Hydropower Generation in the Age of Climate Change, *Leveraging Causal AI*

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28 Apr 2023, AIT, Vienna

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Acknowledgment

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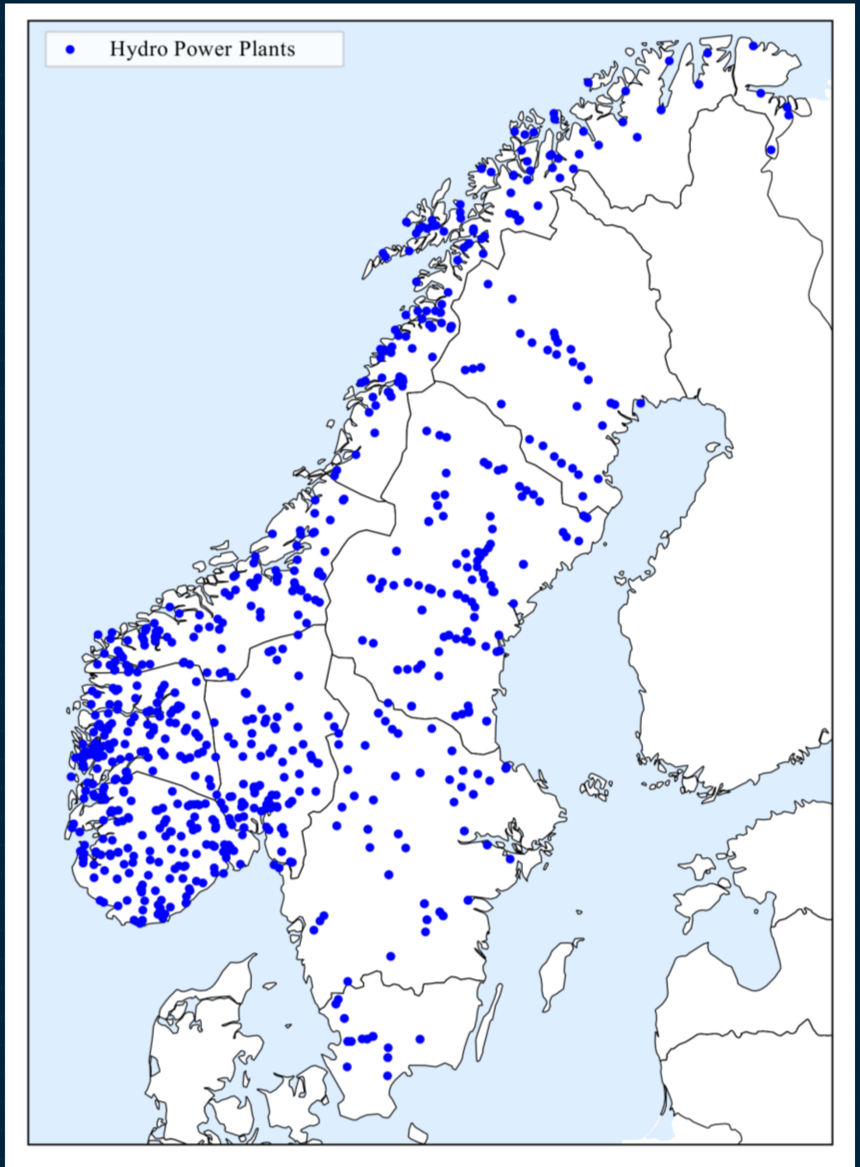
Norway’s Hydropower



https://www.mdpi.com/1996-1073/14/5/1425

- Hydropower’s share of Norway’s electricity production is about 95%.
- Hydropower is a clean and flexible source of energy for Norway and Europe.

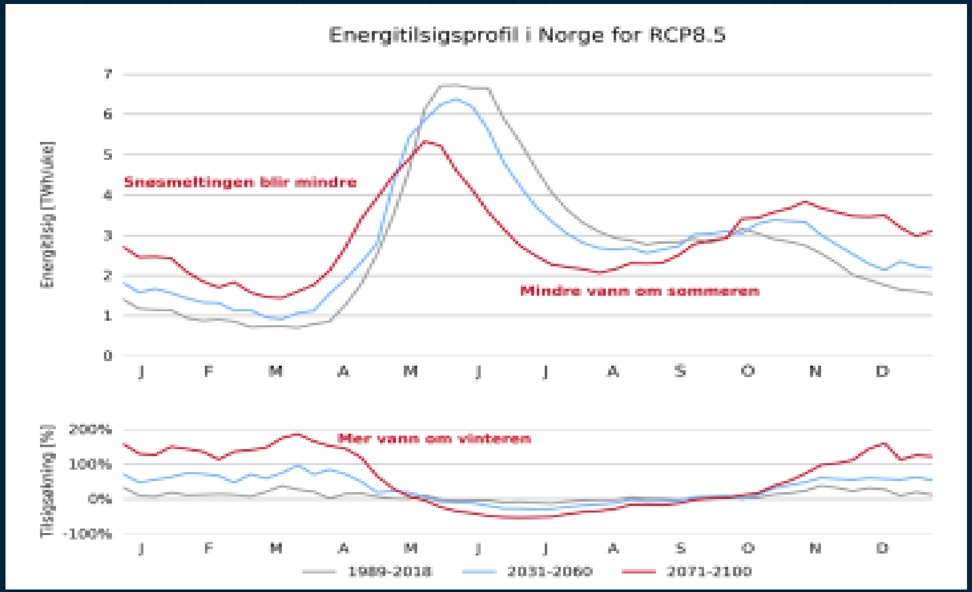
Forecasting water behind dams is complex!

- More connection to Europe and the UK electric grids and their electricity markets.
- The recent energy crises in Europe.

https://blog.sintef.com/sintefenergy/nordic-power-system-hvdc/

Forecasting water behind dams is complex!

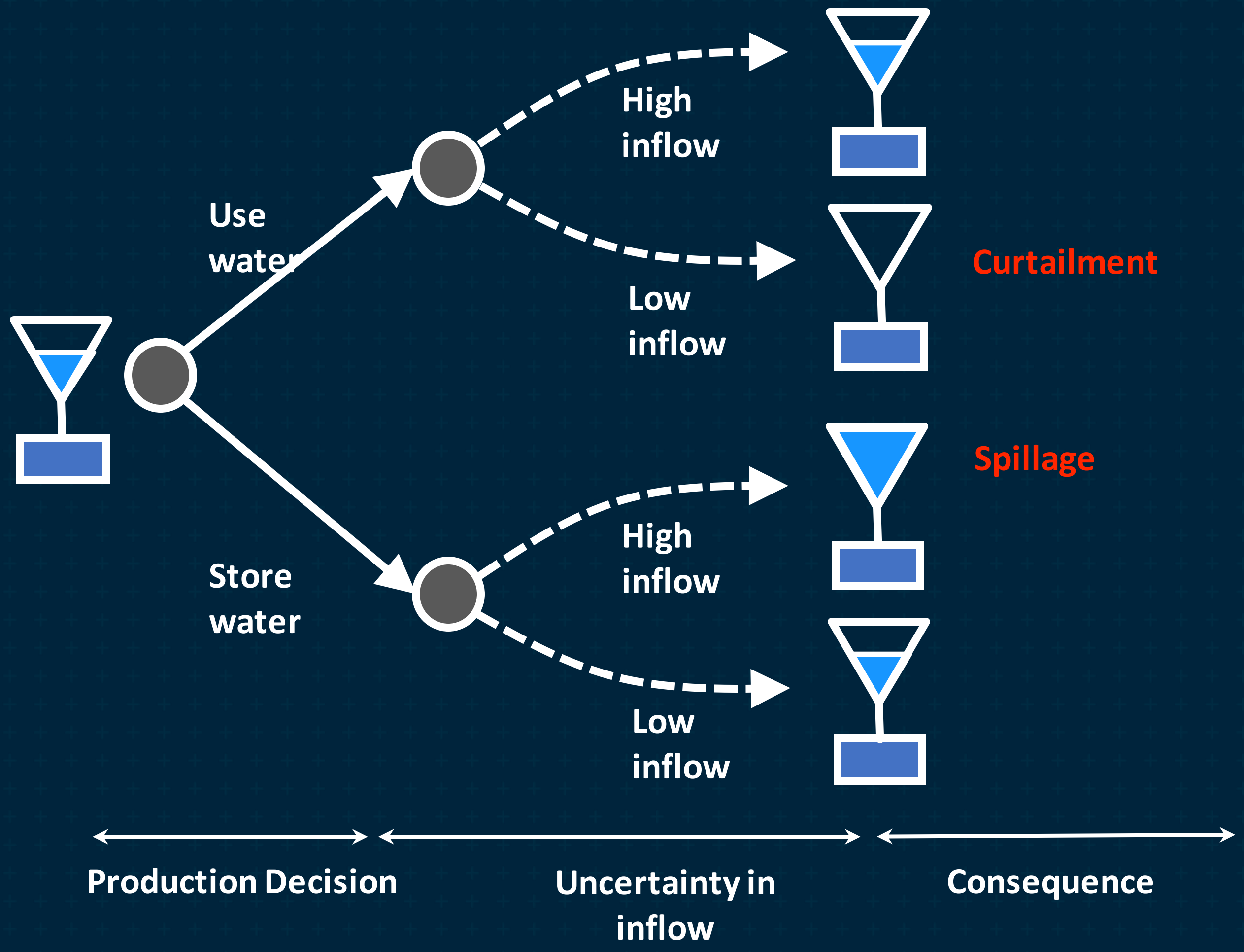
- Climate change (historical meteorological and hydrological data are not valid anymore!)



Forecasting water behind dams is complex!

- Integration of intermittent offshore wind energy (Norway plans 30GW by 2040).

Where and when do we have water?



- 1% improvement in inflow forecasting values billions of Euro!

Power Generation Market Size 2022

Scale	B Euro
Global	1660.3
Europe	682.8
Norway	30.6

Source: https://www.reportlinker.com/p06193685/

[1] Hamlet, A.F.; Lettenmaier, D.P. Columbia River Streamflow Forecasting Based on ENSO and PDO Climate Signals. J. Water Resour. Plan. Manag. 1999, 125, 333–341.

Classical hydropower Scheduling

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Optimization of available hydropower generation resources to fulfill the electricity demand considering various constraints and uncertainties.

Constraints

- Hydro power unit constraints
- Reservoir constraints
- Transition systems constraints
- Environmental and hydrological constraints
- Demand characteristics

Uncertainties

- Water Inflow
- Market price
- Weather Condition
- Renewable Energies

Solving this stochastic and dynamic optimization problem is complex, and time consuming.

Hydropower Scheduling & AI

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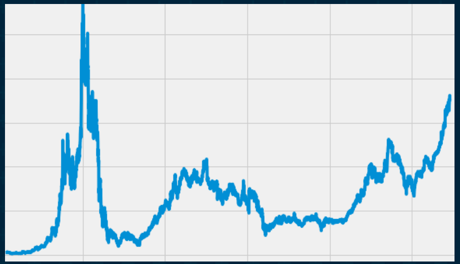
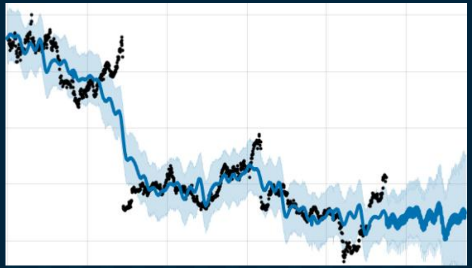
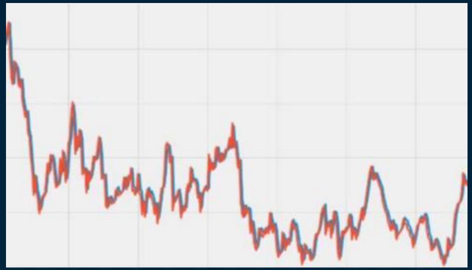
Water Inflow



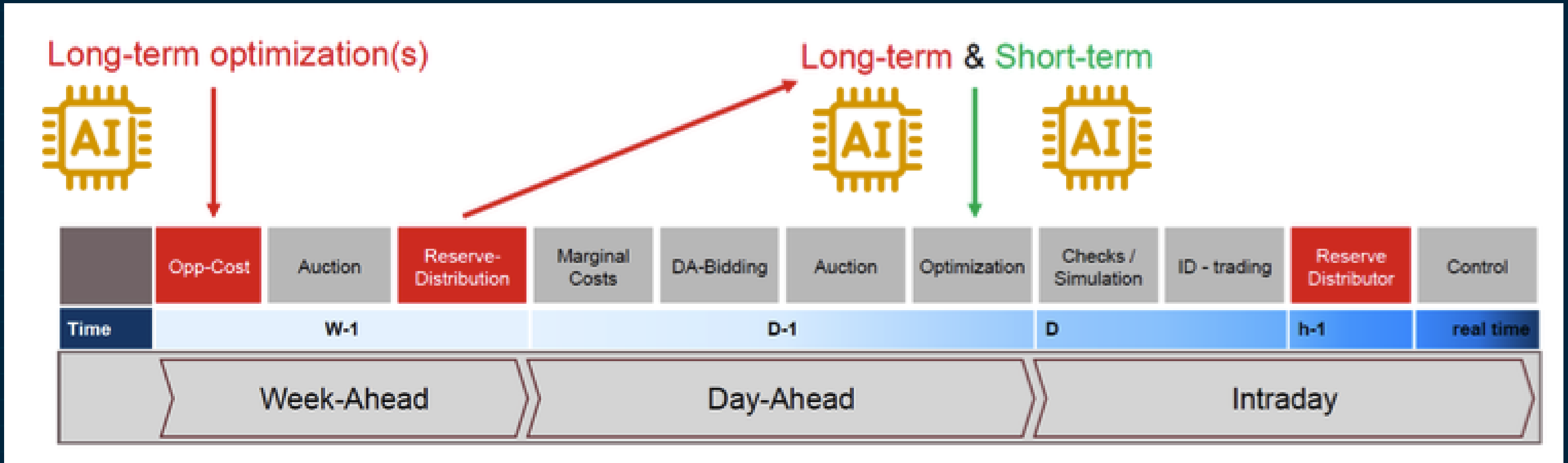
Market Price



Electric Demand



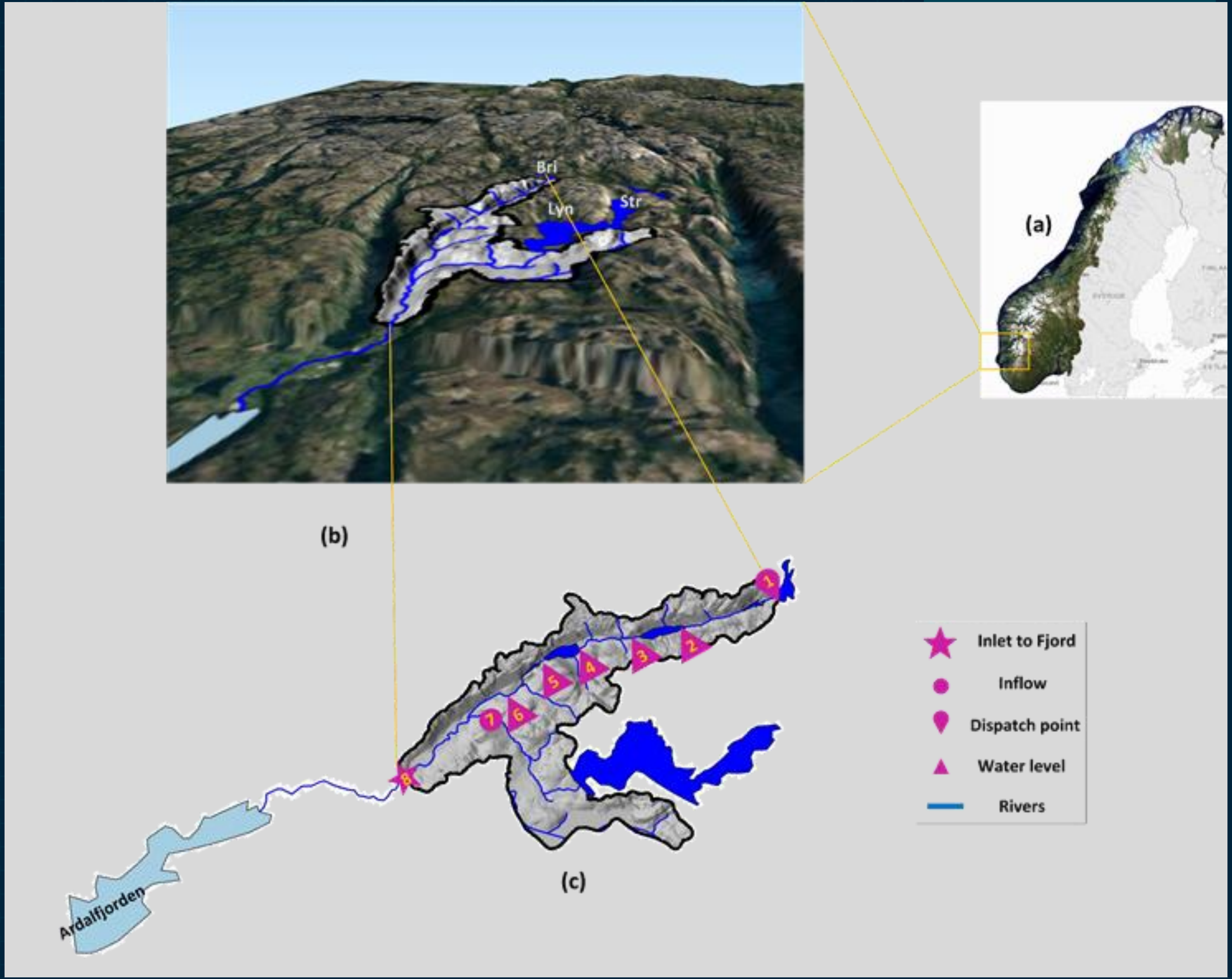
Other Data (Weather,…)



Example of AI Application : Inflow Forecasting

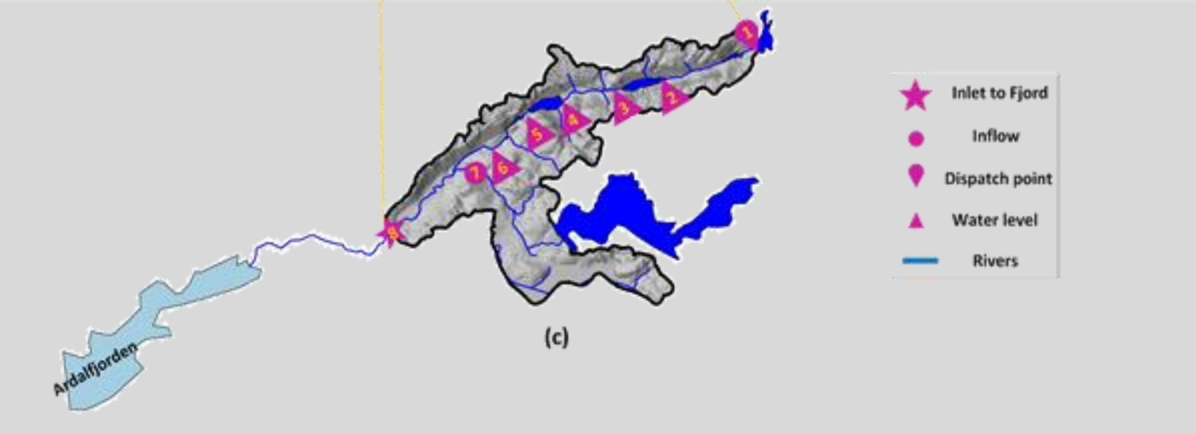
Use Case

- Storåna river in Hjemland, Rogaland
- Lyseboten I and Lyseboten II Hydropower stations
- Data includes Meteorological and Hydrological parameters



Example of AI Application : Inflow Forecasting

Collected data



(c)

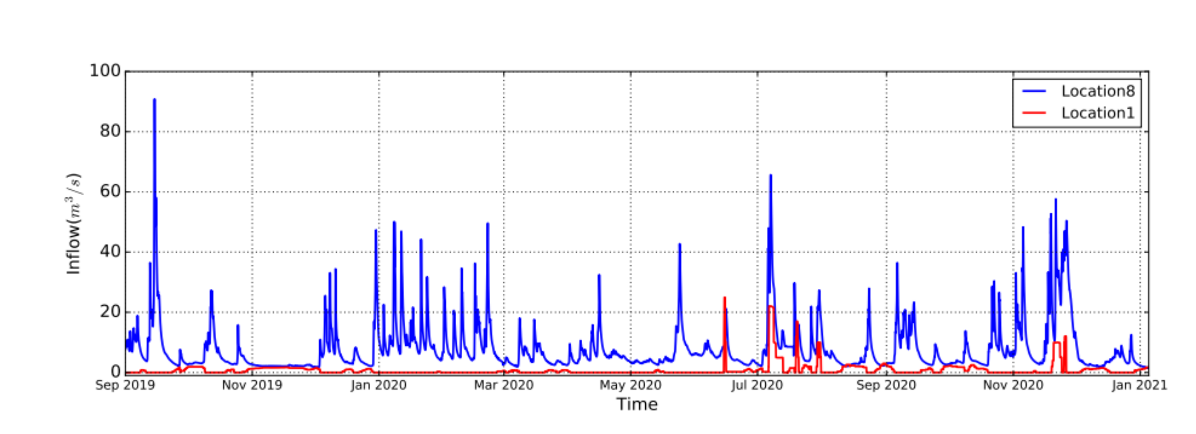


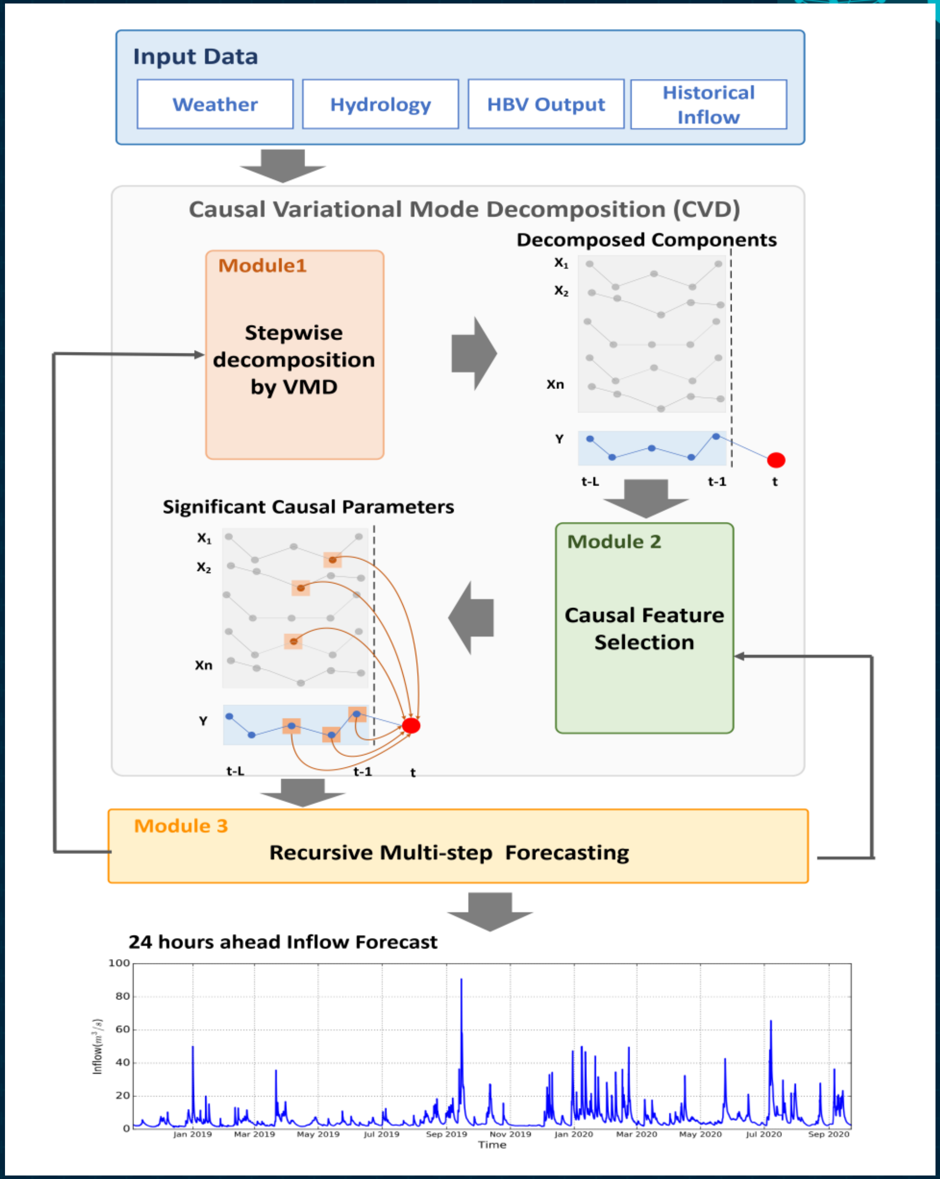
Table 1. Collected data

Group	Variable	Location	Unit
Meteorological	Air temperature	Location8	°C
		Location1 (Briavanet)	°C
	Precipitation	Location8	mm
		Location1	mm
Hydrological	Water level	Location2 (Musdalsvatn)	m
		Location3 (Musdalvatn downstream)	m
		Location4 (Viglesdalsvatn)	m
		Location5 (Hiavatn)	m
		Location6 (Hiafossen)	m
		Location7 (Lyngsåna)	m
	Water temperature	Location2	°C
		Location3	°C
		Location4	°C
		Location5	°C
		Location6	°C
		Location7	°C
		Location8	°C
	Inflow	**Location8**	m^3/s
		Location7	m^3/s
		dispatch at Location1	m^3/s
		spillage at Location7	m^3/s
Simulated hydrological from HBV Model	Inflow	Average of catchment	m^3/s
		kalltviet	m^3/s
	Evaporation	Average of catchment	mm
	Ground water	Average of catchment	mm
	Soil moisture	Average of catchment	mm
	snow water equivalent	Average of catchment	mm
	Snow melt	Average of catchment	mm
	Precipitation	Average of catchment	mm
	Air temperature	Average of catchment	mm

Example of AI Application : Inflow Forecasting

Methodology

- We developed Causal Variational Mode Decomposition (CVD)



Example of AI Application : Inflow Forecasting

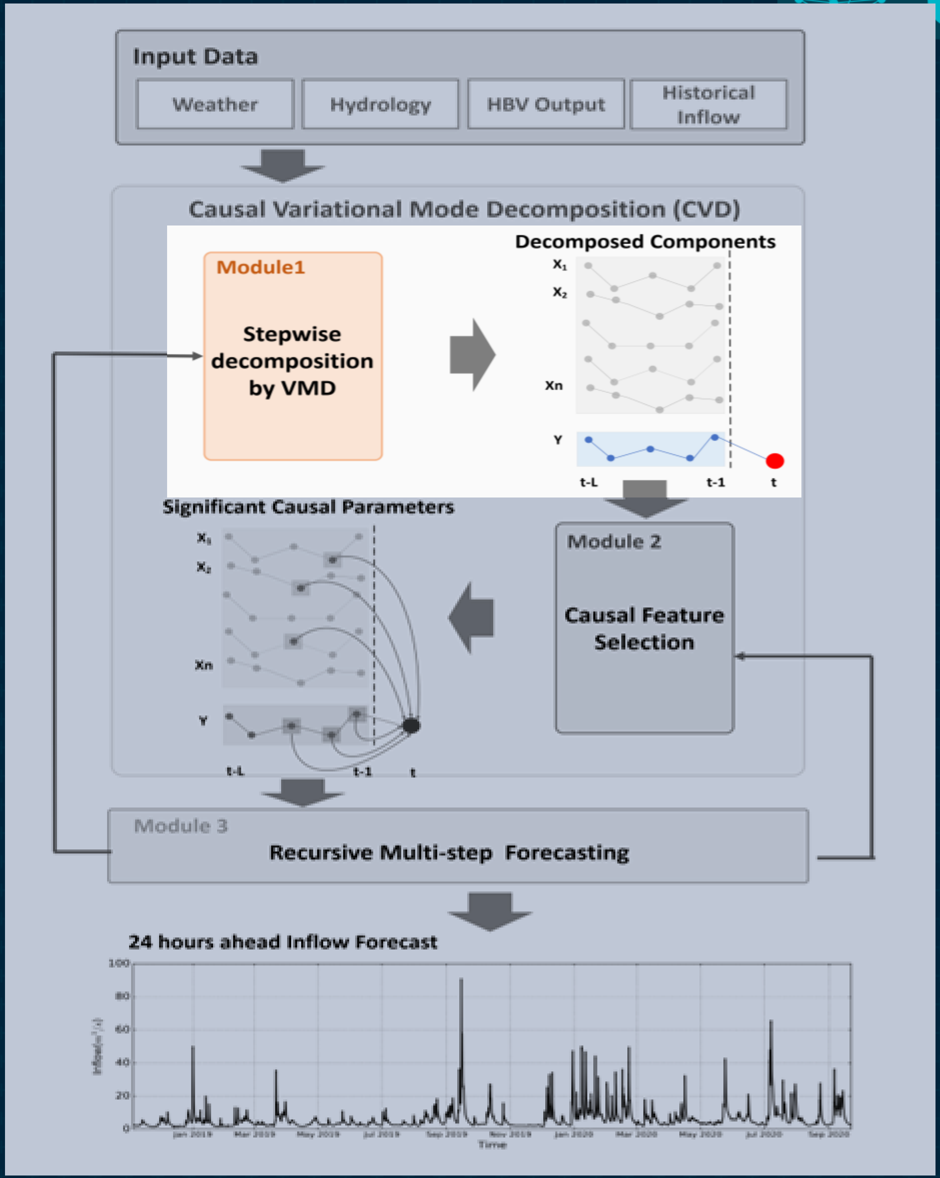
Methodology

Module 1: Stepwise decomposition by VMD:

- It is a non-wavelet signal processing technique
- It is a self-adaptive technique and suitbale for nonlinear and non-stationary data

Benefits:

- Reduce the complexity by breaking down a time-series into sub-elements
- Generate physically meaningful sub-elements



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Inflow Forecasting

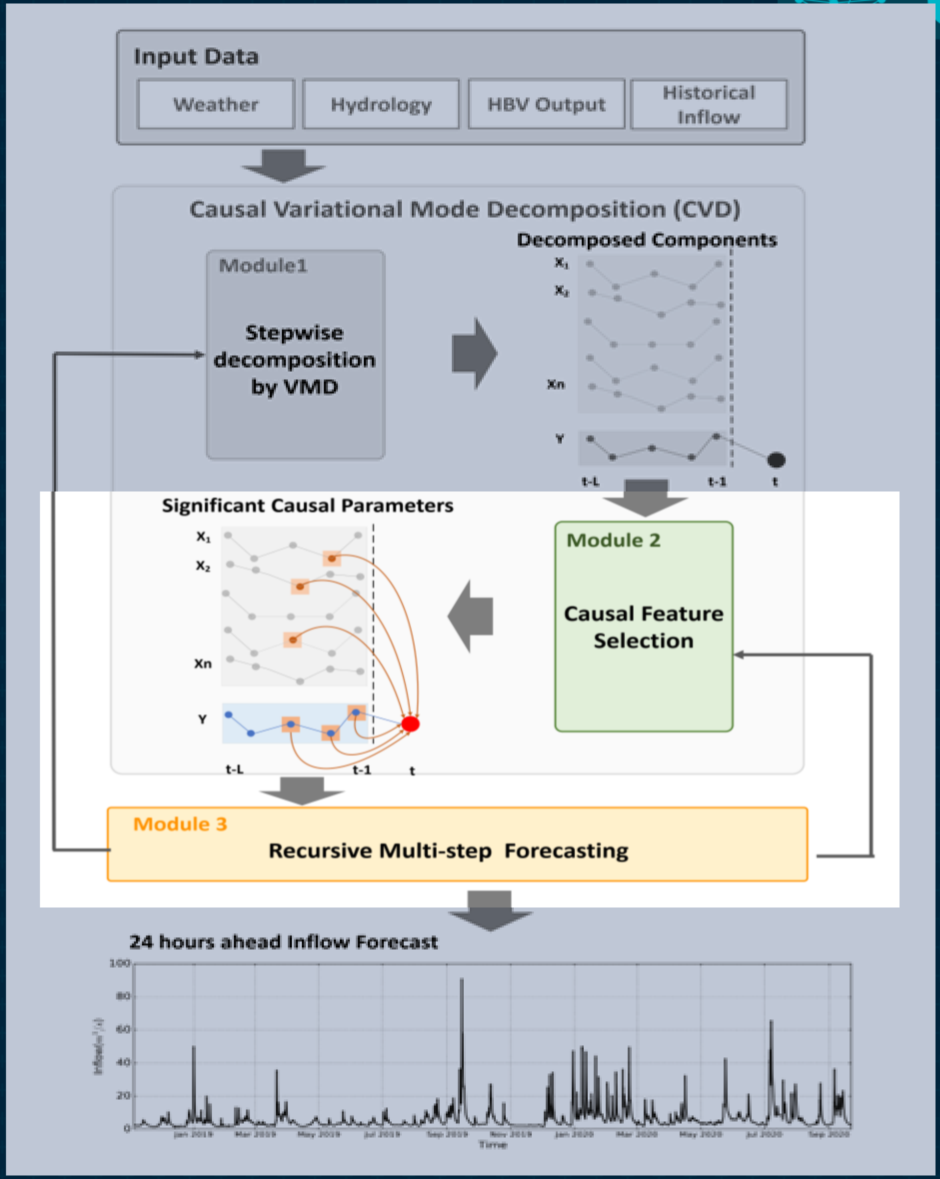
Methodology

Module 2, Causal feature selection:

- It is a feature selection method based on causal inference.
- It finds features which have maximum contribution to the target value (inflow).

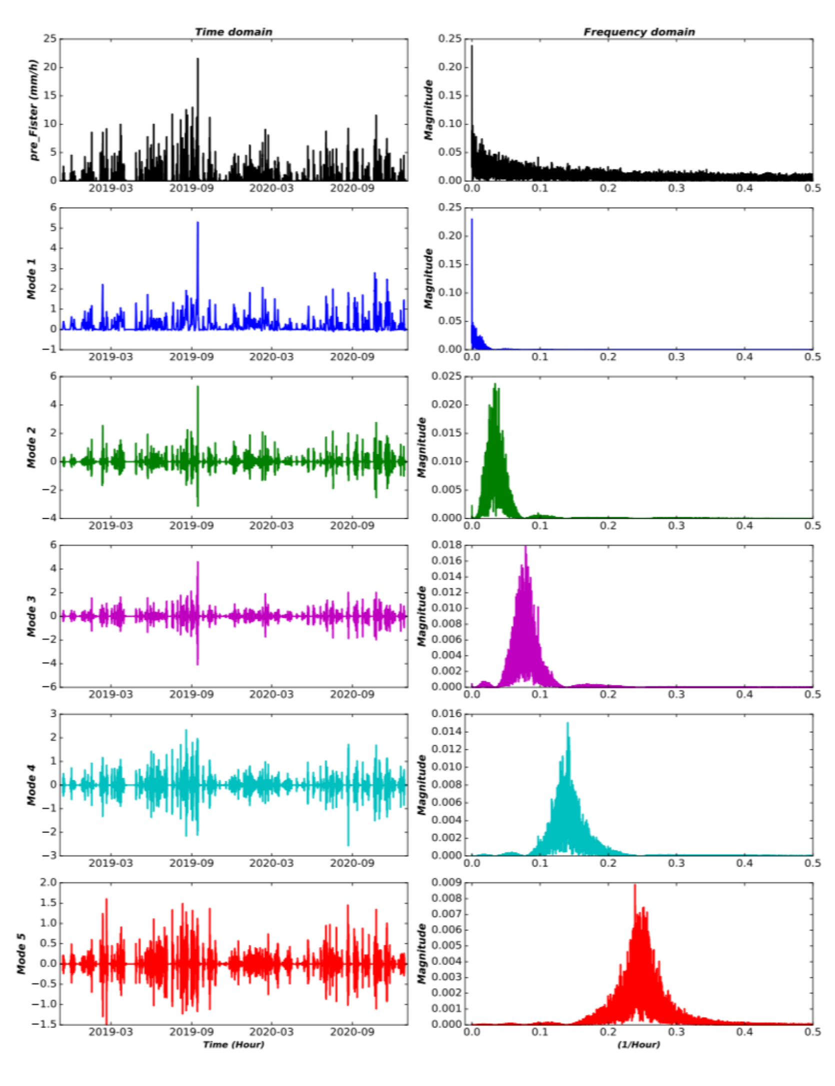
Benefits:

- Reducing the computational time by removing redundant features.
- Improving prediction performance.
- Improving understanding of the data (more explainability).

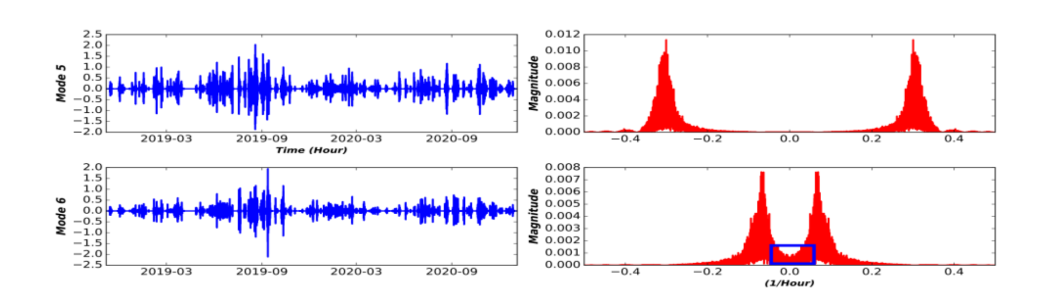


Example of AI Application : Inflow Forecasting
Results

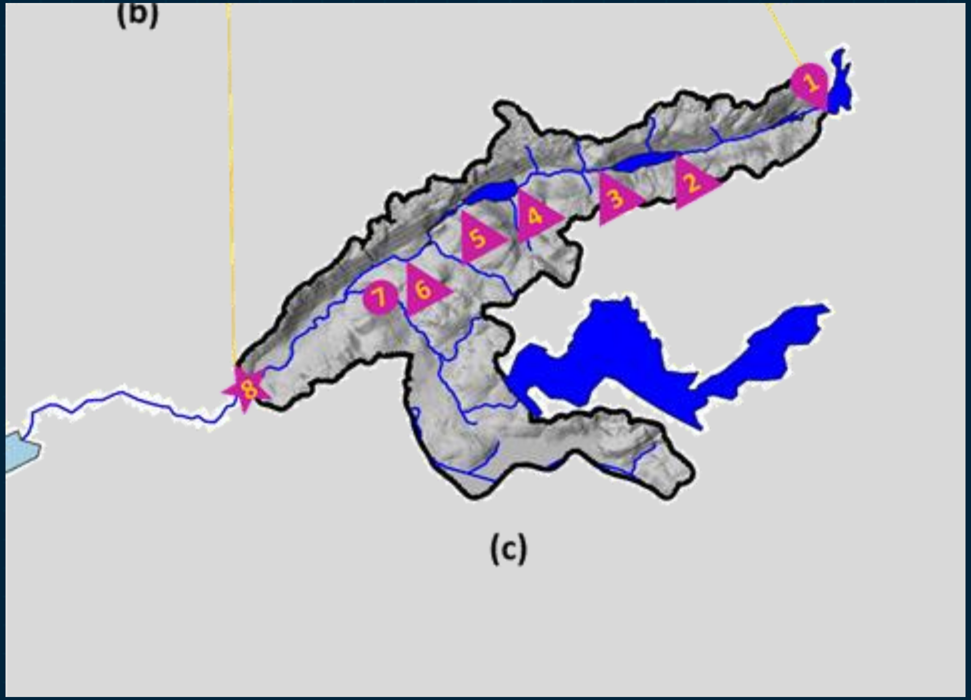
Location 8 Precipitation Decomposition



Why not more than 5 Modes?



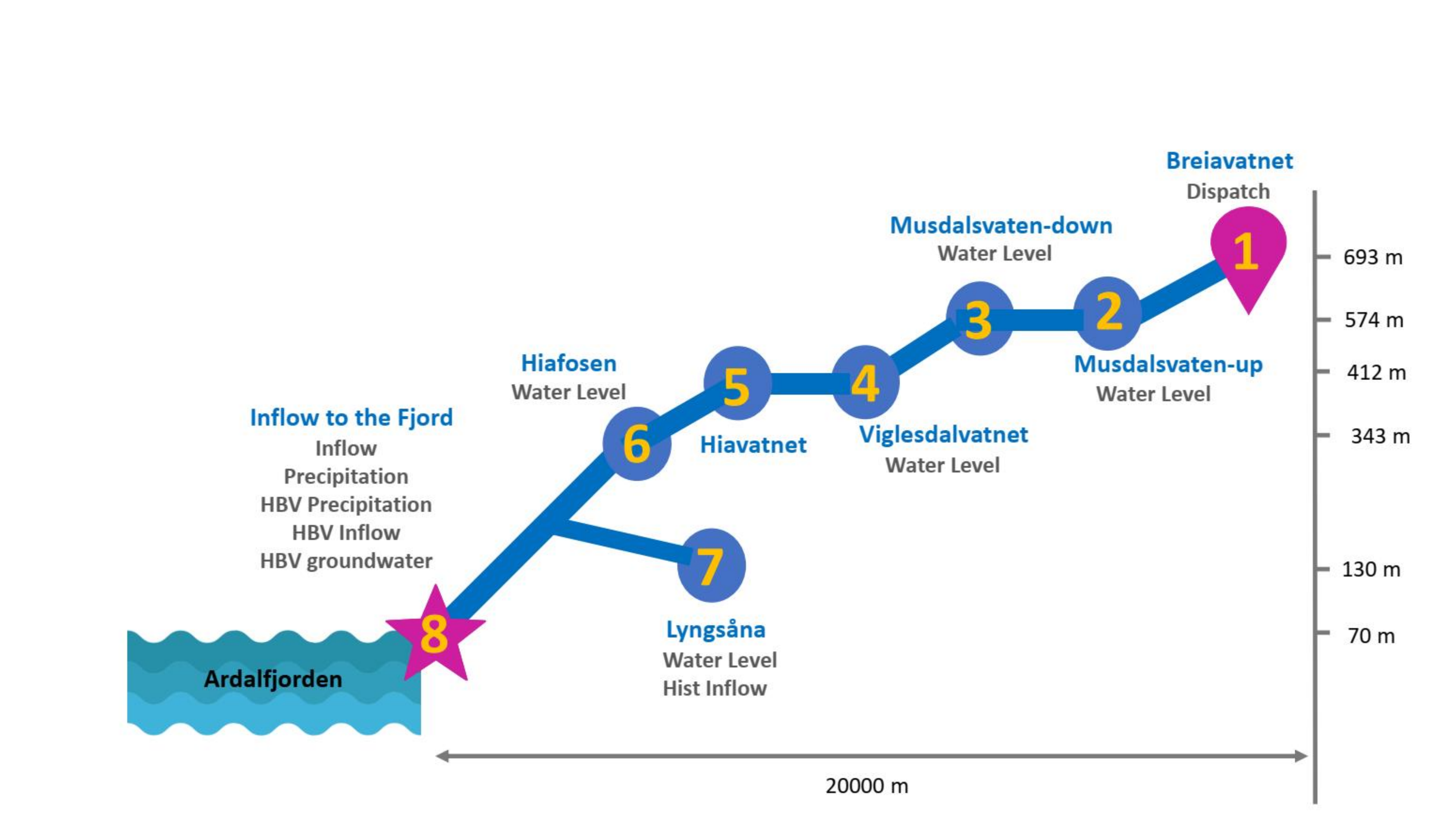
Inflow Forecasting
Results



Variable	Location	Mode	Lag
Precipitation	Location8 actual (Kalltviet)	3	4
	Average of catchment HBV	3 5	3 4
Inflow	Location7 actual (Lyngsåna)	2 3 4 5	6 1 12 12
	Location1 actual (dispatch)	3	12
	Average of catchment HBV	3 4 5	12 1 12
	Location8 HBV	1 2 3 4 5	1 1 5 2 2
Ground water	Average of catchment HBV	4	3
Water level	Location3 actual (Musdalsvatn down stream)	2 5	2 1
	Location7 actual	1 3	1 1
	Location6 actual (Hiafossen)	3 4 5	5 7 2
	Location5 actual (Hiavatn)	3 4 5	12 1 2
	Location2 actual (Musdalsvatn)	3	1

Selected Causal Variabels

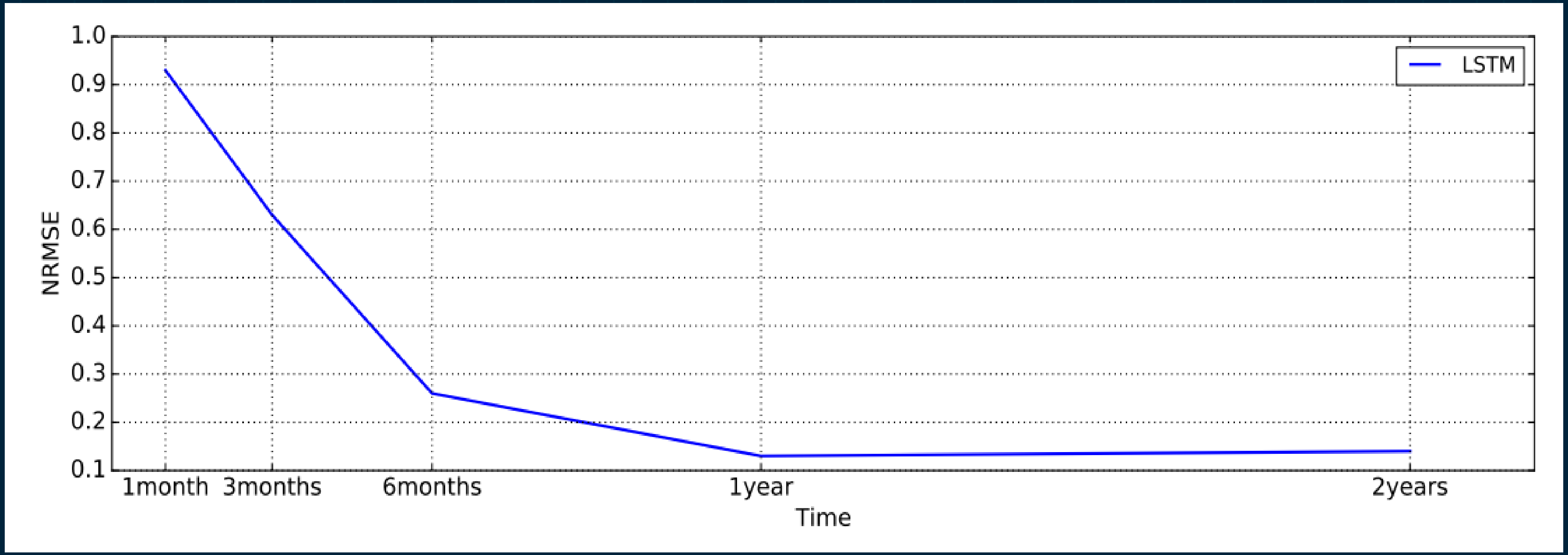
Inflow Forecasting
Results



Geo-spetial relationship between selected causal candidate

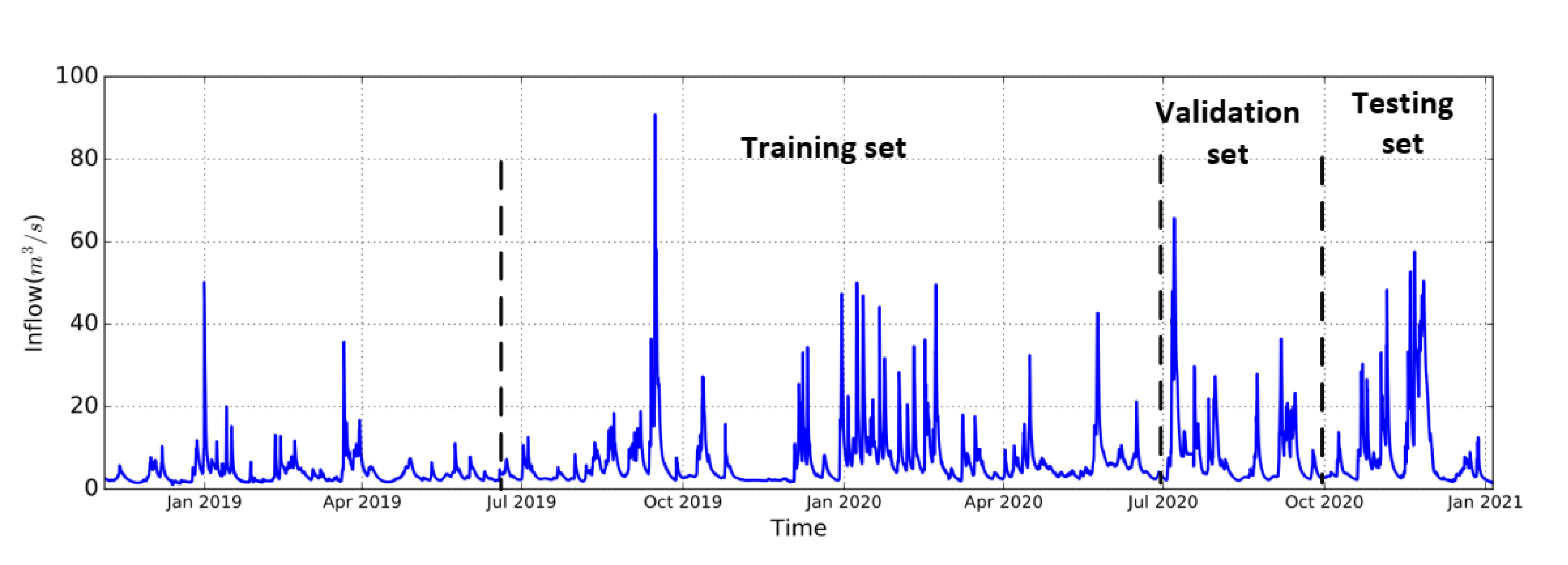
Inflow Forecasting
Results

Sensitivity analysis on different training horizons for inflow forecasting at Location 8



Inflow Forecasting
Results

Data splitting for training, validation and testing



Inflow Forecasting

Results

Input data composition vs. CVD performance for inflow day ahead forecasting

Senarios	Data	Model	period	NRMSE	Computational time (s)
1	Historic inflow	LSTM	t+24	1.7	547
2	Weather	LSTM CVD-LSTM	t+24	1.66 1.03	442 80
3	Weather+ hydrological data	LSTM CVD-LSTM	t+24	1.06 0.8	629 96
4	Weather+ hydrological+ HBV data	LSTM CVD-LSTM	t+24	0.68 **0.51**	900 **76**

70% improvement

25% improvement

Inflow Forecasting

Results

Comparison of CVD performance with different forecasting horizones.

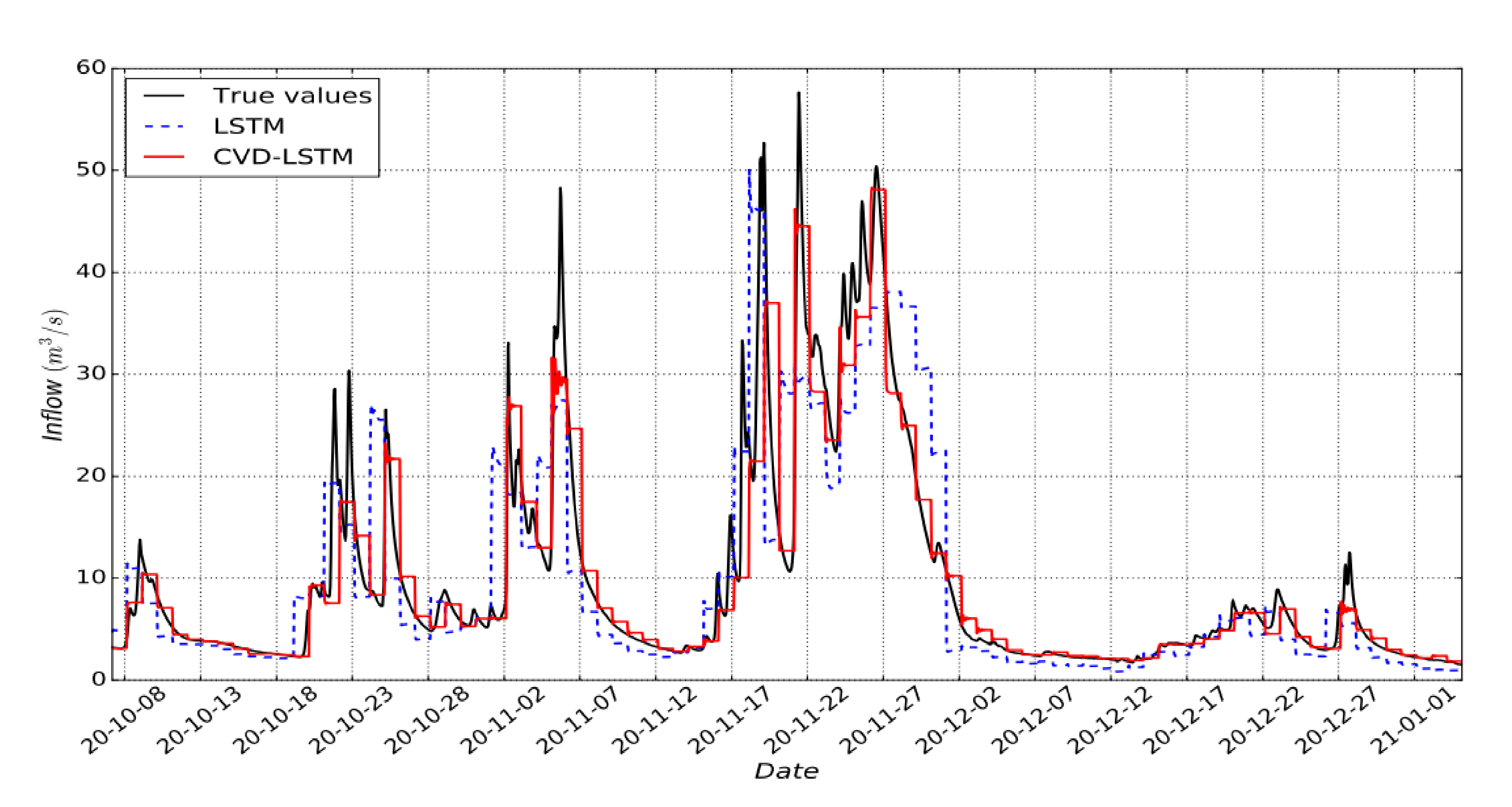
Models	Metrics	Future forecast horizons					
		t+1	t+2	t+6	t+12	t+18	t+24
CVD-RF	NRMSE	0.08	0.13	0.28	0.49	0.57	0.68
	NSE	0.98	0.98	0.93	0.8	0.73	0.61
	Std	0.9	1.27	2.71	4.71	5.53	6.63
CVD-LR	MSE	0.06	0.1	0.28	0.41	0.49	0.55
	NSE	0.99	0.99	0.93	0.85	0.79	0.75
	Std	0.7	1.02	2.65	4.02	4.8	5.27
CVD-MLP	MSE	0.12	0.17	0.32	0.41	0.51	0.53
	NSE	0.97	0.97	0.91	0.86	0.78	0.77
	Std	1.2	1.66	3	3.9	4,89	5.09
CVD-LSTM	MSE	0.1	0.16	0.31	0.38	0.46	0.51
	NSE	0.98	0.97	0.92	0.88	0.84	0.8
	Std	0.8	1.7	3.1	3.8	4.04	4.9

RF: RF: Random Forest ,R: Linear Regression, MLP: Multilayer perceptron, LSTM: Long Short-term memory.

Inflow Forecasting

Results

Inflow Values at Location 8



Publications:

Journal of Hydrology 613 (2022) 128265

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Research papers

Day-ahead inflow forecasting using causal empirical decomposition

Mojtaba Yousefi [a,*], Xiaomei Cheng [b], Michele Gazzea [a], August Hubert Wierling [a], Jayaprakash Rajasekharan [c], Arild Helseth [d], Hossein Farahmand [c], Reza Arghandeh [a]

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Short-term Cascade Inflow Forecasting using Causal Multivariate Variational Mode Decomposition

Mojtaba Yousefi[1,*], Jinghao Wang[2,+], Øivind Fandrem Høivik[3,+], Jayaprakash Rajasekharan[2,+], August Hubert Wierling[1,+], Hossein Farahmand[2,+], and Reza Arghandeh[1,+]

Recent changes in climate affect patterns and uncertainties associated with river water regimes which have a huge impact on hydropower generation and reservoir storage operation. Hence, reliable and accurate short-term inflow forecasting is vital for better facing climate effects and improving hydropower performance. This paper proposes a Causal Variational Mode Decomposition (CVD) preprocessing framework for the multi-step ahead inflow forecasting problem. In other words, CVD is a preprocessing feature selection framework which is built upon multiresolution analysis and causal inference. The CVD can reduce the computation time while increasing the forecasting accuracy by down-selecting the most relevant feature to the target value (inflow in a specific location). Moreover, the proposed CVD framework is a complementary step to any machine learning-based forecasting method as it is used four different forecasting algorithms in this paper. We validated the CVD using actual data from a river system downstream of a hydropower reservoir in the southwest of Norway provided by Lyse Produksjon AS company, one of the largest electricity producers in Norway. The experimental results prove that using CVD improves the day-ahead forecasting accuracy by almost 49%. We will investigate other possible variables and other causal inference methods for future work.

Takeaway

- Climate changes, the presence of renewable energy and the complexity of electricity price market have a huge impact on the hydropower scheduling problem.
- Causal AI can improve hydropower scheduling problems by reducing complexity, uncertainties and time consumption.
- An example of using Causal AI for forecasting water inflow for a dam-regulated reservoir is presented

Thank You

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