Machine learning-based forepart block decomposition model as a precursor to the Scenario fan problem

Jinghao Wang, NTNU
Hydropower scheduling conference, 12-14 Sep 2022
Email: jinghao.wang@ntnu.no
Acknowledgment

Intelligent dispatching and optimal operation of cascade hydropower plants based on big spatiotemporal data (IntHydro), RCN, IKTPLUSS-IKT, 2020-2024 (https://www.ntnu.edu/inthydro#/)
Motivation

• Hydro power is important to Norway.
  1. Most of the energy production relies on hydropower.
  2. Hydropower as a storable energy source, coupling with Renewable Energy Sources (RES) to deal with uncertainty and variability.

• The long-term hydropower scheduling model is well-performed for stochastically, dynamically scheduling problems, but is problematic with computational time.

• Extreme inflows are important in the scheduling problem. How to reveal potential risk by grouping inflow using machine learning (ML)?
Overview of the methodology

• Long-term hydropower scheduling – SFP* → calculate water values
  • Two-stage Stochastic programming using bender’s decomposition
  • Receding horizon
  • Outcome is to simulate hydropower operation for each week considering the look-ahead strategy → representing the future by historical scenarios (50 climate years)

• This approach (fundamental market model) fits modeling future hydropower scheduling where we have a high share of RES

• However, the number of scenarios has a high impact on computational time

• We want to use the benefit of ML to reduce or cluster the scenarios

Interaction between different models

Scenarios

Scenario clustering

New inflow

Scenario Blocks

Scenario Candidates

Scenario Fan Problem

- Water value
- Dispatching information
- Water level
  ...

- New inflow
- Inflow
- Water value
- Scenarios
Self-Organizing-Map (SOM) methodology

• Why?
  • Total energy (vertically) and delay of the release (horizontal)
  • Self-adaptive neural network
    • Adjust weight for point clouds or time-series clouds to update the location of neural
    • Avoid miss placing centroid compared with k-means

• How?

Persistence homology
Distance matrices
SOM
Dynamic time wrapping
Persistence homology (PH)

- Global maximum
- Local minimum, maximum
- Shape of input data
- Birth-death point can provide a straightforward view of how the data fluctuates

Dynamic time warping

- Capture horizon spreading of time-series
- Not point-to-point distance, robust on time-shifts
- Not restricted to the length of time-series

PH-DTW $\rightarrow$ SOM

- Topology Distance -- Vertically
- Geometric Distance -- Horizontal

$$DTW(x(t), S(t)) + Geo(x(t), S(t))$$
Case study

Hydro-thermal system

- 12 connected hydro plants
- 4 thermal plants
- 1 wind farm
- 1 transmission line
- 2 demands/consumers
Clustering of Inflow scenarios

- Aggerated 12 inflows
- Weekly resolution
- 52 weeks (1 year)
- 50 inflow scenarios (50 climate years)

- 9 clusters
- Pick Cluster 2 as input to SFP with an equal probability to show case
Results

- Reservoirs level in aggregated level

![Graph showing reservoir level over weeks with different scenarios and computational times.]

- PH-DTW-SOM: Time: 506 s
- ALL: Time: 3532 s
Future works

• Demonstrate the framework on a real case

• Sensitivity analysis

• Connect the inflow prediction algorithm to the scenario precursor and weighted probability

• Increase the resolution of inflow data
Other Presentations by Our Group

- **Tuesday 13 September (P6- Inflow Modelling at 11:20)** Forecasting down-stream inflow discharge using time-series decomposition and deep learning, Mojtaba Yousefi, Western Norway university of applied science.

References


• **Self-Organizing Maps Tutorial – Algobeans**


• Kate RJ. Using dynamic time warping distances as features for improved time series classification. Data Mining and Knowledge Discovery. 2016 Mar;30(2):283-312.