# 2023 MagNet Challenge Webinar: Equation-Based Baseline Models


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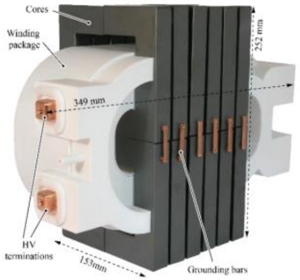
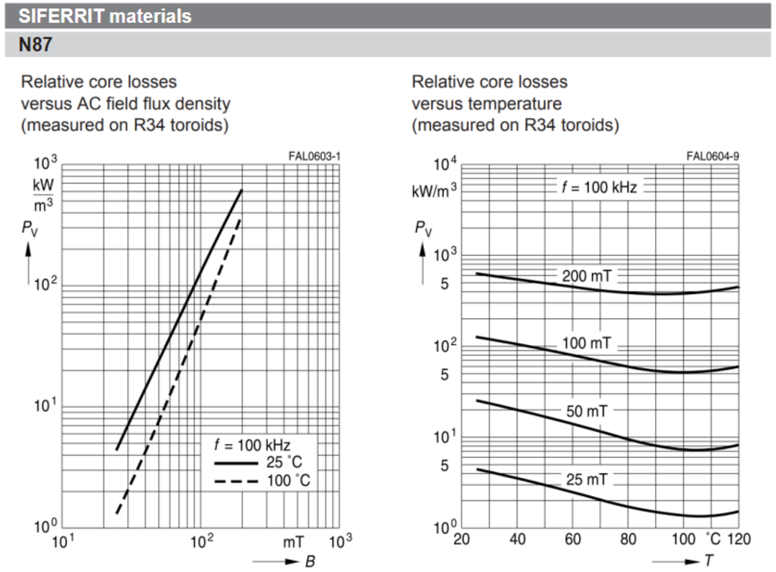
# Magnetic Material Models

- **Magnetics** are a **bottleneck**
  - Bulky, expensive, lossy
  - Challenging design process
- **Soft magnetic** core **material**
  - Inductors, transformers, sensors, etc.
  - Datasheet: only sinusoidal and incomplete
  - Models: inaccurate (up to 100% deviation)
  - No accurate first principles model
- **Better models are required**

[Dartmouth]



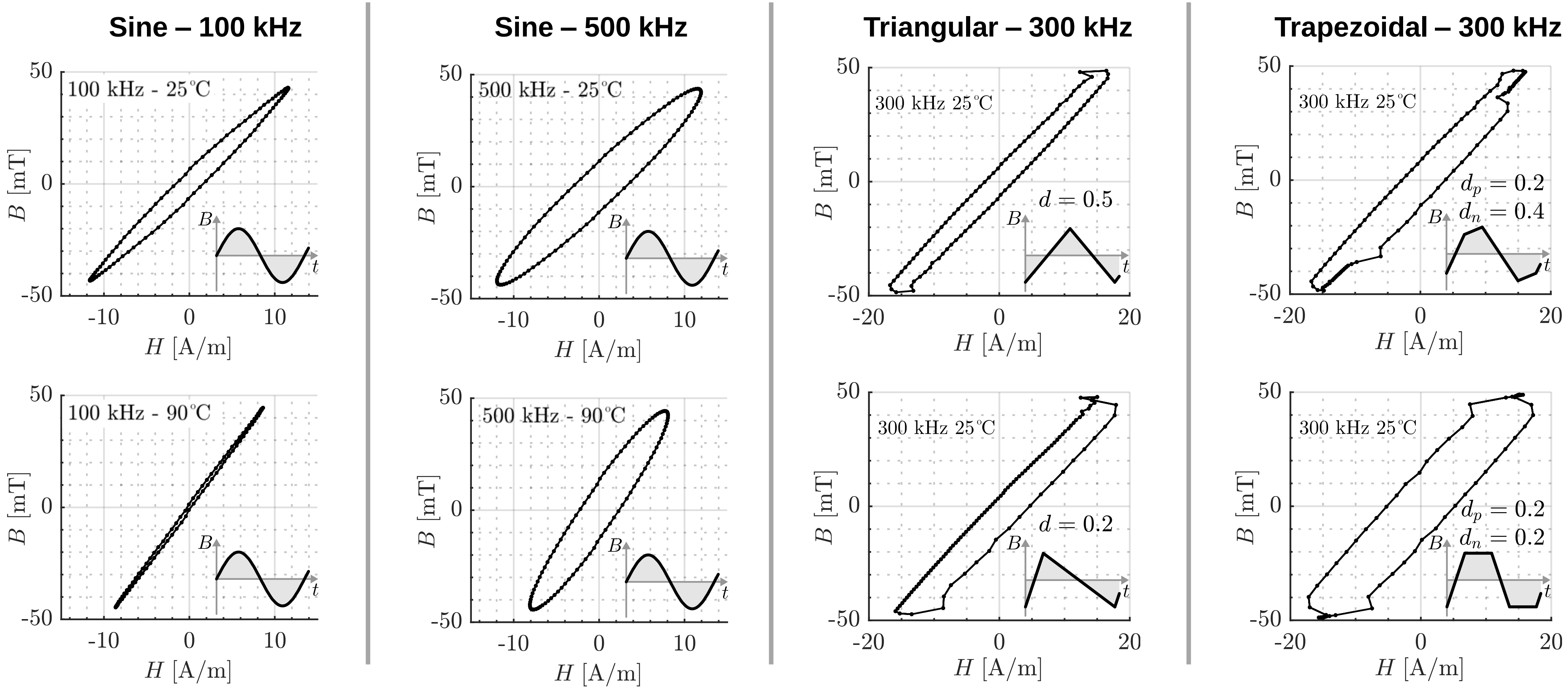

[ETHZ]




[TDK-EPCOS]

# Complex Material Behavior

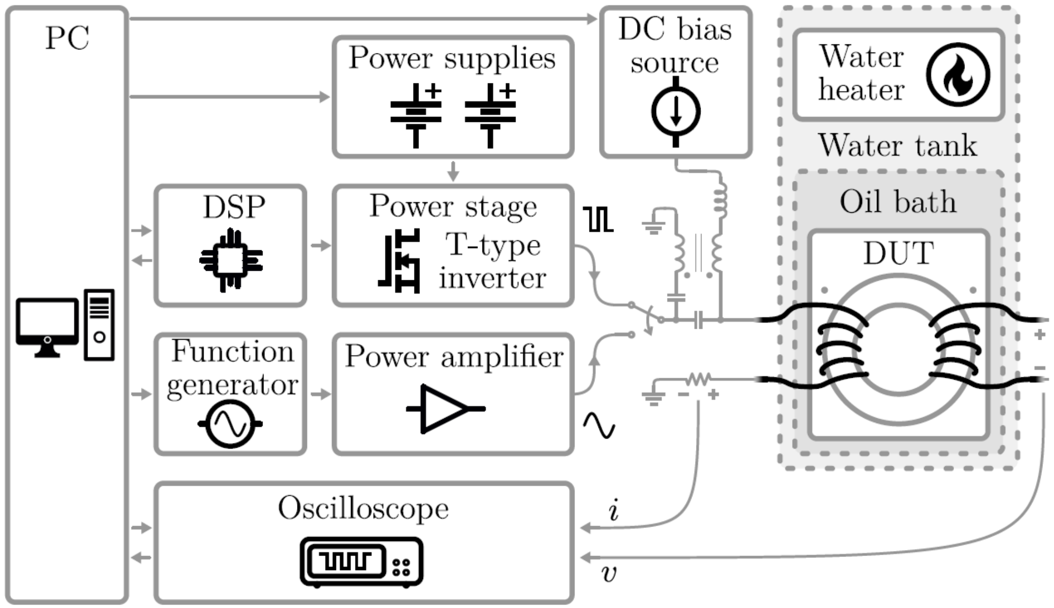
- **Nonlinear →** Amplitude, waveshape, frequency, temperature

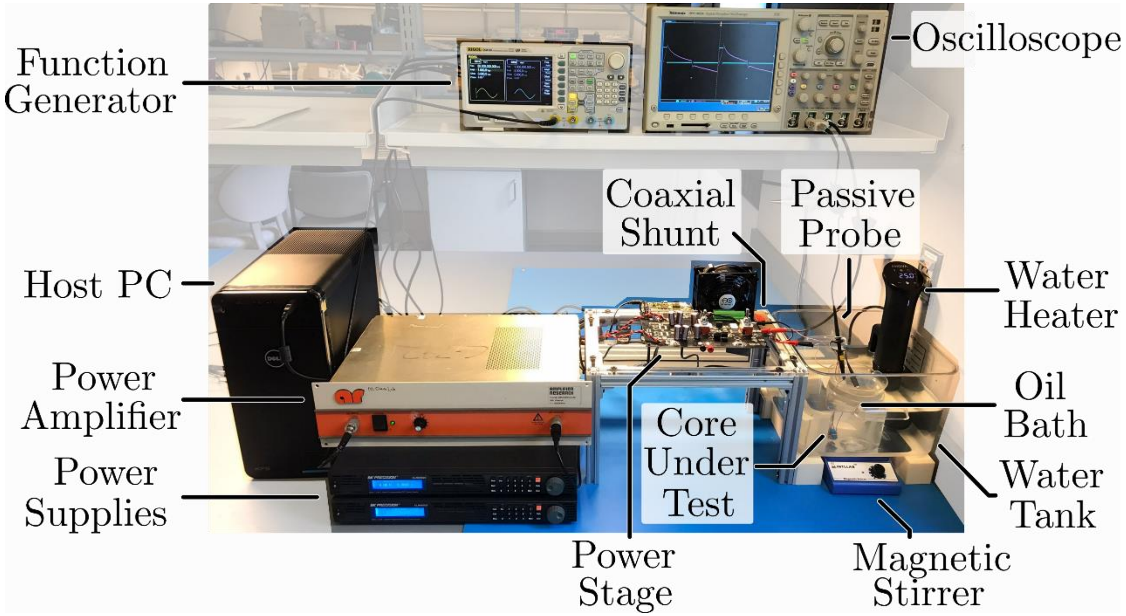



[example for R 22.1×13.7×7.9 N87 core, 7 turns]

# MagNet Dataset

- Large amount of data required
  - Automated set-up
  - 10 different materials
  - Over 500,000 measurements



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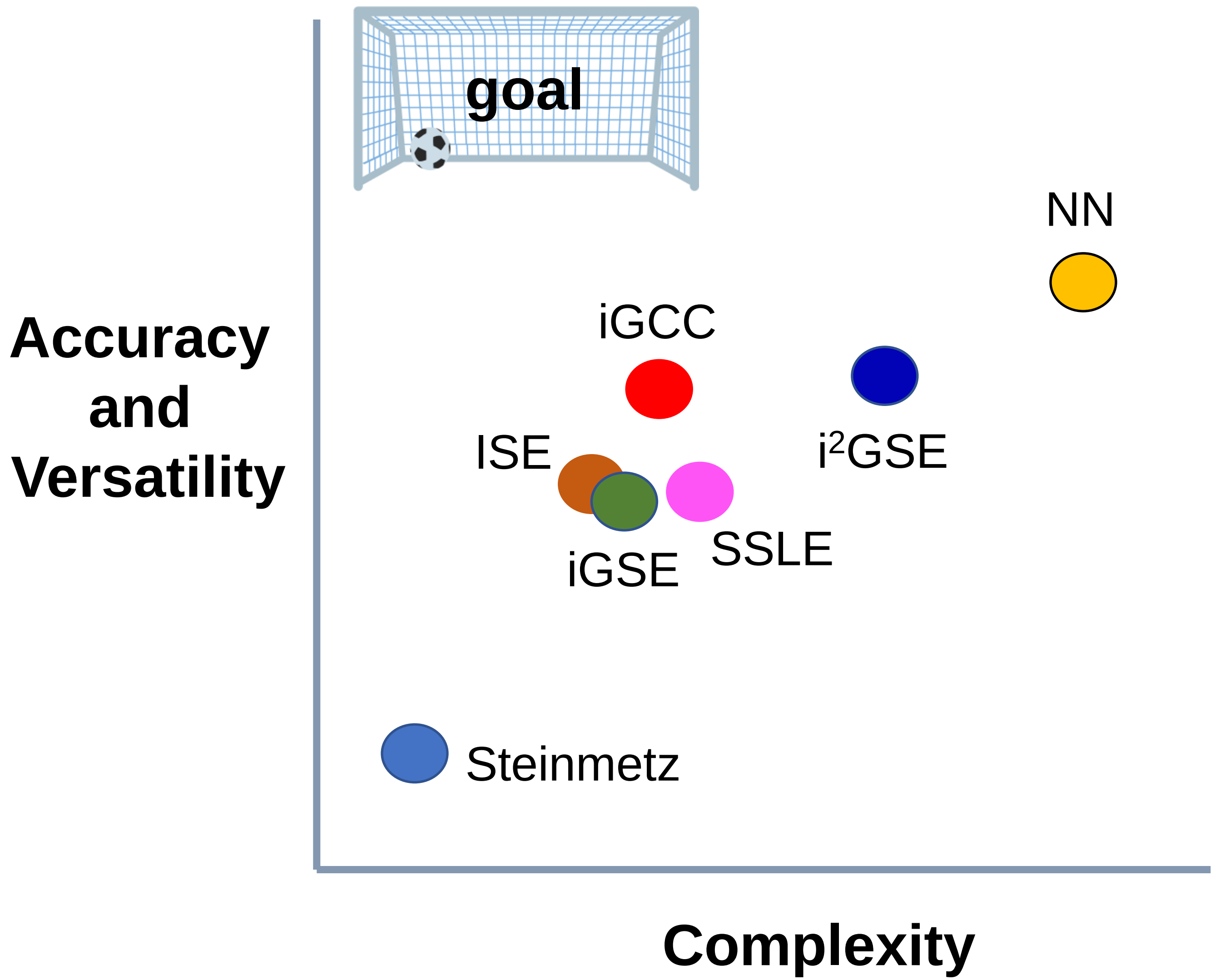
Part I: Equation-Based Models

Part II: Equation-Based vs. Machine Learning

Part III: Implementation of the iGSE

# Part I:
# Equation-Based Models

# State-of-the Art Loss Models




- Trade-off
  - Accuracy and versatility
  - Complexity
- iGSE: only 3 parameters
- NN: up to 50’000 parameters
- Apple to orange comparison !

# Equation-Based Models

- **Equation-based models**
  - Analytical formulation
  - Fully empirical or physics-inspired
  - Empirical parameters extracted from measurements

- **Steinmetz equation [Steinmetz, 1890]**
  - Original form without frequency-dependency
  - Modified in order to include frequency-dependency
  - $P = k f^{\alpha} B_{\mathrm{pkpk}}^{\beta}$
  - Based on the Steinmetz parameters ($k$, $\alpha$, and $\beta$)
  - Parameters are typically fitted with sinusoidal waveforms
  - No dependencies on the waveshape (sine, triangular, trapezoidal, etc.)

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# State of the Art

- **Improved generalized Steinmetz equation (iGSE) [Venkatachalam, 2002]**
  - Loss computation for arbitrary waveforms
  - Based on the Steinmetz parameters ($k$, $\alpha$ , and $\beta$)
  - $P = \frac{1}{T}\int_0^T k \left|\frac{\mathrm{d}B}{\mathrm{d}t}\right|^{\alpha} \left(B_{\mathrm{pkpk}}\right)^{\beta-\alpha}\,\mathrm{d}t$

- **Second derivative based models [Stenglein, 2021]**
  - **SSLE (3 parameters)**

$$P = kf\left(f_{\mathrm{eq}}\right)^{\alpha-1} B_{\mathrm{pkpk}}^{\beta}$$

$$f_{\mathrm{eq}} = \frac{1}{4\pi B_{\mathrm{pkpk}}}\int_0^T \left|\frac{\mathrm{d}^2 B}{\mathrm{d}t^2}\right|\mathrm{d}t$$

  - **SEFLE (5 parameters)**

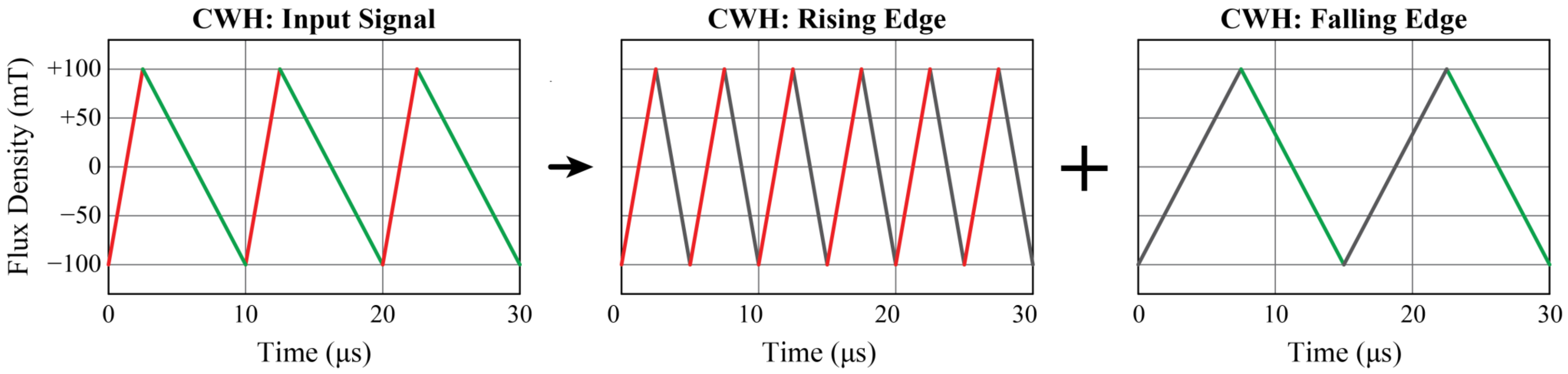
$$P = W_{\mathrm{hyst}} f_{\mathrm{eff}},$$

$$W_{\mathrm{hyst}} = a_1 B_{\mathrm{pkpk}} + a_2 B_{\mathrm{pkpk}}^2 + a_3 B_{\mathrm{pkpk}}^3$$

$$f_{\mathrm{eff}} = f\left(1 + c\left(\frac{1}{B_{\mathrm{pkpk}}}\int_0^T \left|\frac{\mathrm{d}^2 B}{\mathrm{d}t^2}\right|\mathrm{d}t\right)^{\gamma}\right)$$

# Composite Waveform Hypothesis

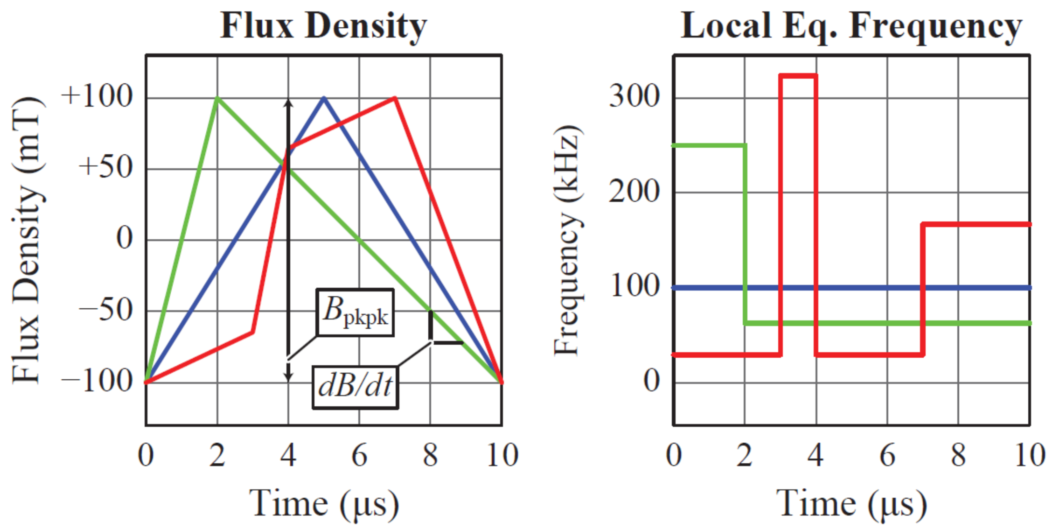
- **Composite waveform hypothesis (CWH) [Sullivan, 2010]**
  - A waveform can be decomposed in segments
  - The losses associated with the segments can be computed separately
  - Many analytical method relies (explicitly or implicitly) on the CWH
- **Triangular waveforms**




$$P = f\frac{W_1+W_2}{2} \qquad W_1 = \frac{P_1}{f_1} \qquad W_2 = \frac{P_2}{f_2}$$

# Extension to Arbitrary Waveforms

- **How to decompose an arbitrary waveform?**
  - Local equivalent frequency: $\widetilde{f}\left(t\right) = \frac{1}{2} \frac{\left|\frac{\mathrm{d}B}{\mathrm{d}t}\right|}{B_{\mathrm{pkpk}}}$
  - Property (after loop splitting): $\int_{0}^{T} \widetilde{f}\left(t\right)\,\mathrm{d}t = 1$

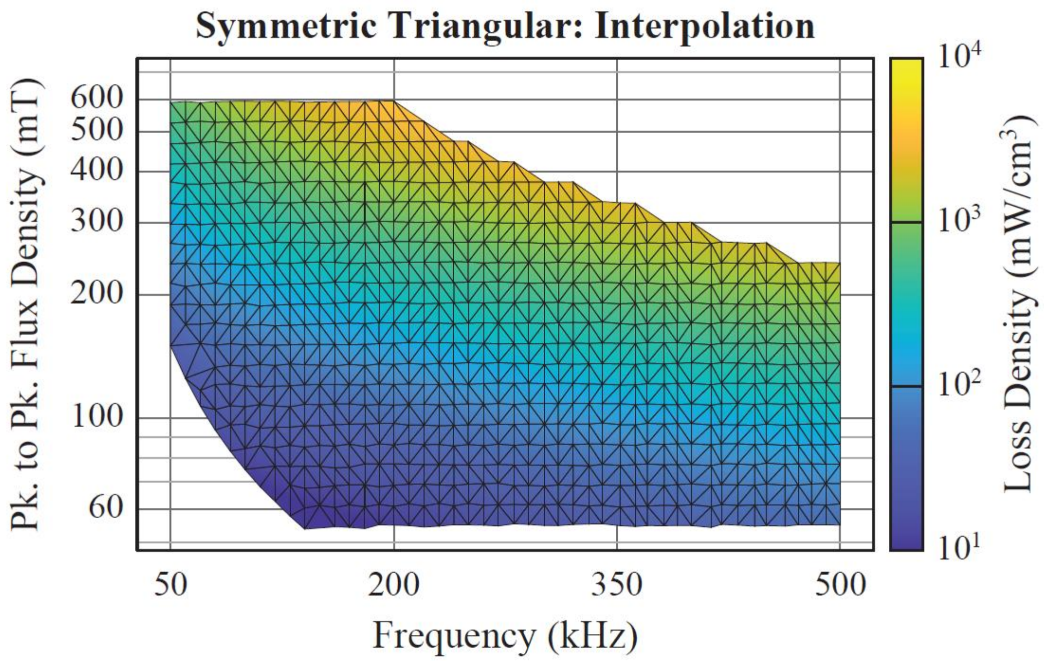


# iGCC Equation

- **Improved Generalized Composite Calculation (iGCC)**
  - Local equivalent frequency : $$\tilde{f}(t) = \frac{1}{2} \frac{\left|\frac{\mathrm{d}B}{\mathrm{d}t}\right|}{B_{\mathrm{pkpk}}}$$
  - Losses of 50% triangular waveforms: $$P_{\mathrm{sym}}\left(f, B_{\mathrm{pkpk}}\right)$$
  - iGCC integral form: $$P = \frac{1}{T} \int_0^T P_{\mathrm{sym}}\left(\tilde{f}(t), B_{\mathrm{pkpk}}\right) \mathrm{d}t$$
  - iGCC piecewise linear form: $$P = f \sum_{i=1}^{n} P_{\mathrm{sym}}\left(\frac{1}{2} \frac{\left|\frac{\Delta B_i}{\Delta t_i}\right|}{B_{\mathrm{pkpk}}}, B_{\mathrm{pkpk}}\right) \Delta t_i$$
- **How to obtain $P_{\mathrm{sym}}\left(f, B_{\mathrm{pkpk}}\right)$ ?**
  - $\mathrm{iGCC}_{\mathrm{int.}}$ : loss map with interpolation
  - $\mathrm{iGCC}_{\mathrm{fit.}}$ : curve fitting of Steinmetz parameters

# iGCC$_{int.}$ Parametrization

- **Loss map with interpolation**
  - 50% triangular waveforms
  - Different frequencies and flux densities
  - Advantage: simple and accurate
  - Drawback: requires a large dataset

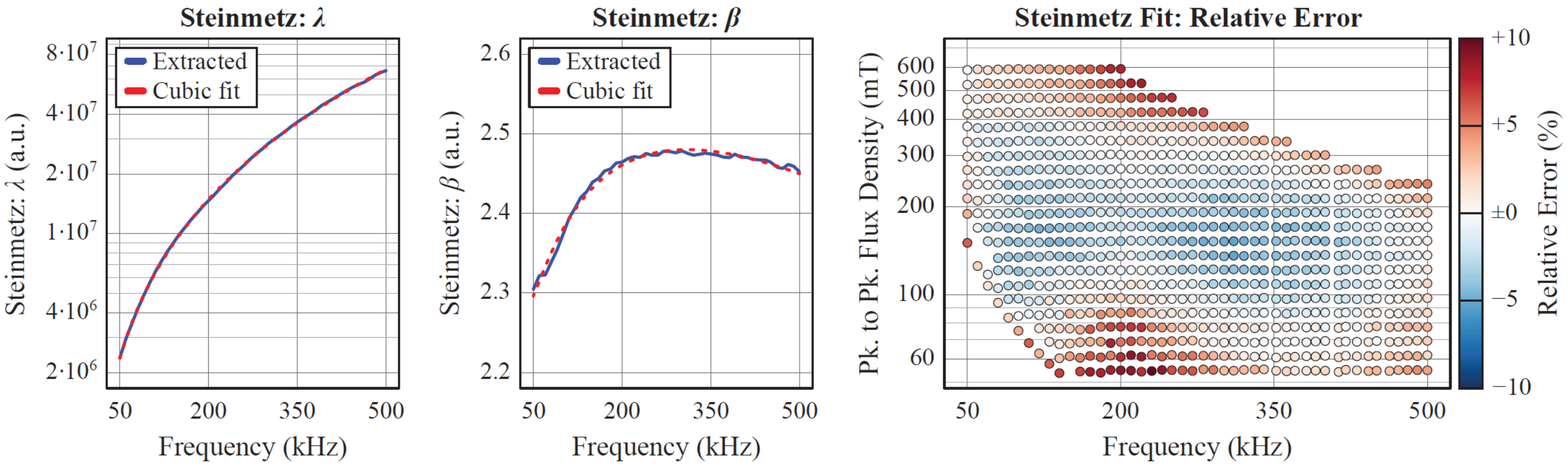



- Linear interpolation (in log scale)
- Meas. points are not on a regular grid
- Delaunay triangulation of the points

[example for N87 at 25°C]

# iGCC$_{\text{fit.}}$ Parametrization

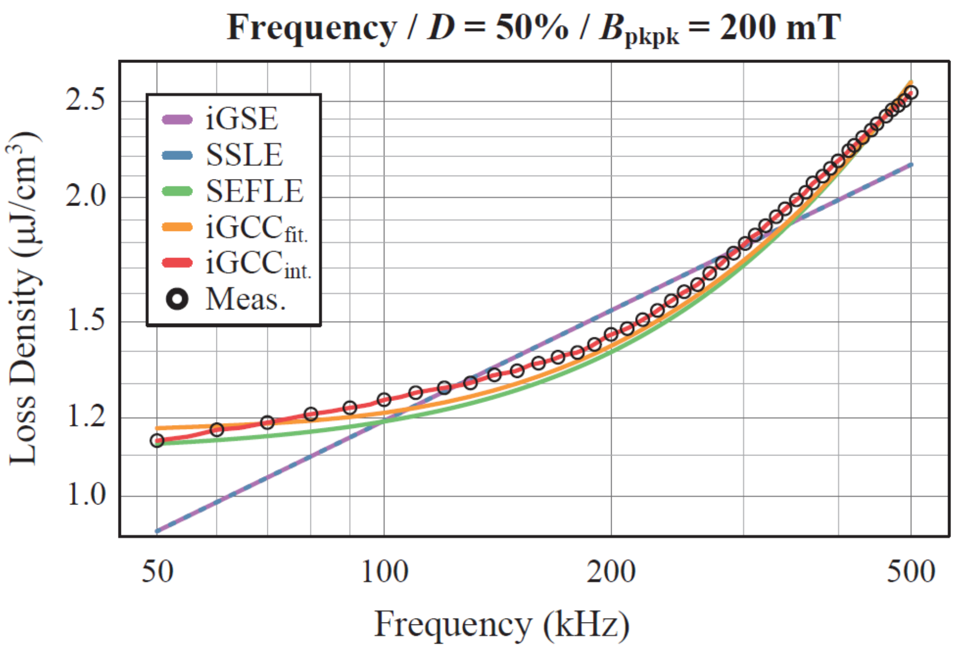
- **Frequency-dependent Steinmetz parameters**
  - Expression: $P_{\mathrm{sym}}\left(f, B_{\mathrm{pkpk}}\right) = \lambda\left(f\right) B_{\mathrm{pkpk}}^{\beta(f)}$
  - Fitting of $\lambda$ and $\beta$ for different frequencies
  - Cubic curve fitting of the obtained values
  - Advantage: no extraction of $\alpha$ is required

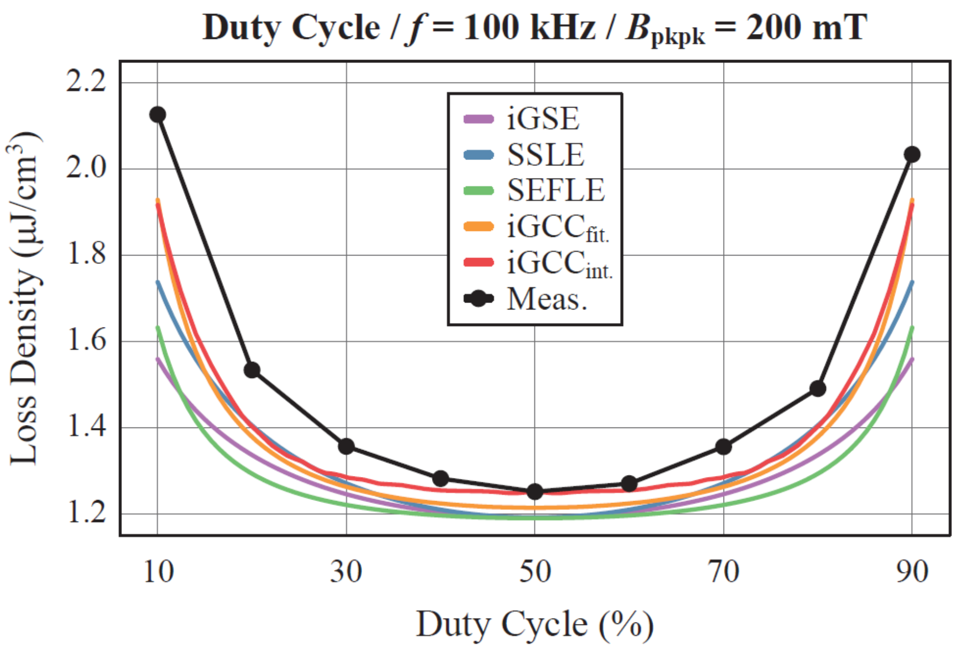



[example for N87 at 25°C]

# Model Performance

- **Triangular signals**
  - N87 material at 25°C
  - iGCC is better at extreme duty cycles
  - iGCC is better in a wide frequency range



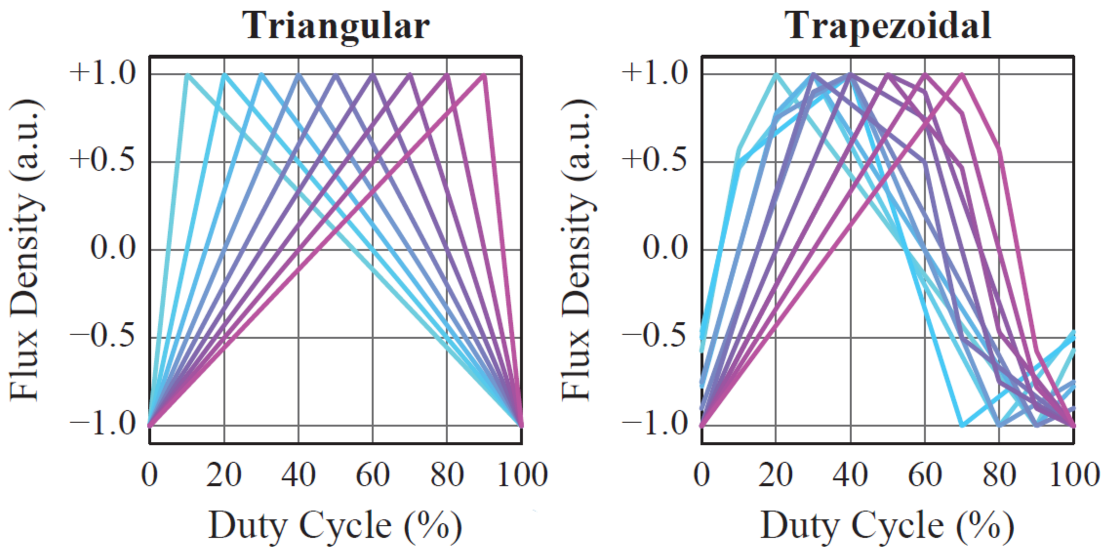




[example for N87 at 25°C with triangular waveforms]

# Model Performance



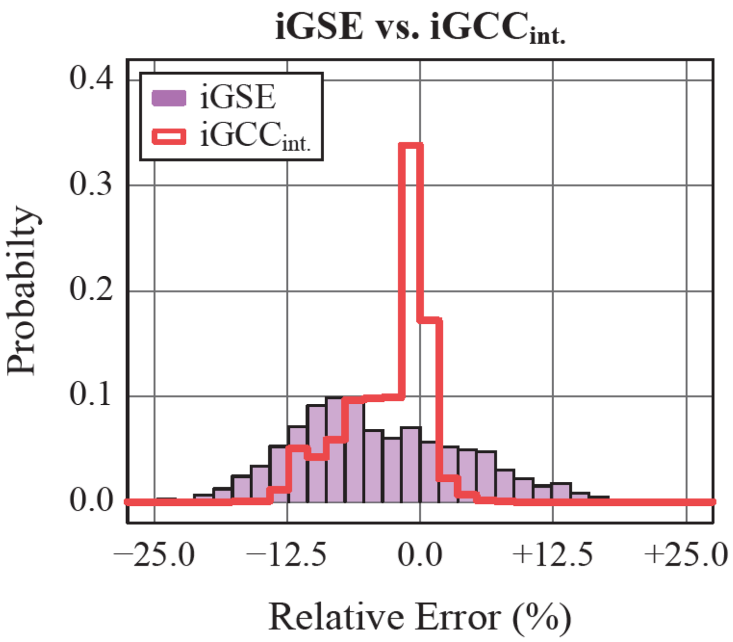
- **Large test dataset**
  - Extracted from the **MagNet** dataset
  - **N87 material**, different frequencies, amplitudes, waveshapes, temperatures
  - 4720 triangular and trapezoidal signals




- N87 Material
- $f \in [50, 500]$ kHz
- $B_{\mathrm{pkpk}} \in [50, 600]$ mT
- $T \in [25, 90]$ °C
- $P > 5\ \mathrm{mW/cm^3}$

# Model Performance

- **Measurements at 25°C**
  - iGCC clearly outperform the iGSE, SSLE, and SEFLE
  - 95th percentile error below 12%

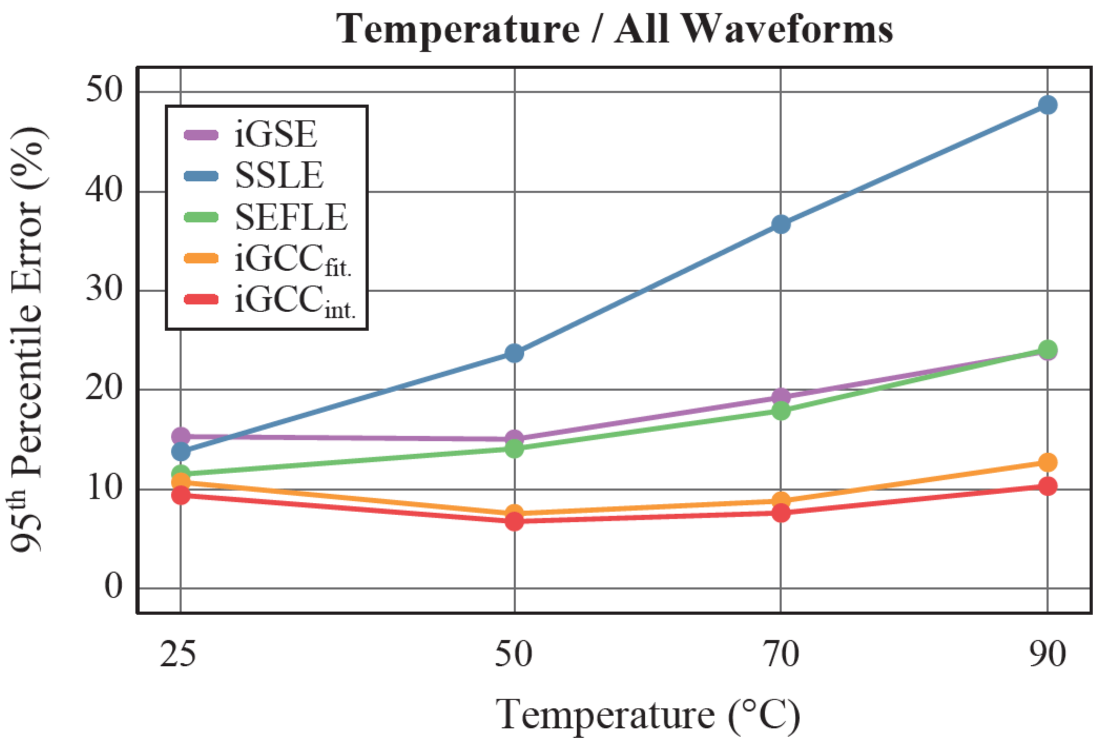



| Model | Avg. | RMS | 95th pct. | Max. |
|---|---|---|---|---|
| **iGSE** | 7.5 % | 9.0 % | 16.2 % | 27.7 % |
| **SSLE** | 6.0 % | 7.4 % | 14.3 % | 20.8 % |
| **SEFLE** | 5.4 % | 6.6 % | 12.4 % | 26.1 % |
| **iGCC$_{fit.}$** | 4.7 % | 5.9 % | 11.9 % | 16.9 % |
| **iGCC$_{int.}$** | 3.3 % | 4.8 % | 11.1 % | 16.9 % |

[example for N87 at 25°C]

# Model Performance

- **Impact of the core temperature**
  - iGCC performs well across the complete range
  - 95th percentile error below 13%




[example for N87 between 25°C and 90°C]

# Limitations and/or Opportunities

- **Limitations** of the **iGSE, iGCC, SSLE, SEFLE**
  - **Relaxation losses** are not considered
  - **Temperature dependencies** are not part of the model
  - **DC biases** are not considered (not relevant for the MagNet Challenge)
  - **Core shape** are not considered (not relevant for the MagNet Challenge)

- **Equation-based model references**
  - K. Venkatachalam et. al., “Accurate Prediction of Ferrite Core Loss with Nonsinusoidal Waveforms using only Steinmetz Parameters,” 2002
  - J. Mühlethaler et al., “Improved Core-Loss Calculation for Magnetic Components Employed in Power Electronic Systems, 2012
  - E. Stenglein et al., “Core Loss Model for Arbitrary Excitations With DC Bias Covering a Wide Frequency Range,” 2021
  - T. Guillod et al., “Calculation of Ferrite Core Losses with Arbitrary Waveforms using the Composite Waveform Hypothesis”, 2023

# Part II:
# Equation-Based vs. Machine Learning

# Eqn. Models vs. Machine Learning

- **Number of parameters**
  - Equation-based: 3 – 30 parameters
  - Machine learning: 500 – 50000 parameters

- **Required dataset**
  - Equation-based: small datasets (3 – 500 points)
  - Machine learning: large datasets (over 1000 points)

- **Link with physical phenomena**
  - Equation-based: relatively easy to achieve
  - Machine learning: possible but much more difficult

- **Model debuggability and interpretability**
  - Equation-based: not easy but achievable
  - Machine learning: extremely difficult

# Eqn. Models vs. Machine Learning



- **Predicting waveshapes that are not in the training/fitting data**
  - Equation-based: standard for state-of-the-art models (iGSE, iGCC, etc.)
  - Machine learning: possible but more difficult and unpredictable
- **Extrapolation outside the training/fitting range**
  - Equation-based: possible but risky
  - Machine learning: extremely risky
- **Detection of poor dataset quality**
  - Equation-based: possible but not guaranteed
  - Machine learning: difficult (garbage in, garbage out)

# Eqn. Models vs. Machine Learning

- **Model versatility (operating conditions, materials, etc.)**
  - Equation-based: limited to the used equations
  - Machine learning: models can “self-adapt” to various conditions

- **Possibly to extend the model (DC bias, temperature, etc.)**
  - Equation-based: require an update of the equations (can be very difficult)
  - Machine learning: easy if the model paradigm allows it

- **Achieved accuracy**
  - Equation-based: good but difficult to achieve over wide ranges
  - Machine learning: extremely good (same range as the dataset accuracy)

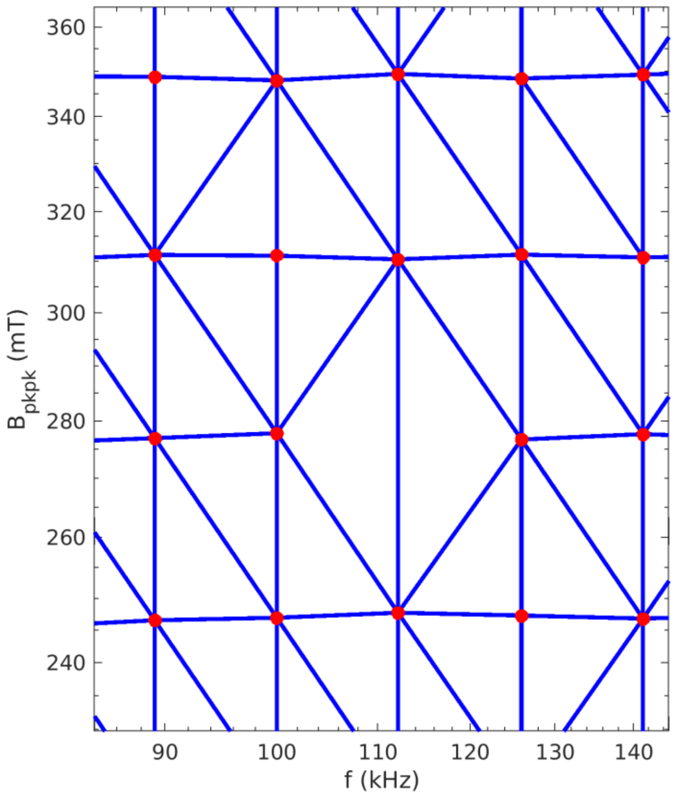
- **Dataset pre-processing**
  - Equation-based: required, dataset should be pre-processed and sorted
  - Machine learning: possible to directly use the raw dataset

# Using the MagNet Dataset

- **For equation-based models, several pitfalls should be avoided**

- **Dataset organization**
  - **Pre-processing, filtering,** and **sorting**
  - The points are **not** on a **regular grid**
  - Some **points** might be **missing**

- **Dataset range**
  - The **dataset range** might not be what you want/need
  - All the points are between **50 kHz** and **500 kHz**
    - N27 material: optimal between 10 kHz and 100 kHz
    - 3F4 material: optimal between 750 kHz and 2000 kHz
    - This can be critical for physics-based models



# Part III:
# Implementation of the iGSE

# Typical Workflow

Original MagNet dataset

**Dataset processing, filtering, sorting, and splitting**

Fitting dataset

**Parametrize the model using the fitting dataset**

Loss Model

**Test the model with the evaluation dataset**

Evaluation dataset

Model Performance

# iGSE Example

- **Disclaimers**
  - The goal of this code is to **highlight** the **typical workflow** of equation-based models
  - The implementation is **not** meant to be **comprehensive and/or accurate**
- **Assumptions**
  - Single material measured at ambient temperature
  - Only triangular signals are considered
  - Simple model parametrization
  - Reduced dataset size
- **MATLAB implementation**
  - Code **snippets** in the **slides** for the iGSE
  - **More complete code** for the iGSE and iGCC on **GitHub**
  - **https://github.com/otvam/magnet_webinar_eqn_models**

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# Main Script

MagNet

```
function run_igse()
% Parametrize and evaluate the iGSE loss model.

% load the fitting and evaluation sets
map_fit = load('data/N87_25C_fit.mat');
map_eval = load('data/N87_25C_eval.mat');

% parametrize the loss model with the loss map
fct_model = get_model(map_fit);

% evaluate a loss model and compare the results
map_eval = get_eval(map_eval, fct_model);

% save the results
save('data/N87_25C_res.mat', '-struct', 'map_eval');

end
```

**Step 1: load the datasets**

**Step 2: fit the model**

**Step 3: eval. the model**

**Step 4: save the data**

# Main Script

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function run_igse()
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% save the results
save('data/N87_25C_res.mat', '-struct', 'map_eval');

end
```

**Step 1: load the datasets**

# Step 1: Load the Datasets

- **Selected material: N87 at 25°C**

- **Fitting set (346 points)**
  - Should only contain **symmetric triangular signals**
  - f_vec — signal frequencies
  - B_pkpk_vec — peak-to-peak flux densities
  - p_meas_vec — measured loss densities (used for fitting)

| Field | Value |
|---|---|
| B_pkpk_vec | 1x346 double |
| f_vec | 1x346 double |
| p_meas_vec | 1x346 double |

- **Evaluation set (2446 points)**
  - Could contain any type of **piecewise linear waveforms**
  - f_vec — signal frequencies
  - d_mat — duty cycles defining the piecewise linear waveforms
  - B_mat — flux densities defining the piecewise linear waveforms
  - p_meas_vec — measured loss densities (used for comparison)

| Field | Value |
|---|---|
| B_mat | 3x2446 double |
| d_mat | 3x2446 double |
| f_vec | 1x2446 double |
| p_meas_vec | 1x2446 double |

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# Main Script

MagNet

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function run_igse()
% Parametrize and evaluate the iGSE loss model.

% load the fitting and evaluation sets
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map_eval = load('data/N87_25C_eval.mat');

% parametrize the loss model with the loss map
fct_model = get_model(map_fit);

% evaluate a loss model and compare the results
map_eval = get_eval(map_eval, fct_model);

% save the results
save('data/N87_25C_res.mat', '-struct', 'map_eval');

end
```

**Step 2: fit the model**

# Step 2: Fit the Model

```
function fct_model = get_model(map_fit)
% Parametrize a loss model (iGSE or iGCC) with a measured loss map.

f_vec = map_fit.f_vec;
B_pkpk_vec = map_fit.B_pkpk_vec;
p_meas_vec = map_fit.p_meas_vec;

% extract the range (frequency and flux density) of the loss map
fct_range = get_range(f_vec, B_pkpk_vec);

% fit the parametrized fitting function with the provided data
param_fit = get_igse_fit(f_vec, B_pkpk_vec, p_meas_vec);

% get a function handle describing the fitted loss model
fct_model = @(f_vec, d_mat, B_mat) get_igse_model(f_vec, d_mat, B_mat, fct_range, param_fit);

end
```

**Get the dataset**

**Find the fitting range**

**Find the optimal fit**

**Get the model**

# Step 2: Fit the Model



```
function fct_model = get_model(map_fit)
% Parametrize a loss model (iGSE or iGCC) with a measured loss map.

f_vec = map_fit.f_vec;
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p_meas_vec = map_fit.p_meas_vec;

% extract the range (frequency and flux density) of the loss map
fct_range = get_range(f_vec, B_pkpk_vec);

% fit the parametrized fitting function with the provided data
param_fit = get_igse_fit(f_vec, B_pkpk_vec, p_meas_vec);

% get a function handle describing the fitted loss model
fct_model = @(f_vec, d_mat, B_mat) get_igse_model(f_vec, d_mat, B_mat, fct_range, param_fit);

end
```

**Find the fitting range**

# Step 2: Find the Range



```matlab
function fct_range = get_range(f_vec, B_pkpk_vec)
% Extract the range (frequency and flux density) of a loss map.

% alpha radius (see alphaShape, 'Inf' for full triangulation)
alpha = 0.2;

% shape object describing the loss map range
shp_obj = alphaShape(log10(f_vec).', log10(B_pkpk_vec).', alpha);

% function testing if query points are within the loss map range
fct_range = @(f, B_pkpk) shp_obj.inShape(log10(f), log10(B_pkpk));

end
```

```matlab
function fct_model = get_model(map_fit)
% Parametrize a loss model (iGSE or iGCC) with a measured loss map.

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% extract the range (frequency and flux density) of the loss map
fct_range = get_range(f_vec, B_pkpk_vec);

% fit the parametrized fitting function with the provided data
param_fit = get_igse_fit(f_vec, B_pkpk_vec, p_meas_vec);

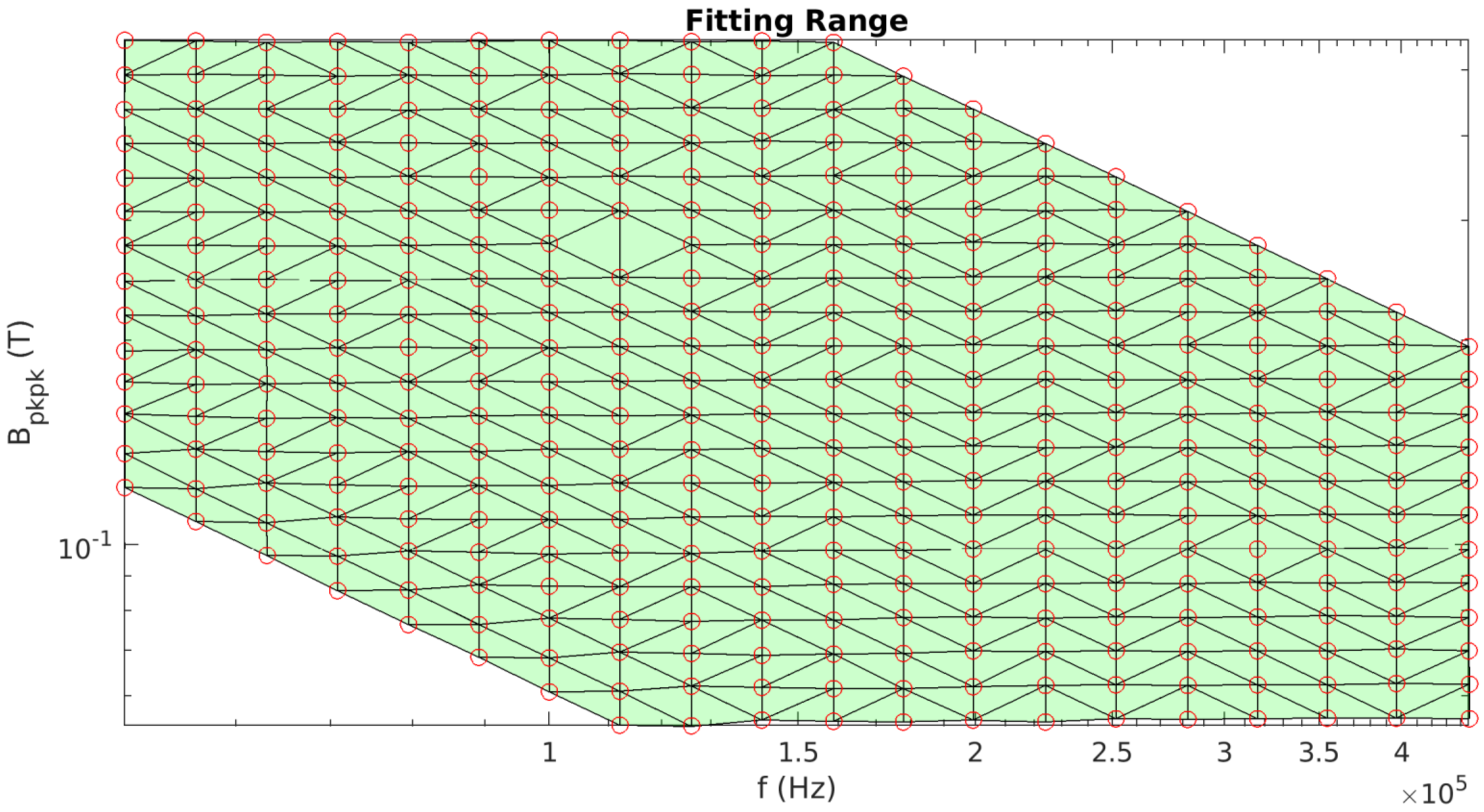
% get a function handle describing the fitted loss model
fct_model = @(f_vec, d_mat, B_mat) get_igse_model(f_vec, d_mat, B_mat, fct_range, param_fit);

end
```

- **Create a shape representing the fitting range**
- **Return a function detecting evaluation outside the range**

# Step 2: Find the Range

- **Find the fitting dataset range**
- **Detect extrapolation during model evaluation**



# Step 2: Fit the Model

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p_meas_vec = map_fit.p_meas_vec;

% extract the range (frequency and flux density) of the loss map
fct_range = get_range(f_vec, B_pkpk_vec);

% fit the parametrized fitting function with the provided data
param_fit = get_igse_fit(f_vec, B_pkpk_vec, p_meas_vec);

% get a function handle describing the fitted loss model
fct_model = @(f_vec, d_mat, B_mat) get_igse_model(f_vec, d_mat, B_mat, fct_range, param_fit);

end
```

**Find the optimal fit**

# Step 2: Find the Optimal Fit

```matlab
function param_fit = get_igse_fit(f_vec, B_pkpk_vec, p_meas_vec)
% Extraction of a least-square fit of a function with respect to a loss map.

% get the initial value vector
x0 = [0.0, 0.0, 0.0];

% function evaluating the fit function for given parameters
fct_eval = @(x) x(1).*(f_vec.^x(2)).*(B_pkpk_vec.^x(3));

% function describing the relative error between the fits and the measurements
fct_fun = @(x) (fct_eval(x)-p_meas_vec)./p_meas_vec;

% get the options for the least-square fitting algoritm
fit_options = struct('FunctionTolerance', 1e-6, 'Display', 'off');

% solve the fitting problem with a least-square fitting algoritm
x = lsqnonlin(fct_fun, x0, [], [], fit_options);

% extract the fitted parameters
param_fit = cell2struct(num2cell(x.'), {'k', 'alpha', 'beta'});

end
```

```matlab
function fct_model = get_model(map_fit)
% Parametrize a loss model (iGSE or iGCC) with a measured loss map.

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p_meas_vec = map_fit.p_meas_vec;

% extract the range (frequency and flux density) of the loss map
fct_range = get_range(f_vec, B_pkpk_vec);

% fit the parametrized fitting function with the provided data
param_fit = get_igse_fit(f_vec, B_pkpk_vec, p_meas_vec);

% get a function handle describing the fitted loss model
fct_model = @(f_vec, d_mat, B_mat) get_igse_model(f_vec, d_mat, B_mat, fct_range, param_fit);

end
```
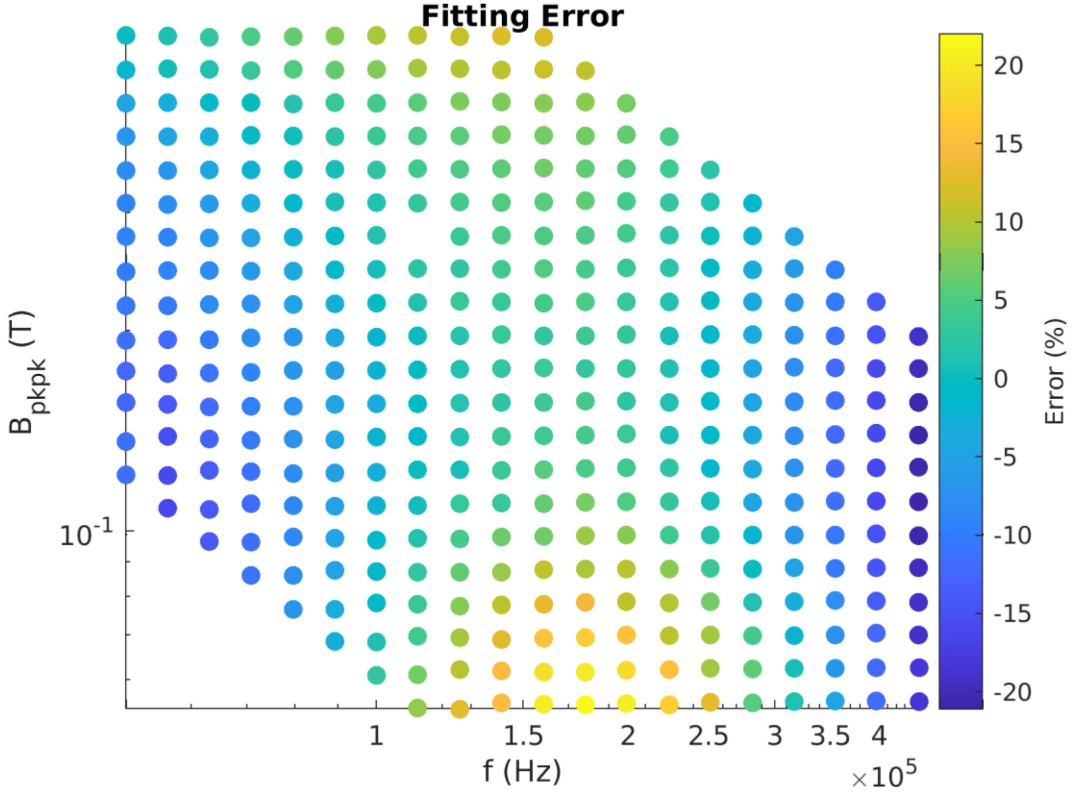

- **Get a function returning the relative errors for given fitting parameters**
- **Find the optimal fitting Steinmetz parameters with a least-square algorithm**

# Step 2: Fit the Model

- **Evaluate the performance of the fit**




```
fit
    errors
        n_points = 346
        err_mean = 6.920 %
        err_rms = 8.646 %
        err_95th = 18.161 %
        err_max = 22.032 %
    parameters
        k = 1.397e+00
        alpha = 1.332e+00
        beta = 2.423e+00
```

# Step 2: Fit the Model

```
function fct_model = get_model(map_fit)
% Parametrize a loss model (iGSE or iGCC) with a measured loss map.

f_vec = map_fit.f_vec;
B_pkpk_vec = map_fit.B_pkpk_vec;
p_meas_vec = map_fit.p_meas_vec;

% extract the range (frequency and flux density) of the loss map
fct_range = get_range(f_vec, B_pkpk_vec);

% fit the parametrized fitting function with the provided data
param_fit = get_igse_fit(f_vec, B_pkpk_vec, p_meas_vec);

% get a function handle describing the fitted loss model
fct_model = @(f_vec, d_mat, B_mat) get_igse_model(f_vec, d_mat, B_mat, fct_range, param_fit);

end
```

**Get the model**

# Step 2: Get the Model



```
function [valid_vec, p_model_vec] = get_igse_model(f_vec, d_mat, B_mat, fct_range, param_fit)
% Definition of the iGSE model.

k = param_fit.k;
alpha = param_fit.alpha;
beta = param_fit.beta;

% compute the duration and gradient of the segments
dd_mat = diff(d_mat, 1, 1);
dB_mat = diff(B_mat, 1, 1);
dB_dt_mat = f_vec.*(dB_mat./dd_mat);

% extract the peak-to-peak flux densities
B_pkpk_vec = max(B_mat, [], 1)-min(B_mat, [], 1);

% check which points are within the fitting range
valid_vec = fct_range(f_vec, B_pkpk_vec);

% compute the iGSE integral (for piecewise linear waveforms)
w_mat = (k./(2.^alpha)).*(B_pkpk_vec.^(beta-alpha)).*(abs(dB_dt_mat).^alpha);
p_model_vec = sum(dd_mat.*w_mat, 1);

end
```

```
function fct_model = get_model(map_fit)
% Parametrize a loss model (iGSE or iGCC) with a measured loss map.

f_vec = map_fit.f_vec;
B_pkpk_vec = map_fit.B_pkpk_vec;
p_meas_vec = map_fit.p_meas_vec;

% extract the range (frequency and flux density) of the loss map
fct_range = get_range(f_vec, B_pkpk_vec);

% fit the parametrized fitting function with the provided data
param_fit = get_igse_fit(f_vec, B_pkpk_vec, p_meas_vec);

% get a function handle describing the fitted loss model
fct_model = @(f_vec, d_mat, B_mat) get_igse_model(f_vec, d_mat, B_mat, fct_range, param_fit);

end
```

- **Compute the gradient of the piecewise linear segments**
- **Get the pk-to-pk flux**
- **Detect extrapolation**
- **Compute the iGSE summation for piecewise linear signals**

# Main Script

```
function run_igse()
% Parametrize and evaluate the iGSE loss model.

% load the fitting and evaluation sets
map_fit = load('data/N87_25C_fit.mat');
map_eval = load('data/N87_25C_eval.mat');

% parametrize the loss model with the loss map
fct_model = get_model(map_fit);

% evaluate a loss model and compare the results
map_eval = get_eval(map_eval, fct_model);

% save the results
save('data/N87_25C_res.mat', '-struct', 'map_eval');

end
```

**Step 3: eval. the model**

# Step 3: Evaluate the Model

```
function map_eval = get_eval(map_eval, fct_model)
% Evaluate a loss model and compare the results with the measurements.

f_vec = map_eval.f_vec;
d_mat = map_eval.d_mat;
B_mat = map_eval.B_mat;
p_meas_vec = map_eval.p_meas_vec;

% evaluate the loss model
[valid_vec, p_model_vec] = fct_model(f_vec, d_mat, B_mat);

% compute the relative error between the loss model and the measurements
err_model_vec = (p_model_vec-p_meas_vec)./p_meas_vec;

% add the predicted losses to the loss map
map_eval.valid_vec = valid_vec;
map_eval.p_model_vec = p_model_vec;
map_eval.err_model_vec = err_model_vec;

end
```

**Get the dataset**

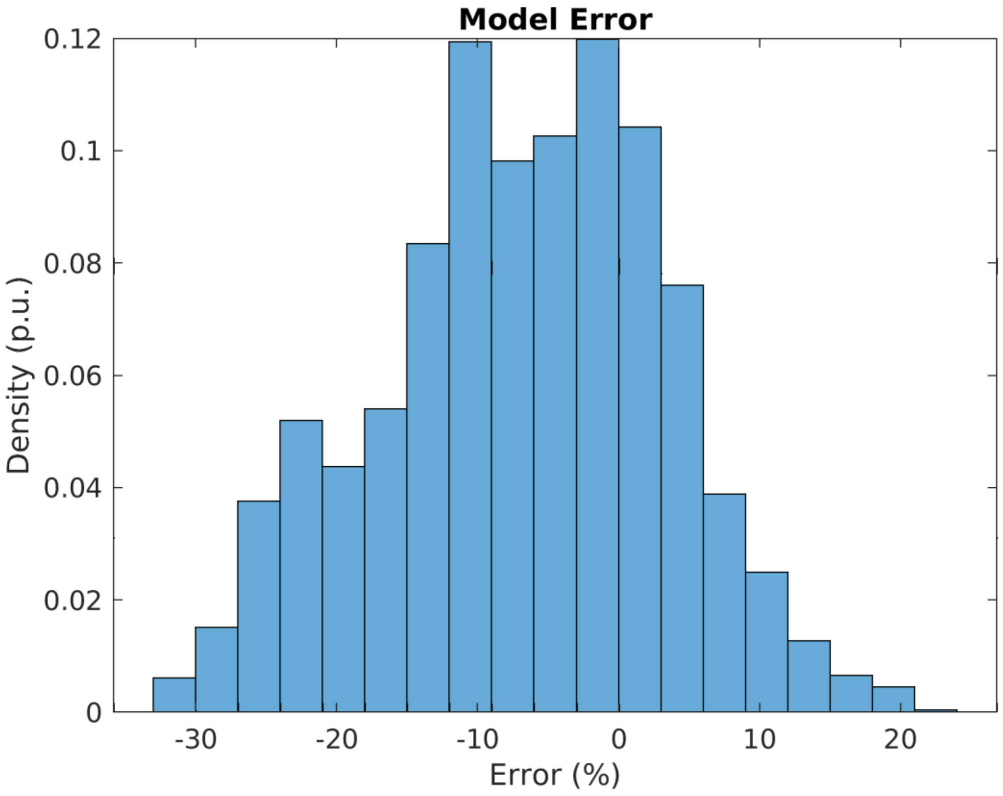
**Evaluate the model**

**Compute the deviation**

**Assign the results**

# Step 3: Evaluate the Model

- **Evaluate the model performance**




```
eval
    all points
        n_points = 2446
        err_mean = 9.642 %
        err_rms = 12.195 %
        err_95th = 24.498 %
        err_max = 32.038 %
    valid points
        n_points = 2279
        err_mean = 9.510 %
        err_rms = 12.139 %
        err_95th = 24.632 %
        err_max = 32.038 %
    invalid points
        n_points = 167
        err_mean = 11.439 %
        err_rms = 12.934 %
        err_95th = 20.696 %
        err_max = 22.796 %
```

# Main Script

```
function run_igse()
% Parametrize and evaluate the iGSE loss model.

% load the fitting and evaluation sets
map_fit = load('data/N87_25C_fit.mat');
map_eval = load('data/N87_25C_eval.mat');

% parametrize the loss model with the loss map
fct_model = get_model(map_fit);

% evaluate a loss model and compare the results
map_eval = get_eval(map_eval, fct_model);

% save the results
save('data/N87_25C_res.mat', '-struct', 'map_eval');

end
```

**Step 4: save the data**

# Programming Tips

- **Essential for development and debugging**
  - Display the results and metrics
  - Plot the results for the complete dataset
  - Plot the results for a single datapoint
- **Between the model fitting and the model evaluation**
  - Minimize the coupling
  - Use clear interfaces
- **Code performance**
  - Use vectorized instructions (no loops)
  - Downsampling of the waveshapes
  - Identify the signals (sine and piecewise linear waveforms)
  - Do not overoptimize the code !

# Thank you!
# Questions?

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

https://github.com/otvam/magnet_webinar_eqn_models

https://github.com/PrincetonUniversity/magnet

https://github.com/minjiechen/magnetchallenge