Multi-Objective Forecast-Informed Reservoir Operation at different time scales using a Neuro-Evolutionary algorithm
Which are the optimal aggregation times? The Lake Como case study

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[1] Motivation

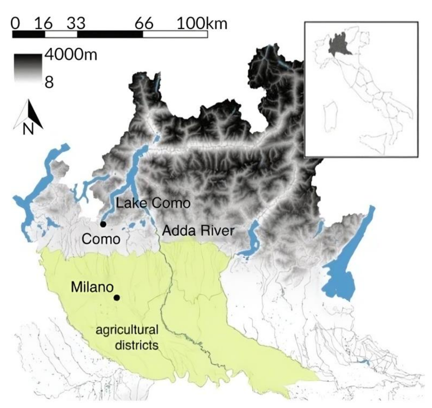
- How to determine optimal forecast products for multi-objective reservoir operations?
- How are they used across different trade offs?
- How does their influence vary over the year?

Proposed solution: automatic selection of the forecasts for each policy

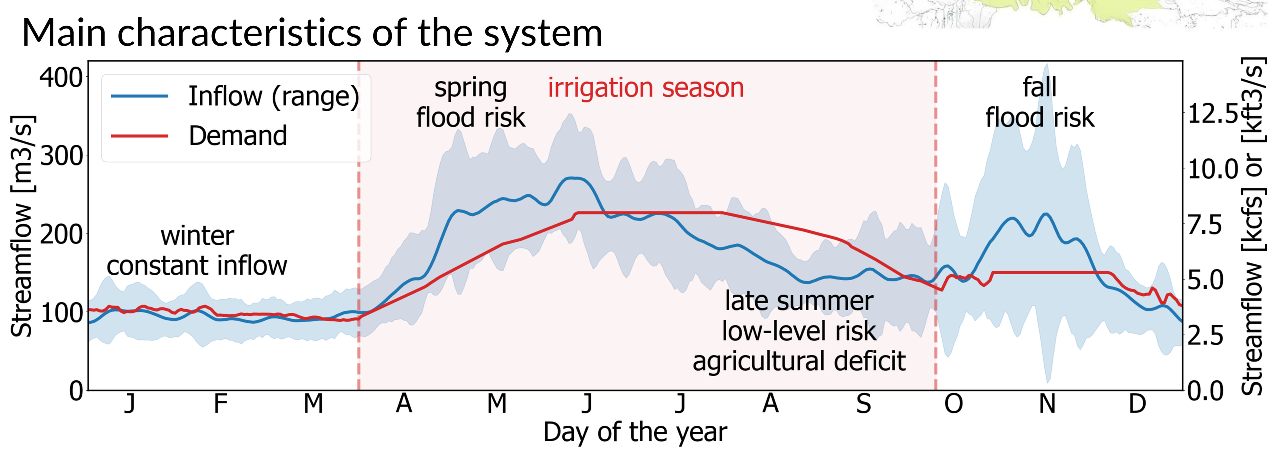
Optimal aggregation times depend on the chosen trade off

[2] Case study

Lake Como, a regulated lake in Northern Italy for flood control, water supply and low-level control



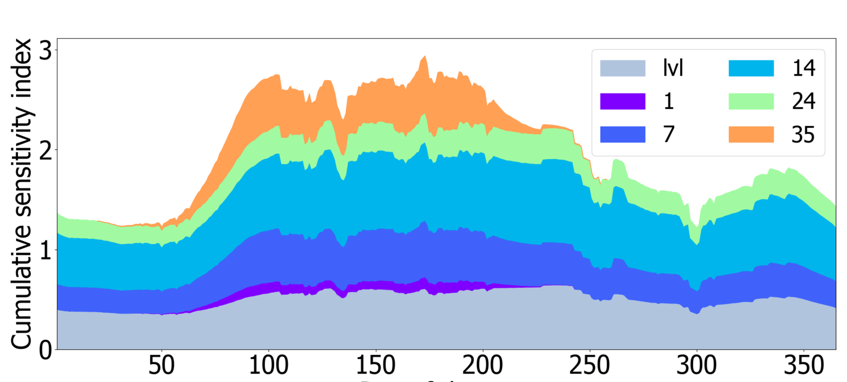
Main characteristics of the system



[3] Methods

Forecast Products Dataset → Concurrent multi-objective policy and forecast selection optimization → Trade off time-varying sensitivity analysis

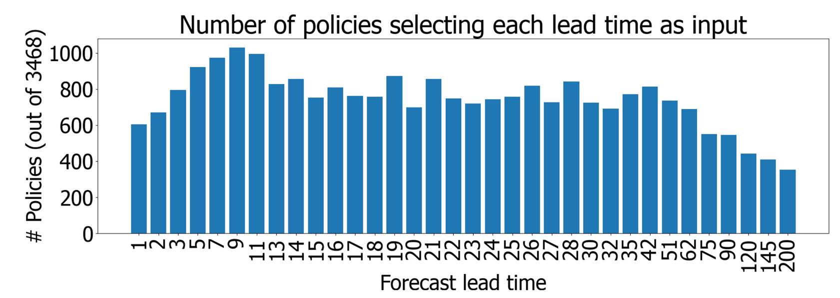
1. Perfect streamflow forecasts aggregated at different lead times.
2. Policies optimization is performed by mutating the architecture of the networks, including its connection to different inputs.[6]
3. Each policy trajectory is perturbated at each time step, for each input, and the change in the release is used as sensitivity index.[5]



This figure shows a single compromise policy and the thickness shows the impact of level and forecasts through the year.

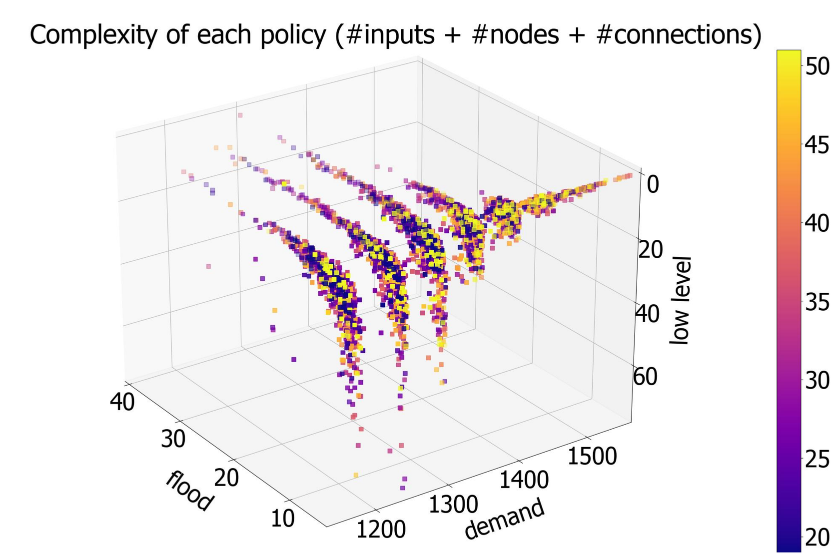
[4] Results

Aggregation times based on selected input density. Average of 100 experiments.



Policies complexity in 3D objective space.

- Layered shape means necessity for more precise ε-approximation of the Pareto front.
- Focusing on the extremes, no clear complexity pattern emerges.



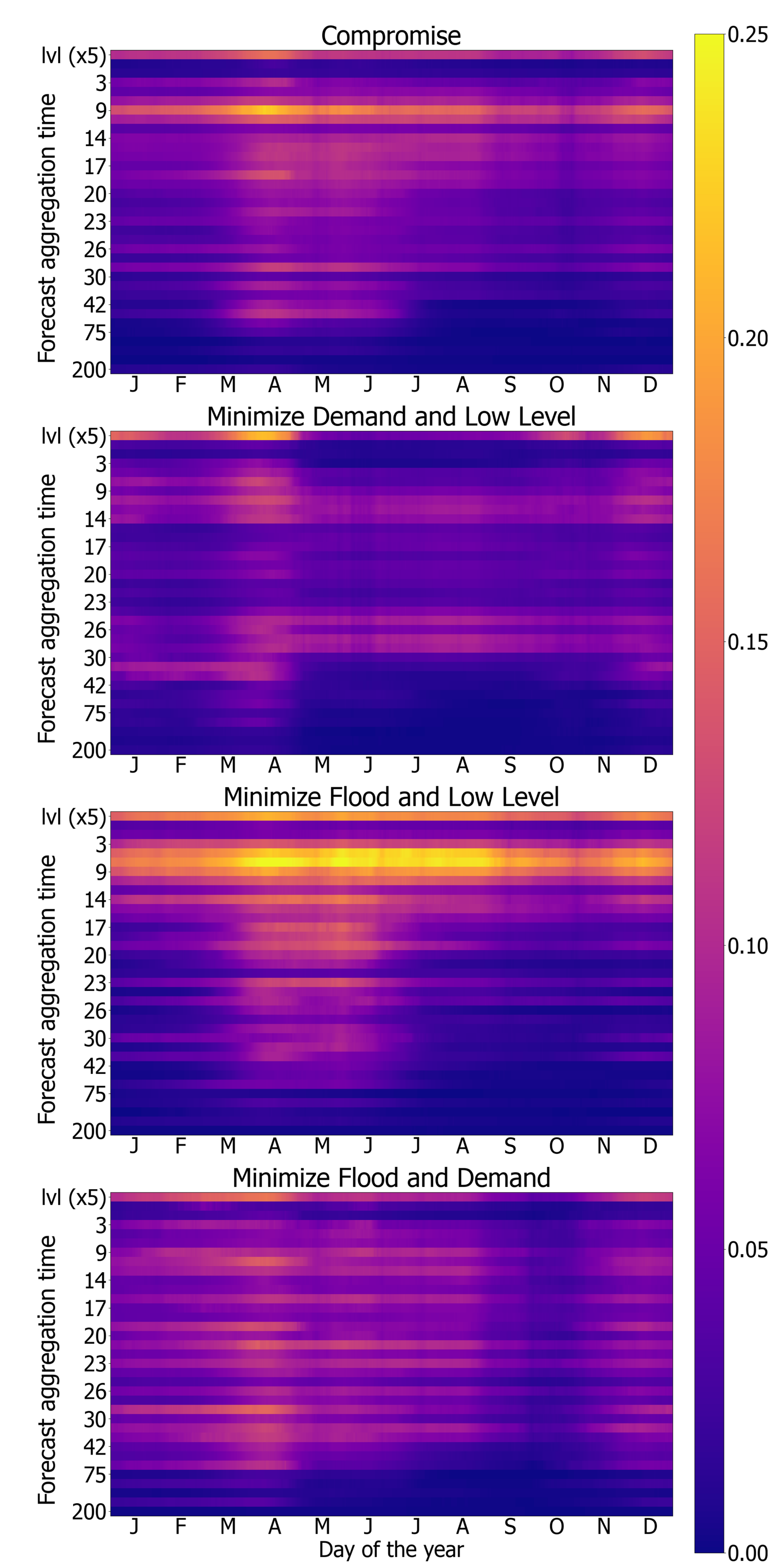
Heatmaps of the impacts of the level (scaled) and each forecast input throughout the year for main trade offs.

- Medium range preference throughout the year.
- Subseasonal forecasts added in spring in preparation of dry summer months.

- Dominance of level input.
- Medium range and subseasonal preference throughout the year.

- Short-to-medium range strong preference.
- Subseasonal forecasts added in spring in preparation of dry summer months.

- No clear preference.
- Greater impact of forecasts in spring rather than in fall.



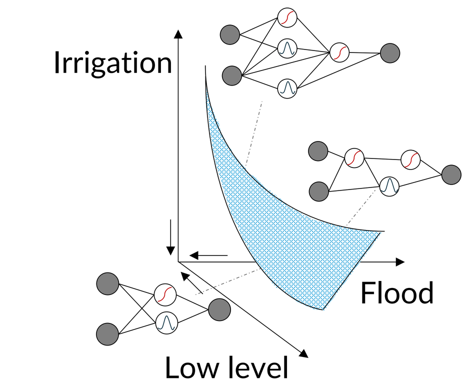
Appendix and future research

[5] Formulas:

- $x_{i,t}^{+}$ ($x_{i,t}^{-}$) positive (negative) perturbation of input i at time t
- $r_{i,t}^{+}$ ($r_{i,t}^{-}$) positive (negative) release with input $x_{i,t}^{+}$ ($x_{i,t}^{-}$)
- $\Delta_{i,t} = \frac{r_{i,t}^{+} - r_{i,t}^{-}}{x_{i,t}^{+} - x_{i,t}^{+}}$ normalized delta of input i at time t
- $S_{i,t} = |\Delta_{i,t}|$ sensitivity index

[6] NEMODPS Principles:

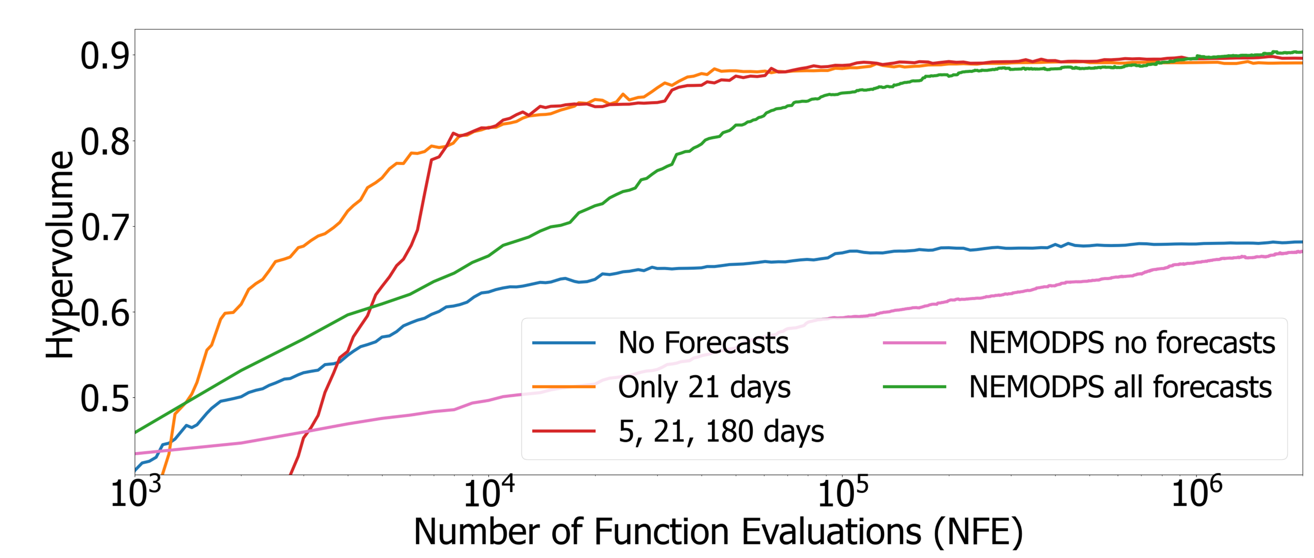
- Each policy in the Pareto front is optimized for architecture (inputs, layers, nodes, connections) and parameters.
- No limits on the number and type of inputs to the NN.
- Future work may update the neuro-evolutionary optimizer



In the figure: how networks differ across the Pareto front.

[7] Comparison with fixed specified inputs:

- NEMODPS shows better results than using a method with fixed selected inputs (EMODPS), given sufficient training time.
- NEMODPS has worse results than EMODPS with no forecasts. Probably due to the longer time required for the optimization.
- NEMODPS has the advantage of not requiring expert knowledge in the selection of the inputs, contrary to EMODPS.
- Future work may use real forecasts and extend training time.



In the figure: improvement in hypervolume during training (number of objective function evaluations). NEMODPS with and without forecasts is compared to its predecessor (EMODPS) with one and three fixed forecasts selected from previous works.

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