From Brute Force Grid Search to Artificial Intelligence: Which Algorithms for Magnetics Optimization?

IEEE APEC 2020: PSMA Industry Session
Design of Magnetics for Different Circuit Topologies

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Acknowledgement

The authors would like to thank

- P. Papamanolis
- Dr. D. Rothmund
- Dr. R. Burkart
- G. Mauro
- Dr. K. Leong
- Dr. M. Kasper
- Dr. G. Deboy

for their contributions.
Design Automation in Power Electronics

Advanced Passives
Automated Design of Converters & Systems
Interdisciplinarity

WBG

2025

Power MOSFETs & IGBTs
Microelectronics
Circuit topologies
Modulation concepts
Control concepts

Super-junct. techn. & WBG
Digital power
Modeling & simulation

Adv. Packaging

SCRs & diodes
Solid-state devices

ETH Zürich
Multi-Objective Optimization

■ Advantages
  • Efficiency, power density, costs, reliability, etc.
  • Virtual prototyping $\rightarrow$ time to market

■ Requirements
  • Models & data
  • Algorithms & objectives

[Adapted from R. Burkart, PhD Thesis, ETHZ, 2016]
Modelling Magnetics

Accuracy
Complexity
Full Numerical Model

- Based on fundamental equations
  - Maxwell
  - Heat transfer
  - Navier–Stokes

- Methods
  - FEM/FVM
  - FDM/FDTD
  - PEEC/MoM

- Properties
  - Highest accuracy
  - High modelling effort
  - High computational effort

- Useful for final validation
- Too time consuming for optimization

[Adapted from T. Guillod, PhD Thesis, ETHZ, 2018]
**Full Analytical Model**

- **Modelling approach**
  - Simplified physics
  - Simple equations
  - Explicit solution

- **Properties**
  - Low accuracy
  - Low modelling effort
  - Low computational effort

**MF transformer analytical model**

- Useful for initial estimation & understanding
- Too many simplifications for virtual prototyping

[Adapted from T. Guillod, IEEE CPSS, 2019]
Semi-Numerical Model

- **Modelling approach**
  - Complex equations
  - Numerical solution
  - Thermal-loss coupling

- **Properties**
  - High accuracy
  - Medium modelling effort
  - Medium computational effort

[Adapted from R. Burkart, PhD Thesis, ETHZ, 2016]
Data-Driven Model

- **Modelling approach**
  - Limited physical meaning
  - From measured or simulated data

- **Methods**
  - Interpolation / regression
  - Artificial intelligence

- **Properties**
  - Versatile method
  - Limited validity range

[Theoretical background: S. Skansi, Introduction to Deep Learning, 2018]
Artificial Neural Networks

- **Artificial neural networks**
  - Machine learning
  - Input/output mapping

- **Advantages**
  - Versatile method
  - Very fast evaluation

- **Difficulties**
  - Choice of the network & data
  - Extrapolation is difficult

Select the network weights in order to reconstruct the outputs with minimal error

[Theoretical background: S. Skanski, Introduction to Deep Learning, 2018]
Artificial Neural Networks

- MF transformer model
  - Semi-numerical model
  - Thermal-loss coupling

- Artificial neural networks
  - 5’000 designs for training
  - Prediction of 130’000 designs

Frequency
Number of turns
Flux density
Current density

Efficiency
Power density

Theoretical background: S. Skansi, Introduction to Deep Learning, 2018
Optimizing Magnetics

Accuracy
Complexity
Model Properties

- Properties (worst case)
  - Multivariable (input/output)
  - Non-linear
  - Non-convex
  - Non-continuous
  - No (explicit) gradient
  - Constrained (explicit/implicit)
  - Mixed-integer (discrete variables)

- Which optimization method?
- The perfect solution does not exist

- Design space to performance space
  - No clear trends
  - No clear mapping
  - No clear optimum
  - Analytical opt. are not sufficient

- Design space diversity

[Adapted from T. Guillod, IEEE CPSS, 2019]
Design Space Diversity

- **MF transformer semi-numerical model**
  - Fixed power: 20kW
  - Fixed volume: 1dm³
  - Loss range: \([P_{opt}, P_{opt} + 15\%]\)

- **300'000 designs with similar performances**
  - Frequency: [50, 300] kHz
  - Flux density: [25, 120] mT
  - Current density: [1.8, 6.5] A/mm²

**Quasi-Optimal Designs**

**Geometrical Aspect Ratio**

- Local optima and/or flat optima
- Robustness of optimization algorithms?
- Opportunities for additional constraints?

[Adapted from T. Guillod, IEEE CPSS, 2019]
Brute Force Grid Search

- **Algorithms properties**
  - Extremely robust
  - No restriction on the model
  - Exponential scaling
  - Relatively slow but parallelizable
  - Can be combined with heuristics

- **A desktop computer makes 25-400 billion floating point operations per second!**
- **A cloud computing server cost 5-10¢ per hour!**

- **DC-DC resonant converter**
  - Semi-numerical model
  - Accurate thermal-loss coupling
  - Vectorized, parallel, and optimized
  - 100’000 designs per second

- **Brute force is (whenever possible) the best solution**

[Theoretical background: S. Rao, Engineering Optimization, 2009]
**Gradient, Simplex, Geometric Programming**

- **Algorithms properties**
  - Extremely fast convergence
  - Problems with local minima
  - Problems with design space diversity

- **Restrictions on the model**
  - Smooth function (gradient opt.)
  - Posynomial function (geom. prog.)
  - No discrete variables (various alg.)
  - No complex constraints (various alg.)

- **Restricted to problems with compatible models and constraints**
- **Can be combined with other approaches (e.g. brute-force)**

[Theoretical background: S. Rao, Engineering Optimization, 2009]
Genetic Optimization, Particle Swarm, Simulated Annealing

- **Algorithms properties**
  - Stochastic approach
  - Slower convergence
  - Compatible with local minima
  - Compatible with design space diversity
  - Few restrictions on the model

- **Genetic algorithm**
  - Initial population
  - Fitness / selection
  - Crossover / mutation

- **Good trade-off between robustness and speed**

[Theoretical background: S. Rao, Engineering Optimization, 2009]
Artificial Neural Networks

- Deep learning
  - Given specifications
  - Extract Pareto Front
  - Within seconds

- Artificial neural networks
  - Prediction the number of sol.
  - Predicting the losses
  - Adjusting the Pareto front

- Difficulties
  - Choice of the network & data
  - Handling discrete data
  - Scaling to large problems

Neural Network for Inductor Pareto Fronts

Training Data from Genetic Alg.

[Infineon Technologies, Villach, Austria]
Artificial Neural Networks

- Generates inductor Pareto fronts in less than 5 seconds!

- For quick comparison between technologies
- For getting a good initial design guess

Infineon Technologies, Villach, Austria
Case Study
MV Converter
Solid-State Transformer
Design Space Diversity
Case Study: Solid-State Transformer for Datacenter

- **Single-stage SST** for datacenters presented by ETH zürich
  - 3.8kV AC input
  - 400V DC output
  - 25kW
  - 10kV SiC technology

- **DC-DC perf. target**: 99% & 3kW/dm³ & single hardware iteration
- **How to optimize using the design space diversity?**

[Adapted from D. Rothmund, IEEE JESTPE, 2018]
Converter Pareto Front

- **Trade-off: switching frequency**
  - Transformer: reduced volt-second product
  - Semiconductors: switching losses

- **Selected frequency: 48kHz**
  - System optimum: 48kHz
  - Transformer optimum: 100kHz

DC-DC Pareto Front

- Global optimum is composed of sub-optimal components
- Design space diversity?

Transformer Pareto Front

[Adapted from T. Guillod, PhD Thesis, ETHZ, 2018]
Converter Pareto Front

- **Trade-off: switching frequency**
  - Transformer: reduced volt-second product
  - Semiconductors: switching losses

- **Selected frequency: 48kHz**
  - System optimum: 48kHz
  - Transformer optimum: 100kHz

**DC-DC Pareto Front**

- Selected: 99.01%

**Transformer Pareto Front**

- Optimal: 99.75%
- Selected: 99.67%

- How to use the design space diversity?
- Brute force grid search / genetic alg.

[Adapted from T. Guillod, PhD Thesis, ETHZ, 2018]
Design Space Diversity: Accommodating Practical Constraints

- Transformer optimization
  - Every core geometry
  - Every litz wire stranding

- Available parts
  - Core & winding
  - Which impact?

- Practical constraints
  - Manufacturability
  - Which impact?

Accommodating available core & litz wires: 0.02% impact
Design space diversity mitigates the impact

[Adapted from T. Guillod, PhD Thesis, ETHZ, 2018]
Design Space Diversity: Adding a Secondary Goal

- Partial load efficiency as an additional trade-off
  - No-load losses (core)
  - Load losses (winding)
  - Negligible impact on the full-load efficiency

- Design space diversity means that additional goals are achievable

DC-DC Converter Loss Distribution

- 99.0% @ 100% load
- 99.0% @ 50% load
- 3.8 kW/dm³

DC-DC Converter Meas. Efficiency

[Adapted from D. Rothmund, IEEE JESTPE, 2018]
Conclusion & Outlook

Model & Optimization
Future Research Areas
Conclusion & Outlook

Models
- Analytical model for basic comparison
- Semi-numerical model for optimization
- Numerical model for verification
- Data-driven model has potential

Design space diversity
- Different designs → same performances
- Enable add. objectives and constraints
- Should be checked → don’t miss opportunities

Optimization
- Brute force is robust and reasonably fast
- Genetic, part. swarm, neural network, etc.
- Care is required: no guarantee for global opt.

Remaining challenges
- Integration in industrial context
- Readily available software, model, data, etc.
Thank You!

Questions? guillod@lem.ee.ethz.ch