Karlsruhe Institute of Technology

Institute for Automation and Applied Informatics (IAI)

Master Thesis

Comparing load forecast models with explainable AI

Working Title: Explaining load forecast errors and comparing models using Shapley Additive Explanations (SHAP)

With increasing shares of fluctuating renewable energy in the electricity mix, short-term forecasts of the electrical load (i.e. electricity demand) and renewable generation are important to foresee energy supply shortages and grid bottlenecks, and then plan redispatch and demand-response measures. Thereby, accurate forecasts help to increase the share of renewable energy and to reduce grid expansion costs.

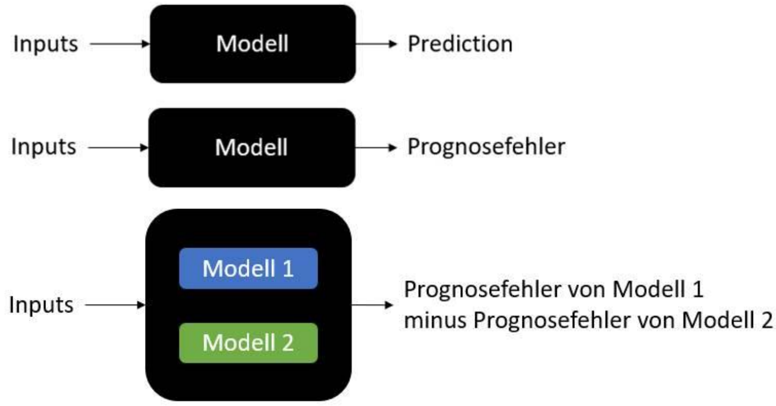

Figure: SHAP explains the influence of the input on the prediction of a black box model (top). In this thesis, SHAP is used to explain the model error (middle) or model differences (bottom).

Many time-series forecasting models exist that can be used to forecast electrical load, from statistical models (e.g. ARIMA) to Machine Learning models (e.g. XGBoost) and Deep Learning models (e.g. Multilayer Perceptrons and Transformers). All these models have their strengths and weaknesses. Even models that achieve a similar forecast accuracy on a year-long test set, make large errors at different days.

The goal of this thesis is to understand when and why these models fail. You will use explainable AI (XAI), in particular the Shapley Additive Explanations (SHAP) framework, to compare multiple forecasting models. Instead of analyzing the impact of input variables on the prediction of a model – which is the common application of SHAP – you will use SHAP to explain forecast accuracy and differences between two models.

Ultimately, the insights gained with this thesis will help selecting and improving load forecasting models.

The proposed thesis consists of the following parts:

- Familiarization with time series forecasting, XAI and SHAP, e.g. using [1-3]
- Training and evaluating multiple load forecasting models
- Applying SHAP [4] to explain forecast errors and to compare models
- Optional: using the derived insights to develop an ensembling strategy or to correct the forecast errors in individual models

This topic can also be done as a „Praxis der Forschung“ module. More information here:
https://formal.kastel.kit.edu/teaching/projektgruppe/aktuell.phtml

We are happy to answer any questions you might have. Feel free to reach out via e-mail and ask for an appointment.

Advisor:
Matthias Hertel
Alexandra Nikoltchovska

Programming language:
Python

System, Framework(s):
SHAP + Machine Learning/Deep Learning framework of your choice

Required skills:

- Experience with training machine learning or deep learning models
- High level of independence (meeting with supervisors every 1 or 2 weeks)

Language(s):
German, English

Starting date:
As soon as possible

For more information, please contact:

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References

[1] Haben, S., Voss, M., & Holderbaum, W. (2023). *Core concepts and methods in load forecasting: With applications in distribution networks* (p. 331). Springer Nature.
[2] Molnar, C. (2020). *Interpretable machine learning*. https://christophm.github.io/interpretable-ml-book/
[3] Molnar, C. (2023). *Interpreting machine learning models with SHAP: A guide with python examples and theory on Shapley values*. Chistoph Molnar c/o MUCBOOK, Heidi Seibold.
[4] https://shap.readthedocs.io/en/latest/