Topics for PhD Projects

Applications of Machine Learning in the Electricity Sector

Traditionally, the electricity sector was characterized by a supply side dominated by few large dispatchable plants and inelastic but predictable demand. Due to the challenges of climate change and the resulting energy transition, the industry is moving towards a new regime where electricity is generated mostly by small renewable plants that are geographically dispersed and have intermittent production, while consumers are likely to be *smart* but at the same time exhibit demand patterns that are harder to predict due to the electrification of mobility and heating.

This transition poses enormous challenges to all players in the industry and increasingly forces grid operators and producers to plan in higher temporal resolution and under increasing uncertainty about prices, supply and demand, as well as the physical state of the grid. The ensuing planning problems are characterized by unstructured, high dimensional decision environments with uncertain inputs.

Conventional decision-making approaches under uncertainty, vulnerable to the curse of dimensionality, often fall short in addressing these complex issues. This PhD project seeks to overcome these limitations by developing cutting-edge decision policies leveraging modern machine learning techniques, such as deep reinforcement learning and approximate dynamic programming.

Possible areas of applications include:

- Short-term algorithmic trading on continuous intraday markets taking into account the state of the order book as well as external factors such as weather and demand shocks.
- Operational planning of smart electric grids comprising of small scale solar plants, community storage, and smart consumers.
- Optimal power flow problems in local low-voltage grids that are possibly co-optimized with a local thermal network.

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Stability, Complexity and Algorithmic Strategies for Stochastic Dual Dynamic Programming

Stochastic Dual Dynamic Programming (SDDP) is an efficient decomposition technique for solving discrete-time, finite-horizon stochastic dynamic programs. The method iteratively *learns* an approximation of the problem's value functions, is able to overcome the curse of dimensionality associated with a growing number of decision stages, and exhibits provable convergence for a large class of convex stochastic programming problems. Furthermore, SDDP and its variants have shown remarkable performance in a range of practical applications in finance, energy, and operations management.

While the original SDDP algorithm was restricted to linear programs and right hand side stage-wise independent randomness, contemporary variants of the algorithm have overcome this restrictions. In particular, the generalization to Markovian stochastic problems significantly broadened the method's applicability. Despite recent remarkable progress in theoretical understanding, numerous issues that prevent SDDP to be applied in certain complex and challenging problems in climate, energy, and sustainable operations management remain open.

The topics of this PhD project seek to address some of these issues, such as:

- Approximation of (possible continuous) Markov process by scenario lattices based on probability metrics that allow an analysis of quantitative stability of the resulting approximate problems.
- Analysis of the computational complexity of Markovian SDDP. While there exist recent results on stage-wise independent SDDP, the complexity of the Markovian version is still an open question.
- Novel learning strategies and algorithmic improvements that lead to faster convergence.
- While regularization is an important tool in decomposition and cutting plane methods, there exist conceptual difficulties with regularization of SDDP. Consequently, while there are some proposals for regularized SDDP in the extant literature, results are of a preliminary nature and do come with not guarantees for improvements in convergence speeds.
- Efficiently computing tight information relaxation bounds for multi-stage stochastic programming problems.

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Multi-Stage Stochastic Programming for Energy Planning

Future electricity system will be populated by players very different from today's large and centralized utilities that dominated power markets for decades. The classical hierarchical market structure of producers, distributors, and consumers will be transformed into a new model consisting of distributed prosumers, service companies that provide market access to these prosumers, and local distributors of electricity.

Taking optimal investment, trading, and risk management decisions in this framework is a challenge that is currently poorly understood. The difficulty stems from the complexity of electricity markets combined with the uncertainty about loads and produced quantities that are mainly driven by environmental conditions that are hard to predict accurately. In particular, electricity markets are usually organized as a cascade of nested futures markets that allow participants to trade in different temporal granularity (months, days, hours, ...) and with different times to maturity. This enables a stepwise re-balancing of positions in ever shorter time intervals while the time of physical delivery approaches. As electricity for the same delivery periods is traded in multiple markets, the bidding problems on these markets are naturally interdependent resulting in largeand complex stochastic decision problems.

This PhD project focuses on stochastic optimization for investment, risk management, and trading decisions in the electricity sector. In particular, the following topics are of interest:

1. Optimal investment and operations for *virtual power plants* (VPPs). VPPs pool a portfolio of distributed resources providing market access to its clients. Optimal decisions concern the composition of the VPP, trading on electricity markets, management of quantity as well as price risks, and investment in equipment such as electricity storage.
2. Management of demand response of equipment whose operation and thereby electricity consumption can be adapted to changing situations on power markets. Examples include most heating and cooling applications with a permissible range of temperatures, water pumps, or district heating.
3. Aggregators of electric vehicles that offer the flexibility of car batteries in order to stabilize the grid or make arbitrage profits on short-term markets.
4. Pricing and management of *power purchasing agreements* (PPAs) that enable large power consumers to buy the random generation of renewable producers for a fixed price.

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