EBERHARD KARLS UNIVERSITÄT TÜBINGEN

Cluster of Excellence Machine Learning

Machine Learning in Sustainable Energy Systems (MLSES)

Bachelor/ Master Topic

Meta-Learning using Domain Knowledge for Energy Demand Forecasting

To forecast different energy time series, we are often faced with selecting the most appropriate algorithm. To overcome simple trial-and-error approaches, meta-learning has shown to be a promising systematic and data-driven way to efficiently choose the best algorithm or architecture. However, not every dataset contains all relevant information to make an unambiguous decision on what is optimal. Therefore, domain knowledge can provide additional information for meta-learning. This thesis aims to quantify the benefit of domain knowledge for meta-learning in energy time series, by evaluating the integration of domain knowledge into meta-learning systems and developing a meta-learning system for the complete machine learning pipeline from raw data to final result. The energy use case could be (probabilistic) forecasting of the energy demand across several buildings or substations that exhibit different characteristics.

Introductory Literature:

- A. Arjmand, R. Samizadeh, and M. Dehghani Saryazdi, "Meta-learning in multivariate load demand forecasting with exogenous meta-features," Energy Efficiency, vol. 13, no. 5, pp. 871–887, 2020. https://link.springer.com/article/10.1007/s12053-020-09851-x
- C. Cui, T. Wu, M. Hu, J. D. Weir, and X. Li, "Short-term building energy model recommendation system: A meta-learning approach," Applied Energy, vol. 172, pp. 251–263, 2016. https://www.sciencedirect.com/science/article/pii/S030626191630438X?casa_token=CH6UUY7D3u8AAAAA:0T5tjerCXU37yTa1-XKRa1ps3EIh0kYiuJB-vPSUk08rqhzCYJ2J06Cx2Q0PtxT84GMeQI1z
- R. Vilalta, C. G. Giraud-Carrier, P. Brazdil, and C. Soares, "Using Meta-Learning to Support Data Mining," International Journal of Computer Science & Applications, vol. 1, no. 1, pp. 31–45, 2004. https://www.csd.uwo.ca/~xling/cs860/papers/Meta_learning_IJCSA04.pdf

Requirements:

- Interest in working with time series data
- Good programming skills in Python or R
- Knowledge of statistical time series analysis would be an advantage
- Knowledge of meta-learning would be an advantage

Earliest starting date: April 2023

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

Cluster of Excellence
Machine Learning

ML

Machine Learning in Sustainable Energy Systems (MLSES)

Bachelor/ Master Topic

Social Learning in Reinforcement Learning for Demand Response

In distributed energy systems, demand response, thus the change of demand behaviour in response to external incentives such as prices, can help stabilise grids with high shares of renewable energy sources. However, consumers (industrial and household) unwillingness to constantly monitor prices and control all their appliances themselves, call for automated solutions. Recently, reinforcement learning for automated demand response has gained more attention. In this thesis we want to investigate whether the overall goal to reduce CO2 emissions is easier to reach when the agents can learn from each other (social learning) or causally influence each other.

Introductory Literature:

- Vazquez-Canteli, J. R., Dey, S., Henze, G., and Nagy, Z. (2020). CityLearn: Standardizing Research in Multi-Agent Reinforcement Learning for Demand Response and Urban Energy Management. arXiv e-prints. arXiv:2012.10504v1.
- Vázquez-Canteli, J. R., and Nagy, Z. (2019). Reinforcement learning for demand response: A review of algorithms and modeling techniques. Applied Energy, 235, 1072 - 1089. doi:10.1016/j.apenergy.2018.11.002.
- Tolovski, F. (2020). Advancing Renewable Electricity Consumption With Reinforcement Learning. arXiv e-prints. arXiv:2003.04310v1.
- Jaques, Natasha, et al. (2019) Social influence as intrinsic motivation for multi-agent deep reinforcement learning. *International conference on machine learning*. PMLR. http://proceedings.mlr.press/v97/jaques19a/jaques19a.pdf
- Lee, D., Jaques, N., Kew, C., Wu, J., Eck, D., Schuurmans, D., & Faust, A. (2021). Joint attention for multi-agent coordination and social learning. *arXiv preprint arXiv:2104.07750*. https://arxiv.org/pdf/2104.07750.pdf

Requirements:

- Interest in working with time series data
- Good programming skills in Python
- Knowledge of reinforcement learning algorithms would be an advantage, e.g., through the lecture Reinforcement Learning

Earliest starting date: April 2023

Bachelor/ Master Topic

Graph Neural Networks for Wind Power Forecasting

Wind power forecasting is crucial for e.g., transmission system operators to optimally include wind power into the existing electricity grid and guarantee an efficient interplay among different kinds of power. Wind power forecasting heavily relies on weather forecasts, and in recent years, numerical weather prediction (NWP) models have become more finely resolved in space and time. However, current approaches do not fully use the potential of this spatio-temporal data, as they focus on single turbines or wind parks and rarely take weather information from surrounding areas into account. Instead, they rely heavily on weather information from the turbine (through its SCADA system), local meteorological masts or NWP model output at the turbine's location only.The potential of using additional spatio-temporal weather information mainly stems from the wind and weather phenomena, such as high- or low-pressure areas, moving through space and time. These synoptic or mesoscale phenomena thus affect multiple wind turbine locations simultaneously or over different time horizons. In this project, we, therefore, want to adapt or develop a graph-based approach to wind power forecasting with a particular focus on propagating the uncertainty in the weather and turbine behaviour through the forecasting model. We aim to mainly explore a data-driven approach, e.g., using spatio-temporal Graph Neural Networks such as DISTANA or other GNN structures. Depending on the method used, constructing or learning a graph representing the data is a significant challenge. For example, the graph could represent the weather input, the underlying electricity network, the feature relationships, or all of the above. Given the different dynamics in spatio-temporal wind power forecasting, the main task is then modelling and predicting the wind power of a single turbine using spatio-temporal weather information of the surrounding area,

Introductory Literature:

- Karlbauer, M., Otte, S., Lensch, H., Scholten, T., Wulfmeyer, V., & Butz, M. V. (2019). A distributed neural network architecture for robust non-linear spatio-temporal prediction. *arXiv preprint arXiv:1912.11141*. https://arxiv.org/abs/1912.11141
- Sun, M., Feng, C., & Zhang, J. (2019). Conditional aggregated probabilistic wind power forecasting based on spatio-temporal correlation. *Applied Energy*, *256*, 113842. https://www.sciencedirect.com/science/article/abs/pii/S0306261919315296
- Fu, X., Gao, F., Wu, J., Wei, X., & Duan, F. (2019, November). Spatiotemporal attention networks for wind power forecasting. In *2019 International Conference on Data Mining Workshops (ICDMW)* (pp. 149-154). IEEE. https://ieeexplore.ieee.org/abstract/document/8955569?casa_token=9GS5gnVmMfUAAAAA:XBXPxpEK55JEx-3oMkpflD5W5NNzwaOcJLMONcL3cgXcEhDH7Iu9wdcMyrNZXxv7TU2zcEM

Requirements:

- Interest in working with time series data
- Good programming skills in Python or R
- Some time series analysis skills would be an advantage

Earliest starting date: April 2023

Bachelor/ Master Topic

Benchmarking Probabilistic Wind Power Forecasting Models

Forecasting wind power is essential in order to integrate the power into the network, as well as detect faults in the turbines or trade on the electricity market. Therefore, a multitude of wind power forecasting models exist. However, they are rarely compared properly, as either different data sources are used or no model comparison takes place. This thesis aims to start benchmarking probabilistic wind power models on open source wind power data. The benchmarks should include statistical models and machine learning models from the literature and compare the results across datasets from different regions in the world.

Introductory Literature:

- Tawn, R., & Browell, J. (2022). A review of very short-term wind and solar power forecasting. *Renewable and Sustainable Energy Reviews*, *153*, 111758. https://www.sciencedirect.com/science/article/pii/S1364032121010285
- Messner, J. W., Pinson, P., Browell, J., Bjerregård, M. B., & Schicker, I. (2020). Evaluation of wind power forecasts—An up-to-date view. *Wind Energy*, *23*(6), 1461-1481. https://onlinelibrary.wiley.com/doi/full/10.1002/we.2497
- Foley, A. M., Leahy, P. G., Marvuglia, A., & McKeogh, E. J. (2012). Current methods and advances in forecasting of wind power generation. *Renewable energy*, *37*(1), 1-8. https://www.sciencedirect.com/science/article/pii/S0960148111002850?casa_token=UNephHjbl7gAAAAA:2EifIxa9_4k2r7FhliebS1umy9MflNDW6m24PStKHcaZsYA0A_Isdpc3IngkwYTFOYMY4CR9

Requirements:

- Interest in working with time series data
- Good programming skills in Python or R
- Some time series analysis skills would be an advantage
- Knowledge of probability theory or probabilistic machine learning would be an advantage, e.g., through the lecture Probabilistic Machine Learning

Earliest starting date: April 2023

Bachelor/ Master Topic

Benchmarking Statistical Downscaling Techniques

Weather and climate data are usually provided on equidistant grids of different sizes. Data weather measurements are available at irregular locations. If data is requested for a specific variable and location (e.g. wind speed at a possible future site to assess wind power potential) the data has to be interpolated to that specific location. The goal of the project is to benchmark different downscaling techniques which aim to compute data on finer grids as provided. Current approaches are bilinear interpolation or nearest neighbor interpolation. The downscaling approaches should be applied to datasets of different grid resolutions and different (for the energy system relevant) weather variables. Main questions could include: Should different techniques be used for regular and irregular grids? Which role does the distance between two data points play for choosing a technique? Which role does the variable that we aim to access play? I would also be happy if we get an easily extensible python repository out of this.

Introductory Literature:

- WeatherBench: A Benchmark Data Set for Data-Driven Weather Forecasting https://arxiv.org/pdf/1906.06622.pdf
- Coburn and Pryor (2023): Projecting Future Energy Production from Operating Wind Farms in North America. https://journals.ametsoc.org/view/journals/apme/62/1/JAMC-D-22-0047.1.xml
- Schmidli et.al. (2006): Downscaling from GCM precipitation: a benchmark for dynamical and statistical downscaling methods. https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/joc.1287
- Yang et. Al (2022): Statistical downscaling of numerical weather prediction based on convolutional neural networks. https://www.sciencedirect.com/science/article/pii/S209651172200038X

Requirements:

- Interest in working with spatial time series data
- Good programming skills in Python
- Some time series analysis skills would be an advantage

Earliest starting date: April 2023