Project Name:

UIUC MSEE Research Project

Sub-Project Name:

Privacy-preserving mechanisms for uncertainty feedback reinforcement learning

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Abstract

This Research Proposal defines the objective, research methodology, and the work plan for a MSEE level applied research project.

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1. Introduction

A growing volume of data permeates the electricity sector at 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.

1.1. Research Proposal

Objective: 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.

The software and systems for the envisioned tool will be developed using Python and/or C/C++ programming languages, depending on the researcher profile. The project development will be supervised by Siemens team of experts and will allow the researcher to be in touch with advanced 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.

2. Methodology

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.**

Bibliographic research will be conducted to select scalable algorithms with high performance. Then, a modular library will be developed in the Python or/and C/C++ 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. Regarding high-performance computing, the algorithms will encompass sparsity treatment, parallel processing on Graphical Processing Units - GPUs, and fast time-series processing.

The following sections provide a brief description of the theoretical background.

2.1. Time Series Forecasting for Electricity Markets

Modern electricity markets aim to provide an efficient and reliable supply of electricity. Multiple market levels encompass these objectives while accounting for characteristics of resource availability (e.g., generation type, resource limits, intertemporal temporal constraints, and capability), transmission network conditions (under normal or contingency conditions), demand level (both temporal and spatial), economic exposure (either in a pool market or purely cost-based) and regulation aspects, through an optimized energy procurement framework [1]. As in any forecast-dependent model, the market clearing is prone to forecasting errors, and hence, the forecasting accuracy has a high impact on energy procurement and prices in the day-ahead and real-time markets.

Forecasting has always been at the forefront of decision-making and planning, with individuals and organizations seeking to minimize risks and maximize utilities. The large number of forecasting applications calls for diverse forecasting methods to tackle real-life challenges. Thousands of energy forecasting papers have been published over the past few decades, including influential review articles and original research papers [2].

Besides the demand forecasting error, the electricity load has its random component, e.g., due to electricity consumption variations, different patterns in different day types, and weather impact [2,3, 4]. Moreover, the increasing introduction of renewable resources (such as solar and wind generation) increases the system-wide uncertainty, in this case, from the generation perspective. Renewable resources forecasts are input to the market clearing, directly its results since the forecasting errors propagate their effects on dispatch and commitment instructions across different market levels. Many aspects affect renewables forecasting errors, such as seasonality, weather conditions, and outages, with increased influence according to their respective capacity in the energy mix [5, 6, 7].

The forecasting models can generally be categorized into three types: time-series, machine learning, and hybrid [2]. Several time-series forecasting methods, like the Autoregressive families and probabilistic methods, have already consolidated their positions in control and operation centers [2, 3, 4, 6]. Machine learning has also been adopted well since the evolution of computational performance, more prominently neural network-based methods [2, 3, 4, 5]. In recent years, Artificial Intelligence (AI) has experienced more hype, largely due to the advancement of computing technologies. Various advanced AI techniques, such as deep learning, reinforcement learning, and transfer learning, have been adopted in energy forecasting [3, 5]. Regarding the hybrid methods, that is joining time-series concepts together with machine learning and AI, the ensemble forecasts have been showing exceptional results, and their adoption has been more common [2, 3, 6], especially incorporating exogenous models to increase accuracy [7] or providing coherence among different levels of the system through hierarchical forecasting [3].

In this research project, energy forecasting will provide the starting point for understanding the role of information in operation centers. One or more forecasting techniques for demand and renewable generation will be explored to provide the initial setup for the reinforcement learning architecture to be developed, as discussed in the next sections.

2.1. Privacy Preserving Algorithms and Emerging Data Markets

The combination of geographically distributed time series data can deliver significant improvements in the forecasting accuracy, for instance, of each renewable energy power plant, as well as for hierarchical forecasting and energy price forecasting [2, 8]. The potential benefits from improved forecasting accuracy for overall power system operations motivated the proposal of collaborative forecasting (or data sharing) frameworks. However, data might have different owners unwilling to share their data due to different reasons, such as securing sensitive information, holding data to its inner processes, understanding the economic benefits of data sharing, etc. To tackle these limitations, recent research explores the new pathways of privacy-preserving analytics and data markets [8, 9, 10].

Privacy-preserving mechanisms can be categorized into data transformation methods, secure multi-party computation protocols, and decomposition-based methods [9]. Such mechanisms have been widely applied to improve time series forecasting by using data sharing, for instance, with convolutional neural networks [10], with differential privacy and reinforcement learning [11], and with federated learning for wind forecasts [12, 13], among others. In this context, differential privacy has developed into a strong standard for privacy guarantees in data analysis, providing a rigorous framework for privacy guarantees under various adversarial attacks.

Regarding data markets, adaptions to data-driven models are necessary in the context of time-series models since they require temporal updates of the input variables. The role of privacy-preserving techniques applied in collaborative forecasting is to combine time series data from multiple data owners to improve forecasting accuracy and keep data private simultaneously [2]. A recent approach in [14] employs a Bayesian framework to support a regression model market to incentive data sharing while learning regression models. Another recent approach in [15] evaluates the effects of data similarity in the data value for regression markets while proposing a privacy-aware data acquisition mechanism. Also, data-sharing can solve data scarcity problems in some use cases of the energy sector, such as forecasting the condition of electrical grid assets [16].

This project will evaluate privacy-preserving techniques in the context of data markets for the energy sector. A testbed architecture for data sharing under a secure platform will be developed so the researcher fully understands the role of privacy under the collaborative forecasting perspective.

2.2. Uncertainty Quantification and Reinforcement Learning

Uncertainty Quantification is the process of quantifying and analyzing the uncertainty in mathematical models, simulations, and data. The primary objective is to assess the reliability of predictions, account for the effects of variability, randomness, or misspecification in models, and ultimately assist in decision-making. Uncertainty, in a general sense, can be divided into aleatoric (inherent randomness of a system) or epistemic (due to limited knowledge, data, or information about the modeled system) [17]. Different computational methods support the task of uncertainty quantification, such as Descriptive Statistics (employing Histograms along with pivotal quantities such as Mean, Median, Variance, and Percentiles), Probabilistic Models (supported by parametric or non-parametric regression or with conditional Bayesian models) or also with Machine Learning Approaches (employing neural networks, entropy-based learning, and deep learning) [18]. Uncertainty quantification has many potential applications in the power systems control and operation centers, for instance, with a pivotal role in enabling flexibility markets [19] or, as proposed in this project, in supporting forecasting methods via reinforcement learning.

Reinforcement Learning encompasses multiple problems in science and engineering that require sequential decision-making under uncertainty. Reinforcement Learning can be formally defined within the Markov Decision Process background and divided into model-based or model-free approaches. A major challenge is identifying good data collection strategies that effectively balance the need to explore the space of all possible policies and the desire to focus data collection on trajectories that yield better outcomes (exploration-exploitation tradeoff) [20, 21, 22]. Such techniques have been widely popularized in recent years due to their feedback nature for improving decision-making. Among the many methods, we can cite Q-learning as the most mainly used [11], Bayesian learning with a solid theoretical framework [21], and also, more recently, robust learning techniques [23].

The final goal of this research project is to enable reinforcement learning techniques based specifically on uncertainty quantification results as feedback information. The envisioned tool will employ probabilistic forecast evaluations to improve accuracy. Other control and exogenous variables may also be employed in a feedback loop.

3. Work Plan

3.1. Development Guidelines

The precepts of agile software development methodologies will guide the project's monitoring. The team members have a solid technical-scientific background, experience in software development with agile methods, and management/execution of national and international projects. The following tools will be used to monitor the project:

- Schedule and scope document.
- Weekly planning & execution meetings.
- Kanban dashboard.

The required tools and infrastructure for software development in Linux / Windows OS are the following:

- Laptop with Linux/Windows OS.
- MS Office 365 package.
- Python and/or C/C++ Programming IDEs, GitLab, compilers, and third-party tools.

3.2. Timeline

The project is planned to be executed in 12 months and the schedule of the project is presented in the table below.

Task Description	**Month 1**	**Month 2**	**Month 3**	**Month 4**	**Month 5**	**Month 6**	**Month 7**	**Month 8**	**Month 9**	**Month 10**	**Month 11**	**Month 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 Desgin		**X**	**X**	**X**	**X**							
- Data Gathering and Study Case Definition		X	X									
- Experimental Prototype			X	X	X							
- Software Desgin				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	
Knowledge Capitalizaiton	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**
Project and Technical Meetings	X	X	X	X	X	X	X	X	X	X	X	X
- White Paper Writing									X	X	X	X
- Final Masters Dissertation										X	X	X
- Internal Workshop												X

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