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

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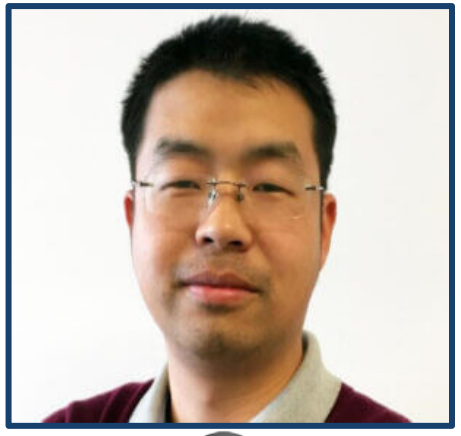
Acknowledgment

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

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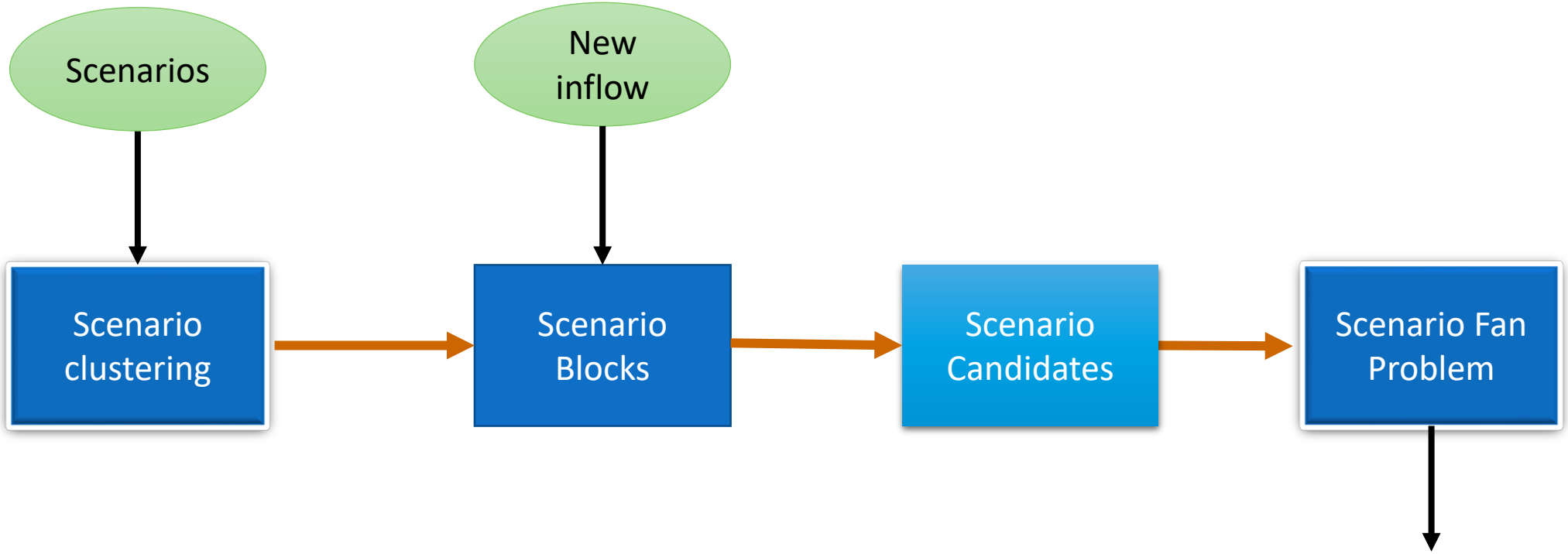
*Reference: Helseth, A., Mo, B. and Warland, G., 2010. Long-term scheduling of hydro-thermal power systems using scenario fans. Energy Systems, 1(4), pp.377-391.

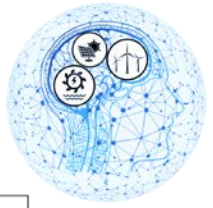
Interaction between different models



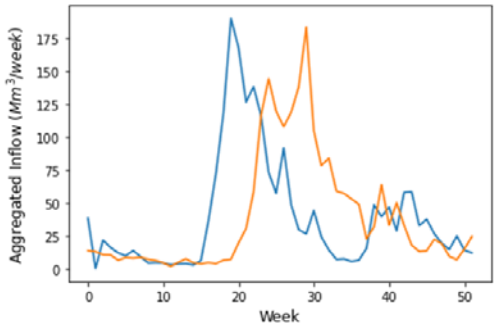
- Water value
- Dispatching information
- Water level

…

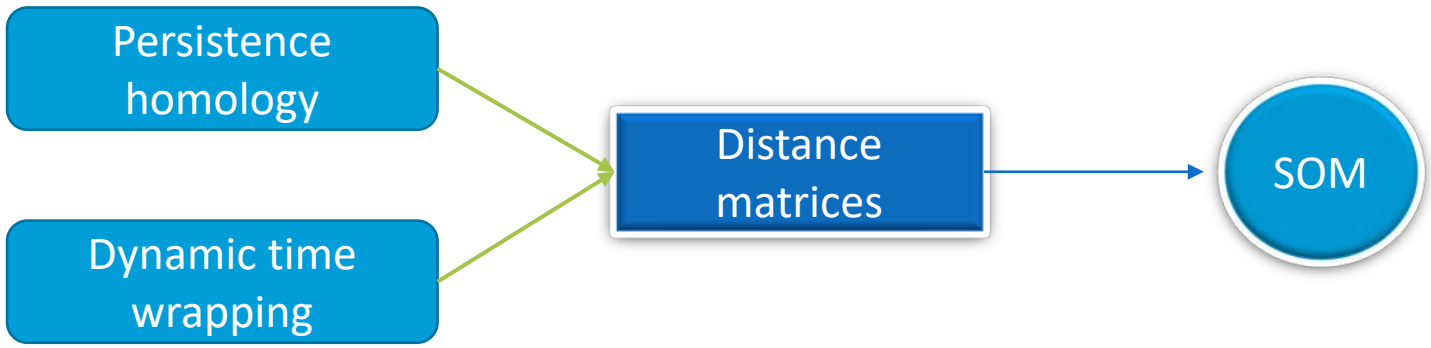
Self-Organizing-Map(SOM) methodology

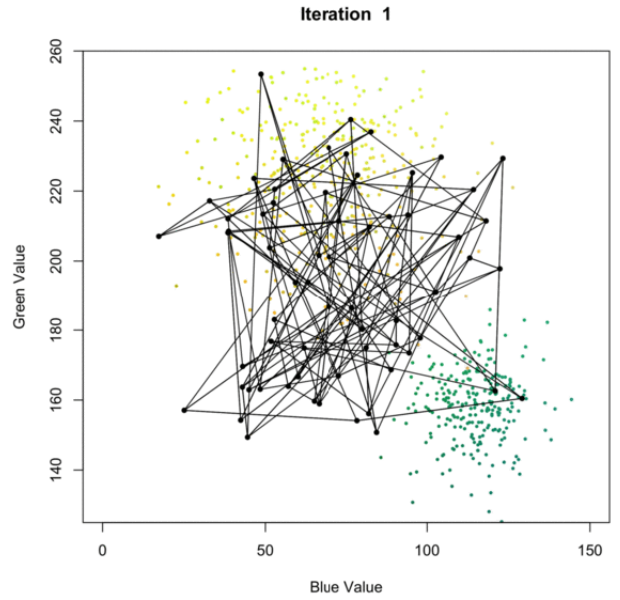


- Why?
  - Total energy (vertically) and delay of the release (horizontal)
  - Self-adaptive neural network
    - Adjust weight for point clouds or time-series clouds to update the location of neural
    - Avoid miss placing centroid compared with k-means



- How?





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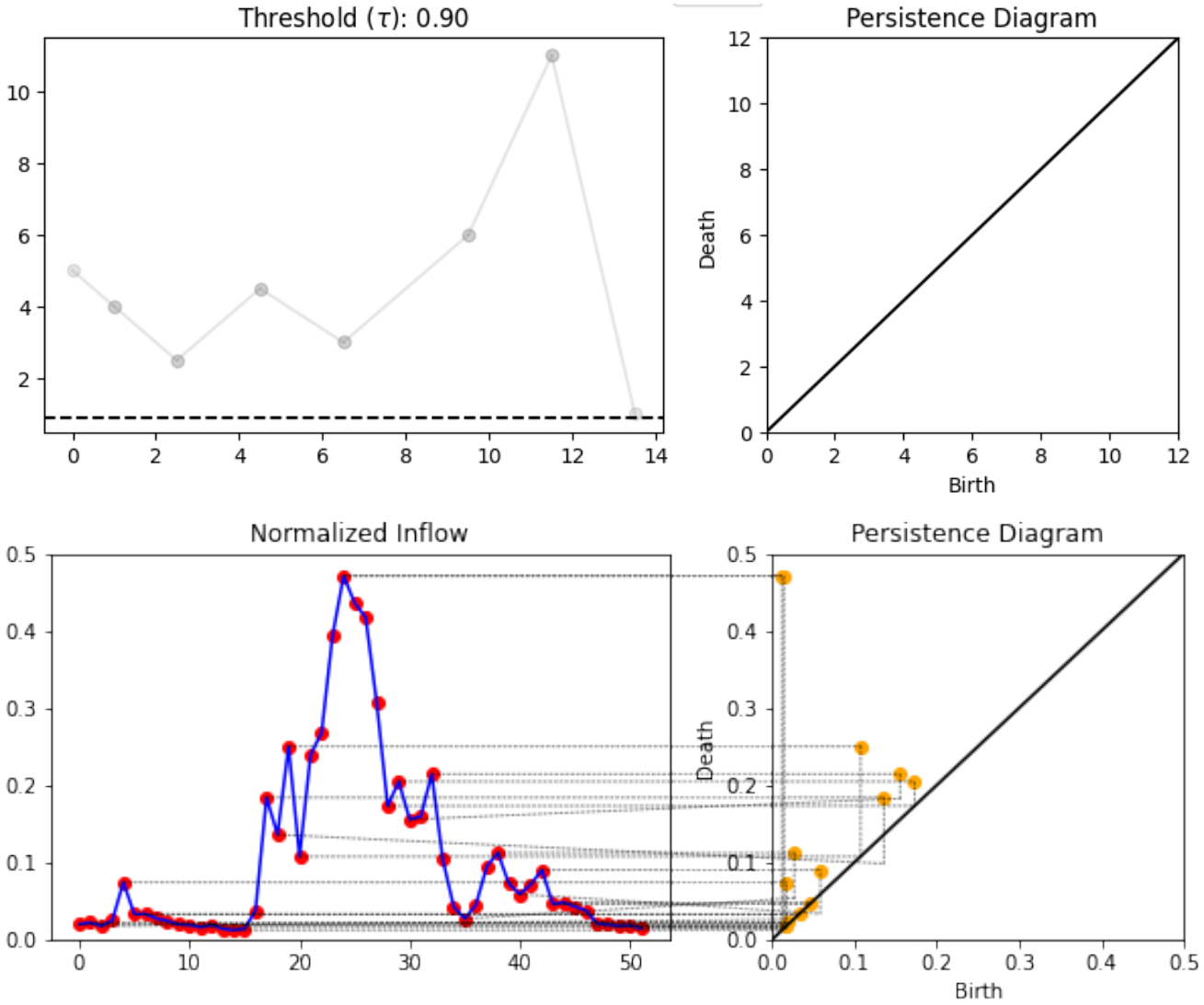
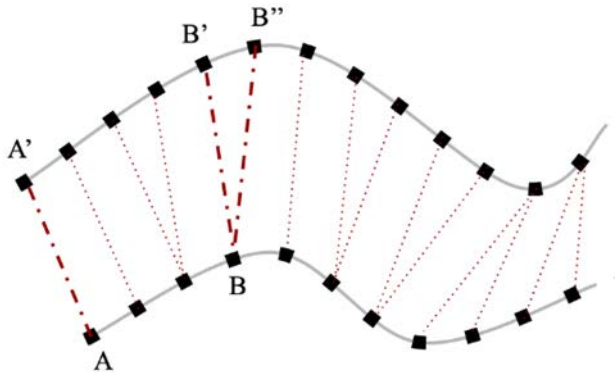
Persistence homology (PH)

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

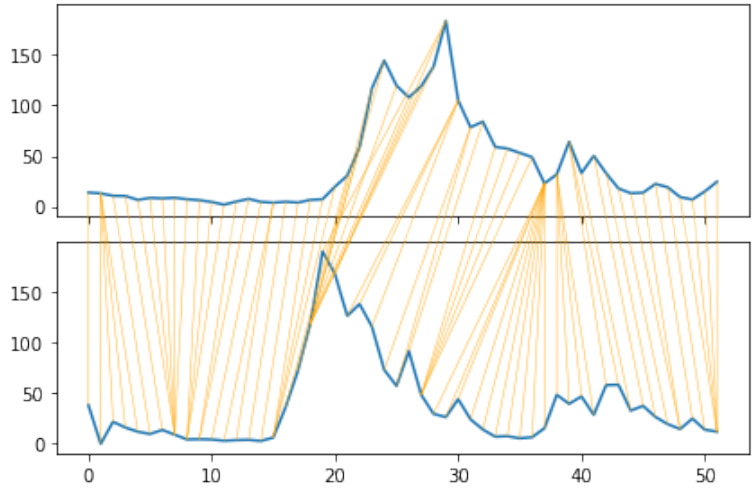


Reference: Emin Aktas M, Akbas E, El Fatmaoui A. Persistence Homology of Networks: Methods and Applications. arXiv e-prints. 2019 Jul:arXiv-1907.

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



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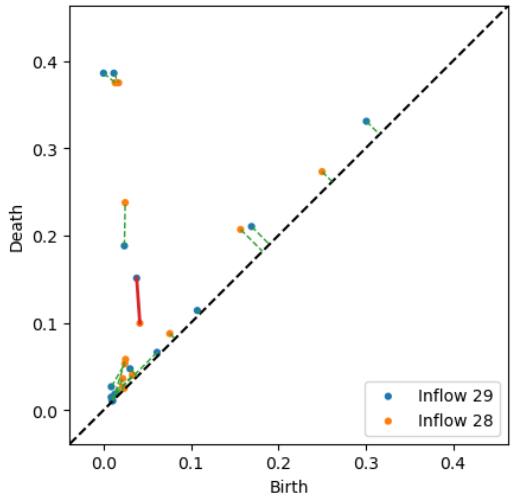
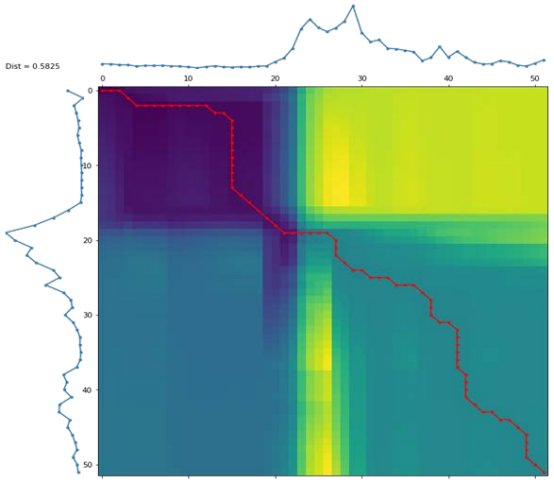
Reference: Kate RJ. Using dynamic time warping distances as features for improved time series classification. Data Mining and Knowledge Discovery. 2016 Mar;30(2):283-312.

PH-DTW → SOM





Topology Distance-- Vertically

Geometric Distance – Horizontal

PH-DTW distance

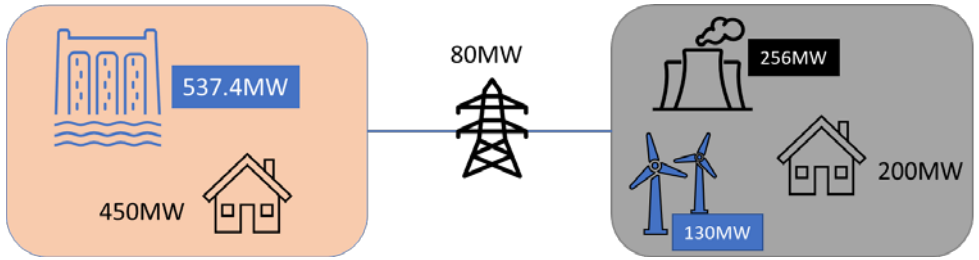
$$DTW\big(x(t), S(t)\big) + Geo\big(x(t), S(t)\big)$$

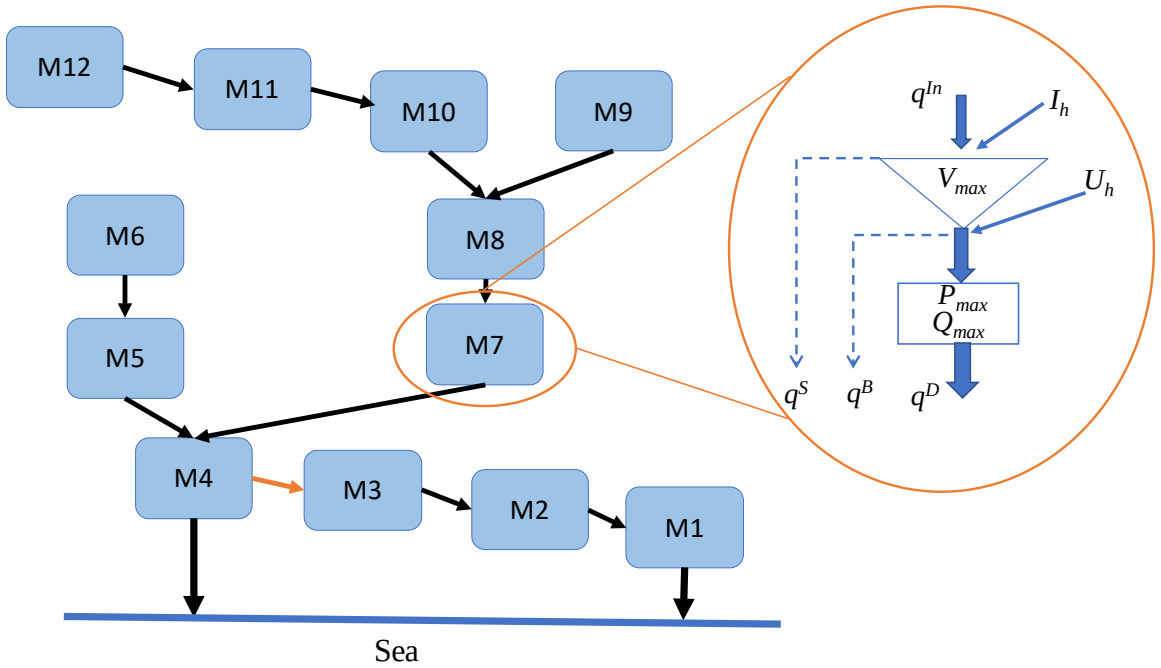
SOM

Case study

Hydro-thermal system

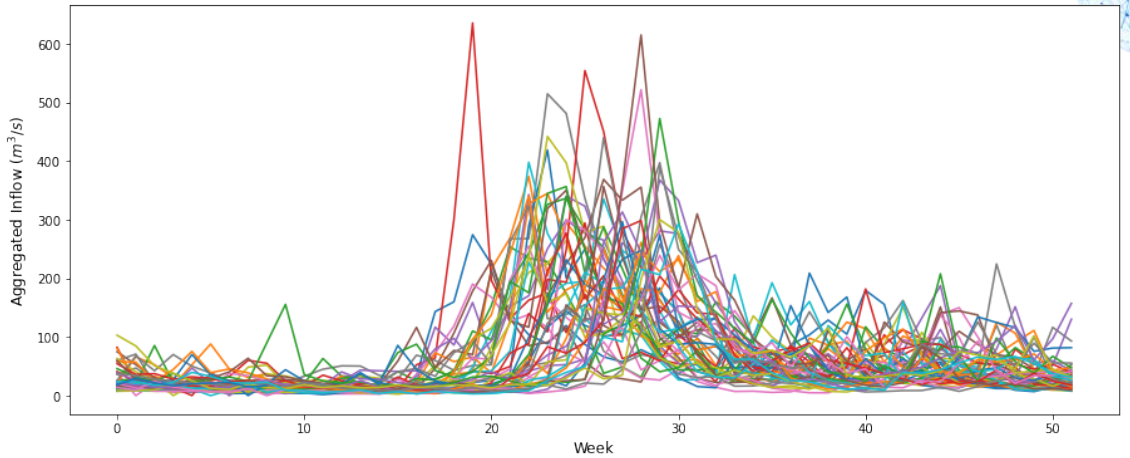
- 12 connected hydro plants
- 4 thermal plants
- 1 wind farm
- 1 transmission line
- 2 demands/consumers



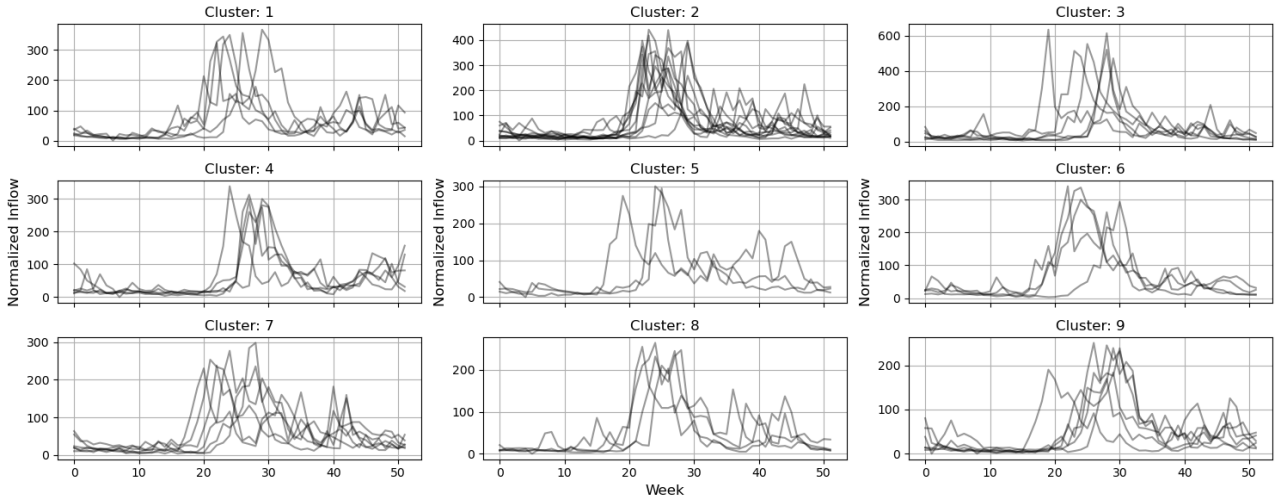


Clustering of Inflow scenarios

- 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



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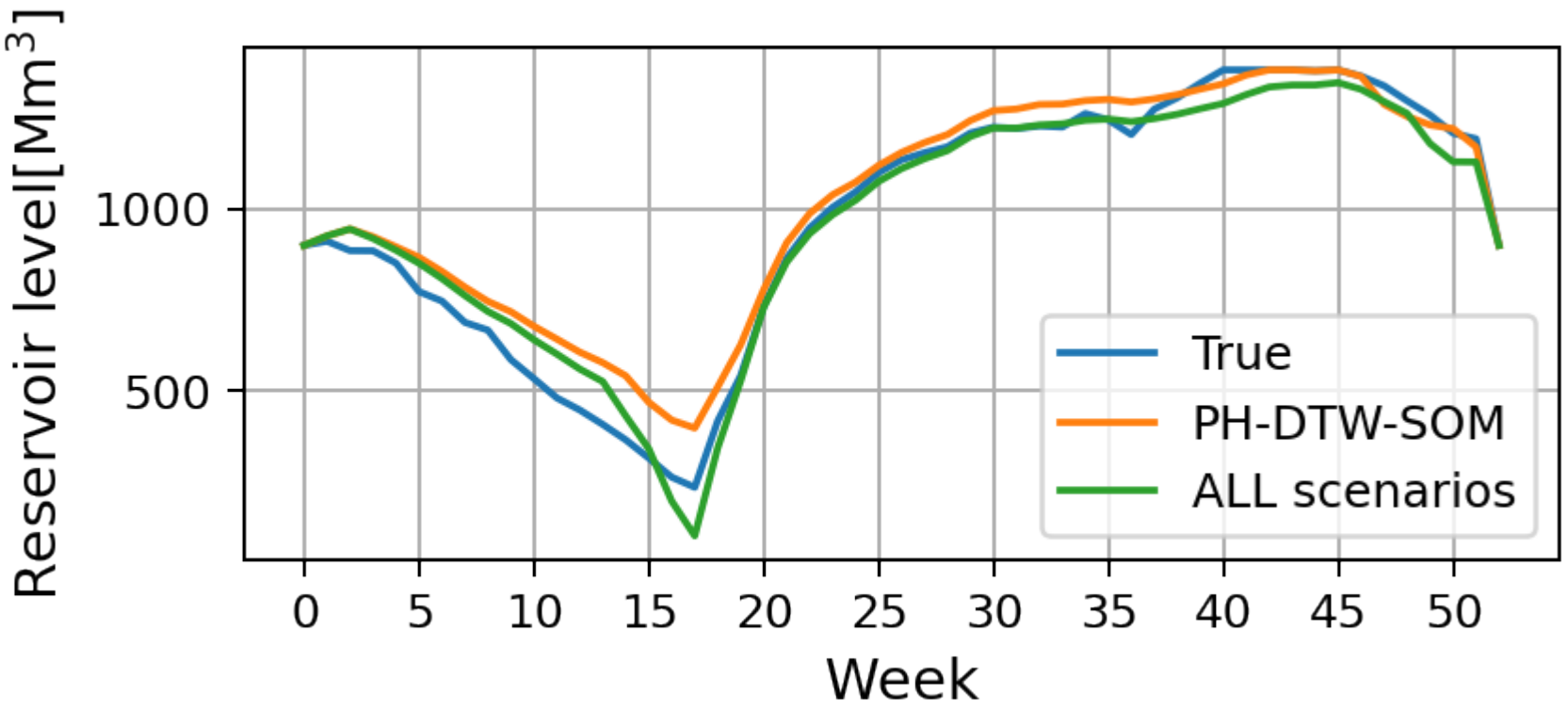
Results

- Reservoirs level in aggregated level



Computational time:

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

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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

- **Tuesday 13 September (P6- Inflow Modelling at 12:20)** A data-driven short-term inflow forecasting model for hydropower scheduling-Chinese use case, Xu Cheng, Smart Innovation Norway

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Any Question

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References

- Helseth, A., Mo, B. and Warland, G., 2010. Long-term scheduling of hydro-thermal power systems using scenario fans. Energy Systems, 1(4), pp.377-391.
- Self-Organizing Maps Tutorial – Algobeans
- Emin Aktas M, Akbas E, El Fatmaoui A. Persistence Homology of Networks: Methods and Applications. arXiv e-prints. 2019 Jul:arXiv-1907.
- 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.