Hydropower scheduling conference 2022

Multi-objective optimization for water management

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Abstract

Problem

- Potential growing conflicts between hydropower and water demands
- Improvements opportunities for internal optimization model.

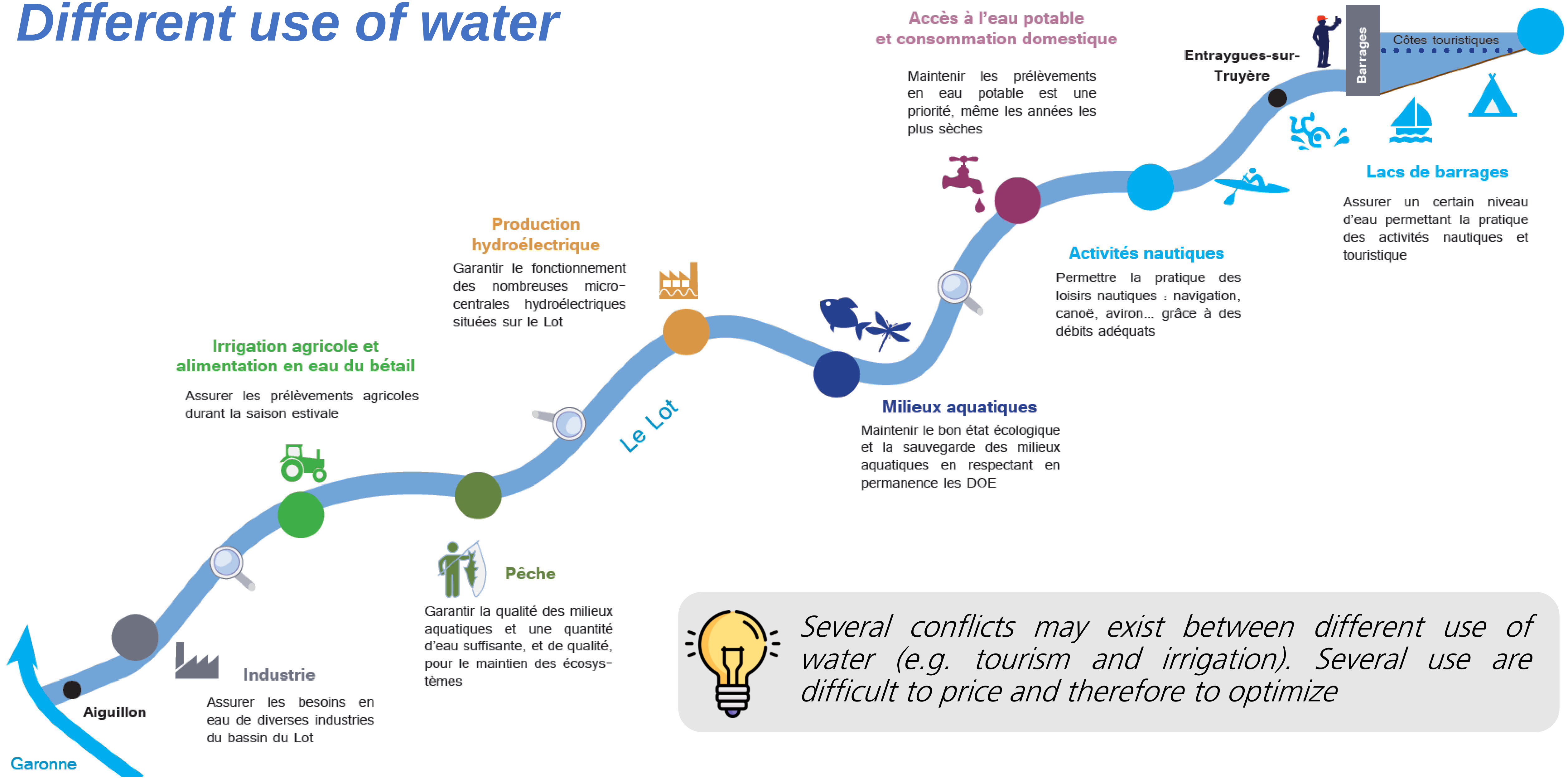
Proposed solution

- Use of the viability framework to digitize some constraints (e.g. water demands) into viability indicators
- Research of compromises between viability indicators using stochastic dynamic programming & goal programming

Perspectives

- Practical application of proposed solution to actual use cases
- Improvements of solution (resolution using SDDP, hierarchical goal programming …)

Different use of water



Several conflicts may exist between different use of water (e.g. tourism and irrigation). Several use are difficult to price and therefore to optimize

source: syndicat mixte du bassin du Lot (www.valleedulot.com)

Motivations

> *"Climate models project decreases of renewable water resources in some regions and increases in others, albeit with large uncertainty in many places. Broadly, water resources are projected to decrease in many mid-latitude and dry subtropical regions, and to increase at high latitudes and in many humid mid-latitude regions. Even where increases are projected, there can be short-term shortages due to more variable streamflow (because of greater variability of precipitation) and seasonal reductions of water supply due to reduced snow and ice storage. Availability of clean water can also be reduced by negative impacts of climate change on water quality; for instance, the quality of lakes used for water supply could be impaired by the presence of algae-producing toxins."*
>
> IPCC WGII AR5 – Chap 3 (2018)

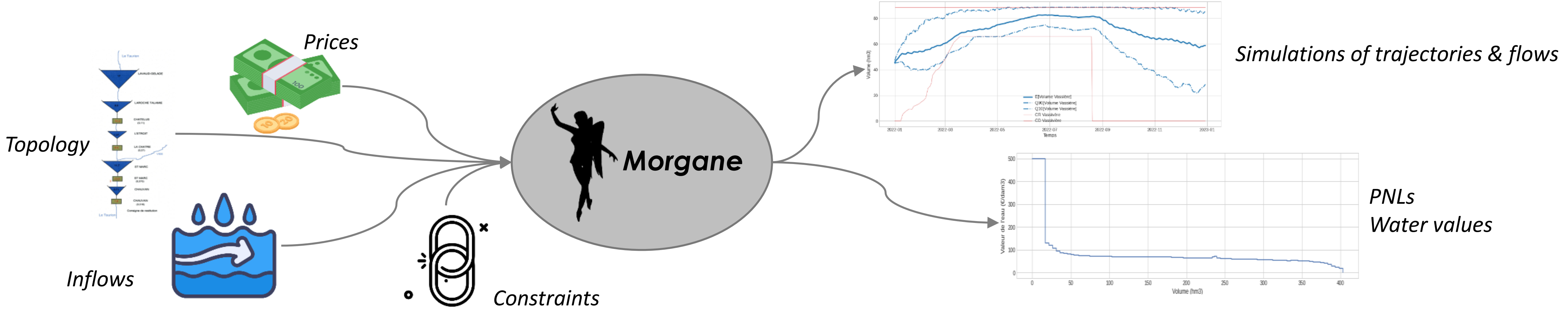
As researchers : there will be a need for methods and tools that handle uncertainty and different usages of water. Such objects shall be used to drive reservoirs' operations and explore alternatives in the design of water infrastructure (cf. hydroeconomic models)

As hydropower producers : EDF manages ~=75% of metropolitan France surface water resource (7.5 billions of m3). Our operations will obviously be impacted by climate change. Despite integrating the different shared use of water is an historical concern for EDF group*, the foreseeable stress on resource forces us to improve our optimization methods

* See https://www.edf.fr/en/the-edf-group/producing-a-climate-friendly-energy/doubling-the-share-of-renewable-energies-by-2030/hydroelectric-energy/our-expertise/water-management

How is it handled so far – Morgane software

Morgane is developed @EDF Lab & use in several operational entities of EDF group. It solves a stochastic optimization under constraints problem, mostly using stochastic dynamic programming.



Portfolio management – Water values computation

Morgane is used several times a week in order to compute « water values ». Those values may be used as variable cost of hydro units in hydropower unit commitment problems.

Portfolio management – Maintenance & constraints scheduling

Morgane is used on a daily basis to evaluate and optimize the cost of several constraints (e.g maintenance or must runs). Around 6000 constraints a year are scheduled using Morgane

Portfolio structuring – business cases assessments

Morgane is used as a simulation software to evaluate several business plants (hydro & some other flexibilities).

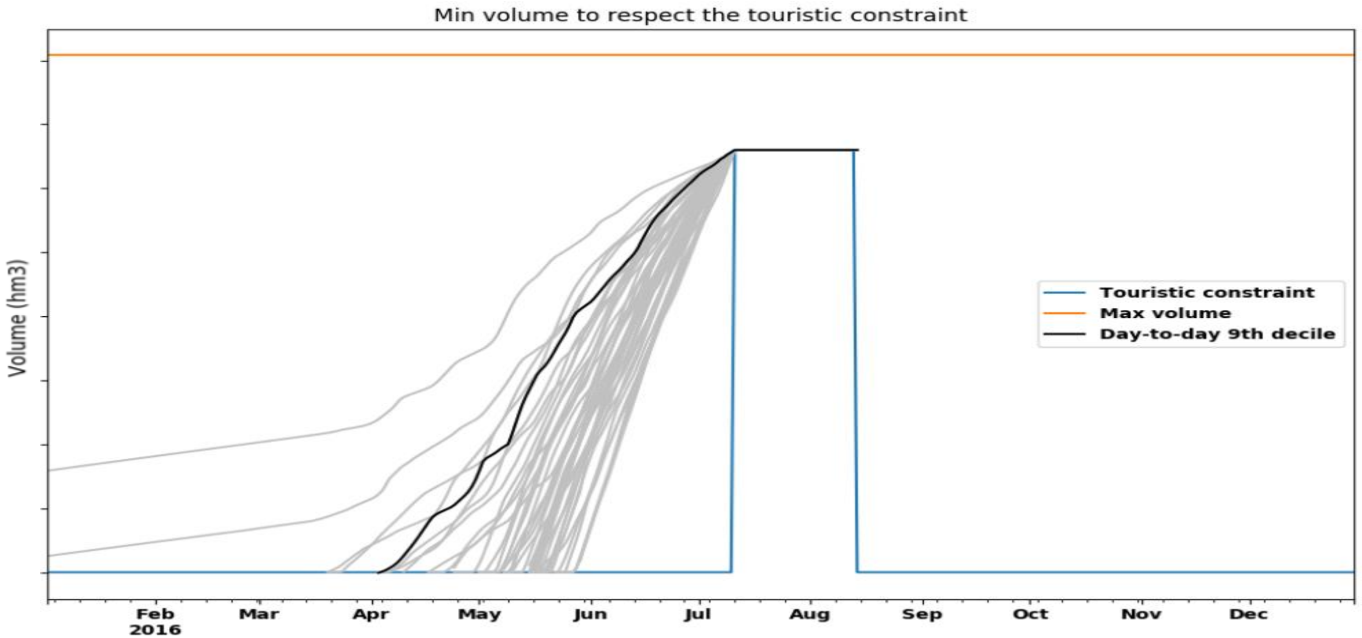
How is it handled so far – Upper / lower bound computation

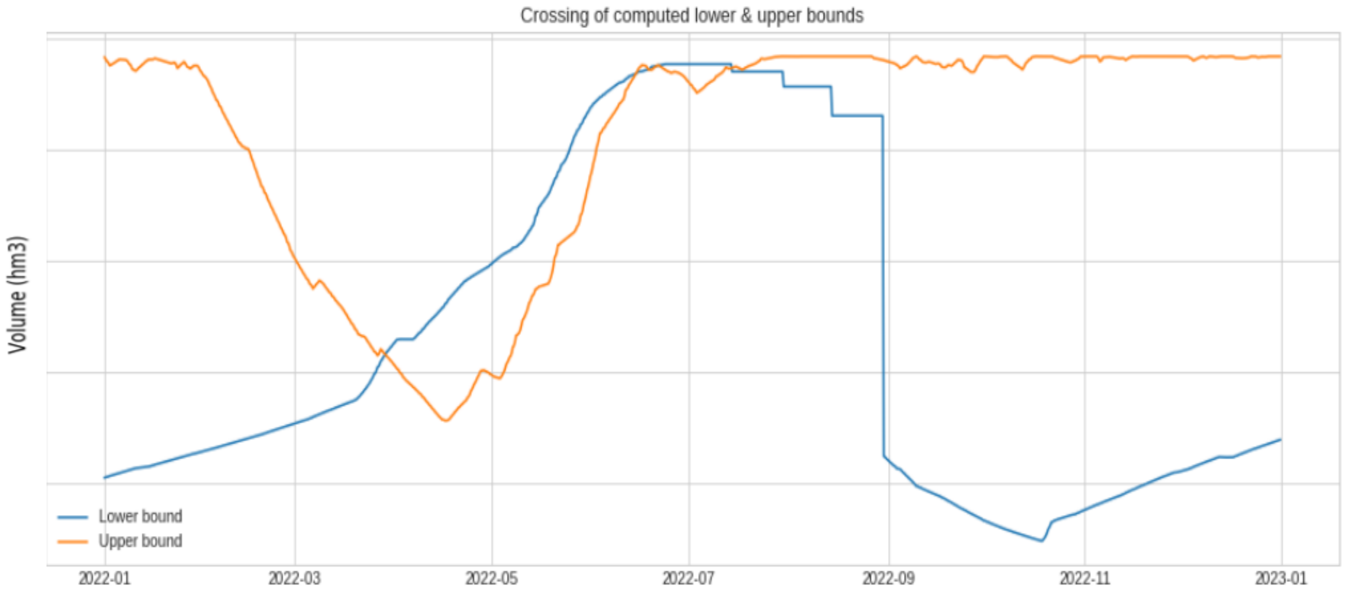
The different use of water are handled as constraints in the optimization problem Morgane solves. Those (probabilistic) constraints are aggregated in upper & lower bounds that restrain the flexibility of the assets (Ouillon, 2018).

The method is fast and "liked" but :

- Requires configuration when the number of reservoirs gets too high.
- It aggregates all the constraints of a kind (i.e. upper or lower)

Some constraints sets may lead to infeasible solutions. Lower bound may be above the upper bound. Asset manager must then choose between the two, i.e. in favor of a group of constraints.





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An approach using the viability framework

The viability theory comes from research in sustainability management. The main idea is to compute the "viability kernel", i.e. all the initial states that respect the constraints. Using small reformulations, this could be applied to dam management !

Global problem

$$\begin{cases} \max_{q_t} E[I_0 |\, I_{T+1} = \tilde{I}_{T+1}] \\ s.c. \\ \forall t = 1..T \\ s_{t+1} = f(s_t, q_t, \omega_t) \\ q_t \in Q_t \\ s_t \in S_t \end{cases}$$

Using principle of optimality

« Local » problem

$$\tilde{I}_t(s_t, \omega_t) = E\left[\max_{q_t}[\tilde{I}_{t+1}(f(s_t, q_t, \omega_t))\, \mathbb{I}_{\{r(s_t,q_t)\}}]\right]$$

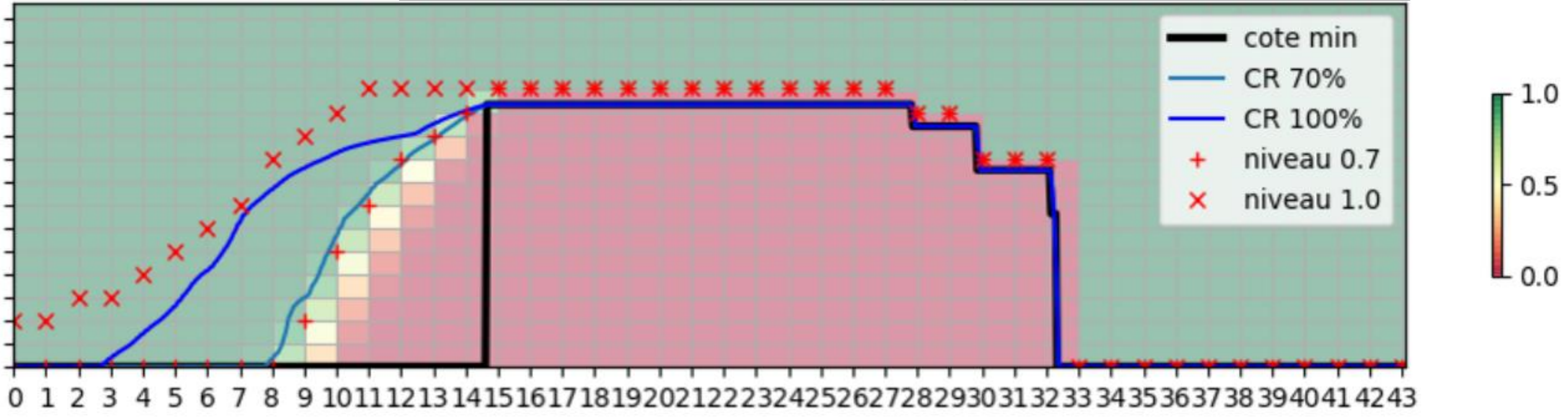
$$\mathbb{I}_{\{r(s_t,q_t)\}} = \begin{cases} 1\ if\ state\ is\ viable \\ 0\ otherwise \end{cases}$$

s_t : *state variable at timestep t (stock level)*
q_t : *command at timestep t (throughput)*
ω_t : *hazard*
$i_t\ (q_t, \omega_t)$: *instant viability level*
$I_t\ (s_t)$: *viability at timestep t*
$\tilde{I}_{T+1}\ (s_{T+1})$: *final viability*

One may compute a viability indicator (~= probability of respect) for a given constraint (or group of constraints) for each state of the problem in a dynamic programming manner

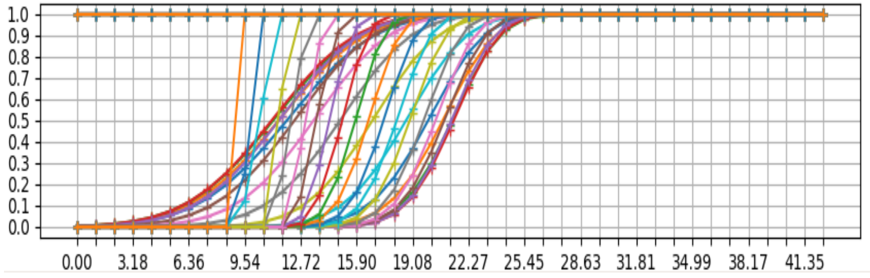
An example of results

Illustration of viability indicator computed for a minimum volume constraint



Interesting results :

- One may compare historical bounds with viability indicators.
- Viability functions look like activation functions. The steeper they are the (probably) better it is to take operational margins if one wants to respect constraints.



Examples of transition functions

Using viability to reach compromises (1/2)

Viability indicators may be used to disaggregate & digitize constraints

Indicators may as well be part of the objective / the constraints

$$\begin{cases} \max_q E\left[\sum_{t=1}^{T} G_t(s_t, q_t, \omega_t) \; + \; \tilde{V}_{T+1}(s_{T+1})\right] \\ with: \\ s_t: stock\ at\ timestep\ t, s_t \in S_t \\ q_t: control\ at\ timestep\ t, q_t \in Q_t \\ \omega_t: hazard\ at\ timestep\ t \\ G_t(s_t, q_t, \omega_t): Earnings \end{cases}$$

$$\begin{cases} \max_{s,q} E\left[\sum_{t=1}^{T} G_t(s_t, q_t, \omega_t)\mathbb{I}_{\{r(s_t,q_t)\}} \; + \; \tilde{V}_{T+1}(s_{T+1})\right] \\ with: \\ s_t: stock\ at\ timestep\ t, s_t \in S_t \\ q_t: control\ at\ timestep\ t, q_t \in Q_t \\ \omega_t: hazard\ at\ timestep\ t \\ G_t(s_t, q_t, \omega_t): Earnings \\ \mathbb{I}_{\{r(s_t,q_t)\}}\ viability\ indicator \end{cases}$$

<u>Transformation of annual problem using viability framework</u>

Using viability to reach compromises (2/2)

$$
\begin{cases}
\max\limits_{q_t} \left(E\left[\sum_{t=1}^{T} G_t(s_t, q_t, \omega_t) + \tilde{V}_{T+1}(s_{T+1}) \right] ; \sum_{k=1}^{J} E[I_0^k] \right) \\
sc. \\
\forall t \in [1, \dots, T] \\
s_{t+1} = f(s_t, q_t, \omega_t) \\
E[I_0^k] \geq \beta^k \\
q_t \in Q_t \ and \ s_t \in S_t \\
\tilde{V}_{T+1}(s_{T+1}) \ known
\end{cases}
$$

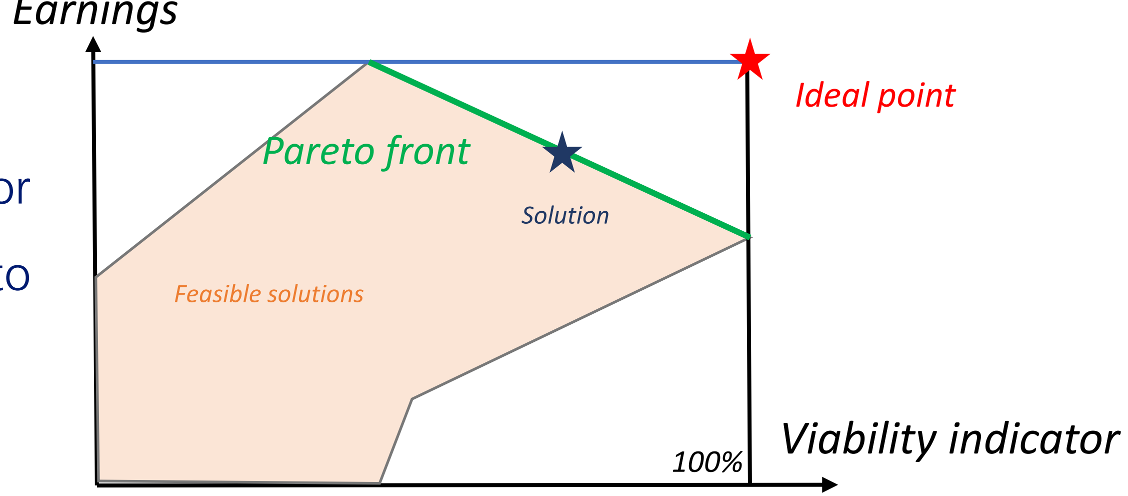
Some viability indicators may now be part of the objective function

The viability indicators may as well appear in constraints

One may solve this problem using SDP (see above).

Each transition problem may be solved goal programming (or compromise programming). This framework may be used to prioritize constraints without giving them a numeric weight.

Illustration of goal programming principle

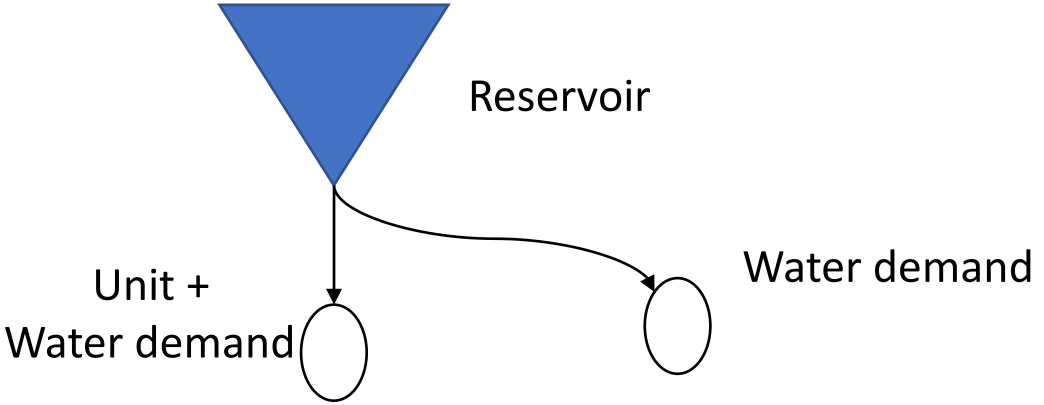


Some results on a toy problem (1/2)

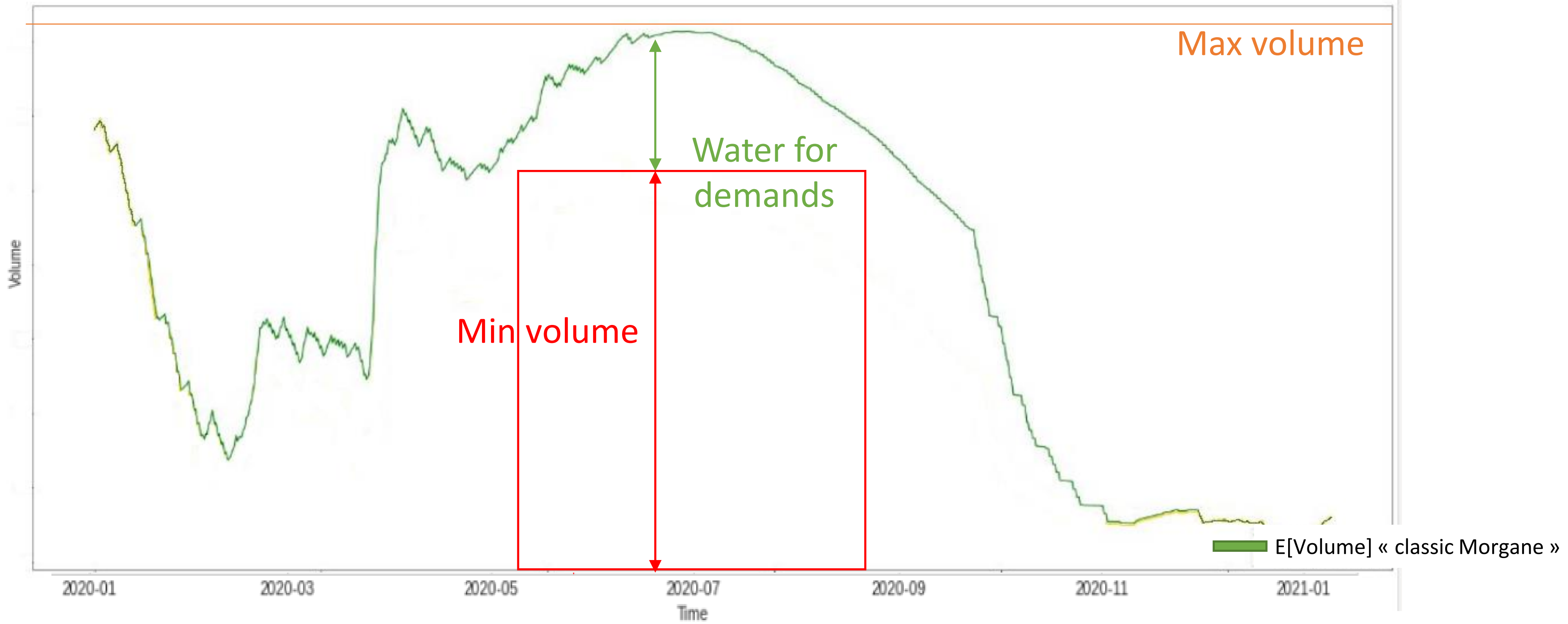
Let's consider one simple hydro valley with 1 lake and 1 unit.

Some characteristics :

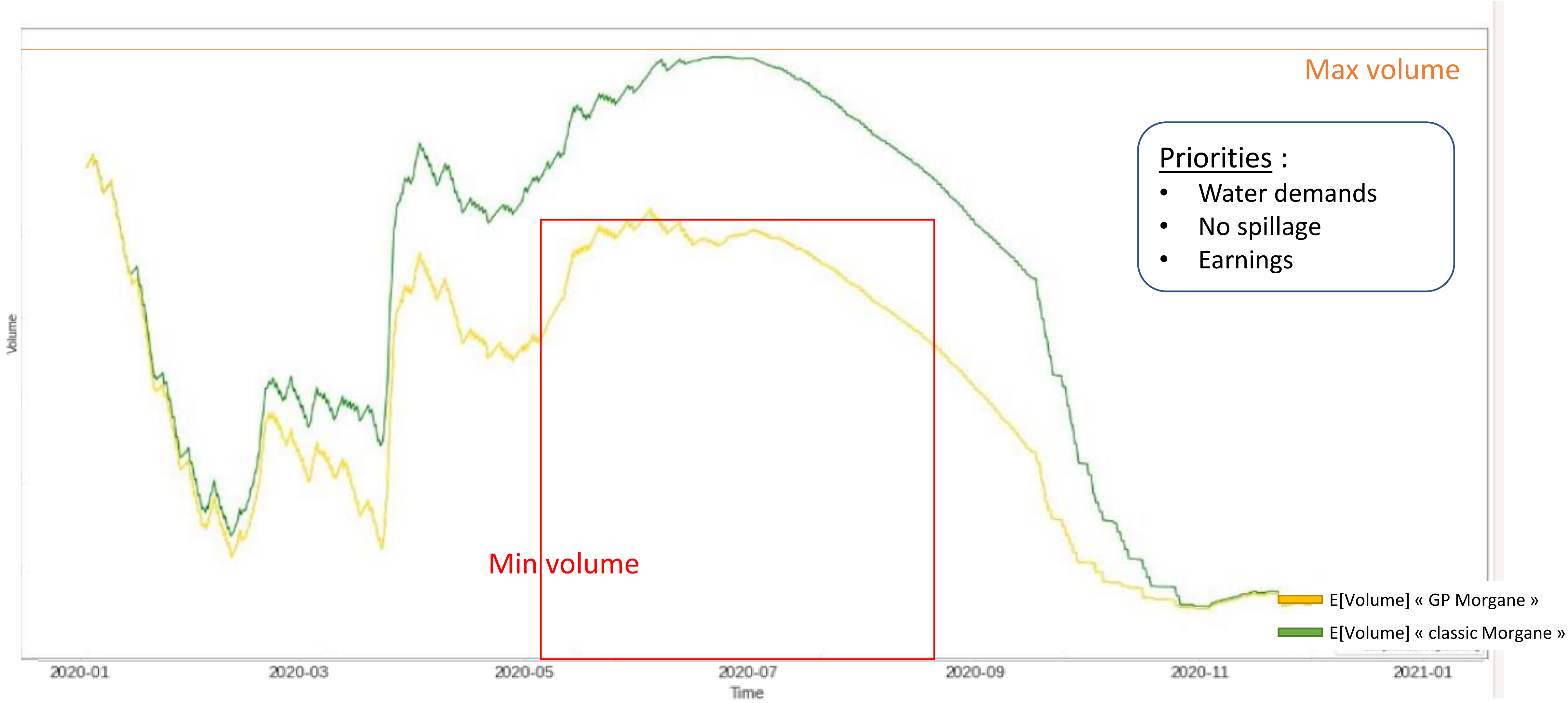
- High variance on inflows
- No spillage allowed
- 2 water demands
- Min volume constraint on lake during summer



<u>Results using “non viability” model</u>



Some results on a toy problem (2/2)



Priorities :
- Water demands
- No spillage
- Earnings

A compromise is reached.
Asset manager has the capability to decide which constraints he may prefers.

Conclusions & perspectives

Main results

- A framework that can be used to digitize constraints and replace actual lower and upper bounds
  Viability indicators may be computed in a SDP scheme (time consuming but easy to implement)
- Compromise between constraints (or earnings) may be reached through transition problems solved using goal programming (therefore no prior penalty / costs as problem input)

Perspectives

- The current implementation of goal programming may be refined to use hierarchical priorities
- Compute the viability indicators using SDDP (speed & scale)

Takk !