ETH zürich

Power Electronic Systems Laboratory

Handling Design Space Diversity of Power Electronics Multi-Objective Optimization

DAPE IEEE Design Automation for Power Electronics
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Acknowledgement

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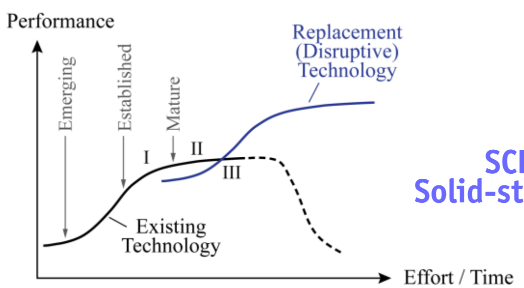
- *P. Papamanolis*
- *Dr. R. Burkart*
- *Dr. M. Leibl*
- *Dr. D. Rothmund*

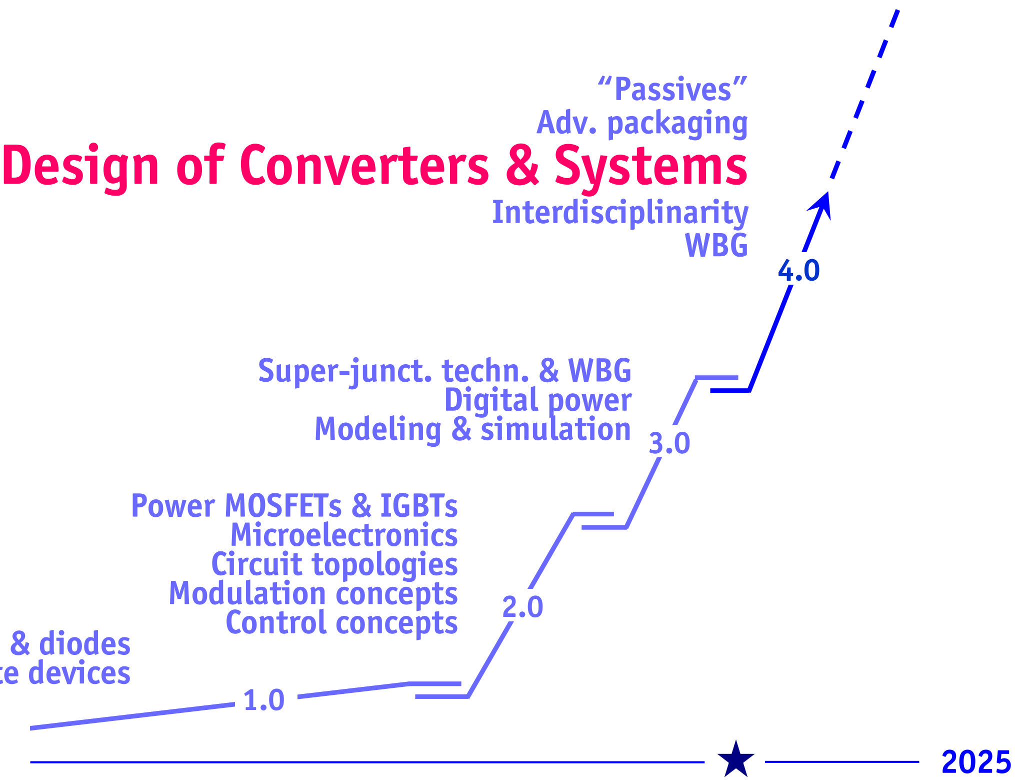
for their contributions.

Introduction

Design Automation
Multi-Objective Optimization

▶ Design Automation in Power Electronics

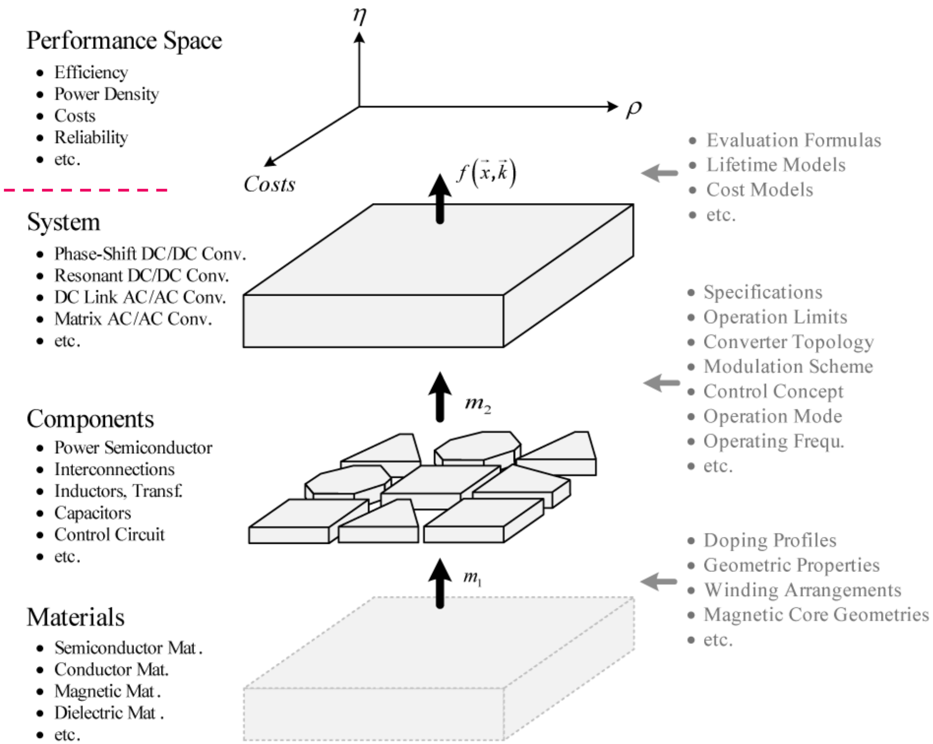




▶ Abstraction of Power Converter Design

Performance space

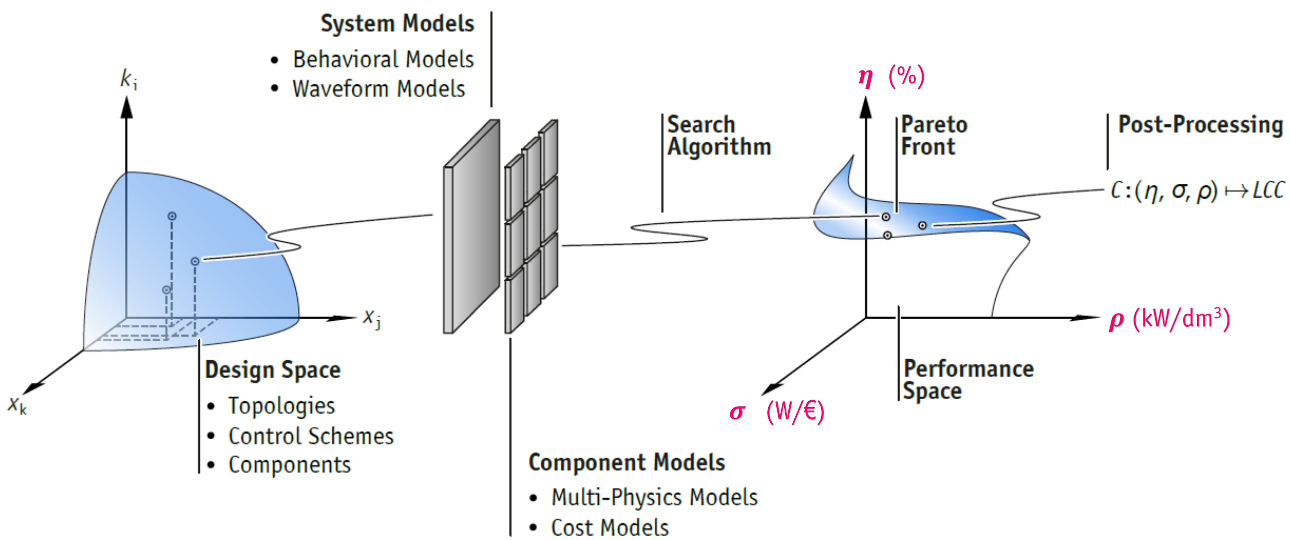
Design space



- Mapping of "design space" into "performance space"

[R. Burkart, PhD Thesis, ETHZ, 2016]

▶ Multi-Objective Optimization



- **Advantages**
  - Efficiency, power density, costs, reliability, etc.
  - Virtual prototyping → time to market
- **Requirements**
  - Models & data
  - Algorithms & objectives

[R. Burkart, PhD Thesis, ETHZ, 2016]

Models and Algorithms

Modelling
Optimization Algorithms

▶ Modelling Power Electronics

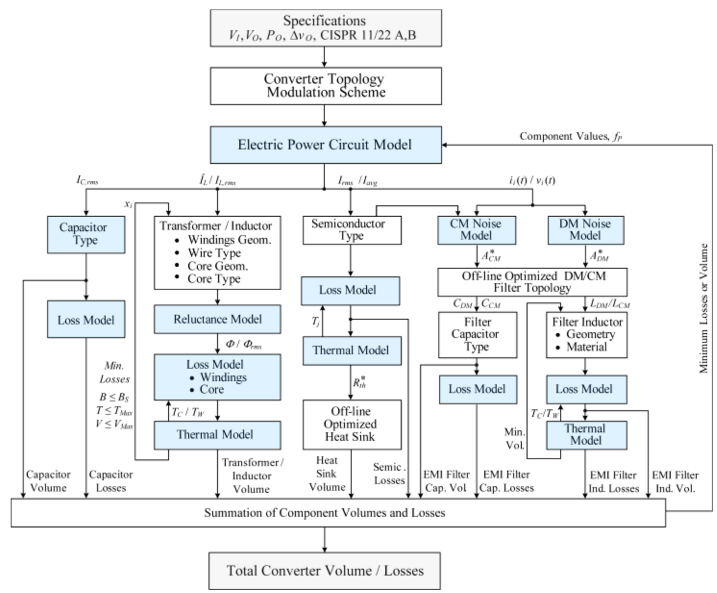
- **Analytical models**
  - Fast
  - Low effort
  - Limited accuracy

- **Numerical models**
  - Slow
  - Moderate/high effort
  - Good accuracy

- **Semi-numerical models**
  - Fast
  - Moderate effort
  - Good accuracy

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

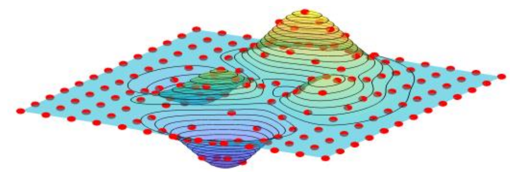
- **Which optimization method?**



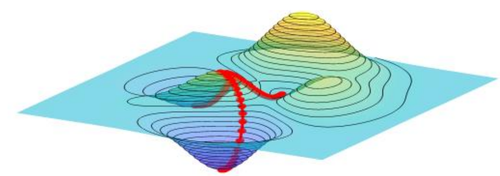
[R. Burkart, PhD Thesis, ETHZ, 2016]

▶ Optimizing Power Electronics

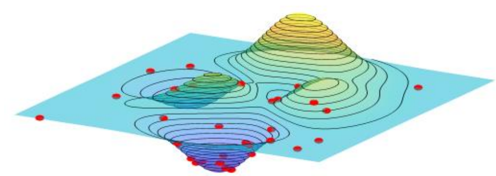
- **Grid search (brute force)**
  - Relatively slow
  - Exponential scaling
  - Extremely robust



- **Gradient, geometric prog., etc.**
  - Fast convergence
  - Strong condition on the function and constraints
  - Difficult for mixed-integer global optimization



- **Particle swarm, genetic, etc.**
  - Moderate speed
  - Relatively robust



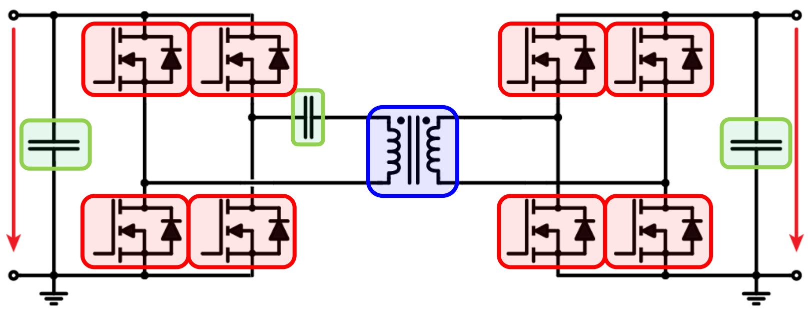
- **The perfect solution does not exist**
  - Guaranteeing global optimum is impossible
  - Simple model: cannot capture all effects

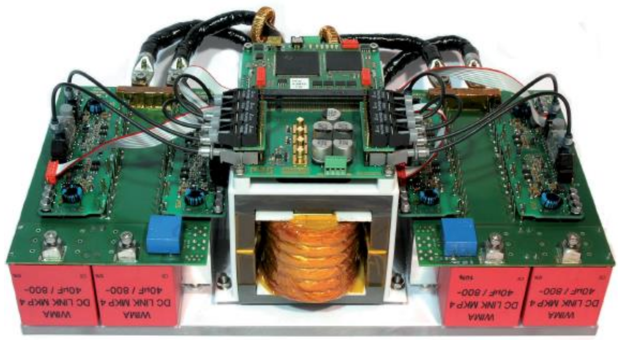
- **How fast should the models be?**

▶ Semi-Numerical: Computational Cost

- **Semi-numerical model**
  - Simple & accurate
  - Potentially time consuming
- **A desktop computer makes 25-400 billion floating point operation per second!**

- **DC-DC resonant converter**
  - Semi-numerical model
  - Accurate thermal-loss coupling
  - Vectorized, parallel, and optimized
- **100’000 designs per second → 10us per design**

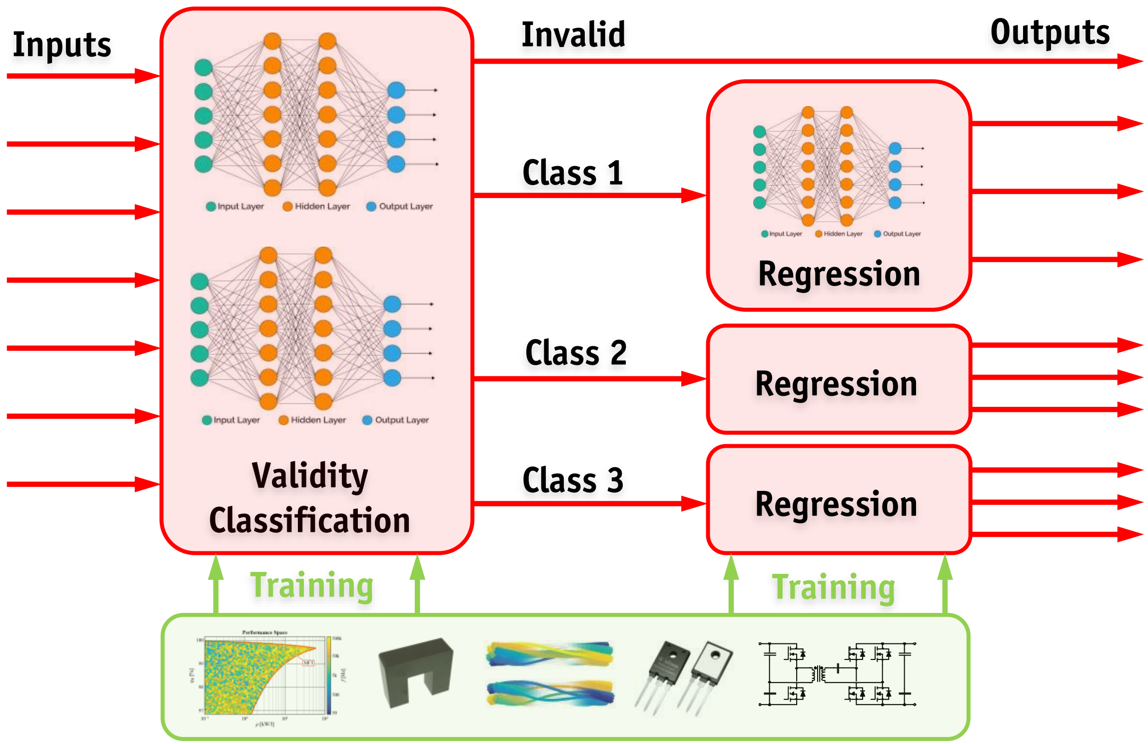




- **Further improvements: caches, pre-computation, GPUs, etc.**

▶ 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

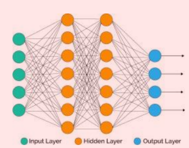


[G. Mauro, submitted to APEC 2020]

▶ 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

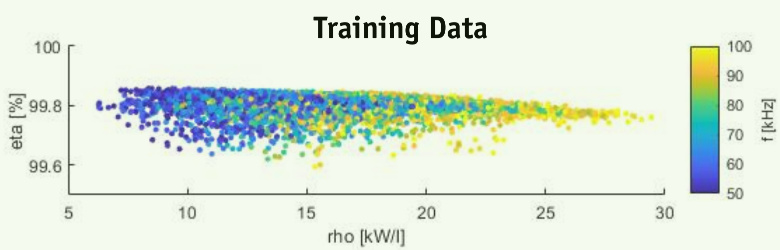
Frequency
Number of turns
Flux density
Current density

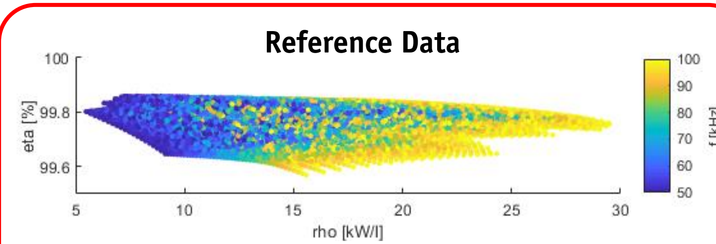


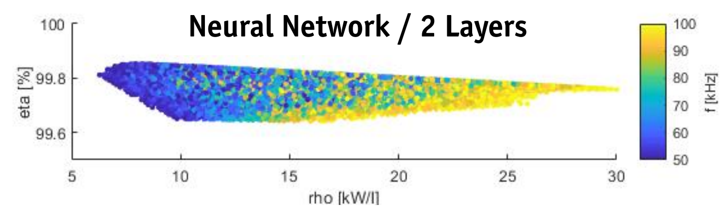
Neural Net.

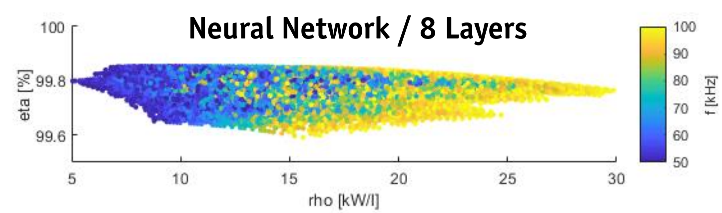
Efficiency
Power density

Training









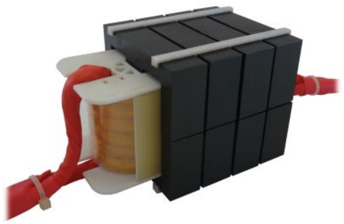
- **1’000’000 designs per second → 1us per design**
- **Promising but the parametrization is tricky!**

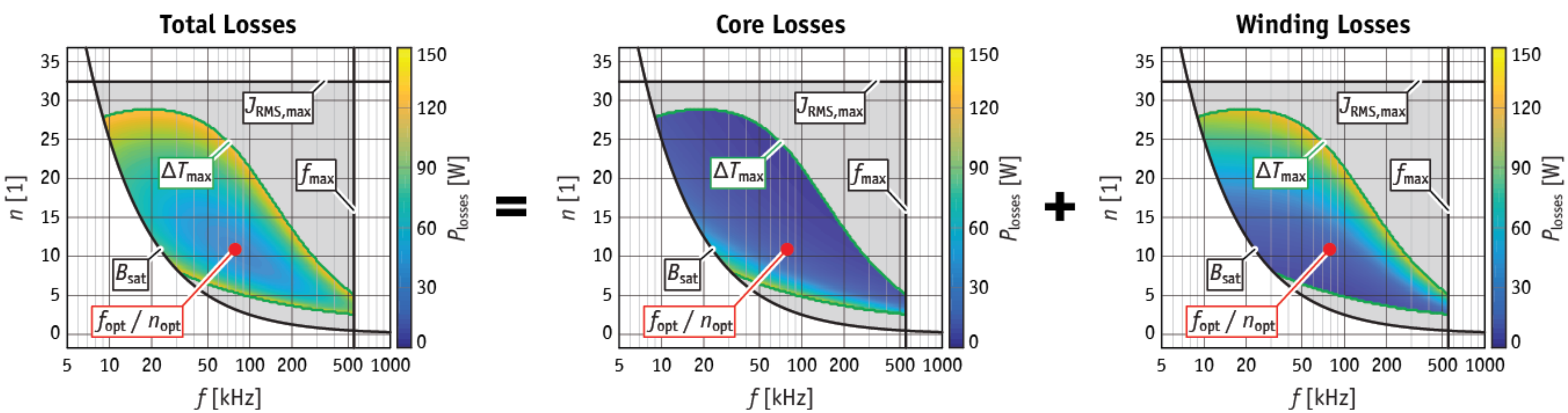
MF Transformer

Modelling & Optimization
Design Space Diversity

▶ Analytical Modelling & Optimization

- **Analytical model**
  - Core losses (GSE)
  - Winding losses (prox. effect)
  - Simple thermal model
- **Optimization**
  - Fixed power and volume
  - Optimal frequency
  - Optimal number of turns



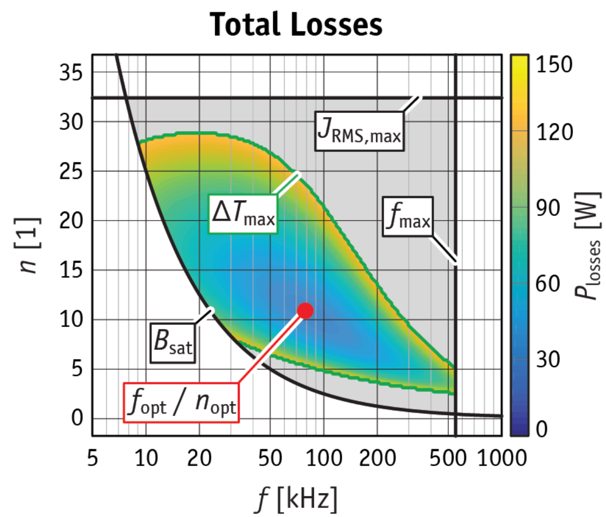


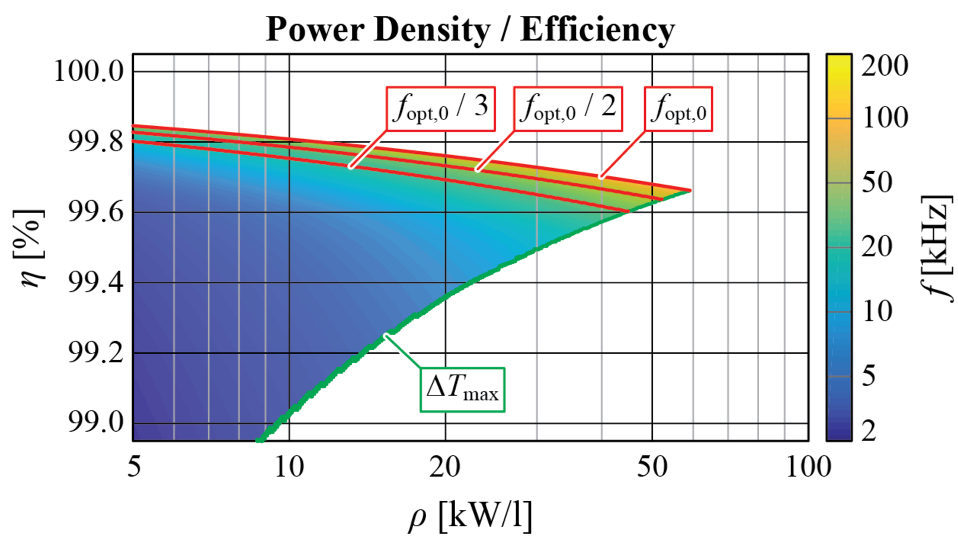
- **Convex problem → clear optimum → analytical solution**

[T. Guillod, PhD Thesis, ETHZ, 2018]

▶ Analytical Optimum Properties

- **Optimum properties**
  - Fixed $P_{core}/P_{winding}$ ratio
  - Fixed R_{AC}/R_{DC} ratio
- **Sensitivity**
  - Transformer optimum is flat
  - $f_{opt}/2$ → max. 15% add. losses



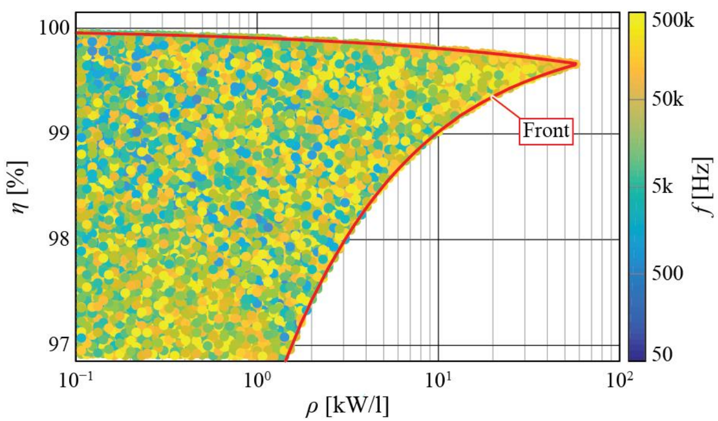


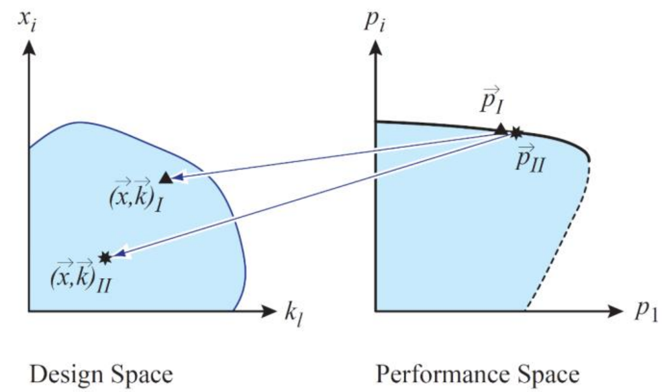
- **How relevant is the analytical optimum?**
- **Opt. converter frequency << opt. transformer frequency**

[T. Guillod, PhD Thesis, ETHZ, 2018]

▶ Design Space Diversity

- **Design space to performance space**
  - No clear trends
  - No clear mapping
- **Where is the optimum?**
  - No clear optimum
  - Analytical opt. is not enough





- **Design space diversity**

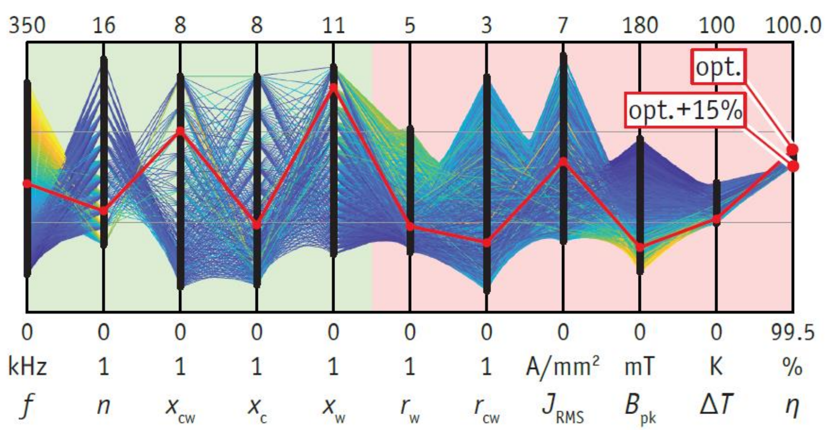
[T. Guillod, PhD Thesis, ETHZ, 2018]

▶ Design Space Diversity

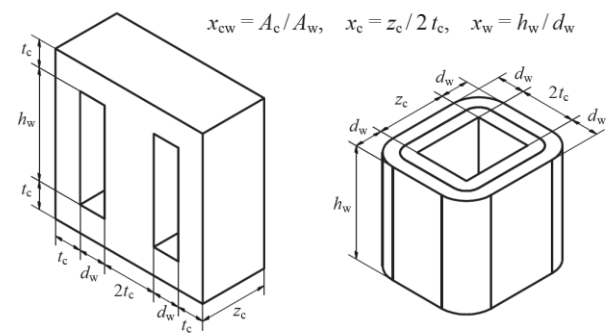
- **Semi-numerical model**
  - Fixed power: 20kW
  - Fixed volume: 1dm^3
  - Loss range: [P_{opt}, P_{opt} +15%]

- **300’000 designs with similar performances**
  - Frequency: [50, 300] kHz
  - Flux density: [25, 120] mT
  - Current density: [1.8, 6.5] A/mm^2

Quasi-Optimal Designs



Geometrical Aspect Ratio



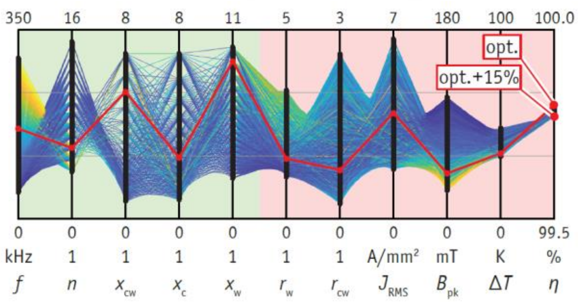
- **Local optima and/or flat optima**
- **Robustness of smart (non brute force) algorithms?**
- **Opportunities for additional constraints?**

[T. Guillod, PhD Thesis, ETHZ, 2018]

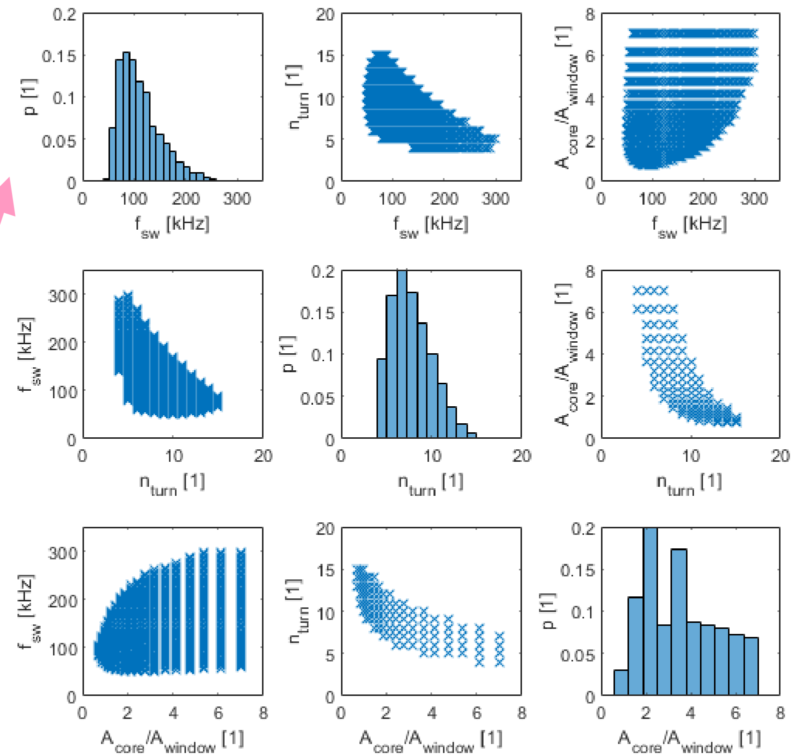
▶ Design Space Diversity

- **Semi-numerical model**
  - Fixed power: 20kW
  - Fixed volume: 1dm³
  - Loss range: [P_{opt}, P_{opt} +15%]

Quasi-Optimal Designs



Quasi Optimal Designs / Correlation



- **Brute force algorithm: 66 millions designs**
- **16 millions valid designs (25%) → 0.3 millions quasi-optimal (0.5%)**
- **Design space diversity ≠ every combination is acceptable**

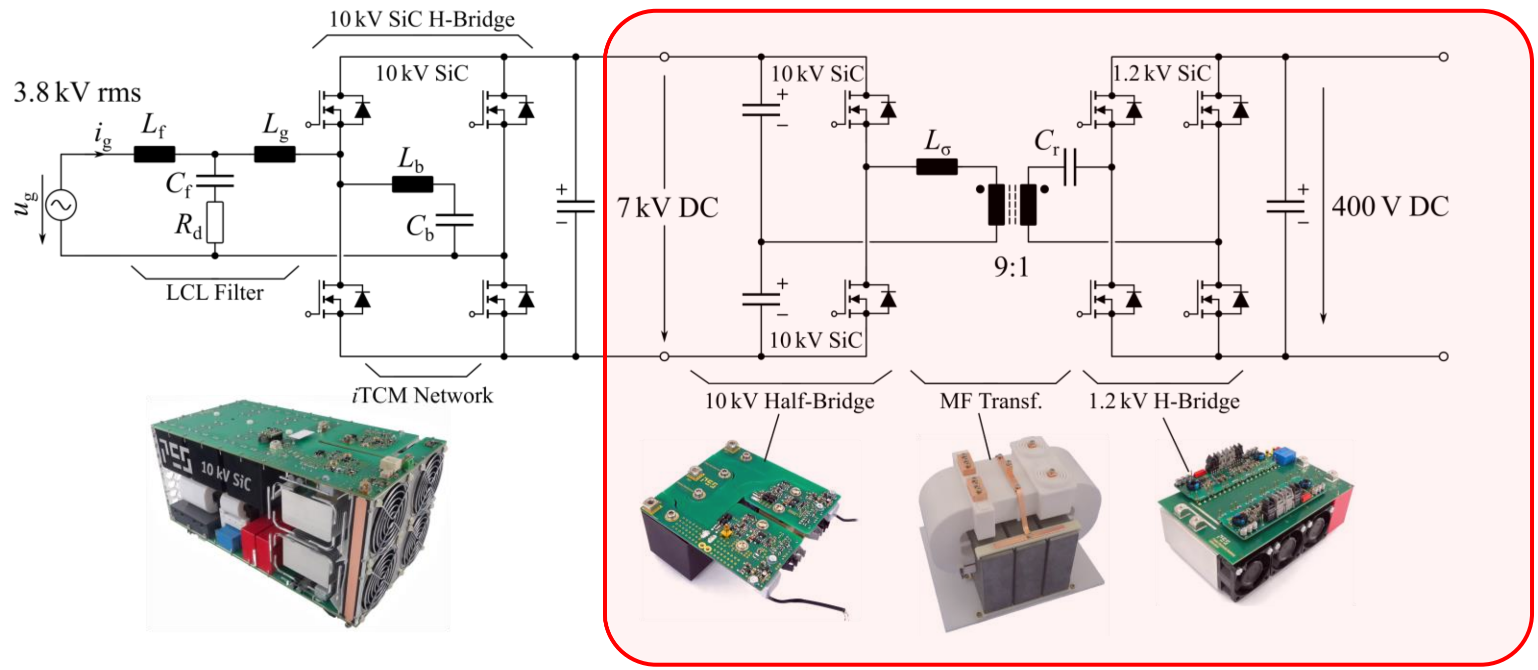
[T. Guillod, PhD Thesis, ETHZ, 2018]

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



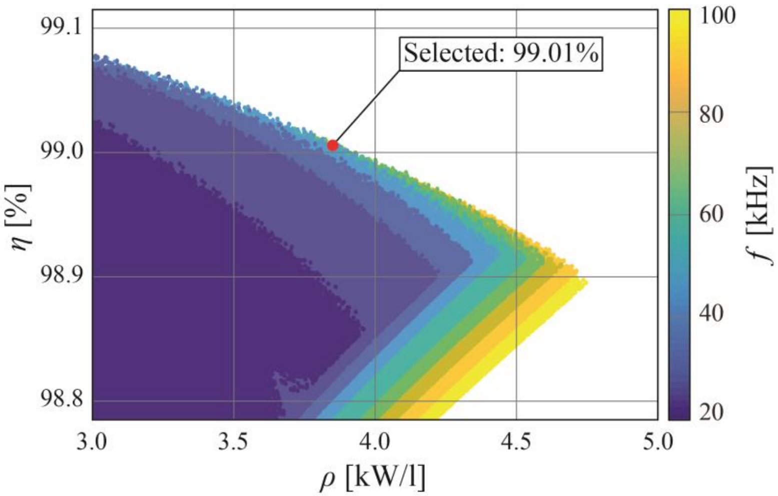
- **DC-DC perf. target: 99% & 3kW/dm^3 & single hardware iteration**
- **How to use design space diversity?**

[D. Rothmund, IEEE JESTPE, 2018]

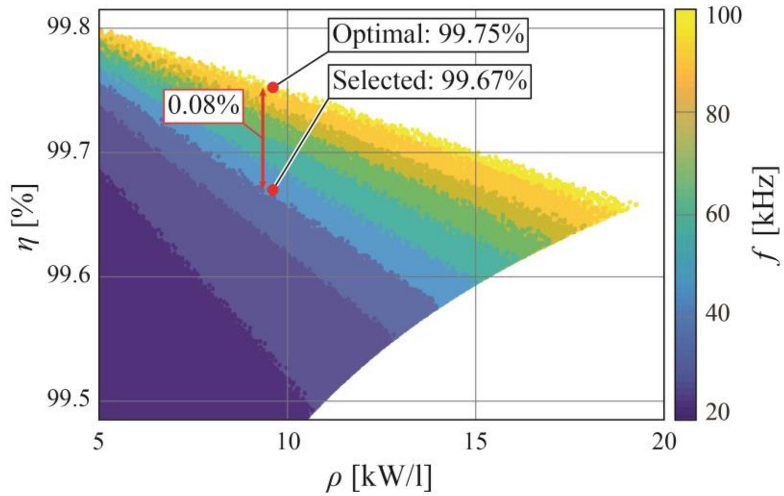
▶ Converter Pareto Front

- **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



Transformer Pareto Front



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

[T. Guillod, PhD Thesis, ETHZ, 2018]

▶ Converter Pareto Front

- **Trade-off: switching frequency**
  - Transformer: reduced volt-second product
  - Semiconductors: switching losses
- **Selected frequency: 48kHz**
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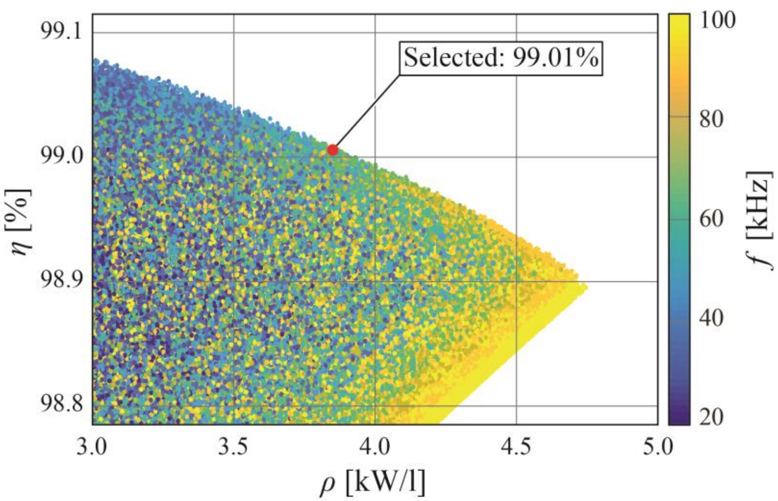
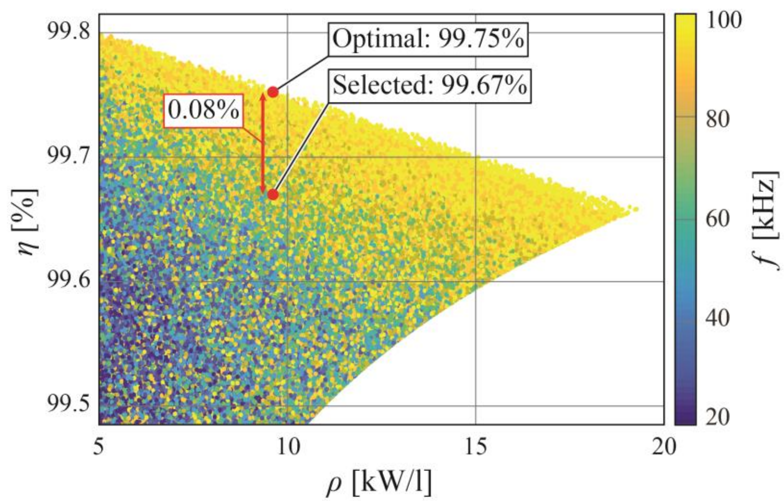
DC-DC Pareto Front



Transformer Pareto Front

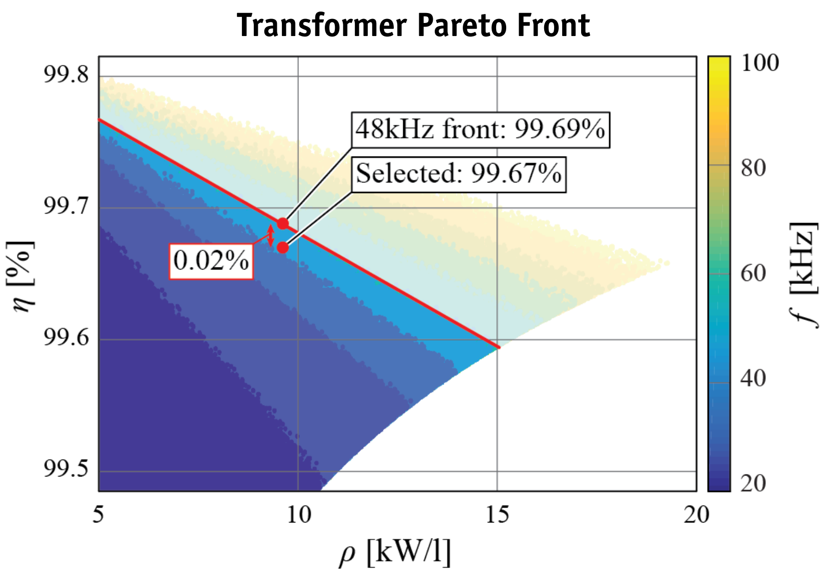


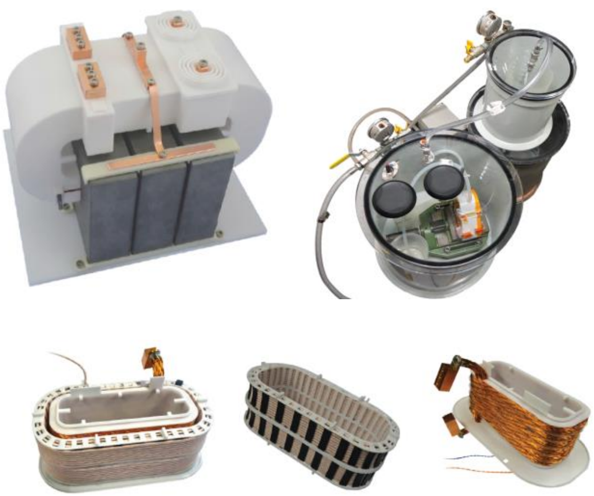
- **How to use the design space diversity?**

[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**

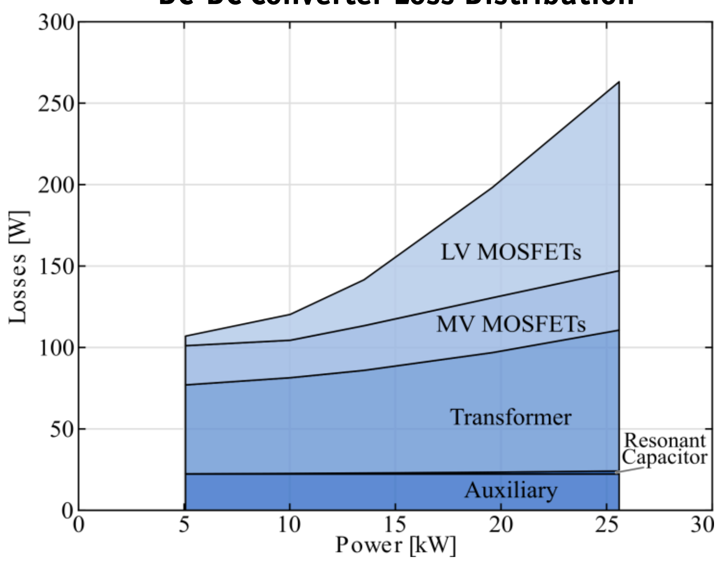
[T. Guillod, PhD Thesis, ETHZ, 2018]

▶ Design Space Diversity: Adding a Secondary Goal

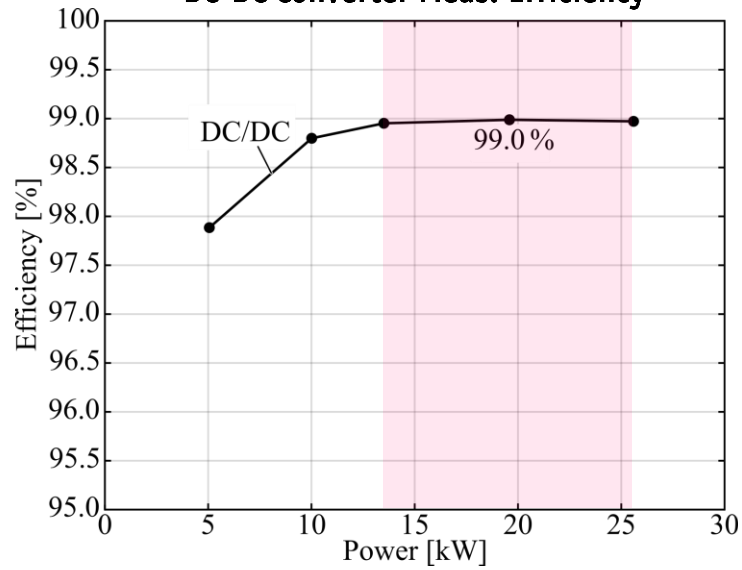
- **Partial load efficiency as an additional trade-off**
  - No-load losses (switching & core)
  - Load losses (conduction & winding)
  - Minor impact on the full-load efficiency

★ **99.0% @ 100% load**
★ **99.0% @ 50% load**
★ **3.8 kW/dm^3**

DC-DC Converter Loss Distribution



DC-DC Converter Meas. Efficiency



- **Design space diversity means that additional goals are achievable**

[D. Rothmund, IEEE JESTPE, 2018]

Conclusion & Outlook

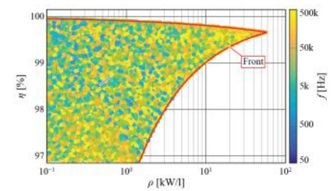
Model & Optimization
Future Research Areas

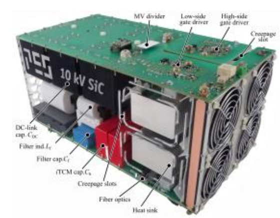
▶ Conclusion & Outlook

- **Simplified analytical models**
  - Clear optimum
  - Sufficient for basic comparison
- **Complex semi-numerical models**
  - Local optima
  - Required for virtual prototyping
- **Algorithms**
  - Brute force is robust and reasonably fast
  - Genetic, part. swarm, neural network, etc.
  - Care is required: no guarantee for global opt.
- **Design space diversity**
  - Different designs → same performances
  - Enable add. objectives and constraints
  - Should be checked → don't miss opportunities
- **Remaining challenges**
  - Integration in industrial context
  - Readily available software, model, data, etc.
  - Standardized interfaces

```
##Objective Function
fun = lambda x: (x[0] - 1)**2 + (x[1]-2.5)**2

#Constraints
cons = ({'type': 'ineq', 'fun': lambda x:  x[0] - 2 * x[1] + 2},
{'type': 'ineq', 'fun': lambda x: -x[0] - 2 * x[1] + 6},
{'type': 'ineq', 'fun': lambda x: -x[0] + 2 * x[1] + 2})
```





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Thank You!

Questions?