On the feasibility of leveraging upper storage zones of Japanese public dam reservoirs for hydro-power generation

A Preprint

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Abstract

Dam operation is a problem of control under uncertainty, as optimal policies are functions of noisy forecasts of river discharges incoming to dam reservoirs. The uncertainty in discharge forecast can be attributed to two main factors: Uncertainty in atmospheric (mostly precipitation) forecasts, and in hydrological (mostly evaporation and runoff) modeling. High levels of uncertainty and abundant alternative sources of power generation have lead Japanese public dam operators to adopt conservative operation strategies so as to minimize the risk of dam failures. However two factors may come to challenge this status quo: First, social and environmental pressures on fossil fuel and nuclear energy production are foreseen to increase the value of hydrological power generation. Second, advances in both environmental modeling and statistical inference models are foreseen to increase the accuracy of forecast. Combined, these two factors may challenge the current risk-benefit analysis of dam operation towards adopting policies more focused on energy production. This work aims to lay out the foundations for a large scale study on the feasibility of implementing such policies. We do so by providing the following three contributions. First we propose a conceptual framework to XXX. Second, we propose a dataset to benchmark the accuracy of different atmospheric and hydrological models on this problem. Finally we investigate the impact of

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1 Introduction

A mountainous topology and a heavy rain climate lend Japan a high potential for hydro power generation . Historically, Japan has extensively relied on its hydrological power generation up until the second world war. As the period of great economic development called for increased energy consumption, fossil fuel plants have come to fill this demand for their ability to quickly and efficiently provide for this sudden jump in demand. Later, the oil shock has seen Japan develop nuclear power generation for strategical reasons, to ensure its energy independency.

Nuclear incidents and international pledges to reduce carbon emissions have come to threaten the long term viability of the current energy mix.

As solar and wind power generation is being pushed forward, they are widely considered as inufficient in their own due to their intermittent nature.

Hydro is low-carbon and a variety of hydro power plant can bring both base load and demand response.

For all its benefits, voices are calling for the optimization of Japanese dam operations.

The fundamental problem of dam operation is that of two opposing objectives: On the one hand energy production (as well as irrigation) benefits from keeping high levels of water into the reservoir. Indeed the higher water levels are, the more potential energy it stores, thus the more energy it can create for a given volume of output water discharge. On the other hand, flood control benefits from low level of reservoir filling, as lower water levels enable to hold more incoming water, thus better buffering high discharge flows to prevent potential floods. An optimal operation policy is one that maximizes energy production while minimizing the risk of flooding. However, keeping appropriate levels in the reservoir at each time requires knowledge of the amount of water flowing into the reservoir ahead of time, i.e. accurate river discharge forecast.

In particular, optimizing dam operation for energy production comes with a risk of dam failures: Dam failure happens when the the dam reaches its full capacity due to large volume of water flowing into the reservoir. In such cases, the reservoir is then brutally emptied to prevent the dam infrastructure to collapse under the forces exerced by the water, thus flooding the downstream areas, at great cost for the population living there.

Highly accurate river discharge forecast enable dam operators to keep reservoirs high to maximize energy production while ensuring dam failures do not occur. In contrast, inaccurate river discharge forecast force dam operators to keep lower water levels in the reservoir to avoid dam failures in case of unexpected sudden inflows, resulting in inefficient power generation policies.

Two main factors are responsible for the uncertainty in river discharge forecast, Atmospheric forecast, and hydrological modeling.

Summary of contributions:

- Data operational
- Operational models for reservoir input flow
- Methodolody: Vertical integration.
- Open-source everything with easy-to-use tutorials for researchers to join.

Limitations

- No multi-purpose
- No multi-dam

Nevertheless, we hope it's useful, and can serve to build more onto.

2 Related Work

Hydro modeling

Hydro forecast

Dam operation.

What else?

3 Methodolody

3.1 Overview

What else

3.2 Meteorological model

The meteorological model provides atmospheric variables.

3.3 Hydrological Model

The hydro model output river discharge incoming to the dam reservoir from the atmospheric variables, either observed or forecasted.

3.4 Dam Model

Reservoir geometry: We infer the maximum volume from the observations. We infer the maximum height from Wikipedia. We then implemented both trapezoid and truncated cone geometry for the dam reservoir.

Operation: We define two doors, one big door that does not produce energy. The dimension of the door is inferred from data (= to the max observed outflow release). One small door that produces electricity (heuristic size = 1/50th of the big door).

3.5 Grid Response

The grid response model defines the reward r obtained for a given power production P at a given time t. This reward can be though of as a profit in a free-market economy, and is the sum of two terms:

$$r = r_p(P, t) + r_n(t)$$

The positive reward quantifies the benefit of energy produced. Currently, we use $r_p(P, t) = P$, considering constant value over time of the generated power. However, hydro's value lies in its non-intermittence to supplement intermittent sources. Integrating the fluctuations of intermitent sources and their impact on the value of hydro power generation at different seasons and time of the day may prove interesting for future research.

The negative reward quantifies the cost of a dam failure. We set this cost to be constant $r_n(t) = C$ per dam, as the maximum positive reward that can be produced by this dam over the whole period of operation, so that the negative impact of a single dam failure over the whole period of activity would outweight the benefits of full power production of the whole dam operation.

3.6 Dam Operation Model

Every hour, the dam operator can either open the big door, the small door or do nothing for one hour: Action space $\mathcal{A} = \{a1, a2, a3\}$

Decisions are made based on the current level of the reservoir as well as the future input discharge forecast for a given horizon. State space S = [Current volume / height, inflow forecasts]

Our goal is to learn a policy function $\Pi : \mathcal{S} \rightarrow \mathcal{A}$ that maximizes reward. The reward for electricity production is proportional to the height of the water level times the volume of water discharged. Negative reward is also associated with dam failures:

4 Proposed Dataset

5 Optimal Dam Operation

We start by optimizing the dam without any uncertainty.

5.1 Baseline

5.2 Optimal Operator

5.3 Operation Under Uncertainty

5.4 Experiment

- Answers the following question:

1. What is the forecast horizon needed in order to keep the dam from overflowing? -> Show as input distribution.

2. Impact of state design on RL baseline.

3. Show the ideal model is brittle. How?

Table 1: Model accuracy

Part		
Name	Description	Size (μm)
Dendrite	Input terminal	$\sim$100
Axon	Output terminal	$\sim$10
Soma	Cell body	up to 10^6

6 Hydrological Uncertainty

In this section, we use assimilated data, no forecast.

6.1 Hydrological Models

Use Camaflood, conceptual rainfall runoff, linear, non-linear and deep machine learning models.

6.2 Experiments

6.2.1 Discharge prediction

Show accuracy of different models.

6.2.2 Dam operation

Show reward of different models.

7 Meteorological Uncertainty

7.1 Meteo Data

7.2 Experiments

Use different data source.

7.3 Meteorological Uncertainty

8 Limitations

- No multi-purpose
- No multi-dam
- No explicit evaporation modeling
- Heuristic dimensioning.
- No river and snow gauge.

9 Conclusion

Conclusion