Towards Federated Short-Term Load Forecasting

Integrierte Netze der Zukunft

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Motivation

The way towards a carbon free power sector is only possible with an increasing and reliable integration of Renewable Energy Resources (RESs) into the existing power grid [1]. To handle the resulting rise of network management tasks, Short-Term Load Forecasting (STLF) based on Machine Learning (ML) methods has shown promising results [2]. However, accurate ML models highly depend on a large amount of available data, which can best be obtained by centralized data storage and data sharing. This, on the other hand, immediately rises data security and privacy concerns [3], which is further enhanced by the General Data Protection Regulation (GDRP) of the European Union [4]. Additionally, transferring large amounts of data between clients and servers needs sufficient bandwidth available for stable communication [5]. Therefore, we propose a Federated Machine Learning (FML) approach for STLF with respect to data privacy as well as reduction of communication payload.

Methodology

Load forecasting, e.g., day-ahead, plays a major role for power grid management tasks and micro grid optimization, while forecast models like Random Forest, Support Vector Machine or Neural Networks yield promising accuracy. Traditionally, ML models are trained on data, which is aggregated on centralized servers. Especially for STLF in the context of Smart Grid (SG) development, this implies transporting highly personal data to remote servers. Additionally, as data sets keep growing and models are getting more complex, a general ML practice is the distribution of the training process over various machines to handle the computational complexity [5]. So, as it is not always transparent to household users, what their data and the developed models is used for in the process, the transactions of data centralization and distribution violate the GDRP. Therefore, we propose an FML approach for STLF as a possible solution for such challenges. Instead of training the model centralized on aggregated data, FML trains the model on end user devices, e.g., micro-computers like a Raspberry PI. Only the aggregation of the resulting parameters is done on centralized servers. Afterwards the parameters are optimized through aver-age weighting and distributed among all participants. This way it is guaranteed that household electricity data is kept only locally.

Results

Based on the previous described FML approach, we develop a model for STLF with a real-world data set [7]. For a well-defined set of residential households, we describe and evaluate the FML development process with respect to different subsets within each training round. Additionally, a comparison of different learning models as well as varying parameter aggregation functions is given. Afterwards, we check the resulting forecast accuracy against others, which had been obtained through traditional ML models trained only on locally available data. For this final evaluation, holdout households are used, which were not involved in the training process at all. This way, we are able to give a valid statement for performance variations between different approaches respecting data privacy ensured by FML. We conclude our paper with idea for improvements and future research works.

Literature

[1] J. Jenkins, M. Luke, and S. Thernstrom. Getting to zero carbon emissions in the electric power sector. Joule, 2(12):2498–2510, 2018.

[2] N. Balta-Ozkan, O. Amerighi, and B. Boteler, “A comparison of consumer perceptions towards smart homes in the UK, Germany and Italy: reflections for policy and future research”, Technology Analysis & Strategic Management, vol. 26, no. 10, pp. 1176–1195, Dec. 2014.

[3] A. Wallis, A. Haber, and S. Hauke. “Menschliches Wissen und Künstliche Intelligenz in einem Prognosemodell für Erneuerbare Energien”, In 16. Symposium Energieinnovation. IEE TU Graz, February 2020.

[4] European Commission. “2018 reform of EU data protection rules”, May 25, 2018. URL: https://ec.europa.eu/commission/sites/beta-political/files/data-protection-factsheet-changes_en.pdf.

[5] J. Konečný, H. B. McMahan, F. X. Yu, et. al. Federated learning: Strategies for improving communication efficiency. In NIPS Workshop on Private Multi-Party Machine Learning, 2016.

[6] J. Verbraeken, M. Wolting, J. Katzy, et. al. A survey on distributed machine learning. ACM Comput. Surv., 53(2), March 2020.

[7] Pecan Street Inc. Pecan Street Dataport, May 25, 2021. URL: https://dataport.pecanstreet.org.