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Learning-based hierarchical control of water reservoir systems

FACULTY OF
SCIENCE



Water management challenges

Introduction

Case study

Modelling
Objectives

Control design

Inner-loop
Outer-loop

Results and discussion



Why do we need better operating policies for water reservoirs¹?



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1. *Making the most of data: an information selection and assessment framework to improve water systems operations*, Giuliani, M., Pianosi, F. and Castelletti, A., *Water Resources Research*, 2015.

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Why do we need better operating policies for water reservoirs¹?

- Failure to produce the level of benefits that economically justified their development



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Why do we need better operating policies for water reservoirs¹?

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- Changing hydroclimatic conditions and socioeconomic forcing



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Why do we need better operating policies for water reservoirs¹?

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- Changing hydroclimatic conditions and socioeconomic forcing

How to operate existing infrastructures more efficiently instead of planning new ones?

1. *Making the most of data: an information selection and assessment framework to improve water systems operations*, Giuliani, M., Pianosi, F. and Castelletti, A., *Water Resources Research*, 2015.



Overview of the presentation

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- 2 The Hoa Binh reservoir
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The Hoa Binh reservoir

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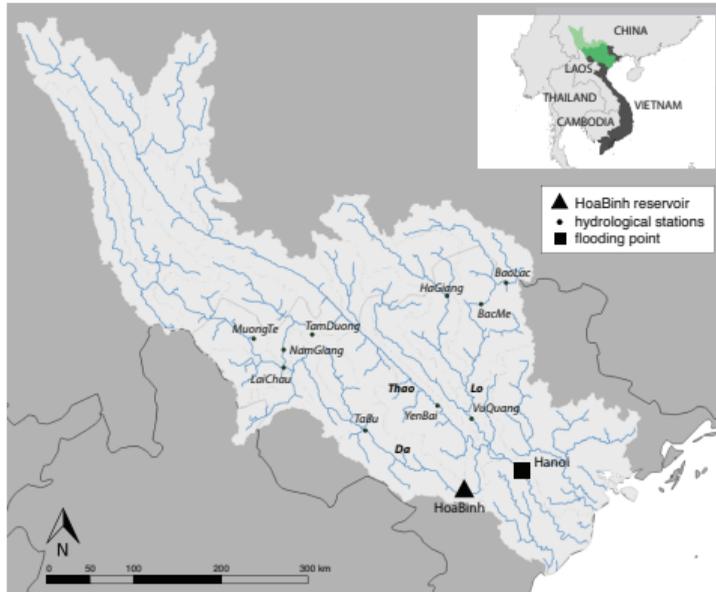
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- Red River basin: 169 000 km² shared by China (48%), Vietnam (51%) and Laos (1%)
- Da River: responsible of 42% of the discharge in Hanoi
- Regulation by the Hoa Binh reservoir
 - Surface area: 198 km²
 - Storage capacity: 6 billions m³
 - Large share of the national electricity production (power plant of 1.920MW)

The Hoa Binh reservoir: Modelling

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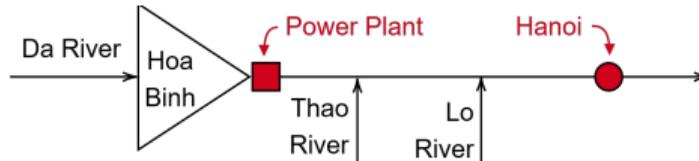
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The Hoa Binh reservoir: Modelling

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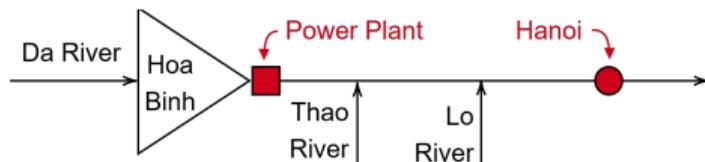
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1 time-step = 1 day

Time subscript $t + 1$ = the variable depends on the realization of the stochastic process in the time interval $[t, t + 1)$

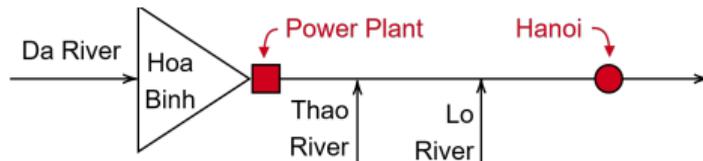
Mass balance equation

$$S_{t+1} = S_t + q_{t+1}^D - r_{t+1}$$

The Hoa Binh reservoir: Modelling

1 time-step = 1 day

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Mass balance equation

$$s_{t+1} = s_t + q_{t+1}^D - r_{t+1}$$

Water release function

$$r_{t+1} = f(s_t, u_t, q_{t+1}^D)$$

$$r_t^{\min}(s_t, q_{t+1}^D) \leq r_t \leq r_t^{\max}(s_t, q_{t+1}^D)$$



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The Hoa Binh reservoir: Modelling

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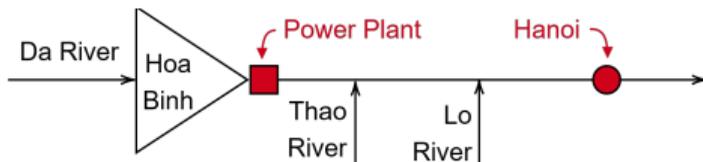
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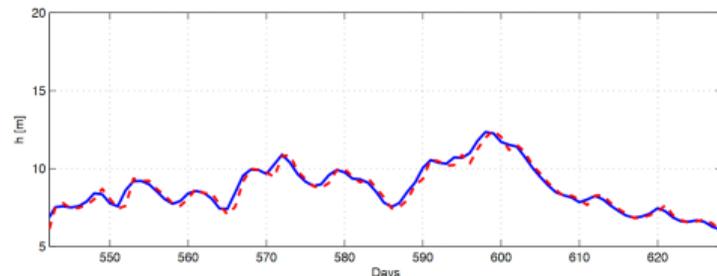
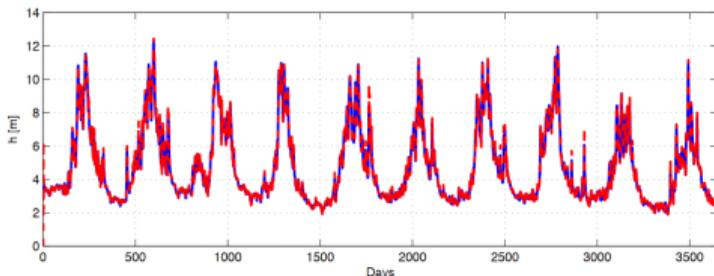
Water release function

$$r_{t+1} = f(s_t, u_t, q_{t+1}^D)$$

Flow routing model

$$h_{t+1} = NN(r_{t+1}, q_{t+1}^T, q_{t+1}^L)$$

$$r_t^{\min}(s_t, q_{t+1}^D) \leq r_t \leq r_t^{\max}(s_t, q_{t+1}^D)$$



Identification of a flow-routing model for the Red river network, F. Pianosi, A. Castelletti, M. Lovera, IFAC Proceedings, 2012.



Objectives and direct policy search

Excess level of water

$$J_{t+1}^F = \max(h_{t+1} - \bar{h}, 0)^2$$

Hydropower production

$$J_{t+1}^H = \eta(\bar{h}_t) g \gamma_w \bar{h}_t q_{t+1}^{Turb} \cdot 10^{-6}$$

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$$\begin{array}{ll} \min_u & -\alpha \frac{1}{T} \sum_{t=0}^{T-1} J_{t+1}^H + (1 - \alpha) \frac{1}{T} \sum_{t=0}^{T-1} J_{t+1}^F \\ \text{s.t} & \text{model dynamics} \end{array}$$

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Objectives and direct policy search

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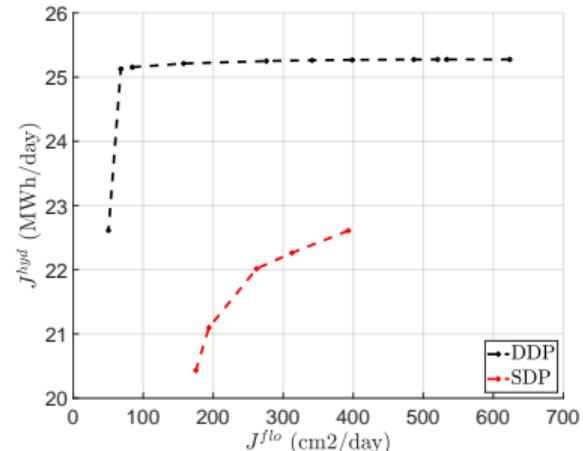
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Dynamic Programming for different α
Training period: 1962-1969



Curses, tradeoffs, and scalable management: Advancing evolutionary multiobjective direct policy search to improve water reservoir operations, M. Giuliani, A. Castelletti, F. Pianosi, E. Mason, and P.M. Reed, Journal of Water Resources Planning and Management, 2016



Objectives and direct policy search

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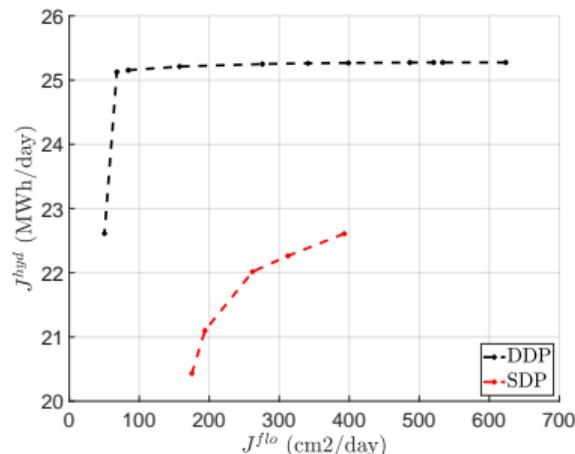
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Dynamic Programming for different α
Training period: 1962-1969

- Curse of *dimensionality*
- Curse of *modelling*
- Curse of *multiple objectives*



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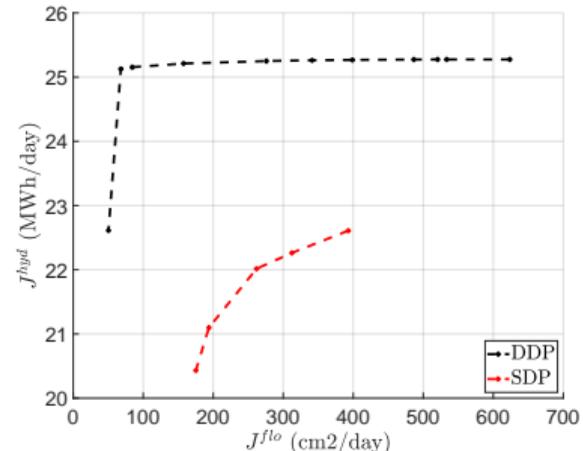
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Dynamic Programming for different α
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- Curse of *dimensionality*
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Need for more scalable and flexible strategies



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$$\min -\alpha \frac{1}{N_p} \sum_{k=1}^{N_p} J_{t+k}^H + (1 - \alpha) \frac{1}{N_p} \sum_{k=1}^{N_p} J_{t+k}^F$$

s.t. prediction model
constraints on s and u

Economic Model Predictive Control

Model-based predictive control

- ✓ Constraints enforcement
- ✓ Online performance optimisation
- ✗ Complex model and partially unmodelled



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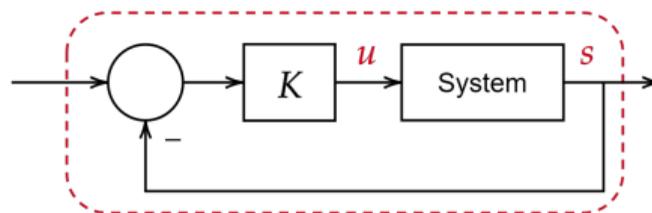
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Reference model M

Data-driven control

- ✗ No constraints enforcement
- ✗ Choice of M is critical
- ✓ A low-level controller is learnt from open-loop data



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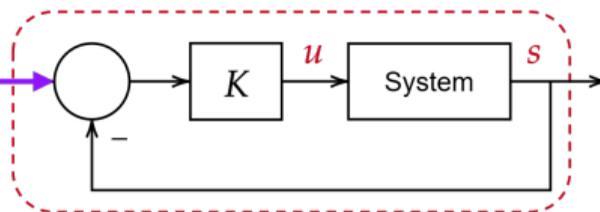
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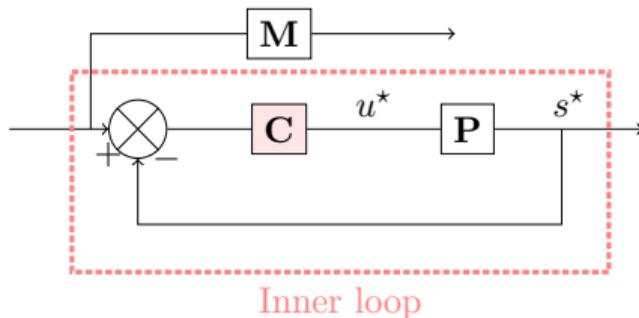


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Direct data-driven control of constrained systems, D. Piga, S. Formentin, and A. Bemporad, *IEEE Transactions on Control Systems Technology*, 2017

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VRFT design

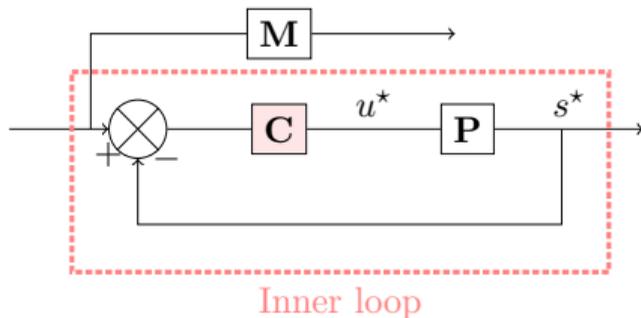
$$\bar{r}_t = M^{-1}(z)s_t^* \quad \bar{e}_t = \bar{r}_t - s^*$$



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VRFT design

$$\bar{r}_t = M^{-1}(z)s_t^* \quad \bar{e}_t = \bar{r}_t - s_t^*$$

$$\min_{\theta} \frac{1}{N} \sum_{t=1}^N (u_t - C(z, \theta)\bar{e}_t)^2$$

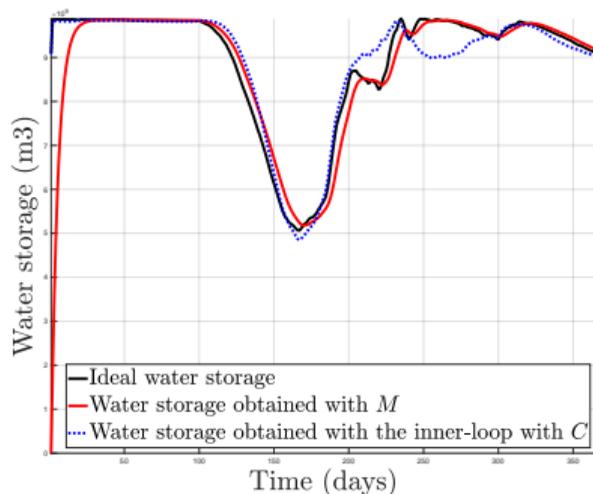
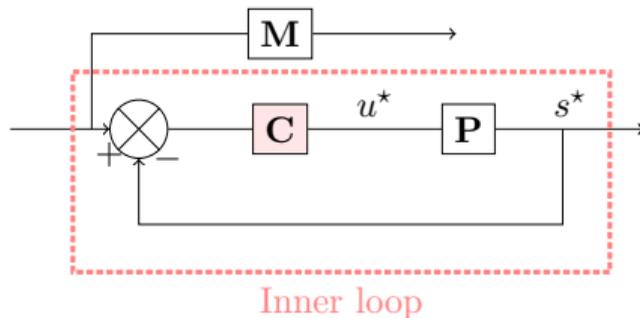
Virtual reference feedback tuning: a direct method for the design of feedback controllers, Campi, M. C., Lecchini, A., and Savaresi, S. M., *Automatica*, 2002.



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VRFT design

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$$\min_{\theta} \frac{1}{N} \sum_{t=1}^N (u_t - C(z, \theta)\bar{e}_t)^2$$

$$M(z) = \frac{0.2z^{-1}}{1 - 0.8z^{-1}}$$

$$C(z, \theta) = \theta_1 + \frac{\theta_2}{1 - z^{-1}} + \theta_3(1 - z^{-1})$$

Virtual reference feedback tuning: a direct method for the design of feedback controllers, Campi, M. C., Lecchini, A., and Savaresi, S. M., *Automatica*, 2002.



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Linear model of the inner-loop

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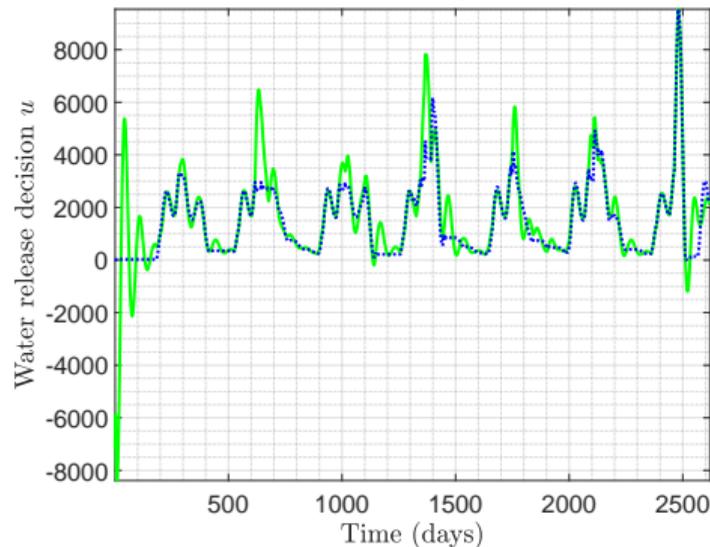
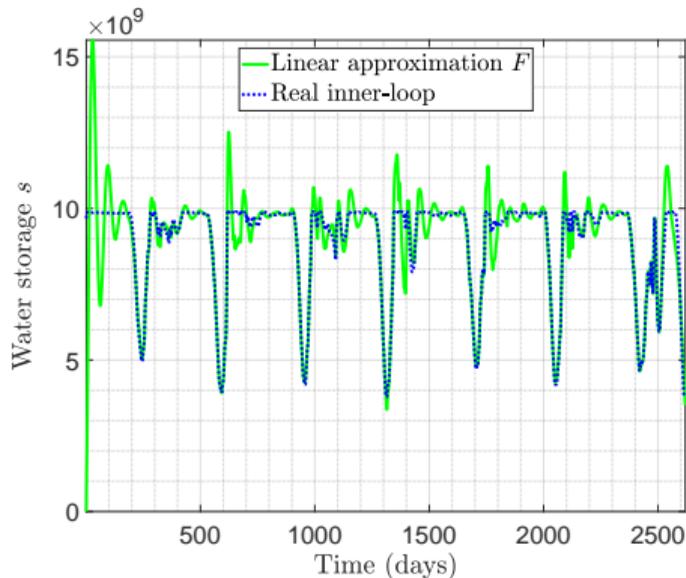
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Linear approximation $F: r_{t+1} \approx u_t$



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$$\min_{s^{ref}} -\alpha \frac{1}{N_p} \sum_{k=1}^{N_p} J_{t+k}^H + (1 - \alpha) \frac{1}{N_p} \sum_{k=1}^{N_p} J_{t+k}^F$$



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$$\text{s.t. } \forall k = 1 \dots N_p :$$

$$\begin{cases} x(t+k+1) = A_F x(t+k) + B_F \begin{pmatrix} s^{ref}(t+k) \\ q^D(t+k) \end{pmatrix} \\ \begin{pmatrix} s(t+k+1) \\ u(t+k+1) \end{pmatrix} = C_F x(t+k) + D_F \begin{pmatrix} s^{ref}(t+k) \\ q^D(t+k) \end{pmatrix} \end{cases}$$

(prediction model)



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$$r^{min}(s_{t+k}, q_{t+k+1}^D) \leq u(t+k) \leq r^{max}(s_{t+k}, q_{t+k+1}^D) \quad (\text{feasibility})$$



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$$s^{min} \leq s(t+k) \leq s^{max} \quad (\text{no overflow})$$



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$$s^{min} \leq s(t+k) \leq s^{max} \quad (\text{no overflow})$$

In practice: recursively feasible for $s_0 \in [s^{min}, s^{max}]$ and for $0 \leq q^D \leq 25000 m^3 / \text{day}$



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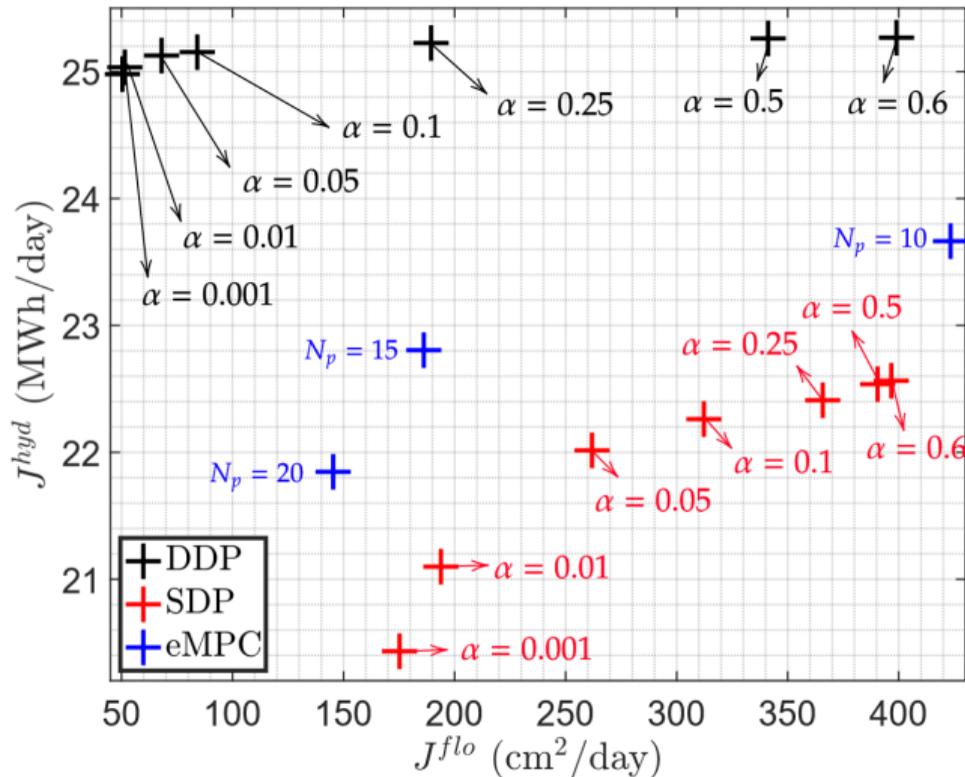
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Training period 1962-1969



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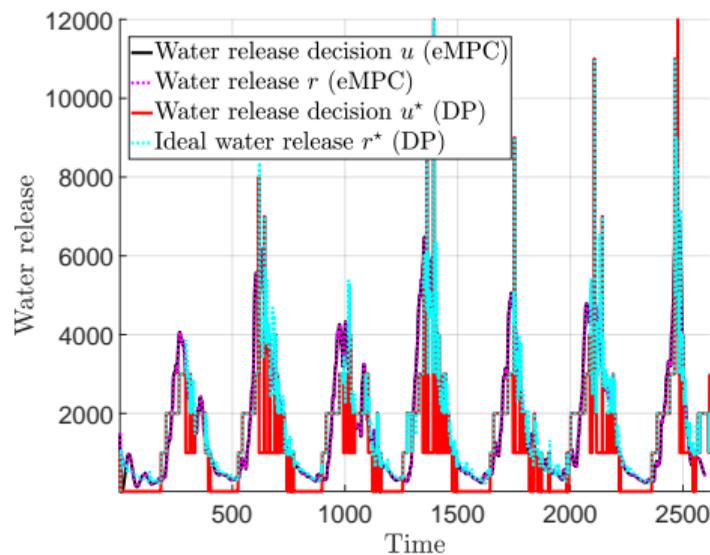
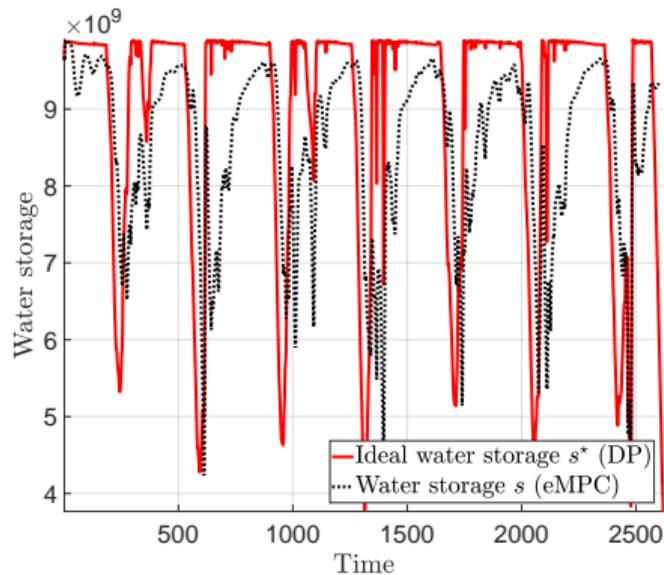
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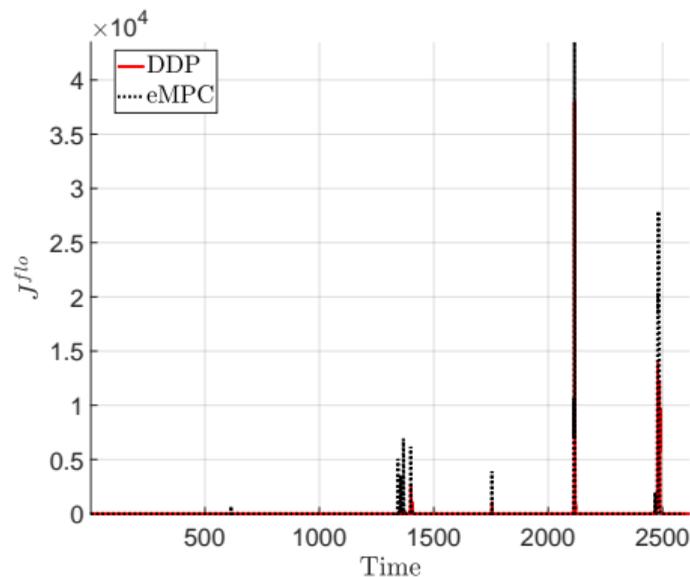
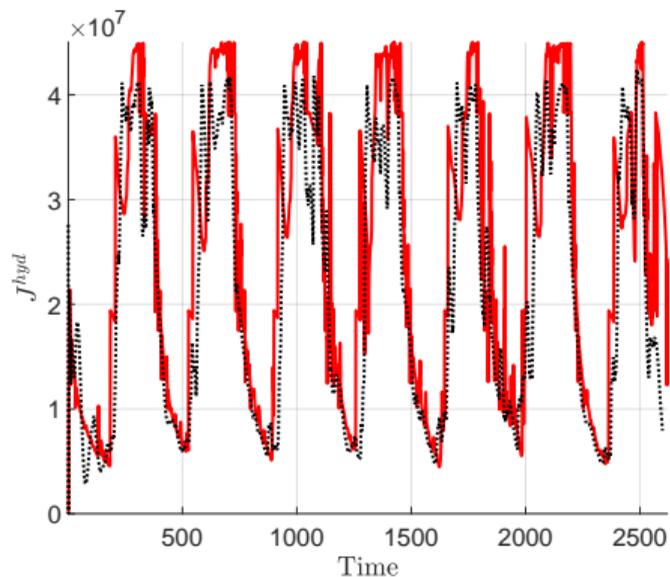
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Training period 1962-1969



Results and discussion

Training period 1962-1969 + Validation period 2007-2008

	1962-1969		2007-2008	
	J^H	J^F	J^H	J^F
VRFT + eMPC	22.8049	186.1333	23.3126	212.9908
SDP	22.015	261.872	23.149	274.186
DDP	25.1267	68.0440		

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DDP	25.1267	68.0440	-	-

Comparison with SDP:

- ✓ Better performances



Results and discussion

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Comparison with SDP:

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Results and discussion

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- Coordinate the dams of the River basin

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Introduction

Case study

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Objectives

Control design

Inner-loop

Outer-loop

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Results and discussion

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