

The Future of Al in Hydropower Scheduling

SINTEF User Meeting 6th – 7th May 2025

Jiehong Kong



InterOpt – Deep integration between machine learning approaches and renewable energy optimization

Background:

Traditional optimization methods repeatedly solve similar problems without accumulating experience. In contrast, machine learning (ML) efficiently gains experience from historical data and previous decisions. The fact that the same **unit commitment (UC) problem** is solved every day with only minor changes in input data is the perfect base for ML. Numerical studies have shown that ML can achieve speedups ranging from 2× to 260× in many large-scale power systems without any observed reduction in solution quality.

Project goals:

- Develop knowledge enabling deep integration between ML approaches and the short-term hydro-dominant UC problem in a deregulated power system
- Realize an ML-based optimization model that can enhance the computational efficiency of generating daily production schedules for Norwegian hydropower producers, accurately represent their physical watercourse, and support their bidding strategies in energy and capacity markets.

Four categories of ML applications to optimization models



Responsible organisation: SINTEF Energy Research Project leader: Jiehong Kong

Partners: NTNU, ANEO AS, Hydro Energi AS, Å Energi Fornybar Forvaltning AS, Universidad Politécnica de Madrid, Université du Québec à Chicoutimi, Centro de Pesquisas de Energia Elétrica (CEPEL)

Project period: 2024.12.1 – 2027.11.30

Project type: Knowledge-building Project for Industry

Total budget: 12 mill. NOK (9.6 mill. NOK from RCN)

Project number: 352879



Previous experiences



Project No.	Project period	Funding (MNOK)	Funding type	Relevant field	ML technologies	Category		
309936 <u>iScheduling</u>	2020- 2022	2	ENERGIX – IPN	Select commands before hydro optimization	Supervised learning	Category 2: Optimization option selection		
	Dr. Jiehong Kong is the project manager, and Dr. Hans Ivar Skjelbred and Prof. Zhirong Yang are the primary researchers for this project (iScheduling). ANEO and Hydro Energy are the industrial partners. This project demonstrated that ML could effectively predict the one-time ON/OFF decision command for medium-size cascaded watercourses.							
309315 <u>KoBas</u>	2020- 2023	3.5	ENERGIX – IPN	Price and volume forecasting in Nordic regulating power markets	Supervised learning	Category 1: Input data improvement		
282395 <u>HAWK</u>	2018- 2020	4.7	ENERGIX – IPN	Surveillance in Norwegian physical power market	Unsupervised learning	Not related to optimization		
	Shweta Tiwari is the researcher for these two projects (KoBas and HAWK).							

Performance evaluation of SINTEF Hydro's case study in IPN iScheduling project

 $vs \ge 0$ $vs \ge v - V^{max}$ $vs \le v - V^{max} \cdot \delta$ $vs \le VS^{max} \cdot \delta$ $qs = c \cdot vs$

- δ is a binary variable.
 - If δ = 0, there is no spill; If δ = 1, there is overflow (physical spill).
 - \circ If δ is relaxed, i.e., it can be any value between [0, 1], the nonphysical spill may occur when the water starts to "spill" before the reservoir runs full.



- If we run SHOP with the default setting, 30 cases will have nonphysical spills. ML correctly predicts the command setting for all these 30 cases, i.e., overflow_mip_flag is set as "on". That is, 100% of nonphysical spills (72.61 million m3) can be avoided under the ML setting.
- The robust setting (i.e., overflow_mip_flag is always set as "on") can guarantee no nonphysical spills in any case but with the cost of excessive calculation time. The total calculation time used in the robust setting is 35,114 seconds, while the time spent in the ML setting is 19,303 seconds. Therefore, 45% of calculation time can be saved with the support of ML.



Lessons we learned from IPN iScheduling project

- We must define the problem very well. The input data for the case study (i.e., historical data and watercourse) should represent the problem to solve.
- The historical data are limited. Can past data reflect future trends?
- It is time-consuming to generate the training datasets for the optimization problem.
- Understanding and improving the structure of the datasets for machine learning is critical.



Real-world dataset:

- The watercourse contains 13 reservoirs, three hydropower plants.
- The historical data available are 11month market price and inflow.
- The number of columns in the dataset generated is 3,867, and the number of rows is 326.

SINTEF dataset:



WP1 – Identify critical features of the UC problem and evaluate the performance of outputs – Led by Dr. Hans Ivar Skjelbred

- *RQ1*: What is the primary expected outcome of ML technique application for industrial partners?
- RQ2: How should ML approaches be embedded into the optimization process?
- RQ3: Will human operators trust the outcomes predicted by ML?

WP2 – Conduct robustness study to determine the error-tolerant optimization options and prepare training datasets – Led by Dr. Christian Øyn Naversen

- RQ4: What are the error-tolerance optimization options for a given problem?
- RQ5: How do we collect enough data and instances that represent the problem to solve?
- RQ6: How can we efficiently generate a stable and reliable dataset for further ML study?

Research questions of KSP InterOpt project

WP3 – Investigate proper ML approaches for prediction tasks – Led by Prof. Zhirong Yang

- *RQ7*: Can self-supervised learning (SSL) enhance prediction accuracy for short-term hydro-dominant UC problems?
- RQ8: Does the proposed ML methodology boost transfer learning performance?
- RQ9: Is ML capable of identifying critical factors in prediction?

WP4 – International cooperation and knowledge dissemination – Led by Dr. Jiehong Kong

- *RQ10*: What is the experience learned, ongoing research, emerging challenges, and new strategies for international cooperators?
 - o UQAC (Canada): published a survey on ML approaches and hydropower
 - UPM (Spain): a Ph.D. student working on a similar topic
 - CEPEL (Brazil): tested ML in the short-term model
- *RQ11*: What are the similarities and differences when applying ML methods to different energy markets?
 - Norway a deregulated market; Quebec a regulated market; Brazil a centralized system; Spain an oligopolistic market
- *RQ12*: How do ML methodologies scale for systems with different sizes?



The primary objective of this project is to develop knowledge enabling deep integration between ML approaches and the short-term hydro-dominant UC problem in a deregulated power system.

The secondary objectives that will lead to the achievement of the primary objectives are to 1) identify the critical marketing and operating challenges the industrial partners are facing; 2) determine the error-tolerant optimization options that can solve the particular problems; 3) find efficient methods to generate good-quality training datasets; 4) investigate suitable ML approaches for the prediction tasks; and 5) realize the smooth connection between ML and optimization in daily operations.

The result will be an innovative decision-making process combining a trustworthy ML module and an optimization model. This approach will enhance the computational efficiency of generating daily production schedules for Norwegian hydropower producers, accurately represent their physical watercourse, and support their bidding strategies in energy and capacity markets. For instance, the ML module will suggest the UC statuses when the binary variables in the time-consuming MIP problem are relaxed and the optimal results fall into infeasible zones. Additionally, the ML module will recommend the appropriate gate connections in a complex tunnel system. Furthermore, the ML module will determine the number of scenarios representing inflow and price uncertainties to be included in the optimization model, facilitating a comprehensive multi-market bidding strategy. Integrating ML into the optimization model will ensure the hydropower producers fully exploit the value of the optimization tool and gain complete control over operating and market conditions.

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Computational efficiency – Enhance SHOP solution methodology

Problem:

- Using MIP in full mode, calculation time is high, but the infeasible operating zone can be avoided.
- Without MIP, calculation time is low, but actual production might be below min production. Current solution: the default setting of gen_turn_off_limit is 0.5. If the production is lower than 0.5*min_limit, the unit will be committed to not running in the incremental mode.

ML application:

Run the model by relaxing binary variables. Then, ML can decide the unit commitment status.

Goal:

- 1. Enhance the computational efficiency of generating daily production schedules
- 2. Next step is to include stochastic prices/inflow



Calculation performance of the benchmarking model (SHOP 17)

- A watercourse consisting of 17 reservoirs and 8 hydropower plants
- The scheduling time for each run is one week, with hourly time resolution
- Each run moves one day forward, and 350 runs are conducted in a year
- Three MIP settings:
 - No_mip: All binary variables are relaxed.
 - All_mip: Binary variables are used.
 - Mixed_mip: Binary variables are used for the first 36 hours and then relaxed.
- Two operational settings:
 - No reserve
 - With reserve obligation for FRR_UP and FRR_DOWN
- MIP gap is set as a relative value: 0.005% without reserve obligation and 0.01% with reserve obligation.

45.4 40 (hours) 30 ime **Expected calculation time after AI is integrated** into the optimization model 3.5 3.6 2.2 2.1 1.6 . 0 all mip no mip mixed mip no mip reserve mixed mip reserve all mip reserve Scenario

Average calculation time for each run:

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16s	21s	23s	36s	37s	467s

Generation Time for 350 cases (SHOP_17)



Complex physical watercourse – **Gate optimization**

Problem:

 In gate optimization, at least and at most, only one gate can connect the reservoir and the plant. It takes a long time to optimize which gate should be connected.

ML application:

ML can decide on the gate connection, as we did in iScheduling, to find the setting for the overflow_mip before running SHOP.

Goal:

- 1. Accurately represent the physical watercourse
- 2. Greatly reduce calculation time



Problem:

- Spatial conditions: The type of watercourse (e.g., river, reservoir) and its flow patterns can impact the availability and predictability of water resources, affecting bidding strategies.
- Temporal conditions: Different energy markets operate on various schedules (e.g., day-ahead, realtime). The ability to predict and respond to these schedules is crucial for multi-market bidding.

ML application:

- Identify the types of watercourse and hydrological situations that necessitate block bidding for hydropower producers
- Evaluate different market conditions and identify the best bidding strategy across multiple markets



Copilot AI-generated image

Goal:

1. Supports bidding strategies in energy and capacity markets



Main activities

Internal comm	unication								
Meeting	SINTEF will arrange bimonthly online meetings to keep all the industrial partners updated with the process.								
Seminar	NTNU will hold regular seminars regarding the latest ML methodologies for industrial partners.								
Workshop	SINTEF will organize annual workshops to discuss the latest developments & applications among project partners.								
	• The first workshop will be held in May in Brazil, together with the Hydronower Scheduling Conference								
External know	edge dissemination								
Education	One three-year Ph.D. student at NTNU who will implem the results under the supervision of Prof. Zhirong Yang an research stays at Universidad Politécnica de Madrid or Universite du Quebee d'encoutinn.								
	 Master students will be included in the project by writin SINTEF will provide summer research jobs for students. Tarjei Reite (Electric Power Engineering, NTNU) 								
	• An open dataset and prediction task will be prepared for the NTNU TDT4173 (Modern Machine Learning in Practice) course project . Students in the Informatikk and Datateknologi programs will get real-world practice through the course project. The winning student solution will, in turn, contribute to the project outputs.								
Conference	Researchers will actively participate in international conferences to present their results. Some well-reputed conferences with a peer-review system are IEEE PowerTech, Power Systems Computation Conference (PSCC), European Energy Market (EEM), International Conference on Machine Learning (ICML), Conference on Neural Information Processing Systems (NeurIPS), and International Joint Conference on Artificial Intelligence (IJCAI).								
Publication	Publish 3-5 scientific papers in high-impact factor journals or peer-reviewed conference proceedings.								







Ongoing Tasks:

- Test the latest SHOP methodology (SHOP 17) as a benchmarking model
- Prepare the open dataset for the Norwegian watercourse
- Conduct a proof-of-concept case study for the unit commitment problem
- Identify case studies from industrial partners

Upcoming Events:

- 2025.5.12: Bimonthly meeting (project partners)
- 2025.5.29: InterOpt workshop in Brazil (open to all)
- 2025.6.11 12: Two-day intensive course for SHOP and InterOpt project (project partners)

"United in collaboration, we unlock the true potential of optimization and machine learning," -- Copilot









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