PSMA Power Technology Roadmap Webinar Series

Traditional and Machine-Learning based Magnetic Core Loss Modeling

Prof. Charles Sullivan, Dartmouth &
Prof. Minjie Chen, Princeton

Dartmouth Magnetics and Power Electronics Research Group
Power Management Integration Center

Outline

Charlie Sullivan, Dartmouth, Power Management Integration Center

- Background on capabilities and objectives of core-loss models
- Model based on observed characteristics

Minjie Chen, Princeton

- Automatic data collection
- Data-driven models

Part I:

Background on Capabilities and Objectives of Core Loss Models

Charles R. Sullivan, Professor

http://dartgo.org/pmic

Power Management Integration Center

Dartmouth Magnetics and Power Electronics Research Group

Thayer School of Engineering at Dartmouth

What we know and what we don't know

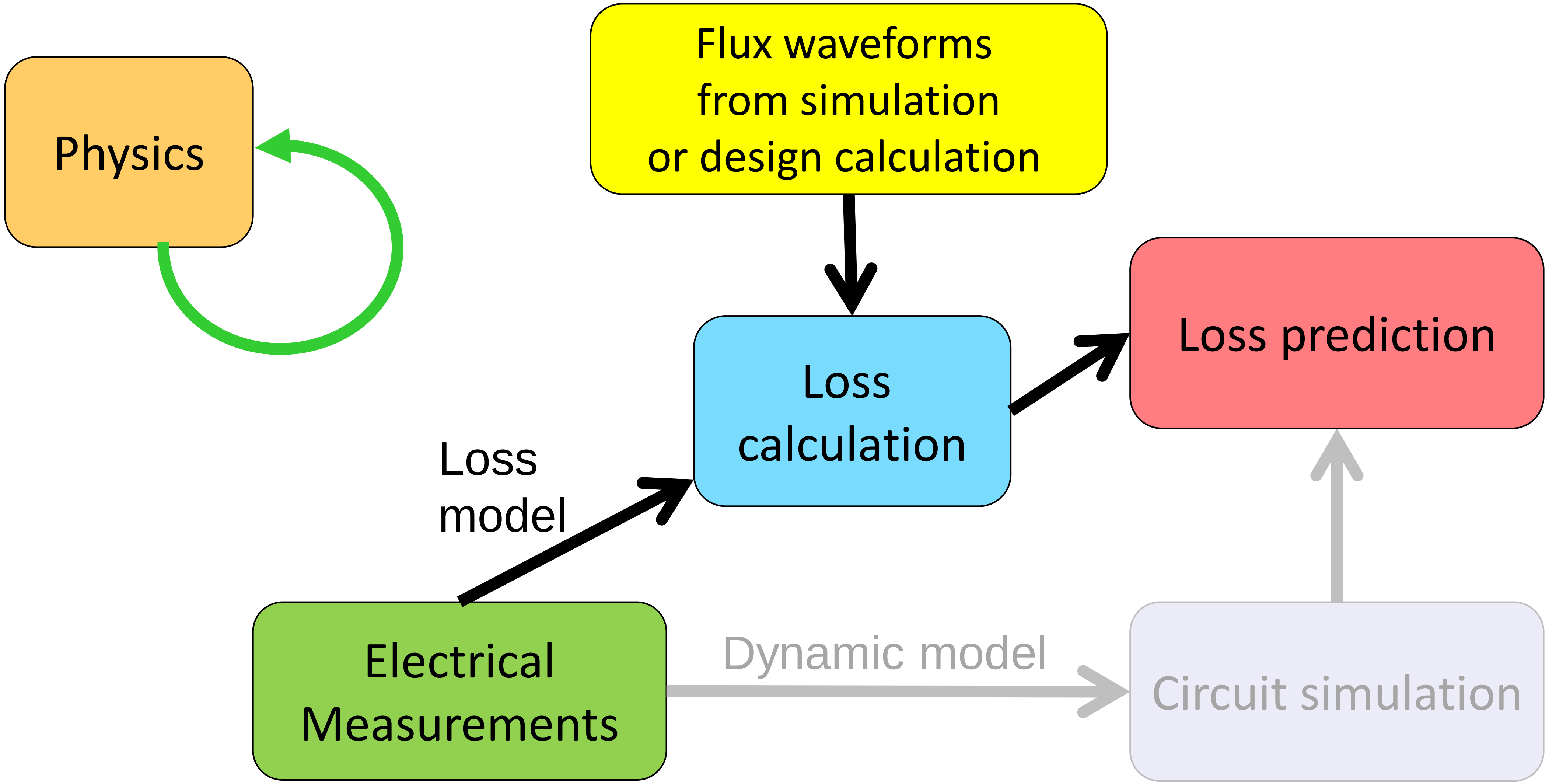
We know:

- How to measure core loss.
- Data for some situations.
- Approximate models, and their limitations.
- A list of loss mechanisms that contribute to loss.

We don't know:

- The physics and physical parameters well enough to make accurate first-principles loss predictions.
- Practical methods to predicting all the relevant loss effects.
- Not enough data is available, especially not publically.

State of the art

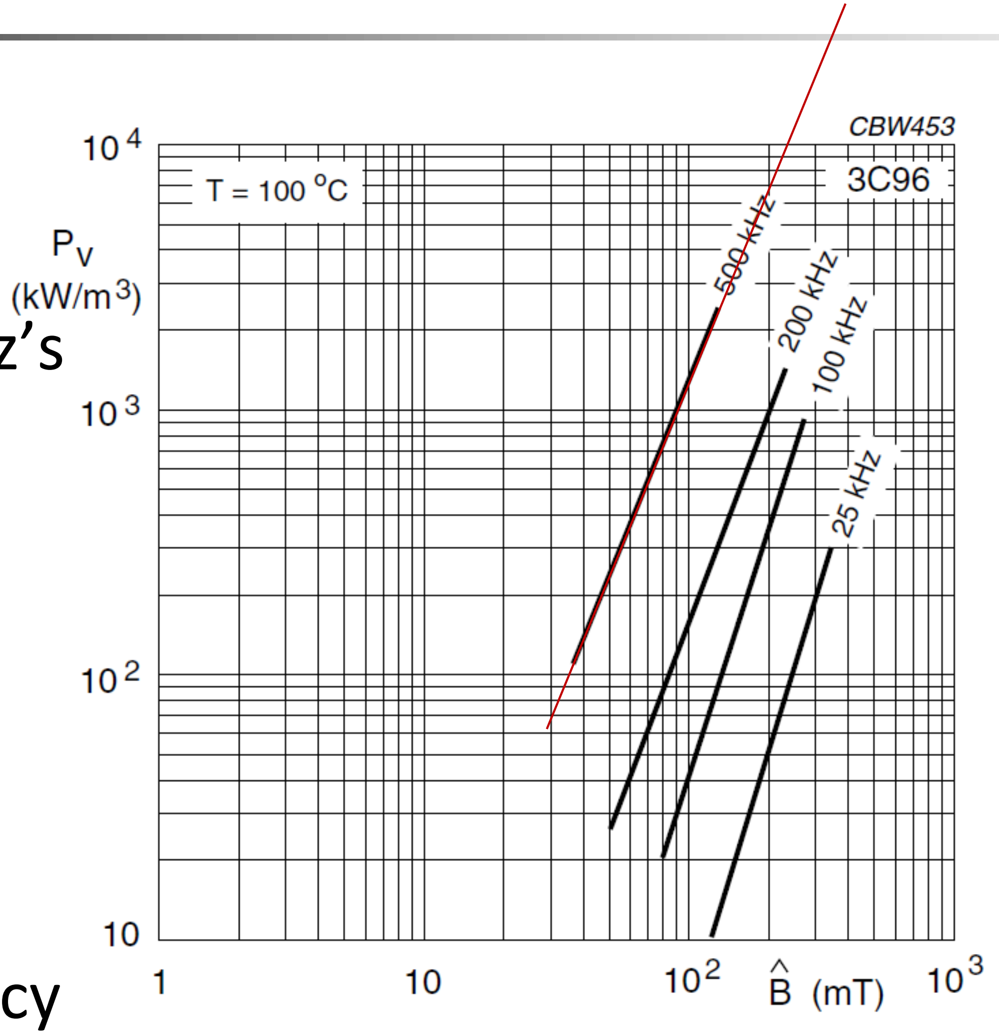


Some data and the Steinmetz model

- For sinusoidal excitation.
- Charles Steinmetz's model: $P = k\hat{B}^{\beta}$
- Typical modern model:

$$P = kf^{\alpha}\hat{B}^{\beta}$$

- Can use different parameters for different frequency ranges.



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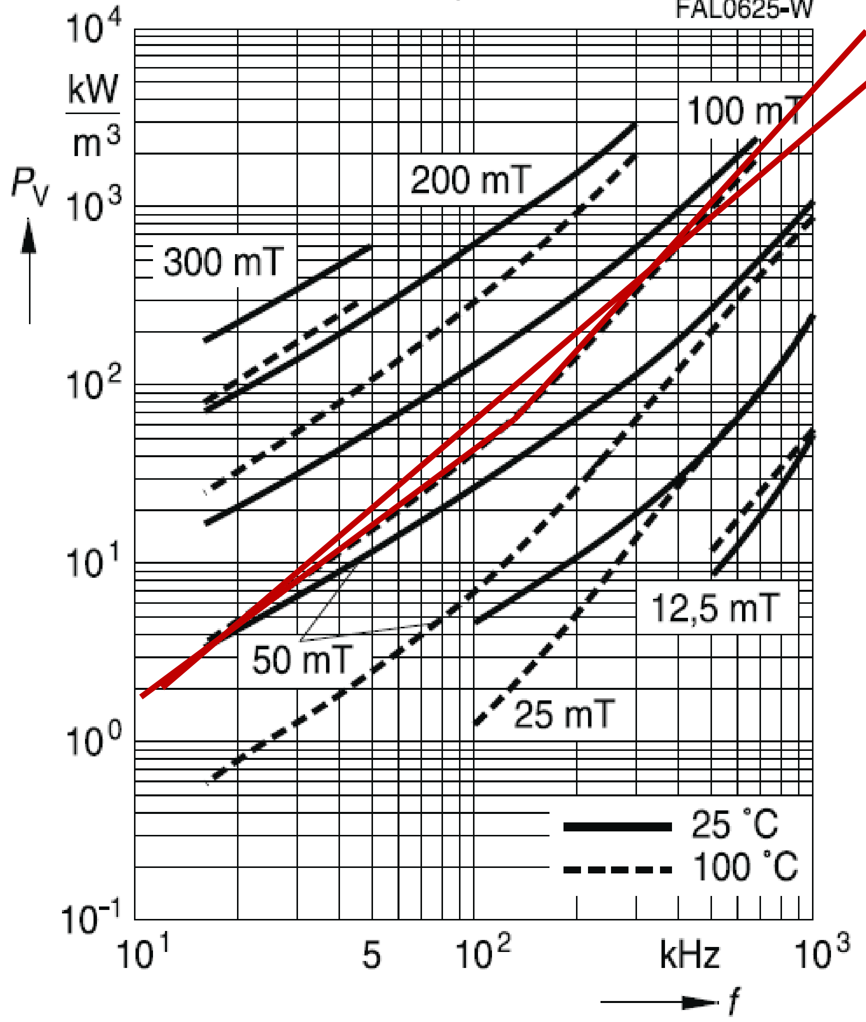
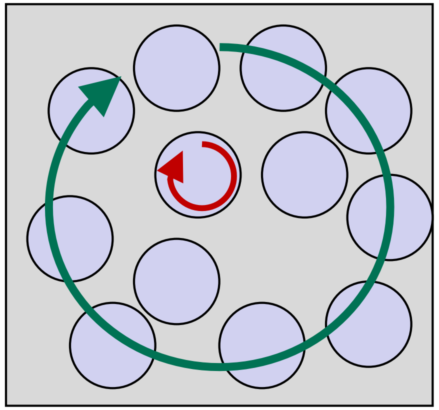


Standard loss mechanisms

- Static hysteresis loss: loop area that's independent of frequency
  $\rightarrow P \propto f$, or $P = k \cdot f \cdot B^{\beta}$
- Eddy-current loss. Expect $P \propto B^2$
  - Scale: individual particle vs. overall core leg.
  - Simple theory: $P \propto f^2$, but,
    - That's for sizes small compared to skin depth.
    - Resistivity can be frequency-dependent
- Anomalous loss, defined as either:
  - Any and all other loss mechanisms—also called "excess loss"
  - Local eddy-current loss induced by rapid domain-wall motion: $P \propto f^{1.5} B^{1.5}$



Summing standard loss mechanisms?

- $P = P_{hyst} + P_{excess} + P_{eddy}$
- True by definition if $P_{excess} \equiv P - P_{hyst} - P_{eddy}$
- But if $P_{anomalous}$ is defined as loss from impeded domain wall motion, P_{hyst} and $P_{anomalous}$ are not truly independent.
- High accuracy requires a more holistic model.

Omitted in all of the above

Behaviors:

- Effect of DC bias
- Effects of non-sinusoidal waveforms.
- Effect of core size and shape.

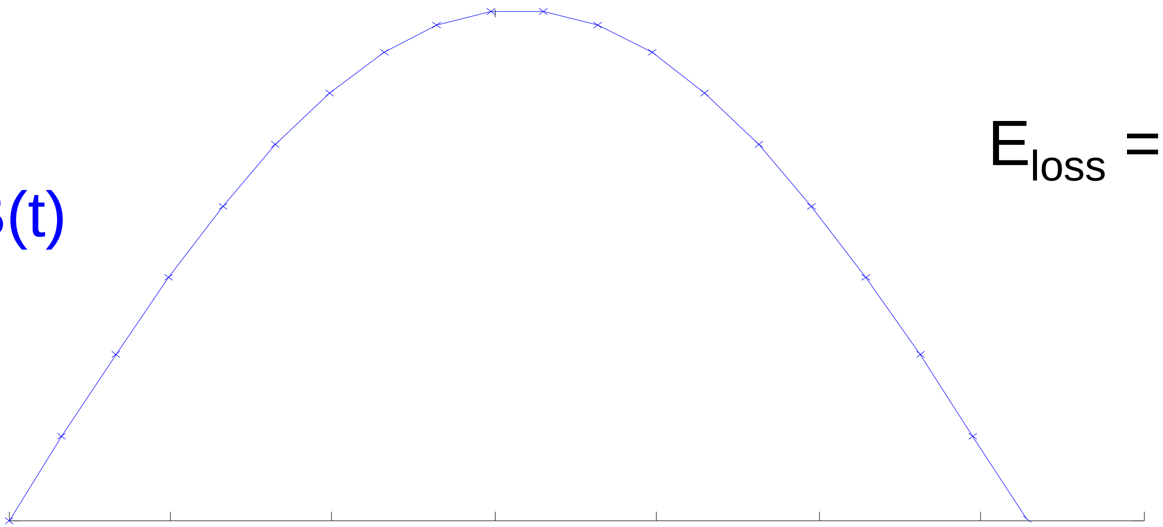
Phenomena:

- Wave propagation and dimensional resonance.
- Magnetostriction and mechanical resonance.
- Flux crowding as affected by core shapes.

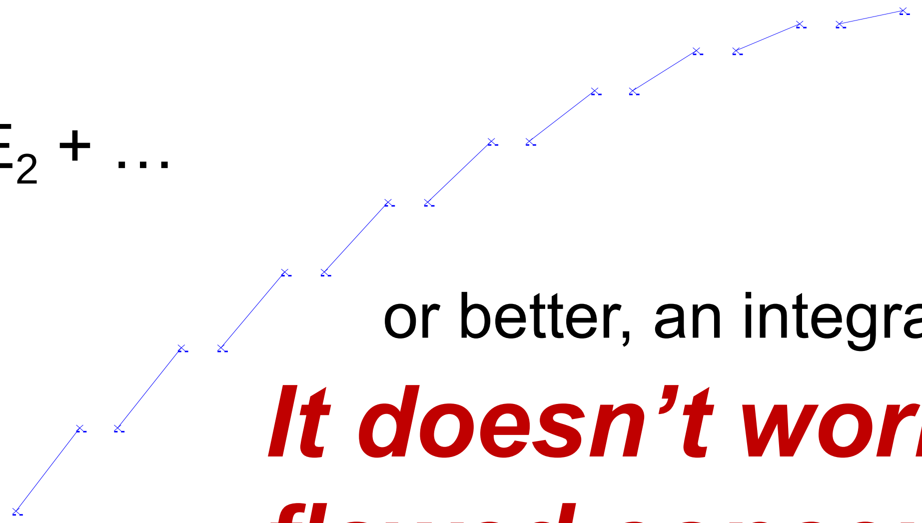
Waveform effect on core loss: Concepts, rather than how-to

- Initial hope in "Generalized Steinmetz Equation" (GSE) model: instantaneous loss depends on B and dB/dt: p(t) = p(B(t), dB/dt)
  - If this worked, you could add up loss for incremental time segments:

B(t)



$$E_{loss} = E_1 + E_2 + \ldots$$

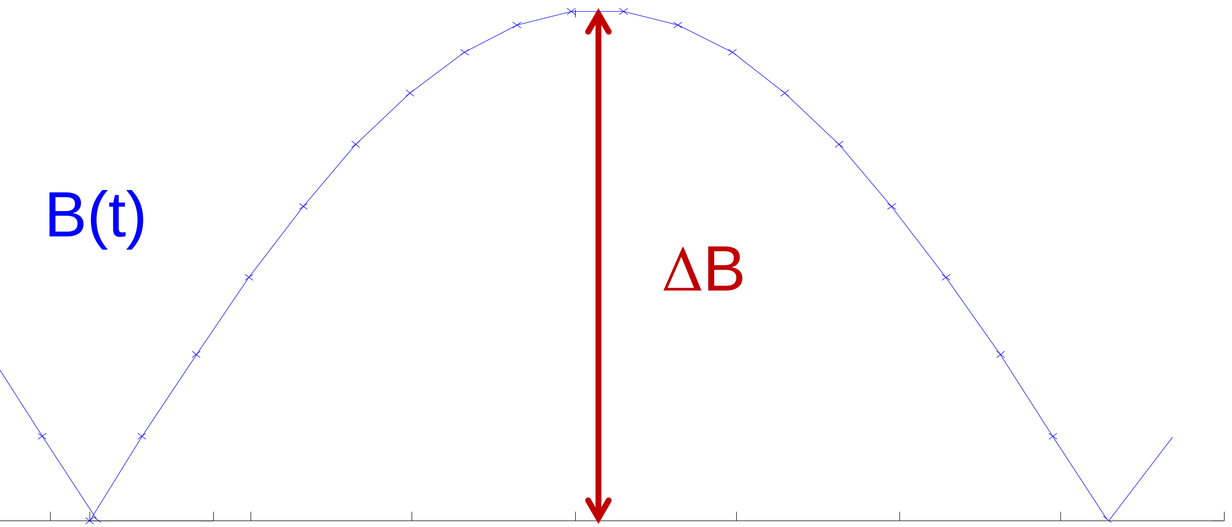


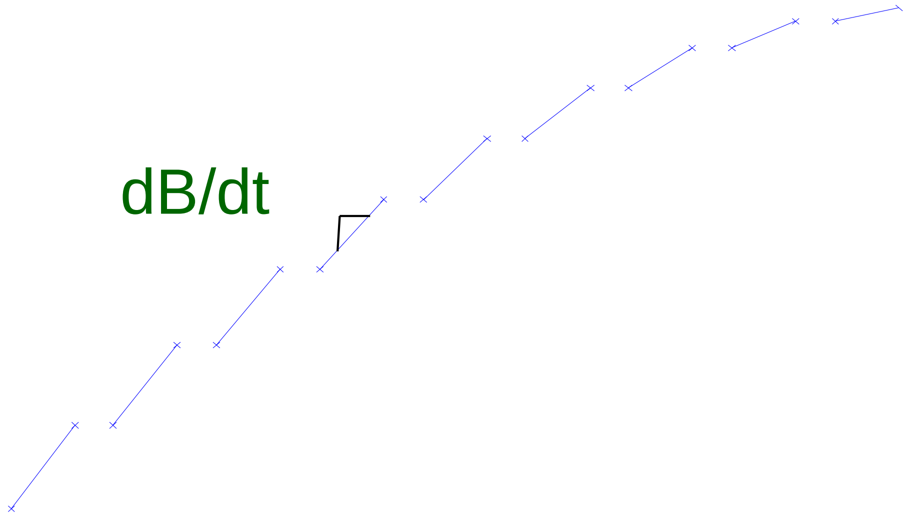
or better, an integral…

It doesn't work: flawed concept

Improvement that enabled iGSE (improved Generalized Steinmetz Equation)

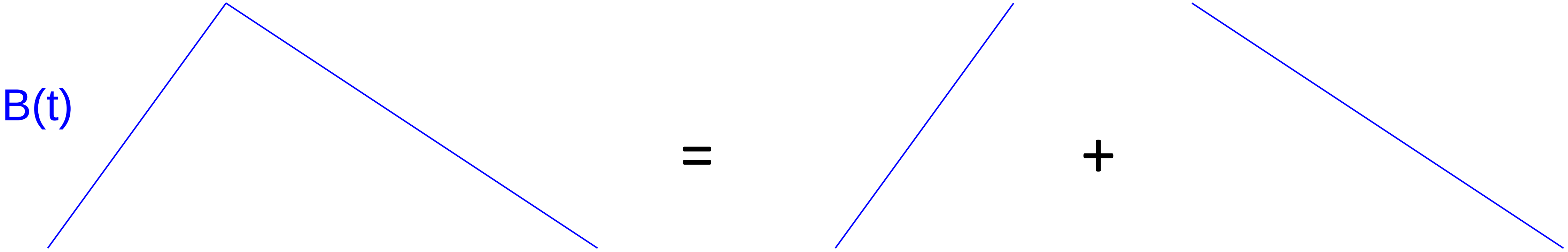
- Loss depends on segment dB/dt and on ***overall*** ΔB
- Still $E_{loss} = E_1 + E_2 + \ldots$, but E_1 depends on a global parameter as well as a local parameter.





Composite waveform method

- Same concept as GSE: add up independent loss for each segment.

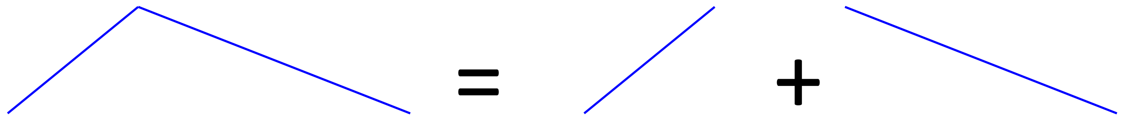


$$E_{loss} = E_1 + E_2$$

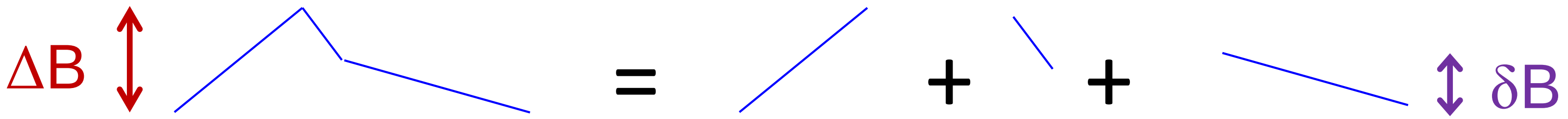
- Unlike the GSE, this works pretty well in simple cases:
  - Waveforms where ΔB is the same for the segment and the whole waveform!
  - It reduces to the same assumptions as the iGSE.

What we know how to do for non-sinusoidal waveforms:

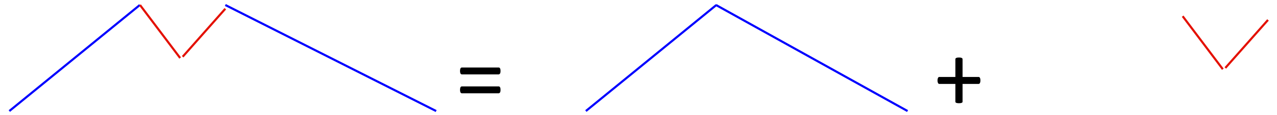
- For simple waveforms, add up the loss in each segment.



- For waveforms with varying slope, add up the loss for each segment, considering overall ΔB and segment δB.



  - See iGSE paper for how those factor in.
- For waveforms with minor loops, separate loops before calculating loss.

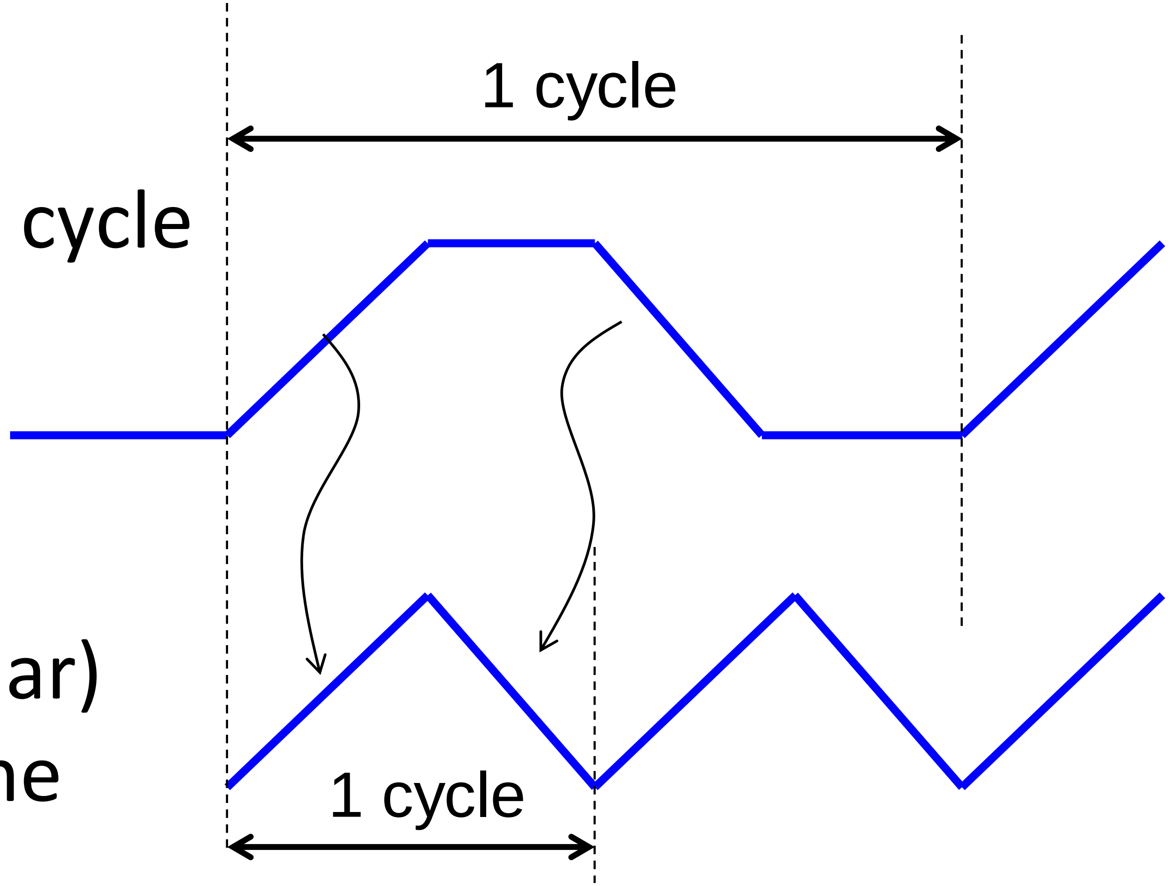


Loss models for each segment

- iGSE derives them from a Steinmetz model
  - Limitation: Steinmetz model holds over a limited frequency range.
- Loss map model uses square-wave data directly for a wide frequency range.
  - Clearly better if you have the data.
  - Can also map with different dc bias levels.
- Sobhi Barg (Trans. Pow. Electr., March 2017) shows that the iGSE gets much more accurate if you use different Steinmetz parameters for each time segment in a triangle wave.

Limitation for all of the above:

- “Relaxation effect”
- Simple theory says loss for one cycle should be the same for both flux waveforms.
- In practice, it’s different.
- i^2GSE (J. Mühlethaler and J. Kolar) captures this but is cumbersome and requires extensive data.



Two strategies for improved models

Use data to tune parameters of a simple model, just complex enough to accurately capture behavior. (Dartmouth)

- If the model structure is right, it can generalize beyond the tested waveforms—requires less data.
- Requires, and drives, better understanding of loss effects.

Feed data into machine learning to create data-driven model without a-priori assumptions about model structure. (Princeton)

- Can accurately capture effects we haven't noticed or understood.
- Requires lots of data and computer power, but that's feasible.

Part II: One approach to an improved model using Princeton data

Charles R. Sullivan, Professor

Dartmouth Magnetics and Power Electronics Research Group

Power Management Integration Center

THAYER SCHOOL OF ENGINEERING AT DARTMOUTH

http://dartgo.org/pmic

Planning model structure

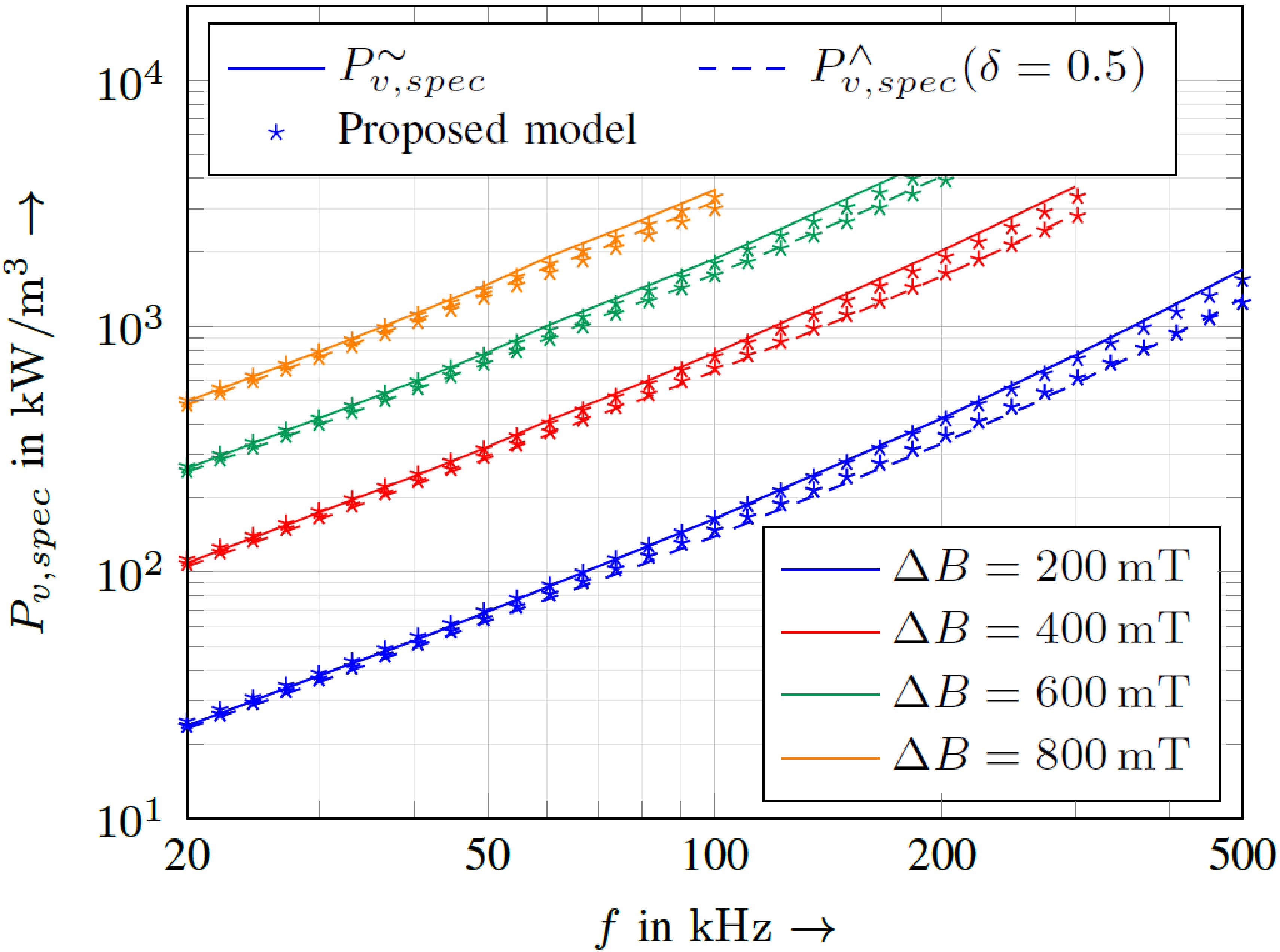
- Start with known characteristics of loss behavior.
  - Observed in measurements—ours and others'.
  - Expected based on physics.
- Develop model structures that produce behavior consistent with the known characteristics.
  - Model structure avoids non-physical behaviors.
  - Model structure accounts for observed behavior not captured by overly simple models.
- Adjust parameters to match measurement data.
  - Models structured to minimize the number of parameters. This may reduce the number of measurements needed for new materials.
  - Minimal set of parameters also makes the model easier to use in practical engineering.

Known behavior of sinusoidal loss: we want a model that matches these features.

- Limit at low-frequency:
  - Static loop, i.e., energy loss per cycle is independent of frequency. This means loss is linearly proportional to frequency.
    - Also implies independent of waveform—see next slide.
  - Amplitude dependence at fixed frequency follows closely the original Steinmetz equation ($P_v = k\,B^{\beta}$).
- Limit at low amplitude: linear behavior, as per the linear system defined by the complex permeability curve.
- Slope of P_v vs. f on a log-log plot increases with f.
- Slope of P_v vs. B on a log-log plot is usually closer to a straight line, but with different slopes at different frequencies.
- DC bias has approximately multiplicative effect on loss, except that loss increase isn't quite as big at high frequency.

Stenglein data on sine vs. triangle.

- Demonstrates shape independence at low frequency.
- True even at 20 kHz.



Erika Stenglein and Thomas Dürbaum, "Empirical Core Loss Model for Arbitrary Core Excitations Including DC bias." *COMPEL* 2020.

Correct behavior for ***non***-sinusoidal waveforms

- Small change in waveform should lead to a small change in loss.
- Minor loop separation should be used.
- Generally behavior follows the "composite waveform hypothesis" with the exception of "relaxation effects".
- 50% duty cycle triangular flux should have lower loss than a sine wave for the same peak flux density and frequency (~85 to 90% at typical frequencies).
- Hypothesis: with the right model, parameters extracted without exhaustive testing of waveforms—ideally just sine waves or just triangle waves.

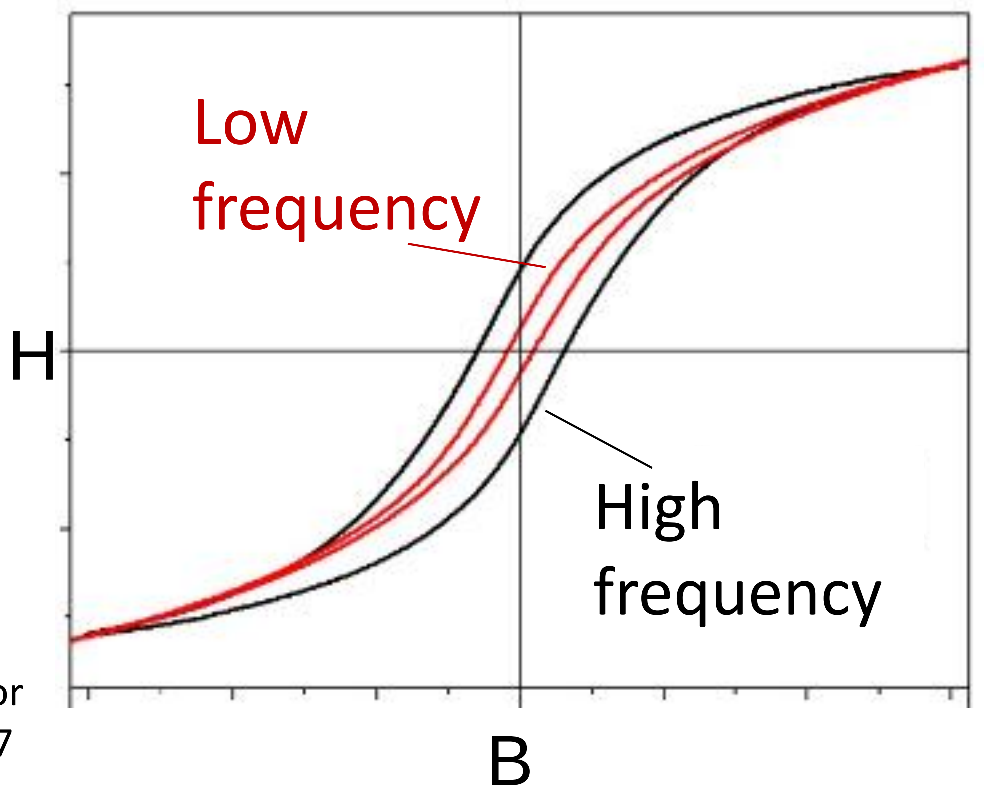
Models for loss from waveforms

- iGSE: improved Generalized Steinmetz Equation. We developed this 20 years ago and it is now the standard technique. Has serious limitations.
- Barg improvements: each segment of a triangle wave uses a different Steinmetz parameters.
- Stenglein: $P_v = E_{hyst}(B_{ac}, B_{dc}) \cdot$ (frequency effect)

$P_v = E_{hyst} \cdot F_{LW} \cdot f_{actual}$

F_{LW} = loop widening factor = $F_{LW}(f_{actual}$, waveform))
=

$$\left[1 + c\left(\frac{1}{\Delta B}\int_0^T \left|\frac{\mathrm{d}^2 B(t)}{\mathrm{d}t^2}\right| \mathrm{d}t\right)^{\gamma}\right]$$



S. Barg, K. Ammous, H. Mejbri and A. Ammous, "An Improved Empirical Formulation for Magnetic Core Losses … under Nonsinusoidal …," in *IEEE Trans. Pow. Electr.*, 32(3) 2017

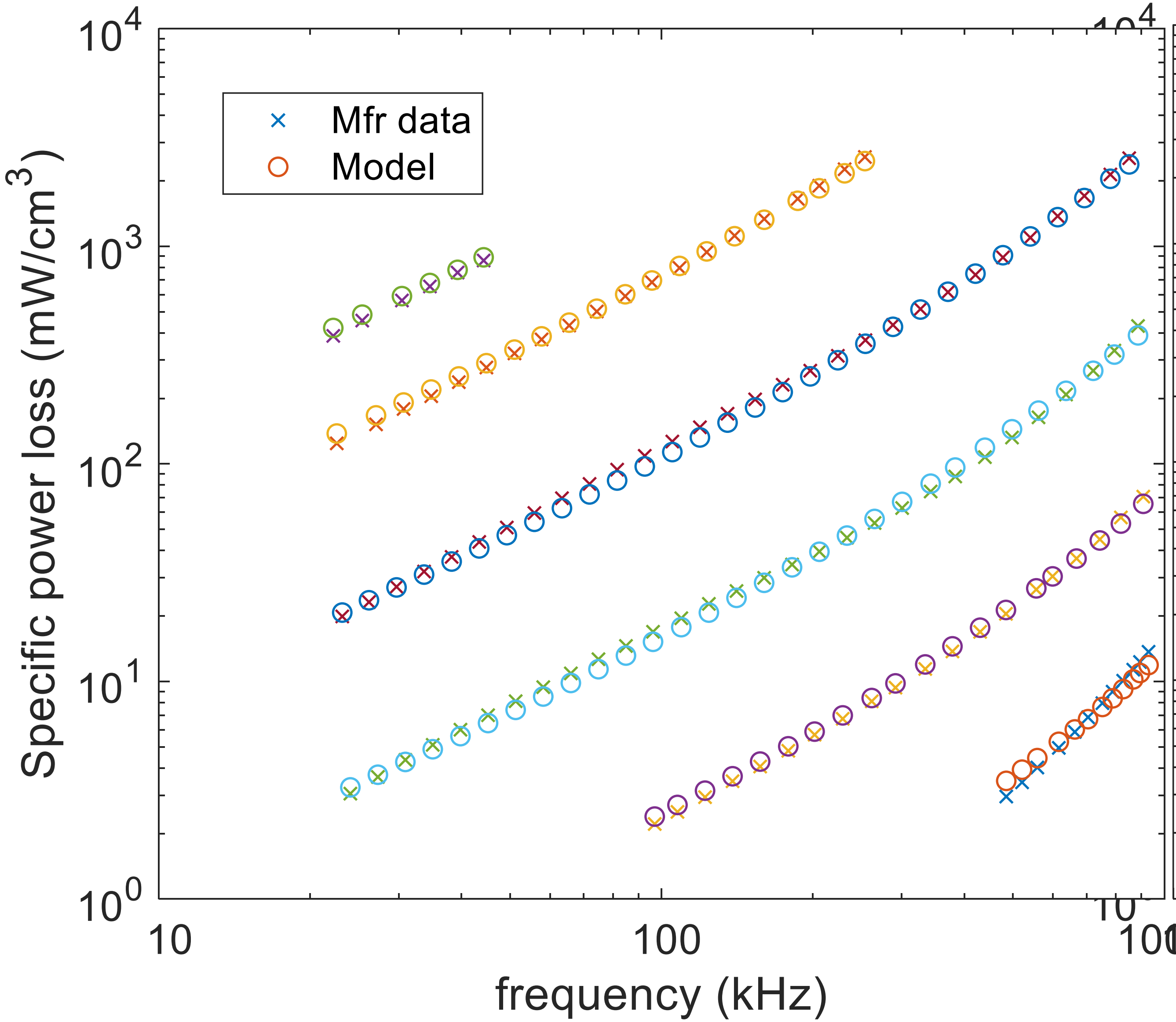
	Low freq. asymptote	Small signal asymptote	Accurate frequency behavior	DC bias	Small change in waveform leads to small change in loss	Composite wavefrms OK	Relaxation effect	Number of params w/o dc model *Special testing needed.
iGSE	✗	✗	✗	✗	✓	✓	✗	3
iGSE Barg	✗	✗	✓	✗	✓	Not in paper but feasible	✗	~3x2 or more
i^2GSE	✗	✗	✗	✗	✓	✓	✓	8*
Stenglein	✓	✗	✓	✓	✗	✓	✗	4
New Model	✓	✓	✓	✓	✓	✓	✓?	4 or 6

Preliminary testing of new model

- Use data extracted from datasheet curves for sinusoidal excitation.
- N49 ferrite chosen for difficult-to-model complex shape of loss curves.
- Simple machine learning adjusts 4 or 6 parameters to minimize RMS value of relative error for full dataset.

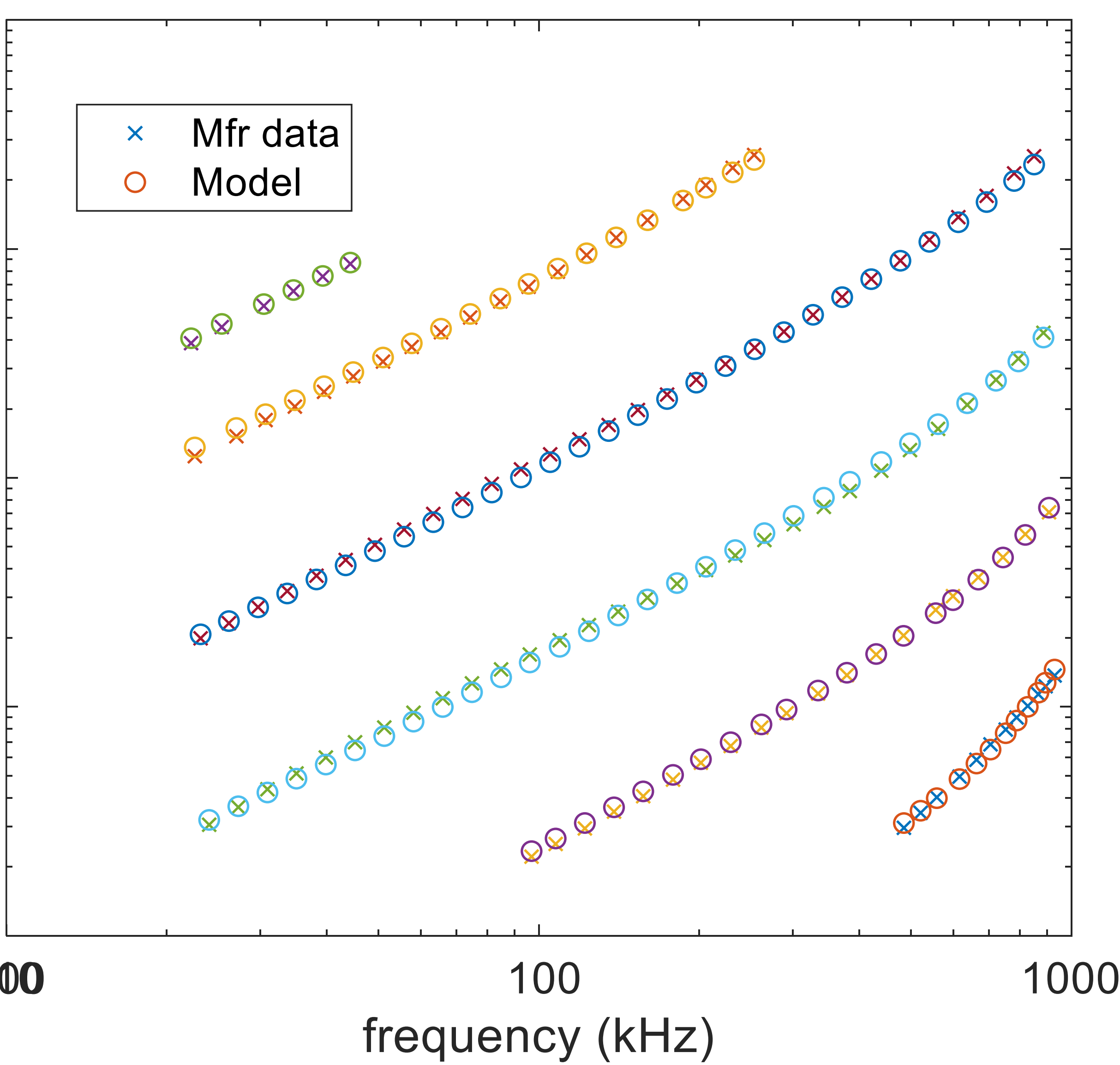
Results

Version 1



- 6.65% RMS error
- 5.64% average error magnitude

Version 2

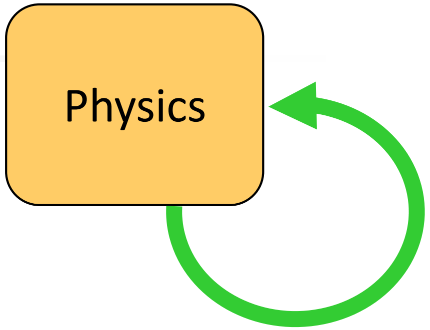


- 4.99% RMS error;
  4.25% average error magnitude

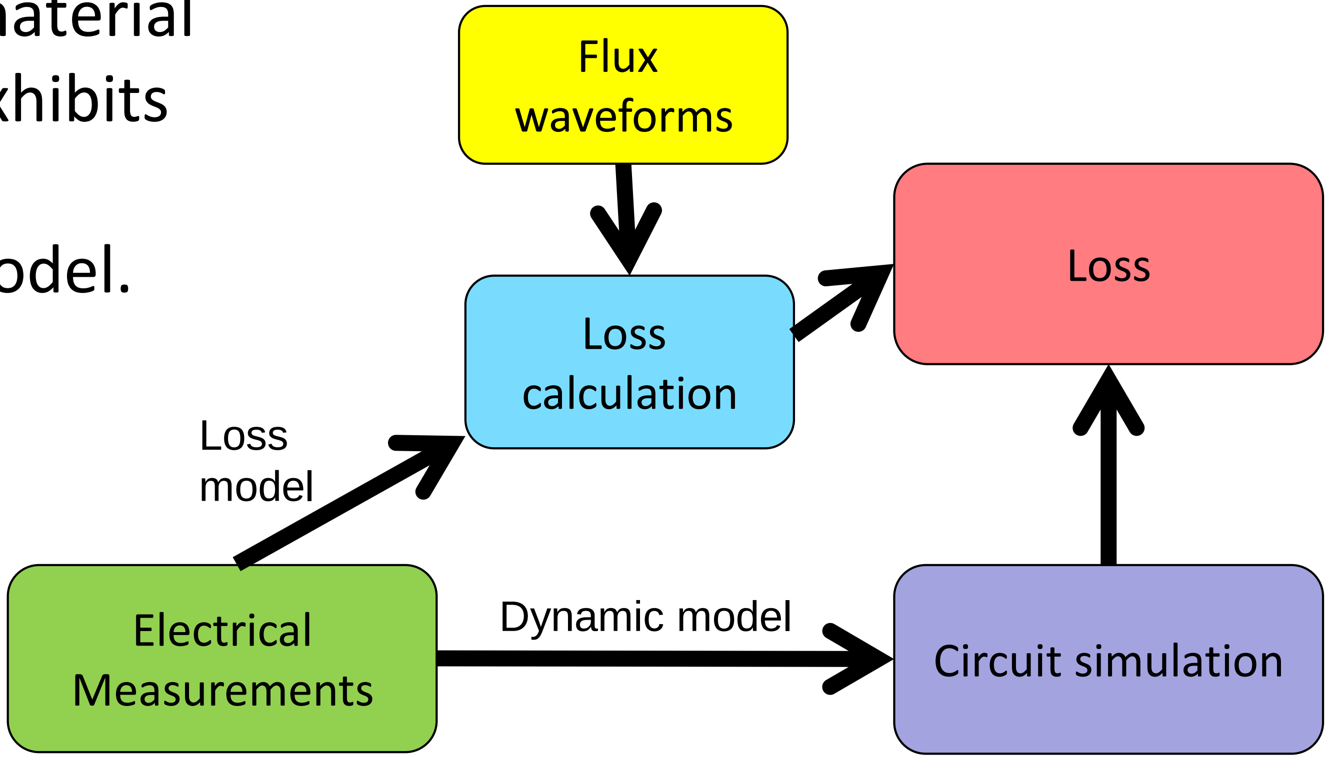
Next steps

- Test with nonsinusoidal waveforms (data being generated at Princeton).
  - Adapt method as needed.
- Develop simulation model (see next slide).
- Consider the effects of core size/shape.

Potential for Simulation model



- Best-practice simulations now use a two-step process:
  - Run a simulation with a basic, linear loss model to get waveforms.
  - Use waveforms in a separate loss model post-processing step.
- Goal: dynamic model for material behavior that inherently exhibits accurate loss behavior: no separate loss prediction model.



Some references

The GSE model: obsolete: don't use this. Jieli Li, T. Abdallah, and C. R. Sullivan, "Improved calculation of core loss with nonsinusoidal waveforms", in Annual Meeting of the IEEE Industry Applications Society, 2001, pp. 2203–2210.

The iGSE model: still a good practical method. K. Venkatachalam, C. R. Sullivan, T. Abdallah, and H. Tacca, "Accurate prediction of ferrite core loss with nonsinusoidal waveforms using only Steinmetz parameters" IEEE Workshop on Computers in Power Electronics (COMPEL), 2002.

The i^2GSE. J. Muhlethaler, J. Biela, J.W. Kolar, A. Ecklebe, "Improved Core-Loss Calculation for Magnetic Components Employed in Power Electronic Systems," IEEE Trans. on Pow.Elec., 27(2), pp.964-973, Feb. 2012 doi: 10.1109/TPEL.2011.2162252

C.R. Sullivan, J.H. Harris, and E. Herbert, "Core loss predictions for general PWM waveforms from a simplified set of measured data," IEEE Applied Power Electronics Conference (APEC), 2010, doi: 10.1109/APEC.2010.5433375

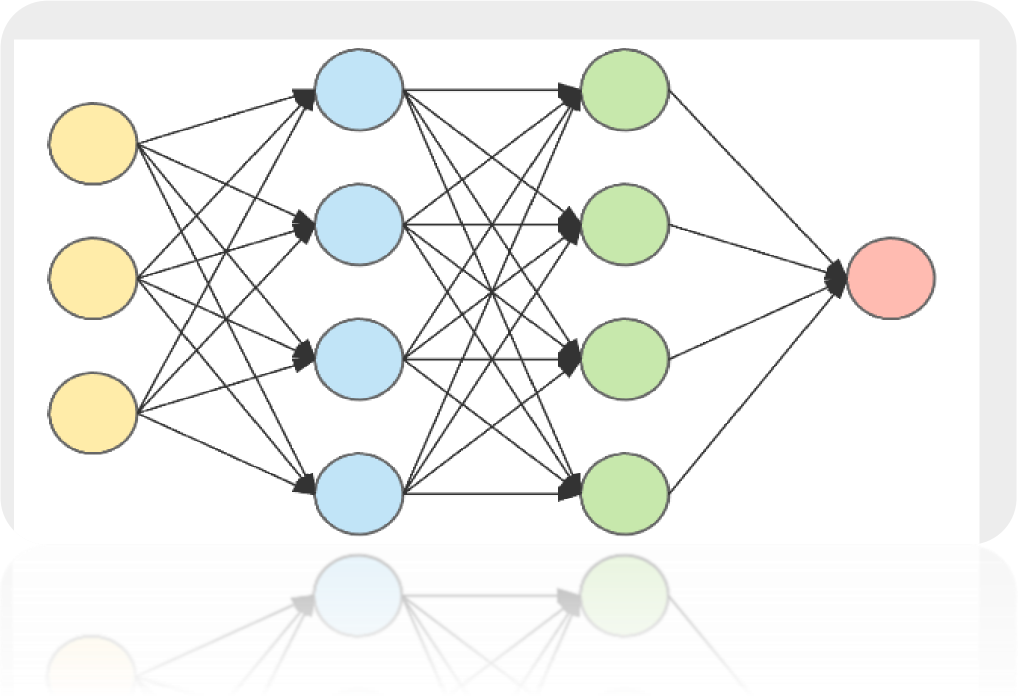
C.R. Sullivan, J.H. Harris, Testing Core Loss for Rectangular Waveforms, Phase II Final Report, 2011, Thayer School of Engineering at Dartmouth, http://www.psma.com/coreloss/phase2.pdf

S. Barg, K. Ammous, H. Mejbri and A. Ammous, "An Improved Empirical Formulation for Magnetic Core Losses … under Nonsinusoidal …," in *IEEE Trans. Pow. Electr.*, 32(3) 2017

Erika Stenglein and Thomas Dürbaum, "Empirical Core Loss Model for Arbitrary Core Excitations Including DC bias." *COMPEL* 2020.

Machine-Learning Methods for Magnetic Core Loss Modeling – A Discussion

Princeton MagNet



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Methods for Magnetic Core Loss Modeling

- **Steinmetz Equation (SE)**

$$P_{\mathrm{v}} = k f^{\alpha} \hat{B}^{\beta}$$

three parameters, sine wave

$k,\ \alpha,\ \beta$

- **Improved GSE (iGSE)**

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

three parameters

$k_i,\ \alpha,\ \beta$

- **Improved – improved GSE (i²GSE)**

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

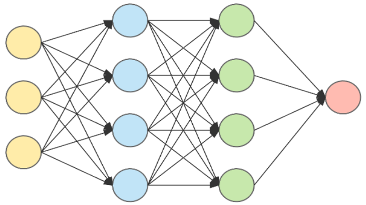
eight parameters

$k_i,\ \alpha,\ \beta,\ \alpha_r,\ \beta_r,\ k_r,\ \tau,\ q_r$

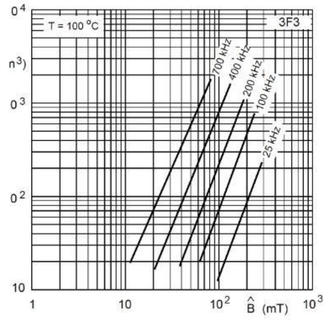
- **Machine Learning based Methods**

thousands of parameters

ringing, dc bias, temperature, memory effect



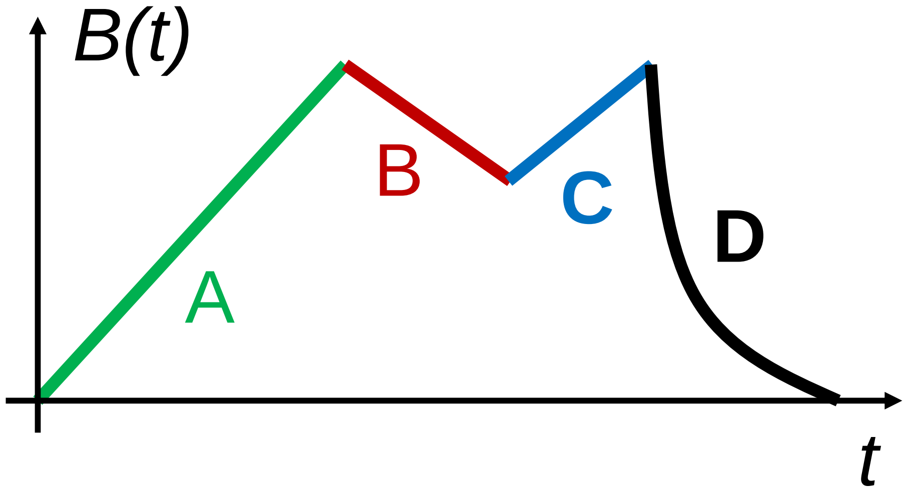
neural network

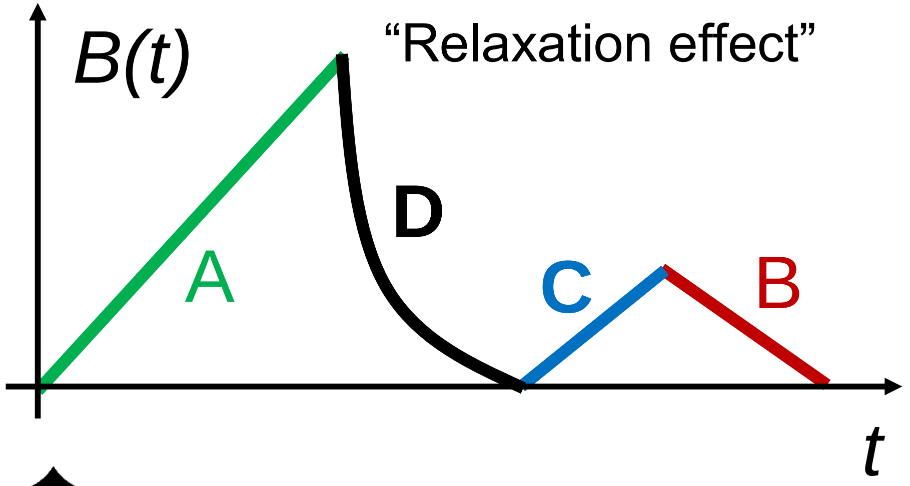


core loss

- C. R. Sullivan et al., "Accurate Prediction of Ferrite Core Loss with Nonsinusoidal Waveforms using only Steinmetz Parameters," *COMPEL02*
- J. W. Kolar et al., "Improved Core-Loss Calculation for Magnetic Components Employed in Power Electronic Systems," *TPEL12*

Motivation for Machine Learning based Methods





iGSE

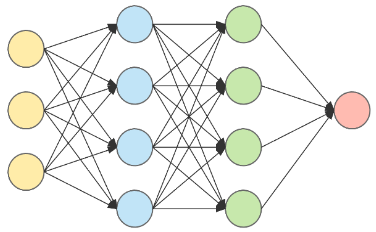
$$P_{\mathrm{v}} = \frac{1}{T}\int_0^T k_i \left|\frac{\mathrm{d}B}{\mathrm{d}t}\right|^{\alpha} (\Delta B)^{\beta-\alpha}\,\mathrm{d}t$$

i^{2}GSE

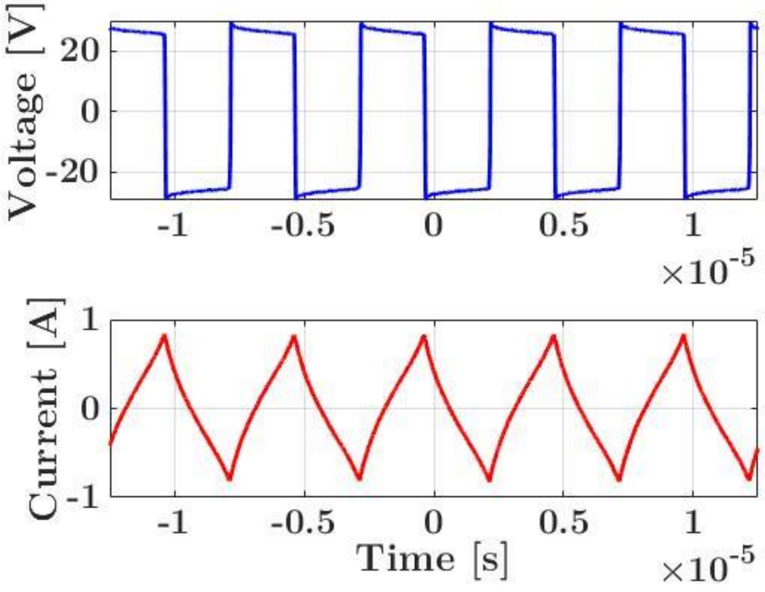
$$P_{\mathrm{v}} = \frac{1}{T}\int_0^T k_i \left|\frac{\mathrm{d}B}{\mathrm{d}t}\right|^{\alpha} (\Delta B)^{\beta-\alpha}\,\mathrm{d}t + \sum_{l=1}^{n} Q_{\mathrm{r}l} P_{\mathrm{r}l}$$

- Analytical models don't work well for these cases
- Difficult to capture dc-bias, temperature, relaxation effect
- Consider core loss modeling as time-domain signal processing, how about we try machine learning?

Speech recognition



Motivation for Machine Learning based Methods



IMAGENET

to

Princeton MagNet

Why machine learning?

- Some analytical methods assume “ideal” waveforms, but real waveforms are usually “non-ideal”.
- Some analytical models do not capture relaxation or memory effects. Models that do capture tend to be very complicated and/or data-driven.
- Adding additional factors into analytical models is usually difficult (temperature, dc-bias), but adding an additional layer, or even changing the architecture of a neural network is relatively easy (a few lines of codes in PyTorch).
- Provide new insights to analytical methods.

MagNet: Machine Learning for Core Loss Modeling

PRINCETON UNIVERSITY

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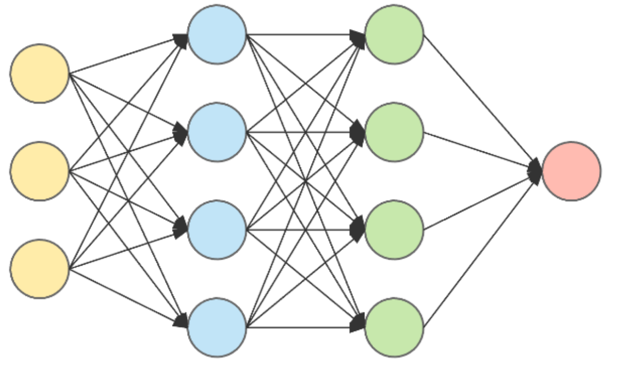
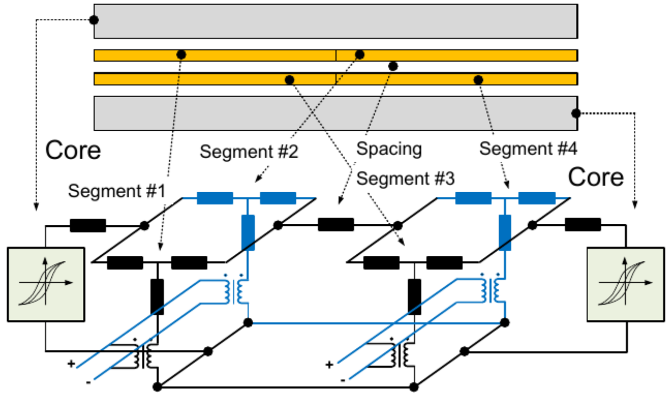
Automatic Data Acquisition

Neural Network Training



Lumped Circuit Model

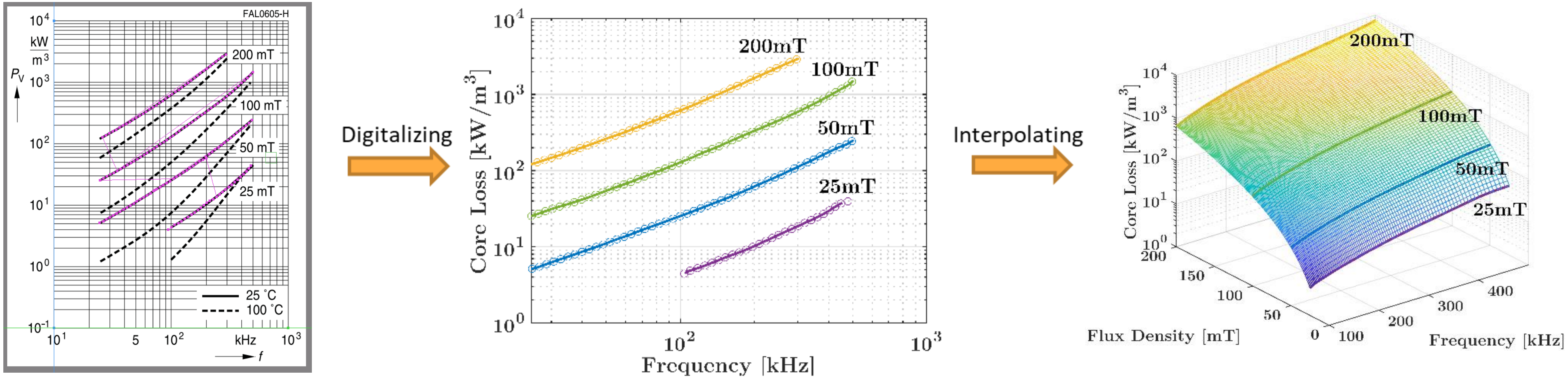


MagNet - Open Source, Industry Collaboration and Student Competition

- H. Li, M. Chen et al. “MagNet: A Machine Learning Framework for Magnetic Core Loss Modeling,” *COMPEL20*
- Github Repository: https://github.com/minjiechen/MagNet

Training ML Models with Data from Datasheet

- **Extract data from datasheet**



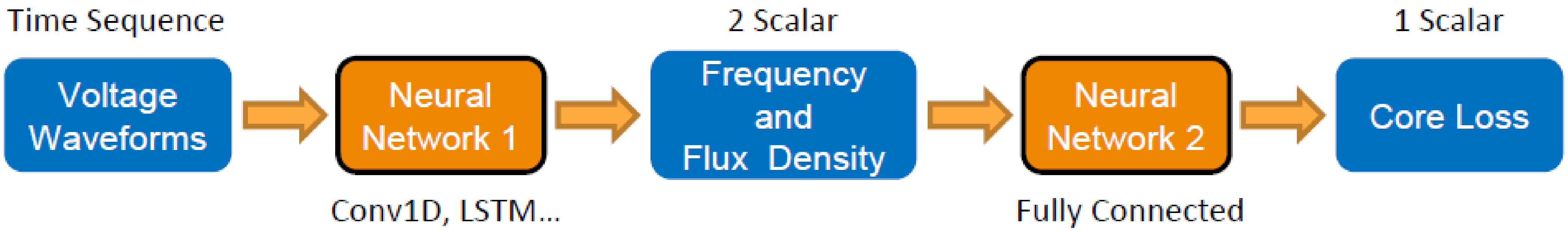
- **Reconstruct the extracted data (f, B, P_V) into voltage and current waveforms (time sequence)**

$$B = \frac{\int V \cdot dt}{N_2 \cdot A} \Rightarrow V_{max} = N_2 \cdot A \cdot 2\pi f \cdot B_{max} \Rightarrow v = V_{max} \cdot \sin(2\pi f \cdot t)$$

assume pure-sinusoidal current waveform

Neural Network Architecture

❑ **Model-based training: a “grey-box” neural network to initial the process**

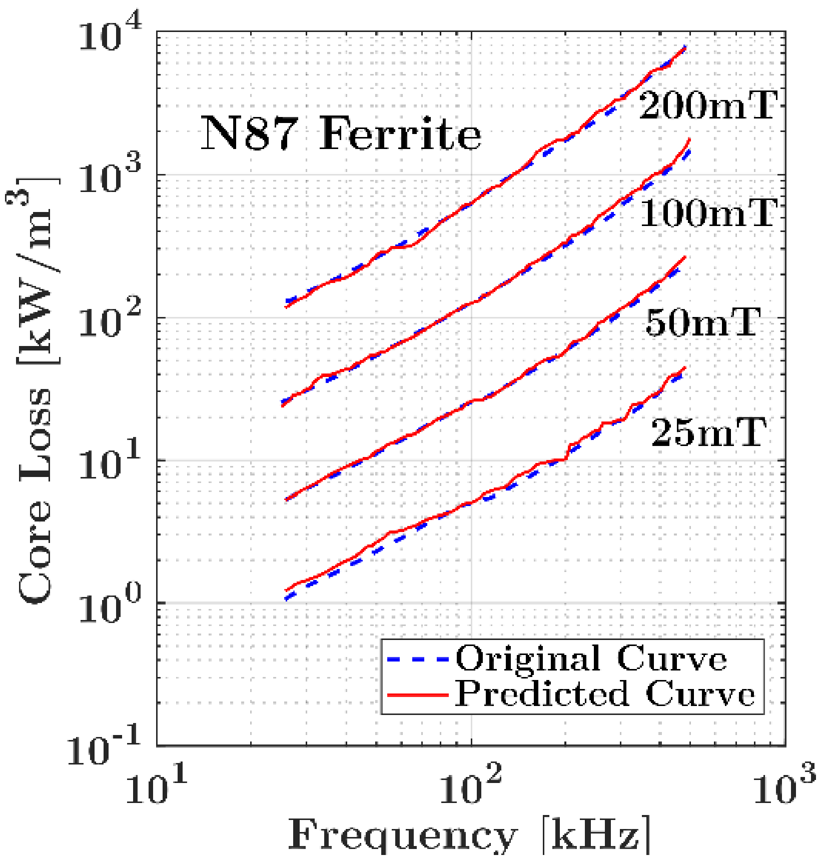


❑ **Data-driven training: a “black-box” neural network optimized for performance**

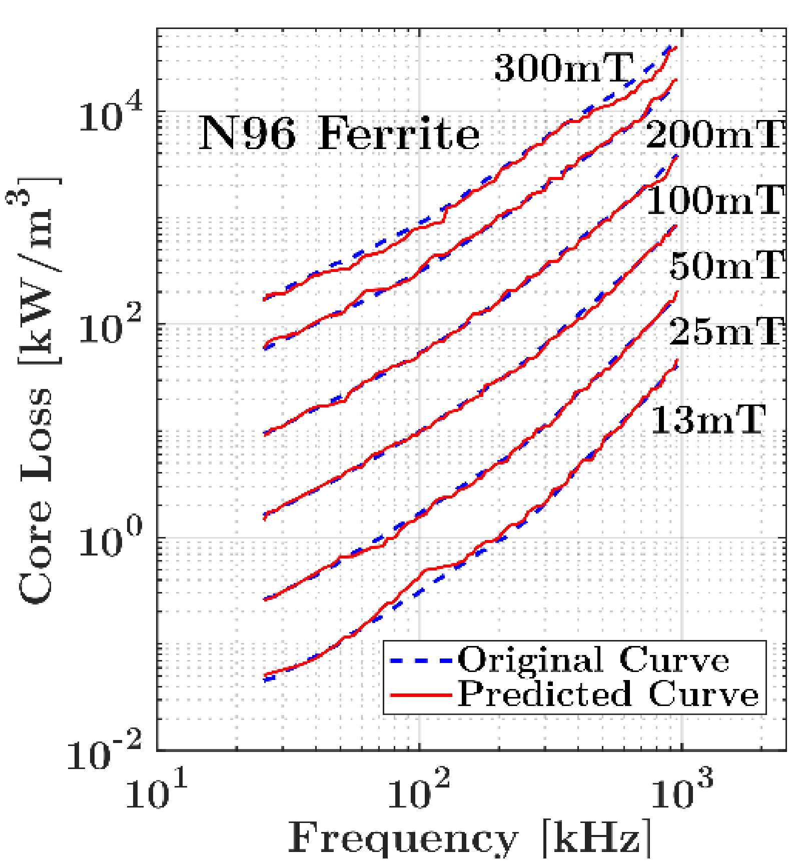
- Github Repository: https://github.com/minjiechen/MagNet

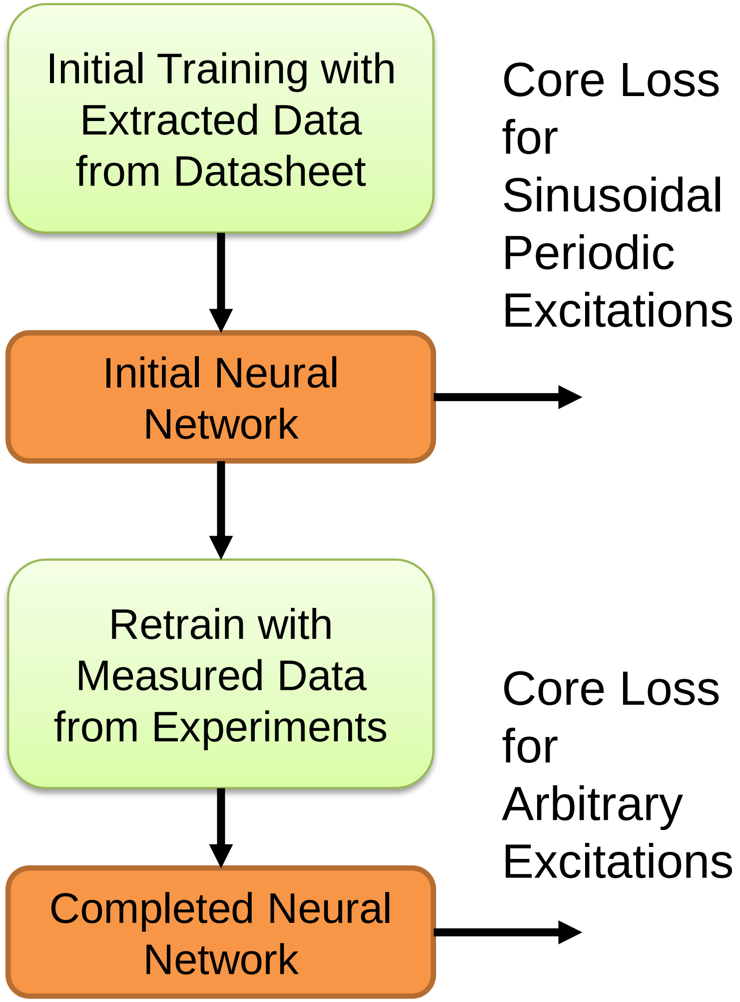
Predicting Core Loss based on Datasheet Data

Average RMS Error: 3.65%



Average RMS Error: 7.62%



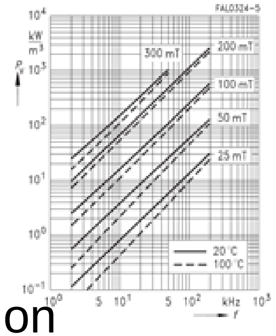


Transfer Learning for 10 Different Materials

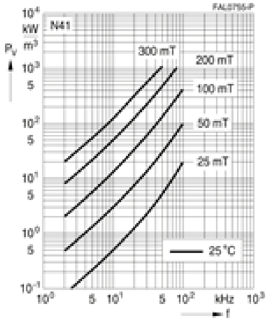
- Reuse the neural network architecture for different materials
- Evaluated 10 different ferrite materials from TDK
- Average RMS error lower than 10%
- Similar core loss curve shapes → lower RMS error

There may exist a few neural network structures that fit most magnetic materials.

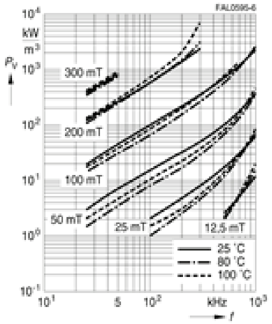
Model Initialization



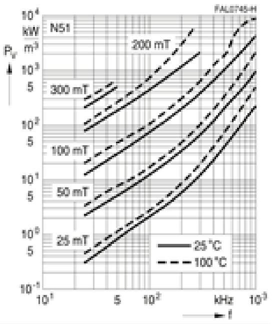
N27: 3.47%



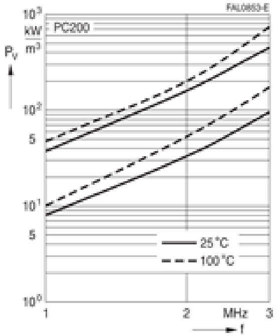
N41: 3.12%



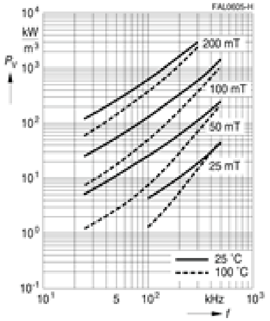
N49: 7.24%



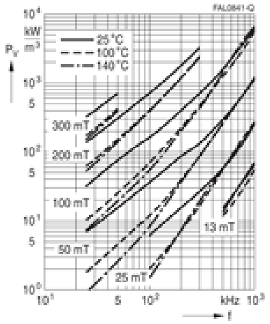
N51: 8.66%



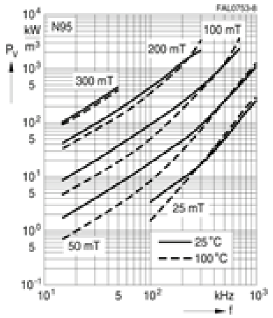
N59: 4.88%



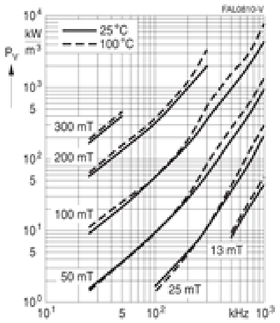
N87: 3.65%



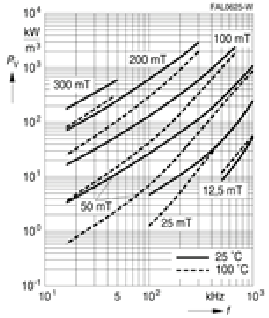
N88: 9.75%



N95: 9.02%

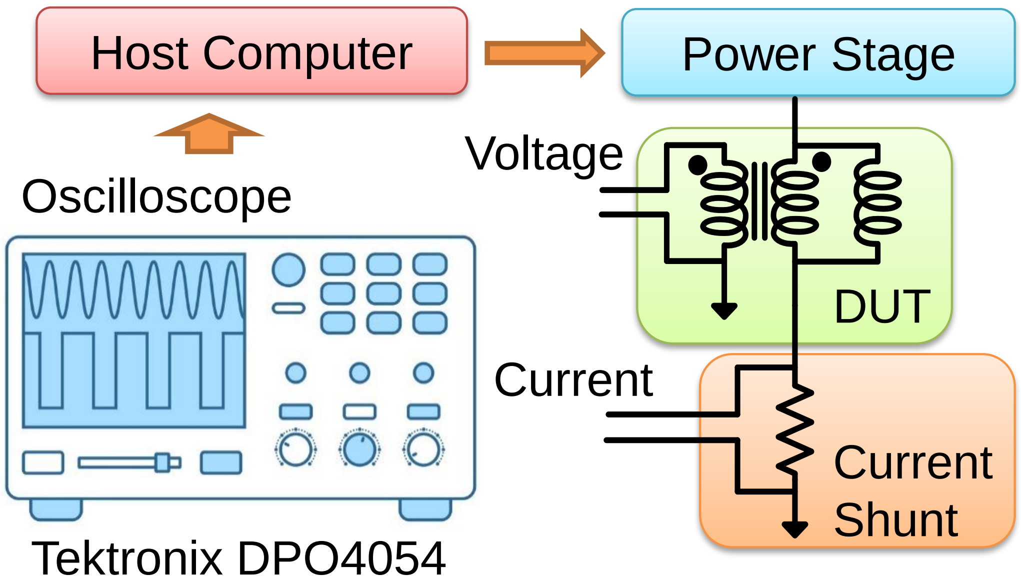


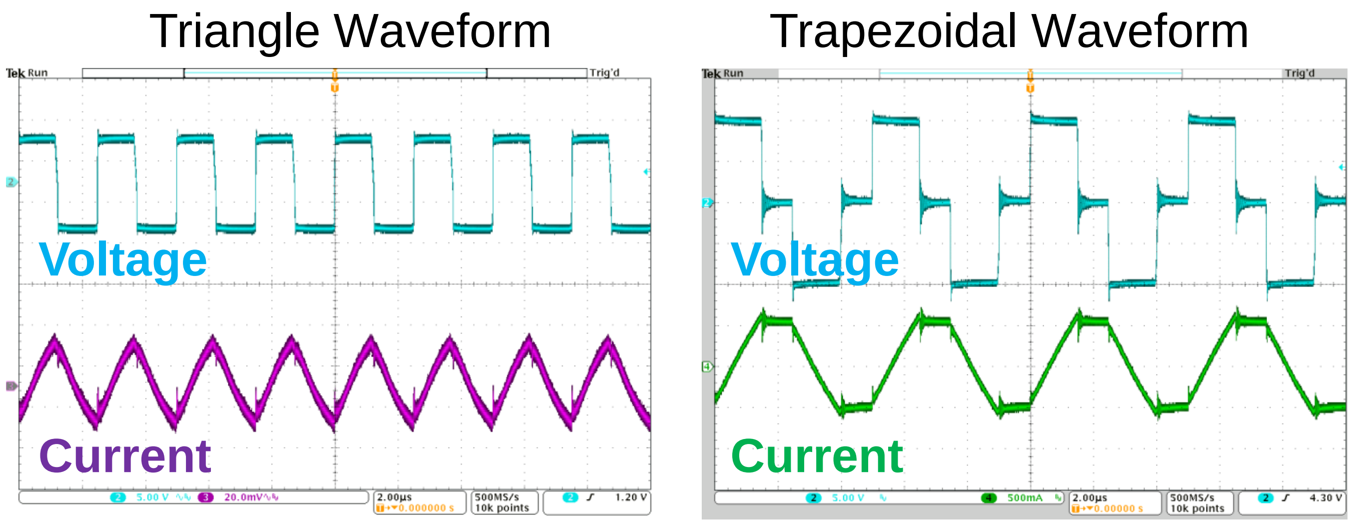
N96: 7.62%



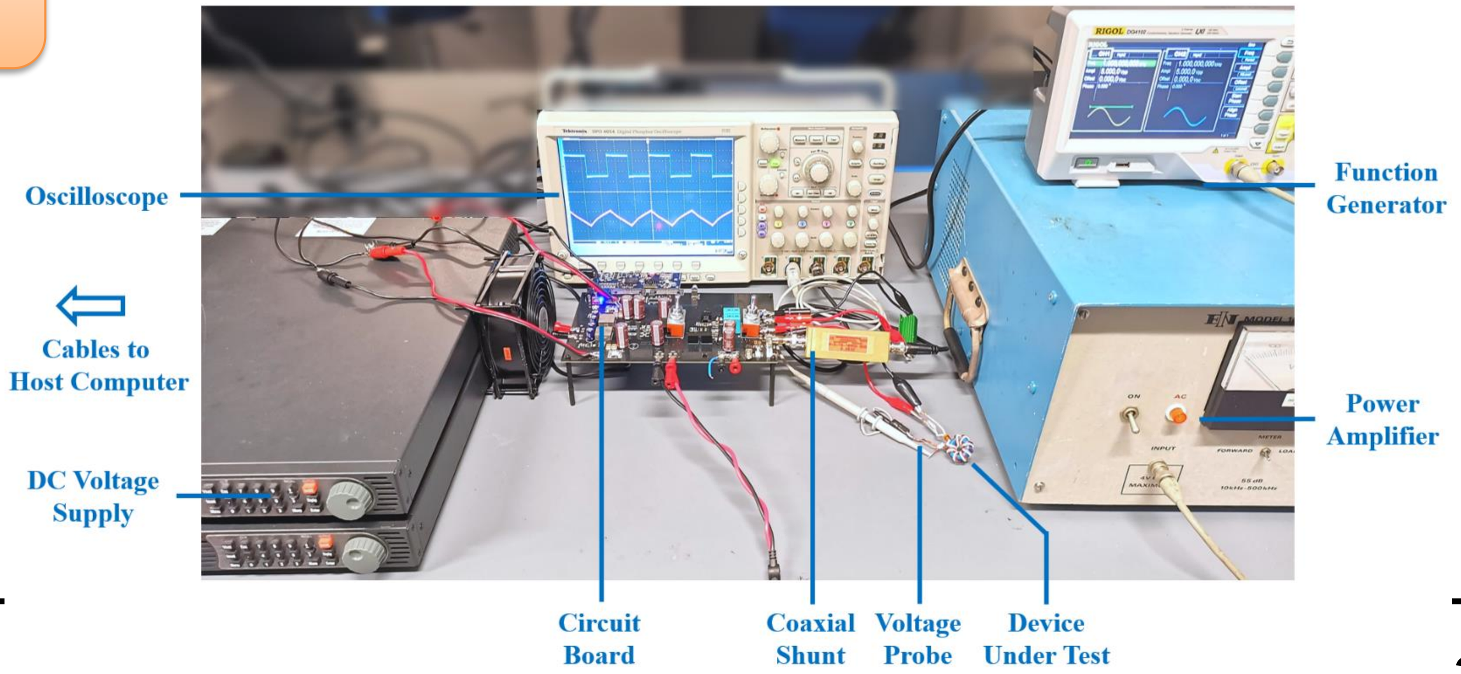
N97: 7.35%

Data Acquisition System for Sine and PWM Excitations



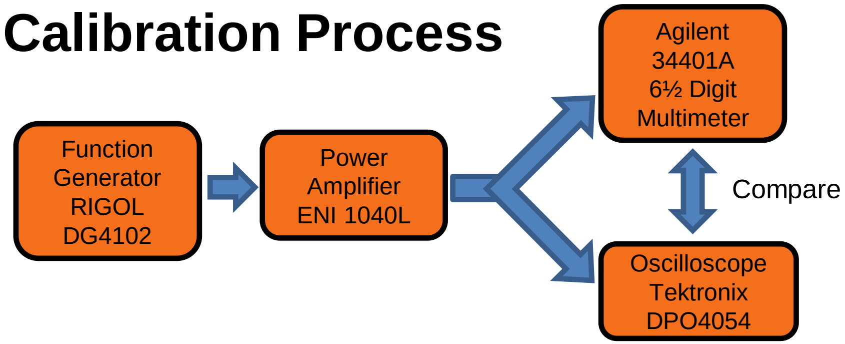


Time Step: 10 ns
Data Length: 10,000
Frequency Range: 10 kHz - 1 MHz
Data Rate: 3 seconds/data
Waveform: Triangle, Trapezoidal, Sine
Types: Periodic / Sequential

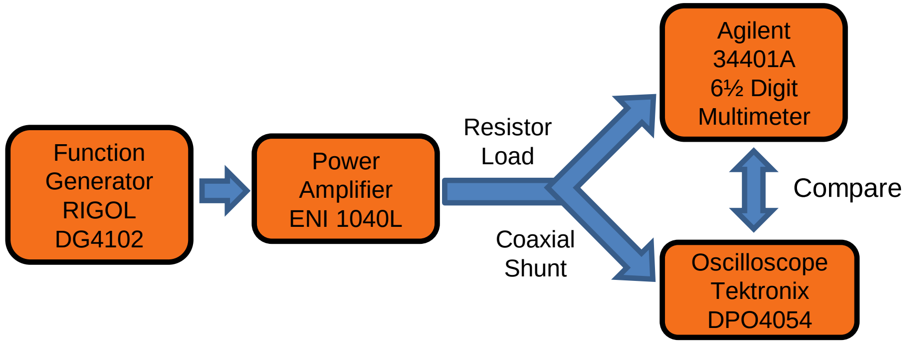


Evaluating the Measurement Accuracy

Calibration Process

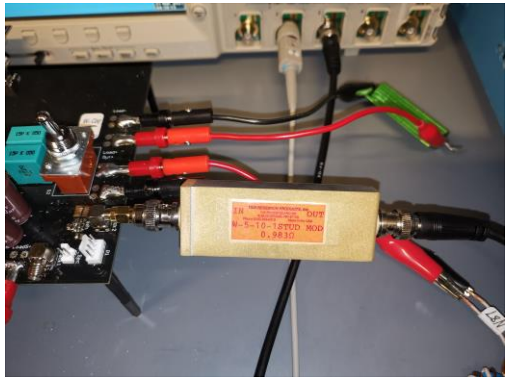


Calibration Setup for Voltage Channel



Calibration Setup for Current Channel

Low parasitics current shunt



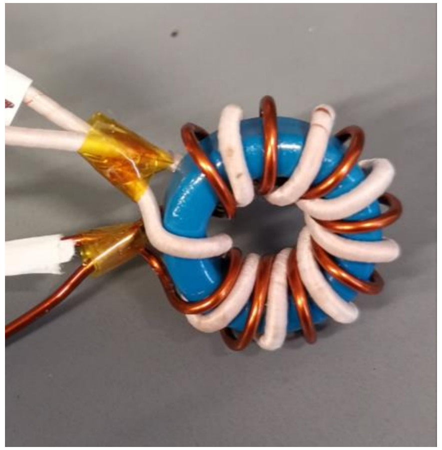
Relative Error	DC Avg. Measurement	AC RMS Measurement
Voltage Channel	Avg = 0.32%, Std = 0.35%	Avg = 0.94%, Std = 1.17%
Current Channel	Avg = 0.25%, Std = 0.29%	Avg = 0.58%, Std = 0.66%

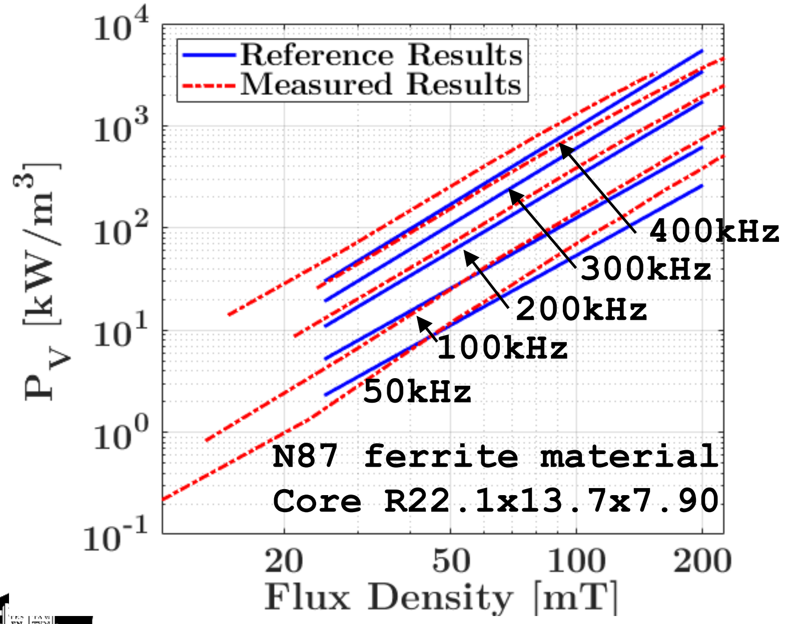
- Voltage measurement error bound (dc offset and ac rms): <1%
- Current measurement error bound (dc offset and ac rms): <1%
- Phase difference (after time skewing) : <1 ns (0.1^{o} @500kHz) ?
- Need a “standard” way to determine the measurement accuracy.
- How “accurate” is “enough” for core loss measurement?

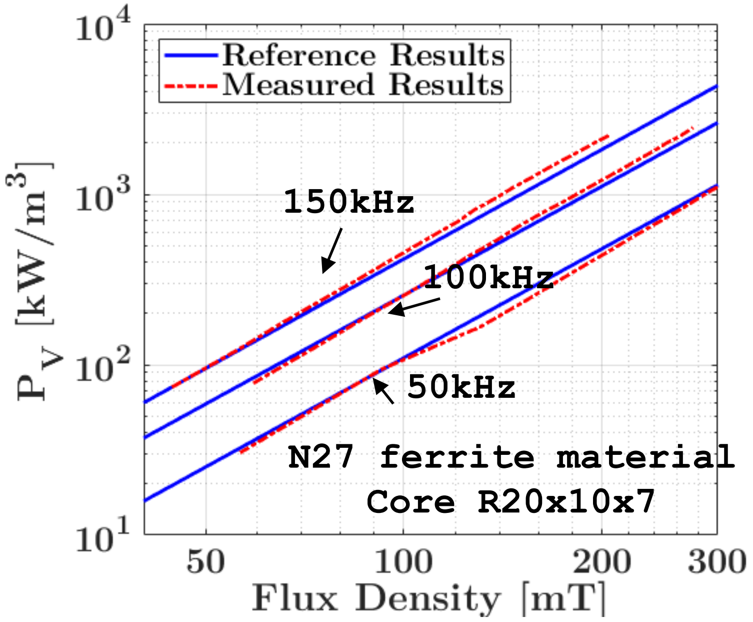
Current Shunt Resistor	Rated Value
Resistance	0.983 ohm
Uncertainty	0.200 %

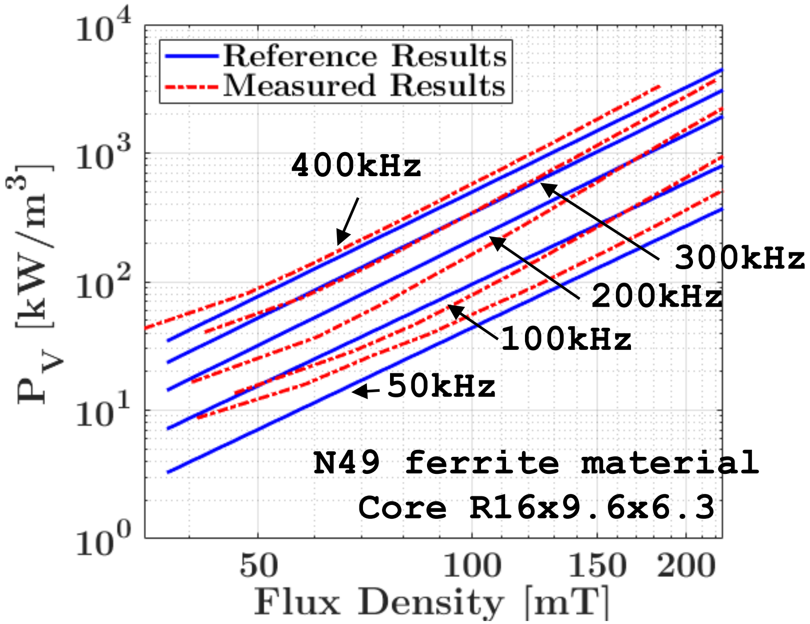
Absolute Accuracy of Core Loss Measurement

- Many sources of core loss mismatch
  - Geometry and material uniformity (a few %?)
  - Equipment accuracy and resolution (a few %?)
  - Model accuracy and flexibility (a few %?)
- Compare measured data against datasheet (sinusoidal)
- Need a “standard equipment” for comparison





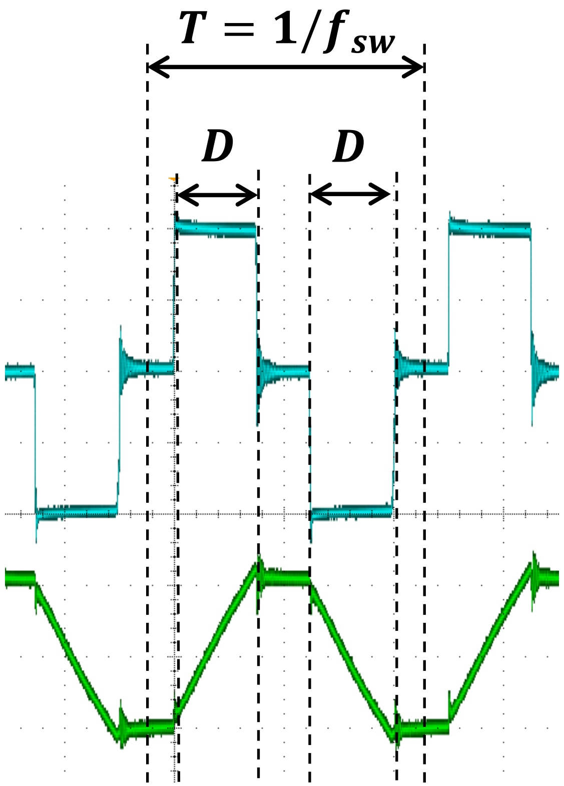


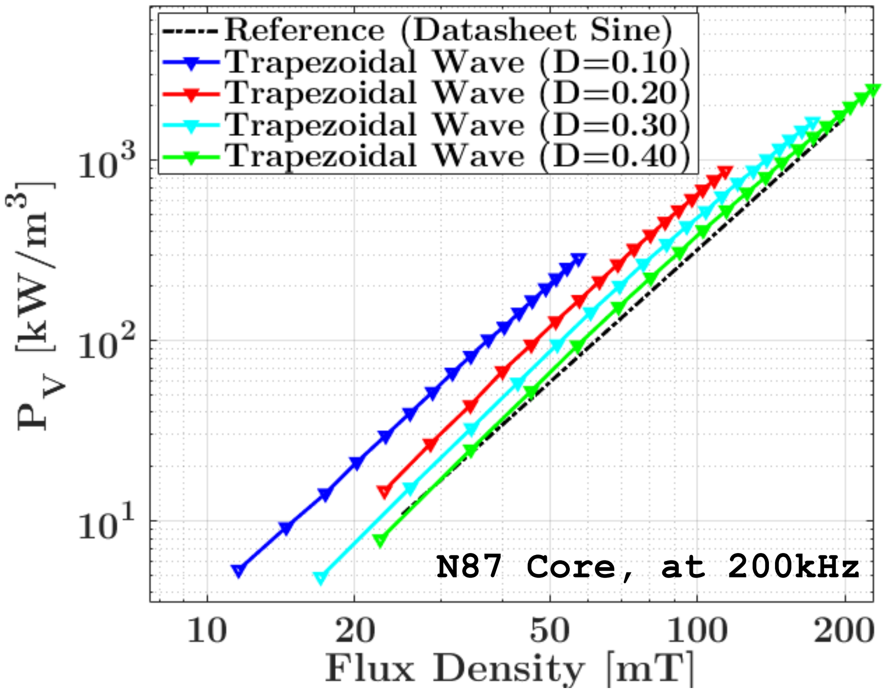


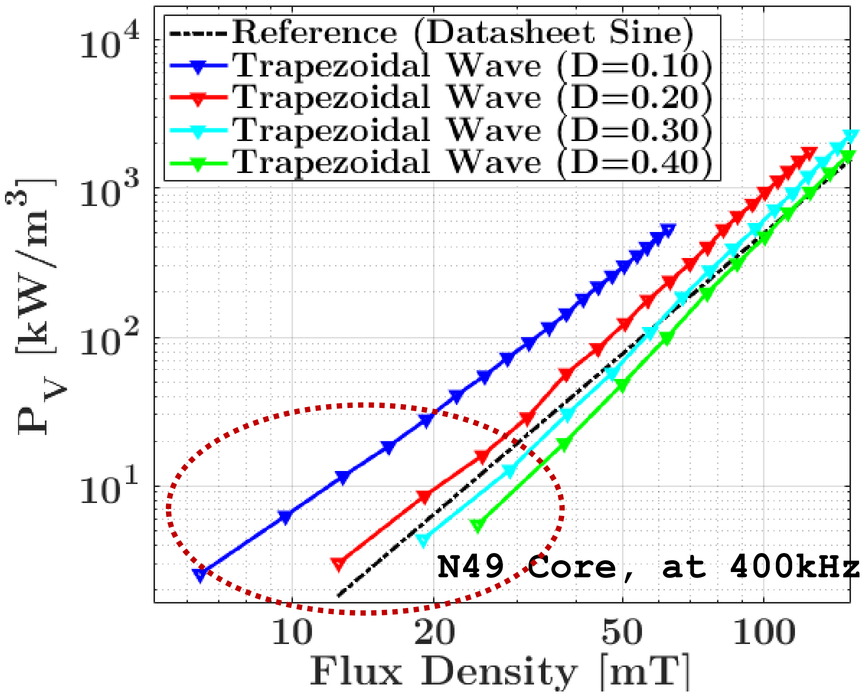
* preliminary data – pending verification

Data Acquisition Accuracy and Model Accuracy

- Core loss for different waveform types and different materials







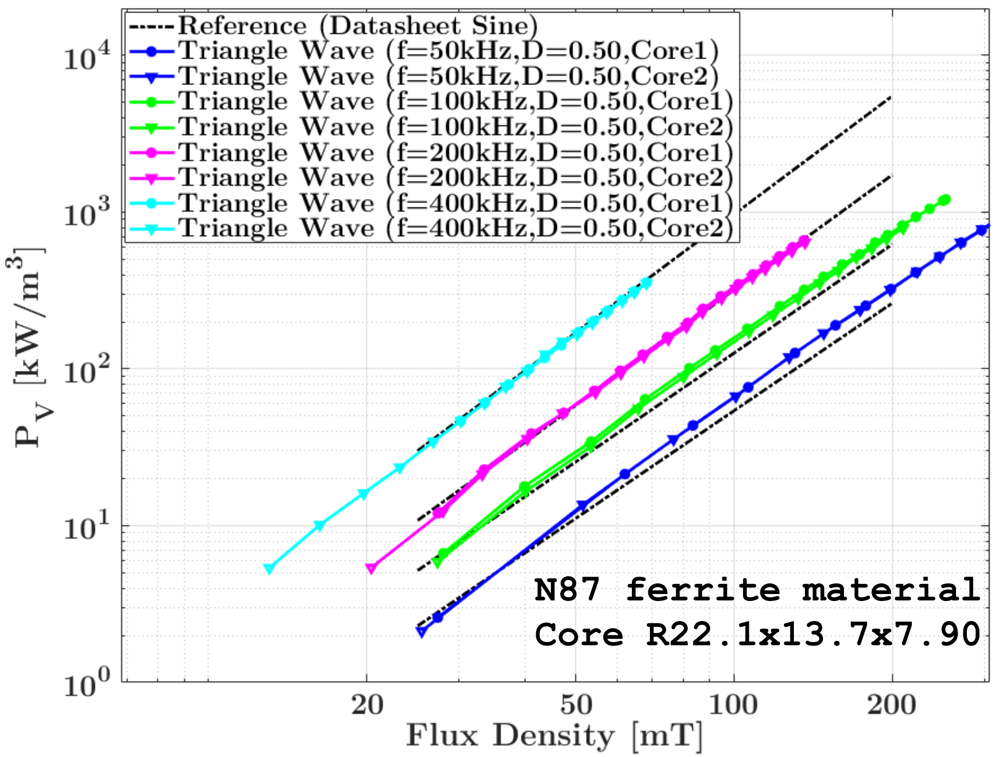
Low flux density, very low loss, perhaps beyond the capability of the measurement setup

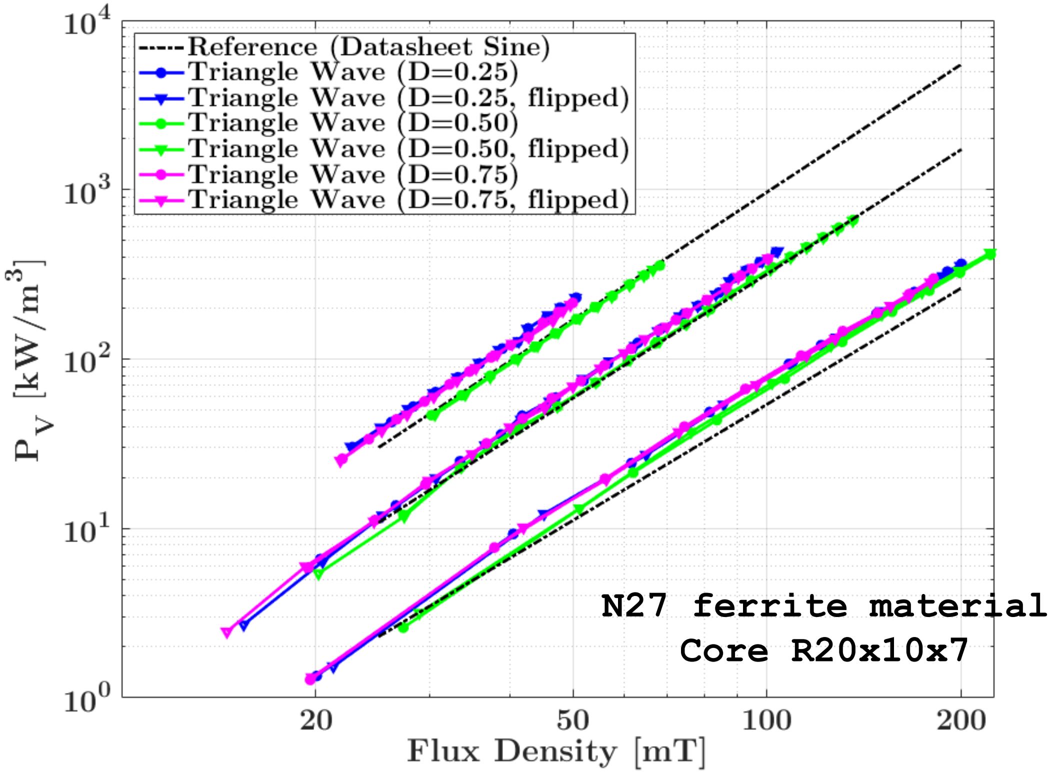
* preliminary data – pending verification

Sample-to-Sample Test and Flip Terminal Test

- Test two identical core samples and compare the measurement results
- The performance of these two cores are very similar (perhaps from the same batch)

- Flip the two terminals of a device-under-test (DUT) and compare the measurement results.
- ***50% triangle*** close to ***sinusoidal***
- ***25%/75% triangle*** higher loss than ***sinusoidal***

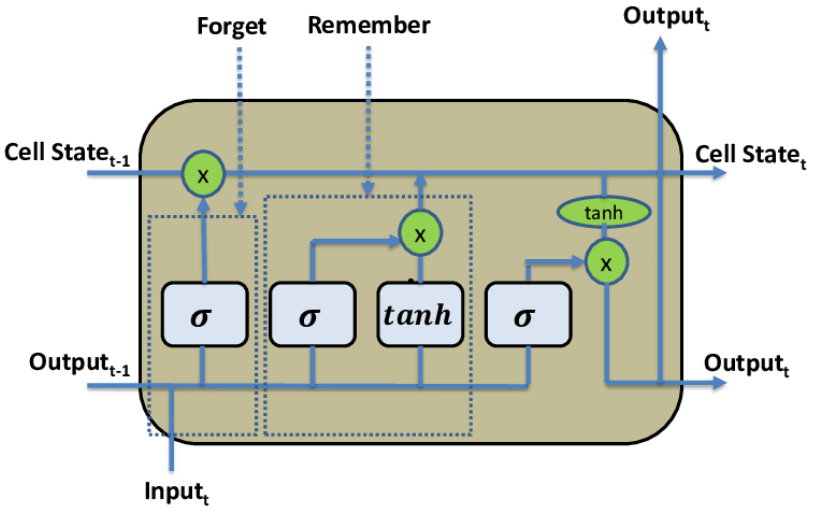




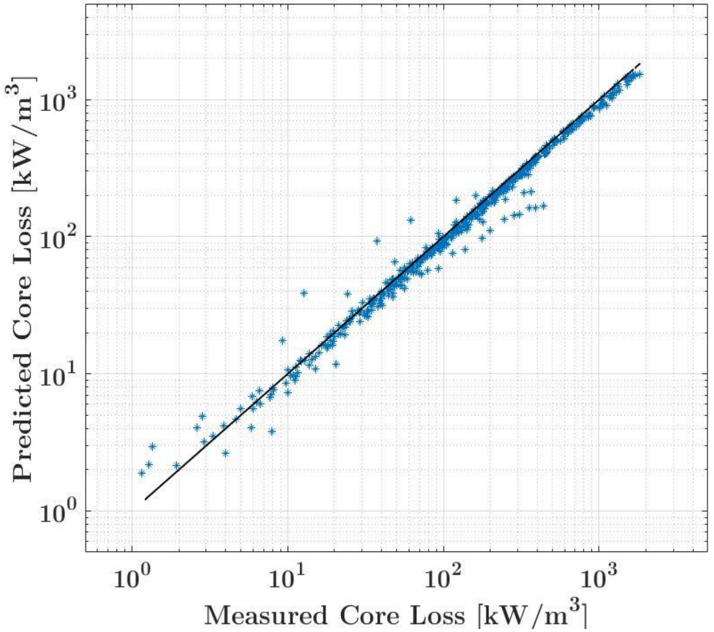
* preliminary data – pending verification

Comparing MagNet with iGSE for Arbitrary Waveform

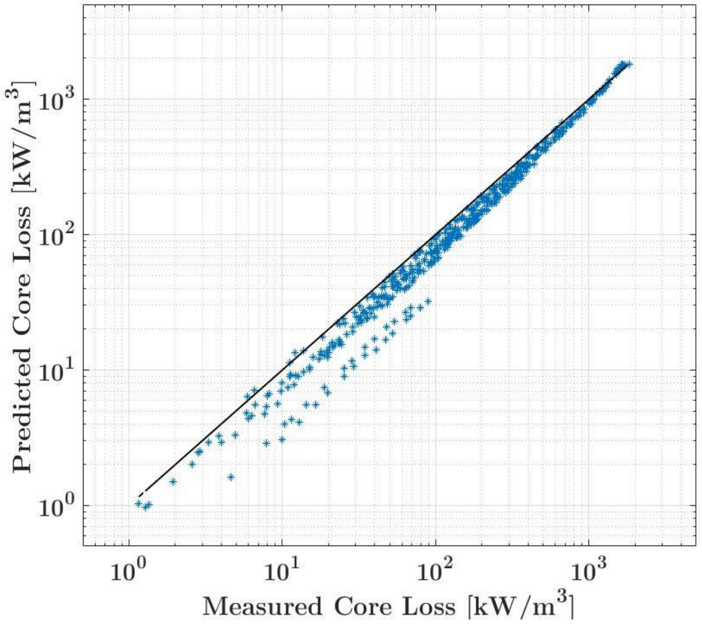
- **Type:** Triangle Wave PWM; **Frequency:** 50kHz ~ 500kHz; **Size:** 6000 data points;
- **Duty ratio:** 10% ~ 90% with step of 10%; **Amplitude:** 3V ~ 60V;



Long-Short-Term-Memory Network
A neural network structure that can capture the "memory effect"



LSTM-based method:
Avg. of relative error: 11.84%
RMS of relative error: 21.21%



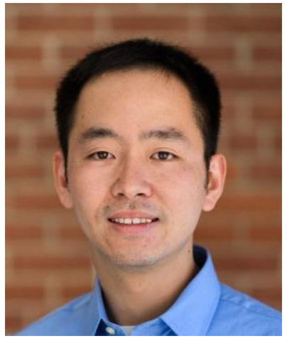
iGSE:
Avg. of relative error: 21.29%
RMS of relative error: 25.68%

Summary

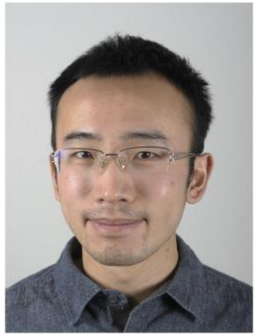
- Machine learning methods may be complementary to analytical methods.
- A 100% data-driven method is also promising.
- Data size and quality is extremely important for a data-driven approach.
- ML can work, but whether it is better or not, still unknown.

Minjie Chen

Haoran Li



Yuxin Chen



Min Luo