PSMA Power Technology Roadmap Webinar Series

Traditional and Machine-Learning based Magnetic Core Loss Modeling

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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
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

- Physics
- Flux waveforms from simulation or design calculation
- Loss calculation
- Loss prediction
- Electrical Measurements
- Dynamic model
- Circuit simulation

Flowchart:
- Physics -> Flux waveforms
- Flux waveforms -> Loss calculation
- Loss calculation -> Loss prediction
- Loss prediction -> Circuit simulation
- Circuit simulation -> Dynamic model
- Dynamic model -> Electrical Measurements
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.
Standard loss mechanisms

- Static hysteresis loss: loop area that’s independent of frequency
  \[ P \propto f, \text{ or } P = k \cdot f \cdot B^\beta \]
- 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:

\[
E_{\text{loss}} = E_1 + E_2 + \ldots
\]

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* $\Delta B$

- Still $E_{\text{loss}} = E_1 + E_2 + ..., \text{ but } E_1$ 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.

\[ B(t) = E_{loss} = E_1 + E_2 \]

- Unlike the GSE, this works pretty well in simple cases:
  - Waveforms where \( \Delta B \) 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 $\Delta B$ and segment $\delta B$.

- 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 Steinmettz 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.
- $i^2$GSE (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

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.

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: \( P_v = E_{\text{hyst}}(B_{ac}, B_{dc}) \cdot (\text{frequency effect}) \)

\[
P_v = E_{\text{hyst}} \cdot F_{\text{LW}} \cdot f_{\text{actual}}
\]

\[
F_{\text{LW}} = \text{loop widening factor} = F_{\text{LW}}(f_{\text{actual}}, \text{waveform})
\]

\[
= 1 + c \left( \frac{1}{\Delta B} \int_0^T \frac{d^2 B(t)}{dt^2} \, dt \right)^\gamma
\]

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<th>Small signal asymptote</th>
<th>Accurate frequency behavior</th>
<th>DC bias</th>
<th>Small change in waveform leads to small change in loss</th>
<th>Composite wavefrms OK</th>
<th>Relaxation effect</th>
<th>Number of params w/o dc model</th>
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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


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

Minjie Chen
Electrical and Computer Engineering
Andlinger Center for Energy and the Environment
Princeton University
Methods for Magnetic Core Loss Modeling

- Steinmetzt Equation (SE)
  \[ P_v = k f^\alpha \dot{B}^\beta \]
  \( P_v \) three parameters, sine wave
  \( k, \alpha, \beta \)

- Improved GSE (iGSE)
  \[ P_v = \frac{1}{T} \int_0^T k_i \left| \frac{dB}{dt} \right|^\alpha (\Delta B)^{\beta - \alpha} dt \]
  \( P_v \) three parameters
  \( k_i, \alpha, \beta \)

- Improved – improved GSE (i^2GSE)
  \[ P_v = \frac{1}{T} \int_0^T k_i \left| \frac{dB}{dt} \right|^\alpha (\Delta B)^{\beta - \alpha} dt + \sum_{l=1}^n Q_{rl} P_{rl} \]
  \( P_v \) eight parameters
  \( k_i, \alpha, \beta, \alpha_r, \beta_r, k_r, \tau, q_r \)

- Machine Learning based Methods
  \( P_v \) 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 Steinmetzt Parameters,” COMPEL02
Motivation for Machine Learning based Methods

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?

Task 1: MIDAS: A ML-Integrated Data Acquisition System
Task 2: MICLM: ML-Integrated Magnetic Core Loss Model
Task 3: MLSPICE: A ML-integrated Planar Magnetics SPICE Modeling Tool

iGSE

\[ P_v = \frac{1}{T} \int_0^T k_i \left| \frac{dB}{dt} \right|^\alpha (\Delta B)^{\beta-\alpha} dt \]

i^2GSE

\[ P_v = \frac{1}{T} \int_0^T k_i \left| \frac{dB}{dt} \right|^\alpha (\Delta B)^{\beta-\alpha} dt + \sum_{l=1}^{n} Q_{rl} P_{rl} \]

- 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

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

Automatic Data Acquisition

Neural Network Training

Lumped Circuit Model

MagNet - Open Source, Industry Collaboration and Student Competition

- 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)

\[
B = \frac{\int V \cdot dt}{N_2 \cdot A}
\]

\[
V_{\text{max}} = N_2 \cdot A \cdot 2\pi f \cdot B_{\text{max}}
\]

\[
v = V_{\text{max}} \cdot \sin(2\pi f \cdot t)
\]

assume pure-sinusoidal current waveform
Neural Network Architecture

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

  - Time Sequence
  - Voltage Waveforms → Neural Network 1 (Conv1D, LSTM... → 2 Scalar (Frequency and Flux Density) → Neural Network 2 (Fully Connected → 1 Scalar (Core Loss)

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

  - Voltage Waveforms → Neural Network 3 → Core Loss

- Github Repository: [https://github.com/minjiechen/MagNet](https://github.com/minjiechen/MagNet)
Predicting Core Loss based on Datasheet Data

**Average RMS Error: 3.65%**

**Average RMS Error: 7.62%**

Initial Training with Extracted Data from Datasheet

Core Loss for Sinusoidal Periodic Excitations

Initial Neural Network

Retrain with Measured Data from Experiments

Completed Neural Network

Core Loss for Arbitrary Excitations
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.
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

- Oscilloscope: Tektronix DPO4054
- Host Computer
- Power Stage
- Voltage
- Current
- DUT
- Current Shunt

---

**Triangle Waveform**
- Voltage
- Current

**Trapezoidal Waveform**
- Voltage
- Current
Evaluating the Measurement Accuracy

Calibration Process

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° @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

\[ T = \frac{1}{f_{sw}} \]

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;

**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%

**Long-Short-Term-Memory Network**
A neural network structure that can capture the “memory effect”
• 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.