Autonomous Hydroelectric Dam Operation under Extreme Flooding

Forecasting turbined and spilled outflows during rare flood events using reinforcement learning and supervised learning.

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Motivation

- **Dams fail** if the water level exceeds the critical maximum;
- **Legal requirement** to prove that dams can withstand frequential flooding;
- Current methods use **outdated software**;
- Hydro Québec has a **wealth of historical data**;
- AI agents can **utilize more data** for a **more reliable result** obtained **faster**.

Jacques Boissinot, archives La Presse.

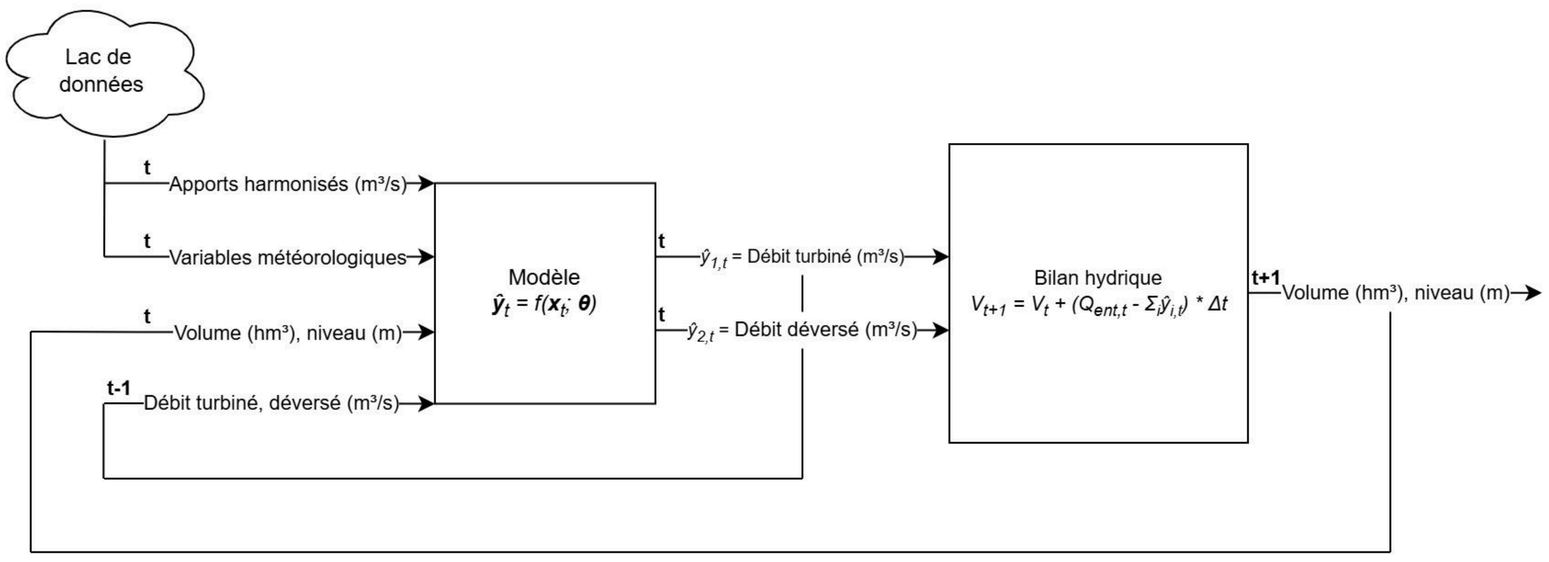
Methodology

Supervised Learning

- Outflows are predicted using **SOTA time-series forecasting** models;
- A **7-day horizon** is rolled out **autoregressively** (70 days total);
- Forecasts are **used as state inputs**.

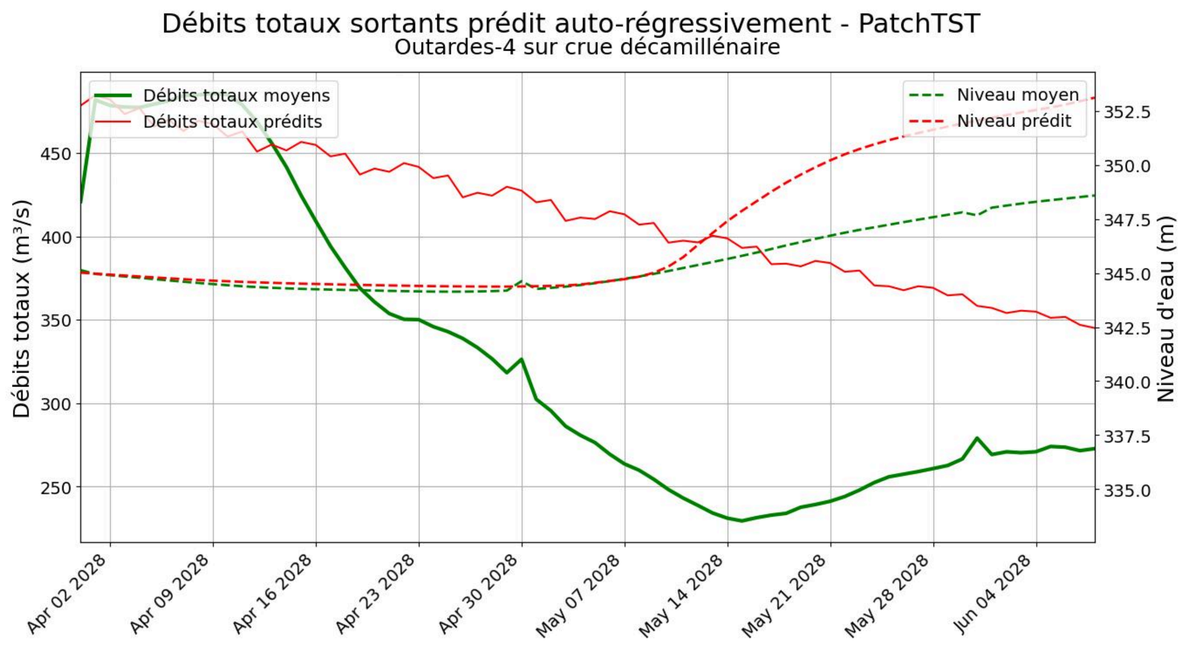
Reinforcement Learning

- Control policies are learned using **actor-critic** methods.
- **Dynamic reward function** balances realistic simulation and flood safety.
- Policies are trained with standard MLP architectures.



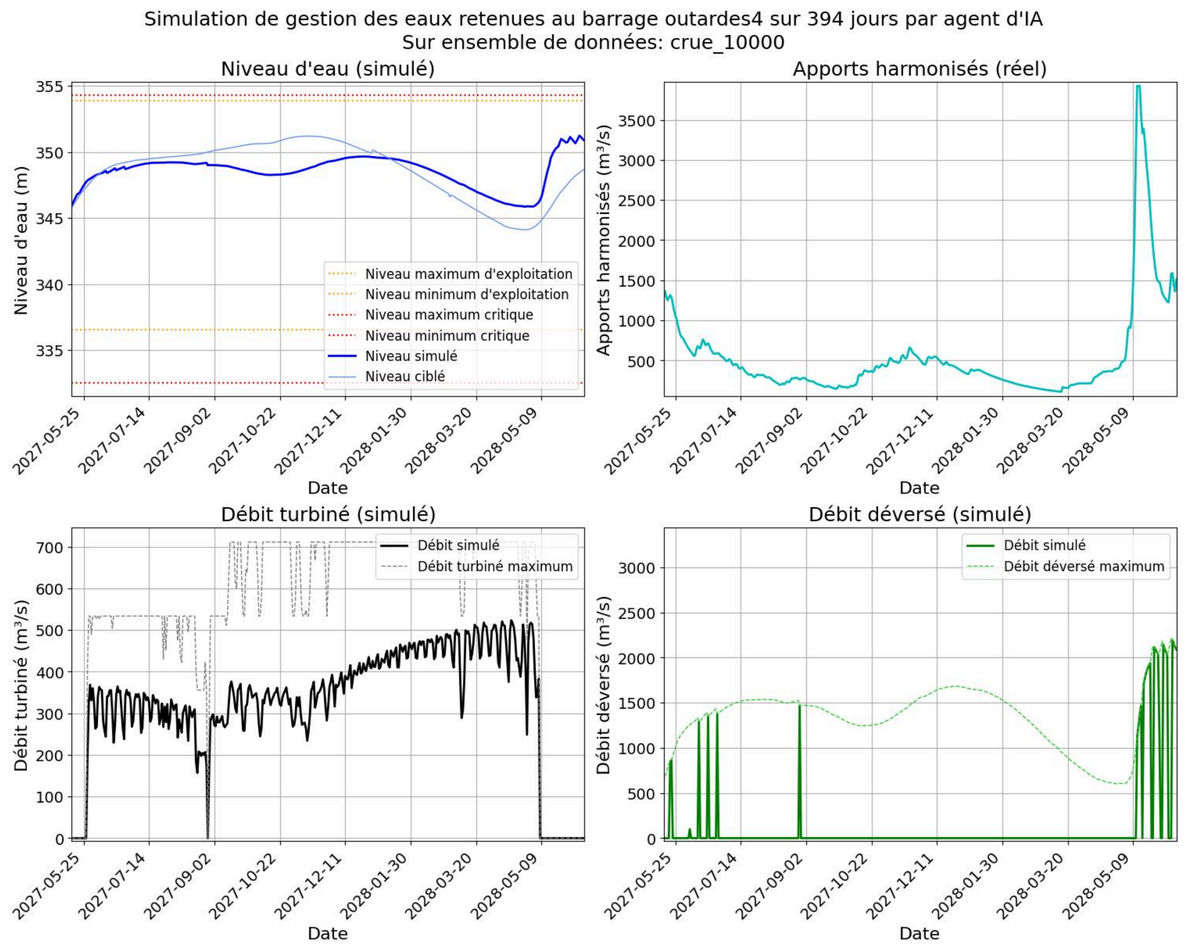
Results

Supervised Learning



PatchTST forecasted over 70 days of 1-in-10,000 year flooding.
Simulated outflow: solid red line.
Simulated water level: dashed red line.
Average historical daily outflow: solid green line.
Average historical daily water level: dashed green line.

Reinforcement Learning



Reinforcement learning simulation over 394 days of a 10,000-year flood.
Top left: simulated water level and target level.
Top right: inflows.
Bottom left: simulated, observed, and maximum turbined outflow.
Bottom right: simulated and maximum spilled outflow.

Findings

- **Supervised learning does not generalize** well to flooding (unseen in training data);
- **Reinforcement learning** ties the learning objective to physical constraints, leading to **generalization on rare flooding events**.