**Capstone Project Proposal**

**Title:** Privacy-preserving mechanisms for uncertainty feedback reinforcement learning

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**Project Problem Statement:** A growing volume of data permeates the electricity sector in all distribution, transmission, and generation levels, aiming at the digitalization of modern electrical grids. In line with this new paradigm, modern energy markets rely on diverse information and data analysis methods, especially for two consolidated applications: uncertainty quantification and demand and generation forecasting. Forecasting capability is among the most important features of electricity markets and ISOs (Independent System Operators). The market clearing process is extremely sensitive about the quality of its input forecasts, which may benefit a lot from reinforcement learning techniques. However, sharing sensitive operational data that could improve those methods can become a liability. This project aims to develop privacy-preserving techniques that can enable feedback of operational data to improve energy forecasting models, without disclosing protected information.

**Plan for conduct as it relates to achieving overall project goals:** The software and systems for the envisioned tool will be developed using Python programming languages. The project development will be supervised by Siemens team of experts who will provide industry experience in software development for the energy sector. The current project has a strong potential for technological impact since it seeks to incorporate new concepts of Data Analytics for the energy sector while using state-of-the-art high-performance computing. This project will aim to reach a TRL level of 3 or 4, with a proof-of-concept and validation in the laboratory environment.

Bibliographic research will be conducted to select scalable algorithms with high performance. Then, a modular library will be developed in the Python programming language to provide a tool for Privacy-Preserving Reinforcement Learning Feedback for Time Series Forecasting Improvement. The software development will pursue software engineering concepts, object orientation, clean code, and design patterns. The following sections provide a brief description of the theoretical background.

**Anticipated deliverables and timelines:** The technical-scientific methodology consists of exploring reinforcement learning methods alongside privacy preserving mechanisms inside the time series forecasting perspective. Initially, three theoretical background pillars are of interest in this project:

**• Time Series Forecasting for Electricity Markets.**

**• Privacy Preserving Algorithms and Emerging Data Markets.**

**• Uncertainty Quantification and Reinforcement Learning.**

The scheduled timeline is stated below:

| Task Description | week 1 | week 2 | week 3 | week 4 | week 5 | week 6 | week 7 | week 8 | week 9 | week 10 | week 11 | week 12 |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Ramp-up and Bibliographic Review** | X | X | X |  |  |  |  |  |  |  |  |  |
| - Ramp-up with Software Development Team | X |  |  |  |  |  |  |  |  |  |  |  |
| - Literature Review | X | X | X |  |  |  |  |  |  |  |  |  |
| - Software Engineering Skills and Prototype Draft |  | X | X |  |  |  |  |  |  |  |  |  |
| **Architecture and Software Design** |  | X | X | X | X |  |  |  |  |  |  |  |
| - Data Gathering and Study Case Definition |  | X | X |  |  |  |  |  |  |  |  |  |
| - Experimental Prototype |  |  | X | X | X |  |  |  |  |  |  |  |
| - Software Design |  |  |  | X | X |  |  |  |  |  |  |  |
| **Software Development** |  |  |  |  | X | X | X | X | X |  |  |  |
| - Interfaces, Data Structures and Pipelines |  |  |  |  | X |  |  |  |  |  |  |  |
| - Data Pre-Processing |  |  |  |  | X | X |  |  |  |  |  |  |
| - Model Building |  |  |  |  |  | X | X |  |  |  |  |  |
| - Core System Development |  |  |  |  |  | X | X | X |  |  |  |  |
| - Computational Performance Improvements |  |  |  |  |  |  | X | X | X |  |  |  |
| **Validation and Testing** |  |  |  |  |  |  |  |  | X | X | X |  |
| - Controlled Laboratory Validations |  |  |  |  |  |  |  |  | X | X | X |  |
| - Computational Refinement |  |  |  |  |  |  |  |  |  | X | X |  |
| - Proof of Concept |  |  |  |  |  |  |  |  |  | X | X |  |
| **Project and Technical Meetings** | X | X | X | X | X | X | X | X | X | X | X | X |

**Professional and project learning objectives:** Research and develop reinforcement learning techniques based on uncertainty feedback and privacy preserving data-sharing within the context of forecasting applications in modern electricity markets.

**Possible literature and state-of-the art research to be used:** State of the art papers related to power system forecasting, uncertainty quantification, reinforcement learning and privacy preserving algorithms are listed below:

[1] D. S. Kirschen, G. Strbac, Fundamentals of Power System Economics, Willey, 2nd ed., July 2018

[2] F. Petropoulos, et. al. Forecasting: theory and practice. International Journal of Forecasting, vol. 38,

no. 3 Sept. 2022, pp. 705-871.

[3] T. Hong, et. al., Energy Forecasting: A Review and Outlook, IEEE Open Access Journal of Power

and Energy, vol. 7, Oct 2020, pp. 376-388

[4] T. Hong, S. Fan, Probabilistic electric load forecasting: A tutorial review, International Journal of

Forecasting, vol. 32, no. 3, Sept. 2016, pp 914-938

[5] C. Sweeney, et. al. The Future of Forecasting for Renewable Energy, Wiley Interdisciplinary

Reviews: Energy and Environment, 2020

[6] J. Jox, et. al. Forecasting and Market Design Advances: Supporting an Increasing Share of

Renewable Energy, IEEE Power and Energy Magazine, vol. 19, no. 6, Dec. 2021, pp. 77-85

[7] J. R. Andrade, R. J. Bessa, Improving Renewable Energy Forecasting With a Grid of Numerical

Weather Predictions, IEEE Transactions on Sustainable Energy, vol. 8, no. 4, Oct. 2017, pp. 1571-1580

[8] C. Gonçalves, P. Pinson, R. J. Bessa, Towards Data Markets in Renewable Energy Forecasting,

IEEE Transactions on Sustainable Energy, vol. 12., no. 1, 2021, pp. 533-542

[9] C. Gonçalves, R. J. Bessa, P. Pinson, A critical overview of privacy-preserving approaches for

collaborative forecasting, International Journal of Forecasting, vol. 37, no. 1, March 2021, pp. 322-342

[10] A. Falcetta, M. Roveri, “Privacy-preserving time series prediction with temporal convolutional neural

networks”, in 2022 International Joint Conference on Neural Networks, Padua, Italy, Sept. 2022

[11] B. Wang, N. Hedge, “Privacy-preserving Q-learning with functional noise in continuous spaces”,

33rd International Conference on Neural Information Processing Systems, Dec. 2019

[12] Y. Zhao, et. al., “Ultra-short-term wind power forecasting based on personalized robust federated

learning with spatial collaboration”, Energy, vol. 288, Feb. 2024

[13] Y. Li, et. al. “Wind power forecasting considering data privacy protection: A federated deep

reinforcement learning approach”, Applied Energy, vol. 329, Jan. 2023

[14] P. Pinson, L. Han, J. Kazempour, Regression markets and application to energy forecasting. TOP,

vol. 30, May 2022, pp. 533–573

[15] T. Falconer, J. Kazempour, P. Pinson, “Bayesian Regression Markets”, (pre-print)

arXiv:2310.14992v1, Oct. 2023

[16] Y. Fan, S. Nowarczyk, T. Rognvaldsson, “Transfer learning for remaining useful life prediction based

on consensus self-organizing models”, Reliability Engineering & System Safety, vol. 203, Nov. 2020

[17] R. C. Smith, “Uncertainty Quantification: Theory, Implementation, and Applications”, SIAM

Computational Science & Engineering, 1st Ed., March 201

[18] M. Abdar, et al. “A review of uncertainty quantification in deep learning: Techniques, applications

and challenges”, in Information Fusion, vol. 76, pp. 243-297, 2021

[19] J. A. D. Massignan, et. al. “Taming Uncertainties from Renewable Resources: Industry Experience

on Data-Driven Models for Flexibility Markets”, in 2023 CIGRE Canada Conference & Exposition,

Vancouver, Canada, Sept. 2023

[20] B. Rolf, et. al. “A review on reinforcement learning algorithms and applications in supply chain

management”, International Journal of Production Research, vol. 61, no. 20, 2023.

[21] M. Ghavamzadeh, S. Mannor, J. Pineau, A. Tamar, “Bayesian Reinforcement Learning: A Survey”

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Now Foundations and Trends, 2015

[22] M. Otterlo, M. Wiering, “Reinforcement Learning and Markov Decision Processes”, Reinforcement

Learning, Adaptation, Learning, and Optimization book series, vol. 12, pp. 3-42.

[23] J. Moos, et. al. “Robust Reinforcement Learning: A Review of Foundations and Recent Advances”,

Machine Learning & Knowledge Extraction, vol. 4, Mar. 2022, pp. 276-315