Design Methodologies for High Frequency Multiwinding Magnetics: from Fundamental Principles to Design Tools

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Design Methodology Webinar Series, 2021
We Need Better Magnetics

- Major breakthroughs in power semiconductor devices

SiC modules  GaN switches  IGBT modules  Packaging & cooling

- Magnetics are lagging behind (both discrete and integrated)

Energy Density vs. Functionality

- Capacitors win in energy / power density
- Magnetic components win in functionality / flexibility
- Larger magnetics offer higher power density
- Small & multifunctional magnetics → high frequency & multiwinding

Source: Robert Pilawa (UC Berkeley)

Source: Charles Sullivan (Dartmouth)

\[ P = VI \propto \epsilon^4 \]

\[ V \propto \epsilon^2 \]

\[ I \propto \epsilon^2 \]

core area

copper area

scaling factor
The “Integrated Magnetic” Concept

The “integrated magnetic” concept is not new...

- **before 1970s**
  - Coupled inductor buck
- **1990s**
  - Multiphase buck
- **2000s**
  - Isolated dc-dc
- **2010s**
  - Solid state xformer

Need design methods and tools for “integrated” magnetics at HF
Two Types of “Integrated” Magnetics

Series Coupled Structure
single flux multi linkage

Parallel Coupled Structure
multi flux single linkage

Geometrical Dual

All multiwinding magnetics are combinations of series and parallel coupled structures

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[M. Chen and C. R. Sullivan, TechRxiv’20]
Outline

- Design methodologies for series coupled structure (planar core)
  ![Series Coupled Structure Diagram]

- Design methodologies for parallel coupled structure (ladder core)
  ![Parallel Coupled Structure Diagram]

- Machine learning based magnetic core loss modeling methods
  ![Machine Learning Diagram]

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1. What is the optimal way to interleave many layers?

<table>
<thead>
<tr>
<th>Copper</th>
<th>Thick Spacing</th>
<th>Copper</th>
<th>Thin Spacing</th>
<th>Copper</th>
<th>Thick Spacing</th>
<th>Copper</th>
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</table>

- Alternating interleave
- Symmetric interleave

1 & 3 as primary, 2 & 4 as secondary
1 & 4 as primary, 2 & 3 as secondary

More complicated?

2. What are the optimal winding stack and winding spacing?

- Thin Middle Spacing
- Thick Middle Spacing

3. Multi-object optimization space
   1) Interleaving options?
   2) Materials?
   3) Geometry?
   4) Size?
   5) Efficiency?
   6) Coupling coefficient?

[M. Chen et al., TPEL'16]
Two Commonly Shared Assumptions

Every model starts from assumptions ...

(1) MQS assumption

- Magneto-Quasi-Static Maxwell’s equations

\[
\begin{align*}
\nabla E &= \frac{\rho}{\varepsilon_0} \\
\nabla B &= 0 \\
\nabla \times E &= -\frac{\partial B}{\partial t} \\
\nabla \times B &= \mu_0 \left( J + \varepsilon_0 \frac{\partial E}{\partial t} \right)
\end{align*}
\]

- Assume \( \frac{\partial E}{\partial t} = 0 \).
- Applicable when the wavelength is much longer than the device size (usually lower than ~100 MHz).

(2) 1-D assumption

- Fields vary only along the thickness direction.
- Applicable when the flux is guided by the magnetic core.

Magnetic core guides the flux

Skin and proximity effects change current distribution
Wave Propagation in Planar Windings

- 1-D energy wave propagation method (Poynting vector)

- Modular lumped circuit models for repeating building blocks

[M. Chen et al., TPEL’16]
Modeling a Single Conductor Layer

Field diffusion equations:

\[ H_X(z) = \frac{H_T \sinh(\Psi z) + H_B \sinh(\Psi (h - z))}{\sinh(\Psi h)} \]

Ampere’s law:

\[ \nabla \times H = J = \sigma E \]

\[ \psi = \frac{1 + j}{\delta} \quad \delta = \frac{2}{\mu \omega \sigma} \]

E field as a function of H and K:

\[
\begin{align*}
E_T &= E_Y(h) = \frac{\psi}{\sigma} \left( \frac{H_T e^{\Psi h} - H_B}{e^{\Psi h} - e^{-\Psi h}} - \frac{H_B - H_T e^{-\Psi h}}{e^{\Psi h} - e^{-\Psi h}} \right) \\
E_B &= E_Y(0) = \frac{\psi}{\sigma} \left( \frac{H_T - H_B e^{-\Psi h}}{e^{\Psi h} - e^{-\Psi h}} - \frac{H_B e^{\Psi h} - H_T}{e^{\Psi h} - e^{-\Psi h}} \right)
\end{align*}
\]

\[
\begin{align*}
Z_a &= \frac{\psi(1 - e^{-\Psi h})}{\sigma(1 + e^{-\Psi h})} \\
Z_b &= \frac{2 \psi e^{-\Psi h}}{\sigma(1 - e^{-2\Psi h})}
\end{align*}
\]

KVL/KCL relationships:

\[
\begin{align*}
E_T &= Z_a H_T + Z_b K & \text{KVL} \\
E_B &= Z_b K - Z_a H_B & \text{KVL} \\
K &= H_T - H_B & \text{KCL}
\end{align*}
\]

Electromagnetic Fields

Modular Layer Model

KVL/KCL relationships:

\[
\begin{align*}
V/m & \quad \Omega & \quad A/m \\
E_T &= Z_a H_T + Z_b K & \text{KVL} \\
E_B &= Z_b K - Z_a H_B & \text{KVL} \\
K &= H_T - H_B & \text{KCL}
\end{align*}
\]

H & K: through variables ~ unit (A/m)

E: across variable ~ unit (V/m)

Z_a, Z_b: impedances ~ unit (Ω)

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[M. Chen et al., TPEL’16]
Modeling Two Adjacent Layers

**Intuition:**
- Two three-terminal networks
- Connected by the $H$ field between them

**Faraday’s Law and Field Continuity**

\[
E_{B1} d - V_1 = -\frac{d\Phi_{B1}}{dt}, \quad E_{T2} d - V_2 = -\frac{d\Phi_{T2}}{dt}
\]

\[
\frac{d\Phi_{T2}}{dt} = \frac{d\Phi_{B1}}{dt} + \frac{d\Phi_A}{dt}
\]

**Flux Linking Two Layers:**

An additional KVL equation

\[
j\omega \mu_0 a_1 H_{S12} = \frac{V_2}{d} - E_{T2} - \frac{V_1}{d} + E_{B1}
\]

\[
\frac{A}{m} \quad \frac{V}{m}
\]

[Circuit Domain ↔ Electromagnetic Domain]
Fields distributions in multiple-turns layers are linearly related to those in single-turn layers

**Multiple turns → Additional Linear Conversions**

**E&M Domain**

**Circuit Domain**

**Intuitive Ideal Transformers**

[M. Chen et al., TPEL’16]
Modeling via is equivalent to adding KVL, KCL constraints:

Layer $i$ and Layer $j$ in series
Layer $k$ and Layer $l$ in parallel

\[
\begin{align*}
V_i + V_j &= V_a \\
V_k &= V_l = V_b \\
I_i &= I_j = I_a \\
I_k + I_l &= I_b
\end{align*}
\]

Connect the layer ports in the same pattern as they are in the real circuit.
An Open-Source SPICE Modeling Tool

1. Geometry Information

   - Magnetic Core
   - Winding stack
   - Side air gap
   - Center air gap
   - Side air gap

2. Modular Layer Model

   - Top Side of the Core
   - Spacing
   - Layer 1
   - Spacing
   - Layer 2
   - Spacing
   - Layer 3
   - Spacing
   - Layer ...
   - Spacing
   - Bottom Side of the Core

3. SPICE Netlist

   - Circuit Domain
   - E&M Domain
   - Series Connection
   - Layer port
   - Winding ports
   - Parallel Connection

Simulations!

Search: M2SPICE

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[M. Chen et al., TPEL’16]
Impacts of Interleaving Patterns

Comparing the $P_{ac}$ and $E_{ac}$ of three 1:1 transformers with three different interleaving patterns

Interleaving has to be done in the right way !!!

$P_{ac} = \sum I^2 R_{ac}$

$E_{ac} = \frac{1}{2} \sum I^2 L_{ac}$
Distributed Phase-Shift Modulation for MIMO Power Flow

DC Bus

Load 1

Load 2

Load 3

Load n

Length: 40 mm

Width: 35 mm

Height: 7.56 mm

Power & Signal Connector

DrMOS

Blocking Cap

Series Inductor

By P. Wang

P. Wang

[Minjie Chen – Princeton University]

[P. Wang, M. Chen et al., TPEL’21]
Power Flow Control of Multi-Active-Bridge

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[P. Wang, M. Chen et al., TPEL’21]
Ultra Efficient DPP System

Efficiency comparison of 50 V-5 V dc-dc systems

- **MAC-DPP**
  - Efficiency: 99.77%
  - Power Density: 700 W/in³

Higher Efficiency

Higher Density

- Delta-E54SJ
- Murata-DBE
- Synqor-PQ500
- Artesyn Embedded-AVO100
- Bel Power-xRSB
- muRATA-ULS
- ABB-Hammerhead
- Vicor DCM3623

- Magnetic Core (Effective Area: 39.5 mm²)
- Main Power Board (4 Layers)
- Bottom Cover (6 Layers)

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[P. Wang, M. Chen et al., TPEL'21]
MIMO Reconfigurable Energy Router

Reconfigurable MIMO Energy Router

[Y. Chen, M. Chen et al., TPEL’20]

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Outline

- Design methodologies for series coupled structure (planar core)
- Design methodologies for parallel coupled structure (ladder core)
- Machine learning based magnetic core loss modeling methods
Circuit Models for Mathematical Modeling

Physical Structure

Current Equalizing Transformer Model

Voltage Equalizing Transformer Model

[Minjie Chen – Princeton University]

[M. Chen and C. R. Sullivan, TechRxiv’20]
Circuit Models for Physical Design

Physical Structure

Gyrator-Capacitor Model

Reluctance Model

Inductance Dual Model

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[M. Chen and C. R. Sullivan, TechRxiv'20]
**Principles of Inductance Dual Model**

**Reluctance Model**

- Through variable: Flux ($\Phi$)
- Cross variable: MMF ($Ni$)
- Element value: Reluctance ($R$)
- Energy storage: $E = \frac{1}{2} R \Phi^2$
- Power: $MMF \frac{d\Phi}{dt}$ or $R \Phi \frac{d\Phi}{dt}$

**Inductance Dual Model**

- Through variable: Current ($I$)
- Cross variable: Voltage ($V$)
- Element value: Inductance ($L$)
- Energy storage: $E = \frac{1}{2} LI^2$
- Power: $VI$

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[M. Chen and C. R. Sullivan, TechRxiv’20]
Simulate for Core Loss and Flux Density

Advantage:
• Simple
• Intuitive
• No coupling relationships
• Explicit design equations
• Capability of capturing core loss
• Visualizing flux distribution

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[M. Chen and C. R. Sullivan, TechRxiv’20]
Geometrical Dual & Topological Dual

Geometrical Dual

Equal $\phi$

Series Coupled

Parallel Coupled

Equal MMF

Topological Dual

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[Minjie Chen and C. R. Sullivan, TechRxiv’20]
Unified Design Methods for CoupL

Benefits of interleaving
- reduced output current ripple

\[ \Gamma = \frac{(k + 1 - DM)(DM - k)}{(1 - D)DM^2} \]

Benefits of coupling
- reduced per-phase current ripple

\[ \delta = \frac{(k + 1 - DM)(DM - k)}{(1 - D)DM} \]

\[ \gamma = \frac{1 + \beta \Gamma}{1 + \beta} \]

Clarified the relationship between multiphase coupling and multiphase interleaving!
Princeton Coupled Magnetics Design Tool

Unifies the design equations for multiphase coupled inductors for different models

http://www.princeton.edu/~minjie/coupL/coupL.html

<table>
<thead>
<tr>
<th>Input Parameters</th>
<th>Design Parameters</th>
<th>Description Matrix</th>
<th>Lumped Circuit Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duty Ratio (D)</td>
<td>$N_2$</td>
<td>$N_2$ and $N_1$</td>
<td>Ideal current regulating transformer</td>
</tr>
<tr>
<td>Number of Phases (M)</td>
<td>$L_0$</td>
<td>$L_{M1}$</td>
<td>Ideal voltage regulating transformer</td>
</tr>
<tr>
<td>Number of Turns per Winding (M)</td>
<td>$I_0$</td>
<td>$I_{M1}$</td>
<td></td>
</tr>
</tbody>
</table>

- $R_C$ for $R_{C1}$
- $L_0$ for $L_{C1}$
- $I_0$ for $I_{C1}$

-M. Chen and C. R. Sullivan, TechRxiv’20-
High Voltage Conversion Ratio
• 48 V: 1 V is the future standard

High Output Current
• Approaching 1000 A

Fast Transient Response
• Over 5 A/ns

Extreme Power Density
• >100 A/cm²

Extreme Efficiency Target
• >95% peak; >80% full load

Collaborators

Hybrid Converter with Coupled Magnetics

LEGO-PoL Architecture

Four-Phase Coupled Magnetics (250 A)

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[J. Baek, M. Chen et al., APEC’20]
Vertical Multiphase Coupled Inductor

Sophisticated design space
- Side leg area
- Center leg area
- Winding area
- Plate thickness
- 2D layout
- 3D structure

Optimization targets
- Smallest leakage inductance
- Largest magnetizing inductance
- Lowest loss
- Smallest size
- Sufficient saturation margin

[J. Baek, M. Chen et al., APEC’20]
Magnetic in Circuit Analysis

Multileg Coupled Magnetics

Topological duality

500 nH

[V_{IN}

\begin{align*}
V_{OUT}
\end{align*}
Vertical Magnetics Optimization

Min Loss: 1.4231W at h=5.5mm, A_{leg}=12.25mm^2

J. Baek
Y. Elasser

Minjie Chen – Princeton University

[J. Baek, M. Chen et al., APEC’20]
Other High Performance PoL Designs


Outline

- Design methodologies for series coupled structure (planar core)
  - Circuit diagram showing series coupling

- Design methodologies for parallel coupled structure (ladder core)
  - Circuit diagram showing parallel coupling

- Machine learning based magnetic core loss modeling methods
  - Machine learning models and waveform diagrams
Machine Learning for Core Loss Modeling

- Generalized Steinmetz Equation (GSE)
  \[ P_v = k f^\alpha \hat{B}^\beta \]  three parameters, sine wave  \( k, \alpha, \beta \)

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

- Improved – improved GSE (i²GSE)
  \[ P_v = \frac{1}{T} \int_0^T k_i \left| \frac{dB}{dt} \right|^\alpha (\Delta B)^{\beta-\alpha} dt + \sum_{l=1}^n Q_{rl} P_{rl} \]  eight parameters, non-sine wave  \( k_i, \alpha, \beta, \alpha_r, \beta_r, k_r, \tau, q_r \)

- Machine Learning based Methods
  lots of parameters automatically trained

- 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

- dc bias, temperature, memory effect, minor loops
- neural network

Waveform1  Waveform2  Waveform3

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MagNet: ML for Core Loss Modeling

Automatic Data Acquisition

Task 1: MIDAS A ML-Integrated Data Acquisition System

Neural Network Training

Task 2: MICLM ML-Integrated Magnetic Core Loss Model

SPICE Lumped Circuit

Task 3: MLSPICE A ML-integrated Planar Magnetics SPICE Tool

MagNet - Large Scale Open Source Database, Online Collaboration and Competition Platform

H. Li

Open source at: GitHub

Machine Learning Methods

- **Supervised learning**: use ML to replace existing design steps

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

  *Limitation: constrained by existing knowledge on magnetic core loss*

- **Unsupervised learning**: end-to-end fully autonomous ML

  Voltage Waveforms
  - Neural Network 3
  - Core Loss

  *Limitation: all information hidden, hard to interpret the results*

[H. Li, M. Chen et al., COMPEL’20]
• Use ML to extract the “weighted” frequency and flux density
Example 2D Scalograms and CNN

Waveform #1
Different Frequencies

Waveform #2
Different Amplitudes

Waveform #3
Different Types

Waveform #4
Different Types

Scalogram #1

Scalogram #2

Scalogram #3

Scalogram #4

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[H. Li, M. Chen et al., COMPEL’20]
Overall Machine Learning Architecture

- Extracted Data from Material Datasheet → Pre-Train → Neural Network 1 → Train → Neural Network 2
- Real Measured Data from Hardware System
- Conv1D-1: 8x3x3 → Conv1D-2: 8x3x3 → Conv1D-3: 8x3x3 → FC Layer: 32 → Output Layer: 1

Optuna

PyTorch

Deep Learning with PyTorch

~2% average error for sine wave
~7% average error for arbitrary wave
Impacts of DC Bias on Core Loss

\[
\text{scalogram} = \begin{bmatrix}
\text{scalogram} \\
K \cdot \text{DC bias}
\end{bmatrix}
\]

Modeling the dc bias

\[
\text{scalogram} = \begin{bmatrix}
0 & \ldots & 0 & \ldots & 0
\end{bmatrix}
\]

\[\text{DC bias}\]
Core Loss Prediction with DC Bias

Before including the DC bias information: 11.12%

After including the DC bias information by modifying the scalogram: 5.23%

This is just scratching the surface of ML-based core loss modeling methods: dc-bias, temperature, air gap, harmonics, degradation, etc…
Transfer Learning for Different Materials

Transfer learning method:

- Train a neural network architecture with data of material A
- Update the neural network parameters with training data of material B
- Test the model accuracy with testing data of material B

[H. Li, M. Chen et al., COMPEL’20]
Towards a MIMO Magnetic Energy Processor

Multiwinding Magnetics

Connection Link
A Magnetic Register in 1960s (Memory)

- A 32 x 32 core memory storing 1024 bits of data
- Instead of processing information, we process energy
Emerging Opportunities for More Sophisticated Magnetics

Information Processor

Energy Processor

32 x 32 Magnetic Memory

10-Port MIMO Power Converter
Related Publications

• **Series Coupled Multiwinding Magnetics: Design Methodologies**

• **Series Coupled Multiwinding Magnetics: Applications**

• **Parallel Coupled Multiwinding Magnetics: Design Methodologies**

• **Parallel Coupled Multiwinding Magnetics: Applications**

• **Machine Learning Methods for Core Loss Modeling**