2nd IEEE International Challenge in Design Methods for Power Electronics

2025 IEEE Power Electronics Society

MagNet Challenge 2

"From Steady-State to Transient Models!"

Tutorial Session 4, June 6, 2025

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MagNet 2025 Organizing Team

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Agenda

- **Webinar 1 – Data and Neural Network Methods**
  - May 16th Friday, 9 AM EST
- **Webinar 2 – Analytical Methods (by Dr. Thomas Guillod)**
  - May 23th, Friday, 9 AM EST
- **Webinar 3 – Model Testing and Evaluation Rules**
  - May 30th, Friday, 9 AM EST
- **Webinar 4 – Brainstorm and Q&A**
  - June 6th, Friday, 9AM EST

Registered Teams

Nagoya Institute of Technology
The Hong Kong Polytechnic University
TU/e Eindhoven University of Technology
Nanyang Technological University Singapore
Hangzhou Dianzi University
Aalborg Universitet
The University of Sydney
Hefei University of Technology
ASU
Universidade Federal de Santa Catarina
National Institute of Technology Calicut
Fuzhou University
Katholieke Universiteit Leuven
TUM
Southeast University
Politecnico di Torino
Tokyo Metropolitan University
SAL Silicon Austria Labs
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MagNetX
Universität Siegen
University of Bristol
Tsinghua University
Fujian University of Technology
Hangzhou Dianzi University
UTS University of Technology, Sydney
Georgia Tech
Princeton University
Dartmouth
Xiamen University of Technology
Indian Institute of Technology Dharwad
Shanghai Jiao Tong University
University of Cambridge
Mizzou University of Missouri
Tianjin University (Peiyang University)
University of Leeds
Universität Paderborn
UESTC
ITG Trusted Innovation Magnetics & EMI Filters
tsmc
pSemi A Murata Company
NVIDIA
Texas Instruments
Würth Elektronik

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Timeline of the MagNet Challenge 2

Feb 13st, 2025	Initial Call for Participation Announcement
Feb 26th, 2025	MagNet Challenge 2 Information Session
March 18th, 2025	APEC Official Announcement
April 1st, 2025	Online Q&A Session
May 1st, 2025	1-Page Letter of Intent Due with Signature [Attached]
June 15th, 2025	2-Page Proposal Due for Eligibility Check [TPEL Format]
July 1st, 2025	Notification of Acceptance [Eligibility Check]
Nov 1st, 2025	Preliminary Submission Due, Finalists Selected
Dec 24th, 2025	Final Submission Due
March 1st, 2026	Winner Announcement and Presentation

April 1st - Large amount of data for 10 materials released

May 1st – 1-Page letter of intent due

June 15th – 2-Page proposal due

July 1st – All participating teams confirmed

Nov 1st – Release small training data for 5 new materials

MagNet Methodology

- Develop methods on **old** materials
- Test methods on **new** materials
- Train models with **small** datasets
- Test models with **large** datasets

Dec 24th – Callable models and predicted core loss (P_v) and B-H trajectory for 10+5 materials under a variety of {B(t), f, T} conditions, and a 5-page TPEL format report due

March 1st , 2026 – Winner Announcement

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Motivation for the MagNet Challenge 2

- No good method to design magnetics in transient.
- **more precise material ↔ more precise model ↔ more precise design.**
- Reduced design margins (thermal, B_{sat}, batch-to-batch variation, …).
- Opportunities to reduce the size of all magnetics by 20%~50%?

An example PFC converter

Make every AC-DC adapters 30% smaller?

MagNet 2025 – A Transient Challenge

Steinmetz Equation
(1890s)

Preisach Model & J-A Model
(1930s) & (1980s)

Foundation Model for Power Magnetics

Read history and predict future based on new inputs

Foundation Model

Frequency agnostic

- Any arbitrary / non steady state waveforms

Universal time step

- Long- or short-time steps

Initial state impact

- Hypothesis: impact of initial state has finite time horizon

Rigorous Mathematical Framework

- Flexible, Accurate
- Converge over time to steady state condition
- Explainable modeling framework
- Physics-based, data-driven, or hybrid …

Outcome: A Callable Prediction Function

Training data:
- 10 training materials
- Lots of long B(t)-H(t) pairs
- Temperature

Testing data:
- 5 new materials
- Temperature
- Practicing: plenty of long B(t) and H(t) pairs
- Testing:
  - B(t) and H(t) pairs from t_0 to t_1
  - B(t) from t_1 to t_2

Output:
- H(t) from t_1 to t_2

Evaluate:
- Total core loss from t_1 to t_2
- H(t) RMS error from t_1 to t_2
- Model size (# of parameters)

- Hyukjae Kwon, Shukai Wang, Haoran Li, et al. "**MagNetX: Extending the MagNet Database for Modeling Power Magnetics in Transient**," *TechRxiv*. December 11, 2024. Accepted to APEC 2025.

Information Flow of MagNet Challenge 2

Next step: $H_{t+1} = function\,(B(t), H(t), B_{t+1}, T)$

Long cycle: $H_{t_1 \to t_2} = function\,(B(t), H(t), B_{t_1 \to t_2}, T)$

Information Flow of MagNet Challenge 2

Next step: $H_{t+1} = function\,(B(t), H(t), B_{t+1}, T)$

Long cycle: $H_{t_1 \to t_2} = function\,(B(t), H(t), B_{t_1 \to t_2}, T)$

New MagNetX Dataset for Transient Dynamics

- How to collect transient data?
  - A mix of high frequency transient and low frequency steady state
  - Applicable to PFC converters, etc.

Example symmetric magnetizing and demagnetizing sequences

15 ferrite materials

13,587 sequences per material

Fixed sampling frequency: 16 MHz

Duty cycle step changes D = 0.2~0.8, min step size = 0.1

Fixed 7 subcycle frequency f = 50kHz~800kHz

Three temperatures: 25°C, 50°C, 70°C

100 subcycles per sequence

- Hyukjae Kwon, Shukai Wang, Haoran Li, et al. "**MagNetX: Extending the MagNet Database for Modeling Power Magnetics in Transient**," *TechRxiv*. December 11, 2024. Accepted to APEC 2025.

MagNetX Database

IEEE pels MagNetX Challenge 2

Material	Data Sequence
Ferroxcube 3C90	13,587
Ferroxcube 3C94	9,224
Ferroxcube 3E6	7,407
Ferroxcube 3F4	10,714
Fair-Rite 77	10,726
Fair-Rite 78	9,845
TDK N27	11,456
TDK N30	10,580
TDK N49	7,266
TDK N87	12,313
Total	103,118

- Collected 10 materials, including 103,118 sequences

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Data Structure

For Training

- Material format:
  - 7 sets of B(t), H(t), T for each material
  - Frequency information not provided
- Sampling frequency for all sequences: 16MHz
  - 50kHz: 32016 steps
  - 80kHz: 20016 steps
  - 125kHz: 12816 steps
  - 200kHz: 8015 steps
  - 320kHz: 4975 steps
  - 500kHz: 3216 steps
  - 800kHz: 2016 steps

Testing

- Same length for all sequences (1000 steps)

Material Folder: 3C90

3C90_1_B	3C90_3_H	3C90_5_T
3C90_1_H	3C90_3_T	3C90_6_B
3C90_1_T	3C90_4_B	3C90_6_H
3C90_2_B	3C90_4_H	3C90_6_T
3C90_2_H	3C90_4_T	3C90_7_B
3C90_2_T	3C90_5_B	3C90_7_H
3C90_3_B	3C90_5_H	3C90_7_T

What we have developed (as tutorials)

Input: B(t) in the past 80 steps
H(t) in the past 80 steps
future B(t) from t_1 to t_2
Output: future H(t) from t_1 to t_2

- Shukai Wang, Hyukjae Kwon, Haoran Li, et al. "**MagNetX: Foundation Neural Network Models for Simulating Power Magnetics in Transient**." *TechRxiv.* December 11, 2024. Accepted to APEC 2025.

Machine Learning Foundation Models

Single next step: $H_{t+1} = function\,(B(t), H(t), B_{t+1}, T)$

What B(t) and H(t) memory information to acquire?

Dataset Setup

Original Dataset: 54 GB-sized file with full training

Freq (kHz)	50	80	125	200	320	500	800
No. of Seqs (M)	647	1459	2252	3252	3269	3300	3090
Seq Length (N)	32016	20016	12816	8015	5008	3216	2016

- Every data point prediction requires information about two memory sequences of *B(t)* and *H(t)*
  - What are the important points?
  - How long of a memory?

Select training points that is in a good range?

$\Delta H = 0 \rightarrow \Delta\mu = \inf$

Dataset Setup

Training Dataset:

Freq (kHz)	50	80	125	200	320	500	800
No. of Seqs (M)	53	82	85	501	1123	1698	2277
Seq Length (N)	10000	6000	6000	1000	600	600	400
No. of Points	530000	492000	510000	501000	673800	1018800	910800
Percentage	11.4%	10.6%	10.9%	10.8%	14.5%	21.9%	19.6%

Training Tutorial

- Please visit MagNet Challenge GitHub: https://github.com/minjiechen/magnetchallenge-2
- Or MagNetX GitHub: https://github.com/PaulShuk/MagNetX

Network Training

This tutorial demonstrates how to train the double LSTM-based model for the seqeunce-to-scalar future hysteresis step prediction. The model may serve as a good starting point for the neural network based transient magnetic modeling. The network model will be trained based on 3C90_Training_Tutorial.h5 file and saved as a state dictionary (.sd) file. The training data is a all frequency inclusive, 50-sequences per freqeuncy dataset with each seuqence containing only 1000 randomly selected time steps for training, operating under all availble temepratures, and flux excitations.

Step 0: Import Packages

In this step we import the important packages that are necessary for the training.

In [1]:

```
from google.colab import drive
drive.mount('/content/drive')

import torch
from torch import Tensor
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import random
import numpy as np
import json
import math
import csv
import time
import h5py
```

```
Mounted at /content/drive
```

Model Evaluation

Single-Step Prediction

Single-Step Prediction

Autoregressive Prediction

Training Tutorial

- Please visit MagNet Challenge GitHub: https://github.com/minjiechen/magnetchallenge-2
- Or MagNetX GitHub: https://github.com/PaulShuk/MagNetX

1: Network Testing

This tutorial demonstrates how to test the double LSTM-based model for the sequence-to-scalar future hysteresis step prediction. The testset seqeunces include data that has the same sampling time steps as the training dataset. The testing data is a single frequency 200kHz data sequence at 25C. Sequence length = 8015 data points

Step 0: Import Packages

In this step we import the important packages that are necessary for the testing.

```
[24] from google.colab import drive
     drive.mount('/content/drive')

     import torch
     from torch import Tensor
     import torch.nn as nn
     import torch.nn.functional as F
     import torch.optim as optim
     import random
     import numpy as np
     import json
     import math
     import csv
     import time
     import h5py
     import matplotlib.pyplot as plt
```

Model Testing

Autoregressive Prediction

Model Testing

$$H_{t_1 \to t_2} = function\,(B_{t_0 \to t_1}(t), H_{t_0 \to t_1}(t), B_{t_1 \to t_2}, T)$$

Arbitrary 1. Memory Length Mismatch

What if memory window ≠ input time steps?

Input (Known values)

Output (Unknown values)

Ideal case:

Input = Window size

Input > Window size

Sequence Length Mismatch

Input < Window size

Arbitrary 2. Sampling frequency Mismatch

What if sampling frequency is different?

Model sampling f
16 MHz

Lower sampling f
Test dataset

Higher sampling f
Test dataset

Foundation Model Evaluation with Testing Data

① Different sampling frequency

Foundation Model

- Frequency agnostic
- Universal time step

$$f_{input} \,!= f_{samp} \begin{cases} f_1 < f_s : \text{ Upsample} \\ f_2 > f_s : \text{Downsample} \end{cases}$$

Foundation Model Evaluation with Testing Data

MagNetX GitHub: https://github.com/PaulShuk/MagNetX

① Different sampling frequency

Demo_LSTM_Evaluation.ipynb

Foundation Model

Frequency agnostic

Universal time step

def get_dataset(…):

```
# 1. Sampling frequency difference: Interpolation if sampling frequency mismatch exists
if sample_freq_model != sample_freq_test:
    # Time axes for original and interpolated data
    t_B_old = np.arange(B_len) * sample_time_test
    t_H_old = np.arange(H_len) * sample_time_test
    t_H_true_old = np.arange(H_true_len) * sample_time_test

    t_B_new = np.arange(0, total_time_B, sample_time_model / time_factor)
    t_H_new = np.arange(0, total_time_H, sample_time_model / time_factor)
    t_H_true_new = np.arange(0, total_time_H_true, sample_time_model / time_factor)

    # Interpolate each sample
    B_inter = np.array([np.interp(t_B_new, t_B_old, B[i]) for i in range(B.shape[0])])
    H_inter = np.array([np.interp(t_H_new, t_H_old, H[i]) for i in range(H.shape[0])])
    H_true_inter = np.array([np.interp(t_H_true_new, t_H_true_old, H_true[i]) for i in range(H_true.shape[0])])

    # Downsample after interpolation
    B_seq = B_inter[:, ::time_factor]
    H_seq = H_inter[:, ::time_factor]
    H_true_seq = H_true_inter[:, ::time_factor]

    data_length_test = H_seq.shape[1]
    print("data_length_test:", data_length_test)
else:
    # If no interpolation is needed
    B_seq, H_seq, H_true_seq = B, H, H_true
```

1 Handling input with different sampling rates

Foundation Model Evaluation with Testing Data

② Different total time steps T_s

Foundation Model

- Frequency agnostic
- T_s Universal time step

$$T_{input} \,!= T_{samp} \begin{cases} T_1 < T_s \\ T_2 > T_s \end{cases}$$

Foundation Model Evaluation with Testing Data

Foundation Model

Frequency agnostic

Universal time step

② Different total time steps

Demo_LSTM_Evaluation.ipynb

def get_dataset(…):

```
# 2. Time step difference: Adjust length of the sequence if different from model input
if data_length_model > data_length_test:
    # Pad the front with the first value if test data is shorter
    B_ftr = B_seq[:, data_length_test:]
    H_ftr = H_true_seq[:, data_length_test:]

    pad_len = data_length_model - data_length_test
    B_seq = np.concatenate([np.tile(B_seq[:, [0]], (1, pad_len)), B_seq[:, :data_length_test]], axis=1)
    H_seq = np.concatenate([np.tile(H_seq[:, [0]], (1, pad_len)), H_seq[:, :data_length_test]], axis=1)
else:
    # Truncate if test data is longer
    B_ftr = B_seq[:, data_length_test:]
    H_ftr = H_true_seq[:, data_length_test:]
    B_seq = B_seq[:, data_length_test - data_length_model:data_length_test]
    H_seq = H_seq[:, data_length_test - data_length_model:data_length_test]
```

2 **Handling input with different memory length**

Testing Dataset for Evaluation

Input (Known values)

Output (Unknown values)

105 sequences

- 7 frequencies
- 3 temperatures
- 5 input/output ratio

Sampling frequency

- 16 MHz
- 62.5 ns

$Temp$

1

Material

- 3C90

Frequency

- 50 kHz
- 80 kHz
- 125 kHz
- 200 kHz
- 320 kHz
- 500 kHz
- 800 kHz

Temperature

- 25 ℃
- 50 ℃
- 70 ℃

Known : Unknown

- 90%:10%
- 70%:30%
- 50%:50%
- 30%:70%
- 10%:90%

Testing dataset is randomly sampled from released data

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Opportunities for Innovation

- How do we determine the training data
  - Sample freq, temp, material
- Model architecture
  - Input (length, format of data, etc.)
  - Output (time series, core loss, etc.)
  - Hidden parameters (physics-informed)
- Model implementation
  - Data driven
  - Analytical
  - Hybrid
- Model generality and scalability
  - Transfer learning
  - General algorithm that works across materials

Testing and Evaluation Tutorial

- Please visit MagNet Challenge GitHub: https://github.com/minjiechen/magnetchallenge-2
- Or MagNetX GitHub: https://github.com/PaulShuk/MagNetX

2: Network Testing

This tutorial demonstrates how to test the double LSTM-based model for the sequence-to-scalar future hysteresis step prediction. The test set seqeunces include data that has the same sampling time steps as the training dataset. However the code is able to decipher the sequence length (provided that it has a sampling frequency), and upsample or downsample as needed to fit the model criteria. If the sequence is longer than the designed memory, then only the most recent time steps (amount to the total training memory time) are taken. If the data length is shorter, then the extra empty memory will take the constant of the most distant memory data point. The test set consists of multiple frequencies (7), temperatures (3), and 5 different combinations of past and future lengths, totaling 105 sequences, each with 1,000 time steps.

Step 0: Import Packages

In this step we import the important packages that are necessary for the testing.

[8]

```python
import torch
from torch import Tensor
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import random
import numpy as np
import json
import h5py
import math
import csv
import time
import matplotlib.pyplot as plt
```

Python

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Testing and Evaluation Results

- H sequence prediction vs measurement

[3C90, 200 kHz, 50 ℃, 10%:90% format]

[3C90, 500 kHz, 70 ℃, 70%:30% format]

Testing and Evaluation Results

- NRMSE of H sequences

```
Memory length 100: Mean NRMSE = 18.74% (0 - 20)
Memory length 300: Mean NRMSE = 20.67% (21 - 41)
Memory length 500: Mean NRMSE = 12.25% (42 - 62)
Memory length 700: Mean NRMSE = 15.57% (63 - 83)
Memory length 900: Mean NRMSE = 13.40% (84 - 104)
```

Testing and Evaluation Results

- Energy loss from B-H loops

$$\int H\,dB$$

$$\begin{bmatrix} dB: [V \cdot s/m^2] \\ H: [A/m] \\ HdB: [J/m^3] \end{bmatrix}$$

```python
def compute_total_energy(B, H):
    """
    Computes energy loss per unit volume [J/m³] for each sequence in B and H.
    B, H: numpy arrays of shape (N_sequences, N_timesteps)
    Returns: energy loss per sequence (N_sequences,)
    """
    dB = np.diff(B, axis=1)                        # shape: (N, T-1)
    H_mid = (H[:, :-1] + H[:, 1:]) / 2             # shape: (N, T-1)
    energy_density = np.sum(H_mid * dB, axis=1)    # shape: (N,)
    return np.abs(energy_density)                  # abs to ensure positive energy
```

$\int H\,dB$ (open loop): Energy exchanged ≠ total core loss (cycle not closed)

NRMSE
39.78 %

Conclusion

Training data

- 10 training materials
- Lots of long B(t)-H(t) pairs
- Temperature

Testing data

- 5 new materials
- Temperature
- Practicing: plenty of long B(t) and H(t) pairs

Input/Output

- Past B(t) and H(t)
- Future B(t)

↓

- Future H(t)

Evaluate

- Total core loss from t_1 to t_2
- H(t) RMS error from t_1 to t_2
- Model size (# of parameters)

$$H_{t_1 \to t_2} = \begin{matrix} \textit{function} \\ B(t) \\ H(t) \\ B_{t_1 \to t_2} \\ T \end{matrix}$$

- Hyukjae Kwon, Shukai Wang, Haoran Li, et al. "**MagNetX: Extending the MagNet Database for Modeling Power Magnetics in Transient**," *TechRxiv*. December 11, 2024. Accepted to APEC 2025.

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Workflow Step 2: Training

Circuit Model for Magnetics

- **Basic equations**
  - $\boldsymbol{V = N \cdot \int \frac{\mathrm{d}B}{\mathrm{d}t} \mathrm{d}A \;\Rightarrow\; V \propto \frac{\mathrm{d}B}{\mathrm{d}t}}$
  - $\boldsymbol{I = \frac{1}{\mathrm{N}} \cdot \int H\,\mathrm{d}l \;\Rightarrow\; I \propto H}$

- **Circuit model with ODEs**
  - Common for dynamic systems
  - Causality is enforced
  - Non-periodic waveforms
  - Compatible with SPICE
  - Compatible with FEM

$$\frac{\mathrm{d}\vec{y}\,(t)}{\mathrm{d}t} = f\left(\vec{y}(t), \frac{\mathrm{d}B(t)}{\mathrm{d}t}\right)$$

$$H(t) = g\left(\vec{y}(t), \frac{\mathrm{d}B(t)}{\mathrm{d}t}\right)$$

Simple Linear R-L Circuit

- **Simplest possible circuit**

$$V(t) = R \cdot i(t) + L\frac{\mathrm{d}i(t)}{\mathrm{d}t}$$

$$\frac{\mathrm{d}B(t)}{\mathrm{d}t} = r \cdot H(t) + \mu_0\mu_r\frac{\mathrm{d}H(t)}{\mathrm{d}t}$$

- **Single (linear) ordinary differential equation**
  - Two free parameters (resistance and permeability)
  - Cannot model saturation behavior
  - Cannot model nonlinear losses

Linear R-L Circuit Results

Nonlinear Circuit Definition

- **Transition to a nonlinear circuit**

- **Two decoupled ODEs**
  - Two resistances ($R_i = R_i(H_i)$)
  - Two inductances ($L_i = L_i(H_i)$)
  - Non-linear equations
  - 10 free parameters

Nonlinear Circuit Results

Limitations and Opportunities

- **Equation-based analytical models have potential**
- **Physics-based** (or inspired) **models**
  - Minor loop splitting / decomposition
  - Steinmetz-based model (e.g. iGSE)
  - Using reluctance or permeance models
  - Landau–Lifshitz–Gilbert equation
  - Preisach Hysteresis model
  - Jiles–Atherton model
- **A last warning about such models:**

Physics-based material model $\not\Rightarrow$ **Fitted parameters have a physical meaning**

Vorperian Model and LLG Model

Vorperian Model

LLG Model

- 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," *2024 IEEE Applied Power Electronics Conference and Exposition (APEC)*, Long Beach, CA, USA, 2024, pp. 396-401.

TI - Lloyd Dixon SPICE Model

An Electrical Circuit Model for Magnetic Cores

Lloyd Dixon

Fig 13. - Magnetic Core Equivalent Circuit Model

https://www.ti.com/lit/ml/slup109/slup109.pdf

Neural Differential Equations

- **Neural ODEs**

$$\frac{\mathrm{d}\vec{y}(t)}{\mathrm{d}t} = f\left(\vec{y}(t), \frac{\mathrm{d}B(t)}{\mathrm{d}t}\right)$$

$$H(t) = g\left(\vec{y}(t), \frac{\mathrm{d}B(t)}{\mathrm{d}t}\right)$$

$$\frac{\mathrm{d}\vec{y}(t)}{\mathrm{d}t} = \text{Neural Network}\left(\vec{y}(t), \frac{\mathrm{d}B(t)}{\mathrm{d}t}\right)$$

$$H(t) = \text{Neural Network}\left(\vec{y}(t), \frac{\mathrm{d}B(t)}{\mathrm{d}t}\right)$$

- **Neural networks are defining the ODE functions**
  - Coupled system of nonlinear differential equations
  - Very similar problem to circuit-based ODEs
  - Most of the code / libraries are the same

Neural Differential Equations

- Standard **multilayer perceptron** (MLP) network
- Neural networks are **small and shallow**
- **Scaling** of the variables is **required**

State dynamics: single network:

$$\begin{bmatrix} \mathrm{d}H_1/\mathrm{d}t \\ \mathrm{d}H_2/\mathrm{d}t \\ \vdots \\ \mathrm{d}H_n/\mathrm{d}t \end{bmatrix} = \mathrm{MLP}\left(\begin{bmatrix} H_1(t) \\ H_2(t) \\ \vdots \\ H_n(t) \\ \mathrm{d}B(t)/\mathrm{d}t \end{bmatrix}\right)$$

State dynamics: two networks:

$$\begin{bmatrix} \mathrm{d}H_1/\mathrm{d}t \\ \mathrm{d}H_2/\mathrm{d}t \\ \vdots \\ \mathrm{d}H_n/\mathrm{d}t \end{bmatrix} = \mathrm{MLP}_1\left(\begin{bmatrix} |H_1(t)| \\ |H_2(t)| \\ \vdots \\ |H_n(t)| \end{bmatrix}\right)\begin{bmatrix} H_1(t) \\ H_2(t) \\ \vdots \\ H_n(t) \end{bmatrix} + \mathrm{MLP}_2\left(\begin{bmatrix} |H_1(t)| \\ |H_2(t)| \\ \vdots \\ |H_n(t)| \end{bmatrix}\right)\mathrm{d}B(t)/\mathrm{d}t$$

Output functions: parallel connections:

$$H(t) = \sum_i H_i$$

Neural ODE Results

Limitations and Opportunities

- **Neural ODEs**
  - No clear physical meaning
  - Opportunity for **compact models**
  - Compatible with **existing tooling**

- **Endless possibilities**
  - Neural SDE, neural CDE, latent ODE, etc.
  - System with discrete states (e.g. Preisach-based)
  - Possibility to implement a physics-informed network

- **Some references**

  - P. Kidger, “On Neural Differential Equations”, 2021, https://doi.org/10.48550/arXiv.2202.02435
  - P. Kidger, “Neural Differential Equations in Machine Learning”, 2021, https://kidger.site/links/KltsP45n2UP5/NDE_presentation.pdf

Part IV:
Conclusion and Outlooks

What is the ideal model?

- **Parameters and dataset**
  - Small number of parameters
  - Small dataset for the parametrization
  - Robust parametrization of the model
- **Model performance**
  - Accurate prediction for the field and the losses
  - Extrapolation outside the training/fitting range
  - Predicting waveshapes that are not in the training/fitting data
  - Transition to special cases (small signal, saturation, static curves, etc.)
  - Low computational cost (training and inference)
- **Other qualities**
  - Link with physical phenomena
  - Model debuggability and interpretability
  - Transfer of knowledge between materials
  - Possibility to extend the model (core geometry, DC bias, etc.)
  - Compatible with existing tooling (SPICE, FEM, etc.)

Advantage for analytical models?
Advantage for machine learning?
Unclear advantage ?

General Tips for the Challenge

- **The dataset is quite large**
  - Don't hesitate to create a "simplified fake dataset"
  - Don't hesitate to start with a subset of the dataset
  - Don't hesitate to downsample / truncate the signals
- **Several factors are critical**
  - The model (structure, parameters, etc.)
  - The training/fitting process (optimizer, scaling, etc.)
  - The error metrics used as an objective
- **Programming tips**
  - Use clear interfaces between the training and inference
  - Use vectorized instructions (avoid loops and branches)
  - Nice data structures for storing the results
  - Make tools for displaying the results

Extended Reading – MagNet Challenge 2

- **J-A Model –** D. Jiles and D. Atherton, "Theory of ferromagnetic hysteresis," Journal of Magnetism and Magnetic Materials, vol. 61, no. 1, pp. 48–60, 1986.
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- **Why MagNet –** D. Serrano et al., "Why MagNet: Quantifying the Complexity of Modeling Power Magnetic Material Characteristics," in IEEE Transactions on Power Electronics, vol. 38, no. 11, pp. 14292-14316, Nov. 2023.
- **How MagNet –** H. Li et al., "How MagNet: Machine Learning Framework for Modeling Power Magnetic Material Characteristics," in IEEE Transactions on Power Electronics, vol. 38, no. 12, pp. 15829-15853, Dec. 2023.
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Extended Reading – MagNet Challenge 2

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- **i2GSE** - J. Muhlethaler, J. Biela, J. W. Kolar and A. Ecklebe, "Improved Core-Loss Calculation for Magnetic Components Employed in Power Electronic Systems," in IEEE Transactions on Power Electronics, vol. 27, no. 2, pp. 964-973, Feb. 2012.
- **iGSE-CD** - D. Menzi et al., "iGSE-CD—An Electric-/Displacement-Field Related Steinmetz Model for Class II Multilayer Ceramic Capacitors Under Low-Frequency Large-Signal Excitation," in IEEE Open Journal of Power Electronics, vol. 4, pp. 107-116, 2023.
- **Stenglein Model -** E. Stenglein and T. Dürbaum, "Core Loss Model for Arbitrary Excitations With DC Bias Covering a Wide Frequency Range," in IEEE Trans. on Magnetics, vol. 57, no. 6, pp. 1-10, June 2021.
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- **MagNetX Models -** S. Wang, H. Kwon, H. Li, et al. "MagNetX: Foundation Neural Network Models for Simulating Power Magnetics in Transient," TechRxiv. December 11, 2024.
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