3D-PEIM
5th Int'l Symp on 3D Power Electronics Integration & Mfgr.
July 8-10, 2025 Nat'l Renewable Energy Lab, Golden, CO, USA

Data-Driven Methods and MagNet Challenge for Power Magnetics Modeling

Minjie Chen
Princeton University

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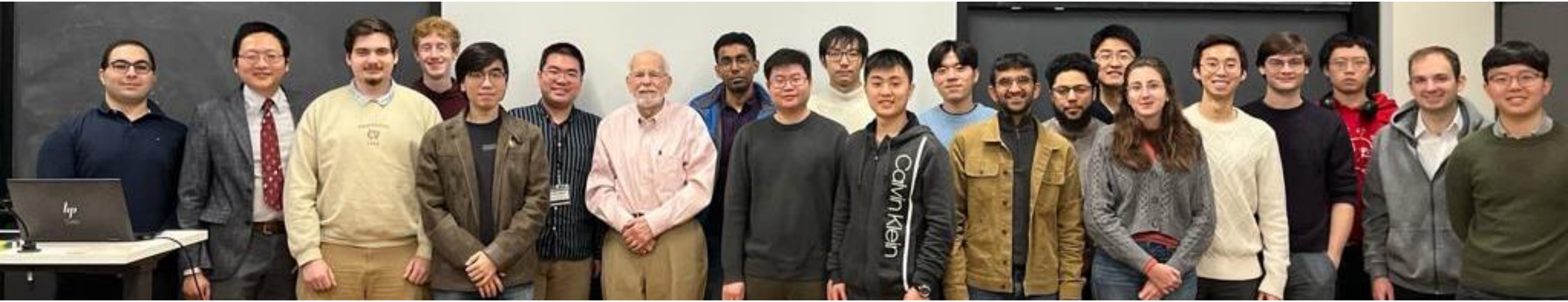

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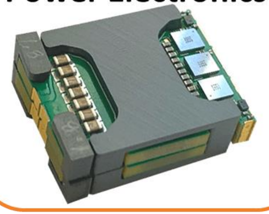
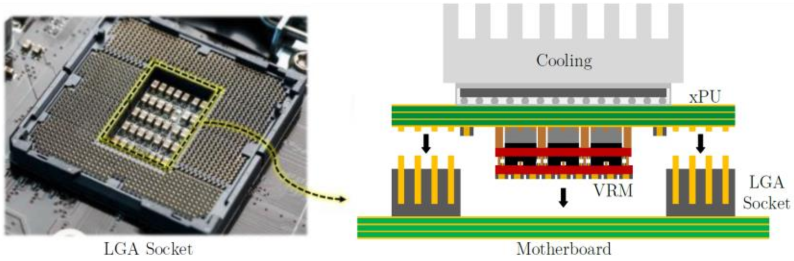
Why are we interested in magnetics?

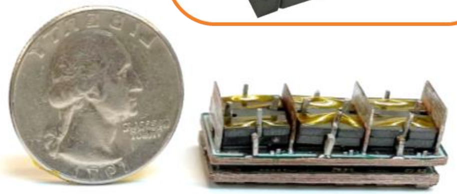
- **Magnetic components are ubiquitous:**
  - Inductors, transformers, EMI filters, coupled inductors
- **Lack of precise models for design:**
  - Complex hysteretic behaviors
  - Simple RLC linear assumptions
- **Complicated design choice:**
  - Wide operating range !
  - Large design margin !

Better tools are needed!!!

High Density Power Electronics

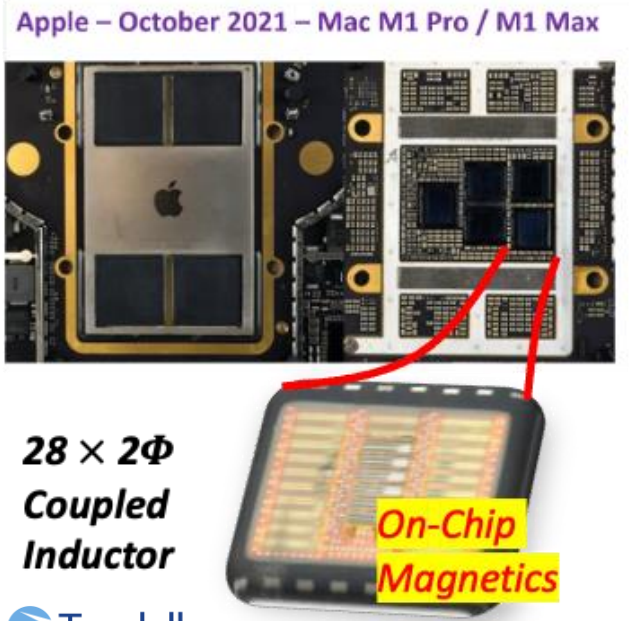






Every mm³ of Magnetics is Cost and Performance …

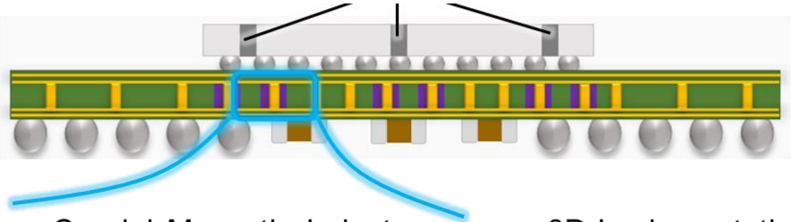
On-Chip Magnetics

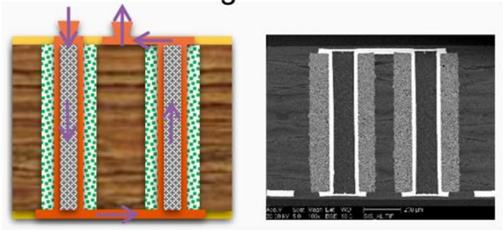


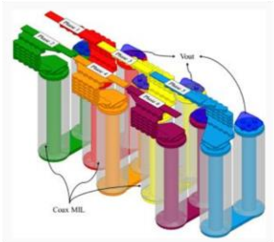
28 × 2Φ Coupled Inductor

Tyndall National Institute
Institiúid Náisiúnta

Vertical Power Delivery and Vertical Magnetics







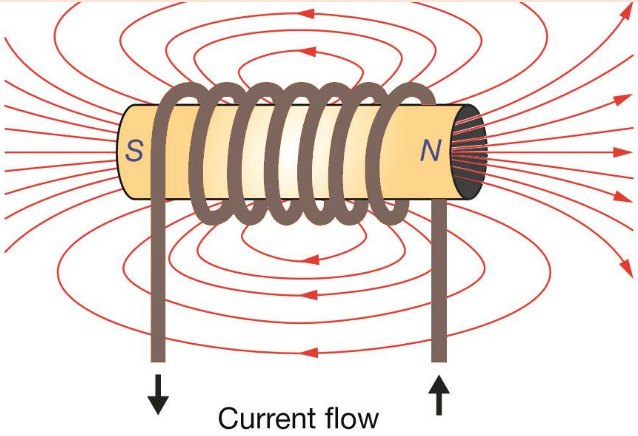
- *M. Chen and C. R. Sullivan, "Unified Models for Coupled Inductors Applied to Multiphase PWM Converters," TPEL'21.*
- *J. Baek et al., "Fully Integrated Voltage Regulators (FIVRs) with Package In-situ Coupled CoaxMIL Inductor for High Power Density Microprocessor Applications," APEC'25.*

Jaeil Baek

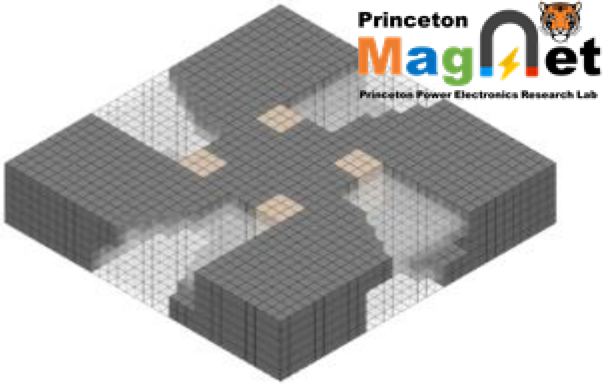
High Precision Power Magnetics Modeling and Design

- Existing design models for passives are **overly simplified** and **inaccurate** …
- Precise engineering of passives (material, geometry, design) **are needed** …
- **Nonlinear, large signal, data-driven** models for power magnetics design …

Approximated Linear Magnetics



Precise & Non-Linear Magnetics



- Memory effects
- Geometry effects
- Temperature impact
- Waveform impact
- Losses
- Saturation

It’s Time to Upgrade the Steinmetz Equation

Charles Steinmetz
(1865-1923)

- **Steinmetz Equation (SE), 1890s**

$$P_V = k \cdot f^{\alpha} \cdot \hat{B}^{\beta}$$

3 parameters

- **iGSE, 2000s**

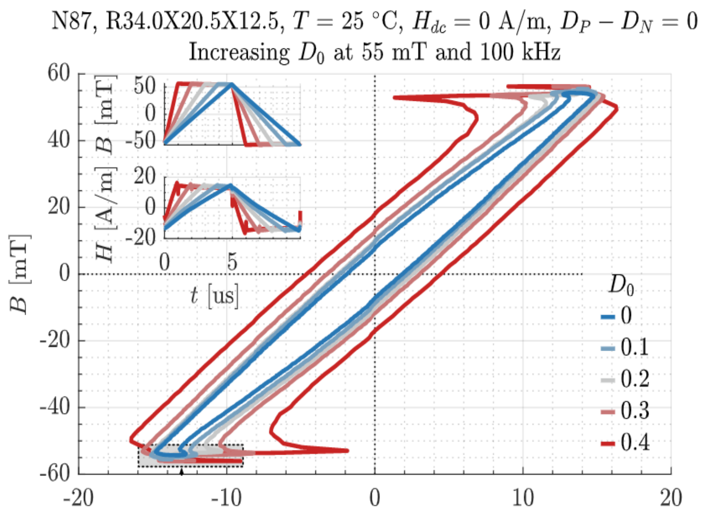
3 parameters

$$P_V = \frac{1}{T}\int_0^T k_i \cdot \left|\frac{\mathrm{d}B}{\mathrm{d}t}\right|^{\alpha} \cdot (\Delta B)^{\beta}\,\mathrm{d}t$$

- **i²GSE, 2010s**

8 parameters

$$P_V = \frac{1}{T}\int_0^T k_i \cdot \left|\frac{\mathrm{d}B}{\mathrm{d}t}\right|^{\alpha} \cdot (\Delta B)^{\beta}\,\mathrm{d}t + \sum_{l=1}^{n} Q_{rl} \cdot P_{rl}$$



More parameters ??? model size vs. accuracy tradeoffs

- *Diego Serrano et al., “Why MagNet: Quantifying the Complexity of Modeling Power Magnetic Material Characteristics,” TPEL’23.*
- *Haoran Li et al., “How MagNet: Machine Learning Framework for Modeling Power Magnetic Material Characteristics,“ TPEL’23.*

Princeton MagNet
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Highly Complex Characteristics of Power Magnetics

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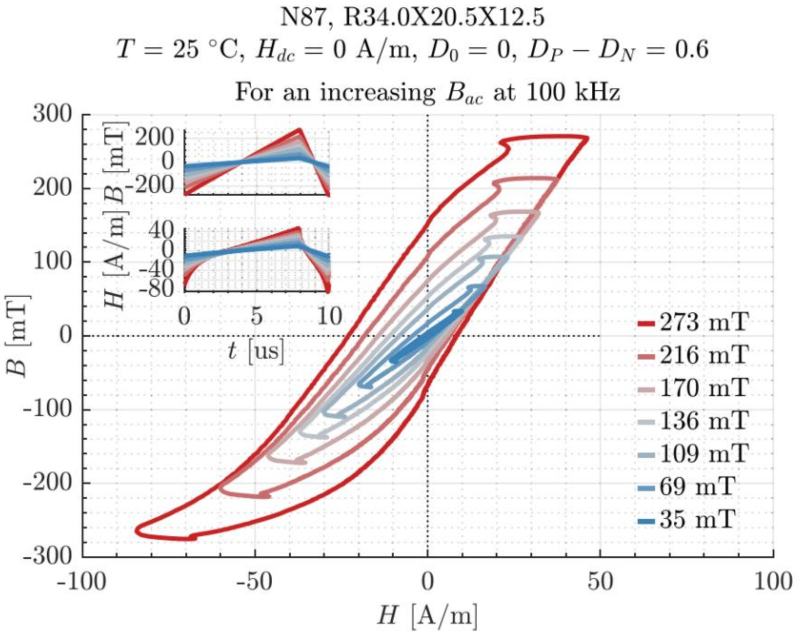
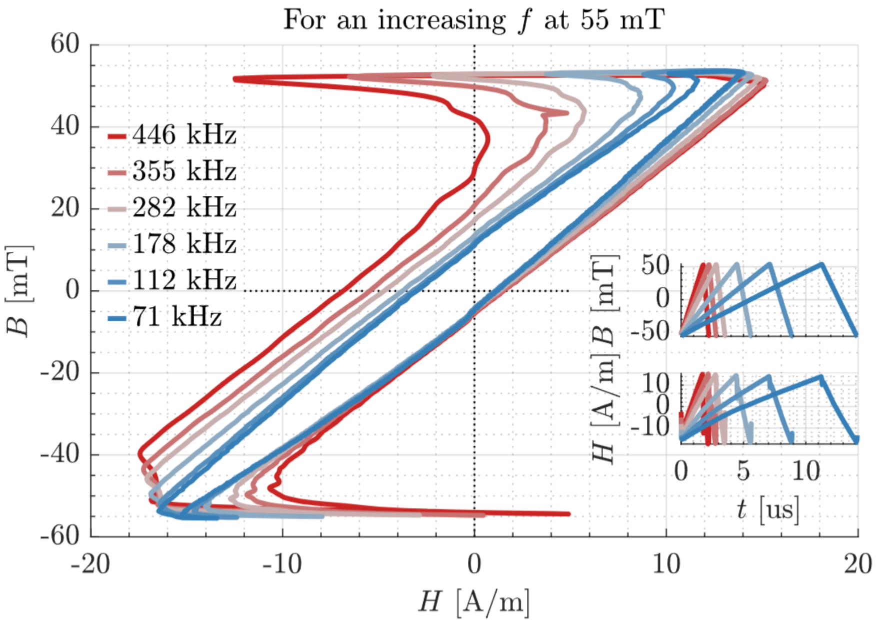
B-H Loop vs. Flux Density



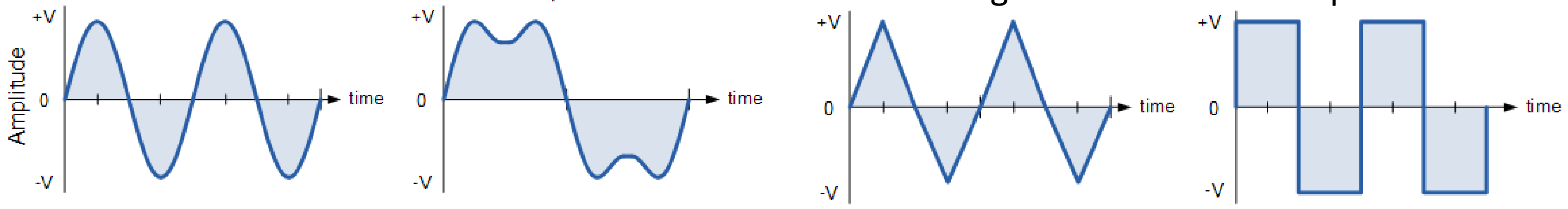
B-H Loop vs. Waveform Shape



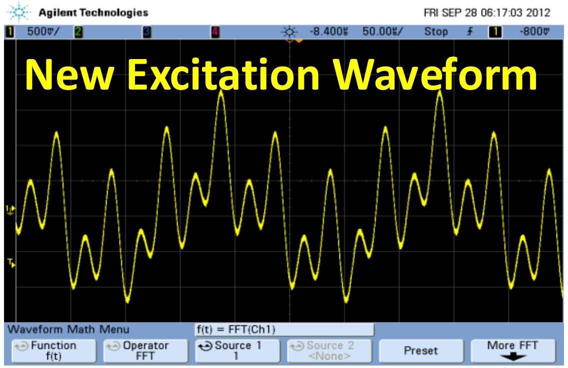
- *D. Serrano et al., "Why MagNet: Quantifying the Complexity of Modeling Power Magnetic Material Characteristics," TPEL'23.*

Steady State Power Magnetics Modeling

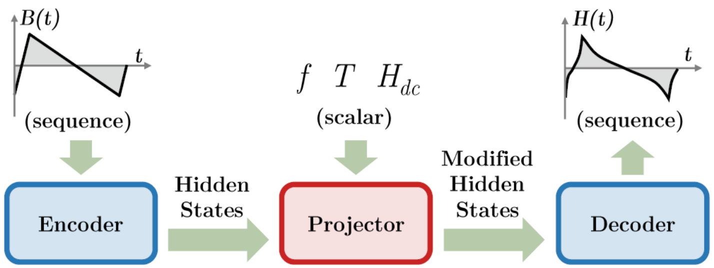
- **Fully automated data acquisition for a wide range of excitations**



- **NN models for arbitrary B-H loop responses**



Seq-2-seq regression model from B(t) to H(t), and P_V



- *H. Li et al., "How MagNet: Machine Learning Framework for Modeling Power Magnetic Material Characteristics," TPEL'23.*

Princeton MagNet Project – From Database to Models

Princeton MagNet

Princeton Power Electronics Research Lab

http://mag-net.princeton.edu

IMAGENET

*Joseph Henry's **Magnet** in 1832 at Princeton*

Website Development → Magnetics Simulation (plexim, electrical engineering software)

Automatic Data Acquisition → MagNet Database → Machine Learning Methods

Data Quality Control

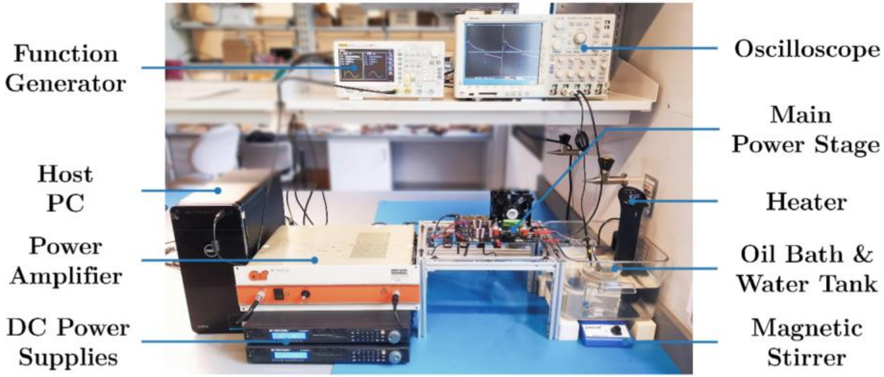
Equation-based Models

- *M. Chen et al., "MagNet Challenge for Data-Driven Power Magnetics Modeling," OJPE'25.*

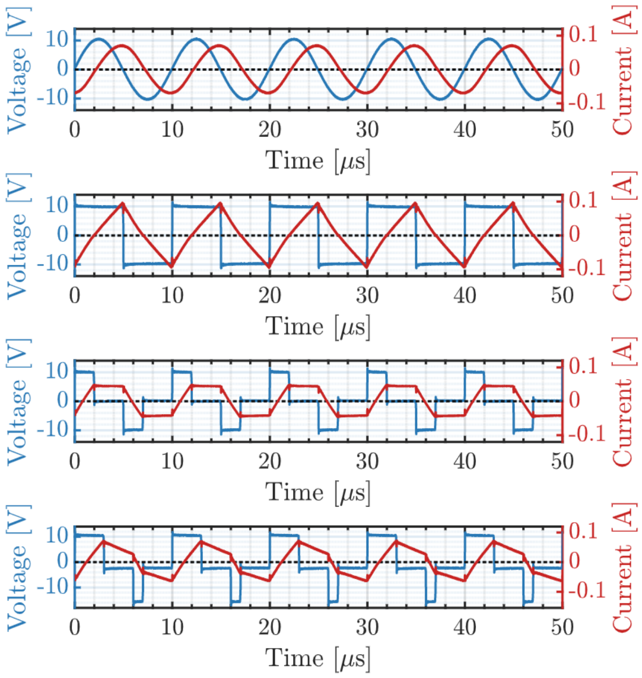
MagNet Core Team Members:

Haoran Li **D. Serrano** **T. Guillod** **S. Wang**

Fully Automated Data Acquisition



50 datapoints/min
3000 datapoints/hour



- Frequency range: 50~500 kHz
- Flux density range: 20~300 mT
- Temperature range: 25~90 °C
- Dc-bias range: 0~300 mT
- Sinusoidal (f, B, THD)
- Triangular (f, B, D)
- Trapezoidal (f, B, D_1, D_2)

More than 1,500,000 B-H loop pairs for 15 materials under different f, T, H_{dc}, and waveforms

Data Quality Control and Model Accuracy

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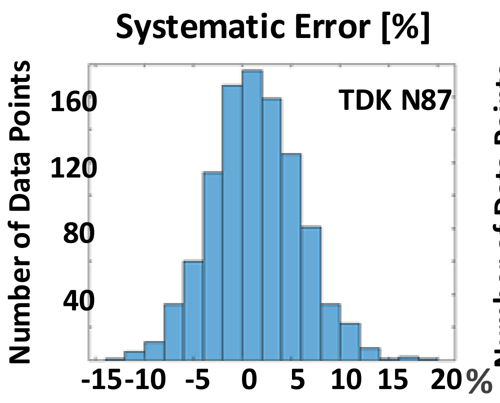
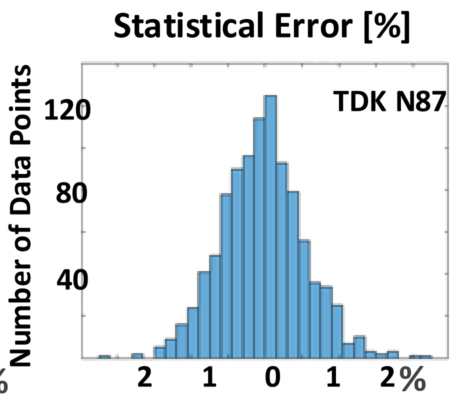
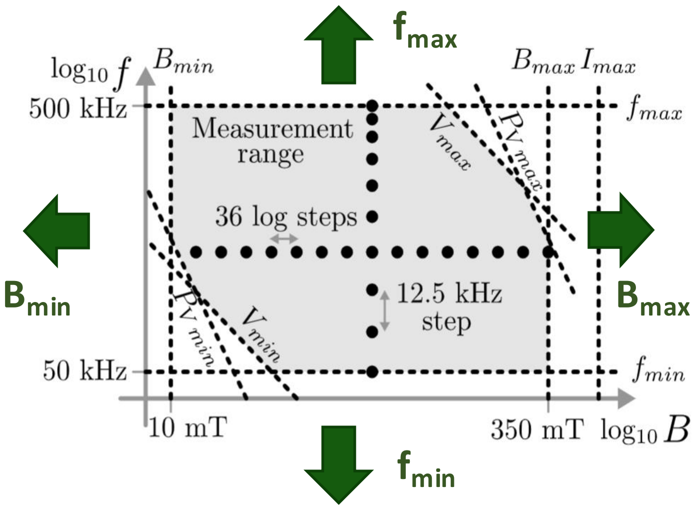




- **Amplitude error**
  - Voltage bias/gain
  - Current bias/gain
- **Phase error**
  - Voltage delay
  - Current delay
- **Parasitic capacitance**
- **Temperature drift**
- …

- **Amplitude noise**
  - Voltage noise
  - Current noise
- **Phase noise**
  - Voltage noise
  - Current noise
- **Quantization error**
- **Core geometry error**
- …



Limited by amplitude error at low loss

MagNet Data Quality (self-evaluated)

- ~15% core loss error (95th percent)
- 5% ~ 20% batch-to-batch variation

Data accuracy limits model accuracy

Machine Learning Methods and Neural Network Models

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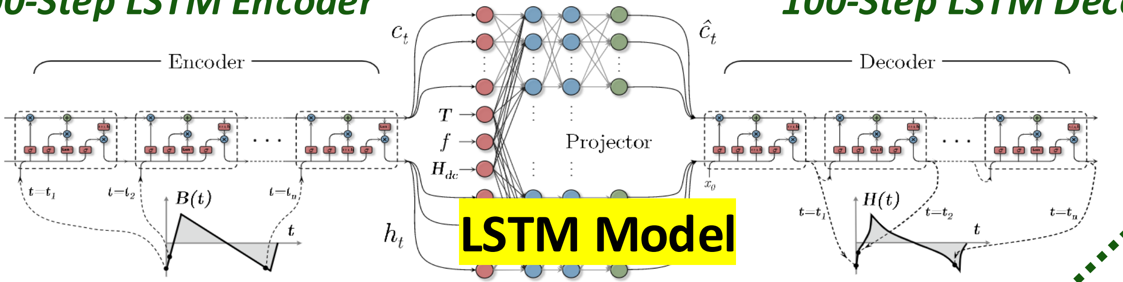
100-Step LSTM Encoder

100-Step LSTM Decoder

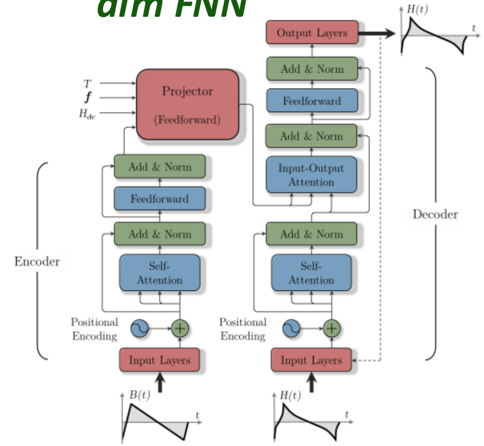


LSTM Model

32-Neuron FNN Projector

Transformer Model

24-dim attention 32-dim FNN



- Evaluated Transformer models and LSTM models
- Transformer tends to perform better than LSTM
  - Due to the positional encoding mechanisms
- "Neural-network as datasheet" for power magnetics

- *Diego Serrano et al., "Why MagNet: Quantifying the Complexity of Modeling Power Magnetic Material Characteristics," TPEL'23.*
- *Haoran Li et al., "How MagNet: Machine Learning Framework for Modeling Power Magnetic Material Characteristics," TPEL'23.*
- *Haoran Li et al., "MagNet-AI: Neural Network as Datasheet for Magnetics Modeling and Material Recommendation," TPEL'23.*

Neural Network Training Process

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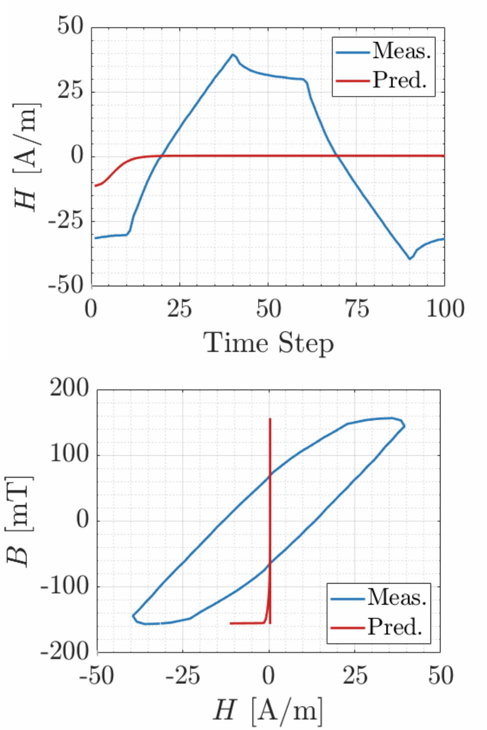
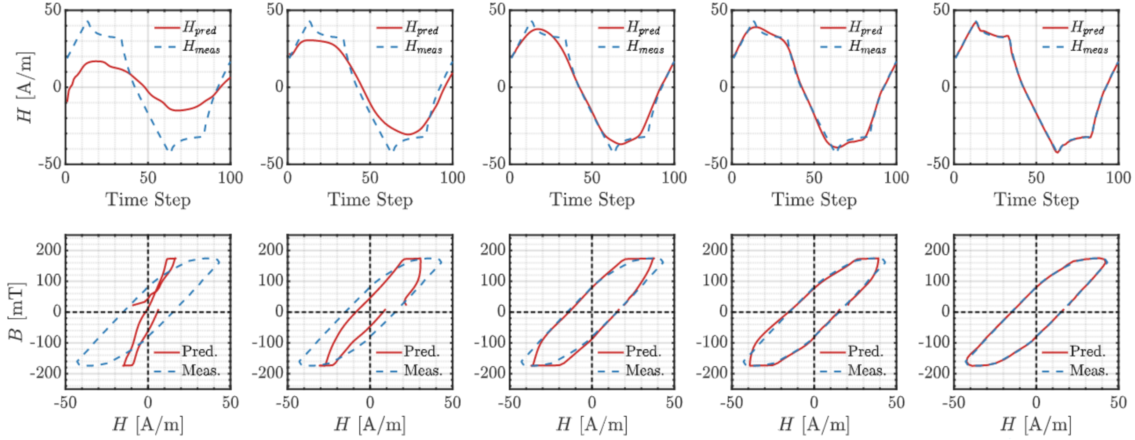
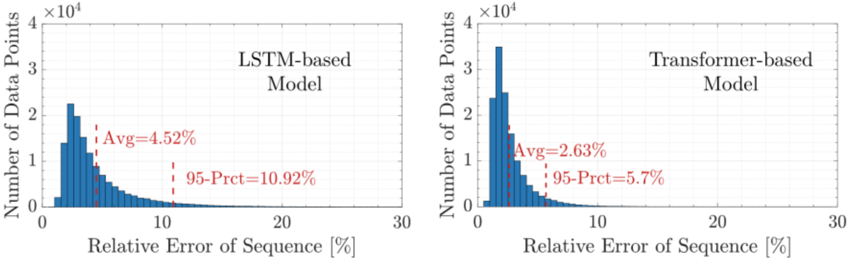
Training Process (N87)

20% 40% 60% 80%

amount of data the model sees







Number of param.: ~ 5,000

NN training time: ~ 4 hrs

Prediction error:

~ 5% Average MSE

~ 15% maximum MSE

Transfer Learning from Materials to Materials

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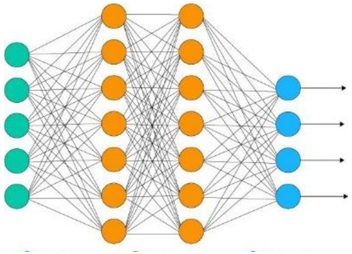
Large Database

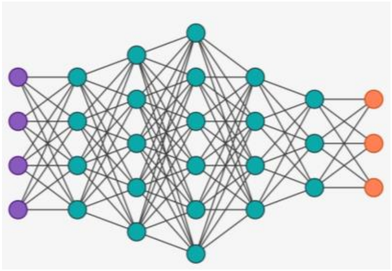
N27, 3C90, 3F3, 3F4, …
25°C, 50°C, 75°C, …
Sine, Triangle, Trapezoidal, …
Bias 0 mT, 100 mT, 200 mT, …

Pre-training
(4 hrs)

General Neural Network



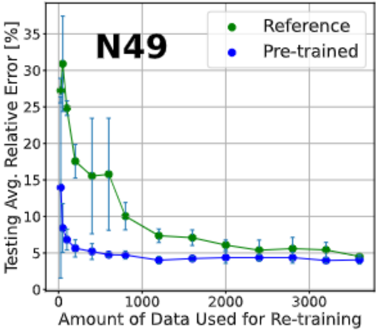
Specific Neural Network

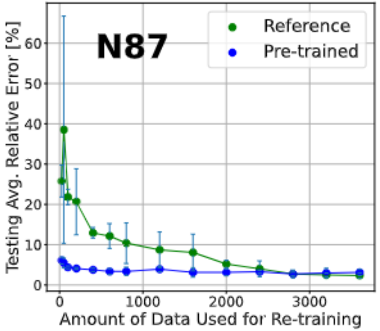


Small Database

A new material
N87, Sine wave, at 25°C
No dc-bias data

Fine-tuning
(10 mins)





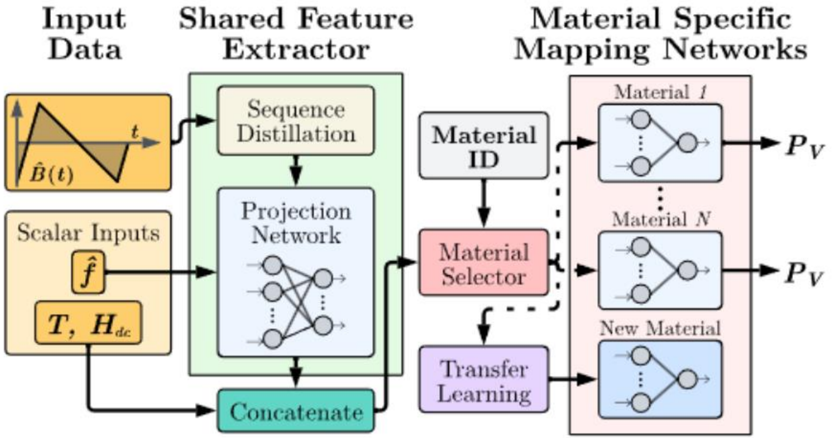
- *E. Dogariu, M. Chen, et al., "Transfer Learning Methods for Magnetic Core Loss Modeling," COMPEL'21.*
- *D. Serrano, M. Chen, et al., "Neural Network as Datasheet: Modeling B-H Loops of Power Magnetics with Sequence-to-Sequence Long-Short-Term-Memory Network," COMPEL'22.*

10× reduction in needed training data

Scalable Neural Network Modules and Building Blocks

https://mag-net.princeton.edu/

General Network **Specific Network**



Model Type	Shared Parameters	Material Specific Parameters	6 Materials Total
Single Material	0	5,569	33,414
Our Framework	14,864	573	18,302

Volumetric Loss: 71.97 kW/m^3

Ranking among included materials:

	Material	Core Loss [kW/m^3]	This or
1	N49	20.5900	
2	3C90	41.1200	
3	3C94	44.7400	
4	78	53.6800	
5	77	61.8300	
6	N30	62.1100	
7	3E6	64.7900	
8	N27	68.8000	
9	N87	71.9700	✓
10	[illegible]	[illegible]	

Better

Worse

- *E. Deleu et. al., "A Compact Machine Learning Framework for Multi-Material Core Loss Modeling," APEC'24.*

MagNet Challenge 1 – Inspiration from ImageNet

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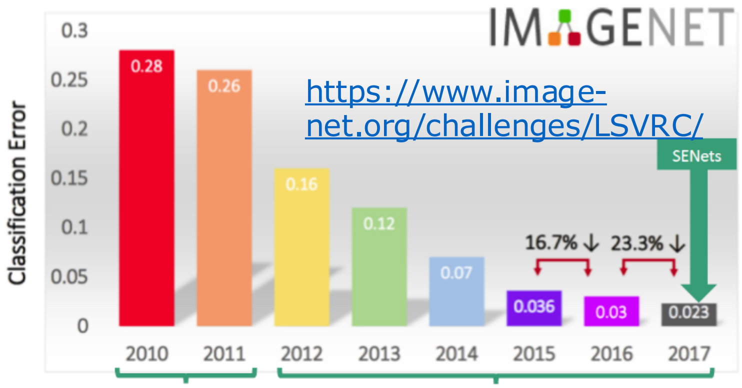
IMAGENET Challenge



https://www.image-net.org/challenges/LSVRC/

[Statistics provided by ILSVRC]

Fei-Fei Li

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Stanford University

pels MagNet challenge

Budget: $55,000

Google

ENPHASE.

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Alan Mantooth

PSMA

Matt Wilkowski

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5th Int'l Symp on 3D Power Electronics Integration & Mfgr.
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MagNet Challenge 1 – Steady State Modeling

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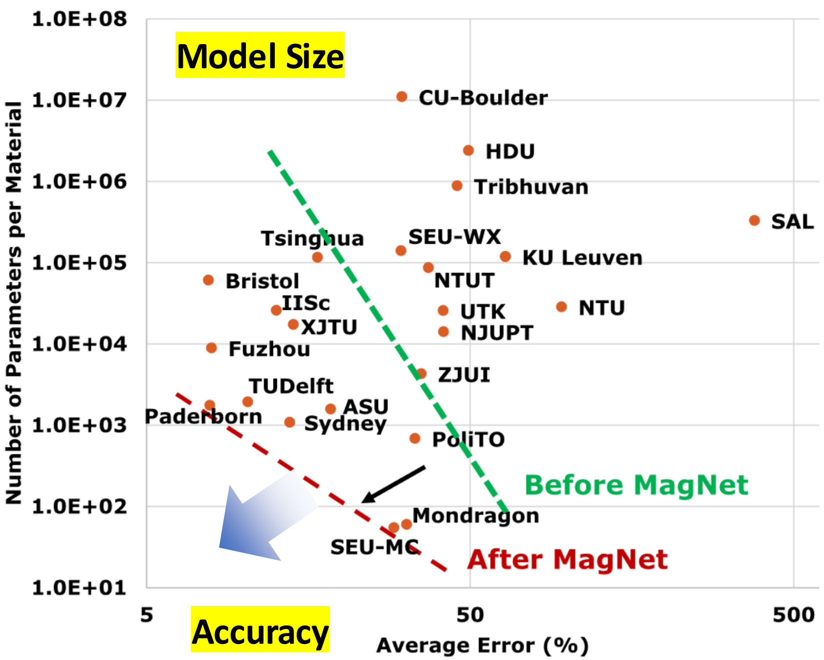

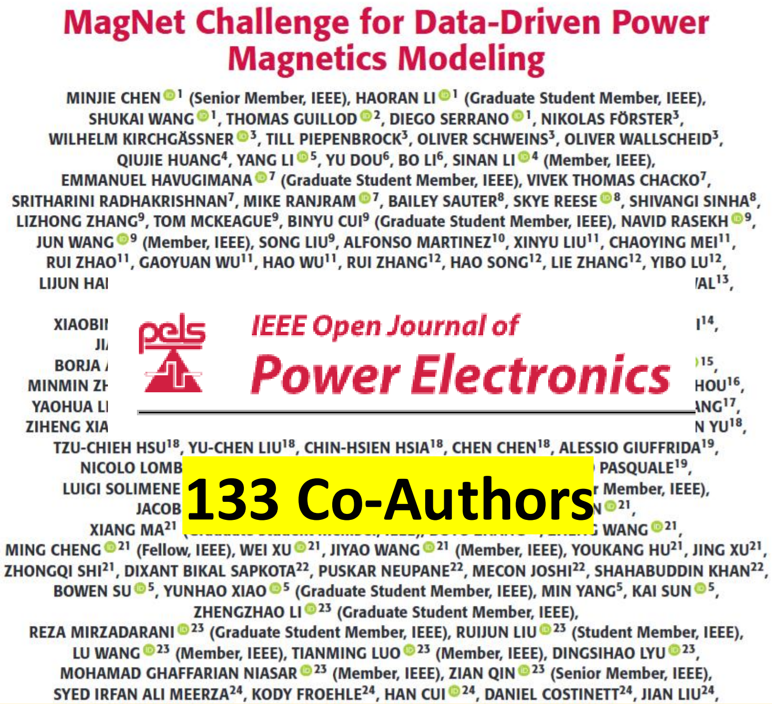

MagNet Challenge for Data-Driven Power Magnetics Modeling

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pels IEEE Open Journal of Power Electronics

133 Co-Authors

- < 1000 parameters for <15% error, across temperature, dc-bias, freq, arbitrary waveforms
- An international open-source community jointly developing various software tools for design

MagNet Challenge 2: Non-Linear Transient Modeling

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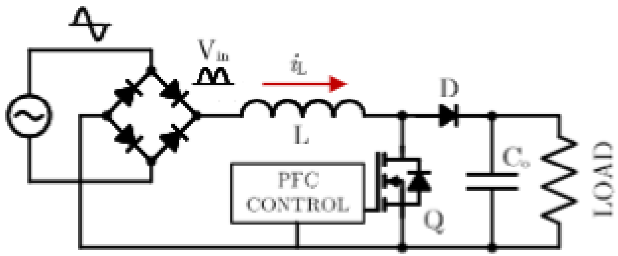
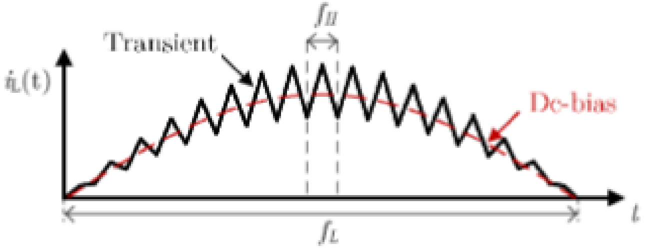
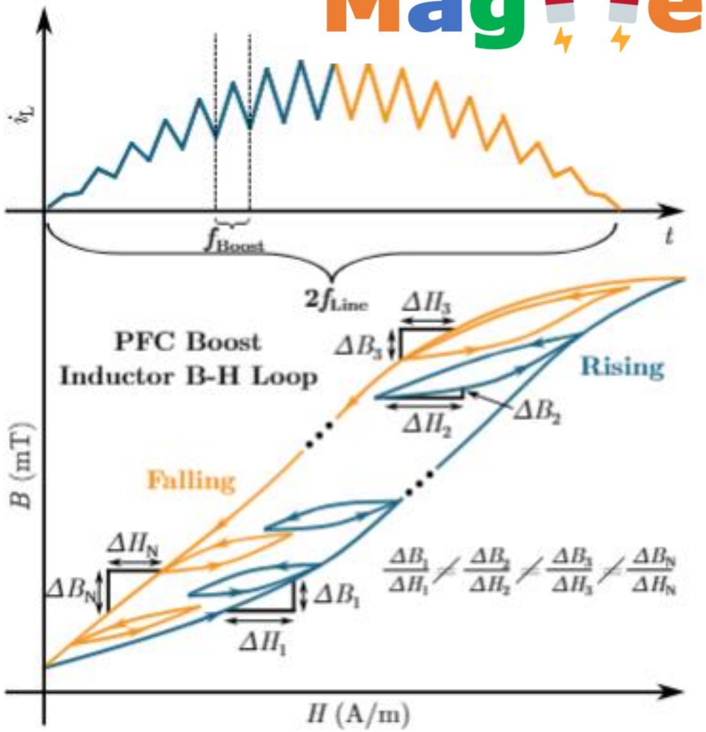
Transient and Quasi-Steady-State

IEEE pels MagNetX Challenge 2







Shukai Wang

Hyukjae Kwon

- H. Kwon et al., "MagNetX: Extending the MagNet Database for Modeling Power Magnetics in Transient," APEC'25.
- S. Wang et al., "MagNetX: Foundation Neural Network Models for Simulating Power Magnetics in Transient," APEC'25.

Foundation Time Domain Models for Power Magnetics

1 Frequency agnostic

- Any arbitrary / non-steady state waveforms in variable frequency

2 Universal time step

- Long- or short-time steps

3 Initial state impact

- Impact of the initial state has finite time horizon

Unified Time Domain Foundation Models for Hysteretic Passive Components

Shukai Wang[◇], Hyukjae Kwon[◇], Davit Grigoryan[◇], Haoran Li[◇], Thomas Guillod[*], Charles R. Sullivan[*], and Minjie Chen[◇]
[◇]Princeton University, USA; [*]Dartmouth College, USA
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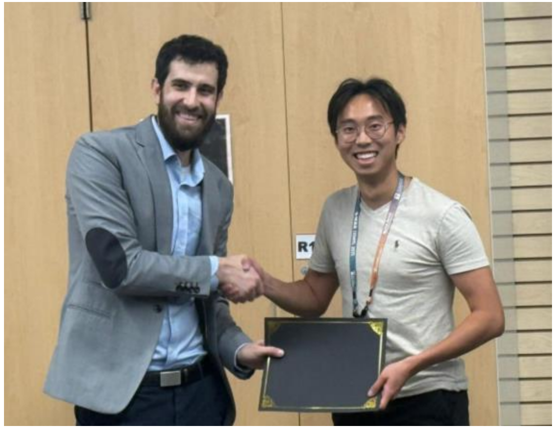
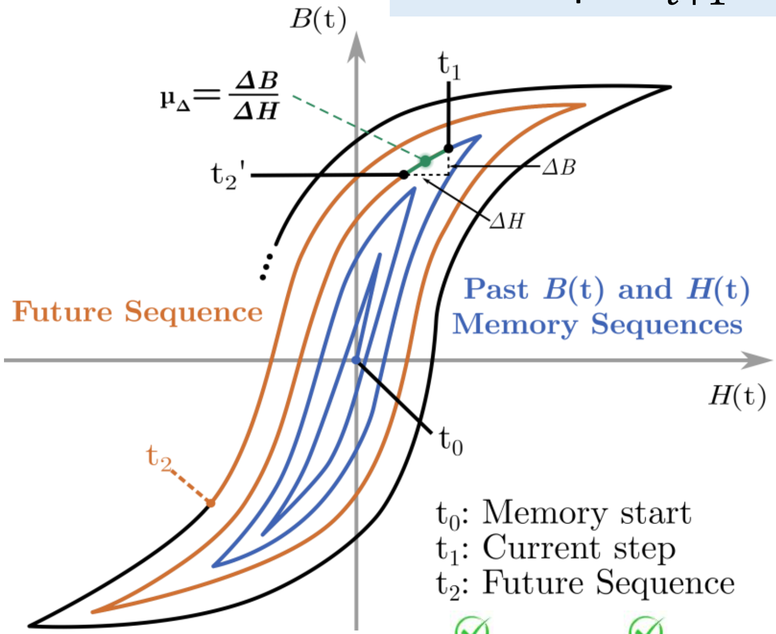
COMPEL'25 Best Paper Award

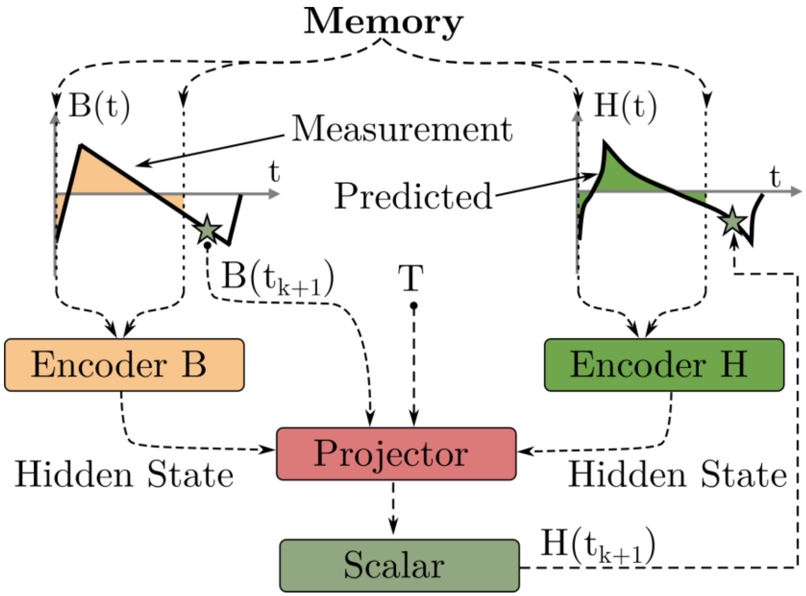


A Example Modeling Framework offered as Tutorials

Next Step: $H_{t+1} = f\ (B(t), H(t), B_{t+1}, Temp)$

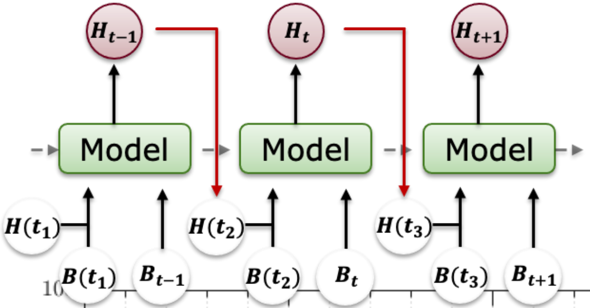


$$H(t_2') = H(t_1) + \frac{B(t_2') - B(t_1)}{\mu_0 \mu_\Delta}$$

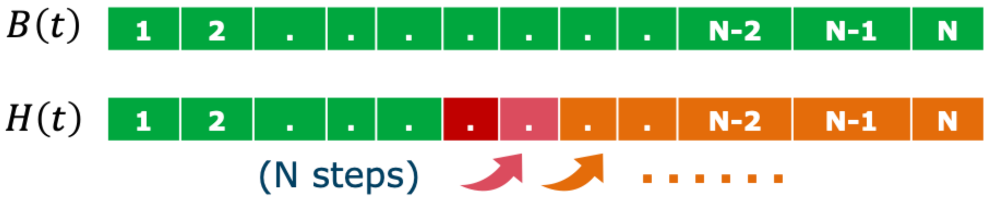


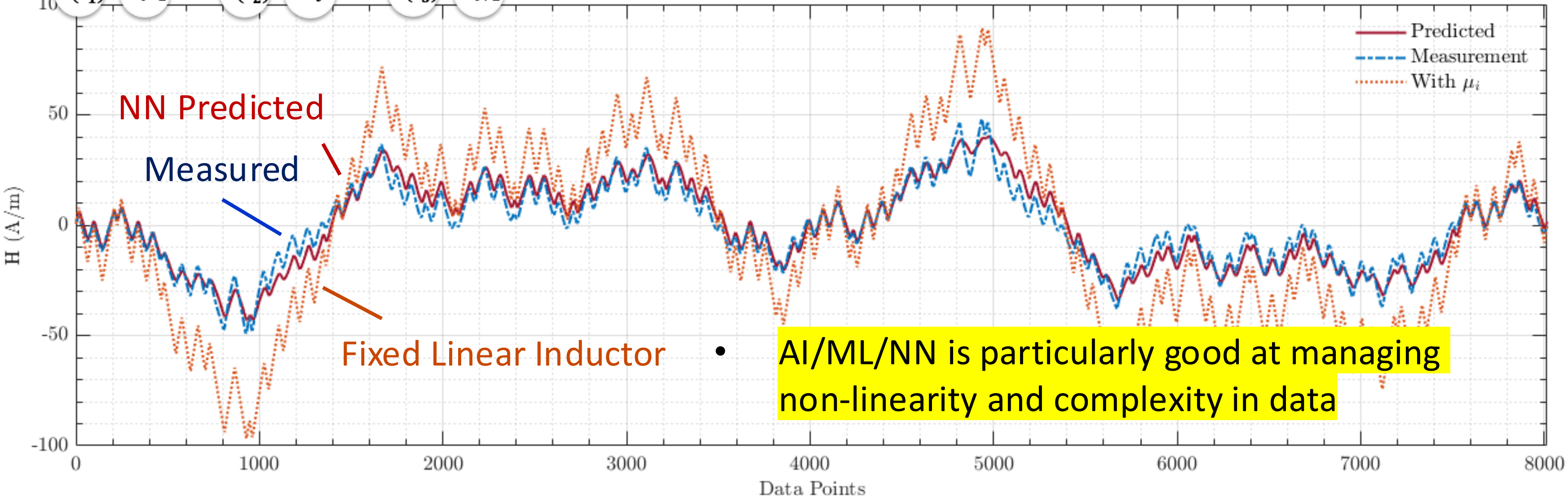
Encoder-Projector-Scalar Architecture

Autoregressive Time Domain Modeling



autoregressive transient prediction

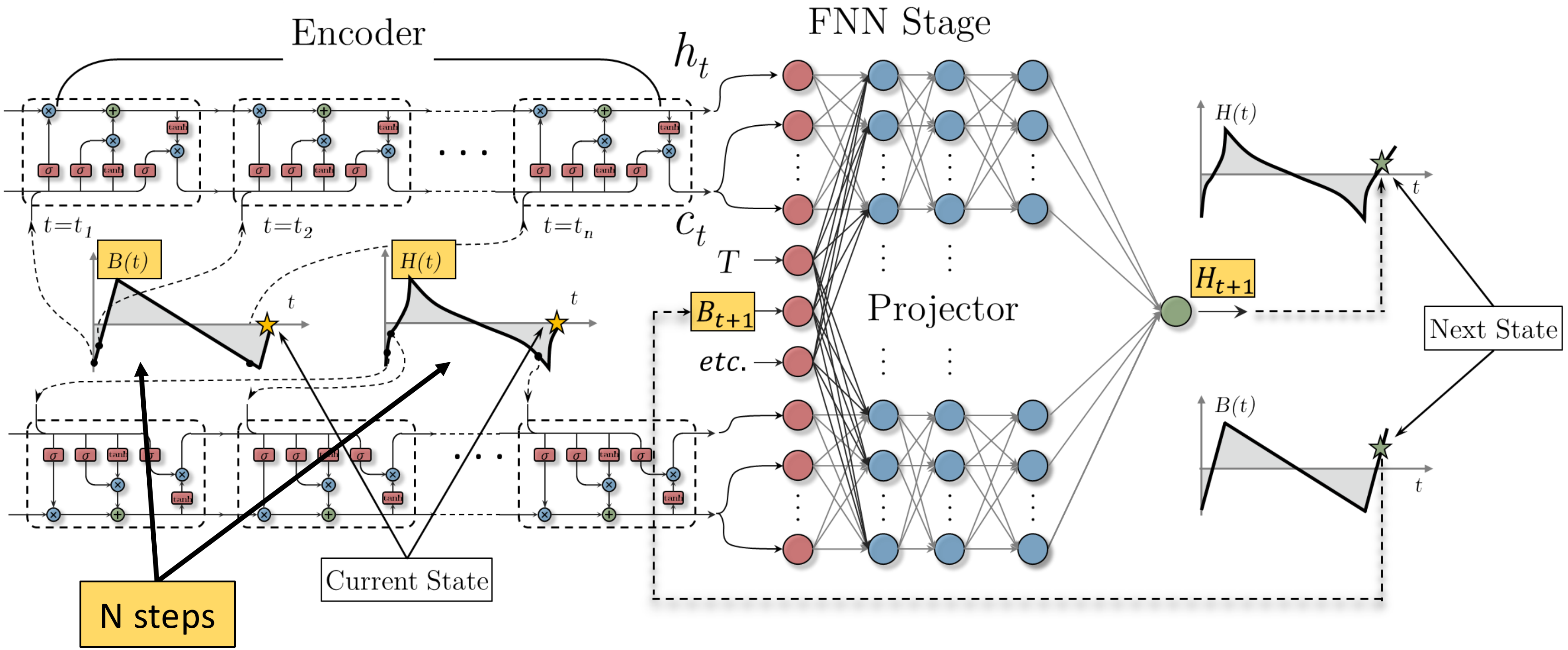




- AI/ML/NN is particularly good at managing non-linearity and complexity in data

Long-Short Term Memory Model

- Double LSTM modules & a projector layer: 771 Parameters



MagNet Challenge 2: A World Cup on Magnetics Modeling

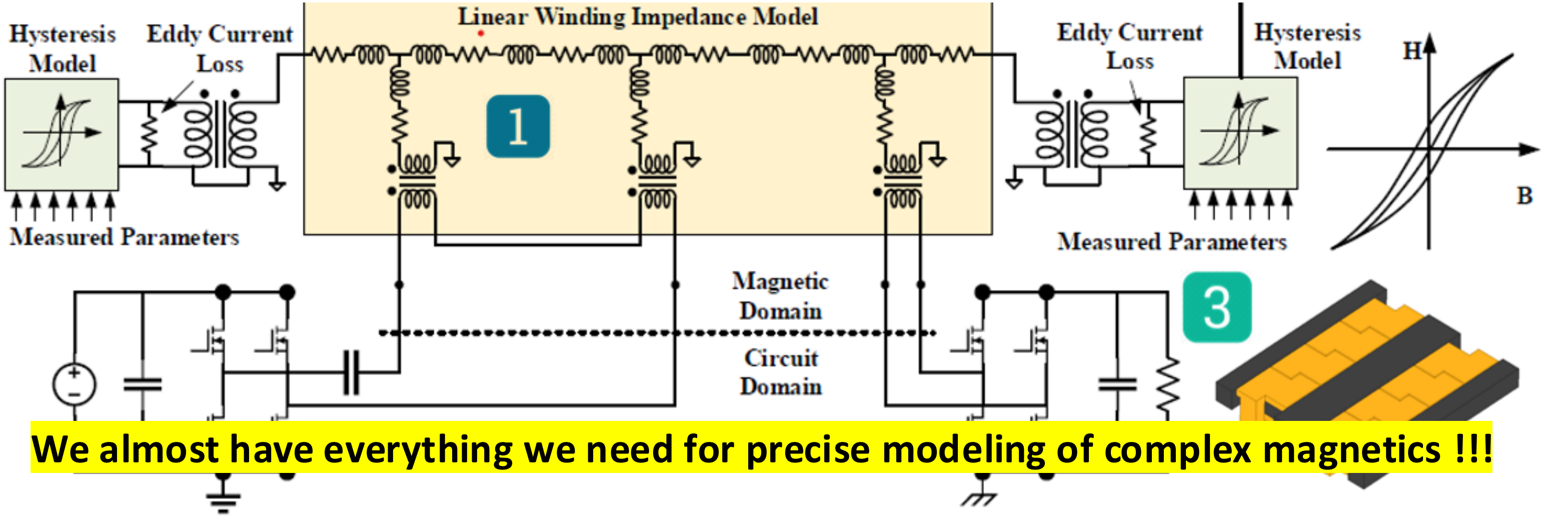
PRINCETON UNIVERSITY

Budget: $60,000

Hybrid Data Driven & Analytical Models for SPICE and FEM

Linear Model for Windings

Non-Linear Model for Materials (LLG/NN)



We almost have everything we need for precise modeling of complex magnetics !!!

Thomas Guillod

Helen Cui

Davit Grigoryan

- *M. Chen, M. Araghchini, K. K. Afridi, J. H. Lang, C. R. Sullivan and D. J. Perreault, "A Systematic Approach to Modeling Impedances and Current Distribution in Planar Magnetics," TPEL'16 Prize Paper.*
- *S. Dulal, S. B. Sohid, H. Cui, G. Gu, D. J. Costinett and L. M. Tolbert, "A Physics-Based Circuit Model for Nonlinear Magnetic Material Characteristics," APEC'24.*

Data-Driven Methods for Extreme Performance Passives

PRINCETON UNIVERSITY

IEEE pels MagNetX Challenge 2

Summary:

- Complex & Precise Design
- Complex & Precise Models
- Time Domain
- Non Linear
- Large Signal
- Data Driven + Hybrid
- AI/NN enhanced SPICE/FEM for Extreme Performance Passives