MODERN OPTIMIZATION OF ROTATING ELECTRIC MACHINES

Gerd Bramerdorfer
Department of Electrical Drives and Power Electronics, Johannes Kepler University Linz, Linz, Austria
gerd.bramerdorfer@jku.at

Antti Lehikoinen
Department of Electrical Engineering
Aalto University
antti.lehikoinen@aalto.fi

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Ass.-Prof. Dipl.-Ing. Dr. Gerd Bramerdorfer

Date of Birth:	February 7, 1981
Place of Birth:	Vöcklabruck, Austria
Nationality:	Austrian
Email:	gerd.bramerdorfer@jku.at
Phone:	+43/(0)732/2468-6431
GoogleScholar:	Gerd@GoogleScholar
LinkedIn:	Gerd@LinkedIn
ResearchGate:	Gerd@ResearchGate

Short Biography:

Gerd Bramerdorfer is an Assistant Professor with Johannes Kepler University Linz and a senior researcher and project leader at the Linz Center of Mechatronics.

He received the Dipl.-Ing. degree in Mechatronics in 2007, and the Ph.D. degree in Electrical Engineering in 2014, both from Johannes Kepler University Linz, Linz, Austria.

Since 2007, he has been with the Department of Electrical Drives and Power Electronics, Johannes Kepler University Linz, where he was involved in various research projects and held classes in the field of electrical machines and actuators and power electronics.

Short Biography cont'd:

Gerd Bramerdorfer is a member of IEEE, IEEE Industrial Electronics Society and its Electric Machines Technical Committee, and the IEEE Industry Applications Society.

He constantly serves for the scientific community, e.g., as guest editor for a special section in IEEE Transactions on Industrial Electronics called "Optimization of Electric Machine Designs", as track co-chair, topic chair, by organizing special sessions and as a reviewer for journals and conferences. He is an Associate Editor of the IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS.

Publications etc. can be found online.

Research stays:

01/2016–03/2016	Guest researcher at the University of Wisconsin, Madison, US and the Wisconsin Electric Machines and Power Electronics Consortium (WEMPEC) Invited by: Prof. Bulent Sarlioglu
03/2016–05/2016	Guest researcher at the Politecnico di Torino, Dipartimento di Energia, Italy Invited by: Prof. Andrea Cavagnino

Main Research Interests

- Design and modeling of electric machines and drives
- Multi-objective optimization of mechatronic systems
- Sensitivity and tolerance analyses
- Robust optimization, optimization for high reliability
- Material characterization for electric machine modeling (1D- and 2D-characterization, impact of manufacturing)
- Nonlinear optimal control of electric machines
- Magnetic levitation and magnetic bearing technology

Motivation / Outline

Motivation

Why should we deal with optimization techniques?

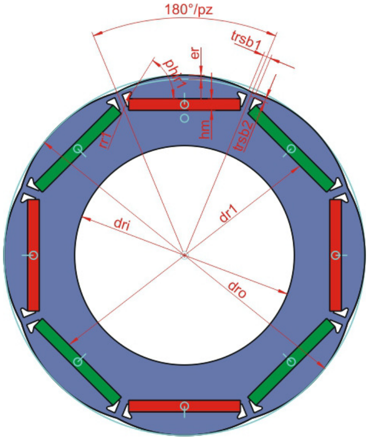
Because we want to have the **best machine design**, the **best power electronics**, the **best control** or the **best overall solution** for a particular application.

Why cannot we trust our feelings and knowledge in electrical engineering?

Because we usually deal with **nonlinear** problems that feature **several (conflicting) objectives**, **many design parameters**, and typically **some constraints**.

Motivation

- Many design parameters
  - diameters
  - magnet height
  - ...
- Multiple objectives
  - efficiency
  - cost
  - torque ripple
  - ripple of DC bus current
  - minimize capacitance
  - torque density
  - ...
- Constraints
  - Motor size
  - Size of PCB
  - Thd
  - ...



Motivation

Why should we deal with optimization techniques?

Because we want to have the **best machine design**, the **best power electronics**, the **best control** or the **best overall solution** for a particular application.

Why cannot we trust our feelings and knowledge in electrical engineering?

Because we usually deal with **nonlinear** problems that feature **several (conflicting) objectives**, **many design parameters**, and typically **some constraints**.

But do not be disappointed, we will see later on knowledge in electrical engineering is priceless when it comes to optimization problems in our field.

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Motivation

Anyway, in order to select a **suitable optimization technique** and to **apply it in an appropriate way**, some knowledge about optimization is very valuable.

Expert in electric machine / device optimization

Classical machine / device design
materials, electromagnetics, winding

Optimization techniques (Math.)
Deterministic (e.g., gradient-based) or stochastic (e.g., evolutionary algorithms) approaches

Multi-physics aspects
thermal, rotor dynamics

Problem formulation (Math. / Engin.)
objectives, constraints, geometry, parameter definition

Power electronics and control

Aspects of automation (Comp. science)
cluster environment, error handling, quality measures

Machine / device evaluation (Math. / Engin.))
analytical, finite elements

Machine / device modeling (Math. / Engin.)
analytical, meta-models

No Goals / Restrictions

- Cover all topics in very much detail and consider all different electromechanical devices.
  We will mainly focus on rotating electric machines.

- Consider all optimization techniques available.
  We will discuss types and characteristics of techniques and classify them, but the field is very emerging and multitudinous.

- Have a universally applicable approach for all problems.
  Problems' variety is incredibly high!

Goals / Focus

- Get a broad overview of fields relevant to electric machine / device optimization.
- Get a good understanding about how fields interact and what affects (optimal) machine / device design.
- Get prepared to solve real-world problems even though an exact equivalent problem was not considered before.

Introduction to Optimization / Optimization Techniques

Generalized optimization problem

Single-objective optimization:

Objective:

$$\min f(\mathbf{x})$$

Design parameters:

$$\mathbf{x}^T = \begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix}$$

Constraints:

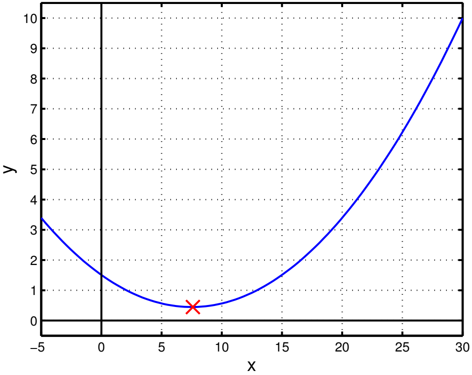
$$\mathbf{g}(\mathbf{x}) \leq \mathbf{0}$$
$$\mathbf{h}(\mathbf{x}) = \mathbf{0}$$

Comments:

- Maximization:
  $$\max f(\mathbf{x}) = \min \; -f(\mathbf{x})$$
- Obtaining the objective value for a design by evaluating
  - an analytic equation (white box model)
  - a sophisticated model (typ. black box)
    e.g., artificial neural networks (ANN), radial basis functions (RBF), support vector machines (SVM)
  - a complex analysis which, for instance, involves a finite element simulation

Properties of objective functions

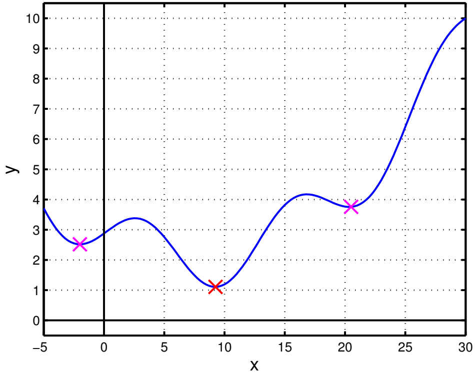
Unimodal function with single design parameter



- "Convex function"
- Gradient-based techniques can be applied
- Single minimum exists

Properties of objective functions

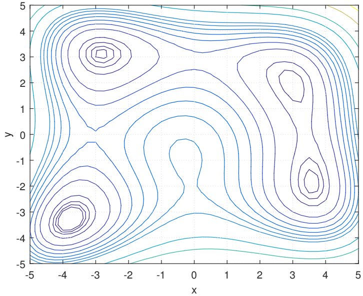
Multimodal function with single design parameter



- Here, just a single global minimum exists
- Gradient-based techniques can be applied, but results higly depend on starting point, because
- local minima exist

Properties of objective functions

Multimodal function with two design parameters

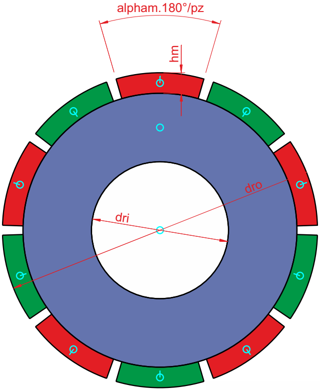


- Usually we deal even with more than two design parameters
- Complexity rises $\rightarrow$ the need for sophisticated optimization techniques rises

Properties of design “parameters”

Design parameters can

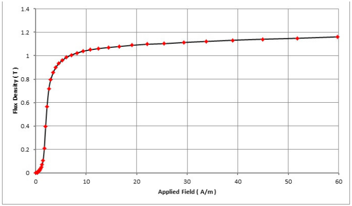
- be single-valued, continuous like
  - magnet height
  - diameter(s)
- be single-valued, discrete like
  - Number of stator slots, poles, phases
  - Number of sheets of the stack



Properties of design “parameters”

Design parameters can

- be single-valued, continuous like
  - magnet height
  - diameter(s)
- be single-valued, discrete like
  - Number of stator slots, poles, phases
  - Number of sheets of the stack
- have binary states like
  - Single-Layer winding?
    (No: double layer winding is applied.)
  - Interior rotor?
    (No: Exterior rotor is used)
- have multiple values like
  - material characteristics (e.g., B/H-curves, stress-strain curves)



But what if we would like to deal with...

multiple objectives

(As it usually will be.)

Generalized optimization problem

Multi-objective optimization:

Objective:

$$\min f(\mathbf{x})$$

$$f(\mathbf{x}) = q_1 f_1(\mathbf{x}) + q_2 f_2(\mathbf{x}) + \ldots + q_m f_m(\mathbf{x})$$

Design parameters:

$$\mathbf{x}^T = \begin{bmatrix} x_1 & x_2 & \ldots & x_n \end{bmatrix}$$

Constraints:

$$\mathbf{g}(\mathbf{x}) \leq \mathbf{0}$$

$$\mathbf{h}(\mathbf{x}) = \mathbf{0}$$

Comments:

- Introducing weighting factors
  $\Rightarrow$ Simplified problem
  $\Rightarrow$ Single-objective techniques can be applied
- Objective space is constrained by the problem formulation
- Problematic for very different objectives
  (How to compare cogging torque, efficiency, and cost?)

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Generalized optimization problem

Multi-objective optimization:

Objective:

$$\min\left(f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})\right)$$

Design parameters:

$$\mathbf{x}^T = \begin{bmatrix} x_1 & x_2 & \ldots & x_n \end{bmatrix}$$

Constraints:

$$\mathbf{g}(\mathbf{x}) \leq \mathbf{0}$$
$$\mathbf{h}(\mathbf{x}) = \mathbf{0}$$

Comments:

- Multiple objectives are optimized at once
- Objective space is not constrained by problem formulation
- But how is now optimality defined?!

Introducing the term Pareto Optimal

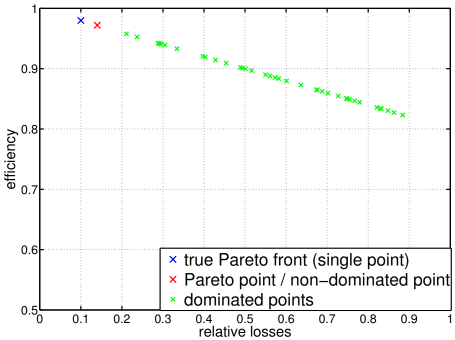
"Named after Vilfredo Pareto, Pareto optimality is a measure of efficiency. An outcome of a game is Pareto optimal if there is no other outcome that makes every player at least as well off and at least one player strictly better off. That is, a Pareto Optimal outcome cannot be improved upon without hurting at least one player."

Source: `http://www.gametheory.net/dictionary/ParetoOptimal.html`

What does this mean in practice?

It says that a design A is Pareto optimal, if there exists no other design that is better in one objective and at least as good as design A for the other objectives.

Pareto Optimality - non-conflicting objectives



true Pareto front:
the (not-known) overall optimum / optima

Pareto-point(s) / non-dominated point(s):
the optimum / optima that was / were already identified in the optimization run

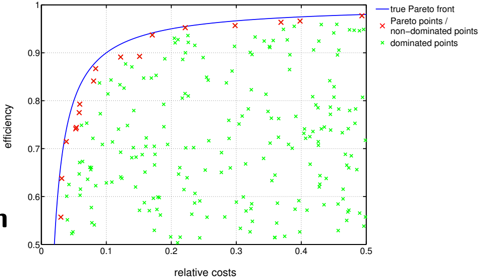
dominated point(s):
points of the optimization run that do not represent optima

Pareto Optimality - conflicting objectives

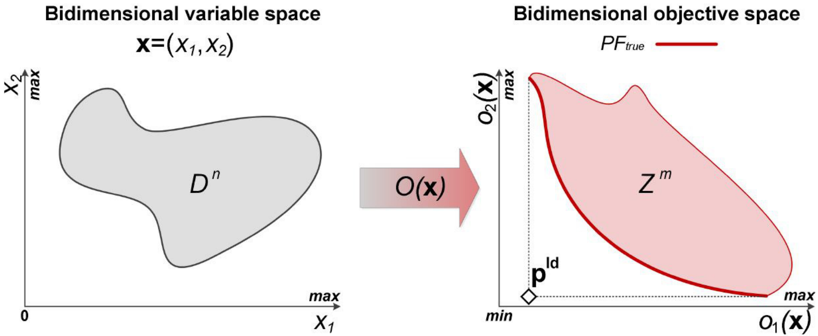
Efficiency and **cost** are usually **conflicting** objectives
$\Rightarrow$ A **tradeoff** has to be found

If **weighting factors** are introduced, a **single-solution** is obtained.

Instead, if a **multi-objective problem** is analyzed (like here) one can study the trend of conflicting objectives **after the optimization** run and **apply (intuitive) weighting factors**.

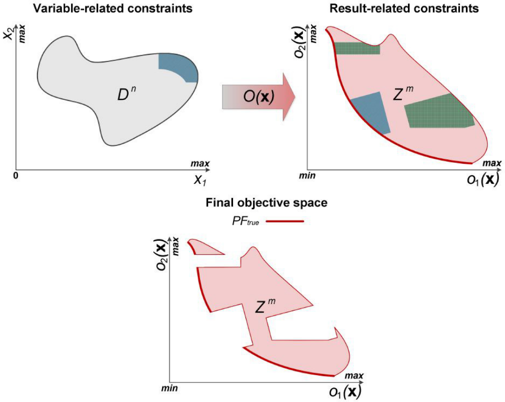


Mapping of two-dimensional design space to two-dimensional objective space



Source: Lecture notes of Ciprian Zavoianu, JKU

Mapping of two-dimensional design space to two-dimensional objective space - constraints



Source: Lecture notes of Ciprian Zavoianu, JKU

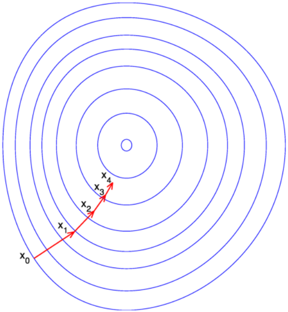
Optimization Techniques

- Gradient-based approaches
- Grid analysis
- Techniques for a (more) efficient exploration of the design / objective space
  - Design of experiments (DOE)
  - Genetic algorithms (GA)
  - Particle swarm optimization (PS)
  - Differential evolution (DE)

Gradient-based approaches...

- are very fast for a local search
- can cause problems if multiple minima (maxima) are present
- famous examples: Newton, Gauss-Newton, Levenberg-Marquardt
- some techniques include mutation, e.g., simulated annealing
- are usually not applicable if many parameters are varied / for multiple objectives

Gradient-based approaches...



Source: SyMSpace documentation

Sketch of equipotential lines and how a gradient-based approach works starting from x_0

Starting point and step-width are crucial parameters to be defined

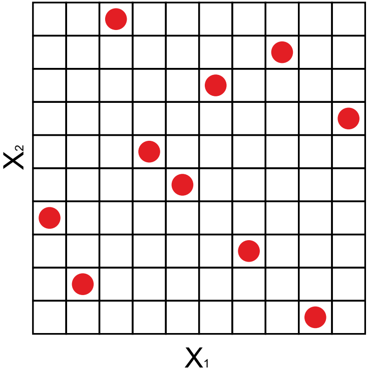
Grid analysis

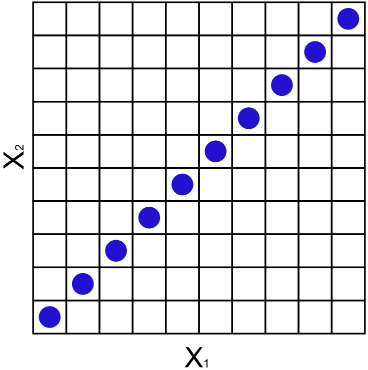
- is a possible choice for a low number of design parameters
- for high number of parameters, too many designs would have to be calculated
  (e.g., 10 steps per param, n params, 10^n designs to be evaluated)
- evaluation of a coarse grid can be a good starting point for other techniques (but usually better to use a technique of DOE)

Design of experiments

- is a theory about selecting “most important” parameter combinations among all possible combinations of a grid
- very often done in advance to the start of an evolutionary algorithm
- famous examples: Latin-Hypercube-sampling (LHS), Box-Behnken-sampling (BBS)

Design of experiments - LHS





LHS - good vs. bad configuration / design space exploration

Genetic algorithms

- inspiration: a population like human beings, but usually of fixed size n_{pop}
- typically, the analysis is split into generations. One generation involves the analysis of n_{pop} individuals
- like in the nature, the genetic algorithm has functions for
  - selection (the strongest shall survive)
  - recombination / crossover (generation of new individuals based on experience)
  - mutation (to not get stuck in local minima)
- Probably most prominent representatives:
  Non-dominated **S**orting **G**enetic **A**lgorithm (NSGA-II),
  Strength **P**areto **E**volutionary **A**lgorithm (SPEA2)

Genetic algorithms - definitions

- Individual: A particular design to be investigated, e.g., a machine design
- Population: A total number of n individuals.
- Gene: A particular property of an individual
  e.g., a binary number or a value in the range of a continuous domain
  (*useInteriorRotor* (binary), *stator outer diameter* (continuous repr.))
- Chromosome: A set of parameters, which defines an individual

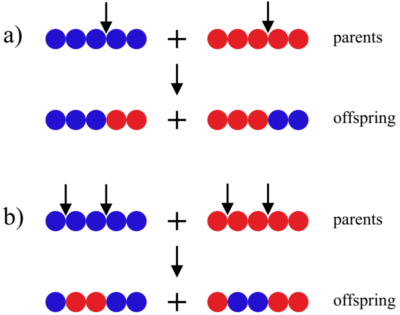
Genetic algorithms - selection

Various selection techniques exist, e.g.:

- Tournament selection: Select the best n_{best} individuals of the population for crossover
- Roulette selection: Chance of being picked is a function of the fitness of the individuals (often important, in order to keep variety in the population)

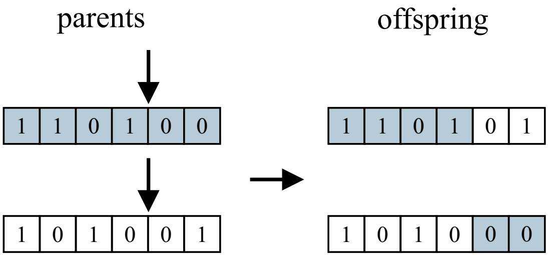
Genetic algorithms - crossover / mutation

- Binary examples



Genetic algorithms - crossover / mutation

- Binary examples



Particle / Glowworm swarm optimization

- inspiration: movement of birds,...
- a crowd of individuals follows to the direction of "best possible values for objectives"
- velocity vector of an individual is based on its own best known position and the best position of the entire crowd
  (or just the best position of individuals within a certain range around that particular individual is used)
- mutation is introduced by adding arbitrary velocity vectors / by "overshooting" the best position

E.g., $newPos = actPos + randomFactor1 * (entireBestPos - actPos) +$
$+ randomFactor2 * (ownBestPos - actPos) + randomFactor3$

Differential evolution (DE)

- Also population based
- Individuals are called agents
- An individual is replaced, if a new individual has (a) better value(s) for the fitness function(s).
- Usually, a new candidate is defined based on two parent vectors
  (a) a parent vector **x** directly chosen from the current population
  (b) a parent (mutant) vector **v** that is constructed according to a particular mutant strategy.
- Parameters: Differential weight F, crossover probability CR, population size NP

Differential evolution - common mutation operators

- rand/1

$$\mathbf{v} = \mathbf{r}_1 + F(\mathbf{r}_2 - \mathbf{r}_3)$$

- rand/2

$$\mathbf{v} = \mathbf{r}_1 + F(\mathbf{r}_2 - \mathbf{r}_3) + F(\mathbf{r}_4 - \mathbf{r}_5)$$

- current-to-rand/1

$$\mathbf{v} = \mathbf{r}_1 + U(\mathbf{r}_1 - \mathbf{x}) + F(\mathbf{r}_2 - \mathbf{r}_3)$$

where $\mathbf{r_i} \neq \mathbf{x}, i \in \mathbb{N} \wedge 1 \leq i \leq 5$ are different, randomly chosen individuals, $F > 0$ is a control parameter and $U \in [0, 1]$ is a uniformly distributed random value.

Source: Lecture notes of Ciprian Zavoianu, JKU

Differential evolution - common crossover types

- **binomial**

$$\mathbf{y}[j] = \begin{cases} \mathbf{v}[j], & \text{if } \; U_j \leq CR \vee j = I \\ \mathbf{x}[j], & \text{if } U_j > CR \wedge j \neq I \end{cases}$$

where $CR \in [0, 1]$ is a control parameter, $I \leq n$ is a randomly chosen integer and U_j is an independent random variable uniformly distributed in [0,1].

- **polynomial**
the starting position k of the crossover process is chosen randomly and the next consecutive L elements (counted in circular manner) are chosen from $\mathbf{v}$ with a probability that decreases exponentially with an increased distance from k.

Source: Lecture notes of Ciprian Zavoianu, JKU

Which algorithm should we select?

"No free lunch theorem:"

In computational complexity and optimization the no free lunch theorem is a result that states that for certain types of mathematical problems, the computational cost of finding a solution, averaged over all problems in the class, is the same for any solution method. No solution therefore offers a 'short cut'. In computing, there are circumstances in which the outputs of all procedures solving a particular type of problem are statistically identical.

Source: `Wikipedia`

Which algorithm should we select?

Interpretation of the "No free lunch theorem":

- "A general-purpose universal optimization strategy is theoretically impossible, and the only way one strategy can outperform another is if it is specialized to the specific problem under consideration."
- "A general-purpose almost-universal optimizer exists theoretically. Each search algorithm performs well on almost all objective functions."
- "An algorithm may outperform another on a problem when neither is specialized to the problem. It may be that both algorithms are among the worst for the problem."

Source: `Wikipedia`

Remarks

- Put all the knowledge you have about the optimization problem to your problem formulation!
  Any kind of design space reduction (without simultaneously excluding feasible, favorable solutions) is advantageous.
- Be aware that evolutionary algorithms, due to their definitions comprising random numbers, obviously have stochastic behavior. If you run a problem ten times, it is highly likely that you end up with 10 different results.
- To conclude, applying your skills (in engineering) is essential to get results that are (close to) best possible solutions and are highly reliable.

We will observe this soon!

Optimization Scenario

Variety of scenarios is incredibly high - an example is given

Selected Scenario:

Cost vs. efficiency of PMSM, SyncRM for particular application

Scenario - Initial situation

Corresponding paper: Comprehensive cost optimization study of high-efficiency brushless synchronous machines [1]

- Due to the increasing significance of energy saving, multiple regulations have been introduced by countries or international organizations regarding the efficiency of electric machines, e.g. the IEC 60034-30.

50 Hz

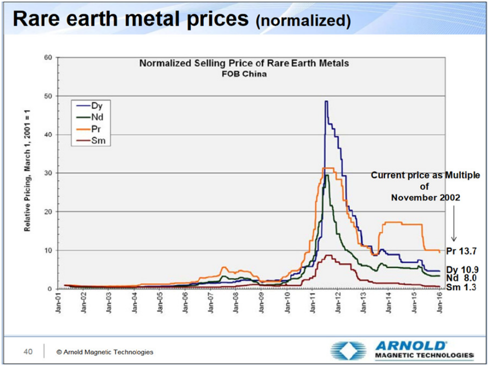
kW	efficiency class IE-2			efficiency class IE-3		
	2 poles	4 poles	6 poles	2 poles	4 poles	6 poles
0,75	77,4	79,6	75,9	80,7	82,5	78,9
1,1	79,6	81,4	78,1	82,7	84,1	81,0
1,5	81,3	82,8	79,8	84,2	85,3	82,5
2,2	83,2	84,3	81,8	85,9	86,7	84,3
3	84,6	85,5	83,3	87,1	87,7	85,6
4	85,8	86,6	84,6	88,1	88,6	86,8
5,5	87,0	87,7	86,0	89,2	89,6	88,0
7,5	88,1	88,7	87,2	90,1	90,4	89,1
11	89,4	89,8	88,7	91,2	91,4	90,3

mandatory efficiencies for induction machines, defined in IEC 60034-30

Excerpt of the IEC efficiency classes.

Scenario - Initial situation

- The use of PMSMs (Permanent magnet excited synchronous machines) leads to a considerable increase of the efficiency, but due to the fluctuating price of permanent magnets, especially of NdFeB-magnets, the cost of PMSMs is hardly predictable.



Source: Arnold Magnetic Technologies

Rare earth material price fluctuation throughout the last years.

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Scenario - Initial situation

- This work deals with a motor with P=3kW and a rated synchronous speed of n=1500rpm.
- Different motor topologies are analyzed regarding the trade off effiency and material cost, including PMSMs and SyncRMs (synchronous reluctance machines). This is done for two different cost scenarios.
- Finally, the cheapest designs fulfilling mandatory efficiency requirements can be determined.

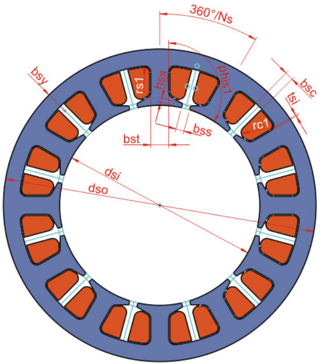
Scenario - Definitions

- Cost scenarios (prices in €/kg)

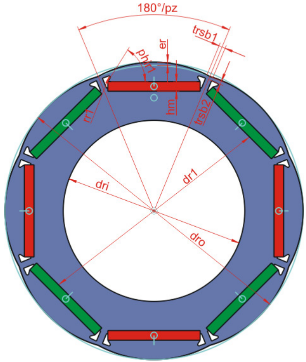
Material	Cost scenario 1	Cost scenario 2
NdFeB magnets, grade N42SH	50	150
Ferrites	10	10
Aluminum	3.5	3.5
Copper	7.5	7.5
Laminated steel, grade M400-50A	2	2

- Motor characteristics calculated for typical working ambient conditions for long-term operation $T_{pm} = 100^\circ C$, $T_{cu,al} = 130^\circ C$.

Scenario - Considered topologies



Parametric stator design
(dimensions as well as number of slots and winding configuration changed during optimization)



Parametric rotor design with embedded magnets (dimensions as well as number of pole pairs changed during optimization)

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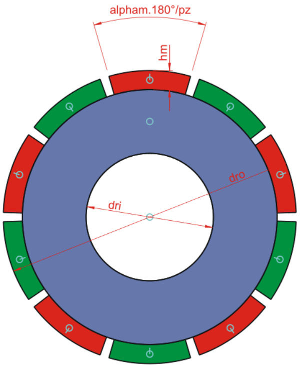
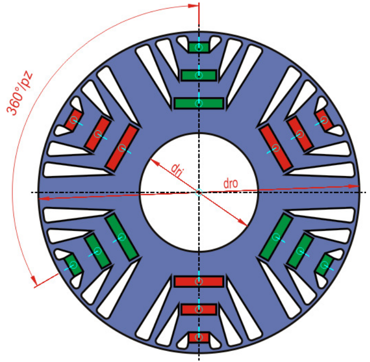
Scenario - Considered topologies



Parametric rotor design with surface mounted magnets (dimensions as well as number of pole pairs changed during optimization)



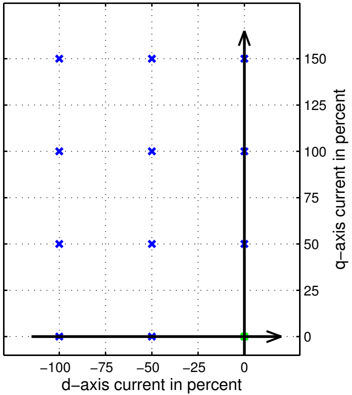
Parametric rotor design with embedded magnets (dimensions as well as number of pole pairs changed during optimization; rotor is analyzed with and without magnets)

Scenario - Analysis of machine designs

with PM excitation

- No load simulation is performed
- No load flux is determined
- 12 currents are dynamically set and calculated. They are defined by the grid and the rated current (is equal to 100% in the grid)

$$i_q^* = \frac{T_{rate}}{\frac{m}{2}\, p\, \psi_{pm}}\ , \quad i_q^* \equiv 100\%$$



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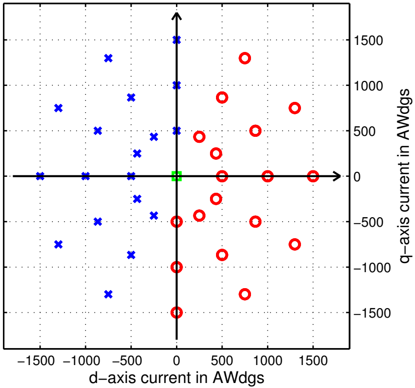
Scenario - Analysis of machine designs

without PM excitation

- 18 currents (blue crosses in the figure on the right) are calculated.
- 18 more currents are calculated from FE-results (red dots in figure).
- Rated current is defined by the maximum current density $\hat{S}$, the number of stator phases and the winding cross section A_{wdg}

$$i_q^* = \frac{m}{2}\,\hat{S}\,A_{wdg}\ ,\ i_q^* \equiv 100\%$$



Scenario - Objectives and Facts

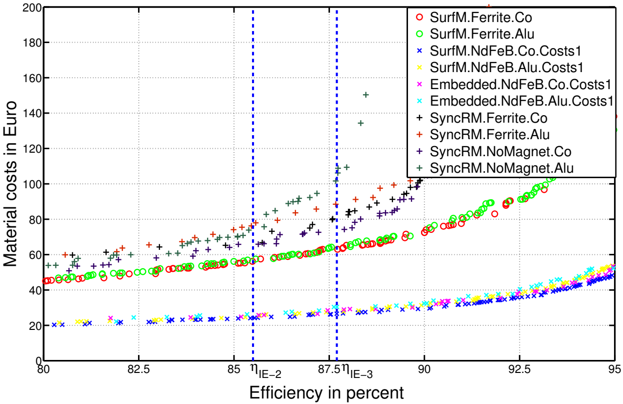
- Cost vs. efficiency is optimized for all rotor / stator combinations with aluminum or copper winding, with ferrite or NdFeB-magnets.
- Cogging torque and torque ripple at load should be lower than 10%.
- For any design under observation, a nonlinear model is automatically derived based on the FE-results [2].
- The optimal current vector fulfilling the torque requirement is then separately computed for any design.

Scenario - Objectives and Facts

- An asynchronous evolutionary algorithm [3] based on SPEA2 [4, 5] is applied to optimize all the design variants.
- Overall, more than 1.5 millions of designs are investigated using FE-simulations (Femag [6]). The calculations are done using a computer cluster that features 300 CPU cores.
- Optimization took several weeks and was performed using MagOpt / SyMSpace [7, 8].

Scenario - Results - Cost scenario 1

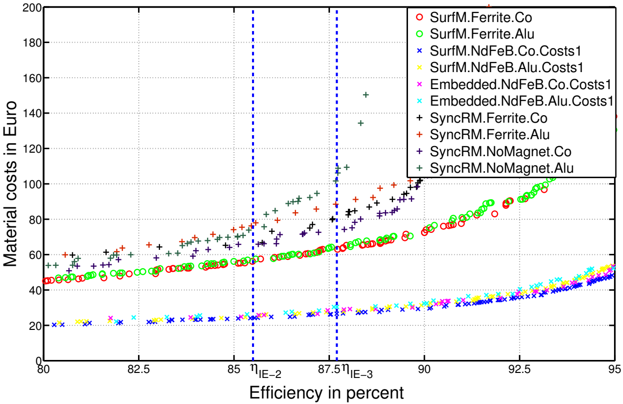
- PMSMs with NdFeB are best regarding the trade off cost vs. efficiency.
- Next are PMSMs with ferrite magnets.



Comparison of the cost vs. efficiency trend for all different topologies - Cost scenario 1

Scenario - Results - Cost scenario 1

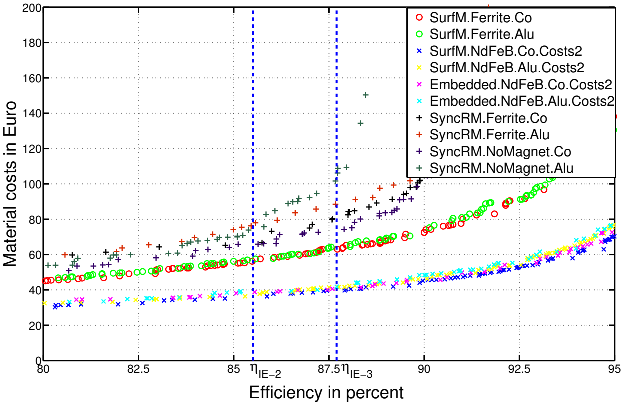
- Aluminum and copper windings perform similar.
- Worst are synchronous reluctance machines.



Comparison of the cost vs. efficiency trend for all different topologies - Cost scenario 1

Scenario - Results - Cost scenario 2

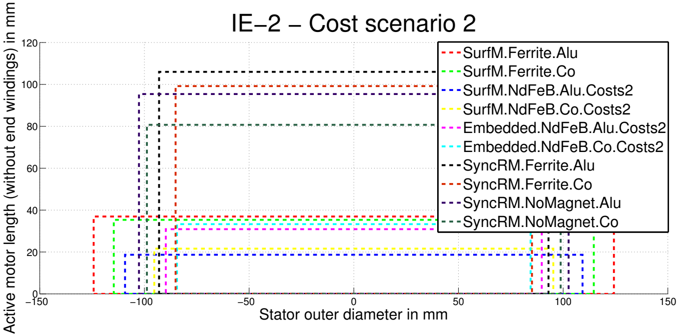
- Results for cost scenario 2 are similar, ...
- ... except that the trend for PMSMs with NdFeB magnets gets closer to the other characteristics



Comparison of the cost vs. efficiency trend for all different topologies - Cost scenario 2

Scenario - Results - Optimal length to diameter ratio

- PMSMs tend to a disc shape (3D-FE verification required)
- SyncRMs tend to a more barrel shape
(end winding effect is relatively reduced)



Optimal size relations for IE2-requirements for all topologies - Cost scenario 2 - end winding not considered in axial length

Conclusions

- Results revealed that **PMSMs featuring NdFeB-magnets** are also **competitive** on the marked for **higher raw material prices**.
- **SyncRMs** tend to a more **barrel shape** than PMSMs
- **Single load point** was considered for optimization / a **particular case study** was evaluated:
  General conclusions can hardly be made because results probably do not generally hold for any
  - arbitrary torque/speed-requirements,
  - multiple load point evaluation,
  - special requirements on construction space,
  - etc.

Automation of Optimization Scenarios

Automation - General comments

- The **"optimizer"** definitely **finds** the **weakness of your model** - optimizations often need some **iterations**

  E.g.: Minimization of torque ripple based on the following definition:

  $$t_{ripp} = \frac{t_{pp}}{t_{mean}}$$

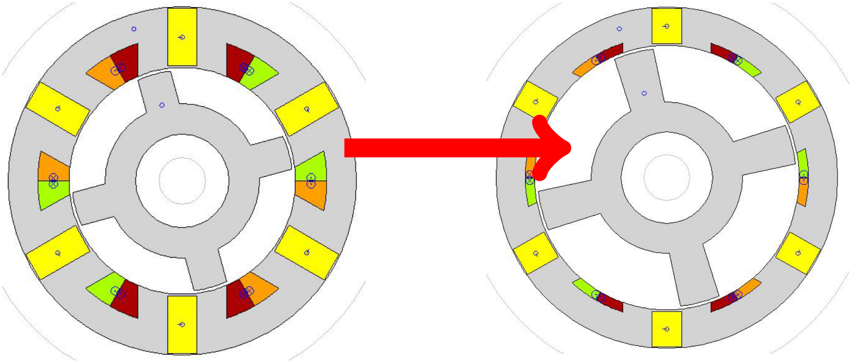
  If, for any reason, the mean torque can have negative values, the torque ripple gets negative $\rightarrow$ the optimizer will merciless enforce those individuals with negative mean torque, as they give the best objective values regarding torque ripple.

  Alternative formulation:

  $$t_{ripp} = \left| \frac{t_{pp}}{t_{mean}} \right|$$

Automation - General comments (tbc)

- Optimization focused on no-load situation: → **small coil area!**



Automation - General comments (tbc)

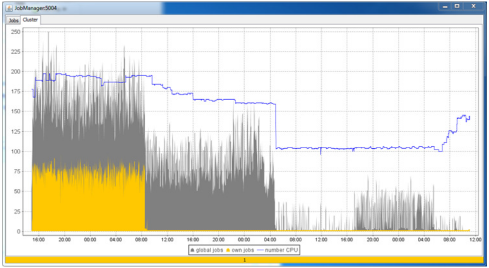
Especially for optimizations including **finite element simulations**:

Is your **mesh definition appropriate** for any kind of parameter combination (chromosome)??

Automation - Cluster / HTCondor

Computationally-expensive evaluations often require a **computer cluster**.

A **sophisticated framework** for job pre-processing / scheduling / evaluation / post-processing **is crucial**.



Job manager of SyMSpace

HTCondor
High Throughput Computing

Source:
https://research.cs.wisc.edu/htcondor/

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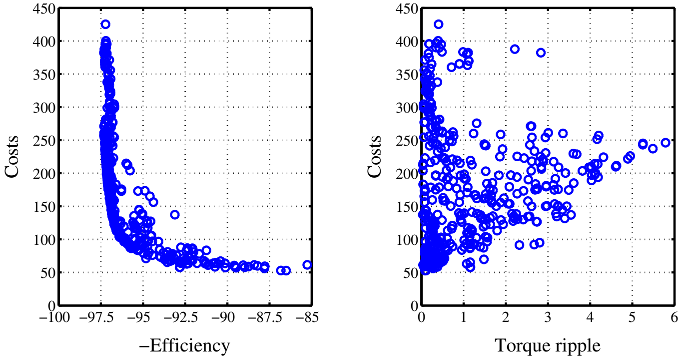
The process of evolution - change of Pareto front with time

Generation: 100



But when...

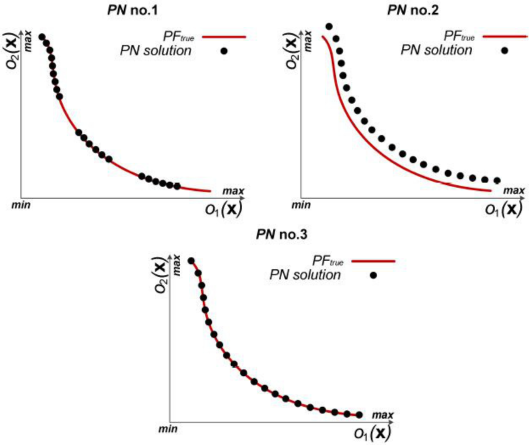
should we stop an optimization run?

Let's discuss quality indicators and measures.

Quality measures...

...should determine the quality in terms of *convergence* and *diversity*.

Quality measures...



Source: Lecture notes of Ciprian Zavoianu, JKU

Quality measures...

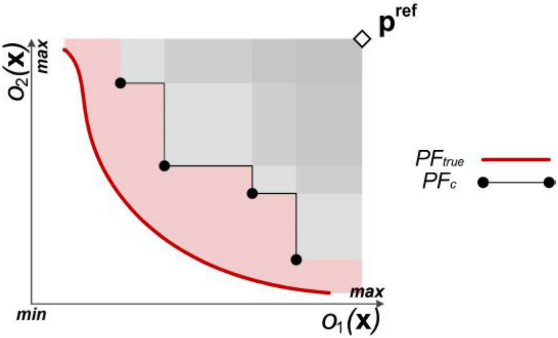
...should determine the quality in terms of *convergence* and *diversity*.

Thus, they are usually classified to

- convergence quantifiers (e.g., epsilon measure; general distance)
- diversity quantifiers (e.g., spread metric, generalized spread)
- both convergence and diversity quantifiers (e.g., inverse generational distance, hypervolume indicator)

Quality measures

Hypervolume indicator:
"how large is the area defined by the current Pareto-front compared to the previous one(s)"



Quality measures

Hypervolume indicator:
"how large is the area defined by the current Pareto-front compared to the previous one(s)"

Other helpful measures:

- "New in Pareto front" / Size of Pareto front
- Distribution of Pareto variables (distinct optimal values?)
- Individuals per generation that cannot be evaluated (errors)

Speed Improvements for Electric Machine and Drive Optimization Scenarios

Motivation

- Many electrical engineers need to optimize electrical machines / drives
- Typically computationally expensive evaluation of designs is required
- A lot of design parameters need to be varied (parameters of the geometry, control parameters, different materials)
- Engineers usually face a multi-objective problem (costs, efficiency, torque ripple,...)
- Results should - as always - be available as fast as possible.

This should serve as reference how speed improvements for optimization runs for electrical machine designs can be achieved

a) from **the theory of machine designs' point of view**

b) from **an optimization strategy point of view**

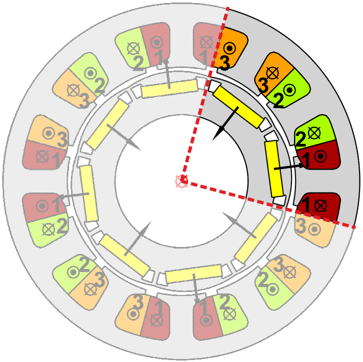
Categorization

- Basic scope for action
- Techniques for an efficient exploration of the design space
- Advanced modeling techniques

Basic scope for action

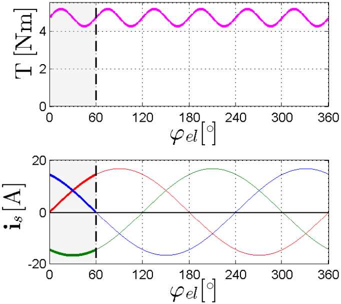
Symmetry considerations / Model simplifications

- It is always recommended to consider symmetries of your machine design.



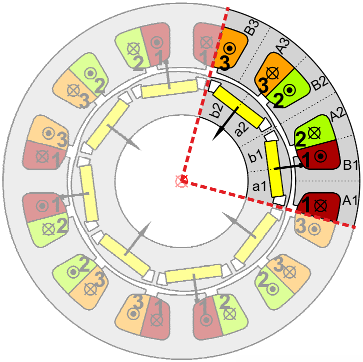
Symmetry considerations / Model simplifications

- It is always recommended to consider symmetries of your machine design.
- As shown in [9], symmetrical three phase machines show periodic behavior with regard to a sixth of an electrical period.



Symmetry considerations / Model simplifications

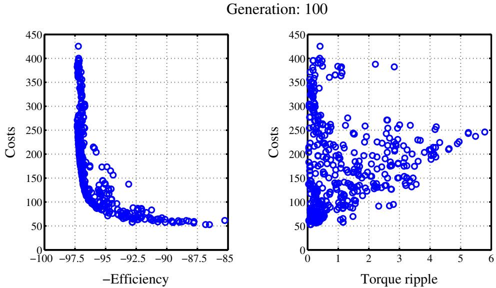
- It is always recommended to consider symmetries of your machine design.
- As shown in [9], symmetrical three phase machines show periodic behavior with regard to a sixth of an electrical period.
- ⇒ If iron losses can be neglected or if iron losses of flux density characteristics of different regions can be extracted of the FE software and separately evaluated, only a sixth of an electrical period needs to be analyzed.



Techniques for an efficient exploration of the design space

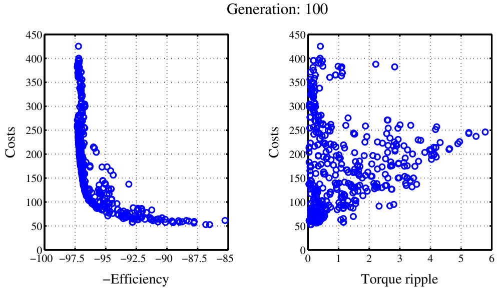
Genetic algorithms - generation-based approach

- Inspired by evolution
- A population evolves over time
- Less individuals need to be analyzed compared to grid search



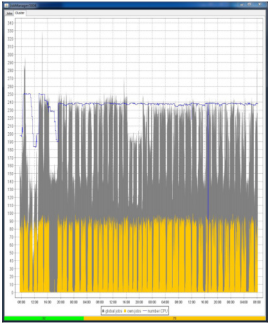
Genetic algorithms - generation-based approach

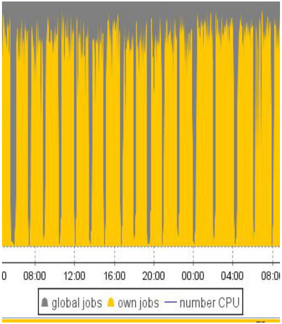
- Inspired by evolution
- A population evolves over time
- Less individuals need to be analyzed compared to grid search
- Analysis of all individuals is done in parallel on a cluster $\rightarrow$ waiting for the slowest nodes leads to non-constant workload / is not time-efficient



Genetic algorithms - generation-based approach

Typical cluster work load





No continuous work load is achieved, as the process needs to **wait for the slowest nodes / the generated last design candidates** for evaluation.

ICEM
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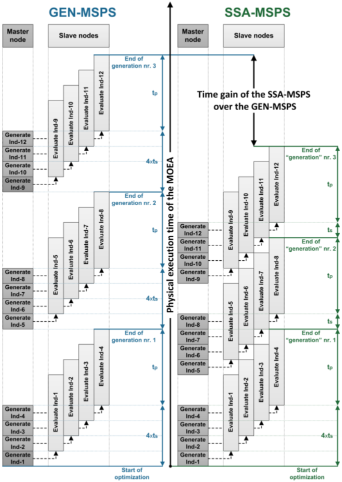
Genetic algorithms - asynchronous approach

- Every time when the analysis of an individual is completed, a new individual is sent to the cluster
- → the cluster can be held at constant load
- → less information is available on average when creating the *i*-th individual compared to the generation-based approach
- → there is a trade off

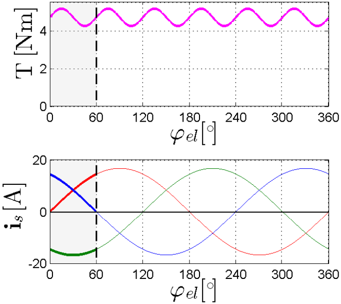
tests show that for optimizations where a considerable evaluation time is spent for the analysis of individuals, the convergence speed is highly increased. [3]



Multi-stage analysis of particular machine designs

Classifying individuals before computationally expensive calculations are started - **different possibilities for** obtaining **a rough estimate** of the performance for a possible design variant exist:

- Analytical forecast
- Analysis of a reduced number of angular positions (e.g., 0° and 15° el.)
- Analysis of a single current vector
- Classification of a design by considering results for similar designs and performing interpolation, e.g. in [10], where Kriging was used.

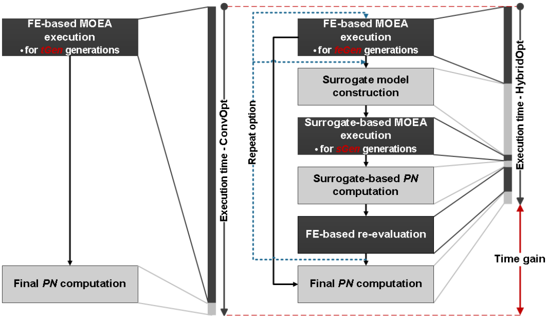


→ **If a promising design was found, an automatized detailed analysis can be done afterwards.**

Advanced modeling techniques

Modeling the targets of an optimization scenario (“Mapping”)

- After the initial phase a surrogate model is constructed.
- The model is used for running the optimization afterwards.
- In the end, promising designs are verified by FE-simulations.



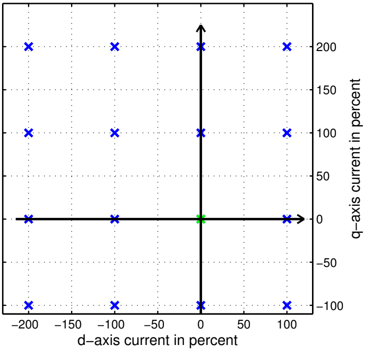
→ **Significant reduction of computation time can be achieved.**
Details can be found in [11].

Modeling the characteristics of a particular machine design

- A certain number of current vectors are defined based on the max. current density (SynRM) or the no load results (PMSM), e.g. using

$$i_{q,nom} = \frac{T_n}{\frac{m}{2}\, p_z\, \Psi_{pm}}$$

- The current vectors are analyzed using FE-simulations.



Modeling the characteristics of a particular machine design

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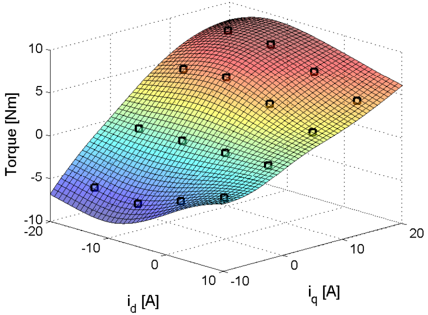

A suitable interpolation function is used (e.g., symbolic regression [9, 12] or radial basis functions [2])

→ Any other load point can be calculated very fast without using FE.

Conclusion

- **Optimization** of electric machines and drives is an **emerging field**.
- **Knowledge of many different disciplines** can help improving the performance of designs and can significantly reduce the run time of optimizations.
- **Even** though **computational power** was **significantly increased**, **apply engineering skills** to appropriately define and perform your optimization runs.
- **Future aspects** are, e.g., with regard to
  - a **“more multi-physics and system-oriented optimization”**
  - including a **tolerance analysis** / **robustness evaluation** to the optimization scenario in order to **avoid negative surprises**.
  - **driving cycle based evaluations** of designs

Finally.... I am (we are) looking forward to working with you in the field of optimization or ....

Source: https://hakanforss.wordpress.com/2014/03/10/are-you-too-busy-to-improve/

Acknowledgment

Gerd Bramerdorfer
gerd.bramerdorfer@jku.at

Department of Electrical Drives
and Power Electronics
Johannes Kepler University Linz
Altenbergerstraße 69
4040 Linz, AUSTRIA

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I further want to thank Ciprian Zavoianu, PhD for sharing his lecture notes for this work.

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D.Sc. Antti Lehikoinen

- Date of birth: December 5, 1988
- Nationality: Finnish
- Email:
  - antti.lehikoinen@aalto.fi
  - antti@smeklab.com

- Mini-bio
  - Thesis (2017): modelling AC winding losses in random-wound machines
  - Post-doc at Aalto University (FIN) since Sep 2017
  - Author of the open-source SMEKlib FEA library for Matlab
  - Sporadic consulting through SMEKlab Ltd
    - E.g. powertrain optimization for an ebike, hairpin winding design, energy storage, fault diagnostics
    - Actively involved in 3 startups
    - Periodic services for others

Contents - Antti

- <u>Winding losses</u>
- Iron losses
  - Hysteresis: skipped
  - Classical eddies: damping
  - <u>Manufacture effects</u>
    - Inter-sheet currents
    - Material degradation

Winding losses

- Let's divide into three components:
  - "DC losses" = $R_{\mathrm{DC}} I^2$
  - Eddy currents = uneven ***J*** within conductor
  - Circulating currents = uneven division of total current between parallel strands

Winding losses - Difficulties

- Phenomenon well-understood
- Numerical analysis often required for accurate-enough prediction
- Long CPU time
  - Complex geometries → dense mesh
  - Short time-step

  → <u>Advanced models</u>

Advanced winding loss models

- Much attention spent on eddy-currents
  - Squared-field derivative
  - Homogenization
- Comparatively less on circulating currents
  - Circuit models (van der Geest)
  - Online FEA approaches (Lehikoinen)
  - Hybrid approaches (Roth)

Squared-field derivative (SFD)

- Widely-used *post-processing* approach
- Idea: $J_{\mathrm{eddy}} \sim \left(\frac{\mathrm{d}B}{\mathrm{d}t}\right)^2$
  - Homogeneous *B* over a round wire assumed → solve (1D) *E* from $\nabla \times E = dB/dt$
  - Feedback from eddy-current density to *B* ignored
- Losses from $\mathrm{P} \sim \int J^2\, dV$

SFD pros and cons

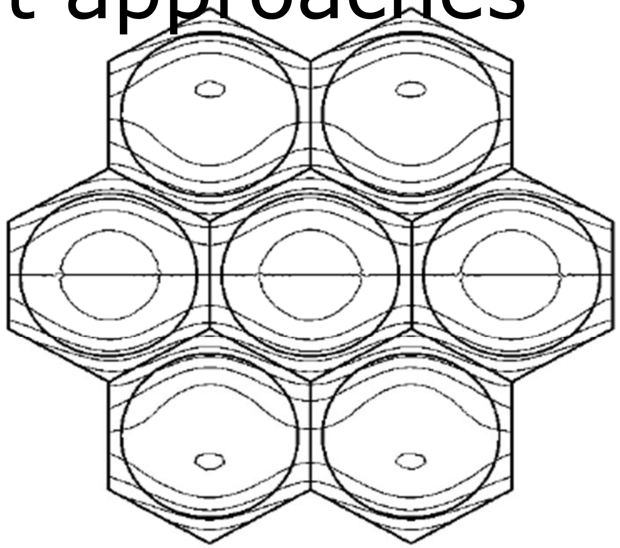
- Pros
  - No deep access to FEA solver needed
  - Series of time-static simulations possible → parallelization
  - Easy to implement
  - Decent accuracy, often
- Cons
  - Accuracy issues with small skin-depths
  - Accuracy issues with large circulating currents

Recent advances to SFD

- ICEM18 paper by C. Roth
  - *'Analytical Model for AC Loss Calculation Applied to Parallel Conductors in Electrical Machines'*
  - Addresses some limitations of original SFD
- Poster session Wed (TT Thermal, Losses and Efficiency Issues)

Homogenization

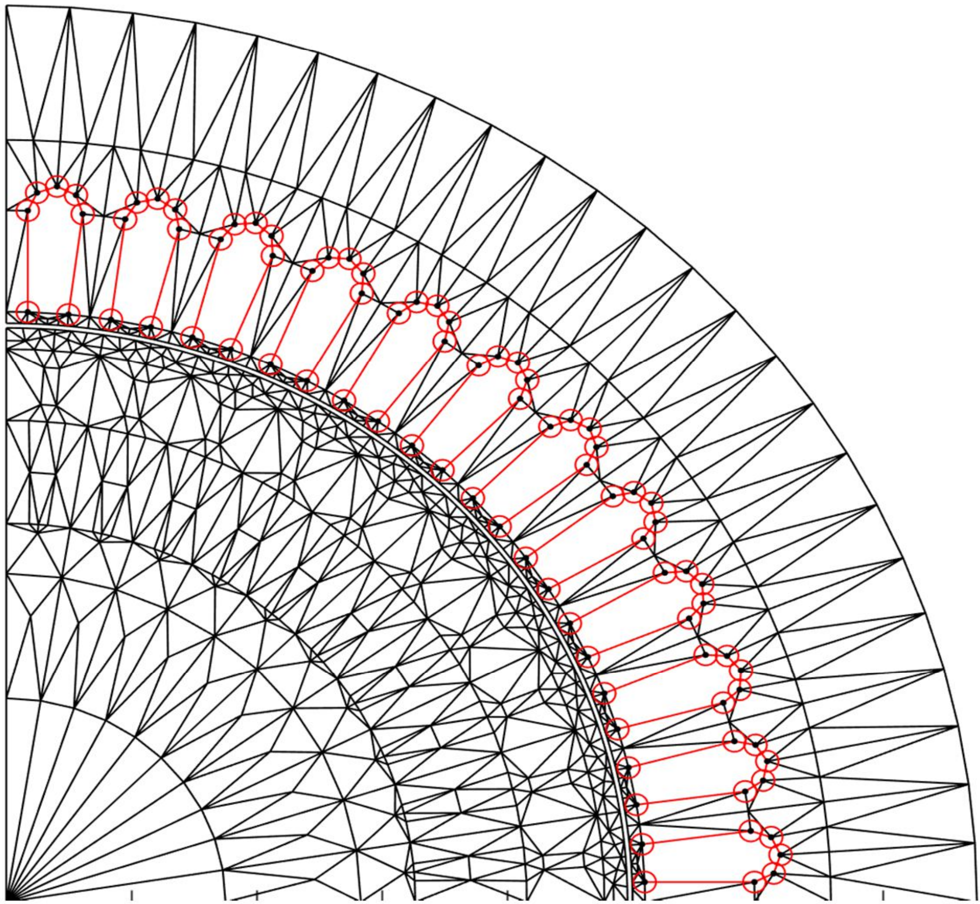
- Idea (harmonic analysis): replace fine winding structure by a complex reluctivity
  - BH-loop → losses
  - Reluctivity defined so that correct loss density obtained
- Idea (time-domain): the same, only now ν is frequency-dependent → ladder circuit approaches



Gyselinck, Sabariego, Dular, '*Time-Domain Homogenization of Windings in 2-D Finite Element Models*

Macro-element approaches

- Different versions (semi-)indendently by Szucs, Lehti, and Lehikoinen
- Idea: eliminate winding domains by linear algebra magic
  - Exact results compared to standard FEA
  - 10-100x speedups
  - All loss components considered
- Presentation (Wed TT2): *'A High-Performance Open-Source Finite Element Analysis Library for Magnetics in MATLAB'*



Iron losses

- Typical division:
  - Classical (macro-scale) eddy-current losses
  - Hysteresis losses
  - Excess losses

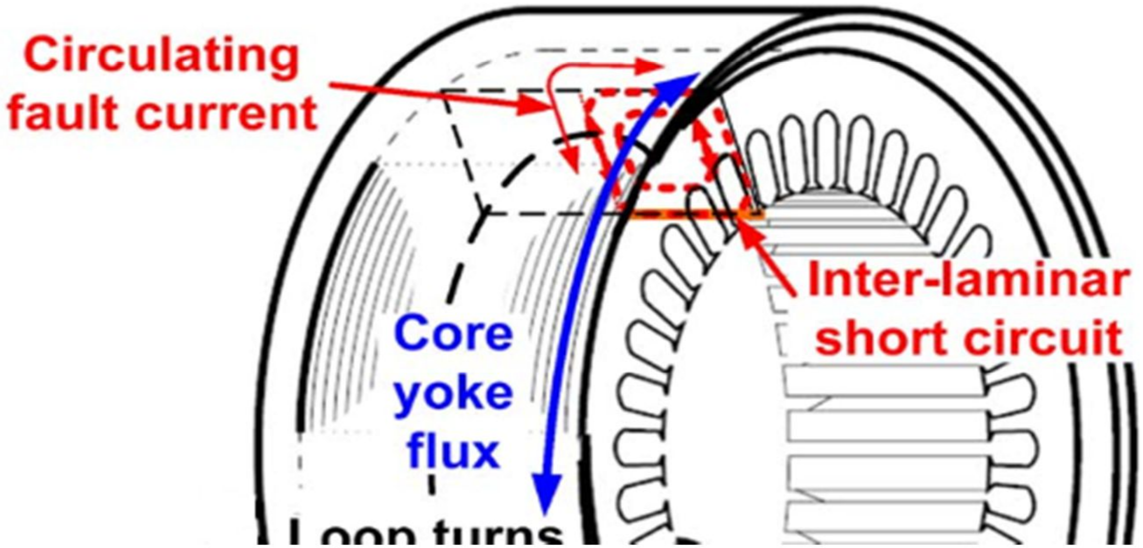
  Difficult
- Lots and lots of research
- Covered today:
  - Classical eddies in online computations
  - Manufacture effects
    - Inter-laminar currents
    - Material degradation

Classical eddy current losses

- Caused by induced currents flowing within lamination sheets
- High frequency and/or thick sheet → damping may be significant
  - *B* lags behind *H* → BH loop widens
  - Post-processing may not be accurate
- First-order 2D solution: replace reluctivity ν by $\nu + \frac{\sigma d^2}{12} \frac{d}{dt}$
  - For more info, check e.g. Rasilo, *' Finite-Element Modeling and Calorimetric Measurement of Core Losses in Frequency-Converter-Supplied Synchronous Machines'*

Interlaminar currents

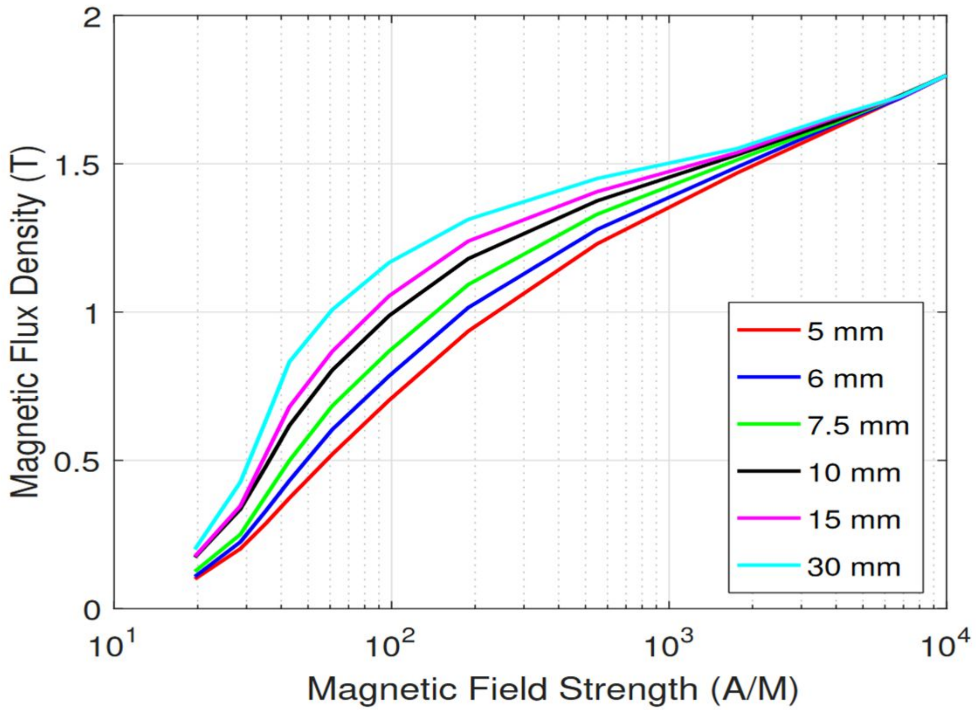
- Galvanic contact between two laminations (usually in tooth area) → closed loop if yoke welded → circulating current
  - Often caused by burrs due to punching
  - Prone to thermal runaway → *core meltdown*
- Modelling:
  - 3D, but decent solution with [2D boundary layer model]
  - Random positions of contacts problematic

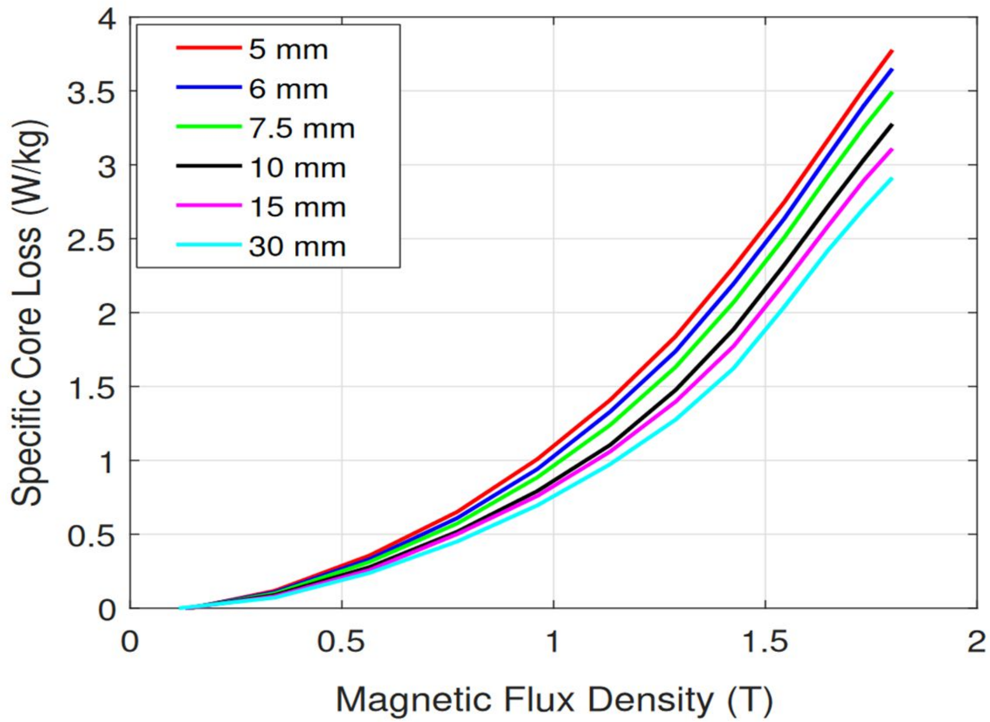


Picture (edited): Lee et al., 'A Stator-Core Quality-Assessment Technique for Inverter-Fed Induction Machines'

Material degradation

- Punching and laser-cutting
  - Decrease permeability especially around 0.8-1.2 T
  - Increase hysteresis losses
- Can be identified by e.g. using different sample widths in Epstein frame

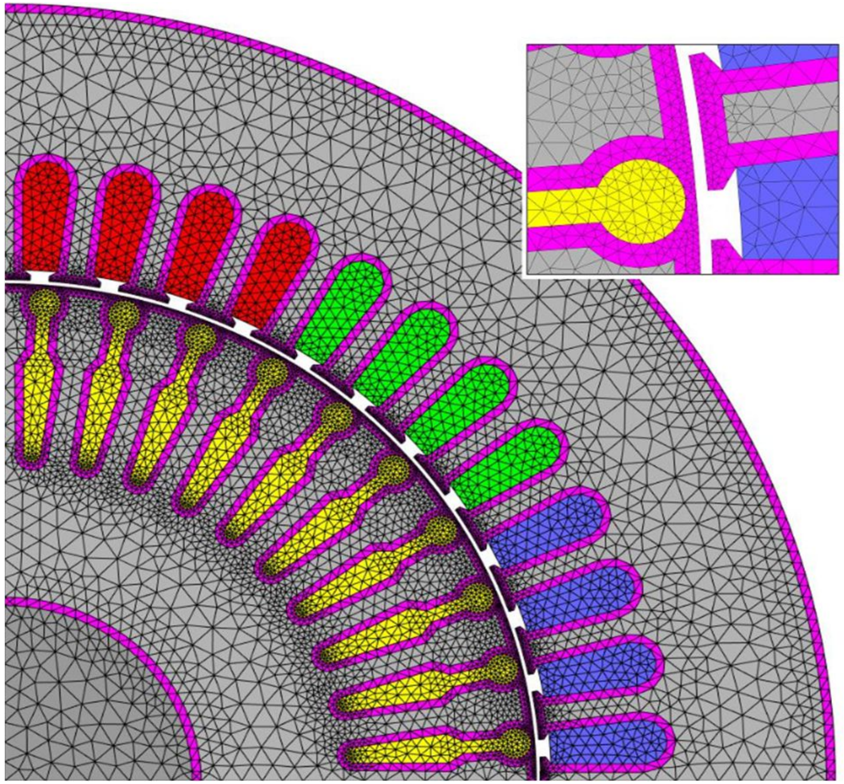




BH and core loss measurements from Sundaria et al., '*Higher-Order Finite Element Modeling of Material Degradation Due to Cutting*'

Modelling material degradation

- Typical approach:
  - Layers near cut edges
  - Individual BH curve for each layer
  + Software independent
  - Tedious, dense mesh



From Rasilo et al., ' *Analysis of Iron Losses on the Cutting Edges of Induction Motor Core Laminations*'

- Novel approach by Sundaria
  - Continuous mat. model

  $$\mu = \mu_{nd}(H)(1 - e^{-ax-bH})$$

  - Good performance with higher-order elements
- Presentation (Tue TT4): 'Loss Model for The Effects of Steel Cutting in Electrical Machines'

Conclusion

- Advanced loss computation approaches needed to
  - Shorten computation times
  - Include non-standard (yet significant) loss components

  → Some presented here at ICEM

- Some access to software usually needed

Thanks for coming!

antti@smeklab.com

THANK YOU!

Gerd and Antti