Dynamical retrieving of most informing inputs to multiobjective reservoir policy design with inconsistent dynamics

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[1] ABSTRACT

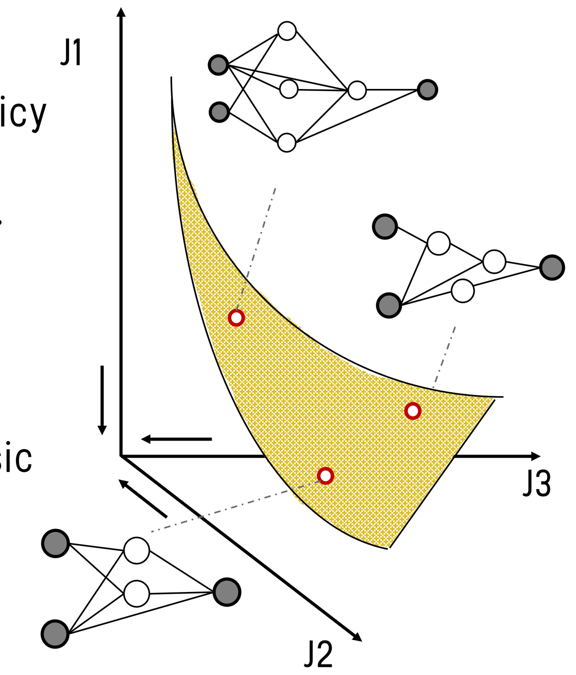
Advances in monitoring and forecasting water availability offer a cost-effective **opportunity to enhance water system resilience**. By enriching the basic information set traditionally used to design reservoir operating policies (i.e., time index and reservoir level) operations could anticipate the onset of abnormal hydrologic conditions (wet or dry years) and prepare for it. Yet, numerous candidate forecasts may potentially be included in the operation design, and the best input set is not inferable a priori. Besides, in multi-purpose systems **the most appropriate information set likely changes according to the objectives tradeoff.** In this work, we contribute a novel Machine Learning approach to ingrain an Input Variable Selection routine into the policy design, in order to retrieve the best policy input set online (i.e., while learning the policy), and Pareto-dynamically. The selected policy search routine is the Neuro-Evolutionary Multi-Objective Direct Policy Search (NEMODPS) which generates flexible policy shapes adaptive to changes in the policy input set. This approach is demonstrated in the Omo basin, in southern Ethiopia, where the effects of climatic oscillations offer a source of predictability of hydrological extremes. We developed a dataset of candidate policy inputs comprising streamflow and precipitation forecast at multiple spatio-temporal scales. Preliminary results suggest that the **appropriate addition of information improves the policy performance**, and different tradeoffs are characterized by different selected information.

[2] FRAMEWORK

1a. Baseline Operating Policies (BOP)

Method: Neuro Evolutionary Multi-Objective Direct Policy Search (NEMODPS, Zaniolo et al., 2019).

Result: optimal operating policies with dynamic structure selection, informed with a basic input set, i.e., time and state of the system (lake level).



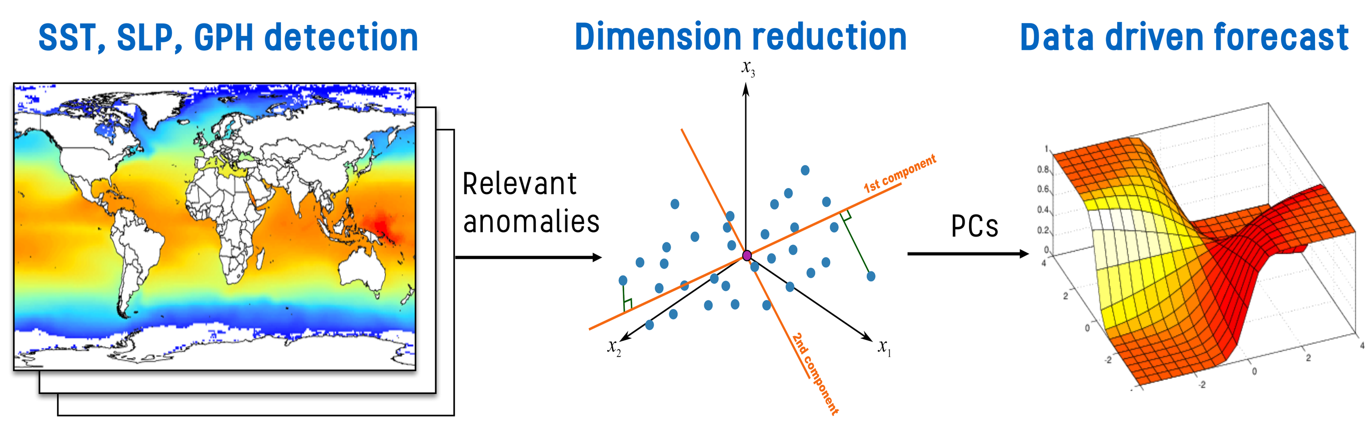
1b. Perfect Operating Policies (POP)

Method: Deterministic Dynamic Programming.

Result: optimal policies with perfect future foresight.

2. Hydroclimatic forecasts at multiple time and spatial aggegations

Method : (i) detection of relevant anomalies in gridded global datasets of SSTs, SLPs, GPH, that correlate significantly to local hydroclimatic anomalies, (ii) dimension reduction of relevant anomalies via PCA, (iii) calibration of a multi-variate non-linear forecast model.



Result: a dataset of data-driven season-ahead forecasts of local hydroclimatic anomalies at different spatio-temporal aggregation.

Baseline operating policy

Perfect operating policy

Dataset of candidate policy inputs

3. Policy Input Selection

Method: Iterative Input Selection (IIS, Giuliani et al., 2015).

Result: Identification of the most informative input for every baseline policy, by selecting the candidate that most correlates to the difference between baseline and perfect policy.

4. Informed Operating Policies (IOP)

Method: NEMODPS (Zaniolo et al., 2019).

Result: selected inputs are plugged into the relative baseline policy via NEMODPS' automatic structural complexification. Resulting informed policies have the ability to anticipate hydroclimatic anomalies.

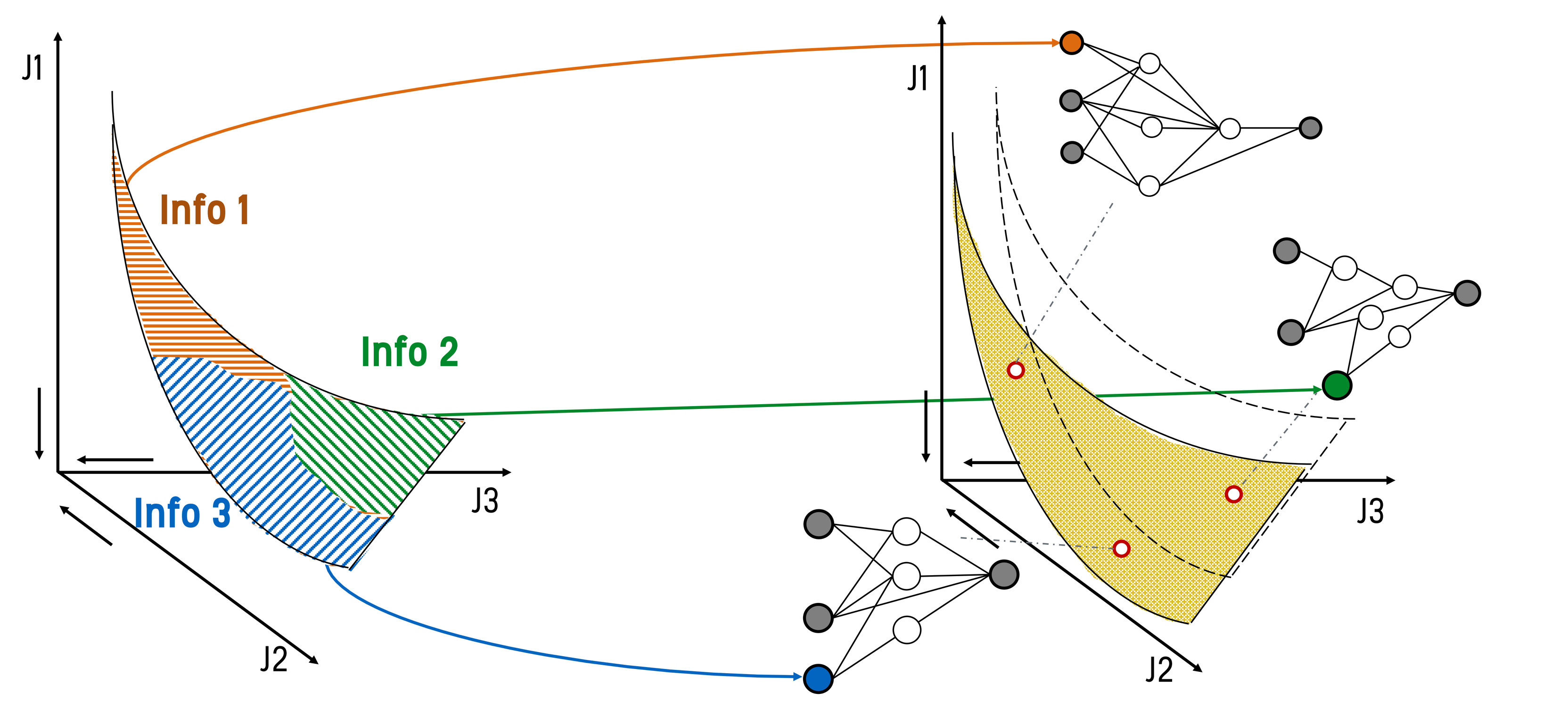


Figure 1. Procedure flowchart.
1. Design of Baseline and Perfect operating policies, informed with a basic input set and a perfect future foresight, respectively.
2. A dataset of candidate policy inputs is populated with long term hydroclimatic forecast produced via machine learning.
3. The dataset is searched via feature selection to identify the most informative policy inputs Pareto-dynamically.
4. Selected policy inputs are ingrained in baseline policies originating Informed operating policies.

[3] STUDY AREA: THE OMO BASIN

Figure 2. The Omo river originates in the Ethiopian highlands and flows southwards through the Omo valley. In correspondence to the Kenyan border, it contributes about 90% of lake Turkana annual inflow, while forming a large delta where seasonal floods support a **biodiverse ecosystem** and local **livelihood**. The recently constructed Gibe III megadam regulates the river hydrology for **hydroelectricity** generation and large scale **irrigation**, yielding to hydrological alterations downstream and social tensions.

[4] RESULTS – HYDROCLIMATIC FORECASTS

Accuracy ρ	daily, AR			monthly, climatic		
	1 d	7 d	14 d	1 m	3 m	6 m
Total Inflow	0.999	0.988	0.960	0.851	0.858	0.749
Lateral inflows	0.996	0.961	0.888			
Upper Omo inflow	0.987	0.931	0.903	0.911	0.927	0.903
Prec upper Omo				0.911	0.960	0.958
Prec lower Omo				0.958	0.778	0.613

Table 1. Forecast accuracy in crossvalidation as measured by the coefficient of linear correlation **ρ**. Daily forecasts are designed with an autoregressive model, while monthly forecast are produced with the as described in point 2 of the flowchart with a monthly timestep.

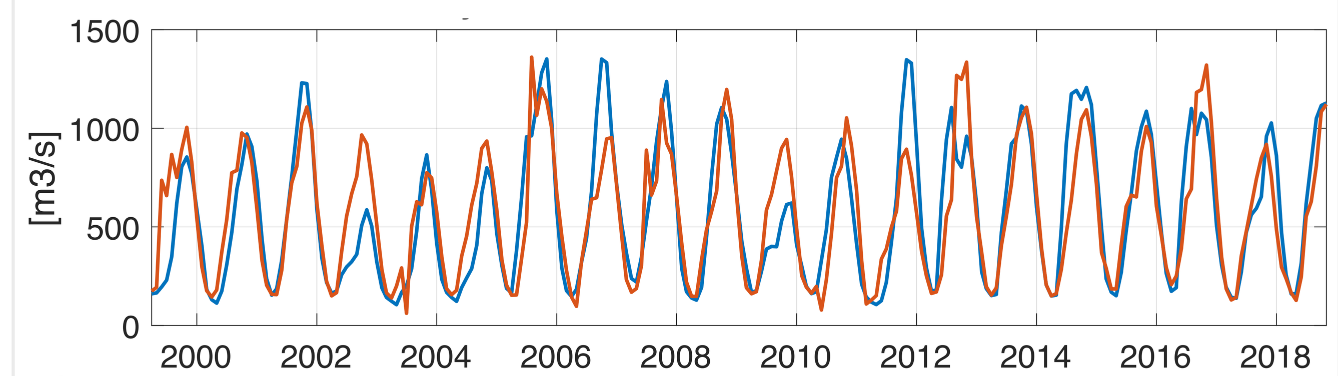


Figure 3. Monthly forecast for 3 months cumulated total inflow in the basin. The forecasts succeeds in **discerning dry and wet seasons**.

[5] RESULTS – INFORMED OPERATING POLICIES

Figure 4. Comparison between the performance of BOP, IOP, and POP with respect to the three competing objectives for Environment, Irrigation, and Hydropower Production (HP). Informed policies dominate Baseline policies indicating that **conditioning operations** with appropriately selected information **of upcoming water availability can reduce conflicts**.

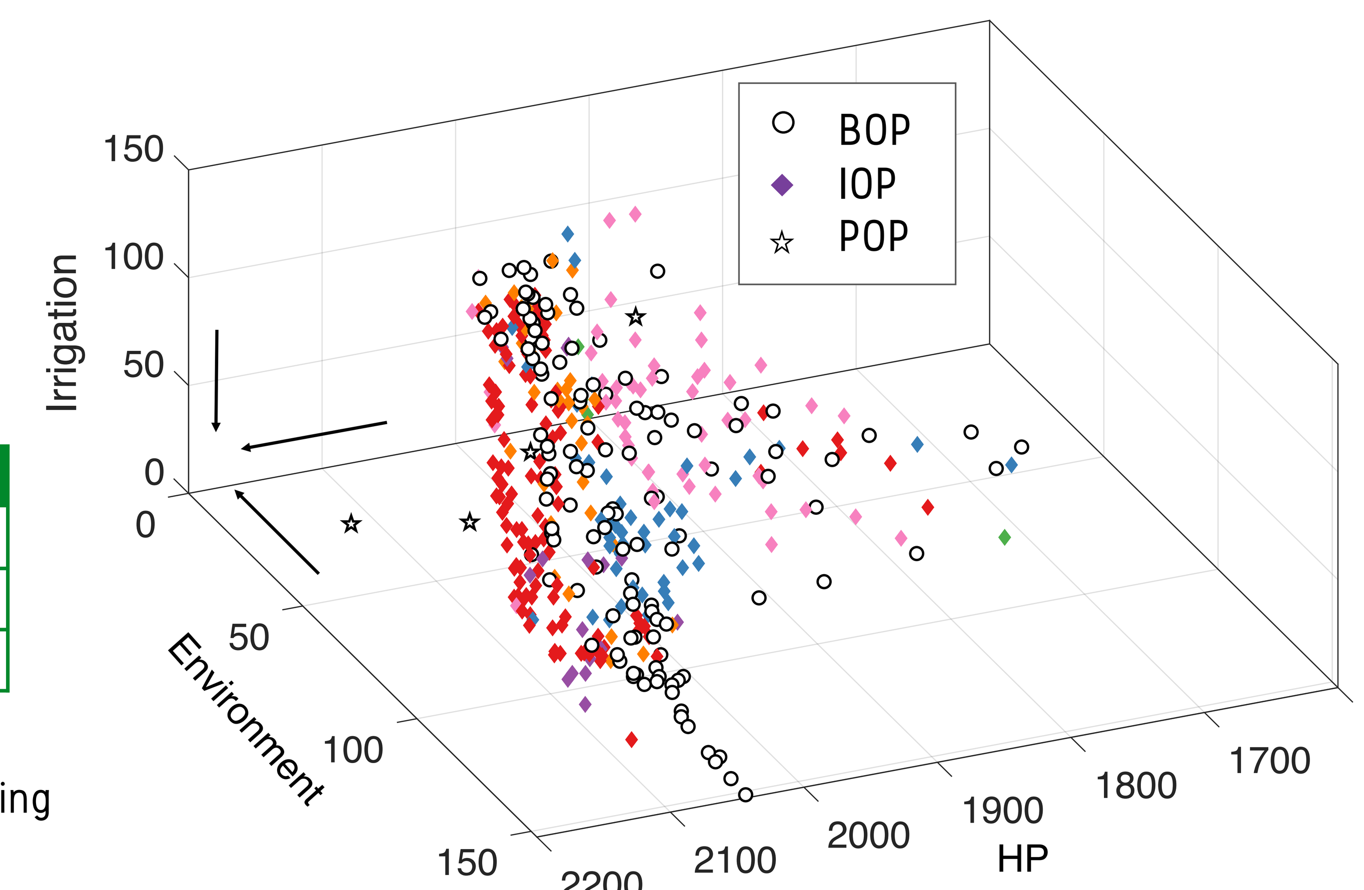
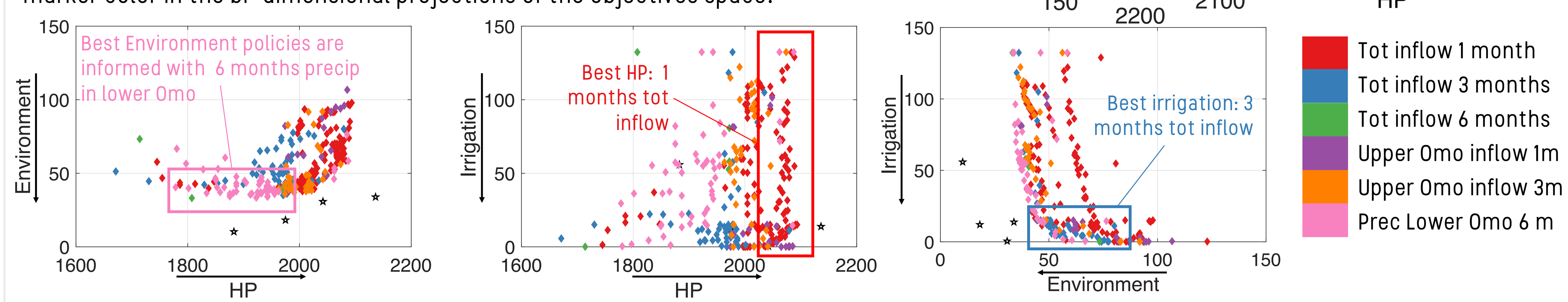


Table 2. The hypervolume metric captures the normalized improvement of IOP with respect to BOP.

Policy	Hypervolume
BOP	0.704
IOP	0.751
POP	1

Figure 5. The selected policy input is represented by the corresponding marker color in the bi-dimensional projections of the objectives space.



[6] HIGHLIGHTS

1) Climatic anomalies related to ocean temperatures and pressure offer an important **source of predictability for local hydroclimatic variability**, especially in regions where the impact of teleconnections is relevant.

2) Informing operating policies with appropriately selected information offers an unconventional **cost-effective opportunity to reduce conflicts** in water systems.

3) In multipurpose systems, the **most informative input set** varies according to the objective tradeoffs.

REFERENCES

(1) Zaniolo et al., (2019), IEEE Transactions on Neural Networks and Learning Systems, under review.
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