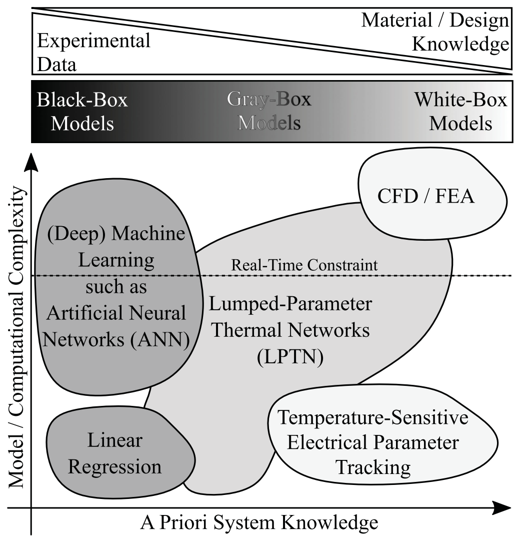
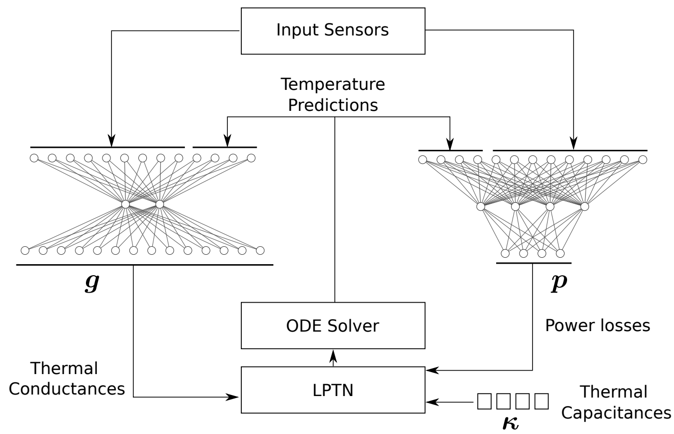
Master thesis

Neural ordinary differential equations (NODEs) for motor drive temperature estimation

Temperature estimation is a crucial aspect in the operation of electrical machines to both prevent thermal overload and to optimize the machine's performance. While temperature sensors can be used for this purpose, they are costly and can fail in the harsh environment of electrical machines. Therefore, the development of model-based temperature estimation methods is of great interest for many applications (e.g., automotive traction drives). In this thesis, the use neural ordinary differential equations (NODEs) [1] to estimate the temperature of an electric motor based on limited electrical and mechanical input measurements should be investigated. A particular focus will be on the hybridization of interpretable engineering as well as data-driven machine learning (ML) model parts, that is, going beyond black-box ML. The goal is to develop an elegant temperature estimation method that is accurate, robust, and computationally efficient to allow real-time deployment.



(a) Temperature model spectrum [2]



(b) Exemplary NODE architecture [3]

Key research questions:

- How to integrate available physics-based knowledge into the NODE's right-hand side?
- What are relevant input signals and derived features for the temperature estimation?
- Where is the sweet spot between model complexity and accuracy?

Necessary requirements:

- Finished course work on machine learning / system identification
- Fundamental knowledge of dynamical systems (ideally electrical machines) and their modeling
- Solid programming skills in scientific programming languages (e.g., Julia, JAX, PyTorch)

WP 1: Literature research **[4 weeks]**
Scanning the scientific literature for relevant publications and patents related to data-driven / data-assisted temperature estimation for electrical drives is the first step. Moreover, relevant work (and implementation examples) in the area of system identification via NODEs in other engineering fields should be found. This includes the identification of relevant keywords as part of the search strategy. Relevant work will be stored in a literature review software (e.g., JabRef) and summarized in the thesis.

WP 2: Model toolchain **[4 weeks]**
Based on available open-source data (e.g., on Kaggle), a training and test toolchain should be developed with an automatic differention capable programming language (e.g., Julia, JAX, PyTorch). The implementation should also focus on computational efficiency and deployment towards hardware accelerators (e.g., GPUs, TPUs).

WP 3: Model search **[5 weeks]**
Based on first-order principle knowledge regarding the electro-thermal behavior of electrical machines, a set of NODE architectures should be investigated and compared. The focus should be on the integration of interpretable engineering knowledge into the NODE's right-hand side. This renders itself a creative modelling procedure in the intersection of expert domain and data science knowledge, which is likely not (or only partly) automatable. The NODEs should be trained and validated on the data set from WP2. The performance of the NODEs should be compared to other data-driven models from the literature.

WP 4: Feature analysis **[4 weeks]**
Electric drives provide a multitude of input signals that can be used for temperature estimation. The most relevant signals should be identified and analyzed in terms of their information content for the temperature estimation. Furthermore, derived features should be investigated to improve the temperature estimation accuracy. The feature analysis should be based on the data set from WP2 and the NODEs from WP3. Eventually, parts of WP3 and WP4 must be iterated to find the best model-features combination.

WP 5: Hyperparameters **[3 weeks]**
NODEs (and other ML-based models) have a multitude of hyperparameters that need to be optimized. This includes the NODE's depth, width, and the training hyperparameters (e.g., learning rate, batch size). The hyperparameter optimization (HPO) can be automated using available open-source toolboxes and should also focus on the complexits vs. accuarcy trade-off by identifying the Pareto front between these two objectives. Depending on the computational load of this WP, the HPO can be parallelized on a high-performance computing cluster.

WP 6: Documentation **[4 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.

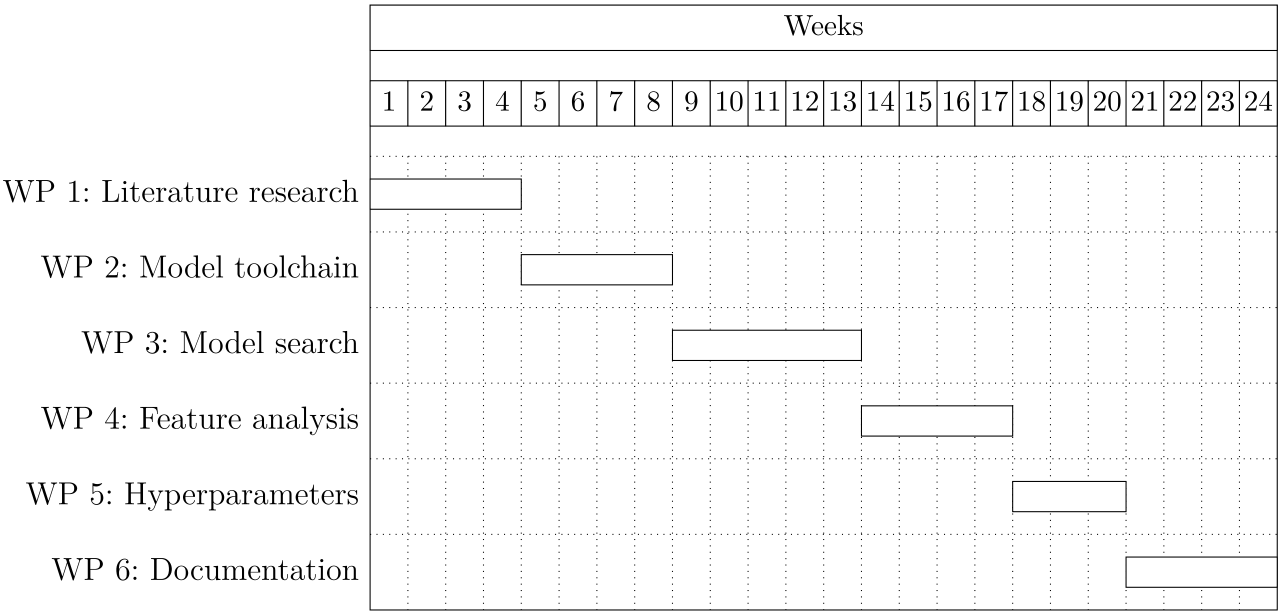


Figure 2: Gantt chart for the thesis.

References

[1] P. Kidger, "On neural differential equations," Ph.D. dissertation, University of Oxford, 2021.

[2] O. Wallscheid, "Thermal monitoring of electric motors: State-of-the-art review and future challenges," *IEEE Open Journal of Industry Applications*, vol. 2, pp. 204–223, 2021.

[3] W. Kirchgässner, O. Wallscheid, and J. Böcker, "Learning thermal properties and temperature models of electric motors with neural ordinary differential equations," in *International Power Electronics Conference (IPEC – ECCE Asia)*, 2022, pp. 2746–2753.