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Towards Mid-Term Scheduling of Cascaded Hydropower Systems: A Decision-Making Framework Driven by Uncertainty-Aware Water Inflow Predictor

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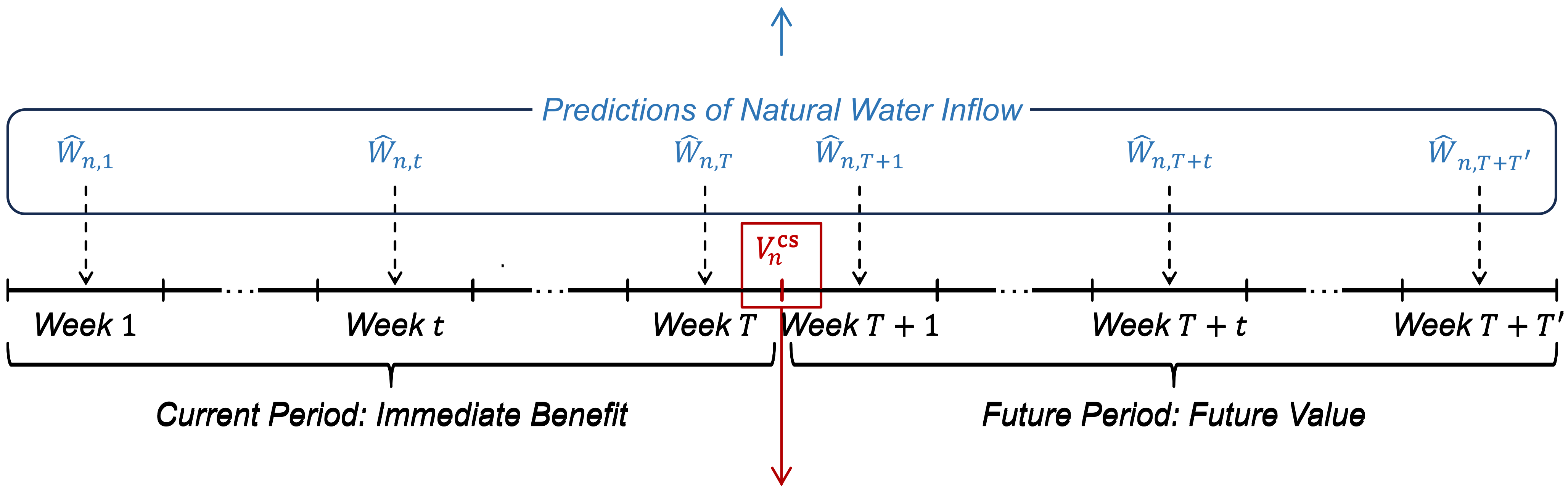
PGE

Background: Mid-Term Scheduling of Cascaded Hydropower Systems

Water inflow to the system: Target to be predicted



Carryover storage at the end of the current period:
Target to be optimized

Challenges

On Prediction

1. How to capture the aleatoric uncertainty and epistemic uncertainty of water inflow?

Aleatoric uncertainty: Whether predictions are accurate enough?
Epistemic uncertainty: Whether predictors are well trained enough?

On Optimization

1. How to leverage the predictions properly?

2. How to quantify the future value in an interpretable, hydrologically adaptive, and easy-to-use way?

A Decision-Making Framework Driven by Uncertainty-Aware Predictor

Prediction Module

1. Uncertainty-aware predictor based on Bayesian mixture density network;

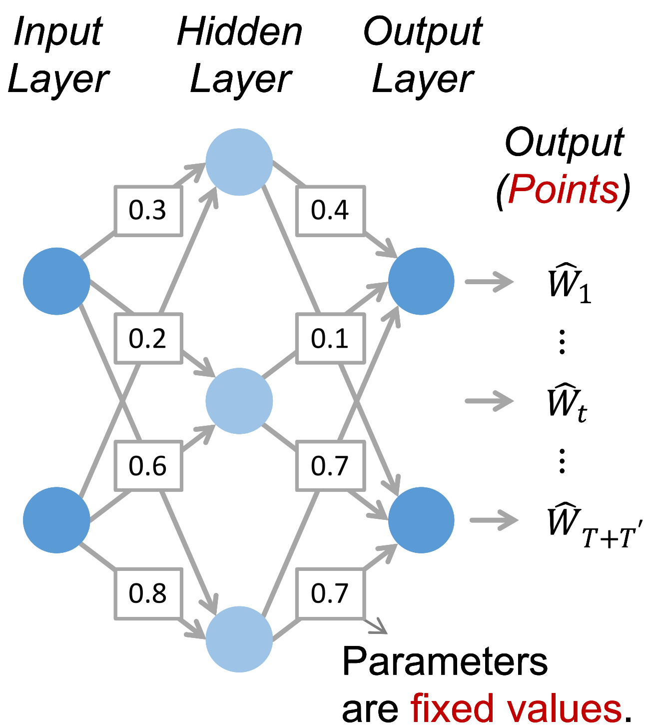
2. Prediction in the form of Gaussian mixture model.

Optimization Module

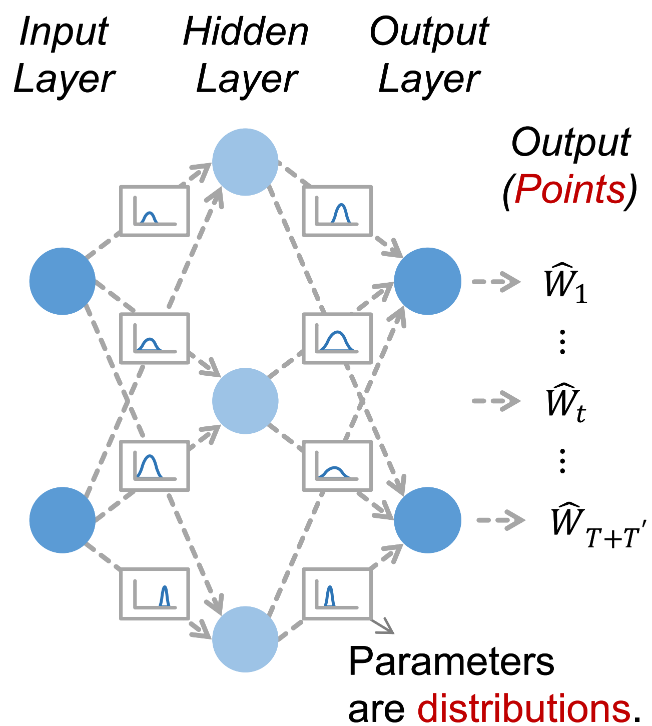
1. Chance-constrained model for the current period;

2. Multi-parametric mixed-integer linear programming to refine locational marginal water value.

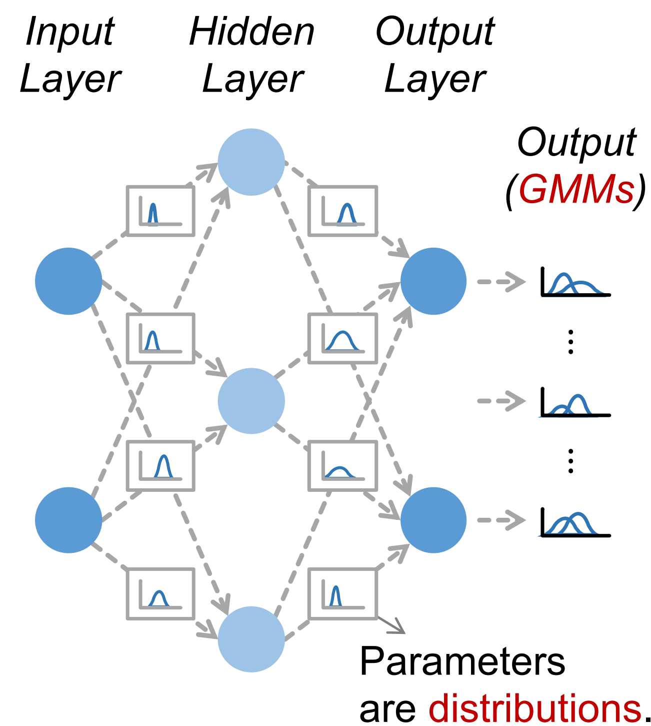
Prediction Module



Deep neural network: Cannot capture uncertainty.



Bayesian neural network: Capture only epistemic uncertainty.



Bayesian mixture density network: Capture both epistemic uncertainty and aleatoric uncertainty.

Optimization Module: Conceptual Model

Objective: max Immediate Benefit + Future Value

↓ Generation of Current Period

↓ Generation of Future Period

GMM-based Water Inflow Predictions →

- Constraints of the current period (Mimic current-period operations considering uncertainties)
- Constraints of the future period (Represent future value with an acceptable complexity)

Optimization Module: Constraints of Current Period

Joint Chance Constraints for Storage Limit

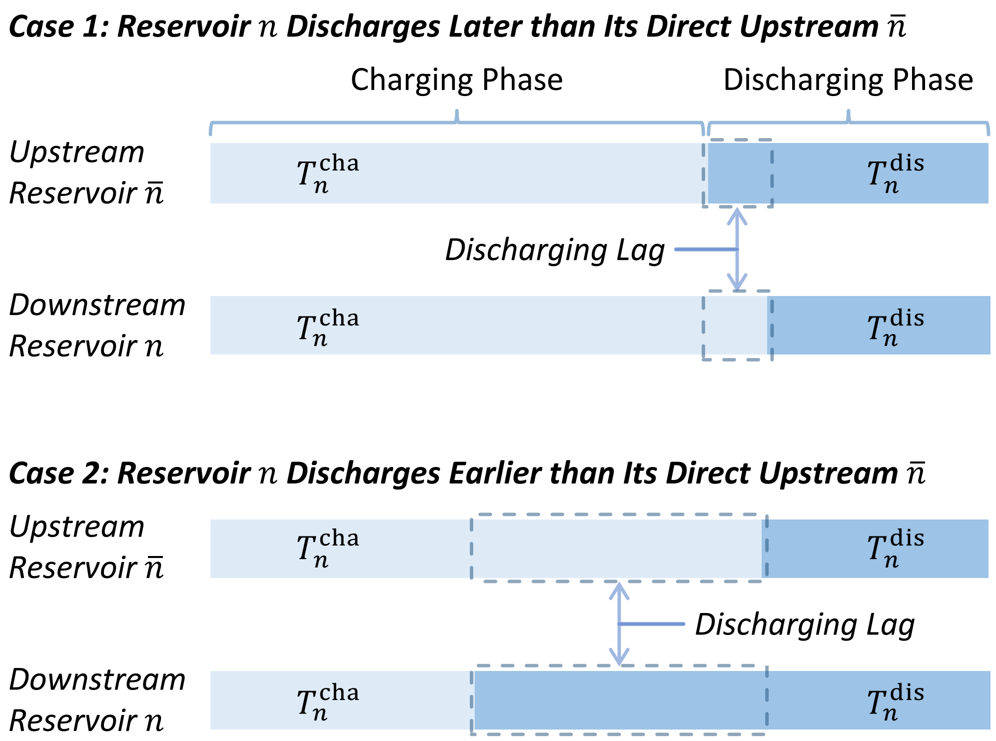
$$\mathbb{P}\left\{V_n^{min} \le V_{n,1}^{bc} + \sum_{k=1}^{t}\left(\widehat{W}_{nk} + W_{nk}^{\Delta}\right) \le V_n^{max}, n = 1, \dots, N\right\} \ge 1 - \alpha_t,$$
$$t = 1, \dots, T$$

Solving Method

1. Use Boole's inequality to decompose each joint chance constraint into individual chance constraints;
2. Convert the individual chance constraints into deterministic constraints based on the affine invariance of GMM.

Optimization Module: Constraints of Future Period

A MILP Model to Quantify the Future Value



Use multi-parametric mixed-integer linear programming to refine the locational marginal water value

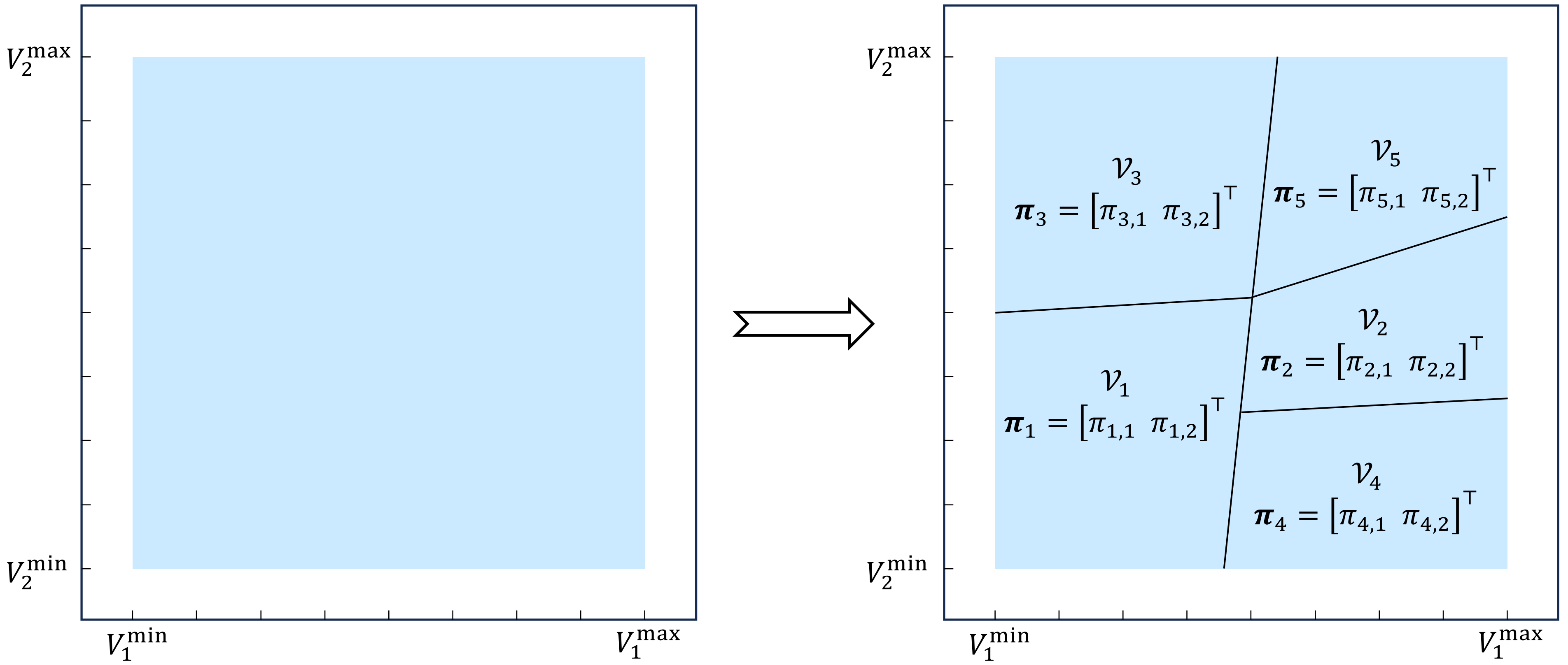
↓

Amount of hydrogeneration that one-unit storage water can bring to the system

Not as comprehensive as the current-period part but enough for quantifying the future value.

Optimization Module: Constraints of Future Period

Refining locational marginal water value $\boldsymbol{\pi}$ via multi-parametric mixed-integer linear programming



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Optimization Module: Constraints of Future Period

Representing the future value as "If-Then" constrains

$$\text{Future Value}(\boldsymbol{V}^{cs}) = \begin{cases} \sum_{n=1}^{N} \pi_{1,n}\left(V_n^{cs} - V_n^{min}\right) & \text{if } \boldsymbol{V}^{cs} \in \mathcal{V}_1 \\ \vdots & \\ \sum_{n=1}^{N} \pi_{R,n}\left(V_n^{cs} - V_n^{min}\right) & \text{if } \boldsymbol{V}^{cs} \in \mathcal{V}_R \end{cases}$$

Easy-to-understand and computationally easy!

Optimization Module: Final Model

A MILP model that is directly solvable by solvers:

$$\max_{\boldsymbol{x},\boldsymbol{y}} \boldsymbol{a}^{\top}\boldsymbol{x} + \boldsymbol{b}^{\top}\boldsymbol{y}$$

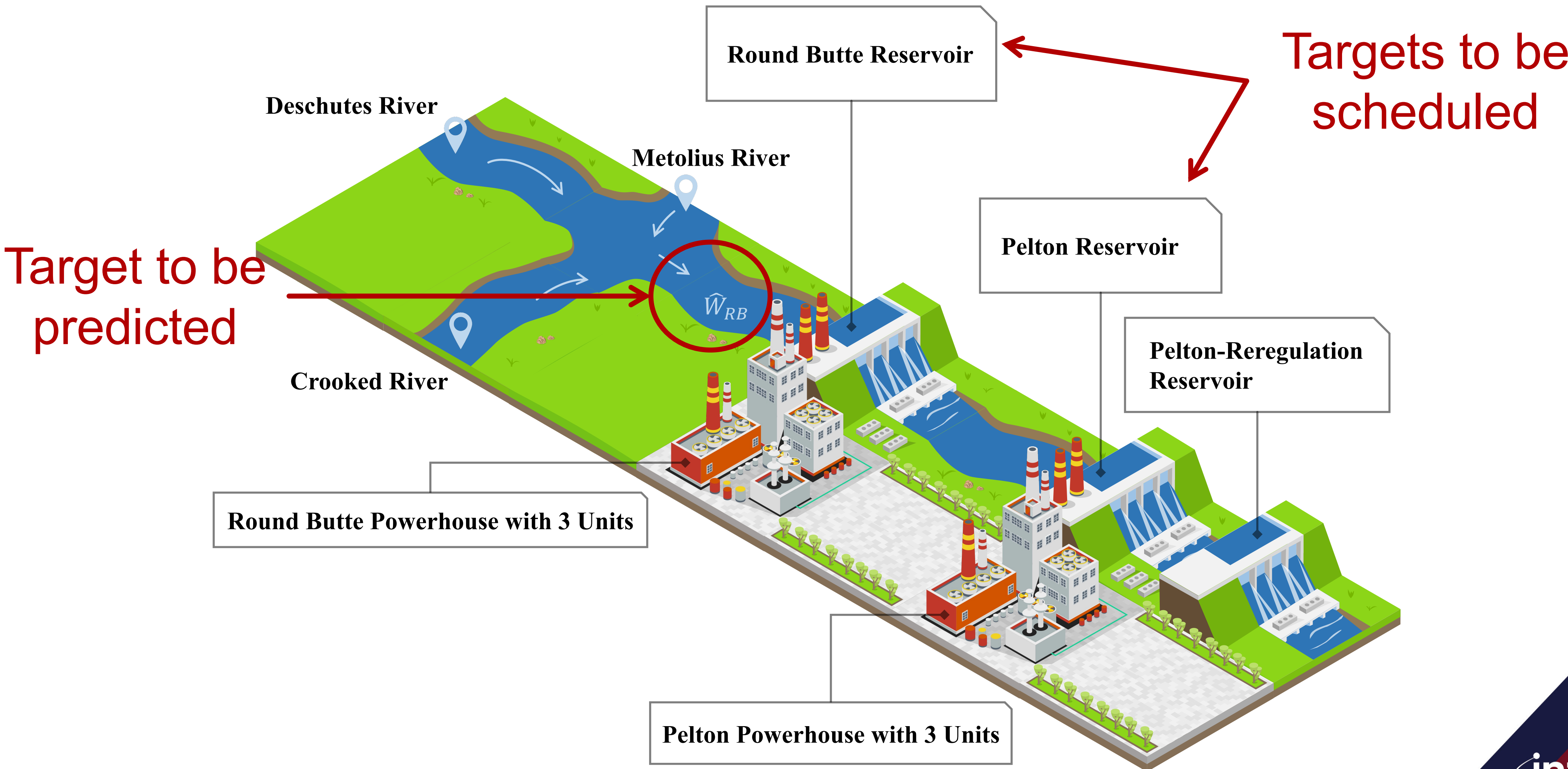
→ Immediate Benefit & Future Value

$$s.t.\ \boldsymbol{x} \in \{0,1\}, \boldsymbol{y} \geq 0;$$

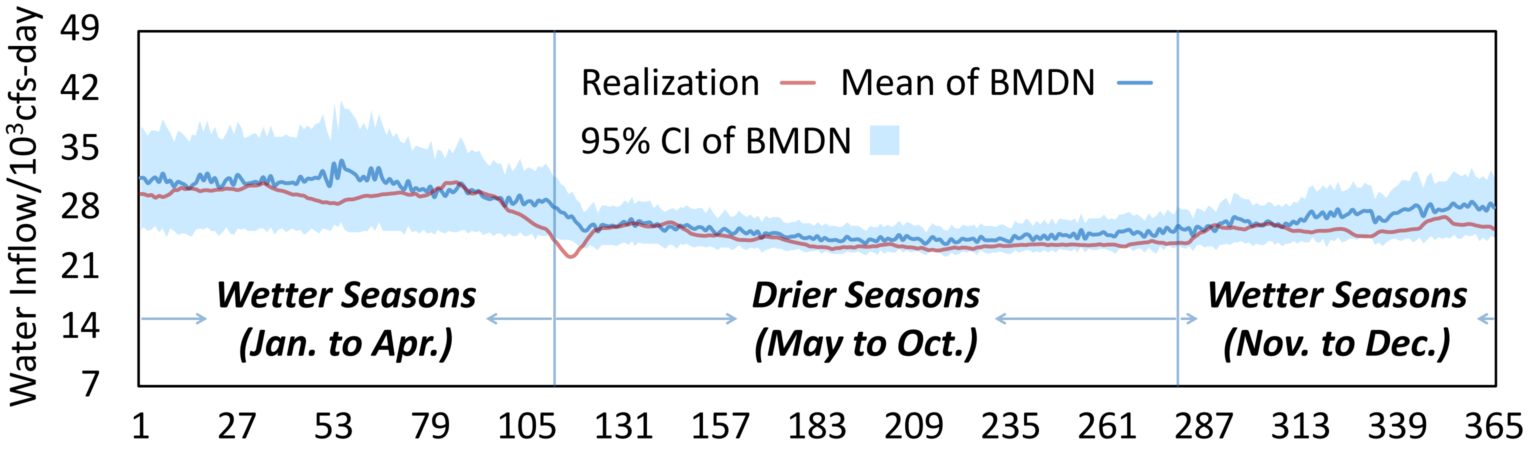
$$\boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{y} \leq \boldsymbol{c}.$$

- Deterministic constraints for base-case operations
- Reformulation of joint chance constraints
- Linear constraints of "If-Then" logic

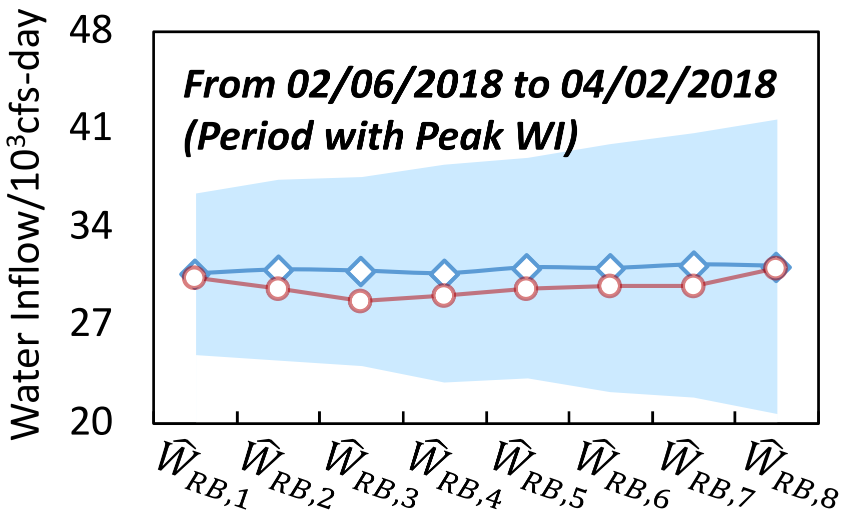
Case Studies: Portland General Electric's System



Case Studies: Prediction Performance

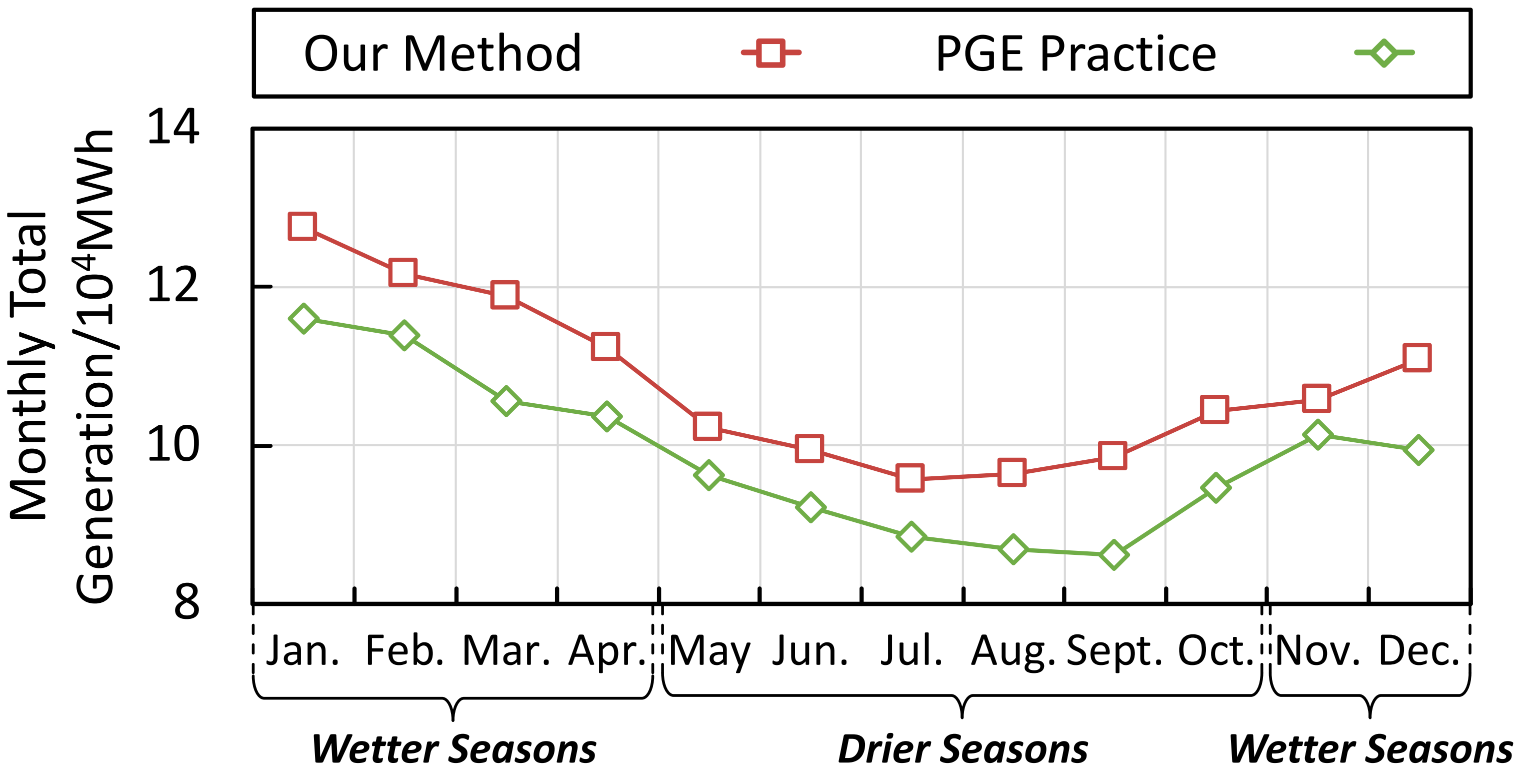


- The confidence interval can cover most realizations. (Tight)



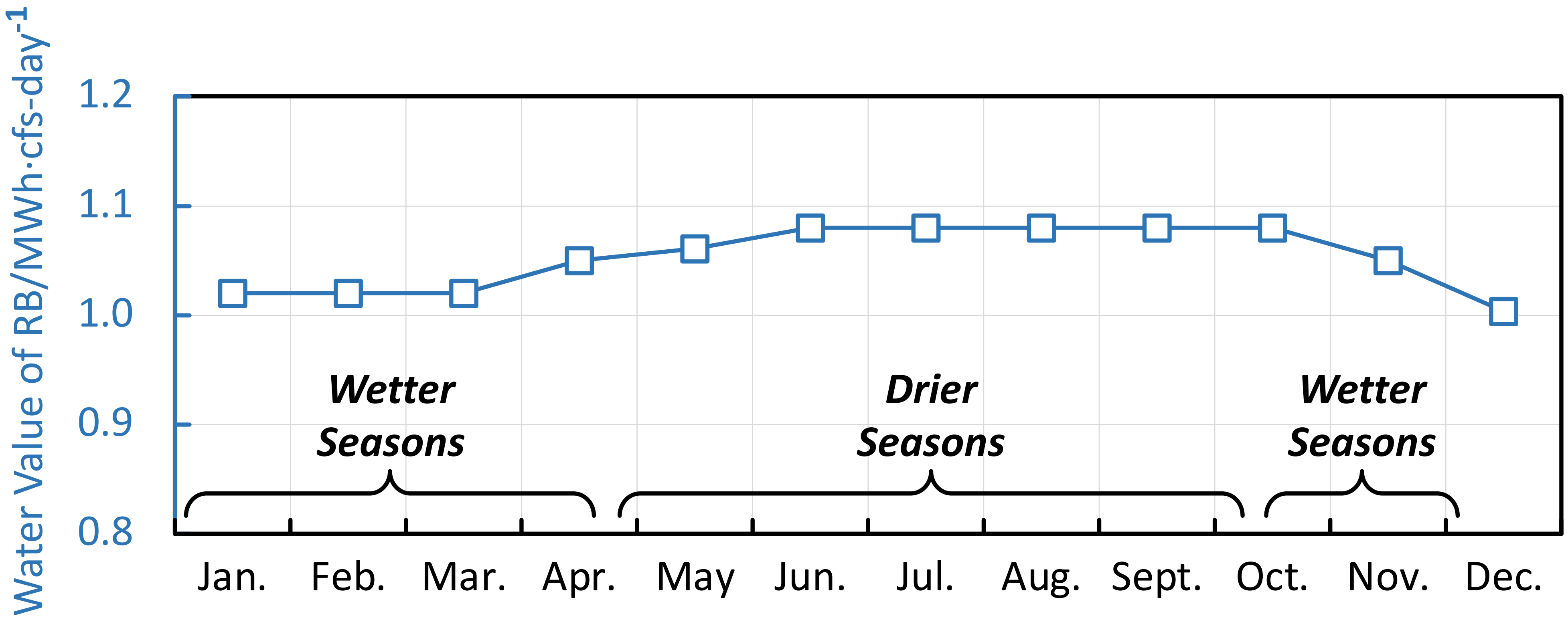
- A shape of trumpet (Confident on next week but not confident for the weeks far from now)

Case Studies: Scheduling Results



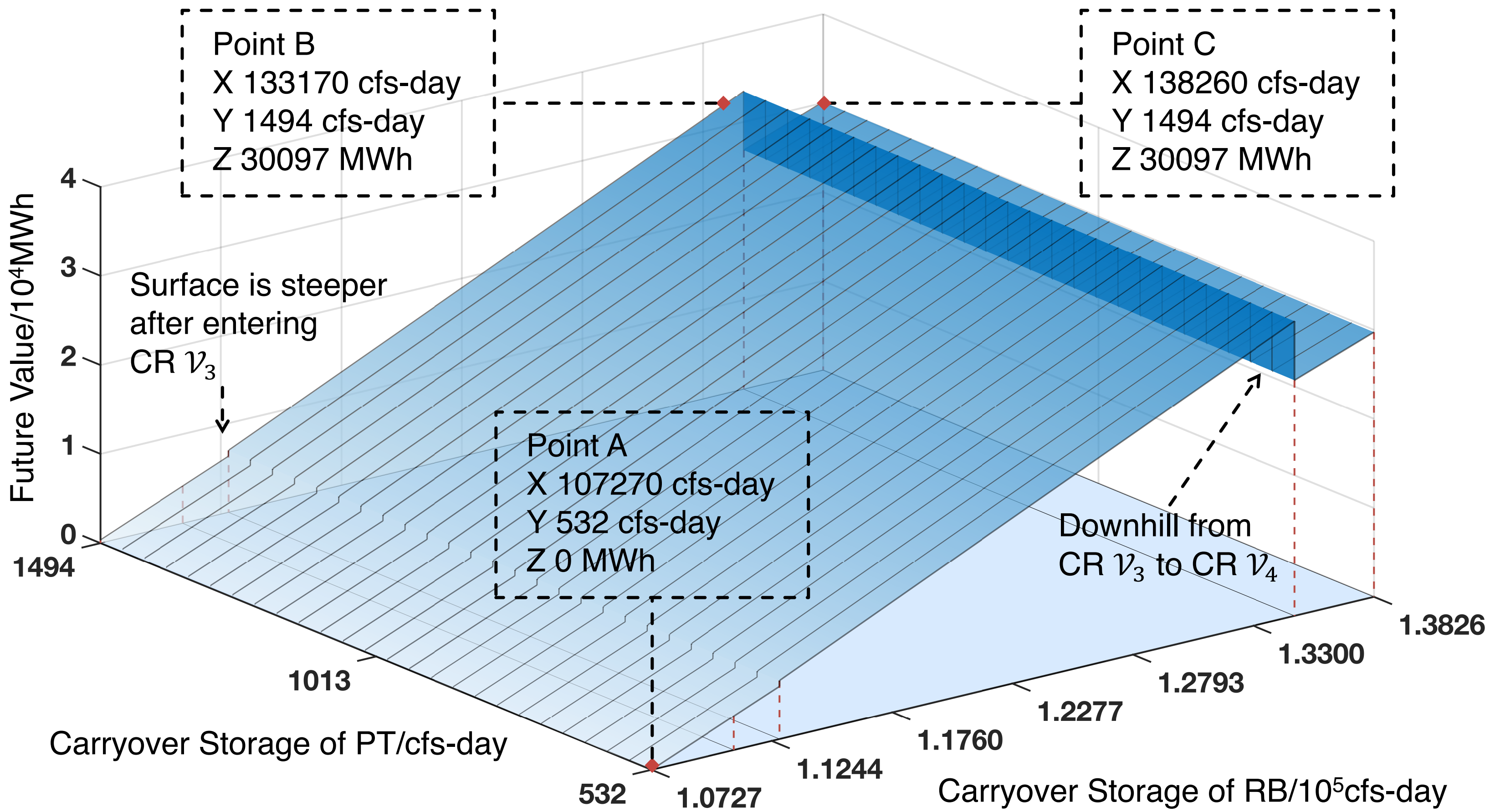
- Our method outperforms the PGE practice in the generation results.

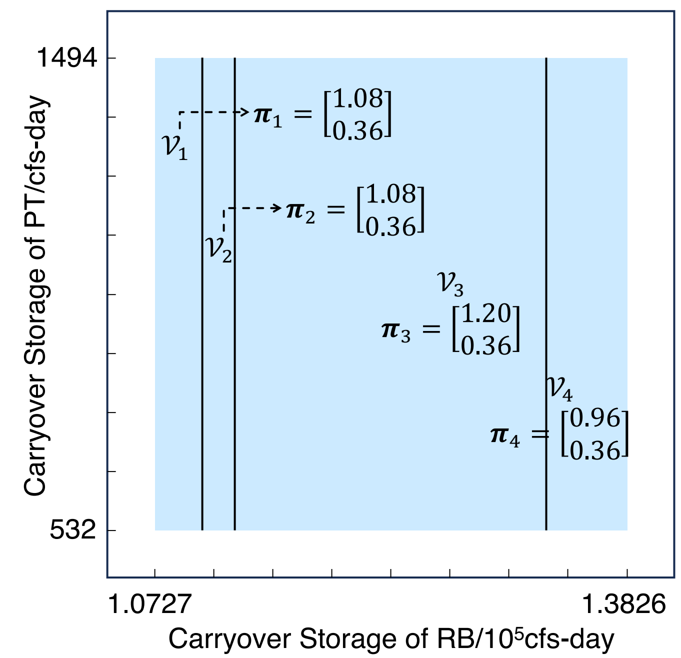
Case Studies: Water Value



- Locational marginal water values are hydrologically adaptive.

Case Studies: Visualization of Future Value





Summary

1. The presented uncertainty-aware predictor can provide high-quality predictions of water inflow;

2. The presented model can leverage the water inflow to improve the hydropower generation;

3. The presented method provides an interpretable, hydrologically adaptive, and easy-to-use way to quantify the future value.