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Integrating machine learning techniques into the decision-making process for hydro scheduling

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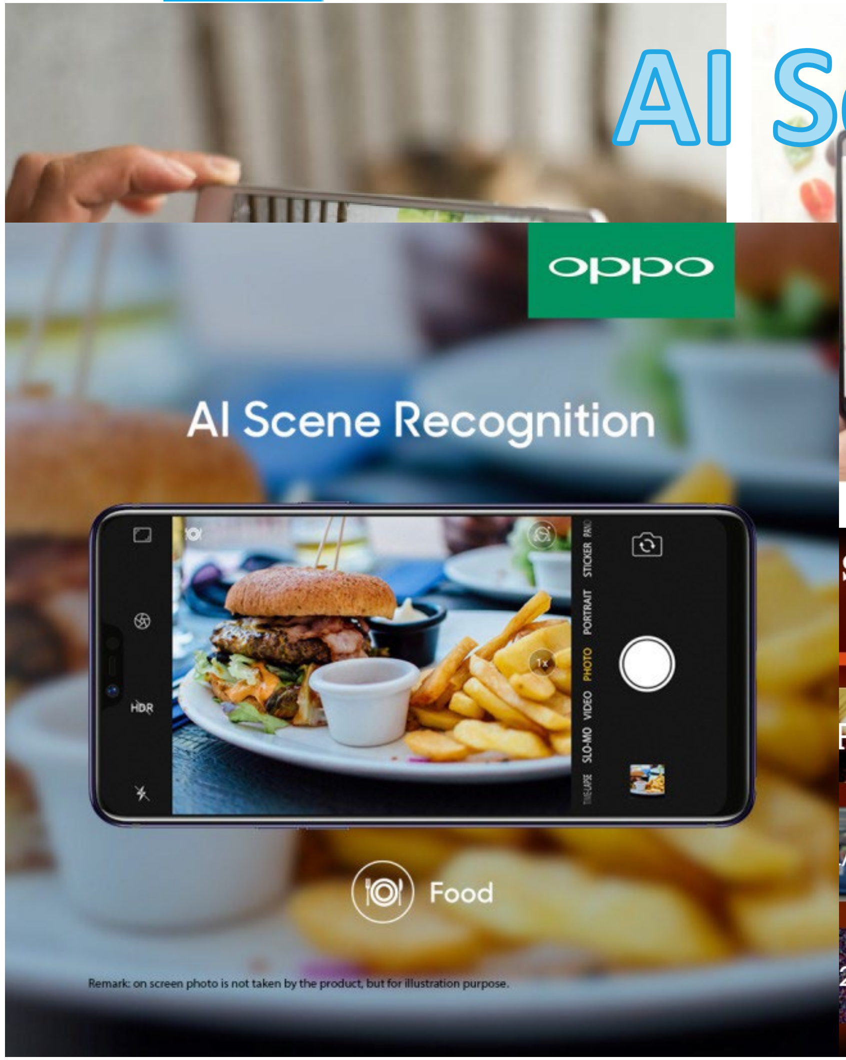
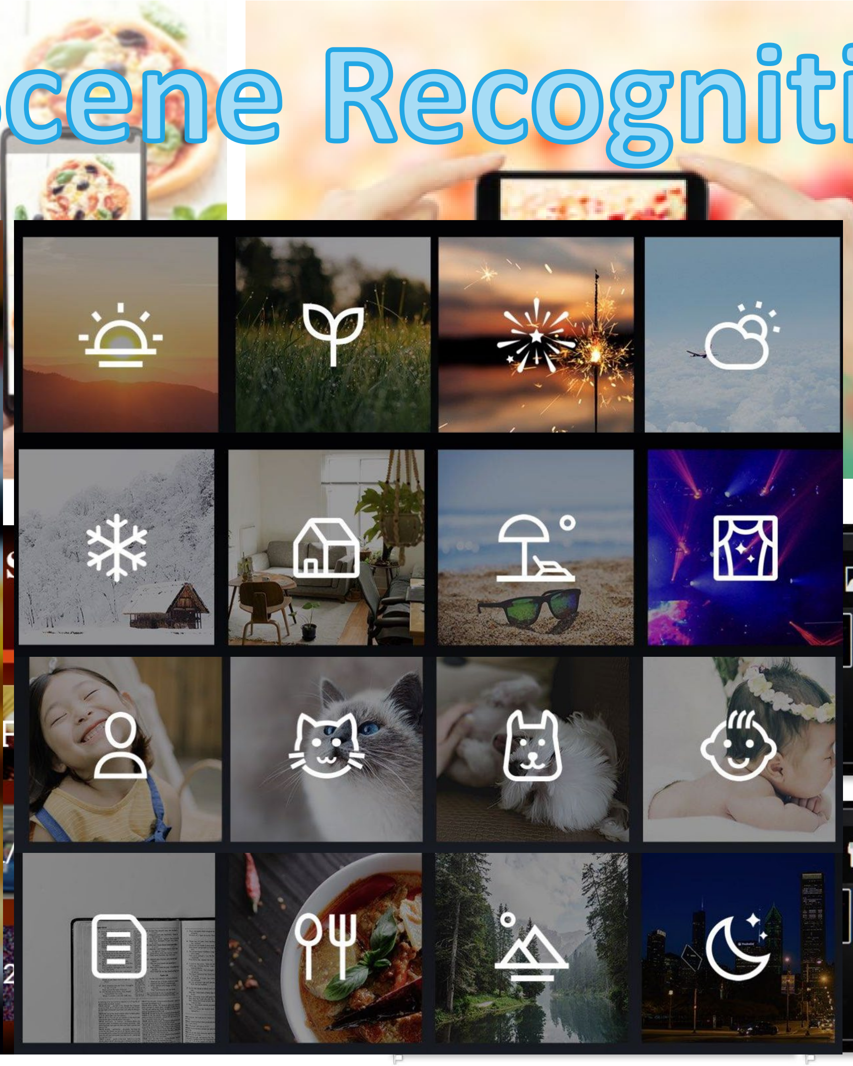
Outline

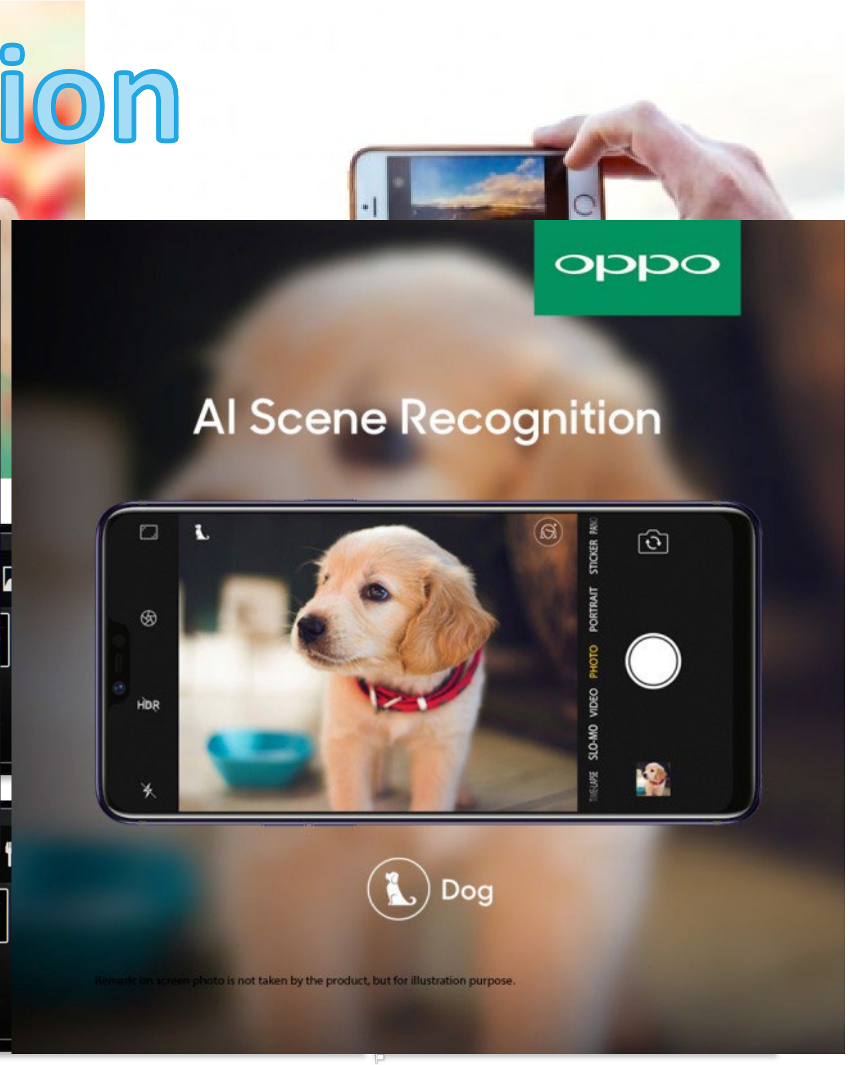
- Overall idea and framework
- Hydro scheduling problem to solve – avoid nonphysical spill
- Dataset generation
- Machine learning technologies
- Performance evaluation
- Possible issues for future research

The Overall idea

AI Scene Recognition







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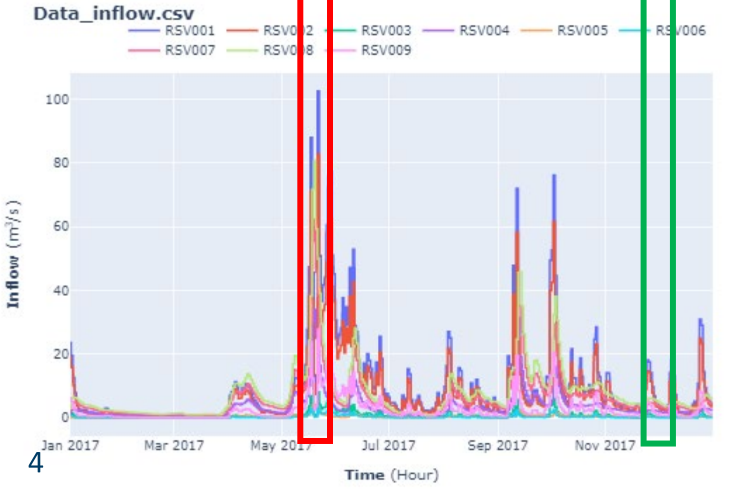
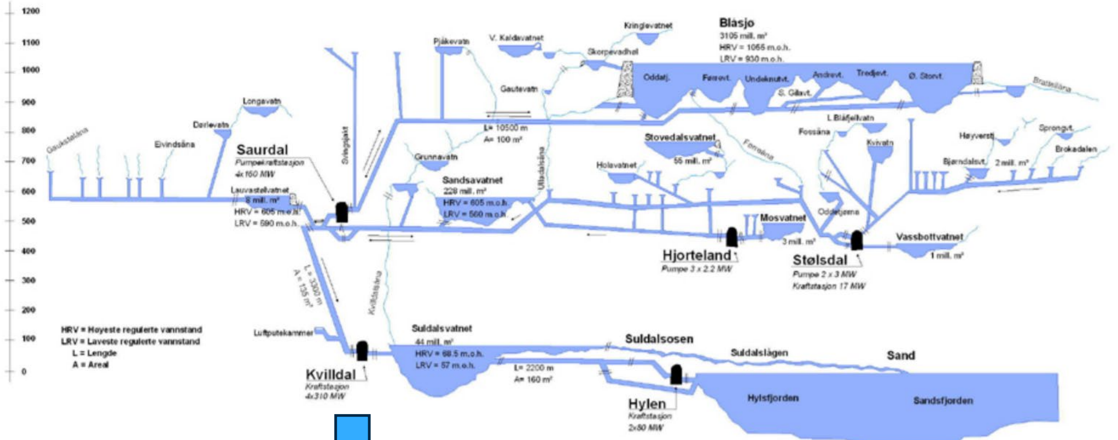
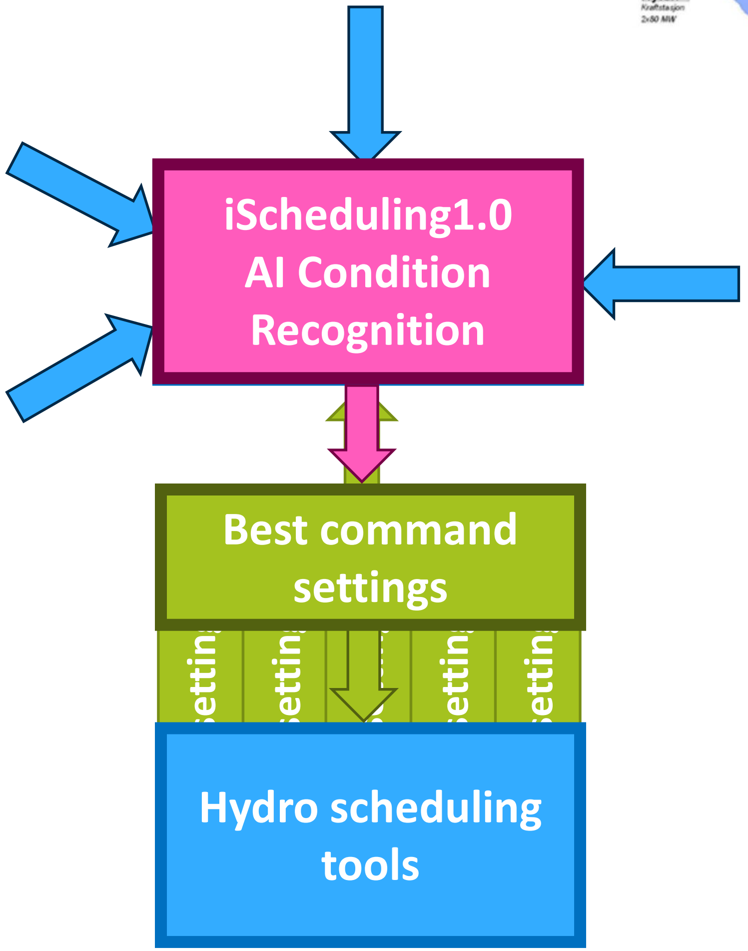
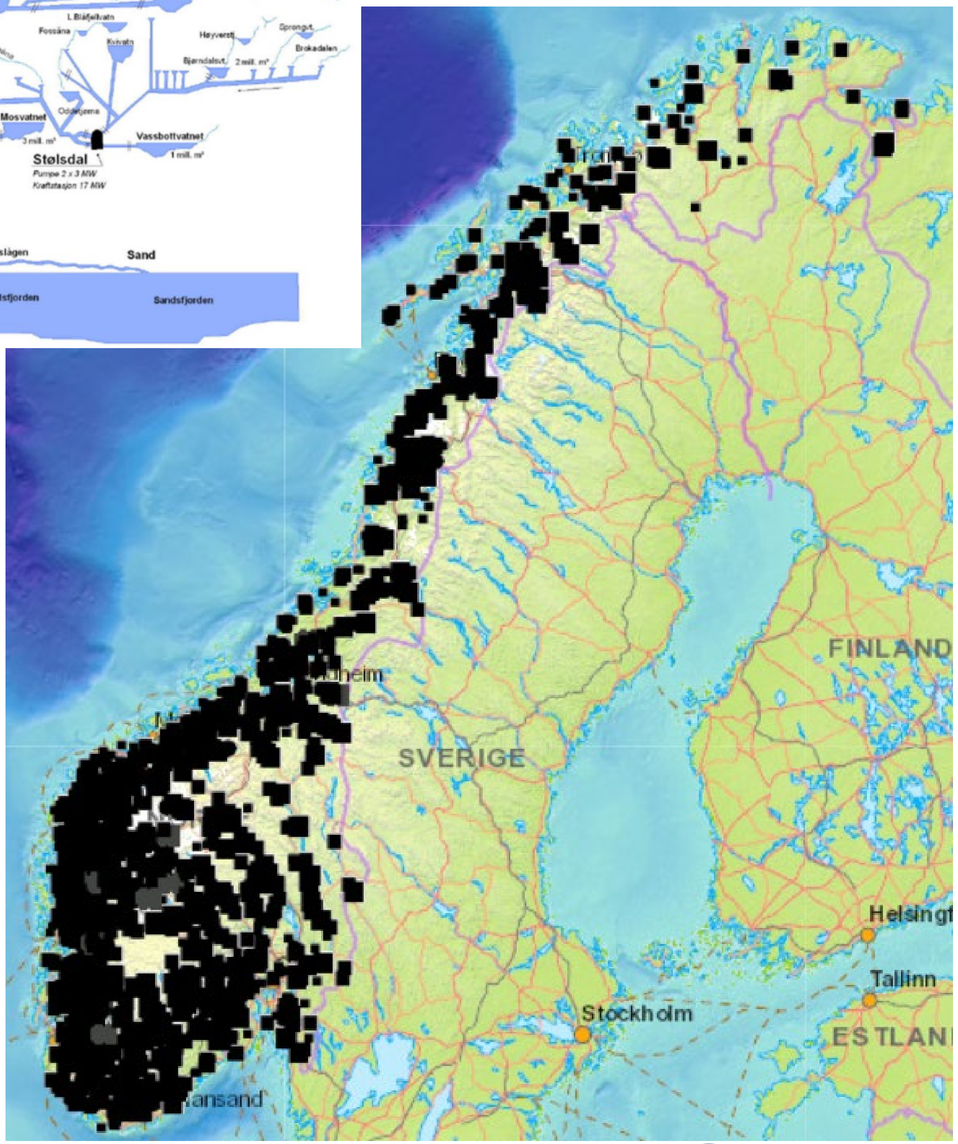
The Overall idea

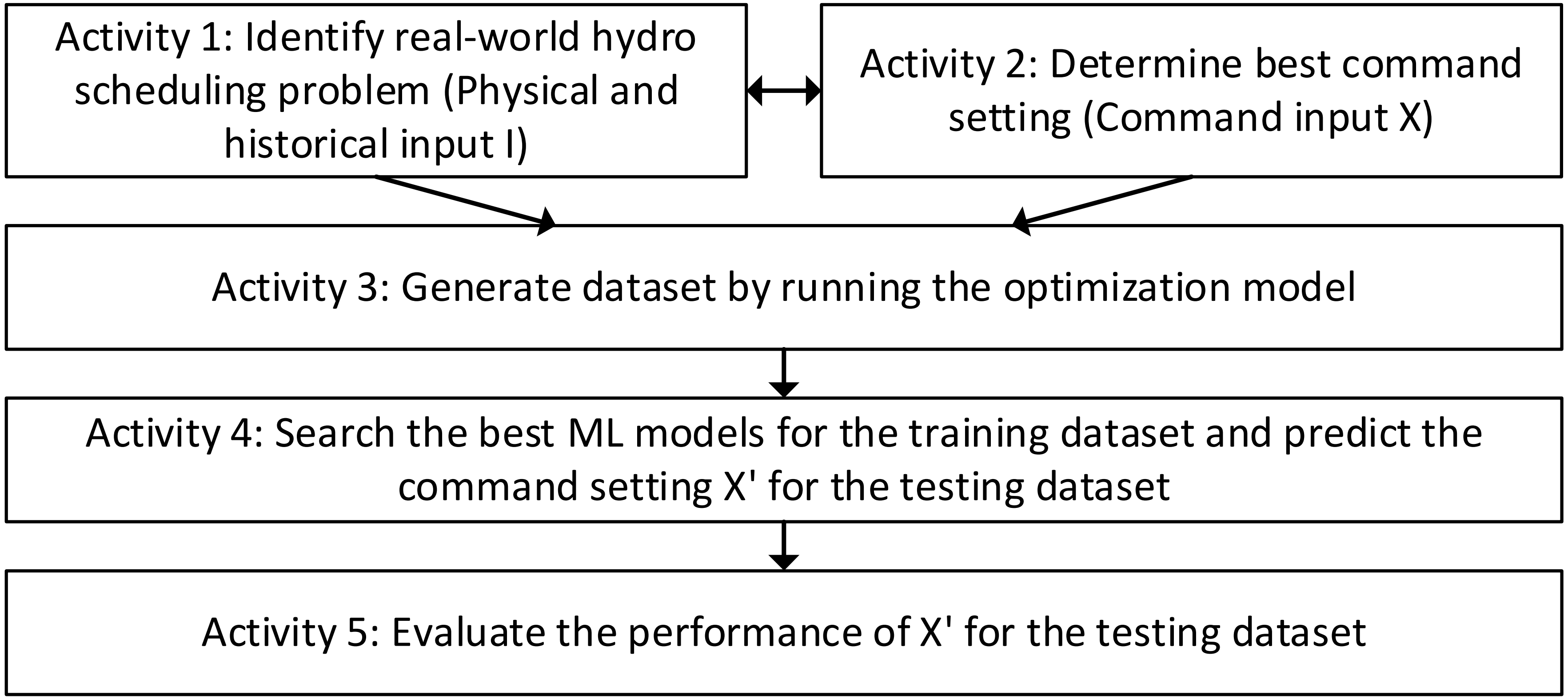






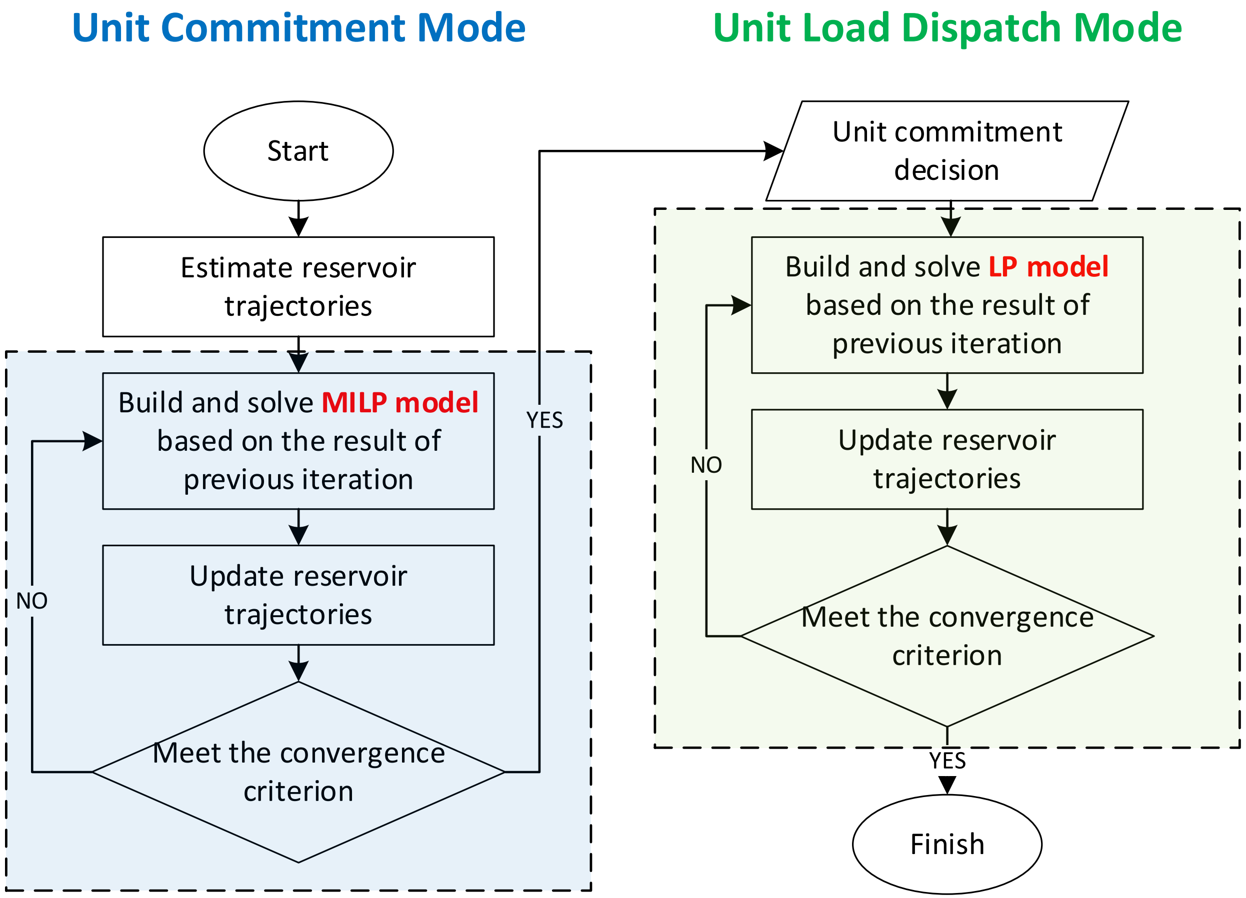


The framework



The scheduling tool

- Short-term Hydro Optimization Program (SHOP)



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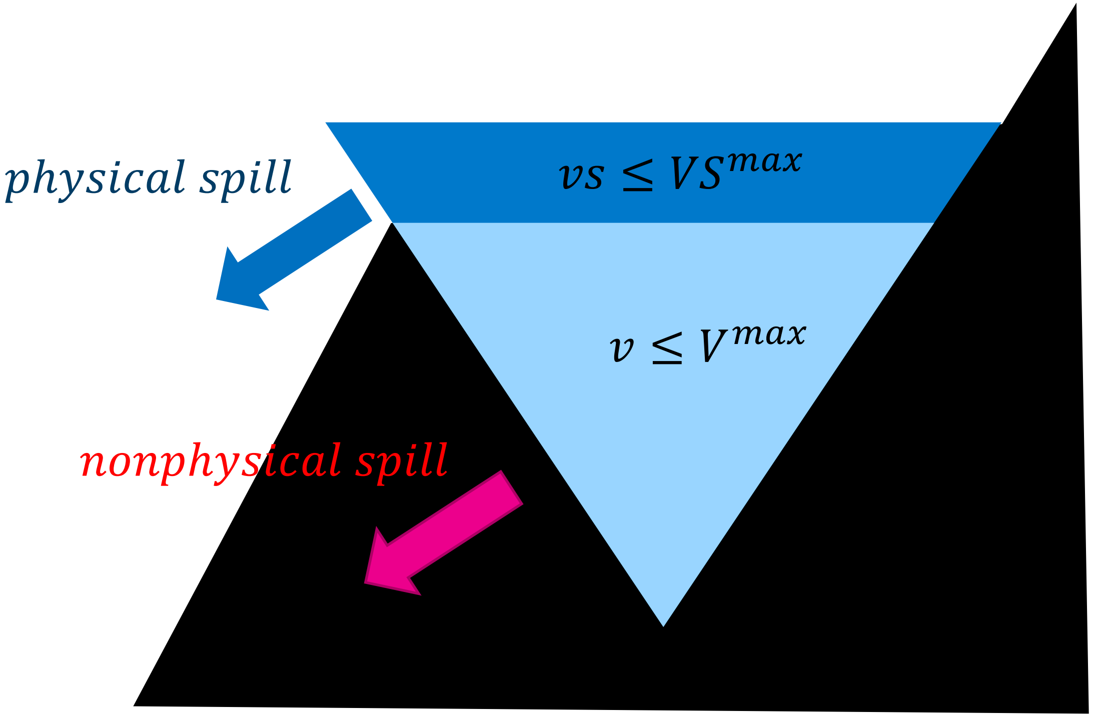
Physical spill VS nonphysical spill

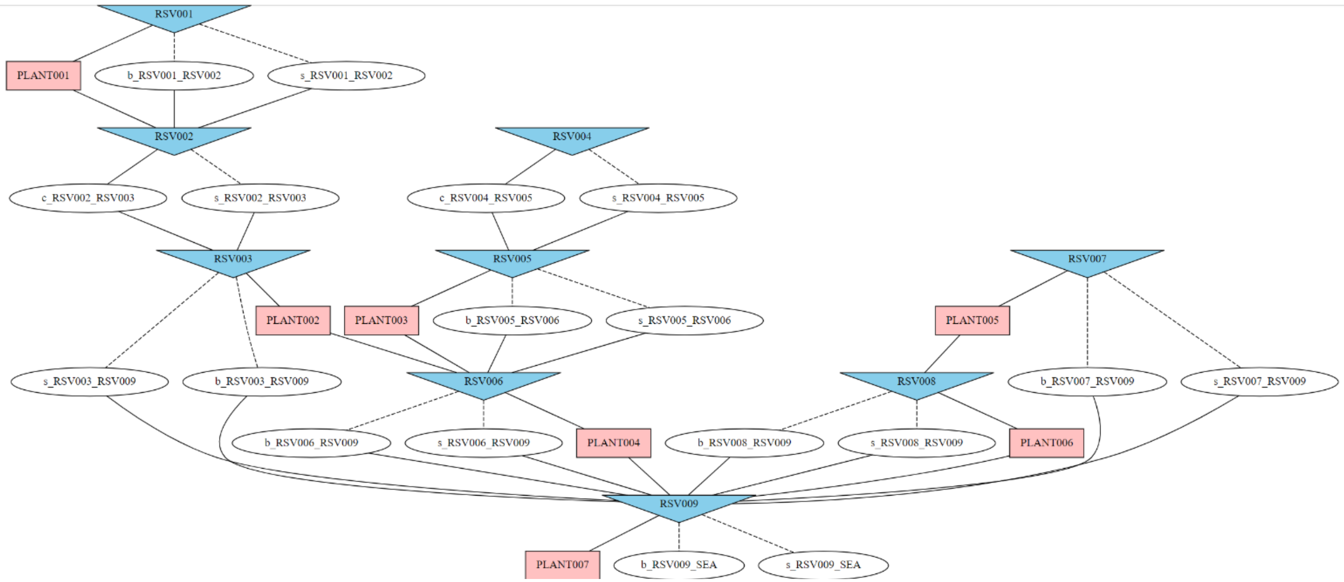
$$vs \geq 0$$
$$vs \geq v - V^{max}$$
$$vs \leq v - V^{max} \cdot \delta$$
$$vs \leq VS^{max} \cdot \delta$$
$$qs = c \cdot vs$$



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

When nonphysical spill may occur

- Much inflow is expected at the end of scheduling period
- Negative measured inflow in small downstream reservoir
- Market price is high and no inflow to the second reservoir
- Downstream plant would like to continuously produce instead of stopping due to high start/stop cost



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Use machine learning to avoid nonphysical spill

- Since using binary variables in the MIP problem will significantly increase the calculation time, the default setting of overflow_mip_flag in SHOP is "off" (δ is relaxed).
- The correction is done after SHOP is run and nonphysical spills occur. Then the producer must set overflow_mip_flag as "on" and run SHOP again to fix the problem.

- This paper aims to find out the correct setting of overflow_mip_flag before running SHOP.
- Given the input data, ML can predict whether overflow_mip_flag should be set as "on" before running SHOP to avoid nonphysical spills or set as "off" when there will be no nonphysical spills to save the calculation time.

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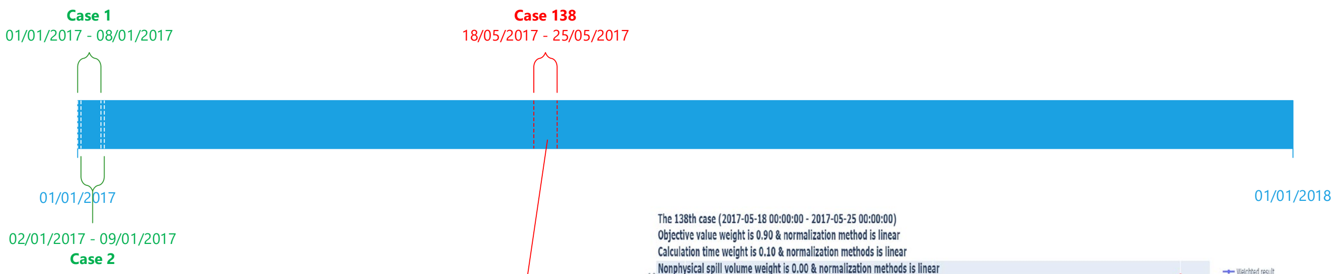
Dataset generation (SINTEF internal test system & data)

- Step 1: Read the input data to SHOP
- Step 2: Set up the scheduling hours for each case

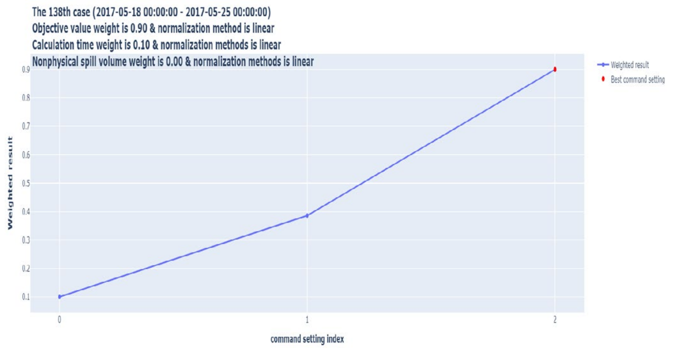
$$\text{total\_case} = \left\lfloor {(\text{total\_hours - scheduling\_hours\_for\_each\_case})}/{\text{hourly\_interval\_between\_each\_case}} \right\rfloor + 1$$

$$= \left\lfloor {(24 \times 365 - 168)}/{24} \right\rfloor + 1 = 359$$

Dataset generation (SINTEF internal test system & data)



- In each case, there are 3 command settings to check:
  - Command setting 0: ['PQ points', '3_3']
  - Command setting 1: ['PQ points', '10_10']
  - Command setting 2: ['PQ points', '25_25']
- Run SHOP with the 3 command settings, respectively
- The command setting gives the highest weighted result will be recorded as the best command setting for this case, i.e., Command setting 2



0	1	2	3	4	5	6	7	8	9	...	1690	1691	1692	1693	1694	1695	1696	1697	1698	1699
138	25.41	23.72	22.43	20.68	22.63	24.61	26.93	28.07	28.63	...	30.786243	36.97828	36.748486	4.89636	4.89636	27.264662	24.990071	8.923113	23.824578	2

Columns 1-168: 168-hr market price

Columns 1,690-1,698: 9 rsv end water value

Case No.

Columns 169-1,680: 9 rsv * 168-hr inflow

Columns 1,681-1,689: 9 rsv initial volume

Column 1699: Best command setting for this case

- Step 3: Determine the command setting
- Step 4: Run SHOP with the command settings and record these values :
  - ✓objective value (in millions NOK)
  - ✓calculation time (in seconds)
  - ✓nonphysical spill volume (in millions m^3)
- Step 5: Normalize the different purposes to a value between 0 to 1

$$x' = (x - x_{min})/(x_{max} - x_{min})$$

- Step 6: Assign weights for the purposes

$$\bar{x} = \sum_{i=1}^{n} w_i x_i \Big/ \sum_{i=1}^{n} w_i$$

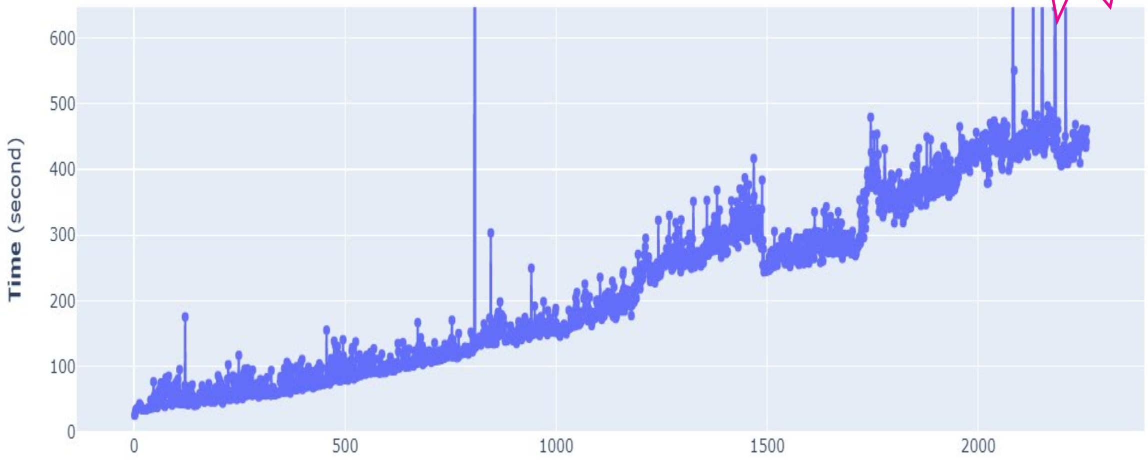
- Step 7: Create the one-pair dataset for the current case

Improvement of dataset generation time

First dataset generation

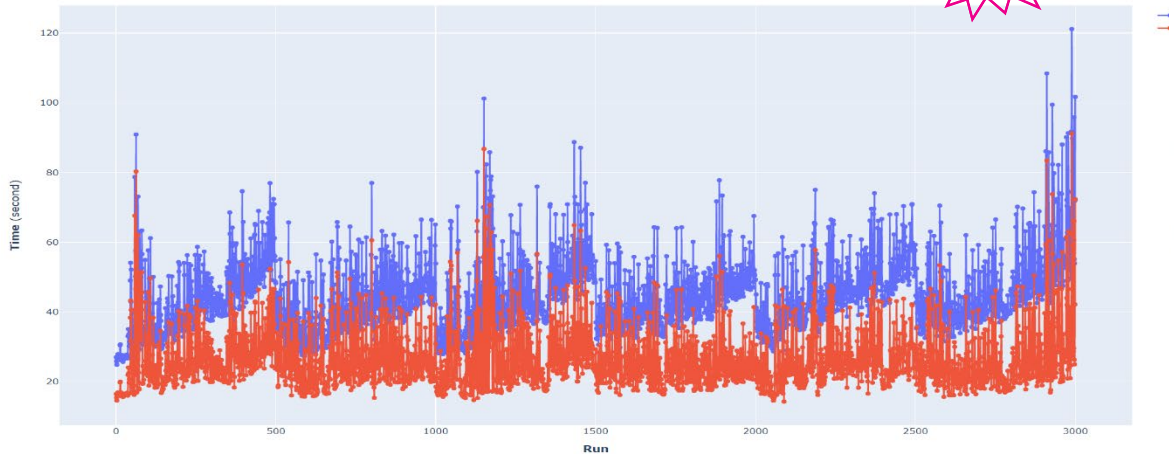
~6 days

There are 36 cases in each run. Total time used for all runs is 521,713.36 seconds



After multiprocessing is used (6 in parallel)

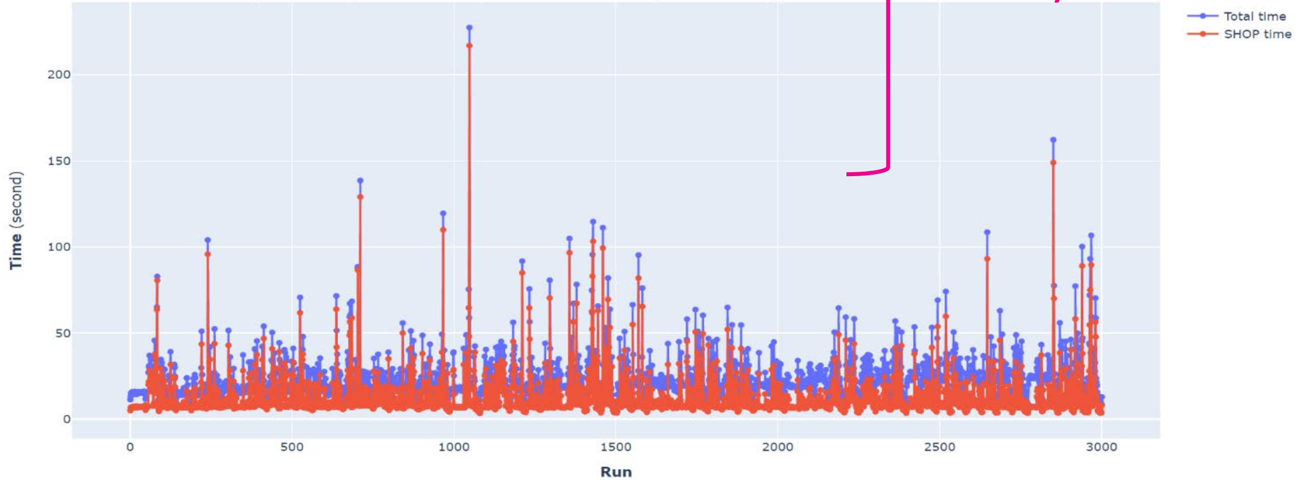
Original run time.
There are 36 command combinations in each run. Total time used for generating dataset is 23,829.88 seconds (6.62 hours).



After High Performance PC is used (64 in parallel)

Original run time. Dataset generation 1.
There are 3 command combinations with 210-hour scheduling period in each run.
Total time used for generating dataset is 1,331.15 seconds (0.37 hours).

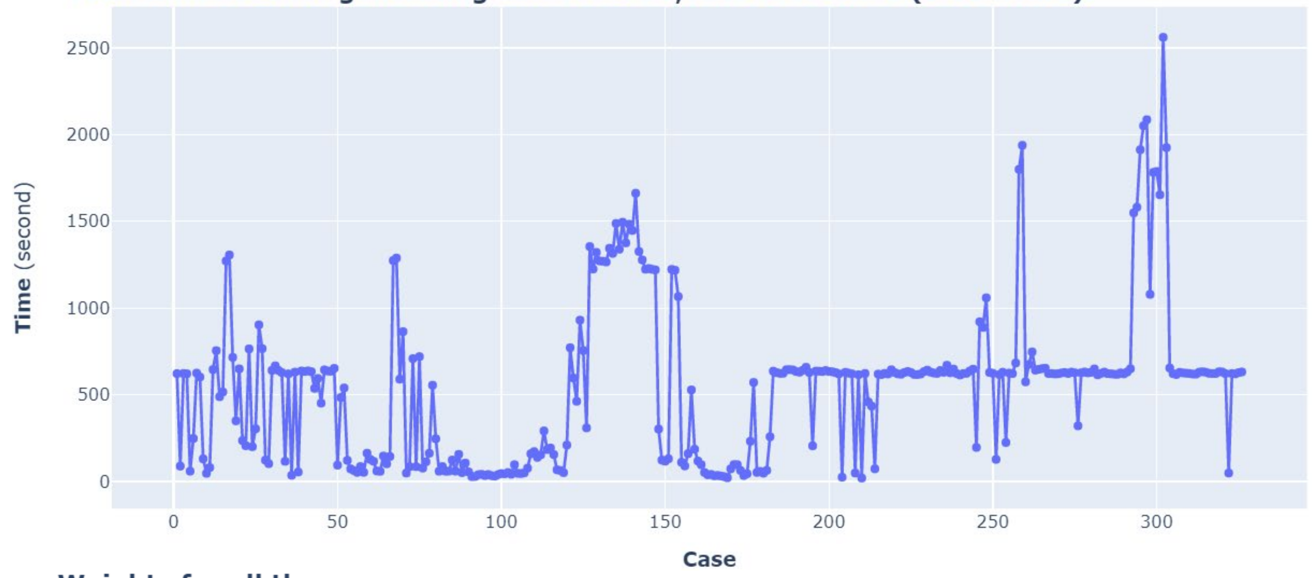
Original run time. Dataset generation 2.
There are 3 command combinations with 210-hour scheduling period in each run.
Total time used for generating dataset is 1,352.84 seconds (0.38 hours).



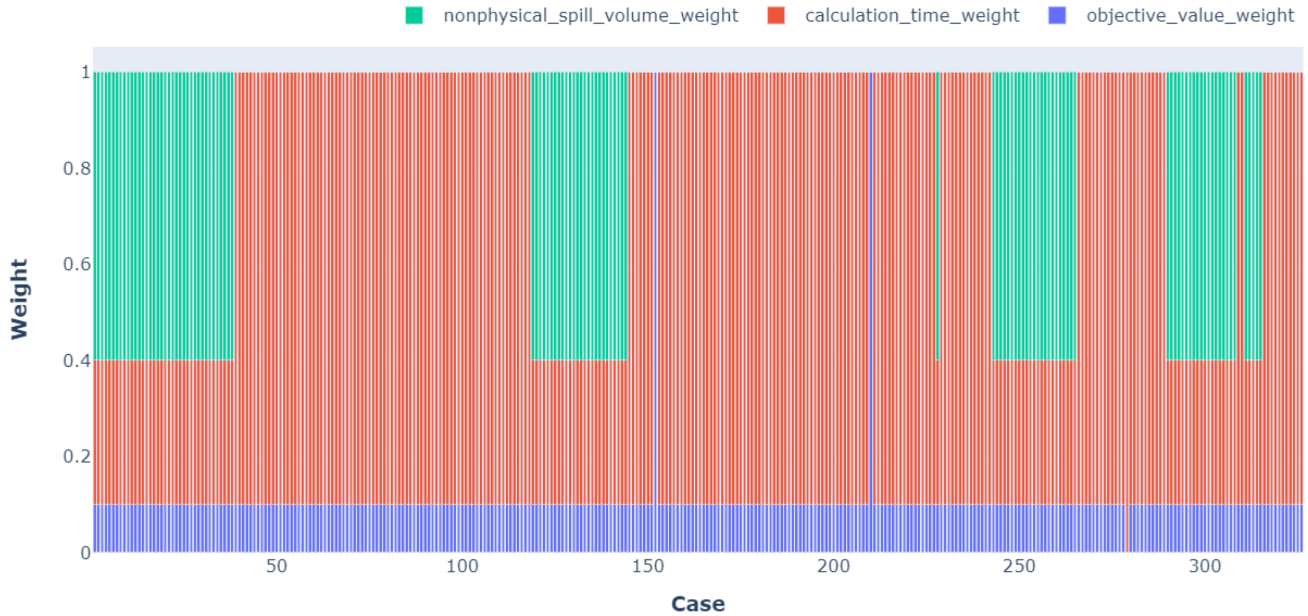
Generation time is very stable

Dataset generation (real-world dataset structure)

Original generation time. Dataset 1.
There are 2 command settings with 240-hour scheduling period in each case.
Total time used for generating dataset is 10,821.45 seconds (3.01 hours).

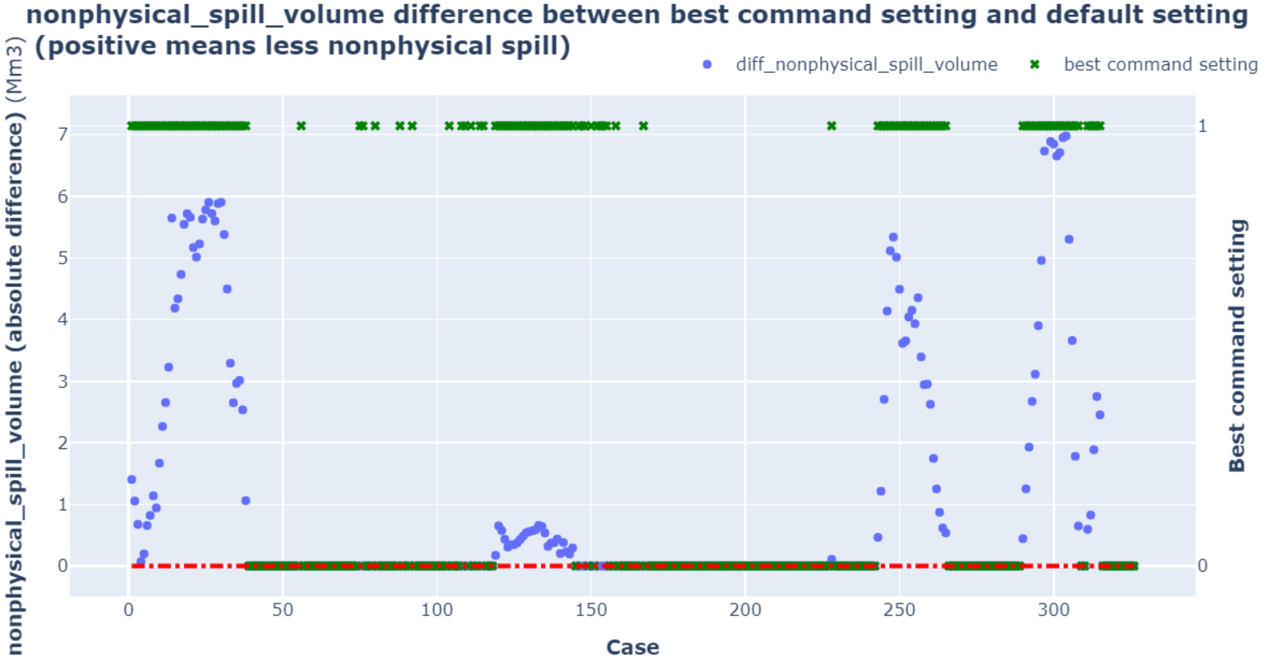


Weights for all the cases



- The real-world watercourse contains 13 reservoirs, three hydropower plants with eight generators and one pump.
- The historical data available are 11-month market price and inflow.
- The command to check is overflow_mip_flag. The default setting is "off," The other choice is "on".
- The scheduling period for each case is 240 hours
- The number of columns in the dataset generated is 3,867, and the number of rows is 326.
- The total generation time is around 3 hours.
- Dynamic weights are applied. When nonphysical spills occur in one case, the weight on nonphysical spill volume is 0.6, calculation time 0.3, and the objective value 0.1. When there are no nonphysical spills, the weight on calculation time becomes 0.9, and the objective value is still 0.1.

Dataset generation (real-world dataset structure)



- Nonphysical spills can be avoided by setting overflow_mip_flag as "on" but with the cost of higher calculation time.
- Can ML effectively analyze the input data and predict overflow_mip_flag to be "on" only when nonphysical spills appear?

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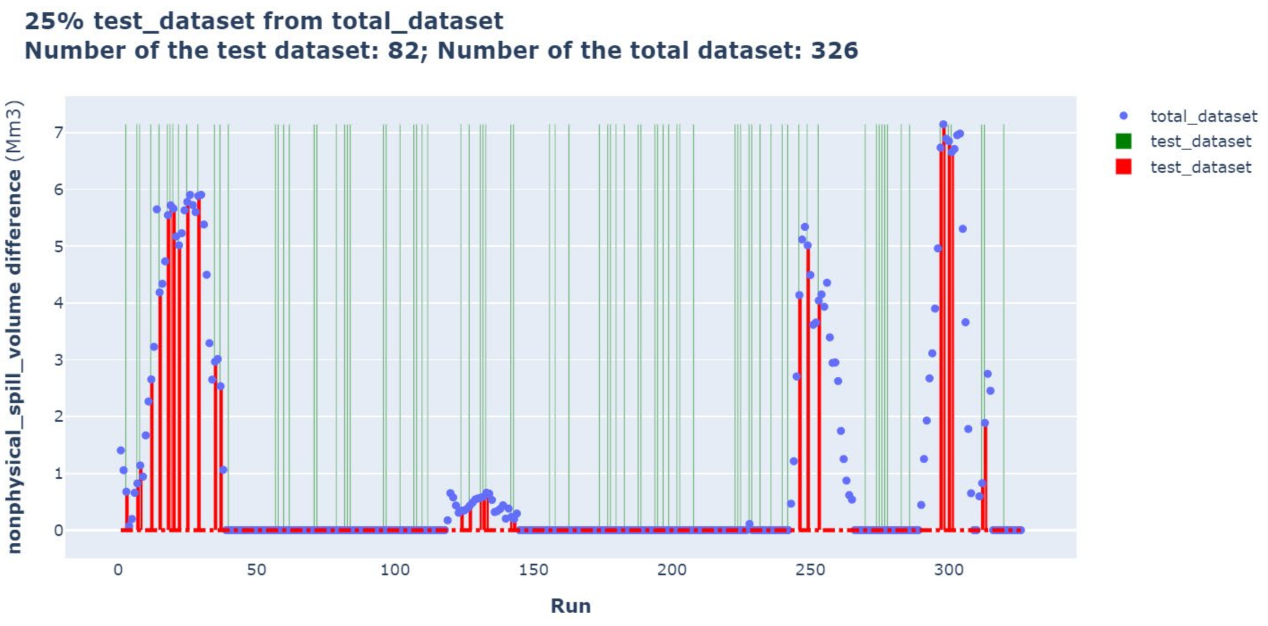
Machine learning technologies



- **The Allocation of Command Settings**

Overflow_mip_flag:	Total dataset	Training dataset (75%)	Testing dataset (25%)
No. of choosing "off"	192 (58.90%)	145 (59.43%)	47 (57.32%)
No. of choosing "on"	134 (41.10%)	99 (40.57%)	35 (42.68%)

- **The Prediction Result in the Testing Dataset**

Overflow_mip_flag:	Predicted result	Correctly predicted	Incorrectly predicted	Accuracy
No. of choosing "off"	44	42	2	89%
No. of choosing "on"	38	33	5	94%

- Classification methods in supervised learning were chosen to work with.
- Feature extraction methods:
  - ✓ use the mean and standard deviation over *N* number of hours to reduce the number of input columns (2 hours and 240 hours are the best)
  - ✓ adopt the data-sampling methods from the imbalanced-learn library to avoid the imbalance issues (the under-sampling method is the best)
- Splitting ensures that the distribution of the classes in the two sub-datasets is roughly the same.
- Machine learning models:
  - ✓ used TPOT to find the best pre-processing methods, ML models, and their parameters for this task
  - ✓ To evaluate the pipelines, we use the balanced accuracy metric, which is the arithmetic average of sensitivity and specificity.

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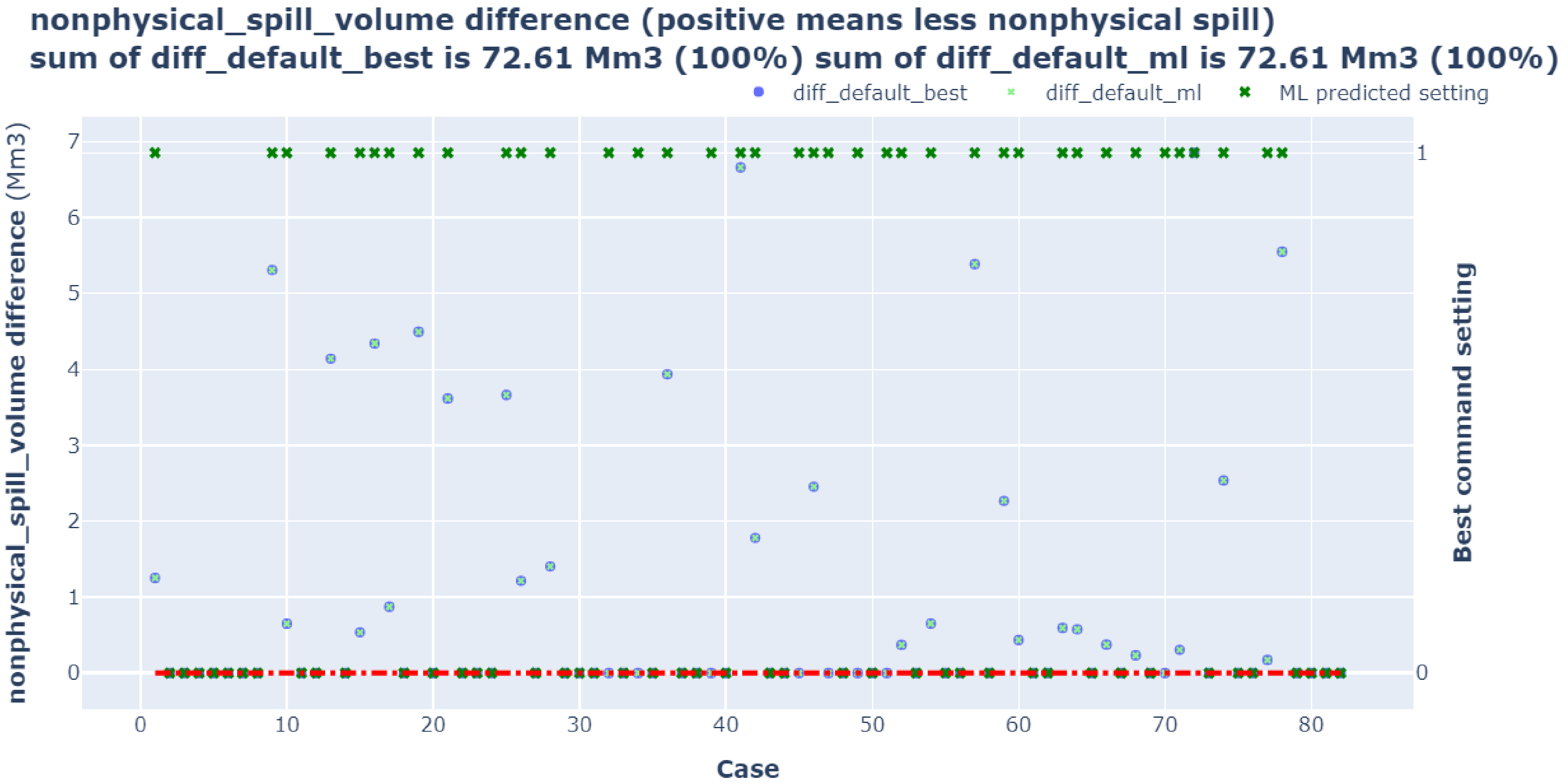
Performance evaluation



- Use the testing dataset to evaluate the performance (82 cases).
- 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.

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Experience we learned from this study

- We must understand the physical system and impact of commands on the results very well.
- The input data (i.e., historical data and watercourse) should represent the problem to solve.
- It is difficult to collect all the necessary historical data. It is also time-consuming to generate the reasonable data that are missing. Heuristics are applied.
- High performance PC is important to get stable and reliable results.
- The right command combination and weight assignment are important.
- The structure of the data for machine learning is critical.

Possible issues for future research

- In current study, all the training dataset is generated based on the historical data, e.g., market price and inflow. However, the extreme weather caused by climate change happens more frequently. Stochastic data and other energy source (i.e., sol and wind) should be taken into consideration to generate a bigger dataset and represent a future-oriented picture.
- In current study, all the commands checked are one-time setting. It is possible to extend to be a time-dependent and object-dependent setting. The cohesion between different commands should also be taken into account.
- In current study, only one hydro scheduling tool is involved. Connection to other hydro scheduling tools, for instance Prodrisk and SHOP, should also be check.
- Several future directions in ML for hydro scheduling: 1) multi-task learning where part of the model is shared across industrial partners and the data-scarce problem would thus be substantially relieved; 2) transfer learning that addresses the data drift from training to testing; 3) structured accuracy which takes different command importance into account; and 4) reinforcement learning that operates in a dynamic environment with feedbacks.

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