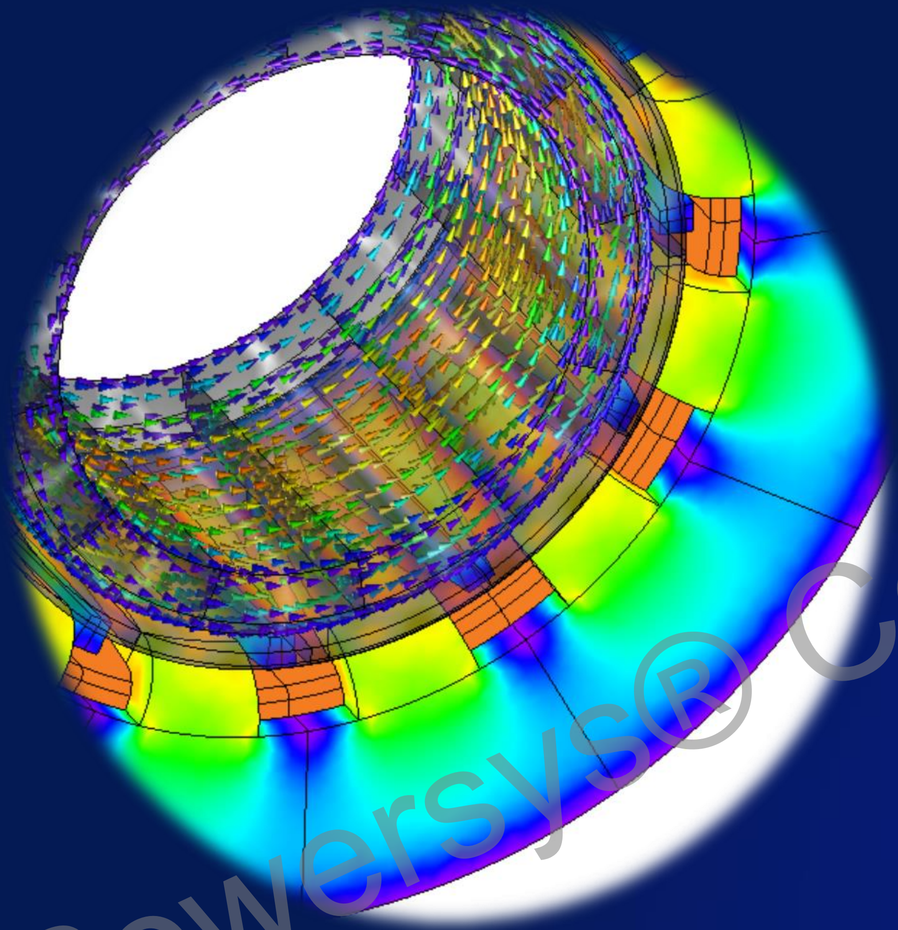


High fidelity 3D optimization of small-scale electrical claw pole drives using design of experiments and machine learning

Powersys Conference – Advanced e-Motor Design with JMAG

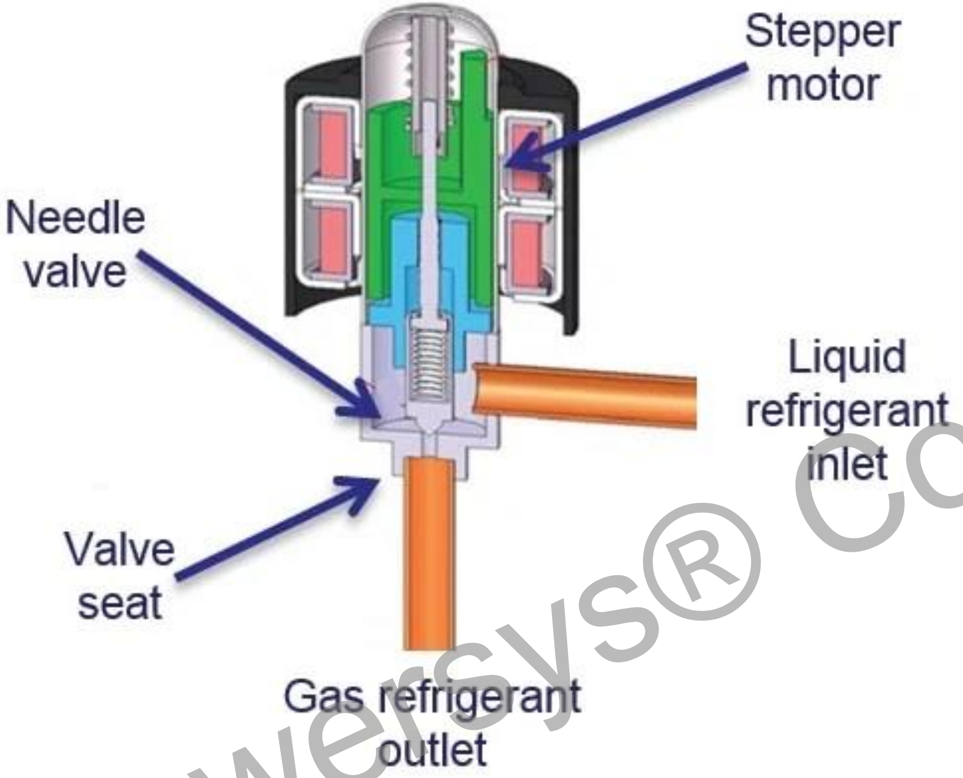
Mathias Lindner, Stuttgart, October 2024

IAV

Scope of application

- Use case and requirements
- Example topology
- Challenges

Use case: expansion valve drive for air-conditioning



Automotive valve drives: cheap³, reliable, useful!

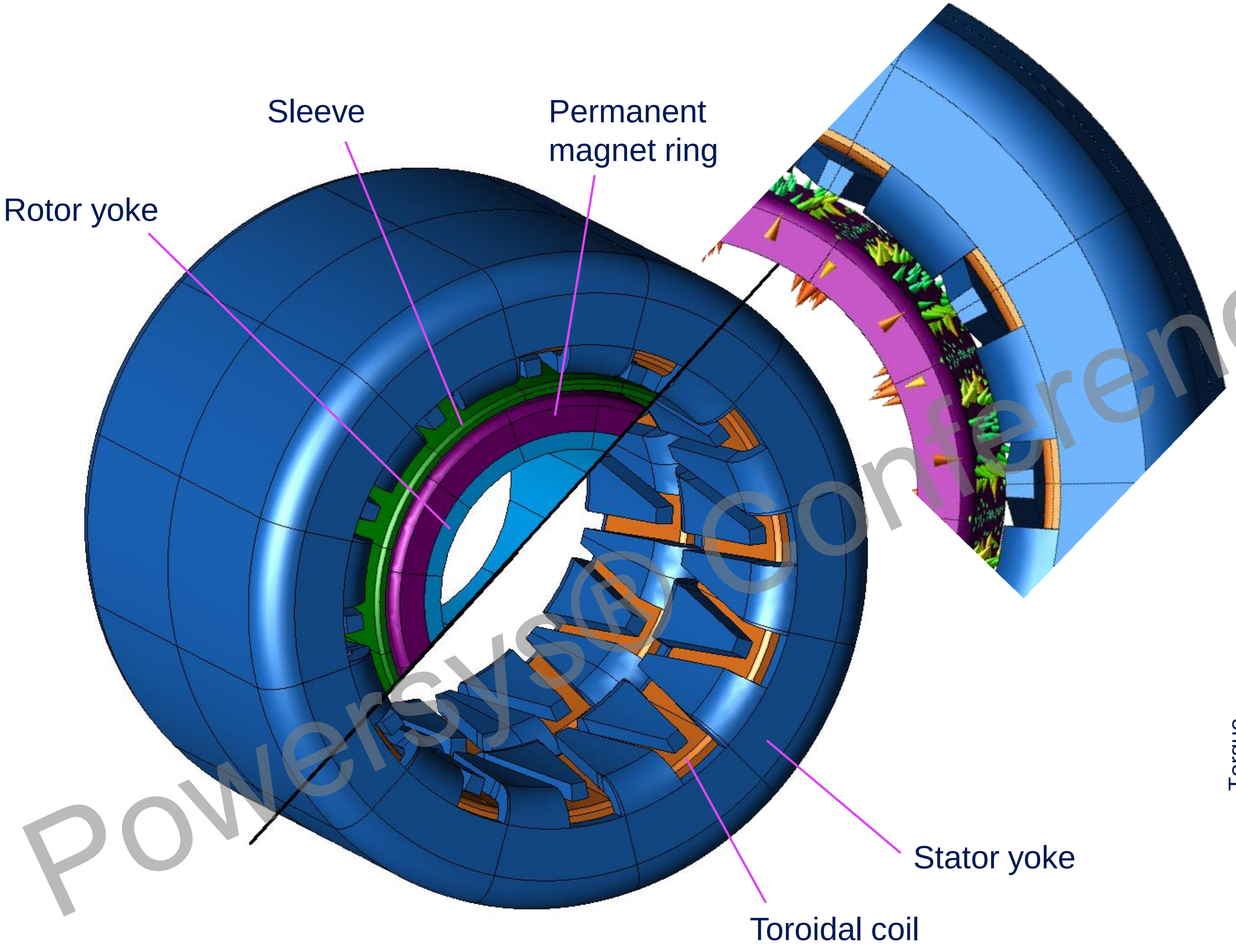
Main requirements:

- Supply from 12 V on-board grid:
  tolerance for low SOC with only 8 V
- Max. DC currents limited
- Min. torque to drive against friction & refrigerant pressure and to overcome sealing adhesion
- Min. speed to open/close the valve in limited time

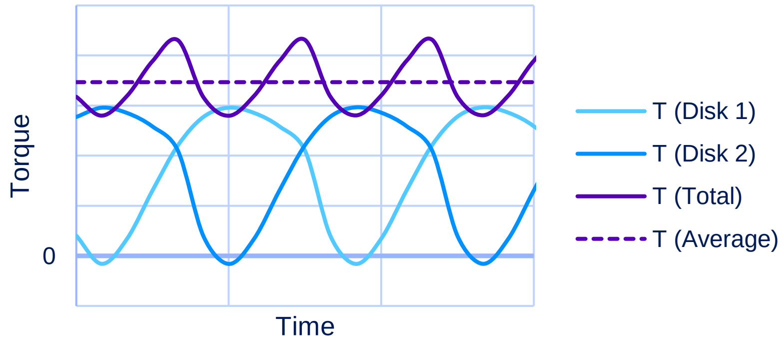
→ Strongly opposing targets!

[Mohamad, Musa, Sumeru, Sulaimon: A Simple Method On Equipment Selection Methodology Of Vapor Compression Refrigerant Electric Vehicle Air-Conditioning System, Journal of Advanced Manufacturing Technology (JAMT), 2014.]

Cost-effective claw-pole machine as stepper

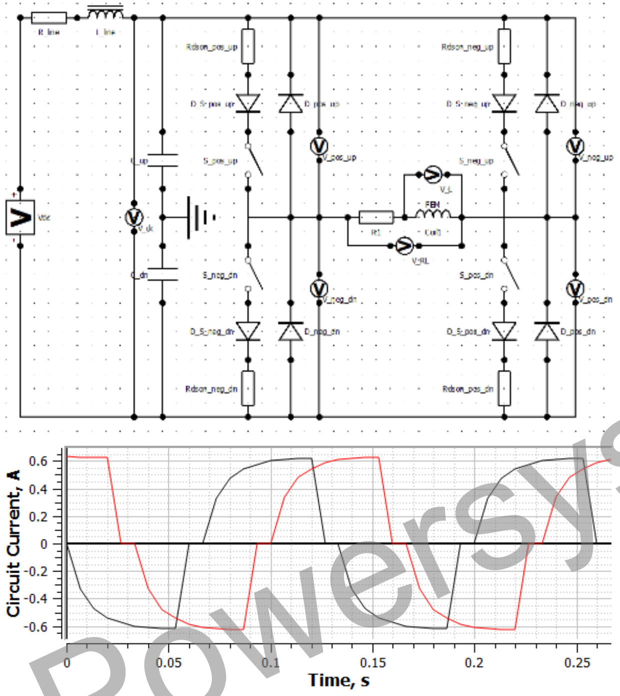


- Stator and rotor yoke from a construction steel sheet
- Permanent magnet from radially magnetized plastic bonded NdFeB
- Sleeve from a construction steel
- Two stator disks, each containing one electrical phase, ½ pole angle skewed

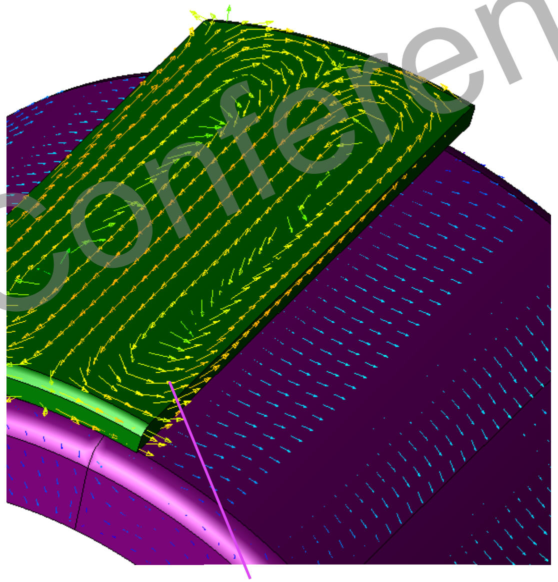


Simulation challenges

Voltage block commutation with dead time
→ full inverter simulation
→ direct influence of frequency-dependent phase impedance onto current and torque

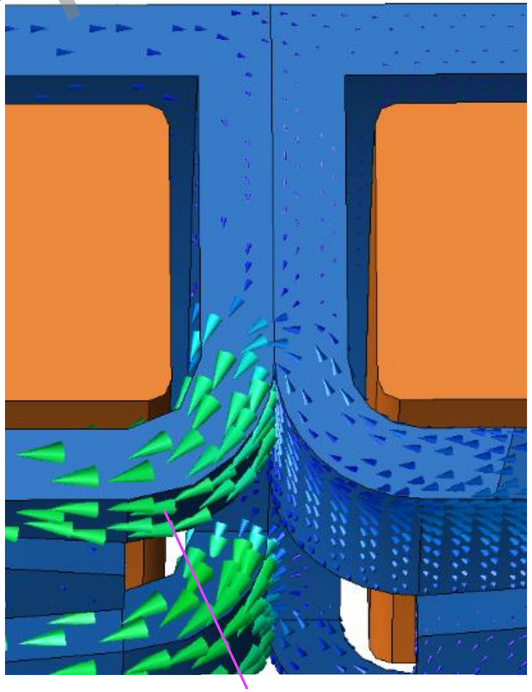


Torque-relevant 3D eddy currents and advanced iron loss calculation
→ simulation of eddy currents in almost all parts (sufficient mesh sizes)
→ usage of iron loss models suitable for wide frequency ranges



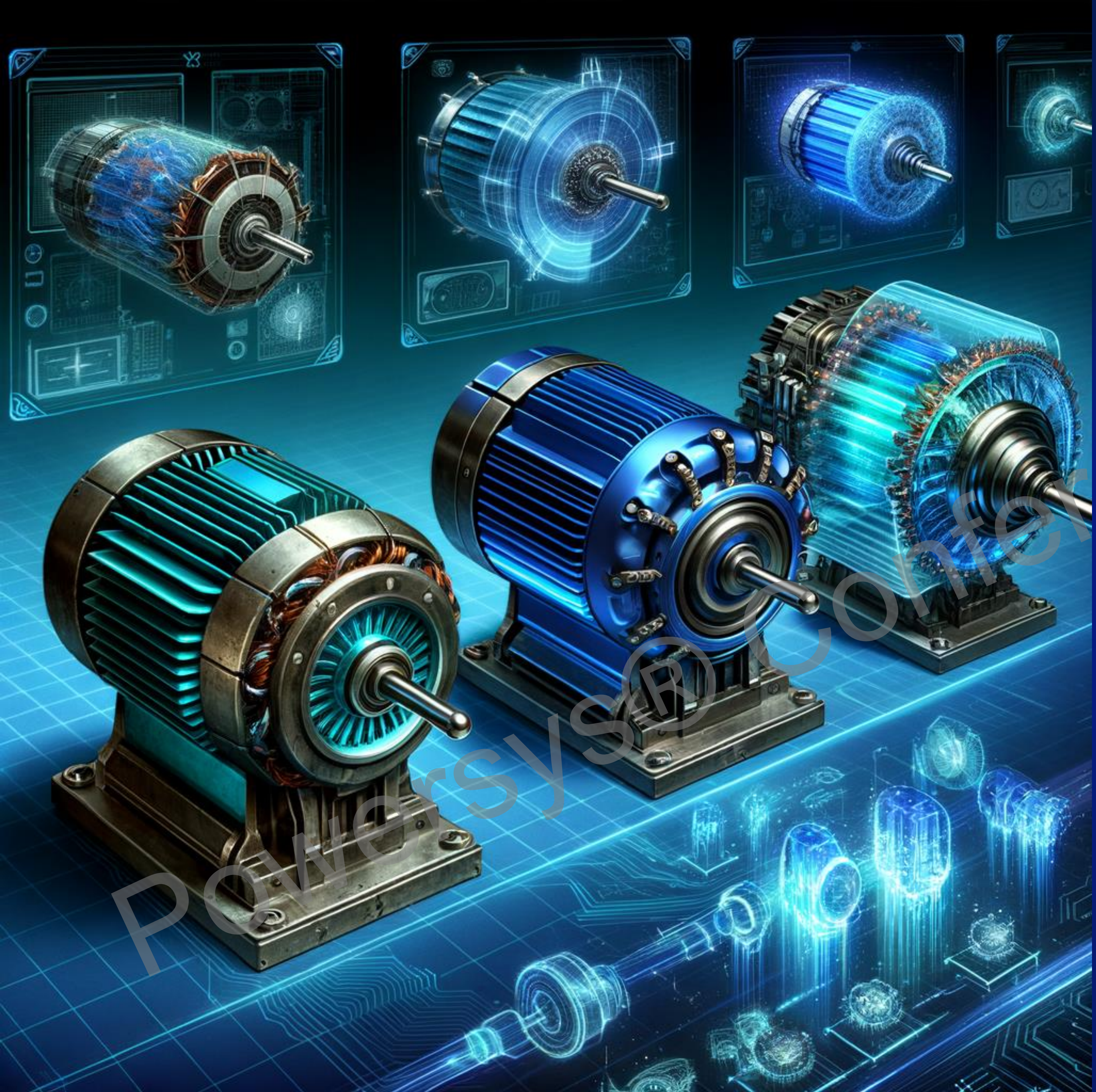
Eddy-currents

Axial flux relief
→ full model simulation or detailed investigation of uncertainties with partial model



Flux density

Larger model size and extended simulation time due to these effects.



Improving designs

- Optimization vs. Design-of-Experiments
- General DoE process

Optimization vs. Design-of-Experiments
Choosing the right process for the task

Optimization

"one solution defines the next design as long as improvement is observed"

- + Finding the mathematical optimum (in best case)
- + Quick convergence possible (few dozens to several hundred simulations)
- – Might miss global optimum depending on initial values and objective function surface (latching onto local optima)
- – Limited information on sensitivities and sub-optimal designs
- – Sequential process (to a great extent)
- – Objective function with target parameters and weighting as well as boundary conditions need to be defined initially; every change involves a complete re-calculation

Design-of-Experiments (DoE)

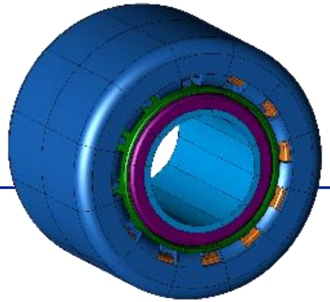
"random examination of designs with subsequent evaluation"

- + Finding the global optimum (no latching onto local optima)
- + Overview about reliability of the solution, sub-optimal designs and sensitivities
- + Massive parallel computing possible
- + Subsequent change of objective function, weighting and boundary conditions intended
- – Extensive simulations required (several hundred to thousands, depending on number of parameters and post-processing algorithm)

General DoE process

Step 1: Reference design

- Rough alignment onto specifications (e.g. preliminary design from a concept phase)



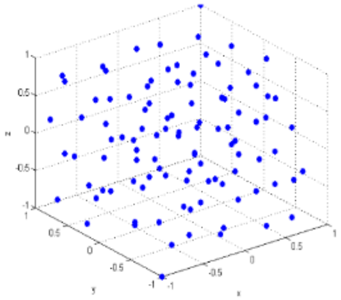
Step 2: Search space definition

- Design parameters with upper and lower limits
- Multidimensional search space

Parameter	Lower	Reference	Upper
Outer radius / mm	16	19	28
Magnet height / mm	2	2.5	4
Claw angle / °	2	6	10
Number of turns	300	440	550
…			

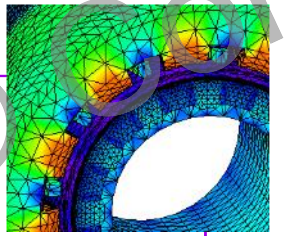
Step 3: DoE designs

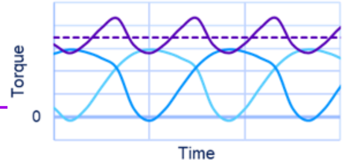
- Stochastic distribution within the search space (number of designs depends on the number of variable parameters)

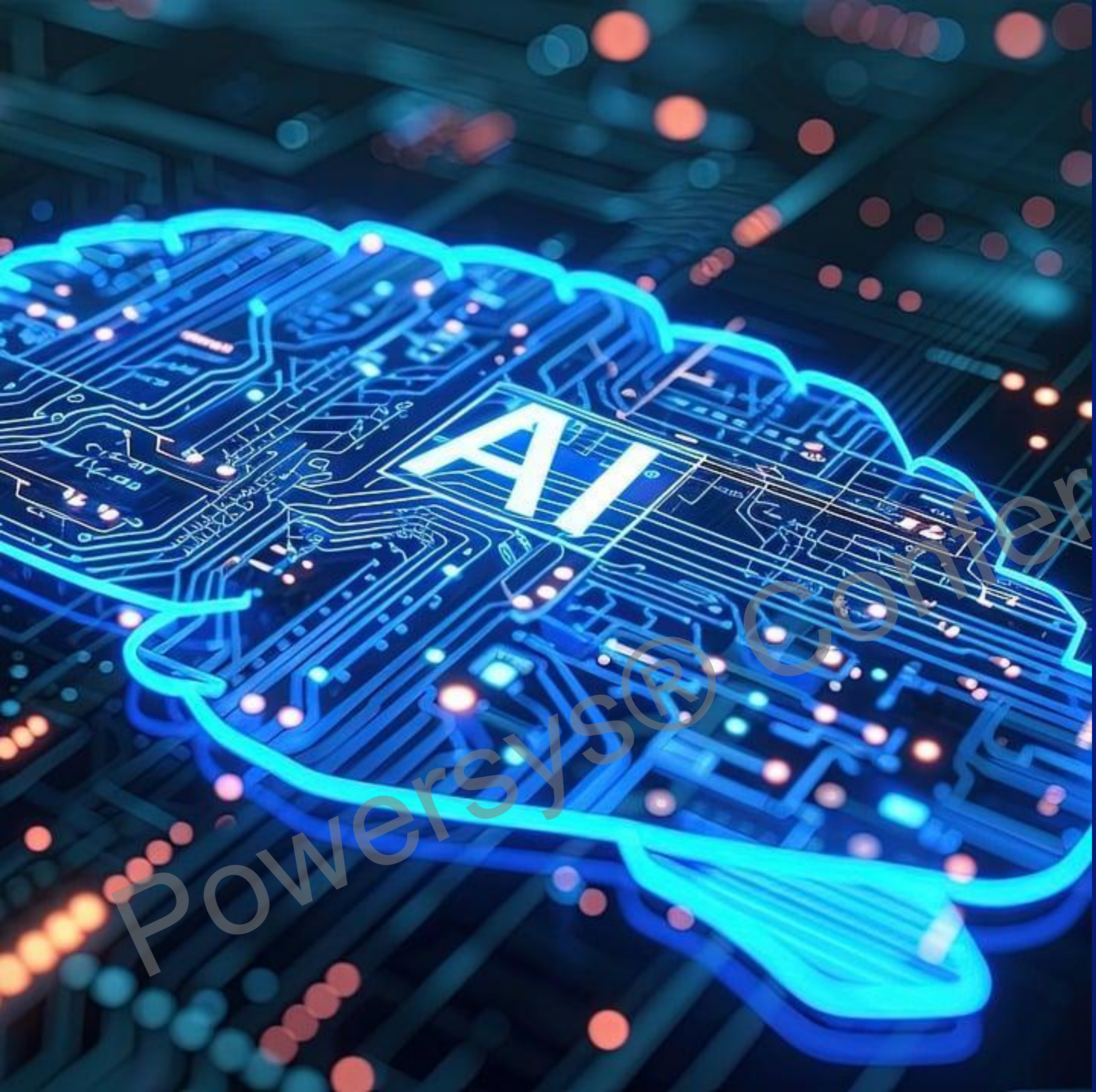


Step 4: JMAG calculations

- FEA-based analysis of the DoE designs
- Fast and accurate calculation of important machine characteristics (e.g. performance, loss analysis, demagnetization behavior, costs, thermal limits, structural-mechanical integrity…)





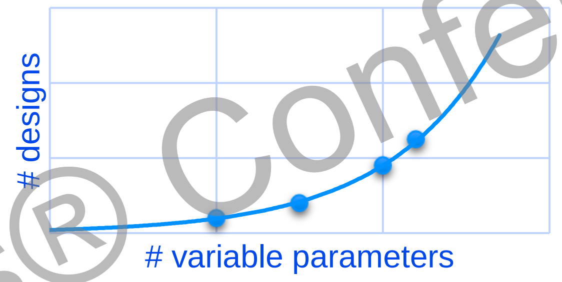


From DoE to ML

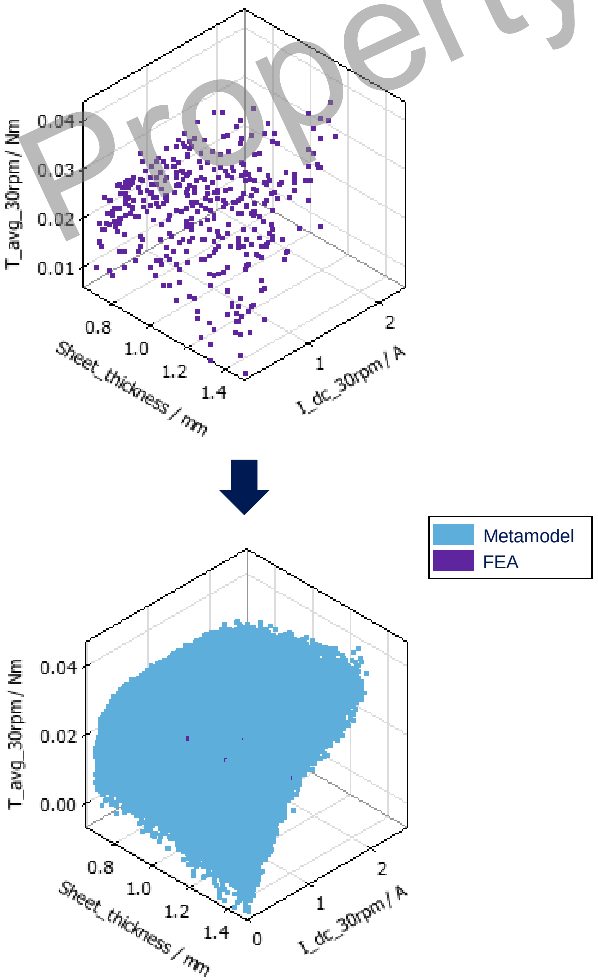
- Limitations of the DoE approach
- Evolution of surrogate models

Limitations of the DoE approach

- Finite number of values per parameter → no continuous replication
- Effort increases exponentially with number of parameters → trade-off between accuracy / continuity and simulation effort
- More designs = better approach towards optimal design



- Two remedies:
  1. Massive parallel computing → HPC / Cluster
  2. Deviation of a metamodel (surrogate model) to describe the dependency between variable parameters and results analytically / continuously



DoE post-process – Overcoming the limitations

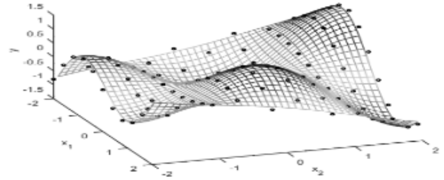
Step 5: DOE table

- ➢ Creation of a DOE table with input and output parameters for all FEA-based designs

Input 1	Input 2	Input 3	Output 1	Output 2	Output 3	Output 4
1.4	76.4	8.5	5.1	1008	654	11.5
1.2	68.7	7.7	5.7	1047	754	12.8
1.7	80.3	9.4	4.7	986	645	11.9
1.5	73.5	9.2	4.9	1101	687	12.1

Step 6: Generation of a surrogate model

- ➢ Fast analytical approach at the expense of estimation errors
- ➢ Considerable extension of the solution set (several million designs)

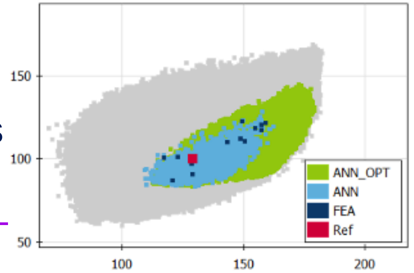


Step 7: Data analysis

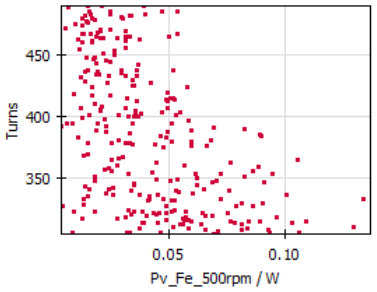
- ➢ Instant (re-)definition of weighted objectives and constraints
- ➢ Optimizations within the surrogate model

Step 8: Visualization and export

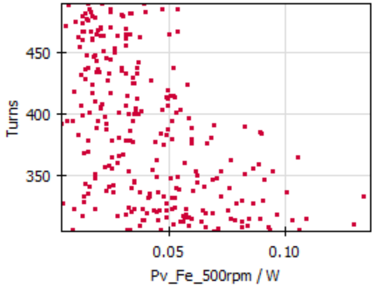
- ➢ Analysis of the solution sets: optimal designs & sensitivities
- ➢ Export of designs into FEA for detailed investigations or into similar DoE processes for drive train analyses

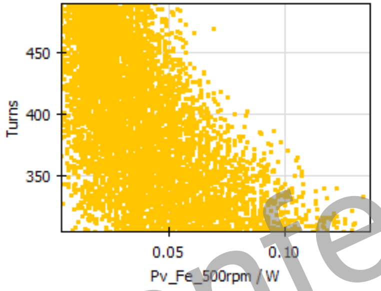


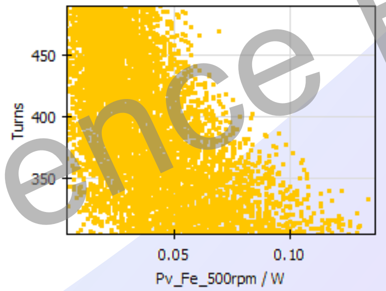
Evolution of surrogate models @ IAV
Qualitative comparison

	No post-processing (or linear interpolation)
	
Max. number of variation parameters	Accuracy rapidly sinks above **10** parameters
Meaningful number of meta designs	–
Time for model building	–
Time for meta design generation	–
Years of usage	before 2019

Evolution of surrogate models @ IAV
Qualitative comparison

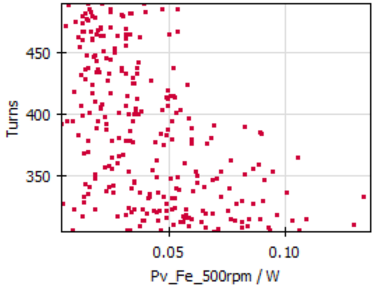
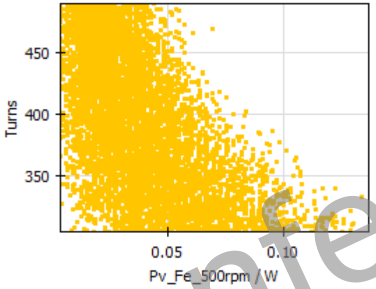
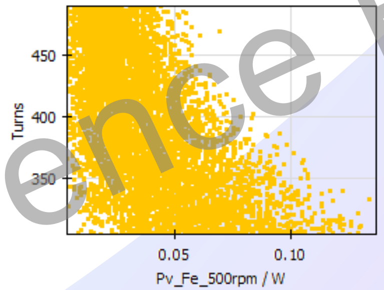
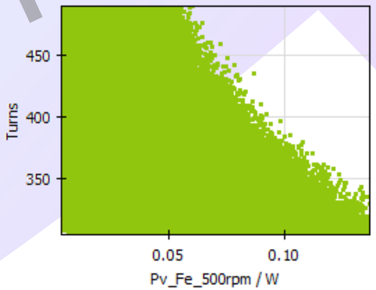






	No post-processing (or linear interpolation)	**Kriging model**	**Gaussian processes**
Max. number of variation parameters	Accuracy rapidly sinks above **10** parameters	Max. **15** with estimation errors <5%	Max. **20-25** with estimation errors <5%
Meaningful number of meta designs	–	50k – 300k	50k – 300k
Time for model building	–	few minutes	few minutes
Time for meta design generation	–	few hours	5 – 10x of Kriging
Years of usage	before 2019	2019-2023	2023

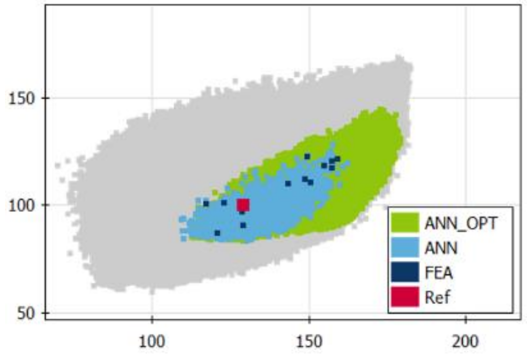
Evolution of surrogate models @ IAV
Qualitative comparison

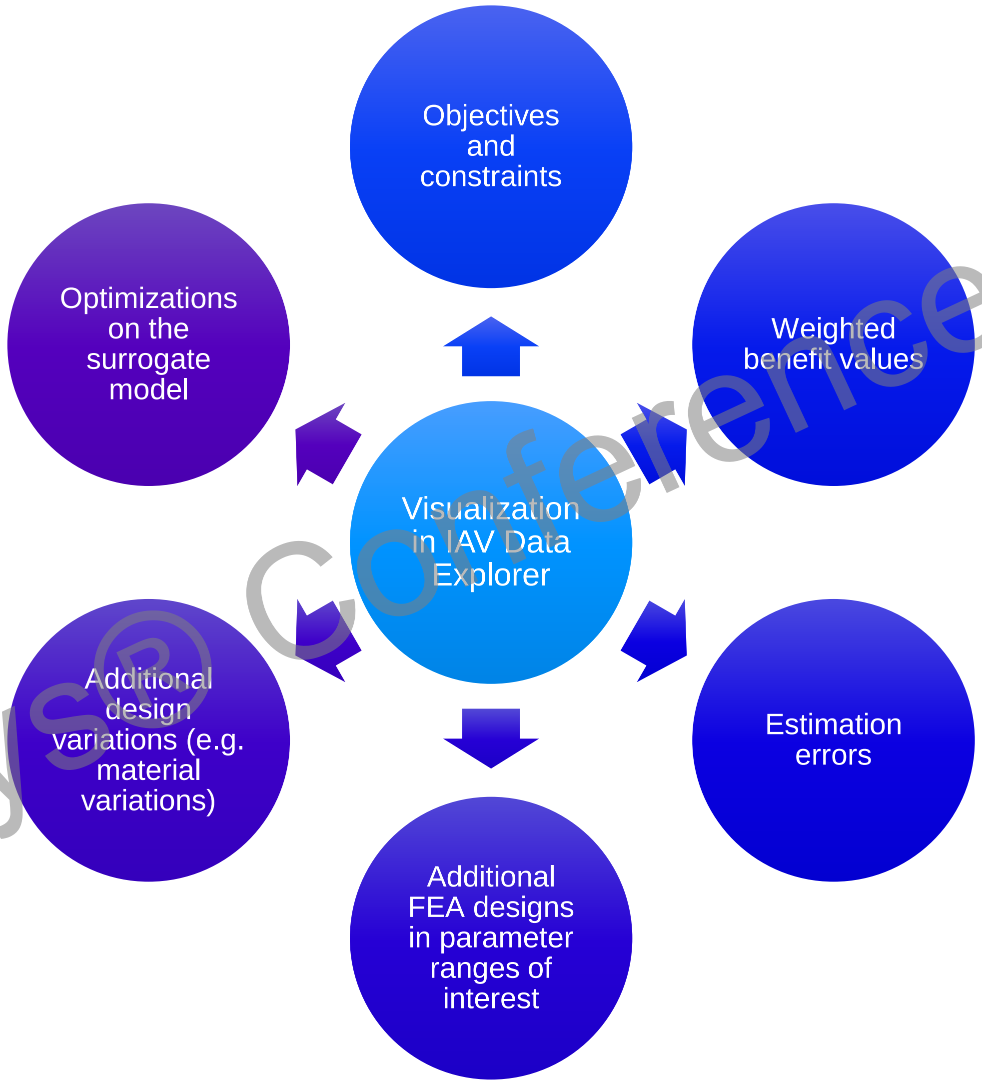
	No post-processing (or linear interpolation)	Kriging model	Gaussian processes	Artificial neural networks (ANN)
				
Max. number of variation parameters	Accuracy rapidly sinks above **10** parameters	Max. **15** with estimation errors <5%	Max. **20-25** with estimation errors <5%	**>25** possible
Meaningful number of meta designs	–	50k – 300k	50k – 300k	500k – >10M
Time for model building	–	few minutes	few minutes	few minutes (1 – 2h if ANN setup should be optimized)
Time for meta design generation	–	few hours	5 – 10x of Kriging	few minutes
Years of usage	before 2019	2019-2023	2023	since 2024

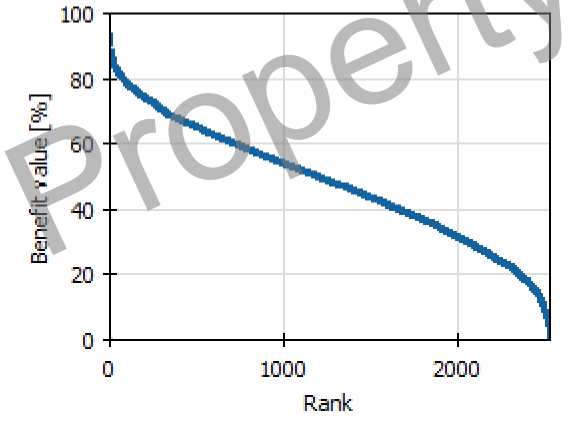
Data Analysis

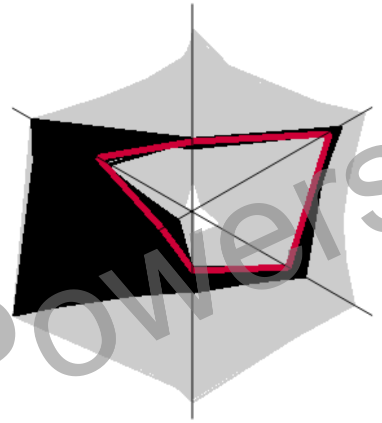
- Creating optimal results
- Key results of the claw-pole machine
- Summary

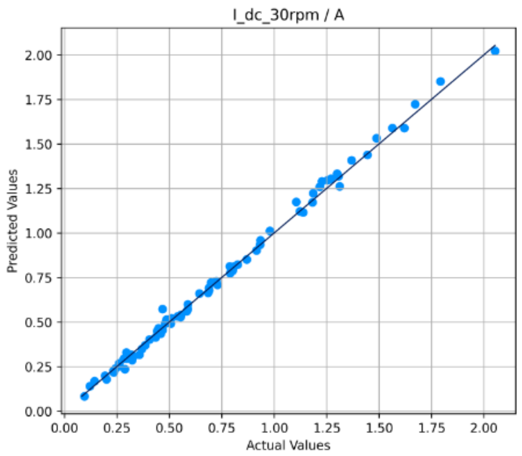
Data Analysis – Creating optimal results











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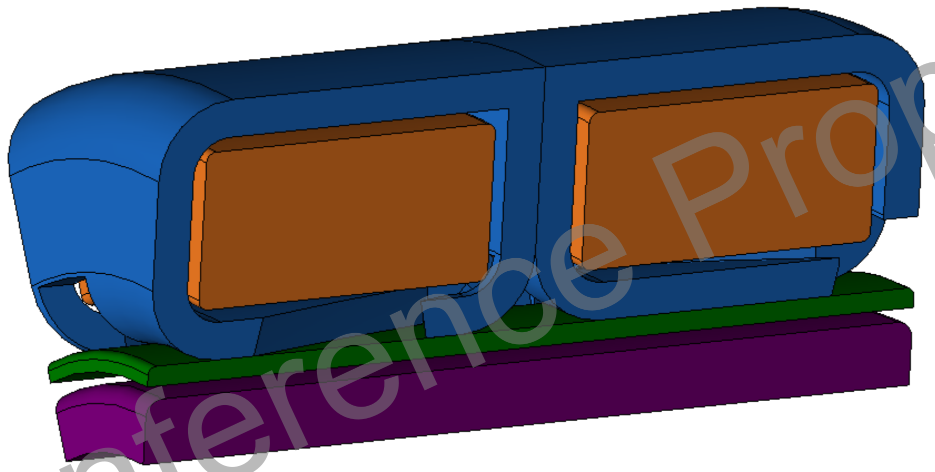
Key results of the claw-pole machine

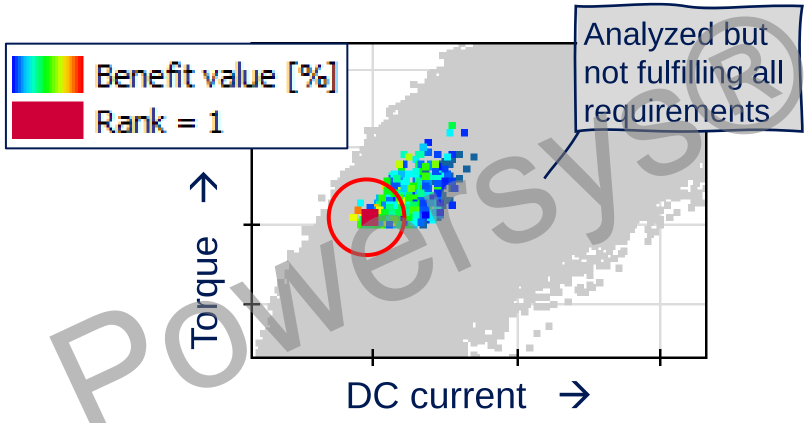
Filter:

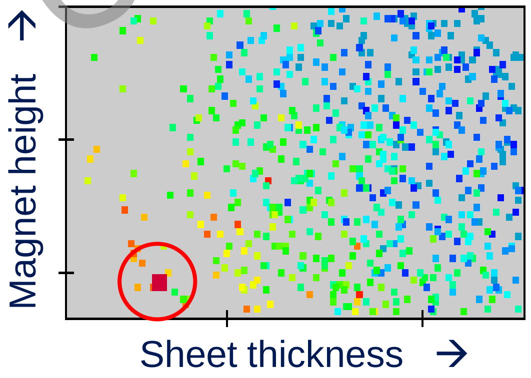
- Respect torque requirements
- Respect current limits

Optimization:

- Minimize magnet height & iron sheet thickness --> costs!
- Minimize current demand

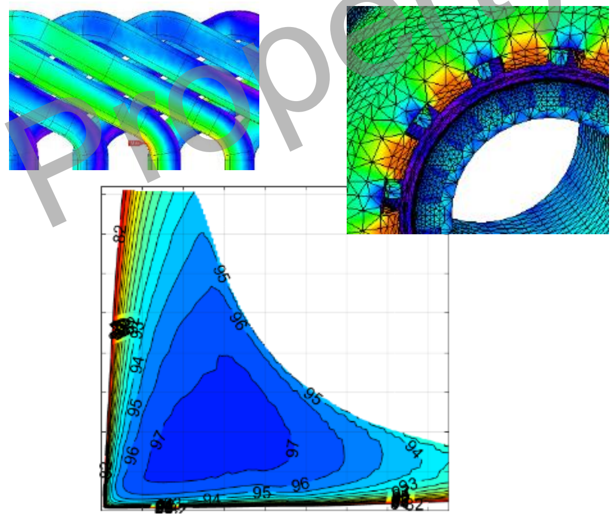






- ✓ 500,000 designs analyzed; 574 fulfill all requirements → ≈ 0.1%
- ✓ Magnet only 13% larger and sheets only 6% thicker than designs with minimum values → cost target reached
- ✓ Current demand almost at minimum possible value

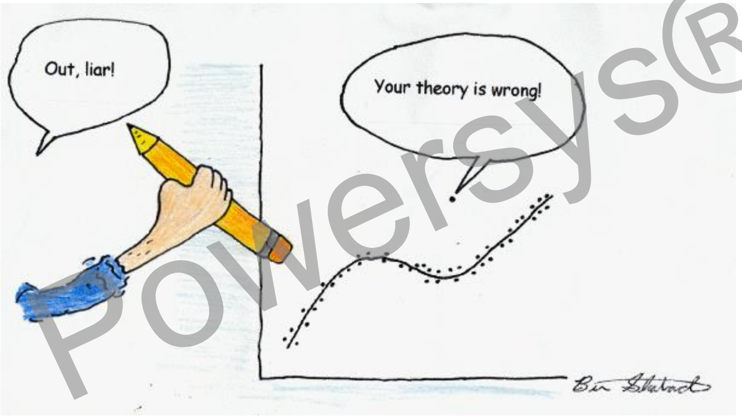
Summary and Outlook



- Optimizing electrical machines can be computationally expensive:
  - Complex models due to elaborate designs or in-depth physical effects
  - Complex analyses as e.g. in traction drives (efficiency map, driving cycle, demagnetization, short-circuiting, structural-mechanics, thermal analysis, …)
  - Huge amount of design variations
- Two approaches cooperate to get results in reasonable time:

  (1) Massive parallelization (HPC application)

  (2) Design-of-Experiments with a sophisticated surrogate model (ANN)



[Ben Shabad, https://davidmlane.com/ben/cartoons.html]

- Evolution instead of revolution:
  - Improving speed, robustness and accuracy of surrogate models & FEA simulations
    → faster optimizations, more variable parameters, reduced need for post-validations
  - Increasing degree of automation
  - Re-using results of previous investigations to complement the data basis
    → less designs to be calculated, more reliability

Contact

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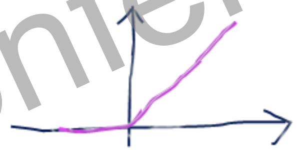
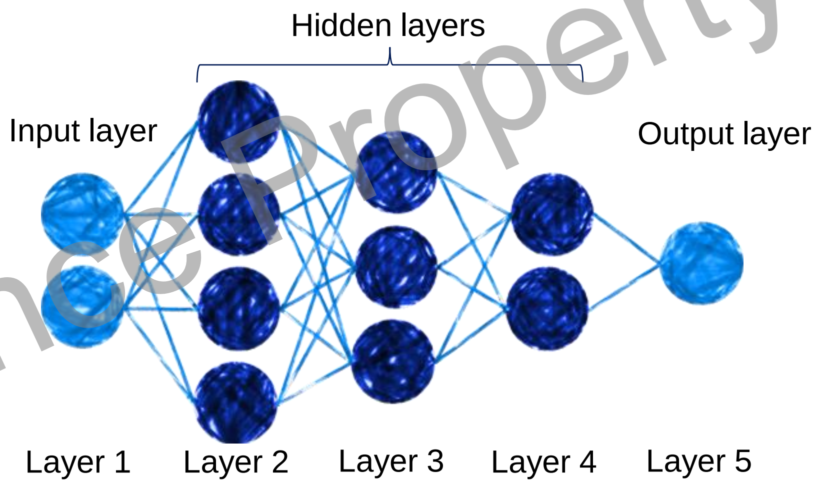
Mysterious machine learning – How does it work (simplified)?

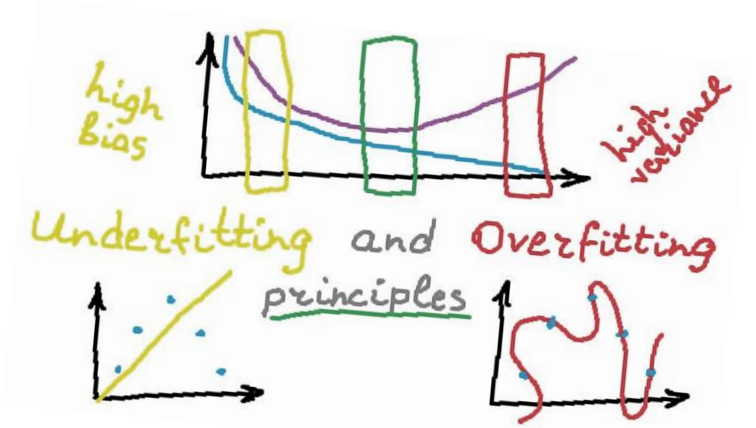
Multi Layer Perception method

- One input and one output layer containing as many neurons as input and output parameters
- Arbitrary number of hidden layers with arbitrary number of neurons
  → this claw pole motor DoE uses one hidden layer with 2884 neurons
- Connections between neurons with weightings w, biases b and activation function Φ: $\Phi(z) = \Phi(w \cdot x + b)$
  → here the Rectified Linear Unit (relu) function was used



- Learning: optimization of all w and b to match prediction to given output values
- Hyperparameter settings: defining the structure that gives the best trade-off between training and test error (number of layers and neurons, activation function, objective function, number of epochs, batch size, regularization, …)





[https://towardsdatascience.com/overfitting-and-underfitting-principles-ea8964d9c45c]