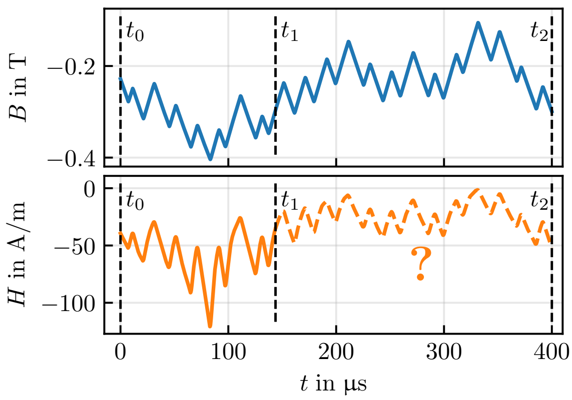
Master thesis

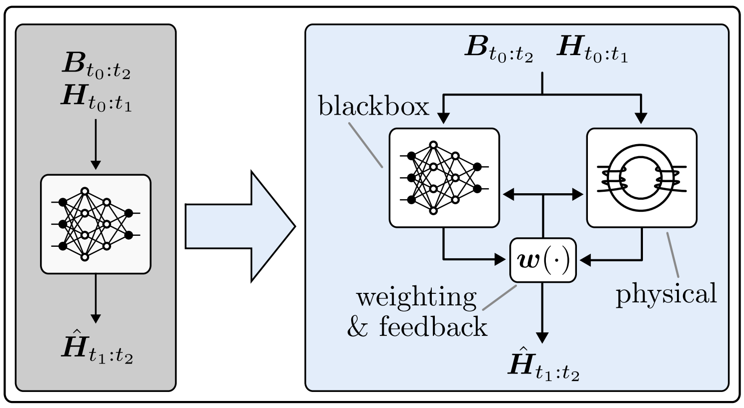
Physics-informed magnetic greybox modeling

Magnetic components are integral to modern power electronics, but are generally the bulkiest part. With the continuous trend towards efficiency and sustainability, the question on how to properly model and optimize such components becomes more relevant. The main issue in that, is that modeling the material behavior is difficult due to saturation and hysteresis effects especially for transient signal shapes and that, as a result, there is an unfulfilled need for accurate and reliable models (see Fig. 1a for an exemplary prediction task).

In the context of the MagNet Challenge 2 (MC2), progress in this direction has been made and a variety of models with varying degrees of physically motivated components have been developed, however, the approaches generally could not beat purely data-driven models in terms of parameter efficiency. Within the context of this thesis, it is to be investigated in detail how two proposed greybox structures compare to blackbox structures and if and how physical knowledge can be incorporated while retaining or improving performance. An exemplary structure combining blackbox and greybox models is shown in Fig. 1b and an adequate data set for training such structures has been provided in the context of MC2 [1].



(a) Exemplary transient prediction task.



(b) Exemplary greybox modeling concept [2].

Key research questions:

- Can a rather small model (likely <1.000 parameters) be combined with the inductor ordinary differential equation (ODE)?
- How can the Preisach model be best combined with data-driven modeling (likely >10.000 parameters)?

Necessary requirements:

- Understanding of magnetic components, hysteresis and saturation effects
- Good programming skills in a scientific programming language (Python or Julia)
- Experience with a machine learning framework (e.g., JAX, PyTorch, TensorFlow, Flux)

WP 1: Literature research **[4 weeks]**
Scanning the scientific literature for relevant publications and patents related to magnetic transient modeling and related fields is the first step. Relevant work will be stored in a literature review software (e.g., JabRef) and summarized in the thesis. Additionally to the literature, the data as well as the results and submissions for the MC2 `https://github.com/minjiechen/magnetchallenge-2` should be considered and studied. Especially, it is advised to consider the submission from the IAS group `https://github.com/upb-lea/RHINO-MAG/`, understand its structure, and do first tests with it.

WP 2: Inductor ODE **[2 weeks]**
Implement the basic inductor ODE and fit static parameters to get an initial idea of its linear performance.

WP 3: Inductor ODE + NN **[4 weeks]**
Combine the previously implemented ODE with a neural network (NN). The static performance with an MLP may be tested, but the target is to apply an RNN.

WP 4: Preisach **[2 weeks]**
Implement the basic Preisach model and fit static parameters to get an initial idea of its performance.

WP 5: Preisach + NN **[4 weeks]**
Combine the previously Preisach model with a neural network (NN). The static performance with an MLP may be tested, but the target is to apply an RNN.

WP 6: Pareto front **[4 weeks]**
Evaluate the models for different sizes and decide on proper parameterization via cross-validation.

WP 7: Documentation **[6 weeks]**
All work packages should be reported in a structured way within the thesis. A LaTeX template should be used for this purpose: `https://github.com/IAS-Uni-Siegen/thesis_latex_template` Writing instructions can be found within the provided template source files. Based on the previous empirical findings, conclusions should be drawn, and future research directions should be outlined.

Gantt chart

The planned timetable is shown in the Gantt diagram below.

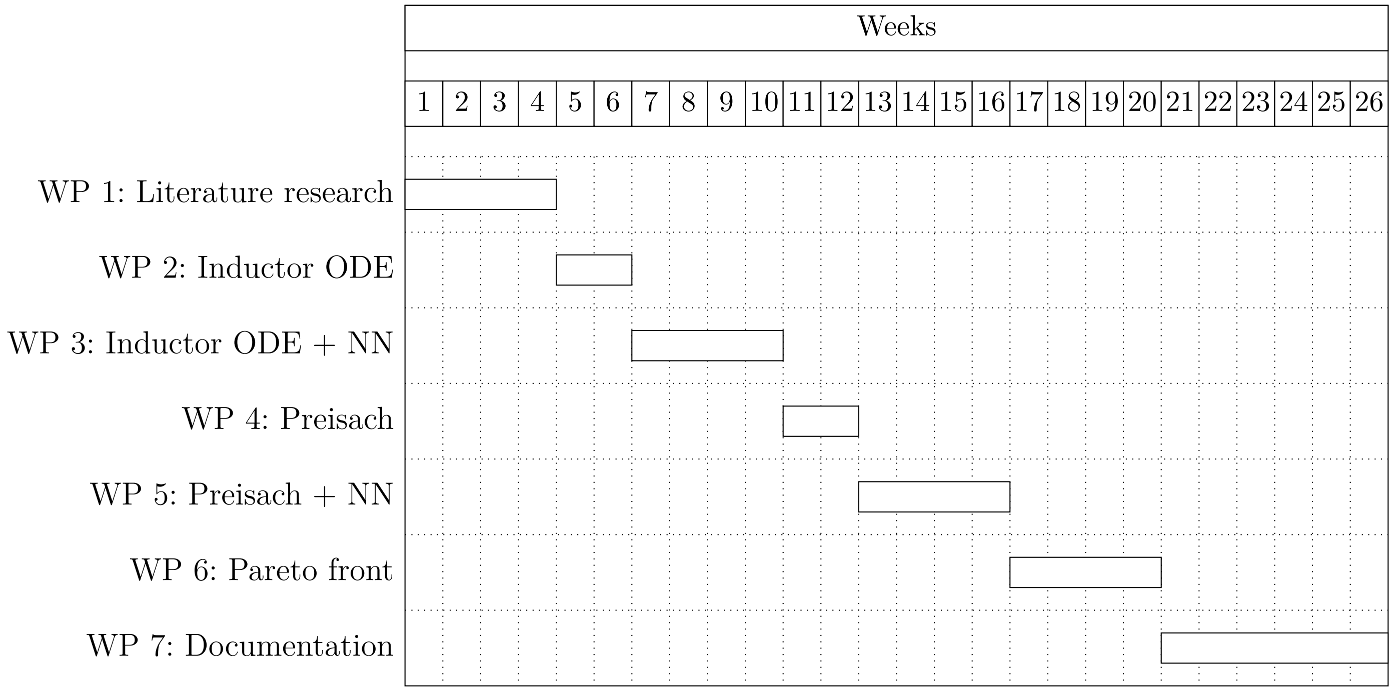


Figure 2: Gantt chart for the thesis.

References

[1] H. Kwon, S. Wang, H. Li, Y. Elasser, G.-G. Kang, D. Zhou, D. Grigoryan, and M. Chen, “Magnetx: Extending the magnet database for modeling power magnetics in transient,” in *2025 IEEE Applied Power Electronics Conference and Exposition (APEC)*, 2025, pp. 566–572.

[2] J. H. Hoekstra, C. Verhoek, R. Tóth, and M. Schoukens, “Learning-based model augmentation with lfrs,” *European Journal of Control*, vol. 86, p. 101 304, Nov. 2025.