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Inverse Coil Design by Machine Learning-based Optimization

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Inductive power transfer is nowadays a popular and widely used technology, e.g. for charging mobile phones and heating cook ware. In such systems usually coplanar spiral coils are used in order to generate the necessary magnetic fields. However, with regard to energy efficiency it is desirable to start from an optimal magnetic field and derive the necessary coil geometry from that. Mathematically, this poses an ill-posed problem which is difficult so solve analytically or numerically respectively.
In our previous work [1], we have shown that optimized coil geometries can be obtained by recurrently solving Biot-Savart's law and optimizing a parameterized geometry by means of Simulated Annealing [2]. However, once additional magnetic components, like field focusing elements, are added to the magnetic circuit, the calculation of the magnetic field using solely Biot-Savart's law is no longer valid. In that case more suitable calculation methods like the finite element method (FEM) have to be used which drastically increases the computation time of the whole optimization process.
In order to solve this problem, we suggest a method that uses a neural network providing a surrogate model for the complex magnetic circuit. Once trained the surrogate model can replace a time-consuming FEM simulation still providing an estimate of the magnetic field. As the calculation of the surrogate model will be several times faster than a full FEM simulation this will speed up the entire optimization process.

Simple optimization method based on solving Biot-Savart's law

Instead of trying to solve the mathematically ill-posed problem of finding a coil geometry from a given magnetic field we have set up an optimization approach where optimized coil geometries are obtained by recurrently solving Biot-Savart's law for a parameterized coil geometry using Simulated Annealing (Fig. 1). Starting from an arbitrary initial geometry the optimal geometry is obtained after a few thousand iterations (Fig. 2).

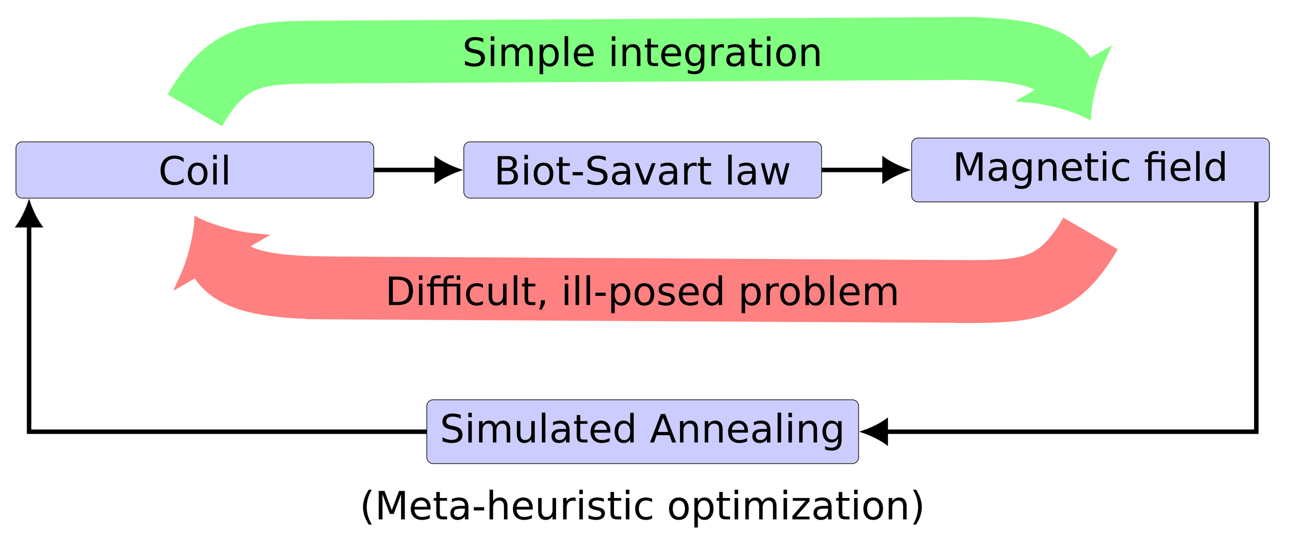

Fig. 1: The optimization loop

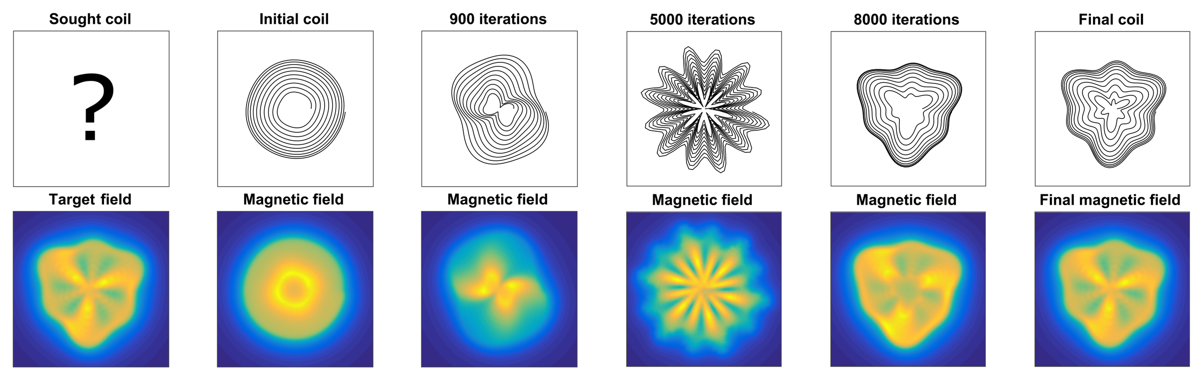

Fig. 2: Starting from a desired magnetic field (here: arbitrarily chosen) a coil can be found using Simulated Annealing.

Advanced method for complex magnetic setups

Once a magnetic setup is used which is more complex than a simple coil, computationally expensive FEM calculations must be used instead of solving Biot-Savart's law (Fig. 3). For example, a setup containing ferrite materials is currently used in induction hobs in order to increase the magnetic field intensity at the position of the cook ware.

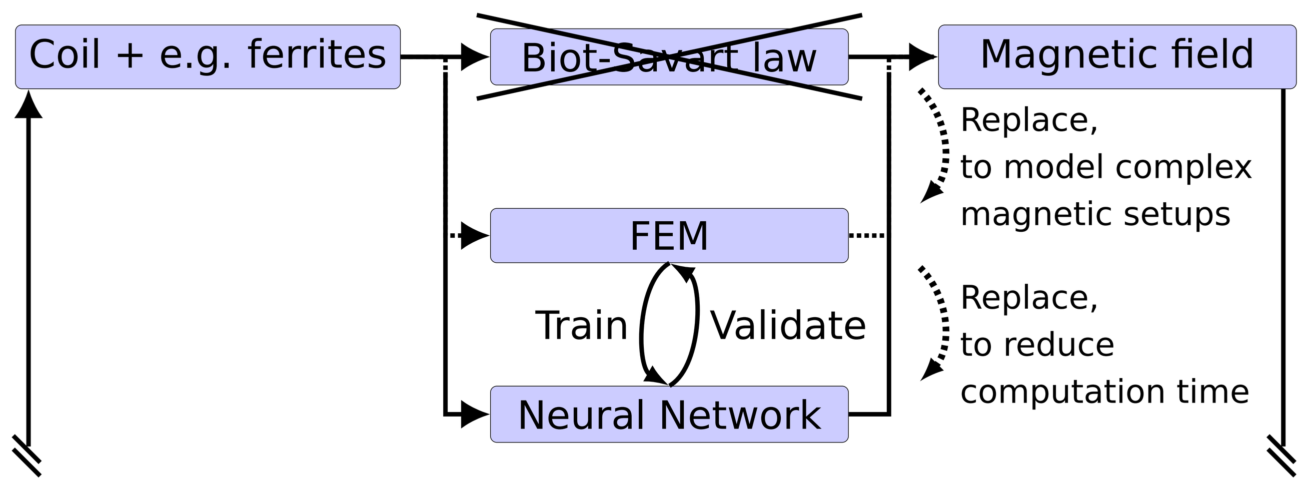

Fig. 3: Advanced method with replaced Biot-Savart law

		Single field calculation	Full optimization process (~100k field calculations)
Biot-Savart	simple coil	$<$ 3 sec.	$\sim$ days
FEM		$\sim$ minutes	
FEM	complex setup	$>$ 10 minutes	$>$ months
Neural Net		$<$ 3 sec.	$\lesssim$ days

Fig. 4: Estimated computation times of different methods

Coils combined with e.g. ferrite materials lead to non-linear material models which increases the overall computational complexity. In this case a lower bound for the computation time is of the order of 10 minutes. However, depending on the magnetic setup simulation times might be considerably higher. (Fig. 4)

In contrast to FEM simulations, calculating a prediction based on a neural network is computationally much less demanding. Consequently, with our neural network approach we can determine the coil geometry of a complex magnetic setup using the same computation time as for the simple coil geometry.

Proposed neural network architecture

We propose an autoencoder-like neuronal network architecture [3] (Fig. 5). The input is a raster graphics-like, 2D representation of the coil. The output is a 2D representation of the resulting magnetic field. The encoder part of the autoencoder consists of several convolutional layers [4] which allow the network to extract important features of the coil geometry. The subsequent decoder layers are used to calculate the magnetic field based on this features.

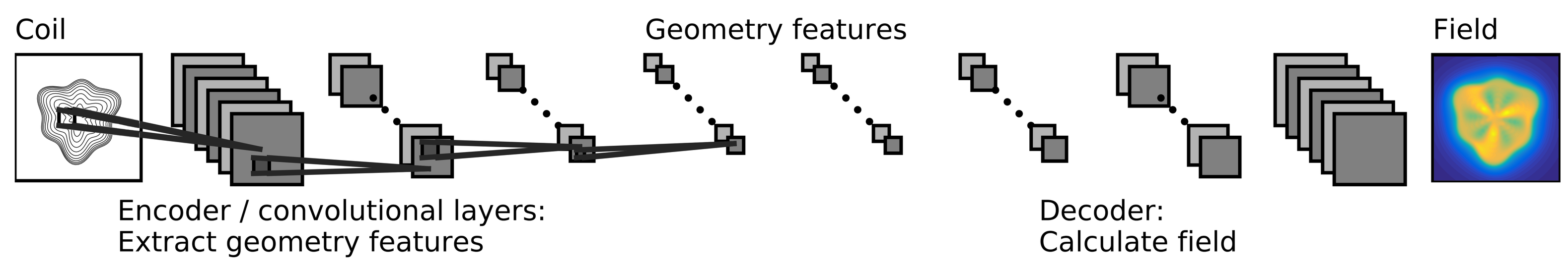

Fig. 5: The propsed neuronal network architecture

Parallel training

The training data must be generated using FEM simulations but those are independent of the optimization process and therefore can be carried out in parallel. Training the network involves minimizing its prediction error E in dependence of the synapses' weights W which is typically done based on a gradient descent algorithm according to Eq. (1):

$$W_{i+1} := W_i - \eta \nabla E(W) \quad (1)$$

This can be parallelized either by distributing the calculation of one gradient descent step (Fig. 6) or by running several minimizers like stochastic gradient descent (SGD) either in a synchronous [5] or asynchronous [6] modus (Fig. 7).

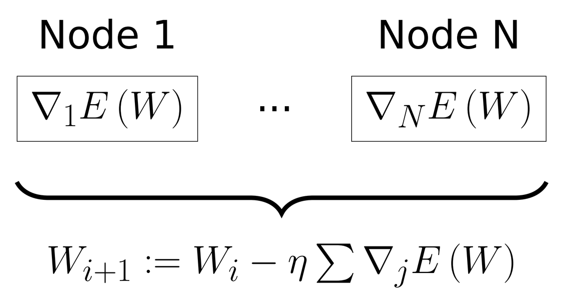

Fig. 6: Distributed gradient calculation

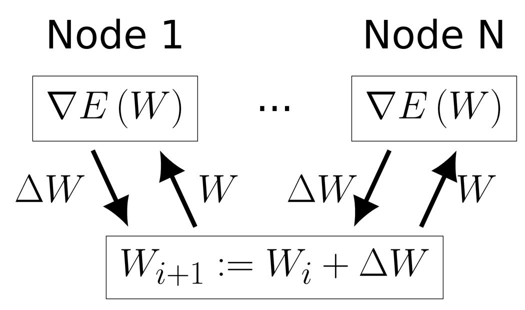

Fig. 7: Distributed asynchronous SGD

'DeepDreaming' of a coil geometry

Previously, it was not possible to use a gradient-based method to solve the problem of finding a coil geometry since no functional description between an arbitrary coil geometry and the generated magnetic field was known. Once the neural network is trained it itself represents such a functional description. Thus, it is feasible to use gradient-based algorithms instead of the previously mentioned Simulated Annealing method.
It has been shown that the backpropagation algorithm that is used for training a neural network can be used for this purpose as well. This approach has recently been used to examine the features learned by neural networks for image classification [7]. Here, stochastic gradient descent is used to perform the gradient descent with respect to the inputs of one network layer while keeping the network's weights fixed.

Application in other fields

Meta-heuristic optimization methods, like Simulated Annealing, are widely used and not specific to the inverse coil design problem described here. The presented approach can be applied to any problem that can be represented by a model, e.g. a simulation, that maps a set of parameters, e.g. the parameterized coil geometry, to a set of properties, e.g. the magnetic field.

Project info

- Partners: Bielefeld University of Applied Sciences, Bielefeld University, Miele & Cie. KG
- Runtime: Until end of 2019
- Staff of complete BMBF project: 3 PhD Students
  - Staff on topic of machine learning: 1 PhD Student
- Funded by the Federal Ministry of Education and Research (BMBF) and Miele & Cie. KG

Workpackages

1. Implementation of an optimization approach based on Biot-Savart's law for simple coils
2. Implementation of a neural network that reproduces a 2D raster image-like representation of a coil
3. Implementation of a network that predicts the magnetic field based on a 2D raster image-like representation of a coil
4. Expanding the implementation to consider complex magnetic setups
5. Expanding the implementation for 3D coils

References

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