An inverse nested approach to optimize planning and operation of water reservoir systems

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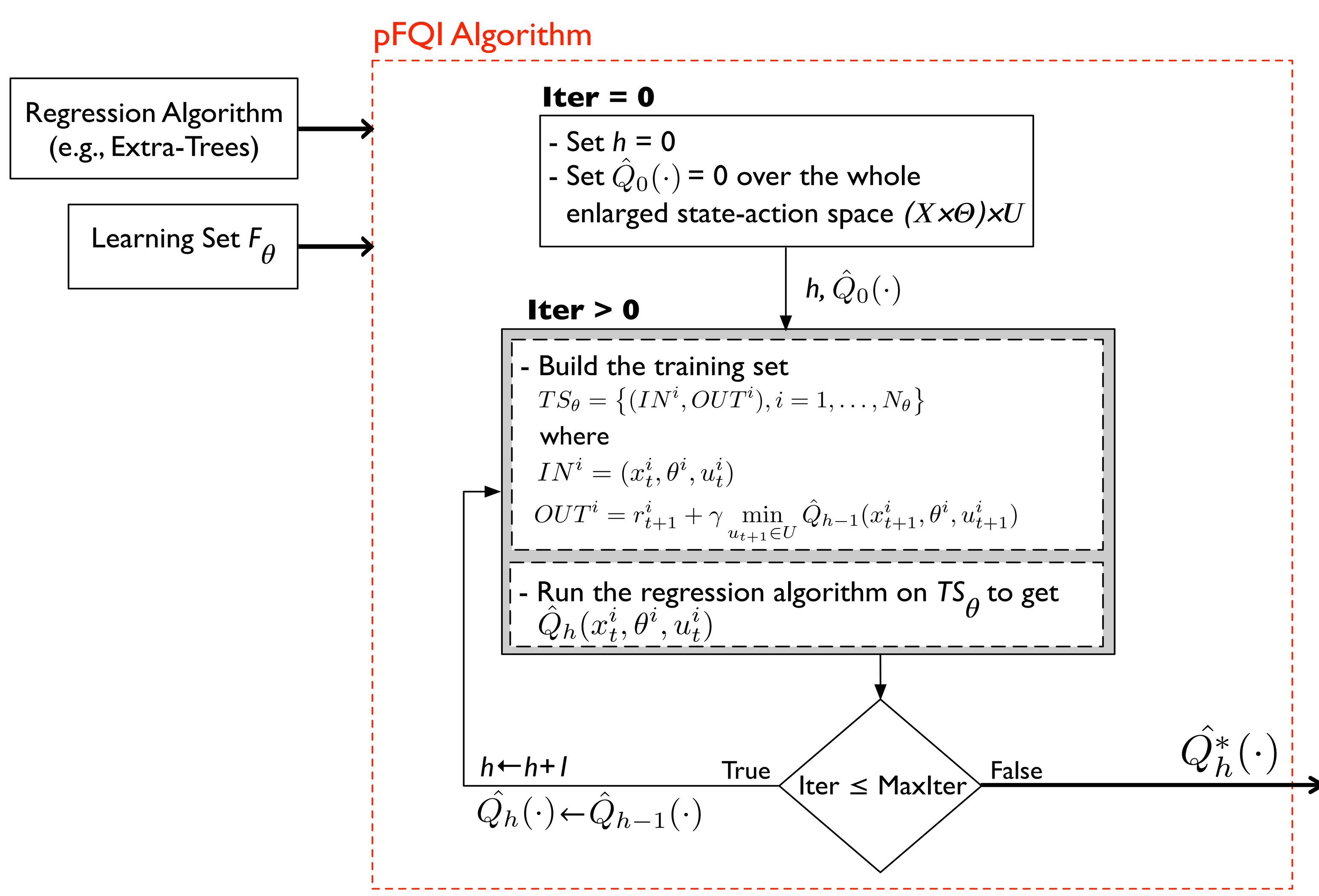
[1] ABSTRACT

In the water resources management scientific literature and practice, **planning** (i.e., reservoir sizing) and **management** (i.e., reservoir operation) are usually considered as two distinct problems and are, generally, coupled by an optimal management problem - designing the optimal operating policy for a given reservoir size - into a global optimization routine - to explore the space of the sizes. These two problems are solved iteratively, causing the computational cost to increase with the number of designs considered. This work contributes an **inverse nested approach**, which first optimizes a single operating policy parametric in the reservoir size and, then, searches the best sizing under its optimal operations as provided by the parametric policy previously designed. The proposed approach relies on a novel algorithm, called **Planning Fitted Q-Iteration** (pFQI), and is tested on a numerical case study of reservoir sizing, where the water reservoir must be planned and managed to meet downstream users' water demand at a minimum construction cost of the reservoir itself. The set of Pareto-efficient reservoir sizes identified via inverse nested approach is **compared** with the optimal ones designed through a **traditional optimal sizing technique** (i.e., Behavior Analysis).

[2] PLANNING FITTED *Q*-ITERATION ALGORITHM



$$\hat{\pi}_h^* = \arg\min_{u_t \in U} \hat{Q}_h^*(x_t, \theta, u_t)$$

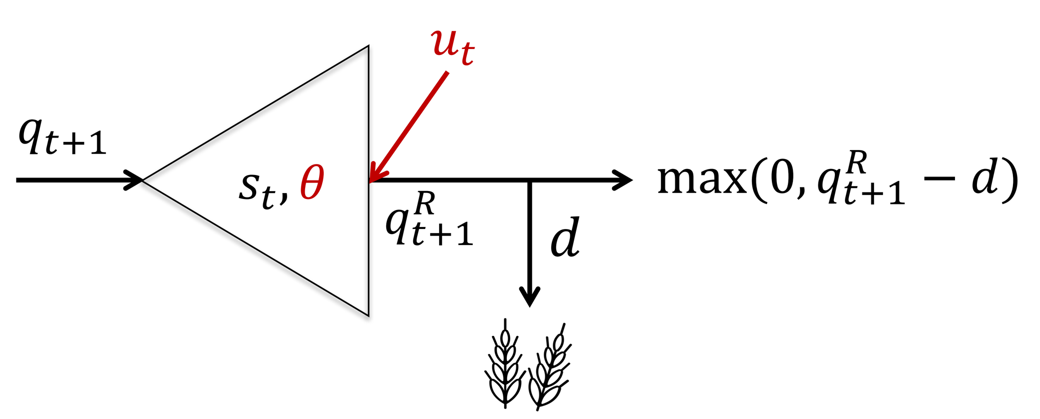
Figure 1. Schematic representation of the Planning Fitted *Q*-Iteration algorithm. h is the number of iterations (*Iter*), whose maximum number (*MaxIter*) has been set to 40.

Output: approximation of the optimal action-value function $\hat{Q}_h^*(\cdot)$ generalized over the enlarged state-action space $(X \times \Theta) \times U$ → approximation of the optimal operating policy $\hat{\pi}_h^*$ that minimizes $\hat{Q}_h^*(\cdot)$ at each time-step t.

For more details regarding the original FQI algorithm and its further applications, see [1], [2] and [3].

[3] SYNTHETIC WATER RESERVOIR

Figure 2. Schematic representation of the system. An inflow time-series is given as input to a controlled water reservoir, which has to be planned and managed for ensuring reliable water supply to downstream users at a minimum construction cost of the reservoir itself.



Input data:
q_{t+1} = inflow time-series
d = downstream irrigation water demand of 370 m^3/s

Decision variables:
θ = reservoir size [m^3]
u_t = reservoir release decision [m^3/s]

State variable:
s_t = reservoir storage [m^3]

Output variable:
q_{t+1}^R = effective release [m^3/s]

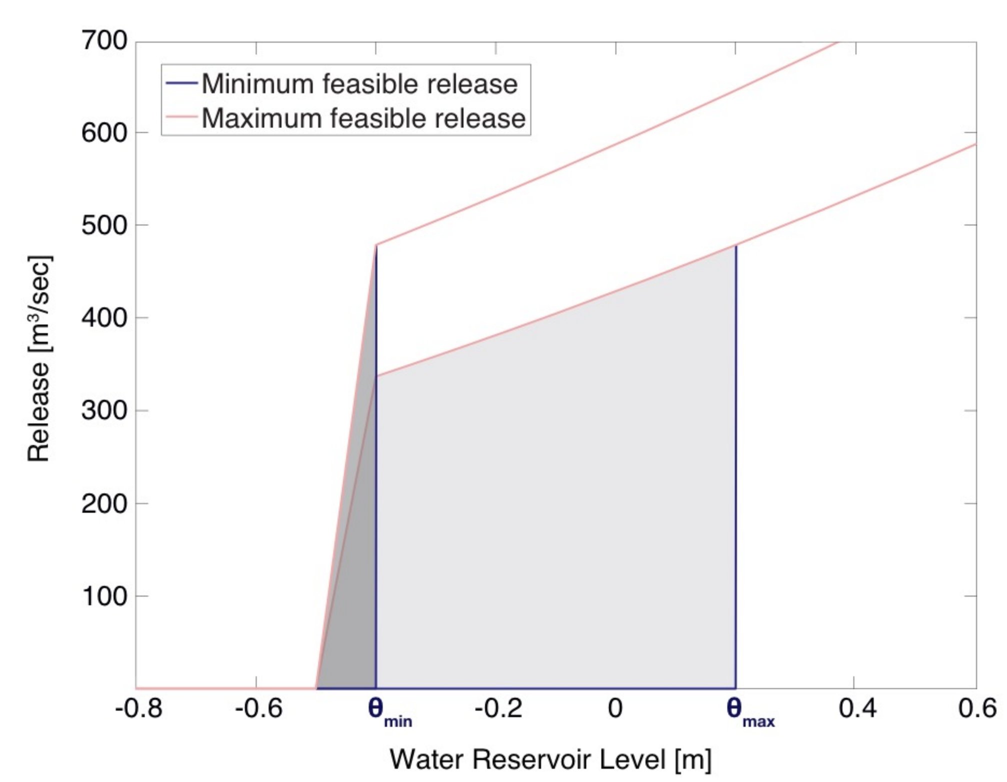


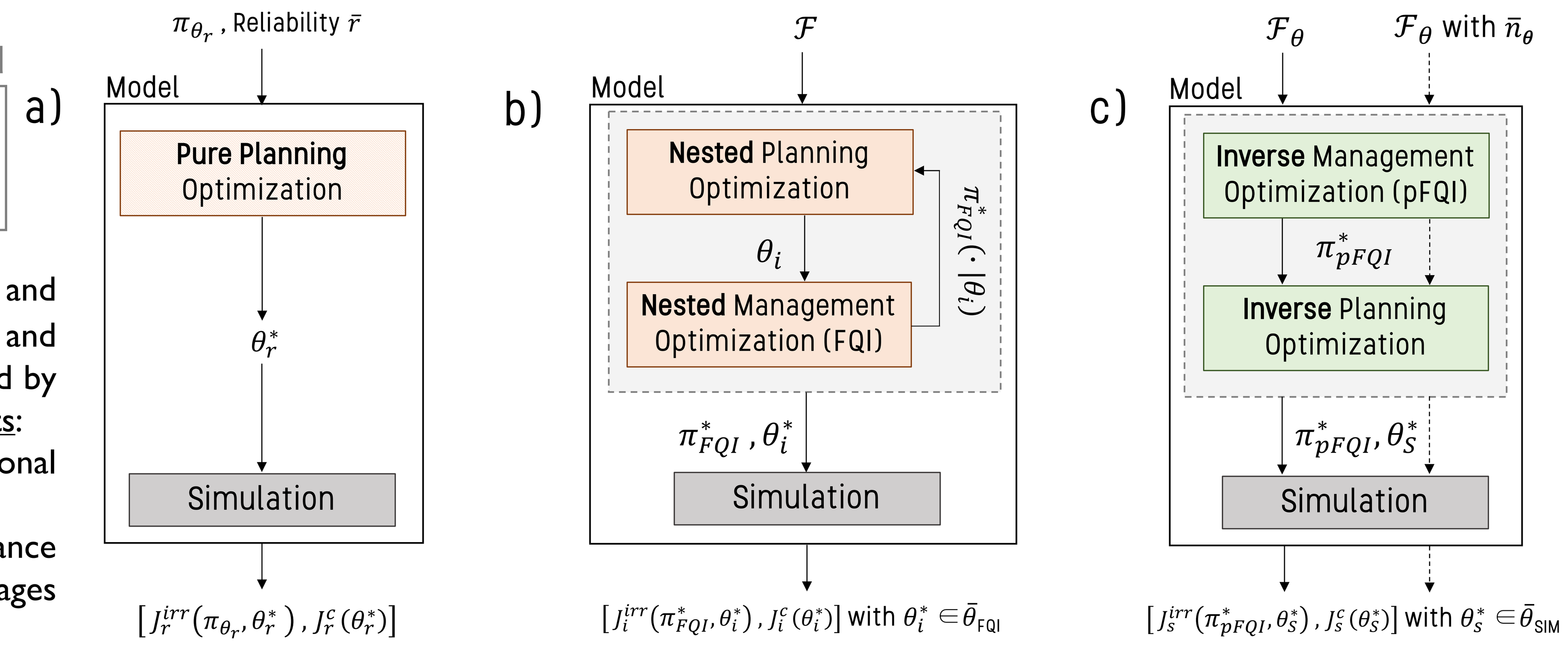
Figure 3. Zone of operation discretion (decision space) bounded by the maximum and minimum feasible release functions for the operation of two distinct water reservoirs that differ in size ($\theta_{min} < \theta_{max}$). The release decision space (grey filled area) enlarges proportionally to the water reservoir size considered.

[4] EXPERIMENT SETTING

Figure 4. Experimental setting setup. Panel a): Traditional optimization approach for pure planning assuming a pre-defined release π_{θ_r} [4]. Panel b and c): Nested and Inverse Nested optimization approach for reservoir planning and management, where the optimal management problem is solved by means of FQI [5] and pFQI respectively. Aim of the experiments:

I. Assess advantages of Inverse Nested w.r.t. traditional optimization techniques (i.e., Optimal Sizing and Nested)
II. Quantify both sensitivity - in terms of system performance w.r.t. several training set sizes - and computational advantages - w.r.t. Nested - of Inverse Nested approach.

Legend
→ Traditional Optimization vs Inverse Design
--→ pFQI Sensitiveness



[5] RESULTS

I. Inverse Nested: Advantages w.r.t. traditional optimization techniques (i.e., Optimal Sizing and Nested approach)

Figure 5. Pareto front generated via pFQI in the planning (i.e., construction costs [10 Mln $]) vs management (i.e., downstream water supply squared deficit [m³/sec]²) objective space when n_θ= 11 reservoir planning decisions are sampled in the learning dataset $\mathcal{F}_\theta$ of the algorithm.

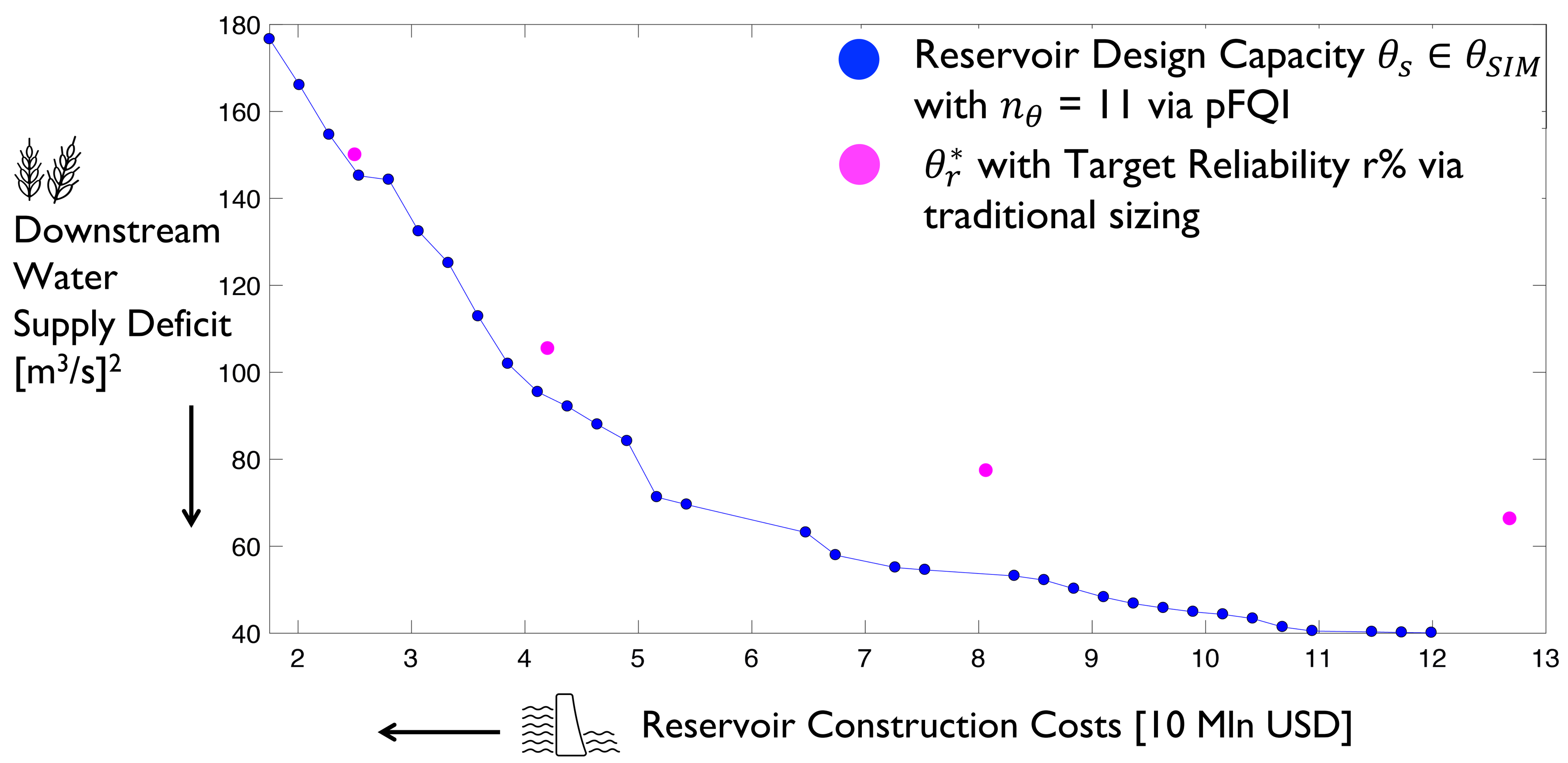


Table 1. Performance of the optimal operating policies π_{FQI}^* and π_{pFQI,n_θ}^* (rows) computed via FQI and pFQI respectively in terms of water supply deficit [m³/sec]² when evaluated over two given planning decisions, i.e. θ_1^* and θ_2^*. The former reservoir size belongs to the learning dataset $\mathcal{F}_\theta$ of the pFQI algorithm, the latter is not experienced by the algorithm during its policy design phase in order to test its interpolation ability over the planning decision space.

	θ_1^*	θ_2^*	$\Delta\theta_2^*$	n_θ
π_{FQI}^*	**42.09**	**143.13**	**-**	**1**
$\pi_{pFQI,2}^*$	42.25	179.97	22.24%	2
$\pi_{pFQI,3}^*$	41.94	159.56	11.48%	3
$\pi_{pFQI,11}^*$	**42.05**	**145.20**	**1.45%**	**11**

II. Inverse Nested: Sensitivity in terms of system performance w.r.t. several $\mathcal{F}_\theta$ sizes and computational advantages w.r.t. Nested

Table 2. CT [min] is the Computational Time required by both FQI and pFQI algorithm to find the optimal operating policy and associated optimal planning decision that identifies one non-dominated solution (i.e., blue point) in Figure 5. CT$_\theta$ [min] is the total Computational Time required to design the entire Pareto front.

	CT [min]	CT$_\theta$ [min]	n_θ
π_{FQI}^*	43	**1763**	1
$\pi_{pFQI,2}^*$	156	**156**	2
$\pi_{pFQI,3}^*$	209	**209**	3
$\pi_{pFQI,11}^*$	859	**859**	11

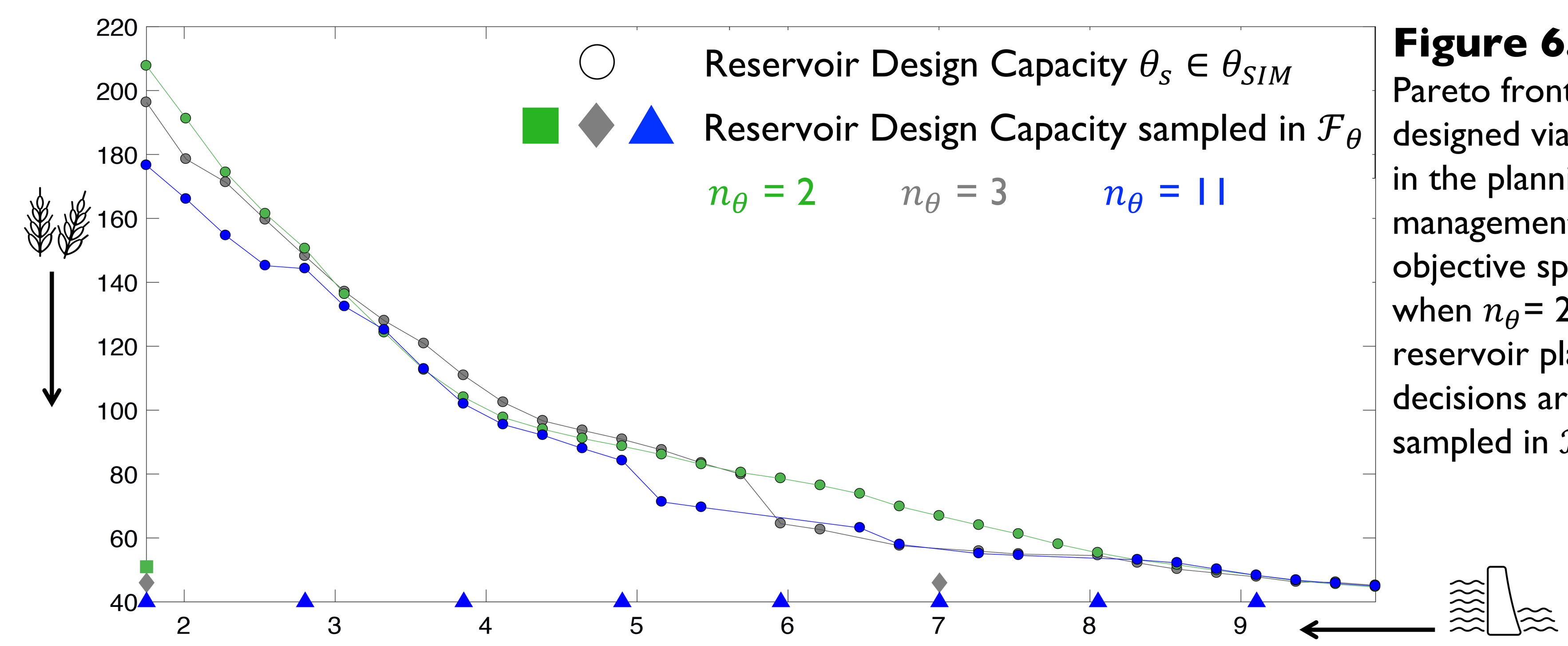


Figure 6. Pareto fronts designed via pFQI in the planning vs management objective space when n_θ= 2, 3, 11 reservoir planning decisions are sampled in $\mathcal{F}_\theta$.

[6] HIGHLIGHTS

a. **Inverse nested** approach identifies Pareto-efficient water reservoir sizes that **dominate** the infrastructure sizes optimized via traditional sizing method
b. **Inverse nested** approach is **computationally more efficient** than traditional nested approach
c. Above a certain size of the learning dataset $\mathcal{F}_\theta$, the **performance** of the operating policy designed via pFQI in terms of management objective becomes **independent** from the number of planning decisions sampled in $\mathcal{F}_\theta$

REFERENCES

1. Bertoni et al., *Proceedings of the 20th IFAC World Congress*, (2017)
2. Castelletti et al., *Water Resources Research*, 46(9), p. W09507, (2010)
3. Castelletti et al., *Networking, Sensing and Control (ICNSC), 2011 IEEE International Conference*, 260-265, (2011)
4. Turner et al., *Environmental Modeling & Software*, 76, pp. 13-19, (2016)
5. Ernst et al., *Journal of Machine Learning Research*, 6(1), pp. 503-556, (2005)

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