

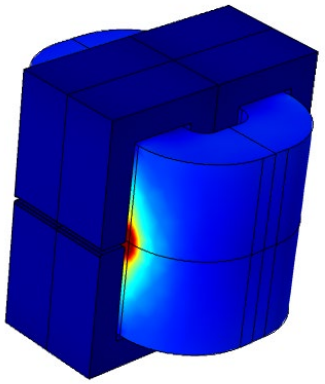
- **Goal**
  - Inductor design tool
  - Accuracy of 3D FEM models
  - Computational cost of analytical models
- **First trial**
  - GAN/CNN networks
  - Generate field patterns
  - Limited accuracy & outlier data
  - Massive complexity
- **Second trial**
  - MLP networks
  - Generate field pattern figures of merit
  - Not cutting-edge machine learning
  - Reasonable complexity
- **Hybrid workflow (ANN+classical models)**



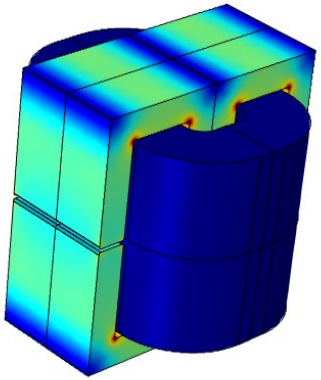
▶ 3D FEM Database

- **Different geometries**
  - Variable sizes
  - Variable shapes
  - Variable air gaps
- **Different concepts**
  - Winding types (e.g., stranding)
  - Core materials (e.g., permeability, losses, saturation)
  - Thermal management (e.g., losses, ambient temperature, air-flow)

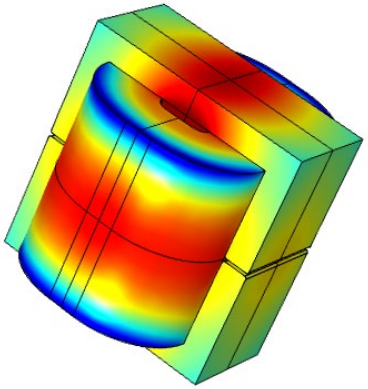
Fringing Field



Mag. Flux



Thermal Stress

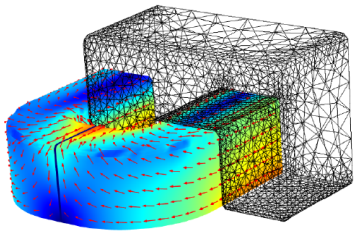


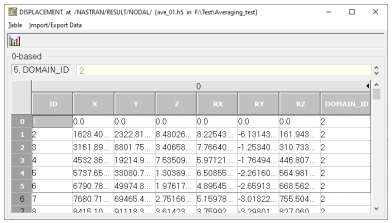
- **Figure of merits from 3D FEM?**

▶ 3D FEM Figures of Merit

- **Magnetic FEM model**
  - $\int B \cdot H \, \mathrm{d}V$ → energy → inductance — fringing field, leakage, saturation
  - $\int B^{\beta} \, \mathrm{d}V$ → flux density → core losses — flux sharing, saturation, materials
  - $\int J^2 \, \mathrm{d}V$ → current density → winding losses — winding geometry, wire types, skin effect
  - $\int H^2 \, \mathrm{d}V$ → magnetic field → winding losses — fringing, wire types, proximity effect

- **Thermal FEM model**
  - $\Delta T(\text{winding,avg})$ → average winding temp. — winding properties (loss coupling)
  - $\Delta T(\text{core,avg})$ → average core temp. — core properties (loss coupling)
  - $\Delta T(\text{winding,max})$ → hotspot winding temp. — thermal feasibility
  - $\Delta T(\text{core,max})$ → hotspot core temp. — thermal feasibility
  - $\Delta T(\text{insulation,max})$ → hotspot insulation temp. — thermal feasibility

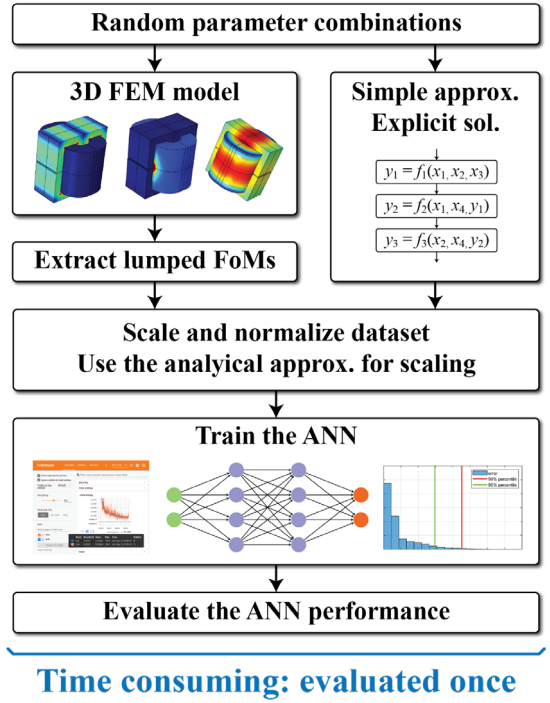




- **3D field pattern can be described with lumped quantities**

▶ FEM/ANN Hybrid Modeling Workflow

- **ANN predict the field pattern FoMs**
- **Analytical pre-computation**
  - ANN predict correction factors
  - Increased regression accuracy
  - Reduced dataset size
  - Give physical insights
- **Custom variable scaling**
- **Implementation**
  - FEM: COMSOL
  - ANN: TensorFlow
  - Code: MATLAB+Python
  - Compatible with HPC
- **Replacing 3D FEM models by ANNs**

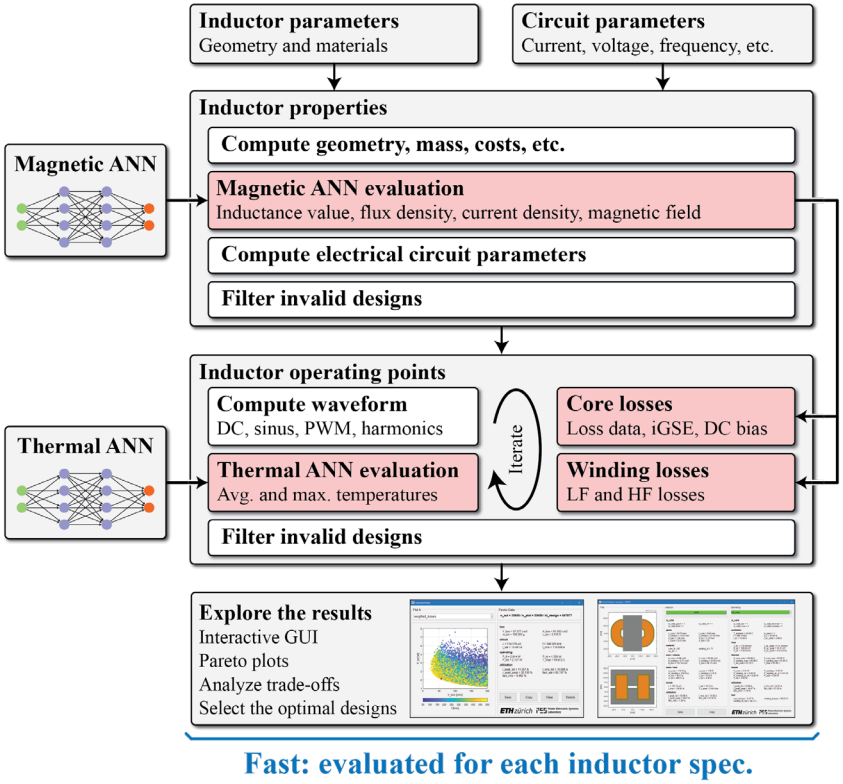


▶ FEM/ANN Hybrid Modeling Workflow

- **Hybrid model**
  - Semi-numerical model
  - ANNs for getting field patterns
  - Extensible & adaptable
  - Give physical insights
  - Vectorized & parallel
  - 30 inputs and 40 outputs

- **Considered effects**
  - Fringing, flux sharing, leakage, saturation
  - Heat conduction & convection
  - Harmonic distortion
  - Skin and proximity effects
  - Core loss-map with DC bias
  - Thermal-loss coupling

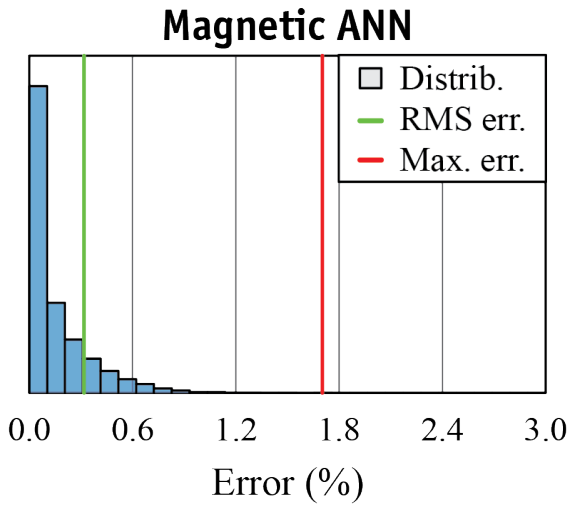
- **Trying to combine the best of both worlds**

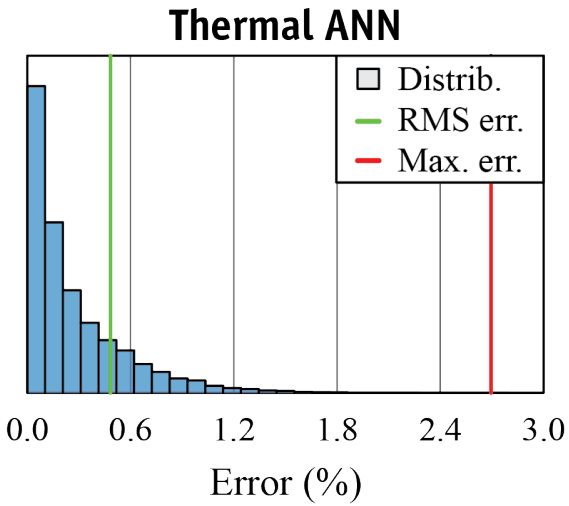


Fast: evaluated for each inductor spec.

▶ ANN Training & Performance

- **Dataset**
  - Random distribution
  - 20'000 magnetic designs, 8 input variables, 4 output variables
  - 20'000 thermal designs, 9 input variables , 5 output variables

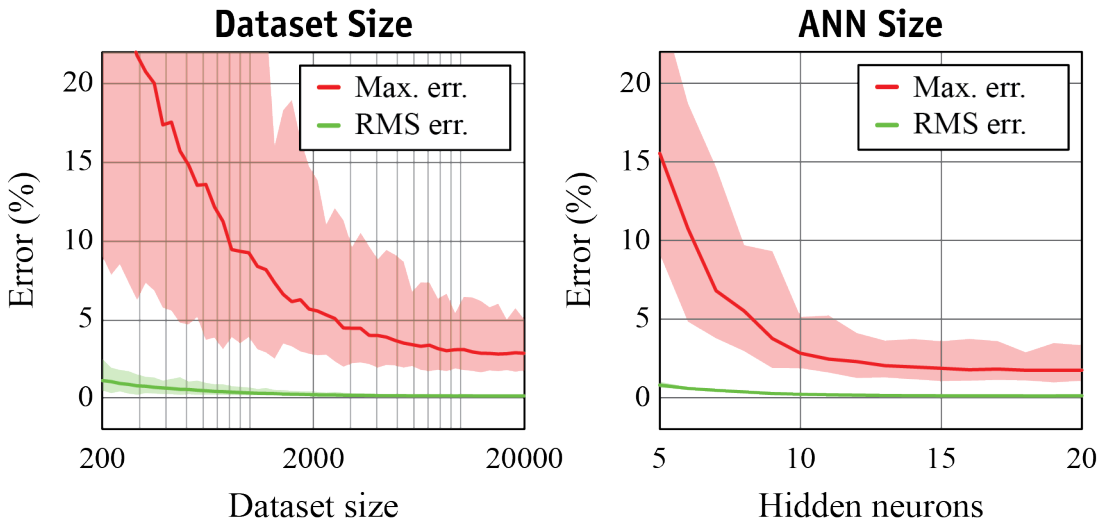




- **ANNs vs 3D FEM: less than 3% error**

▶ ANN Tuning

- **Data set size: 5'000 samples are sufficient**
  - Clearly better than interpolation
  - Regular grid would require: 6^9 = 10'000'000 samples
- **ANN structure: shallow ANNs are sufficient**



- **Simple ANN & small dataset**

▶ Workflow Performance

- **3D FEM is only used for training the ANN**
- **Advantages for the end-user**
  - PDE/FEM competencies are not required
  - No need of a powerful machine
  - No need of a FEM solver / software license
  - Ideal for a SaaS/online tool

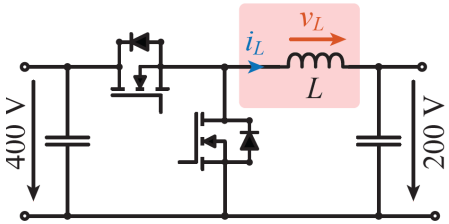
	Intel i7-8650U	2 x AMD EPYC 7742 + GPU
3D FEM	160 hours	**12 hours**
ANN training	10 min	**1 min**
Inductor design eval.	20us / 50'000 per sec.	**0.9us / 1'100'000 per sec.**

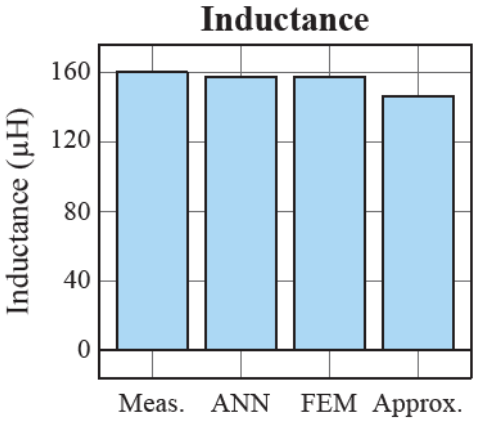
- **Less than 3% deviation with 3D FEM**
- **Can compute a design within microseconds**

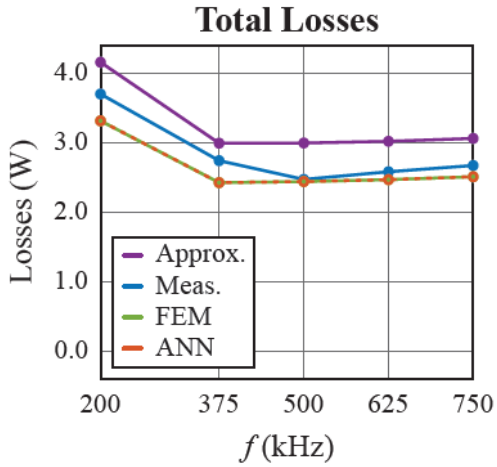
▶ AI-mag Inductor Design Tool

- 2kW Buck converter (400V to 200V)

Core	E55/28/21, TDK N87
Air gap	2 x 400um
Wire	900 x 100um
Winding	16 turns / 2 layers

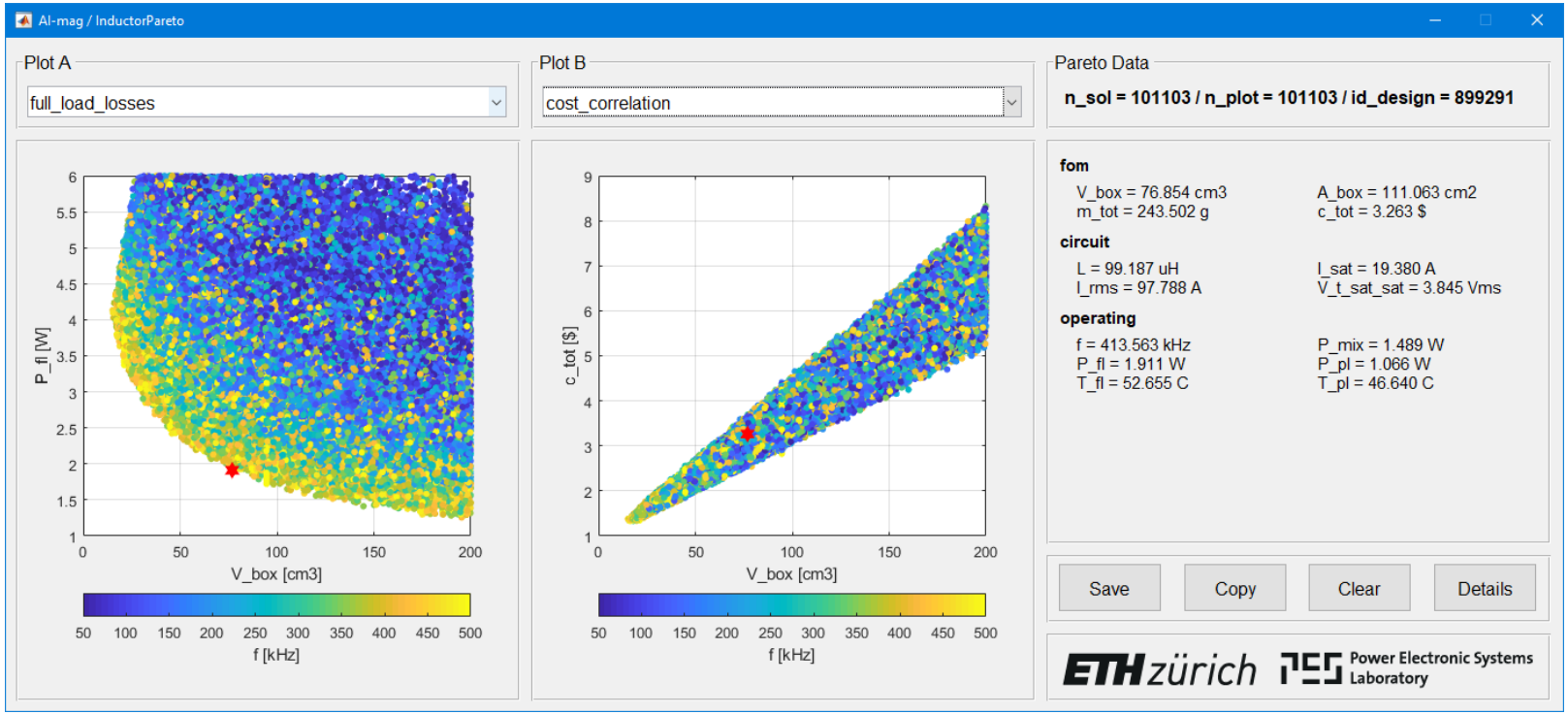






- 0.6% error between ANNs and 3D FEM
- 1.4% error between ANN and meas. for the inductance
- 11.5% error between ANN and meas. for the losses

▶ AI-mag Inductor Design Tool



Open-source / BSD license
MATLAB, Python, TensorFlow, COMSOL
https://doi.org/10.1109/OJPEL.2020.3012777
https://ai-mag.github.io

Conclusion & Outlook

Model & Optimization
Future Research Areas

▶ Conclusion & Outlook

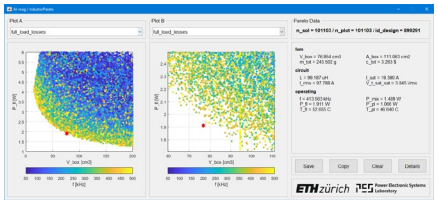
- **Magnetic modeling**
  - Large number of variables
  - Complex design/performance mapping
  - Lack of accurate first principle models
  - High-computational costs
- **ANNs are naturally adapted to such problems**

- **Potential usage of ANNs**
  - System level
  - Component level
  - Sub-component level
  - Integrated model/optimizer
  - Combining heterogenous measurements, simulations, datasheets, etc.
- **ANNs have proven to be competitive/better than classical models**

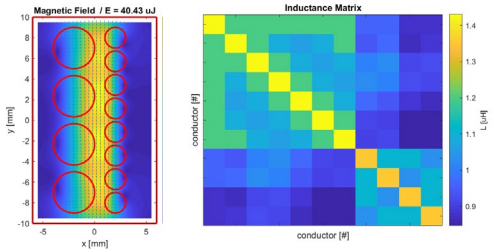
▶ Conclusion & Outlook

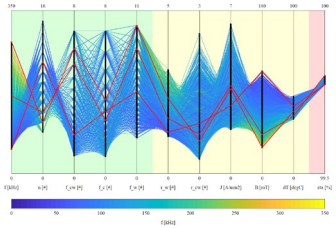
- **Dataset**
  - Large datasets are required
  - Dataset accuracy is critical (systematic errors)
  - Sample distribution is critical (biased dataset)
  - Error analysis, GAN, transfer learning, open-data
- **Blackbox**
  - Difficult to debug
  - Difficult to choose the ANN type/structure
  - Offer limited physical insights
  - Unphysical solutions can be generated
  - Physic-informed ANN, hybrid ANN/classical models
- **Model quality**
  - Outliers with “averaged” error metrics
  - Extrapolation is unreliable & dangerous
  - Careful testing of the ANNs
- **Practical issues**
  - ANN frameworks are quickly evolving and complex
  - Sharing & reproducing results is challenging
  - Open-source design tools

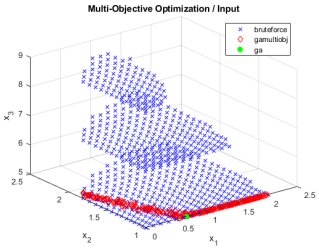
▶ Open-Source Contributions

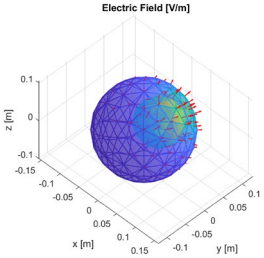


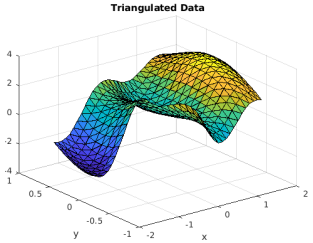
- **Magnetic component design**
  - AI-mag – ANN powered inductor design
  - Semi-numerical optimization for inductors & transformers
- **Magnetic field computations**
  - Mirroring method – magnetic field / inductance matrix
  - Litz wire – FEM post-processing / fully coupled homogenization
- **Multi-objective optimization**
  - Multi-objective optimization – brute-force / genetic / parallel
  - Plotting large datasets – parallel coordinates / big-data scatter plots
- **And much more**
  - Scattered interpolation
  - FEM mesh handling / plotting
  - Inductance/resistance matrix extraction
  - Fourier series with PWM
  - Lab. device remote control

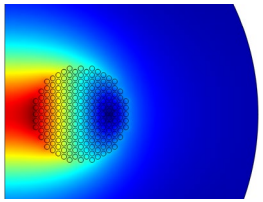












https://github.com/ethz-pes
https://github.com/otvam

Thank You!

Questions?